embedded VISION SUMMIT 2018

Portability and Performance in Embedded Deep Neural Networks: Can We Have Both?

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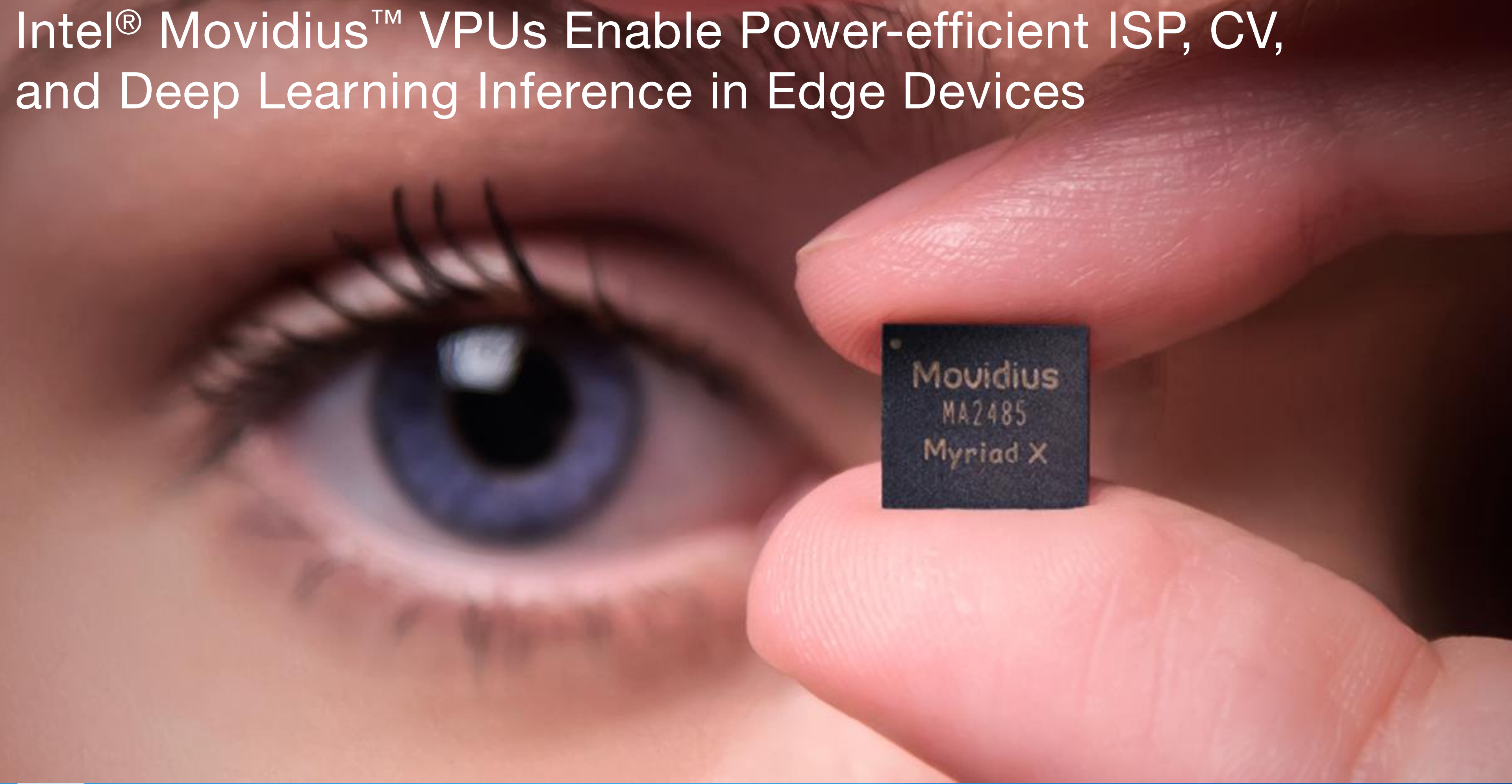
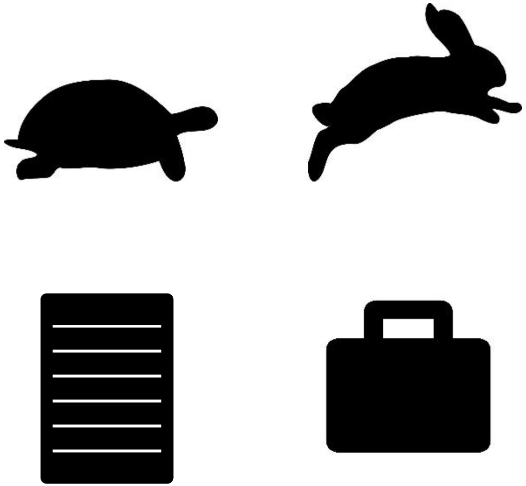


The Question:



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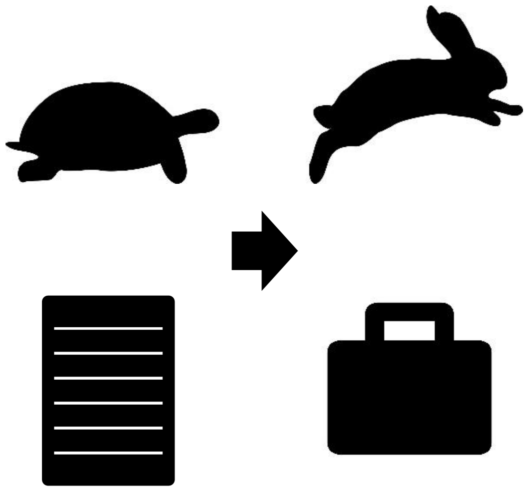
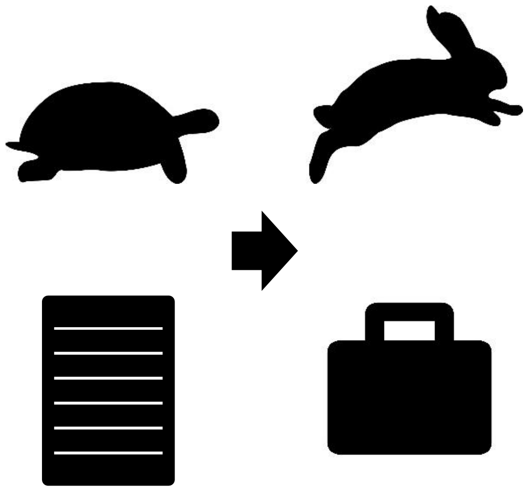


Can we have neural networks that are fast and portable?

The Question (final version):



Can we have neural networks that are fast and portable without losing any accuracy?

Overview

- Selecting a fast network
- Making a fast network faster in a portable way
- Network portability: Ecosystems including ONNX
- Challenges & open items

What is a fast network?

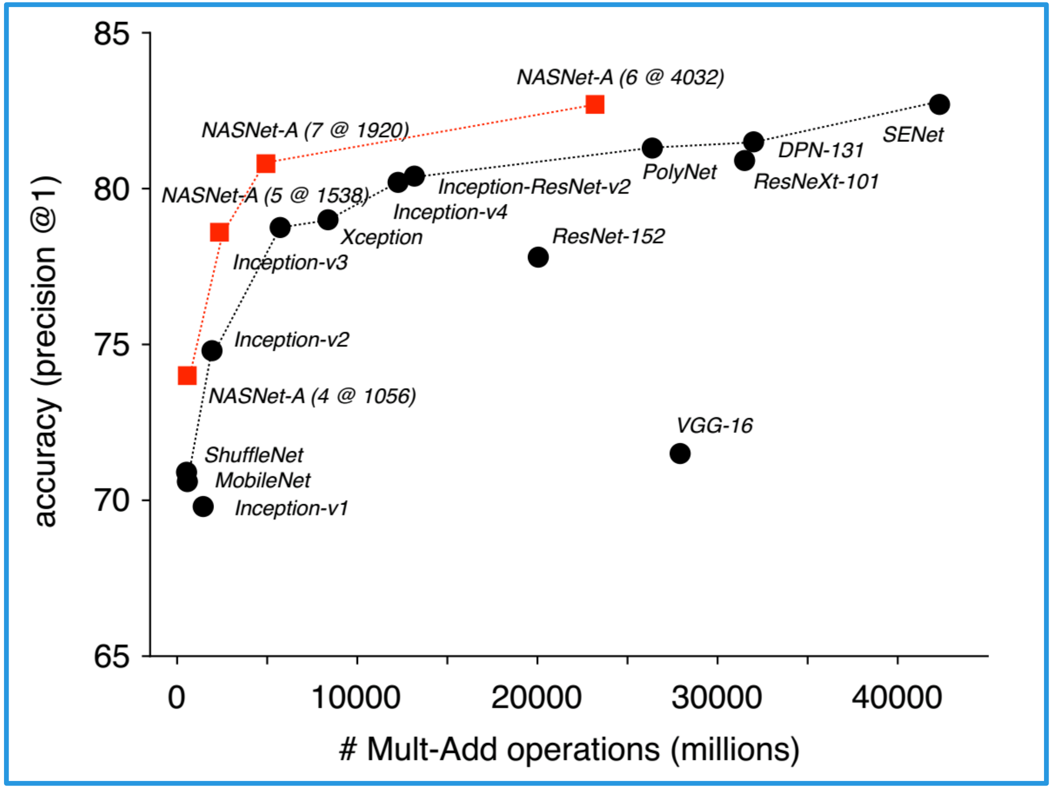
Classical approach, look at:

- Number of FLOPS
- Number of parameters

What is a fast network?

Classical approach, look at:

1. Number of FLOPS

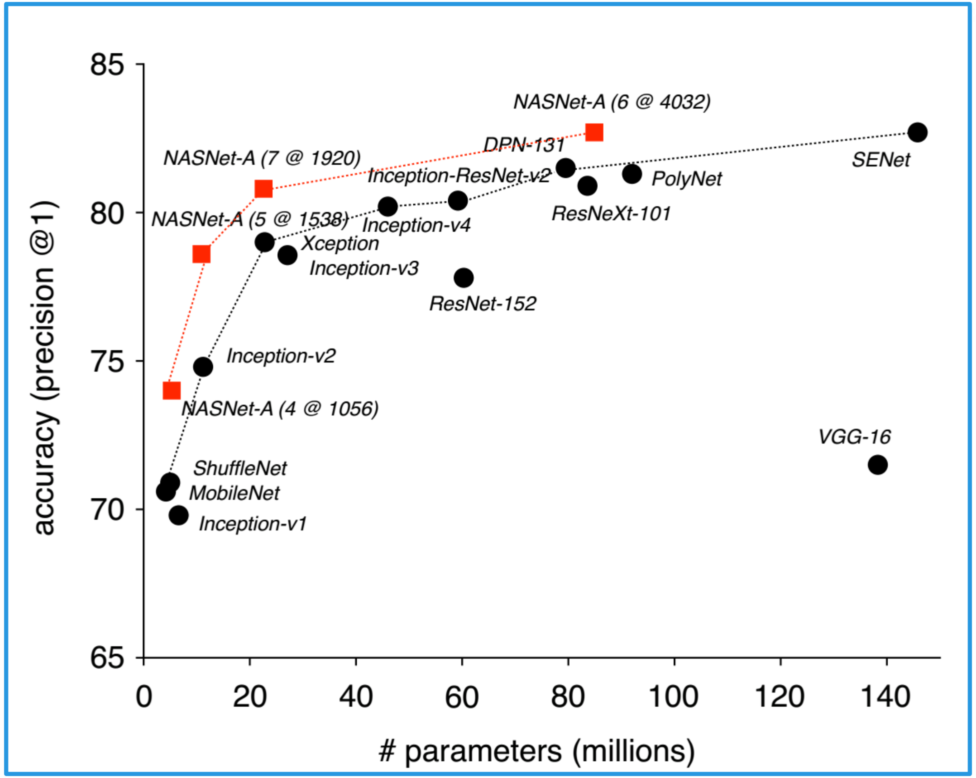


Ref[1]

What is a fast network?

Classical approach, look at:

1. Number of FLOPS
2. Number of parameters



Ref[1]

What is a fast network?

Classical approach, look at:

1. Number of FLOPS
2. Number of parameters

On embedded platforms, dataflow is a key determinant of performance, so we should also consider:

3. Activation heap size

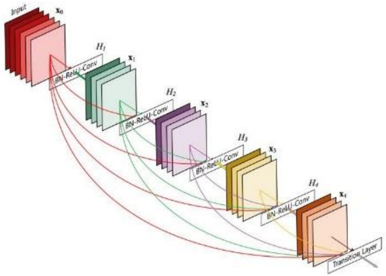
   → *Keep activations in local mem/cache*

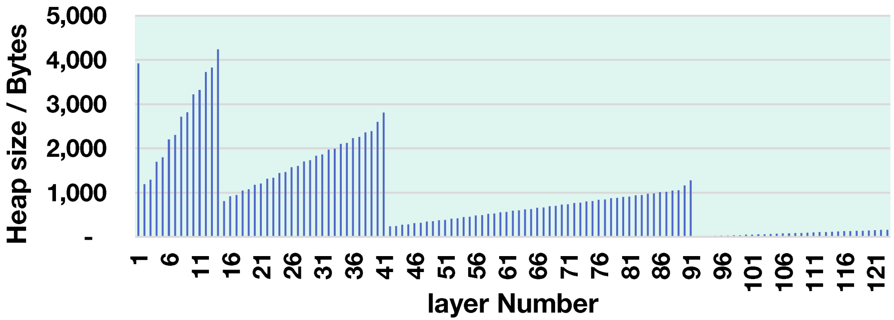
4. FLOPS/param/layer

   → *Avoid being DDR bound on weight fetch*

Activation heap size

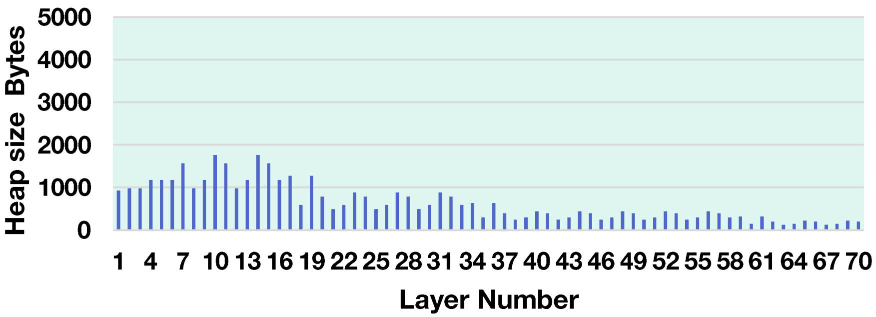
DenseNet





Long lifetime data – larger heap

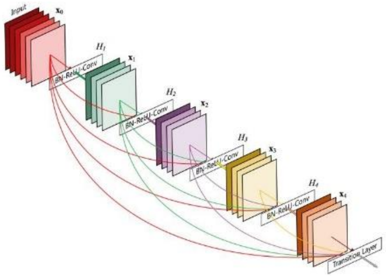
Resnet 50



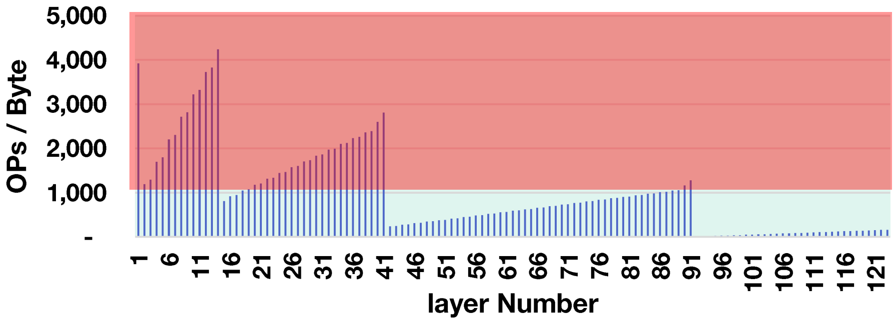
limited lifetime data – smaller heap

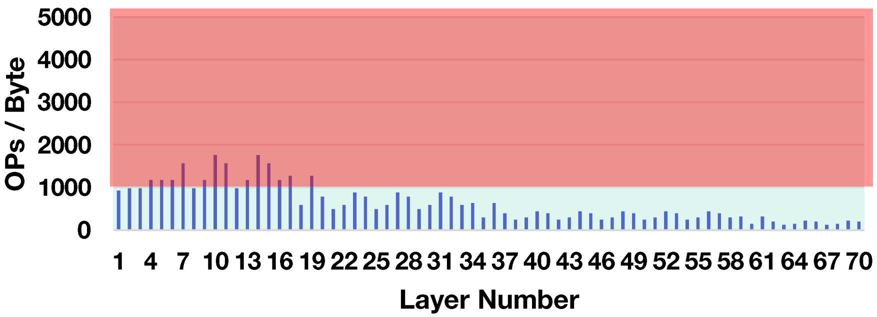
Activation heap size – what if only 1MB L0 mem?

DenseNet



Resnet 50

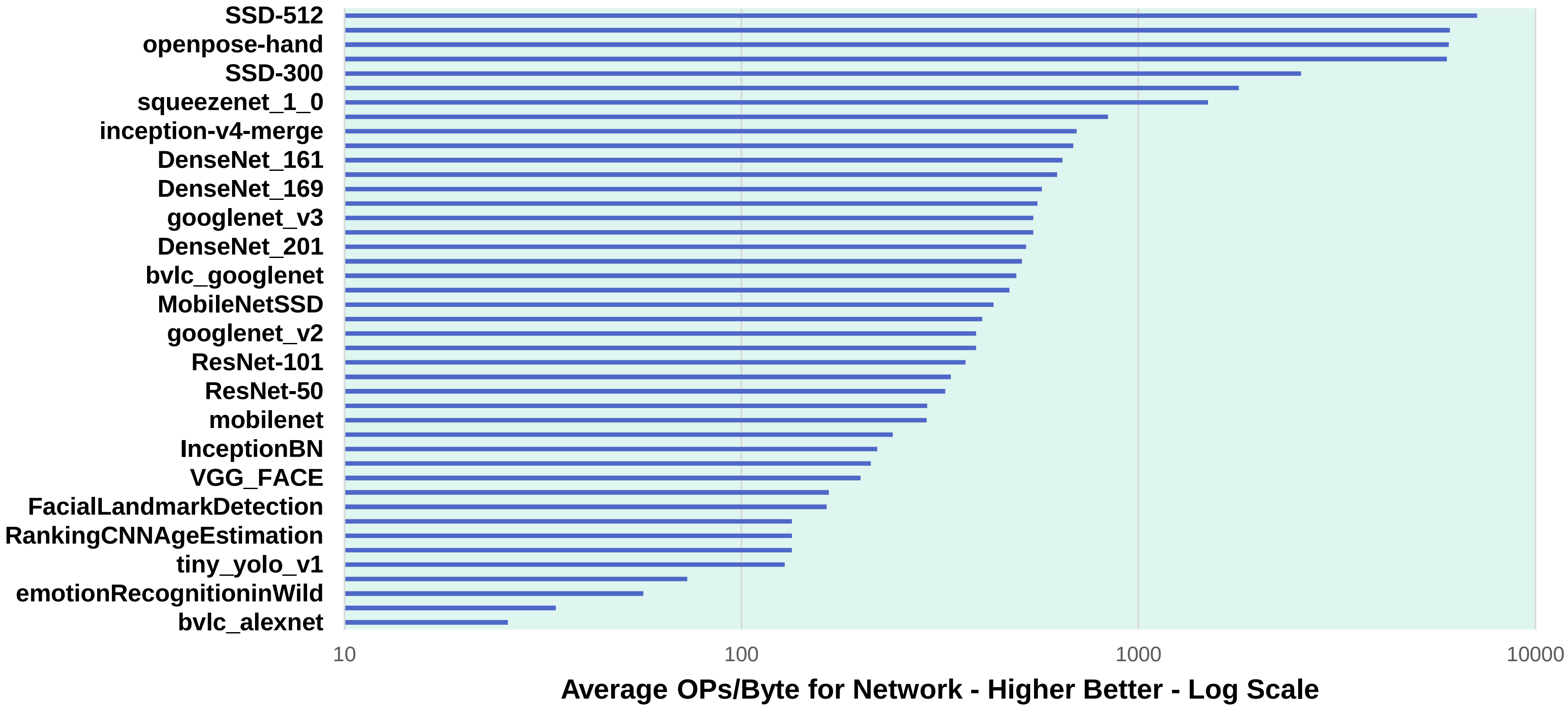




Long lifetime data – larger heap

limited lifetime data – smaller heap

Average OPs/Byte on Common Vision Networks



Refining a fast model to make it faster

Technique	What are we reducing?
Prune networks	OPs, heapSize, #params
Use 8 bits for activation and weights	OPs
Use <8 bits for weights / codebook	Parameter bytes
Sparsify	ModelSize, OPs
Split 3x3 Conv in to DW separable conv	OPs
Use <8 bits for activations	heapSize, OPS

See resources slide for relevant references

Intersection of portability and Model refinement

- Model Pruning
  - Consider pruning to multiples of 8/16 channels. Many hardware implementations have this type of restriction
- Reducing Precision of Weights (4b / 2b / 1b)
  - Using discrete values for weights will
    - Save bandwidth on platforms that directly support low precision weights
    - Save a little less bandwidth on platforms that just support compression
    - Can still work on all platforms

Intersection of portability and Model refinement

- Enhancing portability of 8 bits
  - Dynamic range of activations introduces risks for:
    - Accumulator overflows
    - Edge cases when determining scale factor
  - Solutions:
    - Train with RELU6: $y = \min(\max(x, 0), 6)$
    - Train with Batch Norm, by default keeps $\sigma=1$

Intersection of portability and Model refinement

- Sparsity
  - Good benefit by reducing deployment model size
  - Less Weight bandwidth on platforms supporting compression

Results

(PyTorch) ResNet50	#Param bytes (Non Zero)	TOPs	Accuracy @Top1	Ops/Parameter Byte (higher better)
Baseline	25.5M	7.66	76.01%	300
Fine-grained (80% sparse)	5.1M (5x)	7.66	75.68%	1502
Coarse-grained Pruning	17.2M	3.82 (2x)	74.87%	222
Hybrid: Coarse then Fine (73% sparse thin)	6.9M	3.82	74.32%	554
Hybrid + 4b weights	6.9M	3.82	73.81%	1107

⇒ pruning, sparsity and low precision are compatible and portable
⇒ 0.3%-2.2% accuracy loss, gap reducing over time

Intersection of portability and Model refinement
Summary

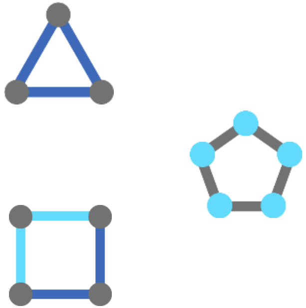
Technique	Portability
Prune Networks	Good, benefit varies
Use 8 bits for activation and weights	Good, when used with care
Use <8 bits for weights / codebook	Good, benefit varies
Sparsify	Good, benefit varies
Split 3x3 conv in to depth-wise separable conv	Varies
Use <8 bits for activations	Poor

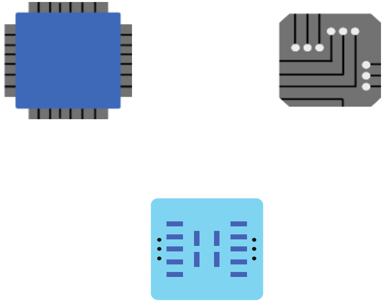
Portable Network Ecosystems

- **Deploying Model on Multiple Targets**
  - OS Specific frameworks
    - DirectML, AndroidNN API, CoreML
  - Network interchange:
    - ONNX

Portability: ONNX Goals

Provide a standard way to represent models so that:

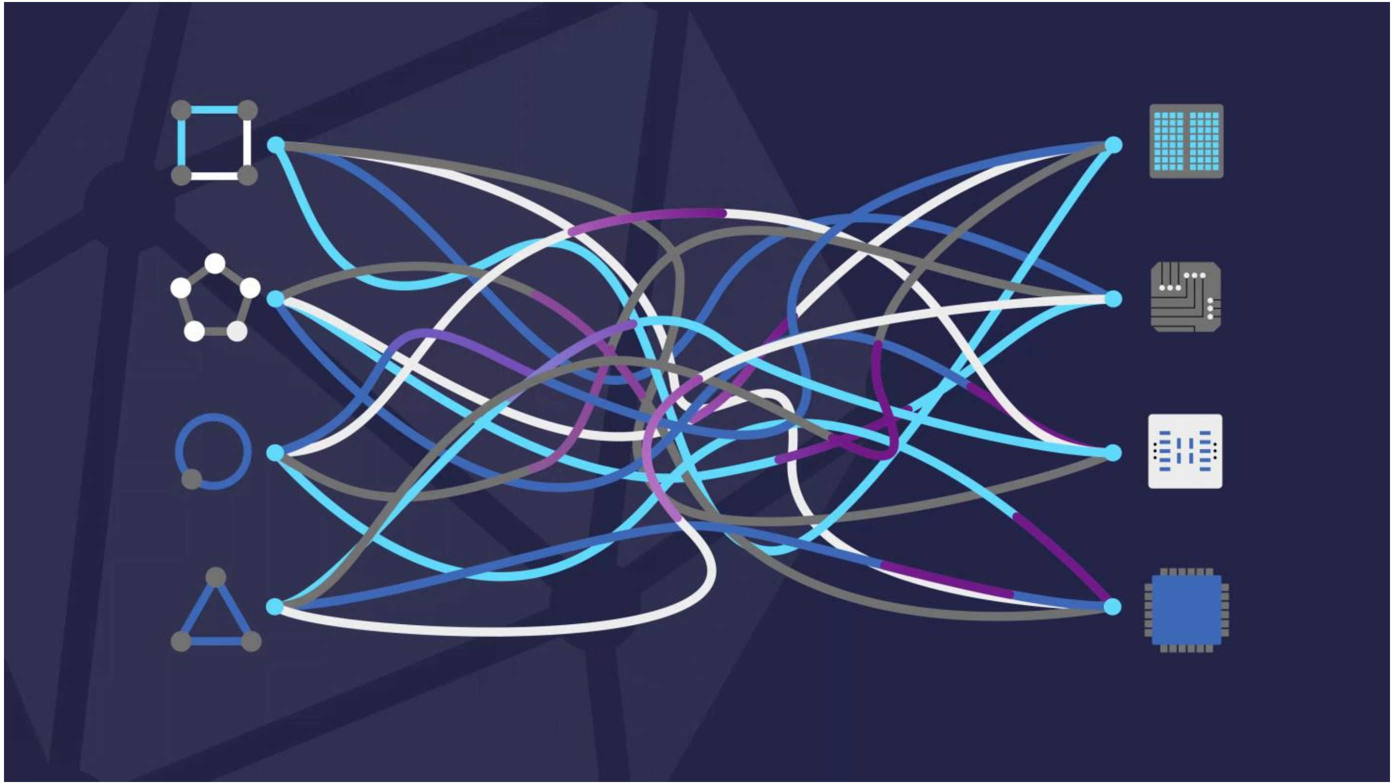




Serialized models are interoperable between frameworks

Have a common target for optimization for different backends

ONNX - Overview



ONNX: Open Ecosystem for AI Models

High level API & Framework Frontends

- Caffe2
- Cognitive Toolkit
- mxnet
- PYTORCH
- Chainer
- PaddlePaddle

ONNX

Hardware Vendor Libraries & Devices

- ML HW
- GPU
- CPU
- FPGA
- DSP

Challenges

- **8-bit Support still emerging**
  - ONNX today does not support this (being fixed quickly)
  - Poor support for 8 bits in training frameworks:
    - Tensorflow notable exception
  - More than 1 flavor of 8 bits (symmetric/asymmetric)

- **Custom layers still a hard problem**
  - Multiple candidate solutions: ANSI-C, directML HLSL, OpenCL, Halide, …

Key Takeaways

- Select network carefully considering dataflow implications
- Optimize networks using portable techniques, specifically:
  - Pruning, 8-bit activations, low precision weights, sparsity
- ONNX has strong momentum as ecosystem for portable models

Resources

- Useful Resources:
  - Intel Nervana AI Academy
  - http://www.arxiv-sanity.com/
- References:

  - [1] Learning Transferable Architectures for Scalable Image Recognition,
    https://arxiv.org/abs/1707.07012
  - [2] MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications,
    https://arxiv.org/abs/1704.04861
  - [3] To prune, or not to prune: exploring the efficacy of pruning for model compression,
    https://arxiv.org/abs/1710.01878
  - [4] Learning both weights and connections for efficient neural networks,
    https://arxiv.org/abs/1506.02626
  - [5] Quantization and Training of Neural Networks for Efficient Integer-Arithmetic-Only Inference,
    https://arxiv.org/abs/1712.05877