Model Compression and Pruning Techniques

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Acknowledgement: Some slides are borrowed from the Song Han's course on TinyML.

Outline

Model compression: a brief introduction

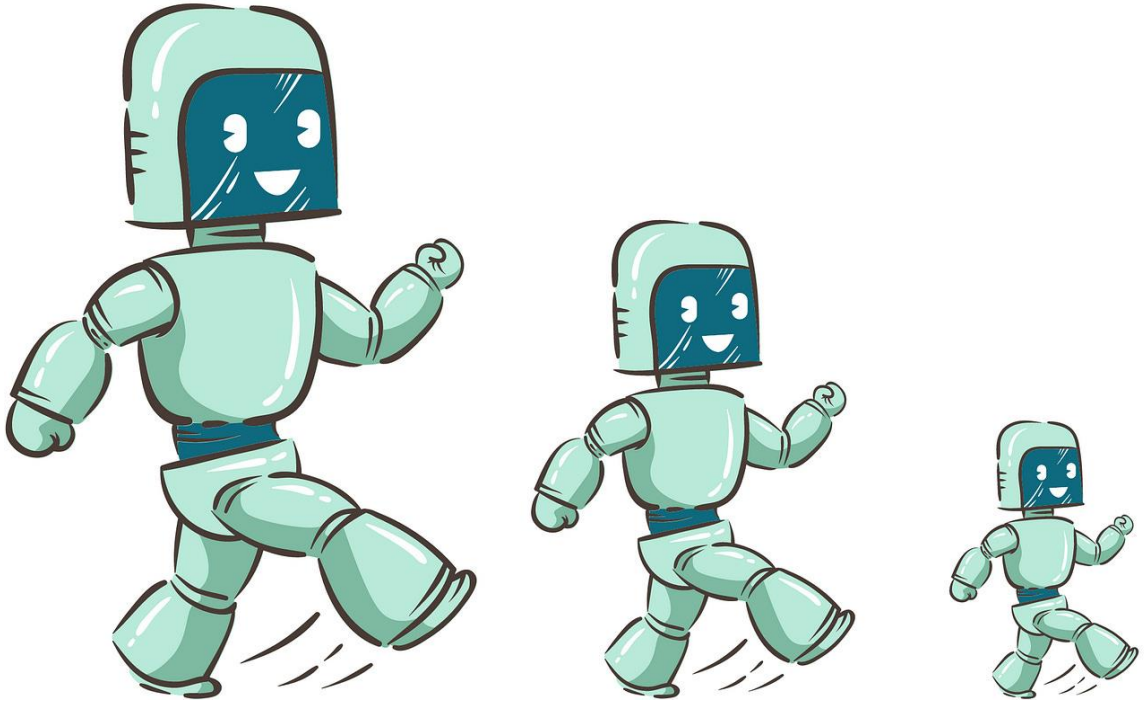
- Pruning
- Quantization
- Knowledge Distillation
- Low Rank Factorization

Pruning in more details

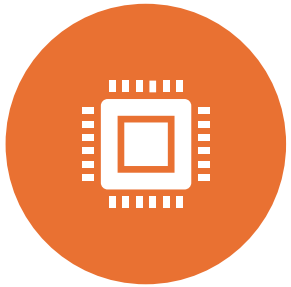
- Pruning criteria
- Pruning granularity
- Pruning ratio
- When to prune

What Is Model Compression?

- Reducing the size of a model
- without significantly compromising its predictive accuracy.

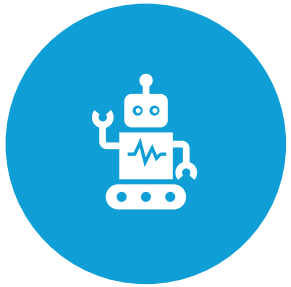


Why Model Compression?



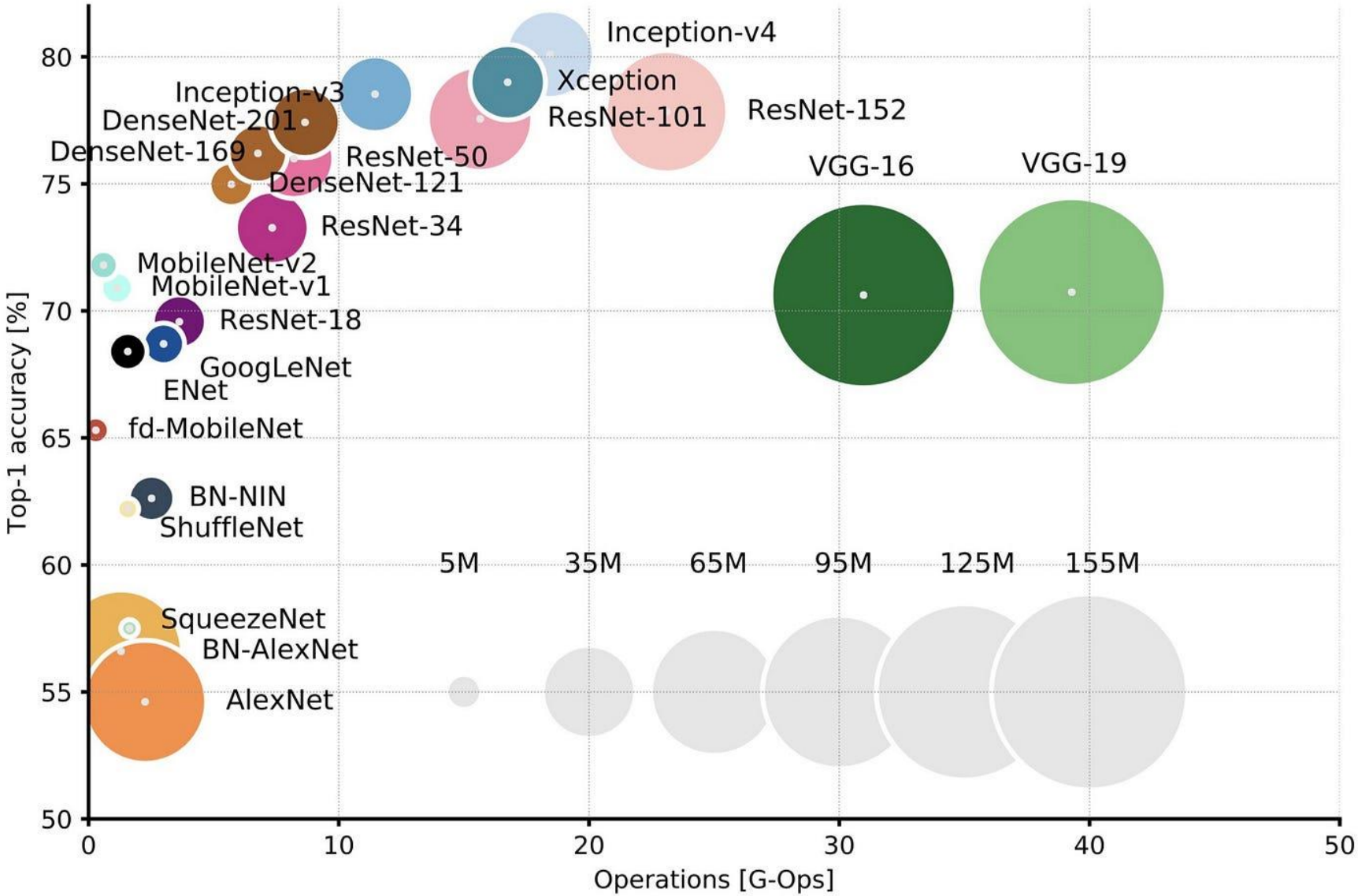
Deep learning models are compute- and memory- intensive.

Edge devices have limited power, memory, and compute.



Model compression enables AI on-device

Applications: AIoT, wearables, autonomous drones.

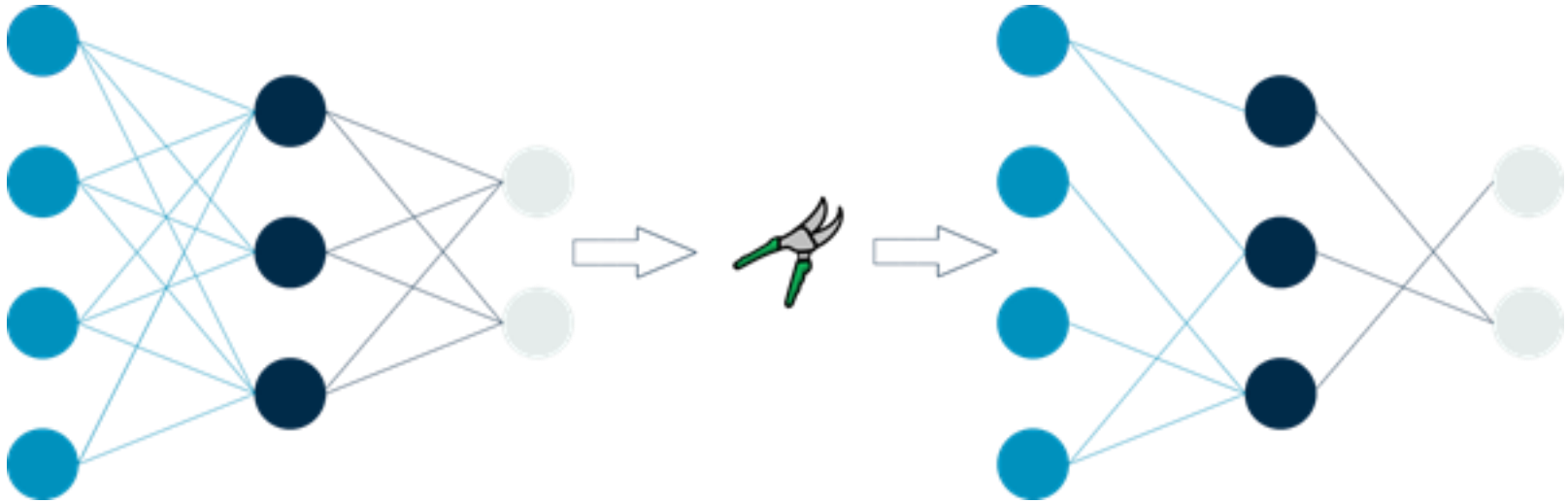

Inception-v4
Inception-v3
Xception
ResNet-101
ResNet-152
DenseNet-201
DenseNet-169
ResNet-50
DenseNet-121
VGG-16
VGG-19
ResNet-34
MobileNet-v2
MobileNet-v1
ResNet-18
GoogLeNet
ENet
fd-MobileNet
BN-NIN
ShuffleNet
5M
35M
65M
95M
125M
155M
SqueezeNet
BN-AlexNet
AlexNet
Top-1 accuracy [%]
80
75
70
65
60
55
50
0
10
20
30
40
50
Operations [G-Ops]

Model Compression Techniques

- Pruning
- Quantization
- Konwledge distillation
- Low rank factorization

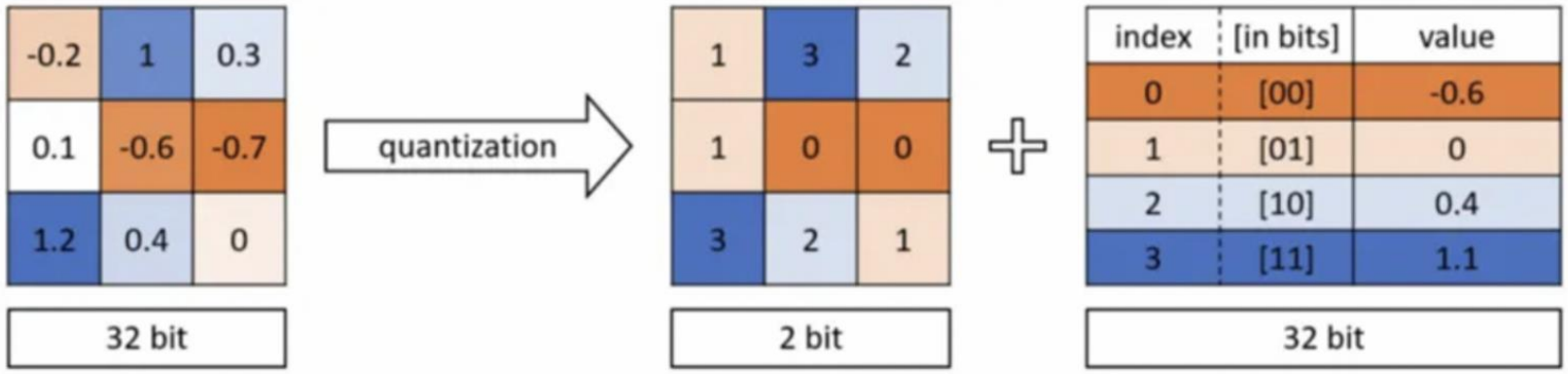
What Is Pruning?

- Systematically removing less significant parameters of a NN



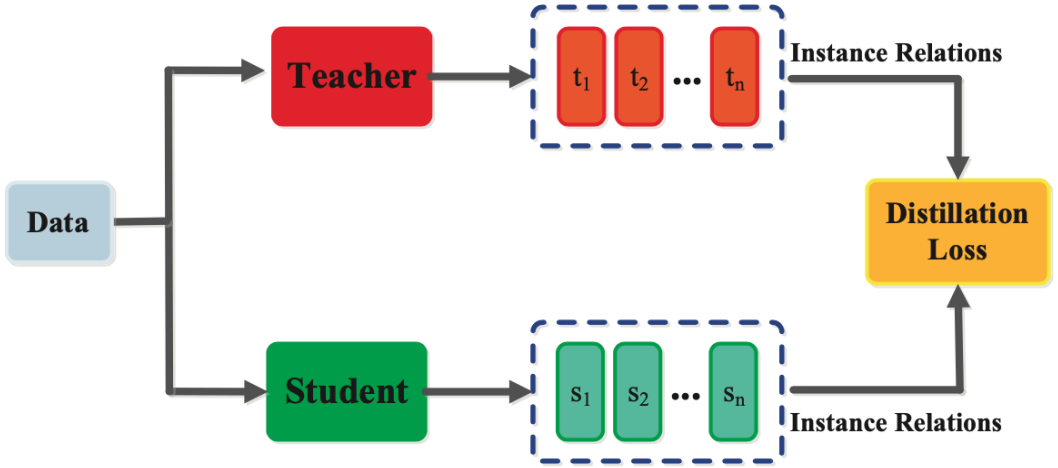
What Is Quantization?

- Reduce the **total number of bits** required to represent each parameter
  - usually converting floating-point numbers into integers



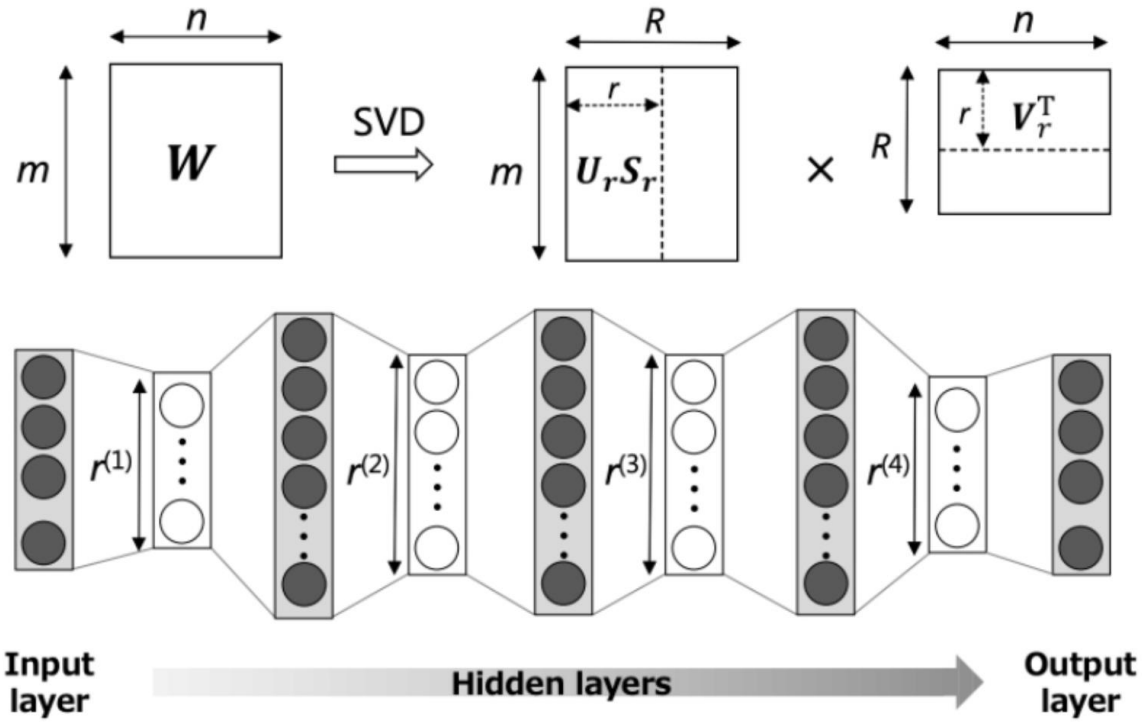
What Is Knowledge Distillation?

- Transferring experience from a largescale model (teacher) to a smaller-scale model (student)
  - extracting the informative aspects of a large model's behaviour
  - instilling this knowledge into a smaller model

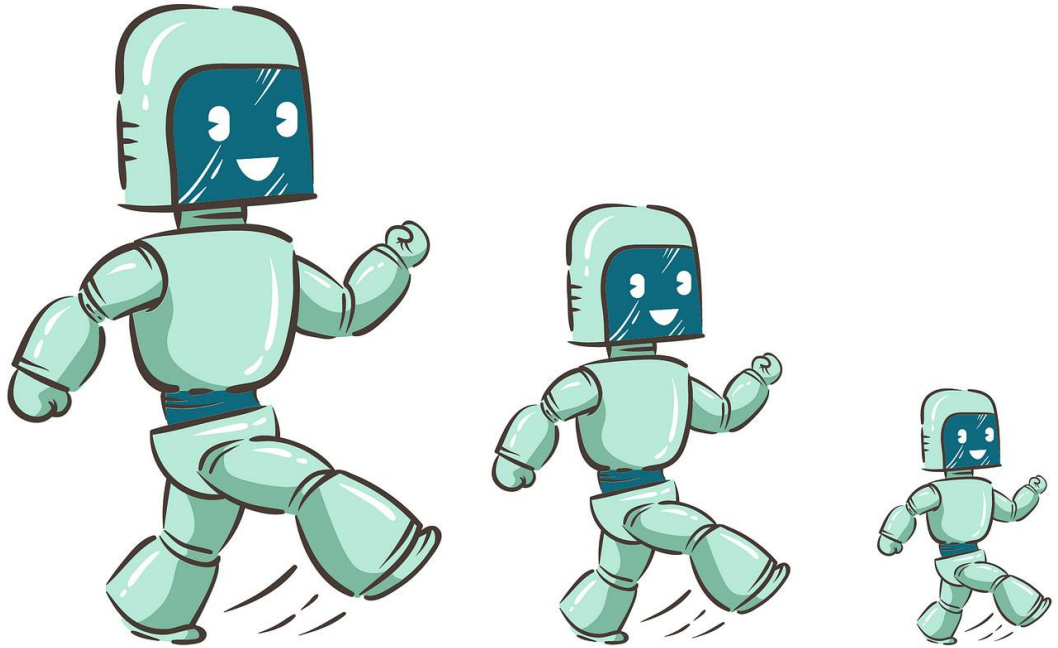


What Is Low-rank Factorization?

Decomposing large, dense weight matrices into smaller, lower-rank matrices.



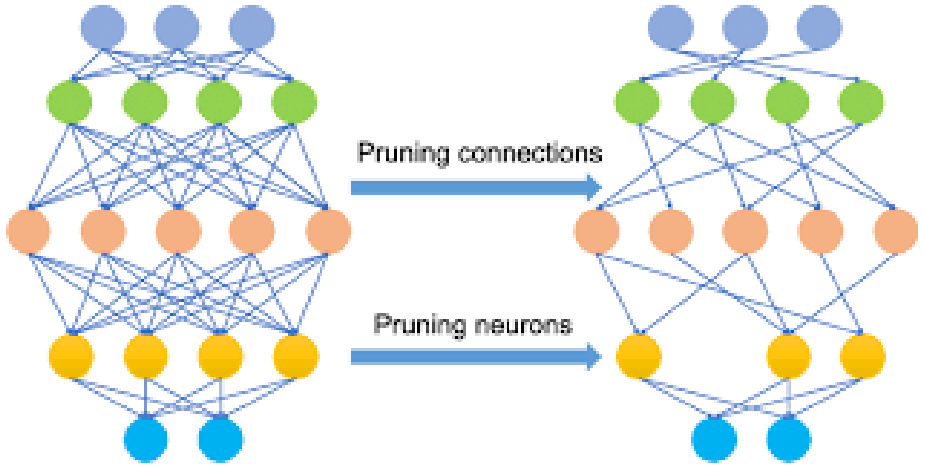
Pruning
in more details



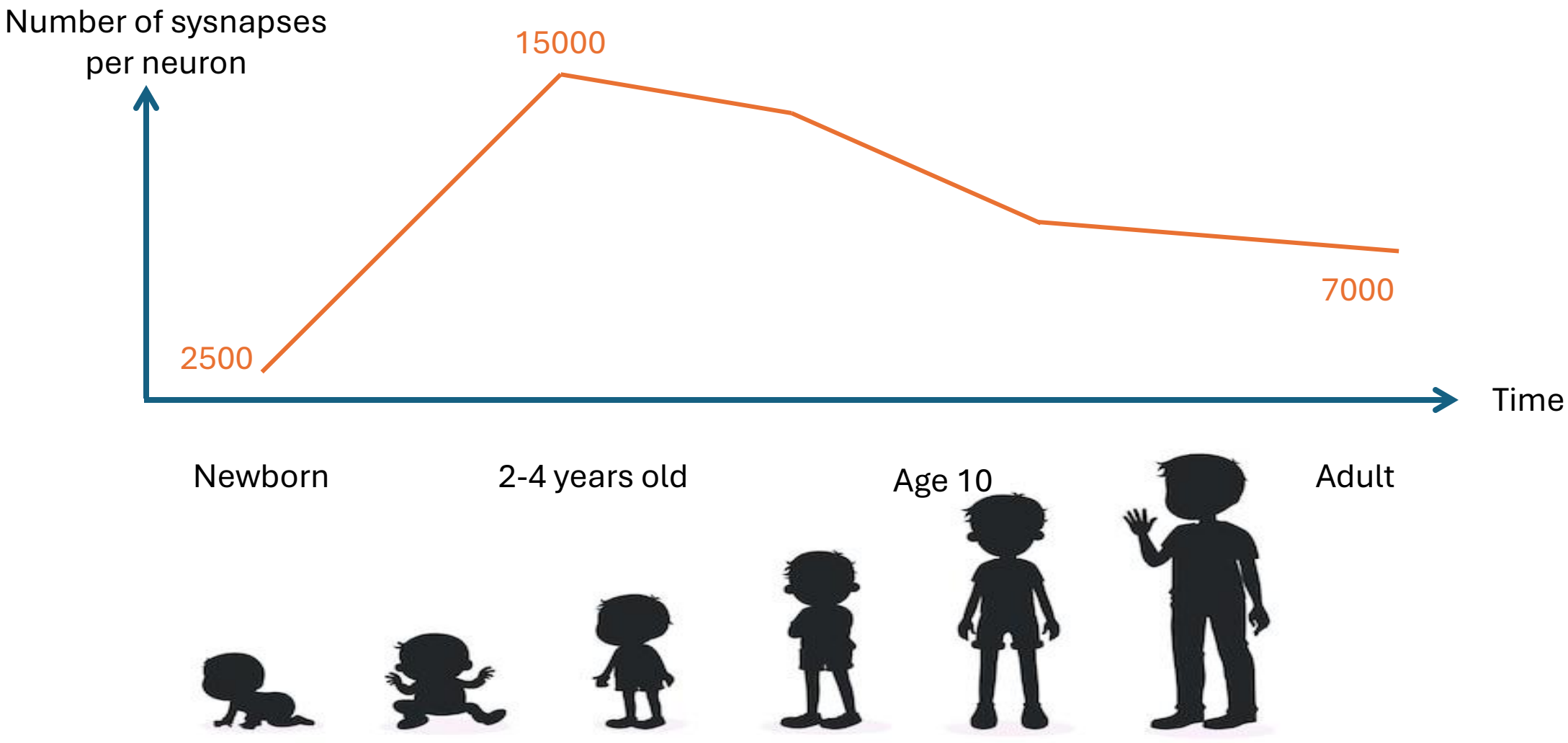
What Is Pruning?

- Also referred to as “Network Sparsification”

- Selective removal of network parameters (weights and neurons)
  - those that contribute the least to the network’s output



Pruning happens in human brain



Neural Network Pruning

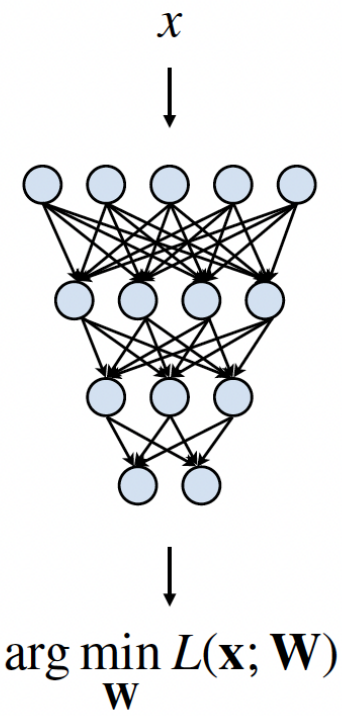
- In general, we could formulate the pruning as follows:

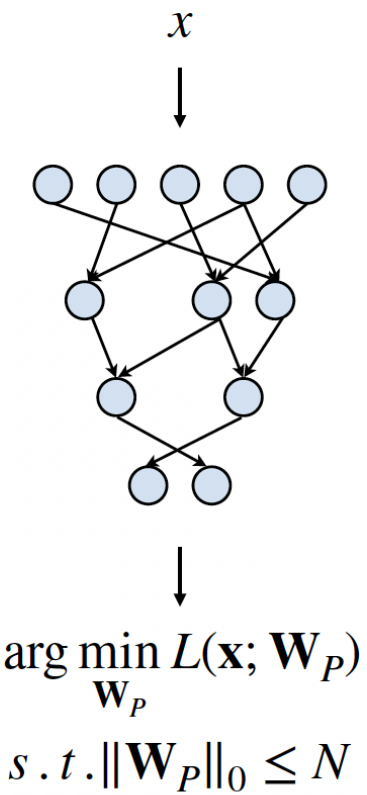
$$\arg\min_{\mathbf{W}_P} L(\mathbf{x}; \mathbf{W}_P)$$

subject to

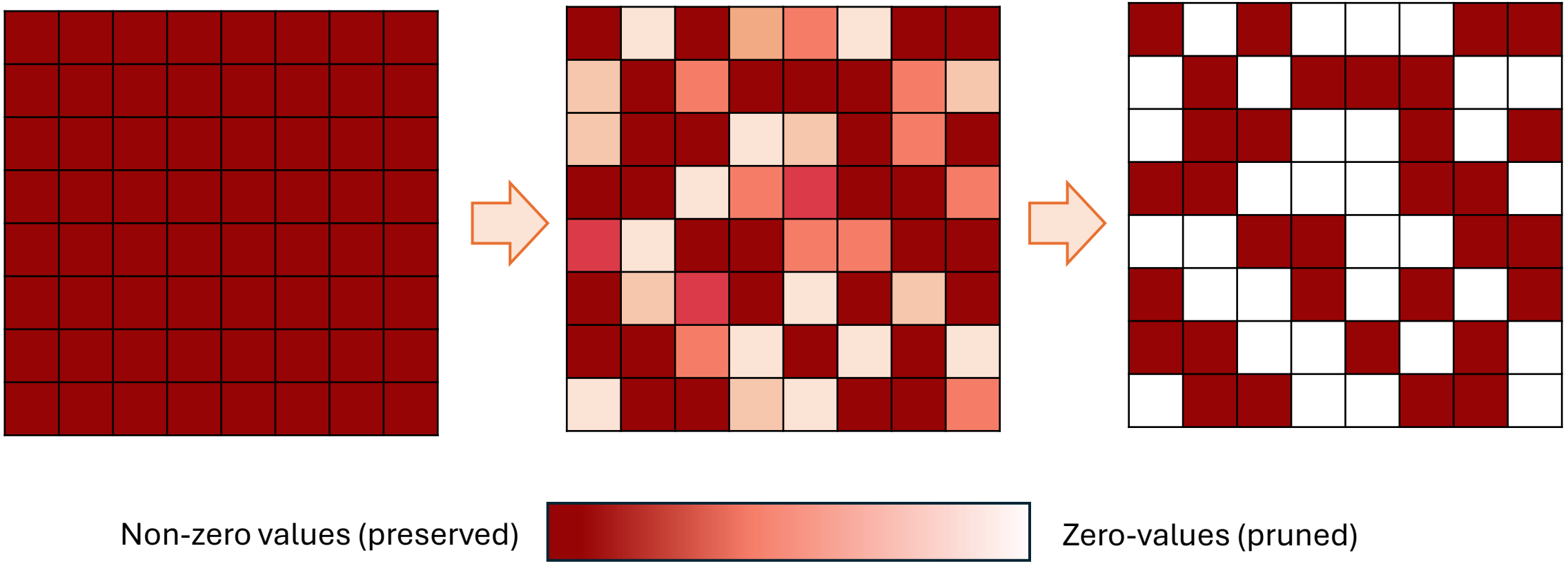
$$\|\mathbf{W}_p\|_0 < N$$

  - 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.





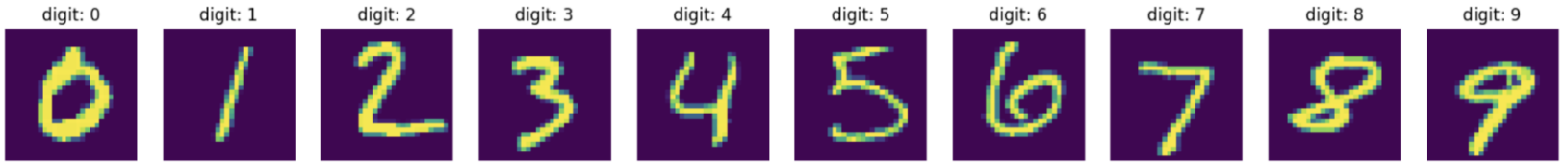
Neural Network Pruning



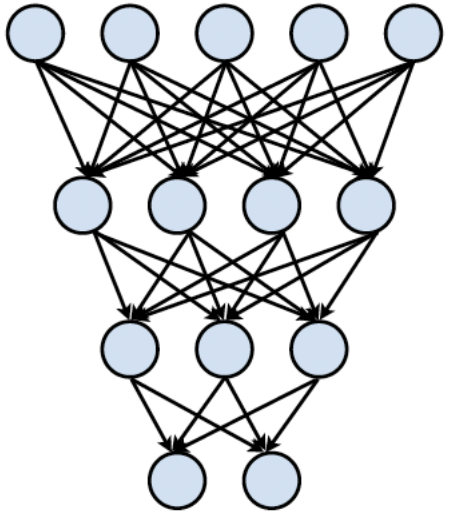
Let's see a demo!

- Refer to the notebook

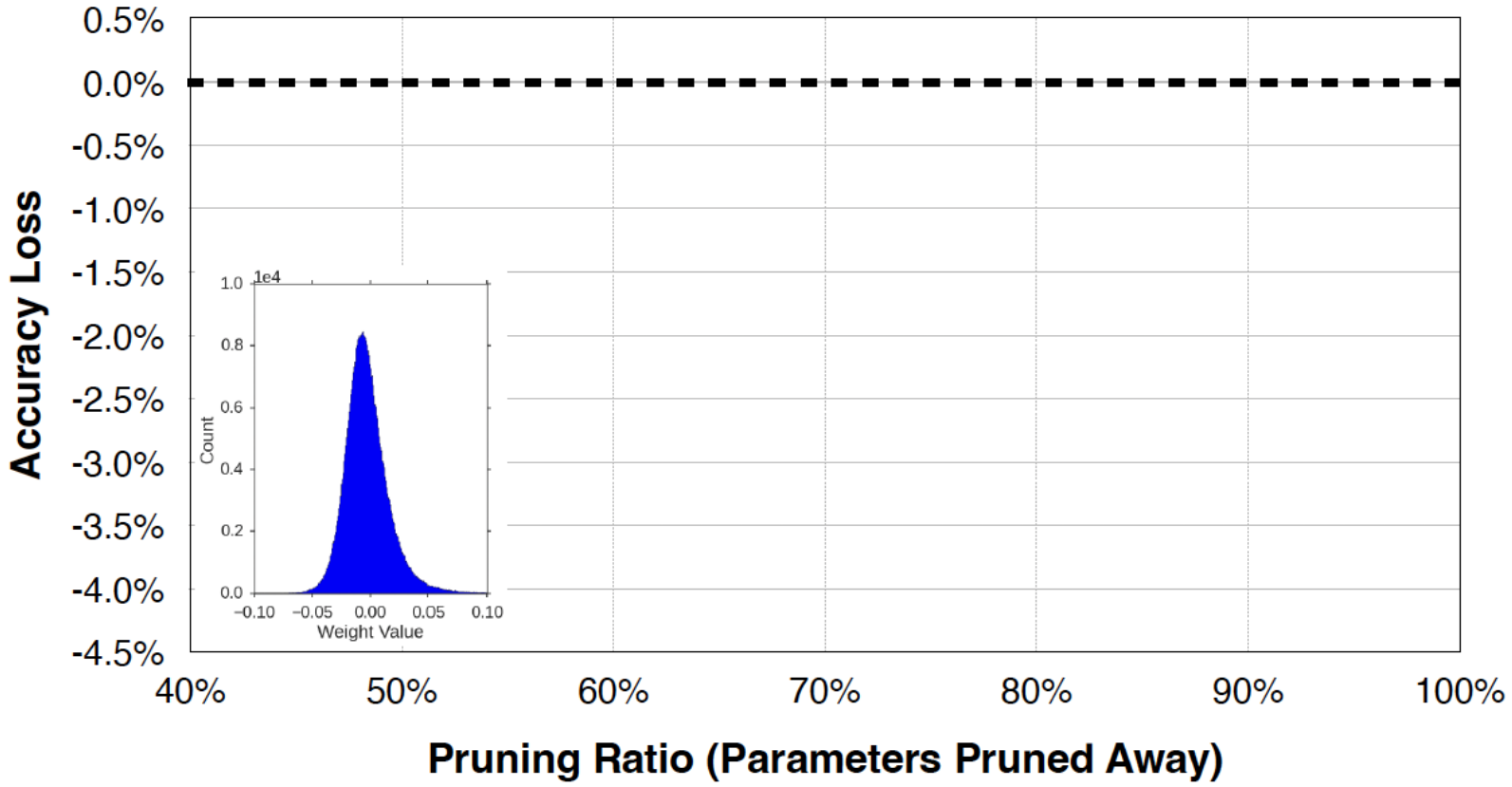
```
class Net(nn.Module):

    def __init__(self):

    super(Net, self).__init__()

    self.conv1 = nn.Conv2d(1, 32, 3, 1) # 1 x 32 x 3 x 3 = 288 parameters
    self.conv2 = nn.Conv2d(32, 64, 3, 1) # 32 x 64 x 3 x 3=18,432 paramters
    self.dropout1 = nn.Dropout(0.25)
    self.dropout2 = nn.Dropout(0.5)
    self.fc1 = nn.Linear(9216, 128) # 9216 x 128 = 1,179,648 parameters
    self.fc2 = nn.Linear(128, 10) # 128 x 10 = 1,280 parameters
```



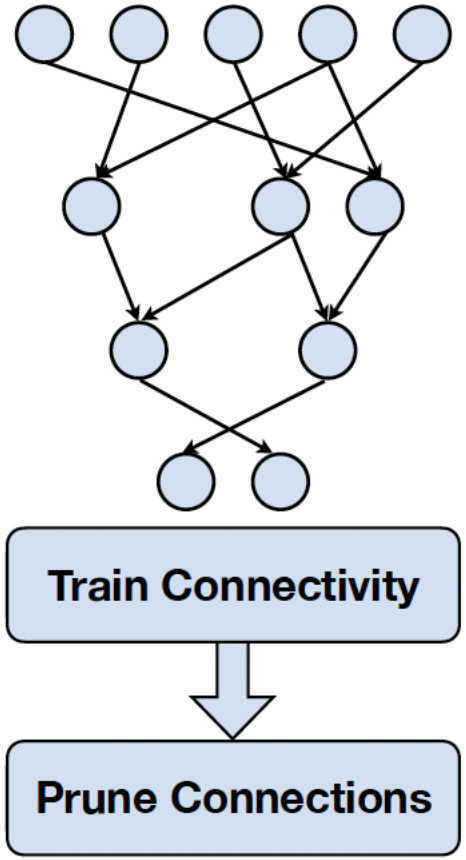
Neural network pruning

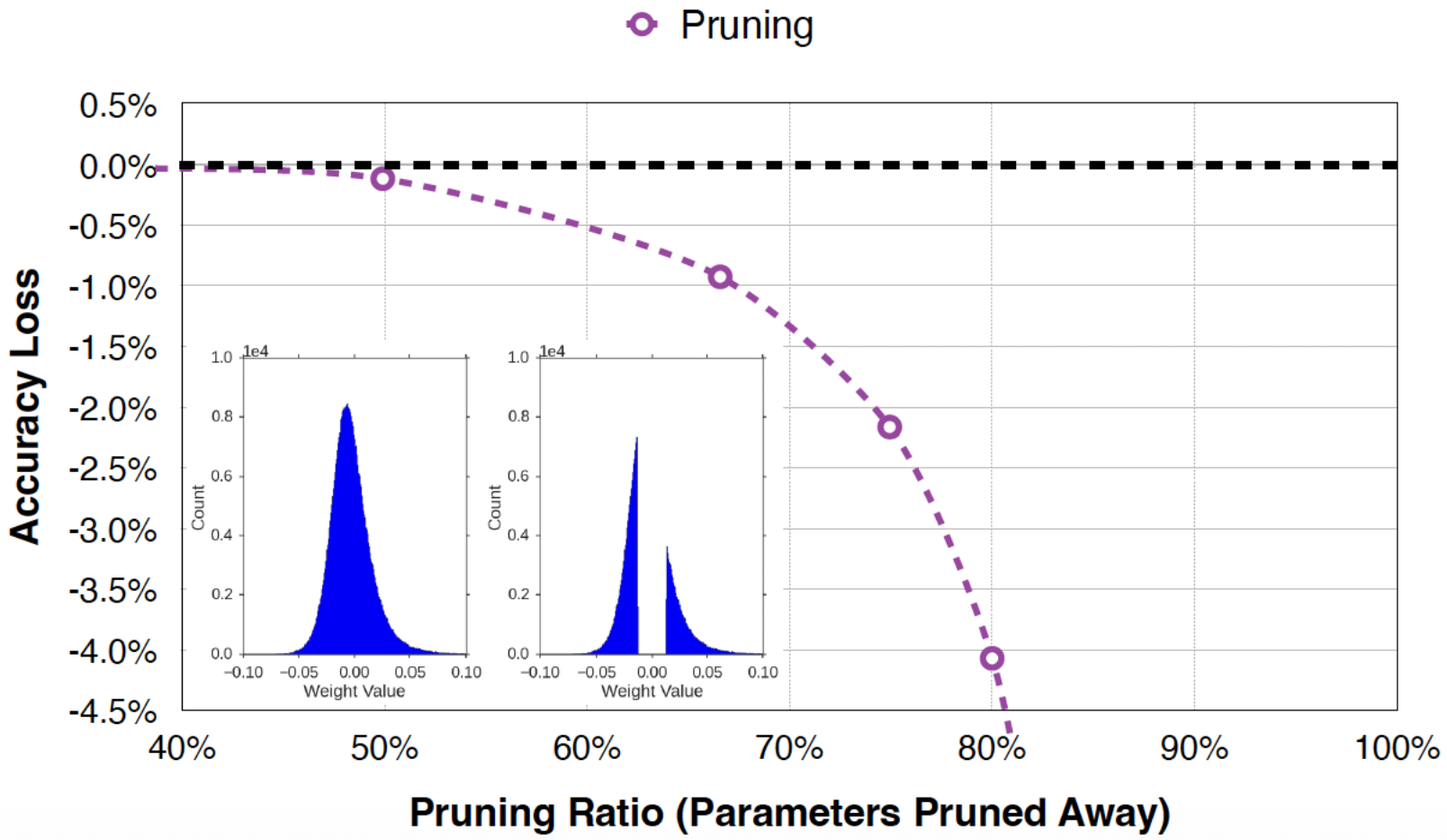


Train Connectivity

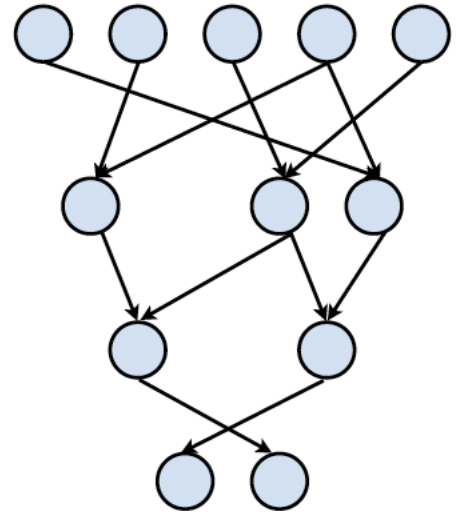


Neural network pruning





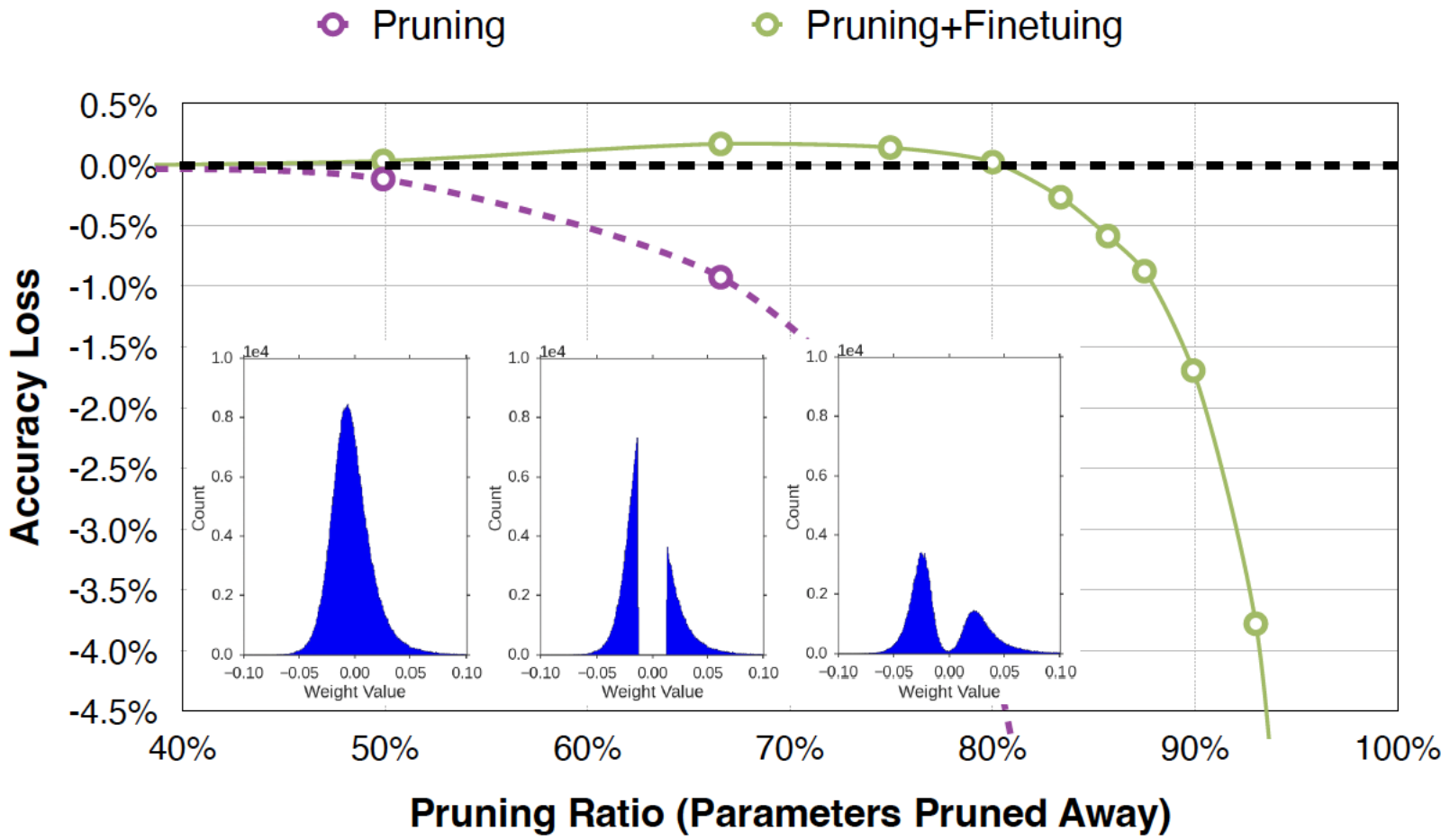
Neural network pruning



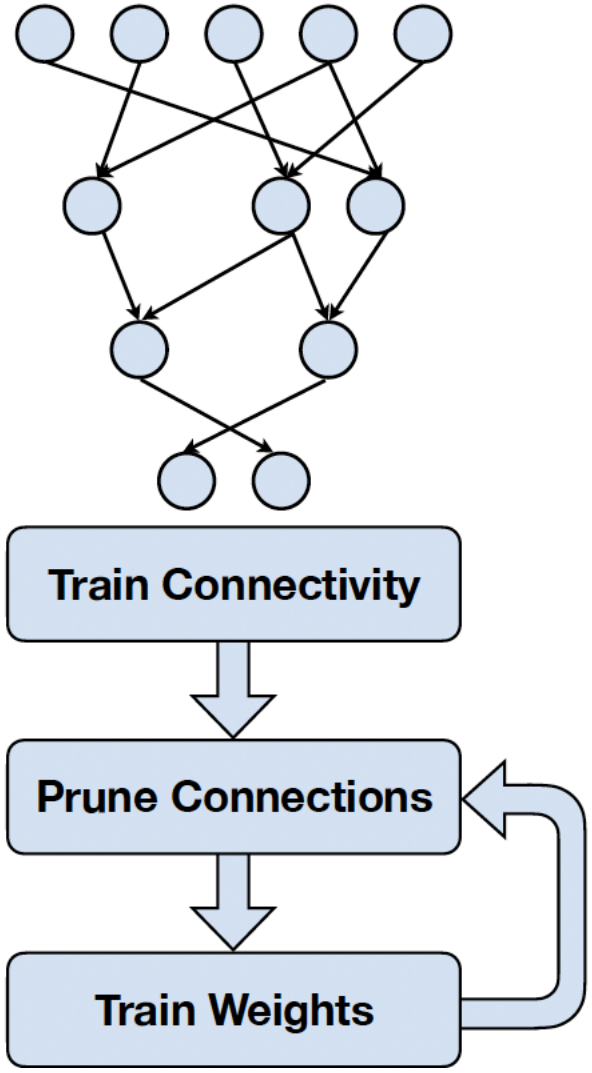
Train Connectivity

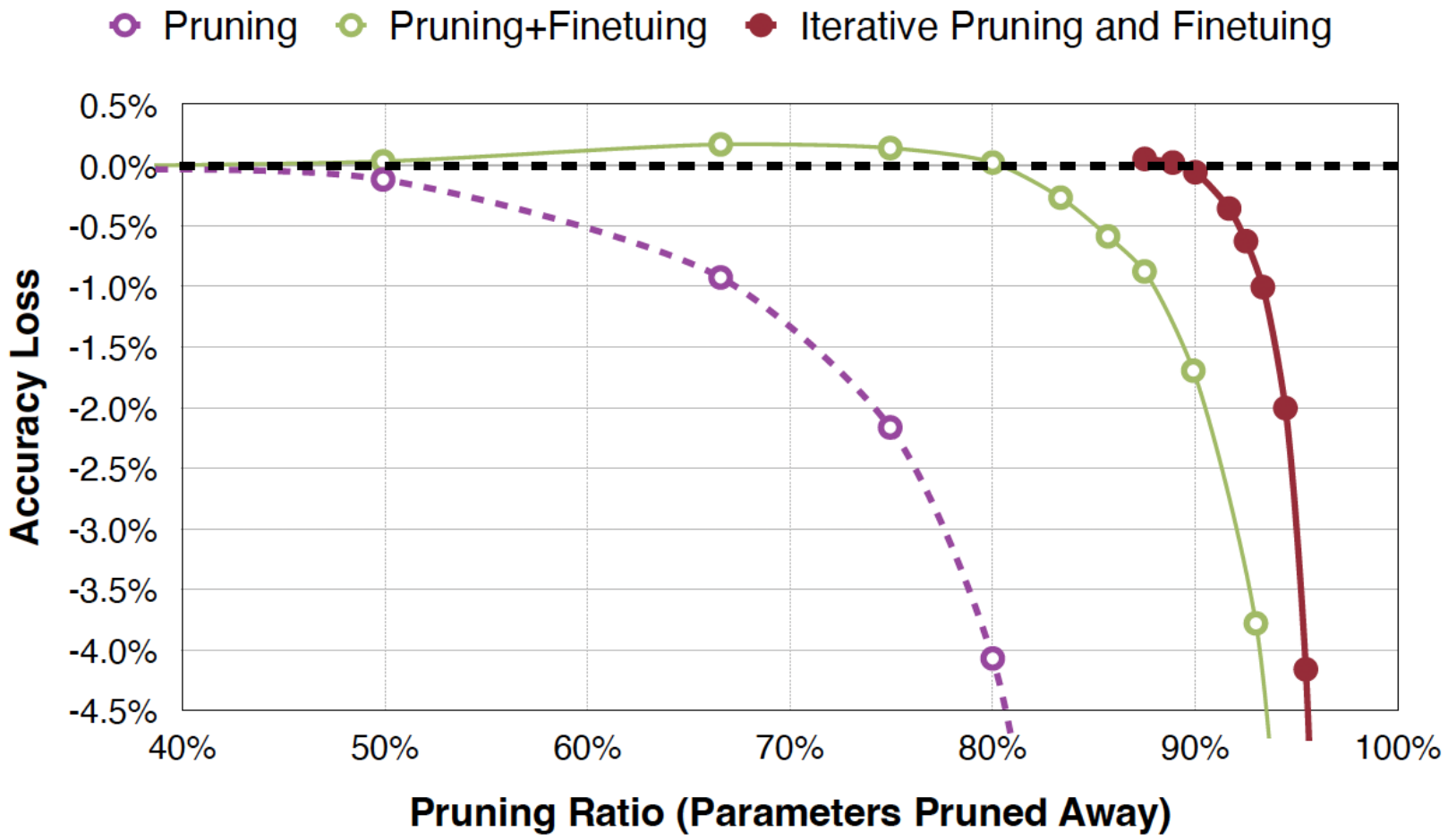
Prune Connections

Train Weights



Neural network pruning





Neural Network Pruning

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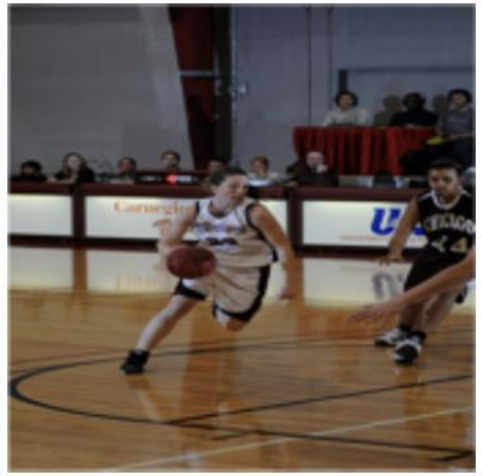
Pruning the NeuralTalk LSTM does not hurt image caption quality.



Baseline: a basketball player in a white uniform is playing with a ball .

Pruned 90%: a basketball player in a white uniform is playing with a basketball.

Baseline: a brown dog is running through a grassy field.

Pruned 90%: a brown dog is running through a grassy area.

Baseline: a man is riding a surfboard on a wave.

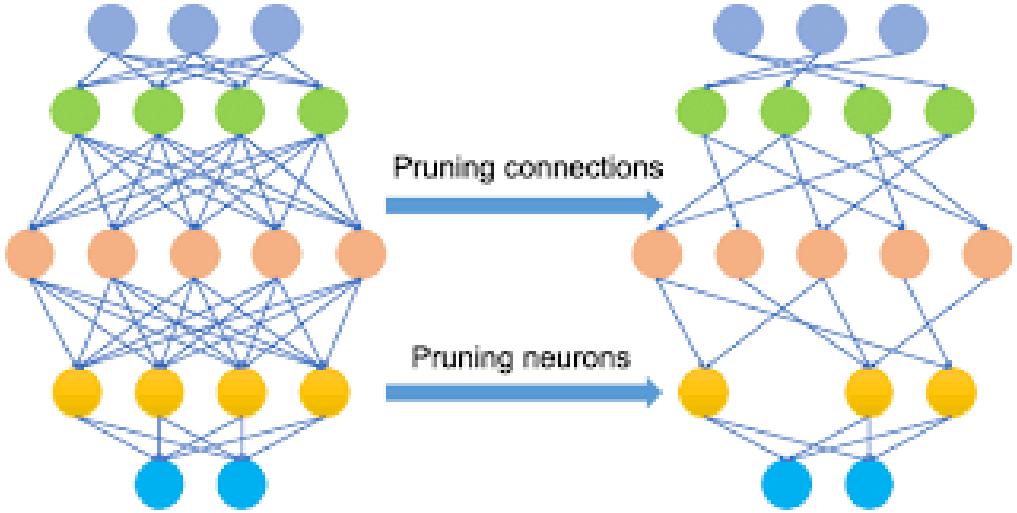
Pruned 90%: a man in a wetsuit is riding a wave on a beach.

Baseline: a soccer player in red is running in the field.

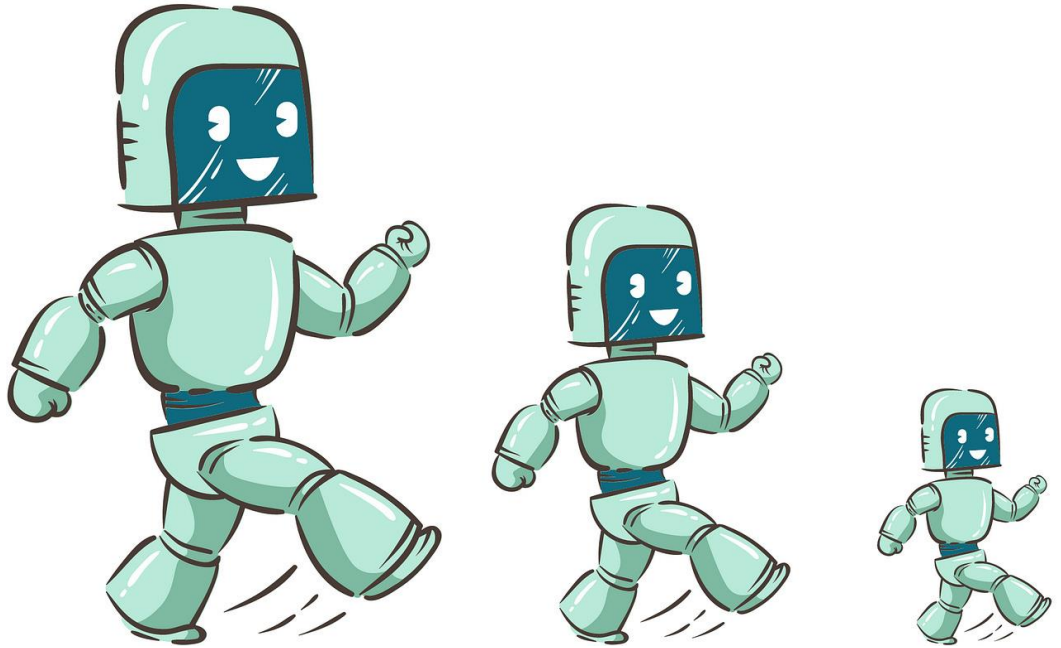
Pruned 95%: a man in a red shirt and black and white black shirt is running through a field.

Neural Network Pruning

- Make NNs smaller by removing connections and neurons
  - Which connections and neurons?
  - With what granularity?
  - How many?
  - When?



Pruning Criteria



Magnitude-based Pruning

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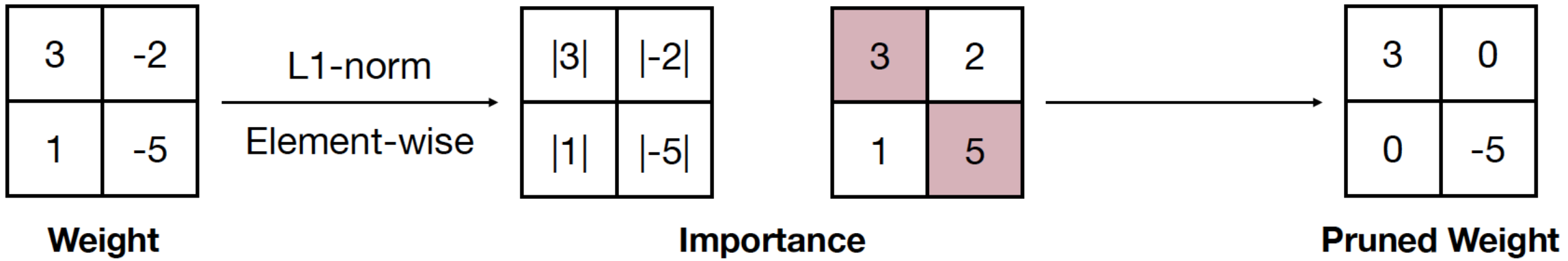
A heuristic pruning criterion

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

$$Importance = |W|$$

- **Example**



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

Magnitude-based Pruning

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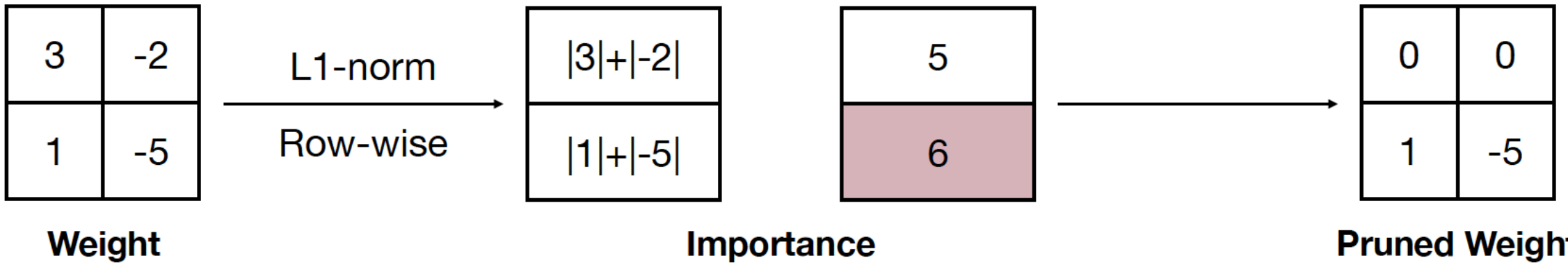
A heuristic pruning criterion

- Magnitude-based pruning considers weights with ***larger absolute values*** are more important than other weights.
  - For row-wise pruning, the L1-norm magnitude can be defined as,

$$Importance = \sum_{i \in S} |w_i|, \text{ where } \mathbf{W}^{(S)} \text{ is the structural set } S \text{ of parameters } \mathbf{W}$$

- **Example**



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

Magnitude-based Pruning

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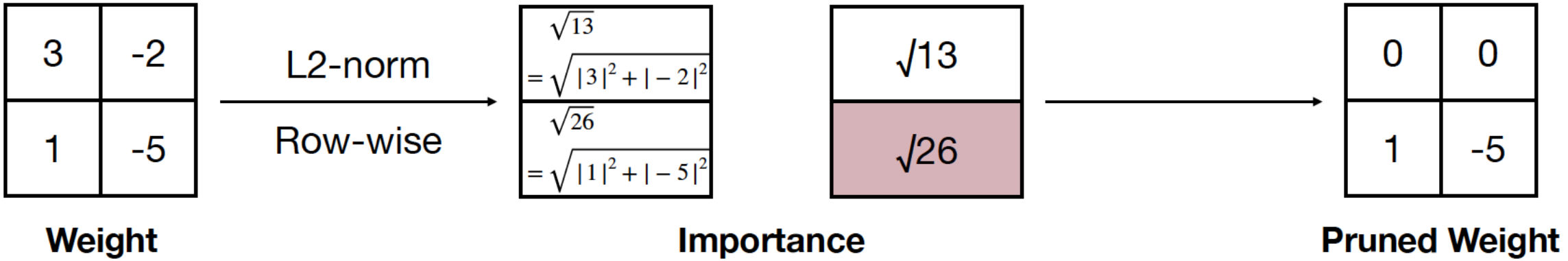
A heuristic pruning criterion

- Magnitude-based pruning considers weights with ***larger absolute values*** are more important than other weights.
  - For row-wise pruning, the L2-norm magnitude can be defined as,

$$Importance = \sqrt{\sum_{i \in S} |w_i|^2}, \text{ where } \mathbf{W}^{(S)} \text{ is the structural set } S \text{ of parameters } \mathbf{W}$$

- **Example**



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

Magnitude-based Pruning

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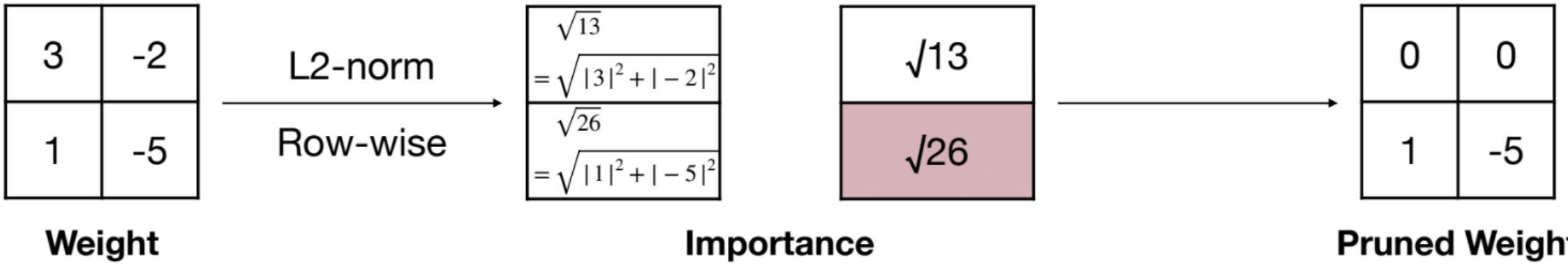
A heuristic pruning criterion

- Magnitude-based pruning considers weights with ***larger absolute values*** are more important than other weights.
- Magnitude is also known as L_p-norm defined as,

$$\|\mathbf{W}^{(S)}\|_p = \left(\sum_{i \in S} |w_i|^p \right)^{\frac{1}{p}}, \text{ where } \mathbf{W}^{(S)} \text{ is a structural set of parameters}$$

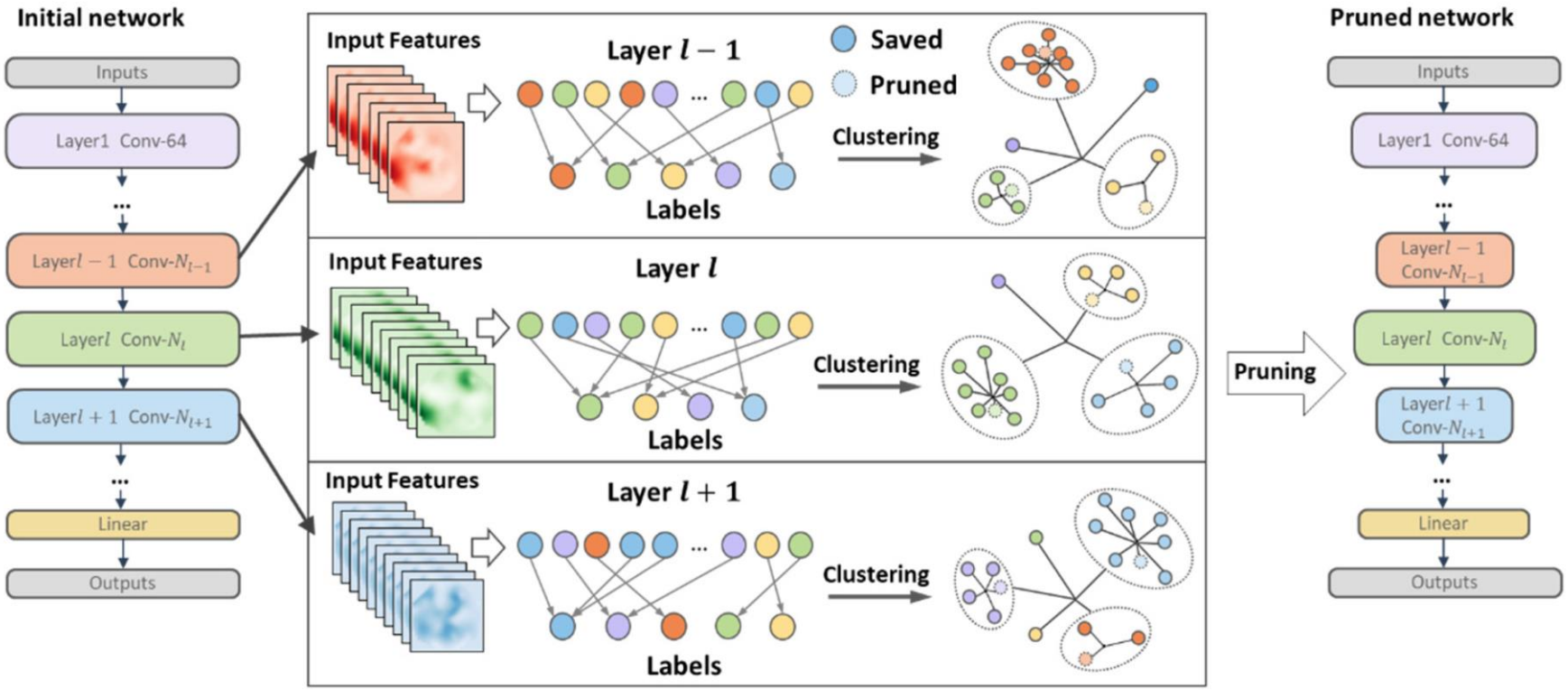
- **Example**



Learning Structured Sparsity in Deep Neural Networks [Wen *et al.*, NeurIPS 2016]

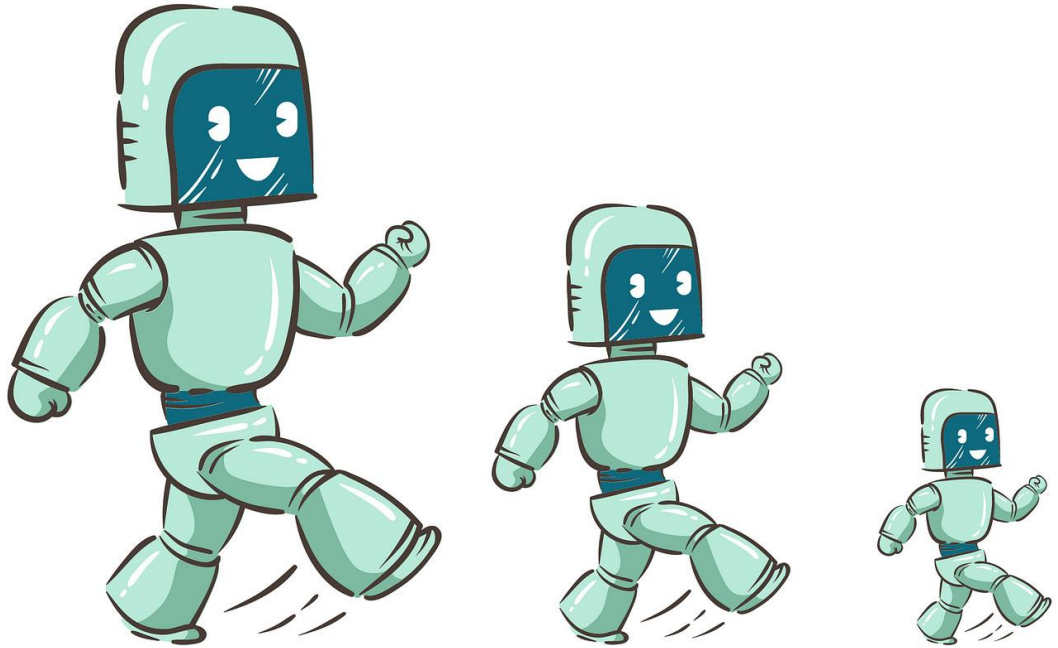
Pruning Based On Similarity And Clustering

- Remove the **redundancy across weights or filters** in the network.



Wu T, Song C, Zeng P, Xia C. Cluster-Based Structural Redundancy Identification for Neural Network Compression. *Entropy*. 2023

Prunning Granularity



Pruning at Different Granularities

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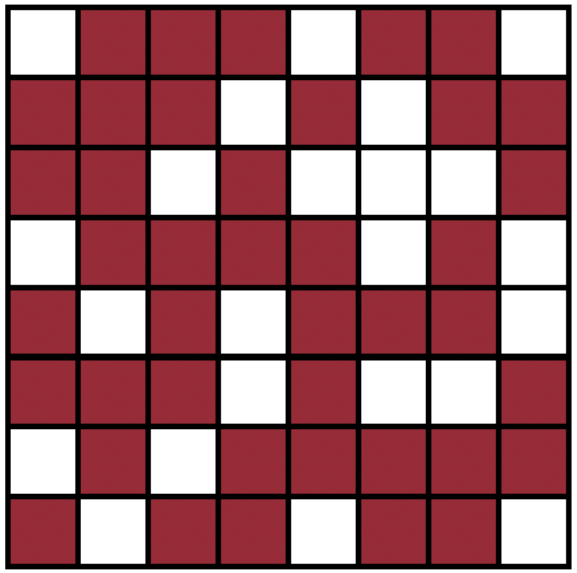
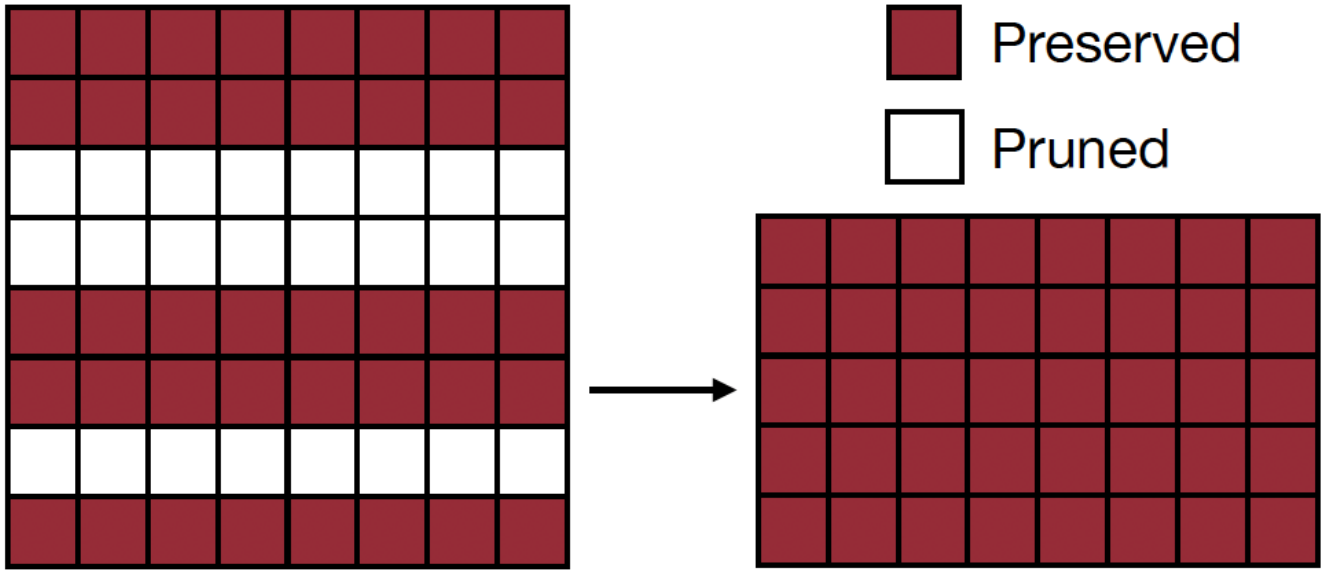
A simple example of 2D weight matrix





Fine-grained/Unstructured

- More flexible pruning index choice
- Hard to accelerate (irregular)

Coarse-grained/Structured

- Less flexible pruning index choice (a subset of the fine-grained case)
- Easy to accelerate (just a smaller matrix!)

Pruning at Different Granularities

RI. SE

The case of convolutional layers

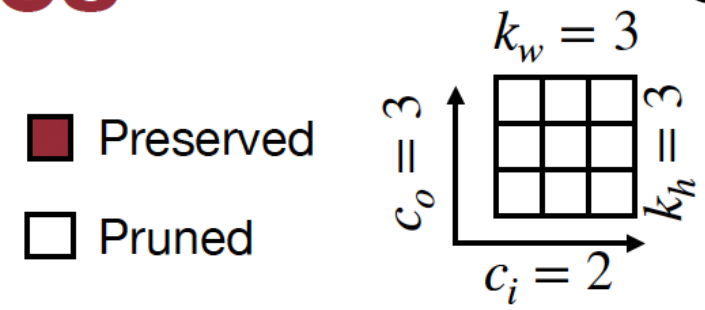
- The weights of convolutional layers have 4 dimensions $[c_o, c_i, k_h, k_w]$:
  - c_i: input channels (or channels)
  - c_o: output channels (or filters)
  - k_h: kernel size height
  - k_w: kernel size width

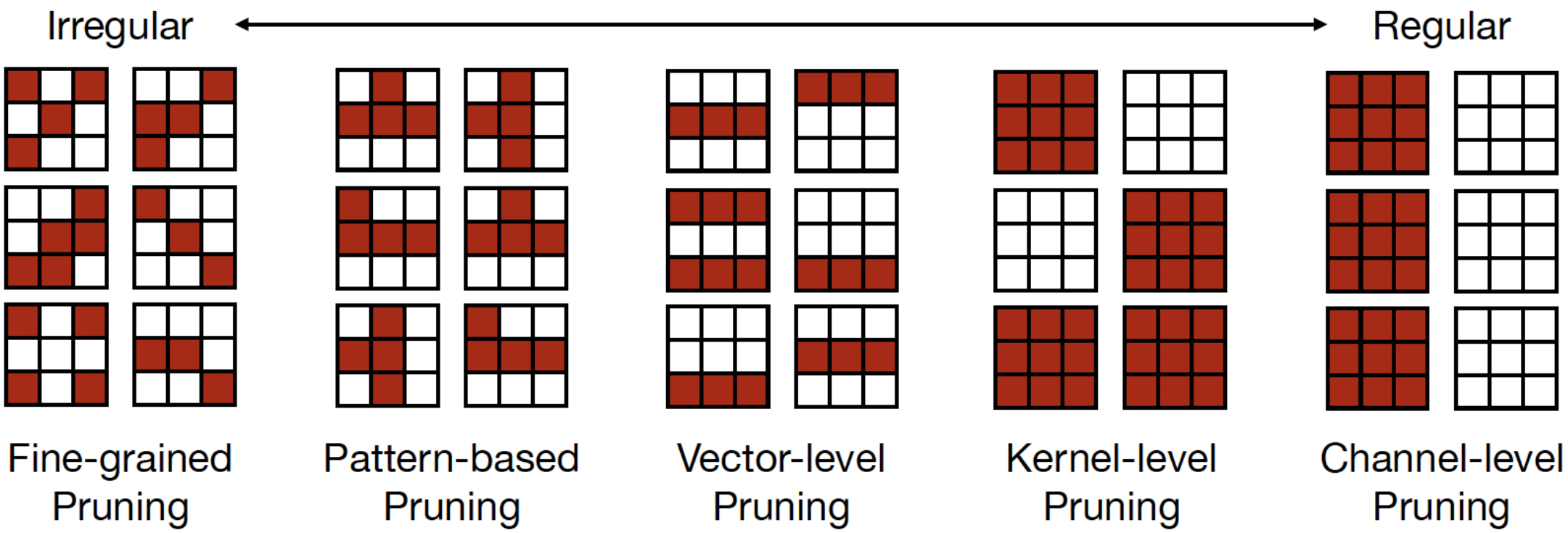
- The 4 dimensions give us more choices to select pruning granularities

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]

Pruning at Different Granularities

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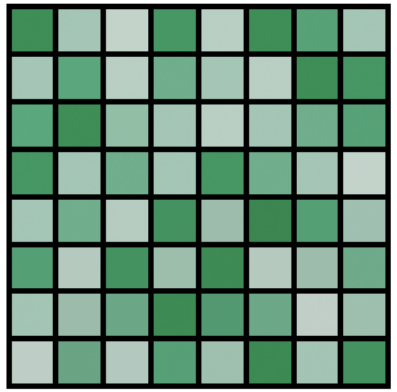
Let's look into some cases

- **Pattern-based Pruning: N:M sparsity**



Dense Matrix

Accelerating Inference with Sparsity Using the NVIDIA Ampere Architecture and NVIDIA TensorRT

Pruning at Different Granularities

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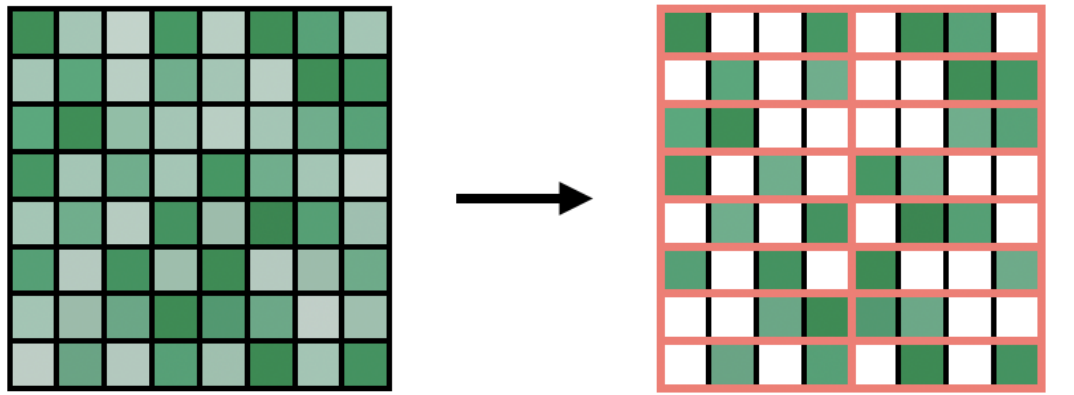
Let's look into some cases

- **Pattern-based Pruning: N:M sparsity**



Dense Matrix

2:4 Sparse Matrix

Pruning at Different Granularities

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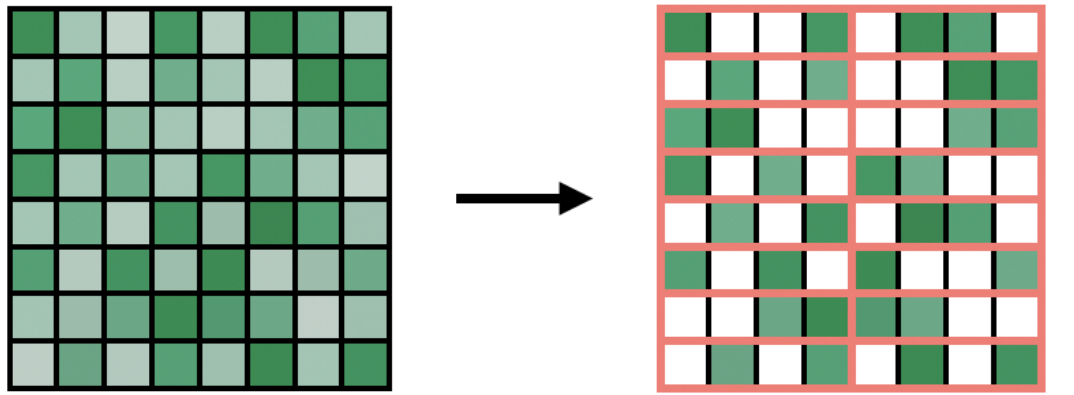
Let's look into some cases

- **Pattern-based Pruning: N:M sparsity**
  - N:M sparsity means that in each contiguous M elements, N of them is pruned
  - A classic case is 2:4 sparsity (50% sparsity)



Dense Matrix

2:4 Sparse Matrix

Pruning at Different Granularities

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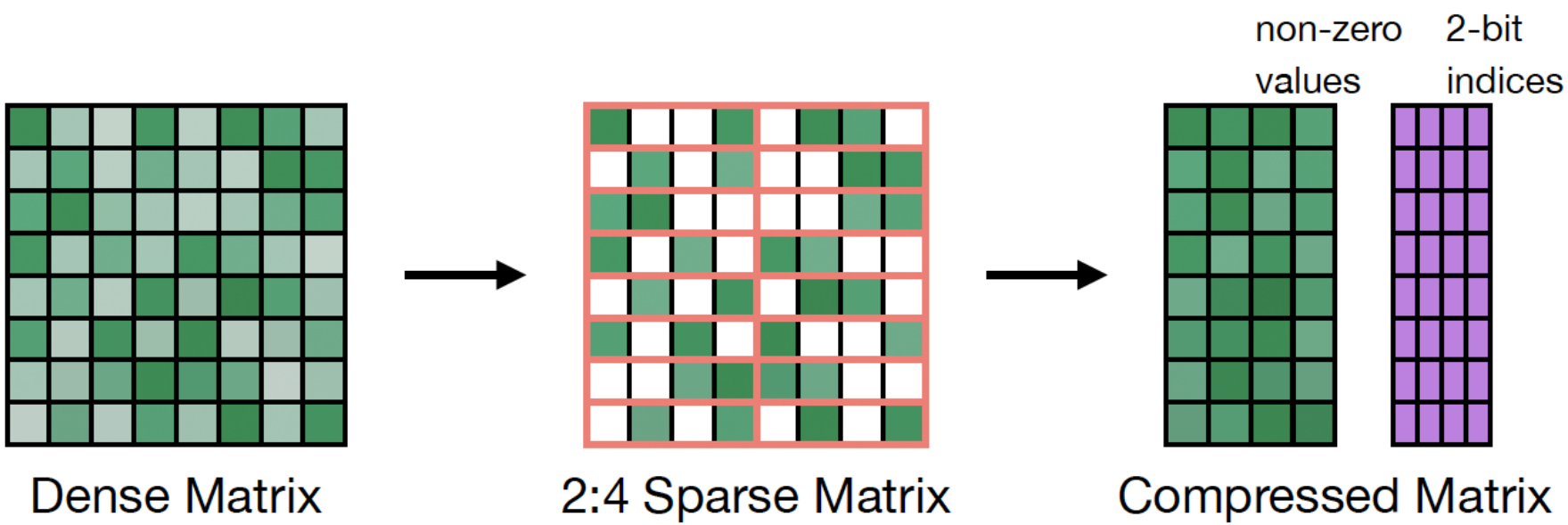
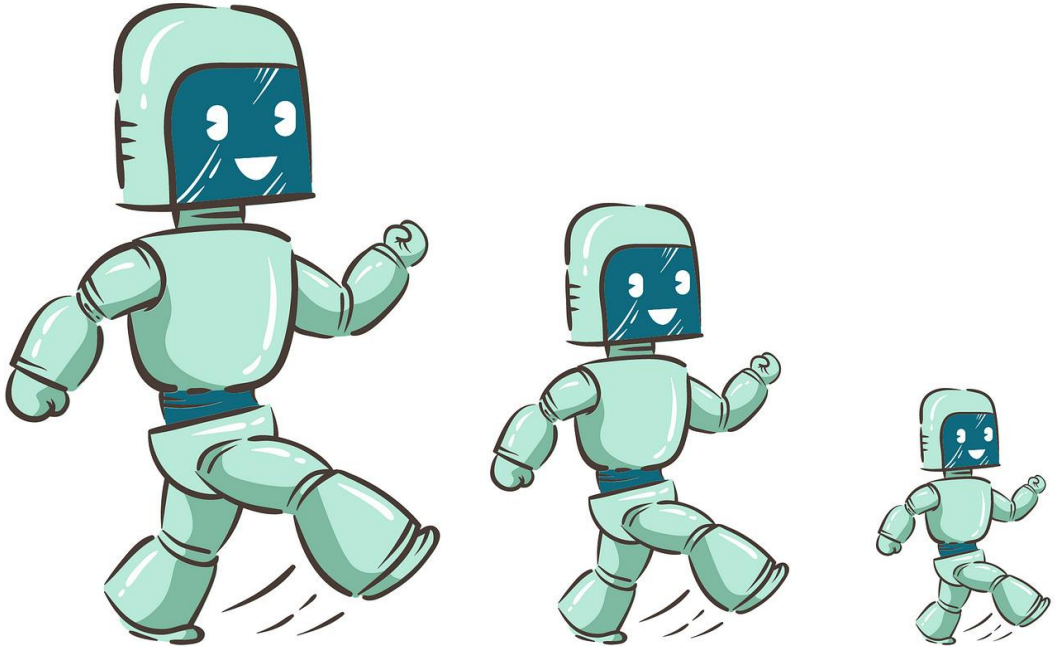
Let's look into some cases

- **Pattern-based Pruning: N:M sparsity**
  - N:M sparsity means that in each contiguous M elements, N of them is pruned
  - A classic case is 2:4 sparsity (50% sparsity)
  - It is supported by NVIDIA's Ampere GPU Architecture, which delivers up to 2x speed up



Accelerating Inference with Sparsity Using the NVIDIA Ampere Architecture and NVIDIA TensorRT

Pruning Ratio



Finding Pruning Ratios

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SE

Analyze the sensitivity of each layer

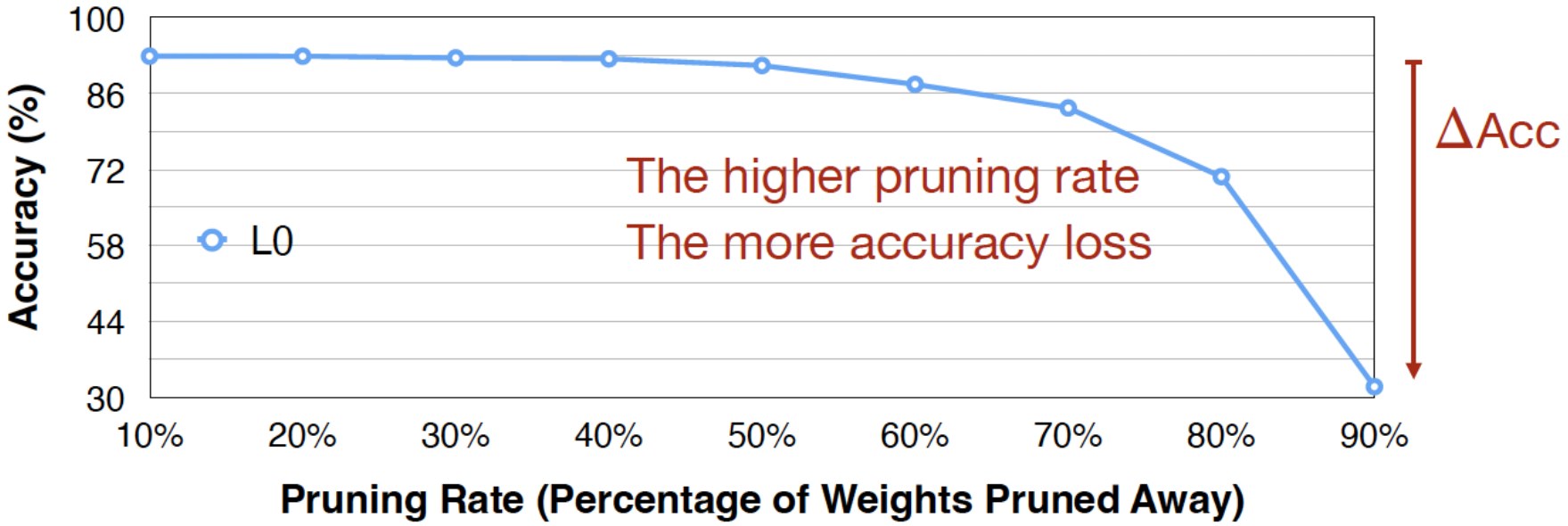
- We need different pruning ratios for each layer since different layers have different **sensitivity**
  - Some layers are more sensitive (e.g., first layer)
  - Some layers are more redundant

Finding Pruning Ratios

RI. SE

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

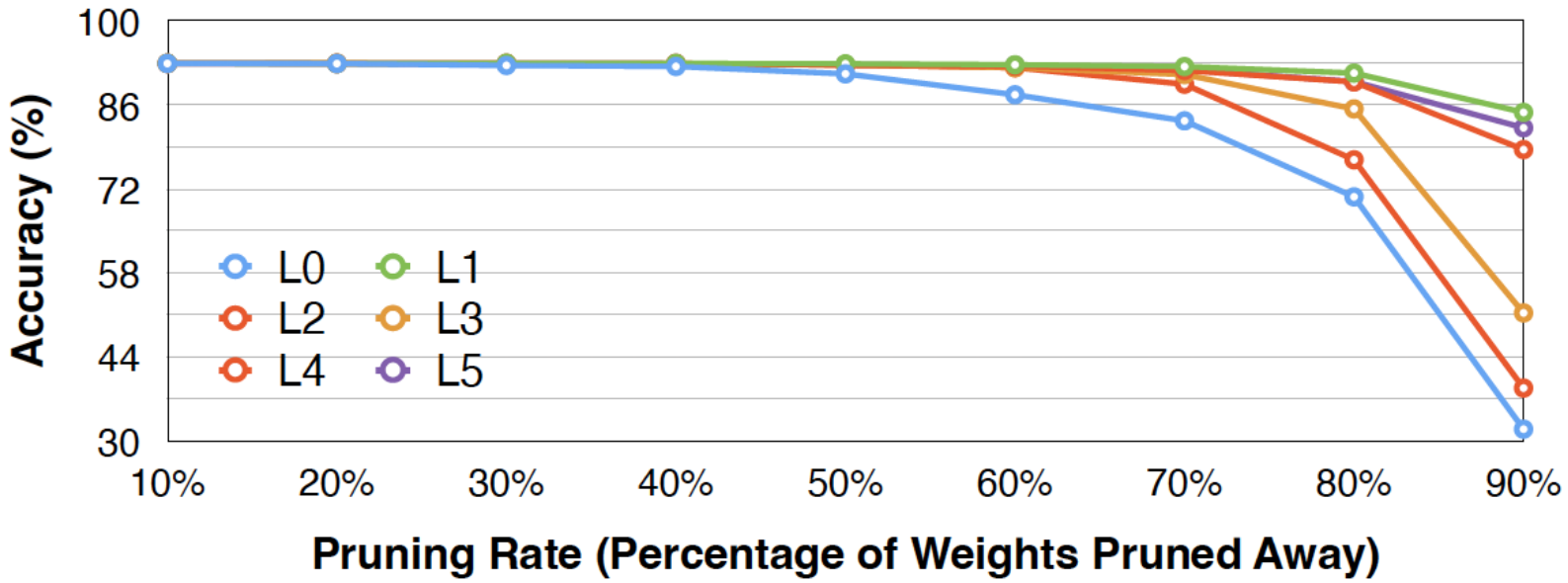


Finding Pruning Ratios

RI. SE

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



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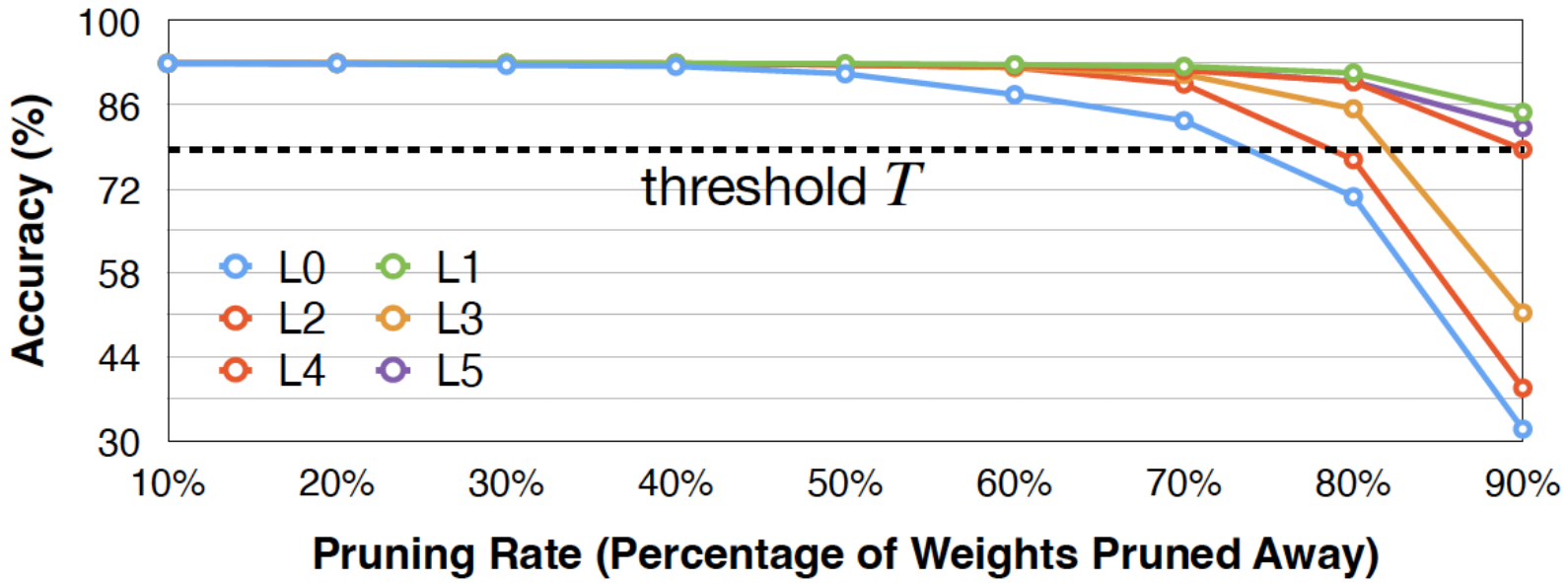
  - Repeat the process for all layers
  - Pick a degradation threshold T such that the overall pruning rate is desired



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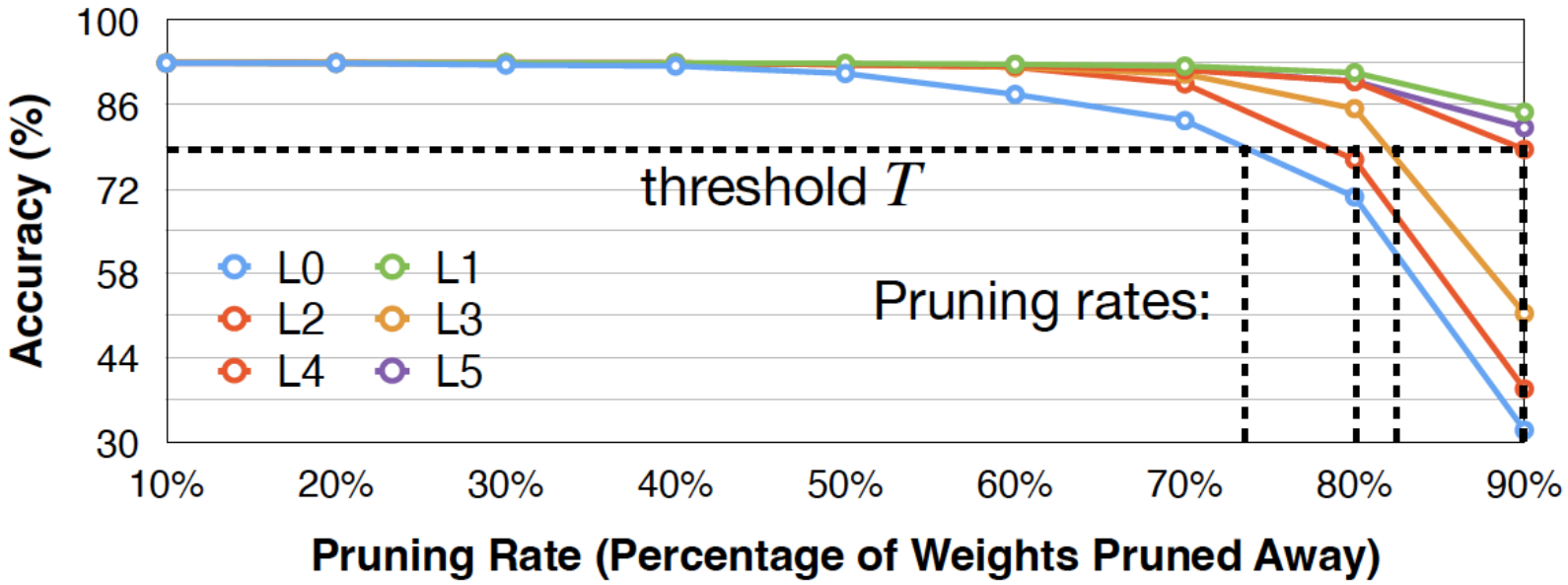
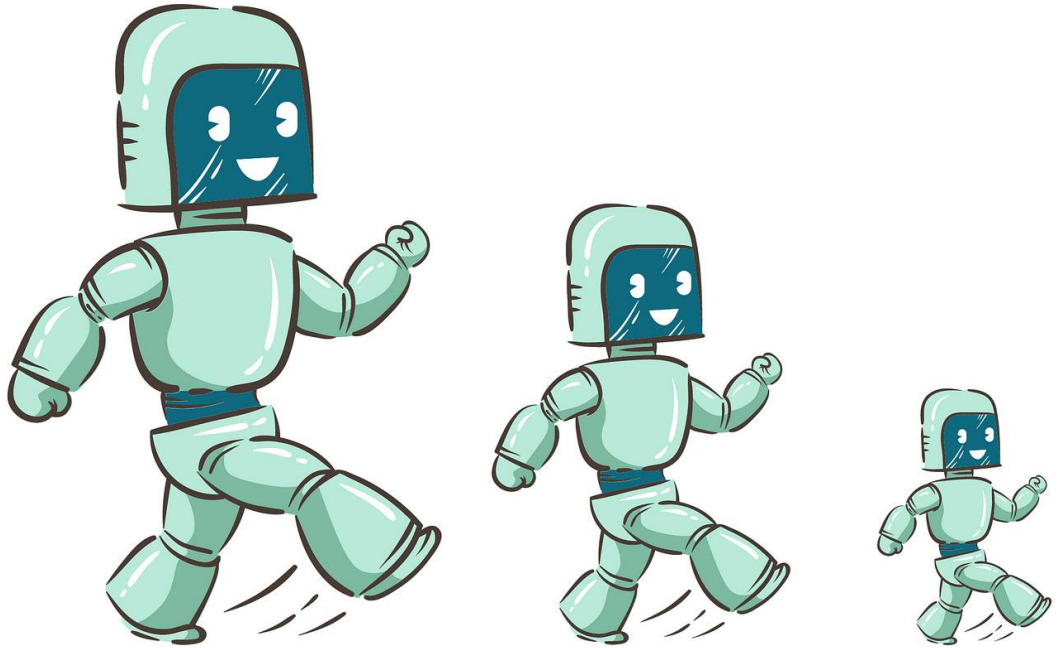
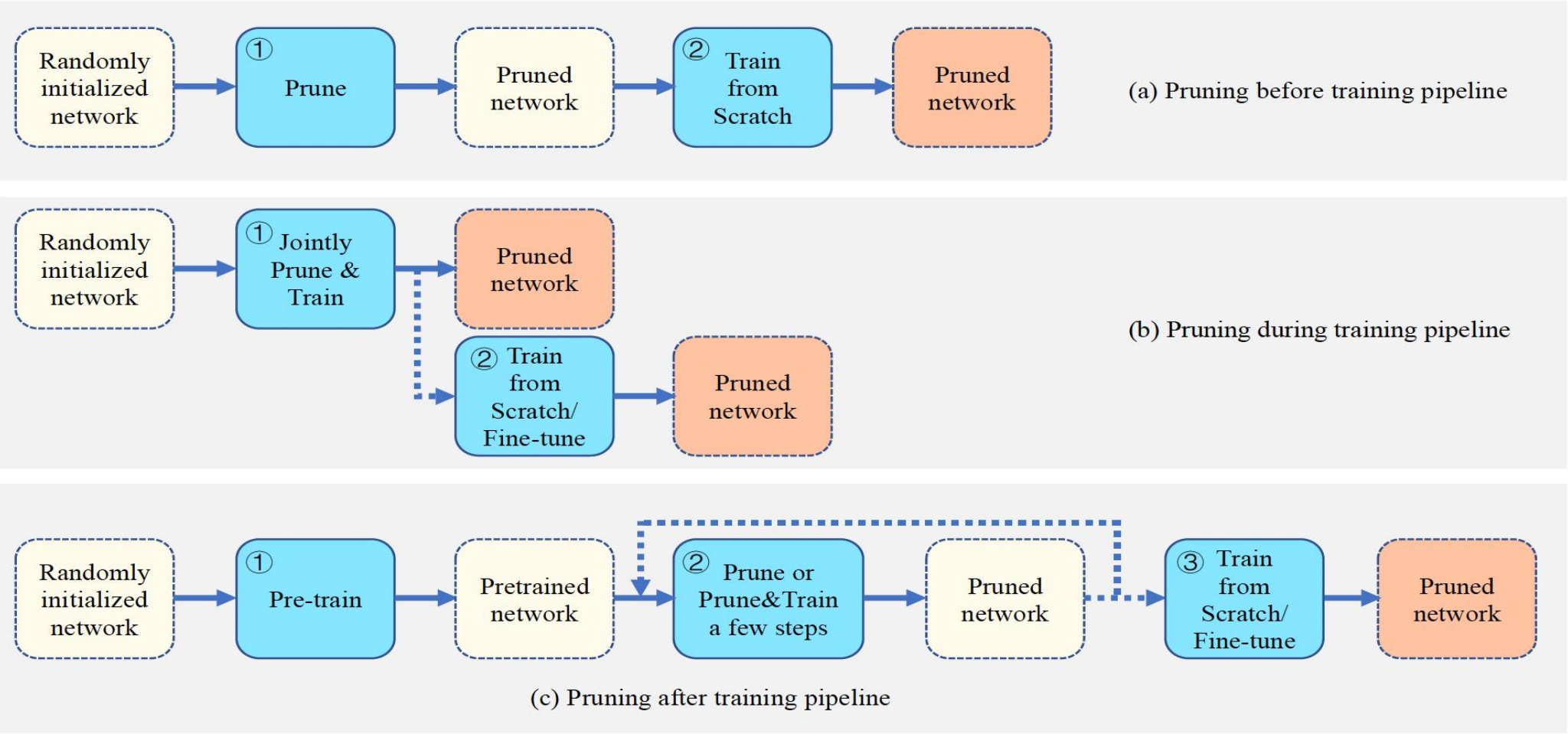


When To Prune?



When To Prune?



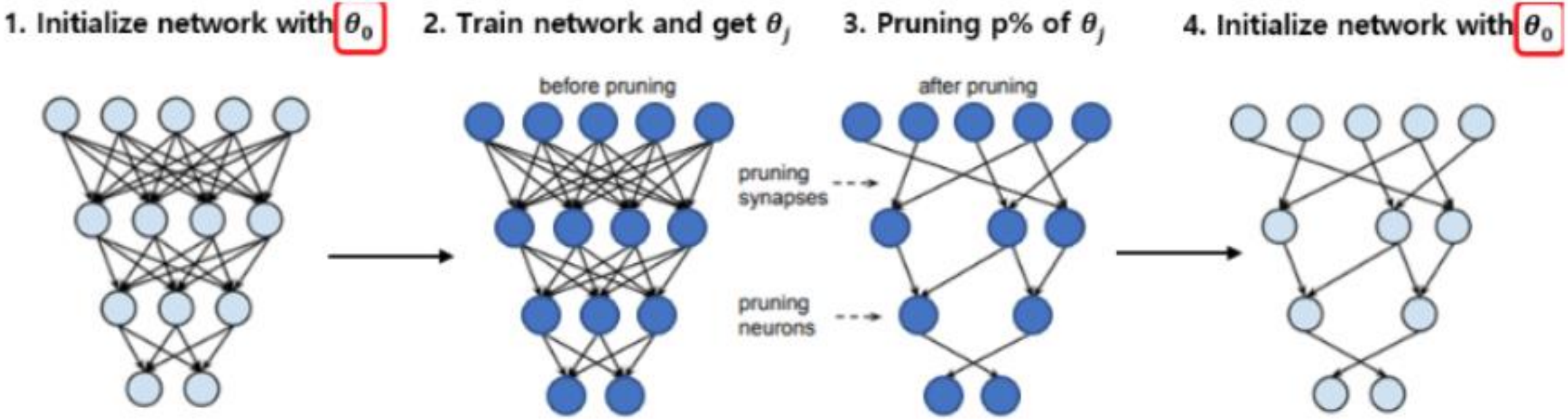
The lottery ticket hypothesis

- Within a **large, randomly-initialized network**, there exists a much **smaller subnetwork** that, if trained in isolation from the beginning with the **same initial weights**, can reach **comparable performance** to the full network.

- That's what they call a *'winning ticket'*

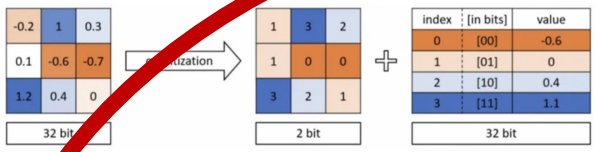
Frankle, J., & Carbin, M. (2018). The lottery ticket hypothesis: Finding sparse, trainable neural networks.

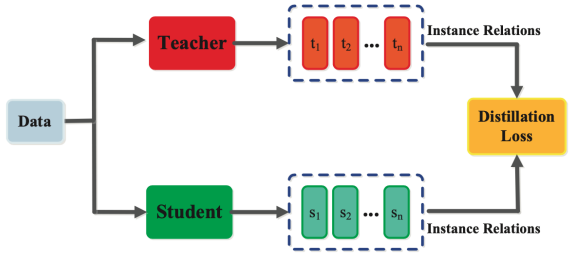
The lottery ticket hypothesis

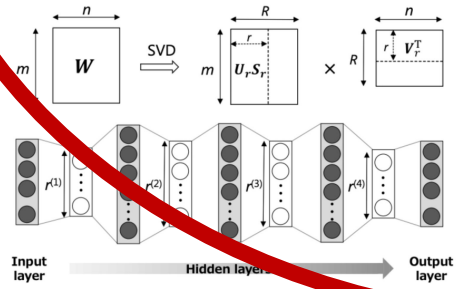


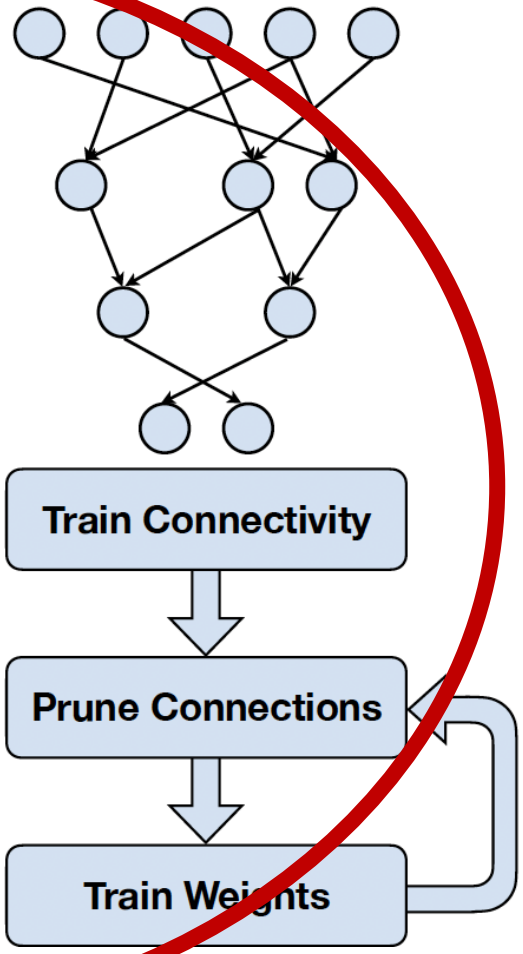
Frankle, J., & Carbin, M. (2018). The lottery ticket hypothesis: Finding sparse, trainable neural networks.

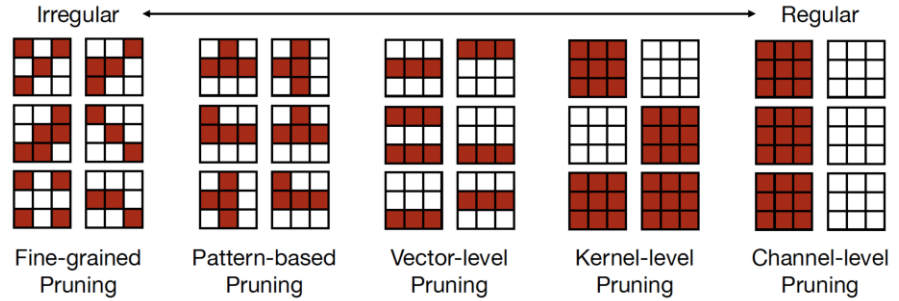
Takeaways

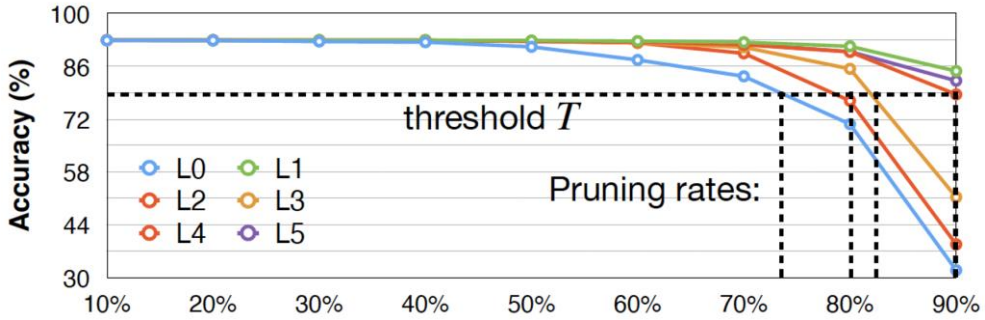

-0.2 1 0.3
0.1 -0.6 -0.7
1.2 0.4 0
32 bit
1 3 2
1 0 0
3 2 1
2 bit
index [in bits] value
0 [00] -0.6
1 [01] 0
2 [10] 0.4
3 [11] 1.1
32 bit

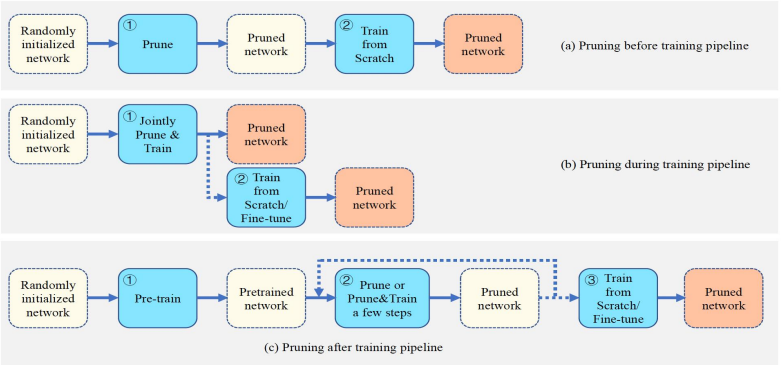

Teacher
Data
Student
Instance Relations
Distillation Loss
Instance Relations


W
SVD
Input layer
Hidden layer
Output layer


Train Connectivity
Prune Connections
Train Weights


Irregular
Regular
Fine-grained Pruning
Pattern-based Pruning
Vector-level Pruning
Kernel-level Pruning
Channel-level Pruning


Accuracy (%)
100
86
72
58
44
30
threshold T
L0 L1
L2 L3
L4 L5
Pruning rates:
10% 20% 30% 40% 50% 60% 70% 80% 90%


Randomly initialized network
① Prune
Pruned network
② Train from Scratch
Pruned network
(a) Pruning before training pipeline
Randomly initialized network
① Jointly Prune & Train
Pruned network
② Train from Scratch/ Fine-tune
Pruned network
(b) Pruning during training pipeline
Randomly initialized network
① Pre-train
Pretrained network
② Prune or Prune&Train a few steps
Pruned network
③ Train from Scratch/ Fine-tune
Pruned network
(c) Pruning after training pipeline

References

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Thank you!