



NVIDIA TensorRT

Developer Guide | NVIDIA Docs

Table of Contents

| | |
|---|----|
| Revision History..... | x |
| Chapter 1. Introduction..... | 1 |
| 1.1. Structure of This Guide..... | 1 |
| 1.2. Samples..... | 1 |
| 1.3. Complementary GPU Features..... | 1 |
| 1.4. Complementary Software..... | 2 |
| 1.5. ONNX..... | 2 |
| 1.6. Code Analysis Tools..... | 3 |
| 1.7. API Versioning..... | 3 |
| 1.8. Deprecation Policy..... | 3 |
| 1.9. Hardware Support Lifetime..... | 4 |
| 1.10. Support..... | 4 |
| 1.11. Reporting Bugs..... | 4 |
| Chapter 2. TensorRT's Capabilities..... | 5 |
| 2.1. C++ and Python APIs..... | 5 |
| 2.2. The Programming Model..... | 5 |
| 2.2.1. The Build Phase..... | 5 |
| 2.2.2. The Runtime Phase..... | 6 |
| 2.3. Plugins..... | 7 |
| 2.4. Types and Precision..... | 7 |
| 2.4.1. Supported Types..... | 7 |
| 2.4.2. Strong Typing vs Weak Typing..... | 8 |
| 2.5. Quantization..... | 9 |
| 2.6. Tensors and Data Formats..... | 9 |
| 2.7. Dynamic Shapes..... | 10 |
| 2.8. DLA..... | 10 |
| 2.9. Updating Weights..... | 10 |
| 2.10. Streaming Weights..... | 10 |
| 2.11. trtexec Tool..... | 11 |
| 2.12. Polygraphy..... | 11 |
| Chapter 3. The C++ API..... | 12 |
| 3.1. The Build Phase..... | 12 |
| 3.1.1. Creating a Network Definition..... | 12 |
| 3.1.2. Importing a Model Using the ONNX Parser..... | 13 |
| 3.1.3. Building an Engine..... | 13 |

| | |
|---|-----------|
| 3.2. Deserializing a Plan..... | 14 |
| 3.3. Performing Inference..... | 14 |
| Chapter 4. The Python API..... | 16 |
| 4.1. The Build Phase..... | 16 |
| 4.1.1. Creating a Network Definition in Python..... | 16 |
| 4.1.2. Importing a Model Using the ONNX Parser..... | 17 |
| 4.1.3. Building an Engine..... | 17 |
| 4.2. Deserializing a Plan..... | 17 |
| 4.3. Performing Inference..... | 18 |
| Chapter 5. How TensorRT Works..... | 19 |
| 5.1. Object Lifetimes..... | 19 |
| 5.2. Error Handling and Logging..... | 19 |
| 5.3. Memory..... | 20 |
| 5.3.1. The Build Phase..... | 20 |
| 5.3.2. The Runtime Phase..... | 20 |
| 5.3.3. CUDA Lazy Loading..... | 22 |
| 5.3.4. L2 Persistent Cache Management..... | 22 |
| 5.4. Threading..... | 22 |
| 5.5. Determinism..... | 23 |
| 5.5.1. IFillLayer Determinism..... | 23 |
| 5.5.2. IScatterLayer Determinism..... | 23 |
| 5.6. Runtime Options..... | 24 |
| 5.7. Compatibility..... | 24 |
| Chapter 6. Advanced Topics..... | 25 |
| 6.1. Version Compatibility..... | 25 |
| 6.1.1. Manually Loading the Runtime..... | 26 |
| 6.1.2. Loading from Storage..... | 26 |
| 6.1.3. Using Version Compatibility with the ONNX Parser..... | 26 |
| 6.2. Hardware Compatibility..... | 27 |
| 6.3. Compatibility Checks..... | 27 |
| 6.4. Refitting an Engine..... | 28 |
| 6.4.1. Weight-Stripping..... | 30 |
| 6.4.2. Refitting a Weight-Stripped Engine Directly from ONNX..... | 31 |
| 6.4.3. Weight-Stripping Work with Lean Runtime..... | 32 |
| 6.4.4. Fine Grained Refit Build..... | 32 |
| 6.4.5. Stripping Weights with Fine-Grained Refit Build..... | 33 |
| 6.5. Algorithm Selection and Reproducible Builds..... | 33 |
| 6.6. Creating a Network Definition from Scratch..... | 35 |

| | |
|--|-----------|
| 6.6.1. C++..... | 35 |
| 6.6.2. Python..... | 36 |
| 6.7. Strongly Typed Networks..... | 38 |
| 6.8. Reduced Precision in Weakly-Typed Networks..... | 38 |
| 6.8.1. Network-Level Control of Precision..... | 38 |
| 6.8.2. Layer-Level Control of Precision..... | 39 |
| 6.8.3. TF32..... | 41 |
| 6.8.4. BF16..... | 41 |
| 6.9. Control of Computational Precision..... | 42 |
| 6.10. I/O Formats..... | 43 |
| 6.11. Explicit vs Implicit Batch..... | 45 |
| 6.12. Sparsity..... | 46 |
| 6.13. Empty Tensors..... | 47 |
| 6.14. Reusing Input Buffers..... | 47 |
| 6.15. Engine Inspector..... | 47 |
| 6.16. Optimizer Callbacks..... | 49 |
| 6.17. Preview Features..... | 49 |
| 6.18. Debug Tensors..... | 50 |
| 6.19. Weight Streaming..... | 51 |
| 6.20. Cross-Platform Compatibility..... | 52 |
| Chapter 7. Working with Quantized Types..... | 53 |
| 7.1. Introduction to Quantization..... | 53 |
| 7.1.1. Quantization Workflows..... | 53 |
| 7.1.2. Explicit Versus Implicit Quantization..... | 53 |
| 7.1.3. Quantization Schemes..... | 55 |
| 7.1.4. Quantization Modes..... | 56 |
| 7.2. Setting Dynamic Range..... | 58 |
| 7.3. Post-Training Quantization Using Calibration..... | 58 |
| 7.3.1. INT8 Calibration Using C++..... | 60 |
| 7.3.2. Calibration Using Python..... | 60 |
| 7.3.3. Quantization Noise Reduction..... | 61 |
| 7.4. Explicit Quantization..... | 61 |
| 7.4.1. Quantized Weights..... | 61 |
| 7.4.2. ONNX Support..... | 62 |
| 7.4.3. TensorRT Processing of Q/DQ Networks..... | 63 |
| 7.4.4. Weight-Only Quantization..... | 65 |
| 7.4.5. Q/DQ Layer-Placement Recommendations..... | 66 |
| 7.4.6. Q/DQ Limitations..... | 71 |

| | |
|---|-----------|
| 7.4.7. Q/DQ Interaction with Plugins..... | 72 |
| 7.4.8. QAT Networks Using TensorFlow..... | 73 |
| 7.4.9. QAT Networks Using PyTorch..... | 73 |
| 7.4.10. QAT Networks Using TransformerEngine..... | 73 |
| 7.5. Quantized Types Rounding Modes..... | 73 |
| Chapter 8. Working with Dynamic Shapes..... | 74 |
| 8.1. Specifying Runtime Dimensions..... | 75 |
| 8.2. Named Dimensions..... | 76 |
| 8.3. Dimension Constraint using IAssertionLayer..... | 77 |
| 8.4. Optimization Profiles..... | 77 |
| 8.5. Dynamically Shaped Output..... | 79 |
| 8.5.1. Looking up Binding Indices for Multiple Optimization Profiles..... | 81 |
| 8.5.2. Bindings For Multiple Optimization Profiles..... | 81 |
| 8.6. Layer Extensions For Dynamic Shapes..... | 82 |
| 8.7. Restrictions For Dynamic Shapes..... | 83 |
| 8.8. Execution Tensors Versus Shape Tensors..... | 83 |
| 8.8.1. Formal Inference Rules..... | 84 |
| 8.9. Shape Tensor I/O (Advanced)..... | 85 |
| 8.10. INT8 Calibration with Dynamic Shapes..... | 86 |
| Chapter 9. Extending TensorRT with Custom Layers..... | 88 |
| 9.1. Adding Custom Layers Using the C++ API..... | 88 |
| 9.1.1. Implementing a Plugin Class..... | 89 |
| 9.1.2. Implementing a Plugin Creator Class..... | 89 |
| 9.1.3. Registering a Plugin Creator with the Plugin Registry..... | 90 |
| 9.1.4. Adding a Plugin Instance to a TensorRT Network..... | 90 |
| 9.1.5. Example: Adding a Custom Layer with Dynamic Shapes using Using C++..... | 91 |
| 9.1.6. Example: Adding a Custom Layer with Data-Dependent and Shape Input- Dependent Shapes Using C++..... | 94 |
| 9.1.7. Example: Adding a Custom Layer with INT8 I/O Support Using C++..... | 97 |
| 9.2. Adding Custom Layers using the Python API..... | 98 |
| 9.2.1. Registration of a Python Plugin..... | 99 |
| 9.2.2. Building and Running TensorRT Engines Containing Python Plugins..... | 99 |
| 9.2.3. Implementing enqueue of a Python Plugin..... | 99 |
| 9.2.4. Translating Device Buffers/CUDA Stream Pointers in enqueue to other Frameworks..... | 100 |
| 9.2.5. Automatic Downcasting..... | 100 |
| 9.2.6. Example: Adding a Custom Layer to a TensorRT Network Using Python..... | 101 |
| 9.3. Enabling Timing Caching and Using Custom Tactics..... | 101 |

| | |
|---|------------|
| 9.4. Sharing Custom Resources Among Plugins..... | 103 |
| 9.4.1. Example: Sharing Weights Downloaded Over a Network Among Different Plugins..... | 103 |
| 9.5. Using Custom Layers When Importing a Model with a Parser..... | 105 |
| 9.6. Plugin API Description..... | 106 |
| 9.6.1. IPluginV3 API Description..... | 106 |
| 9.6.2. IPluginCreatorV3One API Description..... | 108 |
| 9.7. Migrating V2 Plugins to IPluginV3..... | 109 |
| 9.7.1. Plugin Initialization and Termination..... | 110 |
| 9.7.2. Accessing Context-Specific Resources Provided by TensorRT..... | 110 |
| 9.7.3. Plugin Serialization and Deserialization..... | 111 |
| 9.7.4. Migrating Older V2 Plugins to IPluginV3..... | 111 |
| 9.8. Coding Guidelines for Plugins..... | 112 |
| 9.9. Plugin Shared Libraries..... | 113 |
| 9.9.1. Generating Plugin Shared Libraries..... | 113 |
| 9.9.2. Using Plugin Shared Libraries..... | 114 |
| Chapter 10. Working with Loops..... | 115 |
| 10.1. Defining a Loop..... | 115 |
| 10.2. Formal Semantics..... | 118 |
| 10.3. Nested Loops..... | 118 |
| 10.4. Limitations..... | 119 |
| 10.5. Replacing IRNNv2Layer with Loops..... | 119 |
| Chapter 11. Working with Conditionals..... | 120 |
| 11.1. Defining a Conditional..... | 120 |
| 11.2. Conditional Execution..... | 122 |
| 11.3. Nesting and Loops..... | 123 |
| 11.4. Limitations..... | 124 |
| 11.5. Conditional Examples..... | 124 |
| 11.5.1. Simple If-Conditional..... | 124 |
| 11.5.2. Exporting from PyTorch..... | 125 |
| Chapter 12. Working with DLA..... | 126 |
| 12.1. Building and Launching the Loadable..... | 127 |
| 12.1.1. Using trtexec..... | 128 |
| 12.1.2. Using the TensorRT API..... | 128 |
| 12.1.2.1. Running on DLA during TensorRT Inference..... | 128 |
| 12.1.2.2. Example: Run Samples with DLA..... | 129 |
| 12.1.2.3. Example: Enable DLA Mode for a Layer during Network Creation..... | 129 |
| 12.1.3. Using the cuDLA API..... | 130 |

| | |
|---|------------|
| 12.2. DLA-Supported Layers and Restrictions..... | 130 |
| 12.2.1. General Restrictions..... | 130 |
| 12.2.2. Layer Support and Restrictions..... | 131 |
| 12.2.3. Inference on NVIDIA Orin..... | 135 |
| 12.3. GPU Fallback Mode..... | 136 |
| 12.4. I/O Formats on DLA..... | 136 |
| 12.5. DLA Standalone Mode..... | 137 |
| 12.5.1. Building A DLA Loadable Using C++..... | 137 |
| 12.5.1.1. Using trtexec To Generate A DLA Loadable..... | 137 |
| 12.6. Customizing DLA Memory Pools..... | 138 |
| 12.6.1. Determining DLA Memory Pool Usage..... | 138 |
| 12.7. Sparsity on DLA..... | 139 |
| 12.7.1. Structured Sparsity..... | 139 |
| Chapter 13. Performance Best Practices..... | 140 |
| 13.1. Performance Benchmarking using trtexec..... | 140 |
| 13.1.1. Performance Benchmarking with an ONNX File..... | 140 |
| 13.1.2. Performance Benchmarking with ONNX+Quantization..... | 141 |
| 13.1.3. Per-Layer Runtime and Layer Information..... | 142 |
| 13.1.4. Performance Benchmarking with TensorRT Plan File..... | 144 |
| 13.1.5. Duration and Number of Iterations..... | 144 |
| 13.2. Advanced Performance Measurement Techniques..... | 144 |
| 13.2.1. Wall-clock Timing..... | 145 |
| 13.2.2. CUDA Events..... | 145 |
| 13.2.3. Built-In TensorRT Profiling..... | 146 |
| 13.2.4. CUDA Profiling Tools..... | 147 |
| 13.2.4.1. Profiling for DLA..... | 151 |
| 13.2.5. Tracking Memory..... | 152 |
| 13.3. Hardware/Software Environment for Performance Measurements..... | 153 |
| 13.3.1. GPU Information Query and GPU Monitoring..... | 153 |
| 13.3.2. GPU Clock Locking and Floating Clock..... | 153 |
| 13.3.3. GPU Power Consumption and Power Throttling..... | 154 |
| 13.3.4. GPU Temperature and Thermal Throttling..... | 155 |
| 13.3.5. H2D/D2H Data Transfers and PCIe Bandwidth..... | 155 |
| 13.3.6. TCC Mode and WDDM Mode..... | 156 |
| 13.3.7. Enqueue-Bound Workloads and CUDA Graphs..... | 157 |
| 13.3.8. BlockingSync and SpinWait Synchronization Modes..... | 157 |
| 13.4. Optimizing TensorRT Performance..... | 158 |
| 13.4.1. Batching..... | 158 |

| | |
|--|------------|
| 13.4.2. Within-Inference Multi-Streaming..... | 159 |
| 13.4.3. Cross-Inference Multi-Streaming..... | 160 |
| 13.4.4. CUDA Graphs..... | 161 |
| 13.4.5. Enabling Fusion..... | 162 |
| 13.4.5.1. Layer Fusion..... | 162 |
| 13.4.5.2. Types of Fusions..... | 163 |
| 13.4.5.3. PointWise Fusion..... | 165 |
| 13.4.5.4. Q/DQ Fusion..... | 166 |
| 13.4.5.5. Multi-Head Attention Fusion..... | 166 |
| 13.4.6. Limiting Compute Resources..... | 166 |
| 13.4.7. Deterministic Tactic Selection..... | 167 |
| 13.4.8. Overhead of Shape Change and Optimization Profile Switching..... | 168 |
| 13.5. Optimizing Layer Performance..... | 168 |
| 13.6. Optimizing for Tensor Cores..... | 169 |
| 13.7. Optimizing Plugins..... | 170 |
| 13.8. Optimizing Python Performance..... | 171 |
| 13.9. Improving Model Accuracy..... | 171 |
| 13.10. Optimizing Builder Performance..... | 172 |
| 13.10.1. Timing Cache..... | 172 |
| 13.10.2. Tactic Selection Heuristic..... | 173 |
| 13.11. Builder Optimization Level..... | 173 |
| Chapter 14. Troubleshooting..... | 175 |
| 14.1. FAQs..... | 175 |
| 14.2. Understanding Error Messages..... | 178 |
| 14.3. Code Analysis Tools..... | 182 |
| 14.3.1. Compiler Sanitizers..... | 182 |
| 14.3.1.1. Issues with dlopen and Address Sanitizer..... | 182 |
| 14.3.1.2. Issues with dlopen and Thread Sanitizer..... | 182 |
| 14.3.1.3. Issues with CUDA and Address Sanitizer..... | 182 |
| 14.3.1.4. Issues with Undefined Behavior Sanitizer..... | 182 |
| 14.3.2. Valgrind..... | 183 |
| 14.3.3. Compute Sanitizer..... | 183 |
| 14.4. Understanding Formats Printed in Logs..... | 183 |
| 14.5. Reporting TensorRT Issues..... | 184 |
| 14.5.1. Channels for TensorRT Issue Reporting..... | 184 |
| 14.5.2. Reporting a Functional Issue..... | 185 |
| 14.5.3. Reporting an Accuracy Issue..... | 185 |
| 14.5.4. Reporting a Performance Issue..... | 186 |

| | |
|------------------------------------|-----|
| Appendix A. Appendix..... | 187 |
| A.1. Data Format Descriptions..... | 187 |
| A.2. Command-Line Programs..... | 191 |
| A.3. Glossary..... | 198 |
| A.4. ACKNOWLEDGEMENTS..... | 199 |

Revision History

This is the revision history of the NVIDIA TensorRT 10.3.0 Developer Guide.

Chapter 5 Updates

| Date | Summary of Change |
|----------------|---|
| August 5, 2024 | Added enqueue memory as a type of device memory in The Runtime Phase section. |

Chapter 6 Updates

| Date | Summary of Change |
|---------------|---|
| July 23, 2024 | Added a new topic called Cross-Platform Compatibility . |

Chapter 8 Updates

| Date | Summary of Change |
|---------------|--|
| July 18, 2024 | Clarified what happens when a tensor has been classified as an execution tensor in the Execution Tensors Versus Shape Tensors section. |

Chapter 9 Updates

| Date | Summary of Change |
|----------------|---|
| August 2, 2024 | <ul style="list-style-type: none">▶ Added base classes for the <code>IPluginV3</code> plugin in the Implementing a Plugin Class section.▶ Added <code>IPluginV3OneBuildV2</code> to the IPluginV3 API Description section. |

List of Figures

| | |
|---|-----|
| Figure 1. Creating a Graph for FP32 Accumulation Request..... | 42 |
| Figure 2. A quantizable AveragePool layer (in blue) is fused with DQ and Q layers. All three layers are replaced by a quantized AveragePool layer (in green)..... | 63 |
| Figure 3. An illustration depicting a DQ forward-propagation and Q backward-propagation..... | 64 |
| Figure 4. Weight-only Quantization (WoQ)..... | 65 |
| Figure 5. Two examples of how TensorRT fuses convolutional layers. Only the inputs are quantized on the left and the right; both inputs and output are quantized..... | 66 |
| Figure 6. Example of a linear operation followed by an activation function..... | 67 |
| Figure 7. Batch normalization is fused with convolution and ReLU while keeping the same execution order defined in the pre-fusion network. There is no need to simulate BN-folding in the training network..... | 67 |
| Figure 8. The precision of xf1 is a floating point, so the output of the fused convolution is limited to the floating point, and the trailing Q-layer cannot be fused with the convolution..... | 68 |
| Figure 9. When xf1 is quantized to INT8, the output of the fused convolution is also INT8, and the trailing Q-layer is fused with the convolution..... | 69 |
| Figure 10. An example of quantizing a quantizable operation. An element-wise addition is fused with the input DQs and the output Q..... | 70 |
| Figure 11. An example of suboptimal quantization fusions: contrast the suboptimal fusion in A and the optimal fusion in B. The extra pair of Q/DQ operations (highlighted with a glowing green border) forces the separation of the convolution from the element-wise addition..... | 71 |
| Figure 12. An example showing scales of Q1 and Q2 are compared for equality, and if equal, they are allowed to propagate backward. If the engine is refitted with new values for Q1 and Q2 such that $Q1 \neq Q2$, then an exception aborts the refitting process..... | 72 |
| Figure 13. Optimization Profile..... | 82 |
| Figure 14. A TensorRT loop is set by loop boundary layers. Dataflow can leave the loop only by ILoopOutputLayer. The only back edges allowed are the second input to IRecurrenceLayer..... | 116 |

| | |
|---|-----|
| Figure 15. An If-Conditional Construct Abstract Model..... | 122 |
| Figure 16. Controlling Conditional-Execution using IfConditionalInputLayer Placement..... | 123 |
| Figure 17. Workflow for the Building and Runtime Phases of DLA..... | 127 |
| Figure 18. Normal Inference Workloads in Nsight Systems Timeline View..... | 148 |
| Figure 19. The Layer Execution and the Kernel Being Launched on the CPU Side..... | 149 |
| Figure 20. The Kernels Run on the GPU..... | 150 |
| Figure 21. Sample DLA Profiling Report..... | 152 |
| Figure 22. Sample DLA Profiling report..... | 152 |
| Figure 23. Tensor Core Activities on an A100 GPU Running ResNet-50 with FP16 Enabled..... | 170 |
| Figure 24. Layout Format for CHW..... | 188 |
| Figure 25. Layout format for HWC..... | 189 |
| Figure 26. Values of #C/2# HxW Matrices are Pairs of Values of Two Consecutive Channels..... | 190 |
| Figure 27. In NHWC8 Format, the Entries of an HxW Matrix Include the Values of all the Channels..... | 191 |
| Figure 28. Performance Metrics in a Normal trtexec Run under Nsight Systems..... | 193 |

List of Tables

| | |
|---|-----|
| Table 1. Supported I/O Formats..... | 44 |
| Table 2. Implicit Vs Explicit Quantization..... | 55 |
| Table 3. Types of Tensor Cores..... | 169 |

Chapter 1. Introduction

NVIDIA® TensorRT™ is an SDK that facilitates high-performance machine learning inference. It complements training frameworks such as TensorFlow, PyTorch, and MXNet. It focuses on running an already-trained network quickly and efficiently on NVIDIA hardware.

Refer to the [NVIDIA TensorRT Installation Guide](#) for instructions on installing TensorRT.

The [NVIDIA TensorRT Quick Start Guide](#) is for users who want to try out the TensorRT SDK; specifically, it teaches you how to quickly construct an application to run inference on a TensorRT engine.

1.1. Structure of This Guide

Chapter 1 provides information about how TensorRT is packaged and supported and how it fits into the developer ecosystem.

Chapter 2 provides a broad overview of TensorRT capabilities.

Chapters 3 and 4 contain introductions to the C++ and Python APIs.

Subsequent chapters provide more detail about advanced features.

The appendix contains a layer reference and answers to FAQs.

1.2. Samples

The [NVIDIA TensorRT Sample Support Guide](#) illustrates many of the topics discussed in this guide. Additional samples focusing on embedded applications can be found [here](#).

1.3. Complementary GPU Features

[Multi-Instance GPU](#), or MIG, is a feature of NVIDIA GPUs with NVIDIA Ampere Architecture or later architectures that enable user-directed partitioning of a single GPU into multiple smaller GPUs. The physical partitions provide dedicated compute and memory slices with quality of service and independent execution of parallel workloads on fractions of the GPU. For TensorRT applications with low GPU utilization, MIG can

produce higher throughput with little or no latency impact. The optimal partitioning scheme is application-specific.

1.4. Complementary Software

The [NVIDIA Triton™](#) Inference Server is a higher-level library providing optimized inference across CPUs and GPUs. It provides capabilities for starting and managing multiple models and REST and gRPC endpoints for serving inference.

[NVIDIA DALI®](#) provides high-performance primitives for preprocessing image, audio, and video data. TensorRT inference can be integrated as a custom operator in a DALI pipeline. A working example of TensorRT inference integrated into DALI can be found [here](#).

[TensorFlow-TensorRT \(TF-TRT\)](#) is an integration of TensorRT directly into TensorFlow. It selects subgraphs of TensorFlow graphs to be accelerated by TensorRT while leaving the rest to be executed natively by TensorFlow. The result is still a TensorFlow graph that you can execute as usual. For TF-TRT examples, refer to [Examples for TensorRT in TensorFlow](#).

[Torch-TensorRT \(Torch-TRT\)](#) is a PyTorch-TensorRT compiler that converts PyTorch modules into TensorRT engines. Internally, the PyTorch modules are converted into TorchScript/FX modules based on the selected Intermediate Representation (IR). The compiler selects subgraphs of the PyTorch graphs to be accelerated by TensorRT while leaving Torch to execute the rest of the graph natively. The result is still a PyTorch module that you can execute as usual. For examples, refer to [Examples for Torch-TRT](#).

The [TensorFlow-Quantization Toolkit](#) provides utilities for training and deploying Tensorflow 2-based Keras models at a reduced precision. This toolkit quantizes different layers in the graph exclusively based on operator names, class, and pattern matching. The quantized graph can then be converted into ONNX and TensorRT engines. For example, refer to the [model zoo](#).

The [PyTorch Quantization Toolkit](#) provides facilities for training PyTorch models at reduced precision, which can then be exported for optimization in TensorRT.

TensorRT is integrated with NVIDIA's profiling tools, [NVIDIA Nsight™ Systems](#), and [NVIDIA Deep Learning Profiler \(DLProf\)](#).

A restricted subset of TensorRT is certified for use in [NVIDIA DRIVE®](#) products. Some APIs are marked for use only in NVIDIA DRIVE and are not supported for general use.

1.5. ONNX

TensorRT's primary means of importing a trained model from a framework is the [ONNX](#) interchange format. TensorRT ships with an ONNX parser library to assist in importing models. Where possible, the parser is backward compatible up to opset 9; the [ONNX Model Opset Version Converter](#) can assist in resolving incompatibilities.

The [GitHub version](#) may support later opsets than the version shipped with TensorRT. Refer to the ONNX-TensorRT [operator support matrix](#) for the latest information on the

supported opset and operators. For TensorRT deployment, we recommend exporting to the latest available ONNX opset.

The ONNX operator support list for TensorRT can be found [here](#).

PyTorch natively supports [ONNX export](#). For TensorFlow, the recommended method is [tf2onnx](#).

After exporting a model to ONNX, a good first step is to run constant folding using [Polygraphy](#). This can often solve TensorRT conversion issues in the ONNX parser and simplify the workflow. For details, refer to [this example](#). In some cases, modifying the ONNX model further may be necessary, such as replacing subgraphs with plugins or reimplementing unsupported operations in other operations. To make this process easier, you can use [ONNX-GraphSurgeon](#).

1.6. Code Analysis Tools

For guidance using the Valgrind and Clang sanitizer tools with TensorRT, refer to the [Troubleshooting](#) chapter.

1.7. API Versioning

TensorRT version number (MAJOR.MINOR.PATCH) follows [Semantic Versioning 2.0.0](#) for its public APIs and library ABIs. Version numbers change as follows:

1. MAJOR version when making incompatible API or ABI changes
2. MINOR version when adding functionality in a backward-compatible manner
3. PATCH version when making backward-compatible bug fixes

Note that semantic versioning does not extend to serialized objects. To reuse plan files and timing caches, version numbers must match across major, minor, patch, and build versions (with some exceptions for the safety runtime as detailed in the NVIDIA DRIVE OS 6.0 Developer Guide). Calibration caches can typically be reused within a major version, but compatibility is not guaranteed.

1.8. Deprecation Policy

Deprecation informs developers that some APIs and tools are no longer recommended. Beginning with version 8.0, TensorRT has the following deprecation policy:

- ▶ Deprecation notices are communicated in the [NVIDIA TensorRT Release Notes](#).
- ▶ When using the C++ API:
 - ▶ API functions are marked with the `TRT_DEPRECATED_API` macro.
 - ▶ Enums are marked with the `TRT_DEPRECATED_ENUM` macro.
 - ▶ All other locations are marked with the `TRT_DEPRECATED` macro.

- ▶ Classes, functions, and objects will have a statement documenting when they were deprecated.
- ▶ When using the Python API, deprecated methods and classes will issue deprecation warnings at runtime if they are used.
- ▶ TensorRT provides a 12-month migration period after the deprecation.
- ▶ APIs and tools continue to work during the migration period.
- ▶ After the migration period ends, APIs and tools are removed in a manner consistent with semantic versioning.

For any APIs and tools specifically deprecated in TensorRT 7.x, the 12-month migration period starts from the TensorRT 8.0 GA release date.

1.9. Hardware Support Lifetime

TensorRT 8.5.3 was the last release supporting NVIDIA Kepler (SM 3.x) and NVIDIA Maxwell (SM 5.x) devices. These devices are no longer supported in TensorRT 8.6. NVIDIA Pascal (SM 6.x) devices are deprecated in TensorRT 8.6.

1.10. Support

Support, resources, and information about TensorRT can be found online at <https://developer.nvidia.com/tensorrt>. This includes blogs, samples, and more.

In addition, you can access the NVIDIA DevTalk TensorRT forum at <https://devtalk.nvidia.com/default/board/304/tensorrt/> for all things related to TensorRT. This forum offers the possibility of finding answers, making connections, and getting involved in discussions with customers, developers, and TensorRT engineers.

1.11. Reporting Bugs

NVIDIA appreciates all types of feedback. If you encounter any problems, follow the instructions in the [Reporting TensorRT Issues](#) section to report the issues.

Chapter 2. TensorRT's Capabilities

This chapter provides an overview of what you can do with TensorRT. It is intended to be useful to all TensorRT users.

2.1. C++ and Python APIs

TensorRT's API has language bindings for both C++ and Python, with nearly identical capabilities. The API facilitates interoperability with Python data processing toolkits and libraries like NumPy and SciPy. The C++ API can be more efficient and may better meet some compliance requirements, for example, in automotive applications.



Note: The Python API is not available for all platforms. For more information, refer to the [NVIDIA TensorRT Support Matrix](#).

2.2. The Programming Model

TensorRT operates in two phases. In the first phase, usually performed offline, you provide TensorRT with a model definition, and TensorRT optimizes it for a target GPU. In the second phase, you use the optimized model to run inference.

2.2.1. The Build Phase

The highest-level interface for the build phase of TensorRT is the *Builder* ([C++](#), [Python](#)). The builder is responsible for optimizing a model and producing an *Engine*.

To build an engine, you must:

- ▶ Create a network definition.
- ▶ Specify a configuration for the builder.
- ▶ Call the builder to create the engine.

The *NetworkDefinition* interface ([C++](#), [Python](#)) defines the model. The most common path to transfer a model to TensorRT is to export it from a framework in ONNX format and use TensorRT's ONNX parser to populate the network definition. However, you can

also construct the definition step by step using TensorRT's *Layer* ([C++](#), [Python](#)) and *Tensor* ([C++](#), [Python](#)) interfaces.

Whichever way you choose, you must also define which tensors are the inputs and outputs of the network. Tensors that are not marked as outputs are considered to be transient values that the builder can optimize away. Input and output tensors must be named so that TensorRT knows how to bind the input and output buffers to the model at runtime.

The *BuilderConfig* interface ([C++](#), [Python](#)) is used to specify how TensorRT should optimize the model. Among the configuration options available, you can control TensorRT's ability to reduce the precision of calculations, control the tradeoff between memory and runtime execution speed, and constrain the choice of CUDA[®] kernels. Since the builder can take minutes or more to run, you can also control how the builder searches for kernels and cached search results for use in subsequent runs.

After you have a network definition and a builder configuration, you can call the builder to create the engine. The builder eliminates dead computations, folds constants, and reorders and combines operations to run more efficiently on the GPU. It can optionally reduce the precision of floating-point computations, either by simply running them in 16-bit floating point, or by quantizing floating point values so that calculations can be performed using 8-bit integers. It also times multiple implementations of each layer with varying data formats, then computes an optimal schedule to execute the model, minimizing the combined cost of kernel executions and format transforms.

The builder creates the engine in a serialized form called a *plan*, which can be deserialized immediately or saved to disk for later use.



Note:

- ▶ By default, TensorRT engines are specific to both the TensorRT version and the GPU on which they were created. To configure an engine for forward compatibility, refer to the [Version Compatibility](#) and [Hardware Compatibility](#) sections.
- ▶ TensorRT's network definition does not have deep-copy parameter arrays (such as the weights for a convolution). Therefore, you must not release the memory for those arrays until the build phase is complete. When importing a network using the ONNX parser, the parser owns the weights, so it must not be destroyed until the build phase is complete.
- ▶ The builder times algorithms to determine the fastest. Running the builder in parallel with other GPU work may perturb the timings, resulting in poor optimization.

2.2.2. The Runtime Phase

The highest-level interface for the execution phase of TensorRT is the *Runtime* ([C++](#), [Python](#)).

When using the runtime, you will typically carry out the following steps:

- ▶ Deserialize a plan to create an engine.
- ▶ Create an execution context from the engine.

Then, repeatedly:

- ▶ Populate input buffers for inference.
- ▶ Call `enqueueV3()` on the execution context to run inference.

The *Engine* interface ([C++](#), [Python](#)) represents an optimized model. You can query an engine for information about the input and output tensors of the network - the expected dimensions, data type, data format, and so on.

The *ExecutionContext* interface ([C++](#), [Python](#)), created from the engine, is the main interface for invoking inference. The execution context contains all of the states associated with a particular invocation - thus, you can have multiple contexts associated with a single engine and run them in parallel.

You must set up the input and output buffers in the appropriate locations when invoking inference. Depending on the nature of the data, this may be in either CPU or GPU memory. If not obvious, based on your model, you can query the engine to determine which memory space to provide the buffer.

After the buffers are set up, inference can be enqueued (`enqueueV3`). The required kernels are enqueued on a CUDA stream, and control is returned to the application as soon as possible. Some networks require multiple control transfers between CPU and GPU, so control may not return immediately. To wait for completion of asynchronous execution, synchronize on the stream using [`cudaStreamSynchronize`](#).

2.3. Plugins

TensorRT has a *Plugin* interface that allows applications to provide implementations of operations that TensorRT does not support natively. Plugins created and registered with TensorRT's `PluginRegistry` can be found by the ONNX parser while translating the network.

TensorRT ships with a library of plugins; the source for many of these and some additional plugins can be found [here](#).

You can also write your plugin library and serialize it with the engine.

If cuDNN or cuBLAS is needed, install the library as TensorRT no longer ships with them. To obtain `cudaDnnContext*` or `cudaBlasContext*`, the corresponding `TacticSource` flag must be set using `nvinfer1::IBuilderConfig::setTacticSource()`.

Refer to the [Extending TensorRT with Custom Layers](#) chapter for more details.

2.4. Types and Precision

2.4.1. Supported Types

TensorRT supports FP32, FP16, BF16, FP8, INT4, INT8, INT32, INT64, UINT8, and BOOL data types. Refer to the [TensorRT Operator documentation](#) for the specification of the layer I/O data type.

- ▶ FP32, FP16, BF16: unquantized floating point types
- ▶ INT8: low-precision integer type
 - ▶ Implicit quantization
 - ▶ Interpreted as a quantized integer. A tensor with INT8 type must have an associated scale factor (either through calibration or `setDynamicRange` API).
 - ▶ Explicit quantization
 - ▶ Interpreted as a signed integer. Conversion to/from INT8 type requires an explicit Q/DQ layer.
- ▶ INT4: low-precision integer type for weight compression
 - ▶ INT4 is used for weight-only-quantization. Requires dequantization before computing is performed.
 - ▶ Conversion to and from INT4 type requires an explicit Q/DQ layer.
 - ▶ INT4 weights are expected to be serialized by packing two elements per byte. For additional information, refer to the [Quantized Weights](#) section.
- ▶ FP8: low-precision floating-point type
 - ▶ 8-bit floating point type with 1-bit for sign, 4-bits for exponent, 3-bits for mantissa
 - ▶ Conversion to/from the FP8 type requires an explicit Q/DQ layer.
- ▶ UINT8: unsigned integer I/O type
 - ▶ The data type is only usable as a network I/O type.
 - ▶ Network-level inputs in UINT8 must be converted from UINT8 to FP32 or FP16 using a `CastLayer` before the data is used in other operations.
 - ▶ Network-level outputs in UINT8 must be produced by a `CastLayer` explicitly inserted into the network (will only support conversions from FP32/FP16 to UINT8).
 - ▶ UINT8 quantization is not supported.
 - ▶ The `ConstantLayer` does not support UINT8 as an output type.
- ▶ BOOL
 - ▶ A boolean type is used with supported layers.

2.4.2. Strong Typing vs Weak Typing

When providing a network to TensorRT, you specify whether it is strongly or weakly typed, with weakly typed as the default.

For strongly typed networks, TensorRT's optimizer will statically infer intermediate tensor types based on the network input types and the operator specifications, which match type inference semantics in frameworks. The optimizer will then adhere strictly to those types. For more information, refer to [Strongly Typed Networks](#).

TensorRT's optimizer may substitute different precisions for tensors for weakly typed networks if it increases performance. In this mode, TensorRT defaults to FP32 for

all floating-point operations, but there are two ways to configure different levels of precision:

- ▶ To control precision at the model level, `BuilderFlag` options ([C++](#), [Python](#)) can indicate to TensorRT that it may select lower-precision implementations when searching for the fastest (and because lower precision is generally faster, it typically will).

For example, by setting a single flag, you can easily instruct TensorRT to use FP16 calculations for your entire model. For regularized models whose input dynamic range is approximately one, this typically produces significant speedups with negligible change in accuracy.

- ▶ For finer-grained control, where a layer must run at higher precision because part of the network is numerically sensitive or requires high dynamic range, arithmetic precision can be specified for that layer.

Refer to [Reduced Precision in Weakly-Typed Networks](#) for more details.

2.5. Quantization

TensorRT supports quantized floating points, where floating-point values are linearly compressed and rounded to low-precision quantized types (INT8, FP8, INT4). This significantly increases arithmetic throughput while reducing storage requirements and memory bandwidth. When quantizing a floating-point tensor, TensorRT must know its dynamic range - what range of values is important to represent - values outside this range are clamped when quantizing.

The builder can calculate dynamic range information (this is called *calibration*) based on representative input data (this is currently supported only for INT8). Alternatively, you can perform quantization-aware training in a framework and import the model to TensorRT with the necessary dynamic range information.

Refer to the [Working with Quantized Types](#) chapter for more details.

2.6. Tensors and Data Formats

When defining a network, TensorRT assumes that multidimensional C-style arrays represent tensors. Each layer has a specific interpretation of its inputs: for example, a 2D convolution will assume that the last three dimensions of its input are in CHW format - there is no option to use, for example, a WHC format. Refer to [NVIDIA TensorRT Operator's Reference](#) for how each layer interprets its inputs.

Note that tensors are limited to at most $2^{31}-1$ elements.

While optimizing the network, TensorRT performs transformations internally (including to HWC, but also more complex formats) to use the fastest possible CUDA kernels. Formats are generally chosen to optimize performance, and applications cannot control the choices. However, the underlying data formats are exposed at I/O boundaries (network input and output and passing data to and from plugins) to allow applications to minimize unnecessary format transformations.

Refer to the [I/O Formats](#) section for more details.

2.7. Dynamic Shapes

By default, TensorRT optimizes the model based on the input shapes (batch size, image size, and so on) at which it was defined. However, the builder can be configured to adjust the input dimensions at runtime. To enable this, you specify one or more instances of `OptimizationProfile` ([C++](#), [Python](#)) in the builder configuration, containing a minimum and maximum shape for each input and an optimization point within that range.

TensorRT creates an optimized engine for each profile, choosing CUDA kernels that work for all shapes within the [minimum, maximum] range and are fastest for the optimization point - typically different kernels for each profile. You can then select among profiles at runtime.

Refer to the [Working with Dynamic Shapes](#) chapter for more details.

2.8. DLA

TensorRT supports NVIDIA's Deep Learning Accelerator (DLA), a dedicated inference processor on many NVIDIA SoCs that supports a subset of TensorRT's layers. TensorRT allows you to execute part of the network on the DLA and the rest on GPU; for layers that can be executed on either device, you can select the target device in the builder configuration on a per-layer basis.

Refer to the [Working with DLA](#) chapter for more details.

2.9. Updating Weights

When building an engine, you can specify that its weights may later be updated. This can be useful if you frequently update the model's weights without changing the structure, such as in reinforcement learning or when retraining a model while retaining the same structure. Weight updates are performed using the `Refitter` ([C++](#), [Python](#)) interface.

Refer to the [Refitting an Engine](#) section for more details.

2.10. Streaming Weights

TensorRT can be configured to stream the network's weights from host memory to device memory during network execution instead of placing them in device memory at engine load time. This enables models with weights larger than free GPU memory to run, but potentially with significantly increased latency. Weight streaming is an

opt-in feature at both build time (`BuilderFlag::kWEIGHT_STREAMING`) and runtime (`ICudaEngine::setWeightStreamingBudgetV2`).



Note: Weight streaming is only supported with strongly typed networks. For more information, refer to [Weight Streaming](#).

2.11. trtexec Tool

Included in the `samples` directory is a command-line wrapper tool called `trtexec`. `trtexec` is a tool that allows you to use TensorRT without developing your application. The `trtexec` tool has three main purposes:

- ▶ *benchmarking networks* on random or user-provided input data.
- ▶ *generating serialized engines* from models.
- ▶ *generating a serialized timing cache* from the builder.

Refer to the [trtexec](#) section for more details.

2.12. Polygraphy

Polygraphy is a toolkit designed to assist in running and debugging deep learning models in TensorRT and other frameworks. It includes a [Python API](#) and a [command-line interface \(CLI\)](#) built using this API.

Among other things, with Polygraphy, you can:

- ▶ Run inference among multiple backends, like TensorRT and ONNX-Runtime, and compare results ([API, CLI](#)).
- ▶ Convert models to various formats, such as TensorRT engines with post-training quantization ([API, CLI](#)).
- ▶ View information about various types of models (for example, [CLI](#))
- ▶ Modify ONNX models on the command line:
 - ▶ Extract subgraphs (for example, [CLI](#)).
 - ▶ Simplify and sanitize (for example, [CLI](#)).
- ▶ Isolate faulty tactics in TensorRT (for example, [CLI](#)).

For more details, refer to the [Polygraphy repository](#).

Chapter 3. The C++ API

This chapter illustrates the basic usage of the C++ API, assuming you start with an ONNX model. [sampleOnnxMNIST](#) illustrates this use case in more detail.

The C++ API can be accessed through the header `NvInfer.h` and is in the `nvinfer1` namespace. For example, a simple application might begin with:

```
#include "NvInfer.h"

using namespace nvinfer1;
```

Interface classes in the TensorRT C++ API begin with the prefix `I`, such as `ILogger` and `IBuilder`.

A CUDA context is automatically created the first time TensorRT calls CUDA if none exists before that point. However, it is generally preferable to create and configure the CUDA context yourself before the first call to TensorRT.

The code in this chapter does not use smart pointers to illustrate object lifetimes; however, their use is recommended with TensorRT interfaces.

3.1. The Build Phase

To create a builder, you first must instantiate the `ILogger` interface. This example captures all warning messages but ignores informational messages:

```
class Logger : public ILogger
{
    void log(Severity severity, const char* msg) noexcept override
    {
        // suppress info-level messages
        if (severity <= Severity::kWARNING)
            std::cout << msg << std::endl;
    }
} logger;
```

You can then create an instance of the builder:

```
IBuilder* builder = createInferBuilder(logger);
```

3.1.1. Creating a Network Definition

After the builder has been created, the first step in optimizing a model is to create a network definition. The network creation options are specified using a combination of flags OR-d together.

The `kEXPLICIT_BATCH` flag is required to import models using the ONNX parser. For more information, refer to [Explicit vs Implicit Batch](#).

You can also specify that the network should be considered strongly typed using the `NetworkDefinitionCreationFlag::kSTRONGLY_TYPED` flag. For more information, refer to [Strongly Typed Networks](#).

Finally, create a network:

```
INetworkDefinition* network = builder->createNetworkV2(flag);
```

3.1.2. Importing a Model Using the ONNX Parser

Now, the network definition must be populated from the ONNX representation. The ONNX parser API is in the file `NvOnnxParser.h`, and the parser is in the `nvonnxparser` C++ namespace.

```
#include "NvOnnxParser.h"
using namespace nvonnxparser;
```

You can create an ONNX parser to populate the network as follows:

```
IParser* parser = createParser(*network, logger);
```

Then, read the model file and process any errors.

```
parser->parseFromFile(modelFile,
    static_cast<int32_t>(ILogger::Severity::kWARNING));
for (int32_t i = 0; i < parser->getNbErrors(); ++i)
{
    std::cout << parser->getError(i)->desc() << std::endl;
}
```

An important aspect of a TensorRT network definition is that it contains pointers to model weights, which the builder copies into the optimized engine. Since the network was created using the parser, the parser owns the memory occupied by the weights, so the parser object should not be deleted until after the builder has run.

3.1.3. Building an Engine

The next step is to create a build configuration specifying how TensorRT should optimize the model.

```
IBuilderConfig* config = builder->createBuilderConfig();
```

This interface has many properties that you can set to control how TensorRT optimizes the network. One important property is the maximum workspace size. Layer implementations often require a temporary workspace, and this parameter limits the maximum size that any layer in the network can use. If insufficient workspace is provided, it is possible that TensorRT will not be able to find an implementation for a layer. By default, the workspace is set to the total global memory size of the given device; restrict it when necessary, for example, when multiple engines are to be built on a single device.

```
config->setMemoryPoolLimit(MemoryPoolType::kWORKSPACE, 1U << 20);
```

Another significant consideration is the maximum shared memory allocation for the CUDA backend implementation. This allocation becomes pivotal in scenarios where TensorRT needs to coexist with other applications, such as when both TensorRT and DirectX concurrently utilize the GPU.

```
config->setMemoryPoolLimit(MemoryPoolType::kTACTIC_SHARED_MEMORY, 48 << 10);
```

Once the configuration has been specified, the engine can be built.

```
IHostMemory* serializedModel = builder->buildSerializedNetwork(*network, *config);
```

Since the serialized engine contains the necessary copies of the weights, the parser, network definition, builder configuration, and builder are no longer necessary and may be safely deleted:

```
delete parser;
delete network;
delete config;
delete builder;
```

The engine can then be saved to disk, and the buffer into which it was serialized can be deleted.

```
delete serializedModel
```



Note: Serialized engines are not portable across platforms. Engines are specific to the exact GPU model that they were built on (in addition to the platform).

Building engines is intended as an offline process, so it can take significant time. For tips on making the builder run faster, refer to the [Optimizing Builder Performance](#) section.

3.2. Deserializing a Plan

Assuming you have previously serialized an optimized model and want to perform inference, you must create an instance of the `IRuntime` interface. Like the builder, the runtime requires an instance of the logger:

```
IRuntime* runtime = createInferRuntime(logger);
```

After you have read the model into a buffer, you can deserialize it to obtain an engine:

```
ICudaEngine* engine =
    runtime->deserializeCudaEngine(modelData, modelSize);
```

3.3. Performing Inference

The engine holds the optimized model, but you must manage additional states for intermediate activations to perform inference. This is done using the `ExecutionContext` interface:

```
IExecutionContext *context = engine->createExecutionContext();
```

An engine can have multiple execution contexts, allowing one set of weights to be used for multiple overlapping inference tasks. (A current exception to this is when using

dynamic shapes when each optimization profile can only have one execution context unless the preview feature, `kPROFILE_SHARING_0806`, is specified.)

To perform inference, you must pass TensorRT buffers for input and output, which TensorRT requires you to specify with calls to `setTensorAddress`, which takes the tensor's name and the buffer's address. You can query the engine using the names you provided for input and output tensors to find the right positions in the array:

```
context->setTensorAddress(INPUT_NAME, inputBuffer);  
context->setTensorAddress(OUTPUT_NAME, outputBuffer);
```

If the engine was built with dynamic shapes, you must also specify the input shapes:

```
context->setInputShape(INPUT_NAME, inputDims);
```

You can then call TensorRT's method `enqueueV3` to start inference using a CUDA stream:

```
context->enqueueV3(stream);
```

A network will be executed asynchronously or not, depending on the structure and features of the network. A non-exhaustive list of features that can cause synchronous behavior are data-dependent shapes, DLA usage, loops, and synchronous plugins. It is common to enqueue data transfers with `cudaMemcpyAsync()` before and after the kernels to move data from the GPU if it is not already there.

To determine when the kernels (and possibly `cudaMemcpyAsync()`) are complete, use standard CUDA synchronization mechanisms such as events or waiting on the stream.

Chapter 4. The Python API

This chapter illustrates the basic usage of the Python API, assuming you are starting with an ONNX model. The [onnx_resnet50.py](#) sample illustrates this use case in more detail.

The Python API can be accessed through the `trt` module:

```
import trt as trt
```

4.1. The Build Phase

To create a builder, you must first create a logger. The Python bindings include a simple logger implementation that logs all messages preceding a certain severity to `stdout`.

```
logger = trt.Logger(trt.Logger.WARNING)
```

Alternatively, it is possible to define your implementation of the logger by deriving from the `ILogger` class:

```
class MyLogger(trt.ILogger):
    def __init__(self):
        trt.ILogger.__init__(self)

    def log(self, severity, msg):
        pass # Your custom logging implementation here
```

```
logger = MyLogger()
```

You can then create a builder:

```
builder = trt.Builder(logger)
```

Building engines is intended as an offline process, so it can take significant time. For tips on making the builder run faster, refer to the [Optimizing Builder Performance](#) section.

4.1.1. Creating a Network Definition in Python

After the builder has been created, the first step in optimizing a model is to create a network definition. The network definition options are specified using a combination of flags OR-d together.

The `EXPLICIT_BATCH` flag is required to import models using the ONNX parser. For more information, refer to [Explicit vs Implicit Batch](#).

You can also specify that the network should be considered strongly typed using the `NetworkDefinitionCreationFlag.STRONGLY_TYPED` flag. For more information, refer to [Strongly Typed Networks](#).

Finally, create a network:

```
network = builder.create_network(flag)
```

4.1.2. Importing a Model Using the ONNX Parser

Now, the network definition must be populated from the ONNX representation. You can create an ONNX parser to populate the network as follows:

```
parser = trt.OnnxParser(network, logger)
```

Then, read the model file and process any errors:

```
success = parser.parse_from_file(model_path)
for idx in range(parser.num_errors):
    print(parser.get_error(idx))

if not success:
    pass # Error handling code here
```

4.1.3. Building an Engine

The next step is to create a build configuration specifying how TensorRT should optimize the model:

```
config = builder.create_builder_config()
```

This interface has many properties that you can set to control how TensorRT optimizes the network. One important property is the maximum workspace size. Layer implementations often require a temporary workspace, and this parameter limits the maximum size that any layer in the network can use. If insufficient workspace is provided, it is possible that TensorRT will not be able to find an implementation for a layer. By default, the workspace is set to the total global memory size of the given device; restrict it when necessary, for example, when multiple engines are to be built on a single device.

```
config.set_memory_pool_limit(trt.MemoryPoolType.WORKSPACE, 1 << 20) # 1 MiB
```

After the configuration has been specified, the engine can be built and serialized with:

```
serialized_engine = builder.build_serialized_network(network, config)
```

It may be useful to save the engine to a file for future use. You can do that like so:

```
with open("sample.engine", "wb") as f:
    f.write(serialized_engine)
```



Note: Serialized engines are not portable across platforms. Engines are specific to the exact GPU model that they were built on (in addition to the platform).

4.2. Deserializing a Plan

To perform inference, deserialize the engine using the `Runtime` interface. Like the builder, the runtime requires an instance of the logger.

```
runtime = trt.Runtime(logger)
```

You can then deserialize the engine from a memory buffer:

```
engine = runtime.deserialize_cuda_engine(serialized_engine)
```

If you want, first load the engine from a file:

```
with open("sample.engine", "rb") as f:
    serialized_engine = f.read()
```

4.3. Performing Inference

The engine holds the optimized model, but inference requires an additional state for intermediate activations. This is done via the `IEExecutionContext` interface:

```
context = engine.create_execution_context()
```

An engine can have multiple execution contexts, allowing one set of weights to be used for multiple overlapping inference tasks. (A current exception to this is when using dynamic shapes when each optimization profile can only have one execution context unless the preview feature, `PROFILE_SHARING_0806`, is specified.)

To perform inference, you must specify buffers for inputs and outputs:

```
context.set_tensor_address(name, ptr)
```

Several Python packages allow you to allocate memory on the GPU, including, but not limited to, the official CUDA Python bindings, PyTorch, cuPy, and Numba.

After populating the input buffer, you can call TensorRT's `execute_async_v3` method to start inference using a CUDA stream. A network will be executed asynchronously or not, depending on the structure and features of the network. A non-exhaustive list of features that can cause synchronous behavior are data-dependent shapes, DLA usage, loops, and synchronous plugins.

First, create the CUDA stream. Use a pointer to the existing stream if you already have a CUDA stream. For example, for PyTorch CUDA streams, `torch.cuda.Stream()`, you can access the pointer using the `cuda_stream` property; for Polygraphy CUDA streams, use the `ptr` attribute; or you can create a stream using CUDA Python binding directly by calling [cudaStreamCreate\(\)](#).

Next, start inference:

```
context.execute_async_v3(buffers, stream_ptr)
```

It is common to enqueue asynchronous transfers (`cudaMemcpyAsync()`) before and after the kernels to move data from the GPU if it is not already there.

To determine when inference (and asynchronous transfers) are complete, use the standard CUDA synchronization mechanisms such as events or waiting on the stream. For example, with PyTorch CUDA streams or Polygraphy CUDA streams, issue `stream.synchronize()`. With streams created with CUDA Python binding, issue [cudaStreamSynchronize\(stream\)](#).

Chapter 5. How TensorRT Works

This chapter provides more detail on how TensorRT works.

5.1. Object Lifetimes

TensorRT's API is class-based, with some classes acting as factories for other classes. For objects owned by the user, the lifetime of a factory object must span the lifetime of objects it creates. For example, the `NetworkDefinition` and `BuilderConfig` classes are created from the `Builder` class, and objects of those classes should be destroyed before the `Builder` factory object.

An important exception to this rule is creating an engine from a builder. After creating an engine, you may destroy the builder, network, parser, and build config and continue using the engine.

5.2. Error Handling and Logging

When creating TensorRT top-level interfaces (builder, runtime, or refitter), you must provide an implementation of the `Logger` (C++, Python) interface. The logger is used for diagnostics and informational messages; its verbosity level is configurable. Since the logger may be used to pass back information at any point in TensorRT's lifetime, its lifetime must span any use of that interface in your application. The implementation must also be thread-safe since TensorRT may use worker threads internally.

An API call to an object will use the logger associated with the corresponding top-level interface. For example, in a call to `ExecutionContext::enqueueV3()`, the execution context was created from an engine created from a runtime, so TensorRT will use the logger associated with that runtime.

The primary method of error handling is the `ErrorRecorder` (C++, Python) interface. You can implement this interface and attach it to an API object to receive errors associated with it. The recorder for an object will also be passed to any others it creates - for example if you attach an error recorder to an engine and create an execution context from that engine, it will use the same recorder. If you then attach a new error recorder to the execution context, it will receive only errors from that context. If an error is generated but no error recorder is found, it will be emitted through the associated logger.

Note that CUDA errors are generally asynchronous - so when performing multiple inferences or other streams of CUDA work asynchronously in a single CUDA context, an asynchronous GPU error may be observed in a different execution context than the one that generated it.

5.3. Memory

TensorRT uses considerable amounts of device memory (that is, memory directly accessible by the GPU, as opposed to the host memory attached to the CPU). Since device memory is often a constrained resource, it is important to understand how TensorRT uses it.

5.3.1. The Build Phase

During the build, TensorRT allocates device memory for timing layer implementations. Some implementations can consume a lot of temporary memory, especially with large tensors. You can control the maximum amount of temporary memory through the memory pool limits of the builder config. The workspace size defaults to the full size of the device's global memory but can be restricted when necessary. If the builder finds applicable kernels that could not be run because of insufficient workspace, it will emit a logging message indicating this.

Even with relatively little workspace, however, timing requires creating buffers for input, output, and weights. TensorRT is robust against the operating system (OS) returning out-of-memory for such allocations. On some platforms, the OS may successfully provide memory, and then the out-of-memory killer process observes that the system is low on memory and kills TensorRT. If this happens, free up as much system memory as possible before retrying.

During the build phase, at least two copies of the weights will typically be in host memory: those from the original network and those included as part of the engine as it is built. In addition, when TensorRT combines weights (for example, convolution with batch normalization), additional temporary weight tensors will be created.

5.3.2. The Runtime Phase

TensorRT uses relatively little host memory at runtime but can use considerable amounts of device memory.

An engine allocates device memory to store the model weights upon deserialization. Since the serialized engine has almost all the weights, its size approximates the amount of device memory the weights require.

An `ExecutionContext` uses two kinds of device memory:

- ▶ Some layer implementations require persistent memory - for example, some convolution implementations use edge masks, and this state cannot be shared between contexts as weights are because its size depends on the layer input shape, which may vary across contexts. This memory is allocated to the creation of the execution context and lasts for its lifetime.

- ▶ Enqueue memory is used to hold intermediate results while processing the network. This memory is used for intermediate activation tensors (called activation memory). It is also used for temporary storage required by layer implementations (called scratch memory), the bound for which is controlled by `IBuilderConfig::setMemoryPoolLimit()`. TensorRT optimizes memory usage in a couple of ways:
 1. by sharing a block of device memory across activations tensors with disjoint lifetimes.
 2. by allowing transient (scratch) tensors to occupy unused activation memory, where feasible. Therefore, enqueue memory required by TensorRT is in the range of {total activation memory, total activation memory + max scratch memory}.

You may optionally create an execution context without enqueue memory using `ICudaEngine::createExecutionContextWithoutDeviceMemory()` and provide that memory for the duration of network execution. This allows you to share it between multiple contexts not running concurrently or for other uses while inference is not running. The amount of enqueue memory required is returned by `ICudaEngine::getDeviceMemorySizeV2()`.

Information about the amount of persistent memory and scratch memory used by the execution context is emitted by the builder when building the network at severity `KINFO`. Examining the log, the messages look similar to the following:

```
[08/12/2021-17:39:11] [I] [TRT] Total Host Persistent Memory: 106528
[08/12/2021-17:39:11] [I] [TRT] Total Device Persistent Memory: 29785600
[08/12/2021-17:39:11] [I] [TRT] Max Scratch Memory: 9970688
```

By default, TensorRT allocates device memory directly from CUDA. However, you can attach an implementation of TensorRT's `IGpuAllocator` ([C++](#), [Python](#)) interface to the builder or runtime and manage device memory yourself. This is useful if your application wants to control all GPU memory and sub-allocate to TensorRT instead of having TensorRT allocated directly from CUDA.

[NVIDIA cuDNN](#) and [NVIDIA cuBLAS](#) can occupy large amounts of device memory. TensorRT allows you to control whether these libraries are used for inference by using the `TacticSources` ([C++](#), [Python](#)) attribute in the builder configuration. Some plugin implementations require these libraries, so when they are excluded, the network may not be compiled successfully. If the appropriate tactic sources are set, the `cudaDnnContext` and `cudaBlasContext` handles are passed to the plugins using `IPluginV2Ext::attachToContext()`.

The CUDA infrastructure and TensorRT's device code also consume device memory. The amount of memory varies by platform, device, and TensorRT version. You can use `cudaGetMemInfo` to determine the total amount of device memory.

TensorRT measures the memory used before and after critical operations in the builder and runtime. These memory usage statistics are printed to TensorRT's information logger. For example:

```
[MemUsageChange] Init CUDA: CPU +535, GPU +0, now: CPU 547, GPU 1293 (MiB)
```

It indicates that memory use changes with CUDA initialization. `CPU +535, GPU +0` is the increased amount of memory after running CUDA initialization. The content after `now:` is the CPU/GPU memory usage snapshot after CUDA initialization.



Note: In a multi-tenant situation, the reported memory use by `cudaGetMemInfo` and TensorRT is prone to race conditions, where a new allocation/free is done by a different process or thread. Since CUDA does not control memory on unified-memory devices, the results returned by `cudaGetMemInfo` may not be accurate on these platforms.

5.3.3. CUDA Lazy Loading

CUDA lazy loading is a CUDA feature that can significantly reduce the peak GPU and host memory usage of TensorRT and speed up TensorRT initialization with negligible (< 1%) performance impact. The memory usage and time-saving for initialization depend on the model, software stack, GPU platform, etc. It is enabled by setting the environment variable `CUDA_MODULE_LOADING=LAZY`. Refer to the [NVIDIA CUDA documentation](#) for more information.

5.3.4. L2 Persistent Cache Management

NVIDIA Ampere and later architectures support L2 cache persistence, a feature that allows prioritization of L2 cache lines for retention when a line is chosen for eviction. TensorRT can use this to retain cache activations, reducing DRAM traffic and power consumption.

Cache allocation is per-execution context, enabled using the context's `setPersistentCacheLimit` method. The total persistent cache among all contexts (and other components using this feature) should not exceed `cudaDeviceProp::persistingL2CacheMaxSize`. For more information, refer to the [NVIDIA CUDA Best Practices Guide](#).

5.4. Threading

TensorRT objects are generally not thread-safe; the client must serialize access to an object from different threads.

The expected runtime concurrency model is that different threads operate in different execution contexts. The context contains the network state (activation values and so on) during execution, so using a context concurrently in different threads results in undefined behavior.

To support this model, the following operations are thread-safe:

- ▶ Nonmodifying operations on a runtime or engine.
- ▶ Deserializing an engine from a TensorRT runtime.
- ▶ Creating an execution context from an engine.
- ▶ Registering and deregistering plugins.

There are no thread-safety issues with using multiple builders in different threads; however, the builder uses timing to determine the fastest kernel for the parameters provided, and using multiple builders with the same GPU will perturb the timing and TensorRT's ability to construct optimal engines. There are no such issues using multiple threads to build with different GPUs.

5.5. Determinism

The TensorRT builder uses timing to find the fastest kernel to implement a given layer. Timing kernels are subject to noise, such as other work running on the GPU, GPU clock speed fluctuations, etc. Timing noise means that the same implementation may not be selected on successive runs of the builder.

In general, different implementations will use a different order of floating point operations, resulting in small differences in the output. The impact of these differences on the final result is usually very small. However, when TensorRT is configured to optimize by tuning over multiple precisions, the difference between an FP16 and an FP32 kernel can be more significant, particularly if the network has not been well regularized or is otherwise sensitive to numerical drift.

Other configuration options that can result in a different kernel selection are different input sizes (for example, batch size) or a different optimization point for an input profile (refer to the [Working with Dynamic Shapes](#) section).

The *AlgorithmSelector* (C++, Python) interface allows you to force the builder to pick a particular implementation for a given layer. You can use this to ensure the builder picks the same kernels from run to run. For more information, refer to the [Algorithm Selection and Reproducible Builds](#) section.

After an engine has been built, except for `IFillLayer` and `IScatterLayer`, it is deterministic: providing the same input in the same runtime environment will produce the same output.

5.5.1. IFillLayer Determinism

When `IFillLayer` is added to a network using the `RANDOM_UNIFORM` or `RANDOM_NORMAL` operations, the determinism guarantee above is no longer valid. On each invocation, these operations generate tensors based on the RNG state and then update the RNG state. This state is stored on a per-execution context basis.

5.5.2. IScatterLayer Determinism

If `IScatterLayer` is added to a network, and the input tensor `indices` have duplicate entries, the determinism guarantee above is not valid for `ScatterMode::kELEMENT` and `ScatterMode::kND` modes. Additionally, one of the values from the input `updates` tensor will be picked arbitrarily.

5.6. Runtime Options

TensorRT provides multiple runtime libraries to meet a variety of use cases. C++ applications that run TensorRT engines should link against one of the following:

- ▶ The *default* runtime is the main library (`libnvinfer.so/.dll`).
- ▶ The *lean* runtime library (`libnvinfer_lean.so/.dll`) is much smaller than the default library and contains only the code necessary to run a version-compatible engine. It has some restrictions; primarily, it cannot refit or serialize engines.
- ▶ The *dispatch runtime* (`libnvinfer_dispatch.so/.dll`) is a small shim library that can load a lean runtime and redirect calls. The dispatch runtime can load older versions of the lean runtime and, together with the appropriate configuration of the builder, can be used to provide compatibility between a newer version of TensorRT and an older plan file. Using the dispatch runtime is almost the same as manually loading the lean runtime, but it checks that APIs are implemented by the lean runtime loaded and performs some parameter mapping to support API changes where possible.

The lean runtime contains fewer operator implementations than the default runtime. Since TensorRT chooses operator implementations at build time, you must specify that the engine should be built for the lean runtime by enabling version compatibility. It may be slightly slower than an engine built for the default runtime.

The lean runtime contains all the functionality of the dispatch runtime, and the default runtime contains all the functionality of the lean runtime.

TensorRT provides Python packages corresponding to each of the above libraries:

tensorrt

A Python package. It is the Python interface for the *default* runtime.

tensorrt_lean

A Python package. It is the Python interface for the *lean* runtime.

tensorrt_dispatch

A Python package. It is the Python interface for the *dispatch* runtime.

Python applications that run TensorRT engines should import one of the above packages to load the appropriate library for their use case.

5.7. Compatibility

By default, serialized engines are only guaranteed to work correctly when used with the same OS, CPU architectures, GPU models, and TensorRT versions used to serialize the engines. To relax the constraints on TensorRT versions and GPU models, refer to the [Version Compatibility](#) and [Hardware Compatibility](#) sections.

Chapter 6. Advanced Topics

6.1. Version Compatibility

By default, TensorRT engines are compatible only with the version of TensorRT with which they are built. With appropriate build-time configuration, engines that are compatible with later TensorRT versions can be built. TensorRT engines built with TensorRT 8 will also be compatible with TensorRT 9 and TensorRT 10 runtimes, but not vice versa.

Version compatibility is supported from version 8.6; the plan must be built with a version at least 8.6 or higher, and the runtime must be 8.6 or higher.

When using version compatibility, the API supported at runtime for an engine is the intersection of the API supported in the version with which it was built and the API of the version used to run it. TensorRT removes APIs only on major version boundaries, so this is not a concern within a major version. However, users wishing to use TensorRT 8 or TensorRT 9 engines with TensorRT 10 must migrate away from removed APIs and are advised to avoid the deprecated APIs.

The recommended approach to creating a version-compatible engine is to build as follows:

C++

```
builderConfig.setFlag(BuilderFlag::kVERSION_COMPATIBLE);  
IHostMemory* plan = builder->buildSerializedNetwork(network, config);
```

Python

```
builder_config.set_flag(tensorrt.BuilderFlag.VERSION_COMPATIBLE)  
plan = builder.build_serialized_network(network, config)
```

If the network was created with TensorRT 8 or 9, it must have been created with `NetworkDefinitionCreationFlag::kEXPLICIT_BATCH`. TensorRT 10 makes `explicit batch` the default and makes it impossible to turn it off.

The request for a version-compatible engine causes a copy of the lean runtime to be added to the plan. When you deserialize the plan, TensorRT recognizes it contains a copy of the runtime. It loads the runtime to deserialize and execute the rest of the plan. Because this results in code being loaded and run from the plan in the context of the owning process, you should only deserialize trusted plans this way. To indicate to TensorRT that you trust the plan, call:

C++

```
runtime->setEngineHostCodeAllowed(true);
```

Python

```
runtime.engine_host_code_allowed = True
```

The flag for trusted plans is also required if you are packaging plugins in the plan (refer to [Plugin Shared Libraries](#)).

6.1.1. Manually Loading the Runtime

The previous approach ([Version Compatibility](#)) packages a copy of the runtime with every plan, which can be prohibitive if your application uses many models. An alternative approach is to manage the runtime loading yourself. For this approach, build version-compatible plans as explained in the previous section, but also set an additional flag to exclude the lean runtime.

C++

```
builderConfig.setFlag(BuilderFlag::kVERSION_COMPATIBLE);
builderConfig.setFlag(BuilderFlag::kEXCLUDE_LEAN_RUNTIME);
IHostMemory* plan = builder->buildSerializedNetwork(network, config);
```

Python

```
builder_config.set_flag(tensorrt.BuilderFlag.VERSION_COMPATIBLE)
builder_config.set_flag(tensorrt.BuilderFlag.EXCLUDE_LEAN_RUNTIME)
plan = builder.build_serialized_network(network, config)
```

To run this plan, you must have access to the lean runtime for the version with which it was built. Suppose you have built the plan with TensorRT 8.6, and your application is linked against TensorRT 10. You can load the plan as follows.

C++

```
IRuntime* v10Runtime = createInferRuntime(logger);
IRuntime* v8ShimRuntime = v10Runtime->loadRuntime(v8RuntimePath);
engine = v8ShimRuntime->deserializeCudaEngine(v8plan);
```

Python

```
v10_runtime = tensorrt.Runtime(logger)
v8_shim_runtime = v10_runtime.load_runtime(v8_runtime_path)
engine = v8_shim_runtime.deserialize_cuda_engine(v8_plan)
```

The runtime will translate TensorRT 10 API calls for the TensorRT 8.6 runtime, checking to ensure that the call is supported and performing any necessary parameter remapping.

6.1.2. Loading from Storage

TensorRT can load the shared runtime library directly from memory on most OSs. However, on Linux kernels before 3.17, a temporary directory is required. Use the `IRuntime::setTempfileControlFlags` and `IRuntime::setTemporaryDirectory` APIs to control TensorRT's use of these mechanisms.

6.1.3. Using Version Compatibility with the ONNX Parser

When building a version-compatible engine from a TensorRT network definition generated using TensorRT's ONNX parser, you must specify that the parser must use the native `InstanceNormalization` implementation instead of the plugin one.

To do this, use the `IParser::setFlag()` API.

C++

```
auto *parser = nvonnxparser::createParser(network, logger);
parser->setFlag(nvonnxparser::OnnxParserFlag::kNATIVE_INSTANCENORM);
```

Python

```
parser = trt.OnnxParser(network, logger)
parser.set_flag(trt.OnnxParserFlag.NATIVE_INSTANCENORM)
```

In addition, the parser may require plugins to fully implement all ONNX operators used in the network. In particular, if the network is used to build a version-compatible engine, some plugins may need to be included with the engine (either serialized with the engine or provided externally and loaded explicitly).

To query the list of plugin libraries needed to implement a particular parsed network, use the `IParser::getUsedVCPluginLibraries` API:

C++

```
auto *parser = nvonnxparser::createParser(network, logger);
parser->setFlag(nvonnxparser::OnnxParserFlag::kNATIVE_INSTANCENORM);
parser->parseFromFile(filename, static_cast<int>(ILogger::Severity::kINFO));
int64_t nbPluginLibs;
char const* const* pluginLibs = parser->getUsedVCPluginLibraries(nbPluginLibs);
```

Python

```
parser = trt.OnnxParser(network, logger)
parser.set_flag(trt.OnnxParserFlag.NATIVE_INSTANCENORM)

status = parser.parse_from_file(filename)
plugin_libs = parser.get_used_vc_plugin_libraries()
```

Refer to [Plugin Shared Libraries](#) for instructions on using the resulting library list to serialize the plugins or package them externally.

6.2. Hardware Compatibility

By default, TensorRT engines are only compatible with the type of device where they were built. With build-time configuration, engines that are compatible with other types of devices can be built. Currently, hardware compatibility is supported only for Ampere and later device architectures and is not supported on NVIDIA DRIVE OS or JetPack.

For example, to build an engine compatible with all Ampere and newer architectures, configure the `IBuilderConfig` as follows:

```
config->setHardwareCompatibilityLevel(nvinfer1::HardwareCompatibilityLevel::kAMPERE_PLUS);
```

When building in hardware compatibility mode, TensorRT excludes tactics that are not hardware compatible, such as those that use architecture-specific instructions or require more shared memory than is available on some devices. Thus, a hardware-compatible engine may have lower throughput and/or higher latency than its non-hardware-compatible counterpart. The degree of this performance impact depends on the network architecture and input sizes.

6.3. Compatibility Checks

TensorRT records the major, minor, patch, and build versions of the library used to create the plan in a plan. If these do not match the runtime version used to deserialize the plan,

it will fail to deserialize. When using version compatibility, the check will be performed by the lean runtime deserializing the plan data. By default, that lean runtime is included in the plan, and the match is guaranteed to succeed.

TensorRT also records the compute capability (major and minor versions) in the plan and checks it against the GPU on which the plan is being loaded. If they do not match, the plan will fail to deserialize. This ensures that kernels selected during the build phase are present and can run. When using hardware compatibility, the check is relaxed; with `HardwareCompatibilityLevel::kAMPERE_PLUS`, the check will ensure that the compute capability is greater than or equal to 8.0 rather than checking for an exact match.

TensorRT additionally checks the following properties and will issue a warning if they do not match, except when using hardware compatibility:

- ▶ Global memory bus width
- ▶ L2 cache size
- ▶ Maximum shared memory per block and multiprocessor
- ▶ Texture alignment requirement
- ▶ Number of multiprocessors
- ▶ Whether the GPU device is integrated or discrete

If GPU clock speeds differ between engine serialization and runtime systems, the tactics chosen by the serialization system may not be optimal for the runtime system and may incur some performance degradation.

If it is impossible to build a TensorRT engine for each individual type of GPU, you can select several GPUs to build engines with and run the engine on different GPUs with the same architecture. For example, among the NVIDIA RTX 40xx GPUs, you can build an engine with RTX 4090 and an engine with RTX 4070. At runtime, you can use the RTX 4090 engine on an RTX 4080 GPU and the 4070 engine on all smaller GPUs. In most cases, the engine will run without functional issues and with only a small performance drop compared to running the engine built with the same GPU.

However, if the engine requires a large amount of device memory and the device memory available during deserialization is smaller than when the engine was built, deserialization may fail. In this case, it is recommended to build the engine on a smaller GPU or on a larger device with limited compute resources (refer to the [Limiting Compute Resources](#) section).

The safety runtime can deserialize engines generated in an environment where the major, minor, patch, and build version of TensorRT do not match exactly in some cases. For more information, refer to the NVIDIA DRIVE OS 6.0 Developer Guide.

6.4. Refitting an Engine

TensorRT can *refit* an engine with new weights without having to rebuild it. However, the option to do so must be specified when building:

```
...
config->setFlag(BuilderFlag::kREFIT)
```

```
builder->buildSerializedNetwork(network, config);
```

Later, you can create a `Refitter` object:

```
ICudaEngine* engine = ...;
IRefitter* refitter = createInferRefitter(*engine, gLogger)
```

Then, update the weights. For example, to update a set of weights named “Conv Layer Kernel Weights”:

```
Weights newWeights = ...;
refitter->setNamedWeights("Conv Layer Kernel Weight",
                          newWeights);
```

The new weights should have the same count as the original weights used to build the engine. `setNamedWeights` returns `false` if something goes wrong, such as a wrong weights name or a change in the weights count.

You can use `INetworkDefinition::setWeightsName()` to name weights at build time - the ONNX parser uses this API to associate the weights with the names used in the ONNX model. Otherwise, TensorRT will name the weights internally based on the related layer names and weight roles.

You can also pass GPU weights to the refitter via:

```
Weights newBiasWeights = ...;
refitter->setNamedWeights("Conv Layer Bias Weight", newBiasWeights, TensorLocation::kDEVICE);
```

Because of how the engine is optimized, if you change some weights, you might have to supply some other weights, too. The interface can tell you what additional weights must be supplied.

This typically requires two calls to `IRefitter::getMissingWeights`, first to get the number of weights objects that must be supplied, and second to get their layers and roles.

```
int32_t const n = refitter->getMissingWeights(0, nullptr);
std::vector<const char*> weightsNames(n);
refitter->getMissingWeights(n, weightslayerNames.data());
```

You can supply the missing weights in any order:

```
for (int32_t i = 0; i < n; ++i)
    refitter->setNamedWeights(weightsNames[i], Weights{...});
```

The set of missing weights returned is complete because supplying only the missing weights does not require more.

Once all the weights have been provided, you can update the engine:

```
bool success = refitter->refitCudaEngine();
assert(success);
```

If the refit returns `false`, check the log for a diagnostic; perhaps the issue is about weights that are still missing. There is also an async version, `refitCudaEngineAsync`, that can accept a stream parameter.

You can update the weights memory directly and then call `refitCudaEngine/`
`refitCudaEngineAsync` in another iteration. If weights pointers need to be changed, call `setNamedWeights` to override the previous setting. Call `unsetNamedWeights` to unset

previously set weights so that they will not be used in later refitting, and it becomes safe to release these weights.

After refitting is done, you can then delete the refitter:

```
delete refitter;
```

The updated engine behaves like it was built from a network updated with the new weights. After refitting the engine, the previously created execution context can continue to be used.

To view all refittable weights in an engine, use `refitter->getAllWeights(...)`, similar to how `getMissingWeights` was used above.

6.4.1. Weight-Stripping

When `refit` is enabled, all the constant weights in the network can be updated after the engine is built. However, this introduces both a cost to refit the engine with new weights and a potential runtime impact because the inability to constant-fold weights may prevent the builder from performing some optimizations.

This cost is unavoidable when the weights with which the engine will be refitted are unknown at build time. However, in some scenarios, the weights are known. For example, you may use TensorRT as one of multiple back ends to execute an ONNX model and wish to avoid an additional copy of weights in the TensorRT plan.

The weight-stripping build configuration enables this scenario; when enabled, TensorRT enables `refit` only for constant weights that do not impact the builder's ability to optimize and produce an engine with the same runtime performance as a non-fittable engine. Those weights are then omitted from the serialized engine, resulting in a small plan file that can be refitted at runtime using the weights from the ONNX model.

The `trtexec` tool provides the `--- stripWeights` flags for building the weight-stripped engine. Refer to the [trtexec](#) section for more details.

The following steps show how to refit the weights for weight-stripped engines. When working with ONNX models, the ONNX parser library can perform the refit automatically. For more information, refer to [Refitting a Weight-Stripped Engine Directly from ONNX](#).

1. Set the corresponding builder flag to enable the weight-stripped build. Here, the `kSTRIP_PLAN` flag works with either `kREFIT` or `kREFIT_IDENTICAL`. It defaults to the latter. The `REFIT_IDENTICAL` flag instructs the TensorRT builder to optimize under the assumption that the engine will be refitted with weights identical to those provided at build time. The `kSTRIP_PLAN` flag minimizes plan size by stripping out the refittable weights.

C++

```
...
config->setFlag(BuilderFlag::kSTRIP_PLAN);
config->setFlag(BuilderFlag::kREFIT_IDENTICAL);
builder->buildSerializedNetwork(network, config);
```

Python

```
config.flags |= 1 << int(trt.BuilderFlag.STRIP_PLAN)
config.flags |= 1 << int(trt.BuilderFlag.REFIT_IDENTICAL)
```

```
builder.build_serialized_network(network, config)
```

2. After the engine is built, save the plan file and distribute it to the installer.
3. On the client side, when you launch the network for the first time, update all the weights in the engine. Since all the weights in the engine plan were removed, use the `getAllWeights` API here.

C++

```
int32_t const n = refitter->getAllWeights(0, nullptr);
```

Python

```
all_weights = refitter.get_all()
```

4. Update the weights one by one.

C++

```
for (int32_t i = 0; i < n; ++i)
    refitter->setNamedWeights(weightsNames[i], Weights{...});
```

Python

```
for name in wts_list:
    refitter.set_named_weights(name, weights[name])
```

5. Save the full engine plan file.

C++

```
auto serializationConfig = SampleUniquePtr<nvinfer1::ISerializationConfig>(cudaEngine->createSerializationConfig());
auto serializationFlag = serializationConfig->getFlags()
serializationFlag &= ~(1 <<
    static_cast<uint32_t>(nvinfer1::SerializationFlag::kEXCLUDE_WEIGHTS));
serializationConfig->setFlags(serializationFlag)
auto hostMemory = SampleUniquePtr<nvinfer1::IHostMemory>(cudaEngine->serializeWithConfig(*serializationConfig));
```

Python

```
serialization_config = engine.create_serialization_config()
serialization_config.flags &= ~(1 << int(trt.SerializationFlag.EXCLUDE_WEIGHTS))
binary = engine.serialize_with_config(serialization_config)
```

The application can now use the new full engine plan file for future inference.

6.4.2. Refitting a Weight-Stripped Engine Directly from ONNX

When working with weight-stripped engines created from ONNX models, the refit process can be done automatically with the `IParserRefitter` class from the ONNX parser library. The following steps show how to create the class and run the refit process.

1. Create your engine as described in [Weight-Stripping](#), and create an `IRefitter` object.

C++

```
IRefitter* refitter = createInferRefitter(*engine, gLogger);
```

Python

```
refitter = trt.Refitter(engine, TRT_LOGGER)
```

2. Create an `IParserRefitter` object.

C++

```
IParserRefitter* parserRefitter = createParserRefitter(*refitter, gLogger);
```

Python

```
parser_refitter = trt.OnnxParserRefitter(refitter, TRT_LOGGER)
```

3. Call the `refitFromFile()` function of the `IParserRefitter`. Ensure that the ONNX model is identical to the one used to create the weight-stripped engine. This function will return `true` if all the stripped weights are found in the ONNX model; otherwise, it will return `false`.

C++

```
bool result = parserRefitter->refitFromFile("path_to_onnx_model");
```

Python

```
result = parser_refitter.refit_from_file("path_to_onnx_model")
```

4. Call the `refit` function of the `IRefitter` to complete the refit process.

C++

```
refitSuccess = refitter->refitCudaEngine();
```

Python

```
refit_success = refitter.refit_cuda_engine()
```

6.4.3. Weight-Stripping Work with Lean Runtime

Additionally, we can leverage the lean runtime to further reduce the package size for the weight-stripped engine. The lean runtime is the same runtime used in version-compatible engines. The original purpose is to allow you to generate a TensorRT engine with version X and load it with an application built with version Y. The lean runtime library is relatively small, approximately 40 MiB. Therefore, software distributors on top of TensorRT only need to ship the weightless engine along with the 40 MiB lean runtime when the weights are already available on the target customer machine.

The recommended approach to build the engine is as follows:

C++

```
builderConfig.setFlag(BuilderFlag::kVERSION_COMPATIBLE);
builderConfig.setFlag(BuilderFlag::kEXCLUDE_LEAN_RUNTIME);
builderConfig.setFlag(BuilderFlag::kSTRIP_PLAN);
IHostMemory* plan = builder->buildSerializedNetwork(network, config);
```

Python

```
builder_config.set_flag(tensorrt.BuilderFlag.VERSION_COMPATIBLE)
builder_config.set_flag(tensorrt.BuilderFlag.EXCLUDE_LEAN_RUNTIME)
builder_config.set_flag(tensorrt.BuilderFlag.STRIP_PLAN)

plan = builder.build_serialized_network(network, config)
```

Load the engine with the shared lean runtime library path:

C++

```
runtime->loadRuntime("your_lean_runtime_full_path")
```

Python

```
runtime.load_runtime("your_lean_runtime_full_path")
```

For more information about the lean runtime, refer to the [Version Compatibility](#) section.

6.4.4. Fine Grained Refit Build

When using the `kREFIT` builder configuration, all weights are marked as refittable. This is useful when it is difficult to distinguish between trainable and untrainable weights. However, marking all weights as refittable can lead to a performance trade-off. This is because certain optimizations are broken when weights are marked as refittable. For example, in the case of the GELU expression, TensorRT can encode all GELU coefficients in a single CUDA kernel. However, if all coefficients are marked as refittable, TensorRT

may no longer be able to fuse the Conv-GELU operations into a single kernel. To address this, we have introduced the fine-grained refit API. This API provides precise control over which weights are marked as refittable, allowing for more efficient optimization.

Here is an example of marking weights as refittable in the `INetworkDefinition`:

C++

```
...
network->setWeightsName(Weights(weights), "conv1_filter");
network->markWeightsRefittable("conv1_filter"); assert(network-
>areWeightsMarkedRefittable("conv1_filter"));
```

Python

```
...
network.set_weights_name(conv_filter, "conv1_filter")
network.mark_weights_refittable("conv1_filter")
assert network.are_weights_marked_refittable("conv1_filter")
```

Later, we need to update the builder configuration like this:

C++

```
...
config->setFlag(BuilderFlag::kREFIT_INDIVIDUAL)
builder->buildSerializedNetwork(network, config);
```

Python

```
...
config.set_flag(trt.BuilderFlag.REFIT_INDIVIDUAL)
builder.build_serialized_network(network, config)
```

The remaining refit code follows the same steps as refitting all weights workflow.

6.4.5. Stripping Weights with Fine-Grained Refit Build

The fine-grained refit build also works with the weights stripping flag. To run this, we must enable both builder flags in the code after marking the necessary weights as refittable.

Here is an example:

C++

```
...
config->setFlag(BuilderFlag::kSTRIP_PLAN);
config->setFlag(BuilderFlag::kREFIT_INDIVIDUAL);
builder->buildSerializedNetwork(network, config);
```

Python

```
config.flags |= 1 << int(trt.BuilderFlag.STRIP_PLAN)
config.flags |= 1 << int(trt.BuilderFlag.REFIT_INDIVIDUAL)
builder.build_serialized_network(network, config)
```

The remaining refit and inference codes are the same as the [Weight-Stripping](#) sections.

6.5. Algorithm Selection and Reproducible Builds

The default behavior of TensorRT's optimizer is to choose the algorithms that globally minimize the execution time of the engine. It does this by timing each implementation, and sometimes, when implementations have similar timings, system noise may

determine which will be chosen on any particular run of the builder. Different implementations will typically use different orders of accumulation of floating point values, and two implementations may use different algorithms or even run at different precisions. Thus, different invocations of the builder will typically not result in engines that return bit-identical results.

Sometimes, having a deterministic build or recreating an earlier build's algorithm choices is important. You can manually guide algorithm selection by providing an implementation of the `IAlgorithmSelector` interface and attaching it to a builder configuration with `setAlgorithmSelector`.

The method `IAlgorithmSelector::selectAlgorithms` receives an `AlgorithmContext` containing information about the algorithm requirements for a layer and a set of `Algorithm` choices meeting those requirements. It returns the set of algorithms that TensorRT should consider for the layer.

The builder selects the one that minimizes the global runtime for the network from these algorithms. If no choice is returned and `BuilderFlag::kREJECT_EMPTY_ALGORITHMS` is unset, TensorRT interprets this to mean that any algorithm may be used for this layer. To override this behavior and generate an error if an empty list is returned, set the `BuilderFlag::kREJECT_EMPTY_ALGORITHMS` flag.

After TensorRT has finished optimizing the network for a given profile, it calls `reportAlgorithms`, which can be used to record the final choice made for each layer.

To build a TensorRT engine deterministically, return a single choice from `selectAlgorithms`. To replay choices from an earlier build, use `reportAlgorithms` to record the choices and return them in `selectAlgorithms`.

`sampleAlgorithmSelector` demonstrates how to use the algorithm selector to achieve determinism and reproducibility in the builder.



Note:

- ▶ The notion of a “layer” in algorithm selection differs from `ILayer` in `INetworkDefinition`. The “layer” in the former can be equivalent to a collection of multiple network layers due to fusion optimizations.
- ▶ Picking the fastest algorithm in `selectAlgorithms` may not produce the best performance for the overall network, as it may increase reformatting overhead.
- ▶ The timing of an `IAlgorithm` is 0 in `selectAlgorithms` if TensorRT found that layer to be a no-op.
- ▶ `reportAlgorithms` does not provide the timing and workspace information for an `IAlgorithm` provided to `selectAlgorithms`.

6.6. Creating a Network Definition from Scratch

Instead of using a parser, you can define the network directly to TensorRT using the Network Definition API. This scenario assumes that the per-layer weights are ready in host memory to pass to TensorRT during the network creation.

The following examples create a simple network with Input, Convolution, Pooling, MatrixMultiply, Shuffle, Activation, and SoftMax layers.

For more information regarding layers, refer to the [NVIDIA TensorRT Operator's Reference](#).

6.6.1. C++

This example loads the weights into a `weightMap` data structure used in the following code.

First, create the builder and network objects. Note that in the following example, the logger is initialized using the `logger.cpp` file common to all C++ samples. The C++ sample helper classes and functions can be found in the `common.h` header file.

```
auto builder =
SampleUniquePtr<nvinfer1::IBuilder>(nvinfer1::createInferBuilder(sample::gLogger.getTRTLogger()));
const auto explicitBatchFlag = 1U <<
static_cast<uint32_t>(nvinfer1::NetworkDefinitionCreationFlag::kEXPLICIT_BATCH);
auto network = SampleUniquePtr<nvinfer1::INetworkDefinition>(builder-
>createNetworkV2(explicitBatchFlag));
```

Refer to the [Explicit vs Implicit Batch](#) section for more information about the `kEXPLICIT_BATCH` flag.

Add the Input layer to the network by specifying the input tensor's name, datatype, and full dimensions. A network can have multiple inputs, although in this sample, there is only one:

```
auto data = network->addInput(INPUT_BLOB_NAME, datatype, Dims4{1, 1, INPUT_H, INPUT_W});
```

Add the Convolution layer with hidden layer input nodes, strides, and weights for filter and bias.

```
auto conv1 = network->addConvolution(
*data->getOutput(0), 20, DimsHW{5, 5}, weightMap["conv1filter"], weightMap["conv1bias"]);
conv1->setStride(DimsHW{1, 1});
```



Note: Weights passed to TensorRT layers are in host memory.

Add the Pooling layer; note that the output from the previous layer is passed as input.

```
auto pool1 = network->addPooling(*conv1->getOutput(0), PoolingType::kMAX, DimsHW{2, 2});
pool1->setStride(DimsHW{2, 2});
```

Add a Shuffle layer to reshape the input in preparation for matrix multiplication:

```
int32_t const batch = input->getDimensions().d[0];
int32_t const mmInputs = input->getDimensions().d[1] * input->getDimensions().d[2] *
input->getDimensions().d[3];
auto inputReshape = network->addShuffle(*input);
```

```
inputReshape->setReshapeDimensions(Dims{2, {batch, mmInputs}});
```

Now, add a MatrixMultiply layer. Here, the model exporter provided transposed weights, so the `kTRANPOSE` option is specified.

```
IConstantLayer* filterConst = network->addConstant(Dims{2, {nbOutputs, mmInputs}},
  mWeightMap["iplfilter"]);
auto mm = network->addMatrixMultiply(*inputReshape->getOutput(0), MatrixOperation::kNONE,
  *filterConst->getOutput(0), MatrixOperation::kTRANPOSE);
```

Add the bias, which will broadcast across the batch dimension.

```
auto biasConst = network->addConstant(Dims{2, {1, nbOutputs}}, mWeightMap["iplbias"]);
auto biasAdd = network->addElementWise(*mm->getOutput(0), *biasConst->getOutput(0),
  ElementWiseOperation::kSUM);
```

Add the ReLU Activation layer:

```
auto relu1 = network->addActivation(*ipl->getOutput(0), ActivationType::kRELU);
```

Add the SoftMax layer to calculate the final probabilities:

```
auto prob = network->addSoftMax(*relu1->getOutput(0));
```

Add a name for the output of the SoftMax layer so that the tensor can be bound to a memory buffer at inference time:

```
prob->getOutput(0)->setName(OUTPUT_BLOB_NAME);
```

Mark it as the output of the entire network:

```
network->markOutput(*prob->getOutput(0));
```

The network representing the MNIST model has now been fully constructed. For instructions on how to build an engine and run an inference with this network, refer to the [Building an Engine](#) and [Performing Inference](#).

6.6.2. Python

The code corresponding to this section can be found in [network_api_pytorch_mnist](#).

This example uses a helper class to hold some of the metadata about the model:

```
class ModelData(object):
    INPUT_NAME = "data"
    INPUT_SHAPE = (1, 1, 28, 28)
    OUTPUT_NAME = "prob"
    OUTPUT_SIZE = 10
    DTYPE = trt.float32
```

In this example, the weights are imported from the PyTorch MNIST model.

```
weights = mnist_model.get_weights()
```

Create the logger, builder, and network classes.

```
TRT_LOGGER = trt.Logger(trt.Logger.ERROR)
builder = trt.Builder(TRT_LOGGER)
EXPLICIT_BATCH = 1 << (int)(trt.NetworkDefinitionCreationFlag.EXPLICIT_BATCH)
network = builder.create_network(EXPLICIT_BATCH)
```

Refer to the [Explicit vs Implicit Batch](#) section for more information about the `kEXPLICIT_BATCH` flag.

Next, create the input tensor for the network, specifying the name, datatype, and shape of the tensor.

```
input_tensor = network.add_input(name=ModelData.INPUT_NAME, dtype=ModelData.DTYPE,
  shape=ModelData.INPUT_SHAPE)
```

Add a convolution layer, specifying the inputs, number of output maps, kernel shape, weights, bias, and stride:

```
conv1_w = weights["conv1.weight"].cpu().numpy()
conv1_b = weights["conv1.bias"].cpu().numpy()
conv1 = network.add_convolution_nd(
    input=input_tensor, num_output_maps=20, kernel_shape=(5, 5), kernel=conv1_w,
    bias=conv1_b
)
conv1.stride_nd = (1, 1)
```

Add a pooling layer, specifying the inputs (the output of the previous convolution layer), pooling type, window size, and stride:

```
pool1 = network.add_pooling_nd(input=conv1.get_output(0), type=trt.PoolingType.MAX,
    window_size=(2, 2))
pool1.stride_nd = trt.Dims2(2, 2)
```

Add the next pair of convolution and pooling layers:

```
conv2_w = weights["conv2.weight"].cpu().numpy()
conv2_b = weights["conv2.bias"].cpu().numpy()
conv2 = network.add_convolution_nd(pool1.get_output(0), 50, (5, 5), conv2_w, conv2_b)
conv2.stride_nd = (1, 1)

pool2 = network.add_pooling_nd(conv2.get_output(0), trt.PoolingType.MAX, (2, 2))
pool2.stride_nd = trt.Dims2(2, 2)
```

Add a Shuffle layer to reshape the input in preparation for matrix multiplication:

```
batch = input.shape[0]
mm_inputs = np.prod(input.shape[1:])
input_reshape = net.add_shuffle(input)
input_reshape.reshape_dims = trt.Dims2(batch, mm_inputs)
```

Now, add a MatrixMultiply layer. Here, the model exporter provided transposed weights, so the `kTRANPOSE` option is specified.

```
filter_const = net.add_constant(trt.Dims2(nbOutputs, k), weights["fc1.weight"].numpy())
mm = net.add_matrix_multiply(input_reshape.get_output(0), trt.MatrixOperation.NONE,
    filter_const.get_output(0), trt.MatrixOperation.TRANSPOSE);
```

Add bias, which will broadcast across the batch dimension:

```
bias_const = net.add_constant(trt.Dims2(1, nbOutputs), weights["fc1.bias"].numpy())
bias_add = net.add_elementwise(mm.get_output(0), bias_const.get_output(0),
    trt.ElementWiseOperation.SUM)
```

Add the ReLU activation layer:

```
relu1 = network.add_activation(input=fc1.get_output(0), type=trt.ActivationType.RELU)
```

Add the final fully connected layer, and mark the output of this layer as the output of the entire network:

```
fc2_w = weights['fc2.weight'].numpy()
fc2_b = weights['fc2.bias'].numpy()
fc2 = add_matmul_as_fc(network, relu1.get_output(0), ModelData.OUTPUT_SIZE, fc2_w, fc2_b)

fc2.get_output(0).name = ModelData.OUTPUT_NAME
network.mark_output(tensor=fc2.get_output(0))
```

The network representing the MNIST model has now been fully constructed. Refer to sections [Building an Engine](#) and [Performing Inference](#) for how to build an engine and run inference with this network.

6.7. Strongly Typed Networks

By default, TensorRT autotunes tensor types to generate the fastest engine. This can result in accuracy loss when model accuracy requires a layer to run with higher precision than TensorRT chooses. One approach is to use the `ILayer::setPrecision` and `ILayer::setOutputType` APIs to control a layer's I/O types and, hence, its execution precision. This approach works, but it can be challenging to figure out which layers need to be run at high precision to get the best accuracy.

An alternative approach is to specify low precision use in the model itself, using, for example, [Automatic mixed precision training](#) or [quantization-aware training](#), and have TensorRT adhere to the precision specifications. TensorRT will still autotune over different data layouts to find an optimal set of kernels for the network.

When you specify to TensorRT that a network is strongly typed, it infers a type for each intermediate and output tensor using the rules in the [operator type specification](#). Inferred types are adhered to while building the engine. As types are not autotuned, an engine built from a strongly typed network can be slower than one where TensorRT chooses tensor types. On the other hand, the build time may improve as fewer kernel alternatives are evaluated.

Strongly typed networks are not supported with DLA.

You can create a strongly typed network as follows:

C++

```
IBuilder* builder = ...;
INetworkDefinition* network = builder->createNetworkV2(1U <<
    static_cast<uint32_t>(NetworkDefinitionCreationFlag::kSTRONGLY_TYPED))
```

Python

```
builder = trt.Builder(...)
builder.create_network(1 << int(trt.NetworkDefinitionCreationFlag.STRONGLY_TYPED))
```

For strongly typed networks, the layer APIs `setPrecision` and `setOutputType` are not permitted, nor are the builder precision flags `kFP16`, `kBF16`, `kFP8`, and `kINT8`. The builder flag `kTF32` is permitted as it controls TF32 Tensor Core usage for FP32 types rather than controlling the use of TF32 data types.

6.8. Reduced Precision in Weakly-Typed Networks

6.8.1. Network-Level Control of Precision

By default, TensorRT works with 32-bit precision but can also execute operations using 16-bit and 8-bit quantized floating points. Using lower precision requires less memory and enables faster computation.

Reduced precision support depends on your hardware (refer to [Hardware and Precision](#)). You can query the builder to check the supported precision support on a platform:

C++

```
if (builder->platformHasFastFp16()) { ... };
```

Python

```
if builder.platform_has_fp16:
```

Setting flags in the builder configuration informs TensorRT that it may select lower-precision implementations:

C++

```
config->setFlag(BuilderFlag::kFP16);
```

Python

```
config.set_flag(trt.BuilderFlag.FP16)
```

There are three precision flags: FP16, INT8, and TF32, and they may be enabled independently. TensorRT will still choose a higher-precision kernel if it results in a lower runtime or if no low-precision implementation exists.

When TensorRT chooses a precision for a layer, it automatically converts weights as necessary to run the layer.

While using FP16 and TF32 precisions is relatively straightforward, working with INT8 adds additional complexity. For more details, refer to the [Working with Quantized Types](#) chapter.

Note that even if the precision flags are enabled, the engine's input/output bindings default to FP32. Refer to the [I/O Formats](#) section for information on how to set the data types and formats of the input/output bindings.

6.8.2. Layer-Level Control of Precision

The builder flags provide permissive, coarse-grained control. However, sometimes, part of a network requires a higher dynamic range or is sensitive to numerical precision. You can constrain the input and output types per layer:

C++

```
layer->setPrecision(DataType::kFP16)
```

Python

```
layer.precision = trt.fp16
```

This provides a *preferred type* (here, `DataType::kFP16`) for the inputs and outputs.

You may further set preferred types for the layer's outputs:

C++

```
layer->setOutputType(out_tensor_index, DataType::kFLOAT)
```

Python

```
layer.set_output_type(out_tensor_index, trt.fp32)
```

The computation will use the same floating-point type as the inputs. Most TensorRT implementations have the same floating-point types for input and output; however, Convolution, Deconvolution, and FullyConnected can support quantized INT8 input and unquantized FP16 or FP32 output, as sometimes working with higher-precision outputs from quantized inputs is necessary to preserve accuracy.

Setting the precision constraint hints to TensorRT that it should select a layer implementation whose inputs and outputs match the preferred types, inserting reformat operations if the outputs of the previous layer and the inputs to the next layer do not match the requested types. Note that TensorRT will only be able to select an implementation with these types if they are also enabled using the flags in the builder configuration.

By default, TensorRT chooses such an implementation only if it results in a higher-performance network. If another implementation is faster, TensorRT will use it and issue a warning. You can override this behavior by preferring the type constraints in the builder configuration.

C++

```
config->setFlag(BuilderFlag::kPREFER_PRECISION_CONSTRAINTS)
```

Python

```
config.set_flag(trt.BuilderFlag.PREFER_PRECISION_CONSTRAINTS)
```

If the constraints are preferred, TensorRT obeys them unless there is no implementation with the preferred precision constraints, in which case it issues a warning and uses the fastest available implementation.

To change the warning to an error, use `OBEY` instead of `PREFER`:

C++

```
config->setFlag(BuilderFlag::kOBEY_PRECISION_CONSTRAINTS);
```

Python

```
config.set_flag(trt.BuilderFlag.OBEY_PRECISION_CONSTRAINTS);
```

[sampleINT8API](#) illustrates the use of reduced precision with these APIs.

Precision constraints are optional - you can query whether a constraint has been set using `layer->precisionIsSet()` in C++ or `layer.precision_is_set` in Python. If a precision constraint is not set, the result returned from `layer->getPrecision()` in C++ or reading the `precision` attribute in Python is not meaningful. Output type constraints are similarly optional.

If no constraints are set using `ILayer::setPrecision` or `ILayer::setOutputType` API, then `BuilderFlag::kPREFER_PRECISION_CONSTRAINTS` or `BuilderFlag::kOBEY_PRECISION_CONSTRAINTS` are ignored. A layer can choose from precision or output types based on allowed builder precisions.

Note that the `ITensor::setType()` API does not set the precision constraint of a tensor unless it is one of the input/output tensors of the network. Also, there is a distinction between `layer->setOutputType()` and `layer->getOutput(i)->setType()`. The former is an optional type constraining the implementation TensorRT will choose for a layer. The latter specifies the type of a network's input/output and is ignored if the tensor is not a network input/output. If they are different, TensorRT will insert a cast to ensure that both specifications are respected. Thus, if you are calling `setOutputType()` for a layer that produces a network output, you should generally configure the corresponding network output to have the same type.

6.8.3. TF32

TensorRT allows the use of TF32 Tensor Cores by default. When computing inner products, such as during convolution or matrix multiplication, TF32 execution does the following:

- ▶ Rounds the FP32 multiplicands to FP16 precision but keeps the FP32 dynamic range.
- ▶ Computes an exact product of the rounded multiplicands.
- ▶ Accumulates the products in an FP32 sum.

TF32 Tensor Cores can speed up networks using FP32, typically with no loss of accuracy. It is more robust than FP16 for models that require an HDR (high dynamic range) for weights or activations.

There is no guarantee that TF32 Tensor Cores are used, and there is no way to force the implementation to use them - TensorRT can fall back to FP32 at any time and always falls back if the platform does not support TF32. However, you can disable their use by clearing the TF32 builder flag.

C++

```
config->clearFlag(BuilderFlag::kTF32);
```

Python

```
config.clear_flag(trt.BuilderFlag.TF32)
```

Setting the environment variable `NVIDIA_TF32_OVERRIDE=0` when building an engine disables the use of TF32 despite setting `BuilderFlag::kTF32`. When set to 0, this environment variable overrides any defaults or programmatic configuration of NVIDIA libraries, so they never accelerate FP32 computations with TF32 Tensor Cores. This is meant to be a debugging tool only, and no code outside NVIDIA libraries should change the behavior based on this environment variable. Any other setting besides 0 is reserved for future use.



WARNING: Setting the environment variable `NVIDIA_TF32_OVERRIDE` to a different value when running the engine can cause unpredictable precision/performance effects. It is best left unset when an engine is run.



Note: Unless your application requires the higher dynamic range provided by TF32, FP16 will be a better solution since it almost always yields faster performance.

6.8.4. BF16

TensorRT supports the `bfloat16` (brain float) floating point format on NVIDIA Ampere and later architectures. Like other precisions, it can be enabled using the corresponding builder flag:

C++

```
config->setFlag(BuilderFlag::kBF16);
```

Python

```
config.set_flag(trt.BuilderFlag.BF16)
```

Note that not all layers support `bfloat16`. Refer to the [TensorRT Operator documentation](#) for details.

6.9. Control of Computational Precision

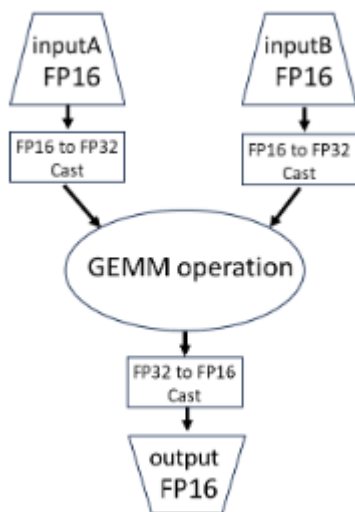
Sometimes, it is desirable to control the internal precision of the computation in addition to setting the input and output precisions for an operator. TensorRT selects the computational precision by default based on the layer input type and global performance considerations.

There are two layers where TensorRT provides additional capabilities to control computational precision:

The `INormalizationLayer` provides a `setPrecision` method to control the precision of accumulation. By default, to avoid overflow errors, TensorRT accumulates in FP32, even in mixed precision mode, regardless of builder flags. You can use this method to specify FP16 accumulation instead.

For the `IMatrixMultiplyLayer`, TensorRT, by default, selects accumulation precision based on the input types and performance considerations, although the accumulation type is guaranteed to have a range at least as great as the input types. When using strongly typed mode, you can enforce FP32 precision for FP16 GEMMs by casting the inputs to FP32. TensorRT recognizes this pattern and fuses the casts with the GEMM, resulting in a single kernel with FP16 inputs and FP32 accumulation.

Figure 1. Creating a Graph for FP32 Accumulation Request



6.10. I/O Formats

TensorRT optimizes a network using many different data formats. To allow efficient data passing between TensorRT and a client application, these underlying data formats are exposed at network I/O boundaries, that is, for Tensors marked as network input or output and when passing data to and from plugins. For other tensors, TensorRT picks formats that result in the fastest overall execution and may insert reformats to improve performance.

You can assemble an optimal data pipeline by profiling the available I/O formats in combination with the formats most efficient for the operations preceding and following TensorRT.

To specify I/O formats, you specify one or more formats as a bitmask.

The following example sets the input tensor format to `TensorFormat::kHWC8`. Note that this format only works for `DataType::kHALF`, so the data type must be set accordingly.

C++

```
auto formats = 1U << TensorFormat::kHWC8;
network->getInput(0)->setAllowedFormats(formats);
network->getInput(0)->setType(DataType::kHALF);
```

Python

```
formats = 1 << int(tensorrt.TensorFormat.HWC8)
network.get_input(0).allowed_formats = formats
network.get_input(0).dtype = tensorrt.DataType.HALF
```

Note that calling `setAllowedFormats()` or `setType()` on a tensor that is not a network input/output has no effect and is ignored by TensorRT.

It is possible to make TensorRT avoid inserting reformatting at the network boundaries by setting the builder configuration flag `DIRECT_IO`. This flag is generally counter-productive for two reasons:

- ▶ The resulting engine might be slower than if TensorRT had been allowed to insert reformatting. Reformatting may sound like wasted work, but it can allow the coupling of the most efficient kernels.
- ▶ The build will fail if TensorRT cannot build an engine without introducing such reformatting. The failure may happen only for some target platforms because of the formats supported by kernels for those platforms.

The flag exists for users who want full control over whether reformatting happens at I/O boundaries, such as to build engines that run solely on DLA without resorting to the GPU for reformatting.

[sampleIOFormats](#) illustrates how to specify I/O formats using C++.

The following table shows the supported formats.

Table 1. Supported I/O Formats

| Format | kINT32 | kFLOAT | kHALF | kINT8 | kBOOL | kUINT8 | kINT64 |
|-------------|----------------|----------------|--|----------------|----------------|----------------|----------------|
| kLINEAR | Only for GPU | Supported | Supported | Supported | Supported | Supported | Supported |
| kCHW2 | Not Applicable | Not Applicable | Only for GPU | Not Applicable | Not Applicable | Not Applicable | Not Applicable |
| kCHW4 | Not Applicable | Not Applicable | Supported | Supported | Not Applicable | Not Applicable | Not Applicable |
| kHWC8 | Not Applicable | Not Applicable | Only for GPU | Not Applicable | Not Applicable | Not Applicable | Not Applicable |
| kCHW16 | Not Applicable | Not Applicable | Supported | Not Applicable | Not Applicable | Not Applicable | Not Applicable |
| kCHW32 | Not Applicable | Only for GPU | Only for GPU | Supported | Not Applicable | Not Applicable | Not Applicable |
| kDHWC8 | Not Applicable | Not Applicable | Only for GPU | Not Applicable | Not Applicable | Not Applicable | Not Applicable |
| kCDHW32 | Not Applicable | Not Applicable | Only for GPU | Only for GPU | Not Applicable | Not Applicable | Not Applicable |
| kHWC | Not Applicable | Only for GPU | Not Applicable | Not Applicable | Not Applicable | Supported | Supported |
| kDLA_LINEAR | Not Applicable | Not Applicable | Only for DLA | Only for DLA | Not Applicable | Not Applicable | Not Applicable |
| kDLA_HWC4 | Not Applicable | Not Applicable | Only for DLA | Only for DLA | Not Applicable | Not Applicable | Not Applicable |
| kHWC16 | Not Applicable | Not Applicable | Only for NVIDIA Ampere Architecture GPUs and later | Not Applicable | Not Applicable | Not Applicable | Not Applicable |
| kDHWC | Not Applicable | Only for GPU | Not Applicable | Not Applicable | Not Applicable | Not Applicable | Not Applicable |

Note that for the vectorized formats, the channel dimension must be zero-padded to the multiple of the vector size. For example, if an input binding has dimensions of `[16, 3, 224, 224]`, `kHALF` data type, and `kHWC8` format, then the actual-required size of the binding buffer would be `16*8*224*224*sizeof(half)` bytes, even though the `engine->getBindingDimension()` API will return tensor dimensions as `[16, 3, 224, 224]`. The values in the padded part (that is, where `C=3, 4, ..., 7` in this example) must be filled with zeros.

Refer to [Data Format Descriptions](#) for how the data are laid out in memory for these formats.

6.11. Explicit vs Implicit Batch

TensorRT supports two modes for specifying a network: explicit batch and implicit batch.

Every tensor has an implicit batch dimension in *implicit batch* mode, and all other dimensions must have constant length. Early versions of TensorRT used this mode and are now deprecated but continue to be supported for backward compatibility.

In *explicit batch* mode, all dimensions are explicit and can be dynamic; their length can change at execution time. Many new features, such as dynamic shapes and loops, are available only in this mode, which is also required by the ONNX parser.

For example, consider a network that processes N images of size $H \times W$ with 3 channels in NCHW format. At runtime, the input tensor has dimensions $[N, 3, H, W]$. The two modes differ in how the `INetworkDefinition` specifies the tensor's dimensions:

- ▶ The network specifies $[N, 3, H, W]$ in explicit batch mode.
- ▶ The network specifies only $[3, H, W]$ in implicit batch mode. The batch dimension N is implicit.

Operations that "talk across a batch" are impossible to express in the implicit batch mode because there is no way to specify the batch dimension in the network. Examples of inexpressible operations in implicit batch mode:

- ▶ reducing across the batch dimension
- ▶ reshaping the batch dimension
- ▶ transposing the batch dimension with another dimension

The exception is that a tensor can be *broadcast* across the entire batch through the `ITensor::setBroadcastAcrossBatch` method for network inputs and implicit broadcasting for other tensors.

Explicit batch mode erases the limitations - the batch axis is axis 0. A more accurate term for explicit batch would be "batch oblivious" because, in this mode, TensorRT attaches no special semantic meaning to the leading axis except as required by specific operations. Indeed, in explicit batch mode, there might not even be a batch dimension (such as a network that handles only a single image) or multiple batch dimensions of unrelated lengths (such as a comparison of all possible pairs drawn from two batches).

The explicit versus implicit batch choice must be specified when creating the `INetworkDefinition` using a flag. Here is the C++ code for explicit batch mode:

```
IBuilder* builder = ...;
INetworkDefinition* network = builder->createNetworkV2(1U <<
    static_cast<uint32_t>(NetworkDefinitionCreationFlag::kEXPLICIT_BATCH));
```

For implicit batch, use `createNetwork` or pass a 0 to `createNetworkV2`.

Here is the Python code for explicit batch mode:

```
builder = trt.Builder(...)
builder.create_network(1 << int(trt.NetworkDefinitionCreationFlag.EXPLICIT_BATCH))
```

For implicit batch, omit the argument or pass a 0.

6.12. Sparsity

NVIDIA Ampere Architecture GPUs support [Structured Sparsity](#). The weights must have at least 2 zeros in every four-entry vector to use this feature to achieve higher inference performance. For TensorRT, the requirements are:

- ▶ For Convolution, for each output channel and each spatial pixel in the kernel weights, every four input channels must have at least two zeros. In other words, assuming that the kernel weights have the shape $[K, C, R, S]$ and $C \% 4 == 0$, then the requirement is verified using the following algorithm:

```
hasSparseWeights = True
for k in range(0, K):
    for r in range(0, R):
        for s in range(0, S):
            for c_packed in range(0, C // 4):
                if numpy.count_nonzero(weights[k, c_packed*4:(c_packed+1)*4, r, s]) > 2 :
                    hasSparseWeights = False
```

- ▶ For MatrixMultiply, of which Constant produces an input, every four elements of the reduction axis (κ) must have at least two zeros.

[Polygraphy](#) (`polygraphy inspect sparsity`) can detect whether the operation weights in an ONNX model follow the 2:4 structured sparsity pattern.

To enable the sparsity feature, set the `kSPARSE_WEIGHTS` flag in the builder config and make sure that `kFP16` or `kINT8` modes are enabled. For example:

C++

```
config->setFlag(BuilderFlag::kSPARSE_WEIGHTS);
config->setFlag(BuilderFlag::kFP16);
config->setFlag(BuilderFlag::kINT8);
```

Python

```
config.set_flag(trt.BuilderFlag.SPARSE_WEIGHTS)
config.set_flag(trt.BuilderFlag.FP16)
config.set_flag(trt.BuilderFlag.INT8)
```

At the end of the TensorRT logs, when the TensorRT engine is built, TensorRT reports which layers contain weights that meet the structured sparsity requirement and which layers TensorRT selects tactics that use the structured sparsity. In some cases, tactics with structured sparsity can be slower than normal, and TensorRT will choose normal tactics. The following output shows an example of TensorRT logs showing information about sparsity:

```
[03/23/2021-00:14:05] [I] [TRT] (Sparsity) Found 3 layer(s) eligible to use sparse tactics:
conv1, conv2, conv3
[03/23/2021-00:14:05] [I] [TRT] (Sparsity) Chose 2 layer(s) using sparse tactics: conv2,
conv3
```

Forcing kernel weights to have structured sparsity patterns can lead to accuracy loss. Refer to the [Automatic Sparsity tool in PyTorch](#) to recover lost accuracy with further fine-tuning.

To measure inference performance with structured sparsity using `trtexec`, refer to the [trtexec](#) section.

6.13. Empty Tensors

TensorRT supports empty tensors. A tensor is an empty tensor if it has one or more dimensions with a length of zero. Zero-length dimensions usually get no special treatment. If a rule works for a dimension of length L for an arbitrary positive value of L , it usually works for $L=0$, too.

For example, when concatenating two tensors with dimensions $[x,y,z]$ and $[x,y,w]$ along the last axis, the result has dimensions $[x,y,z+w]$, regardless of whether x , y , z , or w is zero.

Implicit broadcast rules remain unchanged since only unit-length dimensions are special for broadcast. For example, given two tensors with dimensions $[1,y,z]$ and $[x,1,z]$, their sum computed by `IElementWiseLayer` has dimensions $[x,y,z]$, regardless of whether x , y , or z is zero.

If an engine binding is an empty tensor, it still needs a non-null memory address, and different tensors should have different addresses. This is consistent with the C++ rule that every object has a unique address. For example, `new float[0]` returns a non-null pointer. If using a memory allocator that might return a null pointer for zero bytes, ask for at least one byte instead.

Refer to the [NVIDIA TensorRT Operator's Reference](#) for any special handling of empty tensors per layer.

6.14. Reusing Input Buffers

TensorRT allows specifying a CUDA event to be signaled once the input buffers are free to be reused. This allows the application to immediately refill the input buffer region for the next inference in parallel with finishing the current inference. For example:

C++

```
context->setInputConsumedEvent(&inputReady);
```

Python

```
context.set_input_consumed_event(inputReady)
```

6.15. Engine Inspector

TensorRT provides the `IEngineInspector` API to inspect the information inside a TensorRT engine. Call the `createEngineInspector()` from a deserialized engine to create an engine inspector, and then call `getLayerInformation()` or `getEngineInformation()` inspector APIs to get the information of a specific layer in the engine or the entire engine, respectively. You can print out the information of the first layer of the given engine, as well as the overall information of the engine, as follows:

C++

```
auto inspector = std::unique_ptr<IEngineInspector>(engine->createEngineInspector());
inspector->setExecutionContext(context); // OPTIONAL
```

```
std::cout << inspector->getLayerInformation(0, LayerInformationFormat::kJJSON); // Print
the information of the first layer in the engine.
std::cout << inspector->getEngineInformation(LayerInformationFormat::kJJSON); // Print the
information of the entire engine.
```

Python

```
inspector = engine.create_engine_inspector()
inspector.execution_context = context # OPTIONAL
print(inspector.get_layer_information(0, LayerInformationFormat.JSON)) # Print the
information of the first layer in the engine.
print(inspector.get_engine_information(LayerInformationFormat.JSON)) # Print the
information of the entire engine.
```

Note that the level of detail in the engine/layer information depends on the `ProfilingVerbosity` builder config setting when the engine is built. By default, `ProfilingVerbosity` is set to `kLAYER_NAMES_ONLY`, so only the layer names will be printed. If `ProfilingVerbosity` is set to `kNONE`, then no information will be printed; if it is set to `kDETAILED`, then detailed information will be printed.

Below are some examples of layer information printed by `getLayerInformation()` API depending on the `ProfilingVerbosity` setting:

`kLAYER_NAMES_ONLY`

```
"node_of_gpu_0/res4_0_branch2a_1 + node_of_gpu_0/res4_0_branch2a_bn_1 + node_of_gpu_0/
res4_0_branch2a_bn_2"
```

`kDETAILED`

```
{
  "Name": "node_of_gpu_0/res4_0_branch2a_1 + node_of_gpu_0/res4_0_branch2a_bn_1 +
node_of_gpu_0/res4_0_branch2a_bn_2",
  "LayerType": "CaskConvolution",
  "Inputs": [
    {
      "Name": "gpu_0/res3_3_branch2c_bn_3",
      "Dimensions": [16,512,28,28],
      "Format/Datatype": "Thirty-two wide channel vectorized row major Int8 format."
    }
  ],
  "Outputs": [
    {
      "Name": "gpu_0/res4_0_branch2a_bn_2",
      "Dimensions": [16,256,28,28],
      "Format/Datatype": "Thirty-two wide channel vectorized row major Int8 format."
    }
  ],
  "ParameterType": "Convolution",
  "Kernel": [1,1],
  "PaddingMode": "kEXPLICIT_ROUND_DOWN",
  "PrePadding": [0,0],
  "PostPadding": [0,0],
  "Stride": [1,1],
  "Dilation": [1,1],
  "OutMaps": 256,
  "Groups": 1,
  "Weights": {"Type": "Int8", "Count": 131072},
  "Bias": {"Type": "Float", "Count": 256},
  "AllowSparse": 0,
  "Activation": "RELU",
  "HasBias": 1,
  "HasReLU": 1,
  "TacticName":
"sm80_xmma_fprop_implicit_gemm_interleaved_i8i8_i8i32_f32_nchw_vect_c_32kcrs_vect_c_32_nchw_vect_c_32_ti
  "TacticValue": "0x11bde0e1d9f2f35d"
}
```

In addition, when the engine is built with dynamic shapes, the dynamic dimensions in the engine information will be shown as `-1`, and the tensor format information will not be shown because these fields depend on the actual shape at the inference

phase. To get the engine information for a specific inference shape, create an `IExecutionContext`, set all the input dimensions to the desired shapes, and then call `inspector->setExecutionContext(context)`. After the context is set, the inspector will print the engine information for the specific shape set in the context.

The `trtexec` tool provides the `--profilingVerbosity`, `--dumpLayerInfo`, and `--exportLayerInfo` flags for getting engine information for a given engine. Refer to the [trtexec](#) section for more details.

Currently, only binding information and layer information, including the dimensions of the intermediate tensors, precisions, formats, tactic indices, layer types, and layer parameters, are included in the engine information. In future TensorRT versions, more information may be added to the engine inspector output as new keys in the output JSON object. More specifications about the keys and the fields in the inspector output will also be provided.

In addition, some subgraphs are handled by a next-generation graph optimizer that is not yet integrated with the engine inspector. Therefore, the layer information within these layers is not currently shown. This will be improved in a future version of TensorRT.

6.16. Optimizer Callbacks

The optimizer callback API feature allows you to monitor the progress of the TensorRT build process, for example, to provide user feedback in interactive applications. To enable progress monitoring, create an object that implements the `IProgressMonitor` interface, then attach it to the `IBuilderConfig`, for example:

C++

```
builderConfig->setProgressMonitor(&monitor);
```

Python

```
context.set_progress_monitor(monitor)
```

Optimization is divided into hierarchically nested phases, each consisting of several steps. At the start of each phase, the `phaseStart()` method of `IProgressMonitor` is called, telling you the phase name and how many steps it has. The `stepComplete()` function is called when each step completes, and `phaseFinish()` is called when the phase finishes.

Returning false from `stepComplete()` cleanly forces the build to terminate early.

6.17. Preview Features

The preview feature API is an extension of `IBuilderConfig` that allows the gradual introduction of new features to TensorRT. Selected new features are exposed under this API, allowing you to opt in or opt out. A preview feature remains in preview status for one or two TensorRT release cycles and is then either integrated as a mainstream feature or dropped. When a preview feature is fully integrated into TensorRT, it is no longer controllable through the preview API.

Preview features are defined using a 32-bit `PreviewFeature` enumeration. The feature name and the TensorRT version concatenate feature identifiers.

```
<FEATURE_NAME>_XXYY
```

XX and YY are the major and minor versions of the TensorRT release, respectively, which first introduced the feature. The major and minor versions are specified using two digits with leading-zero padding when necessary.

If the semantics of a preview feature change from one TensorRT release to another, the older preview feature is deprecated, and the revised feature is assigned a new enumeration value and name.

Deprecated preview features are marked per the [deprecation policy](#).

For more information about the C++ API, refer to `nvinfer1::PreviewFeature`, `IBuilderConfig::setPreviewFeature`, and `IBuilderConfig::getPreviewFeature`.

The Python API has similar semantics using the `PreviewFeature` enum `set_preview_feature` and `get_preview_feature` functions.

6.18. Debug Tensors

The debug tensor feature allows you to inspect intermediate tensors as the network executes. There are a few key differences between using debug tensors and marking all required tensors as outputs:

1. Marking all tensors as outputs requires you to provide memory to store tensors in advance, while debug tensors can be turned off during runtime if unneeded.
2. When debug tensors are turned off, the performance impact on the execution of the network is minimized.
3. For a debug tensor in a loop, values are emitted every time it is written.

To enable this feature, perform the following steps:

1. Mark the target tensors before the network is compiled.

C++

```
networkDefinition->markDebug(&tensor);
```

Python

```
network.mark_debug(tensor)
```

2. Define a `DebugListener` class deriving from `IDebugListener` and implement the virtual function for processing the tensor.

C++

```
virtual void processDebugTensor(
    void const* addr,
    TensorLocation location,
    DataType type,
    Dims const& shape,
    char const* name,
    cudaStream_t stream) = 0;
```

Python

```
process_debug_tensor(self, addr, location, type, shape, name, stream)
```


When the function is invoked during execution, the debug tensor is passed via the parameters:

```
location: TensorLocation of the tensor
addr: pointer to buffer
type: data Type of the tensor
shape: shape of the tensor
name: name of the tensor
stream: Cuda stream object
```

The data will be in linear format.

3. Attach your listener to `IEExecutionContext`.

C++

```
executionContext->setDebugListener(&debugListener);
```

Python

```
execution_context.set_debug_listener(debugListener)
```

Because the function is executed as part of `enqueue()`, you must use the stream to synchronize the data reading by, for example, invoking a device function on the stream to process or copy the data.

4. Set the debug state for the tensors of interest before the engine's execution.

C++

```
executionContext->setDebugState(tensorName, flag);
```

Python

```
execution_context.set_debug_state(tensorName, flag)
```

6.19. Weight Streaming

The weight streaming feature allows you to offload some weights from device memory to host memory. During network execution, these weights are streamed from the host to the device as needed. This technique can free up device memory, enabling you to run larger models or process larger batch sizes.

To enable this feature, during engine building, create a network with `kSTRONGLY_TYPED` and set `kWEIGHT_STREAMING` to builder config:

C++

```
...
builder->createNetworkV2(1U <<
    static_cast<uint32_t>(NetworkDefinitionCreationFlag::kSTRONGLY_TYPED));
config->setFlag(BuilderFlag::kWEIGHT_STREAMING);
```

Python

```
builder.create_network(1 << int(trt.NetworkDefinitionCreationFlag.STRONGLY_TYPED))
config.set_flag(trt.BuilderFlag.WEIGHT_STREAMING)
```

During runtime, deserialization allocates a host buffer to store all the weights instead of uploading them directly to the device. This can increase the host's peak memory usage. You can use `IStreamReader` to deserialize directly from the engine file, avoiding needing a temporary buffer, which helps reduce peak memory usage.

After deserializing the engine, set the device memory budget for weights by:

C++

```
...
engine->setWeightStreamingBudgetV2(size)
```

Python

```
...
engine.weight_streaming_budget_v2 = size
```

The following APIs can help to determine the budget:

- ▶ `getStreamableWeightsSize()` returns the total size of streamable weights.
- ▶ `getWeightStreamingScratchMemorySize()` returns the extra scratch memory size for a context when weight streaming is enabled.
- ▶ `getDeviceMemorySizeV2()` returns the total scratch memory size required by a context. If this API is called before enabling weight streaming by `setWeightStreamingBudgetV2()`, the return value will not include the extra scratch memory size required by weight streaming, which can be obtained using `getWeightStreamingScratchMemorySize()`. Otherwise, it will include this extra memory.

Additionally, you can combine information about the current free device memory size, context number, and other allocation needs.

TensorRT can also automatically determine a memory budget by `getWeightStreamingAutomaticBudget()`. However, due to limited information about the user's specific memory allocation requirements, this automatically determined budget may be suboptimal and potentially lead to out-of-memory errors.

If the budget set by `setWeightStreamingBudgetV2` is larger than the total size of streamable weights obtained by `getStreamableWeightsSize()`, the budget will be clipped to the total size, effectively disabling weight streaming.

You can query the budget set by `getWeightStreamingBudgetV2()`.

The budget can be adjusted by setting it again when there is no active context for the engine.

After setting the budget, TensorRT will automatically determine which weights to retain on the device memory to maximize the overlap between computation and weight fetching.

6.20. Cross-Platform Compatibility

By default, TensorRT engines can only be executed on the same platform (operating system and CPU architecture) where they were built. With build-time configuration, engines can be built to be compatible with other types of platforms. For example, to build an engine on Linux x86_64 platforms and expect the engine to run on Windows x86_64 platforms, configure the `IBuilderConfig` as follows:

```
config->setRuntimePlatform(nvinfer1::RuntimePlatform::kWINDOWS_AMD64);
```

The cross-platform engine might have performance differences from the natively built engine on the target platform. Additionally, it will not be able to run on the host platform it was built on.

When building a cross-platform engine that also requires version forward compatibility, `kEXCLUDE_LEAN_RUNTIME` must be set to exclude the target platform lean runtime.

Chapter 7. Working with Quantized Types

7.1. Introduction to Quantization

TensorRT supports the use of low-precision types to represent quantized floating point values. The quantization scheme is *symmetric* quantization—quantized values are represented in signed INT8, FP8E4M3 (FP8 for short), or signed INT4, and the transformation from quantized to unquantized values is simply a multiplication. In the reverse direction, quantization uses the reciprocal scale, followed by clamping and rounding (for integers) or casting (for FP8).

TensorRT quantizes activations as well as weights to INT8 and FP8. For INT4, weight-only-quantization is supported.

7.1.1. Quantization Workflows

There are two workflows for creating quantized networks:

Post-training quantization (PTQ) derives scale factors after training the network. TensorRT provides a workflow for PTQ called *calibration*. It measures the distribution of activations within each activation tensor as the network executes on representative input data and then uses that distribution to estimate scale values for each tensor.

Quantization-aware training (QAT) computes the scale factors during training using fake-quantization, simulating the quantization and dequantization processes. This allows the training process to compensate for the effects of the quantization and dequantization operations.

TensorRT's [Quantization Toolkit](#) is a PyTorch library that helps produce QAT models that can be optimized by TensorRT. The toolkit's PTQ recipe can also perform PTQ in PyTorch and export to ONNX.

7.1.2. Explicit Versus Implicit Quantization

Quantized networks can be processed in two (mutually exclusive) ways: using either implicit or explicit quantization. The main difference between the two processing modes is whether you require explicit control over quantization or let the TensorRT builder

choose which operations and tensors to quantize (implicit). The sections below provide more details. Implicit quantization is only supported when quantizing for INT8. It cannot be used together with strong typing (because types are not auto-tuned, and the only method to convert activations to and from INT8 is via Q/DQ operators).

TensorRT uses explicit quantization mode when a network has `QuantizeLayer` and `DequantizeLayer` layers. TensorRT uses implicit quantization mode when there are no `QuantizeLayer` or `DequantizeLayer` layers in the network, and INT8 is enabled in the builder configuration. Only INT8 is supported in implicit quantization mode.

In *implicitly quantized* networks, each activation tensor candidate for quantization has an associated scale deduced by a calibration process or assigned by the API function `setDynamicRange`. TensorRT will use this scale if it decides to quantify the tensor.

When processing implicitly quantized networks, TensorRT treats the model as a floating-point model when applying the graph optimizations and uses INT8 opportunistically to optimize layer execution time. If a layer runs faster in INT8 and has assigned quantization scales on its data inputs and outputs, then a kernel with INT8 precision is assigned to that layer. Otherwise, a high-precision floating-point (FP32, FP16, or BF16) kernel is assigned. Where a high-precision floating point is required for accuracy at the expense of performance, this can be specified using the APIs `Layer::setOutputType` and `Layer::setPrecision`.

In *explicitly quantized* networks, the quantization and dequantization operations are represented explicitly by `IQuantizeLayer` (C++, Python) and `IDequantizeLayer` (C++, Python) nodes in the graph - these will henceforth be referred to as Q/DQ nodes. By contrast with implicit quantization, the explicit form specifies exactly where conversion to and from a quantized type is performed, and the optimizer will perform only conversions to and from quantized types that are dictated by the semantics of the model, even if:

- ▶ Adding extra conversions could increase layer precision (for example, choosing an FP16 kernel implementation over a quantized type implementation).
- ▶ Adding or removing conversions results in a faster engine (for example, choosing a quantized type kernel implementation to execute a layer specified as having high precision or vice versa).

ONNX uses an explicitly quantized representation: when a model in PyTorch or TensorFlow is exported to ONNX, each fake-quantization operation in the framework's graph is exported as Q, followed by DQ. Since TensorRT preserves the semantics of these layers, users can expect accuracy that is very close to that seen in the framework. While optimizations preserve the arithmetic semantics of quantization and dequantization operators, they may change the order of floating-point operations in the model, so results will not be bitwise identical.

TensorRT's PTQ capability generates a calibration cache with implicit quantization. By contrast, performing either QAT or PTQ in a deep learning framework and then exporting to ONNX will result in an explicitly quantized model.

By contrast, performing either QAT or PTQ in a deep learning framework and then exporting to ONNX will result in an explicitly quantized model.

Table 2. Implicit Vs Explicit Quantization

| | Implicit Quantization | Explicit Quantization |
|--------------------------------|---|--|
| Supported quantized data-types | INT8 | INT8, FP8, INT4 |
| User control over precision | Global builder flags and per-layer precision APIs. | Encoded directly in the model. |
| API | <ul style="list-style-type: none"> ▶ Model + Scales (dynamic range API) ▶ Model + Calibration data | Model with Q/DQ layers. |
| Quantization scales | <p>Weights:</p> <ul style="list-style-type: none"> ▶ Set by TensorRT (internal) ▶ Per-channel quantization ▶ INT8 range [-127, 127] <p>Activations:</p> <ul style="list-style-type: none"> ▶ Set by calibration or specified by the user ▶ Per-tensor quantization ▶ INT8 range [-128, 127] | <p>Weights and activations:</p> <ul style="list-style-type: none"> ▶ Specified using Q/DQ ONNX operators ▶ INT8 range [-128, 127] ▶ FP8 range: [-448, 448] ▶ INT4 range: [-8, 7] <p>Activations use per-tensor quantization.</p> <p>Weights use either per-tensor quantization, per-channel quantization, or block quantization.</p> |

For more background on quantization, refer to the following papers:

- ▶ [Integer Quantization for Deep Learning Inference: Principles and Empirical Evaluation](#)
- ▶ [FP8 Formats for Deep Learning](#)

7.1.3. Quantization Schemes

INT8

Given scale s , we can represent quantization and dequantization operations as follows:

$x_q = \text{quantize}(x, s) = \text{roundWithTiesToEven}(\text{clip}(\frac{x}{s}, -128, 127))$ where:

- ▶ x is a high-precision floating point value to be quantized.
- ▶ x_q is a quantized INT8 value in range [-128,127]. Refer to [Explicit Versus Implicit Quantization](#) for more information.
- ▶ `roundWithTiesToEven` is described [here](#).

$x = \text{dequantize}(x_q, s) = x_q * s$

In explicit quantization, you are responsible for choosing all scales. In implicit quantization mode, you configure or determine the activation scale using one of TensorRT's calibration algorithms (refer to [Post-Training Quantization Using Calibration](#)). TensorRT computes the weight scale according to the following formula:

$$s = \frac{\max(\text{abs}(x_{\min}^{\text{ch}}), \text{abs}(x_{\max}^{\text{ch}}))}{127}$$

where x_{\min}^{ch} and x_{\max}^{ch} are floating point minimum and maximum values for ch of the weights tensor.

Using FP8 and INT8 in the same network is not allowed.

FP8

Only explicit quantization is supported when using FP8; therefore, you are responsible for the values of the quantization scales.

$$x_q = \text{quantize}(x, s) = \text{roundWithTiesToEven}(\text{clip}(\frac{x}{s}, -448, 448))$$

where:

- ▶ x is a high-precision floating point value to be quantized.
- ▶ x_q is a quantized E4M3 FP8 value in the range [-448, 448].
- ▶ s is the quantization scale expressed using a 16-bit or 32-bit floating point.
- ▶ `roundWithTiesToEven` is described [here](#).

$$x = \text{dequantize}(x_q, s) = x_q * s$$

Using FP8 and INT8 in the same network is not allowed.

INT4

Only explicit quantization is supported when using INT4, and you are therefore responsible for the values of the quantization scales.

$$x_q = \text{quantize}(x, s) = \text{roundWithTiesToEven}(\text{clip}(\frac{x}{s}, -8, 7))$$

where:

- ▶ x is a high-precision floating point value to be quantized.
- ▶ x_q is a quantized INT4 value in the range [-8, 7].
- ▶ s is the quantization scale expressed using a 16-bit or 32-bit floating point.
- ▶ `roundWithTiesToEven` is described [here](#).

$$x = \text{dequantize}(x_q, s) = x_q * s$$

TensorRT only supports INT4 for weight-only quantization (refer to [Q/DQ Layer-Placement Recommendations](#)).

7.1.4. Quantization Modes

There are three supported quantization scale granularities:

- ▶ *Per-tensor quantization*: a single scale value (scalar) is used to scale the entire tensor.

- ▶ *Per-channel quantization*: a scale tensor is broadcast along the given axis - for convolutional neural networks, this is typically the channel axis.
- ▶ *Block quantization*: the tensor is divided into fixed-size 1-dimensional blocks along a single dimension. A scale factor is defined for each block.

The quantization scale must contain all positive high-precision float coefficients (FP32, FP16, or BF16). The rounding method is [round-to-nearest ties-to-even](#) and clamps to the valid range, which is $[-128, 127]$ for INT8, $[-448, 448]$ for FP8, and $[-8, 7]$ for INT4.

With explicit quantization, activations can only be quantized using per-tensor quantization. Weights can be quantized in any of the quantization modes.

In implicit quantization, weights are quantized by TensorRT during engine optimization, and only per-channel quantization is used. TensorRT quantizes weights for convolution, deconvolution, fully connected layers, and MatMul, where the second input is constant, and both input matrices are 2D.

When using per-channel quantization with Convolutions, the quantization axis must be the output-channel axis. For example, when the weights of 2D convolution are described using `KCRS` notation, `K` is the output-channel axis, and the weights quantization can be described as:

```
For each k in K:
  For each c in C:
    For each r in R:
      For each s in S:
        output[k,c,r,s] := clamp(round(input[k,c,r,s] / scale[k]))
```

The scale is a vector of coefficients and must have the same size as the quantization axis.

Dequantization is performed similarly except for the pointwise operation that is defined as:

```
output[k,c,r,s] := input[k,c,r,s] * scale[k]
```

Block Quantization

In block quantization, elements are grouped into 1-D blocks, with all elements in a block sharing a common scale factor. Block quantization is supported for only 2-D weight-only quantization (WoQ) with INT4.

When using block quantization, the scale tensor dimensions equal the data tensor dimensions except for one dimension over which blocking is performed (the blocking axis). For example, given a 2-D RS weights input, R (dimension 0) as the blocking axis and B as the block size, the scale in the blocking axis is repeated according to the block size and can be described like this:

```
For each r in R:
  For each s in S:
    output[r,s] = clamp(round(input[r,s] / scale[r//B, s]))
```

The scale is a 2D array of coefficients with dimensions (R//B, S).

Dequantization is performed similarly, except for the pointwise operation that is defined as:

```
output[r,s] = input[r,s] * scale[r//B, s]
```

7.2. Setting Dynamic Range

The dynamic range API is only applicable to INT8 quantization.

TensorRT provides APIs to directly set the *dynamic range* (which must be represented by the quantized tensor) to support implicit quantization where these values have been calculated outside TensorRT.

The API allows setting the dynamic range for a tensor using minimum and maximum values. Since TensorRT currently supports only symmetric range, the scale is calculated using `max(abs(min_float), abs(max_float))`. Note that when `abs(min_float) != abs(max_float)`, TensorRT uses a larger dynamic range than configured, which may increase the rounding error.

You can set the dynamic range for a tensor as follows:

C++

```
tensor->setDynamicRange(min_float, max_float);
```

Python

```
tensor.dynamic_range = (min_float, max_float)
```

[sampleINT8API](#) illustrates the use of these APIs in C++.

7.3. Post-Training Quantization Using Calibration

Calibration is only applicable to INT8 quantization.

In post-training quantization, TensorRT computes a scale value for each tensor in the network. This process, called *calibration*, requires you to supply representative input data on which TensorRT runs the network to collect statistics for each activation tensor.

The amount of input data required is application-dependent, but experiments indicate that about 500 images are sufficient for calibrating ImageNet classification networks.

Given the statistics for an activation tensor, deciding on the best scale value is not an exact science - it requires balancing two sources of error in the quantized representation: *discretization error* (which increases as the range represented by each quantized value becomes larger) and *truncation error* (where values are clamped to the limits of the representable range.) Thus, TensorRT provides multiple calibrators that calculate the scale differently. Older calibrators also performed layer fusion for GPU to optimize away unneeded Tensors before calibration. This can be problematic when using DLA, where fusion patterns may be different and can be overridden using the `kCALIBRATE_BEFORE_FUSION` quantization flag.

Calibration batch size can also affect the *truncation error* for `IInt8EntropyCalibrator2` and `IInt8EntropyCalibrator`. For example, calibrating using multiple small batches of calibration data may result in reduced histogram resolution and poor scale value. For each calibration step, TensorRT updates the histogram distribution for each activation

tensor. If it encounters a value in the activation tensor larger than the current histogram max, the histogram range is increased by a power of two to accommodate the new maximum value. This approach works well unless the histogram reallocates in the last calibration step, resulting in a final histogram with half the empty bins. Such a histogram can produce poor calibration scales. This also makes calibration susceptible to the order of calibration batches; a different order can increase the histogram size at different points, producing slightly different calibration scales. To avoid this issue, calibrate with as large a single batch as possible and ensure that calibration batches are well randomized and have a similar distribution.

IInt8EntropyCalibrator2

Entropy calibration chooses the tensor's scale factor to optimize the quantized tensor's information-theoretic content and usually suppresses outliers in the distribution. This is the current and recommended entropy calibrator and is required for DLA. Calibration happens before Layer fusion by default. Calibration batch size may impact the final result. It is recommended for CNN-based networks.

IInt8MinMaxCalibrator

This calibrator uses the entire range of the activation distribution to determine the scale factor. It seems to work better for NLP tasks. Calibration happens before Layer fusion by default. This is recommended for networks such as NVIDIA BERT (an optimized version of [Google's official implementation](#)).

IInt8EntropyCalibrator

This is the original entropy calibrator. It is less complicated than the `LegacyCalibrator` and typically produces better results. The calibration batch size may impact the final result. By default, calibration happens after Layer fusion.

IInt8LegacyCalibrator

This calibrator is for compatibility with TensorRT 2.0 EA. It requires user parameterization and is a fallback option if the other calibrators yield poor results. Calibration happens after Layer fusion by default. You can customize this calibrator to implement percentile max. For example, 99.99% percentile max is observed to have the best accuracy for NVIDIA BERT and NeMo ASR model QuartzNet.

When building an INT8 engine, the builder performs the following steps:

1. Build a 32-bit engine, run it on the calibration set, and record a histogram for each tensor of the distribution of activation values.
2. Build from the histograms a calibration table providing a scale value for each tensor.
3. Build the INT8 engine from the calibration table and the network definition.

Calibration can be slow; therefore, the output of step 2 (the calibration table) can be cached and reused. This is useful when building the same network multiple times on a given platform and is supported by all calibrators.

Before running calibration, TensorRT queries the calibrator implementation to see if it has access to a cached table. If so, it proceeds directly to step 3. Cached data is passed as a pointer and length.

The calibration cache data is portable across different devices as long as the calibration happens before layer fusion. Specifically, the calibration cache is portable when using the `IInt8EntropyCalibrator2` or `IInt8MinMaxCalibrator` calibrators or when `QuantizationFlag::kCALIBRATE_BEFORE_FUSION` is set. For example, this can simplify

the workflow by building the calibration table on a machine with a discrete GPU and then reusing it on an embedded platform. Fusions are not guaranteed the same across platforms or devices, so calibrating after layer fusion may not result in a portable calibration cache. The calibration cache is, in general, not portable across TensorRT releases.

TensorRT must also quantify weights and quantize activations. It uses symmetric quantization with a quantization scale calculated using the maximum absolute values found in the weight tensor. For convolution, deconvolution, and fully connected weights, scales are per-channel.



Note: When the builder is configured to use INT8 I/O, TensorRT still expects calibration data to be in FP32. You can create FP32 calibration data by casting INT8 I/O calibration data to FP32 precision. Also ensure that FP32 cast calibration data is in the range `[-128.0F, 127.0F]` and so can be converted to INT8 data without any precision loss.

INT8 calibration can be used along with the dynamic range APIs. Setting the dynamic range manually overrides the dynamic range generated from INT8 calibration.



Note: Calibration is deterministic - that is, if you provide TensorRT with the same input to calibration in the same order on the same device, the scales generated will be the same across different runs. The data in the calibration cache will be bitwise identical when generated using the same device with the same batch size when provided with identical calibration inputs. The exact data in the calibration cache is not guaranteed to be bitwise identical when generated using different devices, batch sizes, or calibration inputs.

7.3.1. INT8 Calibration Using C++

To provide calibration data to TensorRT, the `IInt8Calibrator` interface must be implemented.

The builder invokes the calibrator as follows:

- ▶ First, it queries the interface for the batch size and calls `getBatchSize()` to determine the size of the input batch to expect.
- ▶ Then, it repeatedly calls `getBatch()` to obtain batches of input. Batches must be exactly the batch size by `getBatchSize()`. When there are no more batches, `getBatch()` must return `false`.

After you have implemented the calibrator, you can configure the builder to use it:

```
config->setInt8Calibrator(calibrator.get());
```

Implement the `writeCalibrationCache()` and `readCalibrationCache()` methods to cache the calibration table.

7.3.2. Calibration Using Python

The following steps illustrate creating an INT8 calibrator object using the Python API.

1. Import TensorRT:

```
import tensorrt as trt
```

- Similar to test/validation datasets, use a set of input files as a calibration dataset. Ensure that the calibration files represent the overall inference data files. For TensorRT to use the calibration files, you must create a `batchstream` object. A `batchstream` object is used to configure the calibrator.

```
NUM_IMAGES_PER_BATCH = 5
batchstream = ImageBatchStream(NUM_IMAGES_PER_BATCH, calibration_files)
```

- Create an `Int8_calibrator` object with input node names and batch stream:

```
Int8_calibrator = EntropyCalibrator(["input_node_name"], batchstream)
```

- Set INT8 mode and INT8 calibrator:

```
config.set_flag(trt.BuilderFlag.INT8)
config.int8_calibrator = Int8_calibrator
```

7.3.3. Quantization Noise Reduction

For networks with implicit quantization, TensorRT attempts to reduce quantization noise in the output by forcing some layers near the network outputs to run in FP32, even if INT8 implementations are available.

The heuristic attempts to ensure that INT8 quantization is smooth by summing multiple quantized values. Layers considered "smoothing layers" are convolution, deconvolution, a fully connected layer, or matrix multiplication before reaching the network output. For example, if a network consists of a series of (convolution + activation + shuffle) subgraphs and the network output has type FP32, the last convolution will output FP32 precision, even if INT8 is allowed and faster.

The heuristic does not apply in the following scenarios:

- ▶ The network output has type INT8.
- ▶ An operation on the path (inclusively) from the last smoothing layer to the output is constrained by `ILayer::setOutputType` or `ILayer::setPrecision` to output INT8.
- ▶ There is no smoothing layer with a path to the output, or that path has an intervening plugin layer.
- ▶ The network uses explicit quantization.

7.4. Explicit Quantization

When TensorRT detects the presence of Q/DQ layers in a network, it builds an engine using explicit-precision processing logic, and precision-control build flags are not required.

In explicit quantization, network representation changes to and from the quantized data type are explicit; therefore, INT8 and FP8 must not be used as type constraints.

For a [Strongly Typed Networks](#), builder flags are neither required nor allowed.

7.4.1. Quantized Weights

Weights of Q/DQ models may be specified using a high-precision data type (FP32, FP16, or BF16) or a low-precision quantized type (INT8, FP8, INT4). When TensorRT builds an engine, high-precision weights are quantized using the `IQuantizeLayer` scale, which

operates on the weights. The quantized (low-precision) weights are stored in the engine plan file. When using pre-quantized weights (low precision), an `IDequantizeLayer` is required between the weights and the linear operator using the weights.

INT4 quantized weights are stored by packing two elements per byte. The first element is stored in the 4 least significant bits, and the second is stored in the 4 most significant bits.

7.4.2. ONNX Support

When a model trained in PyTorch or TensorFlow using Quantization Aware Training (QAT) is exported to ONNX, each fake-quantization operation in the framework's graph is exported as a pair of `QuantizeLinear` and `DequantizeLinear` ONNX operators. When TensorRT imports ONNX models, the ONNX `QuantizeLinear` operator is imported as an `IQuantizeLayer` instance, and the ONNX `DequantizeLinear` operator is imported as an `IDequantizeLayer` instance.

ONNX introduced support for `QuantizeLinear/DequantizeLinear` in opset 10, and a quantization-axis attribute was added in opset 13 (required for per-channel quantization). PyTorch 1.8 introduced support for exporting PyTorch models to ONNX using opset 13.

ONNX opset 19 added four FP8 formats, of which TensorRT supports `E4M3FN` (also referred to as `tensor(float8e4m3fn)` in the ONNX operator schema). The latest PyTorch version (PyTorch 2.0) does not support FP8 formats, nor does it support export to ONNX using opset 19. To bridge the gap, TransformerEngine exports its FP quantization functions as custom ONNX Q/DQ operators that belong to the "trt" domain (`TRT_FP8_QuantizeLinear` and `TRT_FP8_DequantizeLinear`). TensorRT can parse both the custom operators and standard opset 19 Q/DQ operators; however, it is noted that opset 19 is not fully supported by TensorRT. Other tools like ONNX Runtime cannot parse the custom operators. ONNX opset 21 added support for INT4 data type and block quantization.



WARNING: The ONNX GEMM operator is an example that can be quantized per channel. PyTorch `torch.nn.Linear` layers are exported as an ONNX GEMM operator with `(K, C)` weights layout and the `transB` GEMM attribute enabled (this transposes the weights before performing the GEMM operation). TensorFlow, on the other hand, pre-transposes the weights `(C, K)` before ONNX export:

- ▶ PyTorch: $y = xW^T$
- ▶ TensorFlow: $y = xW$

TensorRT, therefore transposes pyTorch weights. The weights are quantized by TensorRT before they are transposed, so GEMM layers originating from ONNX QAT models that were exported from PyTorch use dimension 0 for per-channel quantization (axis `K = 0`), while models originating from TensorFlow use dimension 1 (axis `K = 1`).

TensorRT does not support pre-quantized ONNX models that use INT8/FP8 quantized operators. Specifically, the following ONNX quantized operators are *not* supported and generate an import error if they are encountered when TensorRT imports the ONNX model:

- ▶ [QLinearConv/QLinearMatmul](#)
- ▶ [ConvInteger/MatmulInteger](#)

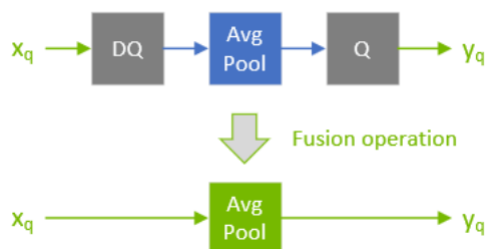
7.4.3. TensorRT Processing of Q/DQ Networks

When TensorRT optimizes a network in Q/DQ mode, the optimization process is limited to optimizations that do not change the arithmetic correctness of the network. Bit-level accuracy is rarely possible since the order of floating-point operations can produce different results (for example, rewriting $a * s + b * s$ as $(a + b) * s$ is a valid optimization). Allowing these differences is fundamental to backend optimization in general, and this also applies to converting a graph with Q/DQ layers to use quantized operations.

Q/DQ layers control the compute and data precision of a network. An `IQuantizeLayer` instance converts a high-precision floating-point tensor to a quantized tensor by employing quantization, and an `IDequantizeLayer` instance converts a quantized tensor to a high-precision floating-point tensor using dequantization. TensorRT expects a Q/DQ layer pair on each input of quantizable layers. Quantizable layers are deep-learning layers that can be converted to quantized layers by fusing with `IQuantizeLayer` and `IDequantizeLayer` instances. When TensorRT performs these fusions, it replaces the quantizable layers with quantized layers that operate on quantized data using compute operations suitable for quantized types.

For the diagrams used in this chapter, green designates low precision (quantized), and blue designates high precision. Arrows represent network activation tensors, and squares represent network layers.

Figure 2. *A quantizable `AveragePool` layer (in blue) is fused with DQ and Q layers. All three layers are replaced by a quantized `AveragePool` layer (in green).*



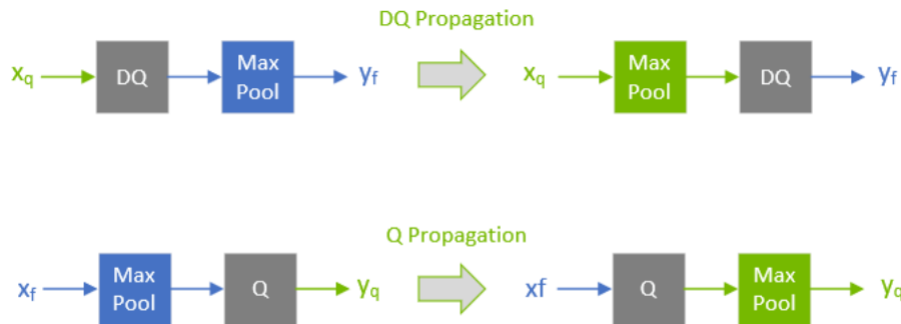
During network optimization, TensorRT moves Q/DQ layers in Q/DQ propagation. The goal in propagation is to maximize the proportion of the graph that can be processed at low precision. Thus, TensorRT propagates Q nodes backward (quantization happens as early as possible) and DQ nodes forward (so dequantization happens as late as possible). Q-layers can swap places with layers that commute with Quantization, and DQ-layers can swap places with layers that commute with Dequantization.

A layer `Op` commutes with quantization if $Q(Op(x)) == Op(Q(x))$

Similarly, a layer Op commutes with dequantization if $Op(DQ(x)) == DQ(Op(x))$

The following diagram illustrates DQ forward propagation and Q backward propagation. These are legal rewrites of the model because Max Pooling has an INT8 implementation and commutes with DQ and Q.

Figure 3. An illustration depicting a DQ forward-propagation and Q backward-propagation.



Note:

To understand Max Pooling commutation, let us look at the output of the maximum-pooling operation applied to some arbitrary input. Max Pooling is applied to groups of input coefficients and outputs the coefficient with the maximum value. For group i composed of coefficients $\{x_0..x_m\}$:

$$\text{output}_i := \max\{\{x_0, x_1, \dots, x_m\}\} = \max\{\{\max\{\{x_0, x_1\}, x_2\}, \dots, x_m\}\}$$

It is, therefore, enough to look at two arbitrary coefficients without loss of generality (WLOG):

$$x_j = \max\{\{x_j, x_k\}\} \text{ for } x_j \geq x_k$$

For the quantization function $Q(a, \text{scale}, x_{\max}, x_{\min}) := \text{truncate}(\text{round}(a/\text{scale}), x_{\max}, x_{\min})$ $\text{scale} > 0$, note that (without providing proof and using simplified notation):

$$Q(x_j, \text{scale}) \geq Q(x_k, \text{scale}) \text{ for } x_j \geq x_k$$

Therefore:

$$\max\{\{Q(x_j, \text{scale}), Q(x_k, \text{scale})\}\} = Q(x_j, \text{scale}) \text{ for } x_j \geq x_k$$

However, by definition:

$$Q(\max\{\{x_j, x_k\}\}, \text{scale}) = Q(x_j, \text{scale}) \text{ for } x_j \geq x_k$$

Function \max commutes with quantization, and so does Max Pooling.

Similarly, for dequantization, function $DQ(a, scale) := a * scale$ with $scale > 0$ we can show that:

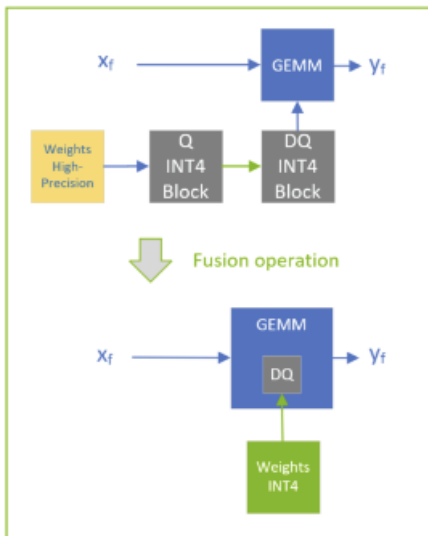
$$\max\{\{DQ(x_j, scale), DQ(x_k, scale)\}\} = DQ(x_j, scale) = DQ(\max\{x_j, x_k\}, scale) \text{ for } x_j \geq x_k$$

There is a distinction between how quantizable layers and commuting layers are processed. Both layers can be computed in INT8/FP8, but quantizable layers also fuse with a DQ input and a Q output layer. For example, an `AveragePooling` layer (quantizable) does not commute with either Q or DQ, so it is quantized using Q/DQ fusion, as illustrated in the first diagram. This is in contrast to how Max Pooling (commuting) is quantized.

7.4.4. Weight-Only Quantization

Weight-only quantization (WoQ) is an optimization useful when memory bandwidth limits the performance of GEMM operations or when GPU memory is scarce. In WoQ, GEMM weights are quantized to INT4 precision while the GEMM input data and compute operation remain high precision. TensorRT's WoQ kernels read the 4-bit weights from memory and dequantize them before performing the dot product in high precision.

Figure 4. Weight-only Quantization (WoQ)



WoQ is available only for INT4 block quantization with GEMM layers. The GEMM data input is specified in high-precision (FP32, FP16, BF16), and the weights are quantized using Q/DQ as usual. TensorRT creates an engine with INT4 weights and a high-precision GEMM operation. The engine reads the low-precision weights and dequantizes them before performing the GEMM operation in high-precision.

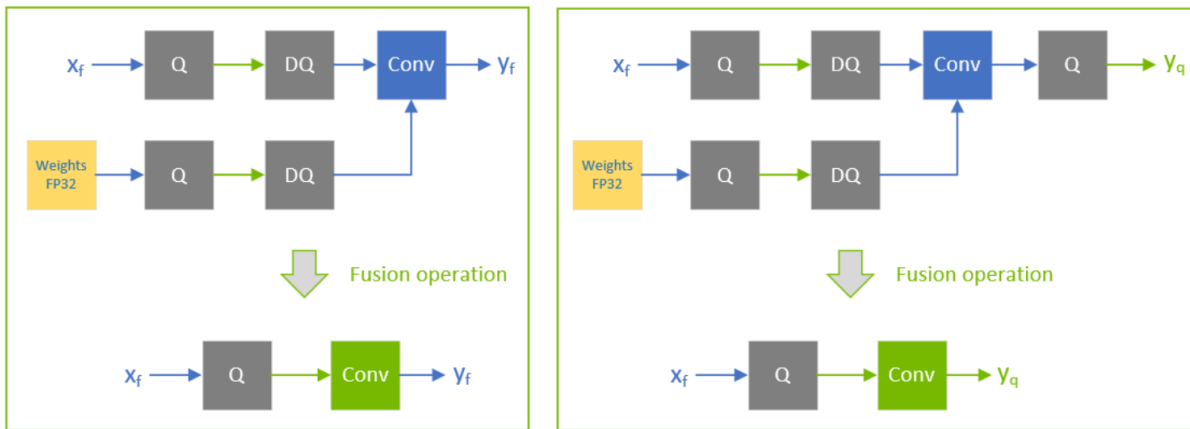
7.4.5. Q/DQ Layer-Placement Recommendations

The placement of Q/DQ layers in a network affects performance and accuracy. Aggressive quantization can lead to degradation in model accuracy because of the error introduced by quantization. But quantization also enables latency reductions. Listed here are some recommendations for placing Q/DQ layers in your network.

Note that older devices may not have low-precision kernel implementations for all layers, and you may encounter a `could not find any implementation` error while building your engine. To resolve this, remove the Q/DQ nodes, which quantize the failing layers.

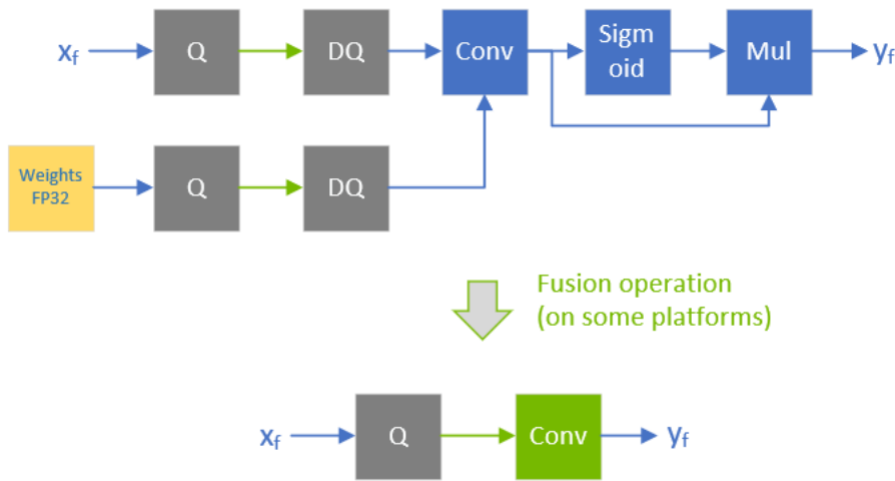
Quantize all inputs of weighted operations (Convolution, Transposed Convolution, and GEMM). Quantizing the weights and activations reduces bandwidth requirements and enables INT8 computation to accelerate bandwidth-limited and compute-limited layers.

Figure 5. Two examples of how TensorRT fuses convolutional layers. Only the inputs are quantized on the left and the right; both inputs and output are quantized.



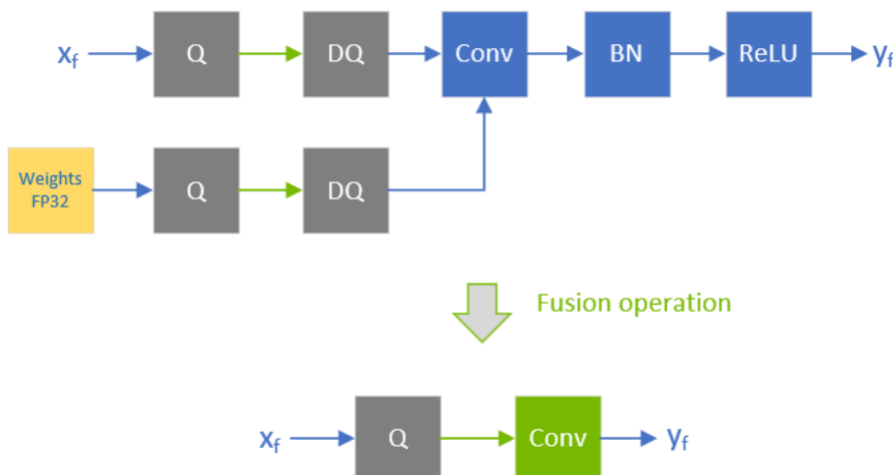
By default, do not quantize the outputs of weighted operations. It is sometimes useful to preserve the higher-precision dequantized output. For example, if the linear operation is followed by an activation function (SiLU, in the following diagram), it requires higher precision input to produce acceptable accuracy.

Figure 6. Example of a linear operation followed by an activation function.



Do not simulate batch normalization and ReLU fusions in the training framework because TensorRT optimizations guarantee the preservation of these operations' arithmetic semantics.

Figure 7. Batch normalization is fused with convolution and ReLU while keeping the same execution order defined in the pre-fusion network. There is no need to simulate BN-folding in the training network.

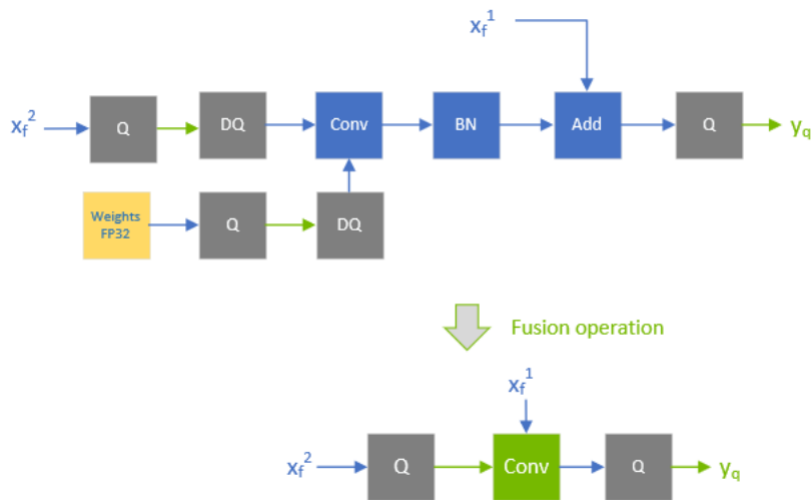


Quantize the residual input in skip connections. TensorRT can fuse element-wise addition following weighted layers, which is useful for models with skip connections like ResNet

and EfficientNet. The precision of the first input to the element-wise addition layer determines the fusion output's precision.

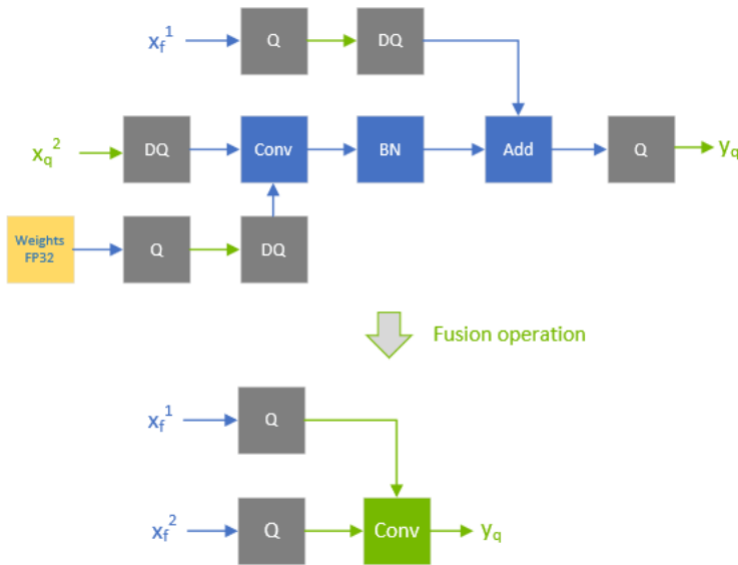
For example, in the following diagram, the precision of x_f^1 is a floating point, so the output of the fused convolution is limited to the floating point, and the trailing Q-layer cannot be fused with the convolution.

Figure 8. The precision of x_f^1 is a floating point, so the output of the fused convolution is limited to the floating point, and the trailing Q-layer cannot be fused with the convolution.



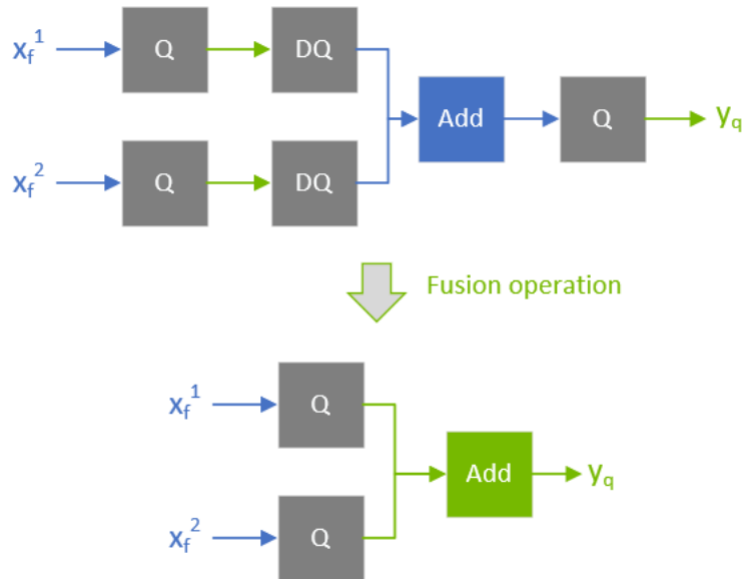
In contrast, when x_f^1 is quantized to INT8, as depicted in the following diagram, the output of the fused convolution is also INT8, and the trailing Q-layer is fused with the convolution.

Figure 9. When x_f^1 is quantized to INT8, the output of the fused convolution is also INT8, and the trailing Q-layer is fused with the convolution.



For extra performance, try quantizing layers that do not commute with Q/DQ. Currently, non-weighted layers with INT8 inputs also require INT8 outputs, so quantize both inputs and outputs.

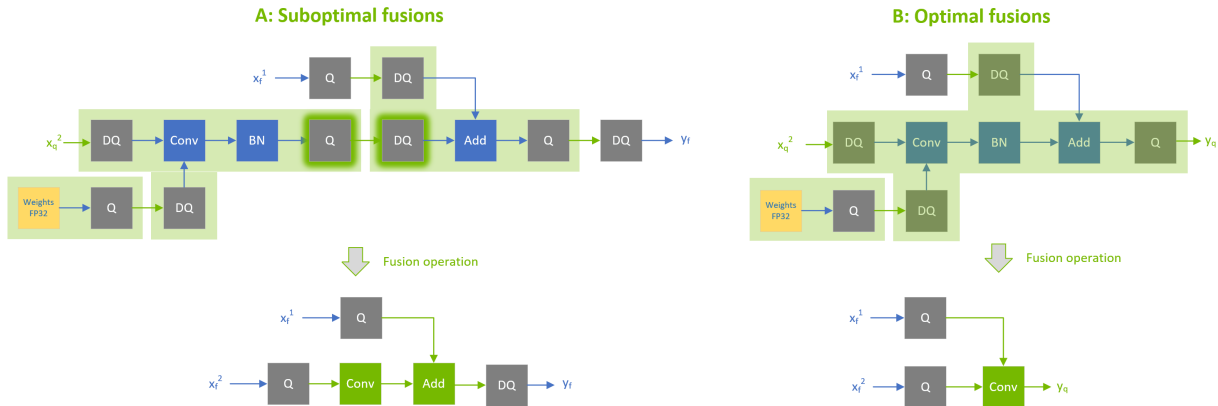
Figure 10. An example of quantizing a quantizable operation. An element-wise addition is fused with the input DQs and the output Q.



Performance can decrease if TensorRT cannot fuse the operations with the surrounding Q/DQ layers, so be conservative when adding Q/DQ nodes and experiment with accuracy and TensorRT performance in mind.

The following figure shows suboptimal fusions (the highlighted light green background rectangles) that can result from extra Q/DQ operations. Contrast the following figure with [Figure 9](#), which shows a more performant configuration. The convolution is fused separately from the element-wise addition because each is surrounded by Q/DQ pairs. The fusion of the element-wise addition is shown in [Figure 10](#).

Figure 11. An example of suboptimal quantization fusions: contrast the suboptimal fusion in A and the optimal fusion in B. The extra pair of Q/DQ operations (highlighted with a glowing green border) forces the separation of the convolution from the element-wise addition.



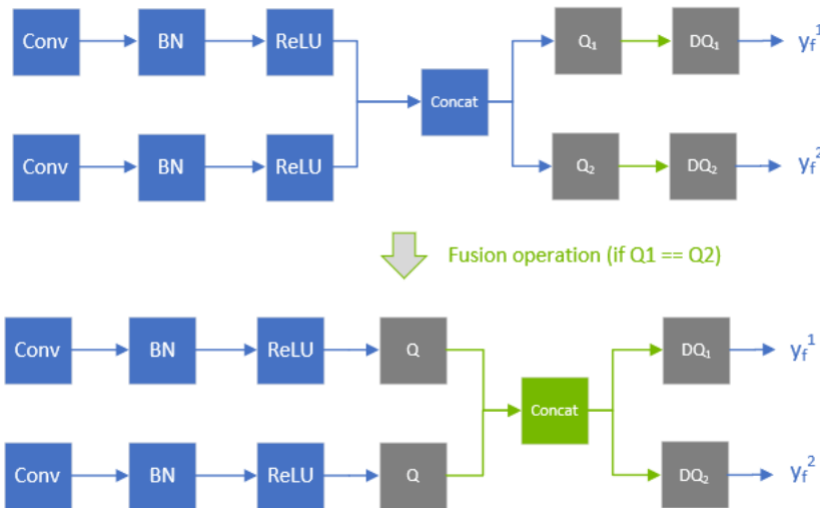
Use per-tensor quantization for activations and per-channel quantization for weights. This configuration has been demonstrated empirically to lead to the best quantization accuracy.

You can further optimize engine latency by enabling FP16. TensorRT attempts to use FP16 instead of FP32 whenever possible (this is not currently supported for all layer types).

7.4.6. Q/DQ Limitations

A few Q/DQ graph-rewrite optimizations that TensorRT performs compare the values of quantization scales between two or more Q/DQ layers and only perform the graph-rewrite if the compared quantization scales are equal. When a refittable TensorRT engine is refitted, the scales of Q/DQ nodes can be assigned new values. During the refitting operation of Q/DQ engines, TensorRT checks if Q/DQ layers that participated in scale-dependent optimizations are assigned new values that break the rewrite optimizations and throw an exception if true.

Figure 12. An example showing scales of Q1 and Q2 are compared for equality, and if equal, they are allowed to propagate backward. If the engine is refitted with new values for Q1 and Q2 such that $Q_1 \neq Q_2$, then an exception aborts the refitting process.



7.4.7. Q/DQ Interaction with Plugins

Plugins extend TensorRT's capabilities by allowing the replacement of a group of layers with a custom and proprietary implementation. You can decide what functionality to include in the plugin and what to leave for TensorRT to handle.

The same applies to a TensorRT network with Q/DQ layers. When a plugin consumes quantized inputs (INT8/FP8) and generates quantized outputs, the input DQ and output Q nodes must be included in the plugin and removed from the network.

Consider a simple case of a sequential graph consisting of a single INT8 plugin (aptly named `MyInt8Plugin`) sandwiched between two convolution layers (ignoring weights quantization):

```
Input > Q -> DQ > Conv > Q -> DQ_i > MyInt8Plugin > Q_o -> DQ > Conv > Output
```

The > arrows indicate activation tensors with FP32 precision, and the -> arrows indicate INT8 precision.

When TensorRT optimizes this graph, it fuses the layers to the following graph (square brackets indicate TensorRT fusions):

```
Input > Q -> [DQ -> Conv -> Q] -> DQ_i > MyInt8Plugin > Q_o -> [DQ -> Conv] > Output
```

In the graph above, the plugin consumes and generates FP32 inputs and outputs. Since the plugin `MyInt8Plugin` uses INT8 precision, the subsequent procedure involves the manual integration of `DQ_i` and `Q_o` with the `MyInt8Plugin`, followed by invoking the `setOutputType(kINT8)` method for this particular plugin layer; TensorRT will see a network like this:

```
Input > Q -> DQ > Conv > Q -> MyInt8Plugin -> DQ > Conv > Output
```

Which it will fuse to:

```
Input > Q -> [DQ -> Conv -> Q] > MyInt8Plugin -> [DQ -> Conv] > Output
```

When "manually fusing" `DQ_i`, you take the input quantization scale and give it to your plugin so it will know how to dequantize (if needed) the input. The same applies to using the scale from `Q_o` to quantize your plugin's output.

7.4.8. QAT Networks Using TensorFlow

We provide an open-source [TensorFlow-Quantization Toolkit](#) to perform QAT in TensorFlow 2 Keras models following NVIDIA's QAT recipe. This leads to optimal model acceleration with TensorRT on NVIDIA GPUs and hardware accelerators. The [NVIDIA TensorFlow-Quantization Toolkit User Guide](#) provides more details.

TensorFlow 1 does not support per-channel quantization (PCQ), which is recommended for weights to preserve the model's accuracy.

7.4.9. QAT Networks Using PyTorch

PyTorch 1.8.0 and forward support ONNX [QuantizeLinear/DequantizeLinear](#) support per channel scales. You can use [pytorch-quantization](#) to do INT8 calibration, run quantization-aware fine-tuning, generate ONNX, and finally use TensorRT to run inference on this ONNX model. More details can be found in the [NVIDIA PyTorch-Quantization Toolkit User Guide](#).

7.4.10. QAT Networks Using TransformerEngine

We provide [TransformerEngine](#), an open-source library for accelerating transformer models' training, inference, and exporting. It includes APIs for building a Transformer layer and a framework-agnostic library in C++, including structs and kernels needed for FP8 support. Modules provided by TransformerEngine internally maintain scaling factors and other values needed for FP8 training. You can use [TransformerEngine](#) to train a mixed precision model, export an ONNX model, and use TensorRT to run inference on this ONNX model.

7.5. Quantized Types Rounding Modes

| Backend | Compute Kernel Quantization (FP32 to INT8/FP8) | Weights Quantization (FP32 to INT8/FP8) | |
|---------|--|--|---|
| | | Quantized Network (QAT) | Dynamic Range API / Calibration |
| GPU | round-to-nearest-with-ties-to-even | round-to-nearest-with-ties-to-even (INT8, FP8, INT4) | round-to-nearest-with-ties-to-positive-infinity (INT8 only) |
| DLA | round-to-nearest-with-ties-to-even | Not Applicable | round-to-nearest-with-ties-to-even (INT8 only) |

Chapter 8. Working with Dynamic Shapes

Dynamic Shapes is the ability to defer specifying some or all tensor dimensions until runtime. Dynamic shapes can be used through both the C++ and Python interfaces.

The following sections provide greater detail; however, here is an overview of the steps for building an engine with dynamic shapes:

1. The network definition must not have an implicit batch dimension.

C++

Create the `INetworkDefinition` by calling

```
IBuilder::createNetworkV2(1U <<  
    static_cast<int>(NetworkDefinitionCreationFlag::kEXPLICIT_BATCH))
```

Python

Create the `tensorrt.INetworkDefinition` by calling

```
create_network(1 <<  
    int(tensorrt.NetworkDefinitionCreationFlag.EXPLICIT_BATCH))
```

These calls request that the network not have an implicit batch dimension.

2. Specify each runtime dimension of an input tensor by using `-1` as a placeholder for the dimension.
3. Specify one or more *optimization profiles* at build time that specify the permitted range of dimensions for inputs with runtime dimensions and the dimensions for which the auto-tuner will optimize. For more information, refer to [Optimization Profiles](#).
4. To use the engine:
 - a). Create an execution context from the engine, the same as without dynamic shapes.
 - b). Specify one of the optimization profiles from step 3 that covers the input dimensions.
 - c). Specify the input dimensions for the execution context. After setting input dimensions, you can get the output dimensions that TensorRT computes for the given input dimensions.
 - d). Enqueue work.

To change the runtime dimensions, repeat steps 4b and 4c, which do not have to be repeated until the input dimensions change.

When the preview features (`PreviewFeature::kFASTER_DYNAMIC_SHAPES_0805`) is enabled, it can potentially, for dynamically shaped networks:

- ▶ reduce the engine build time,
- ▶ reduce runtime, and
- ▶ decrease device memory usage and engine size.

Models most likely to benefit from enabling `kFASTER_DYNAMIC_SHAPES_0805` are transformer-based models and models containing dynamic control flows.

8.1. Specifying Runtime Dimensions

When building a network, use `-1` to denote a runtime dimension for an input tensor. For example, to create a 3D input tensor named `foo` where the last two dimensions are specified at runtime, and the first dimension is fixed at build time, issue the following.

C++

```
networkDefinition.addInput("foo", DataType::kFLOAT, Dims3(3, -1, -1))
```

Python

```
network_definition.add_input("foo", trt.float32, (3, -1, -1))
```

After choosing an optimization profile, you must set the input dimensions at run time (refer to [Optimization Profiles](#)). Let the input have dimensions `[3, 150, 250]`. After setting an optimization profile for the previous example, you would call:

C++

```
context.setInputShape("foo", Dims{3, {3, 150, 250}})
```

Python

```
context.set_input_shape("foo", (3, 150, 250))
```

At runtime, asking the engine for binding dimensions returns the same dimensions used to build the network, meaning you get a `-1` for each runtime dimension. For example:

C++

```
engine.getTensorShape("foo") returns a Dims with dimensions {3, -1, -1}..
```

Python

```
engine.get_tensor_shape("foo") returns (3, -1, -1).
```

To get the actual dimensions, which are specific to each execution context, query the execution context:

C++

```
context.getTensorShape("foo") returns a Dims with dimensions {3, 150, 250}.
```

Python

```
context.get_tensor_shape(0) returns (3, 150, 250).
```



Note: The return value of `setInputShape` for an input only indicates consistency for the optimization profile set for that input. After all input binding dimensions are specified, you can check whether the entire network is consistent with the dynamic input shapes by querying the dimensions of the output bindings of the network. Here is an example that retrieves the dimensions of an output named `bar`:

```
nvinfer1::Dims outDims = context->getTensorShape("bar");
if (outDims.nbDims == -1) {
```

```

    gLogError << "Invalid network output, this might be caused by inconsistent input
    shapes." << std::endl;
    // abort inference
}

```

If a dimension k is data-dependent, for example, it depends on the output of `INonZeroLayer`, `outDims.d[k]` will be -1. For more information on such outputs, refer to [Dynamically Shaped Output](#).

8.2. Named Dimensions

Both constant and runtime dimensions can be named. Naming dimensions provides two benefits:

- ▶ For runtime dimensions, error messages use the dimension's name. For example, if an input tensor `foo` has dimensions `[n, 10, m]`, it is more helpful to get an error message about `m` instead of `(#2 (SHAPE foo))`.
- ▶ Dimensions with the same name are implicitly equal, which can help the optimizer generate a more efficient engine and diagnose mismatched dimensions at runtime. For example, if two inputs have dimensions `[n, 10, m]` and `[n, 13]`, the optimizer knows the lead dimensions are always equal, and accidentally using the engine with mismatched values for `n` will be reported as an error.

You can use the same name for constant and runtime dimensions as long as they are always equal.

The following syntax examples set the name of the third dimension of the tensor to `m`.

C++

```
tensor.setDimensionName(2, "m")
```

Python

```
tensor.set_dimension_name(2, "m")
```

There are corresponding methods to get a dimensions name:

C++

```
tensor.getDimensionName(2) // returns the name of the third dimension of tensor, or
                           nullptr if it does not have a name.
```

Python

```
tensor.get_dimension_name(2) # returns the name of the third dimension of tensor, or None
                             if it does not have a name.
```

When the input network is imported from an ONNX file, the ONNX parser automatically sets the dimension names using the names in the ONNX file. Therefore, if two dynamic dimensions are expected to be equal at runtime, specify the same name for these dimensions when exporting the ONNX file.

8.3. Dimension Constraint using IAssertionLayer

Sometimes, two dynamic dimensions are not equal but are guaranteed equal at runtime. Letting TensorRT know they are equal can help it build a more efficient engine. There are two ways to convey the equality constraint to TensorRT:

- ▶ Give the dimensions the same name as described in [Named Dimensions](#).
- ▶ Use `IAssertionLayer` to express the constraint. This technique is more general since it can convey trickier equalities.

For example, if the first dimension of tensor A is guaranteed to be one more than the first dimension of tensor B, then the constraint can be established by:

C++

```
// Assumes A and B are ITensor* and n is a INetworkDefinition&.
auto shapeA = n.addShape(*A)->getOutput(0);
auto firstDimOfA = n.addSlice(*shapeA, Dims{1, {0}}, Dims{1, {1}}, Dims{1, {1}})-
>getOutput(0);
auto shapeB = n.addShape(*B)->getOutput(0);
auto firstDimOfB = n.addSlice(*shapeB, Dims{1, {0}}, Dims{1, {1}}, Dims{1, {1}})-
>getOutput(0);
static int32_t const oneStorage{1};
auto one = n.addConstant(Dims{1, {1}}, Weights{DataType::kINT32, &oneStorage, 1})-
>getOutput(0);
auto firstDimOfBPlus1 = n.addElementWise(*firstDimOfB, *one, ElementWiseOperation::kSUM)-
>getOutput(0);
auto areEqual = n.addElementWise(*firstDimOfA, *firstDimOfBPlus1,
    ElementWiseOperation::kEQUAL)->getOutput(0);
n.addAssertion(*areEqual, "oops");
```

Python

```
# Assumes `a` and `b` are ITensors and `n` is an INetworkDefinition
shape_a = n.add_shape(a).get_output(0)
first_dim_of_a = n.add_slice(shape_a, (0, ), (1, ), (1, )).get_output(0)
shape_b = n.add_shape(b).get_output(0)
first_dim_of_b = n.add_slice(shape_b, (0, ), (1, ), (1, )).get_output(0)
one = n.add_constant((1, ), np.ones((1, ), dtype=np.int32)).get_output(0)
first_dim_of_b_plus_1 = n.add_elementwise(first_dim_of_b, one,
    trt.ElementWiseOperation.SUM).get_output(0)
are_equal = n.add_elementwise(first_dim_of_a, first_dim_of_b_plus_1,
    trt.ElementWiseOperation.EQUAL).get_output(0)
n.add_assertion(are_equal, "oops")
```

If the dimensions violate the assertion at runtime, TensorRT will throw an error.

8.4. Optimization Profiles

An *optimization profile* describes a range of dimensions for each network input and the dimensions the auto-tuner will use for optimization. You must create at least one optimization profile at build time when using runtime dimensions. Two profiles can specify disjoint or overlapping ranges.

For example, one profile might specify a minimum size of `[3, 100, 200]`, a maximum size of `[3, 200, 300]`, and optimization dimensions of `[3, 150, 250]`, while another profile

might specify min, max, and optimization dimensions of `[3, 200, 100]`, `[3, 300, 400]`, and `[3, 250, 250]`.



Note: The memory usage for different profiles can change dramatically based on the dimensions specified by the min, max, and opt parameters. Some operations have tactics that only work for `MIN=OPT=MAX`, so when these values differ, the tactic is disabled.

To create an optimization profile, first construct an `IOptimizationProfile`. Then, set the min, optimization, and max dimensions and add them to the network configuration. The shapes defined by the optimization profile must define valid input shapes for the network. Here are the calls for the first profile mentioned previously for an input `foo`:

C++

```
IOptimizationProfile* profile = builder.createOptimizationProfile();
profile->setDimensions("foo", OptProfileSelector::kMIN, Dims3(3,100,200);
profile->setDimensions("foo", OptProfileSelector::kOPT, Dims3(3,150,250);
profile->setDimensions("foo", OptProfileSelector::kMAX, Dims3(3,200,300);

config->addOptimizationProfile(profile)
```

Python

```
profile = builder.create_optimization_profile();
profile.set_shape("foo", (3, 100, 200), (3, 150, 250), (3, 200, 300))
config.add_optimization_profile(profile)
```

At runtime, you must set an optimization profile before setting input dimensions. Profiles are numbered in the order they were added, starting at 0. Note that each execution context must use a separate optimization profile.

To choose the first optimization profile in the example, use:

C++

```
context.setOptimizationProfileAsync(0, stream)
```

Python

```
context.set_optimization_profile_async(0, stream)
```

The provided `stream` argument should be the same CUDA stream that will be used for the subsequent `enqueue()`, `enqueueV2()`, or `enqueueV3()` invocation in this context. This ensures that the context executions happen after the optimization profile setup.

If the associated CUDA engine has dynamic inputs, the optimization profile must be set at least once with a unique profile index that is not used by other execution contexts, and that is not destroyed. For the first execution context created for an engine, profile 0 is implicitly chosen.

`setOptimizationProfileAsync()` can be called to switch between profiles. It must be called after any `enqueue()`, `enqueueV2()`, or `enqueueV3()` operations finish in the current context. When multiple execution contexts run concurrently, it can switch to a formerly used profile already released by another execution context with different dynamic input dimensions.

`setOptimizationProfileAsync()` function replaces the now deprecated version of the API `setOptimizationProfile()`. Using `setOptimizationProfile()` to switch between optimization profiles can cause GPU memory copy operations in the subsequent `enqueue()` or `enqueueV2()` operations. To avoid these calls during `enqueue`, use `setOptimizationProfileAsync()` API instead.

8.5. Dynamically Shaped Output

If the output of a network has a dynamic shape, several strategies are available to allocate the output memory.

If the dimensions of the output are computable from the dimensions of inputs, use `IEExecutionContext::getTensorShape()` to get the dimensions of the output after providing the dimensions of the input tensors and [Shape Tensor I/O \(Advanced\)](#). Use the `IEExecutionContext::inferShapes()` method to check if you forgot to supply the necessary information.

Otherwise, or if you do not know if the dimensions of the output are computable in advance or calling `enqueueV3`, associate an `IOutputAllocator` with the output. More specifically:

1. Derive your allocator class from `IOutputAllocator`.
2. Override the `reallocateOutput` and `notifyShape` methods. TensorRT calls the first when it needs to allocate the output memory and the second when it knows the output dimensions. For example, the memory for the output of `INonZeroLayer` is allocated before the layer runs.

Here is an example derived class:

```
class MyOutputAllocator : nvinfer1::IOutputAllocator
{
public:
    void* reallocateOutput(
        char const* tensorName, void* currentMemory,
        uint64_t size, uint64_t alignment) override
    {
        // Allocate the output. Remember it for later use.
        outputPtr = ... depends on strategy, as discussed later...
        return outputPtr;
    }

    void notifyShape(char const* tensorName, Dims const& dims)
    {
        // Remember output dimensions for later use.
        outputDims = dims;
    }

    // Saved dimensions of the output
    Dims outputDims{};

    // nullptr if memory could not be allocated
    void* outputPtr{nullptr};
};
```

Here's an example of how it might be used:

```
std::unordered_map<std::string, MyOutputAllocator> allocatorMap;

for (const char* name : names of outputs)
{
    Dims extent = context->getTensorShape(name);
    void* ptr;
    if (engine->getTensorLocation(name) == TensorLocation::kDEVICE)
    {
        if (extent.d contains a -1)
        {
```

```

        auto allocator = std::make_unique<MyOutputAllocator>();
        context->setOutputAllocator(name, allocator.get());
        allocatorMap.emplace(name, std::move(allocator));
    }
    else
    {
        ptr = allocate device memory per extent and format
    }
}
else
{
    ptr = allocate cpu memory per extent and format
}
context->setTensorAddress(name, ptr);
}

```

Several strategies can be used for implementing `reallocateOutput`:

- A** Defer allocation until the size is known. Do not call `IEExecution::setTensorAddress`, or call it with a `nullptr` for the tensor address.
- B** Preallocate enough memory based on what `IEExecutionTensor::getMaxOutputSize` reports as an upper bound. This guarantees that the engine will not fail due to insufficient output memory, but the upper bound may be so high that it is useless.
- C** If you have preallocated enough memory based on experience, use `IEExecution::setTensorAddress` to tell TensorRT about it. If the tensor does not fit, make `reallocateOutput` return `nullptr`, which will cause the engine to fail gracefully.
- D** Preallocate memory as in C, but have `reallocateOutput` return a pointer to a bigger buffer if there is a fit problem. This increases the output buffer as needed.
- E** Defer allocation until the size is known, like A. Then, attempt to recycle that allocation in subsequent calls until a bigger buffer is requested, and then increase it like in D.

Here's an example derived class that implements E:

```

class FancyOutputAllocator : nvinfer1::IOOutputAllocator
{
public:
    void reallocateOutput(
        char const* tensorName, void* currentMemory,
        uint64_t size, uint64_t alignment) override
    {
        if (size > outputSize)
        {
            // Need to reallocate
            cudaFree(outputPtr);
            outputPtr = nullptr;
            outputSize = 0;
            if (cudaMalloc(&outputPtr, size) == cudaSuccess)
            {
                outputSize = size;
            }
        }
        // If the cudaMalloc fails, outputPtr=nullptr, and engine
        // gracefully fails.
        return outputPtr;
    }

    void notifyShape(char const* tensorName, Dims const& dims)
    {

```

```

    // Remember output dimensions for later use.
    outputDims = dims;
}

// Saved dimensions of the output tensor
Dims outputDims{};

// nullptr if memory could not be allocated
void* outputPtr{nullptr};

// Size of allocation pointed to by output
uint64_t outputSize{0};

~FancyOutputAllocator() override
{
    cudaFree(outputPtr);
}
};

```

8.5.1. Looking up Binding Indices for Multiple Optimization Profiles

If you use `enqueueV3` instead of the deprecated `enqueueV2`, you can skip this section because name-based methods such as `IExecutionContext::setTensorAddress` do not expect a profile suffix.

Each profile has separate binding indices in an engine built from multiple profiles. The names of I/O tensors for the K th profile have `[profile K]` appended to them, with K written in decimal. For example, if the `INetworkDefinition` had the name "foo", and `bindingIndex` refers to that tensor in the optimization profile with index 3, `engine.getBindingName(bindingIndex)` returns "foo [profile 3]".

Likewise, if using `ICudaEngine::getBindingIndex(name)` to get the index for a profile K beyond the first profile ($K=0$), append "`[profile K]`" to the name used in the `INetworkDefinition`. For example, if the tensor was called "foo" in the `INetworkDefinition`, then `engine.getBindingIndex("foo [profile 3]")` returns the binding index of Tensor "foo" in optimization profile 3.

Always omit the suffix for $K=0$.

8.5.2. Bindings For Multiple Optimization Profiles

This section explains the deprecated interface `enqueueV2` and its binding indices. The newer interface `enqueueV3` does away with binding indices.

Consider a network with four inputs, one output, and three optimization profiles in the `IBuilderConfig`. The engine has 15 bindings, five for each optimization profile, conceptually organized as a table:

Figure 13. Optimization Profile

| | | | | | |
|--|----|----|----|----|----|
| | 0 | 1 | 2 | 3 | 4 |
| | 5 | 6 | 7 | 8 | 9 |
| | 10 | 11 | 12 | 13 | 14 |

Each row is a profile. Numbers in the table denote binding indices. The first profile has binding indices 0..4, the second has 5..9, and the third has 10..14.

The interfaces have an "auto-correct" for the case that the binding belongs to the *first* profile, but another profile was specified. In that case, TensorRT warns about the mistake and then chooses the correct binding index from the same column.

For the sake of backward semi-compatibility, the interfaces have an "auto-correct" in the scenario where the binding belongs to the *first* profile, but another profile was specified. TensorRT warns about the mistake in this case and then chooses the correct binding index from the same column.

8.6. Layer Extensions For Dynamic Shapes

Some layers have optional inputs that allow specifying dynamic shape information; `IShapeLayer` can access a tensor's shape at runtime. Furthermore, some layers allow for calculating new shapes. The next section goes into semantic details and restrictions. Here is a summary of what you might find useful in conjunction with dynamic shapes.

`IShapeLayer` outputs a 1D tensor containing the dimensions of the input tensor. For example, if the input tensor has dimensions `[2, 3, 5, 7]`, the output tensor is a four-element 1D tensor containing `{2, 3, 5, 7}`. If the input tensor is a scalar, it has dimensions `[]`, and the output tensor is a zero-element 1D tensor containing `{}`.

`IResizeLayer` accepts an optional second input containing the desired dimensions of the output.

`IShuffleLayer` accepts an optional second input containing the reshaped dimensions before the second transpose is applied. For example, the following network reshapes a tensor `Y` to have the same dimensions as `X`:

C++

```
auto* reshape = networkDefinition.addShuffle(Y);
reshape.setInput(1, networkDefinition.addShape(X)->getOutput(0));
```

Python

```
reshape = network_definition.add_shuffle(y)
reshape.set_input(1, network_definition.add_shape(X).get_output(0))
```


`ISliceLayer` accepts an optional second, third, and fourth input containing the start, size, and stride.

`IConcatenationLayer`, `IElementWiseLayer`, `IGatherLayer`, `IIdentityLayer`, and `IReduceLayer`

can calculate shapes and create new shape tensors.

8.7. Restrictions For Dynamic Shapes

The following layer restrictions arise because the layer's weights have a fixed size:

- ▶ `IConvolutionLayer` and `IDeconvolutionLayer` require that the channel dimension be a build time constant.
- ▶ `IFullyConnectedLayer` requires that the last three dimensions be build-time constants.
- ▶ `Int8` requires that the channel dimension be a build time constant.
- ▶ Layers accepting additional shape inputs (`IResizeLayer`, `IShuffleLayer`, `ISliceLayer`) require that the additional shape inputs be compatible with the dimensions of the minimum and maximum optimization profiles as well as with the dimensions of the runtime data input; otherwise, it can lead to either a build-time or runtime error.

Values that must be build-time constants do not have to be at the API level. TensorRT's shape analyzer propagates constants element by element through layers that perform shape calculations. It is sufficient that the constant propagation discovers that a value is a build-time constant.

For more information regarding layers, refer to the [NVIDIA TensorRT Operator's Reference](#).

8.8. Execution Tensors Versus Shape Tensors

TensorRT 8.5 largely erased the distinctions between execution tensors and shape tensors. However, designing a network or analyzing performance may help to understand the internals and where internal synchronization is incurred.

Engines using dynamic shapes employ a ping-pong execution strategy.

1. Compute the shapes of tensors on the CPU until a shape requiring GPU results is reached.
2. Stream work to the GPU until you run out of work or reach an unknown shape. If the latter, synchronize and go back to step 1.

An *execution tensor* is a traditional TensorRT tensor. A *shape tensor* is a tensor that is related to shape calculations. It must have type `Int32`, `Int64`, `Float`, or `Bool`, its shape must be determinable at build time, and it must have no more than 64 elements. Refer to [Shape Tensor I/O \(Advanced\)](#) for additional restrictions for shape tensors at

network I/O boundaries. For example, there is an `IShapeLayer` whose output is a 1D tensor containing the dimensions of the input tensor. The output is a shape tensor. `IShuffleLayer` accepts an optional second input that can specify reshaping dimensions. The second input must be a shape tensor.

When TensorRT needs a shape tensor, but the tensor has been classified as an execution tensor, the runtime copies the tensor from the GPU to the CPU, which incurs synchronization overhead.

Some layers are "polymorphic" in terms of the kinds of tensors they handle. For example, `IElementWiseLayer` can sum two INT32 execution tensors or two INT32 shape tensors. The type of tensor depends on its ultimate use. If the sum is used to reshape another tensor, it is a "shape tensor."

8.8.1. Formal Inference Rules

The formal inference rules used by TensorRT for classifying tensors are based on a type-inference algebra. Let E denote an execution tensor, and S denote a shape tensor.

`IActivationLayer` has the signature:

```
IActivationLayer:  $E \rightarrow E$ 
```

since it takes an execution tensor as an input and an execution tensor as an output.

`IElementWiseLayer` is polymorphic in this respect, with two signatures:

```
IElementWiseLayer:  $S \times S \rightarrow S, E \times E \rightarrow E$ 
```

For brevity, let us adopt the convention that t is a variable denoting either class of tensor, and all t in a signature refers to the same class of tensor. Then, the two previous signatures can be written as a single polymorphic signature:

```
IElementWiseLayer:  $t \times t \rightarrow t$ 
```

The two-input `IShuffleLayer` has a shape tensor as the second input and is polymorphic concerning the first input:

```
IShuffleLayer (two inputs):  $t \times S \rightarrow t$ 
```

`IConstantLayer` has no inputs but can produce a tensor of either kind, so its signature is:

```
IConstantLayer:  $\rightarrow t$ 
```

The signature for `IShapeLayer` allows all four possible combinations $E \rightarrow E$, $E \rightarrow S$, $S \rightarrow E$, and $S \rightarrow S$, so it can be written with two independent variables:

```
IShapeLayer:  $t_1 \rightarrow t_2$ 
```

Here is the complete set of rules, which also serves as a reference for which layers can be used to manipulate shape tensors:

```
IAssertionLayer:  $S \rightarrow$   
IConcatenationLayer:  $t \times t \times \dots \rightarrow t$   
IIfConditionalInputLayer:  $t \rightarrow t$   
IIfConditionalOutputLayer:  $t \rightarrow t$   
IConstantLayer:  $\rightarrow t$   
IActivationLayer:  $t \rightarrow t$   
IElementWiseLayer:  $t \times t \rightarrow t$   
IFillLayer:  $S \rightarrow t$   
IFillLayer:  $S \times E \times E \rightarrow E$   
IGatherLayer:  $t \times t \rightarrow t$   
IIdentityLayer:  $t \rightarrow t$   
IReduceLayer:  $t \rightarrow t$   
IResizeLayer (one input):  $E \rightarrow E$   
IResizeLayer (two inputs):  $E \times S \rightarrow E$ 
```

```

ISelectLayer:  $t \times t \times t \rightarrow t$ 
IShapeLayer:  $t_1 \rightarrow t_2$ 
IShuffleLayer (one input):  $t \rightarrow t$ 
IShuffleLayer (two inputs):  $t \times S \rightarrow t$ 
ISliceLayer (one input):  $t \rightarrow t$ 
ISliceLayer (two inputs):  $t \times S \rightarrow t$ 
ISliceLayer (three inputs):  $t \times S \times S \rightarrow t$ 
ISliceLayer (four inputs):  $t \times S \times S \times S \rightarrow t$ 
IUnaryLayer:  $t \rightarrow t$ 
all other layers:  $E \times \dots \rightarrow E \times \dots$ 

```

Because an output can be the input of more than one subsequent layer, the inferred "types" are not exclusive. For example, an `IConstantLayer` might feed into one use that requires an execution tensor and another use that requires a shape tensor. The output of `IConstantLayer` is classified as both and can be used in both phase 1 and phase 2 of the two-phase execution.

The requirement that the size of a shape tensor be known at build time limits how `ISliceLayer` can be used to manipulate a shape tensor. Specifically, if the third parameter specifies the result's size and is not a build-time constant, the length of the resulting tensor is unknown at build time, breaking the restriction that shape tensors have constant shapes. The slice will still work but will incur synchronization overhead at runtime because the tensor is considered an execution tensor that has to be copied back to the CPU to do further shape calculations.

The rank of any tensor has to be known at build time. For example, if the output of `ISliceLayer` is a 1D tensor of unknown length that is used as the reshape dimensions for `IShuffleLayer`, the output of the shuffle would have an unknown rank at build time, and hence such a composition is prohibited.

TensorRT's inferences can be inspected using methods `ITensor::isShapeTensor()`, which returns true for a shape tensor, and `ITensor::isExecutionTensor()`, which returns true for an execution tensor. Build the entire network first before calling these methods because their answer can change depending on what uses of the tensor have been added.

For example, if a partially built network sums two tensors, $T1$ and $T2$, to create tensor $T3$, and none are yet needed as shape tensors, `isShapeTensor()` returns false for all three tensors. Setting the second input of `IShuffleLayer` to $T3$ would cause all three tensors to become shape tensors because `IShuffleLayer` requires that its second optional input be a shape tensor, and if the output of `IElementWiseLayer` is a shape tensor, its inputs are too.

8.9. Shape Tensor I/O (Advanced)

Sometimes, the need arises to use a shape tensor as a network I/O tensor. For example, consider a network consisting solely of an `IShuffleLayer`. TensorRT infers that the second input is a shape tensor. `ITensor::isShapeTensor` returns true for it. Because it is an input shape tensor, TensorRT requires two things for it:

- ▶ At build time: the optimization profile *values* of the shape tensor.
- ▶ At run time: the *values* of the shape tensor.

The shape of an input shape tensor is always known at build time. The values must be described since they can be used to specify the dimensions of execution tensors.

The optimization profile values can be set using

`IOptimizationProfile::setShapeValues`. Analogous to how min, max, and optimization dimensions must be supplied for execution tensors with runtime dimensions, min, max, and optimization values must be provided for shape tensors at build time.

The corresponding runtime method is `IExecutionContext::setTensorAddress`, which tells TensorRT where to look for the shape tensor values.

Because the inference of “execution tensor” vs “shape tensor” is based on ultimate use, TensorRT cannot infer whether a network output is a shape tensor. You must tell it using the method `INetworkDefinition::markOutputForShapes`.

Besides letting you output shape information for debugging, this feature is useful for composing engines. For example, consider building three engines, one each for sub-networks A, B, and C, where a connection from A to B or B to C might involve a shape tensor. Build the networks in reverse order: C, B, and A. After constructing network C, you can use `ITensor::isShapeTensor` to determine if an input is a shape tensor and use `INetworkDefinition::markOutputForShapes` to mark the corresponding output tensor in network B. Then check which inputs of B are shape tensors and mark the corresponding output tensor in network A.

Shape tensors at network boundaries must have the type `Int32` or `Int64`. They cannot have type `Float` or `Bool`. A workaround for `Bool` is to use `Int32` for the I/O tensor, with zeros and ones, and convert to/from `Bool` using `IIdentityLayer`.

At runtime, whether a tensor is an I/O shape tensor can be determined via `ICudaEngine::isShapeInferenceIO()`.

8.10. INT8 Calibration with Dynamic Shapes

A calibration optimization profile must be set to run INT8 calibration for a network with dynamic shapes. Calibration is performed using the profile's `kOPT` values, and the calibration input data size must match this profile.

First, construct an `IOptimizationProfile` like a general optimization profile to create a calibration optimization profile. Then, set the profile to the configuration:

C++

```
config->setCalibrationProfile(profile)
```

Python

```
config.set_calibration_profile(profile)
```

The calibration profile must be valid or be `nullptr`. `kMIN` and `kMAX` values are overwritten by `kOPT`. To check the current calibration profile, use `IBuilderConfig::getCalibrationProfile`.

This method returns a pointer to the current calibration profile or `nullptr` if the calibration profile is unset. The `getBatchSize()` calibrator method must return `1` when running calibration for a dynamic-shaped network.



Note: If the calibration optimization profile is not set, the first network optimization profile is used as a calibration optimization profile.

Chapter 9. Extending TensorRT with Custom Layers

NVIDIA TensorRT supports many layers, and its functionality is continually extended; however, there can be cases in which the layers supported do not cater to a model's specific needs. TensorRT can be extended in such cases by implementing custom layers, often called plugins.

TensorRT contains standard plugins that can be loaded into your application. For a list of open-source plugins, refer to [GitHub: TensorRT plugins](#).

To use standard TensorRT plugins in your application, the `libnvinfer_plugin.so` (`nvinfer_plugin.dll` on Windows) library must be loaded, and all plugins must be registered by calling `initLibNvInferPlugins` in your application code. For more information about these plugins, refer to the [NvInferPlugin.h](#) file.

You can write and add your own if these plugins do not meet your needs.

9.1. Adding Custom Layers Using the C++ API

There are four steps to ensure that TensorRT properly recognizes your plugin:

1. Implement a plugin class from one of TensorRT's plugin base classes. Currently, the only recommended one is `IPluginV3`.
2. Implement a plugin creator class tied to your class by deriving from one of TensorRT's plugin creator-base classes. Currently, the only recommended one is `IPluginCreatorV3One`.
3. Register an instance of the plugin creator class with TensorRT's plugin registry.
4. Add an instance of the plugin class to a TensorRT network by directly using TensorRT's network APIs or loading an ONNX model using the TensorRT ONNX parser APIs.

The following sections explore each of these steps in detail.

9.1.1. Implementing a Plugin Class

You can implement a custom layer by deriving from one of TensorRT's plugin base classes. Starting in TensorRT 10.0, the only plugin interface recommended is `IPluginV3`, as others are deprecated. Therefore, this section mostly describes plugin implementation using `IPluginV3`. Refer to the [Migrating V2 Plugins to IPluginV3](#) section for how plugins implementing V2 plugin interfaces can be migrated to `IPluginV3`.

`IPluginV3` is a wrapper for a set of *capability interfaces* that define three capabilities: core, build, and runtime.

Core capability

Refers to plugin attributes and behaviors common to both the build and runtime phases of a plugin's lifetime.

Build capability

Refers to plugin attributes and behaviors that the plugin must exhibit for the TensorRT builder.

Runtime capability

Refers to plugin attributes and behaviors that the plugin must exhibit for it to be executable, either during auto-tuning in the TensorRT build phase or inference in the TensorRT runtime phase.

`IPluginV3OneCore` ([C++](#), [Python](#)), `IPluginV3OneBuild` ([C++](#), [Python](#)), and `IPluginV3OneRuntime` ([C++](#), [Python](#)) are the base classes that an `IPluginV3` plugin must implement to display the core, build, and runtime capabilities, respectively.

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9.1.2. Implementing a Plugin Creator Class

To use a plugin in a network, you must first register it with TensorRT's `PluginRegistry` ([C++](#), [Python](#)). Rather than registering the plugin directly, you register an instance of a factory class for the plugin, derived from a child class of `IPluginCreatorInterface` ([C++](#), [Python](#)). The plugin creator class also provides other information about the plugin: its name, version, and plugin field parameters.

`IPluginCreatorV3One` is the factory class for `IPluginV3`.

`IPluginCreatorV3One::createPlugin()`, which has the signature below, returns a plugin object of type `IPluginV3`.

C++

```
IPluginV3* createPlugin(AsciiChar const *name, PluginFieldCollection const *fc,
    TensorRTPhase phase)
```

Python

```
create_plugin(self: trt.IPluginCreatorV3, name: str, field_collection:
    trt.PluginFieldCollection, phase: trt.TensorRTPhase) -> trt.IPluginV3
```

`IPluginCreatorV3One::createPlugin()` may be called to create a plugin instance in either the build phase of TensorRT or the runtime phase of TensorRT, which is communicated by the `phase` argument of type `TensorRTPhase` ([C++](#), [Python](#)).

- ▶ The returned `IPluginV3` object must have a valid core capability in both phases.
- ▶ In the build phase, the returned `IPluginV3` object must have both a build and runtime capability.
- ▶ In the runtime phase, the returned `IPluginV3` object must have a runtime capability. A build capability is not required and is ignored.

9.1.3. Registering a Plugin Creator with the Plugin Registry

There are two ways that you can register plugins with the registry:

- ▶ TensorRT provides a macro `REGISTER_TENSORRT_PLUGIN` that statically registers the plugin creator with the registry. `REGISTER_TENSORRT_PLUGIN` always registers the creator under the default namespace (`""`).
- ▶ Dynamically register by creating an entry point similar to `initLibNvInferPlugins` and calling `registerCreator` on the plugin registry. This is preferred over static registration as it allows plugins to be registered under a unique namespace. This ensures no name collisions during build time across different plugin libraries.

During serialization, the TensorRT engine internally stores the plugin name, plugin version, and namespace (if it exists) for all plugins, along with any plugin fields in the `PluginFieldCollection` returned by `IPluginV3OneRuntime::getFieldsToSerialize()`. During deserialization, TensorRT looks up a plugin creator with the same plugin name, version, and namespace from the plugin registry and invokes `IPluginCreatorV3One::createPlugin()` on it—the `PluginFieldCollection` that was serialized is passed back as the `fc` argument.

9.1.4. Adding a Plugin Instance to a TensorRT Network

You can add a plugin to the TensorRT network using `addPluginV3()`, which creates a network layer with the given plugin.

For example, you can add a plugin layer to your network as follows:

```
// Look up the plugin in the registry
// Cast to appropriate child class of IPluginCreatorInterface
auto creator = static_cast<IPluginCreatorV3One*>(getPluginRegistry()->getCreator(pluginName,
pluginVersion, pluginNamespace));
PluginFieldCollection const* pluginFC = creator->getFieldNames();
// Populate the fields parameters for the plugin layer
// PluginFieldCollection *pluginData = parseAndFillFields(pluginFC, layerFields);
// Create the plugin object using the layerName and the plugin meta data, for use by the
TensorRT builder
IPluginV3 *pluginObj = creator->createPlugin(layerName, pluginData, TensorRTPhase::kBUILD);
// Add the plugin to the TensorRT network
auto layer = network.addPluginV3(inputs.data(), int(inputs.size()), shapeInputs.data(),
int(shapeInputs.size()), pluginObj);
... (build rest of the network and serialize engine)
// Delete the plugin object
delete pluginObj;
```



```
... (free allocated pluginData)
```



Note: The `createPlugin` method described previously creates a new plugin object on the heap and returns a pointer to it. As shown previously, ensure you delete the `pluginObj` to avoid a memory leak.

When the engine is deleted, the engine destroys any clones of the plugin object created during the build. You are responsible for ensuring the plugin object you created is freed after it is added to the network.



Note:

- ▶ Do not serialize all plugin parameters, only those required to function correctly at runtime. Build time parameters can be omitted.
- ▶ If you are an automotive safety user, you must call `getSafePluginRegistry()` instead of `getPluginRegistry()`. You must also use the macro `REGISTER_SAFE_TENSORRT_PLUGIN` instead of `REGISTER_TENSORRT_PLUGIN`.

9.1.5. Example: Adding a Custom Layer with Dynamic Shapes using Using C++

Imagine that a custom layer is needed for a padding-like operation where each image in an input batch must be reshaped to 32 x 32. The input tensor X would be of shape (B, C, H, W), and the output Y would be of shape (B, C, 32, 32). To accomplish this, a TensorRT plugin can be written using the `IPluginV3` interface; let us call it `PadPlugin`.

Since an `IPluginV3` plugin must possess multiple capabilities, each defined by a separate interface, you could implement a plugin using the principle of composition or multiple inheritance. However, a multiple inheritance approach is easier for most use cases, particularly when coupling build and runtime capabilities in a single class is tolerable.

Using multiple inheritance, `PadPlugin` can be implemented as follows:

```
class PadPlugin : public IPluginV3, public IPluginV3OneCore, public IPluginV3OneBuild, public
  IPluginV3OneRuntime
{
  ...override inherited virtual methods.
};
```

The override of `IPluginV3::getCapabilityInterface` must return pointers to the individual capability interfaces. For each `PluginCapabilityType`, it is imperative to cast through the corresponding capability interface to remove ambiguity for the compiler.

```
IPluginCapability* PadPlugin::getCapabilityInterface(PluginCapabilityType type) noexcept
override
{
  TRY
  {
    if (type == PluginCapabilityType::kBUILD)
    {
      return static_cast<IPluginV3OneBuild*>(this);
    }
    if (type == PluginCapabilityType::kRUNTIME)
    {
      return static_cast<IPluginV3OneRuntime*>(this);
    }
  }
}
```

```

    ASSERT(type == PluginCapabilityType::kCORE);
    return static_cast<IPluginV3OneCore*>(this);
}
CATCH
{
    // log error
}
return nullptr;
}

```

The methods that are of importance in this particular example are:

- ▶ `INetworkDefinition::addPluginV3`
- ▶ `IPluginV3OneBuild::getNbOutputs`
- ▶ `IPluginV3OneBuild::getOutputDataTypes`
- ▶ `IPluginV3OneBuild::getOutputShapes`
- ▶ `IPluginV3OneBuild::supportsFormatCombination`
- ▶ `IPluginV3OneBuild::configurePlugin`
- ▶ `IPluginV3OneRuntime::onShapeChange`
- ▶ `IPluginV3OneRuntime::enqueue`

`INetworkDefinition::addPluginV3` ([C++](#), [Python](#)) can add the plugin to the network.

```

std::vector<ITensor*> inputs(X);

auto pluginLayer = network->addPluginV3(inputs.data(), inputs.size(), nullptr, 0, *plugin);

```

You can communicate that there is a single plugin output by overriding

`IPluginV3OneBuild::getNbOutputs`.

```

int32_t PadPlugin::getNbOutputs() const noexcept override
{
    return 1;
}

```

The output will have the same data type as the input, which can be communicated in the override of `IPluginV3OneBuild::getOutputDataTypes`.

```

int32_t PadPlugin::getOutputDataTypes(
    DataType* outputTypes, int32_t nbOutputs, DataType const* inputTypes, int32_t
    nbInputs) const noexcept override
{
    outputTypes[0] = inputTypes[0];
    return 0;
}

```

The override for `getOutputShapes` returns symbolic *expressions* for the output dimensions in terms of the input dimensions, except in the case of data-dependent output shapes, which will be covered later in [Example: Adding a Custom Layer with Data-Dependent and Shape Input-Dependent Shapes Using C++](#). In the current example, the first two dimensions of the output will equal the first two dimensions of the input, respectively, and the last two dimensions will be constants, each equal to 32. The `IExprBuilder` passed into `getOutputShapes` can be used to define constant symbolic expressions.

```

int32_t PadPlugin::getOutputShapes(DimsExprs const* inputs, int32_t nbInputs, DimsExprs
    const* shapeInputs, int32_t nbShapeInputs, DimsExprs* outputs, int32_t nbOutputs,
    IExprBuilder& exprBuilder) noexcept

```

```

{
    outputs[0].nbDims = 4;
    // first two output dims are equal to the first two input dims
    outputs[0].d[0] = inputs[0].d[0];
    outputs[0].d[1] = inputs[0].d[1];
    // The last two output dims are equal to 32
    outputs[0].d[2] = exprBuilder.constant(32);
    outputs[0].d[3] = exprBuilder.constant(32);
    return 0;
}

```

TensorRT uses `supportsFormatCombination` to ask whether the plugin accepts a given type and format combination for a "connection" at a given position `pos` and given formats/types for lesser-indexed connections. The interface indexes the inputs/outputs uniformly as "connections," starting at 0 for the first input, then the rest of the inputs in order, followed by numbering the outputs. In the example, the input is connection 0, and the output is connection 1.

For the sake of simplicity, the example supports only linear formats and FP32 types.

```

bool PadPlugin::supportsFormatCombination(
    int32_t pos, DynamicPluginTensorDesc const* inOut, int32_t nbInputs, int32_t
    nbOutputs) noexcept override
{
    assert(0 <= pos && pos < 2);
    return inOut[pos].desc.format == PluginFormat::kLINEAR && inOut[pos].desc.type ==
    DataType::kFLOAT;
}

```

TensorRT invokes two methods to allow the plugin to make any configuration choices before `enqueue()`, both during auto-tuning (in the engine build phase), and when the engine is being executed (in the runtime phase).

IPluginV3OneBuild::configurePlugin

Called when a plugin is being prepared for profiling (auto-tuning) but not for any specific input size. The `min`, `max` and `opt` values of the `DynamicPluginTensorDesc` correspond to the bounds on the tensor shape and its shape for auto-tuning. The `desc.dims` field corresponds to the dimensions of the plugin specified at network creation, including any wildcards (-1) for dynamic dimensions.

IPluginV3OneRuntime::onShapeChange

Called during both the build-phase and runtime phase before `enqueue()` to communicate the input and output shapes for the subsequent `enqueue()`. The output `PluginTensorDesc` will contain wildcards (-1) for any data-dependent dimensions specified through `getOutputShapes()`.

This plugin does not need `configurePlugin` and `onShapeChange` to do anything, so they are no-ops:

```

int32_t PadPlugin::configurePlugin(DynamicPluginTensorDesc const* in, int32_t nbInputs,
    DynamicPluginTensorDesc const* out, int32_t nbOutputs) noexcept override
{
    return 0;
}

int32_t PadPlugin::onShapeChange(PluginTensorDesc const* in, int32_t nbInputs,
    PluginTensorDesc const* out, int32_t nbOutputs) noexcept override
{
    return 0;
}

```

Finally, the override `PadPlugin::enqueue` has to do the work. Since shapes are dynamic, `enqueue` is handed a `PluginTensorDesc` that describes each input and output's dimensions, type, and format.

```
int32_t enqueue(PluginTensorDesc const* inputDesc, PluginTensorDesc const* outputDesc, void
const* const* inputs,
void* const* outputs, void* workspace, cudaStream_t stream) noexcept override
{
    // populate outputs and return status code
}
```

9.1.6. Example: Adding a Custom Layer with Data-Dependent and Shape Input-Dependent Shapes Using C++

This section shows an example of a plugin with data-dependent and shape-input-dependent shapes. Note that data-dependent output shapes and adding shape inputs to a plugin are new features not present in V2 plugins.

Data-dependent Shapes (DDS)

The shape of a plugin output could depend on the values of the input tensors.

Shape inputs

A plugin could accept shape and device sensor inputs. These inputs are only visible to the plugin as arguments to `IPluginV3OneBuild::getOutputShapes()`. Therefore, their sole purpose is to aid the plugin in performing output shape calculations.

For example, `BarPlugin` is a plugin with one device input `X`, one shape input `S`, and an output `Y`, where:

- ▶ The first dimension of `Y` depends on the value of `S`
- ▶ The second dimension of `Y` is static
- ▶ The third dimension of `Y` is data-dependent
- ▶ The fourth dimension of `Y` depends on the shape of `X`

Similar to `PadPlugin` in the prior example, `BarPlugin` uses multiple inheritance.

To add the plugin to the network, `INetworkDefinition::addPluginV3` ([C++](#), [Python](#)) can be used similarly. After the device tensor inputs, `addPluginV3` takes two additional arguments to specify the shape tensor inputs.

```
std::vector<ITensor*> inputs{X};
std::vector<ITensor*> shapeInputs{S};

auto pluginLayer = network->addPluginV3(inputs.data(), inputs.size(), shapeInputs.data(),
shapeInputs.size(), *plugin);
```



Note: The TensorRT ONNX parser provides an inbuilt feature to pass shape inputs to custom ops supported by `IPluginV3`-based plugins. The indices of the inputs to be interpreted as shape inputs must be indicated by a node attribute named `tensorrt_plugin_shape_input_indices` as a list of integers. For example, if the custom op has four inputs and the second and fourth inputs should be passed as shape inputs to

the plugin, add a node attribute named `tensorrt_plugin_shape_input_indices` of type `onnx.AttributeProto.ints` containing the value `[1, 3]`.

In the override for `getOutputShapes`, plugins must declare both the position and the bounds of each data-dependent dimension of each output tensor. The bounds can be expressed using a special output called a *size tensor*.

A size tensor is a scalar of either INT32 or INT64 data type, expressed through a value for auto-tuning and an upper bound; these values can either be constants or computed in terms of device input shapes or shape inputs values using `IExprBuilder`.

In this case, there is a singular data-dependent dimension, which we can represent using one size tensor. Note that any size tensor needed to express a data-dependent dimension counts as an output of the plugin; therefore, the plugin will have two outputs in total.

```
int32_t getNbOutputs() const noexcept override
{
    return 2;
}
```

Assume that output Y is the same type as the device input X and that the data-dependent dimension size fits INT32 (the size tensor has type `r`). Then `BarPlugin` expresses the output data types like this:

```
int32_t getOutputDataTypes(
    DataType* outputTypes, int32_t nbOutputs, DataType const* inputTypes, int32_t
    nbInputs) const noexcept override
{
    outputTypes[0] = inputTypes[0];
    outputTypes[1] = DataType::kINT32;
    return 0;
}
```

The method `getOutputShapes` can build symbolic output shape expressions using the `IExprBuilder` passed to it. In what follows, note that size tensors must be explicitly declared as 0-D.

```
int32_t BarPlugin::getOutputShapes(DimsExprs const* inputs, int32_t nbInputs, DimsExprs
    const* shapeInputs, int32_t nbShapeInputs, DimsExprs* outputs, int32_t nbOutputs,
    IExprBuilder& exprBuilder) noexcept
{
    outputs[0].nbDims = 4;
    // The first output dimension depends on the value of S.
    // The value of S is encoded as fictitious dimensions.
    outputs[0].d[0] = shapeInputs[0].d[0];
    // The third output dimension depends on the shape of X
    outputs[0].d[2] = inputs[0].d[0];
    // The second output dimension is static
    outputs[0].d[1] = exprBuilder.constant(3);

    auto upperBound = exprBuilder.operation(DimensionOperation::kPROD, *inputs[0].d[2],
    *inputs[0].d[3]);
    auto optValue = exprBuilder.operation(DimensionOperation::kFLOOR_DIV, *upperBound,
    *exprBuilder.constant(2));

    // output at index 1 is a size tensor
    outputs[1].nbDims = 0; // size tensors must be declared as 0-D
    auto sizeTensor = exprBuilder.declareSizeTensor(1, *optValue, *upperBound);

    // The fourth output dimension is data-dependent
```

```

    outputs[0].d[3] = sizeTensor;

    return 0;
}

```

The override of `supportsFormatCombination` imposes the following conditions:

- ▶ The devices input X must have `DataType::kFLOAT` or `DataType::kHALF`
- ▶ The output Y must have the same type as X
- ▶ The size tensor output has type `DataType::kINT32`



Note: Shape inputs passed to the plugin through `addPluginV3` ([C++](#), [Python](#)) only appear as arguments to `getOutputShapes()` and are not counted or included among plugin inputs in any other plugin interface method.

```

bool BarPlugin::supportsFormatCombination(
    int32_t pos, DynamicPluginTensorDesc const* inOut, int32_t nbInputs, int32_t
    nbOutputs) noexcept override
{
    assert(0 <= pos && pos < 3);
    auto const* in = inOut;
    auto const* out = inOut + nbInputs;

    bool typeOk{false};

    switch (pos)
    {
    case 0: typeOk = in[0].desc.type == DataType::kFLOAT || in[0].desc.type ==
    DataType::kHALF; break;
    case 1: typeOk = out[0].desc.type == in[0].desc.type; break;
    case 2: typeOk = out[1].desc.type == DataType::kINT32; break;
    }

    return inOut[pos].desc.format == PluginFormat::kLINEAR && typeOk;
}

```

The local variables `in` and `out` here allow inspecting `inOut` by input or output number instead of connection number.



Important: The override inspects the format/type for a connection with an index less than `pos` but must never inspect the format/type for a connection with an index greater than `pos`. The example uses case 1 to check connection 1 against connection 0 and not case 0 to check connection 0 against connection 1.

`configurePlugin` and `onShapeChange` would be no-ops here, too; one thing to note is that in `onShapeChange`, the output's `PluginTensorDesc` will contain a wildcard (-1) for the data-dependent dimension.

Implementing `enqueue` with data-dependent output shapes differs greatly from the static or dynamic shape cases. As with any other output, for an output with a data-dependent dimension, the output buffer passed to `enqueue` is guaranteed large enough to hold the corresponding output tensor (based on the upper bound specified through `getOutputShapes`).

9.1.7. Example: Adding a Custom Layer with INT8 I/O Support Using C++

`PoolPlugin` is a plugin that demonstrates how to add INT8 I/O for a custom pooling layer using `IPluginV3`. `PoolPlugin` multiply inherits from `IPluginV3`, `IPluginV3OneCore`, `IPluginV3OneBuild`, and `IPluginV3OneRuntime`, similar to the `PadPlugin` and `BarPlugin` examples above.

The main methods that affect INT8 I/O are:

- ▶ `supportsFormatCombination`
- ▶ `configurePlugin`

The override for `supportsFormatCombination` must indicate which INT8 I/O combination is allowed. This interface is used similarly to [Example: Adding a Custom Layer with Dynamic Shapes using Using C++](#). In this example, the supported I/O tensor format is linear CHW with FP32, FP16, BF16, FP8, or INT8 data type, but the I/O tensor must have the same data type.

```
bool PoolPlugin::supportsFormatCombination(
    int32_t pos, DynamicPluginTensorDesc const* inOut, int32_t nbInputs, int32_t
    nbOutputs) noexcept override
{
    assert(nbInputs == 1 && nbOutputs == 1 && pos < nbInputs + nbOutputs);
    bool condition = inOut[pos].desc.format == PluginFormat::kLINEAR;
    condition &= (inOut[pos].desc.type == DataType::kFLOAT ||
                 inOut[pos].desc.type == DataType::kHALF ||
                 inOut[pos].desc.type == DataType::kBF16 ||
                 inOut[pos].desc.type == DataType::kFP8 ||
                 inOut[pos].desc.type == DataType::kINT8);
    condition &= inOut[pos].desc.type == inOut[0].desc.type;
    return condition;
}
```



Important:

- ▶ If INT8 calibration must be used with a network with INT8 I/O plugins, the plugin must support FP32 I/O, as TensorRT uses FP32 to calibrate the graph.
- ▶ If the FP32 I/O variant is not supported or INT8 calibration is not used, all required INT8 I/O tensor scales must be set explicitly.
- ▶ Calibration cannot determine the dynamic range of a plugin's internal tensors. Plugins that operate on quantized data must calculate their dynamic range for internal tensors.
- ▶ A plugin can be designed to accept FP8 and INT8 I/O types, although note that in TensorRT 9.0, the builder does not allow networks that mix INT8 and FP8.

Information communicated by TensorRT through `configurePlugin` or `onShapeChange` can be used to obtain information about the pooling parameters and the input and output scales. These can be stored as member variables, serialized, and then deserialized to be used during inference.

```
int32_t PoolPlugin::configurePlugin(DynamicPluginTensorDesc const* in, int32_t nbInputs,
    DynamicPluginTensorDesc const* out, int32_t nbOutputs) noexcept override
{
    ...
}
```

```

mPoolingParams.mC = in.desc.d[1];
mPoolingParams.mH = in.desc.d[2];
mPoolingParams.mW = in.desc.d[3];
mPoolingParams.mP = out.desc.d[2];
mPoolingParams.mQ = ou.desc.d[3];
mInHostScale = in[0].desc.scale >= 0.0F ? in[0].desc.scale : -1.0F;
mOutHostScale = out[0].desc.scale >= 0.0F ? out[0].desc.scale : -1.0F;
}

```

INT8 I/O scales per tensor have been obtained from `PluginTensorDesc::scale`.

9.2. Adding Custom Layers using the Python API

Before TensorRT 9.0, custom layer implementations could only be done through the C++ API; adding such a plugin to a TensorRT network in Python required loading a library containing the plugin and accessing the plugin creator through the plugin registry. Implementing custom layers entirely within Python with no additional C++ code is now possible.

Implementing a plugin in Python is similar to C++ in that an implementation of `IPluginV3` and `IPluginCreatorV3One` is necessary. Furthermore, interface methods in Python have mostly similar APIs to their C++ counterparts; most differences are minor and self-explanatory.

The following list includes a few selected changes. Subsequent subsections describe the differences involved in more detail.

- ▶ The following plugin APIs have been omitted in favor of reading/writing to an appropriately named attribute.

| Class | Method | Replaced with Attribute |
|----------------------------------|--|--|
| <code>IPluginV3OneCore</code> | <code>getPluginName()</code> | <code>plugin_name[str]</code> |
| <code>IPluginV3OneCore</code> | <code>getPluginNamespace()</code> | <code>plugin_namespace [str]</code> |
| <code>IPluginV3OneCore</code> | <code>getPluginVersion()</code> | <code>plugin_version [str]</code> |
| <code>IPluginV3OneBuild</code> | <code>getNbOutputs()</code> | <code>num_outputs [int]</code> |
| <code>IPluginV3OneBuild</code> | <code>getTimingCacheID()</code> | <code>timing_cache_id [str]</code> |
| <code>IPluginV3OneBuild</code> | <code>getMetadataString()</code> | <code>metadata_string [str]</code> |
| <code>IPluginV3OneBuild</code> | <code>getFormatCombinationLimit()</code> | <code>format_combination_limit [int]</code> |
| <code>IPluginCreatorV3One</code> | <code>getPluginNamespace()</code> | <code>plugin_namespace [str]</code> |
| <code>IPluginCreatorV3One</code> | <code>getFieldNames()</code> | <code>field_names [PluginFieldCollection]</code> |
| <code>IPluginCreatorV3One</code> | <code>getPluginName()</code> | <code>name [str]</code> |
| <code>IPluginCreatorV3One</code> | <code>getPluginVersion()</code> | <code>plugin_version [str]</code> |

- ▶ Some methods have default implementations; these can be left unimplemented, and the default behaviors outlined below will take effect:

```

class trt.IPluginV3:
    def destroy(self):

```



```

    pass

class trt.IPluginV3OneBuild:
    def get_valid_tactics(self):
        return []

    def get_workspace_size(self, input_desc, output_desc):
        return 0

```

- ▶ Methods that must return integer status codes in `IPluginV3OneBuild` and `IPluginV3OneRuntime` should raise exceptions in Python instead. For example:

C++

```

int32_t configurePlugin(DynamicPluginTensorDesc const* in, int32_t nbInputs,
    DynamicPluginTensorDesc const* out, int32_t nbOutputs)

```

Python

```

configure_plugin(self: trt.IPluginV3OneBuild, in: List[trt.DynamicPluginTensorDesc],
    out: List[trt.DynamicPluginTensorDesc]) -> None

```

For example, you can raise a `ValueError` during `enqueue` if an input has an illegal value.

- ▶ The Python API `IPluginV3.destroy()` has no direct equivalent in the C++ API. Python plugins are expected to perform any functionality that would be performed in a `IPluginV3` C++ destructor within the `IPluginV3.destroy()` method.

For full examples demonstrating Python plugins, refer to the [python_plugin](#) sample.

9.2.1. Registration of a Python Plugin

Python plugins must be registered dynamically through the `IPluginRegistry.register_creator()` API. There is no analog to the `REGISTER_TENSORRT_PLUGIN` available for static registration.

9.2.2. Building and Running TensorRT Engines Containing Python Plugins

It is possible to build TensorRT engines using Python-based plugins. However, running such engines outside of Python is currently impossible since the plugin must be available in the scope where the engine is being deserialized. For example, you cannot use a tool like `trtexec` directly.

9.2.3. Implementing `enqueue` of a Python Plugin

The API for `IPluginV3OneRuntime::enqueue()` in C++ and Python are as follows:

C++

```

int32_t enqueue(PluginTensorDesc const *inputDesc, PluginTensorDesc const *outputDesc,
    void const *const *inputs, void *const *outputs, void *workspace, cudaStream_t stream)

```

Python

```

enqueue(self: trt.IPluginV3OneRuntime, input_desc: List[trt.PluginTensorDesc],
    output_desc: List[trt.PluginTensorDesc], inputs: List[int], outputs: List[int],
    workspace: int, stream: int) -> None

```

Here, `inputs`, `outputs`, and `workspace` are passed in as `intptr_t` casts of the respective device pointers. Similarly, a `stream` is an `intptr_t` cast of a pointer to the CUDA stream

handle. There is flexibility within Python on how to read from and write to these buffers, and this can be achieved depending on the particular use case. For example, with CUDA Python, this is quite simple since `cuda.cuLaunchKernel` accepts `int` representing the pointers wrapped in NumPy arrays:

```
d_input = np.array([inputs[0]], dtype=np.uint64)
d_output = np.array([outputs[0]], dtype=np.uint64)
stream_ptr = np.array([stream], dtype=np.uint64)
args = [d_input, d_output]
kernel_args = np.array([arg.ctypes.data for arg in args], dtype=np.uint64)
...
checkCudaErrors(cuda.cuLaunchKernel(_float_kernel,
                                   num_blocks, 1, 1,
                                   block_size, 1, 1,
                                   0,
                                   stream_ptr,
                                   kernel_args , 0))
```

9.2.4. Translating Device Buffers/CUDA Stream Pointers in `enqueue` to other Frameworks

Constructing CuPy arrays on top of device buffers is possible using CuPy's `UnownedMemory` class.

```
def enqueue(self, input_desc, output_desc, inputs, outputs, workspace, stream):
    ...
    inp_dtype = trt.nptype(input_desc[0].type)
    inp_mem = cp.cuda.UnownedMemory(
        inputs[0], volume(input_desc[0].dims) * cp.dtype(inp_dtype).itemsize, self
    )
    out_mem = cp.cuda.UnownedMemory(
        outputs[0],
        volume(output_desc[0].dims) * cp.dtype(inp_dtype).itemsize,
        self,
    )

    inp_ptr = cp.cuda.MemoryPointer(inp_mem, 0)
    out_ptr = cp.cuda.MemoryPointer(out_mem, 0)

    inp = cp.ndarray((volume(input_desc[0].dims)), dtype=inp_dtype, memptr=inp_ptr)
    out = cp.ndarray((volume(output_desc[0].dims)), dtype=inp_dtype, memptr=out_ptr)
```

If needed, `torch.as_tensor()` can then be used to construct a Torch array:

```
# inp_d = cp.ndarray(tuple(input_desc[0].dims), dtype=inp_dtype, memptr=inp_ptr)
inp_t = torch.as_tensor(inp_d, device='cuda')
```

Similarly, CuPy stream handles can be constructed from the passed-in `stream` pointer through CuPy's `ExternalStream` class.

```
cuda_stream = cp.cuda.ExternalStream(stream)
```

9.2.5. Automatic Downcasting

TensorRT Python bindings will do automatic downcasting for custom types written in Python implementing interfaces like `IPluginCreatorV3One` or `IPluginResource`. For example, take the following method from `IPluginRegistry` as an example:

```
get_creator(self: trt.IPluginRegistry, name: string, version: string,
            namespace: string = "") -> trt.IPluginCreatorInterface
```

The return type is indicated as `IPluginCreatorInterface`. However, in practice, if you were to write a class `MyPluginCreator` implementing `IPluginCreatorV3One` (which in

turn implements `IPluginCreatorInterface`), the `get_creator` method will return an automatically downcasted type of `MyPluginCreator`.

This extends to `trt.IPluginRegistry.all_creators`, which is a `List[trt.IPluginCreatorInterface]`. If you had registered a plugin creator of type `MyPluginCreator` and another type `MyOtherPluginCreator`, both plugin creators will be present as those respective types in the list.

9.2.6. Example: Adding a Custom Layer to a TensorRT Network Using Python

Using plugin nodes, custom layers can be added to any TensorRT network in Python. The Python API has a function called `add_plugin_v3` that enables adding a plugin node to a network. The following example illustrates this. It creates a simple TensorRT network and adds a hypothetical plugin node by looking up the TensorRT plugin registry.

```
import tensorrt as trt
import numpy as np

TRT_LOGGER = trt.Logger()

trt.init_libnvinfer_plugins(TRT_LOGGER, '')
def get_trt_plugin(plugin_name, plugin_version, plugin_namespace):
    plugin = None
    plugin_creator = trt.get_plugin_registry().get_creator(plugin_name, plugin_version,
        plugin_namespace)
    # trt will automatically downcast to IPluginCreator or IPluginCreatorInterface
    # Can inspect plugin_creator.interface_info to make sure
    if plugin_creator is not None:
        lrelu_slope_field = trt.PluginField("epsilon", np.array([0.00000001],
            dtype=np.float32), trt.PluginFieldType.FLOAT32)
        field_collection = trt.PluginFieldCollection([lrelu_slope_field])
        plugin = plugin_creator.create_plugin(name=plugin_name,
            field_collection=field_collection, phase=trt.TensorRTPhase.BUILD)
    return plugin

def main():
    builder = trt.Builder(TRT_LOGGER)
    network = builder.create_network()
    config = builder.create_builder_config()
    config.max_workspace_size = 2**20
    input_layer = network.add_input(name="input_layer", dtype=trt.float32, shape=(1, 1))
    plugin = network.add_plugin_v3(inputs=[input_layer], shape_inputs=[],
        plugin=get_trt_plugin("MY_PLUGIN", "1", ""))
    plugin.get_output(0).name = "outputs"
    network.mark_output(plugin.get_output(0))
```

9.3. Enabling Timing Caching and Using Custom Tactics

`IPluginV3` provides more control over the profiling of custom layers, which were unavailable with V2 plugins and earlier. One such feature is enabling timing caching. If a TensorRT network contains multiple instances of the same plugin, identically configured (for example, same plugin attribute values) and handling identical input-output shapes and types, then it would make sense to time (measure latency) of only one instance,

cache the latency, and skip timing the rest of the instances. This would potentially enable large savings in terms of engine build time.

Timing caching for `IPluginV3` plugins is an opt-in feature; to opt-in, the plugin must advertise a non-null timing cache ID.

C++

```
char const* FooPlugin::getTimingCacheID() noexcept override
{
    // return nullptr to disable timing caching (default behavior)
    // return non-null string to enable timing caching
}
```

Python

```
def FooPlugin(trt.IPluginV3, trt.IPluginV3OneBuild, ...):
    def __init__(self):
        # set to None to disable timing caching
        self.timing_cache_id = value
```

Note the following regarding the timing cache ID:

- ▶ The user-provided timing cache ID should be considered a suffix to a larger cache ID; TensorRT automatically forms a prefix by considering the plugin's input/output shape and format information. Usually, the user-provided timing cache ID could consist of plugin attributes and their values.
- ▶ It must only reflect the plugin's creation state; it must not evolve after the plugin has been created.

For V2 plugins, TensorRT only times the plugin for any (multiple) type/format combinations it claims to support. With `IPluginV3`, plugins also have the ability to make sure custom tactics are timed, and TensorRT uses the fastest tactic. For example, the plugin may have one of two kernels to compute the output, and it may not be possible to predict which one would be fastest on a specific platform and for specific input/output shapes and formats. It is possible to ask TensorRT to time the plugin for each tactic for each format combination, figure out the fastest such configuration, and use that during inference.



Note:

- ▶ TensorRT may choose not to time the plugin if it only supports one type/format combination and either does not use custom tactics or only advertises one.
- ▶ For `IPluginV3OneBuild`, TensorRT times a maximum of `getFormatCombinationLimit()` type/format combinations *for each tactic*; override this method to increase/decrease this limit depending on need.

To get started, advertise the custom tactics to TensorRT:

C++

```
int32_t FooPlugin::getNbTactics() noexcept override
{
    return 2; // return 0 to disable custom tactics (default behavior)
}

int32_t FooPlugin::getValidTactics(int32_t* tactics, int32_t nbTactics) noexcept override
{
    tactics[0] = 1;
    tactics[1] = 2;
    return 0;
}
```

Python

```
def get_valid_tactics(self):
    return [1, 2] # return empty vector to disable custom tactics (default behavior)
```

Any strictly positive integer could be used as a custom tactic value (TensorRT reserves 0 as the default tactic).

When the plugin is timed, `configurePlugin()` is guaranteed to be called with the current input/output format combination before `getValidTactics()` is called. Therefore, it is possible to advertise a different set of tactics per input/output format combination. For example, for a plugin that supports both FP32 and FP16, tactic 1 may be restricted to only FP16 while supporting both tactics 1 and 2 for FP32.

During the engine build, when auto-tuning the plugin, TensorRT will communicate the tactic for the subsequent `enqueue()` by invoking `IPluginV3OneRuntime::setTactic` ([C++](#), [Python](#)). When an engine is deserialized, TensorRT will invoke `setTactic` once the plugin has been created to communicate the best tactic chosen for the plugin. Even if custom tactics are not used, `setTactic` will be called with the default tactic value 0.

9.4. Sharing Custom Resources Among Plugins

Starting in TensorRT 10.0, a key-value store is associated with the plugin registry. This store can store user-implemented `IPluginResource` ([C++](#), [Python](#)) objects against a string key. This functionality can be used to share state or some resources among different plugins. Note that it is not tied to `IPluginV3` (or even to plugin interfaces).

Let us explore an example.

9.4.1. Example: Sharing Weights Downloaded Over a Network Among Different Plugins

Assume that several plugins need access to the same weights, w . Due to licensing restrictions, you may prefer that these weights be downloaded when the engine runs. However, due to w 's large size, it is also desirable that only one copy is downloaded, which is shared among all plugins needing access.

1. Implement `SharedWeights` class, which implements `IPluginResource`.
2. Each plugin that requires access to the weights requests an instance of initialized (downloaded) `SharedWeights` by calling `IPluginRegistry::acquirePluginResource(...)`.

C++

```
IPluginResource* acquirePluginResource(char const* key, IPluginResource* resource)
```

([C++](#), [Python](#))

Python

```
acquire_plugin_resource(self: trt.IPluginRegistry, key: str, resource:
    trt.IPluginResource) -> trt.IPluginResource
```

The first time `acquirePluginResource` is called against a particular `key`, TensorRT registers a *clone* of the provided plugin `resource` instead of the object passed as a `resource`. The registered object is obtained by invoking `resource->clone()`. Therefore, it is best practice to only initialize clones – in this case, the weight download can be done in `IPluginResource::clone()`.

3. After each plugin has finished using the weights, it can call `IPluginRegistry::releasePluginResource()` to signal that it no longer wishes to use them.

C++

```
int32_t releasePluginResource(char const* key)
```

Python

```
release_plugin_resource(self: trt.IPluginRegistry, key: str) -> None
```

TensorRT performs reference counting on the `acquirePluginResource` and `releasePluginResource` calls made against a particular `key` and will call `IPluginResource::release()` if and when the reference count reaches zero. In this example, this functionality can be leveraged to free up the memory used by the weights when all plugins have finished using it.

4. Finally, the `SharedWeights` class can be implemented as follows:

```
class SharedWeights : public IPluginResource
{
public:
    SharedWeights(bool init = false)
    {
        if(init)
        {
            PLUGIN_CHECK(cudaMalloc((void**) &cloned->mWeights, ...));
        }
    }

    int32_t release() noexcept override
    {
        TRY
        {
            if (mWeights != nullptr)
            {
                PLUGIN_CHECK(cudaFree(mWeights));
                mWeights = nullptr;
            }
        }
        CATCH
        {
            return -1;
        }
        return 0;
    }

    IPluginResource* clone() noexcept override
    {
        TRY
        {
            auto cloned = std::make_unique<SharedWeights>(/* init */ true);
            //
            // Download the weights
            //
            // Copy to device memory
            PLUGIN_CHECK(cudaMemcpy(cloned->mWeights, ...));
        }
        CATCH
```

```

        {
            return nullptr;
        }
        return cloned.release();
    }

    ~SharedWeights() override
    {
        if(mWeights)
        {
            release();
        }
    }

    float* mWeights{nullptr};
};

```

Say `FooPlugin` needs access to the weights. It can request the weights when it is being made ready for inference. This can be done in `IPluginV3OneRuntime::onShapeChange`, which will be called at least once for plugins about to be `enqueue()` during both the build and runtime phases.

```

int32_t onShapeChange(
    PluginTensorDesc const* in, int32_t nbInputs, PluginTensorDesc const* out, int32_t
    nbOutputs) noexcept override
{
    SharedWeights w{};
    mW = static_cast<SharedWeights*>(getPluginRegistry()->acquirePluginResource("W",
    &w))->mWeights;
    return 0;
}

```

The acquired weights (`mW`) can then be used in the subsequent `enqueue()`. To wrap up, the plugin can signal intent to release in its destructor (note that there is no separate release resource routine similar to `IPluginV2DynamicExt::terminate()` in `IPluginV3`).

```

~FooPlugin() override
{
    TRY
    {
        PLUGIN_CHECK(getPluginRegistry()->releasePluginResource("W"));
    }
    CATCH
    {
        // Error handling
    }
}

```

Essentially, all plugins requiring access to the weights can use the same code above. The reference counting mechanism will ensure the weights' availability and proper freeing.

9.5. Using Custom Layers When Importing a Model with a Parser

The ONNX parser automatically attempts to import unrecognized nodes as plugins. If a plugin with the same `op_type` as the node is found in the plugin registry, the parser forwards the node's attributes to the plugin creator as plugin field parameters to create the plugin. By default, the parser uses "1" as the plugin version and "" as the

plugin namespace. This behavior can be overridden by setting a `plugin_version` and `plugin_namespace` string attribute in the corresponding ONNX node.

Sometimes, you might want to modify an ONNX graph before importing it into TensorRT. For example, to replace a set of ops with a plugin node. To accomplish this, you can use the [ONNX GraphSurgeon utility](#). For details on how to use ONNX-GraphSurgeon to replace a subgraph, refer to [this example](#).

For more examples, refer to the [onnx_packnet](#) sample.

9.6. Plugin API Description

All new plugins should derive from both `IPluginCreatorV3One` and `IPluginV3` classes. In addition, new plugins should also be registered in the plugin registry, either dynamically by using `IPluginRegistry::registerCreator()` or statically using the `REGISTER_TENSORRT_PLUGIN(...)` macro. Custom plugin libraries can also consider implementing an `init` function equivalent to `initLibNvInferPlugins()` to perform bulk registration.



Note: Automotive safety users must use the `REGISTER_SAFE_TENSORRT_PLUGIN(...)` macro instead of `REGISTER_TENSORRT_PLUGIN(...)`.

9.6.1. IPluginV3 API Description

The following section describes the functions of `IPluginV3` and, by extension, `IPluginV3OneCore`, `IPluginV3OneBuild/IPluginV3OneBuildV2`, and `IPluginV3OneRuntime`.

Since an `IPluginV3` object consists of different capabilities, `IPluginV3::getCapabilityInterface` may be called anytime during its lifetime. An `IPluginV3` object added for the build phase must return a valid capability interface for all capability types: core, build, and runtime. The build capability may be omitted for objects added for the runtime phase.

There are a few methods used to request identifying information about the plugin. They may also be called during any stage of the plugin's lifetime.

`IPluginV3OneCore::getPluginName`

Used to query for the plugin's name.

`IPluginV3OneCore::getPluginVersion`

Used to query for the plugin's version.

`IPluginV3OneCore::getPluginNamespace`

Used to query for the plugin's namespace.

`IPluginV3OneBuild::getMetadataString`

Used to query for a string representation of any metadata associated with the plugin, such as the values of its attributes.

To connect a plugin layer to neighboring layers and set up input and output data structures, the builder checks for the number of outputs and their shapes by calling the following plugin methods:

IPluginV3OneBuild::getNbOutputs

Used to specify the number of output tensors.

IPluginV3OneBuild::getOutputShapes

This function specifies the output shapes as a function of the input shapes or constants. The exception is data-dependent shapes with a specified upper bound and optimal tuning value.

IPluginV3OneBuild::supportsFormatCombination

Used to check if a plugin supports a given data type and format combination.

IPluginV3OneBuild::getOutputDataType

This function is used to get the data types of the output tensors. The returned data types must have a format supported by the plugin.

If the `IPluginV3OneBuildV2` build capability is used, the plugin can also communicate to TensorRT that certain input-output pairs are aliased (share the same data buffer). `IPluginV3OneBuildV2::getAliasedInput` will be queried by TensorRT to determine any such aliasing behavior. To use this feature, `PreviewFeature::kALIASED_PLUGIN_IO_10_03` must be enabled.

Plugin layers can support the following data formats:

- ▶ `LINEAR` single-precision (FP32), half-precision (FP16), brain floating-point (BF16), 8-bit floating-point E4M3 (FP8), integer (INT8), and integer (INT32) tensors
- ▶ `CHW32` single-precision (FP32) and integer (INT8) tensors
- ▶ `CHW2`, `HWC8`, `HWC16`, and `DHWC8` half-precision (FP16) tensors
- ▶ `CHW4` half-precision (FP16), and integer (INT8) tensors
- ▶ `HWC8`, `HWC4`, `NDHWC8`, `NC2HW` brain floating-point (BF16) tensors

`PluginFormat` counts the formats.

Plugins that do not compute all data in place and need memory space in addition to input and output tensors can specify the additional memory requirements with the `IPluginV3OneBuild::getWorkspaceSize` method, which the builder calls to determine and preallocate scratch space.

The layer is configured, executed, and destroyed at build time to discover optimal configurations. After the optimal configuration is selected for a plugin, the chosen tactic and concrete shape/format information (except for data-dependent dimensions) are communicated to the plugin during inference. It is executed as many times as needed for the lifetime of the inference application and finally destroyed when the engine is destroyed.

The builder controls these steps and runtime using the following plugin methods. Methods also called during inference are indicated by (*) - all others are only called by the builder.

IPluginV3OneBuild::attachToContext*

This function requests that a plugin clone be attached to an `ExecutionContext` and allows the plugin to access any context-specific resources.

IPluginV3OneBuild::getTimingCacheId

This function queries for any timing cached ID that TensorRT may use. If provided, it enables timing caching (it is disabled by default).

IPluginV3OneBuild::getNbTactics

Used to query for the number of custom tactics the plugin chooses to use.

IPluginV3OneBuild::getValidTactics

This function queries for any custom tactics the plugin may use. The plugin will be profiled for each tactic up to a maximum indicated by

`IPluginV3OneBuild::getFormatCombinationLimit()`.

IPluginV3OneBuild::getFormatCombinationLimit

This function queries the maximum number of format combinations that may be timed for each tactic (0 if no custom tactics are advertised for the default tactic).

IPluginV3OneRuntime::setTactic*

Communicates the tactic to be used during the subsequent `enqueue()`. If no custom tactics were advertised, this would always be 0.

IPluginV3OneBuild::configurePlugin

Communicates the number of inputs and outputs and their shapes, data types, and formats. The min, opt, and max of each input or output's `DynamicPluginTensorDesc` correspond to the `kMIN`, `kOPT`, and `kMAX` values of the optimization profile that the plugin is currently profiled for. The `desc.dims` field corresponds to the dimensions of plugin inputs specified at network creation. Wildcard dimensions may exist during this phase in the `desc.dims` field.

At this point, the plugin may set up its internal state and select the most appropriate algorithm and data structures for the given configuration.

IPluginV3OneRuntime::onShapeChange*

Communicates the number of inputs and outputs and their shapes, data types, and formats. The dimensions are concrete, except if data-dependent dimensions exist, which wildcards will indicate.

IPluginV3OneRuntime::enqueue*

Encapsulates the actual algorithm and kernel calls of the plugin and provides pointers to input, output, and scratch space, as well as the CUDA stream to be used for kernel execution.

IPluginV3::clone

This is called every time a new builder, network, or engine is created that includes this plugin layer. It must return a new plugin object with the correct parameters.

After the builder completes profiling, before the engine is serialized,

`IPluginV3OneRuntime::getFieldsToSerialize` is called to query for any plugin fields that must be serialized into the engine. These are expected to be data that the plugin needs to function properly during the inference stage once the engine has been deserialized.

9.6.2. IPluginCreatorV3One API Description

The following methods in the `IPluginCreatorV3One` class are used to find and create the appropriate plugin from the plugin registry:

getPluginName

This returns the plugin name and should match the return value of

`IPluginV3OneCore::getPluginName`.

getPluginVersion

Returns the plugin version. For all internal TensorRT plugins, this defaults to 1.

getPluginNamespace

Returns the plugin namespace. The default can be "".

getFieldNames

To successfully create a plugin, you must know all the plugin's field parameters. This method returns the `PluginFieldCollection` struct with the `PluginField` entries populated to reflect the field name and `PluginFieldType` (the data should point to `nullptr`).

createPlugin

This method creates a plugin, passing a `PluginFieldCollection` and a `TensorRTPhase` argument.

During engine deserialization, TensorRT calls this method with the `TensorRTPhase` argument set to `TensorRTPhase::kRUNTIME` and the `PluginFieldCollection` populated with the same `PluginFields` as in the one returned by `IPluginV3OneRuntime::getFieldsToSerialize()`. In this case, TensorRT takes ownership of plugin objects returned by `createPlugin`.

You may also invoke `createPlugin` to produce plugin objects to add to a TensorRT network. In this case, setting the phase argument to `TensorRTPhase::kBUILD` is recommended. The data passed with the `PluginFieldCollection` should be allocated and freed by the caller before destroying the program. The ownership of the plugin object returned by the `createPlugin` function is passed to the caller and must be destroyed.

9.7. Migrating V2 Plugins to IPluginV3

`IPluginV2` and `IPluginV2Ext` have been deprecated since TensorRT 8.5, and `IPluginV2IOExt` and `IPluginV2DynamicExt` are deprecated in TensorRT 10.0. Therefore, new plugins should target `IPluginV3`, and old ones should be refactored.

Keep in mind the following key points when migrating an `IPluginV2DynamicExt` plugin to `IPluginV3`:

- ▶ The plugin creator associated with the plugin must be migrated to `IPluginCreatorV3One`, the factory class for `IPluginV3` (`IPluginCreator` is the factory class for `IPluginV2` derivatives). This simply consists of migrating `IPluginCreator::deserializePlugin`. Refer to the [Plugin Serialization and Deserialization](#) section for more information.
- ▶ There is no equivalent to `IPluginV2::initialize()`, `IPluginV2::terminate()` and `IPluginV2::destroy()` in `IPluginV3`. For more information, refer to [Plugin Initialization and Termination](#).
- ▶ There is no equivalent to `IPluginV2Ext::detachFromContext()` in `IPluginV3`. For more information, refer to [Accessing Context-Specific Resources Provided by TensorRT](#).
- ▶ `IPluginV3OneRuntime::attachToContext()` is markedly different from `IPluginV2Ext::attachToContext()` regarding arguments and behavior. For more information, refer to the [Accessing Context-Specific Resources Provided by TensorRT](#).
- ▶ In `IPluginV3`, plugin serialization is through a `PluginFieldCollection` that gets passed to TensorRT by `IPluginV3OneRuntime::getFieldsToSerialize()` and

deserialization is through the same `PluginFieldCollection` that gets passed back by TensorRT to `IPluginCreatorV3One::createPlugin(...)`. For more information, refer to [Plugin Serialization and Deserialization](#).

- ▶ The `IPluginV3` equivalents of void return methods in `IPluginV2DynamicExt` will expect an integer status code as a return value (for example, `configurePlugin`).
- ▶ `supportsFormatCombination` and `getWorkspaceSize` get dynamic tensor descriptors (`DynamicPluginTensorDesc`) instead of static descriptors (`PluginTensorDesc`).
- ▶ `IPluginV2DynamicExt::getOutputDimensions()` becomes `IPluginV3OneBuild::getOutputShapes()` and changes to an output parameter signature instead of a return value. It also shifts from per-output index querying to one-shot querying. A similar transition applies from `IPluginV2Ext::getOutputDataType` to `IPluginV3OneBuild::getOutputDataTypes`.

9.7.1. Plugin Initialization and Termination

`IPluginV2` provided several APIs for plugin initialization and termination: namely, `IPluginV2::initialize()`, `IPluginV2::terminate()`, and `IPluginV2::destroy()`. In `IPluginV3`, plugins are expected to be constructed in an initialized state; if your V2 plugin had any lazy initialization in `initialize`, it can be deferred to `onShapeChange` or `configurePlugin`. Any resource release or termination logic in `IPluginV2::terminate()` or `IPluginV2::destroy()` can be moved to the class destructor. The exception is in the Python API; `IPluginV3.destroy()` is provided as an alternative for a C++-like destructor.

9.7.2. Accessing Context-Specific Resources Provided by TensorRT

`IPluginV2Ext::attachToContext()` provided plugins access to context-specific resources, namely the GPU allocator and cuDNN and cuBLAS handles. `IPluginV3OneRuntime::attachToContext()` is meant to provide a similar service to plugins, but it instead provides an `IPluginResourceContext`, which in turn exposes resources that plugins may request.

In a departure from `IPluginV2Ext::attachToContext()`, cuDNN and cuBLAS handles are no longer provided by `IPluginResourceContext`; any plugins that depended on those should migrate to initialize their own cuDNN and cuBLAS resources. If sharing cuDNN/cuBLAS resources among plugins is preferred, you can utilize the functionality provided by `IPluginResource` and the plugin registry's key-value store to accomplish this. For more information, refer to the [Sharing Custom Resources Among Plugins](#).

`IPluginV3OneRuntime::attachToContext(...)` is a clone-and-attach operation. It is asked to clone the entire `IPluginV3` object—not just the runtime capability. Therefore, if implemented as a separate class, the runtime capability object may need to hold a reference to the `IPluginV3` object of which it is a part.

Any context-specific resource obtained through `IPluginResourceContext` may be used until the plugin is destroyed. Therefore, any termination logic implemented in `IPluginV2Ext::detachFromContext()` may be moved to the plugin destructor.

9.7.3. Plugin Serialization and Deserialization

For V2 plugins, serialization and deserialization were determined by the implementation of `IPluginV2::serialize`, `IPluginV2::getSerializationSize`, and `IPluginCreator::deserializePlugin`; `IPluginV3OneRuntime::getFieldsToSerialize` and `IPluginCreatorV3One::createPlugin` have replaced these. Note that the workflow has shifted from writing to/reading from a raw buffer to constructing and parsing a `PluginFieldCollection`.

TensorRT handles the serialization of types defined in `PluginFieldType`. Custom types can be serialized as `PluginFieldType::kUNKNOWN`. For example:

```
struct DummyStruct
{
    int32_t a;
    float b;
};

DummyPlugin()
{
    // std::vector<nvinfer1::PluginField> mDataToSerialize;
    // int32_t mIntValue;
    // std::vector<float> mFloatVector;
    // DummyStruct mDummyStruct;
    mDataToSerialize.clear();
    mDataToSerialize.emplace_back(PluginField("intScalar", &mIntValue,
PluginFieldType::kINT32, 1));
    mDataToSerialize.emplace_back(PluginField("floatVector", mFloatVector.data(),
PluginFieldType::kFLOAT32, mFloatVector.size()));
    mDataToSerialize.emplace_back(PluginField("dummyStruct", &mDummyStruct,
PluginFieldType::kUNKNOWN, sizeof(DummyStruct)));
    mFCToSerialize.nbFields = mDataToSerialize.size();
    mFCToSerialize.fields = mDataToSerialize.data();
}

nvinfer1::PluginFieldCollection const* DummyPlugin::getFieldsToSerialize() noexcept override
{
    return &mFCToSerialize;
}
```

9.7.4. Migrating Older V2 Plugins to IPluginV3

If migrating from `IPluginV2` or `IPluginV2Ext` to `IPluginV3`, it is easier to migrate first to `IPluginV2DynamicExt` and then follow the guidelines above to migrate to `IPluginV3`. The new features in `IPluginV2DynamicExt` are as follows:

```
virtual DimsExprs getOutputDimensions(int outputIndex, const DimsExprs* inputs, int nbInputs,
IExprBuilder& exprBuilder) = 0;

virtual bool supportsFormatCombination(int pos, const PluginTensorDesc* inOut, int nbInputs,
int nbOutputs) = 0;

virtual void configurePlugin(const DynamicPluginTensorDesc* in, int nbInputs, const
DynamicPluginTensorDesc* out, int nbOutputs) = 0;

virtual size_t getWorkspaceSize(const PluginTensorDesc* inputs, int nbInputs, const
PluginTensorDesc* outputs, int nbOutputs) const = 0;

virtual int enqueue(const PluginTensorDesc* inputDesc, const PluginTensorDesc* outputDesc,
const void* const* inputs, void* const* outputs, void* workspace, cudaStream_t stream) = 0;
```

Guidelines for migration to `IPluginV2DynamicExt` are

- ▶ `getOutputDimensions` implements the expression for output tensor dimensions given the inputs.
- ▶ `supportsFormatCombination` checks if the plugin supports the format and datatype for the specified I/O.
- ▶ `configurePlugin` mimics the behavior of equivalent `configurePlugin` in `IPluginV2Ext` but accepts tensor descriptors.
- ▶ `getWorkspaceSize` and `enqueue` mimic the behavior of equivalent APIs in `IPluginV2Ext` but accept tensor descriptors.

9.8. Coding Guidelines for Plugins

Memory Allocation

Memory allocated in the plugin must be freed to ensure no memory leak. If resources are acquired in the plugin constructor or at a later stage, like `onShapeChange`, they must be released, possibly in the plugin class destructor.

Another option is to request any additional workspace memory required through `getWorkspaceSize`, which will be available during `enqueue`.

Add Checks to Ensure Proper Configuration and Validate Inputs

A common source for unexpected plugin behavior is improper configuration (for example, invalid plugin attributes) and invalid inputs. As such, it is good practice to add checks/assertions during the initial plugin development for cases where the plugin is not expected to work. The following are places where checks could be added:

- ▶ `createPlugin`: Plugin attributes checks
- ▶ `configurePlugin/onShapeChange`: Input dimension checks
- ▶ `enqueue`: Input value checks

Return Null at Errors for Methods That Create a New Plugin Object

Methods like `createPlugin`, `clone`, and `attachToContext` may be expected to create and return new plugin objects. In these methods, make sure a null object (`nullptr` in C++) is returned in case of any error or failed check. This ensures that non-null plugin objects are not returned when the plugin is incorrectly configured.

Avoid Device Memory Allocations in `clone()`

Since the builder calls `clone` multiple times, device memory allocations could be significantly expensive. One option is to do persistent memory allocations in the constructor, copy to a device when the plugin is ready (for example, in `configurePlugin`), and release during destruction.

Serializing Arbitrary Pieces of Data and Custom Types

Plugin authors can utilize `PluginField` of `PluginFieldType::kUNKNOWN` to indicate arbitrary pieces of data to be serialized. In this case, the `length` of the respective `PluginField` should be the number of bytes corresponding to the buffer pointed to by `data`. The serialization of non-primitive types can be achieved in this way.

9.9. Plugin Shared Libraries

TensorRT contains built-in plugins that can be loaded statically into your application.

You can explicitly register custom plugins with TensorRT using the `REGISTER_TENSORRT_PLUGIN` and `registerCreator` interfaces (refer to [Adding Custom Layers Using the C++ API](#)). However, you may want TensorRT to manage the registration of a plugin library and, in particular, serialize plugin libraries with the plan file so they are automatically loaded when the engine is created. This can be especially useful when you want to include the plugins in a version-compatible engine so that you do not need to manage them after building the engine. To take advantage of this, you can build shared libraries with specific entry points recognized by TensorRT.

9.9.1. Generating Plugin Shared Libraries

To create a shared library for plugins, the library must have the following public symbols defined:

```
extern "C" void setLoggerFinder(ILoggerFinder& finder);
extern "C" IPluginCreator* const* getPluginCreators(int32_t& nbCreators) const;
```

`extern "C"` above is only used to prevent name mangling, and the methods should be implemented in C++. Consult your compiler's ABI documentation for more details.

`setLoggerFinder()` should set a global pointer of `ILoggerFinder` in the library for logging in the plugin code. `getPluginCreators()` returns a list of plugin creators your library contains. An example of implementation of these entry points can be found in `plugin/common/vfcCommon.h/cpp`.

To serialize your plugin libraries with your engine plan, provide the plugin libraries paths to TensorRT using `setPluginsToSerialize()` in `BuilderConfig`.

When building version compatible engines, you may also want to package plugins in the plan. The packaged plugins will have the same lifetime as the engine and will be automatically registered/deregistered when running the engine.

9.9.2. Using Plugin Shared Libraries

After building your shared libraries, you can configure the builder to serialize them with the engine. Next time you load the engine into TensorRT, the serialized plugin libraries will be loaded and registered automatically.



Note: `IPluginRegistry`'s `loadLibrary()` ([C++](#), [Python](#)) functionality, demonstrated below, is not supported for plugin-shared libraries containing V3 plugin creators (`IPluginCreatorV3One`). As a workaround, define the entry point `IPluginCreatorInterface* const* getCreators()` in your library and then query this to enumerate each plugin creator and register it manually using `IPluginRegistry`'s `registerCreator()` ([C++](#), [Python](#)).

Load the plugins for use with the builder before building the engine:

C++

```
for (size_t i = 0; i < nbPluginLibs; ++i)
{
    builder->getPluginRegistry().loadLibrary(pluginLibs[i]);
}
```

Python

```
for plugin_lib in plugin_libs:
    builder.get_plugin_registry().load_library(plugin_lib)
```

Next, decide if the plugins should be included with the engine or shipped externally. You can serialize the plugins with the plan as follows:

C++

```
IBuilderConfig *config = builder->createBuilderConfig();
...
config->setPluginsToSerialize(pluginLibs, nbPluginLibs);
```

Python

```
config = builder.create_builder_config()
...
config.plugins_to_serialize = plugin_libs
```

Alternatively, you can keep the plugins external to the engine. You will need to ship these libraries along with the engine when it is deployed and load them explicitly in the runtime before deserializing the engine:

C++

```
// In this example, getExternalPluginLibs() is a user-implemented method which retrieves
the list of libraries to use with the engine
std::vector<std::string> pluginLibs = getExternalPluginLibs();
for (auto const &pluginLib : pluginLibs)
{
    runtime->getPluginRegistry().loadLibrary(pluginLib.c_str())
}
```

Python

```
# In this example, get_external_plugin_libs() is a user-implemented method which retrieves
the list of libraries to use with the engine
plugin_libs = get_external_plugin_libs()
for plugin_lib in plugin_libs:
    runtime.get_plugin_registry().load_library(plugin_lib)
```

Chapter 10. Working with Loops

NVIDIA TensorRT supports loop-like constructs, which can be useful for recurrent networks. TensorRT loops support scanning over input tensors, recurrent definitions of tensors, and both "scan outputs" and "last value" outputs.

10.1. Defining a Loop

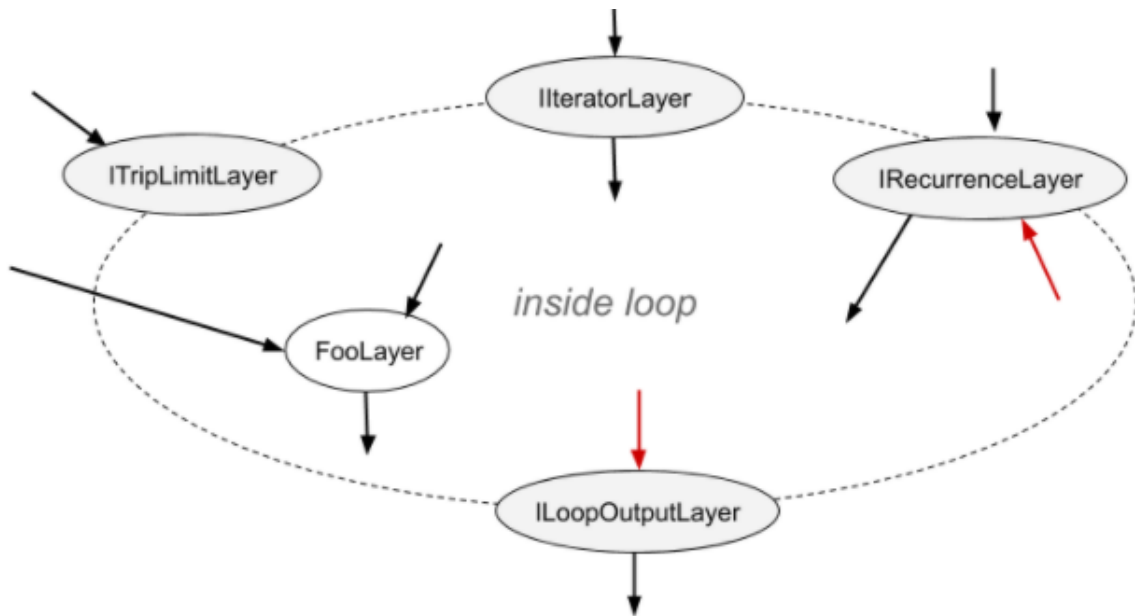
A loop is defined by *loop boundary layers*.

- ▶ `ITripLimitLayer` specifies how many times that the loop iterates.
- ▶ `IIteratorLayer` enables a loop to iterate over a tensor.
- ▶ `IRecurrenceLayer` specifies a recurrent definition.
- ▶ `ILoopOutputLayer` specifies an output from the loop.

Each boundary layer inherits from the class `ILoopBoundaryLayer`, which has a method `getLoop()` for getting its associated `ILoop`. The `ILoop` object identifies the loop. All loop boundary layers with the same `ILoop` belong to that loop.

[Figure 14](#) depicts a loop structure and data flow at the boundary. Loop-invariant tensors can be used directly inside the loop, as shown for `FooLayer`.

Figure 14. A TensorRT loop is set by loop boundary layers. Dataflow can leave the loop only by `ILoopOutputLayer`. The only back edges allowed are the second input to `IRecurrenceLayer`.



As explained later, a loop can have multiple `IIteratorLayer`, `IRecurrenceLayer`, and `ILoopOutputLayer` and, at most, two `ITripLimitLayers`. A loop with no `ILoopOutputLayer` has no output and is optimized by TensorRT.

[Layers For Flow-Control Constructs](#) describes the TensorRT layers that may be used in the loop interior.

Interior layers are free to use tensors defined inside or outside the loop. The interior can contain other loops (refer to [Nested Loops](#)) and other conditional constructs (refer to [Conditionals Nesting](#)).

To define a loop, first create an `ILoop` object using the `INetworkDefinition::addLoop` method. Then, add the boundary and interior layers. The rest of this section describes the features of the boundary layers, using a `loop` to denote the `ILoop*` returned by `INetworkDefinition::addLoop`.

`ITripLimitLayer` supports both counted loops and while-loops.

- ▶ `loop->addTripLimit(t, TripLimit::kCOUNT)` creates an `ITripLimitLayer` whose input `t` is a 0D INT32 tensor that specifies the number of loop iterations.
- ▶ `loop->addTripLimit(t, TripLimit::kWHILE)` creates an `ITripLimitLayer` whose input `t` is a 0D Bool tensor that specifies whether an iteration should occur. Typically, `t` is either the output of an `IRecurrenceLayer` or a calculation based on said output.

A loop can have at most one of each kind of limit.

`IIteratorLayer` supports iterating forwards or backward over any axis.

- ▶ `loop->addIterator(t)` adds an `IIteratorLayer` that iterates over axis 0 of tensor `t`. For example, if the input is the matrix:

```
2 3 5
4 6 8
```

the output is the 1D tensor {2, 3, 5} on the first iteration and {4, 6, 8} for the second iteration. It is invalid to iterate beyond the tensor's bounds.

- ▶ `loop->addIterator(t, axis)` is similar, but the layer iterates over the given axis. For example, if `axis=1` and the input is a matrix, each iteration delivers a column of the matrix.
- ▶ `loop->addIterator(t, axis, reverse)` is similar, but the layer produces its output in reverse order if `reverse=true`.

`ILoopOutputLayer` supports three forms of loop output:

- ▶ `loop->addLoopOutput(t, LoopOutput::kLAST_VALUE)` outputs the last value of `t`, where `t` must be the output of an `IRecurrenceLayer`.
- ▶ `loop->addLoopOutput(t, LoopOutput::kCONCATENATE, axis)` outputs the concatenation of each iteration's input to `t`. For example, if the input is a 1D tensor, with value {a, b, c} on the first iteration and {d, e, f} on the second iteration, and `axis=0`, the output is the matrix:

```
a b c
d e f
```

If `axis=1`, the output is:

```
a d
b e
c f
```

- ▶ `loop->addLoopOutput(t, LoopOutput::kREVERSE, axis)` is similar, but reverses the order.

Both the `kCONCATENATE` and `kREVERSE` forms of `ILoopOutputLayer` require a second input, which is a 0D INT32 shape tensor specifying the length of the new output dimension. When the length is greater than the number of iterations, the extra elements contain arbitrary values. The second input, for example `u`, should be set using `ILoopOutputLayer::setInput(1, u)`.

Finally, there is `IRecurrenceLayer`. Its first input specifies the initial output value, and its second input specifies the next output value. The first input must come from outside the loop; the second one usually comes from inside. For example, the TensorRT analog of this C++ fragment:

```
for (int32_t i = j; ...; i += k) ...
```

could be created by these calls, where `j` and `k` are `ITensor*`.

```
ILoop* loop = n.addLoop();
IRecurrenceLayer* iRec = loop->addRecurrence(j);
ITensor* i = iRec->getOutput(0);
ITensor* iNext = addElementWise(*i, *k,
    ElementWiseOperation::kADD)->getOutput(0);
iRec->setInput(1, *iNext);
```

The second input to `IRecurrenceLayer` is the only case where TensorRT allows a back edge. If such inputs are removed, the remaining network must be acyclic.

10.2. Formal Semantics

TensorRT has applicative semantics, meaning there are no visible side effects other than engine inputs and outputs. Because there are no side effects, intuitions about loops from imperative languages do not always work. This section defines formal semantics for TensorRT's loop constructs.

The formal semantics is based on *lazy sequences* of tensors. Each iteration of a loop corresponds to an element in the sequence. The sequence for a tensor x inside the loop is denoted $\#x_0, x_1, x_2, \dots\#$. Elements of the sequence are evaluated lazily, meaning as needed.

The output from `IIteratorLayer(X)` is $\#x[0], x[1], x[2], \dots\#$ where $x[i]$ denotes subscripting on the axis specified for the `IIteratorLayer`.

The output from `IRecurrenceLayer(X,Y)` is $\#x, y_0, y_1, y_2, \dots\#$.

The input and output from an `ILoopOutputLayer` depend on the kind of `LoopOutput`.

- ▶ `kLAST_VALUE`: Input is a single tensor x , and output is x_n for an n -trip loop.
- ▶ `kCONCATENATE`: The first input is a tensor x , and the second is a scalar shape tensor y . The result is the concatenation of $x_0, x_1, x_2, \dots, x_{n-1}$ with post padding, if necessary, to the length specified by y . It is a runtime error if $y < n$. y is a build time constant. Note the inverse relationship with `IIteratorLayer`. `IIteratorLayer` maps a tensor to a sequence of subtensors; `ILoopOutputLayer` with `kCONCATENATE` maps a sequence of sub tensors to a tensor.
- ▶ `kREVERSE`: Similar to `kCONCATENATE`, but the output is in the reverse direction.

The value of n in the definitions for the output of `ILoopOutputLayer` is determined by the `ITripLimitLayer` for the loop:

- ▶ For counted loops, it is the iteration count, meaning the input to the `ITripLimitLayer`.
- ▶ For while loops, it is the least n such that x_n is false, where x is the sequence for the `ITripLimitLayer`'s input tensor.

The output from a non-loop layer is a sequence-wise application of the layer's function. For example, for a two-input non-loop layer $F(x,y) = \#f(x_0,y_0), f(x_1,y_1), f(x_2,y_2) \dots\#$. If a tensor comes from outside the loop, that is, a loop invariant, then the sequence for it is created by replicating the tensor.

10.3. Nested Loops

TensorRT infers the nesting of the loops from the data flow. For instance, if loop B uses values defined *inside* loop A, then B is considered to be nested inside of A.

TensorRT rejects networks where the loops are not cleanly nested, such as if loop A uses values defined in the interior of loop B and vice versa.

10.4. Limitations

A loop that refers to more than one dynamic dimension can take an unexpected amount of memory.

In a loop, memory is allocated as if all dynamic dimensions take on the maximum value of any of those dimensions. For example, if a loop refers to two tensors with dimensions $[4, x, y]$ and $[6, y]$, memory allocation for those tensors is as if their dimensions were $[4, \max(x, y), \max(x, y)]$ and $[6, \max(x, y)]$.

The input to a `LoopOutputLayer` with `kLAST_VALUE` must be the output from an `IRecurrenceLayer`.

The loop API supports only FP32 and FP16 precision.

10.5. Replacing `IRNNv2Layer` with Loops

`IRNNv2Layer` was deprecated in TensorRT 7.2.1 and will be removed in TensorRT 9.0.

Use the loop API to synthesize a recurrent sub-network. For an example, refer to `sampleCharRNN`, method `SampleCharRNNLoop::addLSTMCell`. Using the loop API, you can express general recurrent networks instead of being limited to the prefabricated cells in `IRNNLayer` and `IRNNv2Layer`.

For more information, refer to [sampleCharRNN](#).

Chapter 11. Working with Conditionals

NVIDIA TensorRT supports conditional if-then-else flow control. TensorRT conditionals are used to implement conditional execution of network subgraphs.

11.1. Defining a Conditional

Conditional boundary layers define an if-conditional:

- ▶ `IConditionLayer` represents the predicate and specifies whether the conditional should execute the true-branch (then-branch) or the false-branch (else-branch).
- ▶ `IIfConditionalInputLayer` specifies an input to one of the two conditional branches.
- ▶ `IIfConditionalOutputLayer` specifies an output from a conditional.

Each boundary layer inherits from class `IIfConditionalBoundaryLayer`, which has a method `getConditional()` for getting its associated `IIfConditional`. The `IIfConditional` instance identifies the conditional. All conditional boundary layers with the same `IIfConditional` belong to that conditional.

A conditional must have exactly one instance of `IConditionLayer`, zero or more instances of `IIfConditionalInputLayer`, and at least one instance of `IIfConditionalOutputLayer`.

`IIfConditional` implements an if-then-else flow-control construct that provides conditional execution of a network subgraph based on a dynamic boolean input. It is defined by a boolean scalar predicate `condition` and two branch subgraphs: a `trueSubgraph`, which is executed when the `condition` evaluates to `true`, and a `falseSubgraph`, which is executed when the `condition` evaluates to `false`:

```
If condition is true then:  
    output = trueSubgraph(trueInputs);  
Else  
    output = falseSubgraph(falseInputs);  
Emit output
```

Both the true branch and the false branch must be defined in a way similar to the ternary operator in many programming languages.

To define an if-conditional, create an `IIfConditional` instance with `INetworkDefinition::addIfConditional`, then add the boundary and branch layers.

```
IIfConditional* simpleIf = network->addIfConditional();
```

The `IIfConditional::setCondition` method takes a single argument: the condition tensor. This OD boolean tensor (scalar) can be computed dynamically by earlier layers in the network. It is used to decide which of the branches to execute. An `IConditionLayer` has a single input (the condition) and no outputs since it is used internally by the conditional implementation.

```
// Create a condition predicate that is also a network input.
auto cond = network->addInput("cond", DataType::kBOOL, Dims{0});
IConditionLayer* condition = simpleIf->setCondition(*cond);
```

TensorRT does not support a subgraph abstraction for implementing conditional branches and instead uses `IIfConditionalInputLayer` and `IIfConditionalOutputLayer` to define the boundaries of conditionals.

- ▶ An `IIfConditionalInputLayer` abstracts a single input to one or both of the branch subgraphs of an `IIfConditional`. The output of a specific `IIfConditionalInputLayer` can feed both branches.

```
// Create an if-conditional input.
// x is some arbitrary Network tensor.
IIfConditionalInputLayer* inputX = simpleIf->addInput(*x);
```

Inputs to the then-branch and the else-branch do not have to be the same type and shape. Each branch can independently include zero or more inputs.

`IIfConditionalInputLayer` is optional and is used to control which layers will be part of the branches (refer to [Conditional Execution](#)). If all of a branch's outputs do not depend on an `IIfConditionalInputLayer` instance, that branch is empty. An empty else-branch can be useful when there are no layers to evaluate when the condition is false, and the network evaluation should proceed following the conditional (refer to [Conditional Examples](#)).

- ▶ An `IIfConditionalOutputLayer` abstracts a single output of the if-conditional. It has two inputs: an output from the true subgraph (input index 0) and an output from the false subgraph (input index 1). The output of an `IIfConditionalOutputLayer` can be considered a placeholder for the final output that will be determined during runtime.

`IIfConditionalOutputLayer` serves a role similar to that of a Φ (Phi) function node in traditional SSA control-flow graphs. Its semantics are: choose either the output of the true subgraph or the false subgraph.

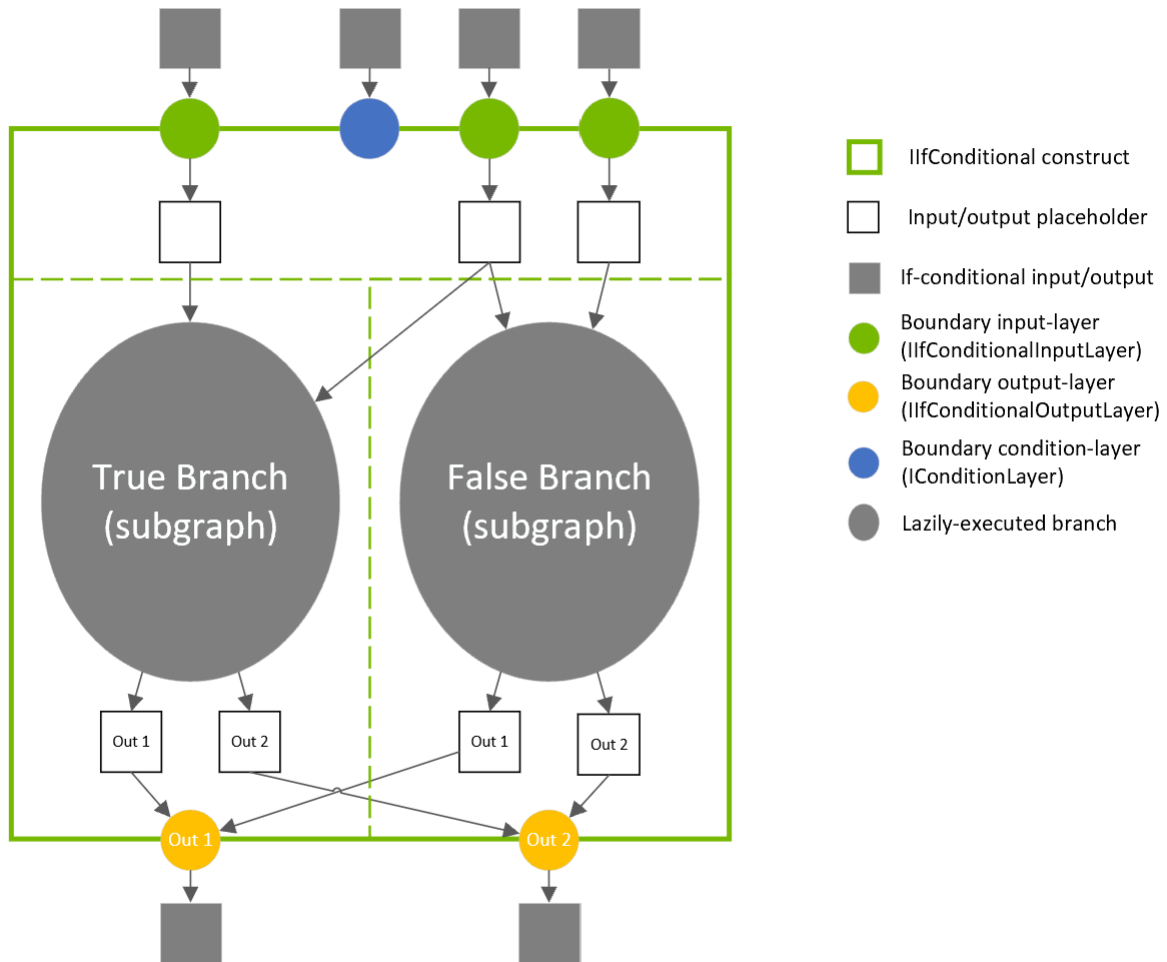
```
// trueSubgraph and falseSubgraph represent network subgraphs
IIfConditionalOutputLayer* outputLayer = simpleIf->addOutput(
    *trueSubgraph->getOutput(0),
    *falseSubgraph->getOutput(0));
```

All outputs of an `IIfConditional` must be sourced at an `IIfConditionalOutputLayer` instance.

An if-conditional without outputs does not affect the rest of the network. Therefore, it is considered ill-formed. Each branch (subgraphs) must also have at least one output. The output of an if-conditional can be marked as the output of the network unless that if-conditional is nested inside another if-conditional or loop.

The diagram below provides a graphical representation of the abstract model of an if-conditional. The green rectangle represents the interior of the conditional, which is limited to the layer types listed in [Layers For Flow-Control Constructs](#).

Figure 15. An If-Conditional Construct Abstract Model



11.2. Conditional Execution

Conditional execution of network layers is a network evaluation strategy in which branch layers (the layers belonging to a conditional subgraph) are executed only if the values of the branch outputs are needed. In conditional execution, either the true branch or the false branch is executed and allowed to change the network state.

In contrast, in predicated execution, both the true branch and the false branch are executed, and only one of these is allowed to change the network evaluation state, depending on the value of the condition predicate (that is, only the outputs of one of the subgraphs is fed into the following layers).

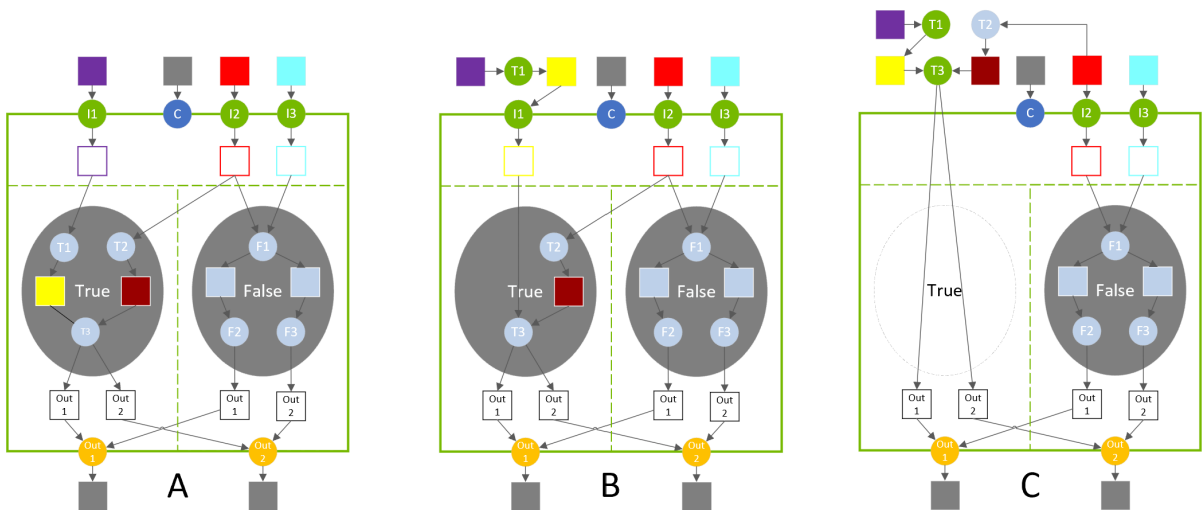
Conditional execution is sometimes called *lazy evaluation*, and predicated execution is sometimes called *eager evaluation*.

Instances of `IIfConditionalInputLayer` can be used to specify which layers are invoked eagerly and which are invoked lazily. This is done by tracing the network layers

backward, starting with each conditional output. Layers that are data-dependent on the output of at least one `IIfConditionalInputLayer` are considered internal to the conditional and are therefore evaluated lazily. In the extreme case that no instances of `IIfConditionalInputLayer` are added to the conditional, all layers are executed eagerly, similarly to `ISelectLayer`.

The three diagrams below depict how the choice of `IIfConditionalInputLayer` placement controls execution scheduling.

Figure 16. Controlling Conditional-Execution using `IIfConditionalInputLayer` Placement



In diagram A, the true branch comprises three layers (T1, T2, T3). These layers execute lazily when the condition evaluates to `true`.

In diagram B, input-layer I1 is placed after layer T1, which moves T1 out of the true branch. Layer T1 executes eagerly before evaluating the if-construct.

In diagram C, input-layer I1 is removed, which moves T3 outside the conditional. T2's input is reconfigured to create a legal network, and T2 also moves out of the true branch. When the condition evaluates to `true`, the conditional does not compute anything since the outputs have already been eagerly computed (but it does copy the conditional relevant inputs to its outputs).

11.3. Nesting and Loops

Conditional branches may nest other conditionals and may also nest loops. Loops may nest conditionals. As in loop nesting, TensorRT infers the nesting of the conditionals and loops from the data flow. For example, if conditional B uses a value defined inside loop A, then B is considered to be nested inside of A.

There can be no cross-edges connecting layers in the true-branch to layers in the false-branch, and vice versa. In other words, the outputs of one branch cannot depend on layers in the other branch.

For example, refer to [Conditional Examples](#) for how nesting can be specified.

11.4. Limitations

The number of output tensors in both true/false subgraph branches must be the same. The type and shape of each output tensor from the branches must be the same.

Note that this is more constrained than the ONNX specification, which requires that the true/false subgraphs have the same number of outputs and use the same output types, but allows for different output shapes.

11.5. Conditional Examples

11.5.1. Simple If-Conditional

The following example shows how to implement a simple conditional that conditionally performs an arithmetic operation on two tensors.

Conditional

```
condition = true
If condition is true:
    output = x + y
Else:
    output = x - y
```

Example

```
ITensor* addCondition(INetworkDefinition& n, bool predicate)
{
    // The condition value is a constant int32 input that is cast to boolean because TensorRT
    // doesn't support boolean constant layers.

    static const Dims scalarDims = Dims{0, {}};
    static float constexpr zero{0};
    static float constexpr one{1};

    float* const val = predicate ? &one : &zero;

    ITensor* cond =
        n.addConstant(scalarDims, DataType::kINT32, val, 1)->getOutput(0);

    auto* cast = n.addIdentity(cond);
    cast->setOutputType(0, DataType::kBOOL);
    cast->getOutput(0)->setType(DataType::kBOOL);

    return cast->getOutput(0);
}

IBuilder* builder = createInferBuilder(gLogger);
```

```

INetworkDefinition& n = *builder->createNetworkV2(0U);
auto x = n.addInput("x", DataType::kFLOAT, Dims{1, {5}});
auto y = n.addInput("y", DataType::kFLOAT, Dims{1, {5}});
ITensor* cond = addCondition(n, true);

auto* simpleIf = n.addIfConditional();
simpleIf->setCondition(*cond);

// Add input layers to demarcate entry into true/false branches.
x = simpleIf->addInput(*x)->getOutput(0);
y = simpleIf->addInput(*y)->getOutput(0);

auto* trueSubgraph = n.addElementWise(*x, *y, ElementWiseOperation::kSUM)->getOutput(0);
auto* falseSubgraph = n.addElementWise(*x, *y, ElementWiseOperation::kSUB)->getOutput(0);

auto* output = simpleIf->addOutput(*trueSubgraph, *falseSubgraph)->getOutput(0);
n.markOutput(*output);

```

11.5.2. Exporting from PyTorch

The following example shows how to export scripted PyTorch code to ONNX. The code in function `sum_even` performs an if-conditional nested in a loop.

```

import torch.onnx
import torch
import tensorrt as trt
import numpy as np

TRT_LOGGER = trt.Logger(trt.Logger.WARNING)
EXPLICIT_BATCH = 1 << (int)(trt.NetworkDefinitionCreationFlag.EXPLICIT_BATCH)

@torch.jit.script
def sum_even(items):
    s = torch.zeros(1, dtype=torch.float)
    for c in items:
        if c % 2 == 0:
            s += c
    return s

class ExampleModel(torch.nn.Module):
    def __init__(self):
        super().__init__()

    def forward(self, items):
        return sum_even(items)

def build_engine(model_file):
    builder = trt.Builder(TRT_LOGGER)
    network = builder.create_network(EXPLICIT_BATCH)
    config = builder.create_builder_config()
    parser = trt.OnnxParser(network, TRT_LOGGER)

    with open(model_file, 'rb') as model:
        assert parser.parse(model.read())
        return builder.build_engine(network, config)

def export_to_onnx():
    items = torch.zeros(4, dtype=torch.float)
    example = ExampleModel()
    torch.onnx.export(example, (items), "example.onnx", verbose=False, opset_version=13,
        enable_onnx_checker=False, do_constant_folding=True)

export_to_onnx()
build_engine("example.onnx")

```

Chapter 12. Working with DLA

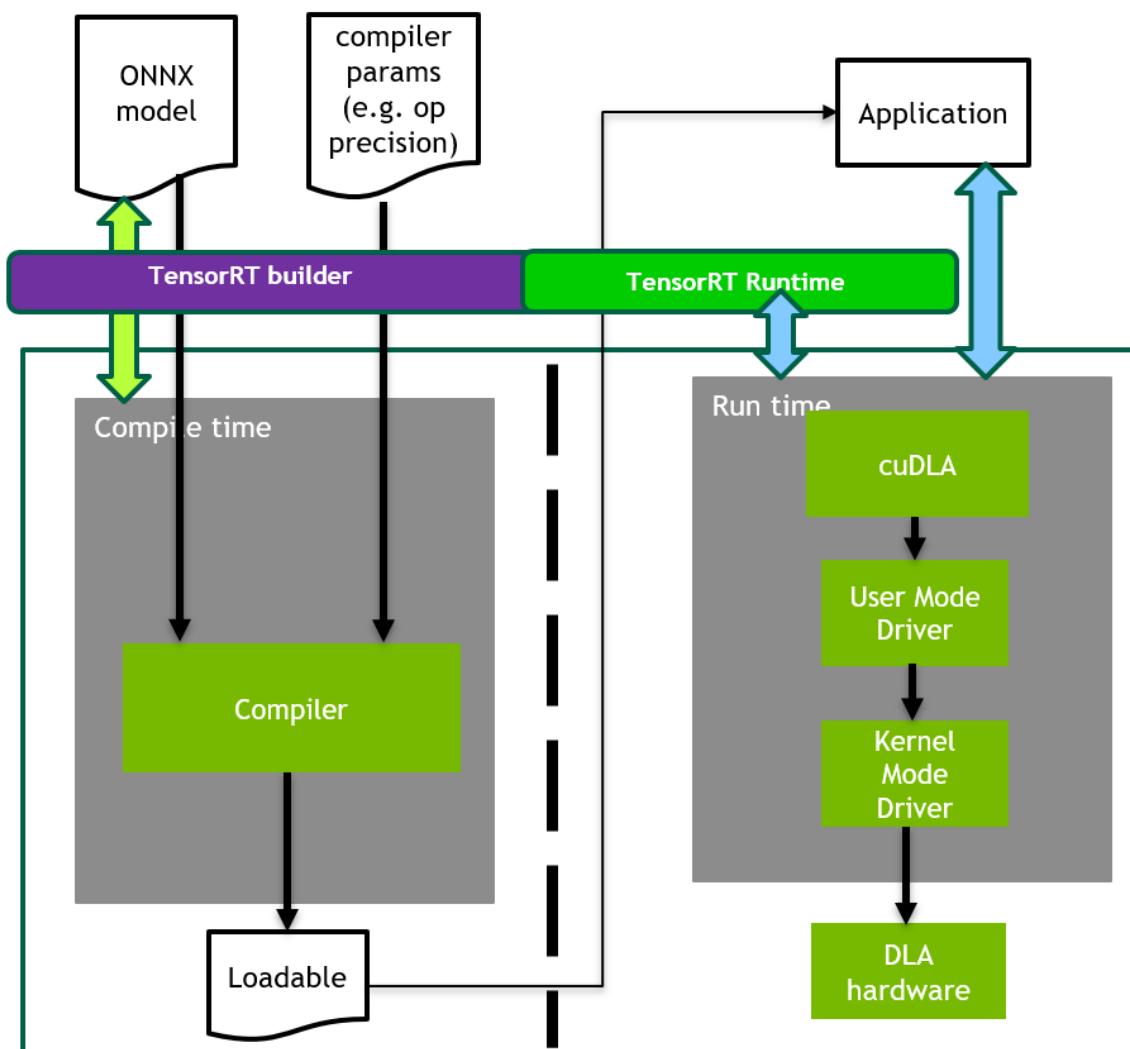
NVIDIA DLA (Deep Learning Accelerator) is a fixed-function accelerator engine targeted for deep learning operations. It is designed to fully hardware accelerate convolutional neural networks. DLA supports various layers, such as convolution, deconvolution, fully connected, activation, pooling, batch normalization, and so on. It does not support [Explicit Quantization](#). For more information about DLA support in TensorRT layers, refer to [DLA-Supported Layers and Restrictions](#).

DLA is useful for offloading CNN processing from the iGPU, and is significantly more power-efficient for these workloads. In addition, it can provide an independent execution pipeline in cases where redundancy is important, for example in mission-critical or safety applications.

For more information about DLA, refer to the [DLA developer page](#) and the DLA tutorial [Getting Started with the Deep Learning Accelerator on NVIDIA Jetson Orin](#).

When building a model for DLA, the TensorRT builder parses the network and calls the DLA compiler to compile the network into a DLA loadable. Refer to [Using trtexec](#) to see how to build and run networks on DLA.

Figure 17. Workflow for the Building and Runtime Phases of DLA



12.1. Building and Launching the Loadable

There are several ways to build and launch a DLA loadable, either embedded in a TensorRT engine or standalone form.

For generating a standalone DLA loadable to be used outside TensorRT, refer to [DLA Standalone Mode](#).

12.1.1. Using trtexec

To allow `trtexec` to use the DLA, you can use the `-useDLACore` flag. For example, to run the ResNet-50 network on DLA core 0 in FP16 mode, with [GPU Fallback Mode](#) for unsupported layers, run:

```
./trtexec --onnx=data/resnet50/ResNet50.onnx --useDLACore=0 --fp16 --allowGPUFallback
```

The `trtexec` tool has additional arguments to run networks on DLA. For more information, refer to [Command-Line Programs](#).

12.1.2. Using the TensorRT API

You can use the TensorRT API to build and run inference with DLA and to enable DLA at the layer level. The relevant APIs and samples are provided in the following sections.

12.1.2.1. Running on DLA during TensorRT Inference

The TensorRT builder can be configured to enable inference on DLA. DLA support is currently limited to networks running in FP16 and INT8 mode. The `DeviceType` enumeration is used to specify the device on which the network or layer executes. The following API functions in the `IBuilderConfig` class can be used to configure the network to use DLA:

setDeviceType(ILayer* layer, DeviceType deviceType)

This function sets the `deviceType` on which the layer must execute.

getDeviceType(const ILayer* layer)

This function can be used to return the `deviceType` that this layer executes on. If the layer is executing on the GPU, this returns `DeviceType::kGPU`.

canRunOnDLA(const ILayer* layer)

This function checks whether a layer can run on DLA.

setDefaultDeviceType(DeviceType deviceType)

This function sets the default `deviceType` to be used by the builder. It ensures that all the layers that can run on DLA runs on DLA unless `setDeviceType` is used to override the `deviceType` for a layer.

getDefaultDeviceType()

This function returns the default `deviceType` set by `setDefaultDeviceType`.

isDeviceTypeSet(const ILayer* layer)

This function checks whether the `deviceType` has been explicitly set for this layer.

resetDeviceType(ILayer* layer)

This function resets the `deviceType` for this layer. The value is reset to the `deviceType` specified by `setDefaultDeviceType` Or `DeviceType::kGPU` if none is specified.

allowGPUFallback(bool setFallbackMode)

This function notifies the builder to use GPU if a layer that was supposed to run on DLA cannot run on DLA. For more information, refer to [GPU Fallback Mode](#).

reset()

This function can reset the `IBuilderConfig` state, which sets the `deviceType` for all layers to `DeviceType::kGPU`. After reset, the builder can be reused to build another network with a different DLA config.

The following API functions in the `IBuilder` class can be used to help configure the network for using the DLA:

`getMaxDLABatchSize()`

This function returns the maximum batch size DLA can support.



Note: For any tensor, the total volume of index dimensions combined with the requested batch size must not exceed the value returned by this function.

`getNbDLACores()`

This function returns the number of DLA cores available to the user.

If the builder is not accessible, such as when a plan file is being loaded online in an inference application, then the DLA to be used can be specified differently using DLA extensions to the `IRuntime`. The following API functions in the `IRuntime` class can be used to configure the network to use DLA:

`getNbDLACores()`

This function returns the number of DLA cores accessible to the user.

`setDLACore(int dlaCore)`

The DLA core to execute on. Where `dlaCore` is a value between 0 and `getNbDLACores() - 1`. The default value is 0.

`getDLACore()`

The DLA core to which the runtime execution is assigned. The default value is 0.

12.1.2.2. Example: Run Samples with DLA

This section details on how to run a TensorRT sample with DLA enabled.

Create the builder:

```
auto builder = SampleUniquePtr<nvinfer1::IBuilder>(nvinfer1::createInferBuilder(gLogger));
if (!builder) return false;
builder->setMaxBatchSize(batchSize);
config->setMaxWorkspaceSize(16_MB);
```

Then, enable `GPUFallback` mode:

```
config->setFlag(BuilderFlag::kGPU_FALLBACK);
config->setFlag(BuilderFlag::kFP16); or config->setFlag(BuilderFlag::kINT8);
```

Enable execution on DLA, where `dlaCore` specifies the DLA core to execute on:

```
config->setDefaultDeviceType(DeviceType::kDLA);
config->setDLACore(dlaCore);
```

With these additional changes, `sampleMNIST` is ready to execute on DLA. To run samples with DLA Core 1, append `--useDLACore=0` to the sample command.

12.1.2.3. Example: Enable DLA Mode for a Layer during Network Creation

In this example, let us create a simple network with Input, Convolution, and Output.

1. Create the builder, builder configuration, and the network:

```
IBuilder* builder = createInferBuilder(gLogger);
IBuilderConfig* config = builder.createBuilderConfig();
INetworkDefinition* network = builder->createNetworkV2(0U);
```

2. Add the Input layer to the network with the input dimensions.

```
auto data = network->addInput(INPUT_BLOB_NAME, dt, Dims3{1, INPUT_H, INPUT_W});
```

3. Add the Convolution layer with hidden layer input nodes, strides, and weights for filter and bias.

```
auto conv1 = network->addConvolution(*data->getOutput(0), 20, DimsHW{5, 5},
    weightMap["conv1filter"], weightMap["conv1bias"]);
conv1->setStride(DimsHW{1, 1});
```

4. Set the convolution layer to run on DLA:

```
if (canRunOnDLA(conv1))
{
    config->setFlag(BuilderFlag::kFP16); or config->setFlag(BuilderFlag::kINT8);
    builder->setDeviceType(conv1, DeviceType::kDLA);
}
```

5. Mark the output:

```
network->markOutput(*conv1->getOutput(0));
```

6. Set the DLA core to execute on:

```
config->setDLACore(0)
```

12.1.3. Using the cuDLA API

cuDLA is an extension of the CUDA programming model that integrates DLA runtime software with CUDA. This integration makes it possible to launch DLA loadables using CUDA programming constructs such as streams and graphs.

Managing shared buffers as well as synchronizing the tasks between GPU and DLA is transparently handled by cuDLA. Refer to the [NVIDIA cuDLA documentation](#) on how the cuDLA APIs can be used for these use cases while writing a cuDLA application.

Refer to the [DLA Standalone Mode](#) section for more information on using TensorRT to build a standalone DLA loadable usable with cuDLA.

12.2. DLA-Supported Layers and Restrictions

This section lists the layers supported by DLA and the constraints associated with each layer.

12.2.1. General Restrictions

The following restrictions apply to all layers while running on DLA:

- ▶ The maximum supported batch size is 4096.
- ▶ The maximum supported size for non-batch dimensions is 8192.
- ▶ DLA does not support dynamic dimensions. Thus, for wildcard dimensions, the `profile's min, max, and opt` values must be equal.
- ▶ The runtime dimensions must be the same as the dimensions used for building.

- ▶ TensorRT may split a network into multiple DLA loadables if any intermediate layers cannot run on DLA and `GPUFallback` is enabled. Otherwise, TensorRT can emit an error and fallback. For more information, refer to [GPU Fallback Mode](#).
- ▶ Due to hardware and software memory limitations, only 16 DLA loadable can be loaded concurrently per core.
- ▶ Each layer must have the same batch size within a single DLA loadable. Layers with different batch sizes will be partitioned into separate DLA graphs.



Note: Batch size for DLA is the product of all index dimensions except the `CHW` dimensions. For example, if input dimensions are `NPQRS`, the effective batch size is `N*P`.

12.2.2. Layer Support and Restrictions

The following list provides layer support and restrictions to the specified layers while running on DLA:

Convolution and Fully Connected layers

- ▶ Only two spatial dimension operations are supported.
- ▶ Both FP16 and INT8 are supported.
- ▶ Each dimension of the kernel size must be in the range `[1, 32]`.
- ▶ Padding must be in the range `[0, 31]`.
- ▶ Dimensions of padding must be less than the corresponding kernel dimension.
- ▶ Dimensions of stride must be in the range `[1, 8]`.
- ▶ The number of output maps must be in the range `[1, 8192]`.
- ▶ Number of input channels `[1, 8192]`.
- ▶ For operations using the formats `TensorFormat::kDLA_LINEAR`, `TensorFormat::kCHW16`, and `TensorFormat::kCHW32`, the number of groups must be in the range `[1, 8192]`.
- ▶ For operations using the format `TensorFormat::kDLA_HWC4`, the number of groups must be in the range `[1, 4]`.
- ▶ Dilated convolution must be in the range `[1, 32]`.
- ▶ Operations are not supported if the CBUF size requirement `wtBanksForOneKernel + minDataBanks` exceeds the `numConvBufBankAllotted` limitation 16, where CBUF is the internal convolution cache that stores input weights and activation before operating on them, `wtBanksForOneKernel` is the minimum banks for one kernel to store the minimum weight/kernel elements needed for convolution, and `minDataBanks` is the minimum banks to store the minimum activation data needed for convolution. Detailed details are displayed in the logging output when a convolution layer fails validation due to CBUF constraints.

Deconvolution layer

- ▶ Only two spatial dimensions are supported.
- ▶ Both FP16 and INT8 are supported.
- ▶ The kernel dimensions and strides must be in the range $[1, 32]$, or must be $1 \times [64, 96, 128]$ and $[64, 96, 128] \times 1$.
- ▶ TensorRT has disabled deconvolution square kernels and strides in the range $[23 - 32]$ on DLA as they significantly slow down compilation.
- ▶ The padding must be 0
- ▶ Grouped deconvolution must be 1.
- ▶ Dilated deconvolutions must be 1.
- ▶ The number of input channels must be in the range $[1, 8192]$.
- ▶ The number of output channels must be in the range $[1, 8192]$.

Pooling layer

- ▶ Only two spatial dimension operations are supported.
- ▶ Both FP16 and INT8 are supported.
- ▶ Operations supported: kMAX, kAVERAGE.
- ▶ Dimensions of the window must be in the range $[1, 8]$.
- ▶ Dimensions of padding must be in the range $[0, 7]$.
- ▶ Dimensions of stride must be in the range $[1, 16]$.
- ▶ With INT8 mode, input and output tensor scales must be the same.

Activation layer

- ▶ Only two spatial dimension operations are supported.
- ▶ Both FP16 and INT8 are supported.
- ▶ Functions supported: ReLU, Sigmoid, TanH, Clipped ReLU, and Leaky ReLU.
 - ▶ A negative slope is not supported for ReLU.
 - ▶ Clipped ReLU only supports values in the range $[1, 127]$.
 - ▶ TanH, Sigmoid INT8 support is supported by auto-upgrading to FP16.

Parametric ReLU layer

- ▶ Slope input must be a build time constant with the same rank as the input tensor.

ElementWise layer

- ▶ Only two spatial dimension operations are supported.
- ▶ Both FP16 and INT8 are supported.

- ▶ **Operations supported:** `Sum`, `Sub`, `Product`, `Max`, `Min`, `Div`, `Pow`, `Equal`, `Greater`, and `Less` (described separately).
- ▶ Broadcasting is supported when one of the operands has one of the following shape configurations:
 - ▶ `NCHW` (that is, shapes equal)
 - ▶ `NC11` (that is, `N` and `C` equal, `H` and `W` are 1)
 - ▶ `N111` (that is, `N` equal, `C`, `H`, and `W` are 1)
- ▶ `Div` operation
 - ▶ The first input (dividend) can be `INT8`, `FP16`, or an `FP32` constant. The second input (divisor) must be `INT8` or an `FP32` constant.
 - ▶ If one of the inputs is constant, all values of its weights must be the same. Additionally, the other input must be non-constant in `INT8`.
- ▶ `Pow` operation
 - ▶ One input must be an `FP32` constant filled with the same value; the other must be an `INT8` non-constant.

Comparison operations (`Equal`, `Greater`, `Less`)

- ▶ It only supports `INT8` layer precision and `INT8` inputs except when using constants, which should be of the `FP32` type and filled with the same value.
- ▶ DLA requires that the comparison operation output be `FP16` or `INT8` type. Thus, the comparison layer must be immediately followed by a `Cast` operation (`IIIdentityLayer/ICastLayer`) to `FP16` or `INT8` and should have no direct consumers other than this `Cast` operation.
- ▶ The `ElementWise` comparison layer and the subsequent `IIIdentityLayer/ICastLayer` mentioned above explicitly set your device types to DLA and their precisions to `INT8`. Otherwise, these layers will run on the GPU.
- ▶ Even with GPU fallback allowed, you should expect failures in engine construction in some cases, such as when DLA loadable compilation fails. If this is the case, unset the device types and/or precisions of both the `ElementWise` comparison layer and `IIIdentityLayer/ICastLayer` to have both offloaded to GPU.

Scale layer

- ▶ Only two spatial dimension operations are supported.
- ▶ Both `FP16` and `INT8` are supported.
- ▶ Mode supported: `Uniform`, `Per-Channel`, and `ElementWise`.
- ▶ Only `scale` and `shift` operations are supported.

LRN (Local Response Normalization) layer

- ▶ Allowed window sizes are 3, 5, 7, or 9.
- ▶ The normalization region supported is `ACROSS_CHANNELS`.
- ▶ `LRN INT8` is supported by auto-upgrading to `FP16`.

Concatenation layer

- ▶ DLA supports concatenation only along the channel axis.
- ▶ Concat must have at least two inputs.
- ▶ All the inputs must have the same spatial dimensions.
- ▶ Both `FP16` and `INT8` are supported.
- ▶ With `INT8` mode, the inputs' dynamic range must be the same.
- ▶ With `INT8` mode, the dynamic range of output must be equal to each of the inputs.

Resize layer

- ▶ The number of scales must be exactly 4.
- ▶ The first two scale elements must be exactly 1 (for unchanged batch and channel dimensions).
- ▶ The last two elements in scales, representing the scale values along height and width dimensions, respectively, must be integer values in the range of `[1, 32]` in nearest-neighbor mode and `[1, 4]` in bilinear mode.
- ▶ Note that for bilinear resize `INT8` mode, when the input dynamic range is larger than the output dynamic range, the layer will be upgraded to `FP16` to preserve accuracy. This can negatively affect the latency.

Unary layer

- ▶ Only the `ABS` operation is supported.
- ▶ DLA supports `ABS`, `SIN`, `COS`, and `ATAN` operation types.
- ▶ For `SIN`, `COS`, and `ATAN`, input precision must be `INT8`.
- ▶ All input non-batch dimensions must be in the range `[1, 8192]`.

Slice layer

- ▶ Both `FP16` and `INT8` are supported.
- ▶ It supports batch sizes up to the general DLA maximum.
- ▶ All input non-batch dimensions must be in the range `[1, 8192]`.
- ▶ Only supports 4-D inputs and slicing at `CHW` dimensions.

- ▶ Only supports static slicing, so slice parameters must be provided statically using TensorRT `ISliceLayer` setter APIs or as constant input tensors.

SoftMax layer

- ▶ Only supported on NVIDIA Orin™, not Xavier™.
- ▶ All input non-batch dimensions must be in the range $[1, 8192]$.
- ▶ The axis must be one of the non-batch dimensions.
- ▶ Supports FP16 and INT8 precision.
- ▶ Internally, there are two modes, and the mode is selected based on the given input tensor shape.
 - ▶ The accurate mode is triggered when all non-batch, non-axis dimensions are 1.
 - ▶ The optimized mode allows the non-batch, non-axis dimensions to be greater than 1 but restricts the axis dimension to 1024 and involves an approximation that may cause a small error in the output. The magnitude of the error increases as the size of the axis dimension approaches 1024.

Shuffle layer

- ▶ Only supports 4-D input tensors.
- ▶ All input non-batch dimensions must be in the range $[1, 8192]$.
- ▶ Note that DLA decomposes the layer into standalone transpose and reshape operations. This means that the above restrictions apply individually to each decomposed operation.
- ▶ Batch dimensions cannot be involved in either reshapes or transposes.

Reduce layer

- ▶ Only supports 4-D input tensors.
- ▶ All input non-batch dimensions must be in the range $[1, 8192]$.
- ▶ Both FP16 and INT8 are supported.
- ▶ Only supports MAX operation type where any combination of the CHW axes is reduced.

12.2.3. Inference on NVIDIA Orin

Due to the difference in hardware specifications between NVIDIA Orin and Xavier DLA, FP16 convolution operations on NVIDIA Orin may experience an increase of up to 2x in latency.

On NVIDIA Orin, DLA stores weights for non-convolution operations (FP16 and INT8) inside loadable as FP19 values (which use 4-byte containers). The channel dimensions are padded to multiples of either 16 (FP16) or 32 (INT8) for those FP19 values. Especially in the case of large per-element `Scale`, `Add`, or `Sub` operations, this can inflate the size

of the DLA loadable, inflating the engine containing such a loadable. Graph optimization may unintentionally trigger this behavior by changing the type of a layer, for example, when an `ElementWise` multiplication layer with a constant layer as weights is fused into a scale layer.

12.3. GPU Fallback Mode

The `GPUFallbackMode` sets the builder to use GPU if a layer marked to run on DLA could not run on DLA. A layer cannot run on DLA due to the following reasons:

1. The `layer` operation is not supported on DLA.
2. The parameters specified are out of the supported range for DLA.
3. The given batch size exceeds the maximum permissible DLA batch size. For more information, refer to [DLA-Supported Layers and Restrictions](#).
4. A combination of layers in the network causes the internal state to exceed what the DLA can support.
5. There are no DLA engines available on the platform.

When GPU fallback is disabled, an error is emitted if a layer cannot be run on DLA.

12.4. I/O Formats on DLA

DLA supports formats that are unique to the device and have constraints on their layout due to vector width byte requirements.

For DLA input tensors, `kDLA_LINEAR (FP16, INT8)`, `kDLA_HWC4 (FP16, INT8)`, `kCHW16 (FP16)`, and `kCHW32 (INT8)` are supported. For DLA output tensors, only `kDLA_LINEAR (FP16, INT8)`, `kCHW16 (FP16)`, and `kCHW32 (INT8)` are supported. For `kCHW16` and `kCHW32` formats, if `C` is not an integer multiple, it must be padded to the next 32-byte boundary.

For `kDLA_LINEAR` format, the stride along the `w` dimension must be padded up to 64 bytes. The memory format is equivalent to a `C` array with dimensions `[N][C][H][roundUp(W, 64/elementSize)]` where `elementSize` is 2 for `FP16` and 1 for `Int8`, with the tensor coordinates `(n, c, h, w)` mapping to array subscript `[n][c][h][w]`.

For `kDLA_HWC4` format, the stride along the `w` dimension must be a multiple of 32 bytes on Xavier and 64 bytes on NVIDIA Orin.

- ▶ When `C == 1`, TensorRT maps the format to the native grayscale image format.
- ▶ When `C == 3` or `C == 4`, it maps to the native color image format. If `C == 3`, the stride for stepping along the `w` axis must be padded to 4 in elements.

In this case, the padded channel is located at the 4th index. Ideally, the padding value does not matter because the DLA compiler paddings the 4th channel in the weights to zero; however, it is safe for the application to allocate a zero-filled buffer of four channels and populate three valid channels.

- ▶ When `C` is `{1, 3, 4}`, then padded `C'` is `{1, 4, 4}` respectively, the memory layout is equivalent to a `C` array with dimensions `[N][H][roundUp(W, 32/C'/elementSize)][C']` where `elementSize` is 2 for FP16 and 1 for Int8. The tensor coordinates `(n, c, h, w)` mapping to array subscript `[n][h][w][c]`, `roundUp` calculates the smallest multiple of `64/elementSize` greater than or equal to `w`.

When using `kDLA_HWC4` as the DLA input format, it has the following requirements:

- ▶ `C` must be 1, 3, or 4
- ▶ The first layer must be convolution.
- ▶ The convolution parameters must meet DLA requirements. Refer to [DLA-Supported Layers and Restrictions](#) for more information.

TensorRT may insert reformatting layers to meet the DLA requirements when GPU fallback is enabled. Otherwise, the input and output formats must be compatible with DLA. In all cases, the strides that TensorRT expects data to be formatted with can be obtained by querying `IEExecutionContext::getStrides`.

12.5. DLA Standalone Mode

If you need to run inference outside of TensorRT, you can use

`EngineCapability::kDLA_STANDALONE` to generate a DLA loadable instead of a TensorRT engine. This loadable can then be used with an API like [the cuDLA API](#).

12.5.1. Building A DLA Loadable Using C++

1. Set the default device type and engine capability to DLA standalone mode.

```
builderConfig->setDefaultDeviceType(DeviceType::kDLA);
builderConfig->setEngineCapability(EngineCapability::kDLA_STANDALONE);
```

2. Specify FP16, INT8, or both. For example:

```
builderConfig->setFlag(BuilderFlag::kFP16);
```

3. DLA standalone mode disallows reformatting; therefore, `BuilderFlag::kDIRECT_IO` needs to be set.

```
builderConfig->setFlag(BuilderFlag::kDIRECT_IO);
```

4. You must set the allowed formats for I/O tensors to one or more of those that are DLA-supported.
5. Finally, build as normal

12.5.1.1. Using `trtexec` To Generate A DLA Loadable

The `trtexec` tool can generate a DLA loadable instead of a TensorRT engine.

Specifying both `--useDLACore` and `--safe` parameters sets the builder capability to `EngineCapability::kDLA_STANDALONE`. Additionally, specifying `--inputIOFormats` and `--outputIOFormats` restricts I/O data type and memory layout. The DLA loadable is saved into a file by specifying `--saveEngine` parameter.

For example, to generate an FP16 DLA loadable for an ONNX model using `trtexec`, run:

```
./trtexec --onnx=model.onnx --saveEngine=model_loadable.bin --useDLACore=0 --fp16 --
inputIOFormats=fp16:chw16 --outputIOFormats=fp16:chw16 --skipInference --safe
```

12.6. Customizing DLA Memory Pools

You can customize the size of the memory pools allocated to each DLA subnetwork in a network using the `IBuilderConfig::setMemoryPoolLimit` C++ API or the `IBuilderConfig.set_memory_pool_limit` Python API. There are three types of DLA memory pools (refer to the `MemoryPoolType` enum for details):

Managed SRAM

- ▶ Behaves like a cache, and larger values may improve performance.
- ▶ If no managed SRAM is available, DLA can still run by falling back to local DRAM.
- ▶ On Orin, each DLA core has 1 MiB of dedicated SRAM. On Xavier, 4 MiB of SRAM is shared across multiple cores, including the 2 DLA cores.

Local DRAM

- ▶ Used to store intermediate tensors in the DLA subnetwork. Larger values may allow larger subnetworks to be offloaded to DLA.

Global DRAM

- ▶ Used to store weights in the DLA subnetwork. Larger values may allow larger subnetworks to be offloaded to DLA.

The memory required for each subnetwork may be less than the pool size, in which case a smaller amount will be allocated. The pool size serves only as an upper bound.

Note that all DLA memory pools require sizes that are powers of 2, with a minimum of 4 KiB. Violating this requirement results in a DLA loadable compilation failure.

In multi-subnetwork situations, it is important to remember that the pool sizes apply per DLA subnetwork, not for the whole network, so it is necessary to know the total amount of resources consumed. In particular, your network can consume at most twice the managed SRAM as the pool size in aggregate.

The default managed SRAM pool size for NVIDIA Orin is set to 0.5 MiB, whereas Xavier has 1 MiB as the default. Orin has a strict per-core limit, whereas Xavier has some flexibility. This Orin default guarantees in all situations that the aggregate managed SRAM consumption of your engine stays below the hardware limit, but if your engine has only a single DLA subnetwork, this would mean your engine only consumes half the hardware limit, so you may see a perf boost by increasing the pool size to 1 MiB.

12.6.1. Determining DLA Memory Pool Usage

Upon successfully compiling loadable from the given network, the builder reports the number of subnetwork candidates that were successfully compiled into loadable, as well as the total amount of memory used per pool by those loadable. For each subnetwork candidate that failed due to insufficient memory, a message will be emitted to point

out which memory pool was insufficient. In the verbose log, the builder also reports the memory pool requirements of each loadable.

12.7. Sparsity on DLA

DLA on the NVIDIA Orin platform supports structured sparsity (SS), which can minimize latency and maximize throughput in production.

12.7.1. Structured Sparsity

Structured sparsity (SS) accelerates a 2:4 sparsity pattern along the C dimension. In each contiguous block of four values, two values must be zero along C. Generally, SS provides the most benefit for INT8 convolutions that are math-bound and have a channel dimension that is a multiple of 128.

SS has several requirements and limitations.

Requirements

- ▶ Only available for INT8 convolution for formats other than NHWC.
- ▶ Channel size must be larger than 64.

Limitations

- ▶ Only convolutions whose quantized INT8 weights are at most 256K can benefit from SS—in practice, the limitation may be more restrictive.
- ▶ Only convolutions with $\kappa \% 64$ in $\{0, 1, 2, 4, 8, 16, 32\}$, where κ is the number of kernels (corresponding to the number of output channels), can benefit from SS in this release.

Chapter 13. Performance Best Practices

13.1. Performance Benchmarking using trtexec

This section introduces how to use `trtexec`, a command-line tool designed for TensorRT performance benchmarking, to get the inference performance measurements of your deep learning models.

If you use the TensorRT NGC container, `trtexec` is installed at `/opt/tensorrt/bin/trtexec`. If you manually installed TensorRT, `trtexec` is part of the installation. Alternatively, you can build `trtexec` from source code using the [TensorRT OSS repository](#).

13.1.1. Performance Benchmarking with an ONNX File

If your model is already in the ONNX format, the `trtexec` tool can measure its performance directly. In this example, we will use the [ResNet-50 v1 ONNX model](#) from the ONNX model zoo to showcase how to use `trtexec` to measure its performance.

For example, the `trtexec` command to measure the performance of ResNet-50 with batch size 4 is:

```
trtexec --onnx=resnet50-v1-12.onnx --shapes=data:4x3x224x224 --fp16 --noDataTransfers --useCudaGraph --useSpinWait
```

- ▶ The `--onnx` flag specifies the path to the ONNX file
- ▶ The `--shapes` flag specifies the input tensor shapes
- ▶ The `--fp16` flag enables FP16 tactics
- ▶ The other flags have been added to make performance results more stable.

The value for the `--shapes` flag is in the format of `name1:shape1,name2:shape2,...`. If you do not know the input tensor names and shapes, you can get the information by

visualizing the ONNX model using tools like [Netron](#) or by running a [Polygraphy](#) model inspection.

For example, running `polygraphy inspect model resnet50-v1-12.onnx` prints out:

```
[I] Loading model: /home/pohanh/trt/resnet50-v1-12.onnx
[I] ===== ONNX Model =====
      Name: mxnet_converted_model | ONNX Opset: 12
      ---- 1 Graph Input(s) ----
      {data [dtype=float32, shape=('N', 3, 224, 224)]}
      ---- 1 Graph Output(s) ----
      {resnetv17_dense0_fwd [dtype=float32, shape=('N', 1000)]}
      ---- 299 Initializer(s) ----
      ---- 175 Node(s) ----
```

It shows that the ONNX model has a graph input tensor named `data` whose shape is `('N', 3, 224, 224)`, where `'N'` represents that the dimension can be dynamic. Therefore, the `trtexec` flag to specify the input shapes with batch size 4 would be `--shapes=data:4x3x224x224`.

After running the `trtexec` command, `trtexec` will parse your ONNX file, build a TensorRT plan file, measure the performance of this plan file, and then print a performance summary as follows:

```
[04/25/2024-23:57:45] [I] === Performance summary ===
[04/25/2024-23:57:45] [I] Throughput: 507.399 qps
[04/25/2024-23:57:45] [I] Latency: min = 1.96301 ms, max = 1.97534 ms, mean = 1.96921 ms, median = 1.96917 ms, percentile(90%) = 1.97122 ms, percentile(95%) = 1.97229 ms, percentile(99%) = 1.97424 ms
[04/25/2024-23:57:45] [I] Enqueue Time: min = 0.0032959 ms, max = 0.0340576 ms, mean = 0.00421173 ms, median = 0.00415039 ms, percentile(90%) = 0.00463867 ms, percentile(95%) = 0.00476074 ms, percentile(99%) = 0.0057373 ms
[04/25/2024-23:57:45] [I] H2D Latency: min = 0 ms, max = 0 ms, mean = 0 ms, median = 0 ms, percentile(90%) = 0 ms, percentile(95%) = 0 ms, percentile(99%) = 0 ms
[04/25/2024-23:57:45] [I] GPU Compute Time: min = 1.96301 ms, max = 1.97534 ms, mean = 1.96921 ms, median = 1.96917 ms, percentile(90%) = 1.97122 ms, percentile(95%) = 1.97229 ms, percentile(99%) = 1.97424 ms
[04/25/2024-23:57:45] [I] D2H Latency: min = 0 ms, max = 0 ms, mean = 0 ms, median = 0 ms, percentile(90%) = 0 ms, percentile(95%) = 0 ms, percentile(99%) = 0 ms
[04/25/2024-23:57:45] [I] Total Host Walltime: 3.00355 s
[04/25/2024-23:57:45] [I] Total GPU Compute Time: 3.00108 s
[04/25/2024-23:57:45] [I] Explanations of the performance metrics are printed in the verbose logs.
```

It prints many performance metrics, but the most important are Throughput and median Latency. In this case, the ResNet-50 model with batch size 4 can run with a throughput of 507 inferences per second (2028 images per second since the batch size is 4) and a median latency of 1.969 ms.

Refer to [Advanced Performance Measurement Techniques](#) for explanations about what Throughput and Latency mean to your deep learning inference applications. Refer to [trtexec](#) for detailed explanations about other `trtexec` flags and other performance metrics that `trtexec` reports.

13.1.2. Performance Benchmarking with ONNX +Quantization

To enjoy the additional performance benefit from quantizations, Quantize/Dequantize operations need to be inserted into the ONNX model to tell TensorRT where to quantize/dequantize the tensors and what scaling factors to use.

Our recommended tool for ONNX quantization is the `ModelOptimizer` package. You can install it by running:

```
pip3 install --no-cache-dir --extra-index-url https://pypi.nvidia.com
nvidia-modelopt
```

Using the `ModelOptimizer`, you can get a quantized ONNX model by running

```
python3 -m modelopt.onnx.quantization --onnx_path resnet50-v1-12.onnx --
quantize_mode int8
--output_path resnet50-v1-12-quantized.onnx
```

It loads the original ONNX model from `resnet50-v1-12.onnx`, runs calibration using random data, inserts Quantize/Dequantize ops into the graph, and then saves the ONNX model with Quantize/Dequantize ops to `resnet50-v1-12-quantized.onnx`.

Now that the new ONNX model contains the INT8 Quantize/Dequantize ops, we can run `trtexec` again using a similar command:

```
trtexec --onnx=resnet50-v1-12-quantized.onnx --shapes=data:4x3x224x224 --stronglyTyped --
noDataTransfers --useCudaGraph --useSpinWait
```

We use the `--stronglyTyped` flag instead of the `--fp16` flag to require TensorRT to strictly follow the data types in the quantized ONNX model, including all the INT8 Quantize/Dequantize ops.

Here is an example output after running this `trtexec` command with the quantized ONNX model:

```
[04/26/2024-00:31:43] [I] === Performance summary ===
[04/26/2024-00:31:43] [I] Throughput: 811.74 qps
[04/26/2024-00:31:43] [I] Latency: min = 1.22559 ms, max = 1.23608 ms, mean = 1.2303
ms, median = 1.22998 ms, percentile(90%) = 1.23193 ms, percentile(95%) = 1.23291 ms,
percentile(99%) = 1.23395 ms
[04/26/2024-00:31:43] [I] Enqueue Time: min = 0.00354004 ms, max = 0.00997925 ms, mean =
0.00431524 ms, median = 0.00439453 ms, percentile(90%) = 0.00463867 ms, percentile(95%) =
0.00476074 ms, percentile(99%) = 0.00512695 ms
[04/26/2024-00:31:43] [I] H2D Latency: min = 0 ms, max = 0 ms, mean = 0 ms, median = 0 ms,
percentile(90%) = 0 ms, percentile(95%) = 0 ms, percentile(99%) = 0 ms
[04/26/2024-00:31:43] [I] GPU Compute Time: min = 1.22559 ms, max = 1.23608 ms, mean =
1.2303 ms, median = 1.22998 ms, percentile(90%) = 1.23193 ms, percentile(95%) = 1.23291 ms,
percentile(99%) = 1.23395 ms
[04/26/2024-00:31:43] [I] D2H Latency: min = 0 ms, max = 0 ms, mean = 0 ms, median = 0 ms,
percentile(90%) = 0 ms, percentile(95%) = 0 ms, percentile(99%) = 0 ms
[04/26/2024-00:31:43] [I] Total Host Walltime: 3.00219 s
[04/26/2024-00:31:43] [I] Total GPU Compute Time: 2.99824 s
[04/26/2024-00:31:43] [I] Explanations of the performance metrics are printed in the verbose
logs.
```

The Throughput is 811 inferences per second, and the median Latency is 1.23 ms. The Throughput has improved by 60% compared to the FP16 performance results in the previous section.

13.1.3. Per-Layer Runtime and Layer Information

In previous sections, we described using `trtexec` to measure the end-to-end latency. This section will show an example of per-layer runtime and per-layer information using `trtexec`. This will help you determine how much latency each layer contributes to the end-to-end latency and in which layers the performance bottlenecks are.

This is an example `trtexec` command to print per-layer runtime and per-layer information using the quantized ResNet-50 ONNX model:

```
trtexec --onnx=resnet50-v1-12-quantized.onnx --shapes=data:4x3x224x224 --stronglyTyped --
noDataTransfers --useCudaGraph --useSpinWait --profilingVerbosity=detailed --dumpLayerInfo --
dumpProfile --separateProfileRun
```

The `--profilingVerbosity=detailed` flag enables detailed layer information capturing, `--dumpLayerInfo` flag shows the per-layer information in the log, and `--dumpProfile --separateProfileRun` flags show the per-layer runtime latencies in the log.

The following code is an example log of the per-layer information for one of the convolution layers in the quantized ResNet-50 model:

```
Name: resnetv17_stage1_conv0_weight + resnetv17_stage1_conv0_weight_QuantizeLinear
+ resnetv17_stage1_conv0_fwd, LayerType: CaskConvolution, Inputs: [ { Name:
resnetv17_pool0_fwd_QuantizeLinear_Output_1, Location: Device, Dimensions:
[4,64,56,56], Format/Datatype: Thirty-two wide channel vectorized row major Int8
format }], Outputs: [ { Name: resnetv17_stage1_relu0_fwd_QuantizeLinear_Output,
Location: Device, Dimensions: [4,64,56,56], Format/Datatype: Thirty-two wide channel
vectorized row major Int8 format }], ParameterType: Convolution, Kernel: [1,1],
PaddingMode: kEXPLICIT_ROUND_DOWN, PrePadding: [0,0], PostPadding: [0,0], Stride:
[1,1], Dilation: [1,1], OutMaps: 64, Groups: 1, Weights: {"Type": "Int8", "Count":
4096}, Bias: {"Type": "Float", "Count": 64}, HasBias: 1, HasReLU: 1, HasSparseWeights:
0, HasDynamicFilter: 0, HasDynamicBias: 0, HasResidual: 0, ConvXASActInputIdx:
-1, BiasAsActInputIdx: -1, ResAsActInputIdx: -1, Activation: RELU, TacticName:
sm80_xmma_fprop_implicit_gemm_interleaved_i8i8_i8i32_f32_nchw_vect_c_32kcrs_vect_c_32_nchw_vect_c_32_tiles
TacticValue: 0x483ad1560c6e5e27, StreamId: 0, Metadata: [ONNX Layer:
resnetv17_stage1_conv0_fwd]
```

The log shows the layer name, the input and output tensor names, tensor shapes, tensor data types, convolution parameters, tactic names, and metadata. The `Metadata` field shows which ONNX ops this layer corresponds to. Since TensorRT has graph fusion optimizations, one engine layer may correspond to multiple ONNX ops in the original model.

The following code is an example log of the per-layer runtime latencies for the last few layers in the quantized ResNet-50 model:

| [04/26/2024-00:42:55] | [I] | Time (ms) | Avg. (ms) | Median (ms) | Time (%) | Layer |
|-----------------------|-----|-----------|-----------|-------------|----------|--|
| [04/26/2024-00:42:55] | [I] | 56.57 | 0.0255 | 0.0256 | 1.8 | resnetv17_stage4_conv7_weight + resnetv17_stage4_conv7_weight_QuantizeLinear + resnetv17_stage4_conv7_fwd |
| [04/26/2024-00:42:55] | [I] | 103.86 | 0.0468 | 0.0471 | 3.3 | resnetv17_stage4_conv8_weight + resnetv17_stage4_conv8_weight_QuantizeLinear + resnetv17_stage4_conv8_fwd |
| [04/26/2024-00:42:55] | [I] | 46.93 | 0.0211 | 0.0215 | 1.5 | resnetv17_stage4_conv9_weight + resnetv17_stage4_conv9_weight_QuantizeLinear + resnetv17_stage4_conv9_fwd + resnetv17_stage4_plus2 + resnetv17_stage4_activation2 |
| [04/26/2024-00:42:55] | [I] | 34.64 | 0.0156 | 0.0154 | 1.1 | resnetv17_pool1_fwd |
| [04/26/2024-00:42:55] | [I] | 63.21 | 0.0285 | 0.0287 | | 2.0 resnetv17_dense0_weight + resnetv17_dense0_weight_QuantizeLinear + transpose_before_resnetv17_dense0_fwd + resnetv17_dense0_fwd + resnetv17_dense0_bias + ONNXTRT_Broadcast + unsqueeze_node_after_resnetv17_dense0_bias + ONNXTRT_Broadcast_ONNXTRT_Broadcast_output + (Unnamed Layer* 851) [ElementWise] |
| [04/26/2024-00:42:55] | [I] | 3142.40 | 1.4149 | 1.4162 | 100.0 | Total |

It shows that the median latency of the `resnetv17_pool1_fwd` layer is 0.0156 ms and contributes to 1.1% of the end-to-end latency. With this log, you can identify which layers take the largest portion of the end-to-end latency and is the performance bottleneck.

The `Total` latency reported in the per-layer runtime log is the summation of the per-layer latencies. It is typically slightly longer than the reported end-to-end latency due to the overheads caused by measuring per-layer latencies. For example, the `Total` median

latency is 1.4162 ms, but the end-to-end latency shown in the previous section is 1.23 ms.

13.1.4. Performance Benchmarking with TensorRT Plan File

If you construct the TensorRT `INetworkDefinition` using TensorRT APIs and build the plan file in a separate script, you can still use `trtexec` to measure the plan file's performance.

For example, if the plan file is saved as `resnet50-v1-12-quantized.plan`, then you can run the `trtexec` command to measure the performance using this plan file:

```
trtexec --loadEngine=resnet50-v1-12-quantized.plan --shapes=data:4x3x224x224 --noDataTransfers --useCudaGraph --useSpinWait
```

The performance summary output is similar to those in the previous sections.

13.1.5. Duration and Number of Iterations

By default, `trtexec` warms up for at least 200 ms and runs inference for at least 10 iterations or at least 3 seconds, whichever is longer. You can modify these parameters by adding the `--warmUp=500`, `--iterations=100`, and `--duration=60` flags, which mean running the warm-up for at least 500 ms and running the inference for at least 100 iterations or at least 60 seconds, whichever is longer.

Refer to [trtexec](#) or run `trtexec --help` for a detailed explanation about other `trtexec` flags.

13.2. Advanced Performance Measurement Techniques

Before starting any optimization effort with TensorRT, it is essential to determine what should be measured. Without measurements, it is impossible to make reliable progress or measure whether success has been achieved.

Latency

A performance measurement for network inference is how much time elapses from an input presented to the network until an output is available. This is the *latency* of the network for a single inference. Lower latencies are better. In some applications, low latency is a critical safety requirement. In other applications, latency is directly visible to users as a quality-of-service issue. For bulk processing, latency may not be important at all.

Throughput

Another performance measurement is how many inferences can be completed in a fixed time. This is the *throughput* of the network. Higher throughput is better. Higher

throughputs indicate a more efficient utilization of fixed compute resources. For bulk processing, the total time taken will be determined by the network's throughput.

Another way of looking at latency and throughput is to fix the maximum latency and measure throughput at that latency. A quality-of-service measurement like this can be a reasonable compromise between the user experience and system efficiency.

Before measuring latency and throughput, you must choose the exact points to start and stop timing. Different points might make sense depending on the network and application.

In many applications, there is a processing pipeline, and the latency and throughput of the entire pipeline can measure the overall system performance. Because the pre-and post-processing steps depend so strongly on the particular application, this section considers the latency and throughput of the network inference only.

13.2.1. Wall-clock Timing

The wall clock time (the elapsed time between the start of a computation and its end) can be useful for measuring the application's overall throughput and latency and placing inference times in context within a larger system. C++11 provides high-precision timers in the `<chrono>` standard library. For example, `std::chrono::system_clock` represents system-wide wall-clock time, and `std::chrono::high_resolution_clock` measures time at the highest precision available.

The following example code snippet shows measuring network inference host time:

C++

```
#include <chrono>

auto startTime = std::chrono::high_resolution_clock::now();
context->enqueueV3(stream);
cudaStreamSynchronize(stream);
auto endTime = std::chrono::high_resolution_clock::now();
float totalTime = std::chrono::duration<float, std::milli>
(endTime - startTime).count()
```

Python

```
import time
from cuda import cudart
err, stream = cudart.cudaStreamCreate()
start_time = time.time()
context.execute_async_v3(stream)
cudart.cudaStreamSynchronize(stream)
total_time = time.time() - start_time
```

If there is only one inference happening on the device at one time, then this can be a simple way of profiling the time-various operations take. Inference is typically asynchronous, so ensure you add an explicit CUDA stream or device synchronization to wait for results to become available.

13.2.2. CUDA Events

One problem with timing on the host exclusively is that it requires host/device synchronization. Optimized applications may have many inferences running parallel on

the device with overlapping data movement. In addition, the synchronization adds some noise to timing measurements.

To help with these issues, CUDA provides an [Event API](#). This API allows you to place events into CUDA streams that the GPU will time-stamp as they are encountered. Differences in timestamps can then tell you how long different operations took.

The following example code snippet shows computing the time between two CUDA events:

C++

```
cudaEvent_t start, end;
cudaEventCreate(&start);
cudaEventCreate(&end);

cudaEventRecord(start, stream);
context->(enqueueV3stream);
cudaEventRecord(end, stream);

cudaEventSynchronize(end);
float totalTime;
cudaEventElapsedTime(&totalTime, start, end);
```

Python

```
from cuda import cudart
err, stream = cudart.cudaStreamCreate()
err, start = cudart.cudaEventCreate()
err, end = cudart.cudaEventCreate()
cudart.cudaEventRecord(start, stream)
context.execute_async_v3(stream)
cudart.cudaEventRecord(end, stream)
cudart.cudaEventSynchronize(end)
err, total_time = cudart.cudaEventElapsedTime(start, end)
```

13.2.3. Built-In TensorRT Profiling

Digging deeper into inference performance requires more fine-grained timing measurements within the optimized network.

TensorRT has a *Profiler* ([C++](#), [Python](#)) interface, which you can implement to have TensorRT pass profiling information to your application. When called, the network will run in a profiling mode. After finishing the inference, the profiler object of your class is called to report the timing for each layer in the network. These timings can be used to locate bottlenecks, compare different versions of a serialized engine, and debug performance issues.

The profiling information can be collected from a regular inference `enqueueV3()` launch or a CUDA graph launch. Refer to `IExecutionContext::setProfiler()` and `IExecutionContext::reportToProfiler()` ([C++](#), [Python](#)) for more information.

Layers inside a loop are compiled into a single monolithic layer; therefore, separate timings for those layers are unavailable. Also, some subgraphs (especially with Transformer-like networks) are handled by a next-generation graph optimizer that has not yet been integrated with the *Profiler* APIs. For those networks, use [CUDA Profiling Tools](#) to profile per-layer performance.

An example showing how to use the *IProfiler* interface is provided in the common sample code (`common.h`).

Given an input network or plan file, you can use `trtexec` to profile a network with TensorRT. For more information, refer to the [trtexec](#) section.

13.2.4. CUDA Profiling Tools

The recommended CUDA profiler is [NVIDIA Nsight™ Systems](#). Some CUDA developers may be more familiar with `nvprof` and `nvvp`. However, these are being deprecated. These profilers can be used on any CUDA program to report timing information about the kernels launched during execution, data movement between host and device, and CUDA API calls used.

Nsight Systems can be configured to report timing information for only a portion of the program's execution or to report traditional CPU sampling profile information and GPU information.

The basic usage of Nsight Systems is to first run the command `nsys profile -o <OUTPUT> <INFERENCE_COMMAND>`, then open the generated `<OUTPUT>.nsys-rep` file in the Nsight Systems GUI to visualize the captured profiling results.

Profile Only the Inference Phase

When profiling a TensorRT application, you should enable profiling only after the engine has been built. During the build phase, all possible tactics are tried and timed. Profiling this portion of the execution will not show any meaningful performance measurements and will include all possible kernels, not the ones selected for inference. One way to limit the scope of profiling is to:

- ▶ First phase: Structure the application to build and then serialize the engines in one phase.
- ▶ Second phase: Load the serialized engines, run inference in a second phase, and profile this second phase only.

If the application cannot serialize the engines or must run through the two phases consecutively, you can also add `cudaProfilerStart()/cudaProfilerStop()` CUDA APIs around the second phase and add the `-c cudaProfilerApi` flag to the Nsight Systems command to profile only the part between `cudaProfilerStart()` and `cudaProfilerStop()`.

Understand Nsight Systems Timeline View

In the Nsight Systems Timeline View, the GPU activities are shown in the rows under CUDA HW, and the CPU activities are shown in the rows under Threads. By default, the rows under CUDA HW are collapsed. Therefore, you must click on it to expand the rows.

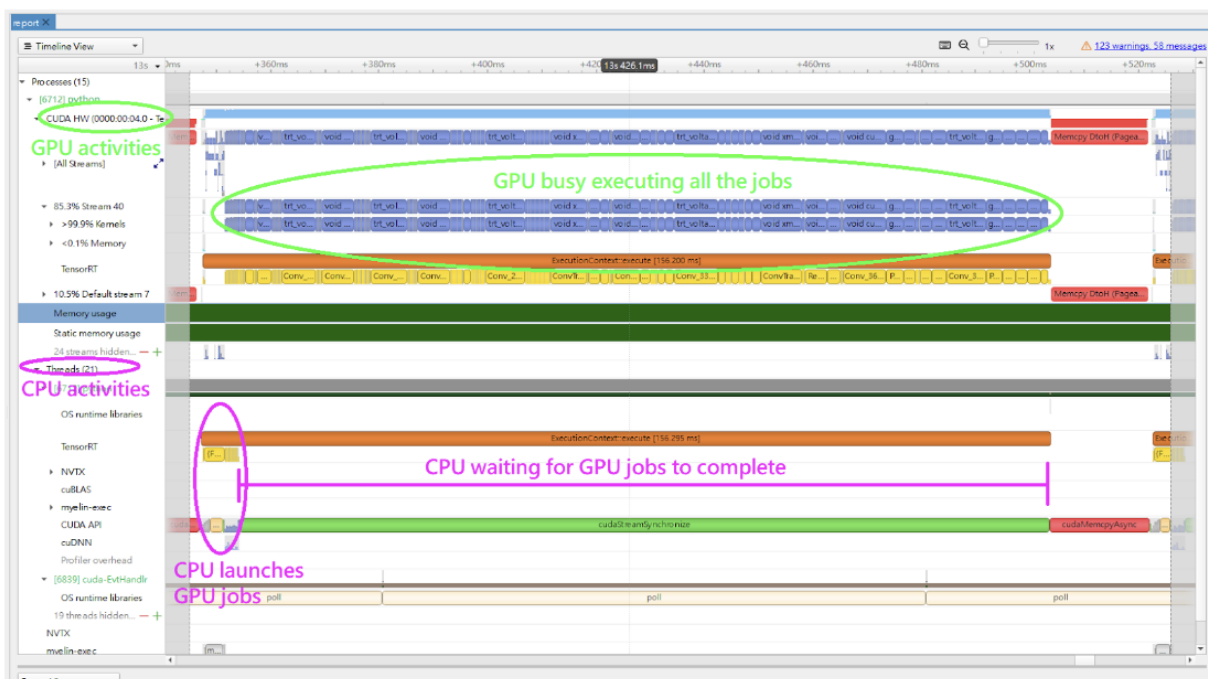
In a typical inference workflow, the application calls the `context->enqueueV3()` or `context->executeV3()` APIs to enqueue the jobs and then synchronize on the stream to wait until the GPU completes the jobs. If you only look at the CPU activities, it may appear that the system is doing nothing for a while in the `cudaStreamSynchronize()` call.

The GPU may be busy executing the enqueued jobs while the CPU waits. The following figure shows an example timeline of the inference of a query.

The `trtexec` tool uses a slightly more complicated approach to enqueue the jobs. It enqueues the next query while the GPU still executes the jobs from the previous query. For more information, refer to the [trtexec](#) section.

The following image shows a typical view of the normal inference workloads in the Nsight Systems timeline view, showing CPU and GPU activities on different rows.

Figure 18. Normal Inference Workloads in Nsight Systems Timeline View



Use the NVTX Tracing in Nsight Systems

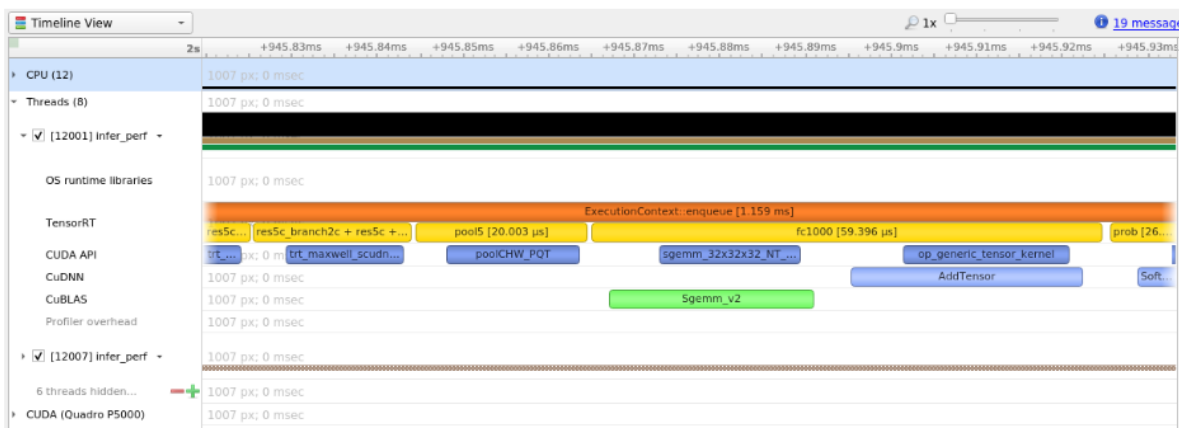
Tracing enables the [NVIDIA Tools Extension SDK \(NVTX\)](#), a C-based API for marking events and ranges in your applications. It allows Nsight Compute and Nsight Systems to collect data generated by TensorRT applications.

Decoding the kernel names back to layers in the original network can be complicated. Because of this, TensorRT uses NVTX to mark a range for each layer, allowing the CUDA profilers to correlate each layer with the kernels called to implement it. In TensorRT, NVTX helps to correlate the runtime engine layer execution with CUDA kernel calls. Nsight Systems supports collecting and visualizing these events and ranges on the timeline. Nsight Compute also supports collecting and displaying the state of all active NVTX domains and ranges in a given thread when the application is suspended.

In TensorRT, each layer may launch one or more kernels to perform its operations. The exact kernels launched depend on the optimized network and the hardware present. Depending on the builder's choices, multiple additional operations that reorder data may be interspersed with layer computations; these reformat operations may be implemented as device-to-device memory copies or custom kernels.

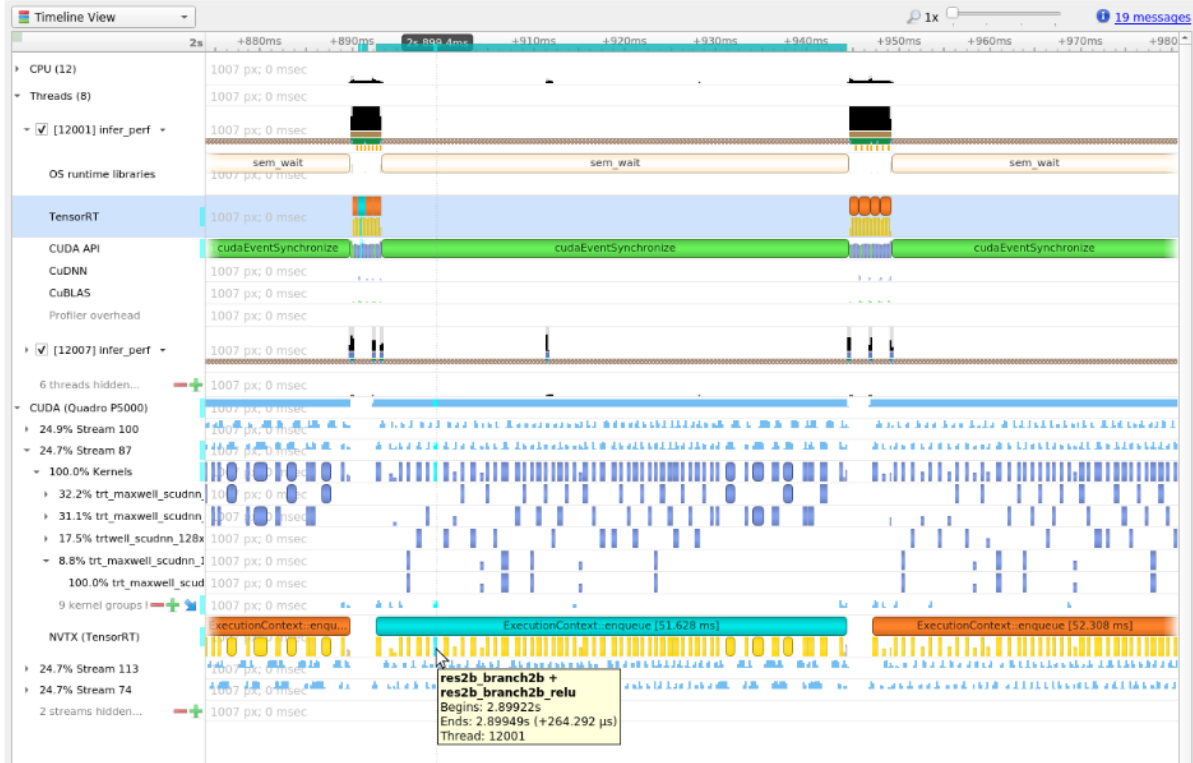
For example, the following screenshots are from Nsight Systems.

Figure 19. The Layer Execution and the Kernel Being Launched on the CPU Side



The kernels run on the GPU; in other words, the following image shows the correlation between the layer execution and kernel launch on the CPU side and their execution on the GPU side.

Figure 20. The Kernels Run on the GPU



Control the Level of Details in NVTX Tracing

By default, TensorRT only shows layer names in the NVTX markers, while users can control the level of details by setting the `ProfilingVerbosity` in the `IBuilderConfig` when the engine is built. For example, to disable NVTX tracing set the `ProfilingVerbosity` to `kNONE`:

C++

```
builderConfig->setProfilingVerbosity(ProfilingVerbosity::kNONE);
```

Python

```
builder_config.profiling_verbosity = trt.ProfilingVerbosity.NONE
```

On the other hand, you can choose to allow TensorRT to print more detailed layer information in the NVTX markers, including input and output dimensions, operations, parameters, tactic numbers, and so on, by setting the `ProfilingVerbosity` to `kDETAILED`:

C++

```
builderConfig->setProfilingVerbosity(ProfilingVerbosity::kDETAILED);
```

Python

```
builder_config.profiling_verbosity = trt.ProfilingVerbosity.DETAILED
```



Note: Enabling detailed NVTX markers increases the latency of `enqueueV3()` calls and could result in a performance drop if the performance depends on the latency of `enqueueV3()` calls.

Run Nsight Systems with `trtexec`

Below is an example of the commands to gather Nsight Systems profiles using the `trtexec` tool:

```
trtexec --onnx=foo.onnx --profilingVerbosity=detailed --saveEngine=foo.plan
nsys profile -o foo_profile --capture-range cudaProfilerApi trtexec --
profilingVerbosity=detailed --loadEngine=foo.plan --warmUp=0 --duration=0 --iterations=50
```

The first command builds and serializes the engine to `foo.plan`, and the second command runs the inference using `foo.plan` and generates a `foo_profile.nsys-rep` file can then be opened in the Nsight Systems user interface for visualization.

The `--profilingVerbosity=detailed` flag allows TensorRT to show more detailed layer information in the NVTX marking, and the `--warmUp=0 --duration=0 --iterations=50` flags allow you to control how many inference iterations to run. By default, `trtexec` runs inference for three seconds, which may result in a large output of the `nsys-rep` file.

If the CUDA graph is enabled, add `--cuda-graph-trace=node` flag to the `nsys` command to see the per-kernel runtime information:

```
nsys profile -o foo_profile --capture-range cudaProfilerApi --cuda-graph-trace=node trtexec
--profilingVerbosity=detailed --loadEngine=foo.plan --warmUp=0 --duration=0 --iterations=50
--useCudaGraph
```

(Optional) Enable GPU Metrics Sampling in Nsight Systems

On discrete GPU systems, add the `--gpu-metrics-device all` flag to the `nsys` command to sample GPU metrics, including GPU clock frequencies, DRAM bandwidth, Tensor Core utilization, and so on. If the flag is added, these GPU metrics appear in the Nsight Systems web interface.

13.2.4.1. Profiling for DLA

To profile DLA, add the `--accelerator-trace nvmedia` flag when using the NVIDIA Nsight Systems CLI or enable Collect other accelerators trace when using the user interface. For example, the following command can be used with the NVIDIA Nsight Systems CLI:

```
nsys profile -t cuda,nvtx,nvmedia,osrt --accelerator-trace=nvmedia --show-output=true
trtexec --loadEngine=alexnet_int8.plan --warmUp=0 --duration=0 --iterations=20
```

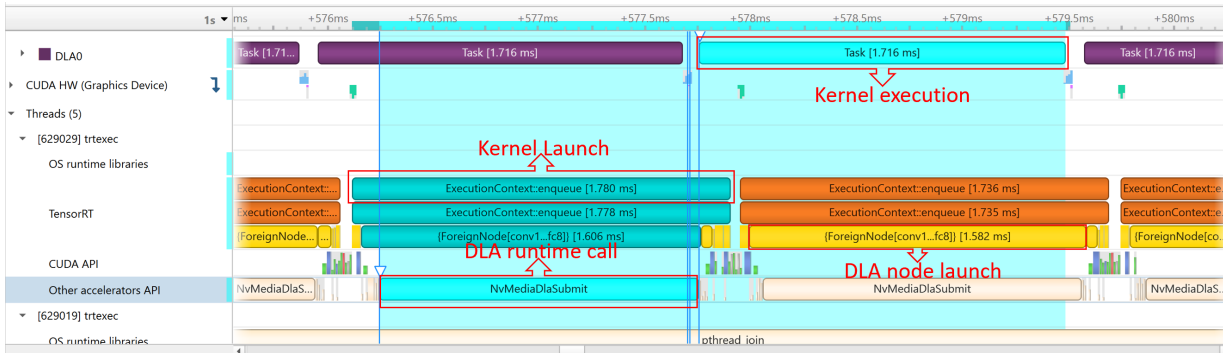
Below is an example report.

- `NvMediaDLASubmit` submits a DLA task for each DLA subgraph. The task's runtime can be found in the DLA timeline under Other accelerators trace.

- ▶ Because GPU fallback was allowed, TensorRT automatically added some CUDA kernels, like `permutationKernelPLC3` and `copyPackedKernel`, which are used for data reformatting.
- ▶ EGLStream APIs were executed because TensorRT uses EGLStreams for data transfer between GPU memory and DLA.

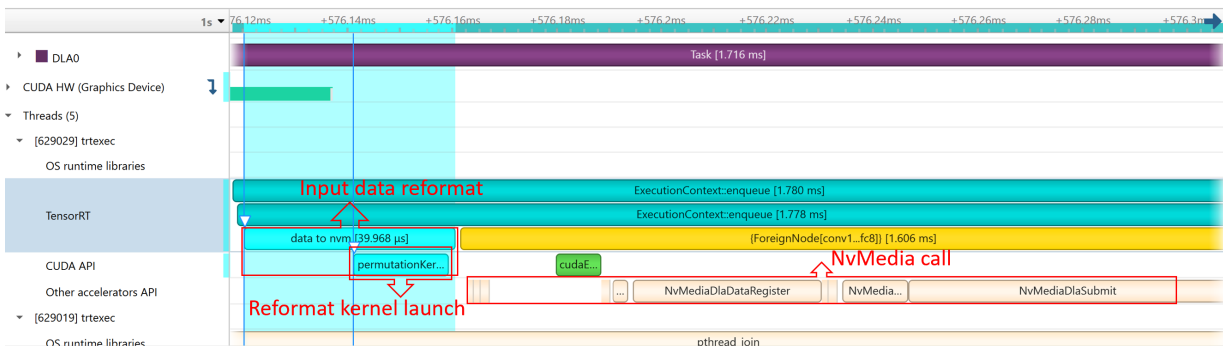
To maximize GPU utilization, `trtexec` enqueues the queries one batch beforehand.

Figure 21. Sample DLA Profiling Report



The runtime of the DLA task can be found under *Other Accelerator API*. Some CUDA kernels and EGLStream API are called for interaction between the GPU and DLA.

Figure 22. Sample DLA Profiling report



13.2.5. Tracking Memory

Tracking memory usage can be as important as execution performance. Usually, the device's memory is more constrained than the host's. To keep track of device memory, the recommended mechanism is to create a simple custom GPU allocator that internally keeps some statistics and then uses the regular CUDA memory allocation functions `cudaMalloc` and `cudaFree`.

A custom GPU allocator can be set for the builder `IBuilder` for network optimizations and `IRuntime` when deserializing engines using the `IGpuAllocator` APIs. One idea for the custom allocator is to keep track of the current amount of memory allocated and

push an allocation event with a timestamp and other information onto a global list of allocation events. Looking through the list of allocation events allows profiling memory usage over time.

On mobile platforms, GPU memory and CPU memory share the system memory. On devices with very limited memory size, like Nano, system memory might run out with large networks; even the required GPU memory is smaller than system memory. In this case, increasing the system swap size could solve some problems. An example script is:

```
echo "#####alloc swap#####"
if [ ! -e /swapfile ];then
  sudo fallocate -l 4G /swapfile
  sudo chmod 600 /swapfile
  sudo mkswap /swapfile
  sudo /bin/sh -c 'echo "/swapfile \t none \t swap \t defaults \t 0 \t 0" >> /etc/fstab'
  sudo swapon -a
fi
```

13.3. Hardware/Software Environment for Performance Measurements

Performance measurements are influenced by many factors, including hardware environment differences like the machine's cooling capability and software environment differences like GPU clock settings. This section summarizes a few items that may affect performance measurements.

Note that the items involving `nvidia-smi` are only supported on dGPU systems, not mobile ones.

13.3.1. GPU Information Query and GPU Monitoring

While measuring performance, it is recommended that you record and monitor the GPU status in parallel to the inference workload. Having the monitoring data allows you to identify possible root causes when you see unexpected performance measurement results.

Before the inference starts, call the `nvidia-smi -q` command to get detailed information on the GPU, including the product name, power cap, clock settings, etc. Then, while the inference workload is running, run the `nvidia-smi dmon -s pcu -f <FILE> -c <COUNT>` command in parallel to print out GPU clock frequencies, power consumption, temperature, and utilization to a file. Call `nvidia-smi dmon --help` for more options about the `nvidia-smi` device monitoring tool.

13.3.2. GPU Clock Locking and Floating Clock

By default, the GPU clock frequency is floating, meaning it sits idle when there is no active workload and boosts the boost clock frequency when the workload starts. This is usually the desired behavior since it allows the GPU to generate less heat at idle and to run at maximum speed when there is an active workload.

Alternatively, you can lock the clock at a specific frequency by calling the `sudo nvidia-smi -lgc <freq>` command (and conversely, you can let the clock float again with the `sudo nvidia-smi -rgc` command). The `sudo nvidia-smi -q -d SUPPORTED_CLOCKS` command can find the supported clock frequencies. After the clock frequency is locked, it should stay at that frequency unless power or thermal throttling occurs, which will be explained in the next sections. When the throttling kicks in, the device behaves like the clock floats.

Running TensorRT workloads with floating clocks or with throttling taking place can lead to more non-determinism in tactic selections and unstable performance measurements across inferences because every CUDA kernel may run at slightly different clock frequencies, depending on which frequency the driver boosts or throttles the clock to at that moment. On the other hand, running TensorRT workloads with locked clocks allows more deterministic tactic selections and consistent performance measurements, but the average performance will not be as good as when the clock is floating or is locked at maximum frequency with throttling taking place.

There is no definite recommendation on whether the clock should be locked or which clock frequency to lock the GPU while running TensorRT workloads. It depends on whether the deterministic and stable performance or the best average performance is desired.

13.3.3. GPU Power Consumption and Power Throttling

Power throttling occurs when the average GPU power consumption reaches the power limit, which can be set by the `sudo nvidia-smi -pl <power_cap>` command. When this happens, the driver has to throttle the clock to a lower frequency to keep the average power consumption below the limit. The constantly changing clock frequencies may lead to unstable performance measurements if the measurements are taken within a short period of time, such as within 20ms.

Power throttling happens by design and is a natural phenomenon when the GPU clock is not locked or is locked at a higher frequency, especially for GPUs with lower power limits, such as NVIDIA T4 and NVIDIA A2 GPUs. To avoid performance variations caused by power throttling, you can lock the GPU clock at a lower frequency to stabilize the performance numbers. However, the average performance numbers will be lower than those with floating clocks or the clock locked at a higher frequency, even though power throttling would happen in this case.

Another issue with power throttling is that it may skew the performance numbers if there are gaps between inferences in your performance benchmarking applications. For example, if the application synchronizes at each inference, there will be periods when the GPU is idle between the inferences. The gaps cause the GPU to consume less power on average, so the clock is throttled less, and the GPU can run at higher clock frequencies on average. However, the throughput numbers measured this way are inaccurate because when the GPU is fully loaded with no gaps between inferences, the actual clock frequency will be lower, and the actual throughput will not reach the throughput numbers measured using the benchmarking application.

To avoid this, the `trtexec` tool is designed to maximize GPU execution by leaving nearly no gaps between GPU kernel executions so that it can measure the true throughput of a TensorRT workload. Therefore, if you see performance gaps between your benchmarking application and what `trtexec` reports, check if the power throttling and the gaps between inferences are the cause.

Lastly, power consumption can depend on the activation values, causing different input performance measurements. For example, if all the network input values are set to zeros or NaNs, the GPU consumes less power than the inputs are normal values because of fewer bit-flips in DRAM and the L2 cache. To avoid this discrepancy, always use the input values that best represent the actual value distribution when measuring the performance. The `trtexec` tool uses random input values by default, but you can specify the input using the `--loadInputs` flag. For more information, refer to the [trtexec](#) section.

13.3.4. GPU Temperature and Thermal Throttling

Thermal throttling happens when the GPU temperature reaches a predefined threshold of around 85 degrees Celsius for most GPUs, and the driver has to throttle the clock to a lower frequency to prevent the GPU from overheating. You can tell this by seeing the temperature logged by the `nvidia-smi dmon` command gradually increasing while the inference workload runs until it reaches ~85C and the clock frequency drops.

If thermal throttling happens on actively cooled GPUs like Quadro A8000, then it is possible that the fans on the GPU are broken or obstacles are blocking the airflow.

If thermal throttling happens on passively cooled GPUs like NVIDIA A10, then it is likely that the GPUs are not properly cooled. Passively cooled GPUs require external fans or air conditioning to cool down the GPUs, and the airflow must go through the GPUs for effective cooling. Common cooling problems include installing GPUs in a server that is not designed for the GPUs or installing the wrong numbers of GPUs into the server. In some cases, the air flows through the “easy path” (the path with the least friction) around the GPUs instead of going through them. Fixing this requires examination of the airflow in the server and installation of airflow guidance if necessary.

Note that higher GPU temperature also leads to more leakage current in the circuits, which increases the power consumed by the GPU at a specific clock frequency. Therefore, for GPUs more likely to be power throttled like NVIDIA T4, poor cooling can lead to lower stabilized clock frequency with power throttling and, thus, worse performance, even if the GPU clocks have not been thermally throttled yet.

On the other hand, ambient temperature, the environment's temperature around the server, does not usually affect GPU performance as long as the GPUs are properly cooled, except for GPUs with lower power limits whose performance may be slightly affected.

13.3.5. H2D/D2H Data Transfers and PCIe Bandwidth

On dGPU systems, the input data must often be copied from the host memory to the device memory (H2D) before an inference starts, and the output data must be copied back from the device memory to the host memory (D2H) after the inference. These H2D/D2H data transfers go through PCIe buses, and they can sometimes influence

the inference performance or even become the performance bottleneck. The H2D/D2H copies can also be seen in the Nsight Systems profiles, appearing as `cudaMemcpy()` or `cudaMemcpyAsync()` CUDA API calls.

To achieve maximum throughput, the H2D/D2H data transfers should run parallel to the GPU executions of other inferences so that the GPU does not sit idle when the H2D/D2H copies occur. This can be done by running multiple inferences in parallel streams or launching H2D/D2H copies in a different stream than the stream used for GPU executions and using CUDA events to synchronize between the streams. The `trtexec` tool shows an example of the latter implementation.

When the H2D/D2H copies run parallel to GPU executions, they can interfere with the GPU executions, especially if the host memory is pageable, which is the default case. Therefore, it is recommended that you allocate pinned host memory for the input and output data using `cudaHostAlloc()` or `cudaMallocHost()` CUDA APIs.

To check whether the PCIe bandwidth becomes the performance bottleneck, you can check the Nsight Systems profiles and see if the H2D or D2H copies of an inference query have longer latencies than the GPU execution part. If PCIe bandwidth becomes the performance bottleneck, here are a few possible solutions.

First, check whether the PCIe bus configuration of the GPU is correct in terms of which generation (for example, Gen3 or Gen4) and how many lanes (for example, x8 or x16) are used. Next, try reducing the amount of data that must be transferred using the PCIe bus. For example, if the input images have high resolutions and the H2D copies become the bottleneck, you can consider transmitting JPEG-compressed images over the PCIe bus and decode the image on the GPUs before the inference workflow instead of transmitting raw pixels. Finally, you can consider using NVIDIA GPUDirect technology to load data directly from/to the network or the filesystems without going through the host memory.

In addition, if your system has AMD x86_64 CPUs, check the machine's NUMA (Non-Uniform Memory Access) configurations with the `numactl --hardware` command. The PCIe bandwidth between a host memory and a device memory located on two different NUMA nodes is much more limited than the bandwidth between the host/device memory located on the same NUMA node. Allocate the host memory on the NUMA node on which the GPU on which the data will be copied resides. Also, pin the CPU threads that trigger the H2D/D2H copies on that specific NUMA node.

Note that the host and the device share the same memory on mobile platforms, so the H2D/D2H data transfers are not required if the host memory is allocated using CUDA APIs and is pinned instead of pageable.

By default, the `trtexec` tool measures the latencies of the H2D/D2H data transfers, which tells the user if the H2D/D2H copies may bottleneck the TensorRT workload. However, if the H2D/D2H copies affect the stability of the GPU Compute Time, you can add the `--noDataTransfers` flag to disable H2D/D2H transfers and measure only the latencies of the GPU execution part.

13.3.6. TCC Mode and WDDM Mode

On Windows machines, there are two driver modes: you can configure the GPU to be in the TCC mode and the WDDM mode. The mode can be specified by calling the

`sudo nvidia-smi -dm [0|1]` command, but a GPU connected to a display shall not be configured into TCC mode. For more information, refer to the [TCC mode documentation](#).

In TCC mode, the GPU is configured to focus on computation work, and graphics support like OpenGL or monitor display is disabled. This is the recommended mode for GPUs that run TensorRT inference workloads. On the other hand, the WDDM mode tends to cause GPUs to have worse and unstable performance results when running inference workloads using TensorRT.

This does not apply to Linux-based OS.

13.3.7. Enqueue-Bound Workloads and CUDA Graphs

The `enqueue()` function of `IExecutionContext` is asynchronous. That is, it returns immediately after all the CUDA kernels are launched without waiting for the completion of CUDA kernel executions. However, in some cases, the `enqueue()` time can take longer than the actual GPU executions, causing the latency of `enqueue()` calls to become the performance bottleneck. We say that this type of workload is "enqueue-bound." Two reasons may cause a workload to be enqueue-bound.

First, if the workload is very tiny in terms of the number of computations, such as containing convolutions with small I/O sizes, matrix multiplications with small GEMM sizes, or mostly element-wise operations throughout the network, then the workload tends to be enqueue-bound. This is because most CUDA kernels take the CPU and the driver around 5-15 microseconds to launch per kernel, so if each CUDA kernel execution time is only several microseconds long on average, the kernel launching time becomes the main performance bottleneck.

To solve this, try increasing the computation per CUDA kernel by increasing the batch size. You can also use [CUDA Graphs](#) to capture the kernel launches into a graph and launch the graph instead of calling `enqueueV3()`.

Second, if the workload contains operations requiring device synchronizations, such as loops or if-else conditions, it is naturally queue-bound. In this case, increasing the batch size may help improve the throughput without increasing the latency.

In `trtexec`, you can tell that a workload is enqueue-bound if the reported `Enqueue Time` is close to or longer than the reported `GPU Compute Time`. In this case, it is recommended that you add the `--useCudaGraph` flag to enable CUDA graphs in `trtexec`, which will reduce the `Enqueue Time` as long as the workload does not contain any synchronization operations.

13.3.8. BlockingSync and SpinWait Synchronization Modes

If performance is measured with `cudaStreamSynchronize()` or `cudaEventSynchronize()`, synchronization overhead variations may lead to performance measurement variations. This section describes the causes of the variations and how to avoid them.

When `cudaStreamSynchronize()` is called, there are two ways in which the driver waits until the stream is completed. If the `cudaDeviceScheduleBlockingSync` flag has been set with `cudaSetDeviceFlags()` calls, then the `cudaStreamSynchronize()` uses the blocking-sync mechanism. Otherwise, it uses the spin-wait mechanism.

A similar idea applies to CUDA events. If a CUDA event is created with the `cudaEventDefault` flag, then the `cudaEventSynchronize()` call uses the spin-wait mechanism; and if a CUDA event is created with the `cudaEventBlockingSync` flag, then the `cudaEventSynchronize()` call will use the blocking-sync mechanism.

When the blocking-sync mode is used, the host thread yields to another thread until the device work is done. This allows the CPUs to sit idle to save power or to be used by other CPU workloads when the device is still executing. However, the blocking-sync mode tends to result in relatively unstable overheads in stream/event synchronizations in some OS, leading to variations in latency measurements.

On the other hand, when the spin-wait mode is used, the host thread is constantly polling until the device work is done. Using spin-wait makes the latency measurements more stable due to shorter and more stable overhead in stream/event synchronizations, but it consumes some CPU computation resources and leads to more power consumption by the CPUs.

Therefore, if you want to reduce CPU power consumption or do not want the stream/event synchronizations to consume CPU resources (for example, you are running other heavy CPU workloads in parallel), use the blocking-sync mode. If you care more about stable performance measurements, use the spin-wait mode.

In `trtexec`, the default synchronization mechanism is in blocking-sync mode. Add the `--useSpinWait` flag to enable synchronizations using the spin-wait mode for more stable latency measurements at the cost of more CPU utilizations and power consumptions.

13.4. Optimizing TensorRT Performance

The following sections focus on the general inference flow on GPUs and some general strategies to improve performance. These ideas apply to most CUDA programmers but may not be as obvious to developers from other backgrounds.

13.4.1. Batching

The most important optimization is to compute as many results in parallel as possible using batching. In TensorRT, a *batch* is a collection of inputs that can all be processed uniformly. Each instance in the batch has the same shape and flows through the network similarly. Therefore, each instance can be trivially computed in parallel.

Each network layer will have some overhead and synchronization required to compute forward inference. By computing more results in parallel, this overhead is paid off more efficiently. In addition, many layers are performance-limited by the smallest dimension in the input. If the batch size is one or small, this size can often be the performance-limiting dimension. For example, the FullyConnected layer with v inputs and k outputs can be implemented for one batch instance as a matrix multiplied by a $1 \times v$ matrix with a

$V \times K$ weight matrix. If N instances are batched, this becomes an $N \times V$ multiplied by the $V \times K$ matrix. The vector-matrix multiplier becomes a matrix-matrix multiplier, which is much more efficient.

Larger batch sizes are almost always more efficient on the GPU. Extremely large batches, such as $N > 2^{16}$, can sometimes require extended index computation, and so should be avoided if possible. But generally, increasing the batch size improves total throughput. In addition, when the network contains MatrixMultiply or FullyConnected layers, batch sizes of multiples of 32 tend to have the best performance for FP16 and INT8 inference because of the utilization of Tensor Cores if the hardware supports them.

On NVIDIA Ada Lovelace or later GPUs, decreasing the batch size may improve the throughput significantly if the smaller batch sizes help the GPU cache the input/output values in the L2 cache. Therefore, various batch sizes should be tried to find the batch size that provides optimal performance.

Sometimes, batching inference work is impossible due to the application's organization. In some common applications, such as a server that makes inferences per request, it is possible to implement opportunistic batching. For each incoming request, wait for a time T . If other requests come in, batch them together. Otherwise, continue with a single-instance inference. This strategy adds fixed latency to each request but can greatly improve the system's maximum throughput.

The [NVIDIA Triton Inference Server](#) provides a simple way to enable dynamic batching with TensorRT engines.

Using batching

The batch dimension is part of the tensor dimensions, and you can specify the range of the batch sizes and the batch size to optimize the engine by adding optimization profiles. For more information, refer to the [Working with Dynamic Shapes](#) section.

13.4.2. Within-Inference Multi-Streaming

In general, CUDA programming streams are a way of organizing asynchronous work. Asynchronous commands put into a stream are guaranteed to run in sequence but may execute out of order concerning other streams. In particular, asynchronous commands in two streams may be scheduled to run concurrently (subject to hardware limitations).

In the context of TensorRT and inference, each layer of the optimized final network will require work on the GPU. However, not all layers can fully use the hardware's computation capabilities. Scheduling requests in separate streams allows work to be scheduled immediately as the hardware becomes available without unnecessary synchronization. Even if only some layers can be overlapped, overall performance will improve.

Starting in TensorRT 8.6, you can use the `IBuilderConfig::setMaxAuxStreams()` API to set the maximum number of auxiliary streams that TensorRT can use to run multiple layers in parallel. The auxiliary streams are in contrast to the "mainstream" provided in the `enqueueV3()` call, and if enabled, TensorRT will run some layers on the auxiliary streams in parallel to the layers running on the mainstream.

For example, to run the inference on at most eight streams (that is, seven auxiliary streams and one mainstream) in total:

C++

```
config->setMaxAuxStreams(7)
```

Python

```
config.max_aux_streams = 7
```

Note that this only sets the maximum number of auxiliary streams. However, TensorRT may use fewer auxiliary streams than this number if it determines that using more streams does not help.

To get the actual number of auxiliary streams that TensorRT uses for an engine, run:

C++

```
int32_t nbAuxStreams = engine->getNbAuxStreams()
```

Python

```
num_aux_streams = engine.num_aux_streams
```

When an execution context is created from the engine, TensorRT automatically creates the auxiliary streams needed to run the inference. However, you can also specify the auxiliary streams you would like TensorRT to use:

C++

```
int32_t nbAuxStreams = engine->getNbAuxStreams();
std::vector<cudaStream_t> streams(nbAuxStreams);
for (int32_t i = 0; i < nbAuxStreams; ++i)
{
    cudaStreamCreate(&streams[i]);
}
context->setAuxStreams(streams.data(), nbAuxStreams);
```

Python

```
from cuda import cudart
num_aux_streams = engine.num_aux_streams
streams = []
for i in range(num_aux_streams):
    err, stream = cudart.cudaStreamCreate()
    streams.append(stream)
context.set_aux_streams(streams)
```

TensorRT will always insert event synchronizations between the mainstream provided using `enqueueV3()` call and the auxiliary streams:

- ▶ At the beginning of the `enqueueV3()` call, TensorRT will ensure that all the auxiliary streams wait on the activities on the mainstream.
- ▶ At the end of the `enqueueV3()` call, TensorRT will ensure that the mainstream waits for the activities on all the auxiliary streams.

Enabling auxiliary streams may increase memory consumption because some activation buffers can no longer be reused.

13.4.3. Cross-Inference Multi-Streaming

In addition to the within-inference streaming, you can enable streaming between multiple execution contexts. For example, you can build an engine with multiple optimization profiles and create an execution context per profile. Then, call the `enqueueV3()` function of the execution contexts on different streams to allow them to run in parallel.

Running multiple concurrent streams often leads to several streams sharing compute resources simultaneously. This means the network may have fewer compute resources available during inference than when the TensorRT engine was optimized. This difference in resource availability can cause TensorRT to choose a suboptimal kernel for the actual runtime conditions. To mitigate this effect, you can limit the amount of available compute resources during engine creation to resemble actual runtime conditions more closely. This approach generally promotes throughput at the expense of latency. For more information, refer to [Limiting Compute Resources](#).

It is also possible to use multiple host threads with streams. A common pattern is incoming requests dispatched to a pool of worker threads waiting for work. In this case, the pool of worker threads will each have one execution context and CUDA stream. Each thread will request work in its stream as the work becomes available. Each thread will synchronize with its stream to wait for results without blocking other worker threads.

13.4.4. CUDA Graphs

[CUDA graphs](#) represent a sequence (or, more generally, a graph) of kernels in a way that allows CUDA to optimize their scheduling. This can be particularly useful when your application performance is sensitive to the CPU time to queue the kernels.

TensorRT's `enqueueV3()` method supports CUDA graph capture for models requiring no mid-pipeline CPU interaction. For example:

C++

```
// Call enqueueV3() once after an input shape change to update internal state.
context->enqueueV3(stream);

// Capture a CUDA graph instance
cudaGraph_t graph;
cudaGraphExec_t instance;
cudaStreamBeginCapture(stream, cudaStreamCaptureModeGlobal);
context->enqueueV3(stream);
cudaStreamEndCapture(stream, &graph);
cudaGraphInstantiate(&instance, graph, 0);

// To run inferences, launch the graph instead of calling enqueueV3().
for (int i = 0; i < iterations; ++i) {
    cudaGraphLaunch(instance, stream);
    cudaStreamSynchronize(stream);
}
```

Python

```
from cuda import cudart
err, stream = cudart.cudaStreamCreate()

# Call execute_async_v3() once after an input shape change to update internal state.
context.execute_async_v3(stream);

# Capture a CUDA graph instance
cudaStreamBeginCapture(stream, cudart.cudaStreamCaptureModeGlobal)
context.execute_async_v3(stream)
err, graph = cudart.cudaStreamEndCapture(stream)
err, instance = cudart.cudaGraphInstantiate(graph, 0)

# To run inferences, launch the graph instead of calling execute_async_v3().
for i in range(iterations):
    cudart.cudaGraphLaunch(instance, stream)
    cudart.cudaStreamSynchronize(stream)
```

Models for which graphs are not supported include those with loops or conditionals. In this case, `cudaStreamEndCapture()` will return `cudaErrorStreamCapture*` errors, indicating that the graph capturing has failed, but the context can continue to be used for normal inference without CUDA graphs.

When capturing a graph, it is important to account for the two-phase execution strategy used in the presence of dynamic shapes.

1. Update the model's internal state to account for any changes in input size.
2. Stream work to the GPU

The first phase requires no per-invocation work for models where input size is fixed at build time. Otherwise, if the input sizes have changed since the last invocation, some work may be required to update derived properties.

The first phase of work is not designed to be captured, and even if the capture is successful may increase model execution time. Therefore, after changing the shapes of inputs or the values of shape tensors, call `enqueueV3()` once to flush deferred updates before capturing the graph.

Graphs captured with TensorRT are specific to the input size and the state of the execution context. Modifying the context from which the graph was captured will result in undefined behavior when executing the graph—in particular, if the application is providing its memory for activations using `createExecutionContextWithoutDeviceMemory()`, the memory address is also captured as part of the graph. Locations of input and output buffers are also captured as part of the graph.

Therefore, the best practice is to use one execution context per captured graph and to share memory across the contexts with `createExecutionContextWithoutDeviceMemory()`.

`trtexec` allows you to check whether the TensorRT engine you built is compatible with CUDA graph capture. For more information, refer to the [trtexec](#) section.

13.4.5. Enabling Fusion

13.4.5.1. Layer Fusion

TensorRT attempts to perform many different types of optimizations in a network during the build phase. In the first phase, layers are fused whenever possible. Fusions transform the network into a simpler form but preserve the same overall behavior. Internally, many layer implementations have extra parameters and options that are not directly accessible when creating the network. Instead, the fusion optimization step detects supported patterns of operations and fuses multiple layers into one layer with an internal options set.

Consider the common case of a convolution followed by ReLU activation. Creating a network with these operations involves adding a Convolution layer with `addConvolution` and following it with an Activation layer using `addActivation` with an `ActivationType` of `kRELU`. The unoptimized graph will contain separate layers for convolution and activation. The internal implementation of convolution supports computing the ReLU function on

the output in one step directly from the convolution kernel without requiring a second kernel call. The fusion optimization step will detect the convolution followed by ReLU. Verify that the operations are supported by the implementation, then fuse them into one layer.

To investigate which fusions have occurred, the builder logs its operations to the logger object provided during construction. Optimization steps are at the `kINFO` log level. To see these messages, ensure you log them in the `ILogger` callback.

Fusions are normally handled by creating a new layer with a name containing the names of both of the layers that were fused. For example, in the MNIST TensorRT sample, a FullyConnected layer (InnerProduct) named `ip1` is fused with a ReLU Activation layer named `relu1` to create a new layer named `ip1 + relu1`.

13.4.5.2. Types of Fusions

The following list describes the types of supported fusions.

Supported Layer Fusions

ReLU Activation

An Activation layer performing ReLU followed by an activation performing ReLU will be replaced by a single activation layer.

Convolution and ReLU Activation

The Convolution layer can be of any type, and values are not restricted. The Activation layer must be of the ReLU type.

Convolution and GELU Activation

The precision of input and output should be the same, with both of them FP16 or INT8. The Activation layer must be GELU type. TensorRT should run on an NVIDIA Turing or later with CUDA version 10.0.

Convolution and Clip Activation

The Convolution layer can be any type, and values are not restricted. The Activation layer must be Clip type.

Scale and Activation

The Scale layer, followed by an Activation layer, can be fused into a single Activation layer.

Convolution and ElementWise Operation

A Convolution layer followed by a simple sum, min, or max in an ElementWise layer can be fused into the Convolution layer. The sum must not use broadcasting unless the broadcasting is across the batch size.

Padding and Convolution/Deconvolution

If all the padding sizes are non-negative, padding followed by a Convolution or Deconvolution can be fused into a single Convolution/Deconvolution layer.

Shuffle and Reduce

A Shuffle layer without reshape, followed by a Reduce layer, can be fused into a single Reduce layer. The Shuffle layer can perform permutations but cannot perform any reshape operation. The Reduce layer must have a `keepDimensions` set of dimensions.

Shuffle and Shuffle

Each Shuffle layer consists of a transpose, a reshape, and a second transpose. A Shuffle layer followed by another can be replaced by a single Shuffle (or nothing). If both Shuffle layers perform reshape operations, this fusion is only allowed if the second transpose of the first shuffle is the inverse of the first transpose of the second shuffle.

Scale

A Scale layer that adds 0, multiplied by 1, or computes powers to the 1 can be erased.

Convolution and Scale

Adjusting the convolution weights can fuse a convolution layer followed by a Scale layer that is `kUNIFORM` or `kCHANNEL` into a single convolution. This fusion is disabled if the scale has a non-constant `power` parameter.

Convolution and Generic Activation

This fusion happens after the pointwise fusion mentioned below. A pointwise with one input and output can be called a generic activation layer. A convolution layer followed by a generic activation layer can be fused into a single convolution layer.

Reduce

It performs average pooling, which a Pooling layer will replace. The Reduce layer must have a `keepDimensions` set and be reduced across `H` and `W` dimensions from the `CHW` input format before batching using the `kAVG` operation.

Convolution and Pooling

The Convolution and Pooling layers must have the same precision. The Convolution layer may already have a fused activation operation from a previous fusion.

Depthwise Separable Convolution

A depthwise convolution with activation followed by a convolution with activation may sometimes be fused into a single optimized `DepSepConvolution` layer. The precision of both convolutions must be `INT8`, and the device's computation capability must be 7.2 or later.

SoftMax and Log

If it has not already been fused with a previous log operation, it can be fused into a single SoftMax layer.

SoftMax and TopK

It can be fused into a single layer. The SoftMax may or may not include a Log operation.

FullyConnected

The FullyConnected layer will be converted into the Convolution layer. All fusions for convolution will take effect.

Supported Reduction Operation Fusions**GELU**

A group of Unary and ElementWise layers representing the following equations can be fused into a single GELU reduction operation.

$$0.5x \times (1 + \tanh(2/\pi(x + 0.044715x^3)))$$

Or the alternative representation:

$$0.5x \times (1 + \operatorname{erf}(x/\sqrt{2}))$$

L1Norm

A Unary layer `kABS` operation followed by a Reduce layer `kSUM` operation can be fused into a single L1Norm reduction operation.

Sum of Squares

A product ElementWise layer with the same input (square operation) followed by a `kSUM` reduction can be fused into a single square Sum reduction operation.

L2Norm

A sum of squares operation followed by a `kSQRT` UnaryOperation can be fused into a single L2Norm reduction operation.

LogSum

A Reduce layer `kSUM` followed by a `kLOG` UnaryOperation can be fused into a single LogSum reduction operation.

LogSumExp

A Unary `kEXP` ElementWise operation followed by a LogSum fusion can be fused into a single LogSumExp reduction.

13.4.5.3. PointWise Fusion

Multiple adjacent PointWise layers can be fused into a single PointWise layer to improve performance.

The following types of PointWise layers are supported, with some limitations:

Activation

Every `ActivationType` is supported.

Constant

Only constant with a single value (size == 1).

ElementWise

Every `ElementWiseOperation` is supported.

PointWise

`PointWise` itself is also a PointWise layer.

Scale

Only support `ScaleMode::kUNIFORM`.

Unary

Every `UnaryOperation` is supported.

The size of the fused PointWise layer is not unlimited, so some layers may not be fused.

Fusion creates a new layer with a name consisting of both fused layers. For example, an ElementWise layer named `add1` is fused with a ReLU Activation layer named `relu1`, creating a new layer named `fusedPointwiseNode(add1, relu1)`.

13.4.5.4. Q/DQ Fusion

For an explanation and suggestions on optimizations of INT8 and FP8 networks containing `QuantizeLinear` and `DequantizeLinear` layers, refer to [Explicit Quantization](#).

13.4.5.5. Multi-Head Attention Fusion

Multi-head attention (MHA) computes $\text{softmax}(Q * K^T / \text{scale} + \text{mask}) * V$ where Q is query embeddings, K is key embeddings, and V is value embeddings. The shape of Q is $[B, N, S_q, H]$, and the shapes of K and V are $[B, N, S_{kv}, H]$ where B is batch size, N is number of attention heads, H is the head/hidden size, S_q and S_{kv} are the sequence lengths of query and key/value respectively.

The following is a list of restrictions for MHA to be fused into a single kernel.

- ▶ SM version must be ≥ 75 .
- ▶ The input types of the two batched matrix multiplications must be FP16, INT8 (refer to the following regarding quantize and dequantize layer placement), or BF16.
- ▶ Head size H must satisfy the constraints $16 \leq H \leq 256$ and $H \% 8 == 0$ for FP16 and BF16.
- ▶ Head size must be 16, 32, or 64, and sequence lengths (S_q, S_{kv}) must be ≤ 512 for INT8.
- ▶ INT8 fused MHA will be generated only if quantized and dequantized layers are placed before the first batched matrix multiplication, after softmax, and after the second batched matrix multiplication.
- ▶ TensorRT may decide not to fuse an MHA graph into a single kernel based on performance evaluation or other constraints.

13.4.6. Limiting Compute Resources

Limiting the number of compute resources available to TensorRT during engine creation is beneficial when the reduced amount better represents the expected conditions during runtime. For example, when the GPU is expected to be performing additional work in parallel to the TensorRT engine or when the engine is expected to be run on a different GPU with fewer resources (note that the recommended approach is to build the engine on the GPU that will be used for inference, but this may not always be feasible).

You can limit the number of available compute resources with the following steps:

1. Start the CUDA MPS control daemon.

```
nvidia-cuda-mps-control -d
```

2. Set the number of computing resources to use with the `CUDA_MPS_ACTIVE_THREAD_PERCENTAGE` environment variable. For example, `export CUDA_MPS_ACTIVE_THREAD_PERCENTAGE=50`.

3. Build the network engine.

4. Stop the CUDA MPS control daemon.

```
echo quit | nvidia-cuda-mps-control
```

The resulting engine is optimized to the reduced number of compute cores (50% in this example) and provides better throughput when using similar conditions during inference. You are encouraged to experiment with different amounts of streams and different MPS values to determine the best performance for your network.

For more details about `nvidia-cuda-mps-control`, refer to the [nvidia-cuda-mps-control](#) documentation and the relevant GPU requirements [here](#).

13.4.7. Deterministic Tactic Selection

TensorRT runs through all the possible tactics in the engine-building phase and selects the fastest ones. Since the selection is based on the tactics' latency measurements, TensorRT may select different tactics across different runs if some have similar latencies. Therefore, different engines built from the same `INetworkDefinition` may behave slightly differently regarding output values and performance. You can inspect the selected tactics of an engine by using the [Engine Inspector](#) or by turning on verbose logging while building the engine.

If deterministic tactic selection is desired, the following lists a few suggestions that may help improve the determinism of tactic selection.

Locking GPU Clock Frequency

By default, the GPU's clock frequency is not locked, meaning that the GPU normally sits at the idle clock frequency and only boosts to the max clock frequency when there are active GPU workloads. However, there is a latency for the clock to be boosted from the idle frequency, and that may cause performance variations while TensorRT is running through the tactics and selecting the best ones, resulting in non-deterministic tactic selections.

Therefore, locking the GPU clock frequency before building a TensorRT engine may improve the determinism of tactic selection. Refer to the [Hardware/Software Environment for Performance Measurements](#) section for more information about how to lock and monitor the GPU clock and the factors that may affect GPU clock frequencies.

Increasing Average Timing Iterations

By default, TensorRT runs each tactic for at least four iterations and takes the average latency. You can increase the number of iterations by calling the `setAvgTimingIterations()` API:

C++

```
builderConfig->setAvgTimingIterations(8);
```

Python

```
Builder_config.avg_timing_iterations = 8
```

Increasing the number of average timing iterations may improve the determinism of tactic selections, but the required engine-building time will become longer.

Using Timing Cache

[Timing Cache](#) records the latencies of each tactic for a specific layer configuration. The tactic latencies are reused if TensorRT encounters another layer with an identical configuration. Therefore, by reusing the same timing cache across multiple engine buildings runs with the same `INetworkDefinition` and builder config, you can make TensorRT select an identical set of tactics in the resulting engines.

Refer to the [Timing Cache](#) section for more information.

13.4.8. Overhead of Shape Change and Optimization Profile Switching

After the `IExecutionContext` switches to a new optimization profile or the shapes of the input bindings change, TensorRT must recompute the tensor shapes throughout the network and recompute the resources needed by some tactics for the new shapes before the next inference can start. That means the first `enqueue()` call after a shape/profile change may be longer than the subsequent `enqueue()` calls.

Optimizing the cost of shape/profile switching is an active development area. However, there are still a few cases where the overhead can influence the performance of the inference applications. For example, some convolution tactics for NVIDIA Volta GPUs or older GPUs have much longer shape/profile switching overhead, even if their inference performance is the best among all the available tactics. In this case, disabling `kEDGE_MASK_CONVOLUTIONS` tactics from tactic sources when building the engine may help reduce the overhead of shape/profile switching.

13.5. Optimizing Layer Performance

The following descriptions detail how you can optimize the listed layers.

Gather Layer

Use an axis of 0 to maximize the performance of a Gather layer. There are no fusions available for a Gather layer.

Reduce Layer

To get the maximum performance out of a Reduce layer, perform the reduction across the last dimensions (tail reduce). This allows optimal memory to read/write patterns through sequential memory locations. If doing common reduction operations, express the reduction in a way that will be fused to a single operation if possible.

RNN Layer

If possible, opt to use the newer RNNv2 interface in preference to the legacy RNN interface. The newer interface supports variable sequence lengths and variable batch sizes, as well as having a more consistent interface. Larger batch sizes are better for maximum performance. In general, sizes that are multiples of 64 achieve the highest performance. Bidirectional RNN mode prevents wavefront propagation because of the added dependency. Therefore, it tends to be slower.

In addition, the newly introduced Loop-based API provides a much more flexible mechanism to use general layers within recurrence without being limited to a small set of predefined RNNv2 interfaces. The `ILoopLayer` recurrence enables a rich set of automatic loop optimizations, including loop fusion, unrolling, and loop-invariant code motion, to name a few. For example, significant performance gains are often obtained when multiple instances of the same `MatrixMultiply` or `FullyConnected` layer are properly combined to maximize machine utilization after loop unrolling along the sequence dimension. This works best if you can avoid a `MatrixMultiply` or `FullyConnected` layer with a recurrent data dependence along the sequence dimension.

Shuffle

Shuffle operations equivalent to identity operations on the underlying data are omitted if the input tensor is only used in the shuffle layer and the input and output tensors of this layer are not input and output tensors of the network. TensorRT does not execute additional kernels or memory copies for such operations.

TopK

To get the maximum performance out of a TopK layer, use small values of κ , reducing the last dimension of data to allow optimal sequential memory access. Reductions along multiple dimensions at once can be simulated using a Shuffle layer to reshape the data and then appropriately reinterpret the index values.

For more information about layers, refer to the [NVIDIA TensorRT Operator's Reference](#).

13.6. Optimizing for Tensor Cores

Tensor Core is a key technology for delivering high-performance inference on NVIDIA GPUs. In TensorRT, Tensor Core operations are supported by all compute-intensive layers: `MatrixMultiply`, `FullyConnected`, `Convolution`, and `Deconvolution`.

Tensor Core layers tend to achieve better performance if the I/O tensor dimensions are aligned to a certain minimum granularity:

- ▶ The alignment requirement is on the I/O channel dimension in the `Convolution` and `Deconvolution` layers.
- ▶ In `MatrixMultiply` and `FullyConnected` layers, the alignment requirement is on matrix dimensions κ and \mathcal{N} in a `MatrixMultiply` that is $\mathcal{M} \times \kappa$ times $\kappa \times \mathcal{N}$.

The following table captures the suggested tensor dimension alignment for better Tensor Core performance.

Table 3. Types of Tensor Cores

| Tensor Core Operation Type | Suggested Tensor Dimension Alignment in Elements |
|----------------------------|--|
| TF32 | 4 |
| FP16 | 8 for dense math, 16 for sparse math |
| INT8 | 32 |

When using Tensor Core implementations in cases where these requirements are unmet, TensorRT implicitly pads the tensors to the nearest multiple of alignment, rounding up the dimensions in the model definition instead to allow for extra capacity in the model without increasing computation or memory traffic.

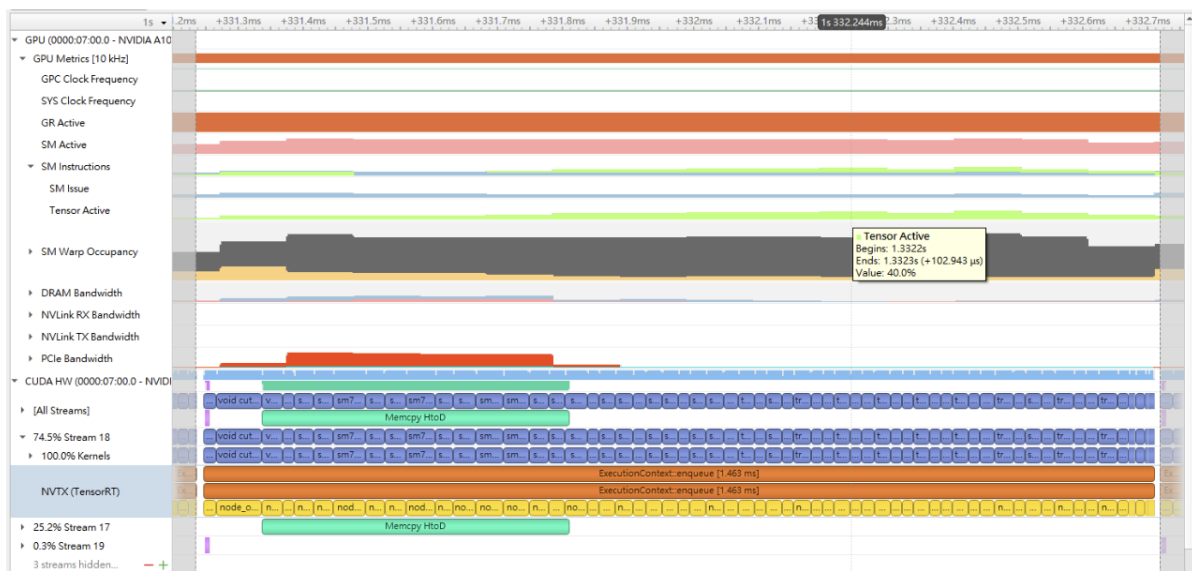
TensorRT always uses the fastest implementation for a layer, and thus, in some cases, it may not use a Tensor Core implementation even if it is available.

To check if Tensor Core is used for a layer, run Nsight Systems with the `--gpu-metrics-device all` flag while profiling the TensorRT application. The Tensor Core usage rate can be found in the profiling result in the Nsight Systems user interface under the SM instructions/Tensor Active row. Refer to the [CUDA Profiling Tools](#) for more information about using Nsight Systems to profile TensorRT applications.

It is impractical to expect a CUDA kernel to reach 100% Tensor Core usage since there are other overheads such as DRAM reads/writes, instruction stalls, other computation units, etc. The more computation-intensive an operation is, the higher the Tensor Core usage rate the CUDA kernel can achieve.

The following image is an example of Nsight Systems profiling.

Figure 23. Tensor Core Activities on an A100 GPU Running ResNet-50 with FP16 Enabled



13.7. Optimizing Plugins

TensorRT provides a mechanism for registering custom plugins that perform layer operations. After a plugin creator is registered, you can search the registry to find the creator and add the corresponding plugin object to the network during serialization/deserialization.

Once the plugin library is loaded, all TensorRT plugins are automatically registered. For more information about custom plugins, refer to [Extending TensorRT with Custom Layers](#).

Plugin performance depends on the CUDA code performing the plugin operation. Standard [CUDA best practices](#) apply. When developing plugins, starting with simple standalone CUDA applications that perform the plugin operation and verify correctness can be helpful. The plugin program can then be extended with performance measurements, more unit testing, and alternate implementations. After the code is working and optimized, it can be integrated as a plugin into TensorRT.

Supporting as many formats as possible in the plugin is important to get the best performance possible. This removes the need for internal reformat operations during the execution of the network. Refer to the [Extending TensorRT with Custom Layers](#) section for examples.

13.8. Optimizing Python Performance

Most of the same performance considerations apply when using the Python API. When building engines, the builder optimization phase will normally be the performance bottleneck, not API calls to construct the network. Inference time should be nearly identical between the Python API and C++ API.

Setting up the input buffers in the Python API involves using `pycuda` or another CUDA Python library, like `cupy`, to transfer the data from the host to device memory. The details of how this works will depend on where the host data comes from. Internally, `pycuda` supports the [Python Buffer Protocol](#), allowing efficient access to memory regions. This means that if the input data is available in a suitable format in `numpy` arrays or another type with support for the buffer protocol, it allows efficient access and transfer to the GPU. For even better performance, allocate a page-locked buffer using `pycuda` and write your final preprocessed input.

For more information about using the Python API, refer to [The Python API](#).

13.9. Improving Model Accuracy

Depending on the builder configuration, TensorRT can execute a layer in FP32, FP16, BF16, FP8, or INT8 precision. By default, TensorRT chooses to run a layer in a precision that results in optimal performance. Sometimes, this can result in poor accuracy. Generally, running a higher-precision layer helps improve accuracy with some performance hits.

There are several steps that we can take to improve model accuracy:

1. Validate layer outputs:
 - a). Use [polygraphy](#) to dump layer outputs and verify no NaNs or Infs. The `--validate` option can check for NaNs and Infs. Also, we can compare layer outputs with golden values from, for example, ONNX runtime.

- b). For FP16 and BF16, a model might require retraining to ensure that intermediate layer output can be represented in FP16/BF16 precision without overflow or underflow.
 - c). For INT8, consider recalibrating with a more representative calibration data set. If your model comes from PyTorch, we also provide [NVIDIA's Quantization Toolkit for PyTorch](#) for QAT in the framework besides PTQ in TensorRT. You can try both approaches and choose the one with more accuracy.
2. Manipulate layer precision:
- a). Sometimes, running a layer with a certain precision results in incorrect output. This can be due to inherent layer constraints (for example, LayerNorm output should not be INT8), model constraints (output gets diverged, resulting in poor accuracy), or reporting a [TensorRT bug](#).
 - b). You can control layer execution precision and output precision.
 - c). An experimental [debug precision](#) tool can help automatically find layers to run with high precision.
3. Use an [Algorithm Selection and Reproducible Builds](#) to disable flaky tactics:
- a). When accuracy changes between build+run to build+run, it might be due to a selection of a bad tactic for a layer.
 - b). Use an algorithm selector to dump tactics from both good and bad runs. Configure the algorithm selector to allow only a subset of tactics (just allow tactics from a good run, and so on).
 - c). You can use [Polygraphy](#) to [automate](#) this process.

Accuracy from run-to-run variation should not change; once the engine is built for a specific GPU, it should result in bit-accurate outputs in multiple runs. If not, file a [TensorRT bug](#).

13.10. Optimizing Builder Performance

The TensorRT builder profiles each layer's available tactics to search for the fastest inference engine plan. The builder time can be long if the model has many layers or complicated topology. The following sections provide options to reduce builder time.

13.10.1. Timing Cache

TensorRT creates a layer-timing cache to reduce builder time and keep the layer-profiling information. The information it contains is specific to the targeted device, CUDA, TensorRT versions, and `BuilderConfig` parameters that can change the layer implementation, such as `BuilderFlag::kTF32` or `BuilderFlag::kREFIT`.

The TensorRT builder skips profiling and reuses the cached result for the repeated layers if other layers have the same IO tensor configuration and layer parameters. If a timing query misses in the cache, the builder times the layer and updates the cache.

The timing cache can be serialized and deserialized. You can load a serialized cache from a buffer using `IBuilderConfig::createTimingCache`:

```
ITimingCache* cache =
  config->createTimingCache(cacheFile.data(), cacheFile.size());
```

Setting the buffer size to 0 creates a new empty timing cache.

You then attach the cache to a builder configuration before building.

```
config->setTimingCache(*cache, false);
```

Due to cache misses, the timing cache can be augmented with more information during the build. After the build, it can be serialized for use with another builder.

```
IHostMemory* serializedCache = cache->serialize();
```

If a builder does not have a timing cache attached, it creates its temporary local cache and destroys it when it is done.

The compilation cache is part of the timing cache, which caches JIT-compiled code and will be serialized as part of the timing cache by default. It can be disabled by setting the `BuilderFlag`.

```
config->setFlag(BuilderFlag::kDISABLE_COMPILATION_CACHE);
```

The cache is incompatible with algorithm selection (refer to the [Algorithm Selection and Reproducible Builds](#) section). It can be disabled by setting the `BuilderFlag`.

```
config->setFlag(BuilderFlag::kDISABLE_TIMING_CACHE);
```



Note: The timing cache supports the most frequently used layer types: Convolution, Deconvolution, Pooling, SoftMax, MatrixMultiply, ElementWise, Shuffle, and tensor memory layout conversion. More layer types will be added in future releases.

13.10.2. Tactic Selection Heuristic

TensorRT allows heuristic-based tactic selection to minimize the builder time in the layer profiling stage. The builder predicts the tactic timing for the given problem size and prunes the tactics that are not likely to be fast before the layer profiling stage. In cases where the prediction is wrong, the engine will not be as performant as when built with a profiling-based builder. This feature can be enabled by setting the `BuilderFlag`.

```
config->setFlag(BuilderFlag::kENABLE_TACTIC_HEURISTIC);
```



Note: The tactic selection heuristic feature is only supported by the NVIDIA Ampere architecture and newer GPUs.

13.11. Builder Optimization Level

Set the optimization level in the builder config to adjust how long TensorRT should spend searching for tactics with potentially better performance. By default, the optimization level is 3. Setting it to a smaller value results in much faster engine building time, but the engine's performance may be worse. On the other hand, setting it to a larger value will increase the engine building time, but the resulting engine may perform better if TensorRT can find better tactics.

For example, to set the optimization level to 0 (the fastest):

C++

```
config->setOptimizationLevel(0);
```

Python

```
config.optimization_level = 0
```

Chapter 14. Troubleshooting

The following sections help answer the most commonly asked questions regarding typical use cases.

14.1. FAQs

This section is to help troubleshoot the problem and answer our most asked questions.

Q: How do I create an optimized engine for several batch sizes?

A: While TensorRT allows an engine optimized for a given batch size to run at any smaller size, the performance for those smaller sizes cannot be as well optimized. To optimize for multiple batch sizes, create optimization profiles at the dimensions assigned to `OptProfilerSelector::kOPT`.

Q: Are calibration tables portable across TensorRT versions?

A: No. Internal implementations are continually optimized and can change between versions. For this reason, calibration tables are not guaranteed to be binary compatible with different versions of TensorRT. Applications must build new INT8 calibration tables when using a new version of TensorRT.

Q: Are engines portable across TensorRT versions?

A: By default, no. Refer to [Version Compatibility](#) for instructions on configuring engines for forward compatibility.

Q: How do I choose the optimal workspace size?

A: Some TensorRT algorithms require additional workspace on the GPU. The method `IBuilderConfig::setMemoryPoolLimit()` controls the maximum amount of workspace that can be allocated and prevents algorithms that require more workspace from being considered by the builder. At runtime, the space is allocated automatically when creating an `IExecutionContext`. The amount allocated is no more than is required, even if the amount set in `IBuilderConfig::setMemoryPoolLimit()` is much higher. Applications should, therefore, allow the TensorRT builder as much workspace as they can afford; at

runtime, TensorRT allocates no more than this and typically less. The workspace size may need to be limited to less than the full device memory size if device memory is needed for other purposes during the engine build.

Q: How do I use TensorRT on multiple GPUs?

A: Each `ICudaEngine` object is bound to a specific GPU when it is instantiated, either by the builder or on deserialization. To select the GPU, use `cudaSetDevice()` before calling the builder or deserializing the engine. Each `IExecutionContext` is bound to the same GPU as the engine from which it was created. When calling `execute()` or `enqueue()`, ensure that the thread is associated with the correct device by calling `cudaSetDevice()` if necessary.

Q: How do I get the version of TensorRT from the library file?

A: There is a symbol in the symbol table named `tensorrt_version_#_#_#_#` which contains the TensorRT version number. One possible way to read this symbol on Linux is to use the `nm` command like in the following example:

```
$ nm -D libnvinfer.so.* | grep tensorrt_version
00000000abcd1234 B tensorrt_version_#_#_#_#
```

Q: What can I do if my network produces the wrong answer?

A: There are several reasons why your network can be generating incorrect answers. Here are some troubleshooting approaches that can help diagnose the problem:

- ▶ Turn on `VERBOSE`-level messages from the log stream and check what TensorRT is reporting.
- ▶ Check that your input preprocessing generates exactly the input format the network requires.
- ▶ If you are using reduced precision, run the network in FP32. If it produces the correct result, lower precision may have an insufficient dynamic range for the network.
- ▶ Try marking intermediate tensors in the network as outputs and verify if they match your expectations.



Note: Marking tensors as outputs can inhibit optimizations and, therefore, can change the results.

You can use [NVIDIA Polygraphy](#) to assist you with debugging and diagnosis.

Q: How do I implement batch normalization in TensorRT?

A: Batch normalization can be implemented using a sequence of `IElementWiseLayer` in TensorRT. More specifically:

```
adjustedScale = scale / sqrt(variance + epsilon)
batchNorm = (input + bias - (adjustedScale * mean)) * adjustedScale
```

Q: Why does my network run slower when using DLA than without DLA?

A: DLA was designed to maximize energy efficiency. Depending on the features supported by DLA and the features supported by the GPU, either implementation can be more performant. Your chosen implementation depends on your latency or throughput requirements and power budget. Since all DLA engines are independent of the GPU and each other, you could also use both implementations to increase the throughput of your network further.

Q: Does TensorRT support INT4 quantization or INT16 quantization?

A: TensorRT supports INT4 quantization for GEMM weight-only quantization. TensorRT does not support INT16 quantization.

Q: When will TensorRT support my network in the UFF parser require layer XYZ?

A: UFF is deprecated. We recommend users switch their workflows to ONNX. The TensorRT ONNX parser is an open-source project.

Q: Can I use multiple TensorRT builders to compile on different targets?

A: TensorRT assumes that all resources for the device it is building on are available for optimization purposes. Concurrent use of multiple TensorRT builders (for example, multiple `trtexec` instances) to compile on different targets (DLA0, DLA1, and GPU) can oversubscribe system resources causing undefined behavior (meaning, inefficient plans, builder failure, or system instability).

Using `trtexec` with the `-saveEngine` argument is recommended to compile for different targets (DLA and GPU) separately and save their plan files. Such plan files can then be reused for loading (using `trtexec` with the `--loadEngine` argument) and submitting multiple inference jobs on the respective targets (DLA0, DLA1, and GPU). This two-step process alleviates over-subscription of system resources during the build phase while also allowing execution of the plan file to proceed without interference by the builder.

Q: Which layers are accelerated by Tensor Cores?

A: Most math-bound operations will be accelerated with tensor cores - convolution, deconvolution, fully connected, and matrix multiply. In some cases, particularly for small channel counts or small group sizes, another implementation may be faster and be selected instead of a tensor core implementation.

Q: Why are reformatting layers observed, although there is no warning message that no implementation obeys reformatting-free rules?

A: Reformat-free network I/O does not mean reformatting layers are not inserted into the entire network. Only that the input and output network tensors can be configured not to require reformatting layers. In other words, TensorRT can insert reformatting layers for internal tensors to improve performance.

14.2. Understanding Error Messages

If an error occurs during execution, TensorRT reports an error message intended to help debug the problem. The following sections discuss some common error messages that developers can encounter.

ONNX Parser Error Messages

The following table captures the common ONNX parser error messages. For specific ONNX node support information, refer to the [Operators' support document](#).

| Error Message | Description |
|---|--|
| <pre><X> must be an initializer! !inputs.at(X).is_weights()</pre> | <p>These error messages signify that an ONNX node input tensor is expected to be an initializer in TensorRT. A possible fix is to run constant folding on the model using TensorRT's Polygraphy tool:</p> <pre>polygraphy surgeon sanitize model.onnx -- fold-constants --output model_folded.onnx</pre> |
| <pre>getPluginCreator() could not find Plugin <operator name> version 1</pre> | <p>This is an error stating that the ONNX parser does not have an import function defined for a particular operator and did not find a corresponding plugin in the loaded registry for the operator.</p> |

TensorRT Core Library Error Messages

The following table captures the common TensorRT core library error messages.

| | Error Message | Description |
|---------------------|--|---|
| Installation Errors | <pre>Cuda initialization failure with error <code>. Please check cuda installation: http://docs.nvidia.com/cuda/cuda-installation-guide-linux/index.html.</pre> | <p>This error can occur if the CUDA or NVIDIA driver installation corrupts. Refer to the URL for instructions</p> |

| | Error Message | Description |
|----------------|--|---|
| | | on installing CUDA and the NVIDIA driver on your OS. |
| Builder Errors | <pre>Internal error: could not find any implementation for node <name>. Try increasing the workspace size with IBuilderConfig::setMemoryPoolLimit().</pre> | <p>This error occurs because there is no layer implementation for the given node in the network that can operate with the given workspace size. This usually occurs because the workspace size is insufficient, but it could also indicate a bug. If increasing the workspace size as suggested does not help, report a bug (refer to Reporting TensorRT Issues).</p> |
| | <pre><layer-name>: (kernel bias) weights has non-zero count but null values <layer-name>: (kernel bias) weights has zero count but non-null values</pre> | <p>This error occurs when a mismatch between the values and count fields in a Weights data structure is passed to the builder. If the count is 0, the values field must contain a null pointer; otherwise, the count must be non-zero, and values must contain a non-null pointer.</p> |
| | <pre>Builder was created on device different from current device.</pre> | <p>This error can show up if you:</p> <ol style="list-style-type: none"> 1. Created an <code>IBuilder</code> targeting one GPU, then 2. Called <code>cudaSetDevice()</code> to target a different GPU, then 3. Attempted to use the <code>IBuilder</code> to create an engine. <p>Ensure you only use the <code>IBuilder</code> when targeting the GPU used to create the <code>IBuilder</code>.</p> |
| | <p>You can encounter error messages indicating that the tensor dimensions do not match the semantics of the given layer.</p> | |

| | Error Message | Description |
|-----------------------------|---|---|
| | Carefully read the documentation on NvInfer.h on the usage of each layer and the expected dimensions of the tensor inputs and outputs to the layer. | |
| INT8 Calibration Errors | <p>Tensor <X> is uniformly zero.</p> | <p>This warning occurs and should be treated as an error when data distribution for a tensor is uniformly zero. In a network, the output tensor distribution can be uniformly zero under the following scenarios:</p> <ol style="list-style-type: none"> 1. Constant tensor with all zero values; not an error. 2. Activation (ReLU) output with all negative inputs; not an error. 3. Data distribution is forced to all zero due to a computation error in the previous layer; emit a warning here.¹ 4. The user does not provide any calibration images; emit a warning here.² |
| | <p>Could not find scales for tensor <X>.</p> | <p>This error indicates that a calibration failure occurred with no scaling factors detected. This could be due to a lack of an INT8 calibrator or insufficient custom scales for network layers.</p> |
| Engine Compatibility Errors | <p>The engine plan file is not compatible with this version of TensorRT, expecting (format library) version <X> got <Y>, please rebuild.</p> | <p>This error can occur if you are running TensorRT using an engine PLAN file that is incompatible with the current version of TensorRT. Ensure you use the same TensorRT</p> |

¹ Evaluating the calibration input or validating the previous layer outputs is recommended.

² Evaluating the calibration input or validating the previous layer outputs is recommended.

| | Error Message | Description |
|-----------------------------|--|--|
| | <p>version when generating and running the engine.</p> <p>The engine plan file is generated on an incompatible device, expecting compute <X> got compute <Y>, please rebuild.</p> <p>Using an engine plan file across different models of devices is not recommended and is likely to affect performance or even cause errors.</p> | <p>This error can occur if you build an engine on a device with a computing capability different from the device used to run the engine.</p> <p>This warning can occur if you build an engine on a device with the same computing capability but not identical to the engine running.</p> <p>As the warning indicates, using a device of the same model is highly recommended when generating the engine and deploying it to avoid compatibility issues.</p> |
| <p>Out Of Memory Errors</p> | <p>GPU memory allocation failed during initialization of (tensor layer): <name> GPU memory</p> <p>Allocation failed during deserialization of weights.</p> <p>GPU does not meet the minimum memory requirements to run this engine ...</p> | <p>These error messages can occur if insufficient GPU memory is available to instantiate a TensorRT engine. Verify that the GPU has sufficient memory to contain the required layer weights and activation tensors.</p> |
| <p>FP16 Errors</p> | <p>Network needs native FP16 and platform does not have native FP16</p> | <p>This error message can occur if you attempt to deserialize an engine that uses FP16 arithmetic on a GPU that does not support FP16 arithmetic. You either must rebuild the engine without FP16 precision inference or upgrade your GPU to a model that supports FP16 precision inference.</p> |
| <p>Plugin Errors</p> | <p>Custom layer <name> returned non-zero initialization</p> | <p>This error can occur if a plugin layer's <code>initialize()</code> method returns a non-zero value. Refer to the implementation of</p> |

| | Error Message | Description |
|--|---------------|---|
| | | that layer to debug this error further. For more information, refer to the NVIDIA TensorRT Operator's Reference . |

14.3. Code Analysis Tools

14.3.1. Compiler Sanitizers

Google sanitizers are a set of [code analysis tools](#).

14.3.1.1. Issues with `dlopen` and Address Sanitizer

There is a known issue with sanitizers, which is [documented here](#). When using `dlopen` on TensorRT under a sanitizer, there will be reports of memory leaks unless one of two solutions is adopted:

1. Do not call `dldclose` when running under the sanitizers.
2. Pass the flag `RTLD_NODELETE` to `dlopen` when running under sanitizers.

14.3.1.2. Issues with `dlopen` and Thread Sanitizer

The thread sanitizer can list errors when using `dlopen` from multiple threads. To suppress this warning, create a file called `tsan.supp` and add the following to the file:

```
race::dlopen
```

When running applications under thread sanitizer, set the environment variable using:

```
export TSAN_OPTIONS="suppressions=tsan.supp"
```

14.3.1.3. Issues with CUDA and Address Sanitizer

The address sanitizer has a known issue with CUDA applications, which is [documented here](#). To successfully run CUDA libraries such as TensorRT under the address sanitizer, add the option `protect_shadow_gap=0` to the `ASAN_OPTIONS` environment variable.

A known bug in CUDA 11.4 can trigger mismatched allocation and free errors in the address sanitizer. To disable these errors, add `alloc_dealloc_mismatch=0` to `ASAN_OPTIONS`.

14.3.1.4. Issues with Undefined Behavior Sanitizer

[UndefinedBehaviorSanitizer \(UBSan\)](#) reports false positives with the `-fvisibility=hidden` option, as [documented here](#). Add the `-fno-sanitize=vptr` option to avoid UBSan reporting such false positives.

14.3.2. Valgrind

[Valgrind](#) is a framework for dynamic analysis tools that can automatically detect memory management and threading bugs in applications.

Some versions of Valgrind and glibc are affected by a [bug](#), which causes false memory leaks to be reported when `dlopen` is used, which can generate spurious errors when running a TensorRT application under Valgrind's `memcheck` tool. To work around this, add the following to a Valgrind suppressions file as [documented here](#):

```
{
  Memory leak errors with dlopen
  Memcheck:Leak
  match-leak-kinds: definite
  ...
  fun:*dlopen*
  ...
}
```

A known bug in CUDA 11.4 can trigger mismatched allocation and free errors in Valgrind. To disable these errors, add the option `--show-mismatched-frees=no` to the Valgrind command line.

14.3.3. Compute Sanitizer

When running a TensorRT application under `compute-sanitizer`, `cuGetProcAddress` can fail with error code 500 due to missing functions. This error can be ignored or suppressed with `--report-api-errors no` option. This is due to CUDA backward compatibility checking if a function is usable on the CUDA toolkit/driver combination. The functions are introduced later in CUDA but unavailable on the current platform.

14.4. Understanding Formats Printed in Logs

In logs from TensorRT, formats are printed as a type followed by stride and vectorization information. For example:

```
Half(60,1:8,12,3)
```

The `Half` indicates that the element type is `DataType::kHALF`, a 16-bit floating point. The `:8` indicates the format packs eight elements per vector and that vectorization is along the second axis. The rest of the numbers are strides in units of vectors. For this tensor, the mapping of a coordinate (n, c, h, w) to an address is:

```
((half*)base_address) + (60*n + 1*floor(c/8) + 12*h + 3*w) * 8 + (c mod 8)
```

The `1:` is common to NHWC formats. For example, here is another example of an NCHW format:

```
Int8(105,15:4,3,1)
```

The `INT8` indicates that the element type is `DataType::kINT8`, and the `:4` indicates a vector size of 4. For this tensor, the mapping of a coordinate (n, c, h, w) to an address is:

```
(int8_t*)base_address + (105*n + 15*floor(c/4) + 3*h + w) * 4 + (c mod 4)
```

Scalar formats have a vector size of 1. For brevity, printing omits the `:1`.

In general, the coordinates to address mappings have the following form:

```
(type*)base_address + (vec_coordinate · strides) * vec_size + vec_mod
```

Where:

- ▶ the dot denotes an inner product
- ▶ strides are the printed strides, that is, strides in units of vectors
- ▶ `vec_size` is the number of elements per vector
- ▶ `vec_coordinate` is the original coordinate with the coordinate along the vectorized axis divided by `vec_size`
- ▶ `vec_mod` is the original coordinate along the vectorized axis modulo `vec_size`

14.5. Reporting TensorRT Issues

If you encounter issues when using TensorRT, confirm that you have followed the instructions in this Developer Guide. Also, check the [FAQs](#) and the [Understanding Error Messages](#) sections to look for similar failing patterns. For example, many engine building failures can be solved by sanitizing and constant-folding the ONNX model using [Polygraphy](#) with the following command:

```
polygraphy surgeon sanitize model.onnx --fold-constants --output
  model_folded.onnx
```

In addition, it is highly recommended that you first try our latest TensorRT release before filing an issue if you have not done so since it may have been fixed in the latest release.

14.5.1. Channels for TensorRT Issue Reporting

If none of the [FAQs](#) or the [error message suggestions](#) work, you can report the issue through the [NVIDIA Developer Forum](#) or the [TensorRT GitHub Issue page](#). These channels are constantly monitored to provide feedback to the issues you encounter.

Here are the steps to report an issue on the NVIDIA Developer Forum:

1. Register for the [NVIDIA Developer website](#).
2. Log in to the developer site.
3. Click on your name in the upper right corner.
4. Click My Account > My Bugs and select Submit a New Bug.
5. Fill out the bug reporting page. Be descriptive and, if possible, provide the steps to reproduce the problem.
6. Click Submit a bug.

When reporting an issue, provide setup details and include the following information:

- ▶ Environment information:
 - ▶ OS or Linux distro and version
 - ▶ GPU type

- ▶ NVIDIA driver version
- ▶ CUDA version
- ▶ cuDNN version
- ▶ Python version (if Python is used).
- ▶ TensorFlow, PyTorch, and ONNX versions (if any of them are used).
- ▶ TensorRT version
- ▶ NGC TensorRT container version (if TensorRT container is used).
- ▶ Jetson (if used), include OS and hardware versions
- ▶ A thorough description of the issue.
- ▶ Steps to reproduce the issue:
 - ▶ ONNX file (if ONNX is used).
 - ▶ Minimal commands or scripts to trigger the issue
 - ▶ Verbose logs by enabling `kVERBOSE` in `ILogger`

Depending on the type of the issue, providing more information listed below can expedite the response and debugging process.

14.5.2. Reporting a Functional Issue

When reporting functional issues, such as linker errors, segmentation faults, engine building failures, inference failures, and so on, provide the scripts and commands to reproduce the issue as well as a detailed description of the environment. Having more details helps us debug the functional issue faster.

Since the TensorRT engine is specific to a specific TensorRT version and a specific GPU type, do not build the engine in one environment and use it to run it in another environment with different GPUs or dependency software stack, such as TensorRT version, CUDA version, cuDNN version, and so on. Also, ensure the application is linked to the correct TensorRT, and cuDNN shared object files by checking the environment variable `LD_LIBRARY_PATH` (or `%PATH%` on Windows).

14.5.3. Reporting an Accuracy Issue

When reporting an accuracy issue, provide the scripts and the commands used to calculate the accuracy metrics. Describe the expected accuracy level and, if possible, share the steps to get the expected results using other frameworks like ONNX-Runtime.

The [Polygraphy](#) tool can debug the accuracy issue and produce a minimal failing case. For instructions, refer to the [Debugging TensorRT Accuracy Issues](#) documentation. Having a Polygraphy command that shows the accuracy issue or having a minimal failing case expedites the time it takes for us to debug your accuracy issue.

Note that it is not practical to expect bitwise identical results between TensorRT and other frameworks like PyTorch, TensorFlow, or ONNX-Runtime even in FP32 precision since the order of the computations on the floating-point numbers can result in

slight differences in output values. In practice, small numeric differences should not significantly affect the accuracy metric of the application, such as the mAP score for object-detection networks or the BLEU score for translation networks. If you see a significant drop in the accuracy metric between TensorRT and other frameworks such as PyTorch, TensorFlow, or ONNX-Runtime, it may be a genuine TensorRT bug.

If you are seeing NaNs or infinite values in TensorRT engine output when FP16/BF16 precision is enabled, it is possible that intermediate layer outputs in the network overflow in FP16/BF16. Some approaches to help mitigate this include:

- ▶ Ensuring that network weights and inputs are restricted to a reasonably narrow range (such as [-1, 1] instead of [-100, 100]). This may require making changes to the network and retraining.
 - ▶ Consider pre-processing input by scaling or clipping it to the restricted range before passing it to the network for inference.
- ▶ Overriding precision for individual layers vulnerable to overflows (for example, Reduce and Element-Wise Power ops) to FP32.

Polygraphy can help you diagnose common problems by using reduced precision. Refer to Polygraphy's [Working with Reduced Precision](#) how-to guide for more details.

For possible solutions to accuracy issues, refer to the [Improving Model Accuracy](#) section and the [Working with Quantized Types](#) section for instructions about using INT8/FP8 precision.

14.5.4. Reporting a Performance Issue

If you are reporting a performance issue, share the full `trtexec` logs using this command:

```
trtexec --onnx=<onnx_file> <precision_and_shape_flags> --verbose --
profilingVerbosity=detailed --dumpLayerInfo --dumpProfile --separateProfileRun --useCudaGraph
--noDataTransfers --useSpinWait --duration=60
```

The verbose logs help us to identify the performance issue. If possible, also share the [Nsight Systems](#) profiling files using these commands:

```
trtexec --onnx=<onnx_file> <precision_and_shape_flags> --verbose --
profilingVerbosity=detailed --dumpLayerInfo --saveEngine=<engine_path>
nsys profile --cuda-graph-trace=node -o <output_profile> trtexec --loadEngine=<engine_path>
<precision_and_shape_flags> --useCudaGraph --noDataTransfers --useSpinWait --warmUp=0 --
duration=0 --iterations=20
```

Refer to the [trtexec](#) section for more instructions to using the `trtexec` tool and the meaning of these flags.

If you do not use `trtexec` to measure performance, provide the scripts and the commands you use to measure the performance. If possible, compare the performance measurement from your script with that from the `trtexec` tool. If the two numbers differ, there may be some issues about the performance measurement methodology in your scripts.

For some environment factors that may affect performance, refer to the [Hardware/Software Environment for Performance Measurements](#) section.

Appendix A. Appendix

A.1. Data Format Descriptions

TensorRT supports different data formats. There are two aspects to consider: data type and layout.

Data Type Format

The data type is the representation of each value. Its size determines the range of values and the precision of the representation, which are:

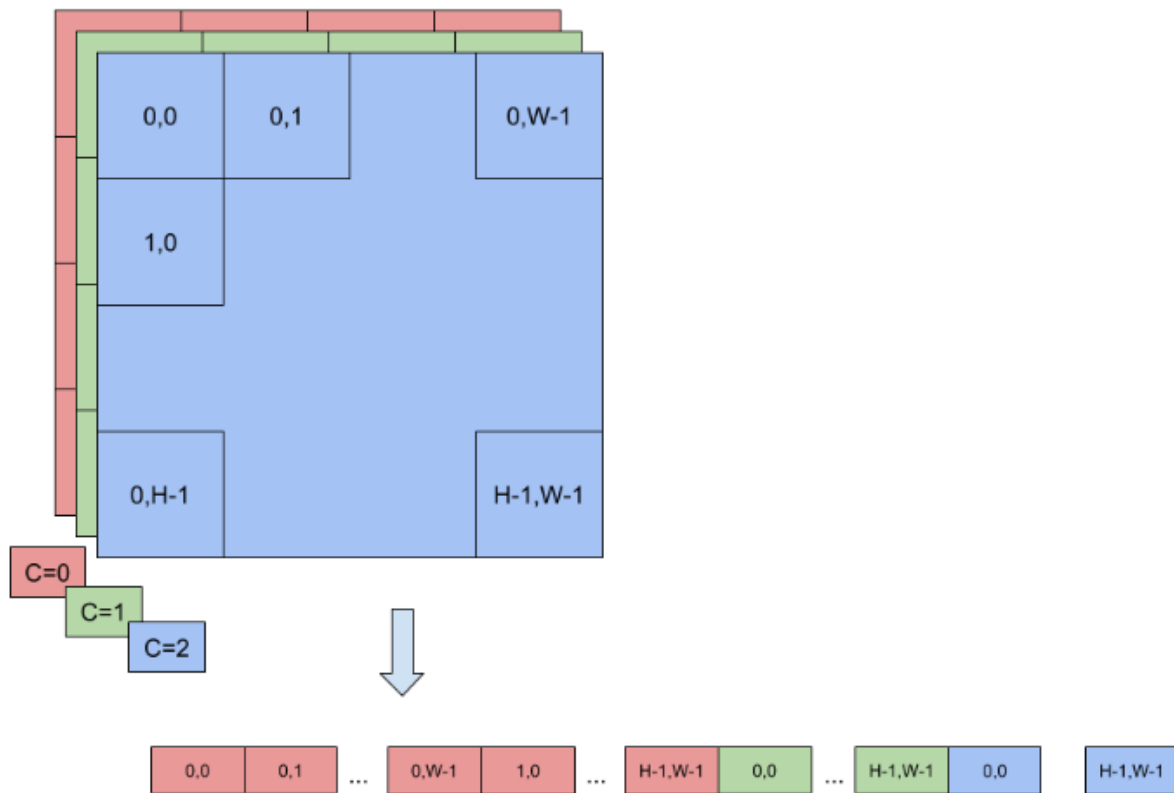
- ▶ FP32 (32-bit floating point or single precision)
- ▶ FP16 (16-bit floating point or half precision)
- ▶ BF16 (1-bit sign, 8-bit exponent, 7-bit mantissa)
- ▶ FP8 (1-bit sign, 4-bit exponent, 3-bit mantissa)
- ▶ INT64 (64-bit integer)
- ▶ INT32 (32-bit integer)
- ▶ INT8 (8-bit integer)
- ▶ UINT8 (unsigned 8-bit integer)
- ▶ INT4 (4-bit integer)

Layout Format

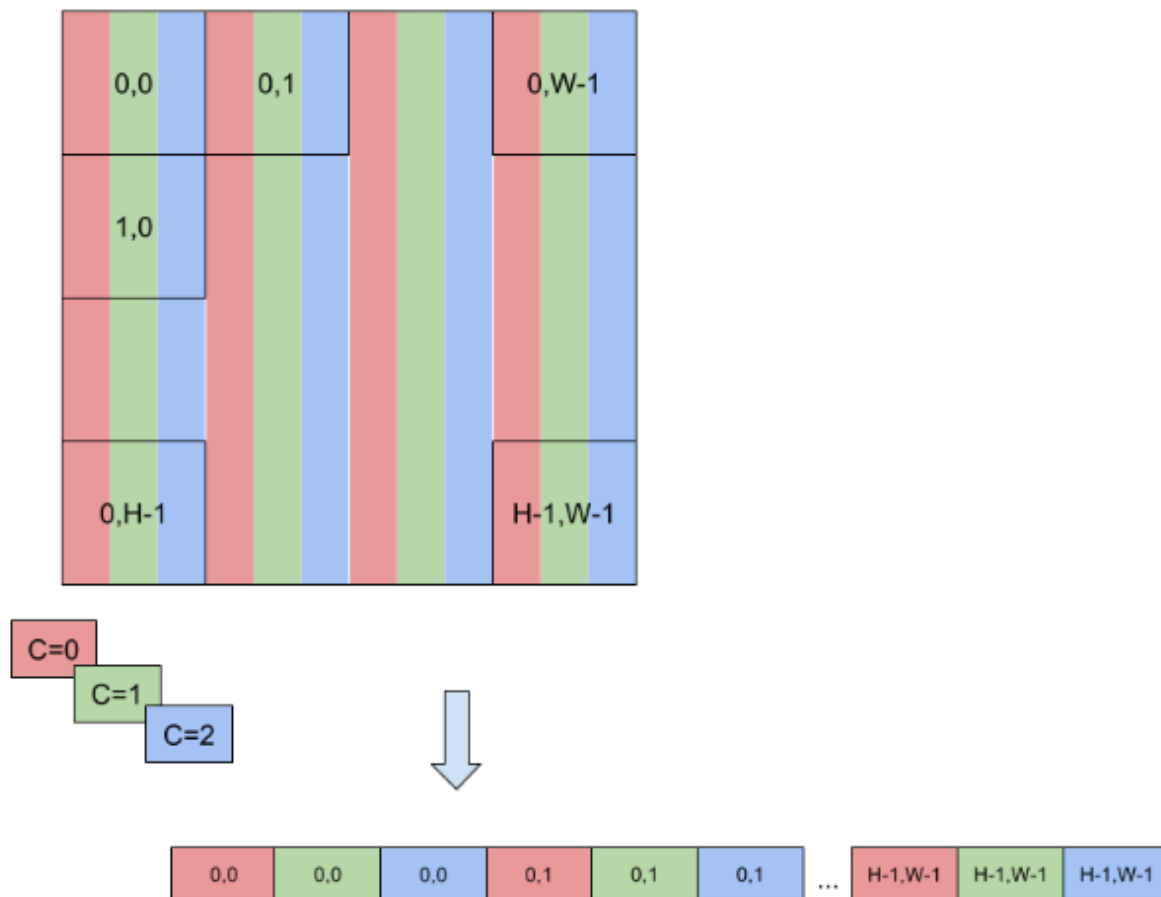
The layout format determines the ordering in which values are stored. Typically, batch dimensions are the leftmost dimensions, and the other dimensions refer to aspects of each data item, such as c is channel, h is height, and w is width in images. Ignoring batch sizes, which always precede these, c , h , and w are typically sorted as CHW (refer to [Figure 24](#)) or HWC (refer to [Figure 25](#)).

The following image is divided into $H \times W$ matrices, one per channel, and the matrices are stored in sequence; all channel values are stored contiguously.

Figure 24. Layout Format for CHW



The image is stored as a single $H \times W$ matrix, whose value is C-tuple, with a value per channel; all the values of a point (pixel) are stored contiguously.

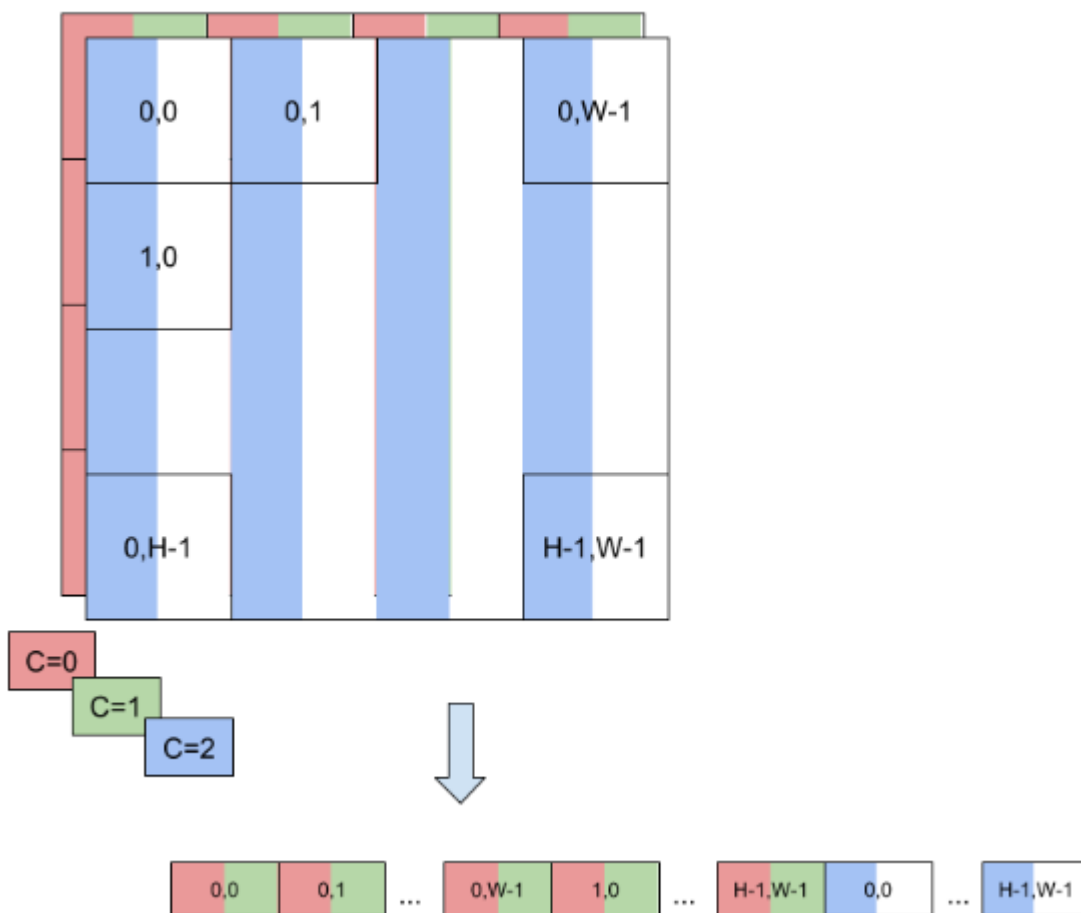
Figure 25. Layout format for HWC 

More formats are defined to pack together channel values and use reduced precision to enable faster computations. For this reason, TensorRT also supports formats like NC , $2HW2$, and $NHWC8$.

In NC , $2HW2$ (`TensorFormat::kCHW2`), pairs of channel values are packed together in each $H \times W$ matrix (with an empty value in the case of an odd number of channels). The result is a format in which the values of $\#C/2\#$ $H \times W$ matrices are pairs of values of two consecutive channels (refer to [Figure 26](#)); notice that this ordering interleaves dimension as values of channels that have stride 1 if they are in the same pair and stride $2 \times H \times W$ otherwise.

A pair of channel values is packed together in each $H \times W$ matrix. The result is a format in which the values of $\#C/2\#$ $H \times W$ matrices are pairs of values of two consecutive channels.

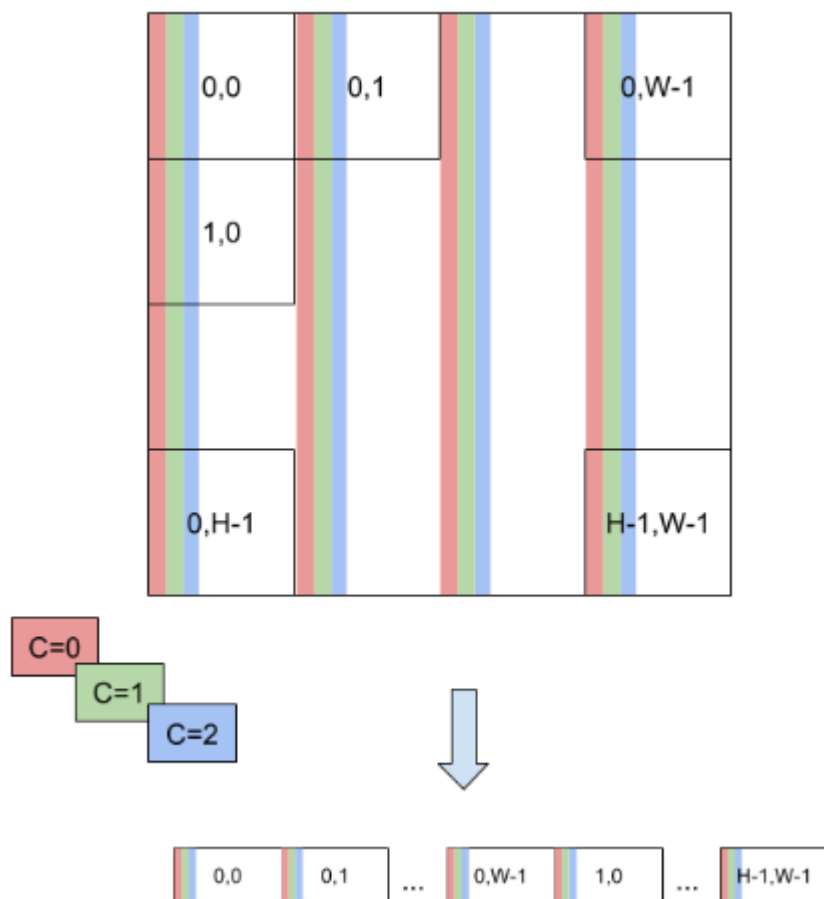
Figure 26. Values of $\#C/2\#$ $H \times W$ Matrices are Pairs of Values of Two Consecutive Channels



In NHWC8 (TensorFormat::kHWC8), the entries of an $H \times W$ matrix include the values of all the channels (refer to [Figure 27](#)). In addition, these values are packed together in $\#C/8\#$ 8-tuples, and c is rounded up to the nearest multiple of 8.

In this NHWC8 format, the entries of an $H \times W$ matrix include the values of all the channels.

Figure 27. In `NHWC8` Format, the Entries of an $H \times W$ Matrix Include the Values of all the Channels



Other `TensorFormat` follows similar rules to `TensorFormat::kCHW2` and `TensorFormat::kHWC8` mentioned previously.

A.2. Command-Line Programs

A.2.1. `trtexec`

Included in the `samples` directory is a command-line wrapper tool called `trtexec`. `trtexec` is a tool to quickly utilize TensorRT without having to develop your own application. The `trtexec` tool has three main purposes:

- ▶ It is useful for *benchmarking networks* on random or user-provided input data.
- ▶ It is useful for *generating serialized engines* from models.
- ▶ It is useful for *generating a serialized timing cache* from the builder.

A.2.1.1. Benchmarking Network

If you have a model saved as an ONNX file, you can use the `trtexec` tool to test the performance of running inference on your network using TensorRT. The `trtexec` tool has many options for specifying inputs and outputs, iterations for performance timing, precision allowed, and other options.

To maximize GPU utilization, `trtexec` enqueues the inferences one batch ahead of time. In other words, it does the following:

```
enqueue batch 0 -> enqueue batch 1 -> wait until batch 0 is done -> enqueue batch 2 -> wait
until batch 1 is done -> enqueue batch 3 -> wait until batch 2 is done -> enqueue batch 4 -
> ...
```

If [cross-inference multi-stream](#) (`--infStreams=N` flag) is used, then `trtexec` follows this pattern on each stream separately.

The `trtexec` tool prints the following performance metrics. The following figure shows an example of an Nsight System profile of a `trtexec` run with markers showing each performance metric.

Throughput

The observed throughput is computed by dividing the number of inferences by the Total Host Walltime. If this is significantly lower than the reciprocal of GPU Compute Time, the GPU may be underutilized because of host-side overheads or data transfers. CUDA graphs (with `--useCudaGraph`) or disabling H2D/D2H transfers (with `--noDataTransfer`) may improve GPU utilization. The output log guides which flag to use when `trtexec` detects that the GPU is underutilized.

Host Latency

The summation of H2D Latency, GPU Compute Time, and D2H Latency. This is the latency to infer a single inference.

Enqueue Time

The host latency to enqueue an inference, including calling H2D/D2H CUDA APIs, running host-side heuristics, and launching CUDA kernels. If this is longer than the GPU Compute Time, the GPU may be underutilized, and the throughput may be dominated by host-side overhead. Using CUDA graphs (with `--useCudaGraph`) may reduce Enqueue Time.

H2D Latency

The latency for host-to-device data transfers for input tensors of a single inference. Add `--noDataTransfer` to disable H2D/D2H data transfers.

D2H Latency

The latency for device-to-host data transfers for output tensors of a single inference. Add `--noDataTransfer` to disable H2D/D2H data transfers.

GPU Compute Time

The GPU latency to execute the CUDA kernels for an inference.

Total Host Walltime

The Host Walltime from when the first inference (after warm-ups) is enqueued to when the last inference was completed.

Total GPU Compute Time

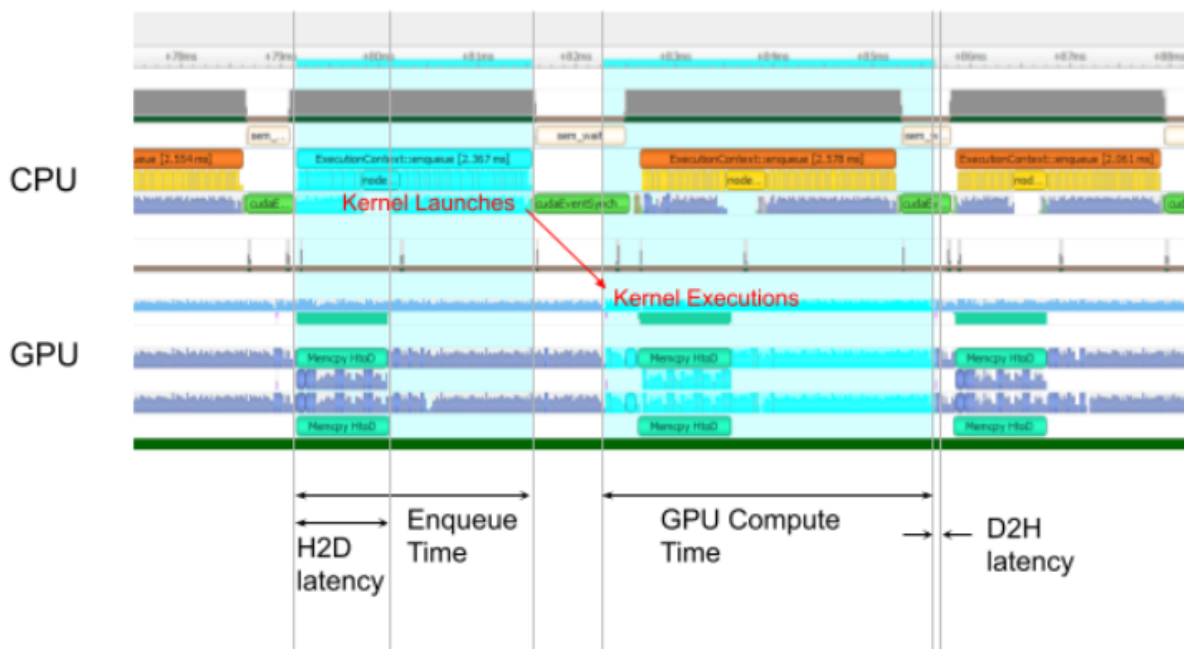
The summation of the GPU Compute Time of all the inferences. If this is significantly shorter than the Total Host Walltime, the GPU may be under-utilized because of host-side overheads or data transfers.

Performance metrics in a normal `trtexec` run under Nsight Systems (ShuffleNet, BS=16, best, TitanRTX at 1200 MHz).



Note: In the latest Nsight Systems, the GPU rows appear above the CPU rows rather than beneath them.

Figure 28. Performance Metrics in a Normal `trtexec` Run under Nsight Systems



$$\text{Host latency} = (\text{H2D latency}) + (\text{GPU Compute latency}) + (\text{D2H latency})$$

$$\text{Throughput} = (\text{Total host wall time for N queries}) / N$$

Add the `--dumpProfile` flag to `trtexec` to show per-layer performance profiles, which allows users to understand which layers in the network take the most time in GPU execution. The per-layer performance profiling also works with launching inference as a CUDA graph. In addition, build the engine with the `--profilingVerbosity=detailed` flag and add the `--dumpLayerInfo` flag to show detailed engine information, including per-layer detail and binding information. This allows you to understand which operation each layer in the engine corresponds to and their parameters.

A.2.1.2. Serialized Engine Generation

If you generate a saved serialized engine file, you can pull it into another inference application. For example, you can use the [NVIDIA Triton Inference Server](#) to run the engine with multiple execution contexts from multiple threads in a fully pipelined asynchronous way to test parallel inference performance. There are some caveats; for

example, in INT8 mode, `trtexec` sets random dynamic ranges for tensors unless the calibration cache file is provided with the `--calib=<file>` flag, so the resulting accuracy will not be as expected.

A.2.1.3. Serialized Timing Cache Generation

If you provide a timing cache file to the `--timingCacheFile` option, the builder can load existing profiling data from it and add new profiling data entries during layer profiling. The timing cache file can be reused in other builder instances to improve the builder execution time. This cache is suggested to be reused only in the same hardware/software configurations (for example, CUDA/cuDNN/TensorRT versions, device model, and clock frequency); otherwise, functional or performance issues may occur.

A.2.1.4. Commonly Used Command-line Flags

The section lists the commonly used `trtexec` command-line flags.

Flags for the Build Phase

- ▶ `--onnx=<model>`: Specify the input ONNX model.
- ▶ If the input model is in ONNX format, use the `--minShapes`, `--optShapes`, and `--maxShapes` flags to control the range of input shapes, including batch size.
- ▶ `--minShapes=<shapes>`, `--optShapes=<shapes>`, and `--maxShapes=<shapes>`: Specify the range of the input shapes to build the engine with. Only required if the input model is in ONNX format.
- ▶ `--memPoolSize=<pool_spec>`: Specify the maximum size of the workspace that tactics are allowed to use, and the sizes of the memory pools that DLA will allocate per loadable. Supported pool types include `workspace`, `dlaSRAM`, `dlaLocalDRAM`, `dlaGlobalDRAM`, and `tacticSharedMem`.
- ▶ `--saveEngine=<file>`: Specify the path to save the engine.
- ▶ `--fp16`, `--bf16`, `--int8`, `--fp8`, `--noTF32`, and `--best`: Specify network-level precision.
- ▶ `--stronglyTyped`: Create a strongly typed network.
- ▶ `--sparsity=[disable|enable|force]`: Specify whether to use tactics that support structured sparsity.
 - ▶ `disable`: Disable all tactics using structured sparsity. This is the default.
 - ▶ `enable`: Enable tactics using structured sparsity. Tactics will only be used if the ONNX file weights meet the structured sparsity requirements.
 - ▶ `force`: Enable tactics using structured sparsity and allow `trtexec` to overwrite the weights in the ONNX file to enforce them to have structured sparsity.

patterns. Note that the accuracy is not preserved, so this is only to get inference performance.



Note: This has been deprecated. Use [Polygraphy](#) (`polygraphy surgeon prune`) to rewrite the weights of ONNX models to a structured-sparsity pattern and then run with `--sparsity=enable`.

- ▶ `--timingCacheFile=<file>`: Specify the timing cache to load from and save to.
- ▶ `--noCompilationCache`: Disable the compilation cache in the builder, which is part of the timing cache (the default is to enable the compilation cache).
- ▶ `--verbose`: Turn on verbose logging.
- ▶ `--skipInference`: Build and save the engine without running inference.
- ▶ `--profilingVerbosity=[layer_names_only|detailed|none]`: Specify the profiling verbosity to build the engine.
- ▶ `--dumpLayerInfo, --exportLayerInfo=<file>`: Print/Save the layer information of the engine.
- ▶ `--precisionConstraints=spec`: Control precision constraint setting.
 - ▶ `none`: No constraints.
 - ▶ `prefer`: Meet precision constraints set by `--layerPrecisions/--layerOutputTypes` if possible.
 - ▶ `obey`: Meet precision constraints set by `--layerPrecisions/--layerOutputTypes` or fail otherwise.
- ▶ `--layerPrecisions=spec`: Control per-layer precision constraints. Effective only when `precisionConstraints` are set to `obey` or `prefer`. The specs are read left to right and later override earlier ones. "*" can be used as a `layerName` to specify the default precision for all the unspecified layers.
 - ▶ For example: `--layerPrecisions=*:fp16, layer_1:fp32` sets the precision of all layers to FP16 except for `layer_1`, which will be set to FP32.
- ▶ `--layerOutputTypes=spec`: Control per-layer output type constraints. Effective only when `precisionConstraints` are set to `obey` or `prefer`. The specs are read left to right and later override earlier ones. "*" can be used as a `layerName` to specify the default precision for all the unspecified layers. If a layer has more than one output, then multiple types separated by "+" can be provided for this layer.
 - ▶ For example: `--layerOutputTypes=*:fp16, layer_1:fp32+fp16` sets the precision of all layer outputs to FP16 except for `layer_1`, whose first output will be set to FP32 and whose second output will be set to FP16.
- ▶ `--layerDeviceTypes=spec`: Explicitly set per-layer device type to GPU or DLA. The specs are read left to right and later override earlier ones.
- ▶ `--useDLACore=N`: Use the specified DLA core for layers that support DLA.
- ▶ `--allowGPUFallback`: Allow layers unsupported on DLA to run on GPU instead.

- ▶ `--versionCompatible`, `--vc`: Enable version-compatible mode for engine build and inference. Any engine built with this flag enabled is compatible with newer versions of TensorRT on the same host OS when run with TensorRT's dispatch and lean runtimes. Only supported with explicit batch mode.
- ▶ `--excludeLeanRuntime`: When `--versionCompatible` is enabled, this flag indicates that the generated engine should not include an embedded lean runtime. If this is set, you must explicitly specify a valid lean runtime when loading the engine. Only supported with explicit batch and weights within the engine.
- ▶ `--tempdir=<dir>`: Overrides the default temporary directory TensorRT will use when creating temporary files. Refer to the `IRuntime::setTemporaryDirectory` API documentation for more information.
- ▶ `--tempfileControls=controls`: Controls what TensorRT can use when creating temporary executable files. It should be a comma-separated list with entries in the format `[in_memory|temporary]:[allow|deny]`.
 - ▶ Options include:
 - ▶ `in_memory`: Controls whether TensorRT can create temporary in-memory executable files.
 - ▶ `temporary`: Controls whether TensorRT can create temporary executable files in the filesystem (in the directory given by `--tempdir`).
 - ▶ Example usage: `--tempfileControls=in_memory:allow,temporary:deny`
- ▶ `--dynamicPlugins=<file>`: Load the plugin library dynamically and serialize it with the engine when included in `--setPluginsToSerialize` (can be specified multiple times).
- ▶ `--setPluginsToSerialize=<file>`: Set the plugin library to be serialized with the engine (can be specified multiple times).
- ▶ `--builderOptimizationLevel=N`: Set the builder optimization level to build the engine with. A higher level allows TensorRT to spend more building time for more optimization options.
- ▶ `--maxAuxStreams=N`: Set the maximum number of auxiliary streams per inference stream that TensorRT can use to run kernels in parallel if the network contains ops that can run in parallel, with the cost of more memory usage. Set this to 0 for optimal memory usage. Refer to the [Within-Inference Multi-Streaming](#) section for more information.
- ▶ `--stripWeights`: Strip weights from the plan. This flag works with either `refit` or `refit` with identical weights. It defaults to `refit` with identical weights; however, you can switch to `refit` by enabling both `stripWeights` and `refit` simultaneously.
- ▶ `--markDebug`: Specify a list of tensor names to be marked as debug tensors. Separate names with a comma.
- ▶ `--allowWeightStreaming`: Enables an engine that can stream its weights. Must be specified with `--stronglyTyped`. TensorRT will automatically choose the appropriate

weight streaming budget at runtime to ensure model execution. A specific amount can be set with `--weightStreamingBudget`.

Flags for the Inference Phase

- ▶ `--loadEngine=<file>`: Load the engine from a serialized plan file instead of building it from the input ONNX model.
- ▶ If the input model is in ONNX format or the engine is built with explicit batch dimension, use `--shapes` instead.
- ▶ `--shapes=<shapes>`: Specify the input shapes to run the inference with.
- ▶ `--loadInputs=<specs>`: Load input values from files. The default is to generate random inputs.
- ▶ `--warmUp=<duration in ms>`, `--duration=<duration in seconds>`, `--iterations=<N>`: Specify the minimum duration of the warm-up runs, the minimum duration for the inference runs, and the minimum iterations of the inference runs. For example, setting `--warmUp=0 --duration=0 --iterations=N` allows you to control exactly how many iterations to run the inference for.
- ▶ `--useCudaGraph`: Capture the inference to a CUDA graph and run inference by launching the graph. This argument may be ignored when the built TensorRT engine contains operations not permitted under CUDA graph capture mode.
- ▶ `--noDataTransfers`: Turn off host to device and device-to-host data transfers.
- ▶ `--useSpinWait`: Actively synchronize on GPU events. This option makes latency measurement more stable but increases CPU usage and power.
- ▶ `--infStreams=<N>`: Run inference with multiple cross-inference streams in parallel. Refer to the [Cross-Inference Multi-Streaming](#) section for more information.
- ▶ `--verbose`: Turn on verbose logging.
- ▶ `--dumpProfile`, `--exportProfile=<file>`: Print/Save the per-layer performance profile.
- ▶ `--dumpLayerInfo`, `--exportLayerInfo=<file>`: Print layer information of the engine.
- ▶ `--profilingVerbosity=[layer_names_only|detailed|none]`: Specify the profiling verbosity to run the inference.
- ▶ `--useRuntime=[full|lean|dispatch]`: TensorRT runtime to execute engine. `lean` and `dispatch` require `--versionCompatible` to be enabled and are used to load a VC engine. All engines (VC or not) must be built with full runtime.
- ▶ `--leanDLLPath=<file>`: External lean runtime DLL to use in version-compatible mode. Requires `--useRuntime=[lean|dispatch]`.
- ▶ `--dynamicPlugins=<file>`: Load the plugin library dynamically when the library is not included in the engine plan file (can be specified multiple times).

- ▶ `--getPlanVersionOnly`: Print the TensorRT version when the loaded plan is created. Works without deserialization of the plan. Use together with `--loadEngine`. Supported only for engines created with 8.6 and later.
- ▶ `--saveDebugTensors`: Specify a list of tensor names to turn on the debug state and a filename to save raw outputs. These tensors must be specified as debug tensors during build time.
- ▶ `--allocationStrategy`: Specify how the internal device memory for inference is allocated. You can choose from `static`, `profile`, and `runtime`. The first option is the default behavior that pre-allocates enough size for all profiles and input shapes. The second option enables `trtexec` to allocate only what's required for the profile to use. The third option enables `trtexec` to allocate only what's required for the actual input shapes.
- ▶ `--weightStreamingBudget`: Manually set the weight streaming budget. Base-2 unit suffixes are supported: B (Bytes), G (Gibibytes), K (Kibibytes), and M (Mebibytes). If the weights don't fit on the device, a value of 0 will choose the minimum possible budget. A value of -1 will disable weight streaming at runtime.

Refer to `trtexec --help` with all the supported flags and detailed explanations.

Refer to the [GitHub: trtexec/README.md](#) file for detailed information about building this tool and examples of its usage.

A.3. Glossary

Data-Dependent Shape

A tensor shape with a dynamic dimension not calculated solely from network input dimensions and shape tensors.

Device

A specific GPU. Two GPUs are considered identical devices if they have the same model name and configuration.

Explicitly Data-Dependent Shape

A tensor shape that depends on the dimensions of an output of `INonZeroLayer` or `INMSLayer`.

Implicitly Data-Dependent Shape

A tensor shape with a dynamic dimension calculated from data other than network input dimensions, network input shape tensors, and `INonZeroLayer` or `INMSLayer`. For example, a shape with a dimension calculated from data output by a convolution.

Platform

A combination of architecture and operating system. Examples of these platforms are Linux on x86 and QNX Standard on Aarch64. Platforms with different architectures or different operating systems are considered different platforms.

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RESNET-50 Caffe models

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