TENSORRT SAMPLES

SWE-SWDOCTR-001-SAMG_vTensorRT 6.0.1 | September 2019

Support Guide
TABLE OF CONTENTS

Chapter 1. Introduction.........................................................................................1
  1.1. C++ Samples............................................................................................... 4
  1.2. Python Samples........................................................................................... 5
Chapter 2. Application Areas............................................................................... 7
Chapter 3. Cross Compiling Samples For AArch64 Users........................................... 10
  3.1. Prerequisites..............................................................................................10
  3.2. Building Samples For QNX AArch64............................................................. 11
  3.3. Building Samples For Linux AArch64............................................................ 11
  3.4. Building Samples For Android AArch64......................................................... 11
Chapter 4. “Hello World” For TensorRT..............................................................13
Chapter 5. Building A Simple MNIST Network Layer By Layer................................14
Chapter 6. Importing The TensorFlow Model And Running Inference......................15
Chapter 7. “Hello World” For TensorRT From ONNX...........................................16
Chapter 8. Building And Running GoogleNet In TensorRT......................................17
Chapter 9. Building An RNN Network Layer By Layer...........................................18
Chapter 10. Performing Inference In INT8 Using Custom Calibration......................19
Chapter 11. Performing Inference In INT8 Precision.............................................20
Chapter 12. Adding A Custom Layer To Your Network In TensorRT..........................21
Chapter 13. Object Detection With Faster R-CNN................................................22
Chapter 15. Movie Recommendation Using Neural Collaborative Filter (NCF).............24
Chapter 16. Movie Recommendation Using MPS (Multi-Process Service)....................25
Chapter 17. Object Detection With SSD..............................................................26
Chapter 18. “Hello World” For Multilayer Perceptron (MLP).......................................27
Chapter 19. Specifying I/O Formats Using The Reformat Free I/O APIs......................28
Chapter 20. Adding A Custom Layer That Supports INT8 I/O To Your Network In TensorRT...29
Chapter 21. Using The NvMedia API To Run A TensorRT Engine..............................30
Chapter 22. Digit Recognition With Dynamic Shapes In TensorRT...........................31
Chapter 23. Neural Machine Translation (NMT) Using A Sequence To Sequence (seq2seq) Model.................................................................................................................32
Chapter 24. Object Detection And Instance Segmentations With A TensorFlow Mask R-CNN Network.................................................................................................................33
Chapter 26. Introduction To Importing Caffe, TensorFlow And ONNX Models Into TensorRT Using Python.................................................................................................................37
Chapter 27. “Hello World” For TensorRT Using TensorFlow And Python....................38
Chapter 28. “Hello World” For TensorRT Using PyTorch And Python.........................39
Chapter 29. Adding A Custom Layer To Your Caffe Network In TensorRT In Python........40
Chapter 30. Adding A Custom Layer To Your TensorFlow Network In TensorRT In Python....41
Chapter 31. Object Detection With The ONNX TensorRT Backend In Python.................42
Chapter 1.
INTRODUCTION

The following samples show how to use TensorRT in numerous use cases while highlighting different capabilities of the interface.

<table>
<thead>
<tr>
<th>Title</th>
<th>TensorRT Sample Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>trtexec</td>
<td>giexec</td>
<td>A tool to quickly utilize TensorRT without having to develop your own application.</td>
</tr>
<tr>
<td>“Hello World” For TensorRT</td>
<td>sampleMNIST</td>
<td>Performs the basic setup and initialization of TensorRT using the Caffe parser.</td>
</tr>
<tr>
<td>Building A Simple MNIST Network Layer By Layer</td>
<td>sampleMNISTAPI</td>
<td>Uses the TensorRT API to build an MNIST (handwritten digit recognition) layer by layer, sets up weights and inputs/outputs and then performs inference.</td>
</tr>
<tr>
<td>Importing The TensorFlow Model And Running Inference</td>
<td>sampleUffMNIST</td>
<td>Imports a TensorFlow model trained on the MNIST dataset.</td>
</tr>
<tr>
<td>“Hello World” For TensorRT From ONNX</td>
<td>sampleOnnxMNIST</td>
<td>Converts a model trained on the MNIST dataset in ONNX format to a TensorRT network.</td>
</tr>
<tr>
<td>Building And Running GoogleNet In TensorRT</td>
<td>sampleGoogleNet</td>
<td>Shows how to import a model trained with Caffe into TensorRT using GoogleNet as an example.</td>
</tr>
<tr>
<td>Building An RNN Network Layer By Layer</td>
<td>sampleCharRNN</td>
<td>Uses the TensorRT API to build an RNN network layer by layer, sets up weights and inputs/outputs and then performs inference.</td>
</tr>
<tr>
<td>Performing Inference In INT8 Using Custom Calibration</td>
<td>sampleINT8</td>
<td>Performs INT8 calibration and inference. Calibrates a network for execution in INT8.</td>
</tr>
<tr>
<td>Performing Inference In INT8 Precision</td>
<td>sampleINT8API</td>
<td>Sets per tensor dynamic range and computation precision of a layer.</td>
</tr>
<tr>
<td>Title</td>
<td>TensorRT Sample Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------------------------------------------------------------</td>
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<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Adding A Custom Layer To Your Network In TensorRT</td>
<td>samplePlugin</td>
<td>Defines a custom layer that supports multiple data formats that can be serialized and deserialized. Enables a custom layer in NvCaffeParser.</td>
</tr>
<tr>
<td>Object Detection With Faster R-CNN</td>
<td>sampleFasterRCNN</td>
<td>Uses TensorRT plugins, performs inference, and implements a fused custom layer for end-to-end inferencing of a Faster R-CNN model.</td>
</tr>
<tr>
<td>Object Detection With A TensorFlow SSD Network</td>
<td>sampleUffSSD</td>
<td>Preprocess the TensorFlow SSD network, performs inference on the SSD network in TensorRT, and uses TensorRT plugins to speed up inference.</td>
</tr>
<tr>
<td>Movie Recommendation Using Neural Collaborative Filter (NCF)</td>
<td>sampleMovieLens</td>
<td>An end-to-end sample that imports a trained TensorFlow model and predicts the highest rated movie for each user.</td>
</tr>
<tr>
<td>Movie Recommendation Using MPS (Multi-Process Service)</td>
<td>sampleMovieLensMPS</td>
<td>An end-to-end sample that imports a trained TensorFlow model and predicts the highest rated movie for each user using MPS (Multi-Process Service).</td>
</tr>
<tr>
<td>Object Detection With SSD</td>
<td>sampleSSD</td>
<td>Preprocess the input to the SSD network, performs inference on the SSD network in TensorRT, uses TensorRT plugins to speed up inference, and performs INT8 calibration on an SSD network.</td>
</tr>
<tr>
<td>“Hello World” For Multilayer Perceptron (MLP)</td>
<td>sampleMLP</td>
<td>Shows how to create a network that triggers the multi-layer perceptron (MLP) optimizer.</td>
</tr>
<tr>
<td>Specifying I/O Formats Using The Reformat Free I/O APIs</td>
<td>sampleReformatFreeIO</td>
<td>Uses a Caffe model that was trained on the MNIST dataset and performs engine building and inference using TensorRT. The correctness of outputs is then compared to the golden reference.</td>
</tr>
<tr>
<td>Adding A Custom Layer That Supports INT8 I/O To Your Network In TensorRT</td>
<td>sampleUffPluginV2Ext</td>
<td>Demonstrates how to extend INT8 I/O for a plugin that is introduced in TensorRT 6.x.x.</td>
</tr>
<tr>
<td>Using The NvMedia API To Run A TensorRT Engine</td>
<td>sampleNvmedia</td>
<td>Demonstrates how to use an API to construct a network of a single ElementWise layer and builds the engine. The engine runs in DLA safe mode using Nvmedia runtime.</td>
</tr>
<tr>
<td>Digit Recognition With Dynamic Shapes In TensorRT</td>
<td>sampleDynamicReshape</td>
<td>Demonstrates how to use dynamic input dimensions in TensorRT.</td>
</tr>
<tr>
<td>Title</td>
<td>TensorRT Sample Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------------------------------------------------------------</td>
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<td>------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>TensorRT by creating an engine for resizing dynamically shaped inputs to the correct size for an ONNX MNIST model.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neural Machine Translation (NMT) Using A Sequence To Sequence (seq2seq) Model</td>
<td>sampleNMT</td>
<td>Demonstrates the implementation of Neural Machine Translation (NMT) based on a TensorFlow seq2seq model using the TensorRT API.</td>
</tr>
<tr>
<td>Object Detection And Instance Segmentations With A TensorFlow Mask R-CNN Network</td>
<td>sampleUffMaskRCNN</td>
<td>Performs inference on the Mask R-CNN network in TensorRT. Mask R-CNN is based on the Mask R-CNN paper which performs the task of object detection and object mask predictions on a target image.</td>
</tr>
<tr>
<td>Object Detection With A TensorFlow Faster R-CNN Network</td>
<td>sampleUffFasterRCNN</td>
<td>Serves as a demo of how to use pretrained Faster-R-CNN model in Transfer Learning Toolkit to do inference with TensorRT.</td>
</tr>
<tr>
<td>Introduction To Importing Caffe, TensorFlow And ONNX Models Into TensorRT Using Python</td>
<td>introductoryParser_samples</td>
<td>Uses TensorRT and its included suite of parsers (the UFF, Caffe and ONNX parsers), to perform inference with ResNet-50 models trained with various different frameworks.</td>
</tr>
<tr>
<td>“Hello World” For TensorRT Using TensorFlow And Python</td>
<td>end_to_end_tensorflow_mnist</td>
<td>An end-to-end sample that trains a model in TensorFlow and Keras, freezes the model and writes it to a protobuf file, converts it to UFF, and finally runs inference using TensorRT.</td>
</tr>
<tr>
<td>“Hello World” For TensorRT Using PyTorch And Python</td>
<td>network_api_pytorch_mnist</td>
<td>An end-to-end sample that trains a model in PyTorch, recreates the network in TensorRT, imports weights from the trained model, and finally runs inference with a TensorRT engine.</td>
</tr>
<tr>
<td>Adding A Custom Layer To Your Caffe Network In TensorRT In Python</td>
<td>fc_plugin_caffe_mnist</td>
<td>Implements a FullyConnected layer using cuBLAS and cuDNN, wraps the implementation in a TensorRT plugin (with a corresponding plugin factory), and generates Python bindings for it using pybind11. These bindings are then used to register the plugin factory with the CaffeParser.</td>
</tr>
<tr>
<td>Adding A Custom Layer To Your TensorFlow Network In TensorRT In Python</td>
<td>uff_custom_plugin</td>
<td>Implements a clip layer (as a CUDA kernel), wraps the implementation in a TensorRT plugin (with a corresponding</td>
</tr>
</tbody>
</table>

www.nvidia.com
TensorRT Samples

SWE-SWDOCTRRT-001-SAMG_vTensorRT 6.0.1 | 3
<table>
<thead>
<tr>
<th>Title</th>
<th>TensorRT Sample Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Object Detection With The ONNX TensorRT Backend In Python</td>
<td>yolov3_onnx</td>
<td>Implements a full ONNX-based pipeline for performing inference with the YOLOv3-608 network, including pre and post-processing.</td>
</tr>
<tr>
<td>Object Detection With SSD In Python</td>
<td>uff_ssd</td>
<td>Implements a full UFF-based pipeline for performing inference with an SSD (InceptionV2 feature extractor) network. The sample downloads a pretrained ssd_inception_v2_coco_2017_11_17 model and uses it to perform inference. Additionally, it superimposes bounding boxes on the input image as a post-processing step.</td>
</tr>
<tr>
<td>INT8 Calibration In Python</td>
<td>int8_caffe_mnist</td>
<td>Demonstrates how to calibrate an engine to run in INT8 mode.</td>
</tr>
<tr>
<td>Refitting An Engine In Python</td>
<td>engine_refit_mnist</td>
<td>Trains an MNIST model in PyTorch, recreates the network in TensorRT with dummy weights, and finally refits the TensorRT engine with weights from the model.</td>
</tr>
</tbody>
</table>

1.1. C++ Samples

You can find the C++ samples in the `/usr/src/tensorrt/samples` package directory as well as on GitHub. The following C++ samples are shipped with TensorRT:

- “Hello World” For TensorRT
- Building A Simple MNIST Network Layer By Layer
- Importing The TensorFlow Model And Running Inference
- “Hello World” For TensorRT From ONNX
- Building And Running GoogleNet In TensorRT
- Building An RNN Network Layer By Layer
- Performing Inference In INT8 Using Custom Calibration
- Performing Inference In INT8 Precision
- Adding A Custom Layer To Your Network In TensorRT
- Object Detection With Faster R-CNN
- Object Detection With A TensorFlow SSD Network
- Movie Recommendation Using Neural Collaborative Filter (NCF)
Introduction

- Movie Recommendation Using MPS (Multi-Process Service)
- Object Detection With SSD
- “Hello World” For Multilayer Perceptron (MLP)
- Specifying I/O Formats Using The Reformat Free I/O APIs
- Adding A Custom Layer That Supports INT8 I/O To Your Network In TensorRT
- Using The NvMedia API To Run A TensorRT Engine
- Digit Recognition With Dynamic Shapes In TensorRT
- Neural Machine Translation (NMT) Using A Sequence To Sequence (seq2seq) Model
- Object Detection And Instance Segmentations With A TensorFlow Mask R-CNN Network
- Object Detection With A TensorFlow Faster R-CNN Network

Getting Started With C++ Samples

Every C++ sample includes a README.md file in GitHub: <sample name> that provides detailed information about how the sample works, sample code, and step-by-step instructions on how to run and verify its output.

Running C++ Samples on Linux

If you installed TensorRT using the debian files, copy /usr/src/tensorrt to a new directory first before building the C++ samples. If you installed TensorRT using the tar file, then the samples are located in {TAR_EXTRACT_PATH}/samples. To build all the samples and then run one of the samples, use the following commands:

```
$ cd <samples_dir>
$ make -j4
$ cd ../bin
$ ./<sample_bin>
```

Running C++ Samples on Windows

All of the C++ samples on Windows are provided as Visual Studio Solution files. To build a sample, open its corresponding Visual Studio Solution file and build the solution. The output executable will be generated in (ZIP_EXTRACT_PATH)\bin. You can then run the executable directly or through Visual Studio.

1.2. Python Samples

You can find the Python samples in the /usr/src/tensorrt/samples/python package directory. The following Python samples are shipped with TensorRT:

---

1 This sample is located in GitHub only; this is not part of the product package.
2

---
Introduction

- Introduction To Importing Caffe, TensorFlow And ONNX Models Into TensorRT Using Python
- “Hello World” For TensorRT Using TensorFlow And Python
- “Hello World” For TensorRT Using PyTorch And Python
- Adding A Custom Layer To Your Caffe Network In TensorRT In Python
- Adding A Custom Layer To Your TensorFlow Network In TensorRT In Python
- Object Detection With The ONNX TensorRT Backend In Python
- Object Detection With SSD In Python
- INT8 Calibration In Python
- Refitting An Engine In Python

Getting Started With Python Samples

Every Python sample includes a README.md file. Refer to the /usr/src/tensorrt/samples/python/<sample-name>/README.md file for detailed information about how the sample works, sample code, and step-by-step instructions on how to run and verify its output.

Running Python Samples

To run one of the Python samples, the process typically involves two steps:

1. Install the sample requirements:

   ```bash
   python<x> -m pip install -r requirements.txt
   ```
   where python<x> is either python2 or python3.

2. Run the sample code with the data directory provided if the TensorRT sample data is not in the default location. For example:

   ```bash
   python<x> sample.py [-d DATA_DIR]
   ```

For more information on running samples, see the README.md file included with the sample.
Chapter 2.
APPLICATION AREAS

The TensorRT samples focus on the following application areas:

Recommenders
Recommender systems are used to provide product or media recommendations to users of social networking, media content consumption and e-commerce platforms. MLP-based Neural Collaborative Filter (NCF) recommenders employ a stack of fully-connected or matrix multiplication layers to generate recommendations.

Some examples of TensorRT recommenders samples include the following:
- Movie Recommendation Using Neural Collaborative Filter (NCF)
- Movie Recommendation Using MPS (Multi-Process Service)
- “Hello World” For Multilayer Perceptron (MLP)

Machine translation

Machine translation systems are used to translate text from one language to another language. Recurrent neural networks (RNN) are one of the most popular deep learning solutions for machine translation.

Some examples of TensorRT machine translation samples include the following:
- Neural Machine Translation (NMT) Using A Sequence To Sequence (seq2seq) Model
- Building An RNN Network Layer By Layer

Character recognition

Character recognition, especially on the MNIST dataset, is a classic machine learning problem. The MNIST problem involves recognizing the digit that is present in an image of a handwritten digit.

Some examples of TensorRT character recognition samples include the following:
- “Hello World” For TensorRT
Image classification

Image classification is the problem of identifying one or more objects present in an image. Convolutional neural networks (CNN) are a popular choice for solving this problem. They are typically composed of convolution and pooling layers.

Some examples of TensorRT image classification samples include the following:

- Building And Running GoogleNet In TensorRT
- Performing Inference In INT8 Precision
- Introduction To Importing Caffe, TensorFlow And ONNX Models Into TensorRT And Python

Object detection

Object detection is one of the classic computer vision problems. The task, for a given image, is to detect, classify and localize all objects of interest. For example, imagine that you are developing a self-driving car and you need to do pedestrian detection - the object detection algorithm would then, for a given image, return bounding box coordinates for each pedestrian in an image.

There have been many advances in recent years in designing models for object detection.

Some examples of TensorRT object detection samples include the following:

- Object Detection With SSD In Python
- Object Detection With The ONNX TensorRT Backend In Python
- Object Detection With A TensorFlow SSD Network
- Object Detection With Faster R-CNN
- Object Detection With SSD
Application Areas

- Object Detection And Instance Segmentations With A TensorFlow Mask R-CNN Network
- Object Detection With A TensorFlow Faster R-CNN Network

Integration

Integration samples demonstrate “how to” rather than “what to do”, which are different from the samples mentioned above. In some cases, the TensorRT workflow may differ from the standard workflow. In order to let developers know how to handle such cases, integration samples are made to show workflows as well as API call sequences. As an example, sampleNvmedia shows how to run the TensorRT engine on a safety certified DLA, which involves NvMedia APIs.

Some examples of TensorRT integration samples include the following:

- Using The NvMedia API To Run A TensorRT Engine
Chapter 3.
CROSS COMPILING SAMPLES FOR AARCH64 USERS

The following sections show how to cross compile TensorRT samples for AArch64 QNX, Linux and Android platforms under x86_64 Linux.

3.1. Prerequisites

1. Install the CUDA cross-platform toolkit for the corresponding target and set the environment variable `CUDA_INSTALL_DIR`.

   ```bash
   $ export CUDA_INSTALL_DIR="your cuda install dir"
   ```

   Where `CUDA_INSTALL_DIR` is set to `/usr/local/cuda` by default.

2. Install the cuDNN cross-platform libraries for the corresponding target and set the environment variable `CUDNN_INSTALL_DIR`.

   ```bash
   $ export CUDNN_INSTALL_DIR="your cudnn install dir"
   ```

   Where `CUDNN_INSTALL_DIR` is set to `CUDA_INSTALL_DIR` by default.

3. Install the TensorRT cross compilation debian packages for the corresponding target.

   If you are using the tar file release for the target platform, then you can safely skip this step. The tar file release already includes the cross compile libraries so no additional packages are required.

   - **QNX AArch64**
     - `libnvinfer-dev-cross-qnx, libnvinfer5-cross-qnx`
   - **Linux AArch64**
     - `libnvinfer-dev-cross-aarch64, libnvinfer5-cross-aarch64`
   - **Android AArch64**
     - No debian packages are available.
3.2. Building Samples For QNX AArch64

Download the QNX tool-chain and export the following environment variables.

```
$ export QNX_HOST=/path/to/your/qnx/toolchains/host/linux/x86_64
$ export QNX_TARGET=/path/to/your/qnx/toolchain/target/qnx
```

Build the samples by issuing:

```
$ cd /path/to/TensorRT/samples
$ make TARGET=qnx
```

3.3. Building Samples For Linux AArch64

For Linux AArch64 you need to first install the corresponding GCC compiler, `aarch64-linux-gnu-g++`. In Ubuntu, this can be installed via:

```
$ sudo apt-get install g++-aarch64-linux-gnu
```

Build the samples by issuing:

```
$ cd /path/to/TensorRT/samples
$ make TARGET=aarch64
```

3.4. Building Samples For Android AArch64

Download the Android NDK (r16b) from https://developer.android.com/ndk/. After downloading the Android NDK, create a standalone tool-chain, for example:

```
$ $NDK/build/tools/make_standalone_toolchain.py \
  --arch arm64 \
  --api 26 \
  --install-dir=/path/to/my-toolchain
```

You can find more information by visiting: https://developer.android.com/ndk/guides/standalone_toolchain

Build the samples by issuing:

```
$ cd /path/to/TensorRT/samples
$ make TARGET=android64 ANDROID_CC=/path/to/my-toolchain/bin/aarch64-linux-android-clang++
```

Getting Started With C++ Samples

Every C++ sample includes a `README.md` file in GitHub: samples/opensource that provides detailed information about how the sample works, sample code, and step-by-step instructions on how to run and verify its output.
Running C++ Samples on Linux

If you installed TensorRT using the debian files, copy /usr/src/tensorrt to a new directory first before building the C++ samples. If you installed TensorRT using the tar file, then the samples are located in {TAR_EXTRACT_PATH}/samples. To build all the samples and then run one of the samples, use the following commands:

```bash
$ cd <samples_dir>
$ make -j4
$ cd ../bin
$ ./<sample_bin>
```

Running C++ Samples on Windows

All of the C++ samples on Windows are provided as Visual Studio Solution files. To build a sample, open its corresponding Visual Studio Solution file and build the solution. The output executable will be generated in (ZIP_EXTRACT_PATH)\bin. You can then run the executable directly or through Visual Studio.
Chapter 4.
“HELLO WORLD” FOR TENSORRT

What does this sample do?
This sample, sampleMNIST, is a simple hello world example that performs the basic setup and initialization of TensorRT using the Caffe parser.

Where is this sample located?
This sample is maintained under the samples/opensource/sampleMNIST directory in the GitHub: sampleMNIST repository.

How do I get started?
Refer to the GitHub: sampleMNIST/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 5.
BUILDING A SIMPLE MNIST NETWORK LAYER BY LAYER

What does this sample do?
This sample, sampleMNISTAPI, uses the TensorRT API to build an engine for a model trained on the MNIST dataset. It creates the network layer by layer, sets up weights and inputs/outputs, and then performs inference. This sample is similar to sampleMNIST. Both of these samples use the same model weights, handle the same input, and expect similar output.

Where is this sample located?
This sample is maintained under the samples/opensource/sampleMNISTAPI directory in the GitHub: sampleMNISTAPI repository.

How do I get started?
Refer to the GitHub: sampleMNISTAPI/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 6.
IMPORTING THE TENSORFLOW MODEL AND RUNNING INFERENCE

**What does this sample do?**

This sample, sampleUffMNIST, imports a TensorFlow model trained on the MNIST dataset.

The MNIST TensorFlow model has been converted to UFF (Universal Framework Format) using the explanation described in Working With TensorFlow.

The UFF is designed to store neural networks as a graph. The NvUffParser that we use in this sample parses the UFF file in order to create an inference engine based on that neural network.

With TensorRT, you can take a TensorFlow trained model, export it into a UFF protobuf file (.uff) using the UFF converter, and import it using the UFF parser.

**Where is this sample located?**

This sample is maintained under the samples/opensource/sampleUffMNIST directory in the GitHub: sampleUffMNIST repository.

**How do I get started?**

Refer to the GitHub: sampleUffMNIST/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 7.
“HELLO WORLD” FOR TENSORRT FROM ONNX

What does this sample do?
This sample, sampleOnnxMNIST, converts a model trained on the MNIST dataset in Open Neural Network Exchange (ONNX) format to a TensorRT network and runs inference on the network.

ONNX is a standard for representing deep learning models that enables models to be transferred between frameworks.

Where is this sample located?
This sample is maintained under the samples/opensource/sampleOnnxMNIST directory in the GitHub: sampleOnnxMNIST repository.

How do I get started?
Refer to the GitHub: sampleOnnxMNIST/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 8.
BUILDING AND RUNNING GOOGLENET IN TENSORRT

What does this sample do?
This sample, sampleGoogleNet, demonstrates how to import a model trained with
Caffe into TensorRT using GoogleNet as an example. Specifically, this sample builds a
TensorRT engine from the saved Caffe model, sets input values to the engine, and runs
it.

Where is this sample located?
This sample is maintained under the samples/opensource/sampleGoogleNet
directory in the GitHub: sampleGoogleNet repository.

How do I get started?
Refer to the GitHub: sampleGoogleNet/README.md file for detailed information about
how this sample works, sample code, and step-by-step instructions on how to run and
verify its output.
Chapter 9.
BUILDING AN RNN NETWORK LAYER BY LAYER

What does this sample do?

This sample, sampleCharRNN, uses the TensorRT API to build an RNN network layer by layer, sets up weights and inputs/outputs and then performs inference. Specifically, this sample creates a CharRNN network that has been trained on the Tiny Shakespeare dataset. For more information about character level modeling, see char-rnn.

TensorFlow has a useful RNN Tutorial which can be used to train a word level model. Word level models learn a probability distribution over a set of all possible word sequence. Since our goal is to train a char level model, which learns a probability distribution over a set of all possible characters, a few modifications will need to be made to get the TensorFlow sample to work. These modifications can be seen here.

Where is this sample located?

This sample is maintained under the samples/opensource/sampleCharRNN directory in the GitHub: sampleCharRNN repository.

How do I get started?

Refer to the GitHub: sampleCharRNN/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 10.
PERFORMING INFERENCE IN INT8 USING CUSTOM CALIBRATION

What does this sample do?
This sample, sampleINT8, performs INT8 calibration and inference.
Specifically, this sample demonstrates how to perform inference in 8-bit integer (INT8). INT8 inference is available only on GPUs with compute capability 6.1 or 7.x. After the network is calibrated for execution in INT8, output of the calibration is cached to avoid repeating the process. You can then reproduce your own experiments with Caffe in order to validate your results on ImageNet networks.

Where is this sample located?
This sample is maintained under the samples/opensource/sampleINT8 directory in the GitHub: sampleINT8 repository.

How do I get started?
Refer to the GitHub: sampleINT8/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 11.
PERFORMING INFERENCE IN INT8 PRECISION

What does this sample do?

This sample, sampleINT8API, performs INT8 inference without using the INT8 calibrator; using the user provided per activation tensor dynamic range. INT8 inference is available only on GPUs with compute capability 6.1 or 7.x and supports Image Classification ONNX models such as ResNet-50, VGG19, and MobileNet.

Specifically, this sample demonstrates how to:

- Use `nvinfer1::ITensor::setDynamicRange` to set per tensor dynamic range
- Use `nvinfer1::ILayer::setPrecision` to set computation precision of a layer
- Use `nvinfer1::ILayer::setOutputType` to set output tensor data type of a layer
- Perform INT8 inference without using INT8 calibration

Where is this sample located?

This sample is maintained under the `samples/opensource/sampleINT8API` directory in the GitHub: `sampleINT8API` repository.

How do I get started?

Refer to the GitHub: `sampleINT8API/README.md` file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 12.
ADDING A CUSTOM LAYER TO YOUR NETWORK IN TENSORRT

What does this sample do?
This sample, samplePlugin, defines a custom layer that supports multiple data formats and demonstrates how to serialize/deserialize plugin layers. This sample also demonstrates how to use a fully connected plugin (FCPlugin) as a custom layer and the integration with NvCaffeParser.

Where is this sample located?
This sample is maintained under the samples/opensource/samplePlugin directory in the GitHub: samplePlugin repository.

How do I get started?
Refer to the GitHub: samplePlugin/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 13.
OBJECT DETECTION WITH FASTER R-CNN

What does this sample do?
This sample, sampleFasterRCNN, uses TensorRT plugins, performs inference, and implements a fused custom layer for end-to-end inferencing of a Faster R-CNN model. Specifically, this sample demonstrates the implementation of a Faster R-CNN network in TensorRT, performs a quick performance test in TensorRT, implements a fused custom layer, and constructs the basis for further optimization, for example using INT8 calibration, user trained network, etc. The Faster R-CNN network is based on the paper Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks.

Where is this sample located?
This sample is maintained under the samples/opensource/sampleFasterRCNN directory in the GitHub: sampleFasterRCNN repository.

How do I get started?
Refer to the GitHub: sampleFasterRCNN/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 14. 
OBJECT DETECTION WITH A TENSORFLOW SSD NETWORK

What does this sample do?

This sample, sampleUffSSD, preprocesses a TensorFlow SSD network, performs inference on the SSD network in TensorRT, using TensorRT plugins to speed up inference.

This sample is based on the [SSD: Single Shot MultiBox Detector](https://arxiv.org/abs/1512.02325) paper. The SSD network performs the task of object detection and localization in a single forward pass of the network.

The SSD network used in this sample is based on the TensorFlow implementation of SSD, which actually differs from the original paper, in that it has an inception_v2 backbone. For more information about the actual model, download [ssd_inception_v2_coco](https://github.com/TF-Team/tensorflow-models/blob/master/research/object_detection/samples/configs/ssd_inception_v2_coco.config). The TensorFlow SSD network was trained on the InceptionV2 architecture using the [MSCOCO dataset](https://cocodataset.org/#dapi) which has 91 classes (including the background class). The config details of the network can be found [here](https).

Where is this sample located?

This sample is maintained under the `samples/opensource/sampleUffSSD` directory in the [GitHub: sampleUffSSD](https://github.com/NVIDIA/nnablas) repository.

How do I get started?

Refer to the [GitHub: sampleUffSSD/README.md](https://github.com/NVIDIA/nnablas/blob/master/sampleUffSSD/README.md) file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 15.
MOVIE RECOMMENDATION USING NEURAL COLLABORATIVE FILTER (NCF)

What does this sample do?
This sample, sampleMovieLens, is an end-to-end sample that imports a trained TensorFlow model and predicts the highest rated movie for each user. This sample demonstrates a simple movie recommender system using a multi-layer perceptron (MLP) based Neural Collaborative Filter (NCF) recommender.

Specifically, this sample demonstrates how to generate weights for a MovieLens dataset that TensorRT can then accelerate.

Where is this sample located?
This sample is maintained under the samples/opensource/sampleMovieLens directory in the GitHub: sampleMovieLens repository.

How do I get started?
Refer to the GitHub: sampleMovieLens/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 16.
MOVIE RECOMMENDATION USING MPS (MULTI-PROCESS SERVICE)

What does this sample do?
This sample, sampleMovieLensMPS, is an end-to-end sample that imports a trained TensorFlow model and predicts the highest rated movie for each user using MPS (Multi-Process Service).

MPS allows multiple CUDA processes to share single GPU context. With MPS, multiple overlapping kernel execution and memcpy operations from different processes can be scheduled concurrently to achieve maximum utilization. This can be especially effective in increasing parallelism for small networks with low resource utilization such as those primarily consisting of a series of small MLPs.

This sample is identical to Movie Recommendation Using Neural Collaborative Filter (NCF) in terms of functionality, but is modified to support concurrent execution in multiple processes. Specifically, this sample demonstrates how to generate weights for a MovieLens dataset that TensorRT can then accelerate.

Currently, sampleMovieLensMPS supports only Linux x86-64 (includes Ubuntu and RedHat) desktop users.

Where is this sample located?
This sample is maintained under the samples/opensource/sampleMovieLensMPS directory in the GitHub: sampleMovieLensMPS repository.

How do I get started?
Refer to the GitHub: sampleMovieLensMPS/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 17.
OBJECT DETECTION WITH SSD

What does this sample do?
This sample, sampleSSD, is based on the SSD: Single Shot MultiBox Detector paper. The SSD network performs the task of object detection and localization in a single forward pass of the network. This network is built using the VGG network as a backbone and trained using PASCAL VOC 2007+ 2012 datasets.

Unlike Faster R-CNN, SSD completely eliminates proposal generation and subsequent pixel or feature resampling stages and encapsulates all computation in a single network. This makes SSD straightforward to integrate into systems that require a detection component.

Where is this sample located?
This sample is maintained under the samples/opensource/sampleSSD directory in the GitHub: sampleSSD repository.

How do I get started?
Refer to the GitHub: sampleSSD/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 18.
“HELLO WORLD” FOR MULTILAYER PERCEPTRON (MLP)

What does this sample do?
This sample, sampleMLP, is a simple hello world example that shows how to create a network that triggers the multilayer perceptron (MLP) optimizer. The generated MLP optimizer can then accelerate TensorRT.

Where is this sample located?
This sample is maintained under the samples/opensource/sampleMLP directory in the GitHub: sampleMLP repository.

How do I get started?
Refer to the GitHub: sampleMLP/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 19.
SPECIFYING I/O FORMATS USING THE
REFORMAT FREE I/O APIS

What does this sample do?
This sample, sampleReformatFreeIO, uses a Caffe model that was trained on the MNIST dataset and performs engine building and inference using TensorRT. The correctness of outputs is then compared to the golden reference. Specifically, it shows how to use reformat free I/O APIs to explicitly specify I/O formats to `TensorFormat::kLINEAR`, `TensorFormat::kCHW2` and `TensorFormat::kHWC8` for Float16 and INT8 precision.

`ITensor::setAllowedFormats` is invoked to specify which format is expected to be supported so that the unnecessary reformatting will not be inserted to convert from/to FP32 formats for I/O tensors. `BuilderFlag::kSTRICT_TYPES` is also assigned to the builder configuration to let the builder choose a reformat free path rather than the fastest path.

Where is this sample located?
This sample is maintained under the `samples/opensource/sampleReformatFreeIO` directory in the GitHub: sampleReformatFreeIO repository.

How do I get started?
Refer to the GitHub: sampleReformatFreeIO/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 20.
ADDING A CUSTOM LAYER THAT SUPPORTS INT8 I/O TO YOUR NETWORK IN TENSORRT

What does this sample do?

This sample, sampleUffPluginV2Ext, implements the custom pooling layer for the MNIST model (data/samples/lenet5_custom_pool.uff). Since cuDNN function cudnnPoolingForward with float precision is used to simulate an INT8 kernel, the performance for INT8 precision does not speed up. Nevertheless, the main purpose of this sample is to demonstrate how to extend INT8 I/O for a plugin that is introduced in TensorRT 6.0. This requires the interface replacement from IPlugin/IPluginV2/IPluginV2Ext to IPluginV2IOExt (or IPluginV2DynamicExt if dynamic shape is required).

Where is this sample located?

This sample is maintained under the samples/opensource/sampleUffPluginV2Ext directory in the GitHub: sampleUffPluginV2Ext repository.

How do I get started?

Refer to the GitHub: /sampleUffPluginV2Ext/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 21.
USING THE NVMEDIA API TO RUN A TENSORRT ENGINE

What does this sample do?

This sample, sampleNvmedia, uses an API to construct a network of a single ElementWise layer and builds the engine. The engine runs in DLA safe mode using NvMedia runtime. In order to do that, the sample uses NvMedia APIs to do engine conversion and NvMedia runtime preparation, as well as the inference.

Specifically, this sample demonstrates how to:

‣ The single-layered network is built by TensorRT.
‣ `NvMediaDlaCreate` and `NvMediaDeviceCreate` are called to create DLA device.
‣ `NvMediaDlaLoadFromMemory` is called to load the engine memory for DLA use.
‣ `NvMediaTensorCreate` is called to create
  `NvMediaTensor.NvMediaDlaSubmitTimeout` is called to submit the inference task.

sampleNvmedia is included only in the Automotive releases and therefore works only on TensorRT Standard configurations in the auto build on QNX and D5L.

Where is this sample located?

This sample is maintained under the `samples/opensource/sampleNvmedia` directory in the GitHub: sampleNvmedia repository.

How do I get started?

Refer to the GitHub: sampleNvmedia/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 22.
DIGIT RECOGNITION WITH DYNAMIC SHAPES IN TENSORRT

What does this sample do?
This sample, sampleDynamicReshape, demonstrates how to use dynamic input dimensions in TensorRT by creating an engine for resizing dynamically shaped inputs to the correct size for an ONNX MNIST model. For more information, see Working With Dynamic Shapes in the TensorRT Developer Guide.

This sample creates an engine for resizing an input with dynamic dimensions to a size that an ONNX MNIST model can consume.

Specifically, this sample demonstrates how to:
- Create a network with dynamic input dimensions to act as a preprocessor for the model
- Parse an ONNX MNIST model to create a second network
- Build engines for both networks
- Run inference using both engines

Where is this sample located?
This sample is maintained under the samples/opensource/sampleDynamicReshape directory in the GitHub: sampleDynamicReshape repository.

How do I get started?
Refer to the GitHub: sampleDynamicReshape/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 23.
NEURAL MACHINE TRANSLATION (NMT) USING A SEQUENCE TO SEQUENCE (SEQ2SEQ) MODEL

What does this sample do?
This sample, sampleNMT, demonstrates the implementation of Neural Machine Translation (NMT) based on a TensorFlow seq2seq model using the TensorRT API. The TensorFlow seq2seq model is an open sourced NMT project that uses deep neural networks to translate text from one language to another language.

Specifically, this sample is an end-to-end sample that takes a TensorFlow model, builds an engine, and runs inference using the generated network. The sample is intended to be modular so it can be used as a starting point for your machine translation application.

This sample implements German to English translation using the data that is provided by and trained from the TensorFlow NMT (seq2seq) Tutorial.

Where is this sample located?
This sample is maintained under the samples/opensource/sampleNMT directory in the GitHub: sampleNMT repository.

How do I get started?
Refer to the GitHub: sampleNMT/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
What does this sample do?

This sample, sampleUffMaskRCNN, performs inference on the Mask R-CNN network in TensorRT. Mask R-CNN is based on the Mask R-CNN paper which performs the task of object detection and object mask predictions on a target image. This sample’s model is based on the Keras implementation of Mask R-CNN and its training framework can be found in the Mask R-CNN Github repository. We have verified that the pre-trained Keras model (with backbone ResNet101 + FPN and dataset coco) provided in the v2.0 release can be converted to UFF and consumed by this sample. And, it is also feasible to deploy your customized Mask R-CNN model trained with specific backbone and datasets.

This sample is available only in GitHub and is not packaged with the product.

This sample makes use of TensorRT plugins to run the Mask R-CNN model. To use these plugins, the Keras model should be converted to Tensorflow .pb model. Then this .pb model needs to be preprocessed and converted to the UFF model with the help of GraphSurgeon and the UFF utility.

Where is this sample located?

This sample is maintained under the samples/opensource/sampleUffMaskRCNN directory in the GitHub: sampleUffMaskRCNN repository.
How do I get started?

Refer to the [GitHub: sampleUffMaskRCNN/README.md](https://github.com/NVIDIA-TensorRT/samplesUffMaskRCNN/blob/master/README.md) file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 25.
OBJECT DETECTION WITH A TENSORFLOW FASTER R-CNN NETWORK

What does this sample do?

This sample, sampleUffFasterRCNN, is a UFF TensorRT sample for Faster-RCNN in NVIDIA Transfer Learning Toolkit SDK. This sample serves as a demo of how to use pretrained Faster-RCNN model in Transfer Learning Toolkit to do inference with TensorRT. Besides the sample itself, it also provides two TensorRT plugins: Proposal and CropAndResize to implement the proposal layer and ROIPooling layer as custom layers in the model since TensorRT has no native support for them.

This sample is available only in GitHub and is not packaged with the product.

In this sample, we provide a UFF model as a demo. While in the Transfer Learning Toolkit workflow, we can't provide the UFF model. Instead, we can only get the .tlt model during training and the .etlt model after tlt-export. Both of them are encrypted models and the Transfer Learning Toolkit user will use tlt-converter to decrypt the .etlt model and generate a TensorRT engine file in a single step. Therefore, in the Transfer Learning Toolkit workflow, we will consume the TensorRT engine instead of a UFF model. However, this sample can still serve as a demo on how to use the UFF Faster R-CNN model regardless of its format.

Where is this sample located?

This sample is maintained under the samples/opensource/sampleUffFasterRCNN directory in the GitHub: sampleUffFasterRCNN repository.
How do I get started?
Refer to the GitHub: sampleUffFasterRCNN/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.
Chapter 26.
INTRODUCTION TO IMPORTING CAFFE, TENSORFLOW AND ONNX MODELS INTO TENSORRT USING PYTHON

What Does This Sample Do?
This sample, introductory_parser_samples, is a Python sample which uses TensorRT and its included suite of parsers (tUFF, Caffe and ONNX parsers), to perform inference with ResNet-50 models trained with various different frameworks.

Where Is This Sample Located?
This sample is installed in the /usr/src/tensorrt/samples/python/introductory_parser_samples directory.

Getting Started:
Refer to the /usr/src/tensorrt/samples/python/introductory_parser_samples/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.

A summary of the README.md file is included in this section for your reference, however, you should always refer to the README.md within the package for the most recent documentation updates.
Chapter 27.
“HELLO WORLD” FOR TENSORRT USING TENSORFLOW AND PYTHON

What Does This Sample Do?
This sample, end_to_end_tensorflow_mnist, trains a small, fully-connected model on the MNIST dataset and runs inference using TensorRT.

Where Is This Sample Located?
This sample is installed in the /usr/src/tensorrt/samples/python/end_to_end_tensorflow_mnist directory.

Getting Started:
Refer to the /usr/src/tensorrt/samples/python/end_to_end_tensorflow_mnist/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.

A summary of the README.md file is included in this section for your reference, however, you should always refer to the README.md within the package for the most recent documentation updates.
What Does This Sample Do?
This sample, network_api_pytorch_mnist, trains a convolutional model on the MNIST dataset and runs inference with a TensorRT engine.

Where Is This Sample Located?
This sample is installed in the /usr/src/tensorrt/samples/python/network_api_pytorch_mnist directory.

Getting Started:
Refer to the /usr/src/tensorrt/samples/python/network_api_pytorch_mnist/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.

A summary of the README.md file is included in this section for your reference, however, you should always refer to the README.md within the package for the most recent documentation updates.
Chapter 29.
ADDING A CUSTOM LAYER TO YOUR CAFFE NETWORK IN TENSORRT IN PYTHON

What Does This Sample Do?
This sample, fc_plugin_caffe_mnist, demonstrates how to implement a custom FullyConnected layer using cuBLAS and cuDNN, wraps the implementation in a TensorRT plugin (with a corresponding plugin factory), and generates Python bindings for it using pybind11. These bindings are then used to register the plugin factory with the CaffeParser.

The Caffe InnerProduct/FullyConnected layer is normally handled natively in TensorRT using the IFullyConnected layer. However, in this sample, we use a plugin implementation for instructive purposes.

Where Is This Sample Located?
This sample is installed in the /usr/src/tensorrt/samples/python/fc_plugin_caffe_mnist directory.

Getting started:
Refer to the /usr/src/tensorrt/samples/python/fc_plugin_caffe_mnist/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.

A summary of the README.md file is included in this section for your reference, however, you should always refer to the README.md within the package for the most recent documentation updates.
Chapter 30.
ADDING A CUSTOM LAYER TO YOUR TENSORFLOW NETWORK IN TENSORRT IN PYTHON

What Does This Sample Do?
This sample, uff_custom_plugin, demonstrates how to use plugins written in C++ with the TensorRT Python bindings and UFF Parser. This sample uses the MNIST dataset.

Where Is This Sample Located?
This sample is installed in the /usr/src/tensorrt/samples/python/uff_custom_plugin directory.

Getting Started:
Refer to the /usr/src/tensorrt/samples/python/uff_custom_plugin/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.

A summary of the README.md file is included in this section for your reference, however, you should always refer to the README.md within the package for the most recent documentation updates.
Chapter 31.
OBJECT DETECTION WITH THE ONNX TENSORRT BACKEND IN PYTHON

What Does This Sample Do?
This sample, yolov3_onnx, implements a full ONNX-based pipeline for performing inference with the YOLOv3 network, with an input size of 608x608 pixels, including pre and post-processing. This sample is based on the YOLOv3-608 paper.

This sample is not supported on Ubuntu 14.04 and older. Additionally, the yolov3_to_onnx.py script does not support Python 3.

Where Is This Sample Located?
This sample is installed in the /usr/src/tensorrt/samples/python/yolov3_onnx directory.

Getting Started:
Refer to the /usr/src/tensorrt/samples/python/yolov3_onnx/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.

A summary of the README.md file is included in this section for your reference, however, you should always refer to the README.md within the package for the most recent documentation updates.
Chapter 32.  
OBJECT DETECTION WITH SSD IN PYTHON

What Does This Sample Do?

This sample, uff_ssd, implements a full UFF-based pipeline for performing inference with an SSD (InceptionV2 feature extractor) network.

This sample is based on the SSD: Single Shot MultiBox Detector paper. The SSD network, built on the VGG-16 network, performs the task of object detection and localization in a single forward pass of the network. This approach discretizes the output space of bounding boxes into a set of default boxes over different aspect ratios and scales per feature map location. At prediction time, the network generates scores for the presence of each object category in each default box and produces adjustments to the box to better match the object shape. Additionally, the network combines predictions from multiple features with different resolutions to naturally handle objects of various sizes.

This sample is based on the TensorFlow implementation of SSD. For more information, download ssd_inception_v2_coco. Unlike the paper, the TensorFlow SSD network was trained on the InceptionV2 architecture using the MSCOCO dataset which has 91 classes (including the background class). The config details of the network can be found here.

Where Is This Sample Located?

This sample is installed in the /usr/src/tensorrt/samples/python/uff_ssd directory.

Getting Started:

Refer to the /usr/src/tensorrt/samples/python/uff_ssd/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.

A summary of the README.md file is included in this section for your reference, however, you should always refer to the README.md within the package for the most recent documentation updates.
Chapter 33.
INT8 CALIBRATION IN PYTHON

What Does This Sample Do?
This sample, int8_caffe_mnist, demonstrates how to create an INT8 calibrator, build and calibrate an engine for INT8 mode, and finally run inference in INT8 mode.

Where Is This Sample Located?
This sample is installed in the /usr/src/tensorrt/samples/python/int8_caffe_mnist directory.

Getting Started:
Refer to the /usr/src/tensorrt/samples/python/int8_caffe_mnist/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.

A summary of the README.md file is included in this section for your reference, however, you should always refer to the README.md within the package for the most recent documentation updates.
Chapter 34.
REFITTING AN ENGINE IN PYTHON

What Does This Sample Do?
This sample, engine_refit_mnist, trains an MNIST model in PyTorch, recreates the network in TensorRT with dummy weights, and finally refits the TensorRT engine with weights from the model. Refitting allows us to quickly modify the weights in a TensorRT engine without needing to rebuild.

Where Is This Sample Located?
This sample is installed in the /usr/src/tensorrt/samples/python/engine_refit_mnist directory.

Getting Started:
Refer to the /usr/src/tensorrt/samples/python/engine_refit_mnist/README.md file for detailed information about how this sample works, sample code, and step-by-step instructions on how to run and verify its output.

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