

DEPLOYING INTEL® FPGA FOR DEEP LEARNING INFERENCE WITH OPENVINO™ TOOLKIT

Class 3

What's Been Discussed So Far

In class 1:

- Refresher on deep learning CNN algorithms
- What FPGAs are and why they are excellent accelerators that provide a flexible, deterministic low-latency, high-throughput, and energy-efficient solution for accelerating the constantly changing networks and precisions for Deep Learning (DL) inference

In class 2:

- The components that make up a computer vision application that includes deep learning inference
- Intel is providing software that abstracts away the hardware platforms allowing computer vision applications to run on heterogenous systems
- Common programming languages and libraries for computer vision applications



Agenda

Introduction to the Open Visual Inference Neural Network Optimization (OpenVINO™) Toolkit

- Overview
- Model Optimizer
- Inference Engine



Objectives

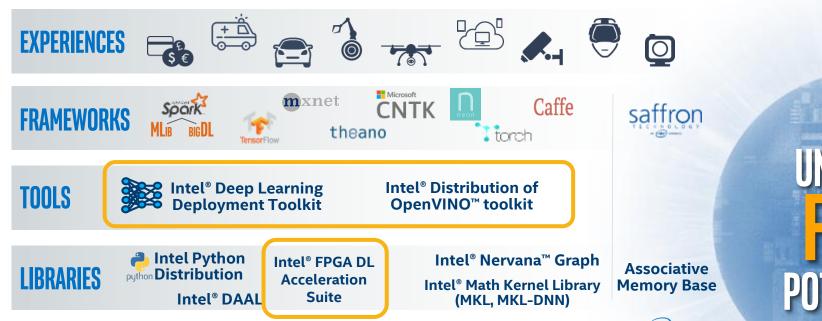
Explain the components of the Intel® Distribution of OpenVINO™ toolkit.

Explain how to optimize a model from frameworks such as Caffe* or TensorFlow*, into a format that the inference engine requires.

Use the inference engine to target the CPU or FPGA accelerator.



Intel[®] Al Portfolio

























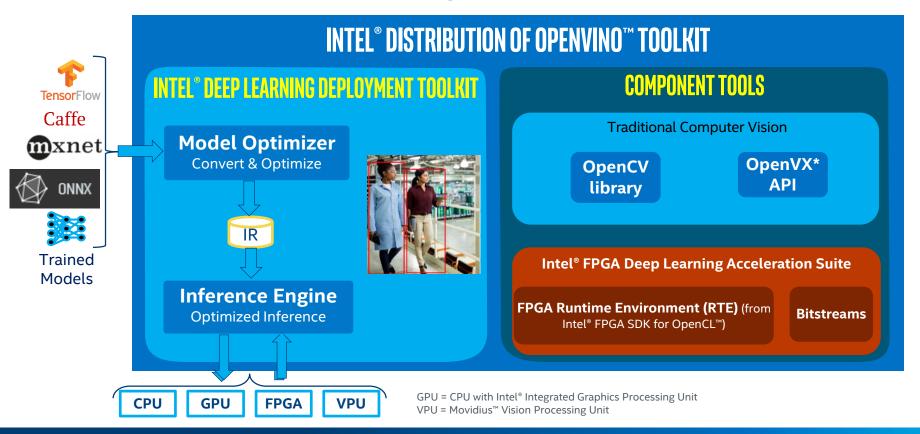




Memory & Storage Networking



Intel® Distribution of OpenVINO™ Toolkit





Deep Learning Deployment Toolkit

Enable deployment of trained model on all Intel® architectures

■ CPU, GPU, VPU, FPGA, ...

Optimize for best execution

Enable user to validate and tune

Easy-to-use runtime API across all devices CPU Plugin Caffe **TensorFlow**™ Common A .xml Inference **GPU Plugin** Model Load, Infer **Optimizer** MxNet .bin **FPGA Plugin** Others Converts and optimizes for given target

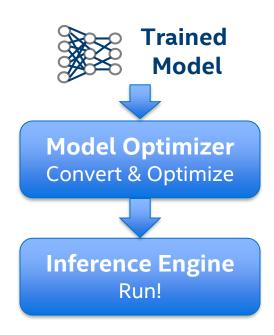
Deep Learning Deployment Toolkit Details

Model Optimizer

- Imports trained models from popular deep learning frameworks regardless of training hardware
- Conservative topology transformations
- Converts to a range of data types (Matched to HW)

Inference Engine

- Optimizes Inference execution for target hardware (computational graph analysis, scheduling, model compression, quantization)
- Enables seamless integration with application logic



Deployment Toolkit Benefits

To **Speed up deployment** by

adjusting trained model

for target device

& providing unified optimized inference runtime

Easy-to-use Tools:
Model Optimizer, Inference Engine,
Validation Application

Model Optimizer Quantization, Batch-Normalization Merging

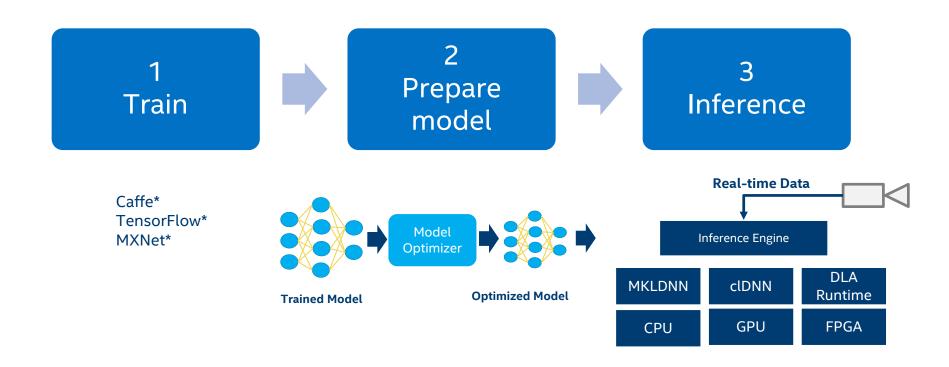
CPU, GPU, FPGA & more

Inference Engine: Simple to use unified API of Inference Runtime

- API independent of training framework
 & target device
- Lightweight to run on IoT devices



End-to-End Machine Learning



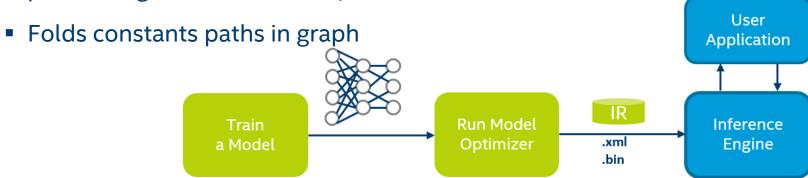
Agenda

- Introduction to Deep Learning Inference on FPGAs
- Model Optimizer
- Inference Engine

Model Optimizer

- Convert models from frameworks (Caffe*, TensorFlow*, MXNet*, ONNX*)
 - Caffe2, PyTorch, and others via ONNX format
- Converts to a unified Model (IR, later n-graph)

 Optimizes topologies (Node merging, batch normalization elimination, performing horizontal fusion)



Model Optimizer Performed Optimizations

- Node merging
- Horizontal fusion
- Batch normalization to scale shift
- Fold scale shift with convolution
- Drop unused layers (dropout)
- FP16/Int8 quantization
- Model optimizer can add normalization and mean operations, so some preprocessing is 'added' to the deep learning model
 - --mean_values (104.006, 116.66, 122.67)
 - --scale_values (0.07, 0.075, 0.084)

Model Optimizer Options

Python script: \$MO_DIR/mo.py

Option for Deployment	Description
input_model	Network binary weights file TensorFlow* .pb Caffe* .caffemodel MXNet* .params
input_proto	Caffe .prototxt file
data_type	IP Precision (i.e., FP16)
scale	Network normalization factor (Optional)
output_dir	Output directory path (Optional)

Full Model Optimizer options covered in Model Optimizer documentations



Run Model Optimizer Caffe*

To generate IR .xml and .bin files for Inference Engine

```
$ source $MO DIR/venv/bin/activate
                                                Start working...
$ cd $MO DIR/
                                                Framework plugin: CAFFE
$ python mo.py \
                                                Network type: CLASSIFICATION
--input model <model dir>/<weights>.caffemodel \
                                               Batch size: 1
--scale 1 \
                                                Precision: FP16
--data type FP16 \
--output dir <output dir>
                                               Layer fusion: false
                                                Horizontal layer fusion: NONE
                                                Output directory: /home/student/work
                                                Custom kernels directory:
                                                Network input normalization: 1
                                                Writing binary data to:
                                                /.../GoogleNet/GoogleNet.bin
```

Configure Model Optimizer for TensorFlow*

Location \$MO_DIR/mo.py

Configure MO for TensorFlow*

- Install Prerequisites (Python*, Bazel*)
- 2. Install TensorFlow
 - 1. Clone TensorFlow source, checkout appropriate branch, prepare environment, build TensorFlow, Install TensorFlow wheel
- 3. Build the Graph Transform Tool via bazel
- 4. Run model_optimizer_tensorflow/configure.py script
- Install Model Optimizer as Python package (setup.py)

Details of each step described in the Model Optimizer documentation



Convert TensorFlow* Models using Model Optimizer

Generate protobuf binary file (.pb)

- Clone Repository with Models
- Checkout specific revision
- Go to slim directory and modify downloading logic of synset files
- Generate inference graph for model with export_inference_graph.py
- Build tool for freezing inference graph
- Freeze inference graph with freeze_graph

Get input and output layer names for the model using summarize_graph

Build and run summarize_graph

Run Model Optimizer (mo.py)

Run Model Optimizer for TensorFlow*

To generate IR .xml and .bin files for Inference Engine

```
$ cd $MO_DIR

$ python3 mo.py \
   --input_model=$MODEL_DIR/<model>.pb \
   --input=<name of input layer> \
   --output=<name of output layer> \
   --data_type=FP16 \
   --input_shape 1,244,244,3 \
   --model_name <Model Name>

   Output File Name

Batch size, height, width, number of channels

Output File Name
```

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Inference Engine Structure

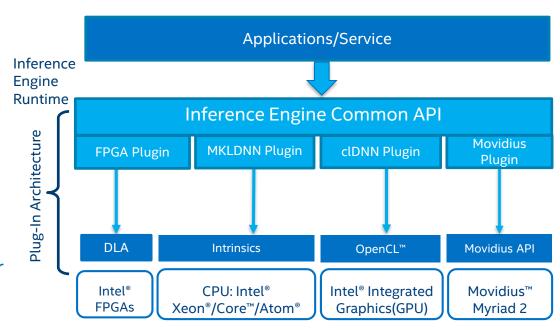
Simple & Unified API for Inference across all Intel® architecture (IA)

Optimized inference on large IA hardware targets (CPU/GPU/FPGA)

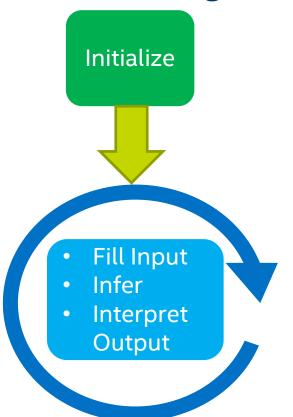
Heterogeneity support allows execution of layers across hardware types

Asynchronous execution improves performance

Futureproof/scale your development for future Intel® processors



Inference Engine Workflow



Initialization

Load model and weights
Set batch size (if needed)
Load Inference Plugin (CPU, GPU, FPGA)
Load network to plugin
Allocate input, output buffers

Main loop

Fill input buffer with data Run inference Interpret output results



Inference Engine Details

A runtime with a unified API for integrating inference with application logic

 Delivers optimized inference solution with reduced footprint on inference execution for target hardware

libinference_engine.so library implements core functions

- Loading and parsing of model IR
- Preparation of input and output blobs
- Triggers inference using specified plug-in

Include file: inference_engine.hpp

Inference Engine Plugins

CPU MKLDNN Plugin (Intel® Math Kernel Library for Deep Neural Networks)

- Supports Intel® Xeon®/Core®/Atom® platform
- Widest set of network classes supported, easiest way to enable topology

GPU clDNN Plugin (Compute Library for Deep Neural Networks)

- Supports 9th generation and above Intel[®] HD and Iris graphics processors
- Extensibility mechanism to develop custom layers through OpenCL™

FPGA DLA Plugin

- Supports Intel® Arria 10 GX and above devices
- Basic set of layers are supported on FPGA, non-supported layers inferred through other plugins



Inference Engine Classes

Class	Details
InferencePlugin, InferenceEnginePluginPtr	Main plugin interface
PluginDispatcher	Finds suitable plug-in for specified device
CNNNetReader	Build and parse a network from given IR
CNNNetwork	Neural Network and binary information
Blob, TBlob, BlobMap	Container object representing a tensor
InputInfo, InputsDataMap	Information about input of the network

Inference Engine API Usage (1)

1. Load Plugin

- FPGA Plugin: libdliaPlugin.so
 - Others: libclDNNPlugin.so (GPU), libMKLDNNPlugin.so (CPU)
- Plugin Dir: <OpenVINO install dir>/inference_engine/lib/<OS>/intel64

```
InferenceEngine::PluginDispatcher dispatcher(<pluginDir>);
InferenceEngine::InferenceEnginePluginPtr enginePtr;
enginePtr = dispatcher.getSuitablePlugin(TargetDevice::eFPGA);
```

2. Load Network

```
InferenceEngine::CNNNetReader netBuilder
netBuilder.ReadNetwork("<Model>.xml");
netBuilder.ReadWeights("<Model>.bin");
```

Inference Engine API Usage (2)

3. Prepare Input and Output Blobs

- For Input Blobs
 - Allocate based on the size of the input, number of channels, batch size, etc.
 - Set input precision
 - Fill in data (i.e., from RGB value of image)
- For Output Blobs
 - Set output precision
 - Allocate based on output format

Inference Engine API Usage (3)

4. Load the model to the plugin

```
InferenceEngine::StatusCode status=enginePtr->LoadNetwork(netBuilder.getNetwork(), &resp);
```

5. Perform inference

```
status= enginePtr->Infer(inputBlobs, outputBlobs, &resp);
```

6. Process output blobs

```
const TBlob<float>::Ptr fOutput =
std::dynamic_pointer_cast<TBlob<float>>(outputBlobs.begin()->second);
```

Using the Inference Engine API

```
CNN Network
                                      instance
               Parse
                                                        Load Network
                                                                                 Infer
      (using CNNNetReader)
                                     Create Engine
                                       Instance
                                                       CNNNetwork instance
auto netBuilder = new InferenceEngine::CNNNetReader();
netBuilder->ReadNetwork("Model.xml");
netBuilder->ReadWeights("Model.bin")
auto enginePtr = new InferenceEngine::InferenceEnginePluginPtr(getSuitablePlugin(eFPGA));
enginePtr->LoadNetwork(*netBuilder->network, &resp);
InferenceEngine::TBlob<float> output;
InferenceEngine::SizeVector inputDims;
netBuilder->getInputDimentions(inputDims);
InferenceEngine::TBlob<short> input(inputDims);
input.allocate();
enginePtr->Infer(input, output, &resp);
```



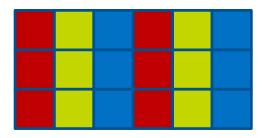
Pre-processing

Most image formats are interleaved (RGB, BGR, BGRA, etc.)

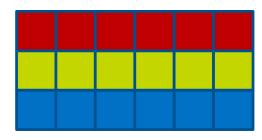
Models usually expect RGB planar format:

R-plane, G-plane, B-plane

Interleaved



Planar





Batch Execution

For better performance, using a larger batch size will likely help

Allocate input and output Blob according to batch size

Set the Batch size on the network

netBuilder.getNetwork().setBatchSize(<size>);



Automatic Fallback with Hetero Plugin

```
$ classification_sample -d HETERO:FPGA,CPU ...
The "priorities" define search order
Keeps all layers that can be executed on the device (FPGA)
Carefully respecting the topological and other limitations
Then follows priorities when searching (e.g. CPU)
```

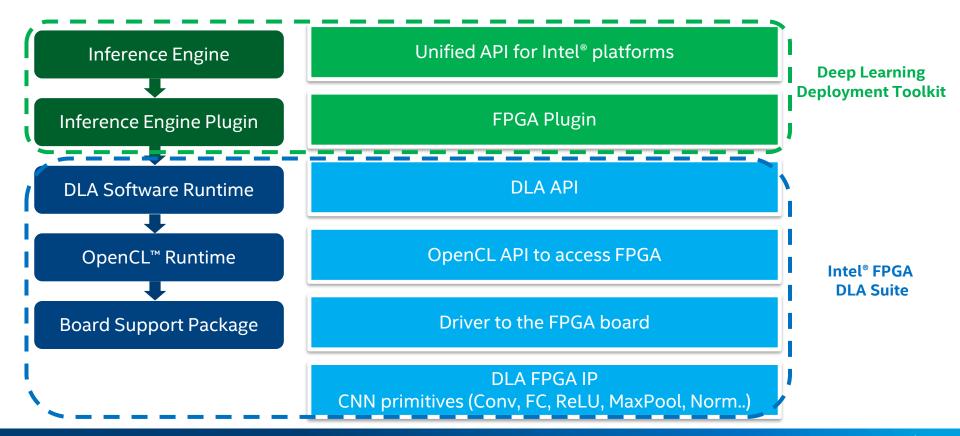


Inference Engine Example Applications

Execute samples and demos with FPGA support

- Shipped with the Intel® Distribution of OpenVINO™ toolkit
- classification_sample
- object_detection_sample_ssd
- and many others

IE Software Architecture with FPGAs



Prepare FPGA Environment for Inference

Intel® FPGA Runtime Environment for OpenCL™

Prepare FPGA Board for OpenCL

Set environment

Use script to ensure DLA and OpenCL libraries part of LD_LIBRARY_PATH

Load FPGA Image and Execute IE Application

FPGAs needs to be preconfigured with primitives prior to application execution

Choose FPGA bitstream from the DLA suite

- Based on topology needs and data type requirements
- Option to create custom FPGA bitstream based on requirements

```
[xkqi@centos-z620 ~]$ aocl program acl0 $DLA_AOCX
aocl program: Running program from /opt/intelFPGA_pro/17.0/hld/board/a10_ref/linux64/libexec
Programming device: a10gx : Arria 10 Reference Platform (acla10_ref0)
Reprogramming device [0] with handle 1
Program succeed.
[xkqi@centos-z620 ~]$
```

Execute User or Example Application

[xkqi@centos-z620 work]\$ classification_sample -i mypic.BMP -m GoogleNet/GoogleNet.xml -d FPGA -ni 100

FPGA Image Selection

Precompiled FPGA image available with the toolkit

Choose image based on

- Primitives needed (architecture)
- Data type support for accuracy/performance trade-off
- K (filter) and C (channel depth) vectorization for performance
- Data path width
- On-chip stream buffer depth

May also generate customized FPGA image to meet your needs

Heterogeneous FPGA + CPU Execution

Use HETERO plugin

- Functions the FPGA does not support falls back to the CPU
- Fallback happens automatically

Manual splitting of original network may be required

- One network fully accelerated on the FPGA device
- Second network (consumes output of the first) executed on CPU or other devices
- Easier to split in original framework model
 - Create separate IR and load to different Inference Engine devices

Summary

Intel® Distribution of OpenVINO™ toolkit provides a simple to use tool flow with a common front end to take models from common frameworks and target different hardware platforms easily

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