

Optimizing Deep Learning models

Theory, tools & best-practices









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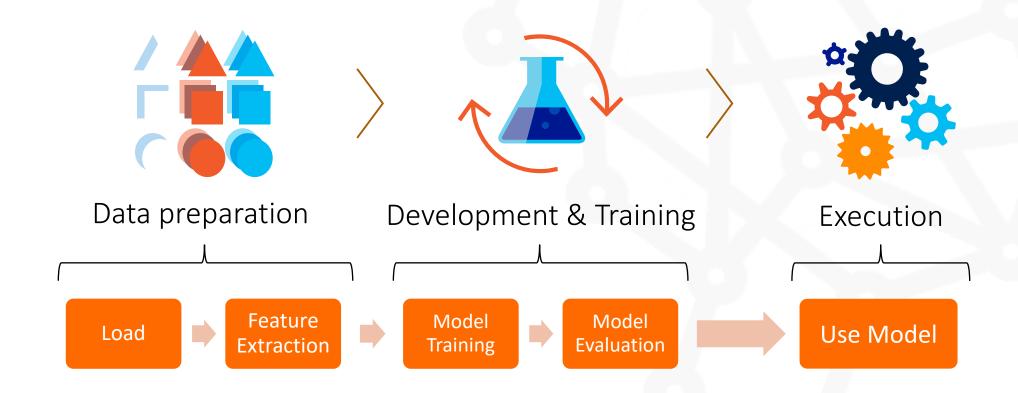


Disclaimer



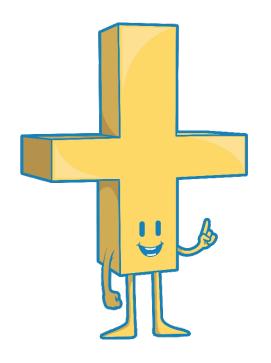


Model lifecycle





Advantages & Disadvantages



Size reduction

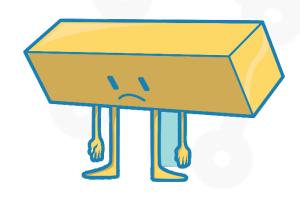
Speed improvements

Energy/Costs savings

Additional steps

Evaluation metrics drops

Not easy





Self Organizing Tree Algorithm & Techniques

Unstructured/semi-structured pruning

- Remove individual (or groups) weights by masking to 0
- Algorithms: Magnitude (0th order), Movement (1st order), WoodFisher (2nd order)

Structured pruning

Remove large sections of weights by changing tensor shapes

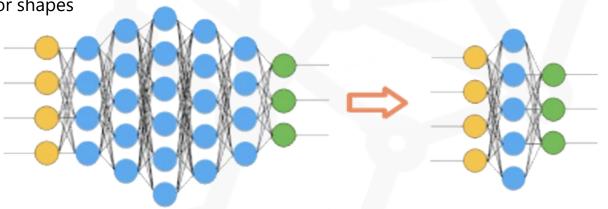
Channel, Filter, Layer, Attention head

Quantization

- Reduce the precision of activations and weights
- INT8 vs. < INT8; dynamic vs static

Distillation

- Distil information from a lager, teacher into a student model
- Response, feature, relation





Applying Optimization to a Model

Post training (One Shot)

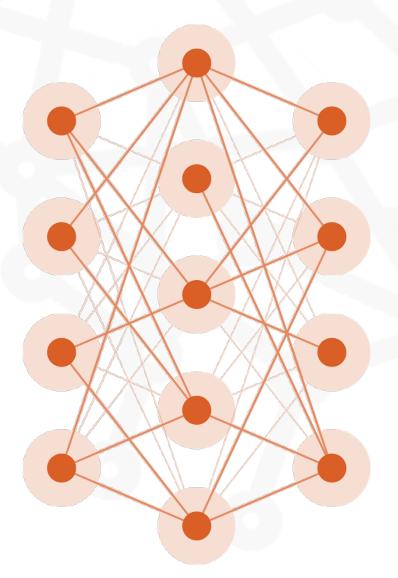
- Applied after training using the model and sample data
- Works well for dynamic quantization
- Currently does not work well for pruning

Training-Aware

- Optimization are applied during training
- Works well for pruning and quantization

Sparse Transfer

• Fine-tune a pre-sparsified model onto a new dataset





Tools

PyTorch and TensorFlow built-in

- O PyTorch
- TensorFlow

- Limited algorithms support
- Optimizations defined in code

NVIDIA TLT/TensorRT and Intel NNCF

- Good one-shot support
- Limited integration and training capabilities

Research Libraries

- Good single algorithm support
- Limited integration and multi-model support
- Nebuly, OctoML, Deci

Wrap the above tools with some additional algorithm support







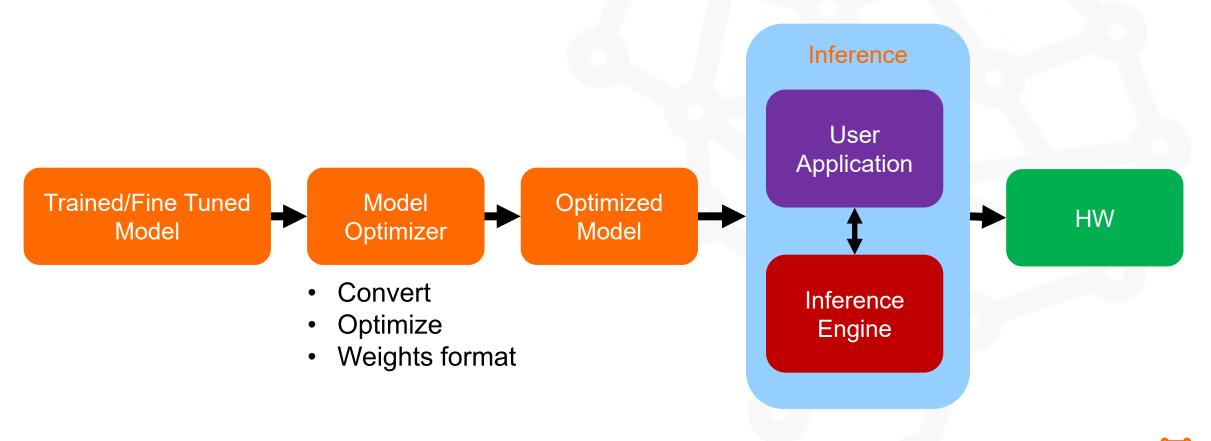






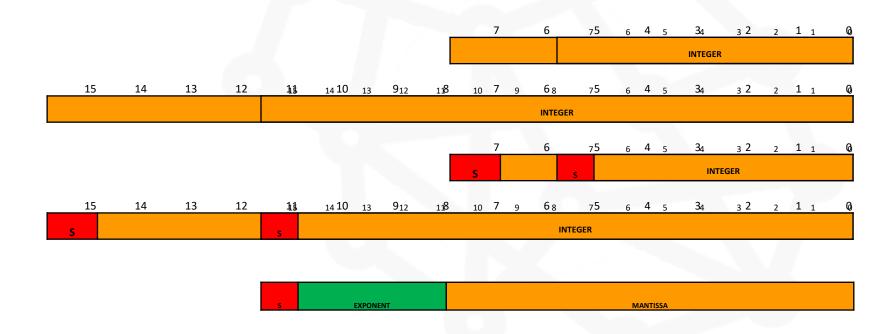


Optimizer Flow





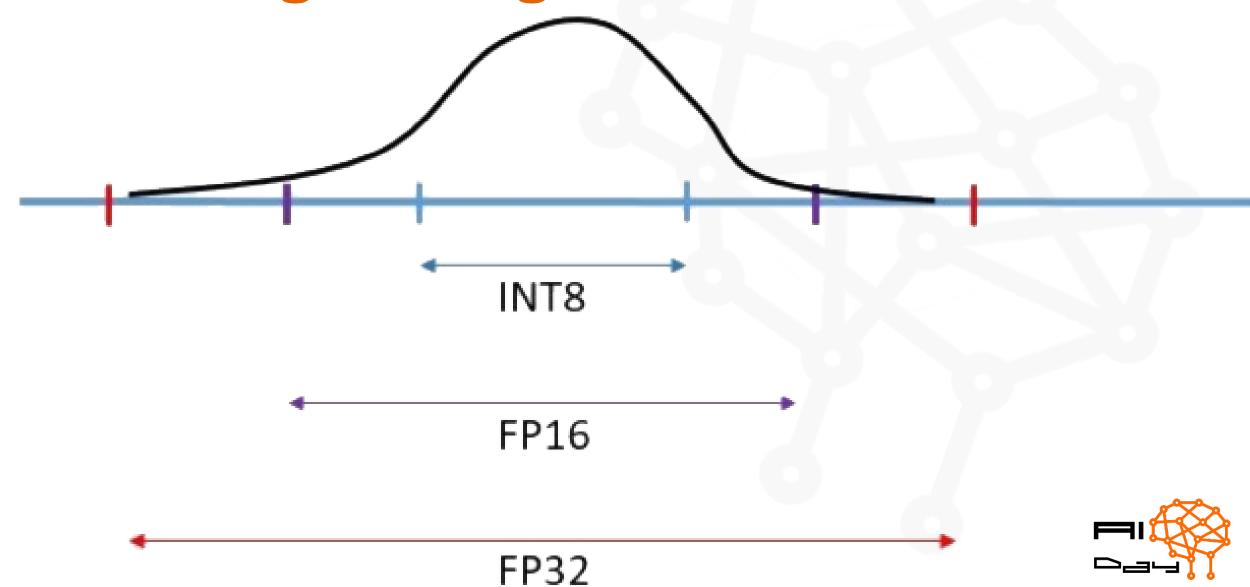
Choosing the Right Precision



S EXPONENT MANTISSA



Choosing the Right Precision



Quantization

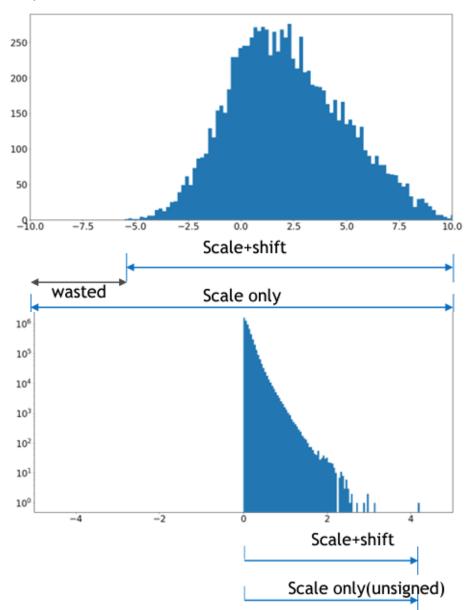


Image Classification, top-1 accuracy

| | FP32 | Int8 Scale | Int8 Scale+Shift |
|----------------------|-------|---------------|---------------------|
| Mobilenet-v1_1_224 | 70.90 | 70.70 | 70.00 |
| Mobilenet-v2_1_224 | 71.90 | 71.10 | 70.90 |
| Nasnet-Mobile | 74.00 | 73.00 | 73.00 |
| Mobilenet-v2_1.4_224 | 74.90 | 74.50 | 73.50 |
| Inception-v3 | 78.00 | 78.00 | 78.00 |
| Resnet-v1_50 | 75.20 | 75.00 | 75.00 |
| Resnet-v2_50 | 75.60 | 75.00 | 75.00 |
| Resnet-v1_152 | 76.80 | 76.20 | 76.50 |

Object Detection, mAP

| | FP32 | Int8 Scale | Int8 Scale+Shift |
|-------------------------------|------|---------------|---------------------|
| faster_rcnn_resnet101_coco* | 0.38 | 0.37 | 0.38 |
| faster_rcnn_nas_coco* | 0.56 | 0.55 | 0.55 |
| faster_rcnn_inception_v2_coco | 0.28 | 0.28 | 0.279 |



Source: https://arxiv.org/abs/1806.08342

Quantization: Math Throughput

Relative to fp32 math

| Input Type | Accumulation Type | Relative math throughput | Bandwidth savings |
|------------|----------------------|--------------------------|-------------------|
| FP16 | FP16 | 8x | 2x |
| INT8 | INT32 | 16x | 4x |
| INT4 | INT32 | 32x | 8x |
| INT1 | INT32 | 128x | 32x |



Source: Nvidia.com

Inference Speedup over FP32

Input size 224x224 for all, except 299x299 for Inception networks

| | Batch size 1 | | | Batch size 8 | | | Batch size 128 | | |
|-----------------|--------------|------|------|--------------|------|------|----------------|------|------|
| | FP32 | FP16 | Int8 | FP32 | FP16 | Int8 | FP32 | FP16 | Int8 |
| MobileNet v1 | 1 | 1.91 | 2.49 | 1 | 3.03 | 5.50 | 1 | 3.03 | 6.21 |
| MobileNet v2 | 1 | 1.50 | 1.90 | 1 | 2.34 | 3.98 | 1 | 2.33 | 4.58 |
| ResNet50 (v1.5) | 1 | 2.07 | 3.52 | 1 | 4.09 | 7.25 | 1 | 4.27 | 7.95 |
| VGG-16 | 1 | 2.63 | 2.71 | 1 | 4.14 | 6.44 | 1 | 3.88 | 8.00 |
| VGG-19 | 1 | 2.88 | 3.09 | 1 | 4.25 | 6.95 | 1 | 4.01 | 8.30 |
| Inception v3 | 1 | 2.38 | 3.95 | 1 | 3.76 | 6.36 | 1 | 3.91 | 6.65 |
| Inception v4 | 1 | 2.99 | 4.42 | 1 | 4.44 | 7.05 | 1 | 4.59 | 7.20 |
| ResNext101 | 1 | 2.49 | 3.55 | 1 | 3.58 | 6.26 | 1 | 3.85 | 7.39 |

Tested with TensorRT on Tesla T4 GPU



Source: Nvidia.com

Quantized Inference

- Quantization:
 - Using lower precision to represent weights and activations
 - Using lower precision math
- Benefits:
 - Speed up inference:
 - Math limited layers due to high throughput math
 - Memory limited layers due to bandwidth saving
 - Reduce resource requirements: memory footprint, etc.
- Challenge:
 - Maintaining model accuracy



Supported Model Formats

| Plugin | FP32 | FP16 | | |
|--------|------------------------|-------------------------|--|--|
| CPU | Supported and prefered | Not supported | | |
| GPU | Supported | Supported and preferred | | |
| FPGA | Supported | Supported | | |
| VPU | Not supported | Supported | | |
| GNA | Supported | Not supported | | |



Source: https://docs.openvino.ai

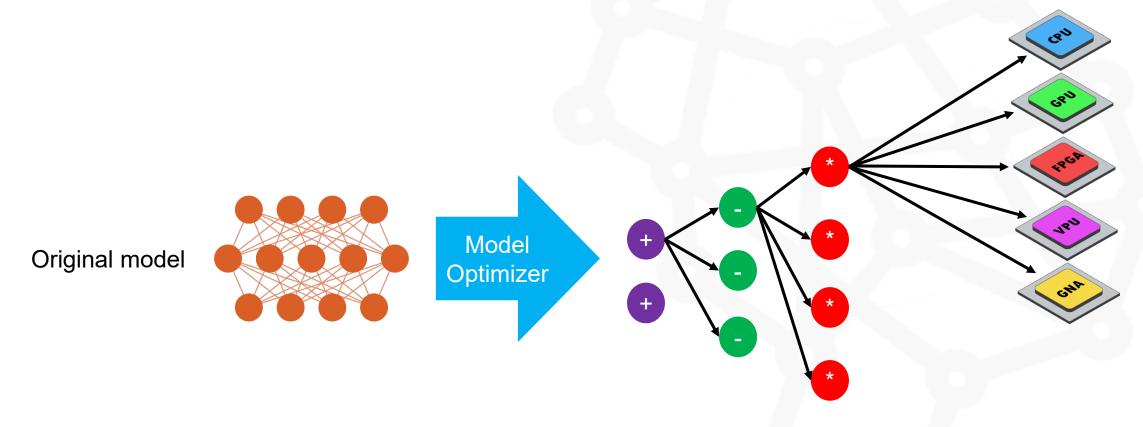
Supported Input Precision

| Plugin | FP32 | FP16 | U8 | U16 | 18 | I16 |
|--------|-----------|---------------|---------------|---------------|---------------|----------------------|
| CPU | Supported | Not Supported | Supported | Supported | Not Supported | Supported |
| GPU | Supported | Supported | Supported | Supported | Not Supported | Supported |
| FPGA | Supported | Supported | Supported | Supported | Not Supported | Supported |
| VPU | Supported | Supported | Supported | Not Supported | Not Supported | Not Supported |
| GNA | Supported | Not Supported | Not Supported | Not Supported | Supported | Supported |



Source: https://docs.openvino.ai

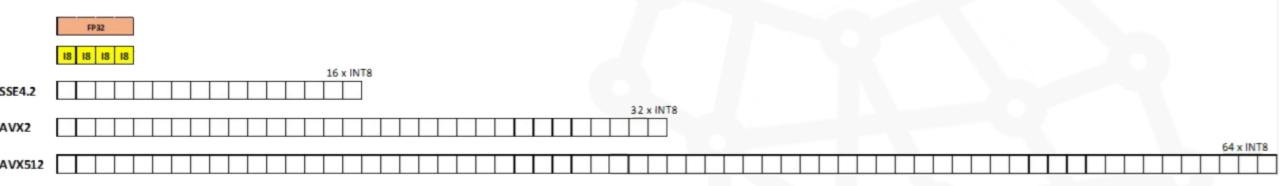
Inference Optimization



- Network level optimizations
- Memory level optimizations
- Kernel level optimizations



INT8 and **VNNI**

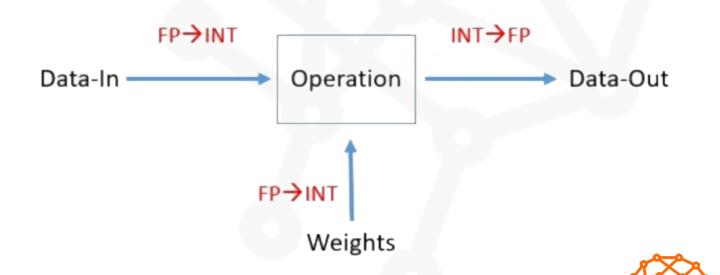


Intel CPUs supporting

- SSE4.2
- AVX2
- AVX512

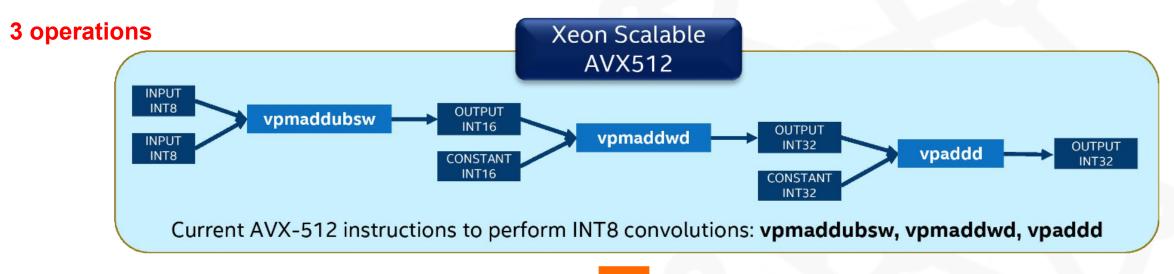
Supported INT8 operations (R1 2019):

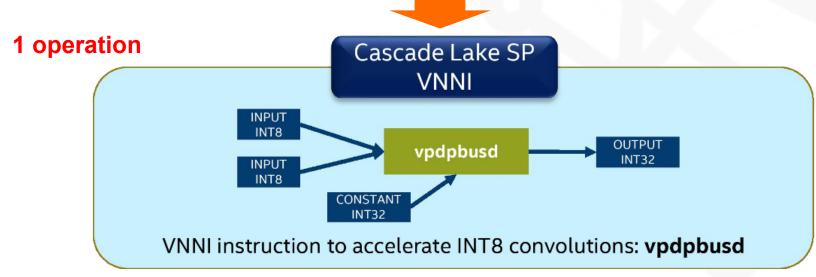
- Convolution
- ReLU
- Pooling
- Eltwise
- Concat



https://www.intel.it/content/www/it/it/architecture-and-technology/avx-512-overview.html

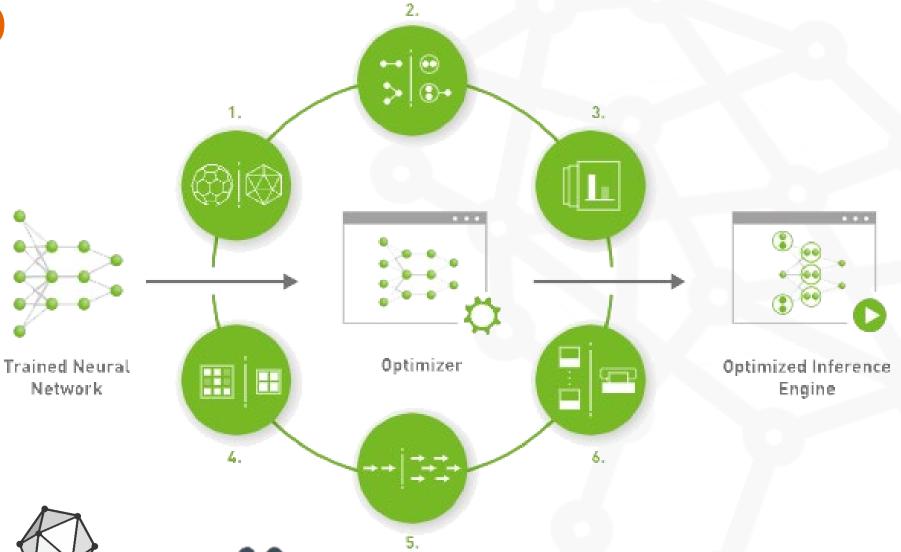
INT8 and VNNI







DEMO













Take aways

- We can improve the performance of our AI models
- We can reduce costs and optimize resources

!! IT'S NOT EASY!!

- Dedicate proper time and team to optimization
- Requires specific knowledge & skills



Thank You!





























Slides/Demo repository

Deltatre Innovation Lab





DOWNLOAD ME

https://github.com/deltatrelabs/deltatre-aiday-2022-demo

About us







R&D Senior Software Engineer @ deltatre

- **Augmented/Mixed/Virtual Reality**
- Artificial Intelligence, Machine Learning, Deep Learning
- **Internet of Things**
- **Hybrid Clusters**
- **Multimodal Tracking**





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Ing. Gianni ROSA GALLINA 💟 @giannirg



- Al, Machine Learning, Deep Learning on multimedia content
- Virtual/Augmented/Mixed Reality
- Immersive video streaming & 3D graphics for sport events
- Cloud solutions, web backends, serverless, video workflows
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- End-to-end solutions with Microsoft Azure















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