



ACCELERATE DEEP LEARNING INFERENCE USING INTEL TECHNOLOGIES

OBJECT DETECTION USING INTEL® DISTRIBUTION OF OPENVINO™ TOOLKIT

March 2019

Core and Visual Computing Group

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Smart Video Workshop Overview

Introduction

1. Introduction to Intel technologies for deep learning inference
2. Hardware acceleration techniques

Each module contains a hands-on lab exercise that introduces various Intel technologies to accelerate computer vision application with hardware heterogeneity.

Intel® Distribution of OpenVINO™ 101

Hardware Acceleration

Optimization

Application

2. Basic End-to-End Object Detection Example

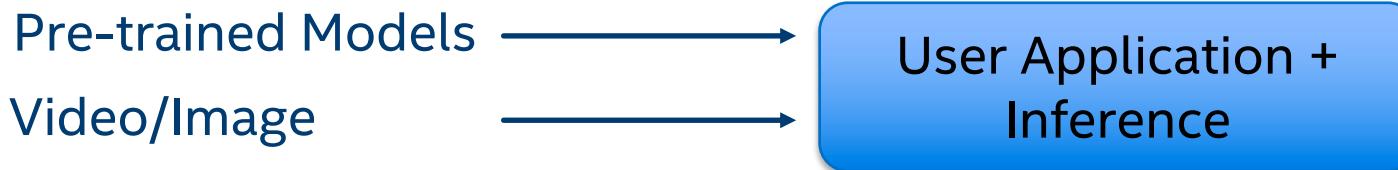
3./4./5. Hardware Acceleration with CPU, Integrated GPU, Intel® Movidius™ NCS, FPGA

6. Optimization Tools and Techniques

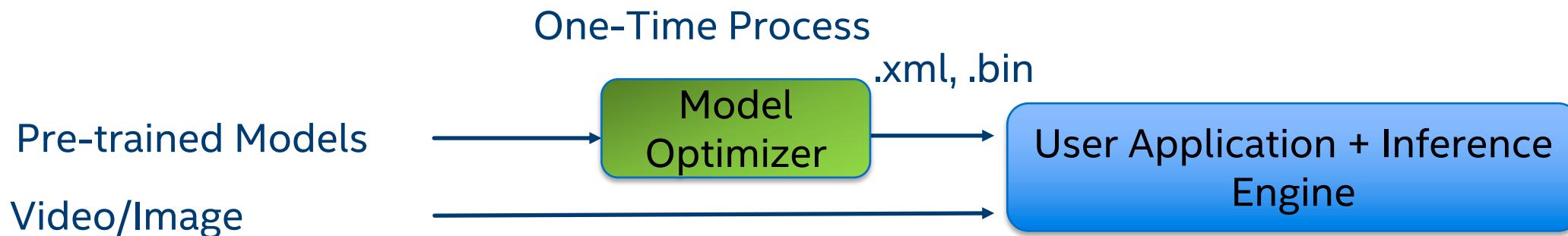
7. Advanced Video Analytics

Deep Learning Application Deployment

Traditional

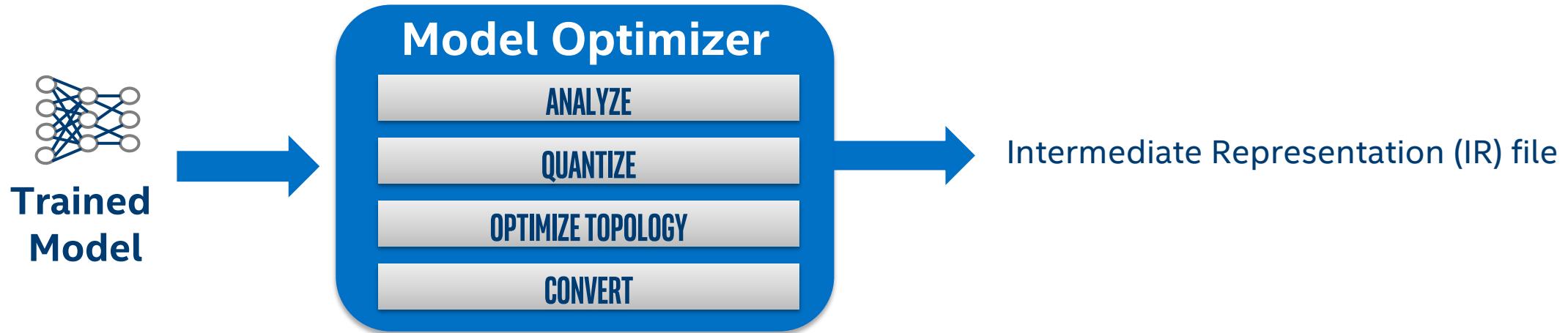


With Intel® Distribution of OpenVINO™ Toolkit



Model Optimizer

Improve Performance with Model Optimizer



- Easy to use, Python*-based workflow does not require rebuilding frameworks.
- Import Models from various supported frameworks - Caffe*, TensorFlow*, MXNet*, ONNX*, Kaldi*.
- 100+ models for Caffe, MXNet and TensorFlow validated. All public models on ONNX* model zoo supported.
- With Kaldi support, the model optimizer extends inferencing for non-vision networks.
- IR files for models using standard layers or user-provided custom layers do not require Caffe.
- Fallback to original framework is possible in cases of unsupported layers, but requires original framework.

Model Optimizer

Model optimizer performs generic optimization:

- 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 IR

--mean_values (104.006, 116.66, 122.67)

--scale_values (0.07, 0.075, 0.084)

	FP32	FP16	FP11	INT8
CPU	yes	no	no	yes
GPU	yes	recommended	no	no
MYRIAD	no	yes	no	no
FPGA/DLA	no	yes	yes	no

Model Optimization Techniques

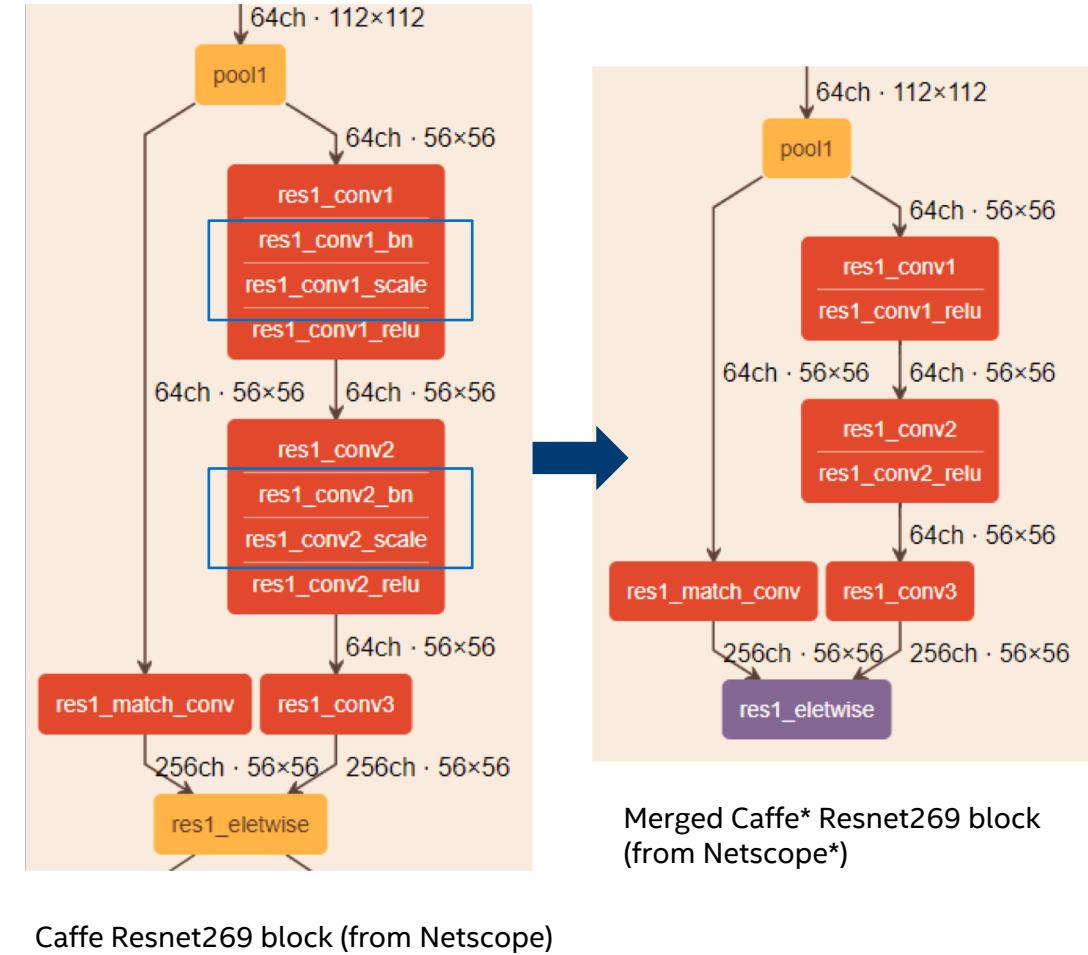
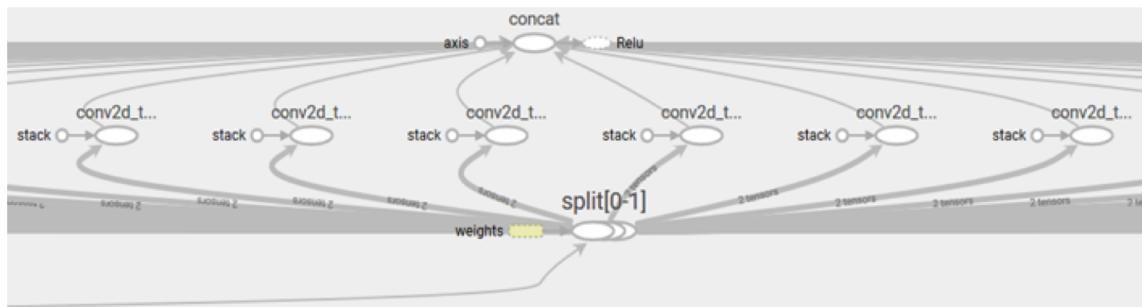
Linear Operation Fusing & Grouped Convolutions Fusing

Linear Operation Fusing: 3 stages

1. **BatchNorm and ScaleShift decomposition:** BN layers decomposes to *Mul->Add->Mul->Add* sequence; ScaleShift layers decomposes to *Mul->Add* sequence.
2. **Linear operations merge:** Merges sequences of Mul and Add operations to the **single** Mul->Add instance.
3. **Linear operations fusion:** Fuses Mul and Add operations to Convolution or FullyConnected layers.

Grouped Convolutions Fusing

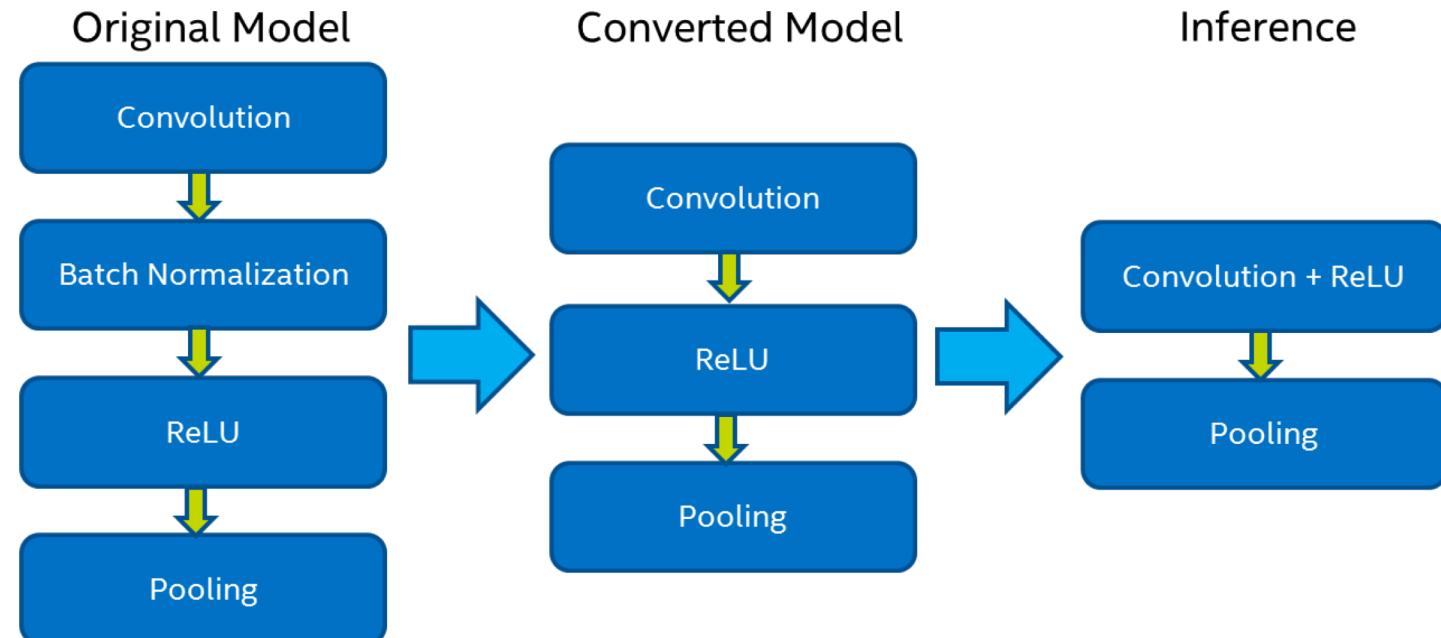
Specific optimization that applies for TensorFlow* topologies. (Xception*)



Model Optimizer: Linear Operation Fusing

Example

1. Remove Batch normalization stage.
2. Recalculate the weights to 'include' the operation.
3. Merge Convolution and ReLU into one optimized kernel.



Model Optimizer: Cutting Off Parts of a Model

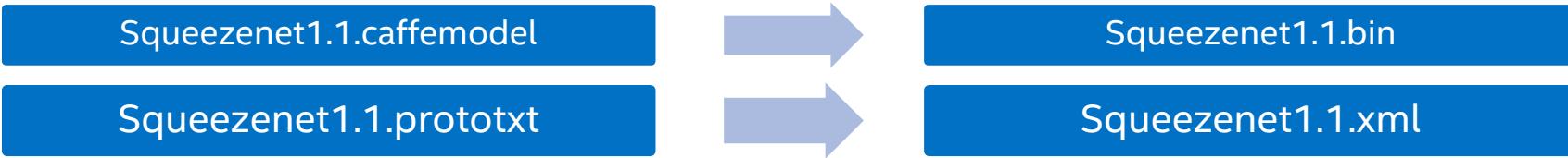
Model optimizer can cut out a portion of the network:

- Model has pre/post-processing parts that cannot be mapped to existing layers.
- Model has a training part that is not used during inference.
- Model is too complex and cannot be converted in one shot.

Command line options

- Model Optimizer provides command line options `--input` and `--output` to specify new entry and exit nodes ignoring the rest of the model:
- `--input` option accepts a comma-separated list of layer names of the input model that should be treated as new entry points to the model;
- `--output` option accepts a comma-separated list of layer names of the input model that should be treated as new exit points from the model.

Intermediate Representation (IR)



```
layer {
    name: "data"
    type: "Input"
    top: "data"
    input_param { shape: { dim: 1 dim: 3 dim: 227 dim: 227 } }
}
layer {
    name: "conv1"
    type: "Convolution"
    bottom: "data"
    top: "conv1"
    convolution_param {
        num_output: 64
        kernel_size: 3
        stride: 2
    }
}
```

```
<net batch="1" name="model" version="2">
<layers>
<layer id="100" name="data" precision="FP32" type="Input">
<output>
<port id="0">
<dim>1</dim>
<dim>3</dim>
<dim>227</dim>
<dim>227</dim>
</port>
</output>
</layer>
<layer id="129" name="conv1" precision="FP32" type="Convolution">
<data dilation-x="1" dilation-y="1" group="1" kernel-x="3" kernel-y="3" output="64" pad="0" type="NCHW"/>
<input>
<port id="0">
<dim>1</dim>
<dim>3</dim>
<dim>227</dim>
<dim>227</dim>
</port>
</input>
<output>
<port id="3">
<dim>1</dim>
<dim>64</dim>
<dim>113</dim>
<dim>113</dim>
</port>
</output>
<blobs>
<weights offset="2275104" size="6912"/>
<biases offset="4805920" size="256"/>
</blobs>
..
```

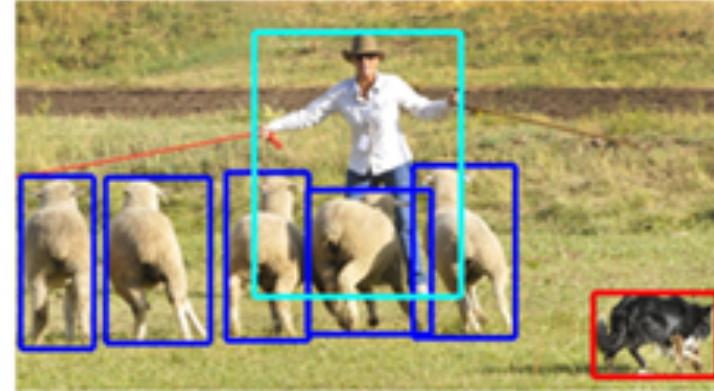
Inference Engine

Inference on an Intel® Edge Systems

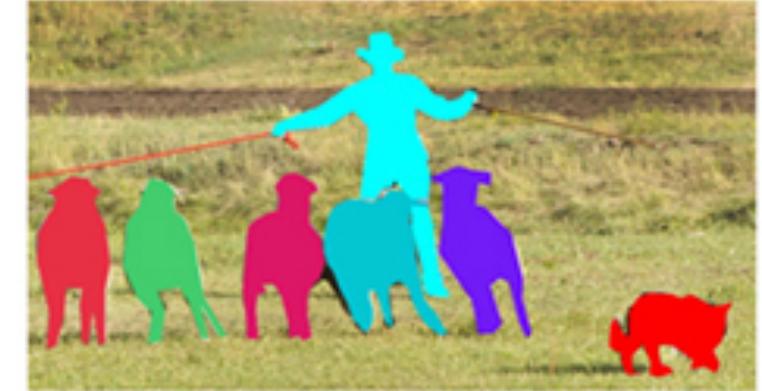
Many deep learning networks are available—choose the one you need.



(a) classification



(b) detection

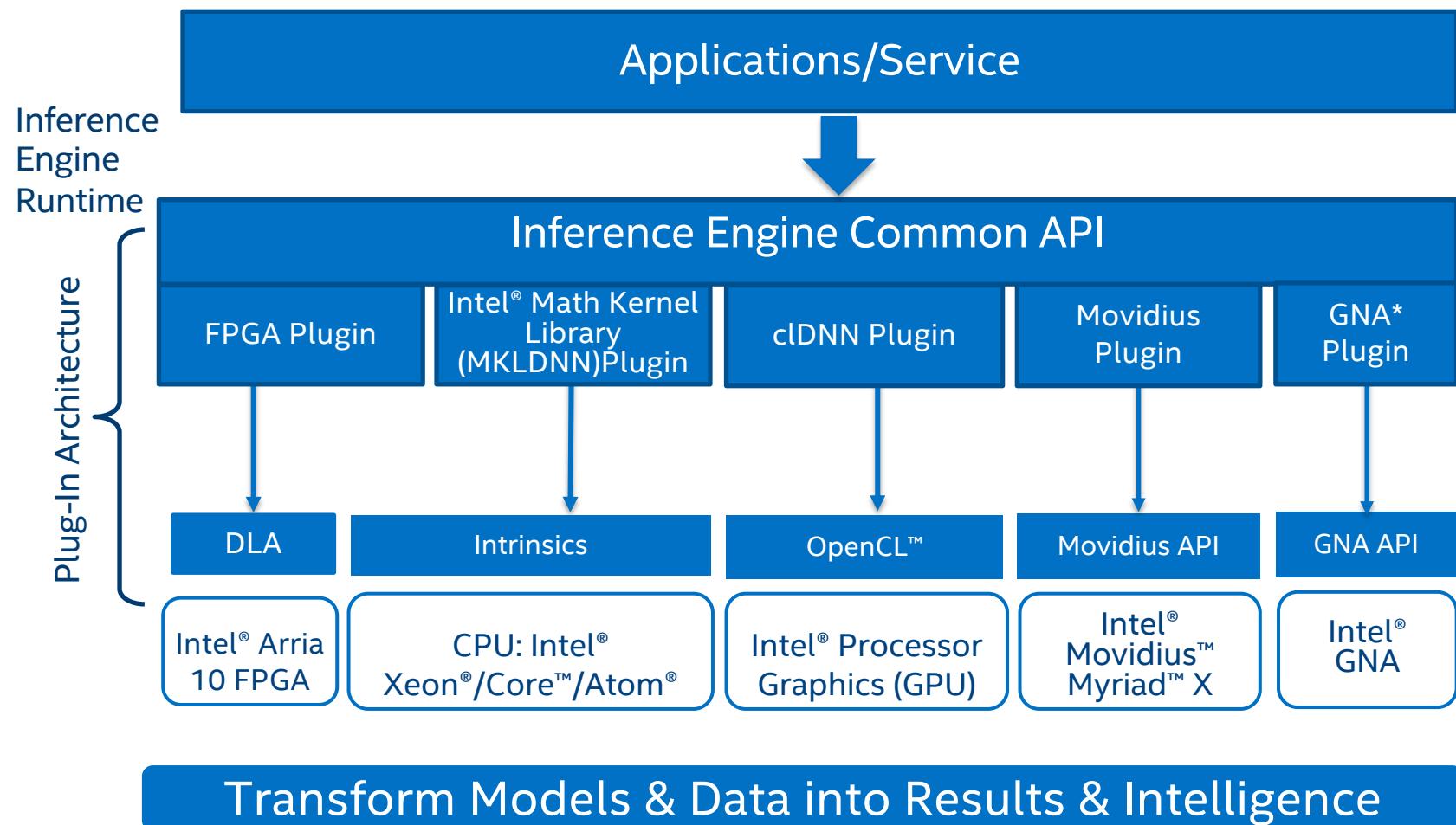


(c) segmentation

The complexity of the problem (data set) dictates the network structure. The more complex the problem, the more 'features' required, the deeper the network.

Optimal Model Performance Using the Inference Engine

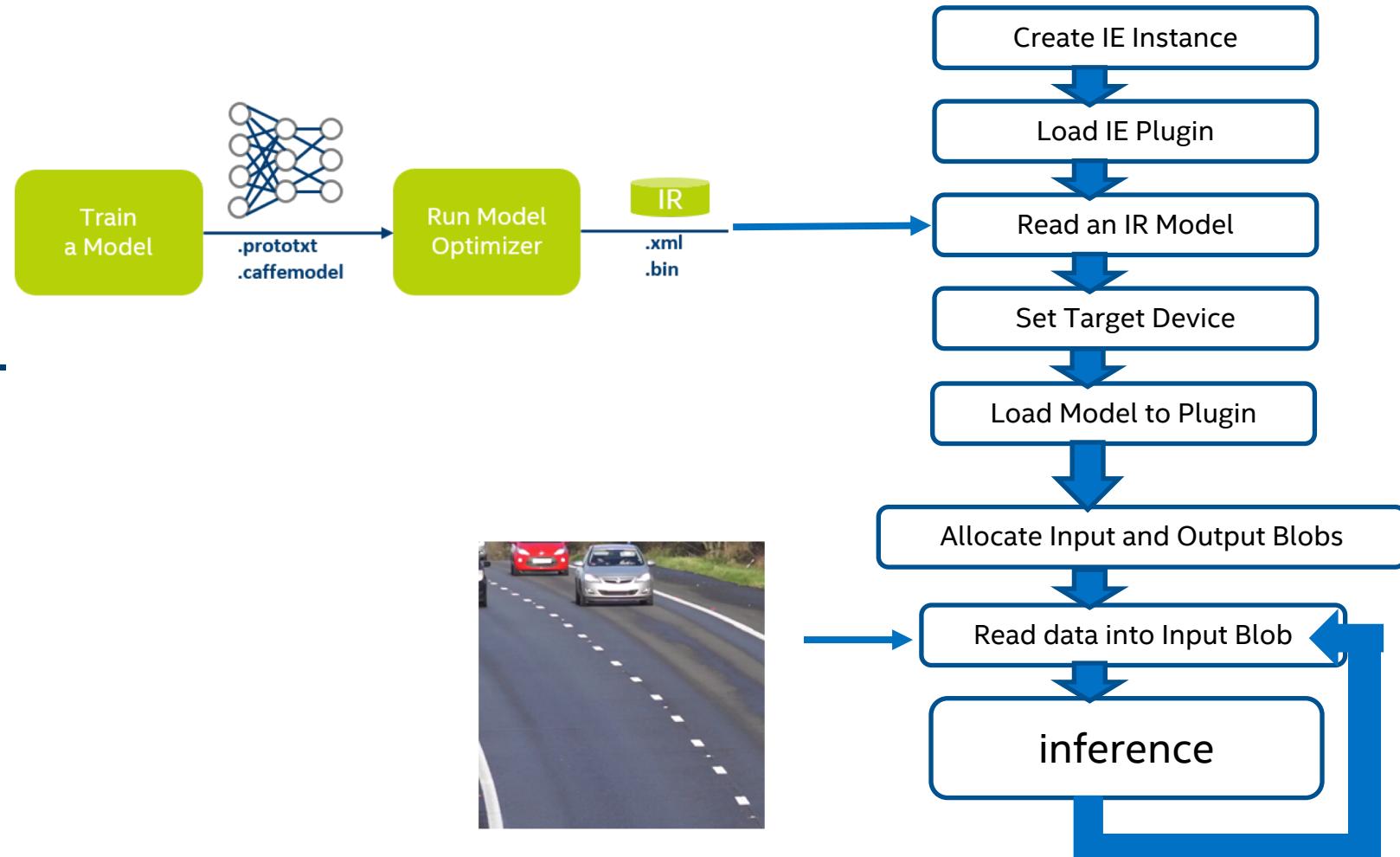
- Simple & Unified API for Inference across all Intel® architecture
- Optimized inference on large IA hardware targets (CPU/GEN/FPGA)
- Heterogeneity support allows execution of layers across hardware types
- Asynchronous execution improves performance
- Futureproof/scale your development for future Intel® processors



GPU = Intel CPU with integrated graphics/Intel® Processor Graphics/GEN
GNA = Gaussian mixture model and Neural Network Accelerator

Workflow of Applying IE in CV Applications

- Integrate inference engine (IE) API into the application.
- Intel® MKL-DNN plugin for CPU, CI-DNN for GPU.
- Target device could be CPU/GPU/Intel® Movidius™ NCS/FPGA.

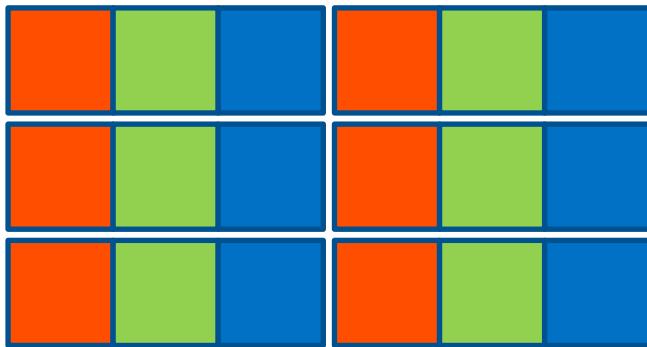


Pre-processing

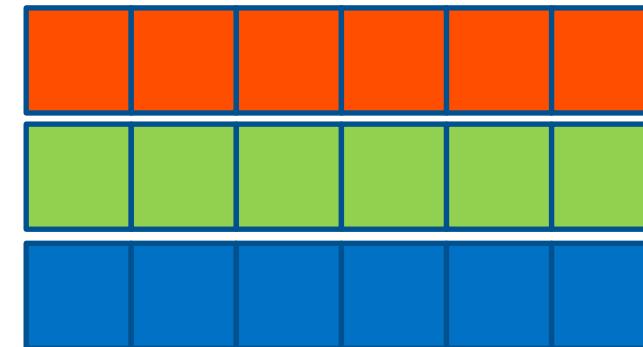
Most of the image formats are interleaved formats (RGB, BGR, BGRA, and so forth). Inference engine expects input to be in RGB planar format, such as:

R-plain, G-plain, B-plain

Interleaved



Planar



Post-processing

Developers are responsible for parsing inference output.

Many output formats are available. Some examples include:

- **Simple Classification (alexnet*)**: an array of float confidence scores, # of elements=# of classes in the model
- **SSD**: Many “boxes” with a confidence score, label #, xmin,ymin, xmax,ymax

Unless a model is well documented, the output pattern may not be immediately obvious.

OpenVINO™ Installation Directory Structure



Lab1 - Basic End to End Object Detection Example

URL: <https://github.com/intel-iot-devkit/smart-video-workshop/blob/master/object-detection/README.md>

Objective: This Lab uses a Single Shot MultiBox Detector (SSD) on a trained mobilenet-ssd* Caffe model to walk you through the basic steps of using two key components of the Intel® Distribution of OpenVINO™ toolkit: Model Optimizer and Inference Engine.

Estimated Complete Time: 30min

Lab2 - Tensor Flow example

URL: https://github.com/intel-iot-devkit/smart-video-workshop/blob/master/advanced-video-analytics/tensor_flow.md

Objective: This Lab showcases how to convert and freeze the TensorFlow Inception_v1 model, and use the converted IR model with the Intel® Distribution of OpenVINO™ toolkit inference engine on a classification sample.

Estimated Complete Time: 30min

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Intel® Distribution of OpenVINO™ 101

Hardware Acceleration on laptop and devcloud

Optimization

Application

2. Basic End-to-End Object Detection Example

- 3./4./5. Hardware Acceleration with CPU, Integrated GPU, Intel® Movidius™ NCS, FPGA

6. Optimization Tools and Techniques

7. Advanced Video Analytics

CPU/GPU/FPGA/Intel® Movidius™ Neural Compute Stick

Hardware Heterogeneity

Heterogeneous Dichotomies

Data vs. Task Parallelism

- Data parallelism between devices is usually explicit and extremely error-prone (like in OpenCL™).
- Inference engine heterogeneity support is inherently **task-oriented** (node-level).

Dynamic vs. Static

- **User-defined work split** vs. adaptive schemes (like load-balancing).
- For both, there is a question on the granularity (communications costs, next).

Heterogeneity is basically Fallback.

Introducing Heterogeneous Plugin

The heterogeneous plugin enables computing for inference on one network on several devices. Purposes to execute networks in heterogeneous mode

- To utilize accelerators power and calculate heaviest parts of network on accelerator and execute not supported layers on fallback devices like CPU
- To utilize all available hardware more efficiently during one inference

The execution through heterogeneous plugin can be divided to two independent steps:

- Setting of affinity to layers (binding them to devices in `InferenceEngine::ICNNNetwork`)
- Loading a network to the Heterogeneous plugin, splitting the network to parts, and executing them through the plugin

These steps are decoupled. The setting of affinity can be done automatically using fallback policy or in manual mode.

Apply Device Affinities to Layers Automatically Using Fallback Policy (1 of 2)

```
$ ./object_detection_sample_ssd -m <path_to_model>/Model.xml -i  
<path_to_pictures>/picture.jpg -d HETERO:FPGA,CPU
```

The “priorities” defines a greedy behavior:

- Keeps all layers that can be executed on the device (FPGA)
- Carefully respects topological and other limitations
- Follows priorities when searching (for example, CPU)

Apply Device Affinities to Layers Automatically Using Fallback Policy (2 of 2)

```
1. InferenceEngine::PluginDispatcher dispatcher({ FLAGS_pp,  
    archPath , "" }) ;  
2. InferenceEngine::InferenceEnginePluginPtr enginePtr;  
3. enginePtr =  
    dispatcher.getPluginByDevice("HETERO:FPGA,CPU") ;  
4. InferencePlugin plugin(enginePtr) ;  
5. CNNNetReader reader;  
6. reader.ReadNetwork("Model.xml") ;  
7. reader.ReadWeights("Model.bin") ;  
8. auto executable_network = plugin.LoadNetwork(network,  
    {});
```

Apply Device Affinities to Layers Manually

```
1. InferenceEngine::PluginDispatcher dispatcher({ FLAGS_pp,  
    archPath , "" }) ;  
2. InferenceEngine::InferenceEnginePluginPtr enginePtr;  
3. enginePtr =  
    dispatcher.getPluginByDevice("HETERO:FPGA,CPU") ;  
4. HeteroPluginPtr hetero(enginePtr) ;  
5. hetero->SetAffinity(network, { }, &resp) ;  
6. network.getLayerByName("qqq")->affinity = "CPU" ;  
7. InferencePlugin plugin(enginePtr) ;  
8. CNNNetReader reader ;  
9. reader.ReadNetwork("Model.xml") ;  
10. reader.ReadWeights("Model.bin") ;  
11. auto executable_network = plugin.LoadNetwork(network,  
    { } ) ;
```

Lab3 - Hardware Heterogeneity

URL: <https://github.com/intel-iot-devkit/smart-video-workshop/blob/master/hardware-heterogeneity/README.md>

Objective: This example shows how to use hetero plugin to define preferences to run different network layers on different hardware types, then use option -pc to get performance data on each subgraph.

Estimated Complete Time: 20min

Intel® Movidius™ Neural Compute Stick 2

Intel® Movidius™ Neural Compute Stick 2



Intel® Movidius™ Neural Compute Stick 2

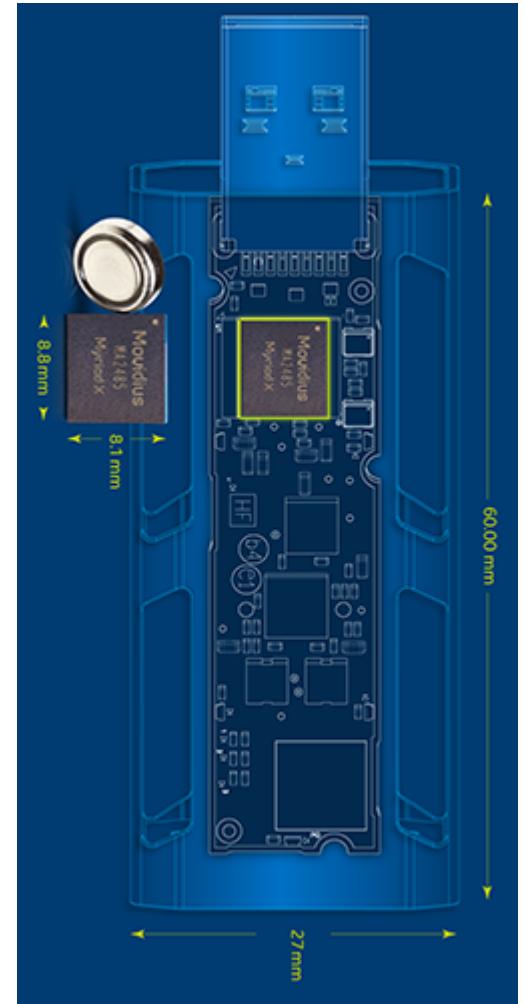
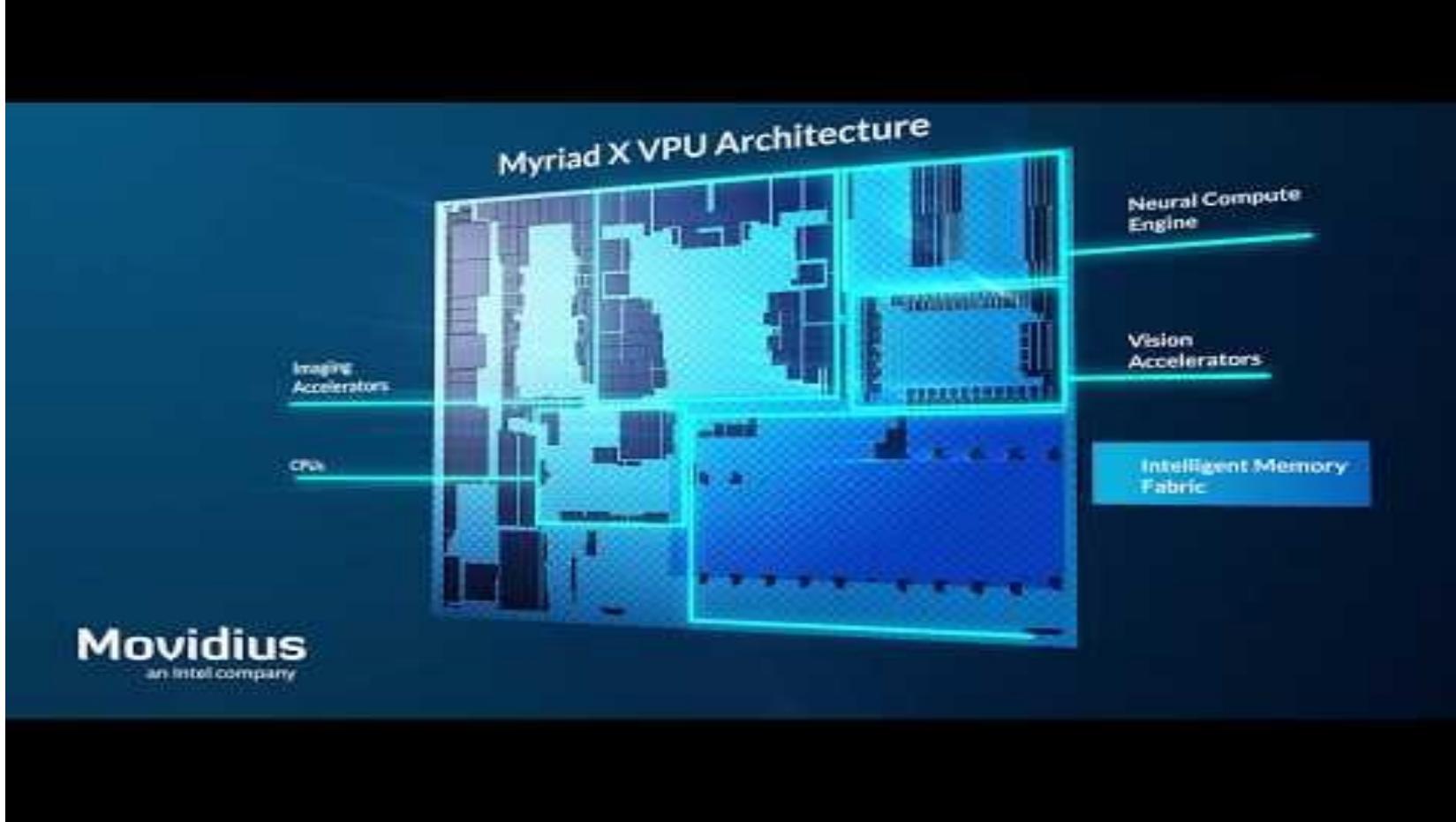
Redefining the AI Developer Kit

Technical Specifications*

- Processor: Intel® Movidius™ Myriad™ X Vision Processing Unit (VPU)
- Supported frameworks: TensorFlow* and Caffe*
- Connectivity: USB 3.0 Type-A
- Dimensions: 2.85 in. x 1.06 in. x 0.55 in. (72.5 mm x 27 mm x 14 mm)
- Operating temperature: 0° C to 40° C
- Compatible operating systems: Ubuntu* 16.04.3 LTS (64 bit), CentOS* 7.4 (64 bit), and Windows® 10 (64 bit)



Intel® Movidius™ Neural Compute Stick 2



Lab4 - HW Acceleration with Intel® Movidius™ Neural Compute Stick

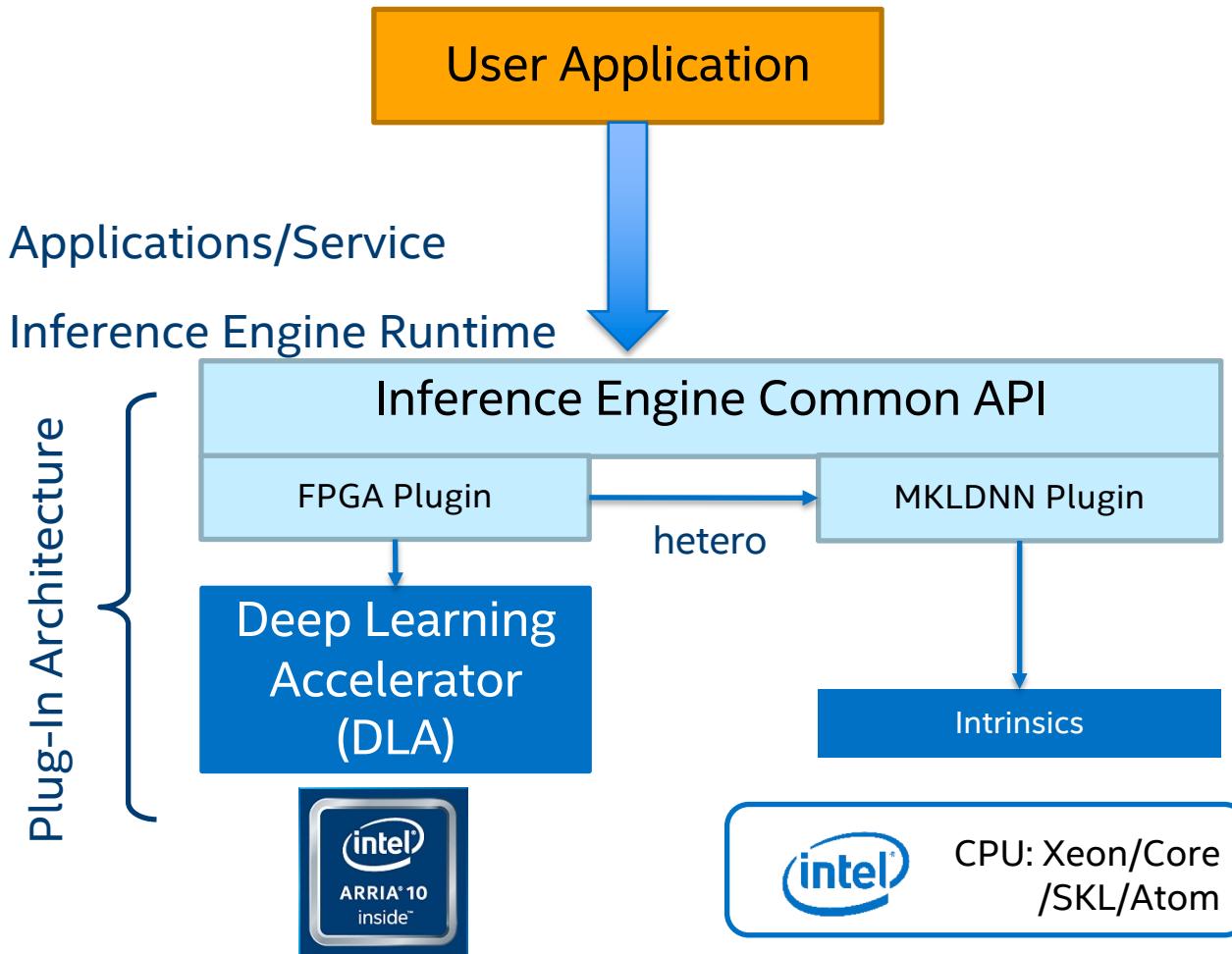
URL: <https://github.com/intel-iot-devkit/smart-video-workshop/blob/master/HW-Acceleration-with-Movidious-NCS/README.md>

Objective: This lab shows how the Intel® Distribution of OpenVINO™ toolkit provides hardware abstraction to run the sample object detection application which was built in previous modules on Intel® Movidius™ Neural Compute Stick.

Estimated Complete Time: 20min

HW Acceleration with Intel® FPGA

Software stack



FPGA implementation is “Deep Learning Accelerator” (DLA)

Additional step: FPGA RTE (aocl) loads bitstream with desired version of DLA to FPGA before running

HW Acceleration with Intel® FPGA



Programmers' Introduction to the Intel® FPGA Deep Learning Acceleration Suite

