10-605/10-805: Machine Learning with Large Datasets

Fall 2022

Inference & Model Compression

Announcements

- HW4: please shut down all AWS resources!
- Mini-project Proposals due on 11/11 (this Friday!)
- Recitation this week: HW4 review
- **Guest lecture Thursday (11/17)**: Krishna Rangasayee SiMa.ai
  - Topic: ML on Embedded Edge Devices)
  - Virtual / Zoom
  - Will not be recorded — please show up!

WHERE ARE WE NOW?

Key course topics

Data preparation

- Data cleaning
- Data summarization
- Visualization
- Dimensionality reduction

Training

- Distributed ML
- Large-scale optimization
- Scalable deep learning
- Efficient data structures
- Hyperparameter tuning

Inference

- Hardware for ML
- Techniques for low-latency inference (compression, pruning, distillation)

Infrastructure / Frameworks

- Apache Spark
- TensorFlow
- AWS / Google Cloud / Azure

Advanced topics

- Federated learning
- Neural Architecture Search
- Productionizing ML

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MOVING FORWARD

What makes deep learning expensive?

Training requires lots of computation

- Specialized hardware (GPUs, TPUs) can help with matrix computations
- Can use advanced iterative optimization methods
- Can parallelize training

Hyperparameter tuning and neural architecture search (NAS) make this worse

- Lots of knobs to tune!

Resulting models can be large!

- Can be expensive to store model, perform inference

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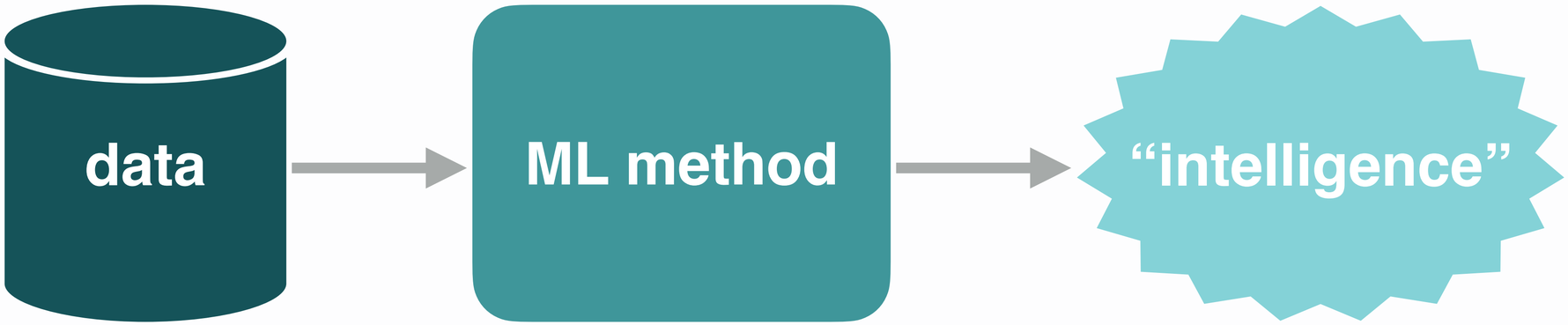
Outline

1. Why inference?
2. Techniques for model compression

A SIMPLIFIED

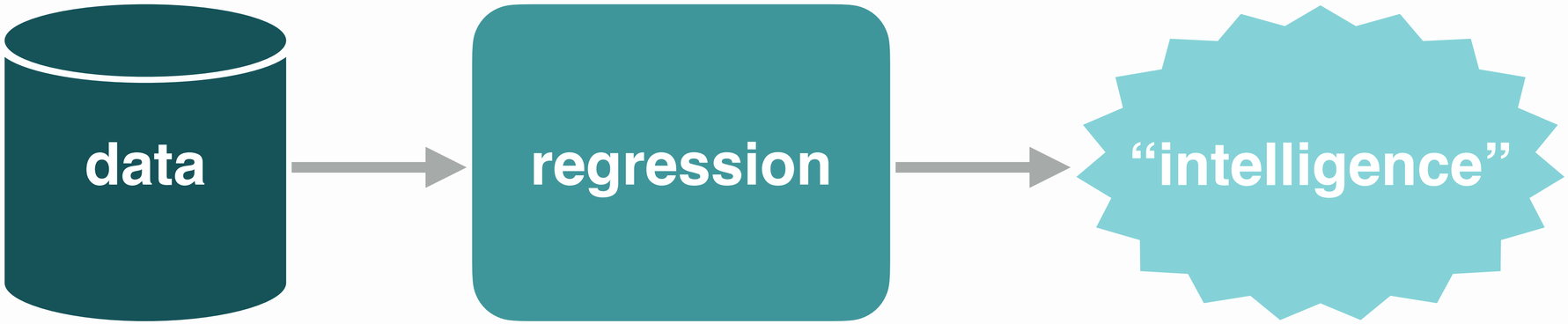
Machine learning pipeline

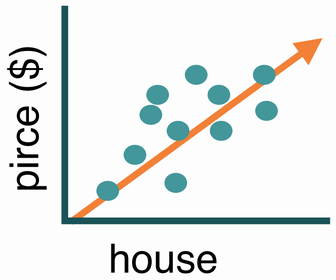


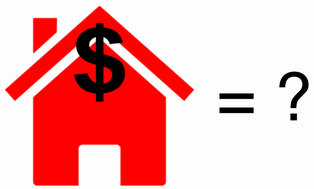
EXAMPLE 1:

Regression

How much should you sell your house for?







input: houses & features

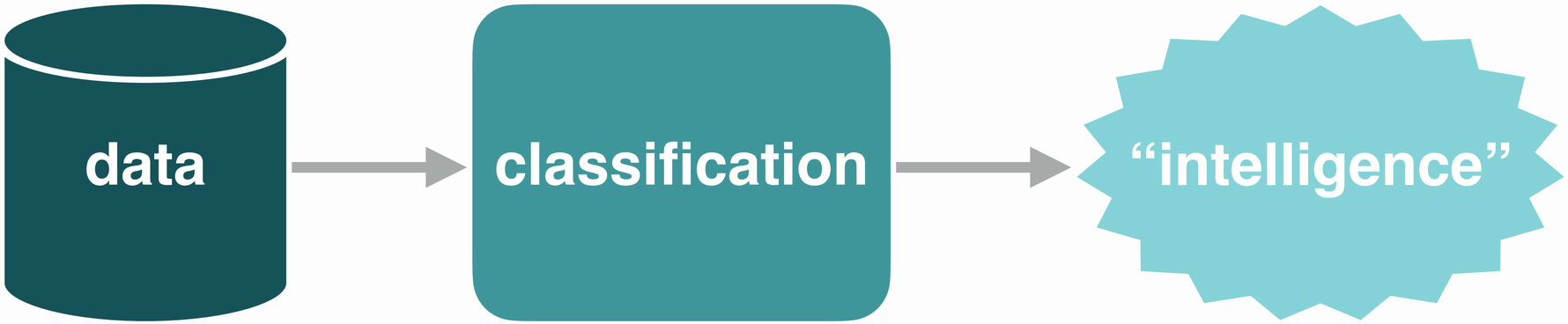
learn: x → y relationship

predict: y (continuous)

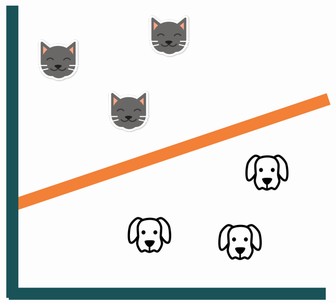
EXAMPLE 2:

Classification

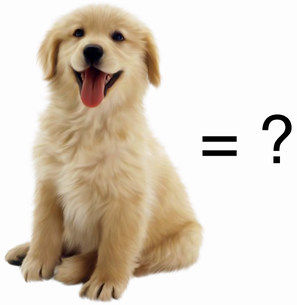
Cat or dog?



input: cats & dogs



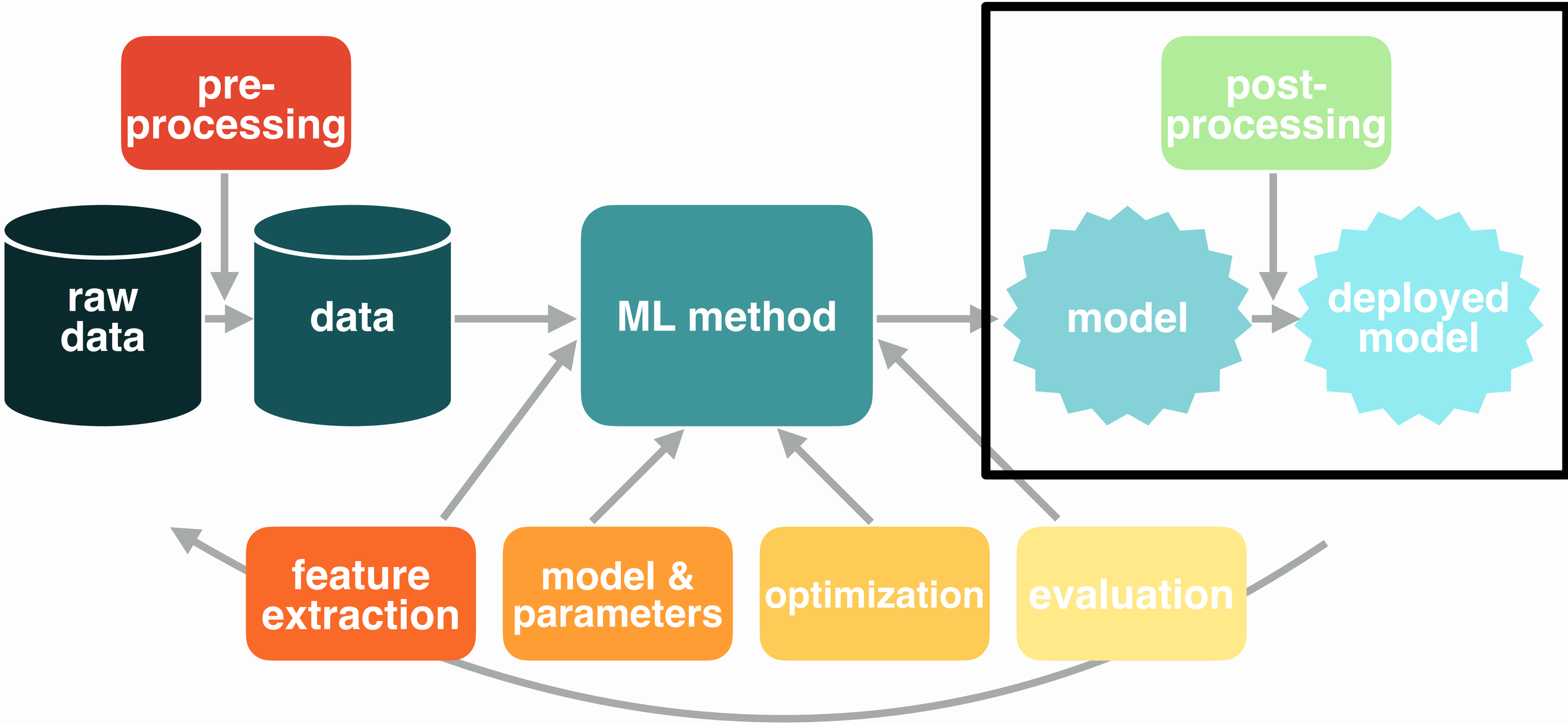
learn: x → y relationship



predict: y (categorical)

A MORE REALISTIC

Machine learning pipeline



Inference: Why should we care?

Train once, infer many times

- Many production machine learning systems just do inference

Often want to run inference on low-power edge devices

- Cell phones, wearable devices, security cameras
- Limited memory on these devices to store models

Need to predict quickly

- E.g., for web applications, want to respond to users in realtime

RECALL

Empirical risk minimization

$$\hat{f}_n = \arg\min_{f \in F} \frac{1}{n} \sum_{i=1}^{n} \ell(f(x_i), y_i)$$

- A popular approach in supervised ML
- Given a loss ℓ and data (x_1, y_1), … (x_n, y_n), we estimate a predictor *f* by minimizing the *empirical risk*
- We typically restrict this predictor to lie in some class, *F*
  - Could reflect our prior knowledge about the task
  - Or may be for computational convenience

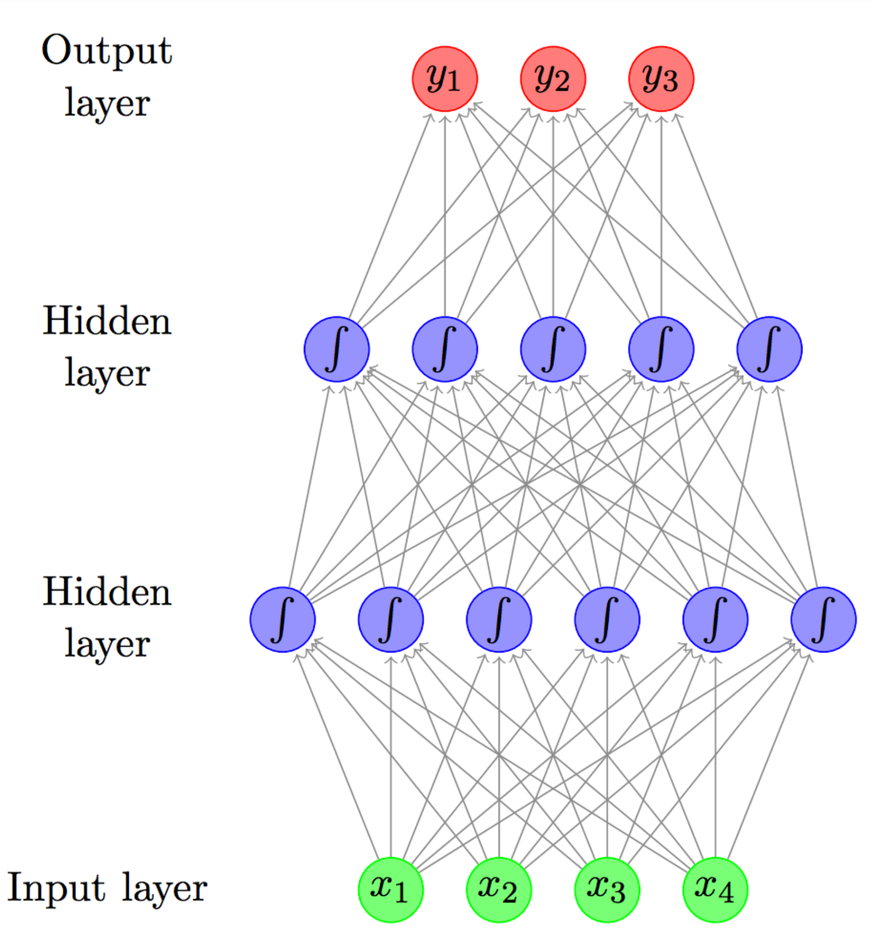
inference involves computing: $\hat{y} = f(\hat{x})$ *for some new observation* $\hat{x}$

COST OF INFERENCE

Feedforward neural networks

We can consider adding L hidden layers, each with their own activation functions σ_l and corresponding weights $\mathbf{W}_l$

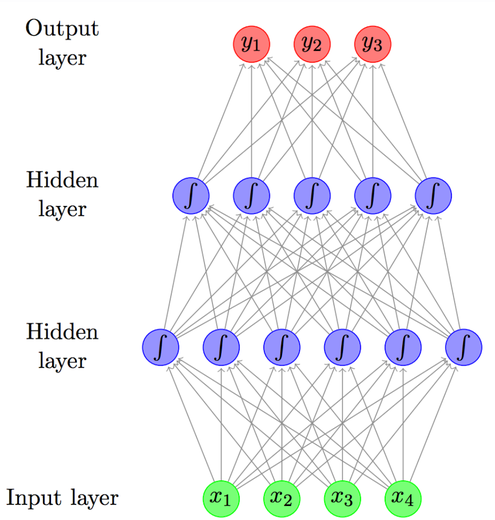
Using this layering technique, the resulting model becomes:



$$f(\mathbf{x}) = \mathbf{w}^\top \sigma_L(\mathbf{W}_L^\top(\sigma_{L-1}(\mathbf{W}_{L-1}^\top \ldots \sigma_2(\mathbf{W}_2^\top \sigma_1(\mathbf{W}_1^\top \mathbf{x}))\ldots)$$

COST OF INFERENCE

Feedforward neural networks



Can express NN model with the following recurrence:

$$\mathbf{o}_0 = \mathbf{x}$$

$$\forall l \in \{1,\ldots,L\},\ \mathbf{h}_l = \mathbf{W}_l^\top \mathbf{o}_l$$

$$\forall l \in \{1,\ldots,L\},\ \mathbf{o}_l = \sigma_l(\mathbf{h}_l)$$

$$f(\mathbf{x}) = \mathbf{o}_L$$

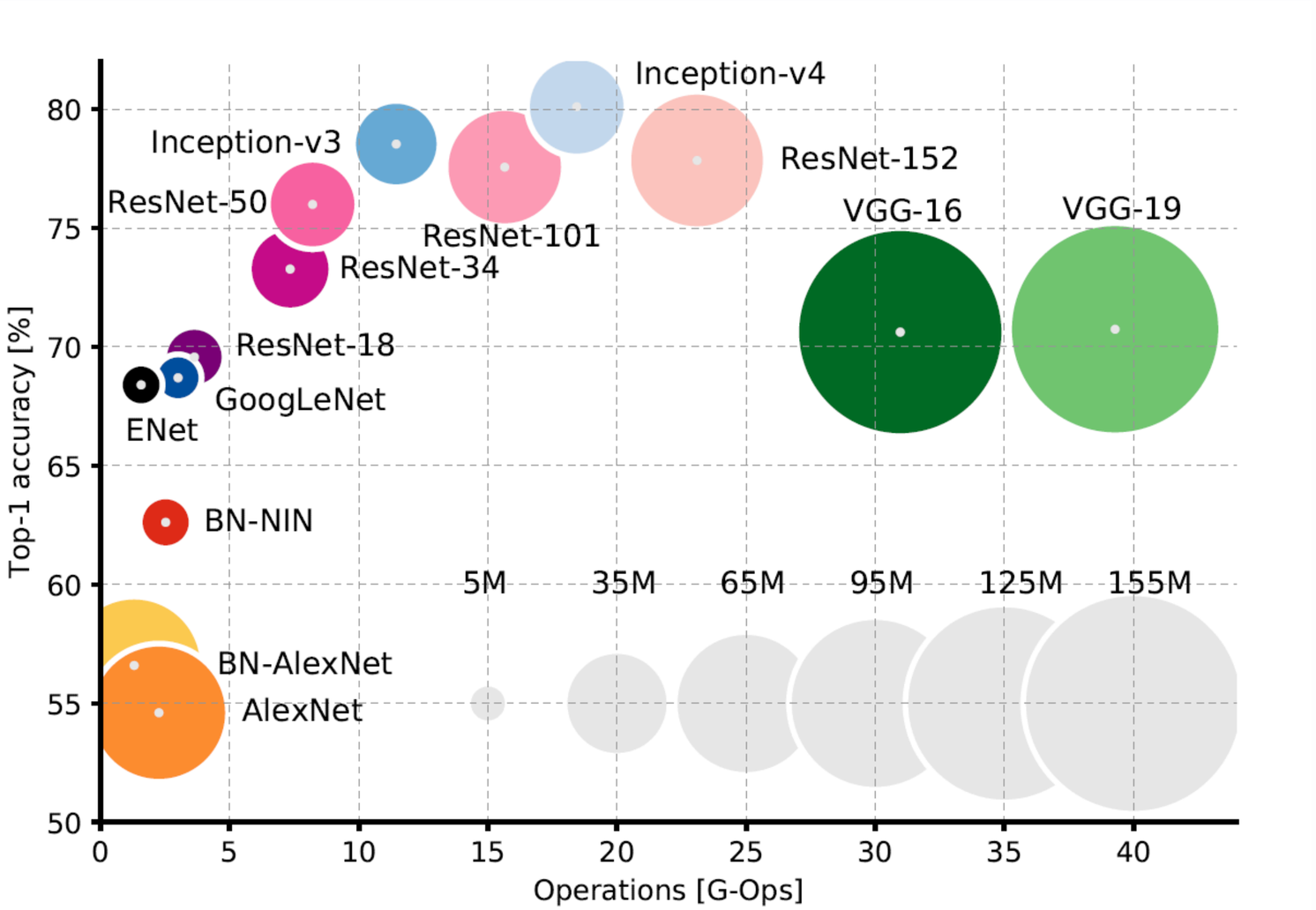
What dominates the cost?

Matrix(-vector) multiplies

O(nm) for n x m matrix, m x 1 vector

COST OF INFERENCE

Deep learning



- Operations required for one forward pass vs. accuracy
- Circle size proportional to the number of network parameters
- Correlation between operation count & accuracy

Canziani et al, 2016

Inference metrics

Accuracy

- How accurate is the deployed model at making predictions?

Model size

- How many bytes are needed to store or transmit the model?

Latency

- How much time does it take to make a prediction for a single observation?

Throughput

- How many observations we can predict within some amount of time?

Energy

- How much energy do we use to produce each prediction?

Cost

- How much money does it cost to deploy the model / perform inference?

Where do we perform inference?

The cloud (e.g., AWS, GCP)
Common concerns: latency, cost

User devices (e.g., phone, laptop)
Common concerns: memory/model size

IoT devices (e.g., wearable device, sensor)
Common concerns: energy, memory

Where do we perform inference?

Cortex M0	Cortex M4	Cortex M7	Raspberry Pi Zero 1Ghz ARM11	Raspberry Pi 3 4x1.2GHz Cortex A53	Smartphone 4x2.3 GHz Mongoose & 4x1.6 GHz Cortex A53
50 DMIPS	200 DMIPS	850 DMIPS	1250 DMIPS	11,000 DMIPS	50,000 DMIPS
32 KB	128 KB	384 KB	512 MB	1 GB	4 GB

Credit: Ofer Dekel

Outline

1. Why inference?
2. Techniques for model compression

Model compression

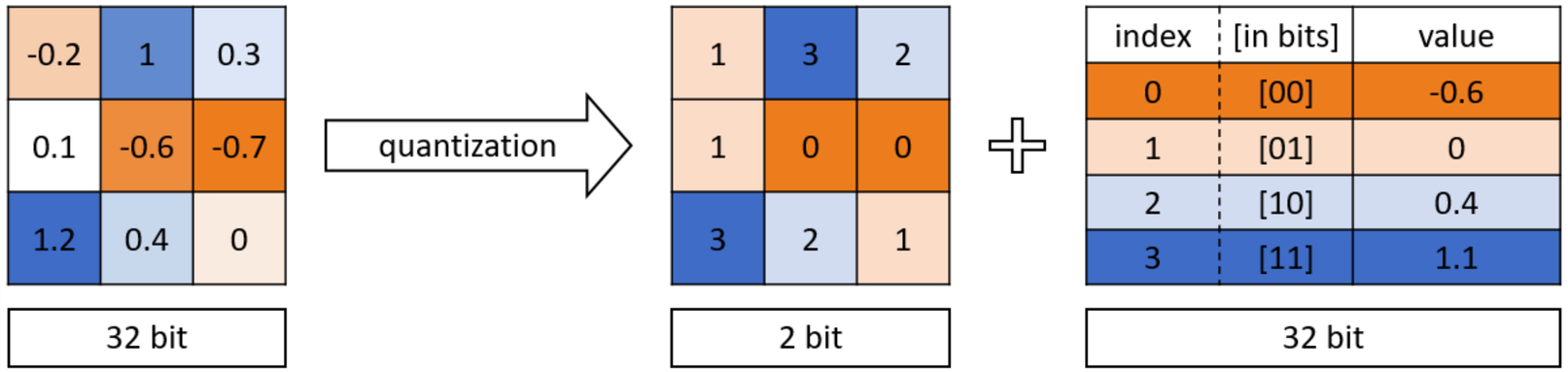
Goal: find a smaller, cheaper model with the same (or similar) accuracy

Many techniques:

- Quantization (low-precision inference)
- Pruning
- Knowledge distillation
- Efficient architectures (+ architecture search)

Low precision / Quantized NNs

- Simple technique: use low-precision arithmetic in inference
- Can make any signals in the model low precision
- How to determine the ‘right’ amount of precision?
  - One heuristic: keep lowering the precision of signals until the accuracy decreases
- Extreme example: binarization (1-bit {-1,1} or {0,1})



Low precision / Quantized NNs

“XNOR-Net: ImageNet Classification Using Binary Convolutional Neural Networks”, Rastegari et al, ECCV 2016

Classification Accuracy(%)									
Binary-Weight				Binary-Input-Binary-Weight				Full-Precision	
BWN		BC[11]		XNOR-Net		BNN[11]		AlexNet[1]	
Top-1	Top-5	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5
56.8	**79.4**	35.4	61.0	**44.2**	**69.2**	27.9	50.42	56.6	80.2

binary weights → ~32x savings in memory

Low precision / Quantized NNs

"XNOR-Net: ImageNet Classification Using Binary Convolutional Neural Networks",
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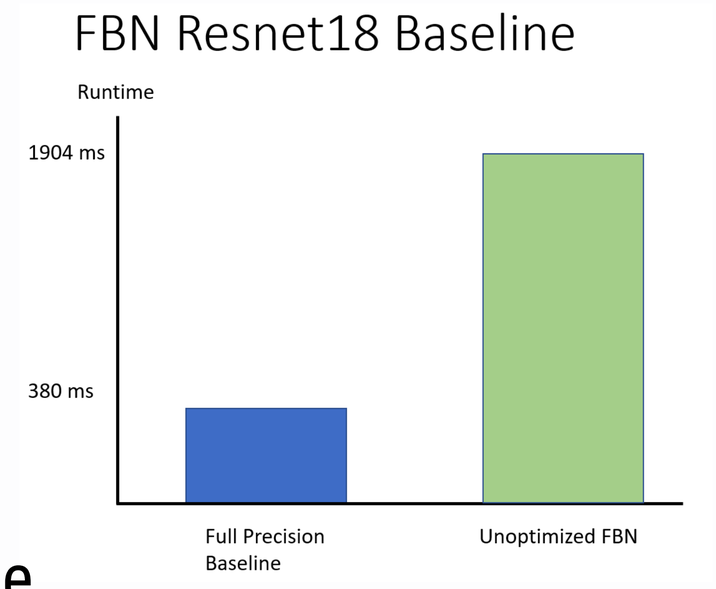
	ResNet-18		GoogLenet	
Network Variations	top-1	top-5	top-1	top-5
Binary-Weight-Network	60.8	83.0	65.5	86.1
XNOR-Network	51.2	73.2	N/A	N/A
Full-Precision-Network	69.3	89.2	71.3	90.0

binary weights → ~32x savings in memory

BUT WHAT ABOUT LATENCY?

Low precision



"*Riptide: Fast End-to-End Binarized Neural Networks*,"
Fromm, Cowan, Philipose, Ceze, and Patel, MLSys 2020

Motivation:

- Quantized NNs show promise for reducing inference time
- But, it can be difficult to achieve speedups on real-world processors

Why?

- Implementation matters: Current libraries like OpenBLAS have been engineered to work with full precision arithmetic
- Focus has also been on quantizing the main bottlenecks (e.g., convolutions), not the other operations ('glue layers')

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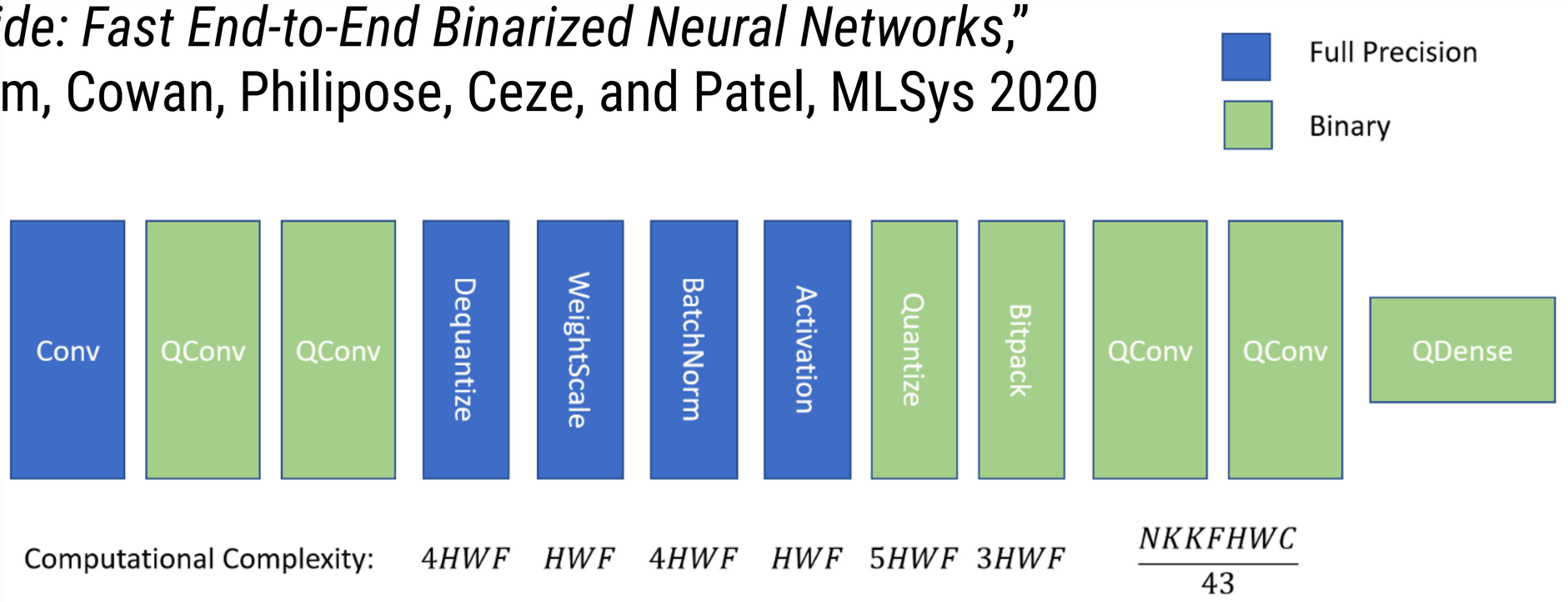


- Important to reduce/remove these "glue layers", which become the bottleneck
- Leads to speedups of up to 12x using the DL compiler TVM

AN ASIDE…

Deep learning compilers

For training, we discussed a few common options for hardware:

- CPUs, GPUs, TPUs

This list becomes much longer when we additionally consider hardware for inference (e.g., mobile phones IoT devices, specialized accelerators)

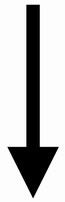
Q: How do we get our software (TensorFlow, PyTorch, etc) running on various hardware?

A: Need to compile it into hardware-specific language

AN ASIDE…

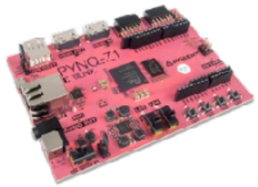
Deep learning compilers

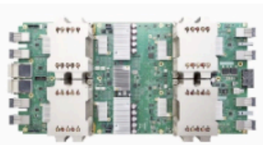
Frameworks express high-level computation



???

Hardware executes a series of low level operations





Credit: Tianqi Chen

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Deep learning compilers

Frameworks express high-level computation

OpenBlas

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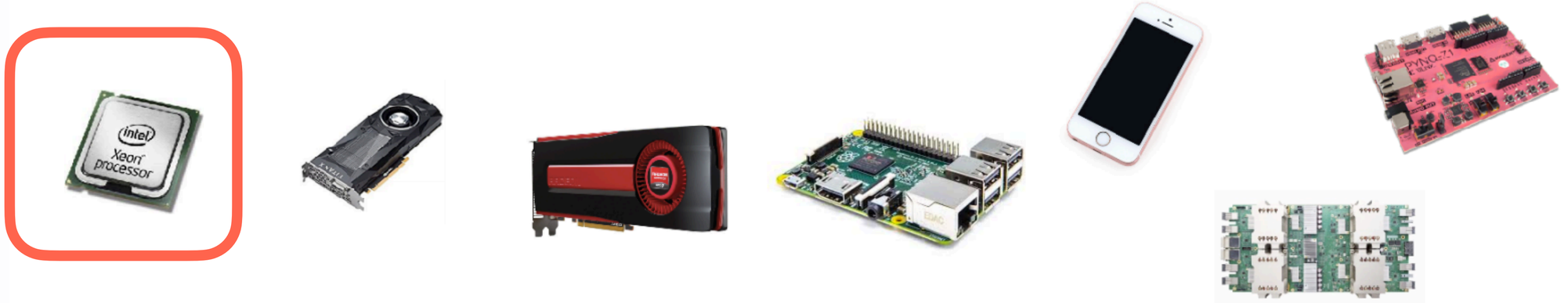

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Deep learning compilers

Frameworks express high-level computation

CUDA

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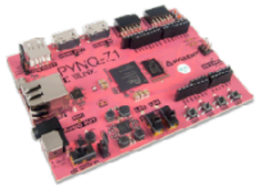

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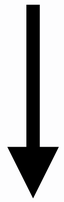


TVM

Hardware executes a series of low level operations

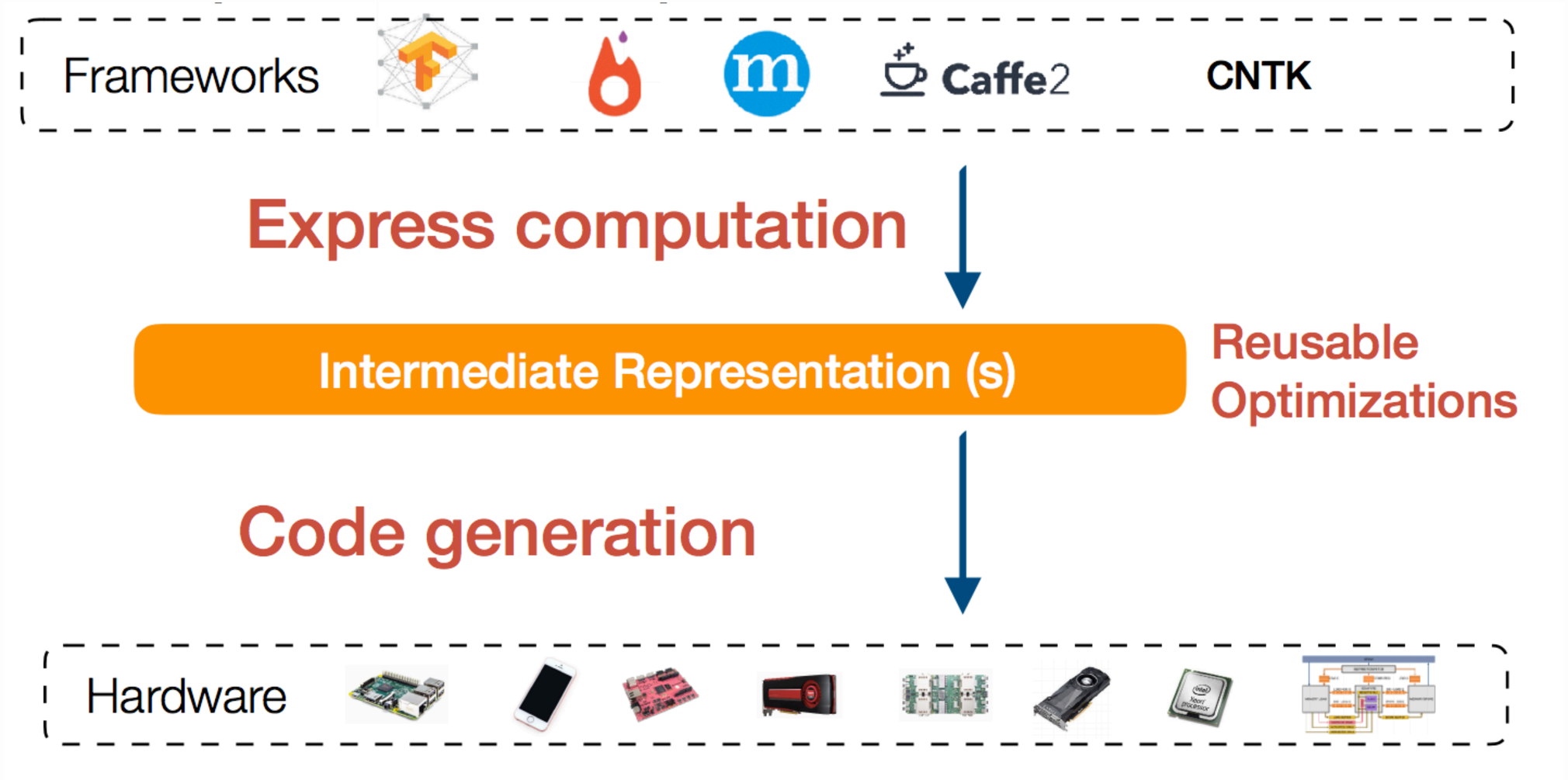
Credit: Tianqi Chen

AN ASIDE…

Deep learning compilers

OctoML

Automate efficient AI/ML ops through a unified software foundation.



Credit: Tianqi Chen

Model compression

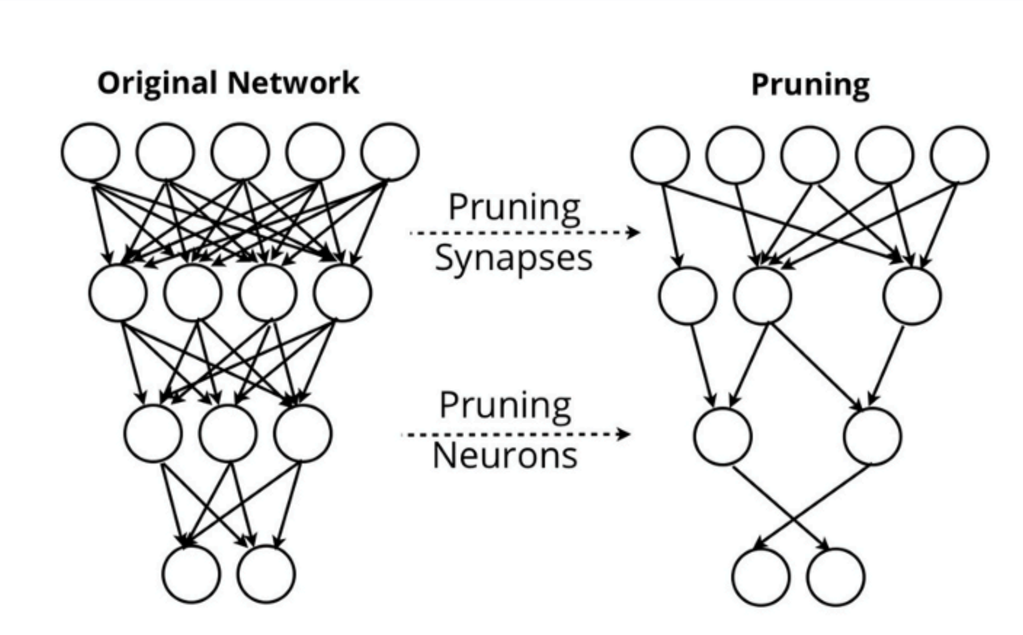
Goal: find a smaller, cheaper model with the same (or similar) accuracy

Many techniques:

- Quantization (low-precision inference)
- Pruning
- Knowledge distillation
- Efficient architectures (+ architecture search)

Pruning

- Remove ‘low impact’ weights or activations
- Effectively creates a smaller model (less weights to store)
- Makes it easy to retrain if necessary, since we’re training a smaller model
- Simple heuristic: remove all weights/ activations less than some threshold
- Will explore pruning heuristics in MP-A …



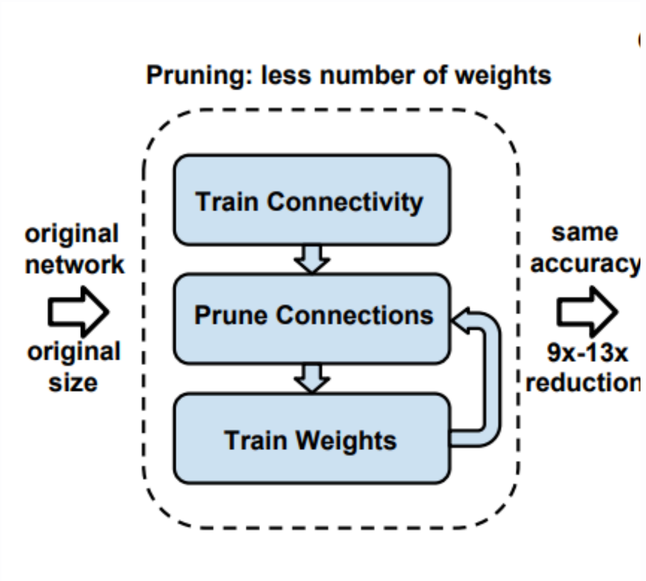
Pruning

Techniques may differ in terms of:

- What structures to prune?
  - unstructured: don’t consider relationships between weights
  - structured: remove entire neurons, filters, or channels
- How to rank which weights to prune?
  - magnitude, first or second order information
- When / how often prune?
  - one-shot pruning (at the end of training)
  - iterative pruning (train, prune, re-train multiple times)
  - after training vs during training (e.g., dropout)

Pruning

can also combine pruning and quantization



Han et al, ICLR 2016

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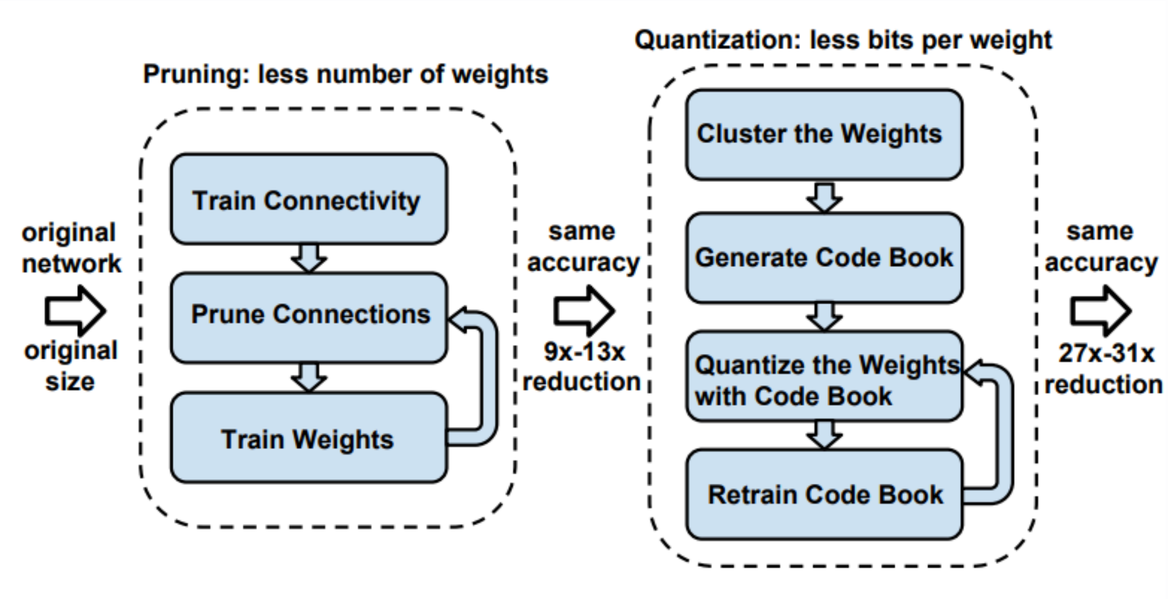

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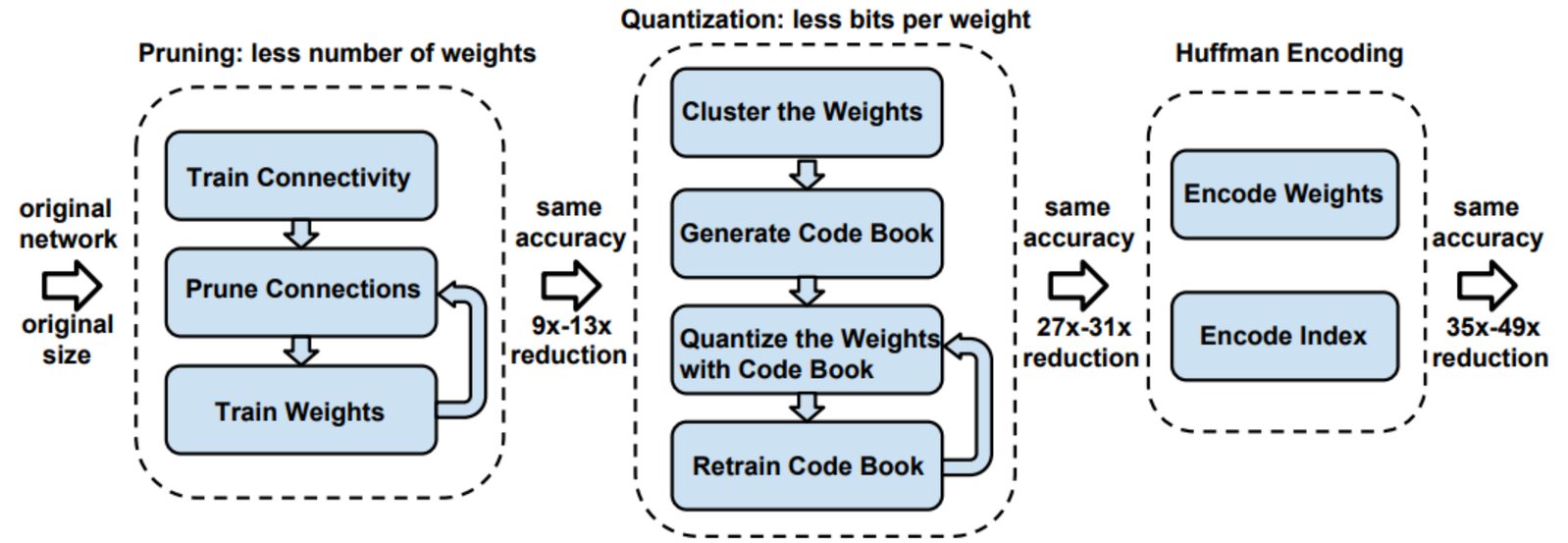
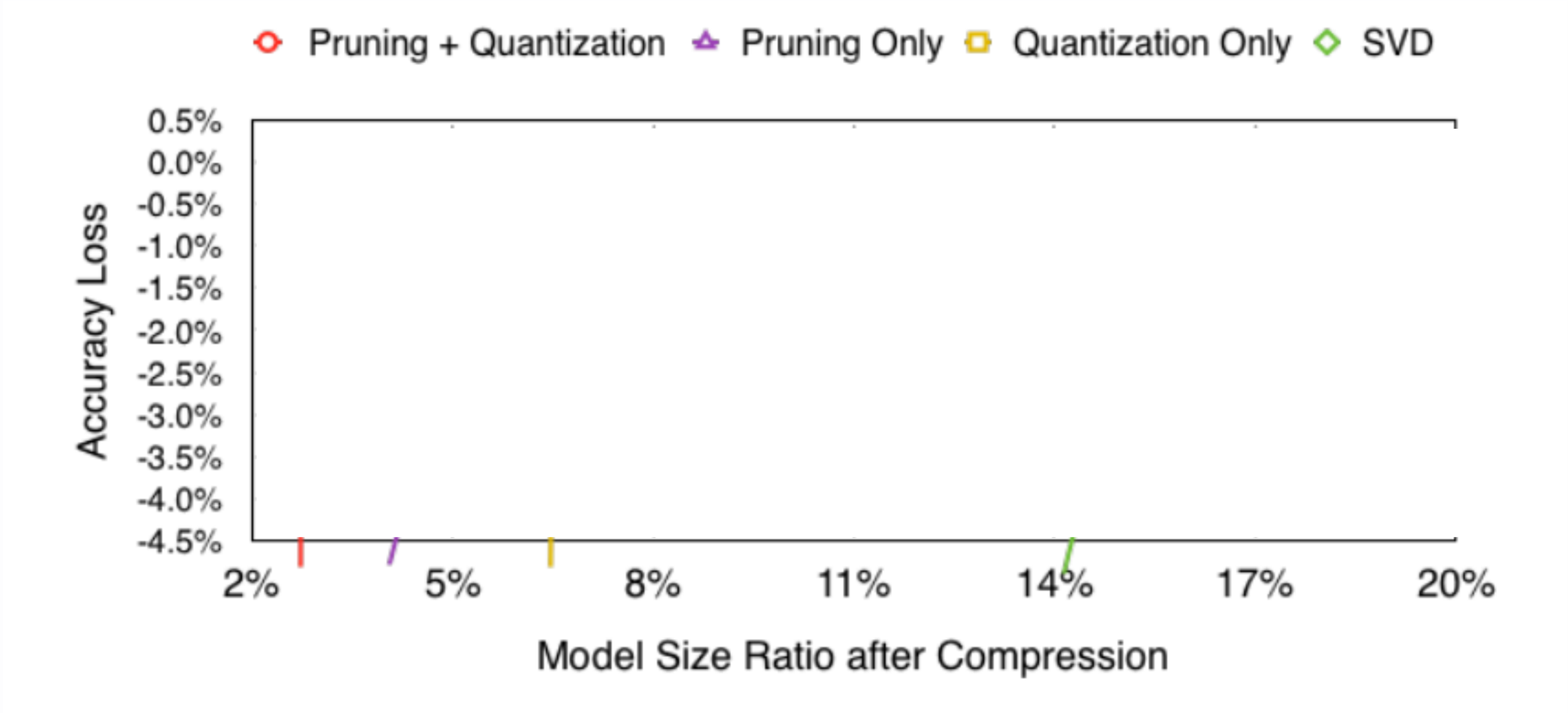


Figure 1: The three stage compression pipeline: pruning, quantization and Huffman coding. Pruning reduces the number of weights by $10\times$, while quantization further improves the compression rate: between $27\times$ and $31\times$. Huffman coding gives more compression: between $35\times$ and $49\times$. The compression rate already included the meta-data for sparse representation. The compression scheme doesn't incur any accuracy loss.

Han et al, ICLR 2016

Pruning

can also combine pruning and quantization



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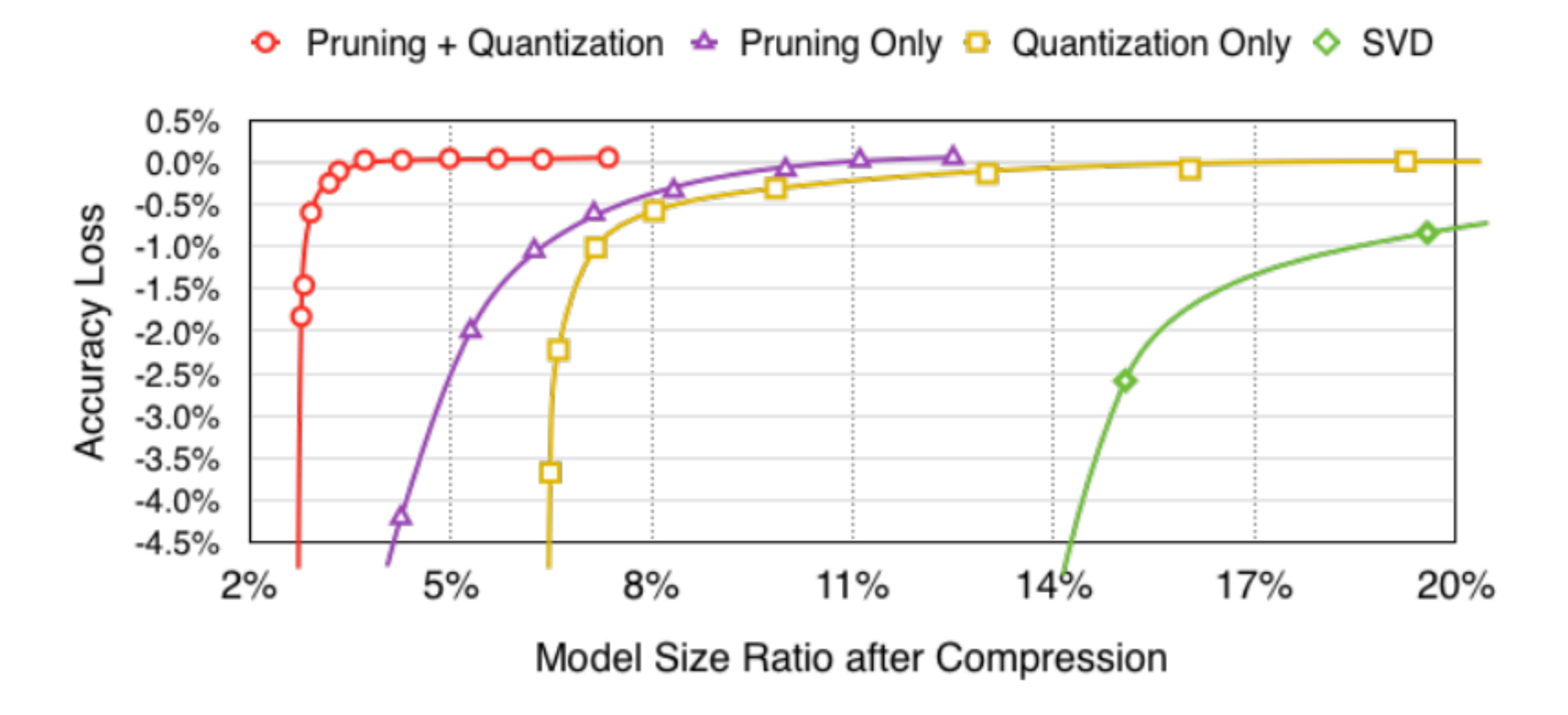

Han et al, ICLR 2016

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Many techniques:

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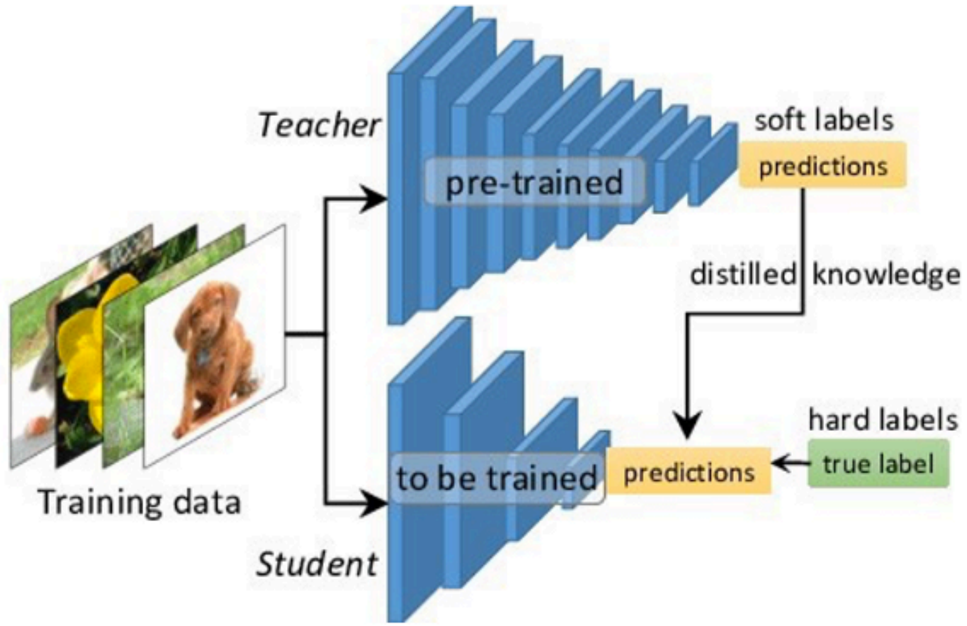
- Knowledge distillation
- Efficient architectures (+ architecture search)

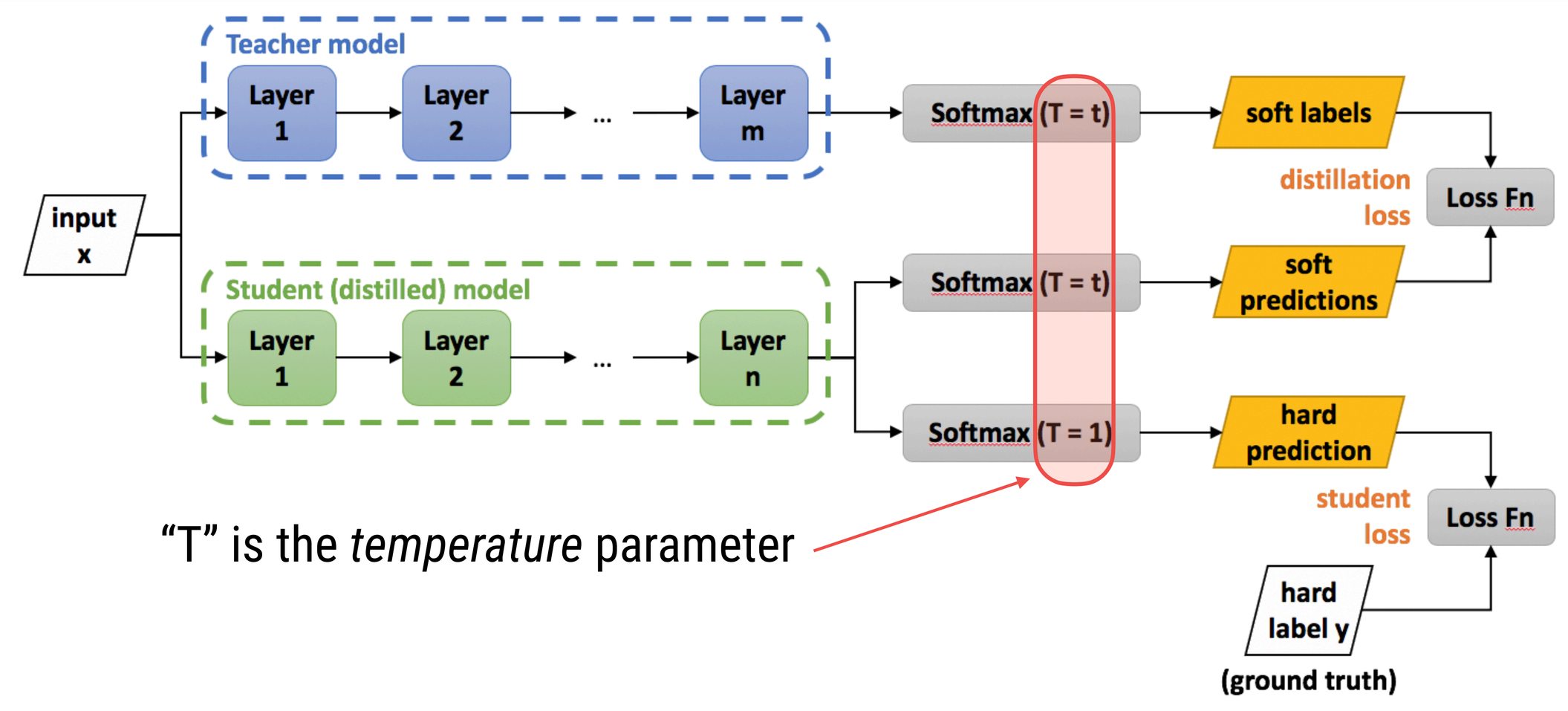
Knowledge distillation

- Idea: take a large/complex model and train a smaller network to match its output
- Possible benefit over pruning/quantization: Smaller architecture can differ significantly
- *Why might this heuristic work?*
  Intuition is that it's easier to learn from the model's output [the teacher] than the true labels



Bucila et al, 2006; Hinton et al, 2015

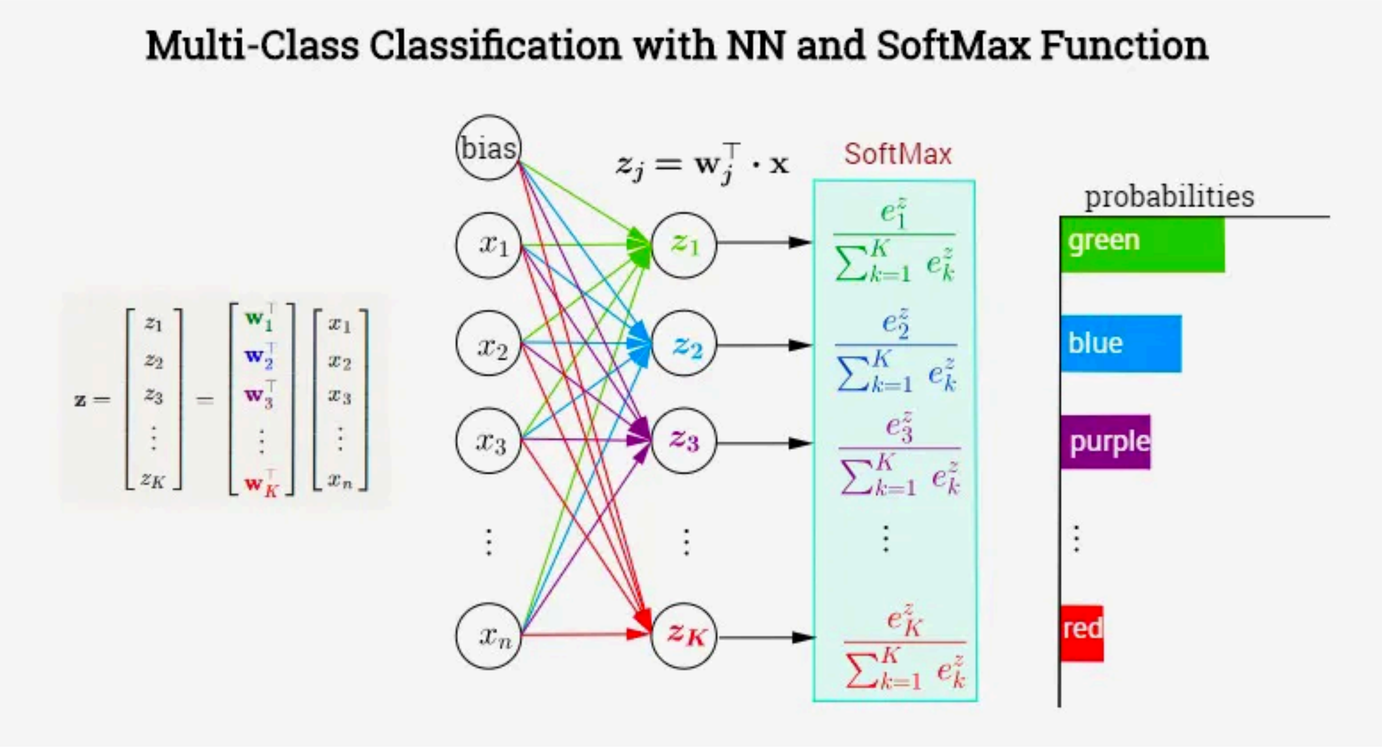
Knowledge distillation



Hinton et al, 2015

Softmax temperature

- Recall: softmax function is used to determine predicted probabilities for multiple classes

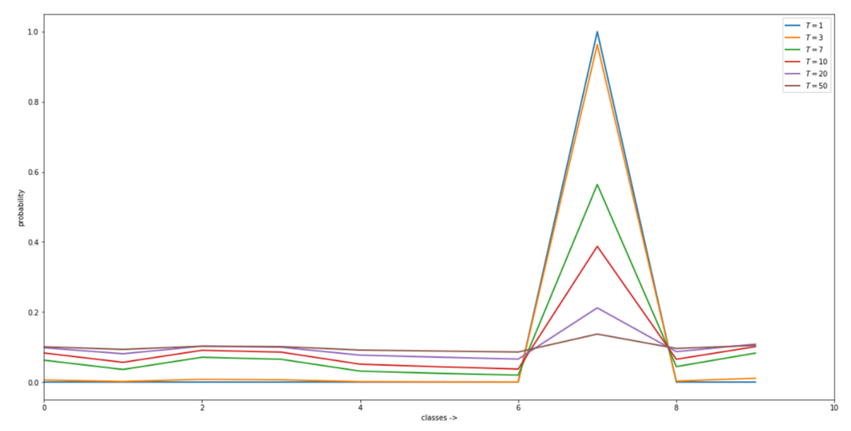


Hinton et al, 2015

Softmax temperature

- Potential issue: output of teacher's softmax will have very high probability on correct class, low probability on other classes → *doesn't provide much information beyond ground truth labels*
- Idea: use a slight variant of the usual softmax function with 'temperature' hyperparameter, T
- Provides a 'softer' distribution

$$p_i = \frac{\exp\left(\frac{z_i}{T}\right)}{\exp\left(\sum_j \frac{z_j}{T}\right)}$$



Hinton et al, 2015

PUTTING IT ALL TOGETHER …

Knowledge Distillation

- Train student network from scratch, using the following loss function:

$$\mathcal{L}(x; W) = \alpha * \mathcal{H}(y, \sigma(z_s; T = 1)) + \beta * \mathcal{H}(\sigma(z_t; T = \tau), \sigma(z_s, T = \tau))$$

student loss

teacher loss

- α, β, τ are all hyperparameters that must be set
- in initial experiments, $\tau \in [1,20]$ (use small τ for smaller students)
- generally set α to be smaller than β

Hinton et al, 2015

Model compression

Goal: find a smaller, cheaper model with the same (or similar) accuracy

Many techniques:

- Quantization (low-precision inference)
- Pruning
- Knowledge distillation
- Efficient architectures (+ architecture search)

Efficient architectures

- Some neural network architectures are designed to be efficient at inference time
  - e.g., mobilenet, shufflenet
- These networks are often based on sparsely connected units
- For efficiency, we can start by training one of these networks (in contrast to training a larger model and then compressing it)

Table 8. MobileNet Comparison to Popular Models

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
GoogleNet	69.8%	1550	6.8
VGG 16	71.5%	15300	138

Howard et al, 2017

ONE LAST OPTION …

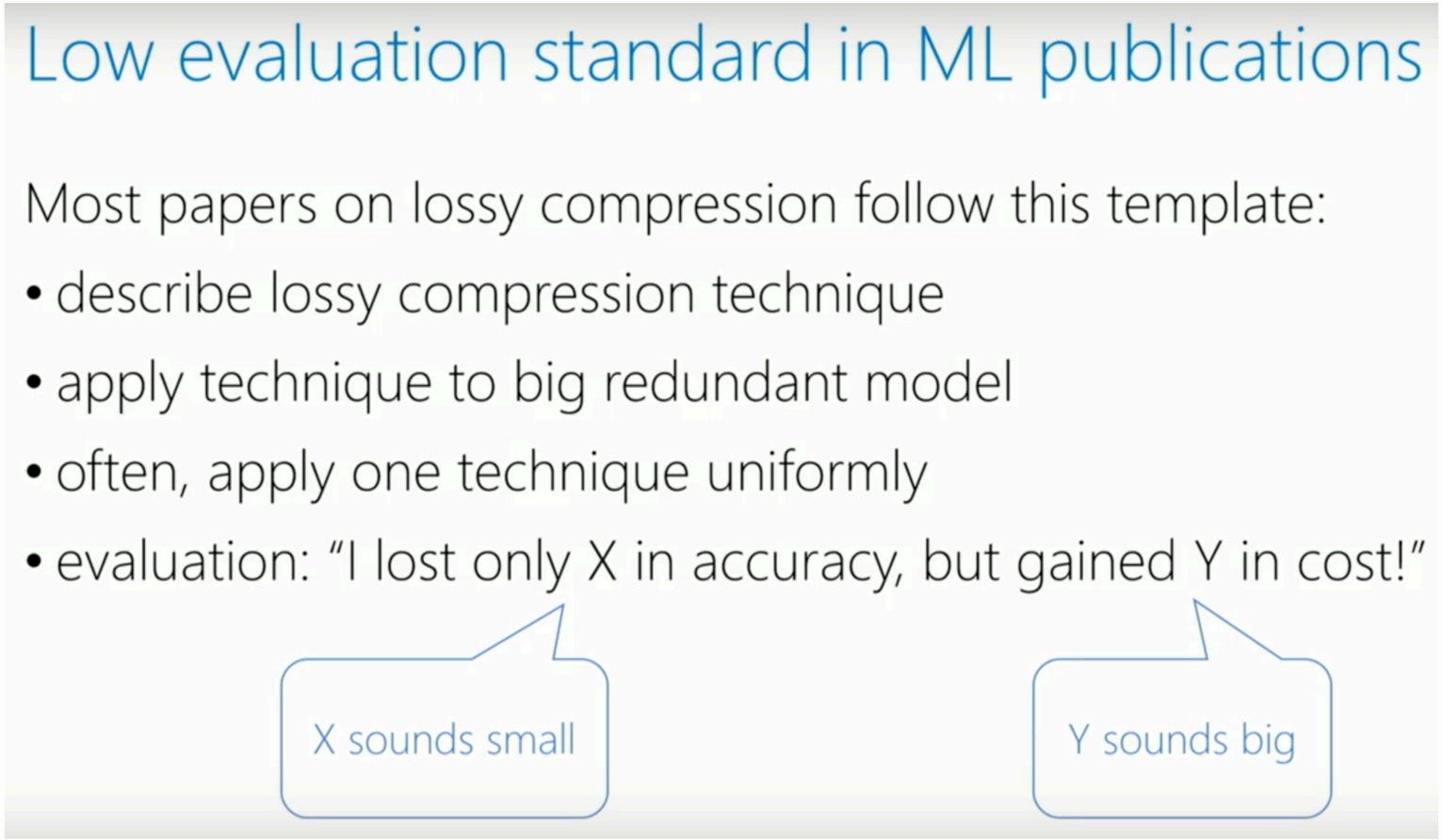
Pick a different model class!

- Finally, you can also train and use a model that is not a DNN …
- Linear models can be much faster and might be necessary in some applications

A WORD OF CAUTION

Performance on the Pareto frontier

MLSys 2019 keynote: Compiling AI for the Edge, Ofer Dekel (MSR)



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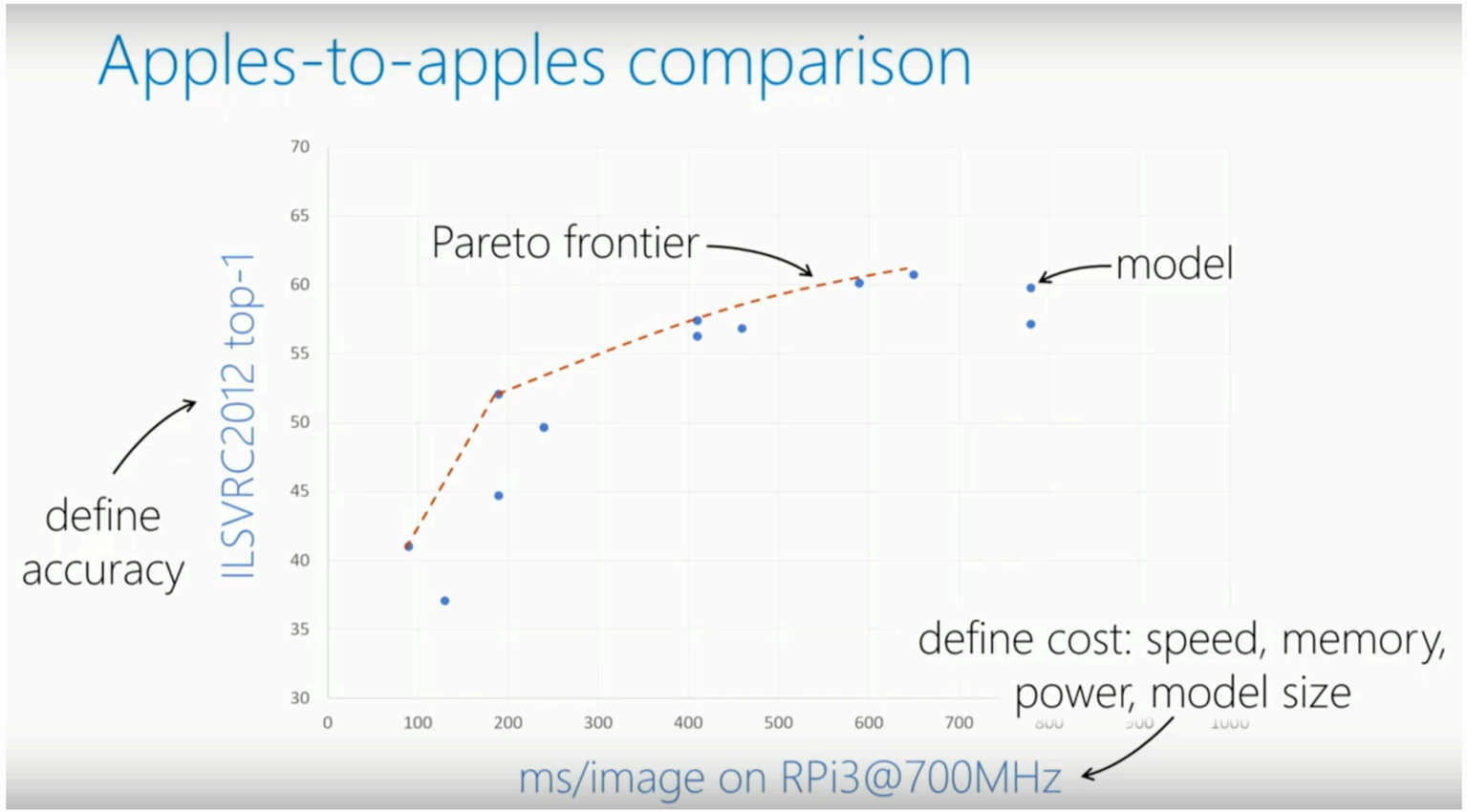

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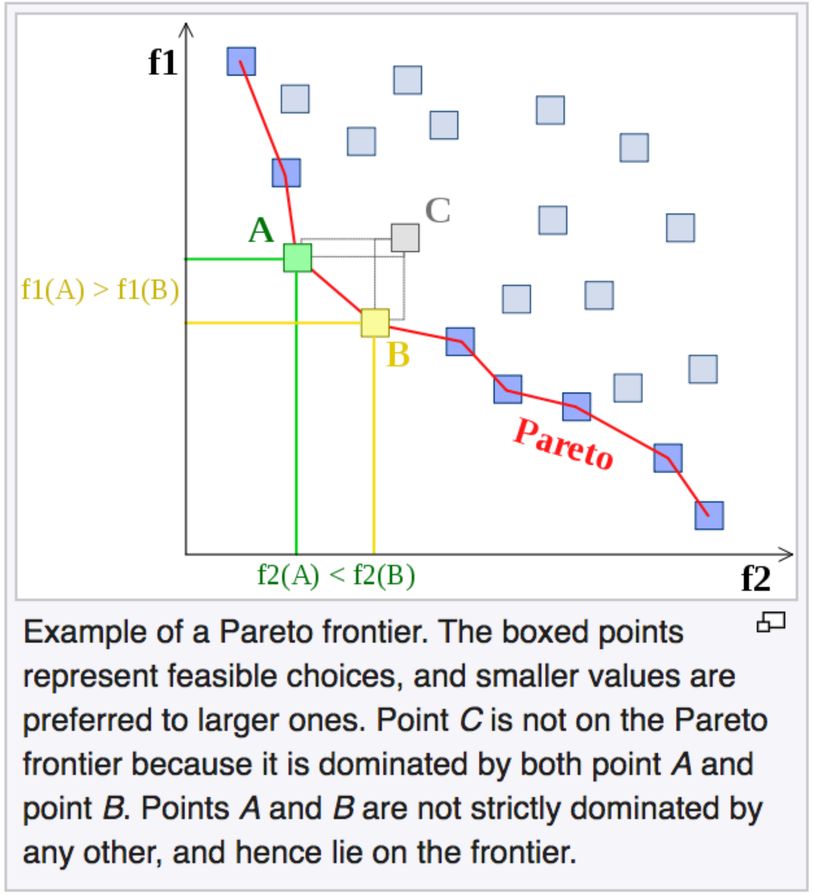

Example of a Pareto frontier. The boxed points represent feasible choices, and smaller values are preferred to larger ones. Point *C* is not on the Pareto frontier because it is dominated by both point *A* and point *B*. Points *A* and *B* are not strictly dominated by any other, and hence lie on the frontier.

Issue: there are two metrics we care about:

- accuracy
- cost

What models/techniques are the best?

- it depends on what accuracy / cost you care about
- goal: demonstrate optimality on the Pareto frontier
  - i.e., there are no other models with the same (or lower) cost that achieve the same (or higher) accuracy

A WORD OF CAUTION

Performance on the Pareto frontier

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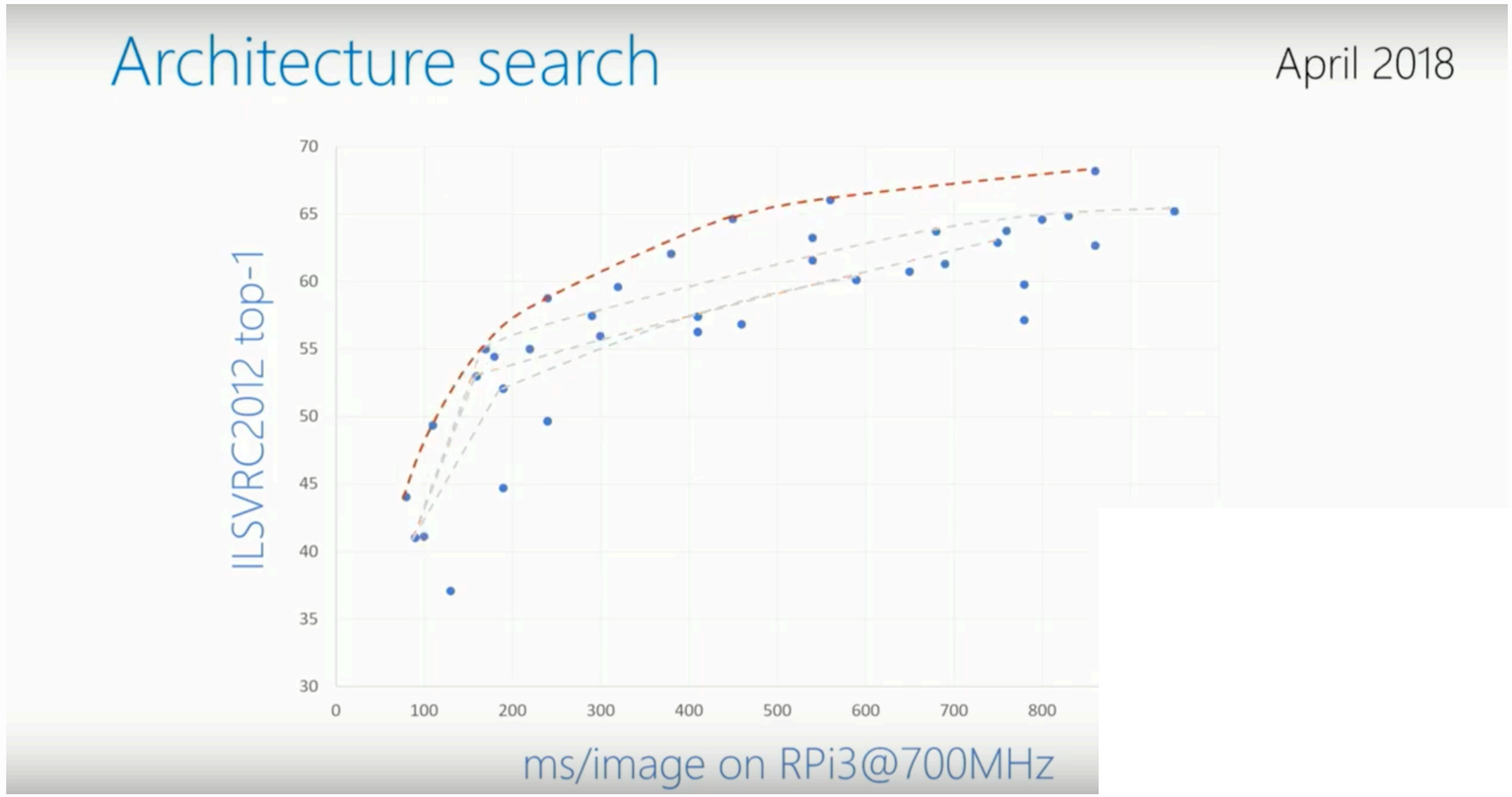

for this problem: architecture search pushed the Pareto frontier

A WORD OF CAUTION

Performance on the Pareto frontier

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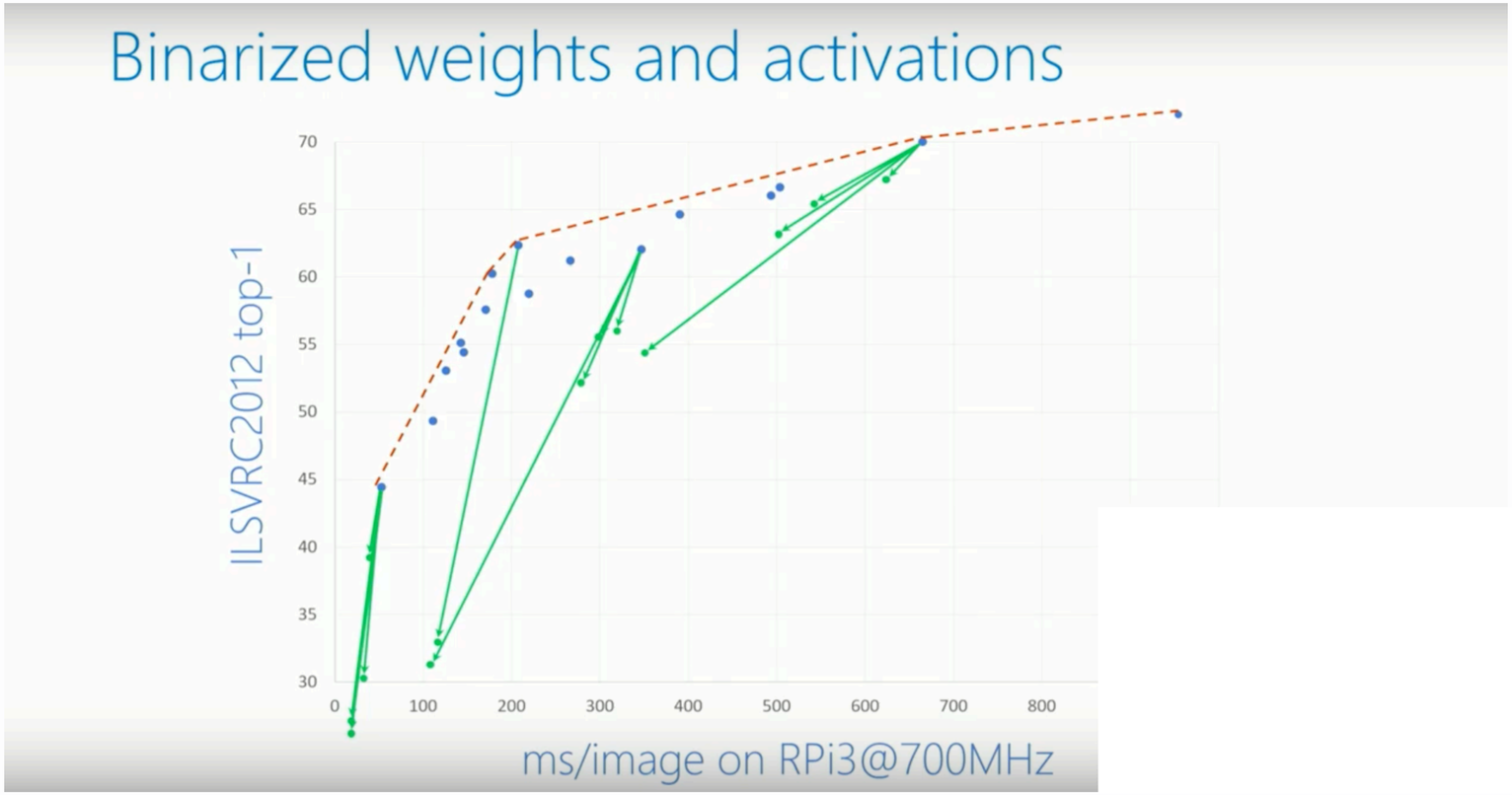

for this problem: quantization did not

A WORD OF CAUTION

Performance on the Pareto frontier

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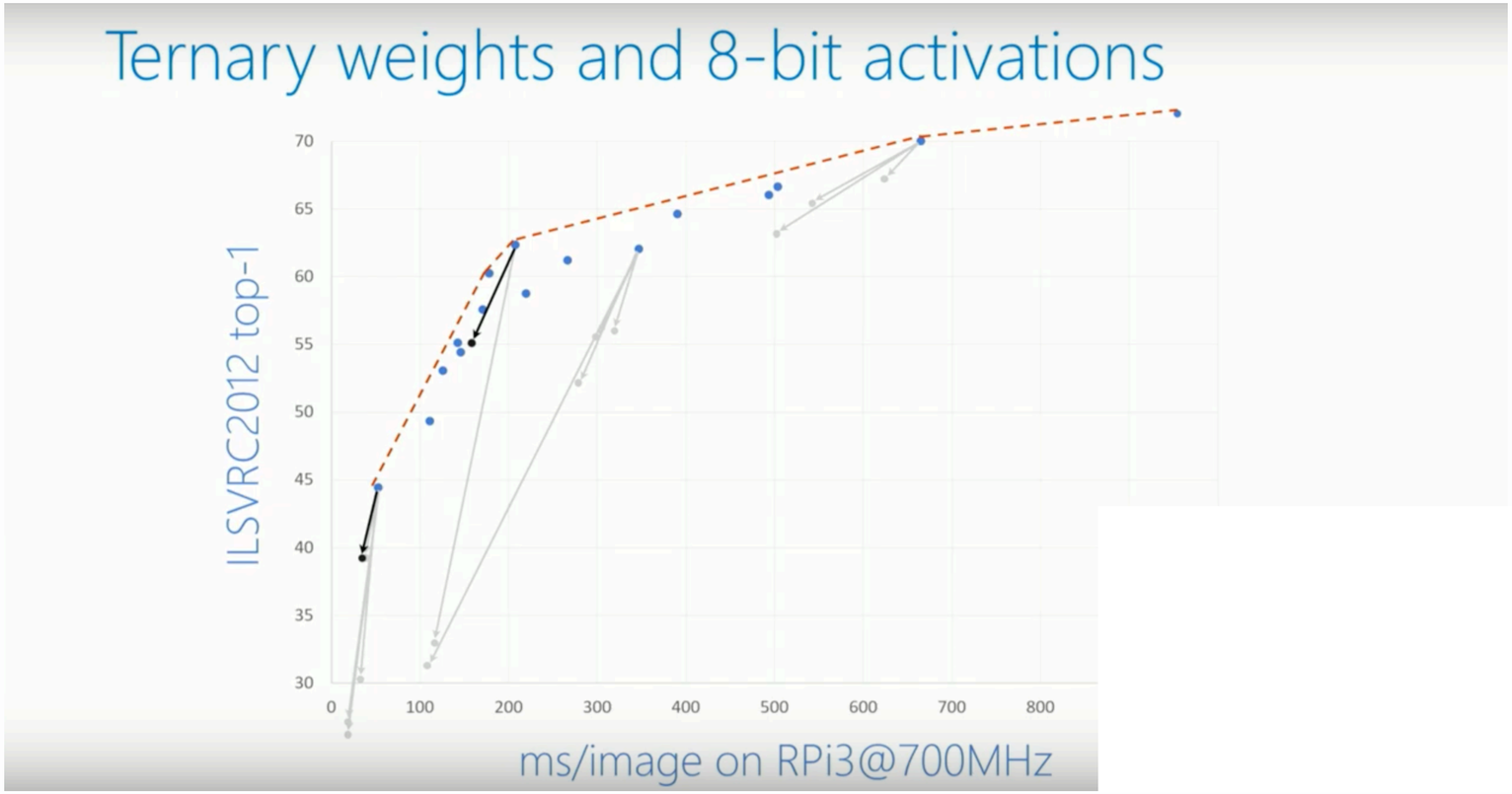

for this problem: quantization did not

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Performance on the Pareto frontier

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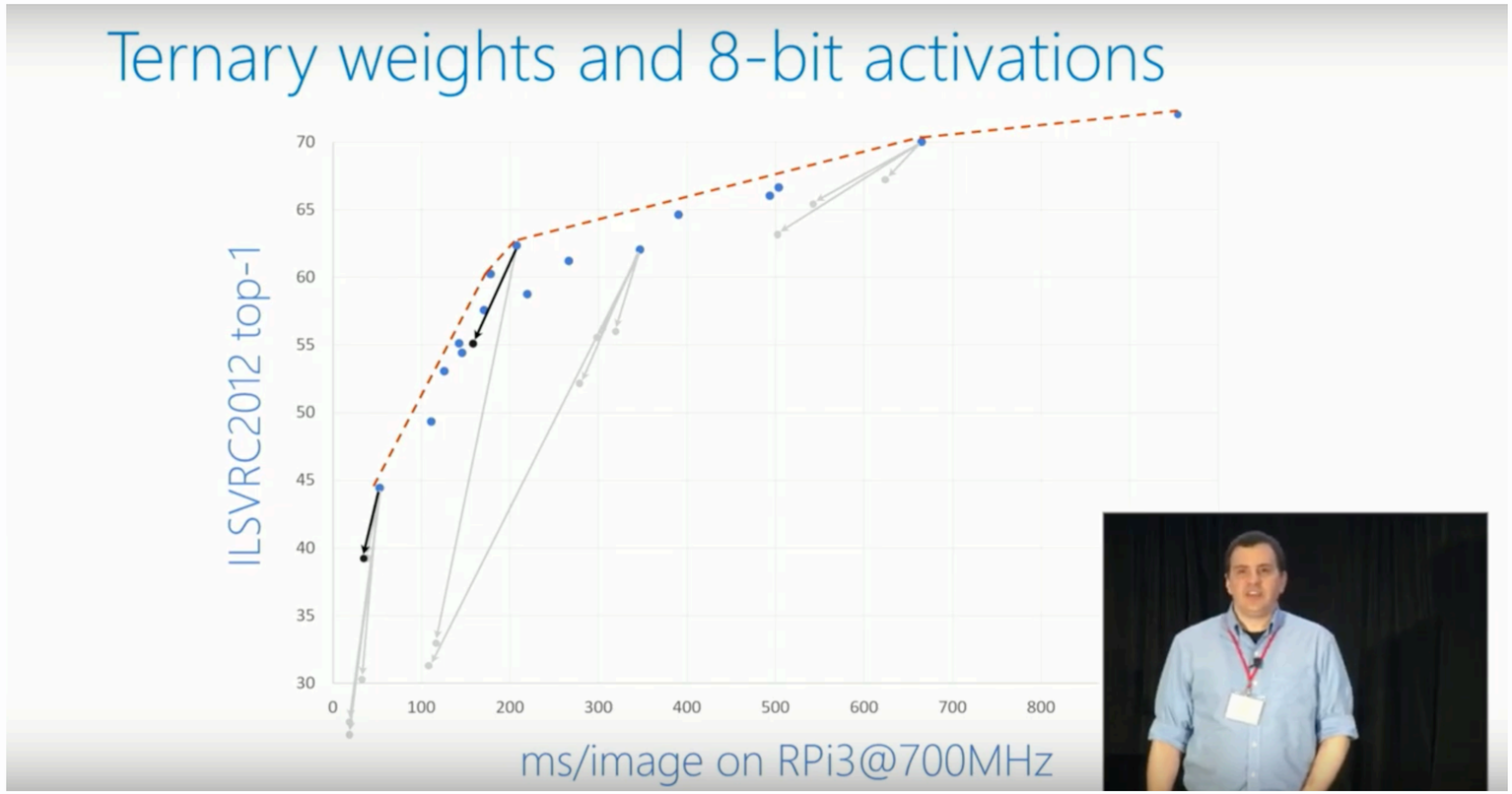

for this problem: quantization did not

(Virtual) Guest Lecture Next Thursday

Krishna Rangasayee, CEO of SiMa.ai

Will not be recorded: PLEASE SHOW UP!