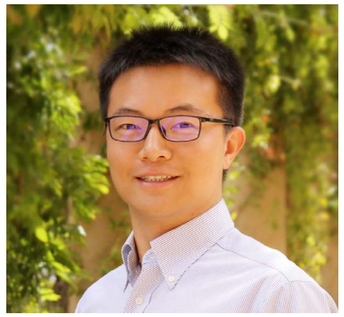
MIT HAN LAB

EfficientML.ai Lecture 04: Pruning and Sparsity

Part II



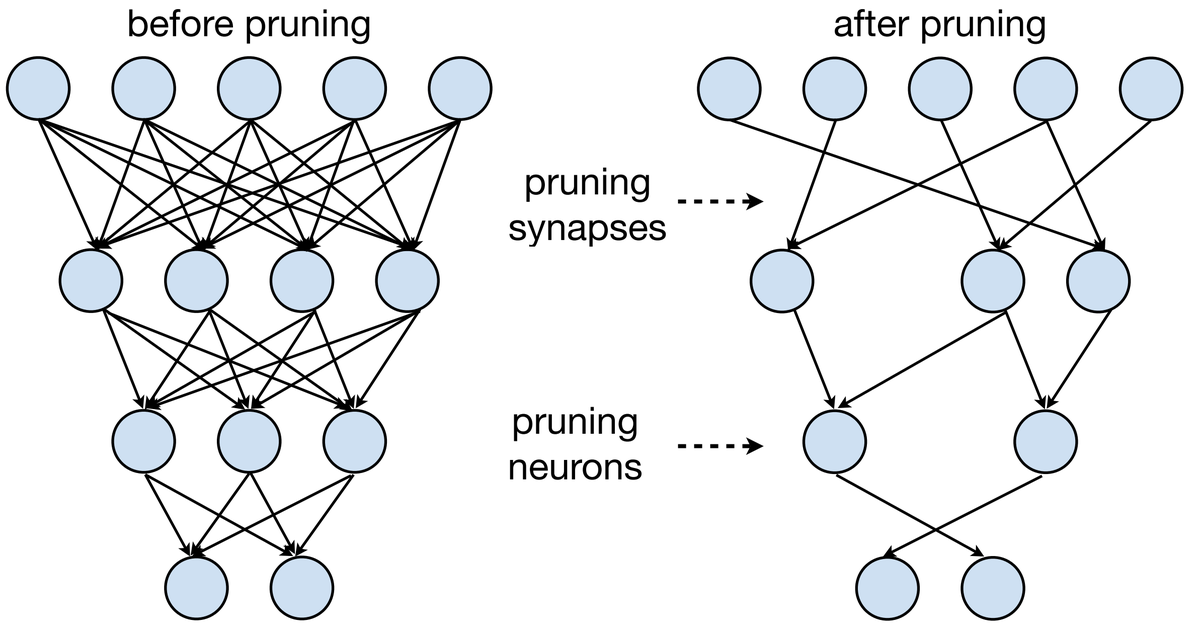
Song Han

Associate Professor, MIT
Distinguished Scientist, NVIDIA

@SongHan_MIT

Neural Network Pruning

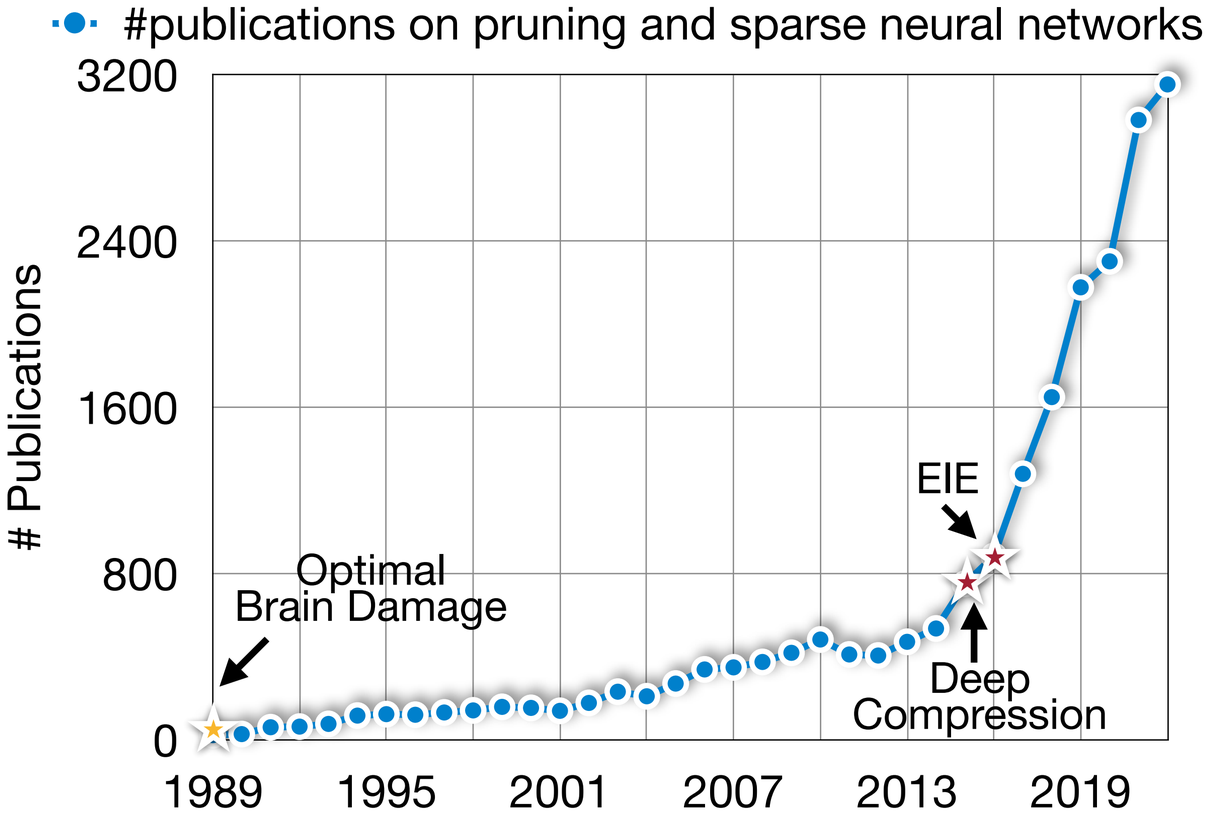
- **Introduction to Pruning**
  - What is pruning?
  - How should we formulate pruning?
- **Determine the Pruning Granularity**
  - In what pattern should we prune the neural network?
- **Determine the Pruning Criterion**
  - What synapses/neurons should we prune?
- **Determine the Pruning Ratio**
  - What should target sparsity be for each layer?
- **Fine-tune/Train Pruned Neural Network**
  - How should we improve performance of pruned models?

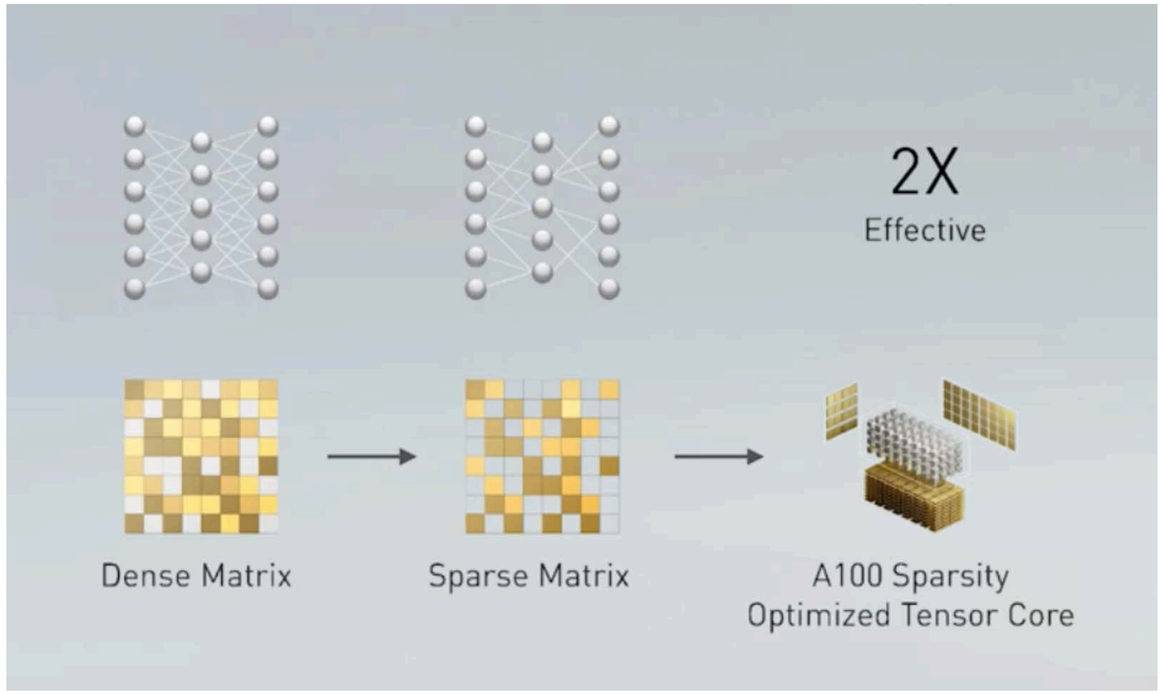


Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

Neural Network Pruning

Make neural network smaller by removing synapses and neurons





2:4 sparsity in A100 GPU
2X peak performance, 1.5X measured BERT speedup

Souce: https://github.com/mit-han-lab/pruning-sparsity-publications

Neural Network Pruning

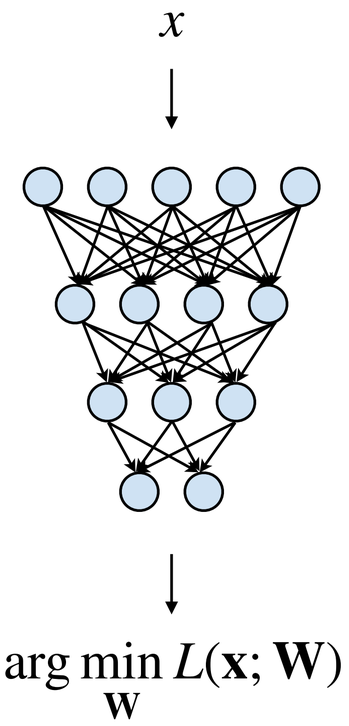
- In general, we could formulate the pruning as follows:

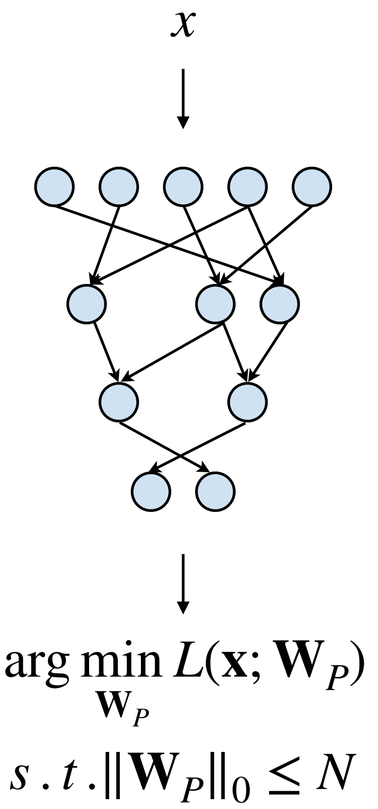
$$\arg\min_{\mathbf{W}_P} L(\mathbf{x}; \mathbf{W}_P)$$

subject to

$$\|\mathbf{W}_p\|_0 < N$$

  - L represents the objective function for neural network training;
  - $\mathbf{x}$ is input, $\mathbf{W}$ is original weights, $\mathbf{W}_P$ is pruned weights;
  - $\|\mathbf{W}_p\|_0$ calculates the #nonzeros in W_P, and N is the target #nonzeros.

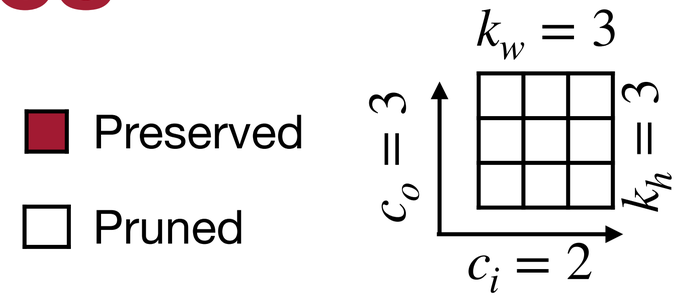


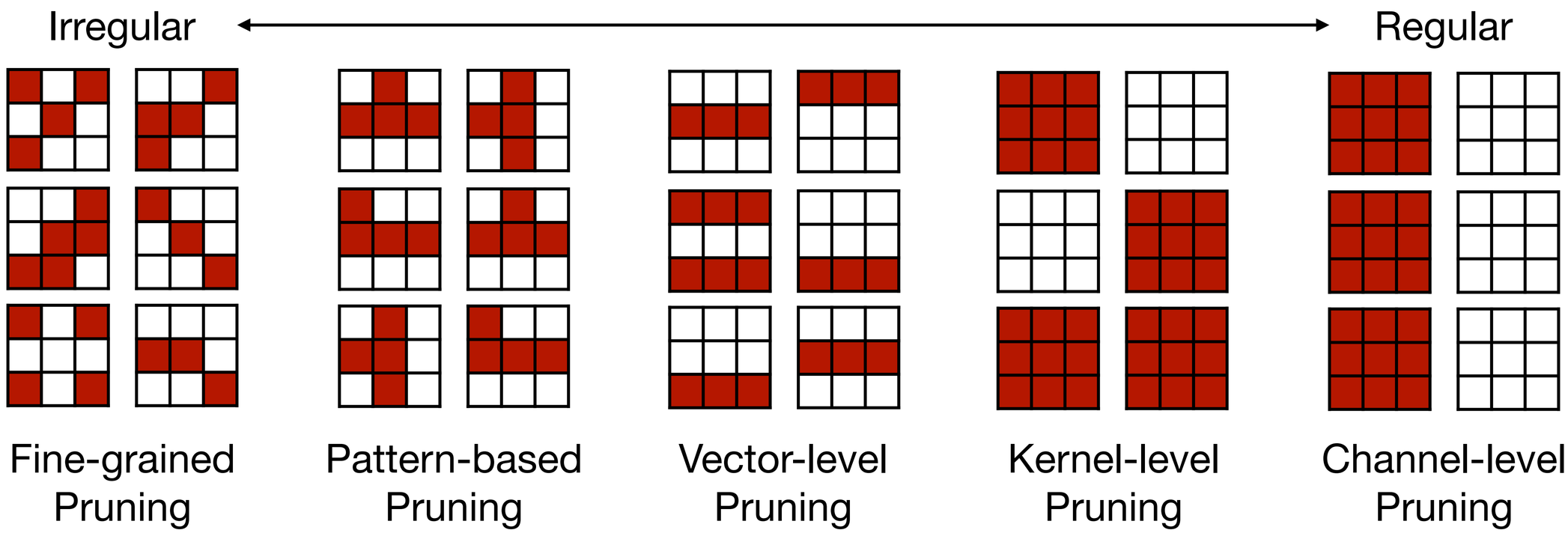


Pruning at Different Granularities

The case of convolutional layers

- Some of the commonly used pruning granularities





like Tetris :)

Exploring the granularity of sparsity in convolutional neural networks [Mao *et al.*, CVPR-W]

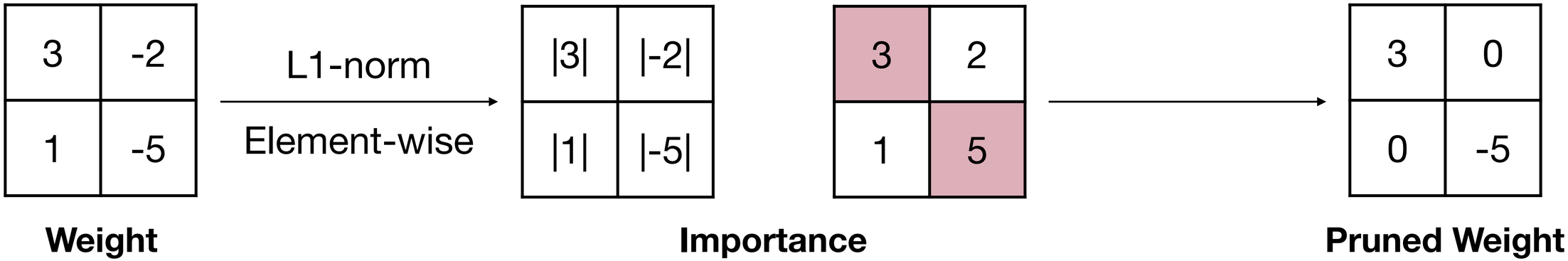
Selection of Synapses to Prune

- When removing parameters from a neural network model,
  - ***the less important*** the parameters being removed are,
  - the better the performance of pruned neural network is.

- **Magnitude-based pruning** considers weights with ***larger absolute values*** are more important than other weights.
  - For element-wise pruning,

$$Importance = |W|$$

  - **Example**

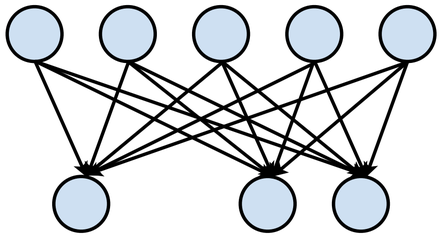


Selection of Neurons to Prune

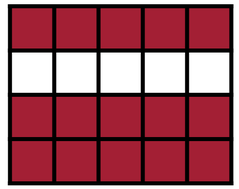
- When removing neurons from a neural network model,
  - ***the less useful*** the neurons being removed are,
  - the better the performance of pruned neural network is.

Recall: Neuron pruning is coarse-grained pruning indeed.

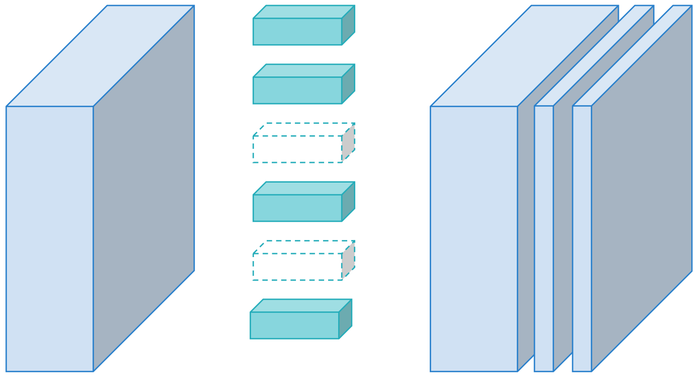
Neuron Pruning in Linear Layer

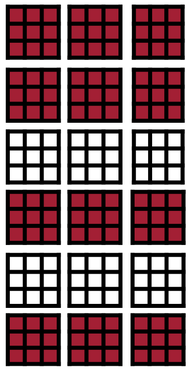


Weight Matrix



Channel Pruning in Convolution Layer

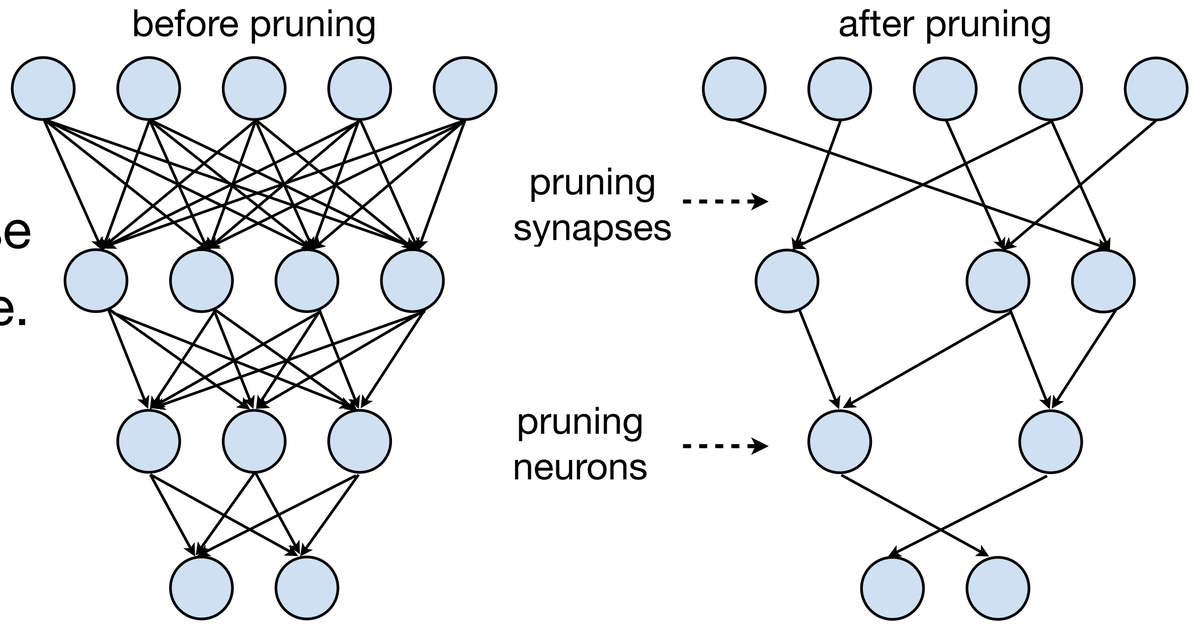




Lecture Plan

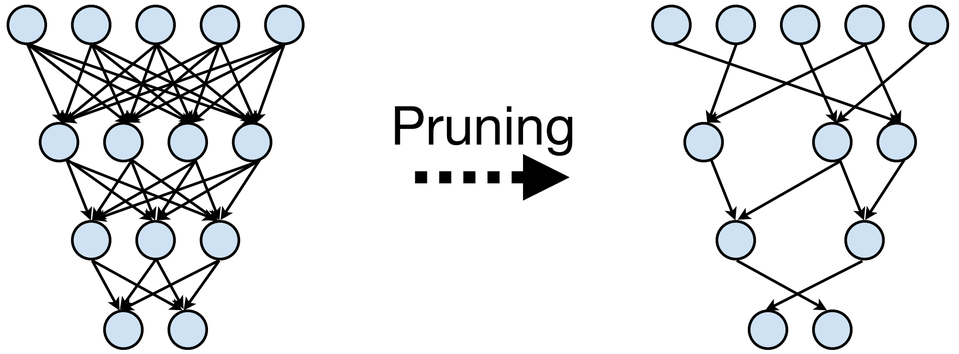
Today we will:

1. Go through all steps of pruning, and introduce how to select ***pruning ratio*** and how to ***fine-tune*** in neural network pruning.
2. Introduce ***Lottery Ticket Hypothesis*** in neural network pruning which shows that training a sparse neural network from scratch is sometimes possible.
3. Introduce the ***system and hardware support for the sparsity***, and elaborate how to translate the computation reduction to measured speedup on general-purpose and specialized hardware by utilizing weight sparsity (NVIDIA Tensor Core), activation sparsity (TorchSparse, PointAcc) and weight & activation sparsity (EIE).



Neural Network Pruning

- **Introduction to Pruning**
  - What is pruning?
  - How should we formulate pruning?
- **Determine the Pruning Granularity**
  - In what pattern should we prune the neural network?
- **Determine the Pruning Criterion**
  - What synapses/neurons should we prune?
- **Determine the Pruning Ratio**
  - What should target sparsity be for each layer?
- **Fine-tune/Train Pruned Neural Network**
  - How should we improve performance of pruned models?



prune 30%?

prune 50%?

prune 70%?

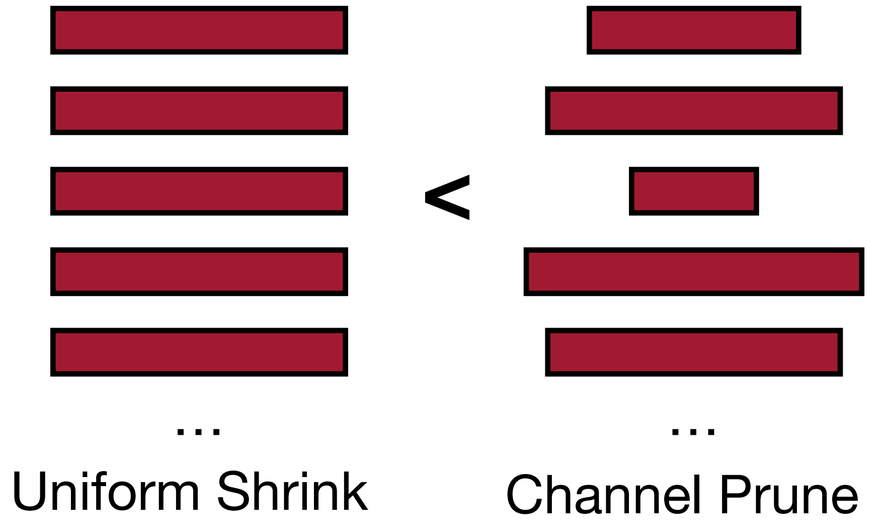
Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

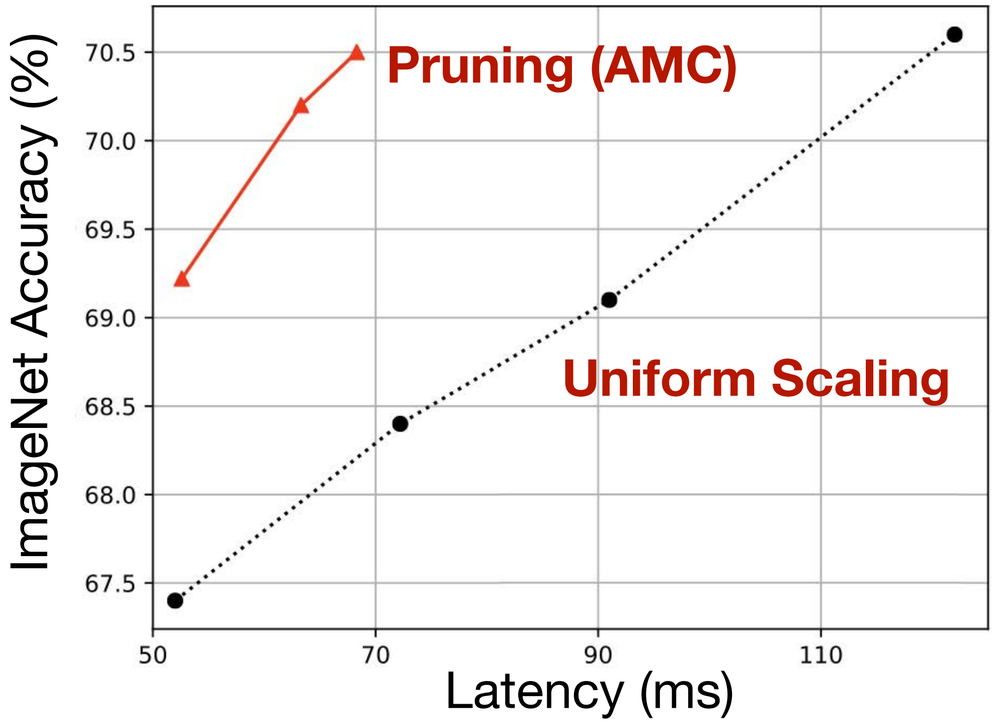
Section 1: Pruning Ratio

How should we find per-layer pruning ratios?

Recap

Non-uniform pruning is better than uniform shrinking

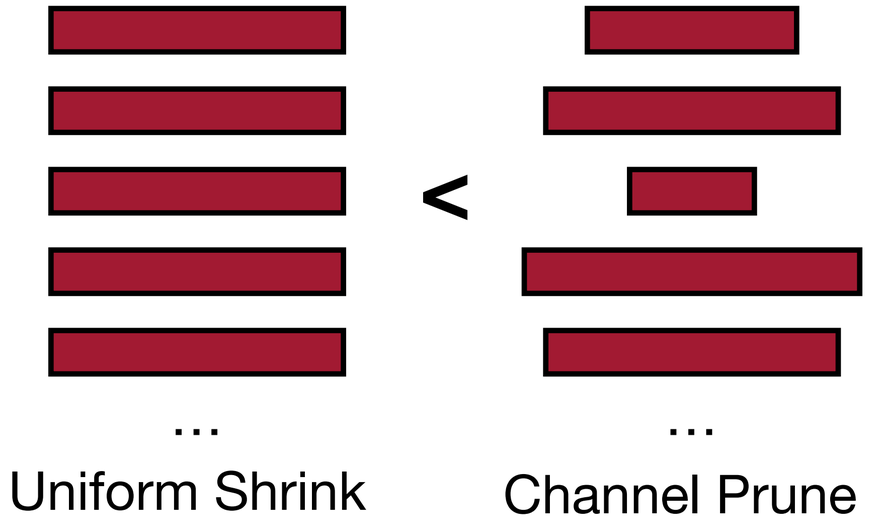


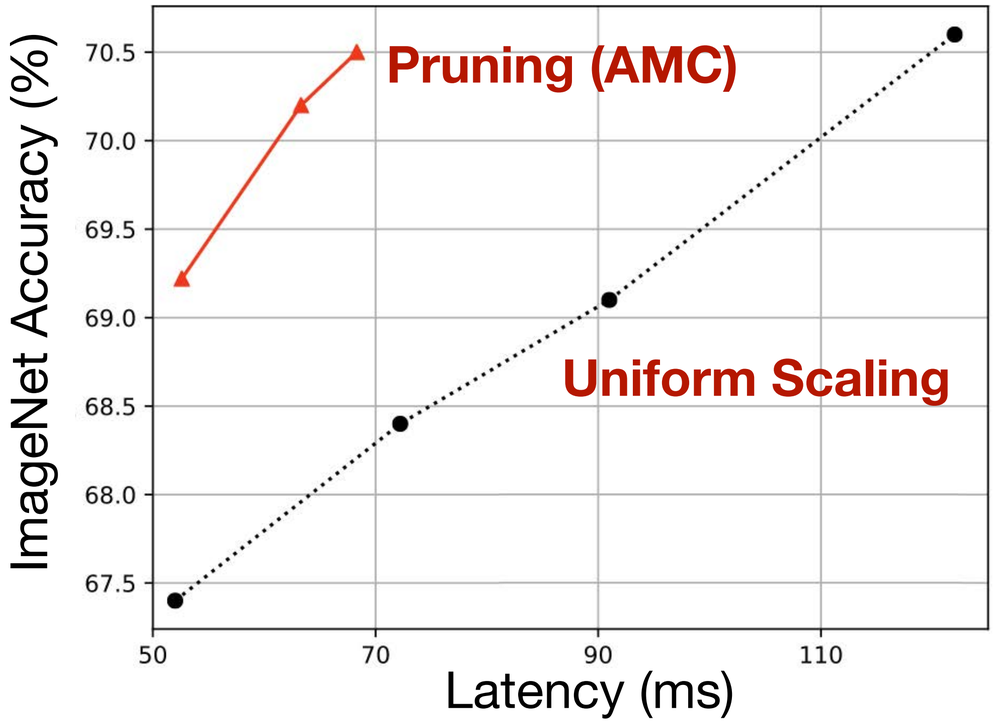


AMC: Automl for Model Compression and Acceleration on Mobile Devices [He *et al.*, ECCV 2018]

Recap

Non-uniform pruning is better than uniform shrinking





Question: how should we find ratios for each layer?

AMC: Automl for Model Compression and Acceleration on Mobile Devices [He *et al.*, ECCV 2018]

Finding Pruning Ratios

Analyze the sensitivity of each layer

- We need different pruning ratios for each layer since different layers have different **sensitivity**
  - Some layers are more sensitive (e.g., first layer)
  - Some layers are more redundant

Finding Pruning Ratios

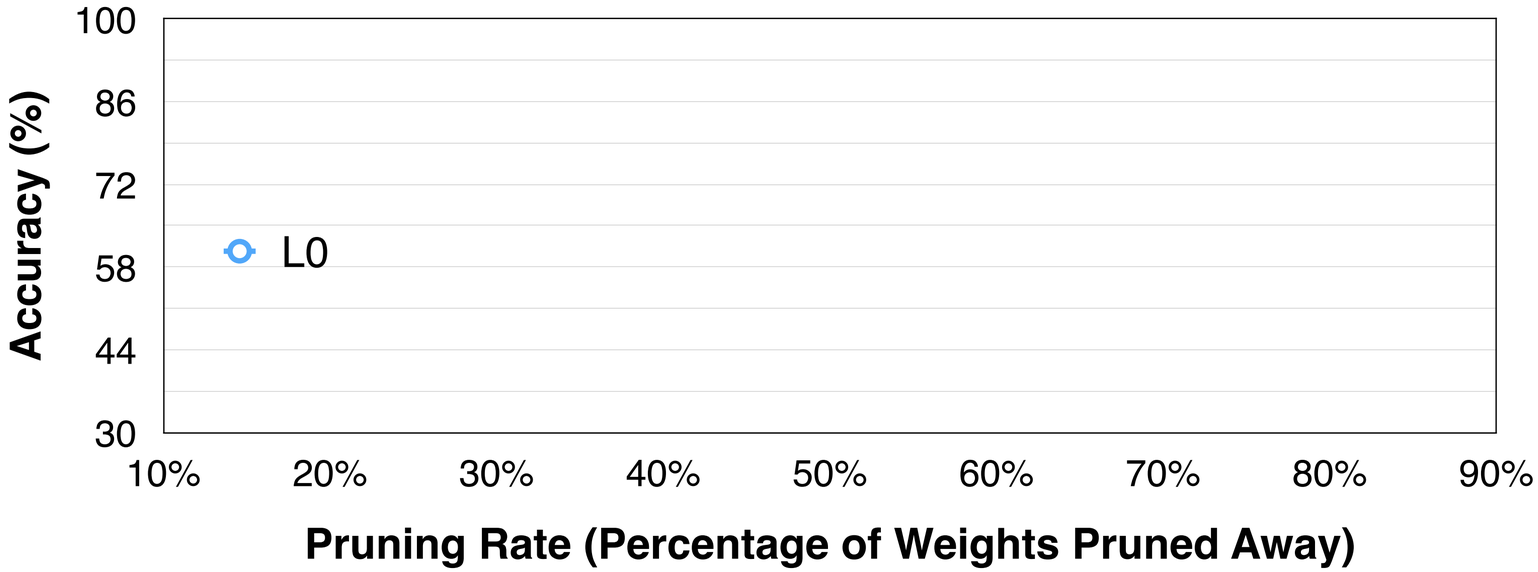
Analyze the sensitivity of each layer

- We need different pruning ratios for each layer since different layers have different **sensitivity**
  - Some layers are more sensitive (e.g., first layer)
  - Some layers are more redundant
- We can perform **sensitivity analysis** to determine the per-layer pruning ratio

Finding Pruning Ratios

Analyze the sensitivity of each layer

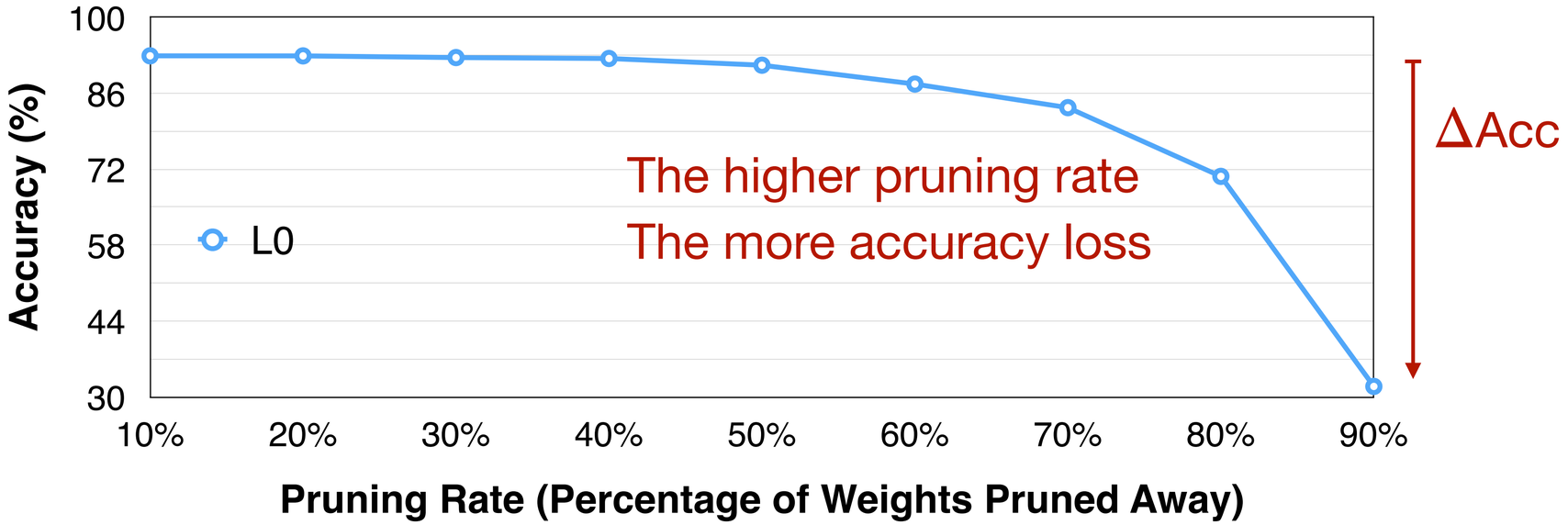
- The process of Sensitivity Analysis (* VGG-11 on CIFAR-10 dataset)
  - Pick a layer L_i in the model



Finding Pruning Ratios

Analyze the sensitivity of each layer

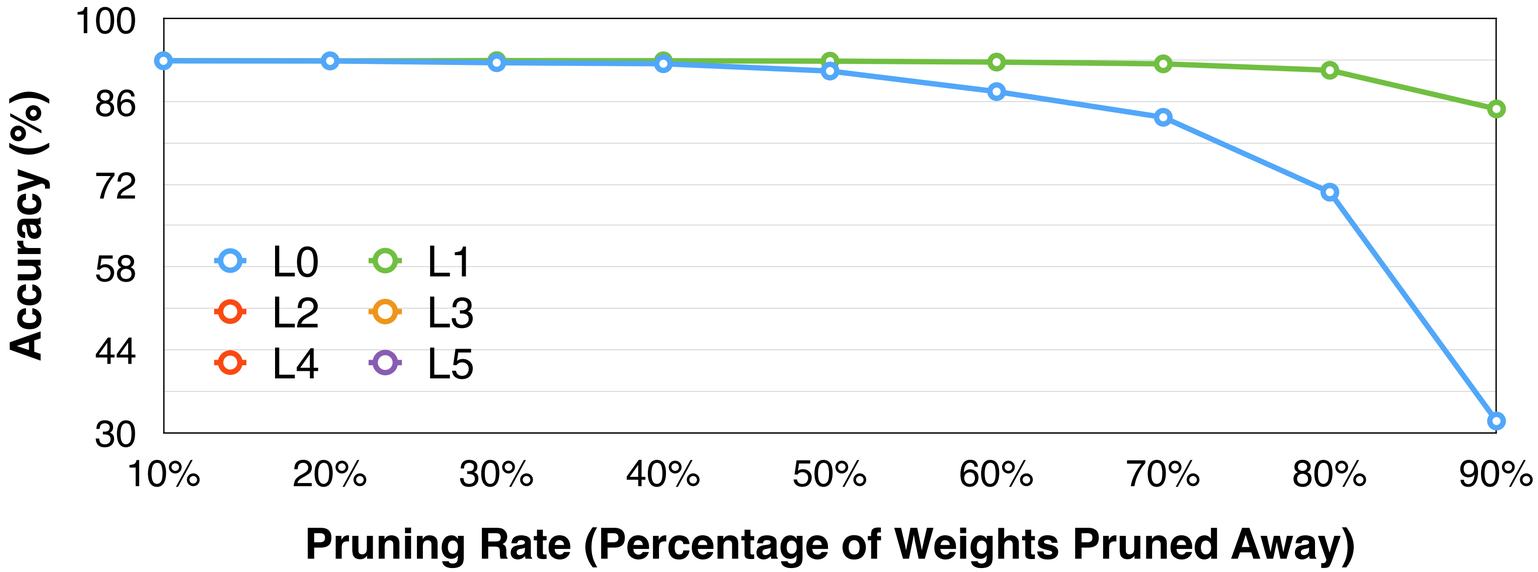
- The process of Sensitivity Analysis (* VGG-11 on CIFAR-10 dataset)
  - Pick a layer L_i in the model
    - Prune the layer L_i with pruning ratio $r \in \{0, 0.1, 0.2, ..., 0.9\}$ (or other strides)
    - Observe the accuracy degrade ΔAcc_r^i for each pruning ratio



Finding Pruning Ratios

Analyze the sensitivity of each layer

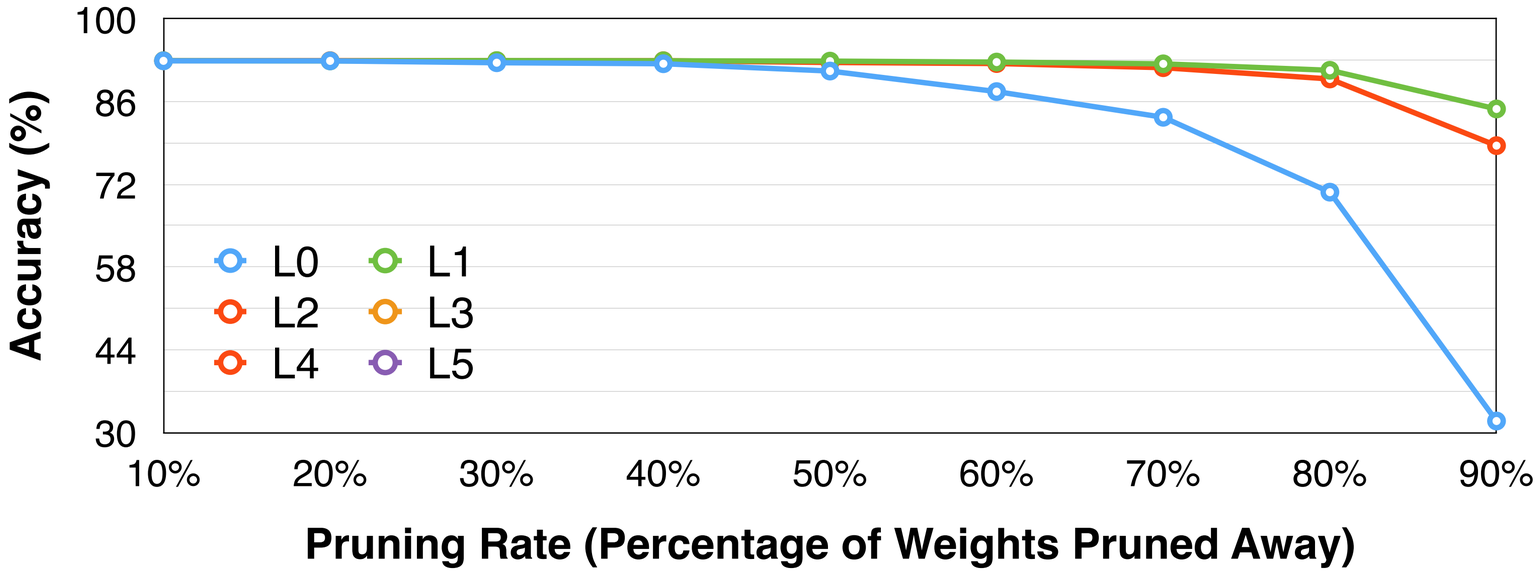
- The process of Sensitivity Analysis (* VGG-11 on CIFAR-10 dataset)
  - Pick a layer L_i in the model
    - Prune the layer L_i with pruning ratio $r \in \{0, 0.1, 0.2, ..., 0.9\}$ (or other strides)
    - Observe the accuracy degrade ΔAcc_r^i for each pruning ratio
  - Repeat the process for all layers



Finding Pruning Ratios

Analyze the sensitivity of each layer

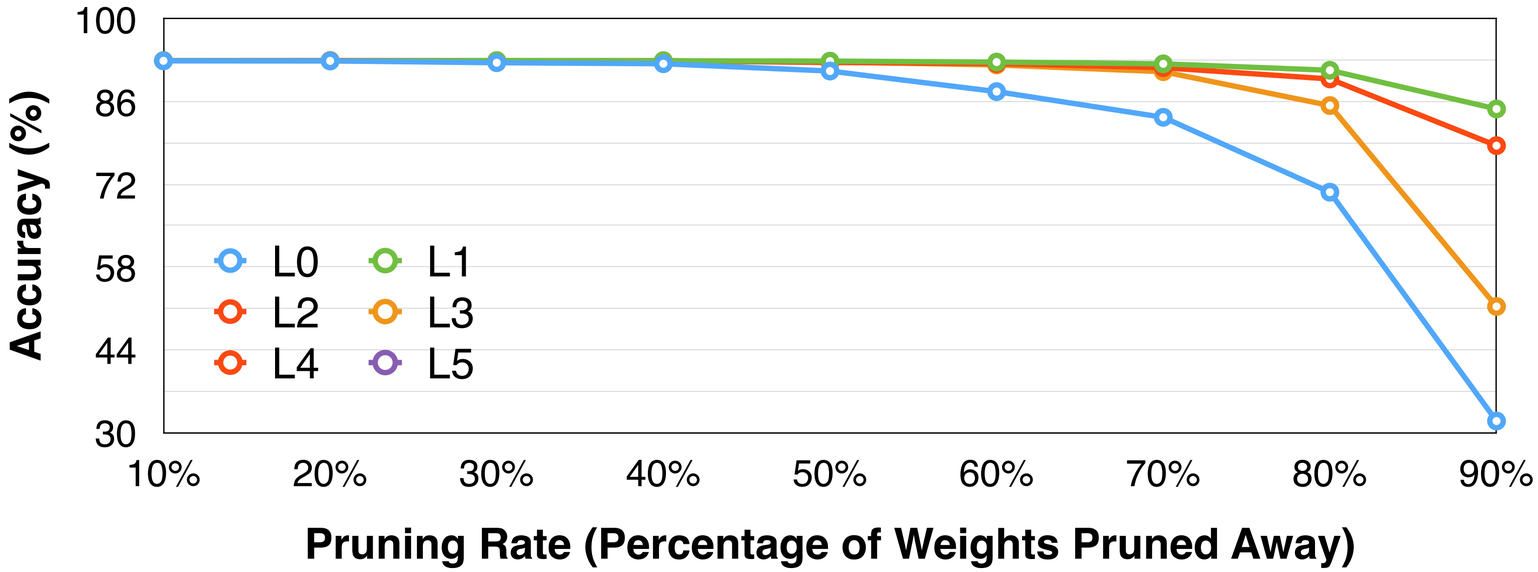
- The process of Sensitivity Analysis (* VGG-11 on CIFAR-10 dataset)
  - Pick a layer L_i in the model
    - Prune the layer L_i with pruning ratio $r \in \{0, 0.1, 0.2, ..., 0.9\}$ (or other strides)
    - Observe the accuracy degrade ΔAcc_r^i for each pruning ratio
  - Repeat the process for all layers



Finding Pruning Ratios

Analyze the sensitivity of each layer

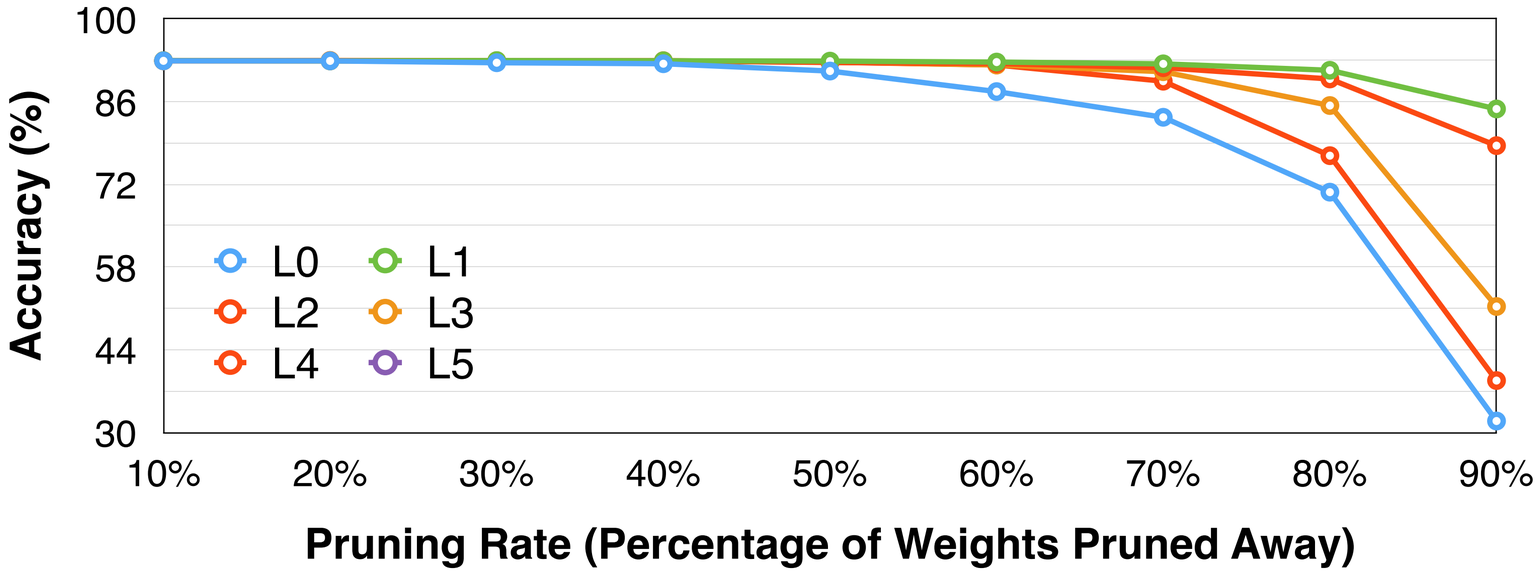
- The process of Sensitivity Analysis (* VGG-11 on CIFAR-10 dataset)
  - Pick a layer L_i in the model
    - Prune the layer L_i with pruning ratio $r \in \{0, 0.1, 0.2, ..., 0.9\}$ (or other strides)
    - Observe the accuracy degrade ΔAcc_r^i for each pruning ratio
  - Repeat the process for all layers



Finding Pruning Ratios

Analyze the sensitivity of each layer

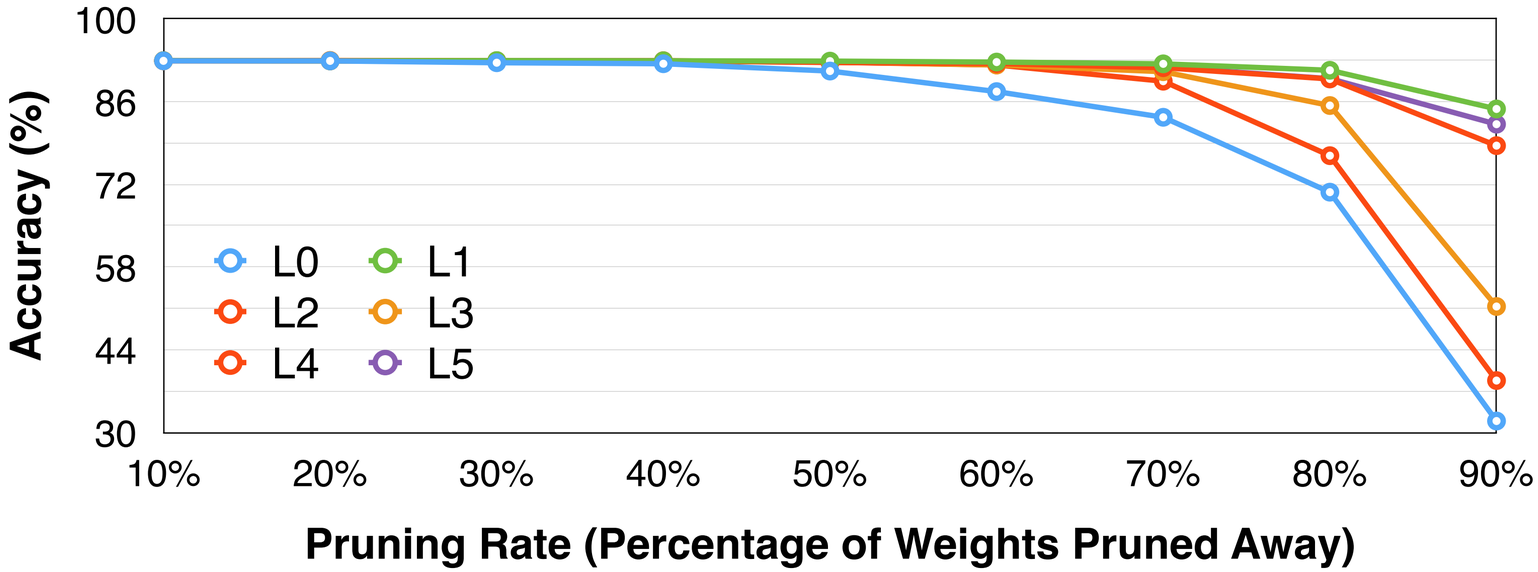
- The process of Sensitivity Analysis (* VGG-11 on CIFAR-10 dataset)
  - Pick a layer L_i in the model
    - Prune the layer L_i with pruning ratio $r \in \{0, 0.1, 0.2, ..., 0.9\}$ (or other strides)
    - Observe the accuracy degrade ΔAcc_r^i for each pruning ratio
  - Repeat the process for all layers



Finding Pruning Ratios

Analyze the sensitivity of each layer

- The process of Sensitivity Analysis (* VGG-11 on CIFAR-10 dataset)
  - Pick a layer L_i in the model
    - Prune the layer L_i with pruning ratio $r \in \{0, 0.1, 0.2, ..., 0.9\}$ (or other strides)
    - Observe the accuracy degrade ΔAcc_r^i for each pruning ratio
  - Repeat the process for all layers

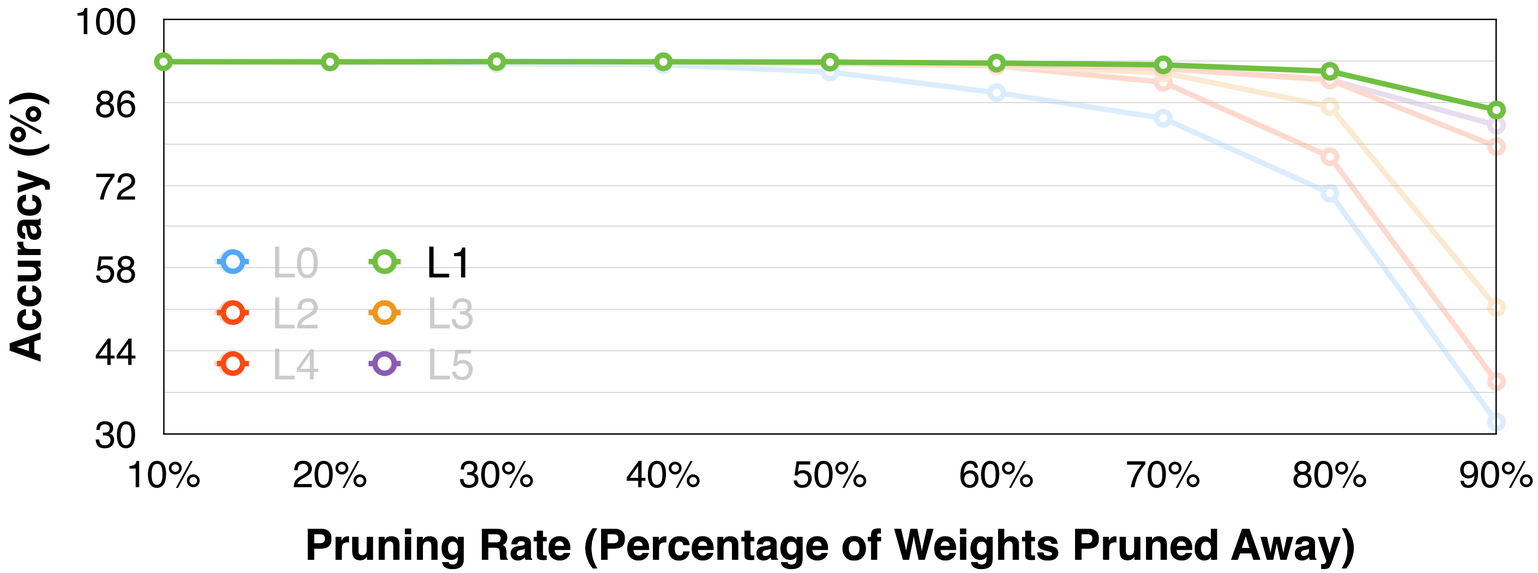


Finding Pruning Ratios

Analyze the sensitivity of each layer

- The process of Sensitivity Analysis (* VGG-11 on CIFAR-10 dataset)
  - Pick a layer L_i in the model
    - Prune the layer L_i with pruning ratio $r \in \{0, 0.1, 0.2, ..., 0.9\}$ (or other strides)
    - Observe the accuracy degrade ΔAcc_r^i for each pruning ratio
  - Repeat the process for all layers

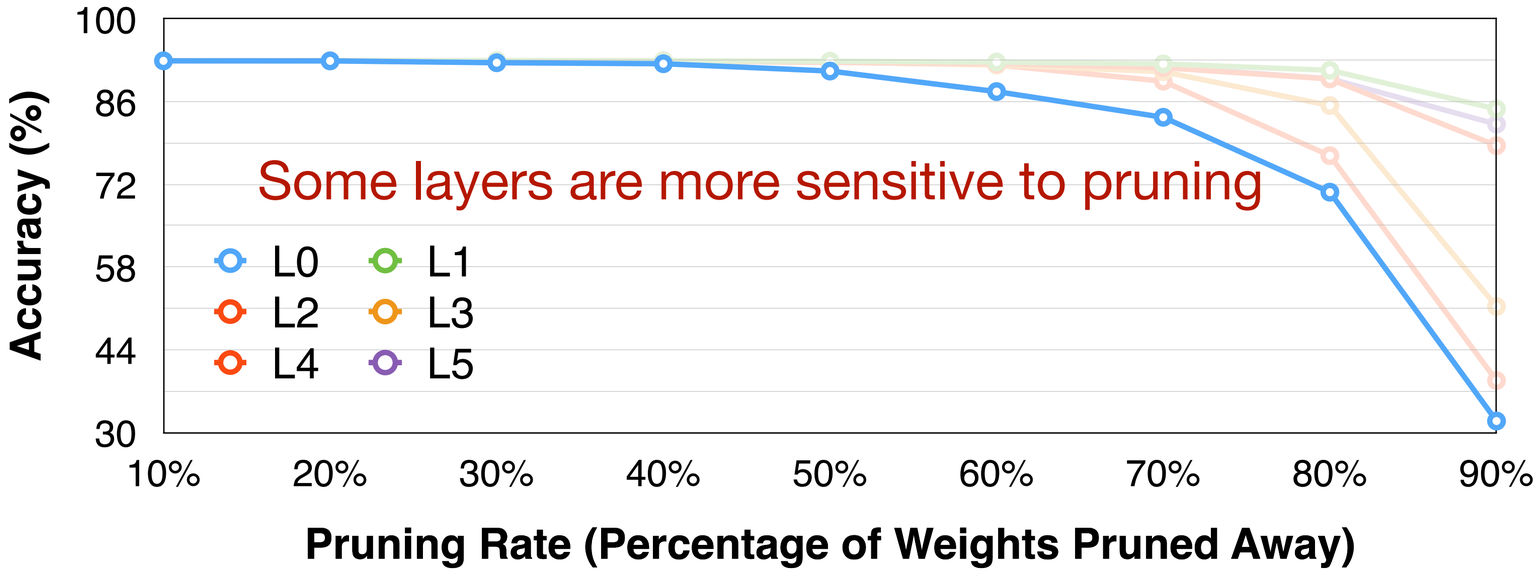
Some layers are less sensitive to pruning



Finding Pruning Ratios

Analyze the sensitivity of each layer

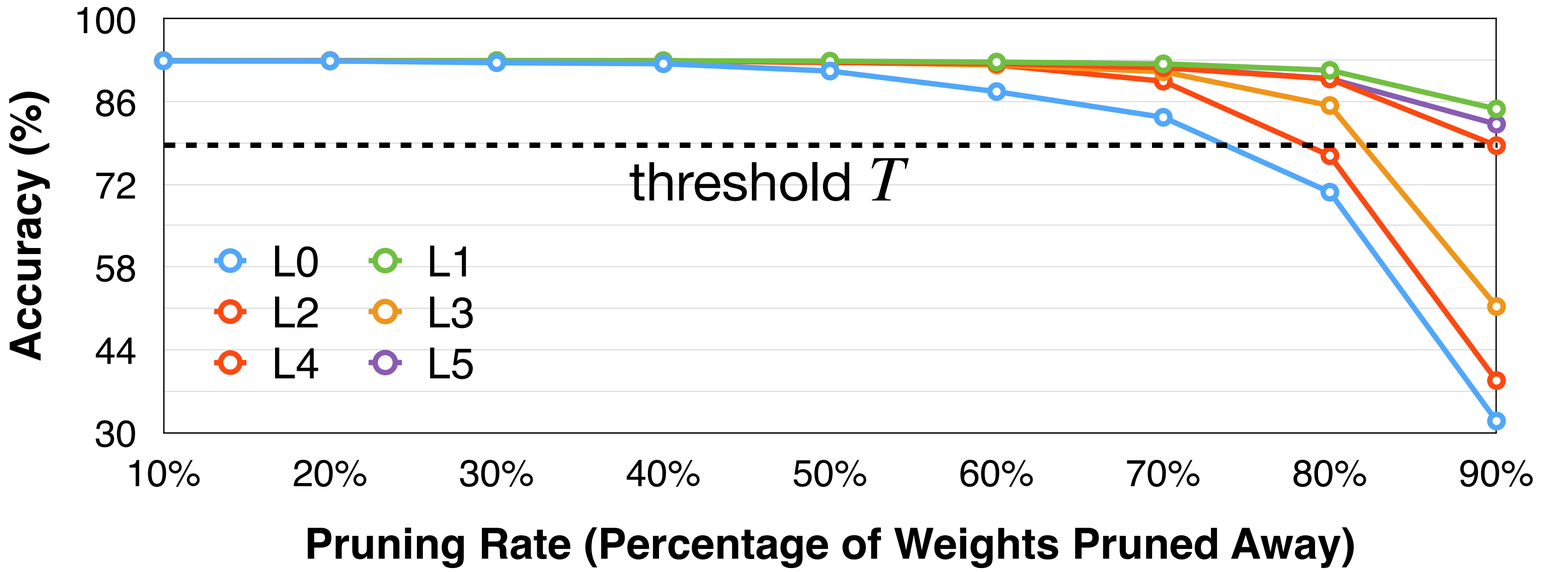
- The process of Sensitivity Analysis (* VGG-11 on CIFAR-10 dataset)
  - Pick a layer L_i in the model
    - Prune the layer L_i with pruning ratio $r \in \{0, 0.1, 0.2, ..., 0.9\}$ (or other strides)
    - Observe the accuracy degrade ΔAcc_r^i for each pruning ratio
  - Repeat the process for all layers



Finding Pruning Ratios

Analyze the sensitivity of each layer

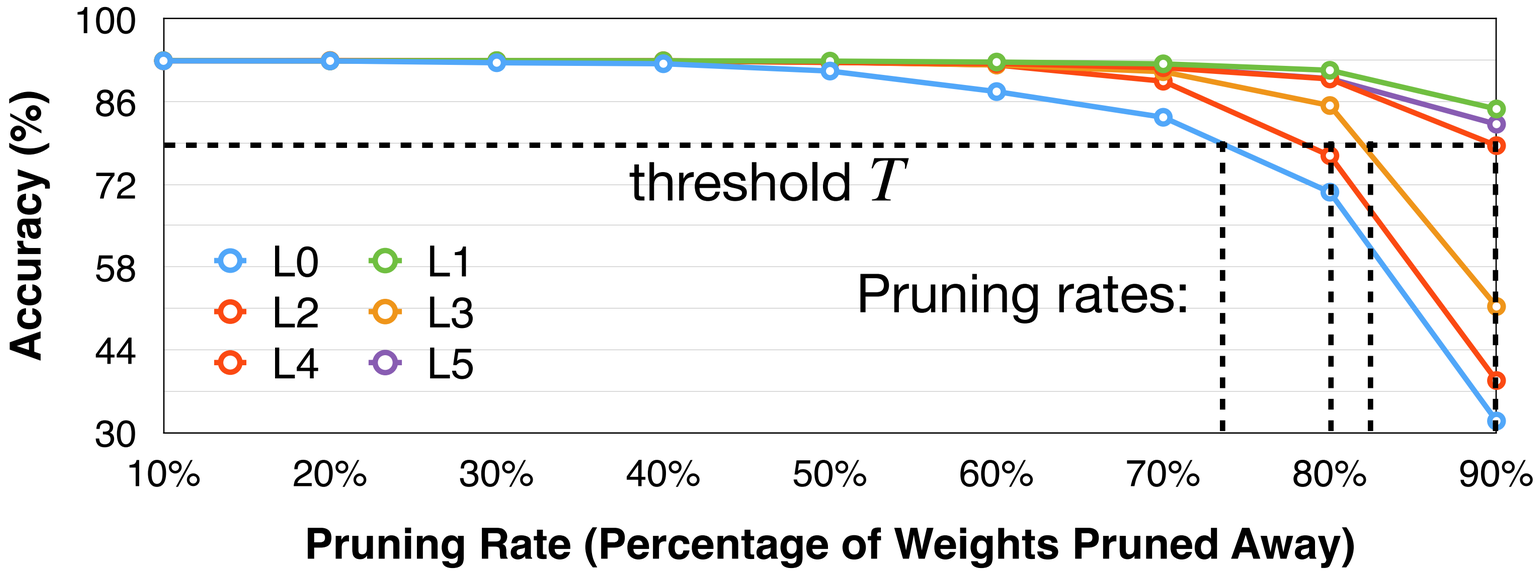
- The process of Sensitivity Analysis (* VGG-11 on CIFAR-10 dataset)
  - Pick a layer L_i in the model
    - Prune the layer L_i with pruning ratio $r \in \{0, 0.1, 0.2, ..., 0.9\}$ (or other strides)
    - Observe the accuracy degrade ΔAcc_r^i for each pruning ratio
  - Repeat the process for all layers
  - Pick a degradation threshold T such that the overall pruning rate is desired



Finding Pruning Ratios

Analyze the sensitivity of each layer

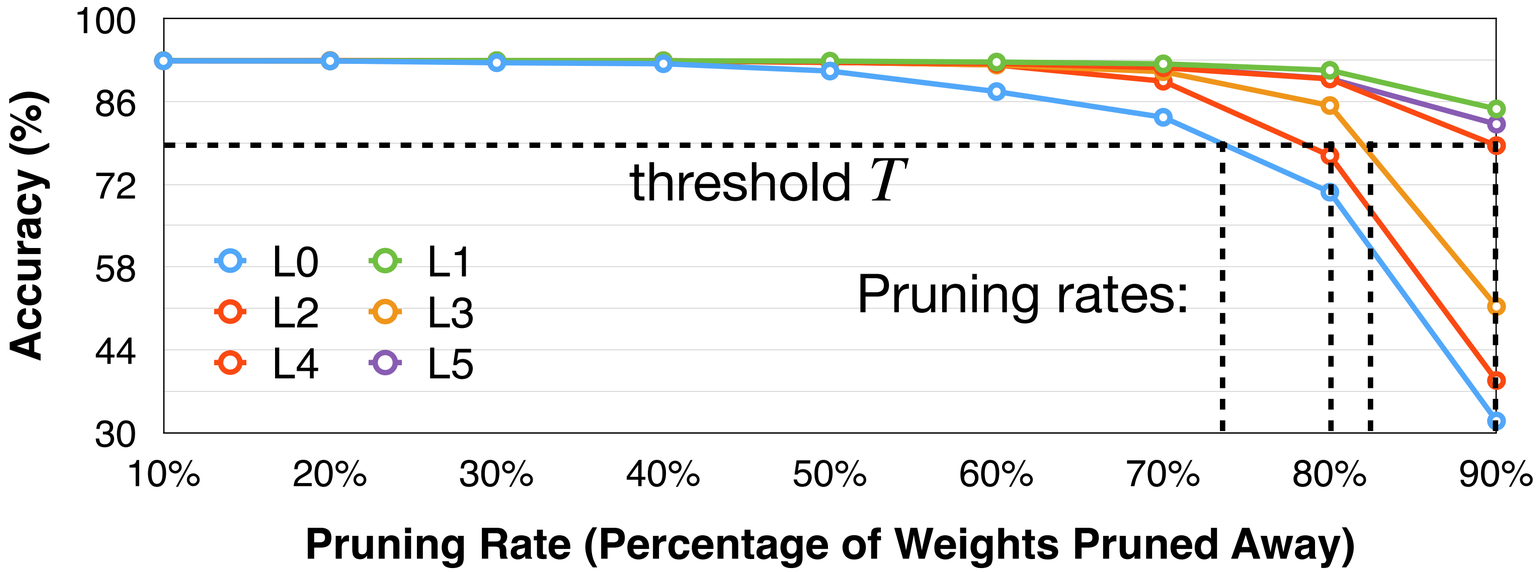
- The process of Sensitivity Analysis (* VGG-11 on CIFAR-10 dataset)
  - Pick a layer L_i in the model
    - Prune the layer L_i with pruning ratio $r \in \{0, 0.1, 0.2, ..., 0.9\}$ (or other strides)
    - Observe the accuracy degrade ΔAcc_r^i for each pruning ratio
  - Repeat the process for all layers
  - Pick a degradation threshold T such that the overall pruning rate is desired



Finding Pruning Ratios

Analyze the sensitivity of each layer

- Is this optimal?
  - Maybe not. We do not consider the interaction between layers.
- Can we go beyond the heuristics?
  - Yes!

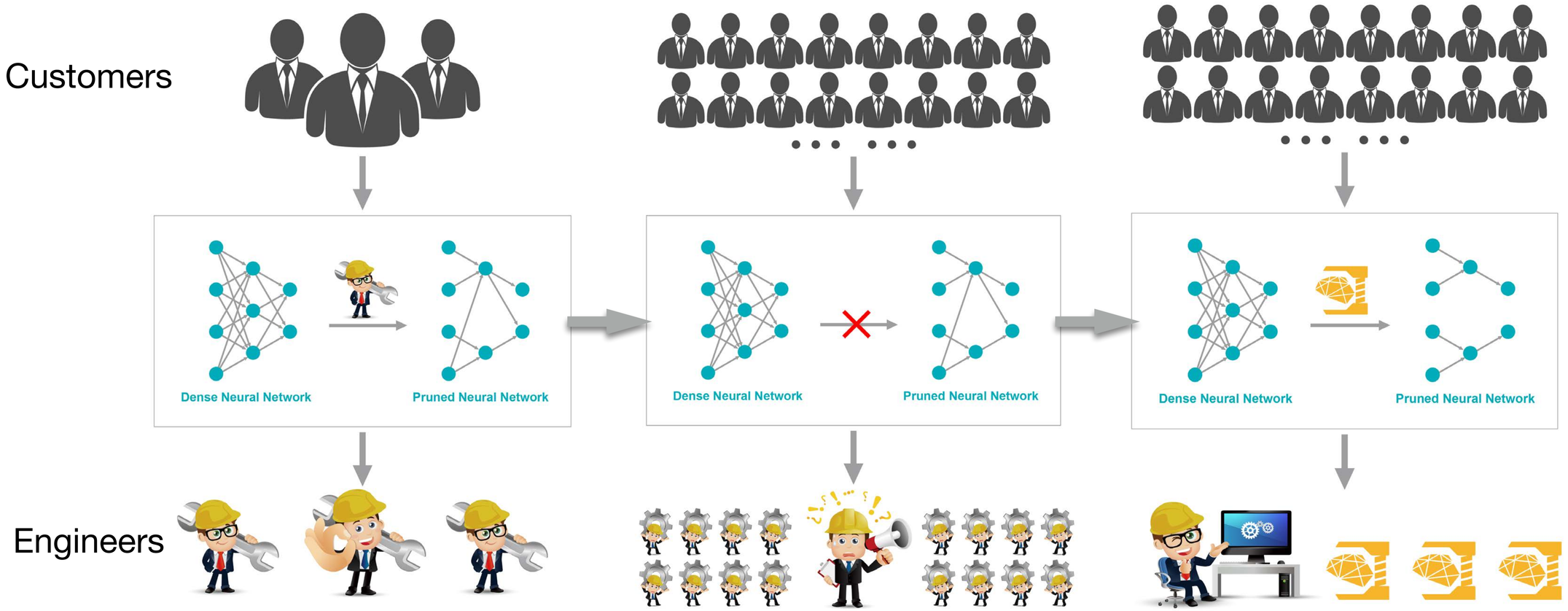


Automatic Pruning

- Given an **overall** compression ratio, how do we choose **per-layer** pruning ratios?
  - Sensitivity analysis ignores the interaction between layers -> sub-optimal

Automatic Pruning

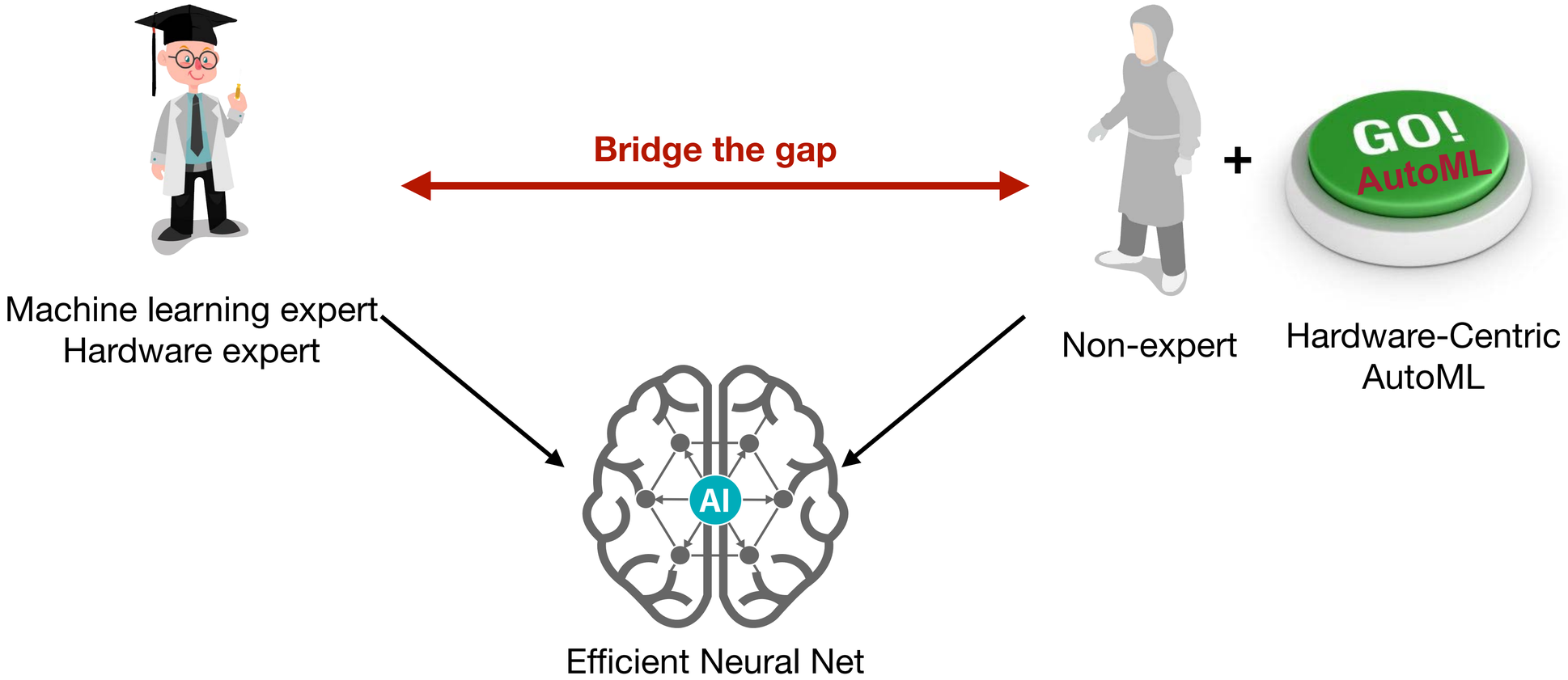
- Given an **overall** compression ratio, how do we choose **per-layer** pruning ratios?
  - Sensitivity analysis ignores the interaction between layers -> sub-optimal
- Conventionally, such process relies on human expertise and trials and errors



AMC: AutoML for Model Compression and Acceleration on Mobile Devices [He *et al.*, ECCV 2018]

Automatic Pruning

- Can we develop a push-the-button solution?

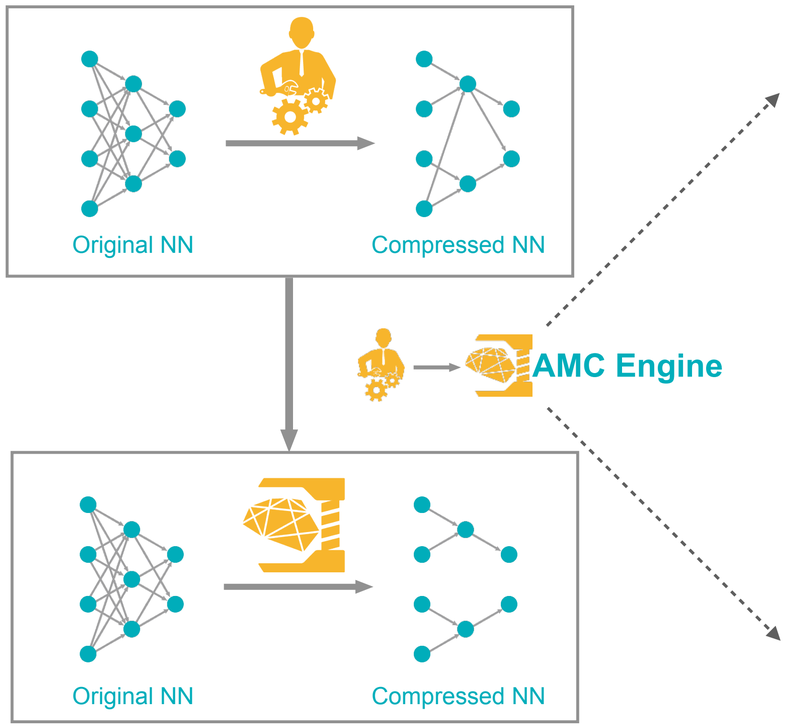


AMC: AutoML for Model Compression and Acceleration on Mobile Devices [He *et al.*, ECCV 2018]

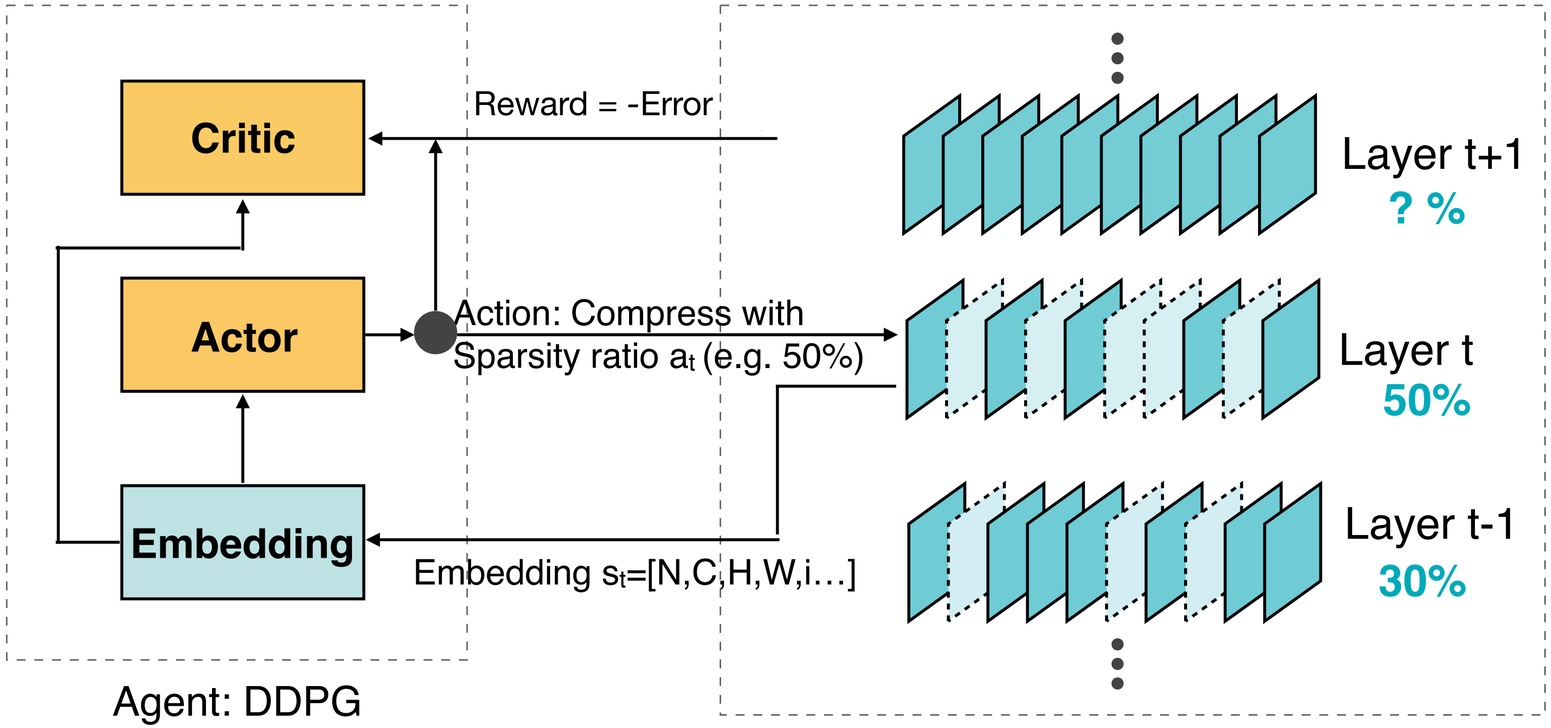
AMC: AutoML for Model Compression

Pruning as a reinforcement learning problem

Model Compression by Human:
Labor Consuming, Sub-optimal



Model Compression by AI:
Automated, Higher Compression Rate, Faster



Agent: DDPG

Environment: Channel Pruning

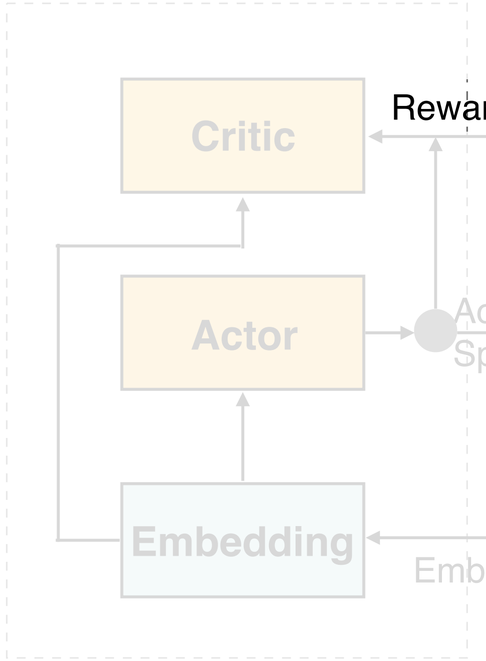
AMC: AutoML for Model Compression and Acceleration on Mobile Devices [He *et al.*, ECCV 2018]

AMC: AutoML for Model Compression

Pruning as a reinforcement learning problem

Model Compression by Human:
Labor Consuming, Sub-optimal

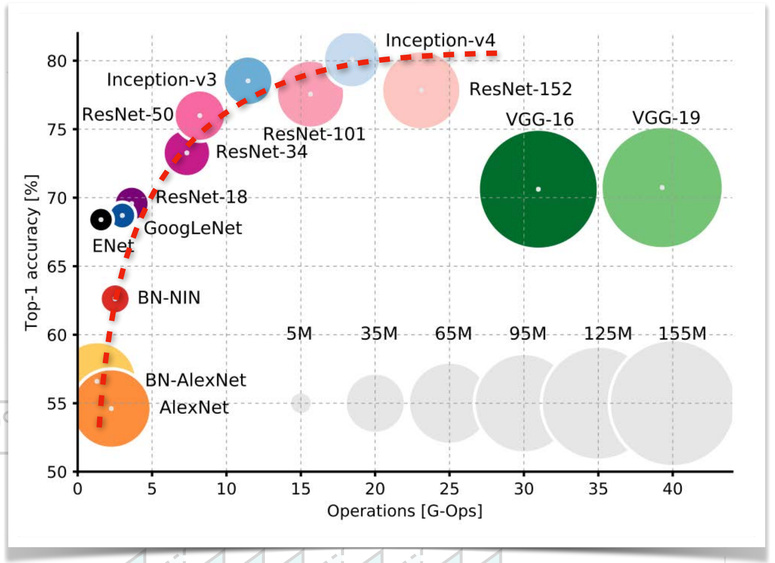
Model Compression by AI:
Automated, Higher Compression Rate, Faster

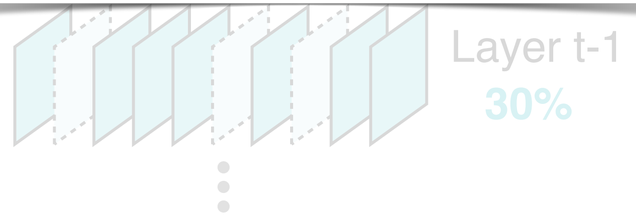


Reward= -Error*log(FLOP)

Action: Compress with
Sparsity ratio a_t (e.g. 50%

Embedding s_t=[N,C,H,W,i…]





Environment: Channel Pruning

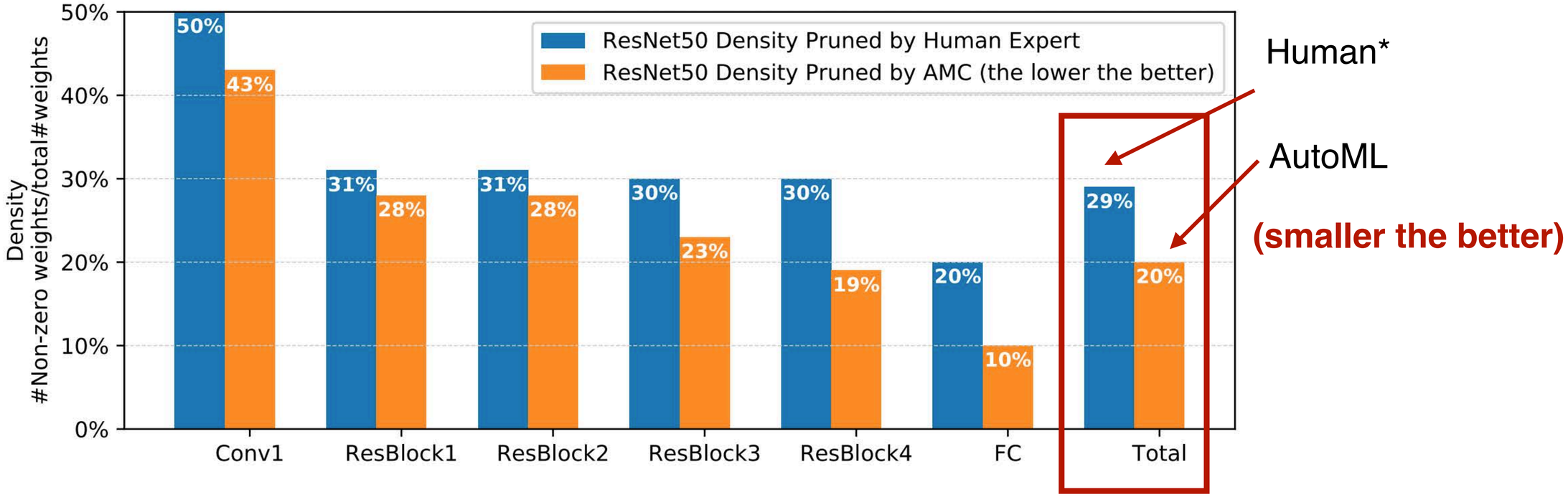
An Analysis of Deep Neural Network Models for Practical Applications [Canziani *et al.*, 2016]

AMC: AutoML for Model Compression

- AMC uses the following setups for the reinforcement learning problem
  - **State**: 11 features (including layer indices, channel numbers, kernel sizes, FLOPs, …)
  - **Action**: A continuous number (pruning ratio) $a \in [0,1)$
  - **Agent**: DDPG agent, since it supports continuous action output
  - **Reward**: $R = \begin{cases} -\text{Error}, & \text{if satisfies constrains} \\ -\infty, & \text{if not} \end{cases}$
    - We can also optimize latency constraints with a pre-built lookup table (LUT)

AMC: AutoML for Model Compression and Acceleration on Mobile Devices [He *et al.*, ECCV 2018]

AMC: AutoML for Model Compression



* Efficient Methods and Hardware for Deep Learning [Han, *thesis*]

AMC: AutoML for Model Compression

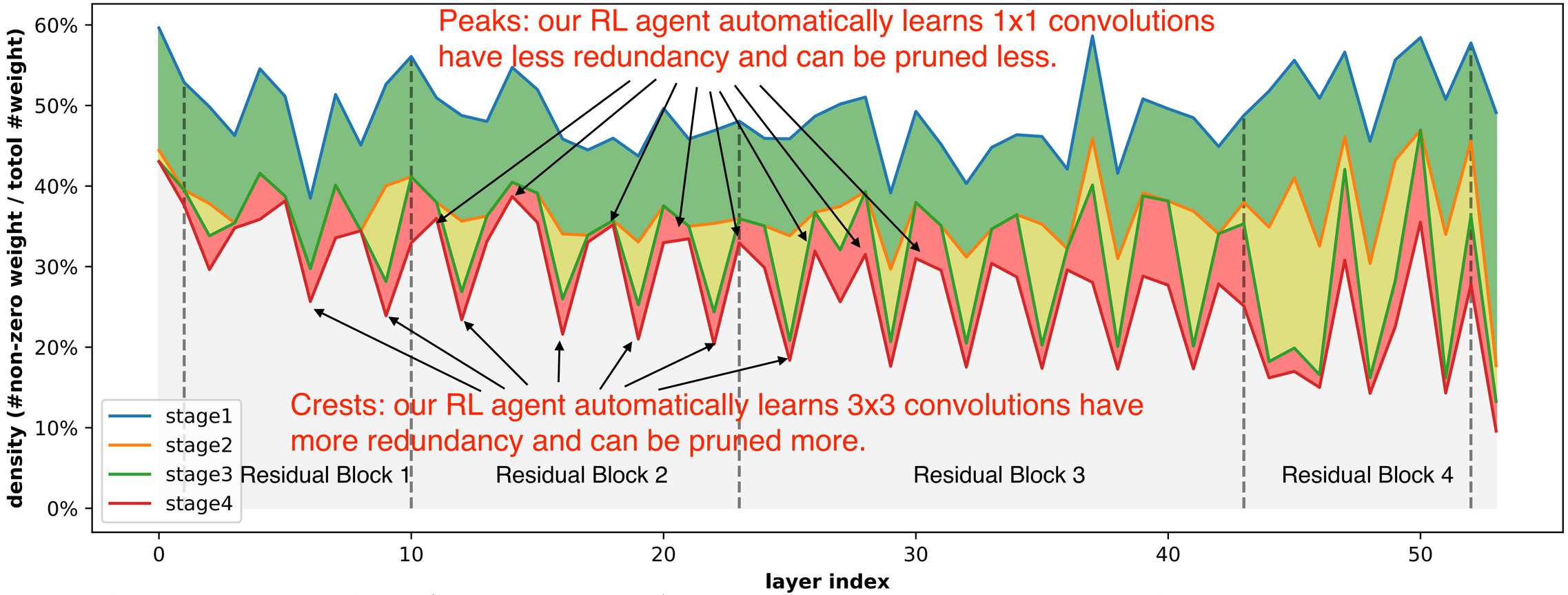


Figure 14: The pruning policy (sparsity ratio) given by our reinforcement learning agent for ResNet-50.

AMC: AutoML for Model Compression

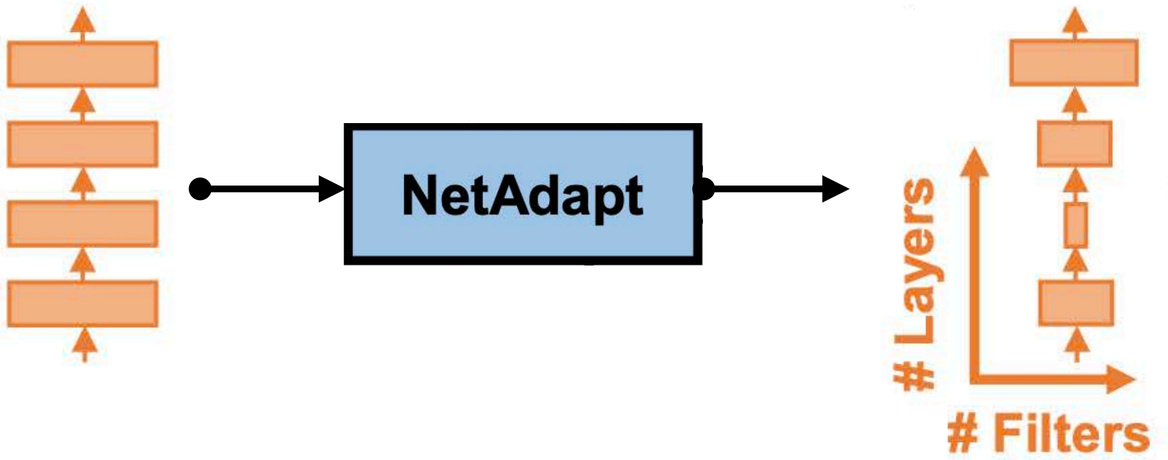
Model	MAC	Top-1	Latency*	Speedup	Memory
1.0 MobileNet	569M	70.6%	119.0ms	1x	20.1MB
AMC (50% **FLOPs**)	285M	**70.5%**	64.4ms	**1.8x**	14.3MB
AMC (50% **Time**)	272M	**70.2%**	59.7ms	**2.0x**	13.2MB
0.75 MobileNet	325M	68.4%	69.5ms	1.7x	14.8MB

* Measured with TF-Lite on Samsung Galaxy S7 Edge, which has Qualcomm Snapdragon SoC
Single core, Batch size = 1(mobile, latency oriented)

NetAdapt

A rule-based iterative/progressive method

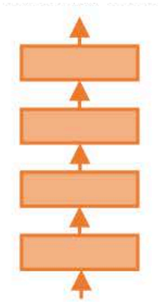
- The goal of NetAdapt is to find a per-layer pruning ratio to meet a global resource constraint (e.g., latency, energy, …)
- The process is done iteratively
- We take **latency** constraint as an example



NetAdapt: Platform-Aware Neural Network Adaptation for Mobile Applications [Yang *et al.*, ECCV 2018]

NetAdapt

- For each iteration, we aim to reduce the latency by a certain amount ΔR (manually defined)

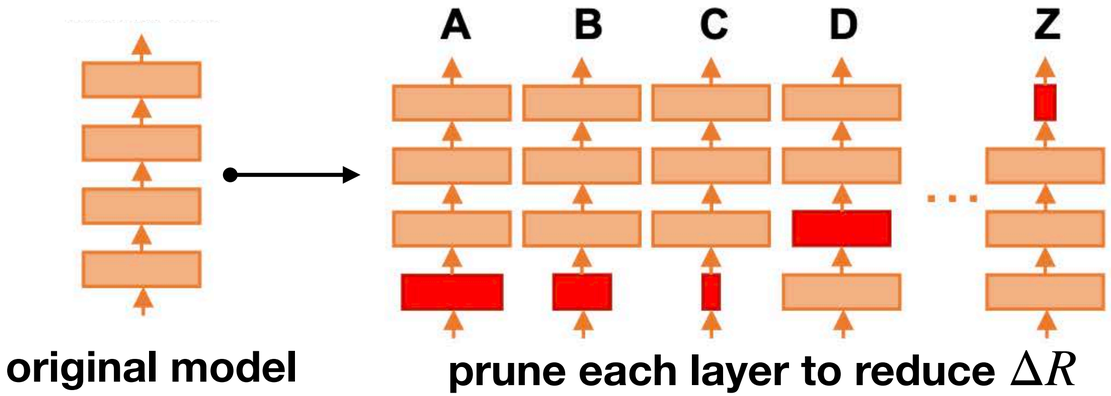


original model

NetAdapt: Platform-Aware Neural Network Adaptation for Mobile Applications [Yang *et al.*, ECCV 2018]

NetAdapt

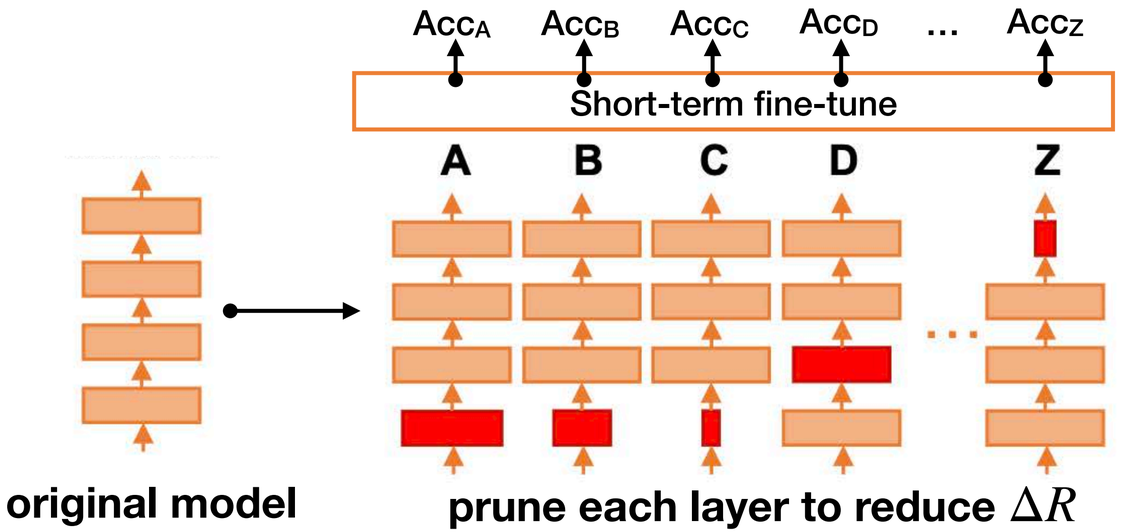
- For each iteration, we aim to reduce the latency by a certain amount ΔR (manually defined)
  - For each layer L_k (k in A-Z in the figure)
    - Prune the layer s.t. the latency reduction meets ΔR (based on a pre-built lookup table)



NetAdapt: Platform-Aware Neural Network Adaptation for Mobile Applications [Yang *et al.*, ECCV 2018]

NetAdapt

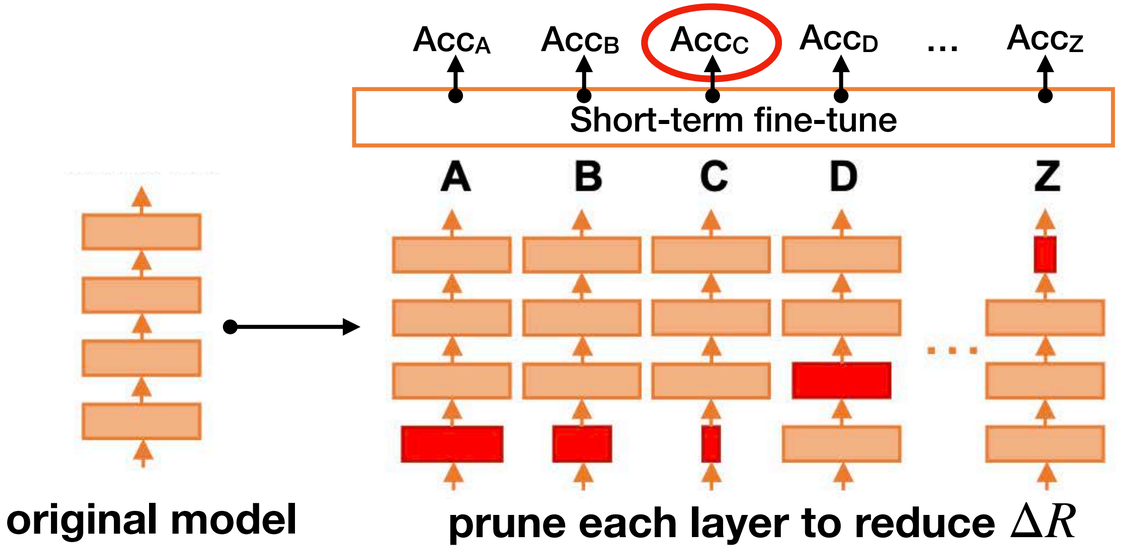
- For each iteration, we aim to reduce the latency by a certain amount ΔR (manually defined)
  - For each layer L_k (k in A-Z in the figure)
    - Prune the layer s.t. the latency reduction meets ΔR (based on a pre-built lookup table)
    - Short-term fine-tune model (10k iterations); measure accuracy after fine-tuning



NetAdapt: Platform-Aware Neural Network Adaptation for Mobile Applications [Yang *et al.*, ECCV 2018]

NetAdapt

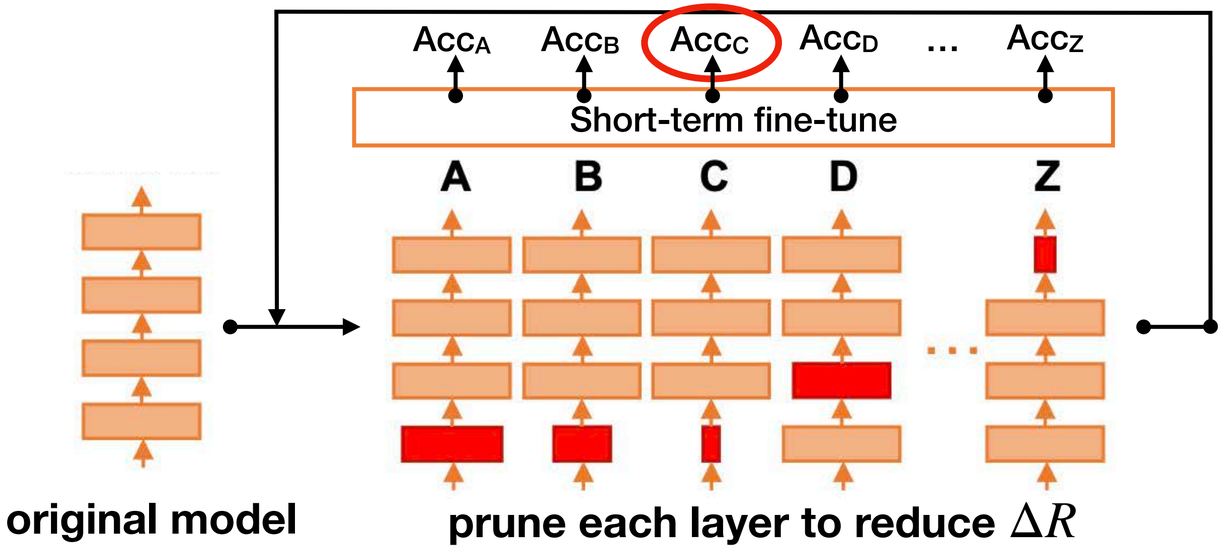
- For each iteration, we aim to reduce the latency by a certain amount ΔR (manually defined)
  - For each layer L_k (k in A-Z in the figure)
    - Prune the layer s.t. the latency reduction meets ΔR (based on a pre-built lookup table)
    - Short-term fine-tune model (10k iterations); measure accuracy after fine-tuning
  - Choose and prune the layer with the highest accuracy



NetAdapt: Platform-Aware Neural Network Adaptation for Mobile Applications [Yang *et al.*, ECCV 2018]

NetAdapt

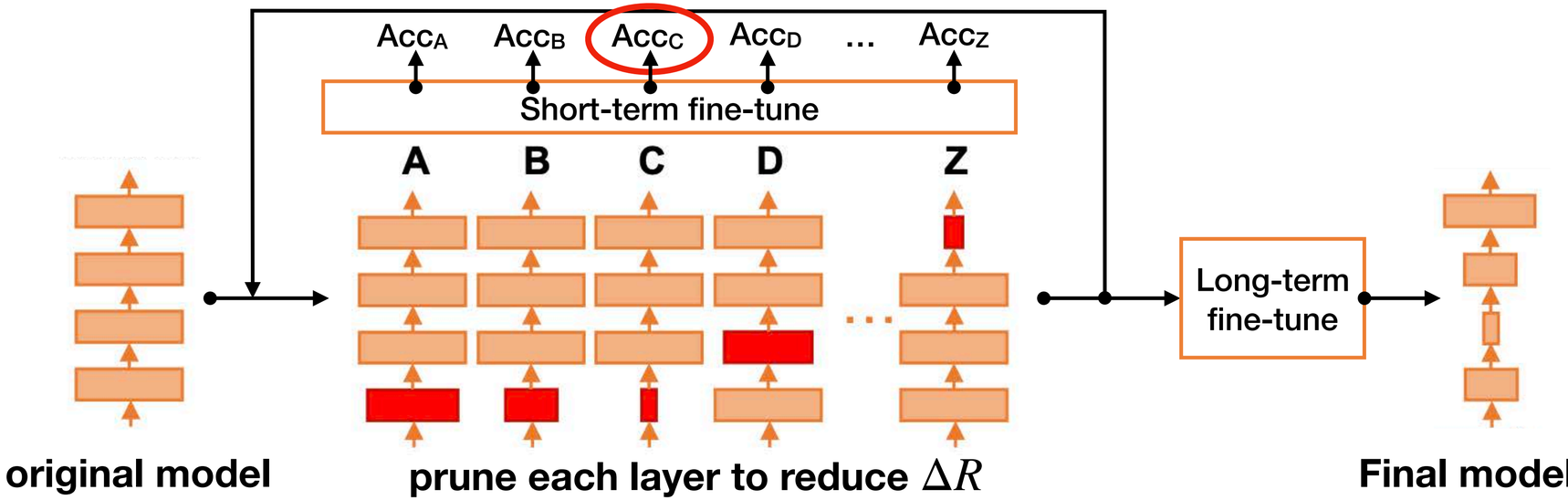
- For each iteration, we aim to reduce the latency by a certain amount ΔR (manually defined)
  - For each layer L_k (k in A-Z in the figure)
    - Prune the layer s.t. the latency reduction meets ΔR (based on a pre-built lookup table)
    - Short-term fine-tune model (10k iterations); measure accuracy after fine-tuning
  - Choose and prune the layer with the highest accuracy
- Repeat until the total latency reduction satisfies the constraint



NetAdapt: Platform-Aware Neural Network Adaptation for Mobile Applications [Yang *et al.*, ECCV 2018]

NetAdapt

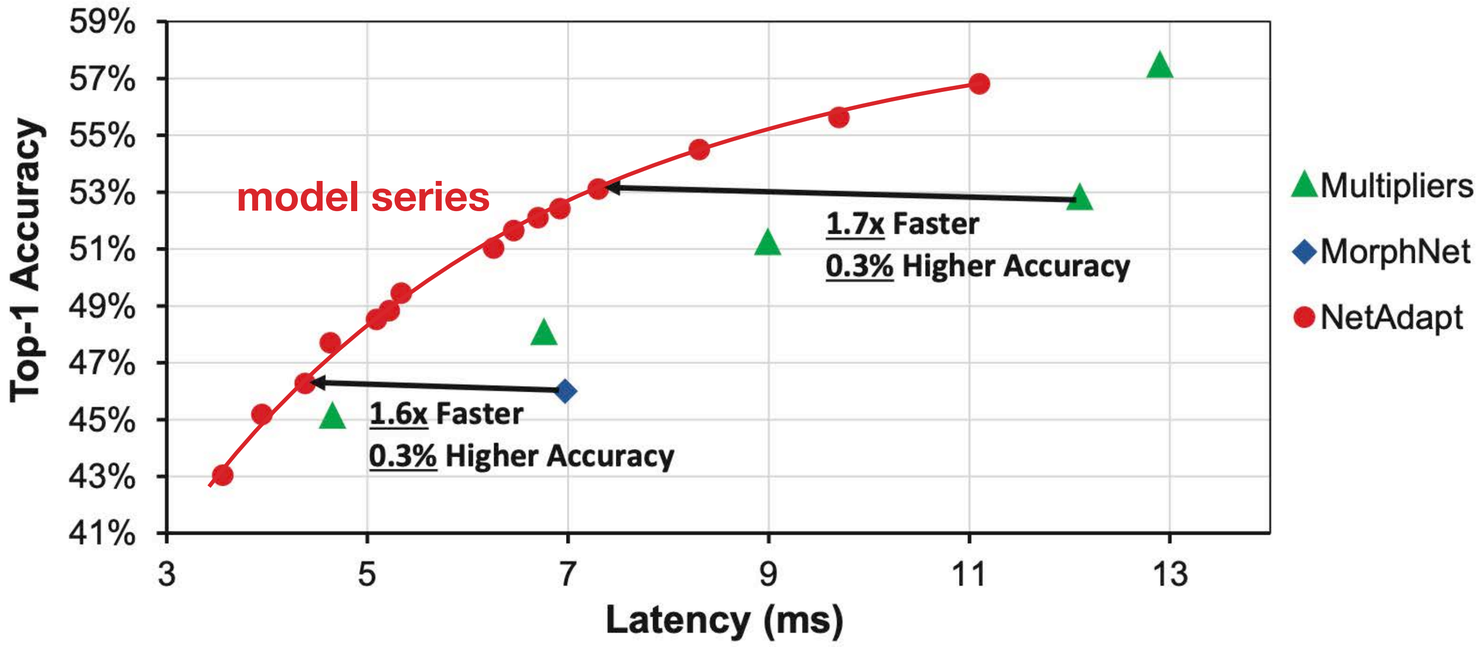
- For each iteration, we aim to reduce the latency by a certain amount ΔR (manually defined)
  - For each layer L_k (k in A-Z in the figure)
    - Prune the layer s.t. the latency reduction meets ΔR (based on a pre-built lookup table)
    - Short-term fine-tune model (10k iterations); measure accuracy after fine-tuning
  - Choose and prune the layer with the highest accuracy
- Repeat until the total latency reduction satisfies the constraint
- Long-term fine-tune to recover accuracy



NetAdapt: Platform-Aware Neural Network Adaptation for Mobile Applications [Yang *et al.*, ECCV 2018]

NetAdapt

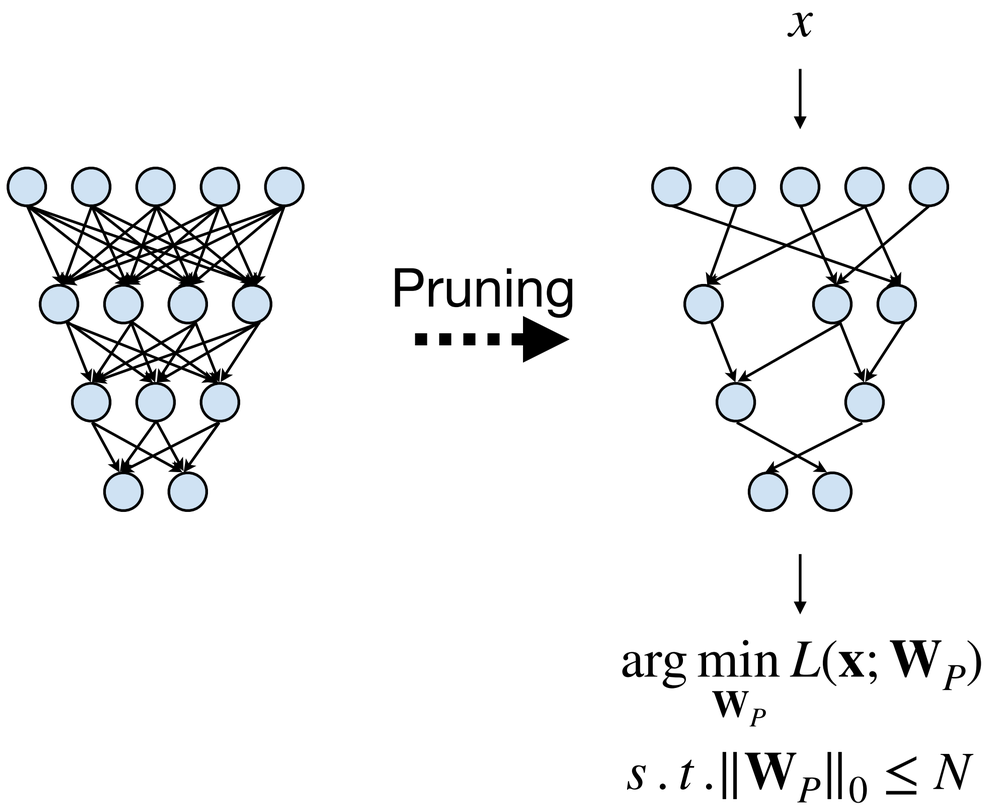
- The iterative nature allows us to obtain **a serial of** models with different costs
  - #models = #iterations



NetAdapt: Platform-Aware Neural Network Adaptation for Mobile Applications [Yang *et al.*, ECCV 2018]

Neural Network Pruning

- **Introduction to Pruning**
  - What is pruning?
  - How should we formulate pruning?
- **Determine the Pruning Granularity**
  - In what pattern should we prune the neural network?
- **Determine the Pruning Criterion**
  - What synapses/neurons should we prune?
- **Determine the Pruning Ratio**
  - What should target sparsity be for each layer?
- **Fine-tune/Train Pruned Neural Network**
  - How should we improve performance of pruned models?



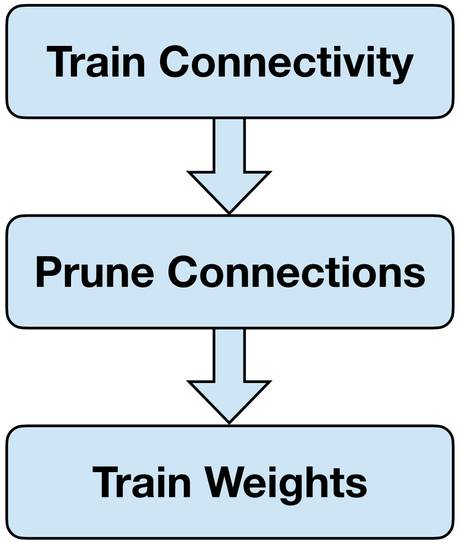
Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

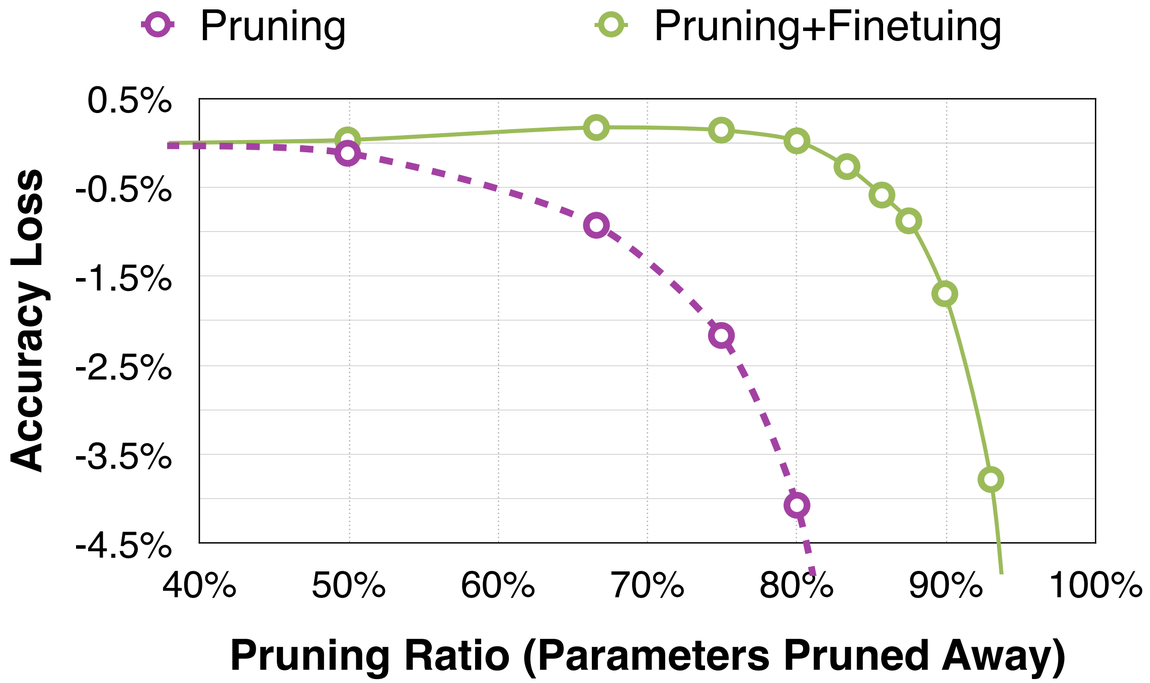
Section 2: Fine-tuning / Training

How should we improve performance of sparse models?

Finetuning Pruned Neural Networks

- After pruning, the model may decrease, especially for larger pruning ratio.
- Fine-tuning the pruned neural networks will help recover the accuracy and push the pruning ratio higher.
  - **Learning rate for fine-tuning is usually 1/100 or 1/10 of the original learning rate.**

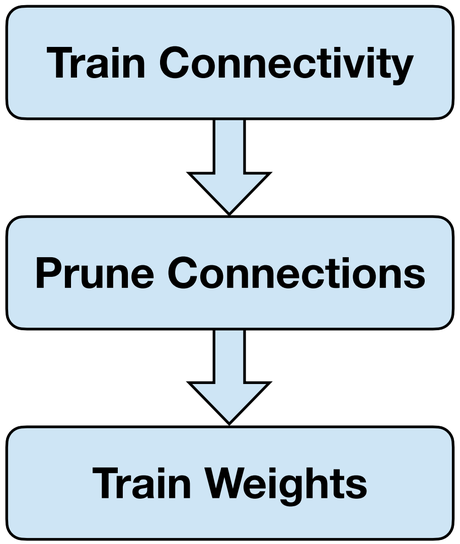


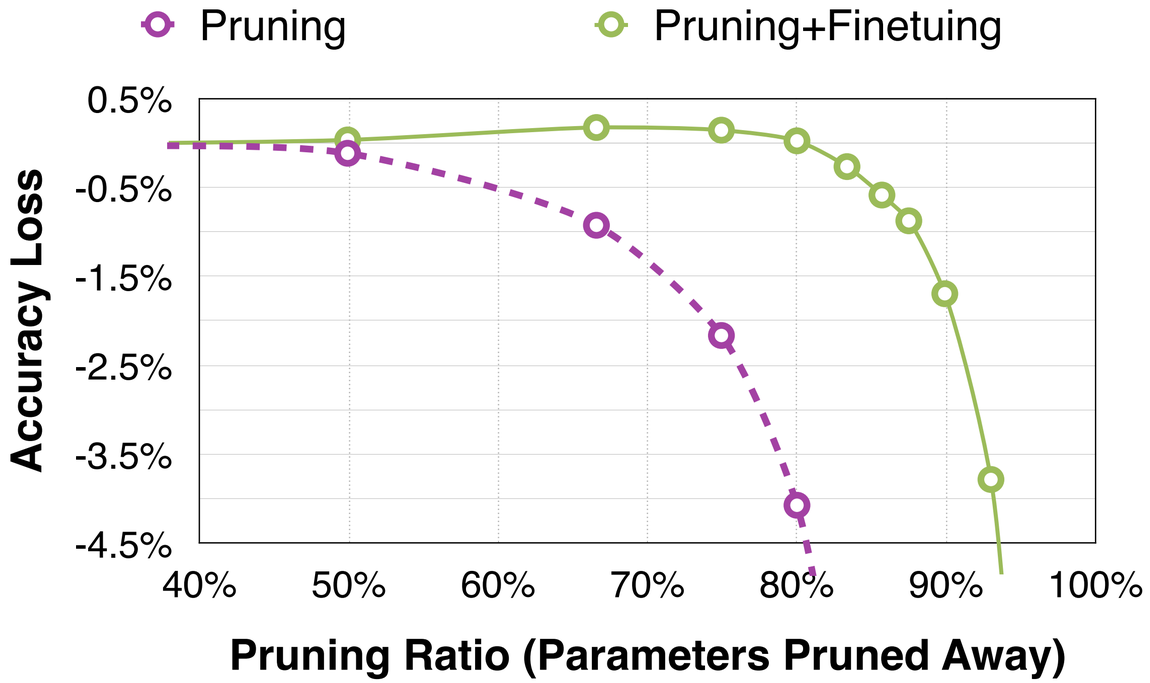


Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

Iterative Pruning

- Consider pruning followed by a fine-tuning is one iteration.
- Iterative pruning gradually increases the target sparsity in each iteration.

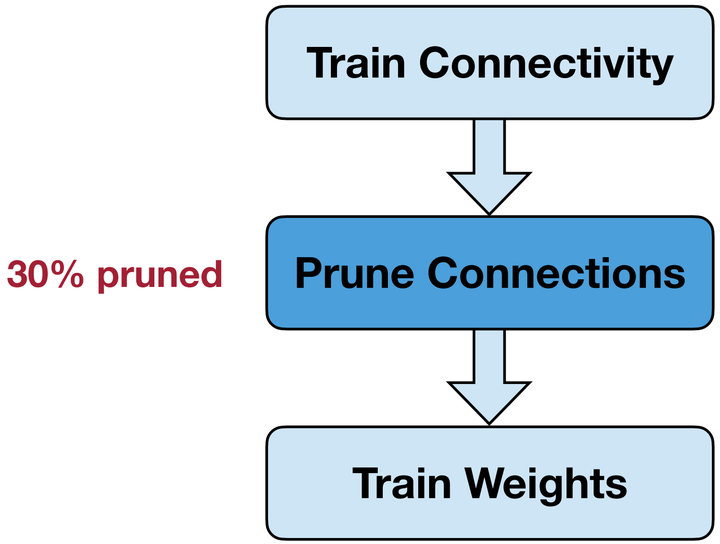


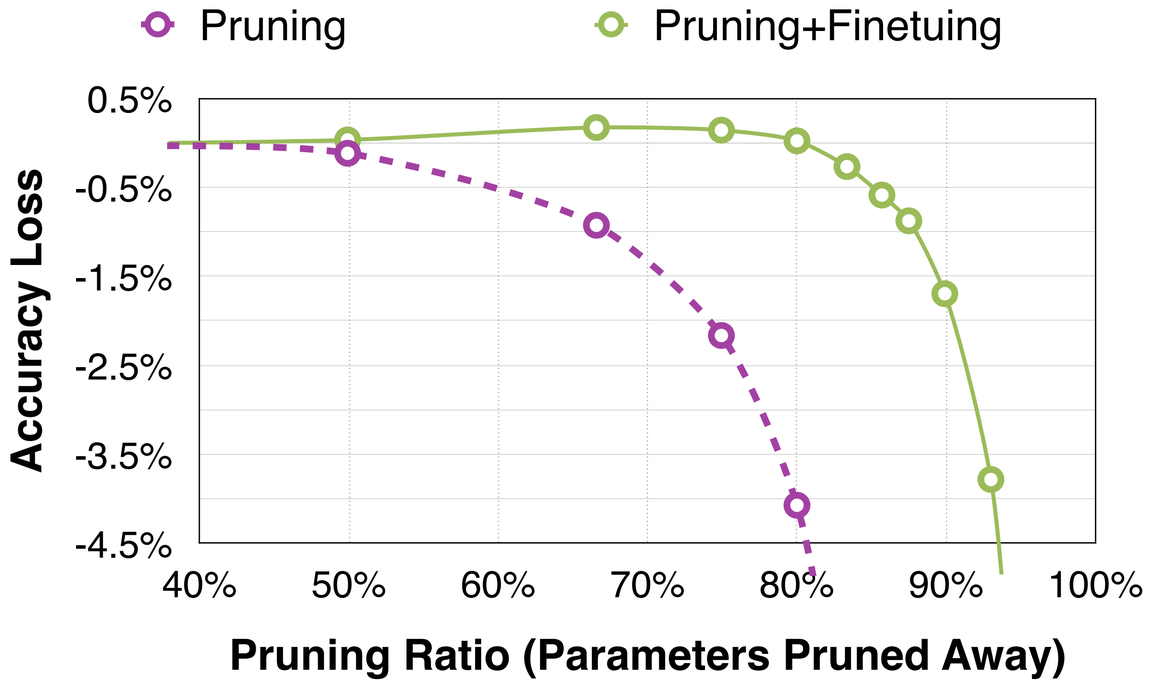


Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

Iterative Pruning

- Consider pruning followed by a fine-tuning is one iteration.
- Iterative pruning gradually increases the target sparsity in each iteration.

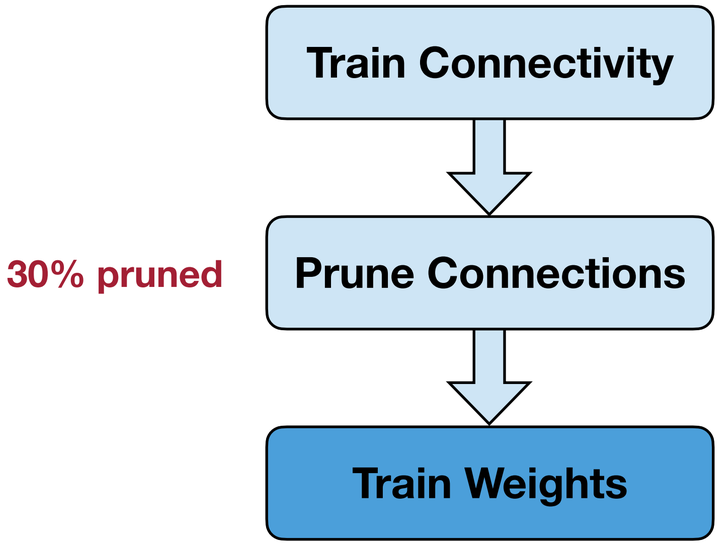


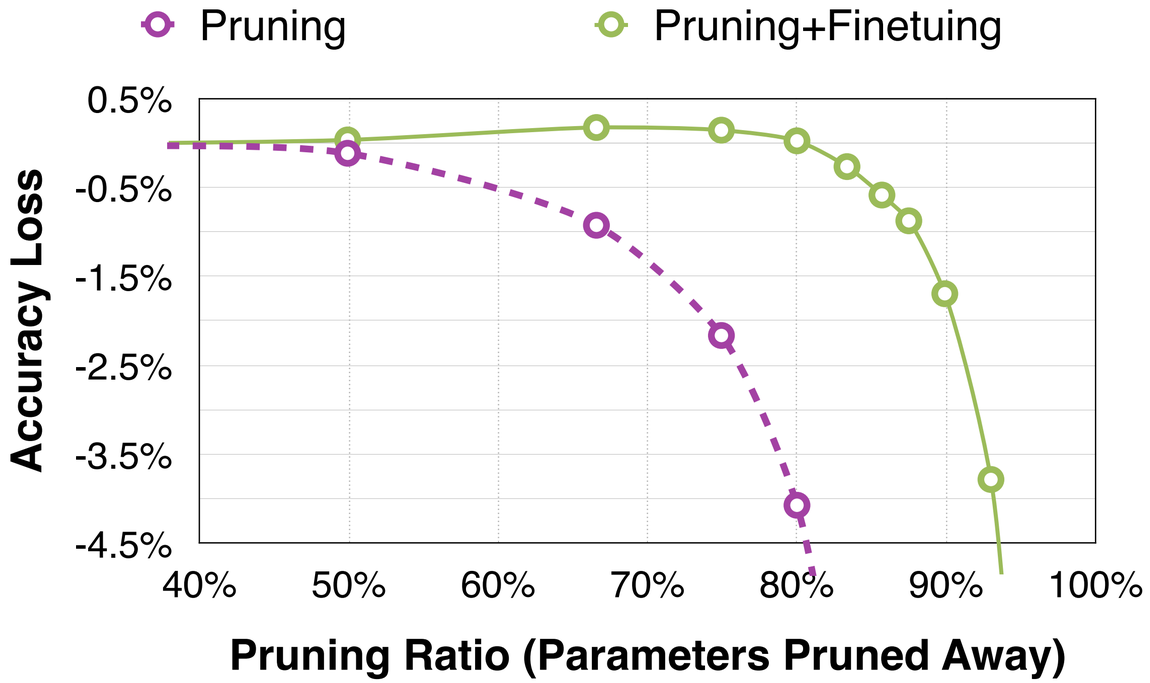


Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

Iterative Pruning

- Consider pruning followed by a fine-tuning is one iteration.
- Iterative pruning gradually increases the target sparsity in each iteration.

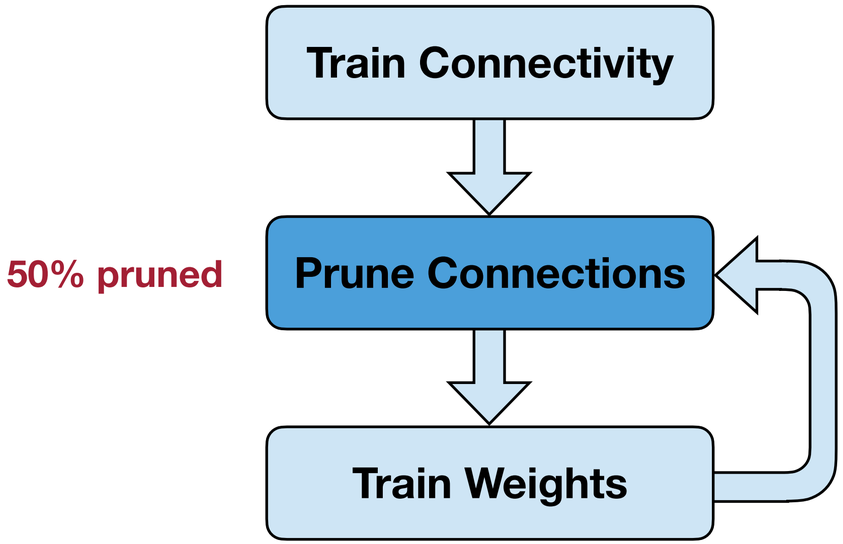


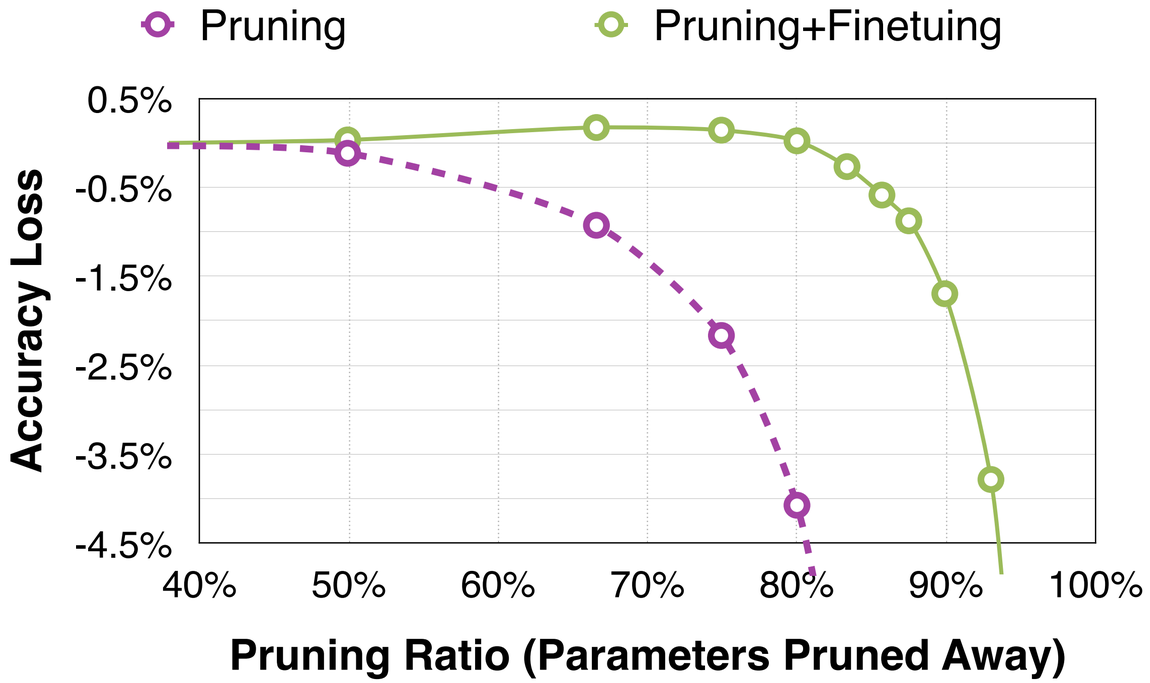


Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

Iterative Pruning

- Consider pruning followed by a fine-tuning is one iteration.
- Iterative pruning gradually increases the target sparsity in each iteration.

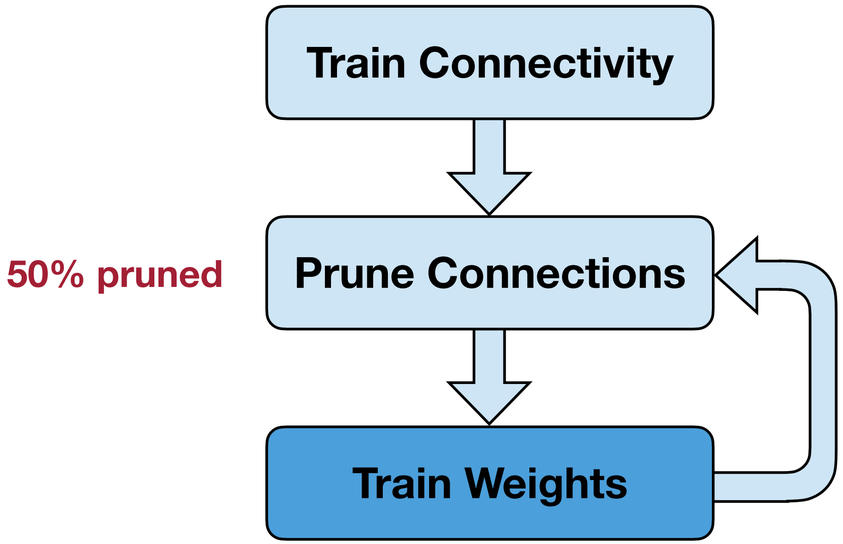


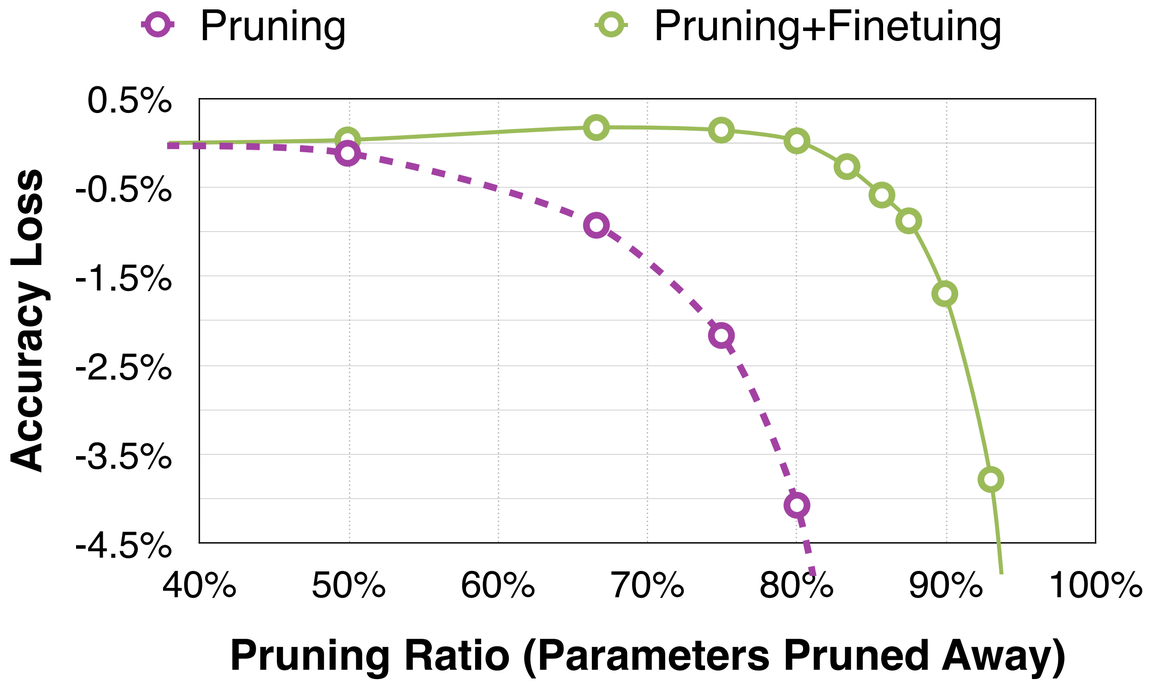


Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

Iterative Pruning

- Consider pruning followed by a fine-tuning is one iteration.
- Iterative pruning gradually increases the target sparsity in each iteration.

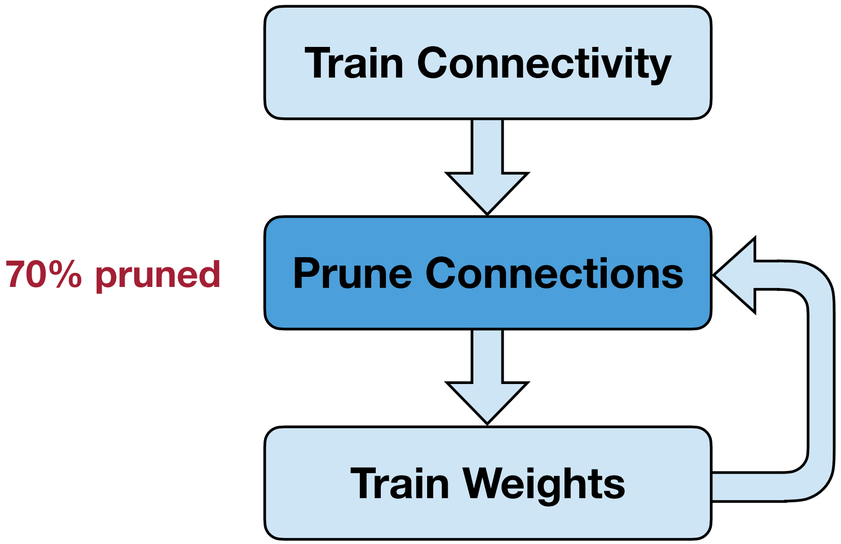


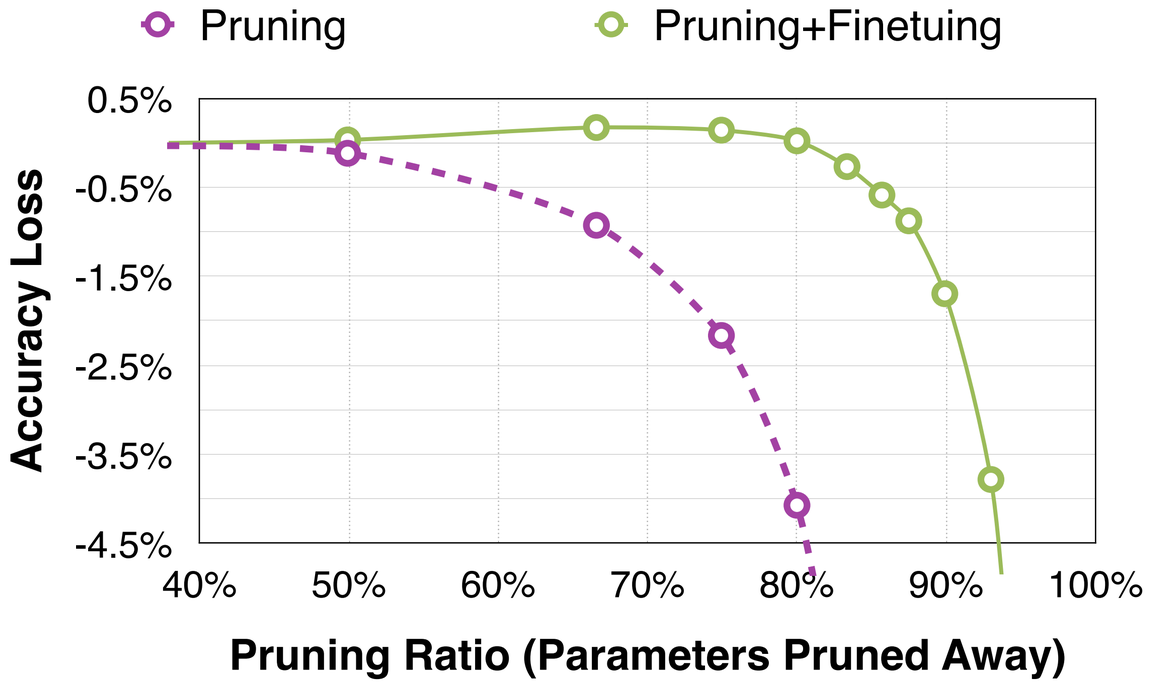


Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

Iterative Pruning

- Consider pruning followed by a fine-tuning is one iteration.
- Iterative pruning gradually increases the target sparsity in each iteration.

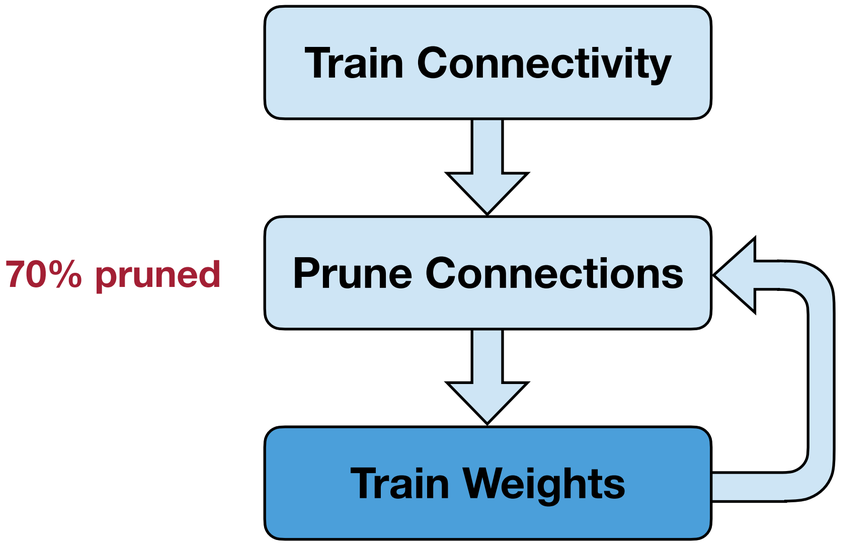


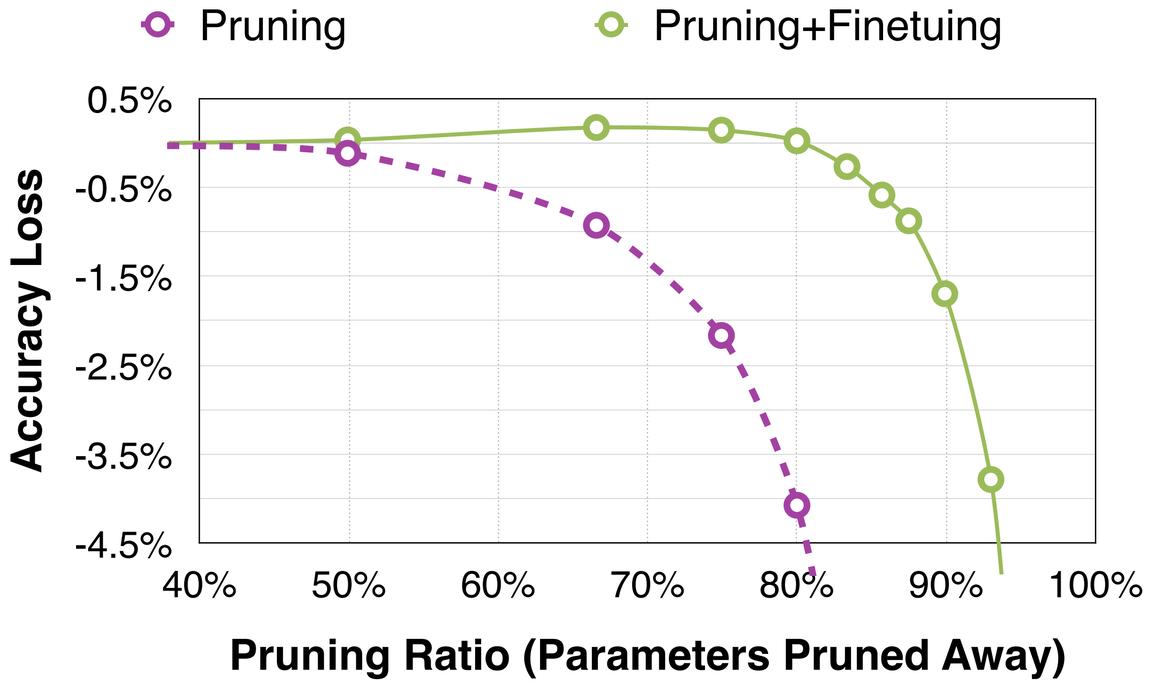


Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

Iterative Pruning

- Consider pruning followed by a fine-tuning is one iteration.
- Iterative pruning gradually increases the target sparsity in each iteration.

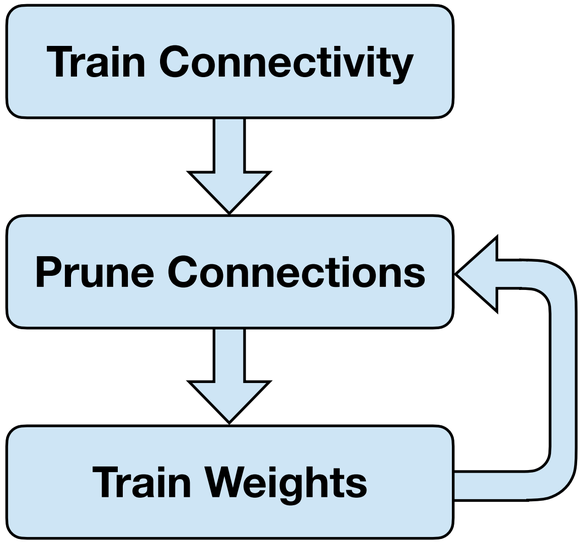


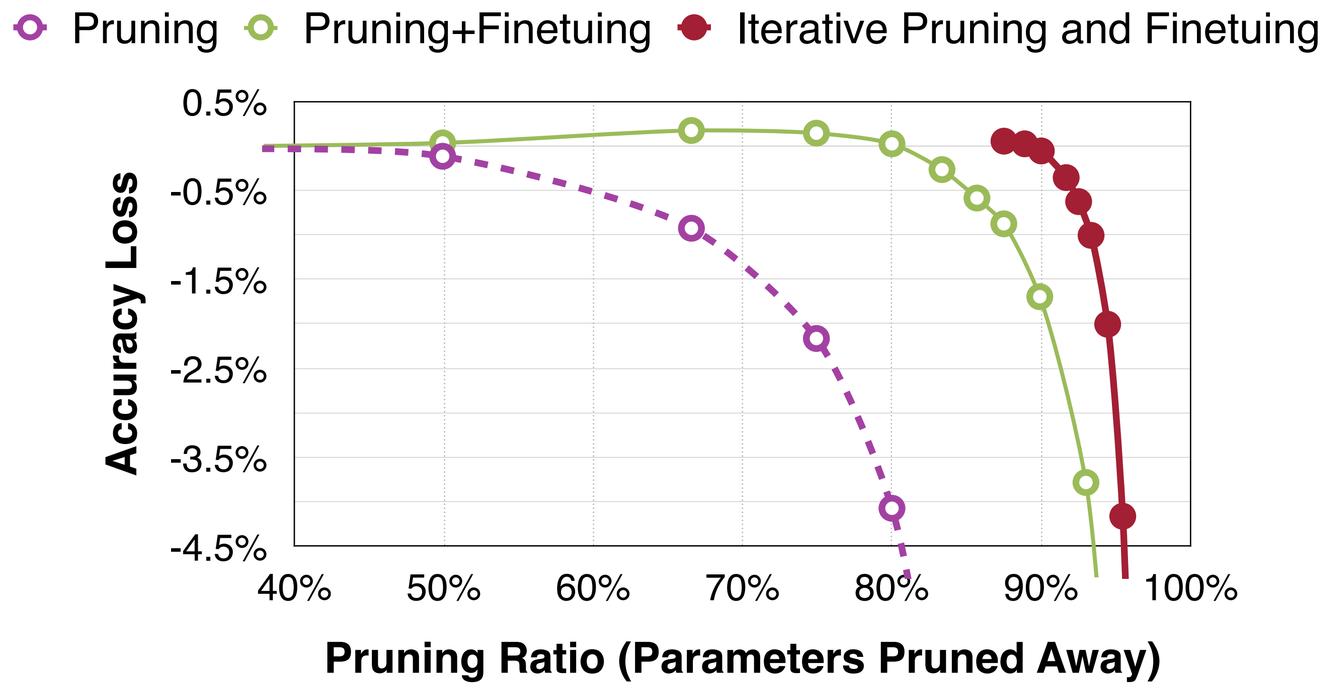


Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

Iterative Pruning

- Consider pruning followed by a fine-tuning is one iteration.
- Iterative pruning gradually increases the target sparsity in each iteration.
  - boost pruning ratio from 5× to 9× on AlexNet compared to single-step aggressive pruning.





Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

Regularization

- When training neural networks or fine-tuning quantized neural networks, regularization is added to the loss term to
  - ***penalize non-zero parameters***
  - ***encourage smaller parameters***
- The most common regularization for improving performance of pruning is L1/L2 regularization.
  - L1-Regularization

$$L' = L(\mathbf{x}; \mathbf{W}) + \lambda |\mathbf{W}|$$

  - L2-Regularization

$$L' = L(\mathbf{x}; \mathbf{W}) + \lambda ||\mathbf{W}||^2$$

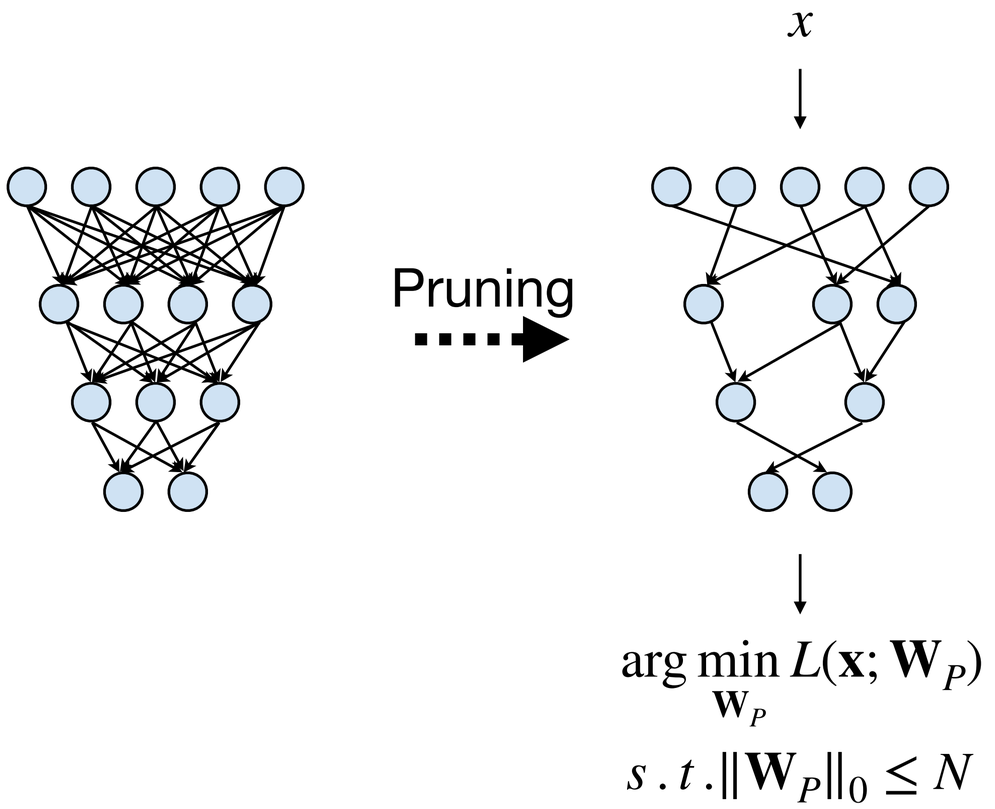
  - **Examples:**
    - Magnitude-based Fine-grained Pruning applies L2 regularization on weights
    - Network Slimming applies smooth-L1 regularization on channel scaling factors.

Learning Efficient Convolutional Networks through Network Slimming [Liu et al., ICCV 2017]

Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

Neural Network Pruning

- **Introduction to Pruning**
  - What is pruning?
  - How should we formulate pruning?
- **Determine the Pruning Granularity**
  - In what pattern should we prune the neural network?
- **Determine the Pruning Criterion**
  - What synapses/neurons should we prune?
- **Determine the Pruning Ratio**
  - What should target sparsity be for each layer?
- **Fine-tune/Train Pruned Neural Network**
  - How should we improve performance of pruned models?

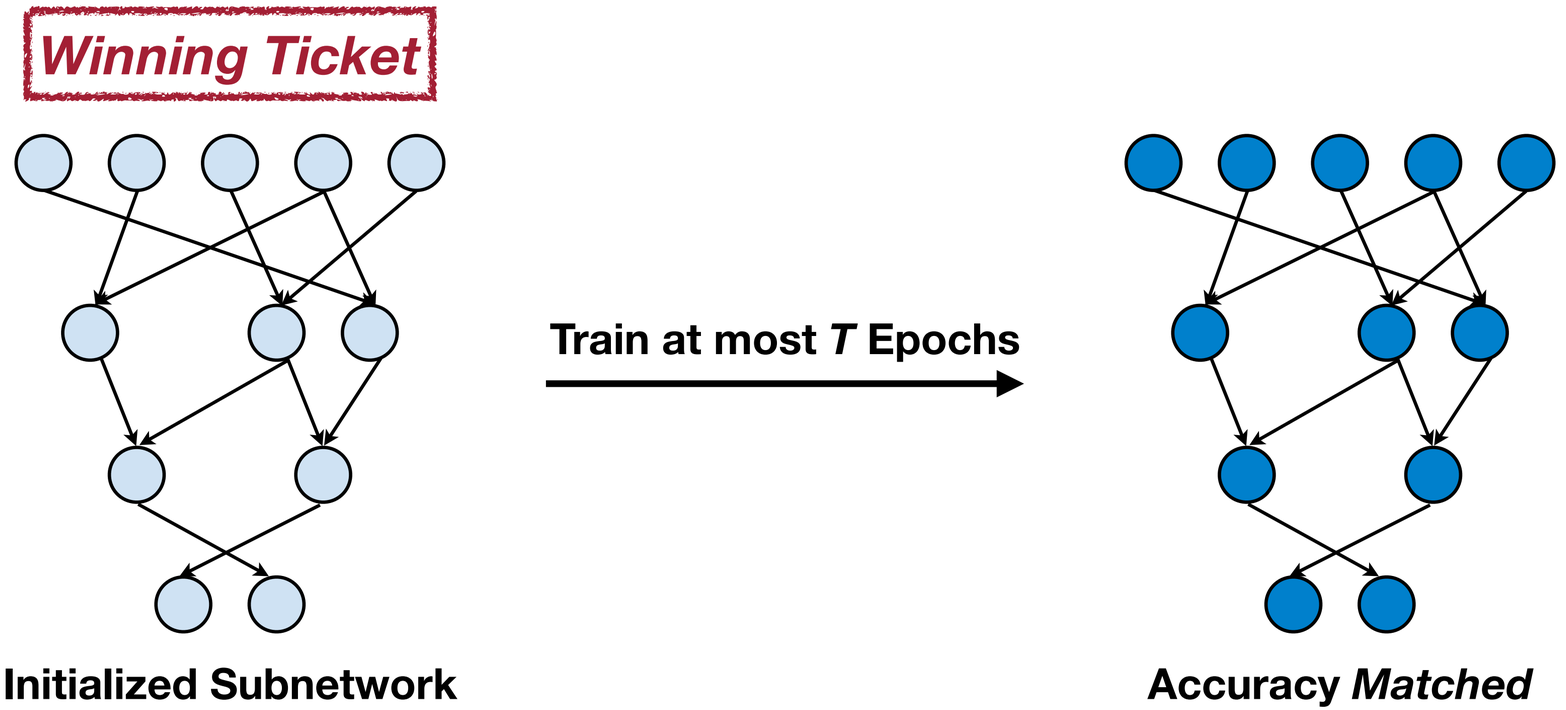


Learning Both Weights and Connections for Efficient Neural Network [Han *et al.*, NeurIPS 2015]

The Lottery Ticket Hypothesis

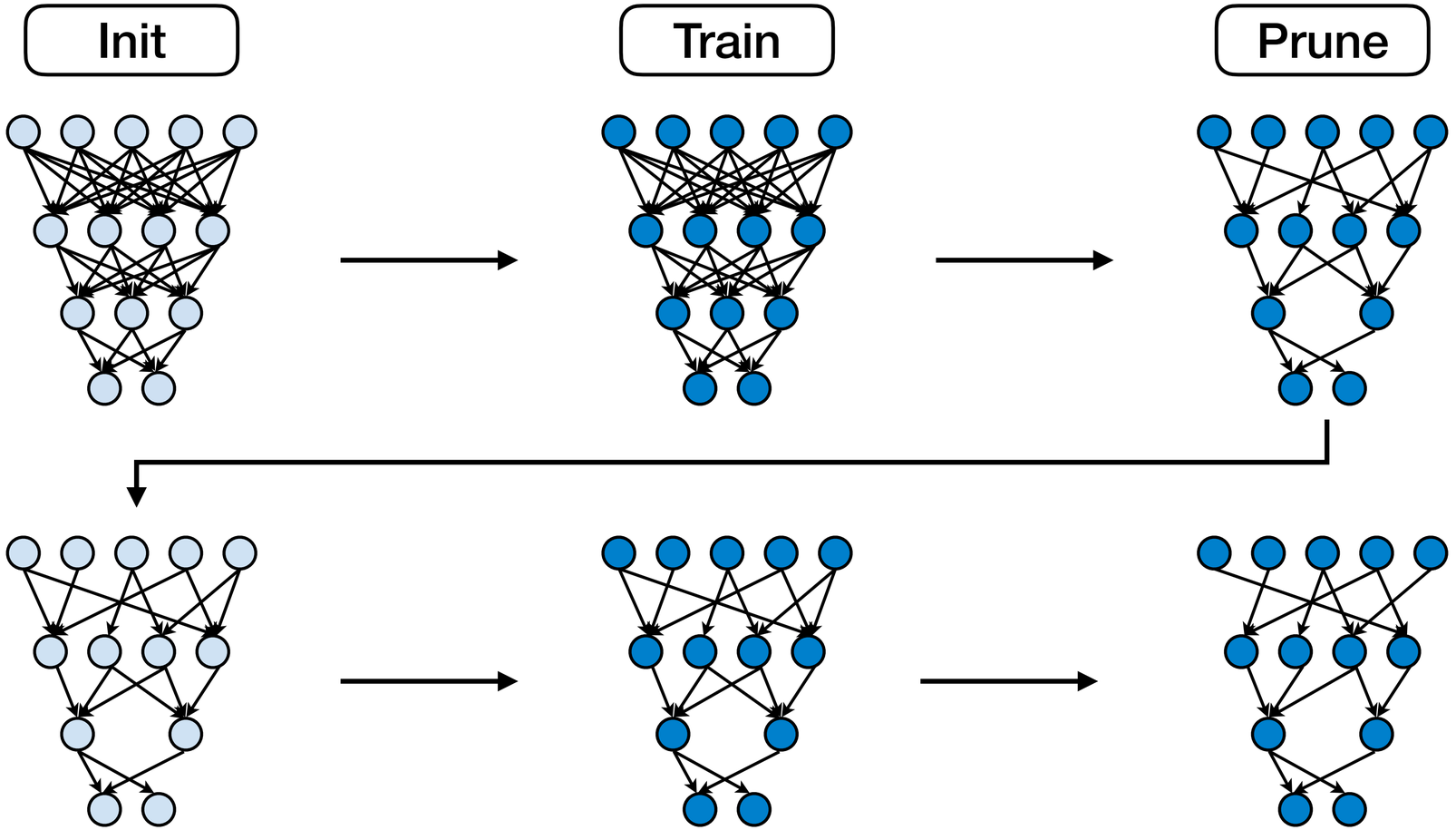
A randomly-initialized, dense neural network contains ***a subnetwork*** *that is initialized such that—when* ***trained in isolation*** *—it can* ***match the test accuracy*** *of the original network after training for* ***at most the same number of iterations****.*

—The Lottery Ticket Hypothesis



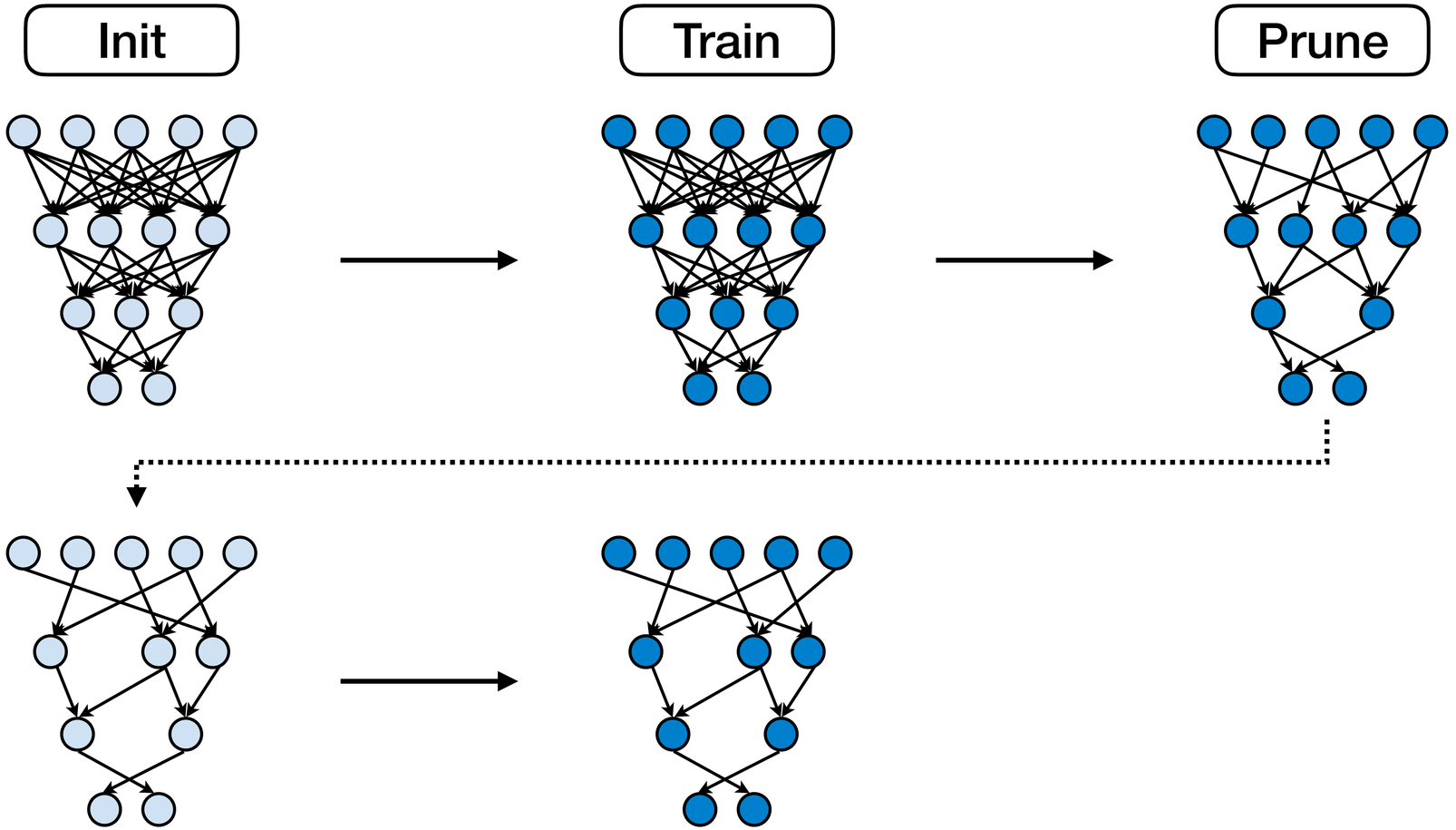
The Lottery Ticket Hypothesis: Finding Sparse, Trainable Neural Networks [Frankle *et al.*, ICLR 2019]

Iterative Magnitude Pruning



The Lottery Ticket Hypothesis: Finding Sparse, Trainable Neural Networks [Frankle *et al.*, ICLR 2019]

Iterative Magnitude Pruning



The Lottery Ticket Hypothesis: Finding Sparse, Trainable Neural Networks [Frankle *et al.*, ICLR 2019]

System Support for Sparsity

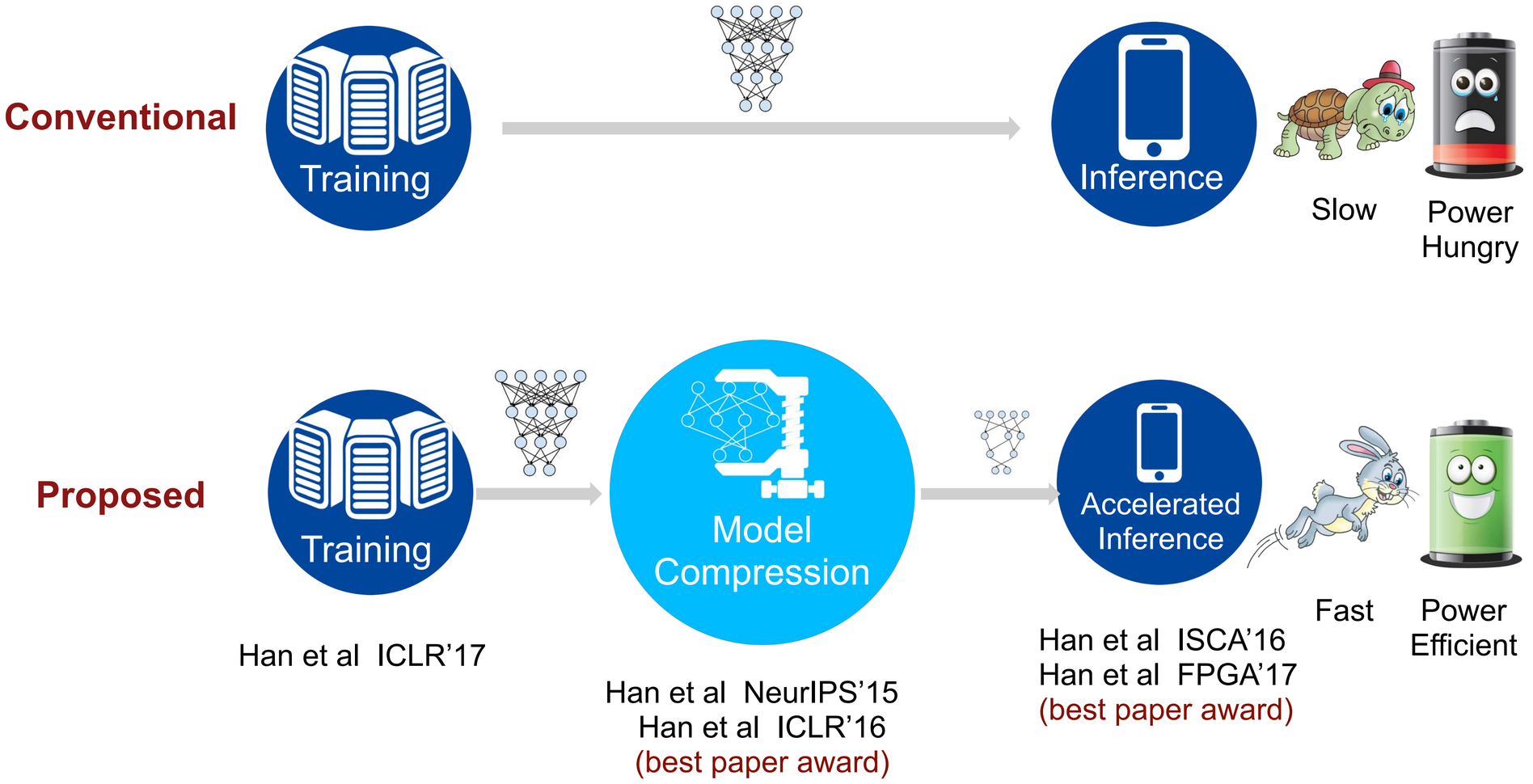
System & Hardware Support for Sparsity

- EIE: Weight Sparsity + Activation Sparsity for GEMM
- NVIDIA Tensor Core: M:N Weight Sparsity Sparsity
- TorchSparse & PointAcc: Activation Sparsity for Sparse Convolution

System & Hardware Support for Sparsity

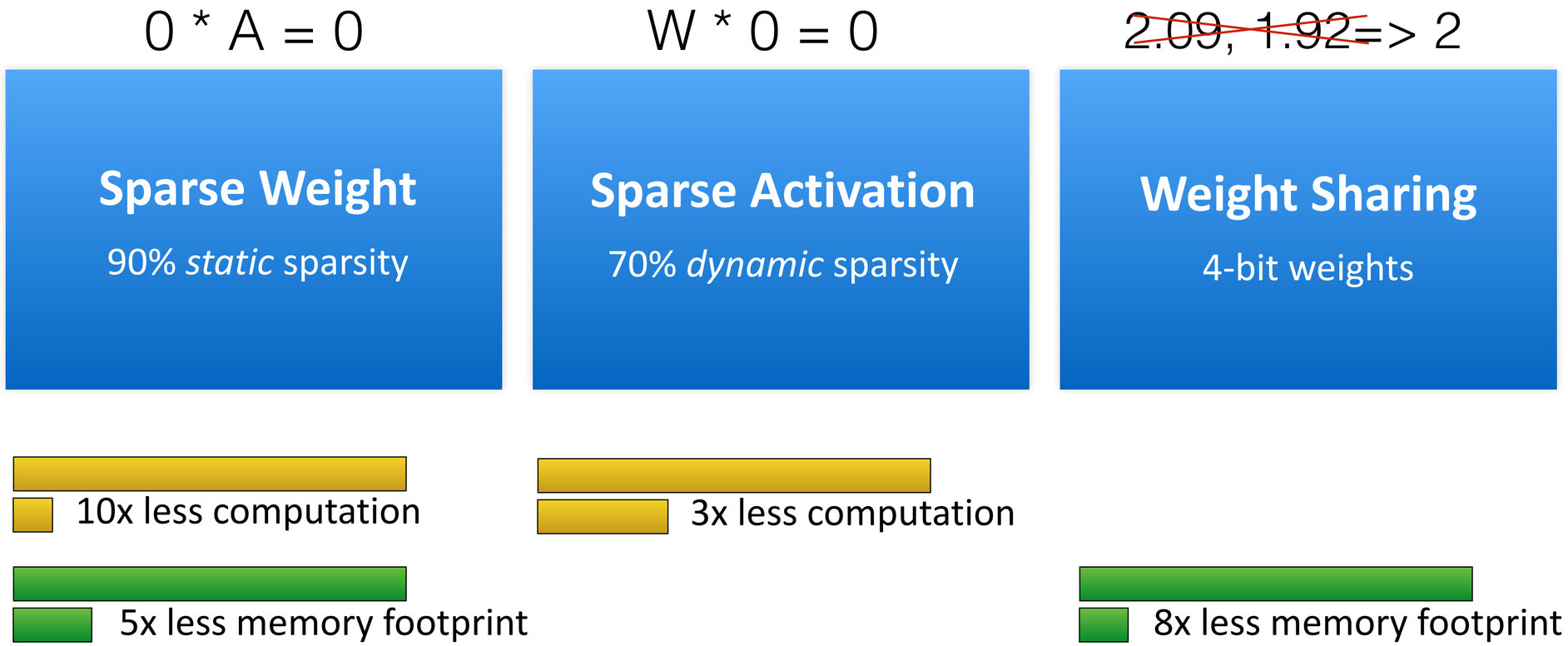
- **EIE: Weight Sparsity + Activation Sparsity for GEMM**
- NVIDIA Tensor Core: M:N Weight Sparsity Sparsity
- TorchSparse & PointAcc: Activation Sparsity for Sparse Convolution

Proposed Paradigm



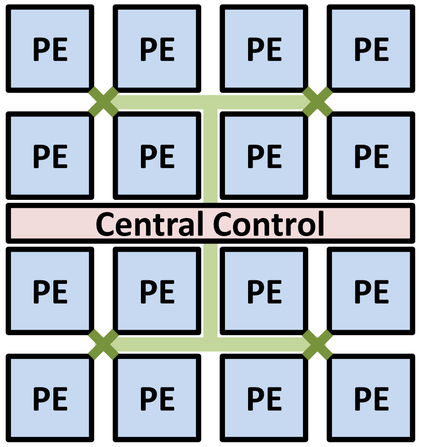
EIE: Efficient Inference Engine

The First DNN Accelerator for Sparse, Compressed Model



EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

EIE: Parallelization on Sparsity

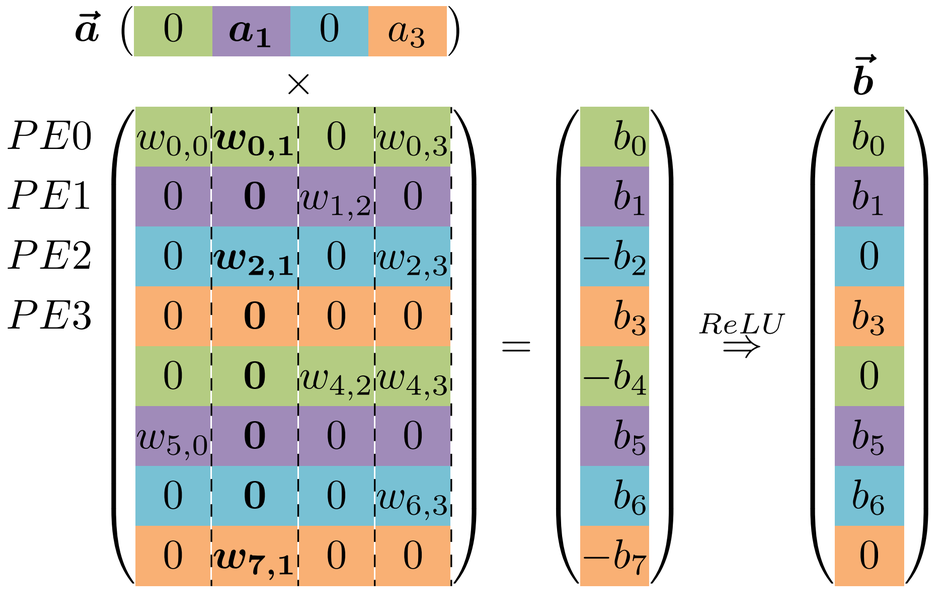


$$\vec{a}\ (0\ \ \boldsymbol{a_1}\ \ 0\ \ a_3) \times \begin{matrix} PE0 \\ PE1 \\ PE2 \\ PE3 \end{matrix} \begin{pmatrix} w_{0,0} & \boldsymbol{w_{0,1}} & 0 & w_{0,3} \\ 0 & \boldsymbol{0} & w_{1,2} & 0 \\ 0 & \boldsymbol{w_{2,1}} & 0 & w_{2,3} \\ 0 & \boldsymbol{0} & 0 & 0 \\ 0 & \boldsymbol{0} & w_{4,2} & w_{4,3} \\ w_{5,0} & \boldsymbol{0} & 0 & 0 \\ 0 & \boldsymbol{0} & 0 & w_{6,3} \\ 0 & \boldsymbol{w_{7,1}} & 0 & 0 \end{pmatrix} = \begin{pmatrix} b_0 \\ b_1 \\ -b_2 \\ b_3 \\ -b_4 \\ b_5 \\ b_6 \\ -b_7 \end{pmatrix} \overset{ReLU}{\Rightarrow} \vec{b} \begin{pmatrix} b_0 \\ b_1 \\ 0 \\ b_3 \\ 0 \\ b_5 \\ b_6 \\ 0 \end{pmatrix}$$

EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

EIE: Parallelization on Sparsity

logically

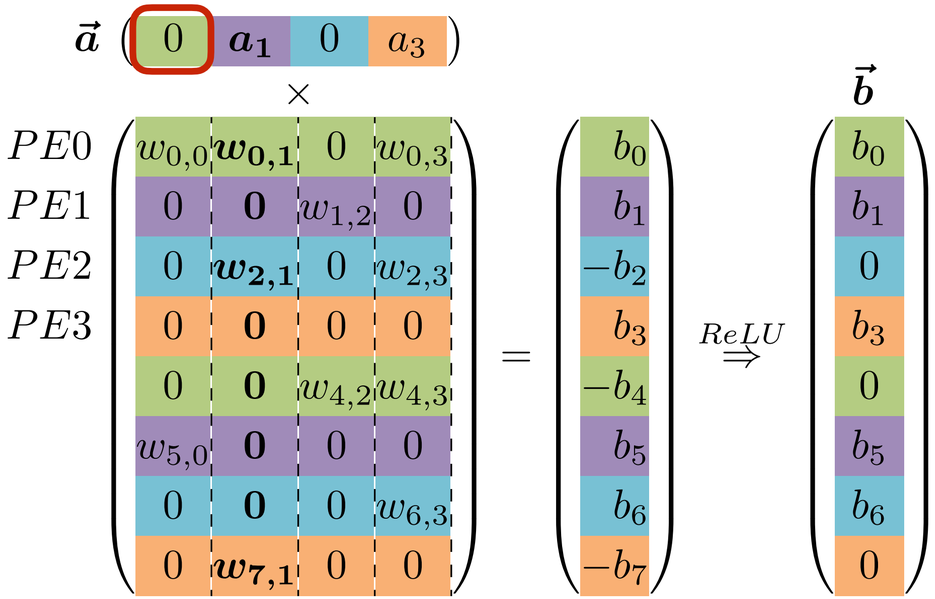


physically

Virtual Weight	$W_{0,0}$	$W_{0,1}$	$W_{4,2}$	$W_{0,3}$	$W_{4,3}$
Relative Index	0	1	2	0	0
Column Pointer	0	1	2	3	5

EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Dataflow

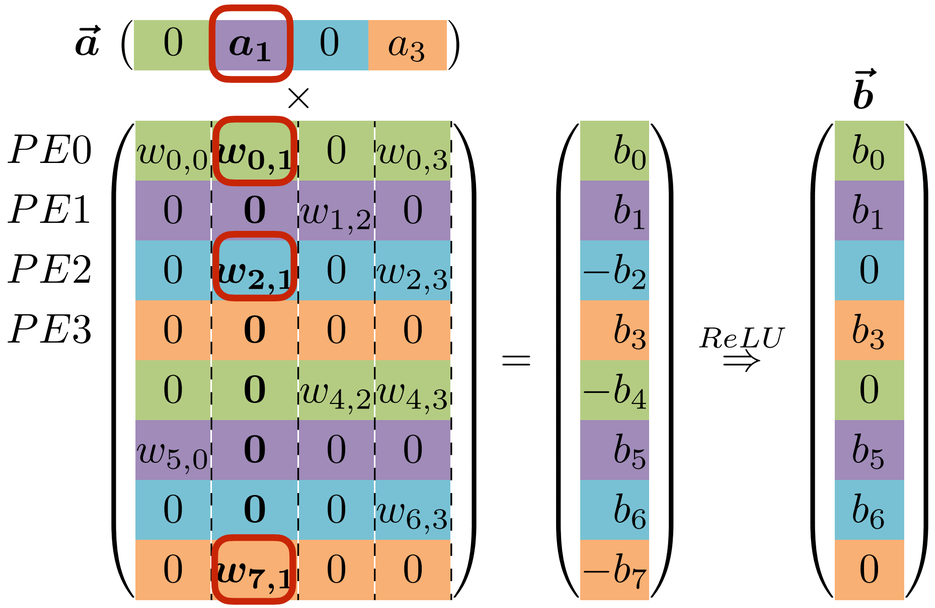


rule of thumb:

0 * A = 0 W * 0 = 0

EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Dataflow

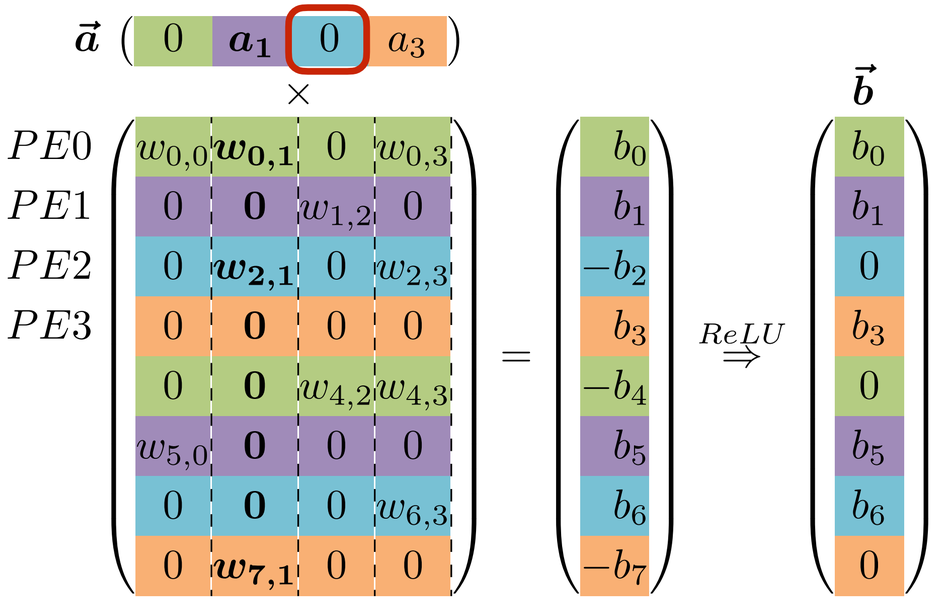


rule of thumb:

0 * A = 0 W * 0 = 0

EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Dataflow

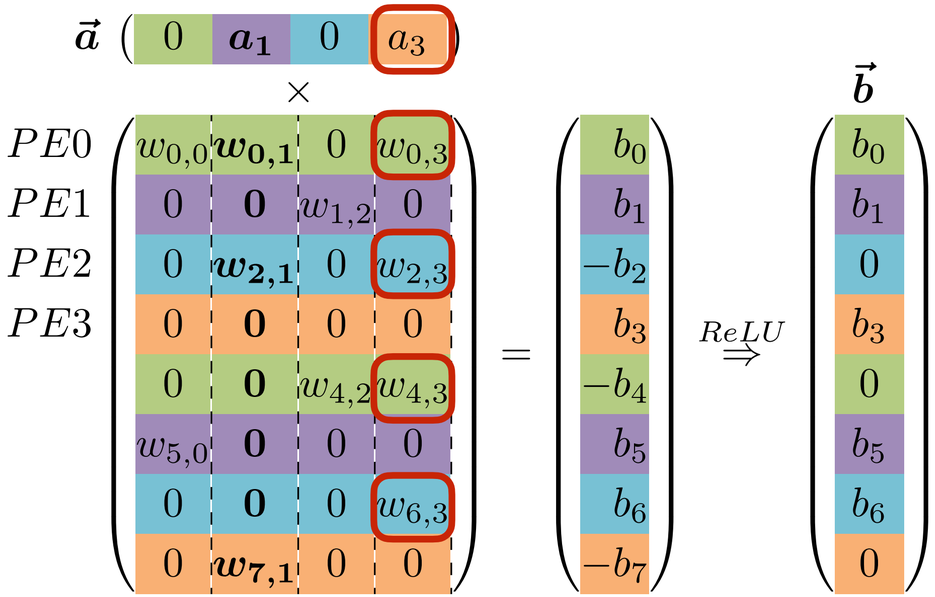


rule of thumb:

0 * A = 0 W * 0 = 0

EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Dataflow

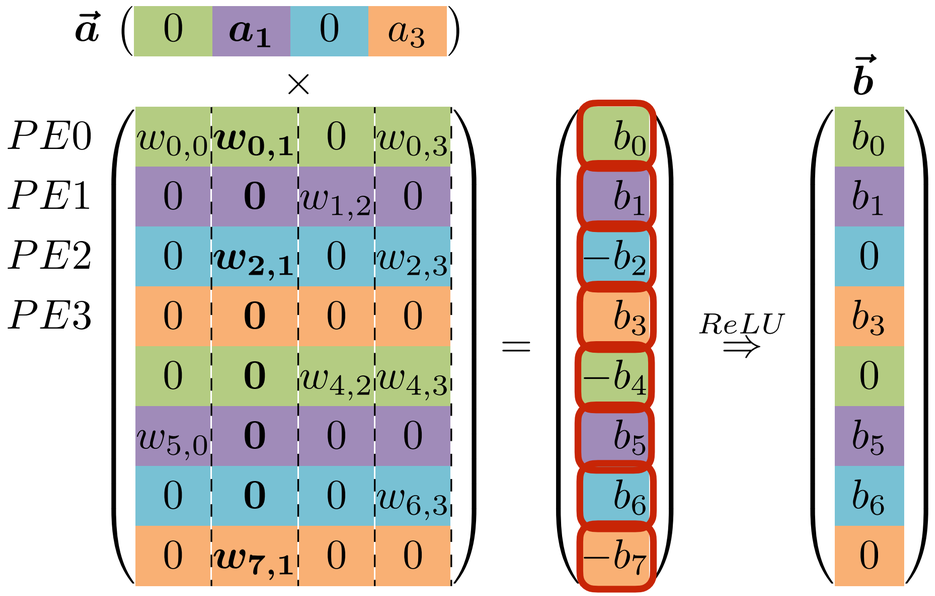


rule of thumb:

0 * A = 0 W * 0 = 0

EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Dataflow

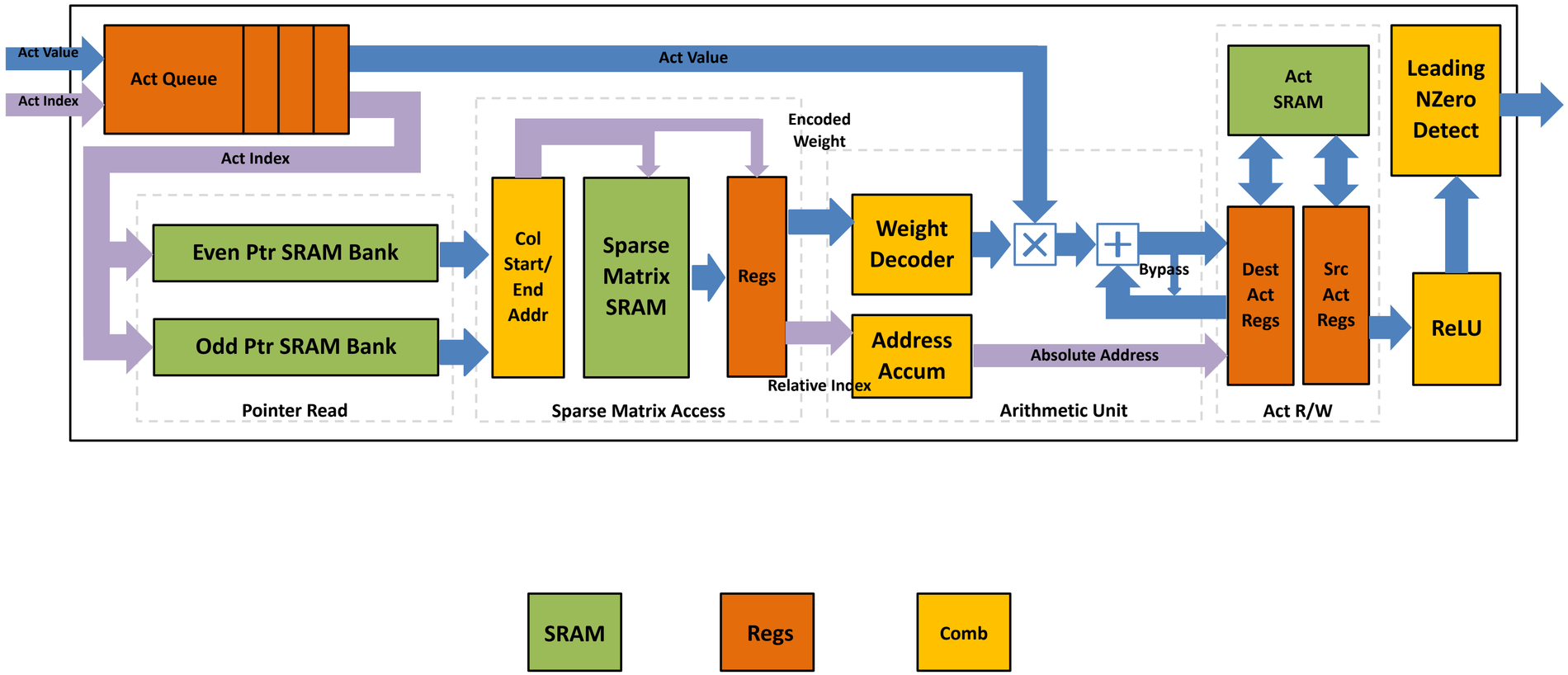


rule of thumb:

0 * A = 0 W * 0 = 0

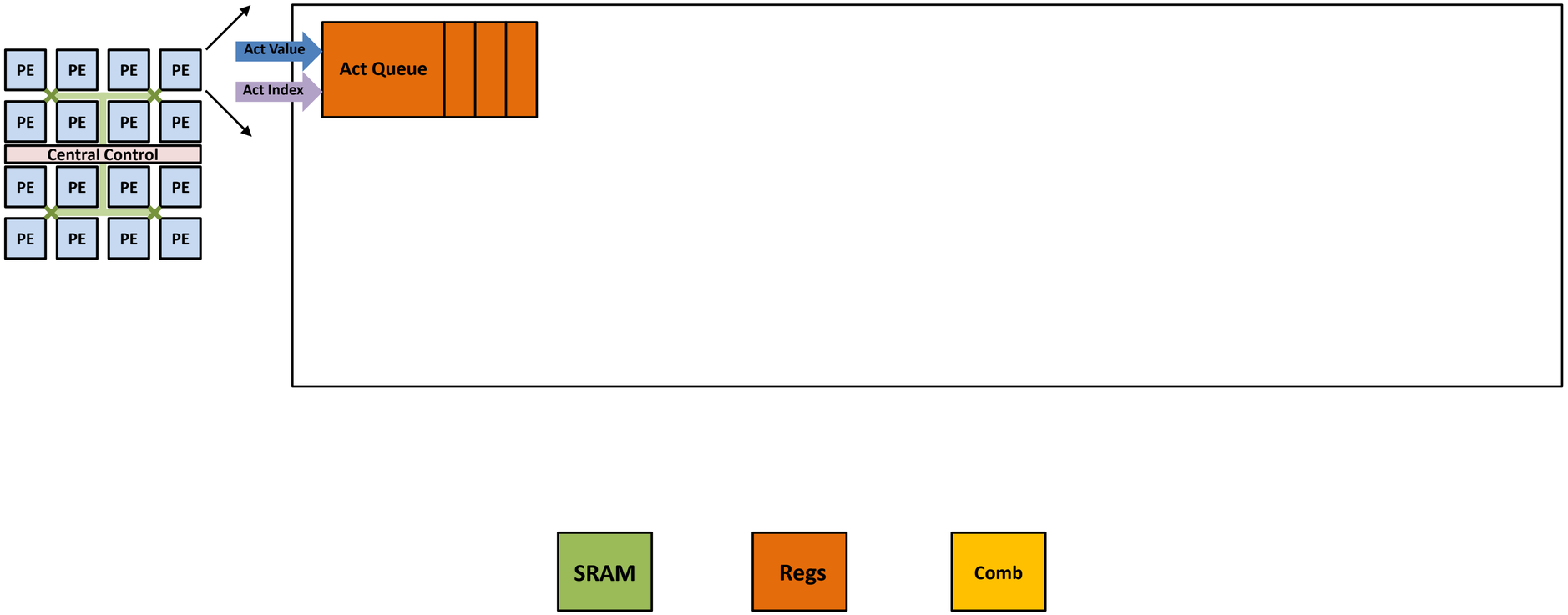
EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Micro Architecture for each PE



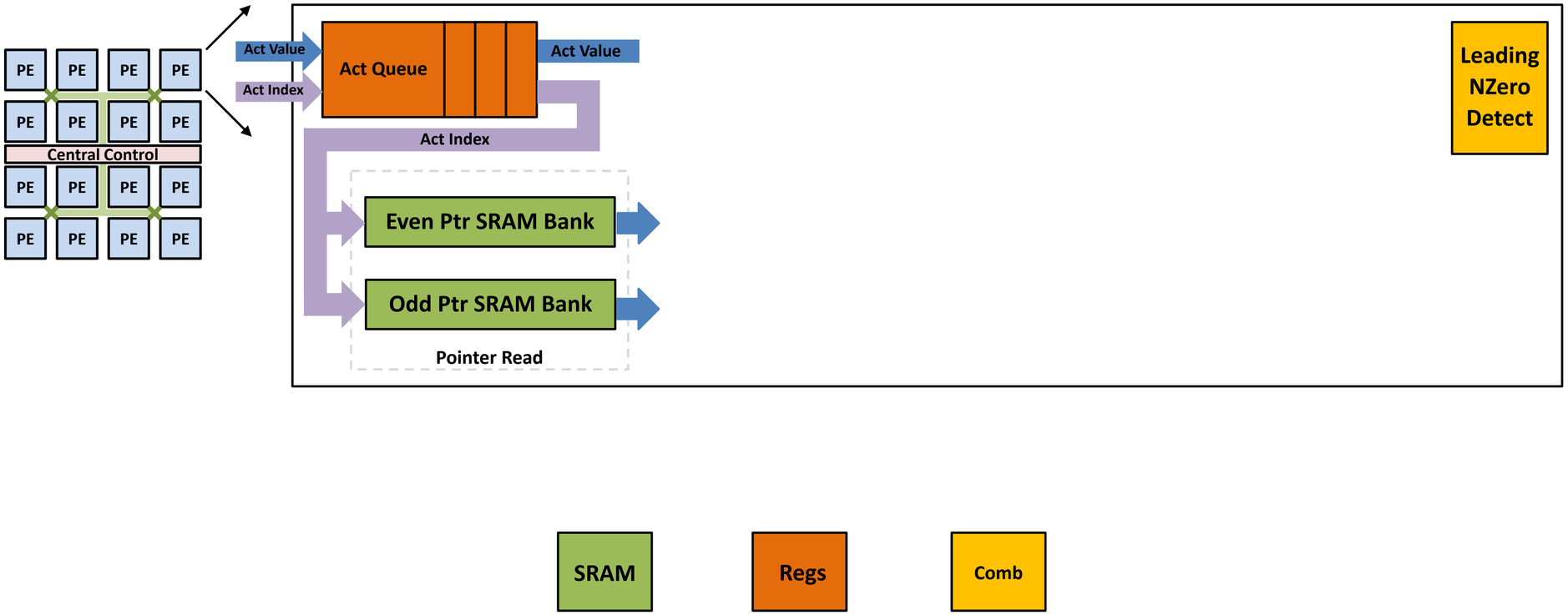
EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.*, ISCA 2016]

Load Balance



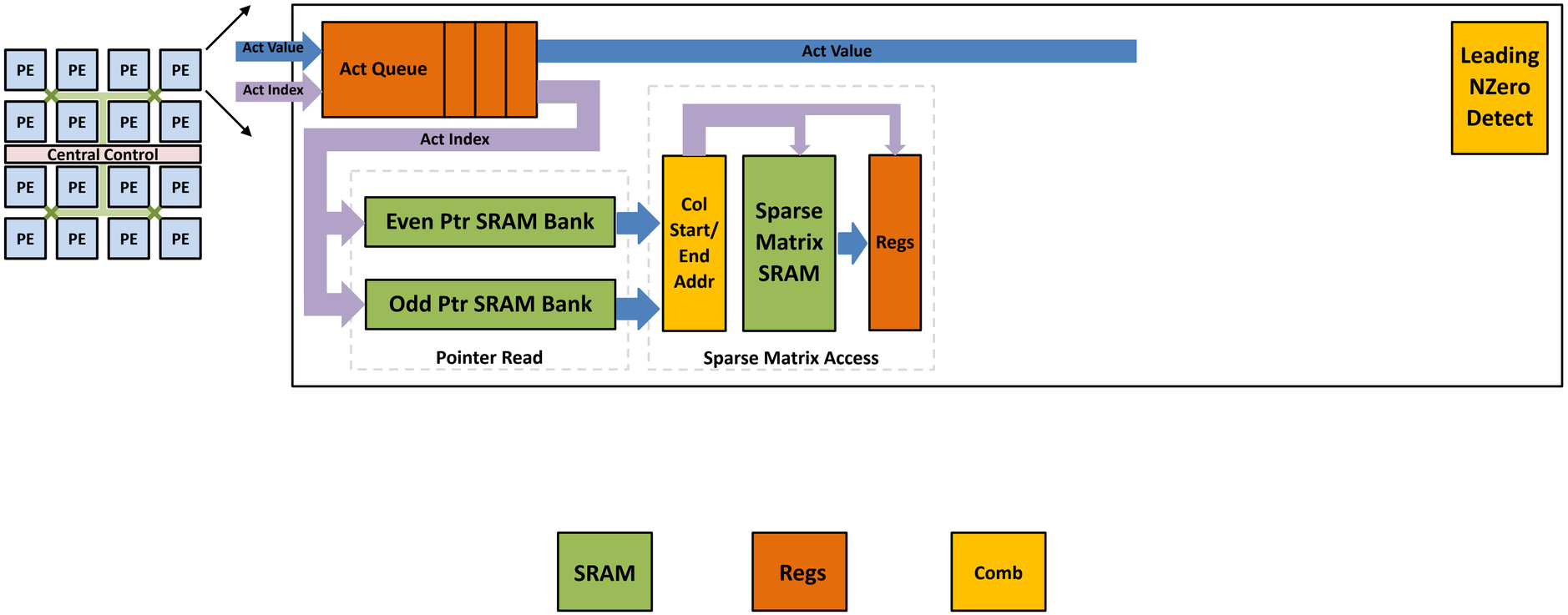
EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Activation Sparsity



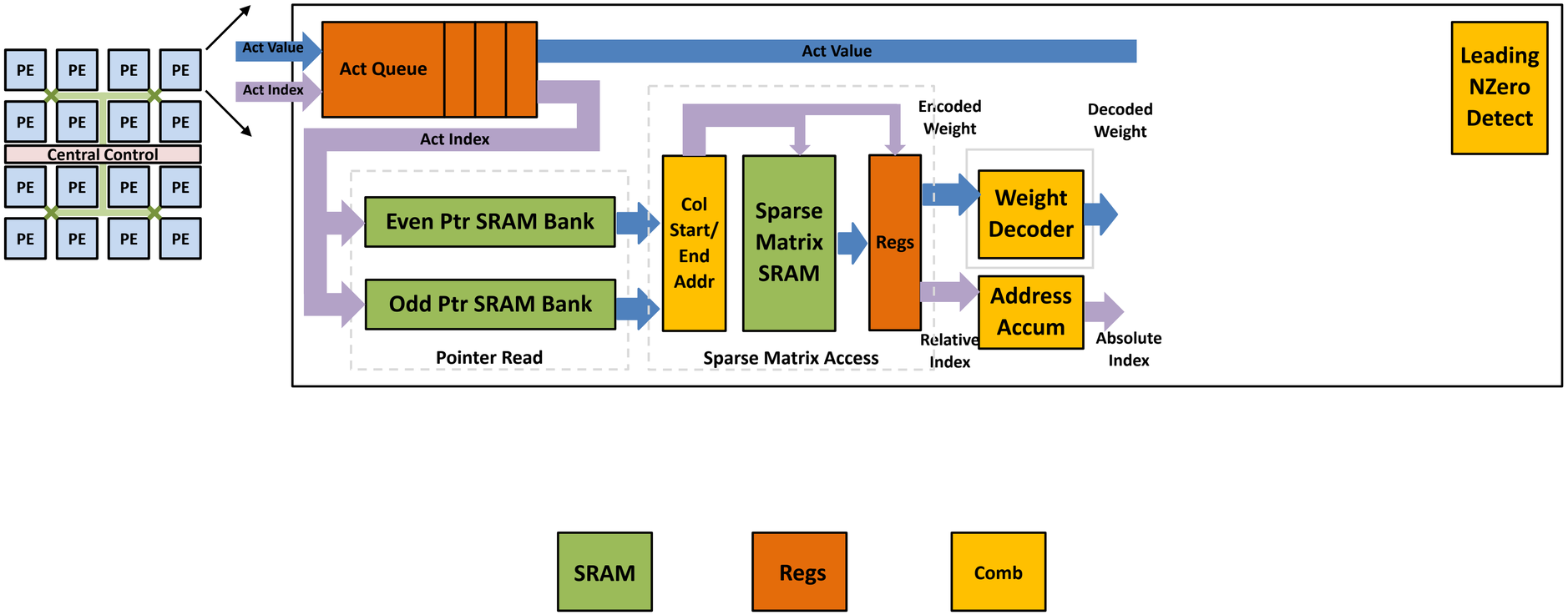
EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Weight Sparsity



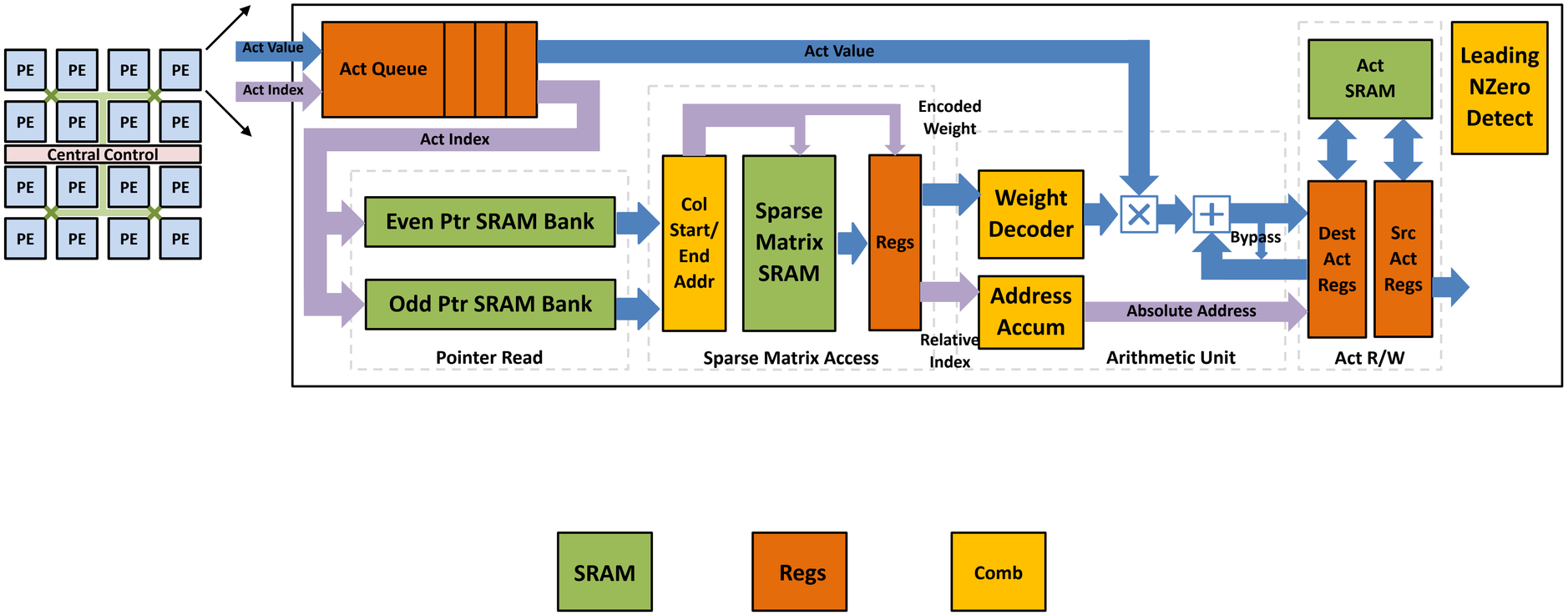
EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Weight Sharing



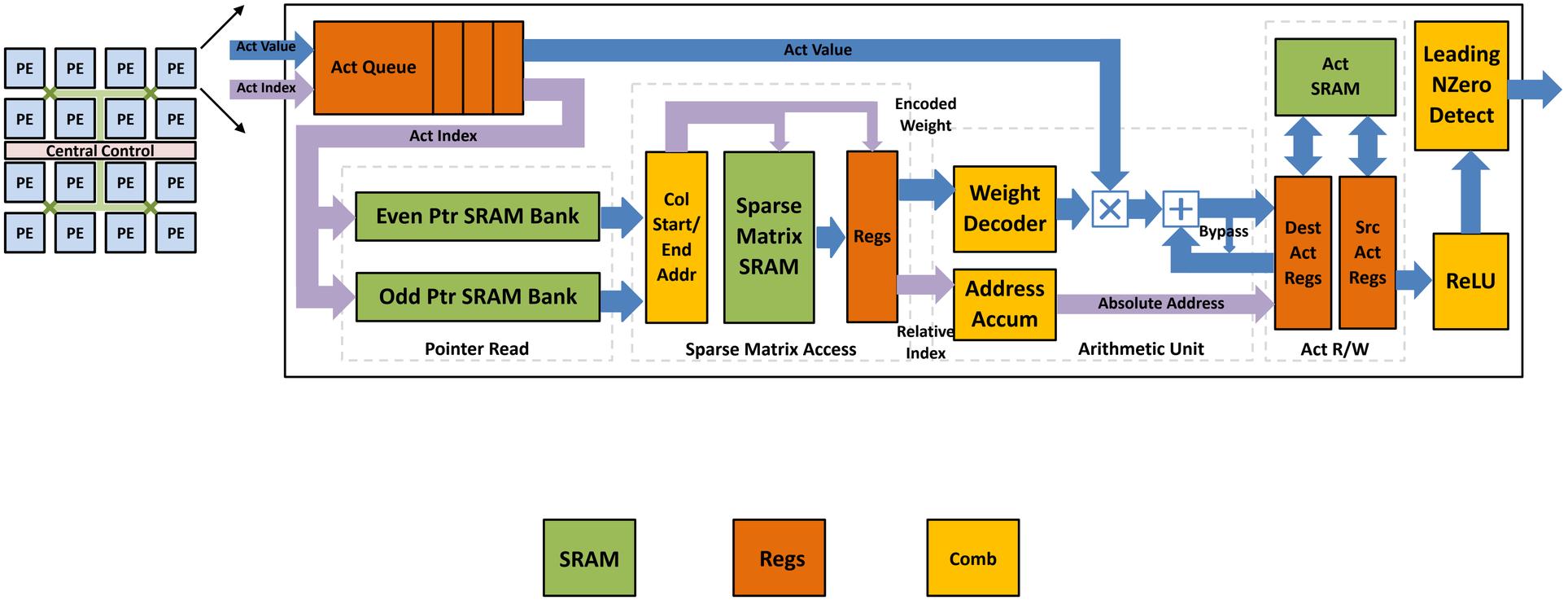
EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Arithmetic & Write Back



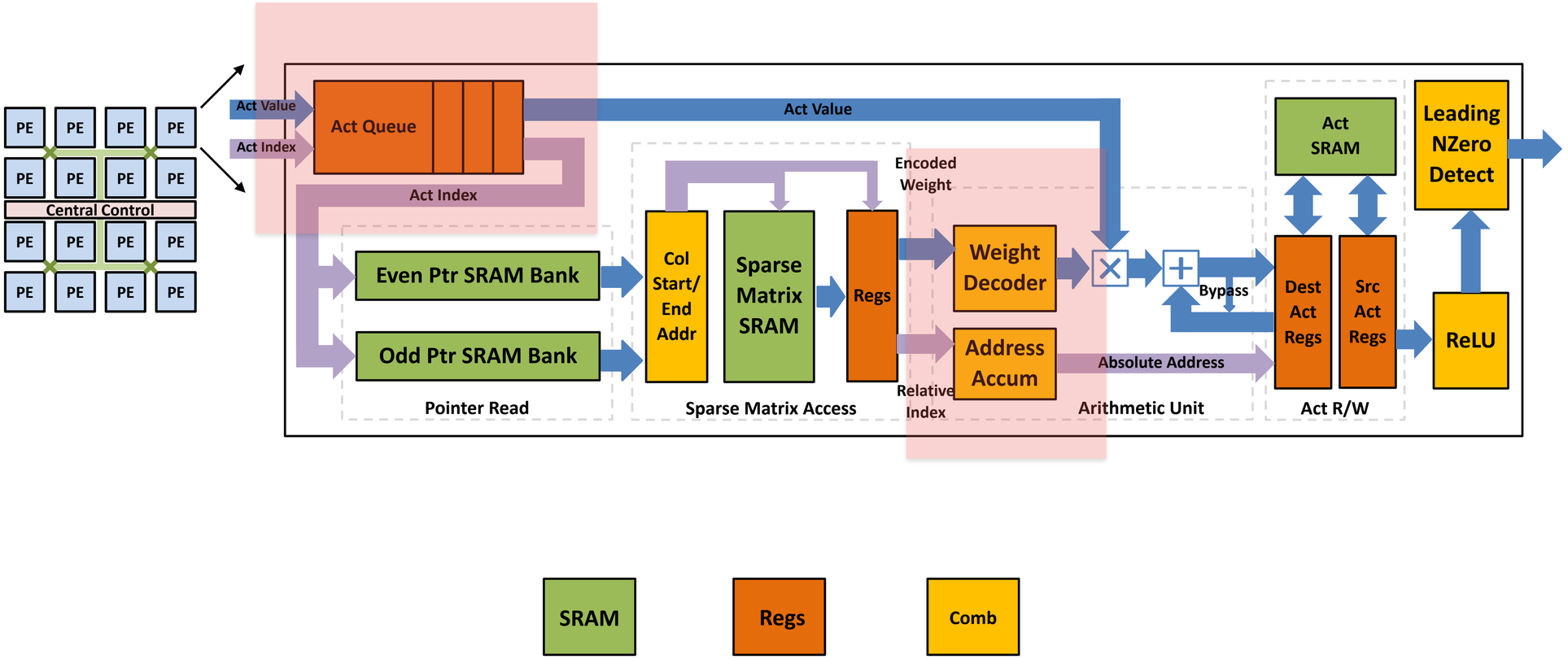
EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Relu, Non-zero Detection



EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

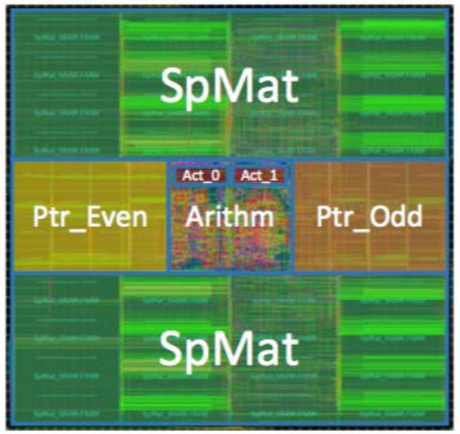
What's Special



EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.*, ISCA 2016]

Post Layout Result of EIE

- ALU width: with accuracy
  - **32bit float**: no loss
  - **32 bit Int**: 0.3% loss
  - **16 bit Int**: 0.5% loss
  - **8 bit Int**: 27% loss
- FIFO queue depth
- number of PEs



Technology	40 nm
# PEs	64
on-chip SRAM	8 MB
Max Model Size	84 Million
Static Sparsity	10x
Dynamic Sparsity	3x
Quantization	4-bit
ALU Width	16-bit
Area	40.8 mm^2
MxV Throughput	81,967 layers/s
Power	586 mW

1. **Post layout result**
2. **Throughput measured on AlexNet FC-7**

EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

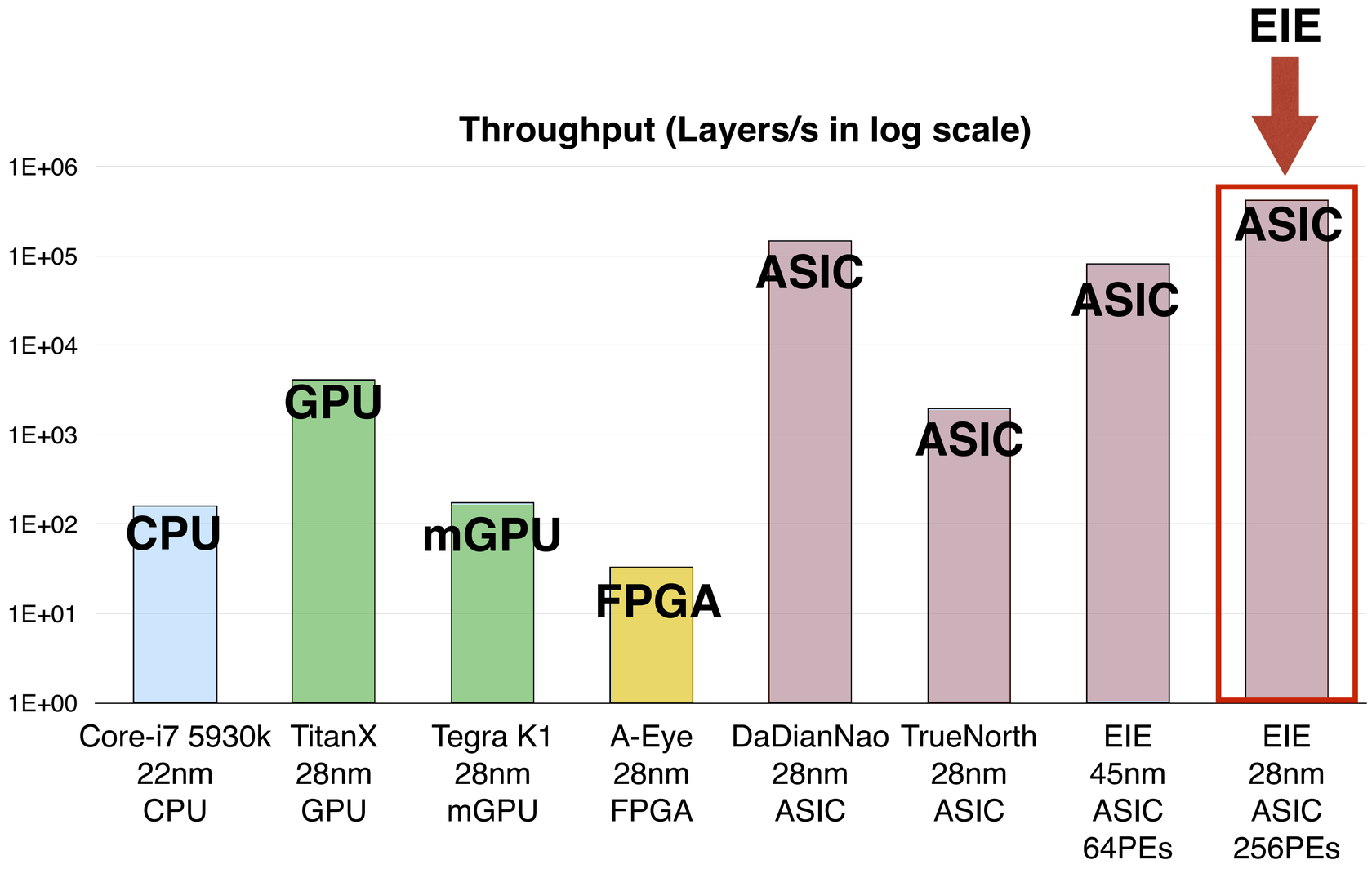
Benchmark

- CPU: Intel Core-i7 5930k
- GPU: NVIDIA TitanX
- Mobile GPU: NVIDIA Jetson TK1

Layer	Size	Weight Density	Activation Density	FLOP Reduction	Description
AlexNet-6	4096 × 9216	9%	35%	**33x**	AlexNet for image classification
AlexNet-7	4096 × 4096	9%	35%	**33x**	
AlexNet-8	1000 × 4096	25%	38%	**10x**	
VGG-6	4096 × 25088	4%	18%	**100x**	VGG-16 for image classification
VGG-7	4096 × 4096	4%	37%	**50x**	
VGG-8	1000 × 4096	23%	41%	**10x**	
NeuralTalk-We	600 × 4096	10%	100%	**10x**	RNN and LSTM for image caption
NeuralTalk-Wd	8791 × 600	11%	100%	**10x**	
NeuralTalk-LSTM	2400 × 1201	10%	100%	**10x**	

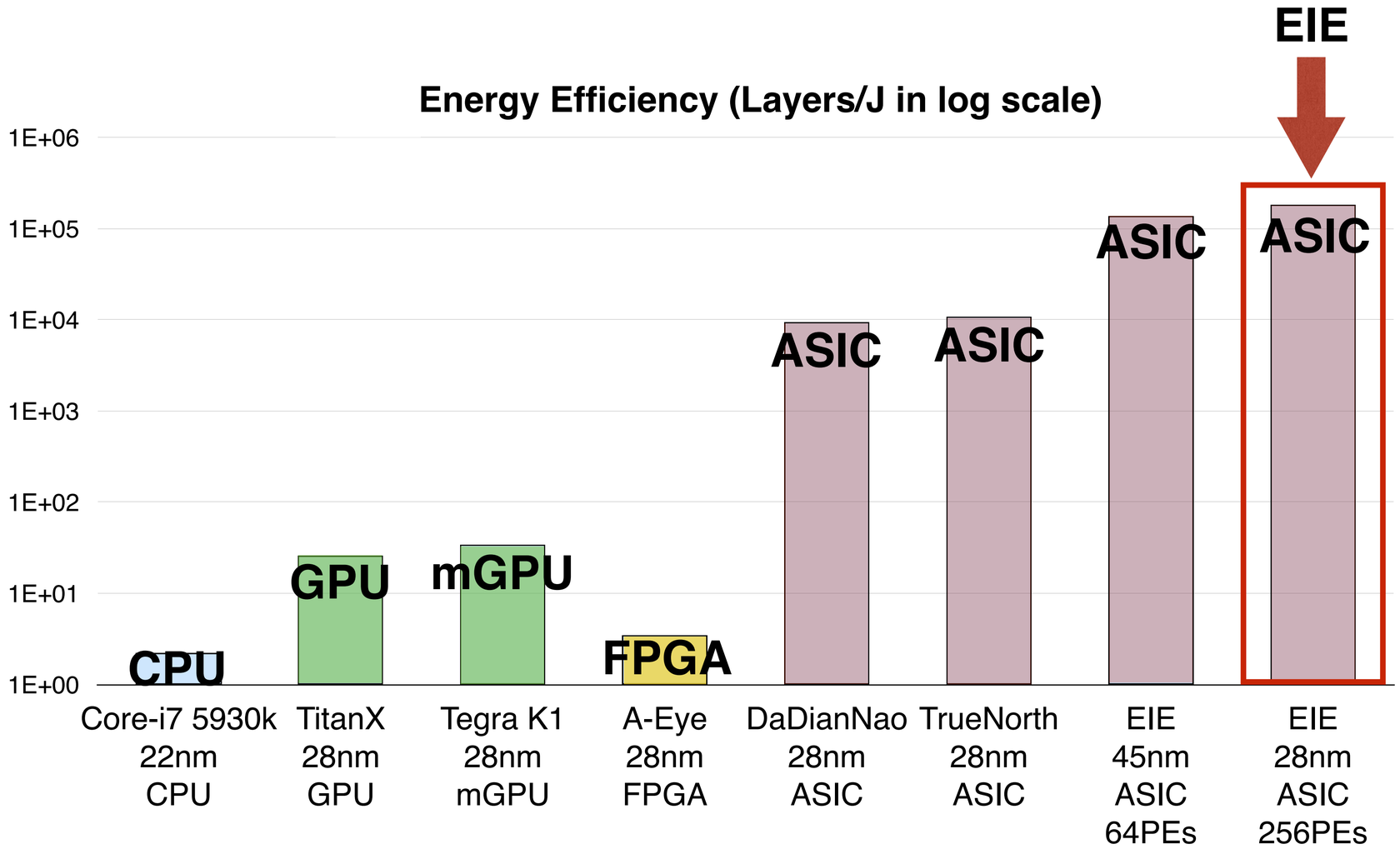
EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Comparison: Throughput



EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Comparison: Energy Efficiency



EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han *et al.,* ISCA 2016]

Top-5 most cited papers in 50 years of ISCA

Rank	*Citations*	*Year*	*Title (★ means it won the ISCA Influential Paper Award)*	First Author + *HOF Authors*	*Type*	*Topic*
1	5351	1995	The SPLASH-2 programs: Characterization and methodological considerations	Stephen Woo, *Anoop Gupta*	Tool	Benchmark
2	4214	2017	In-datacenter performance analysis of a Tensor Processing Unit	*Norm Jouppi, David Patterson*	Arch	Machine Learning
3	3834	2000	★ Wattch: A framework for architectural-level power analysis and optimizations	*David Brooks, Margaret Martonosi*	Tool	Power
4	3386	1993	★ Transactional memory: Architectural support for lock-free data structures	Maurice Herlihy	Micro	Parallelism
5	2690	2016	EIE: Efficient inference engine on compressed deep neural network	Song Han, *Bill Dally, Mark Horowitz*	Arch	Machine Learning

Retrospective: EIE: Efficient Inference Engine on Sparse and Compressed Neural Network

Song Han[1,3], Xingyu Liu[4], Huizi Mao[3], Jing Pu[5], Ardavan Pedram[2,6], Mark A. Horowitz[2], William J. Dally[2,3],
[1]MIT [2]Stanford [3] NVIDIA [4] CMU [5] Google [6] Samsung

Pro:

- EIE demonstrated that special-purpose hardware can make it cost-effective to do sparse operations with matrices that are up to 50% dense
- EIE exploits both weight sparsity and activation sparsity, not only saves energy by skipping zero weights, but also saves the cycle by not computing it.
- EIE supports fine-grained sparsity, and allows pruning to achieve a higher pruning ratio.
- Aggressive weight quantization (4bit) to save memory footprint. To maintain accuracy, EIE decodes the weight to 16bit and uses 16bit arithmetic. W4A16 approach is reborn in LLM: GPTQ, AWQ, llama.cpp, MLC LLM

Con:

- EIE isn't as easily applied to arrays of vector processors — improve: structured sparsity (N:M sparsity)
- EIE's Control flow overhead, storage overhead — improve: coarse grain sparsity
- EIE only support FC layers - actually reborn in LLM
- EIE fits everything on SRAM - practical for TinyML, not LLM

Retrospective: EIE: Efficient Inference Engine on Sparse and Compressed Neural Network

Song Han[1,3], Xingyu Liu[4], Huizi Mao[3], Jing Pu[5], Ardavan Pedram[2,6], Mark A. Horowitz[2], William J. Dally[2,3],
[1]MIT [2]Stanford [3] NVIDIA [4] CMU [5] Google [6] Samsung

The first principle of efficient AI computing is to be lazy: avoid redundant computation, quickly reject the work, or delay the work.

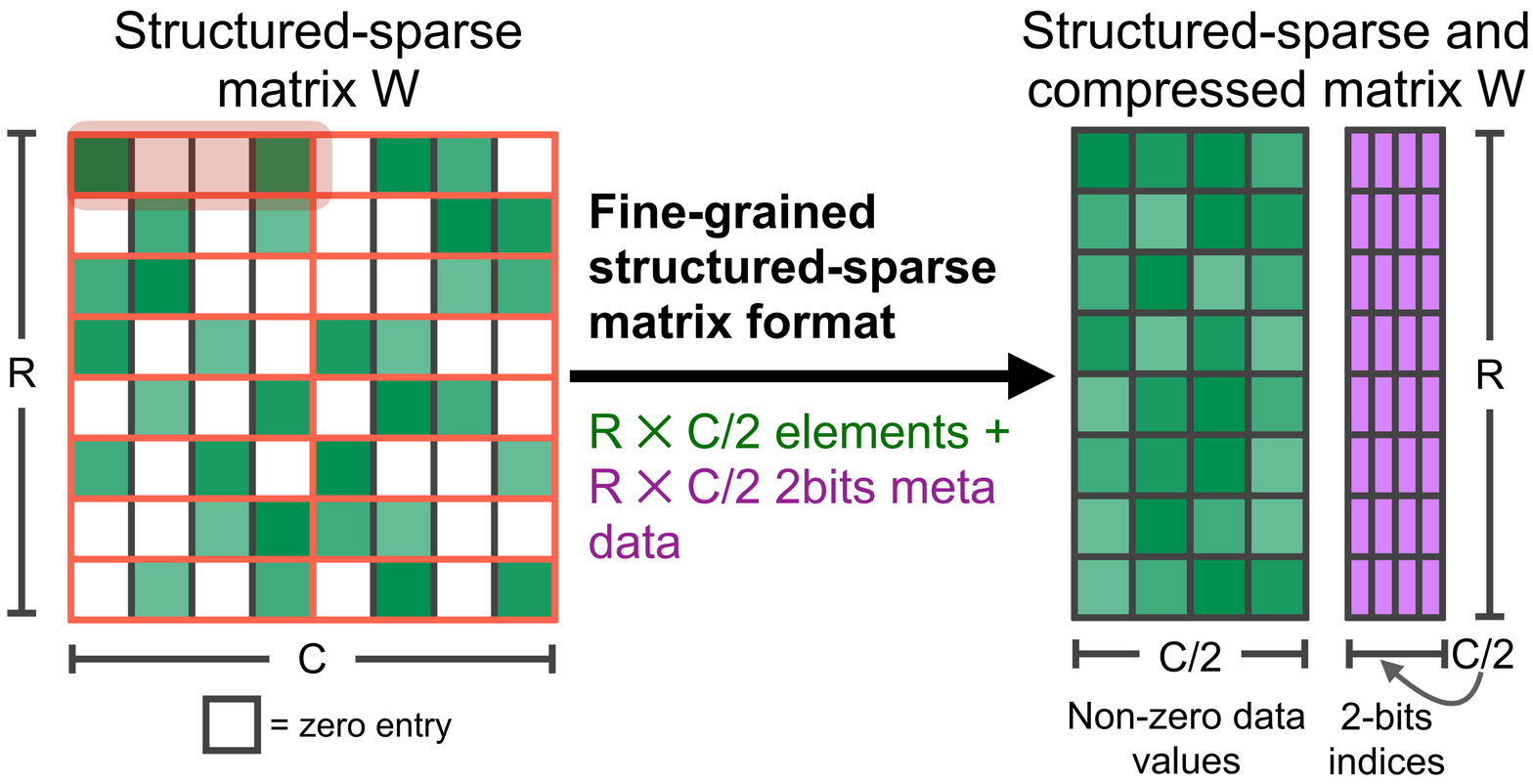
- Generative AI: spatial sparsity [SIGE, NeurIPS'22]
- Transformer: token sparsity, progressive quantization [SpAtten, HPCA'21]
- Video: temporal sparsity [TSM, ICCV'19]
- Point cloud: spatial sparsity [TorchSparse, MLSys'22 & PointAcc, Micro'22]

We envision future AI models will be sparse at various granularity and structures. Co-designed with specialized accelerators, sparse models will become more efficient and accessible.

System & Hardware Support for Sparsity

- EIE: Weight Sparsity + Activation Sparsity for GEMM
- **NVIDIA Tensor Core: M:N Weight Sparsity Sparsity**
- TorchSparse & PointAcc: Activation Sparsity for Sparse Convolution

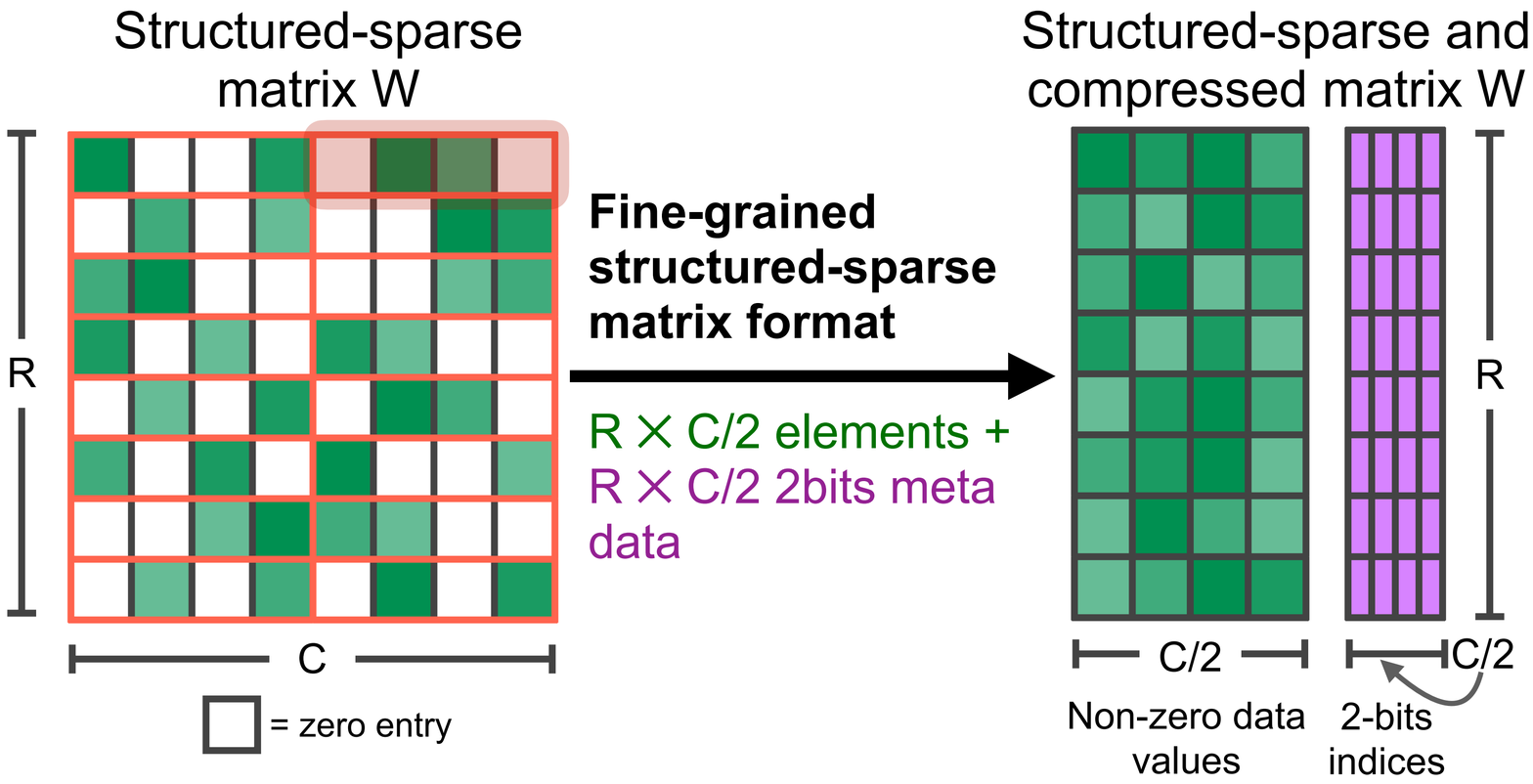
M:N Sparsity



Two weights are nonzero out of four consecutive weights (2:4 sparsity).

Accelerating Sparse Deep Neural Networks [Mishra *et al.*, arXiv 2021]

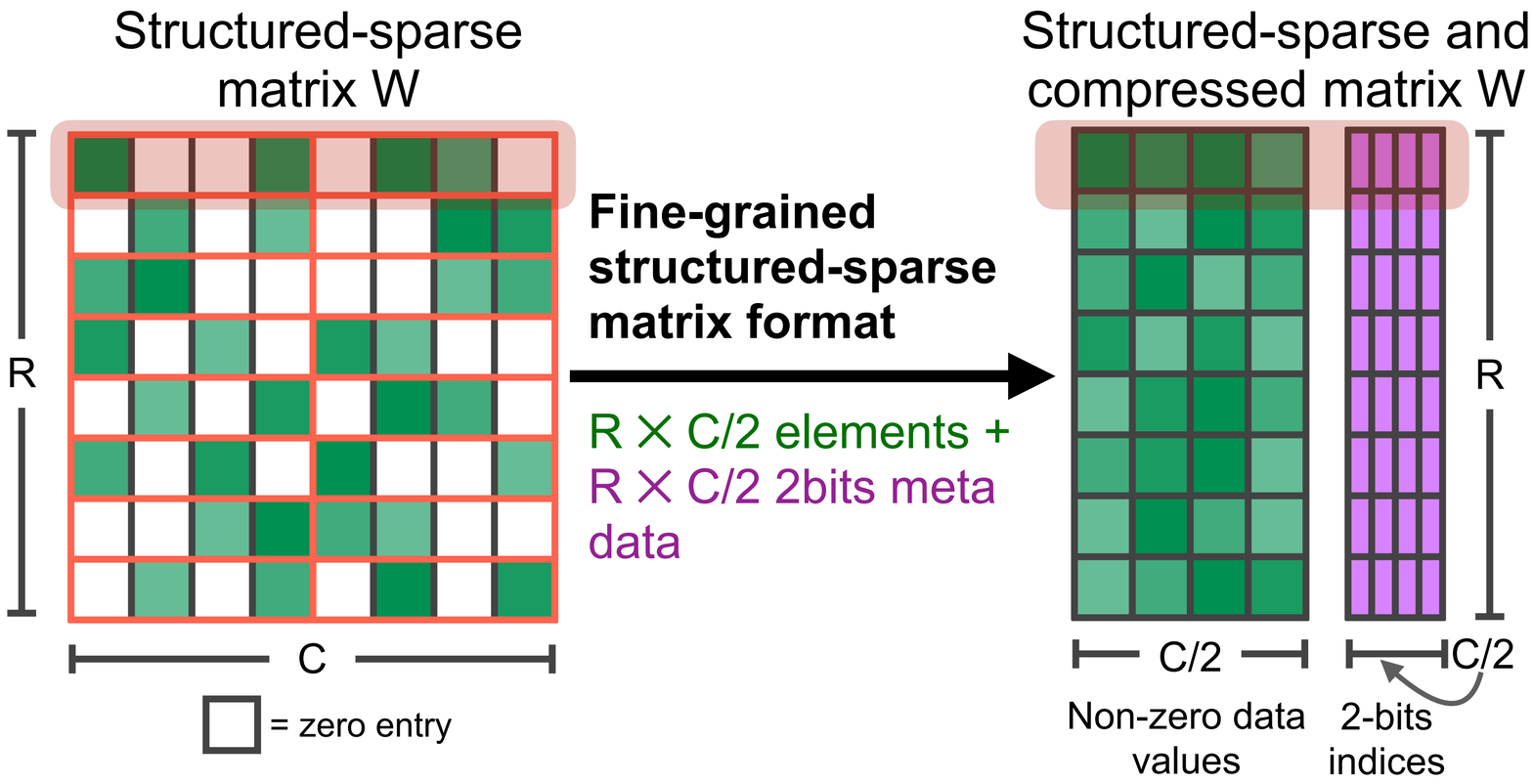
M:N Sparsity



Two weights are nonzero out of four consecutive weights (2:4 sparsity).

Accelerating Sparse Deep Neural Networks [Mishra *et al.*, arXiv 2021]

M:N Sparsity

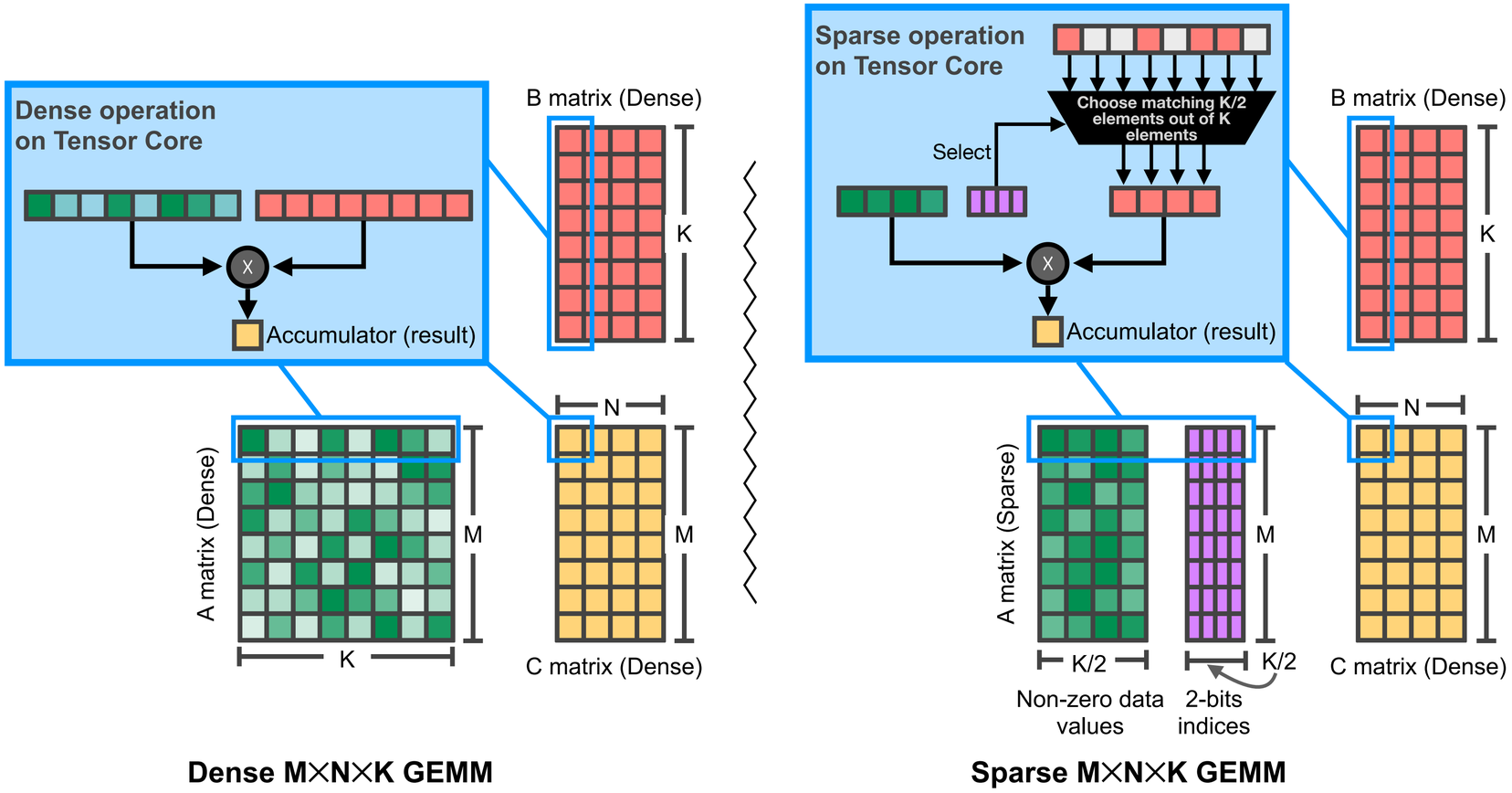


Push all the nonzero elements to the left in memory: save storage and computation.

Accelerating Sparse Deep Neural Networks [Mishra *et al.*, arXiv 2021]

System Support for M:N Sparsity

Mapping M:N sparse matrices onto NVIDIA tensor cores



The indices are used to mask out the inputs. Only 2 multiplications will be done out of four.

Accelerating Sparse Deep Neural Networks [Mishra *et al.*, arXiv 2021]

System Support for M:N Sparsity

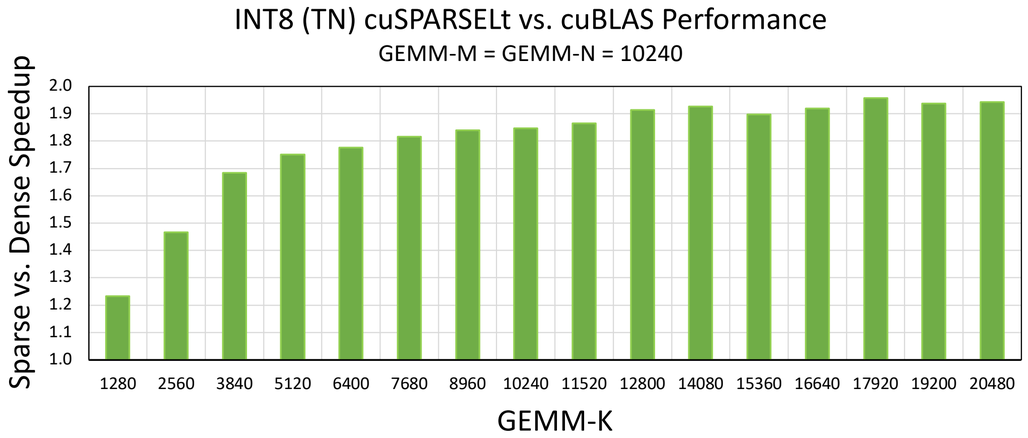


Fig. 3. Comparison of sparse and dense INT8 GEMMs on NVIDIA A100 Tensor Cores. Larger GEMMs achieve nearly a 2× speedup with Sparse Tensor Cores.

Network	Accuracy		
	Dense FP16	Sparse FP16	Sparse INT8
ResNet-34	73.7	73.9	73.7
ResNet-50	76.1	76.2	76.2
ResNet-50 (SWSL)	81.1	80.9	80.9
ResNet-101	77.7	78.0	77.9
ResNeXt-50-32x4	77.6	77.7	77.7
ResNeXt-101-32x16	79.7	79.9	79.9
ResNeXt-101-32x16 (WSL)	84.2	84.0	84.2
DenseNet-121	75.5	75.3	75.3
DenseNet-161	78.8	78.8	78.9
Wide ResNet-50	78.5	78.6	78.5
Wide ResNet-101	78.9	79.2	79.1
Inception v3	77.1	77.1	77.1
Xception	79.2	79.2	79.2
VGG-11	70.9	70.9	70.8
VGG-16	74.0	74.1	74.1
VGG-19	75.0	75.0	75.0
SUNet-128	75.6	76.0	75.4
SUNet-7-128	76.4	76.5	76.3
DRN26	75.2	75.3	75.3
DRN-105	79.4	79.5	79.4

Pruning CNNs with 2:4 sparsity will bring about large speedup for GEMM workloads and it will not incur performance drop for DNN models.

Accelerating Sparse Deep Neural Networks [Mishra *et al.*, arXiv 2021]

System & Hardware Support for Sparsity

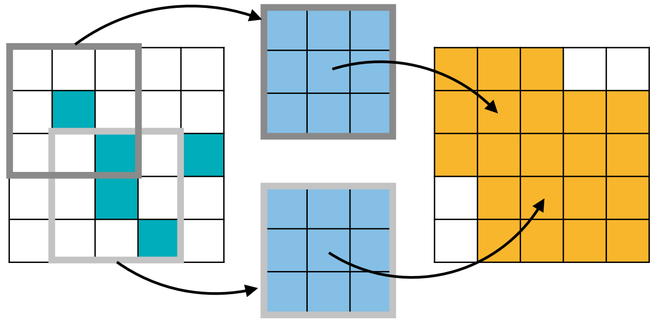
- EIE: Weight Sparsity + Activation Sparsity for GEMM
- NVIDIA Tensor Core: M:N Weight Sparsity Sparsity
- **TorchSparse & PointAcc: Activation Sparsity for Sparse Convolution**

System & Hardware Support for Sparsity

- EIE: Weight Sparsity + Activation Sparsity for GEMM
- NVIDIA Tensor Core: M:N Weight Sparsity Sparsity
- **TorchSparse & PointAcc: Activation Sparsity for Sparse Convolution**
  - **TorchSparse: Sparse Convolution Library**
  - **PointAcc: Hardware Accelerator for Sparse Convolution**

Sparse convolution on sparse inputs

Conventional Convolution

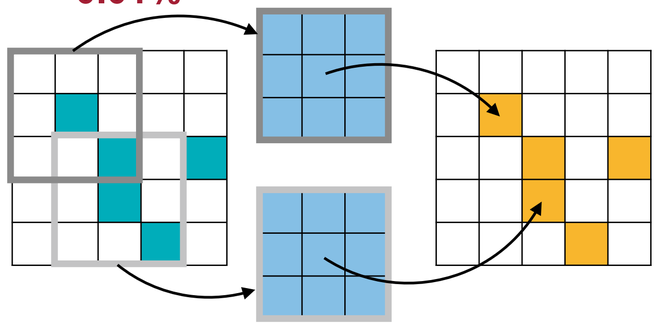


Input sparsity from ReLU

Nonzeros will dilate

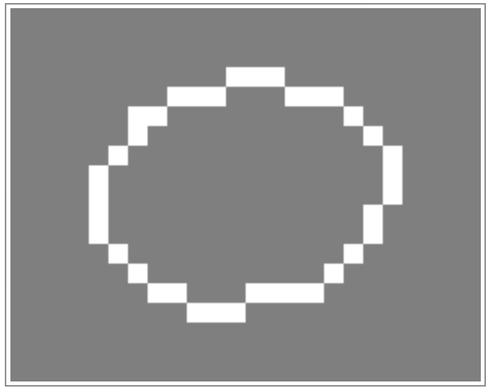
Sparse Convolution

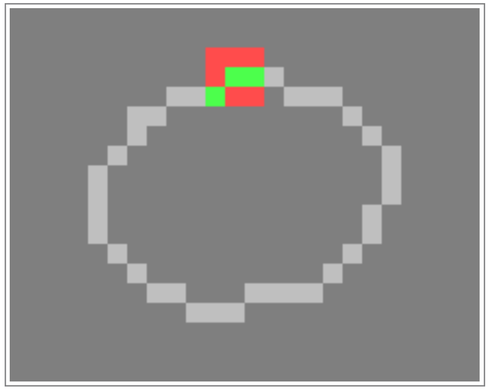
~0.01%



Input sparsity from the distribution in physical space

Nonzeros **will not** dilate



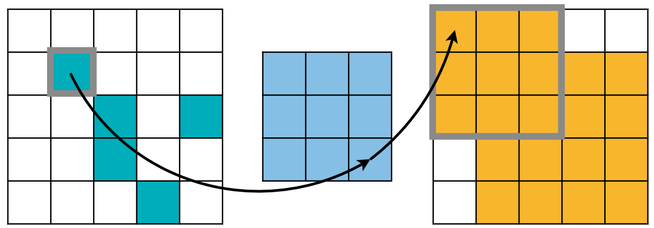


Submanifold Sparse Convolutional Neural Networks [Graham, BMVC 2015]

Sparse convolution computation

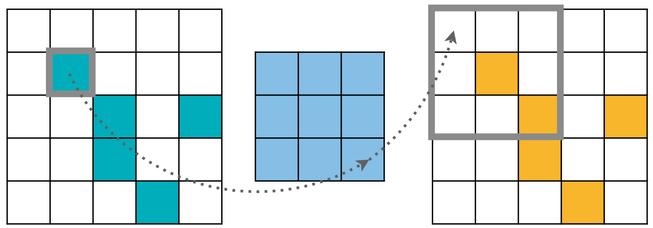
A *sparse* set of *dense* MMA, with rules defined by *maps*

Conventional Convolution



(P_0, Q_0, $W_{1,1}$)

Sparse Convolution



No compute

Maps
(In, Out, Wgt)

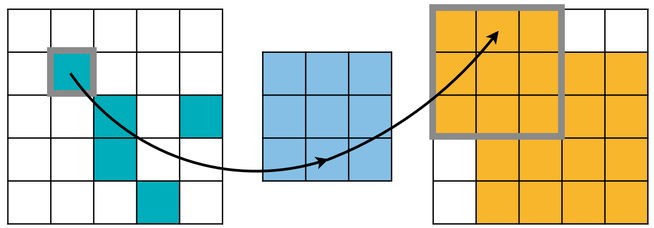
Computation
($f_{Out} = f_{Out} + f_{In} \times W_{Wgt}$) for each entry in the maps

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

Sparse convolution computation

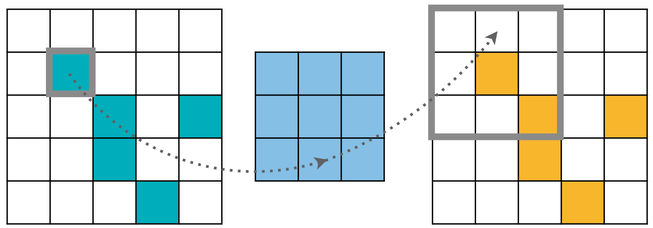
A *sparse* set of *dense* MMA, with rules defined by *maps*

Conventional Convolution



(P_0, Q_0, $W_{1,1}$)
(P_0, Q_1, $W_{1,0}$)

Sparse Convolution



No compute
No compute

Maps
(In, Out, Wgt)

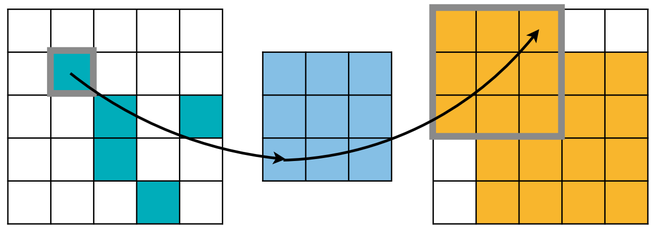
Computation
($f_{Out} = f_{Out} + f_{In} \times W_{Wgt}$) for each entry in the maps

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

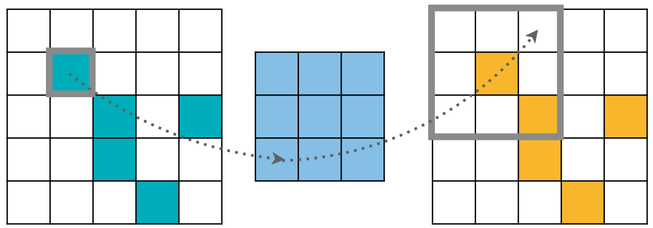
Sparse convolution computation

A *sparse* set of *dense* MMA, with rules defined by *maps*

Conventional Convolution



Sparse Convolution



Maps
(In, Out, Wgt)

(P_0, Q_0, $W_{1,1}$)
(P_0, Q_1, $W_{1,0}$)
(P_0, Q_2, $W_{1,-1}$)

No compute
No compute
No compute

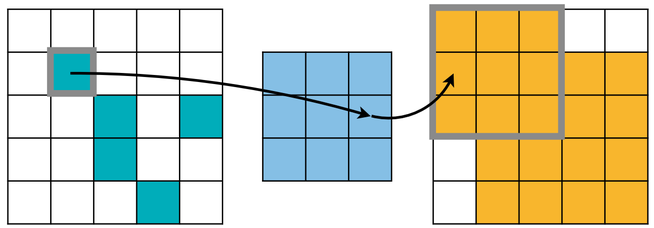
Computation
($f_{Out} = f_{Out} + f_{In} \times W_{Wgt}$) for each entry in the maps

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

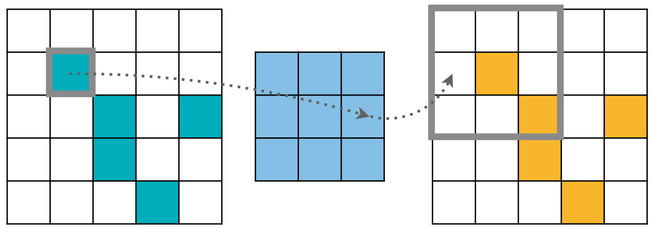
Sparse convolution computation

A *sparse* set of *dense* MMA, with rules defined by *maps*

Conventional Convolution



Sparse Convolution



Maps
(In, Out, Wgt)

$(P_0, Q_0, W_{1,1})$
$(P_0, Q_1, W_{1,0})$
$(P_0, Q_2, W_{1,-1})$
$(P_0, Q_3, W_{0,1})$

No compute
No compute
No compute
No compute

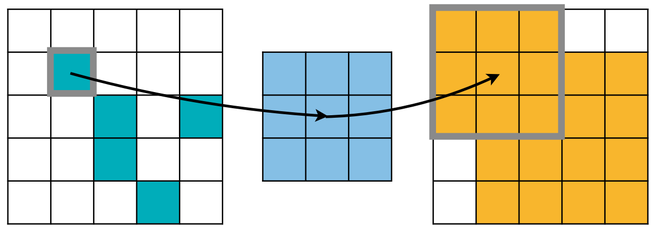
Computation
($f_{Out} = f_{Out} + f_{In} \times W_{Wgt}$) for each entry in the maps

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

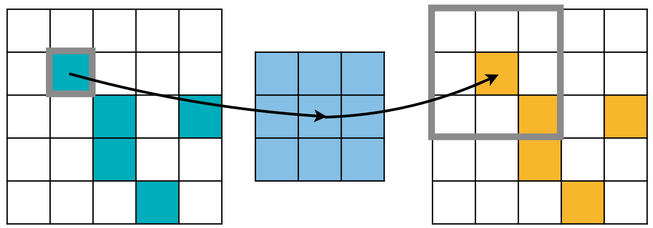
Sparse convolution computation

A *sparse* set of *dense* MMA, with rules defined by *maps*

Conventional Convolution



Sparse Convolution



Maps
(In, Out, Wgt)

$(P_0, Q_0, W_{1,1})$
$(P_0, Q_1, W_{1,0})$
$(P_0, Q_2, W_{1,-1})$
$(P_0, Q_3, W_{0,1})$
$(P_0, Q_4, W_{0,0})$

No compute
No compute
No compute
No compute
$(P_0, Q_0, W_{0,0})$

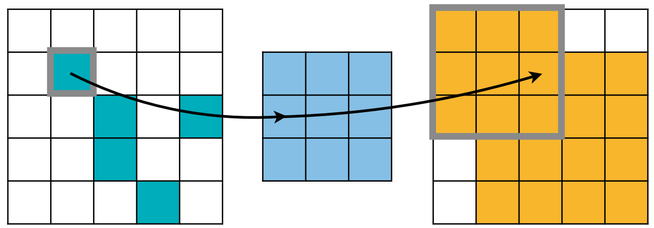
Computation
($f_{Out} = f_{Out} + f_{In} \times W_{Wgt}$) for each entry in the maps

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

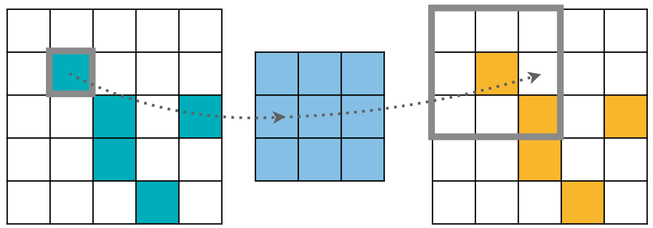
Sparse convolution computation

A *sparse* set of *dense* MMA, with rules defined by *maps*

Conventional Convolution



Sparse Convolution



Maps
(**In**, **Out**, **Wgt**)

Computation
(**f_{Out} = f_{Out} + f_{In} × W_{Wgt}**) for each entry in the maps

(P_0, Q_0, $W_{1,1}$)
(P_0, Q_1, $W_{1,0}$)
(P_0, Q_2, $W_{1,-1}$)
(P_0, Q_3, $W_{0,1}$)
(P_0, Q_4, $W_{0,0}$)
(P_0, Q_5, $W_{0,-1}$)

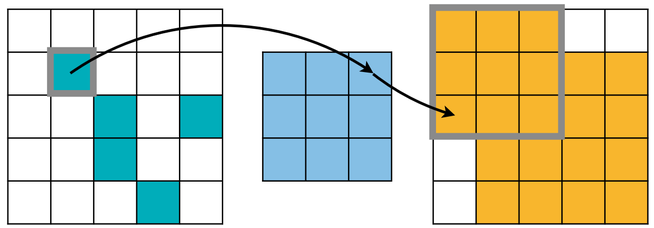
No compute
No compute
No compute
No compute
No compute
(P_0, Q_0, $W_{0,0}$)
No compute

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

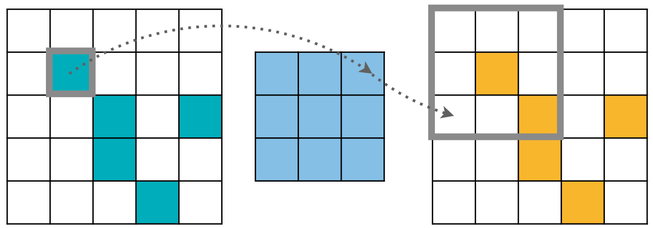
Sparse convolution computation

A *sparse* set of *dense* MMA, with rules defined by *maps*

Conventional Convolution



Sparse Convolution



Maps
(**In**, **Out**, **Wgt**)

Computation
(**$f_{Out} = f_{Out} + f_{In} \times W_{Wgt}$**) for each entry in the maps

(P_0, Q_0, $W_{1,1}$)
(P_0, Q_1, $W_{1,0}$)
(P_0, Q_2, $W_{1,-1}$)
(P_0, Q_3, $W_{0,1}$)
(P_0, Q_4, $W_{0,0}$)
(P_0, Q_5, $W_{0,-1}$)
(P_0, Q_8, $W_{-1,1}$)

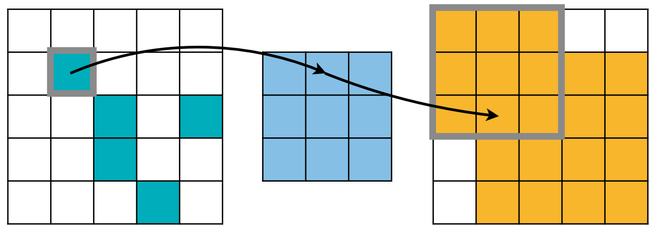
No compute
No compute
No compute
No compute
No compute
(P_0, Q_0, $W_{0,0}$)
No compute
No compute

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

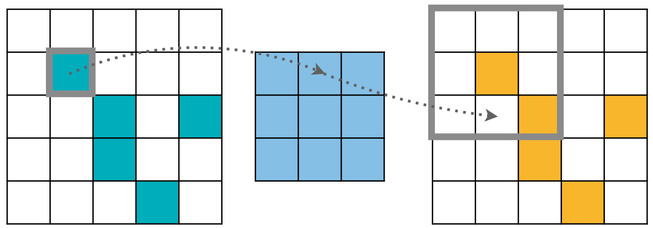
Sparse convolution computation

A *sparse* set of *dense* MMA, with rules defined by *maps*

Conventional Convolution



Sparse Convolution



Maps
(**In**, **Out**, **Wgt**)

Computation
($f_{Out} = f_{Out} + f_{In} \times W_{Wgt}$) for each entry in the maps

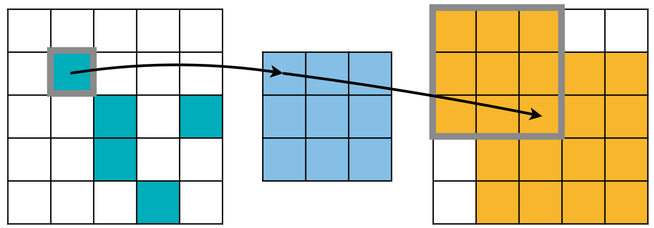
Conventional Convolution	Sparse Convolution
(P_0, Q_0, $W_{1,1}$)	No compute
(P_0, Q_1, $W_{1,0}$)	No compute
(P_0, Q_2, $W_{1,-1}$)	No compute
(P_0, Q_3, $W_{0,1}$)	No compute
(P_0, Q_4, $W_{0,0}$)	(P_0, Q_0, $W_{0,0}$)
(P_0, Q_5, $W_{0,-1}$)	No compute
(P_0, Q_8, $W_{-1,1}$)	No compute
(P_0, Q_9, $W_{-1,0}$)	No compute

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

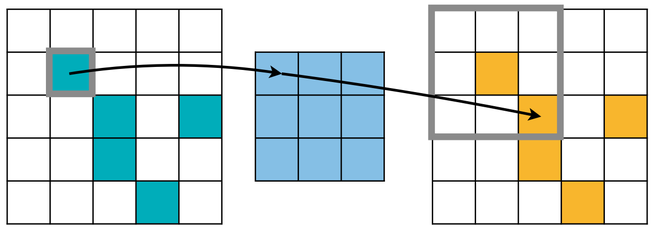
Sparse convolution computation

A *sparse* set of *dense* MMA, with rules defined by *maps*

Conventional Convolution



Sparse Convolution



Maps
(In, Out, Wgt)

Computation
($f_{Out} = f_{Out} + f_{In} \times W_{Wgt}$) for each entry in the maps

(P_0, Q_0, $W_{1,1}$)	No compute
(P_0, Q_1, $W_{1,0}$)	No compute
(P_0, Q_2, $W_{1,-1}$)	No compute
(P_0, Q_3, $W_{0,1}$)	No compute
(P_0, Q_4, $W_{0,0}$)	(P_0, Q_0, $W_{0,0}$)
(P_0, Q_5, $W_{0,-1}$)	No compute
(P_0, Q_8, $W_{-1,1}$)	No compute
(P_0, Q_9, $W_{-1,0}$)	No compute
(P_0, Q_{10}, $W_{-1,-1}$)	(P_0, Q_1, $W_{-1,-1}$)

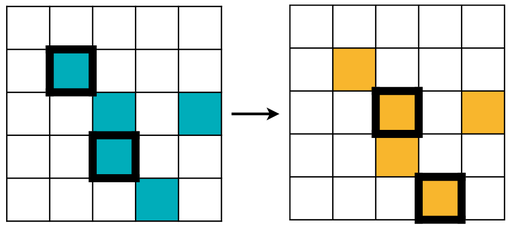
9 matrix multiplications

2 matrix multiplications

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

Existing GPU implementation of sparse convolution

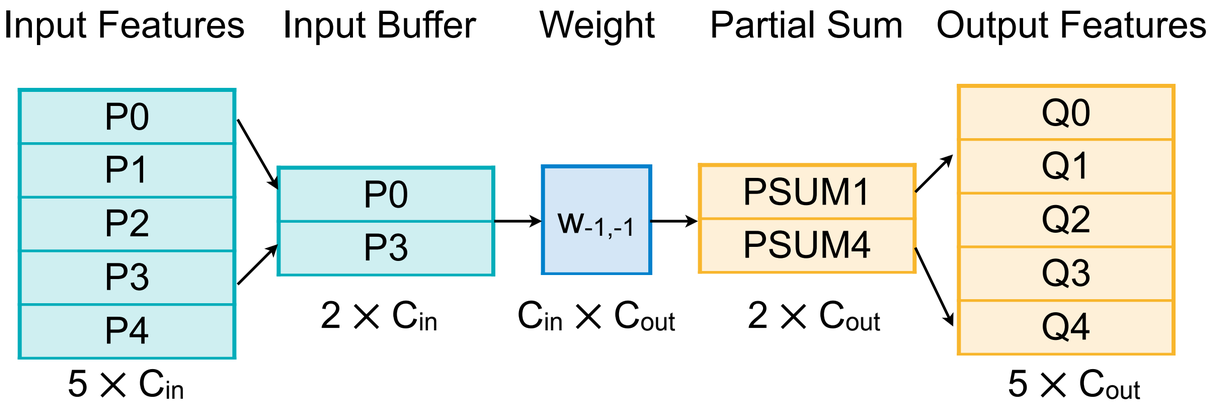
Weight-stationary computation, separate matmul for different weights



Workload

Maps
(In, Out, Wgt)

(P_0, Q_1, $W_{-1,-1}$)
(P_3, Q_4, $W_{-1,-1}$)
(P_1, Q_3, $W_{-1,0}$)
(P_0, Q_0, $W_{0,0}$)
(P_1, Q_1, $W_{0,0}$)
(P_2, Q_2, $W_{0,0}$)
(P_3, Q_3, $W_{0,0}$)
(P_4, Q_4, $W_{0,0}$)
(P_3, Q_1, $W_{1,0}$)
(P_1, Q_0, $W_{1,1}$)
(P_4, Q_3, $W_{1,1}$)



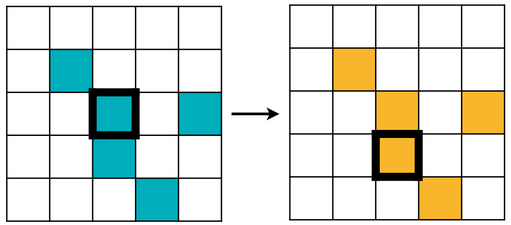
$f_1 = f_1 + f_0 \times W_{-1,-1}$

$f_4 = f_4 + f_3 \times W_{-1,-1}$

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

Existing GPU implementation of sparse convolution

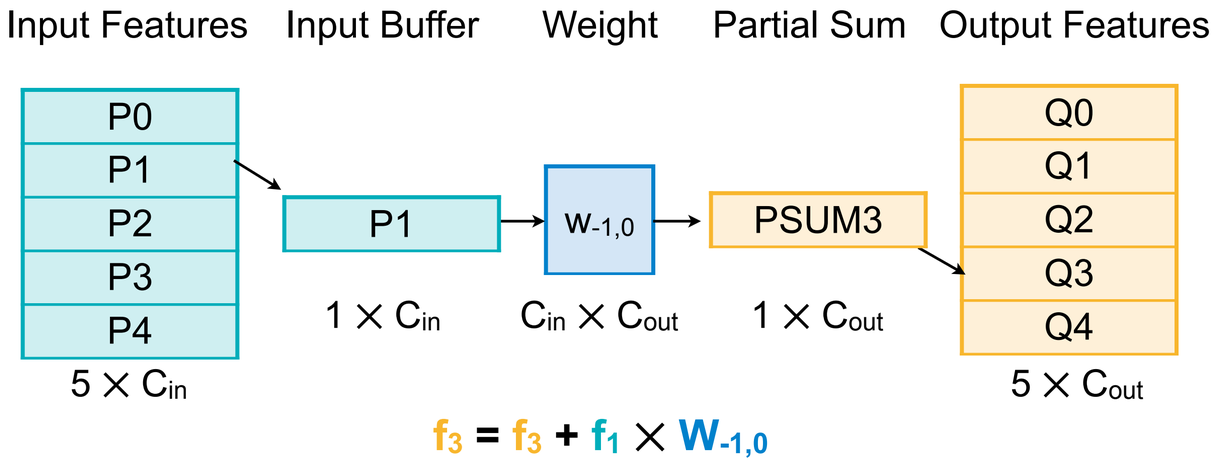
Weight-stationary computation, separate matmul for different weights



Workload

Maps
(In, Out, Wgt)

(P_0, Q_1, $W_{-1,-1}$)
(P_3, Q_4, $W_{-1,-1}$)
(P_1, Q_3, $W_{-1,0}$)
(P_0, Q_0, $W_{0,0}$)
(P_1, Q_1, $W_{0,0}$)
(P_2, Q_2, $W_{0,0}$)
(P_3, Q_3, $W_{0,0}$)
(P_4, Q_4, $W_{0,0}$)
(P_3, Q_1, $W_{1,0}$)
(P_1, Q_0, $W_{1,1}$)
(P_4, Q_3, $W_{1,1}$)

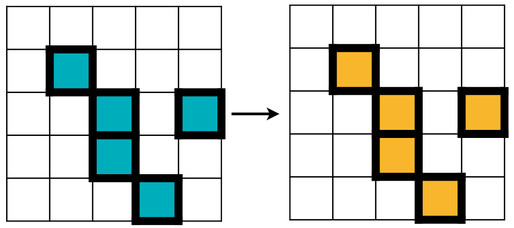


$f_3 = f_3 + f_1 \times W_{-1,0}$

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

Existing GPU implementation of sparse convolution

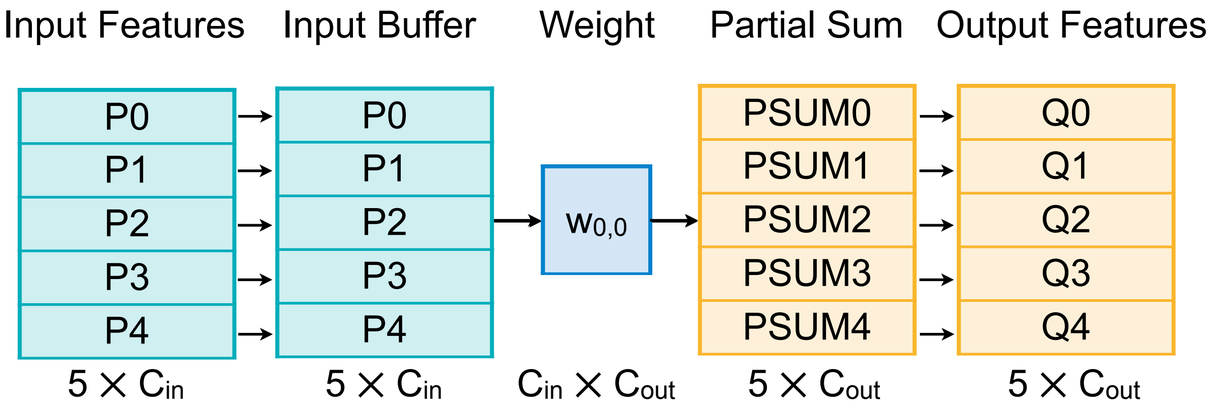
Weight-stationary computation, separate matmul for different weights



Workload

Maps
(In, Out, Wgt)

(P_0, Q_1, $W_{-1,-1}$)
(P_3, Q_4, $W_{-1,-1}$)
(P_1, Q_3, $W_{-1,0}$)
(P_0, Q_0, $W_{0,0}$)
(P_1, Q_1, $W_{0,0}$)
(P_2, Q_2, $W_{0,0}$)
(P_3, Q_3, $W_{0,0}$)
(P_4, Q_4, $W_{0,0}$)
(P_3, Q_1, $W_{1,0}$)
(P_1, Q_0, $W_{1,1}$)
(P_4, Q_3, $W_{1,1}$)



$$f_i = f_i + f_i \times W_{0,0}$$

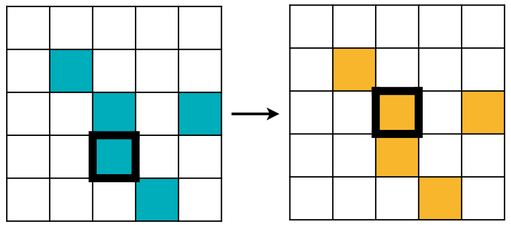
$$i = 0, 1, 2, 3, 4$$

Note: maps for $W_{0,0}$ contains all entries.

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

Existing GPU implementation of sparse convolution

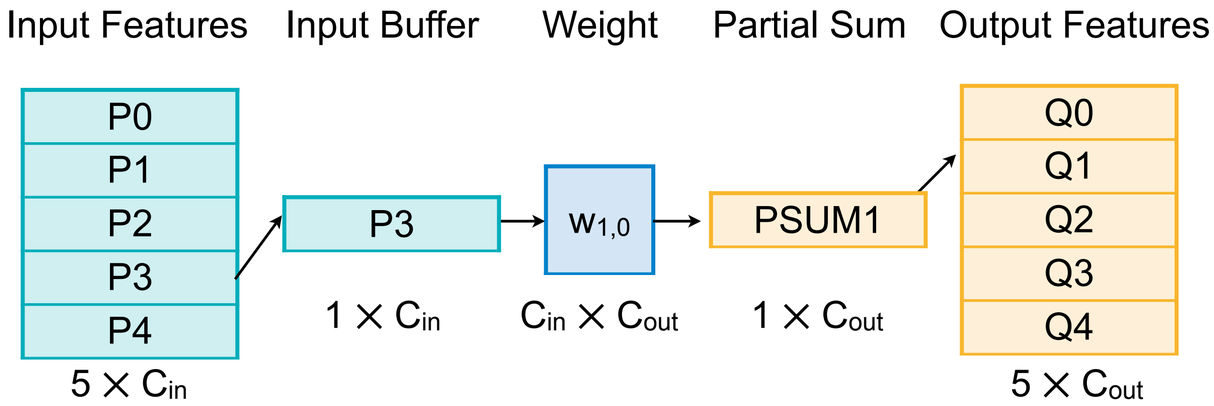
Weight-stationary computation, separate matmul for different weights



Workload

Maps
(In, Out, Wgt)

(P_0, Q_1, $W_{-1,-1}$)
(P_3, Q_4, $W_{-1,-1}$)
(P_1, Q_3, $W_{-1,0}$)
(P_0, Q_0, $W_{0,0}$)
(P_1, Q_1, $W_{0,0}$)
(P_2, Q_2, $W_{0,0}$)
(P_3, Q_3, $W_{0,0}$)
(P_4, Q_4, $W_{0,0}$)
(P_3, Q_1, $W_{1,0}$)
(P_1, Q_0, $W_{1,1}$)
(P_4, Q_3, $W_{1,1}$)

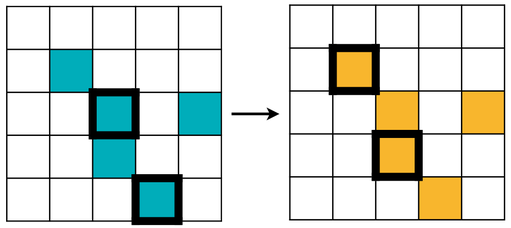


$f_1 = f_1 + f_3 \times W_{1,0}$

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

Existing GPU implementation of sparse convolution

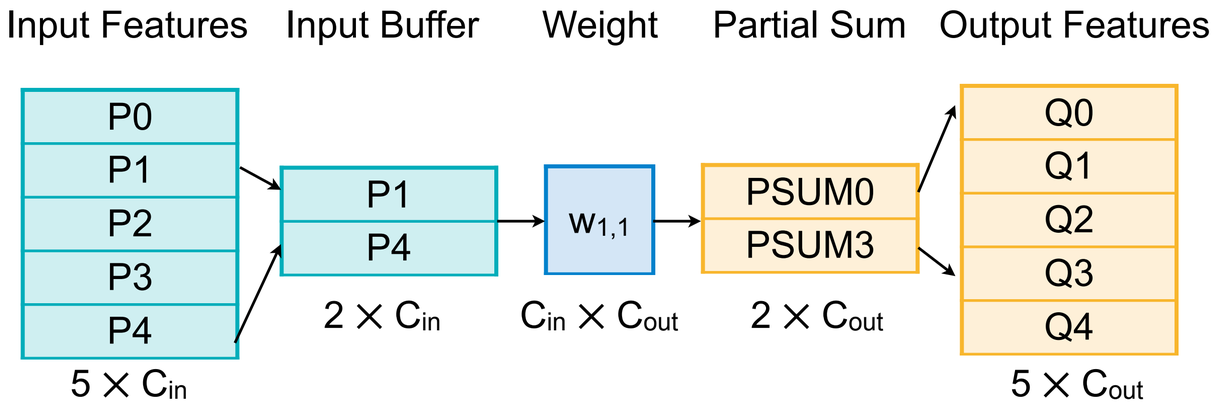
Weight-stationary computation, separate matmul for different weights



Workload

Maps
(In, Out, Wgt)

(P_0, Q_1, $W_{-1,-1}$)
(P_3, Q_4, $W_{-1,-1}$)
(P_1, Q_3, $W_{-1,0}$)
(P_0, Q_0, $W_{0,0}$)
(P_1, Q_1, $W_{0,0}$)
(P_2, Q_2, $W_{0,0}$)
(P_3, Q_3, $W_{0,0}$)
(P_4, Q_4, $W_{0,0}$)
(P_3, Q_1, $W_{1,0}$)
(P_1, Q_0, $W_{1,1}$)
(P_4, Q_3, $W_{1,1}$)

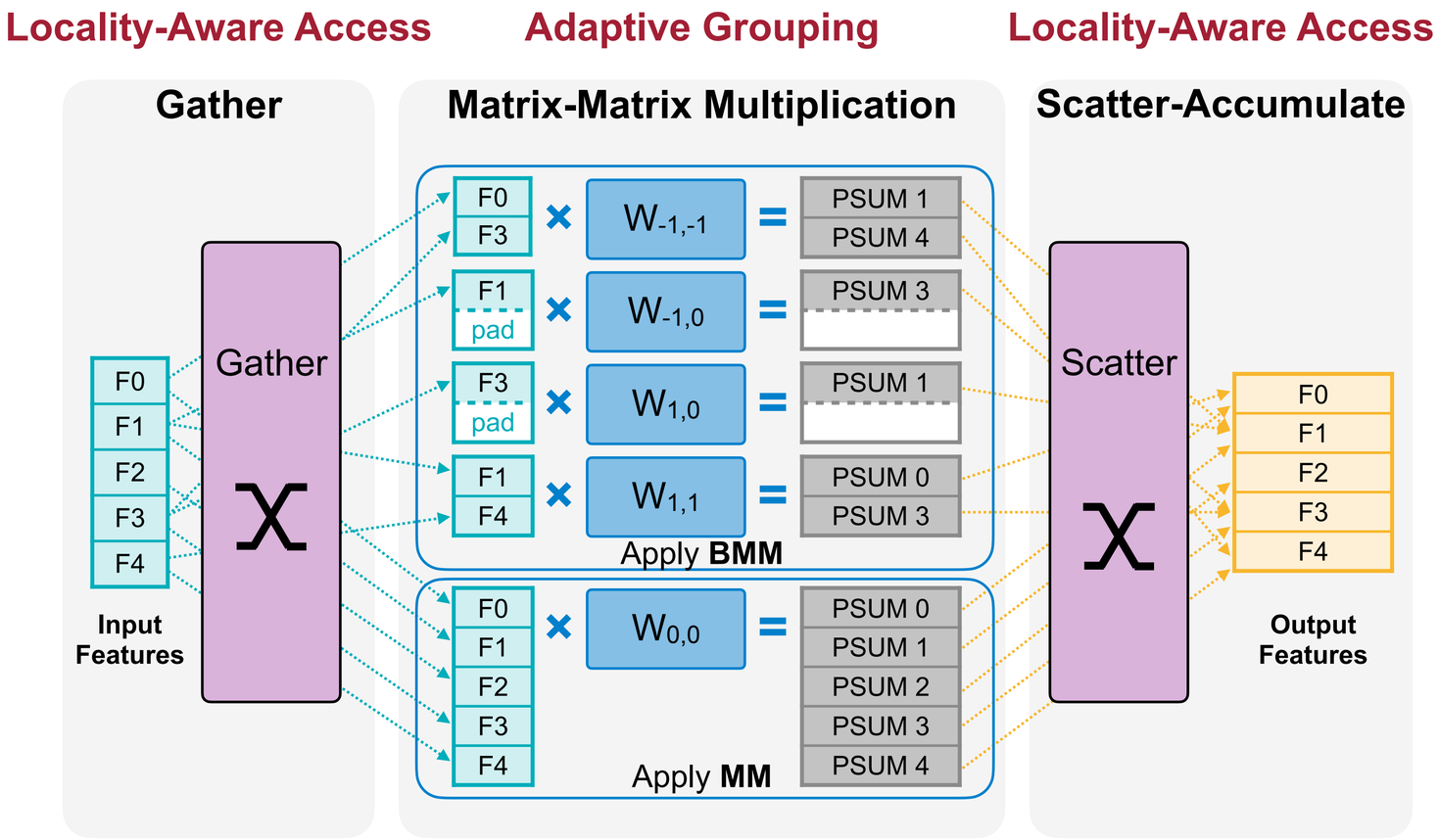


$f_0 = f_0 + f_1 \times W_{1,1}$

$f_3 = f_3 + f_4 \times W_{1,1}$

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

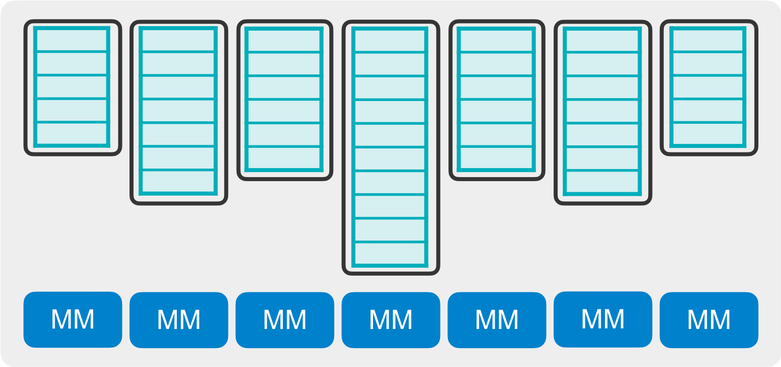
TorchSparse optimization overview



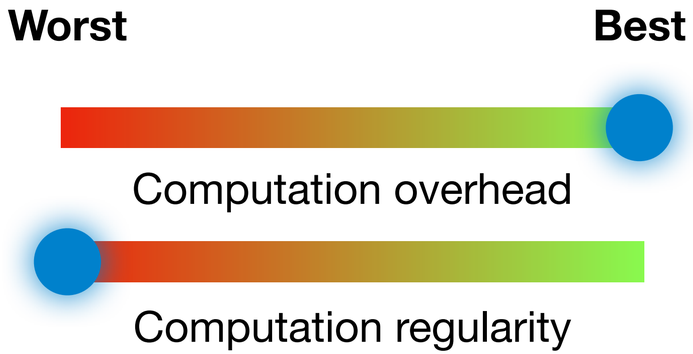
TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

Trading computation for regularity

Separate computation (baseline) : many kernel calls, low device utilization



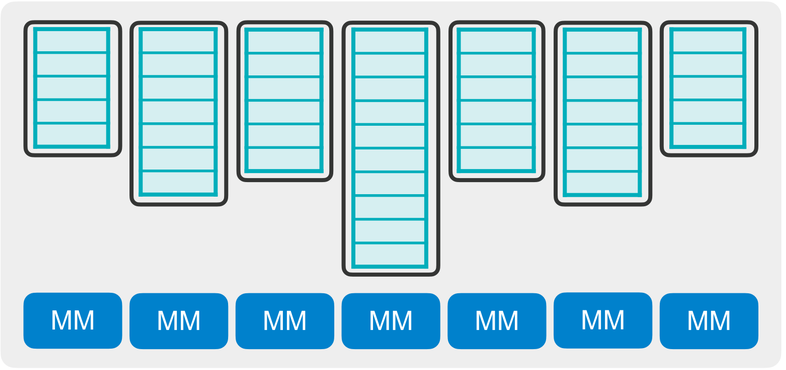
Separate Computation



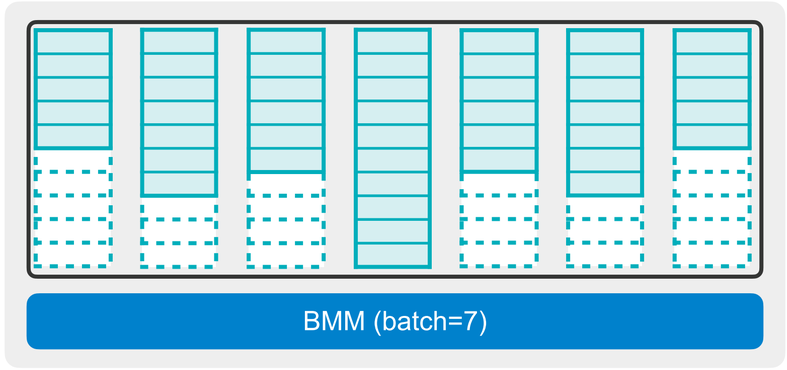
TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

Trading computation for regularity

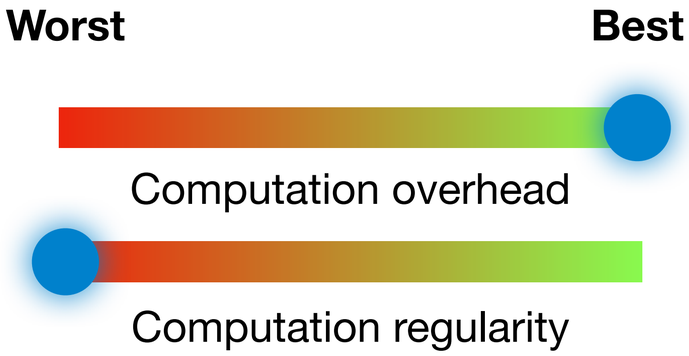
Dense convolution: best regularity but large computation overhead

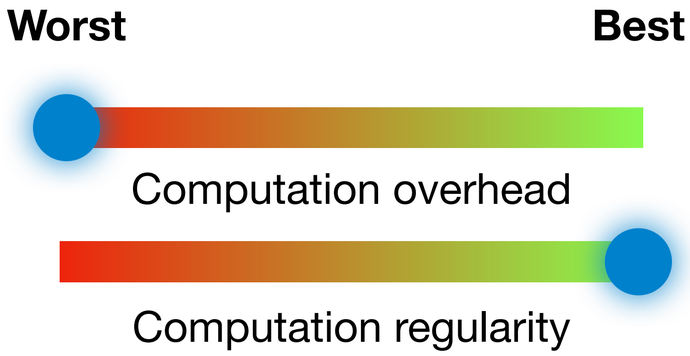


Separate Computation



Dense Convolution

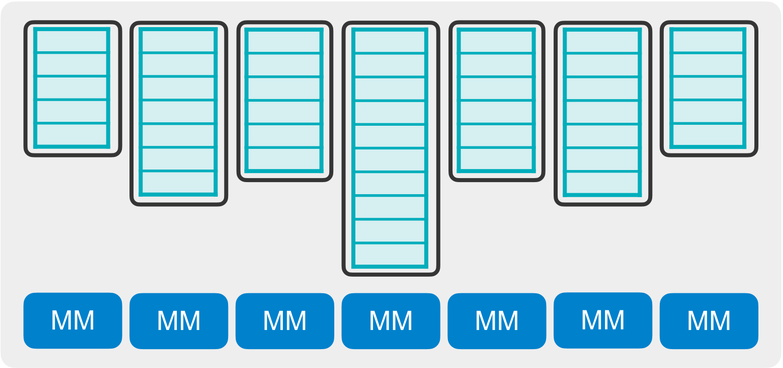




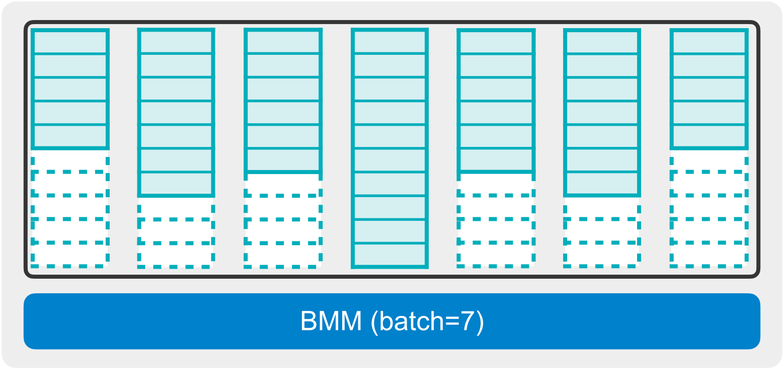
TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

Trading computation for regularity

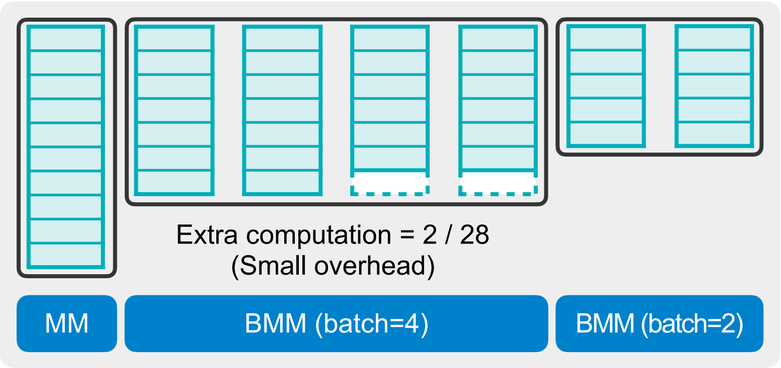
Computation with grouping: balancing overhead and regularity



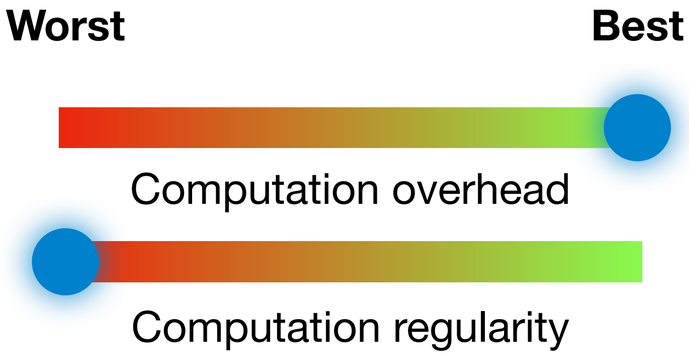
Separate Computation

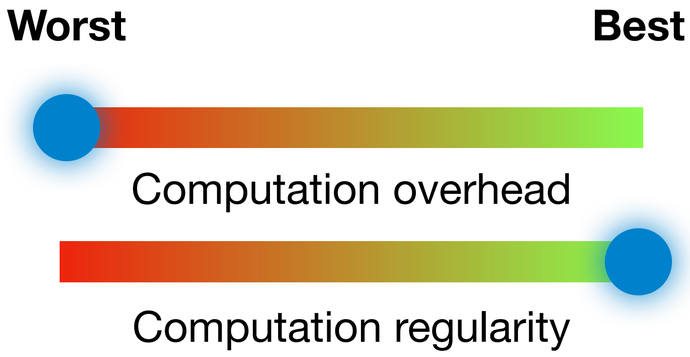


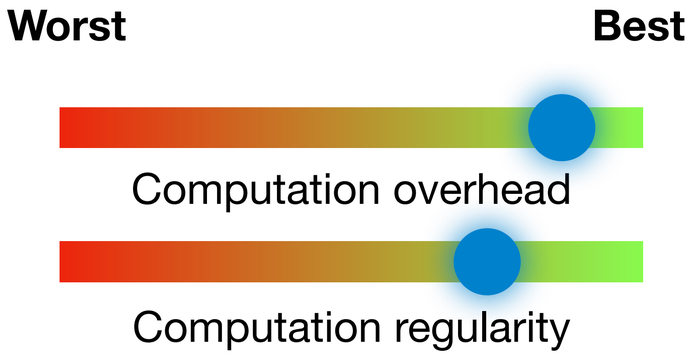
Dense Convolution



Computation with grouping



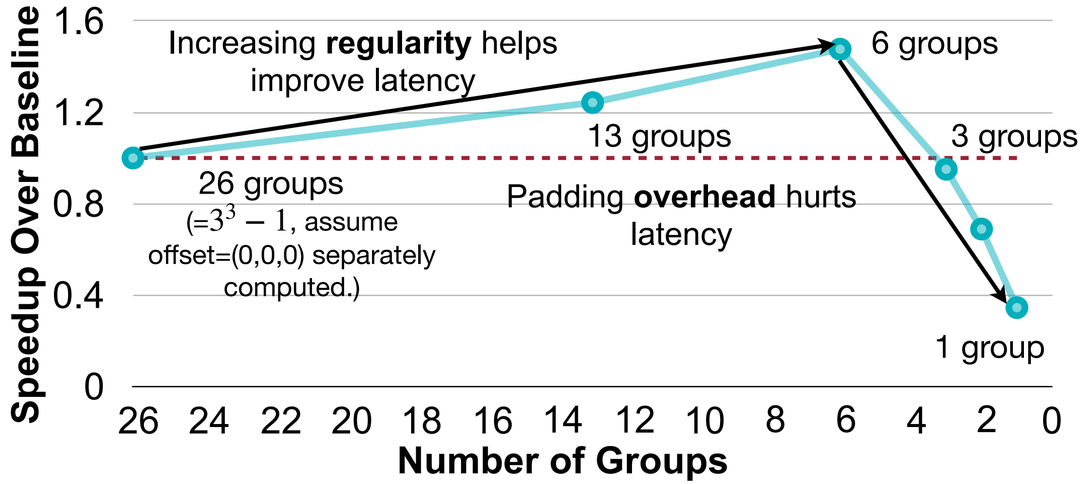


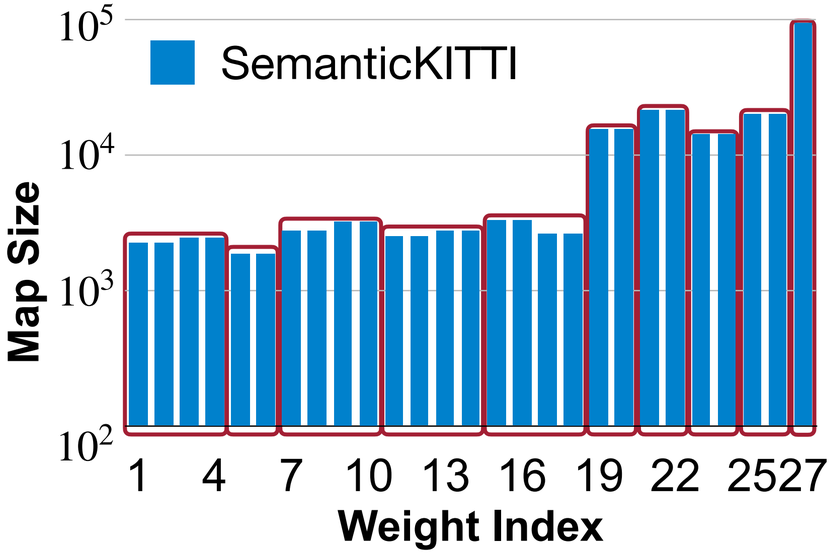


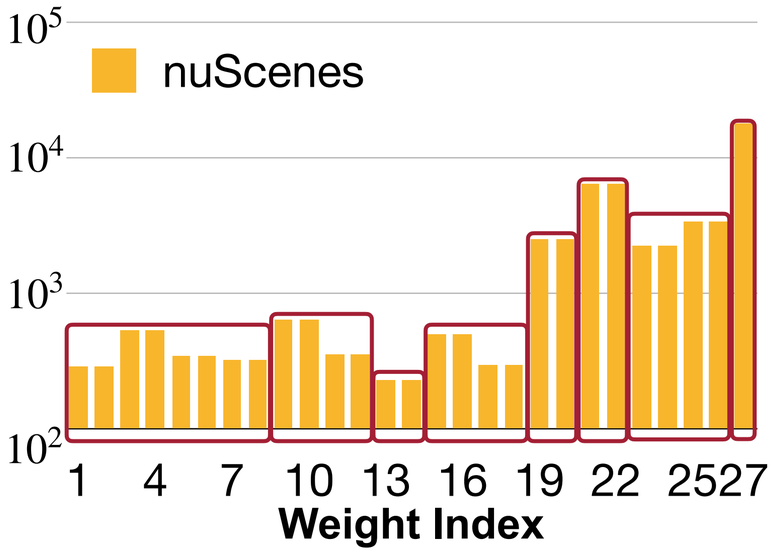
TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

Trading computation for regularity

Searching customized strategy for different model and datasets

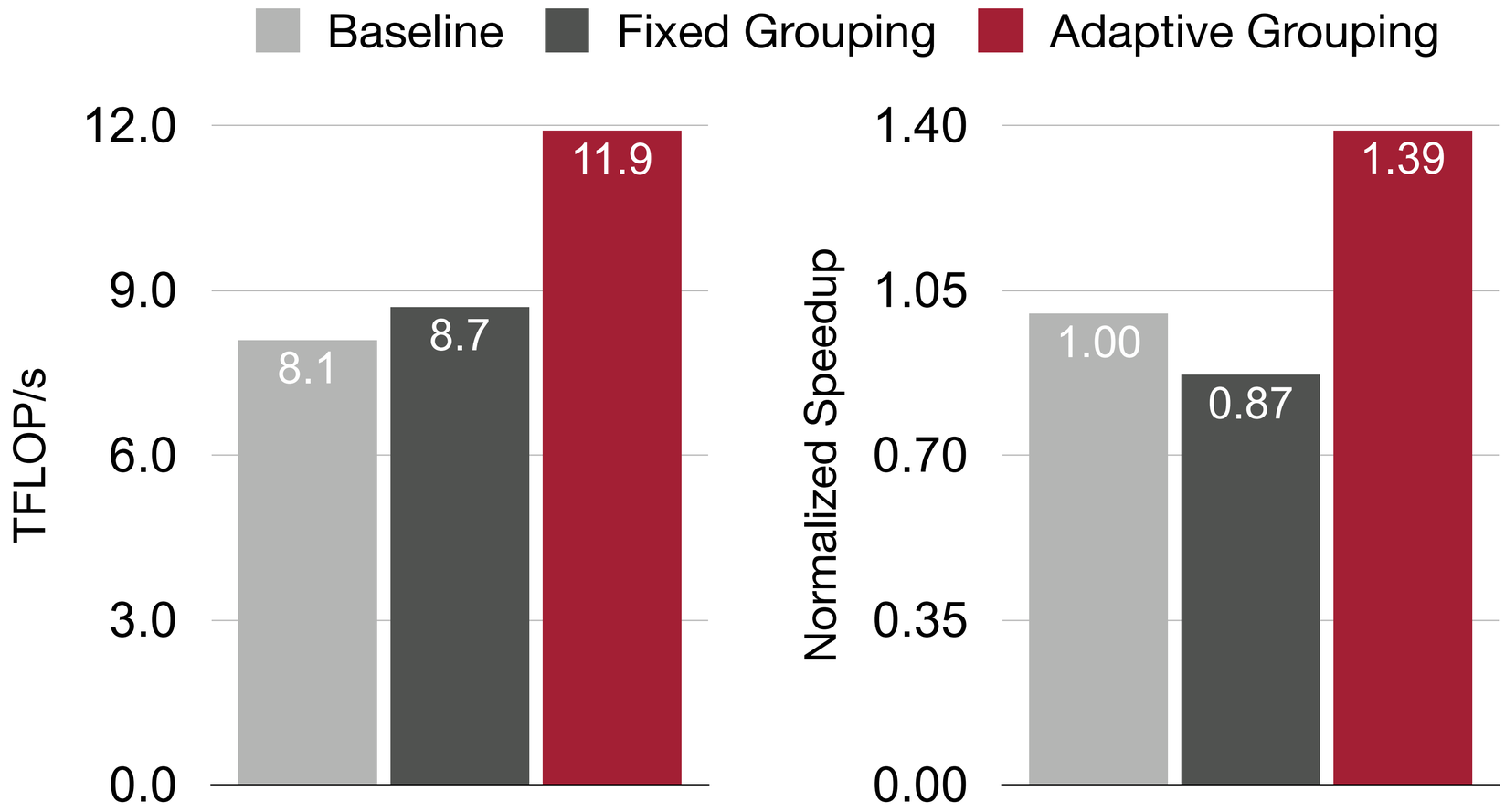






Results on matrix multiplication optimizations

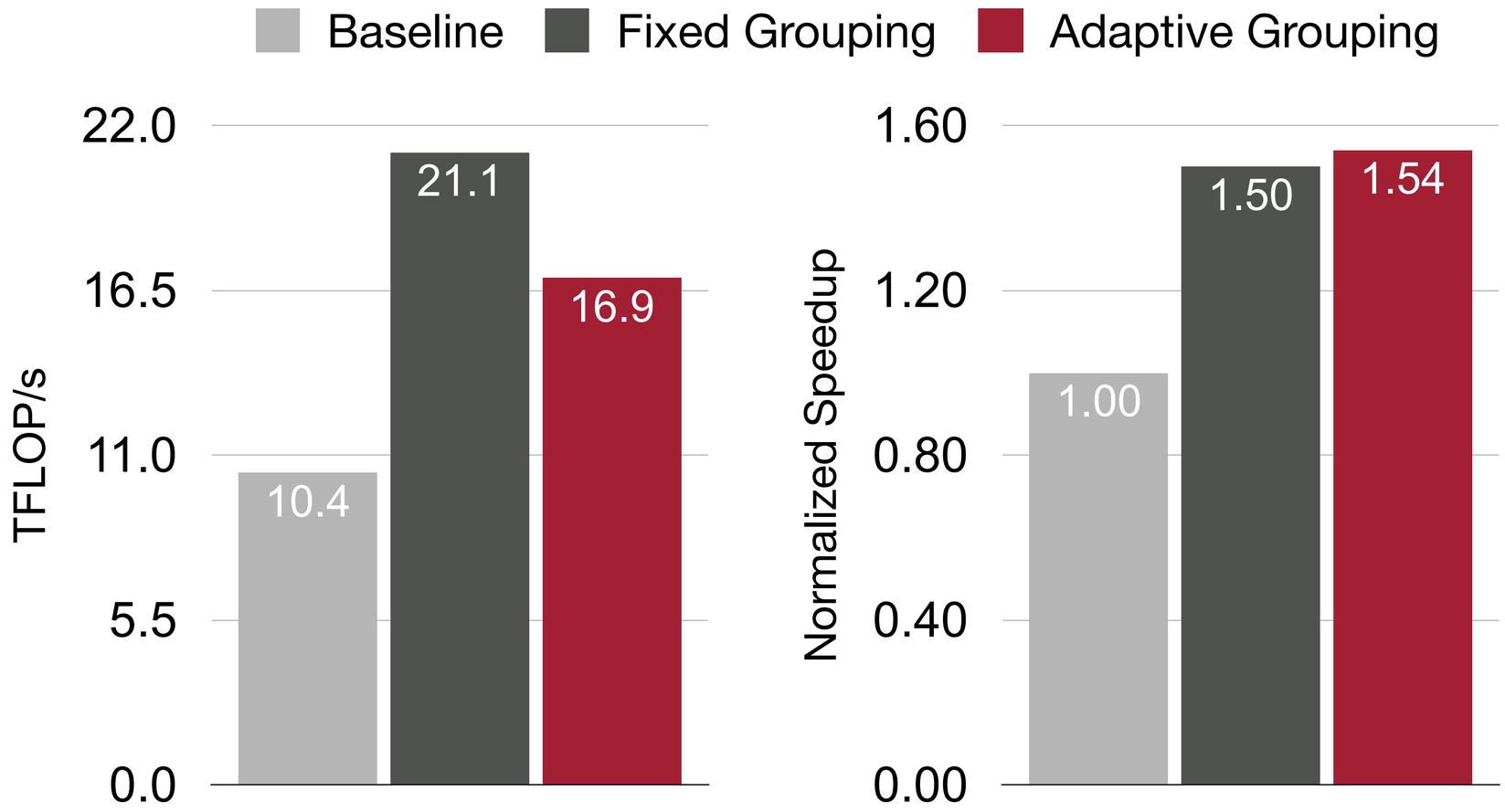
SemanticKITTI



TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

Results on matrix multiplication optimizations

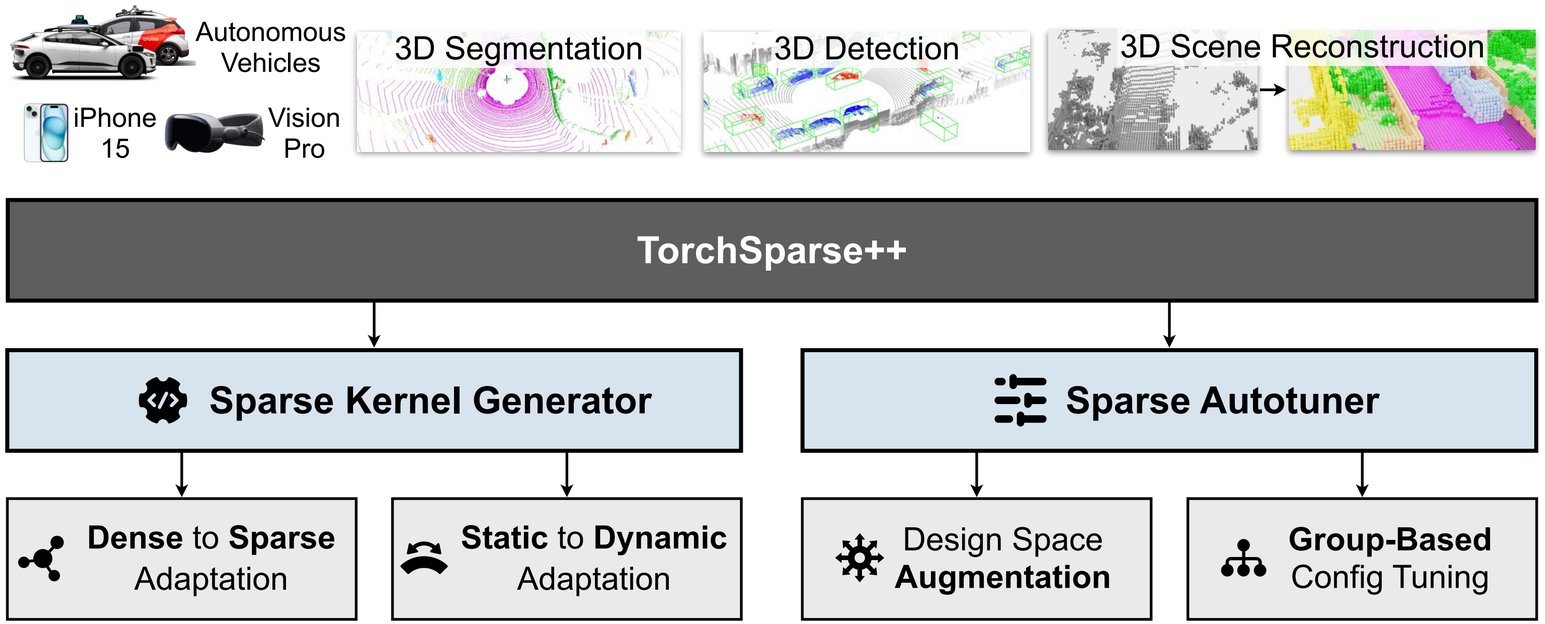
nuScenes: fixed grouping has best TFLOP/s but adaptive grouping is faster

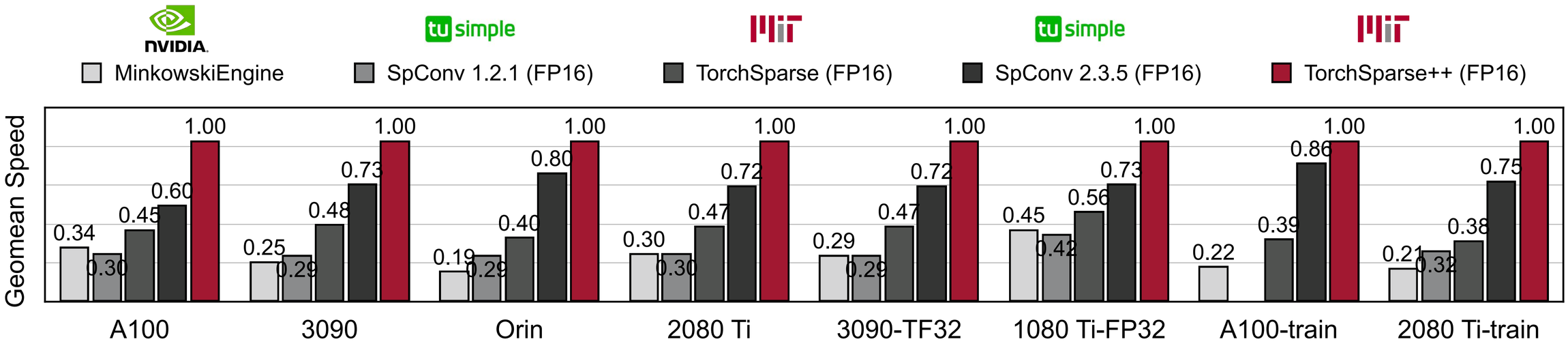


This is because fixed grouping introduced large amount of **redundant computation**.

TorchSparse: Efficient Point Cloud Inference Engine [Tang *et al.*, MLSys 2022]

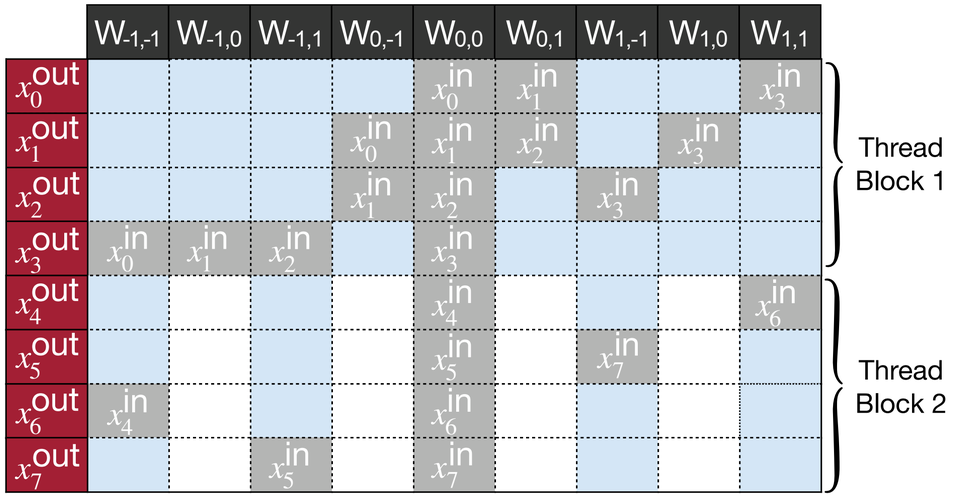
TorchSparse++: Overlapped memory and computation



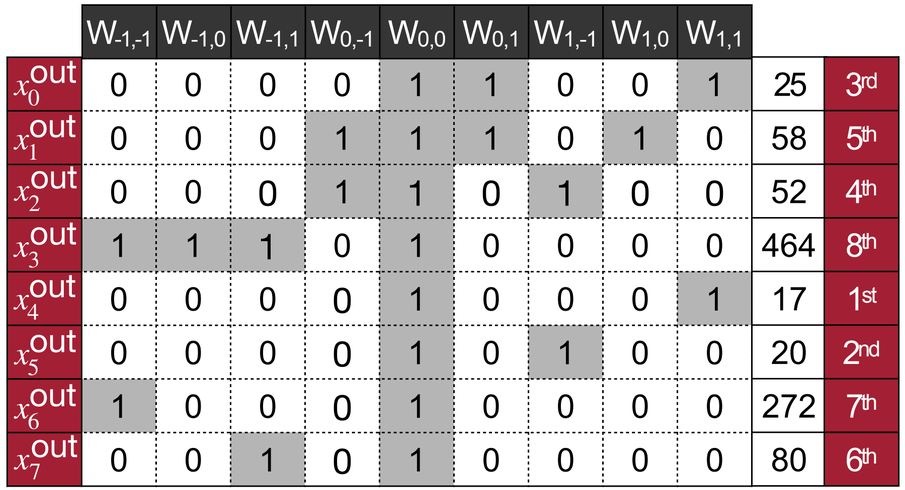


TorchSparse++ [Tang and Yang *et. al*, MICRO 2023]

TorchSparse++: Overlapped memory and computation



redundant computation=**34**



	W-1,-1	W-1,0	W-1,1	W0,-1	W0,0	W0,1	W1,-1	W1,0	W1,1		
x_0^{out}	0	0	0	0	1	1	0	0	1	25	3rd
x_1^{out}	0	0	0	1	1	1	0	1	0	58	5th
x_2^{out}	0	0	0	1	1	0	1	0	0	52	4th
x_3^{out}	1	1	1	0	1	0	0	0	0	464	8th
x_4^{out}	0	0	0	0	1	0	0	0	1	17	1st
x_5^{out}	0	0	0	0	1	0	1	0	0	20	2nd
x_6^{out}	1	0	0	0	1	0	0	0	0	272	7th
x_7^{out}	0	0	1	0	1	0	0	0	0	80	6th

Output point 0

redundant computation=**22**

redundant computation=**26**

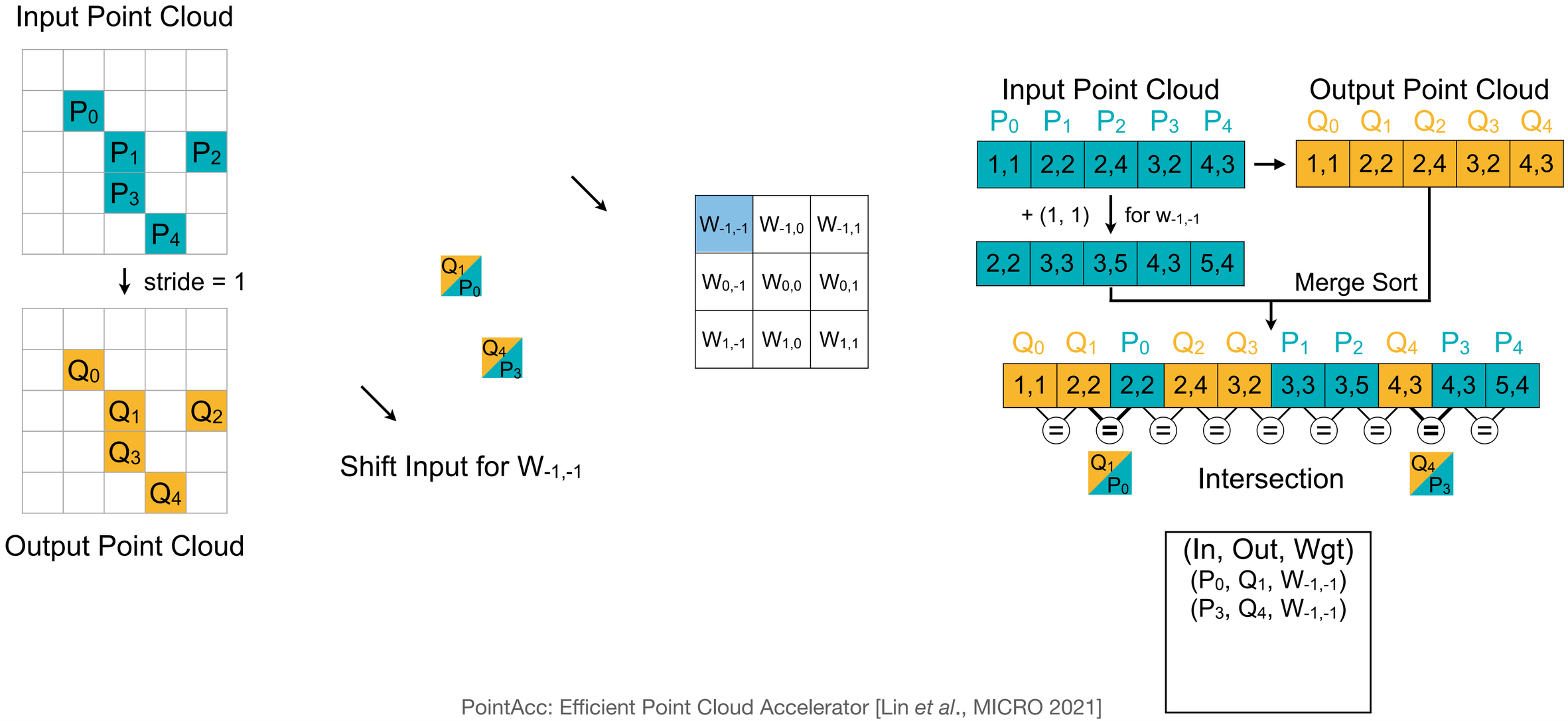
TorchSparse++ [Tang and Yang *et. al*, MICRO 2023]

System & Hardware Support for Sparsity

- EIE: Weight Sparsity + Activation Sparsity for GEMM
- NVIDIA Tensor Core: M:N Weight Sparsity Sparsity
- **TorchSparse & PointAcc: Activation Sparsity for Sparse Convolution**
  - **TorchSparse: Sparse Convolution Library**
  - **PointAcc: Hardware Accelerator for Sparse Convolution**

Mapping Unit

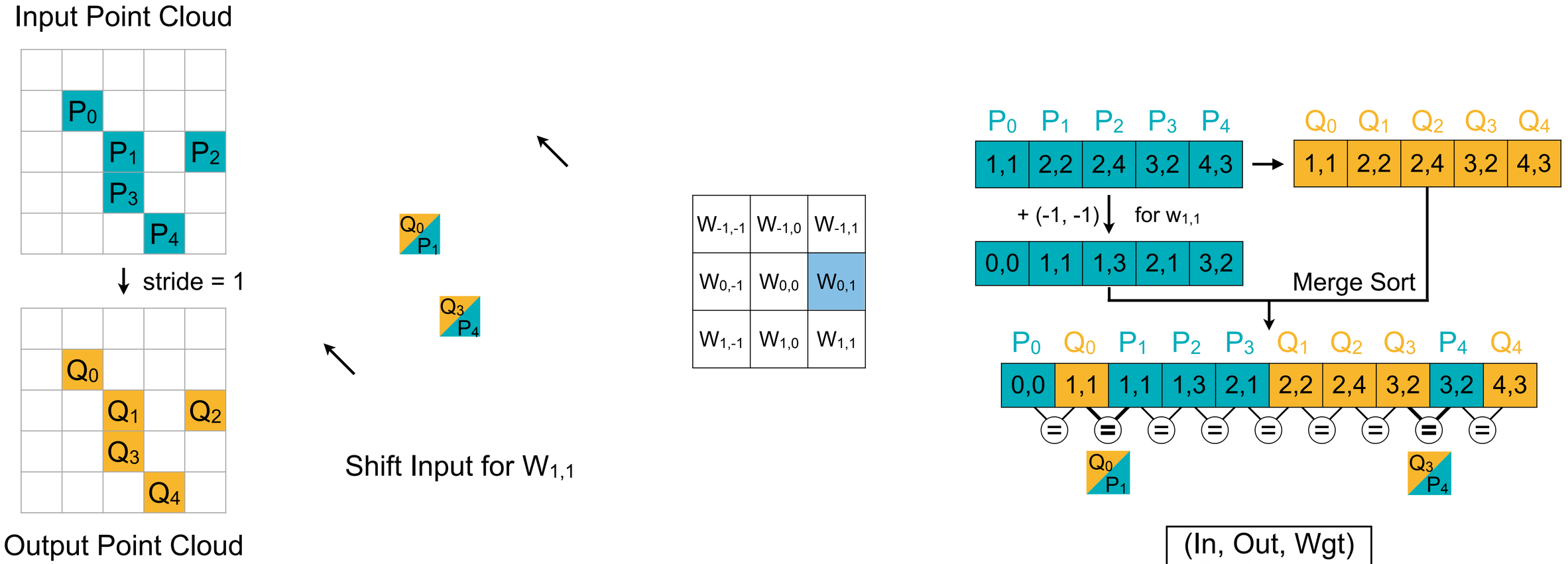
Merge sort can be used to find mappings in sparse convolution



PointAcc: Efficient Point Cloud Accelerator [Lin *et al.*, MICRO 2021]

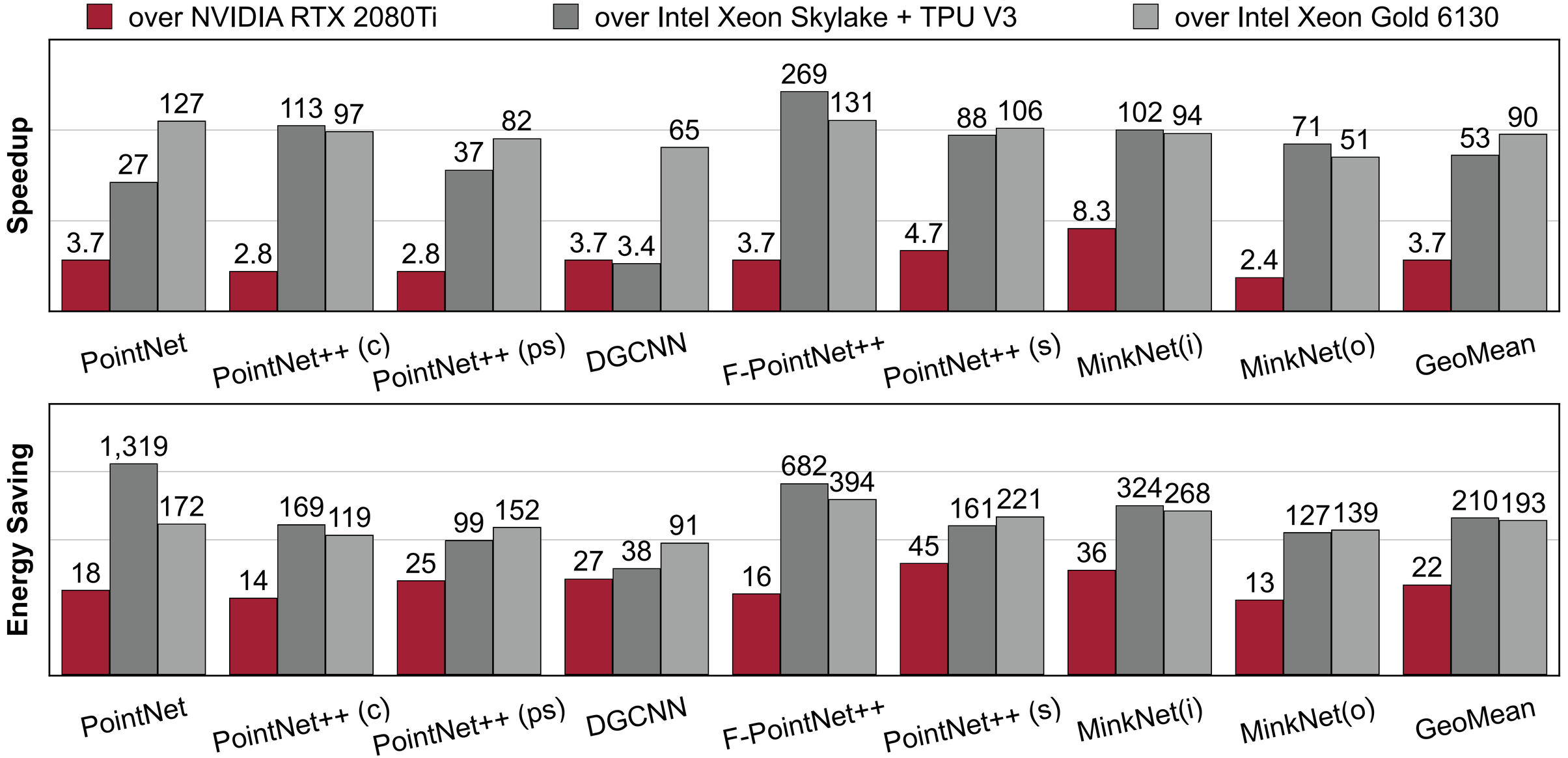
Mapping Unit

Merge sort can be used to find mappings in sparse convolution



PointAcc: Efficient Point Cloud Accelerator [Lin *et al.*, MICRO 2021]

PointAcc: Speedup and Energy Saving



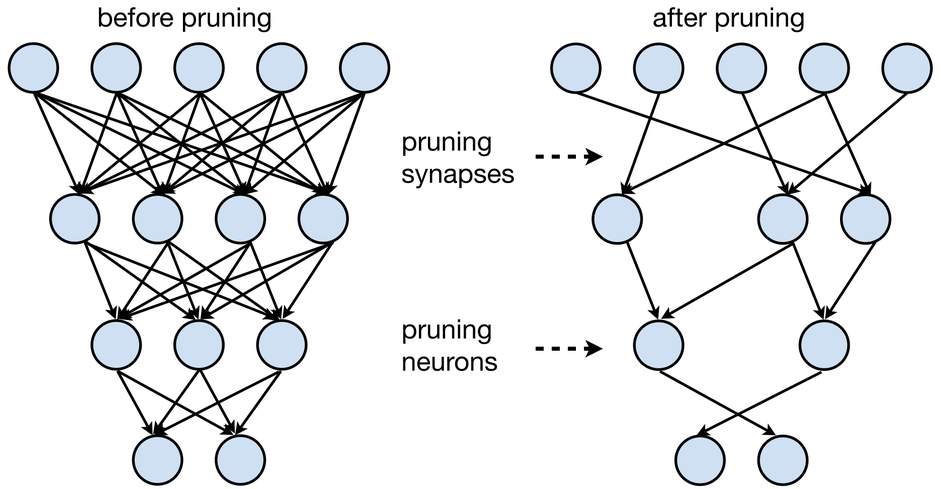
PointAcc: Efficient Point Cloud Accelerator [Lin *et al.*, MICRO 2021]

Summary of Today's Lecture

In this lecture, we introduced:

- Automated ways to find pruning ratios
- Lottery ticket hypothesis
- System and hardware support for different granularities

- **We will cover in the next lecture:**
  - Numeric data types in modern computer systems
  - Basic concept of neural network quantization
  - Common neural network quantization methods



References

1. Learning Both Weights and Connections for Efficient Neural Network [Han et al., NeurIPS 2015]
2. Exploring the granularity of sparsity in convolutional neural networks [Mao et al., CVPR-W]
3. Learning Structured Sparsity in Deep Neural Networks [Wen et al., NeurIPS 2016]
4. Learning Efficient Convolutional Networks through Network Slimming [Liu et al., ICCV 2017]
5. A Systematic DNN Weight Pruning Framework using Alternating Direction Method of Multipliers [Zhang et al., ECCV 2018]
6. AMC: Automl for Model Compression and Acceleration on Mobile Devices [He et al., ECCV 2018]
7. Accelerating Inference with Sparsity Using the NVIDIA Ampere Architecture and NVIDIA TensorRT
8. EIE: Efficient Inference Engine on Compressed Deep Neural Network [Han et al., ISCA 2016]
9. ESE: Efficient Speech Recognition Engine with Sparse LSTM on FPGA [Han et al., FPGA 2017]
10. Block Sparse Format [NVIDIA, 2021]
11. Accelerating Sparse Deep Neural Networks [Mishra et al., arXiv 2021]