

# Pruning (Part II)

서울대학교 컴퓨터공학부 이영기



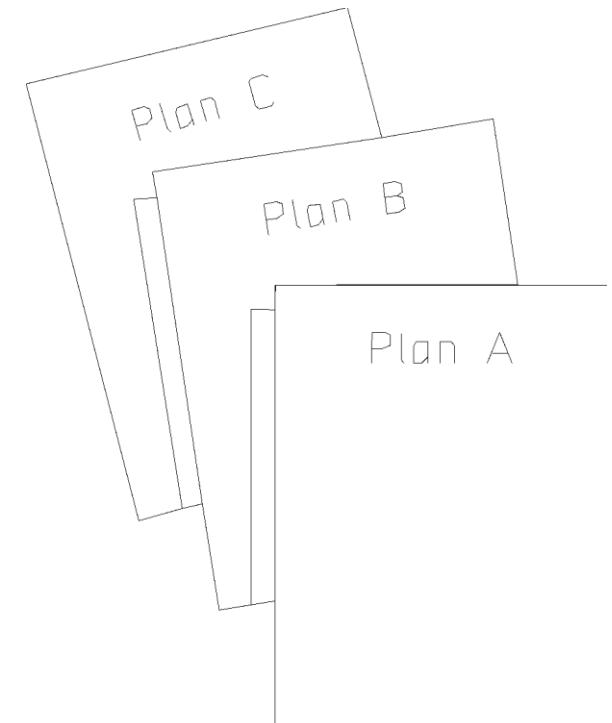
Human-Centered  
Computer Systems Lab



SEOUL NATIONAL UNIVERSITY

# Overview

- **Objective**
  - To discuss how to select pruning ratio and how to fine-tune in NN pruning
  - To understand Lottery ticket Hypothesis
- **Content**
  - Determine the Pruning Ratio
  - Fine-tune/train Pruned Neural Network

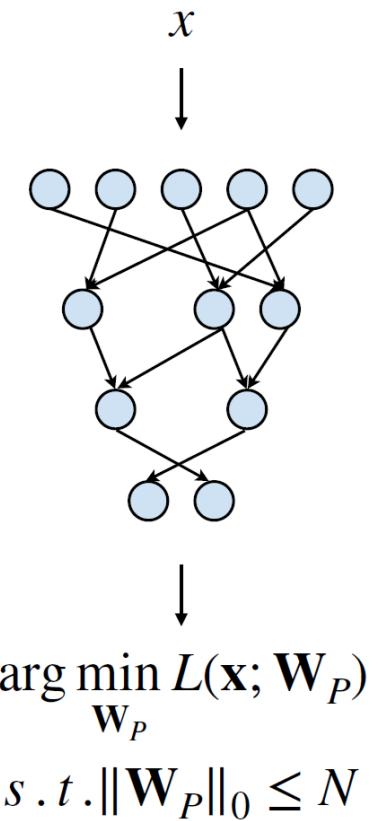
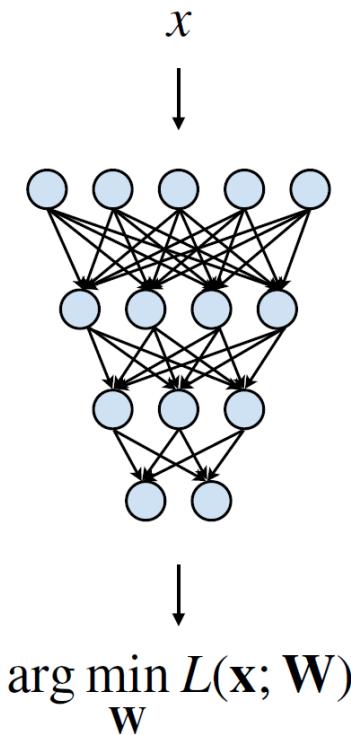


# Recap: Pruning Problem Formulation

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

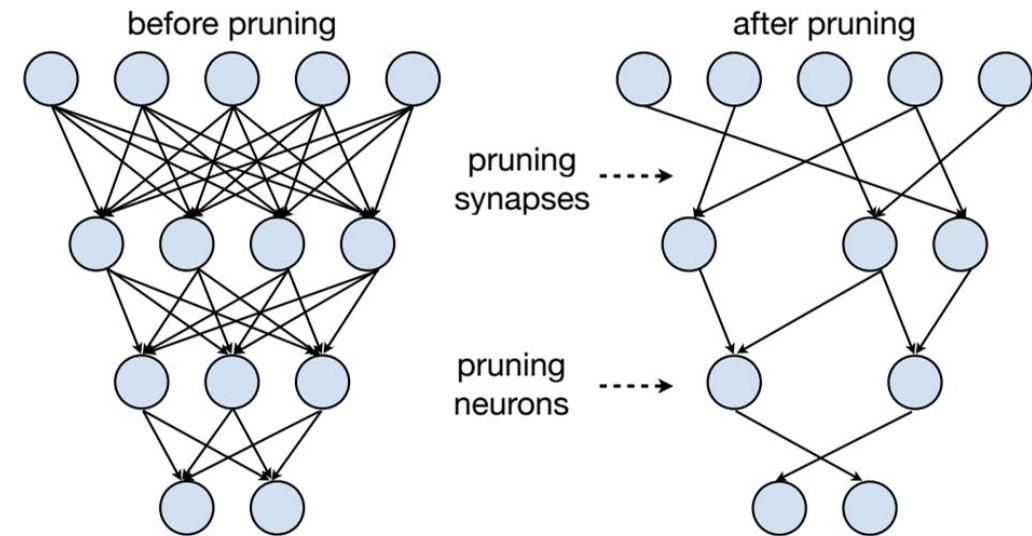
$$\arg \min_{\mathbf{W}_P} L(\mathbf{x}; \mathbf{W}_P) \text{ subject to } \|\mathbf{W}_P\|_0 < N$$

- $L$  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  $\mathbf{W}_p$ , and  $N$  is the target #nonzeros .



# Neural Network Pruning

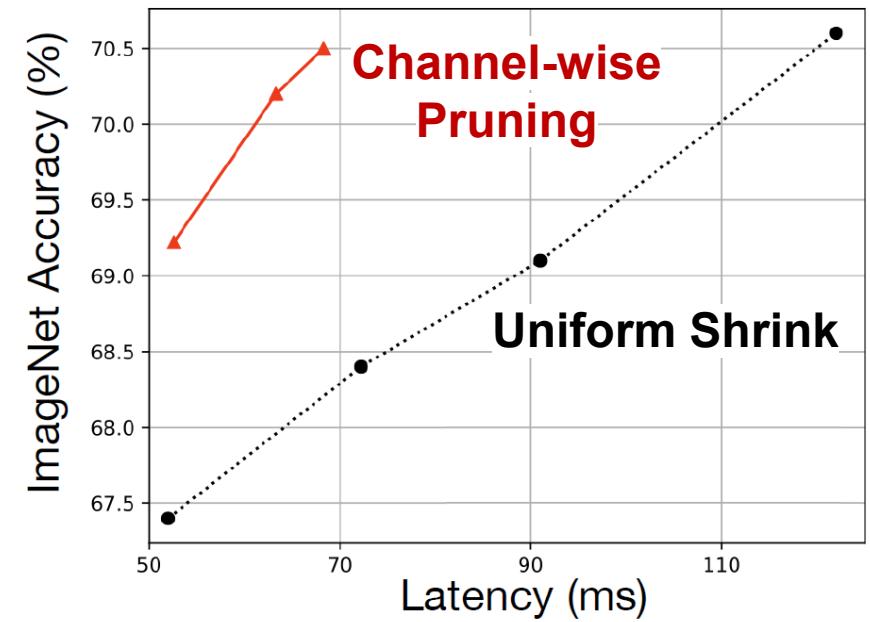
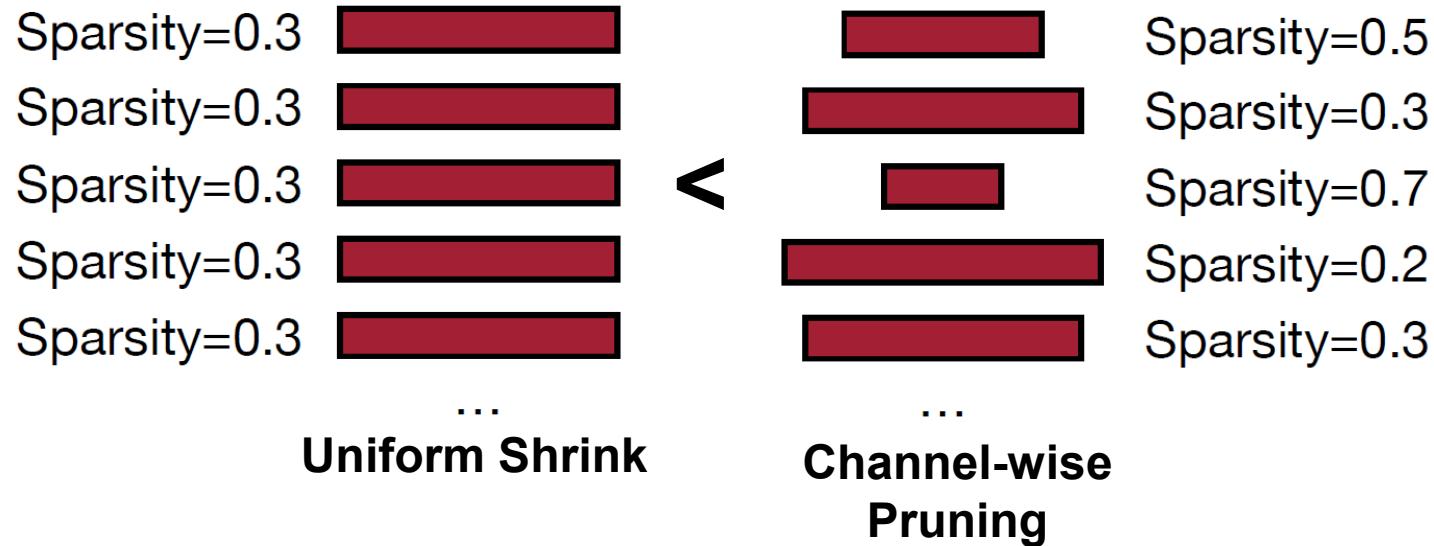
- **Introduction to Pruning**
  - What is pruning?
  - How should we formulate pruning?
- **Determine the Pruning Granularity**
  - In what pattern should we prune the neural network?
- **Determine the Pruning Criterion**
  - What synapses/neurons should we prune?
- **Determine the Pruning Ratio**
 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



Prune 30%?  
Prune 50%?  
Prune 70%?

# How Should We Select Ratios For Each Layer?

- Non-uniform pruning is better than uniform shrinking



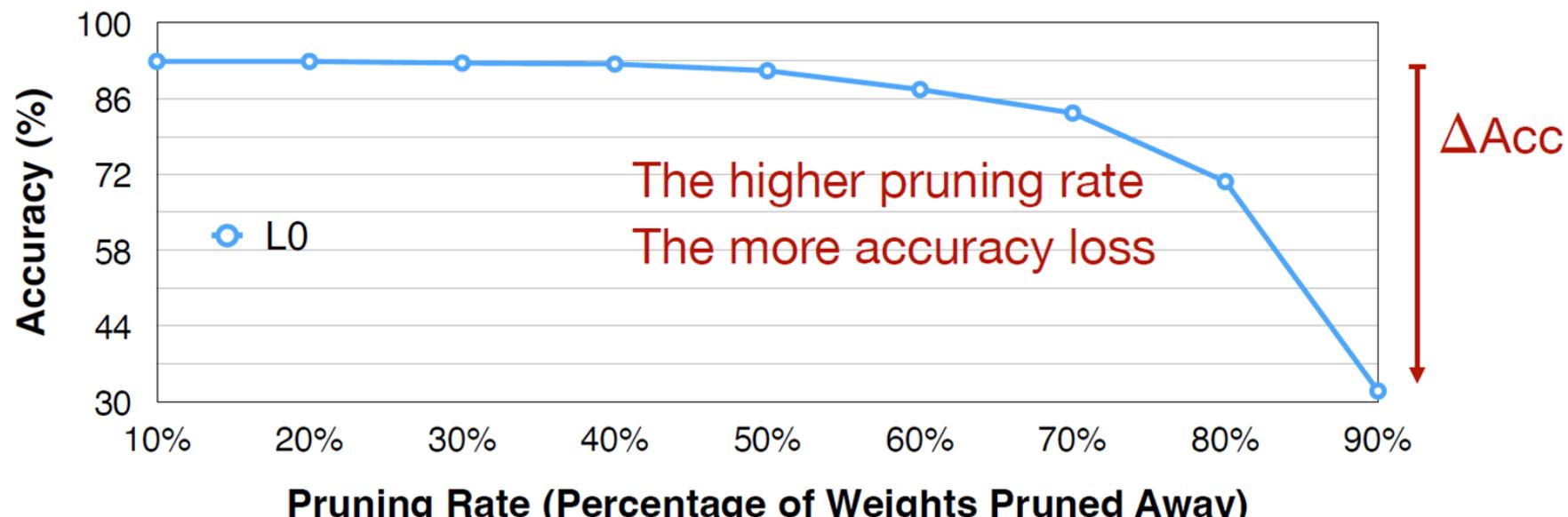
Analyze the sensitivity of each layer

# Analyze the Sensitivity of Each Layer

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

# Analyze the Sensitivity of Each Layer

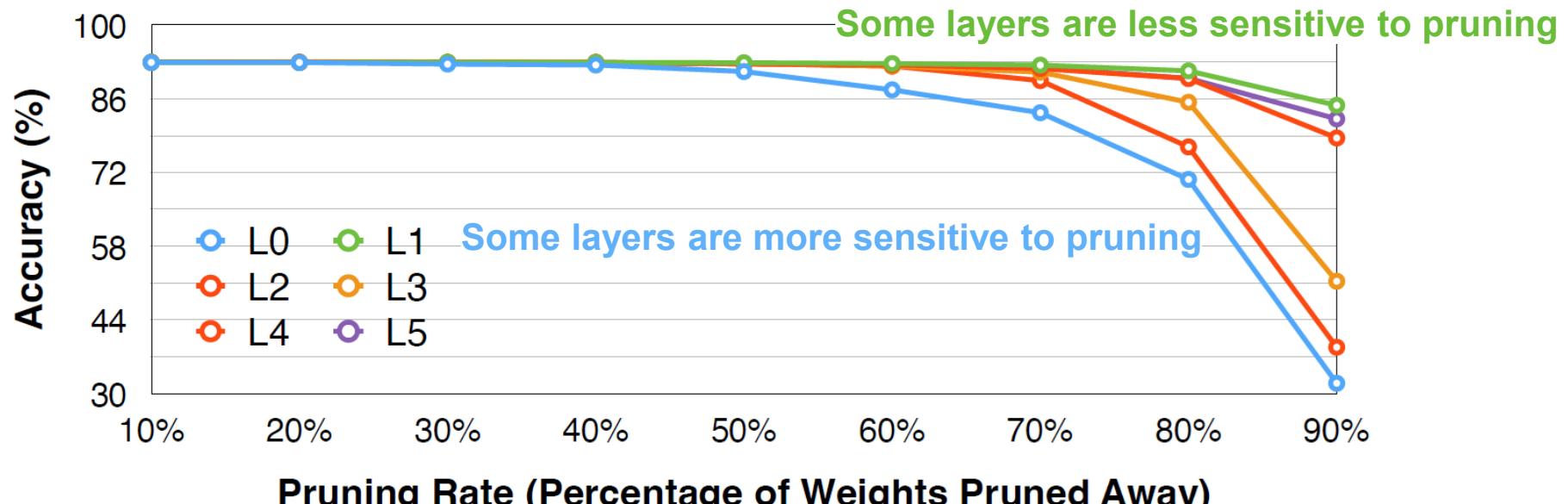
- We can perform **sensitivity analysis** to determine the per-layer pruning ratio
  - Pick a layer  $L_i$  in the model
    - Prune the layer  $L_i$  with pruning ratio  $r \in \{0, 0.1, 0.2, \dots, 0.9\}$  (or other strides)
    - Observe the accuracy degradation,  $\Delta \text{Acc}_r^i$  for each pruning ratio



\* Analysis on VGG-11 on CIFAR-10 dataset

# Analyze the Sensitivity of Each Layer

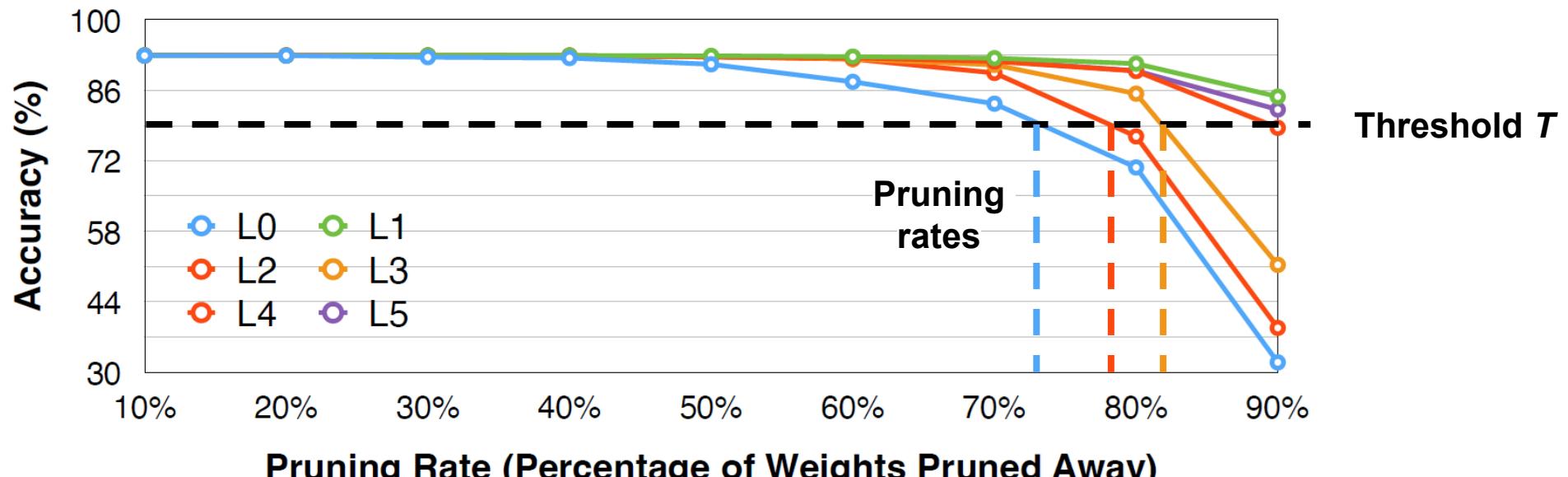
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  - Repeat the process for all layers
  - Pick a degradation threshold  $T$  such that the overall pruning rate is desired



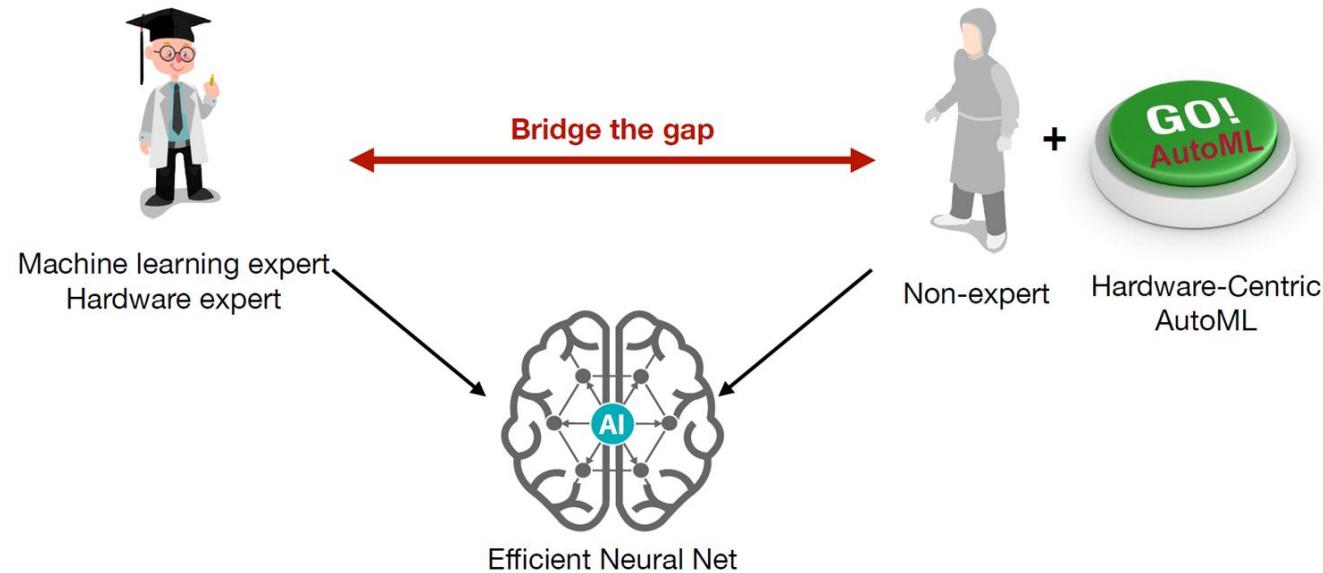
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# Is this Optimal?

- Maybe not. We do not consider the interaction between layers.
- Can we go beyond the heuristics? Yes, automatic pruning!

# Automatic Pruning

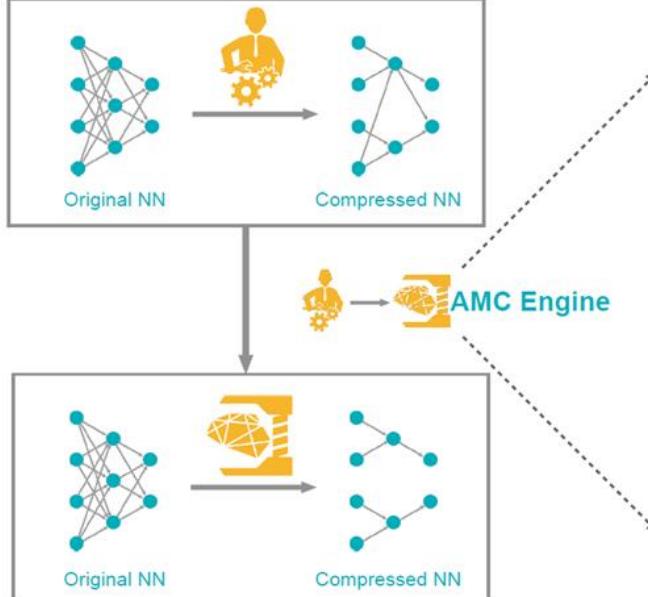
- Given an overall compression ratio, how do we select per-layer pruning ratios?
  - Sensitivity analysis ignores the interaction between layers ☐ sub-optimal solution
- Conventionally, such process relies on human expertise with trials and error
  - Can we do better?



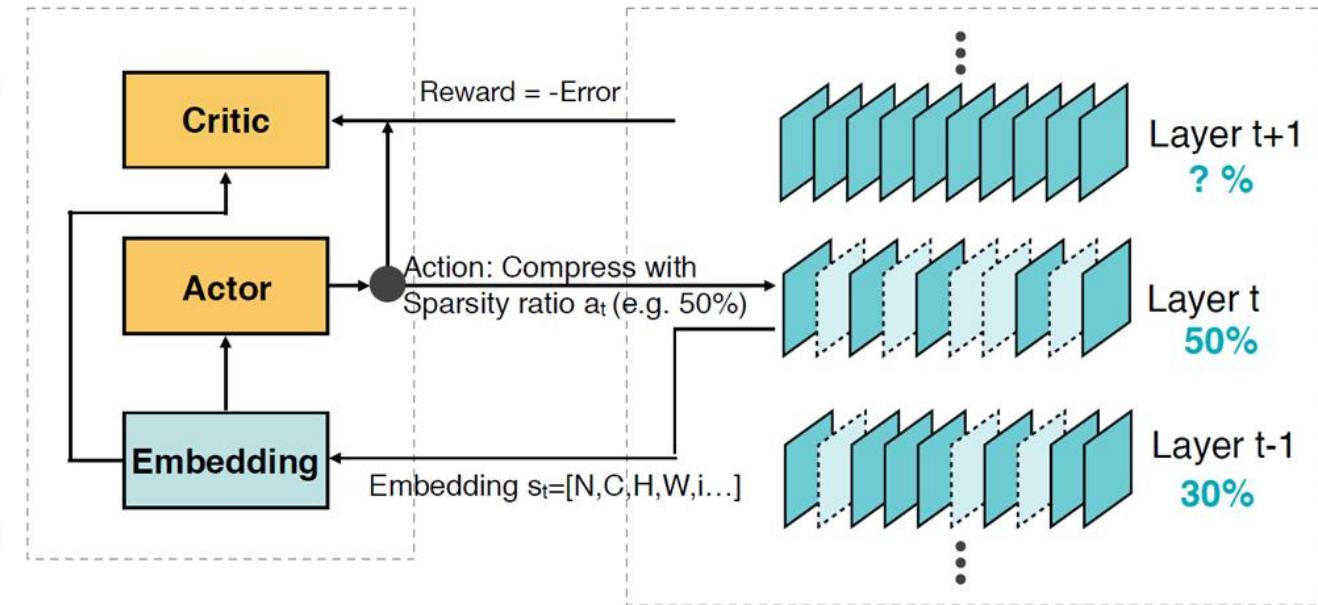
# AMC: AutoML for Model Compression

- Pruning as a reinforcement learning problem

**Model Compression by Human:**  
Labor Consuming, Sub-optimal



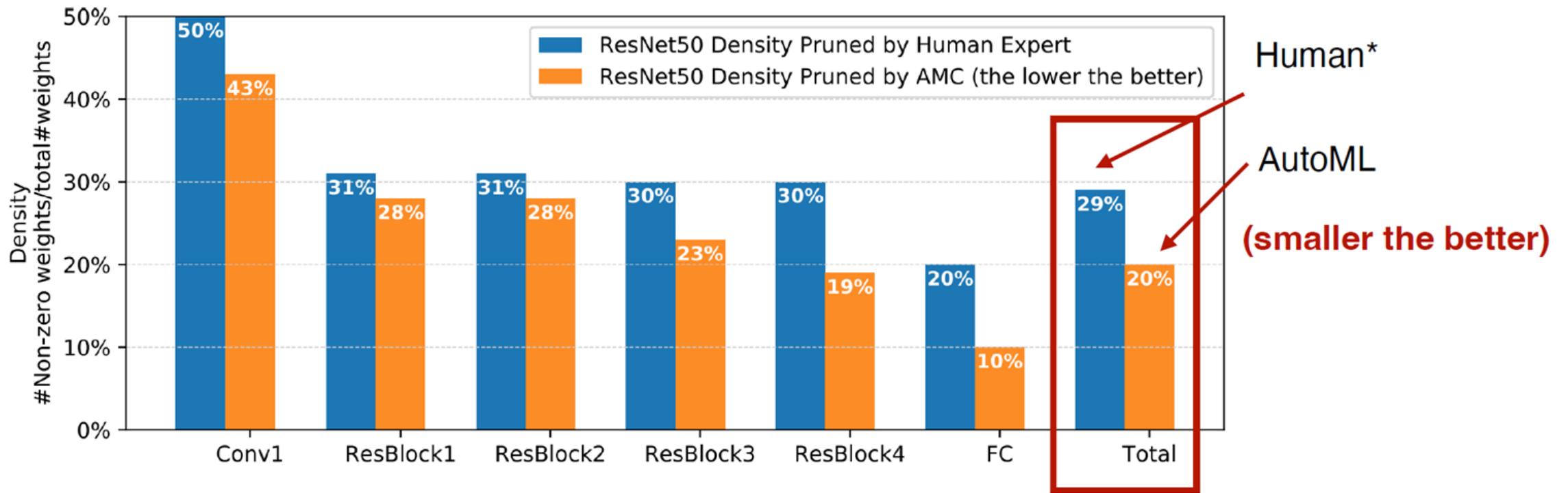
e.g.) channel pruning



**Model Compression by AI:**  
Automated, High Compression Rate, Faster

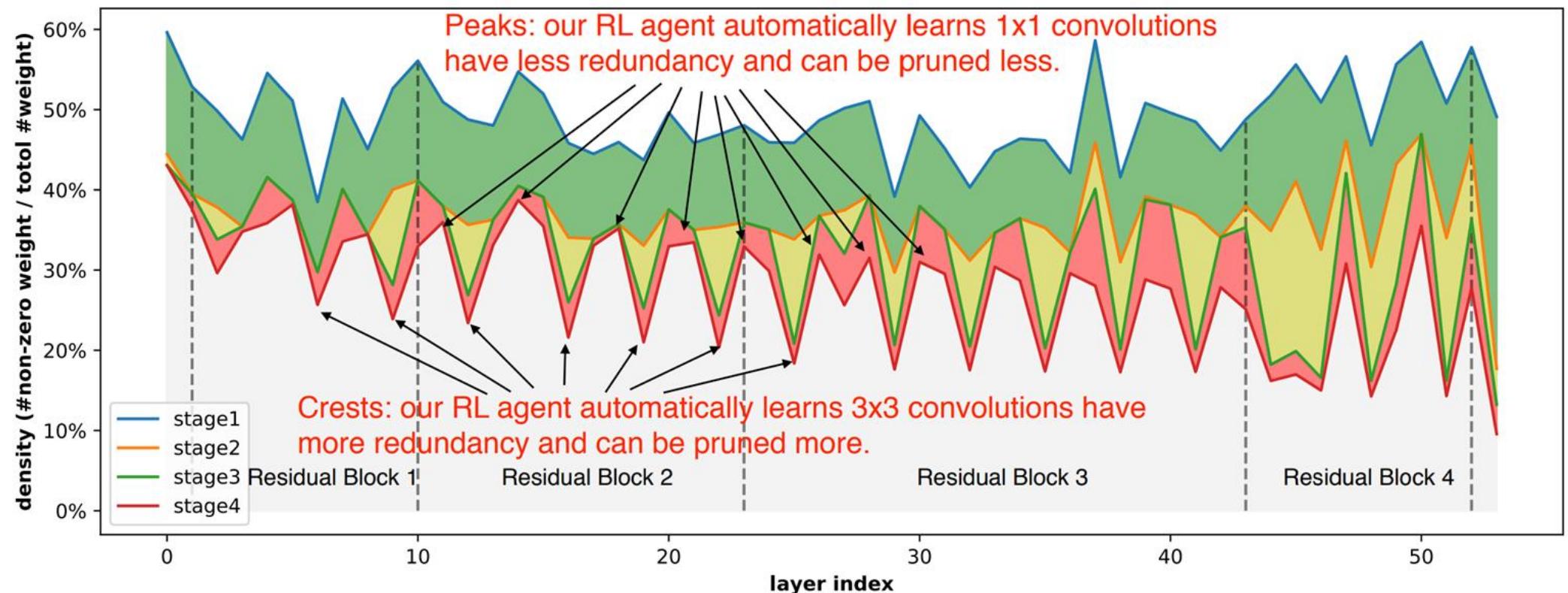
# AMC: AutoML for Model Compression

- AMC shows higher compression rate than human expert (or heuristic method)



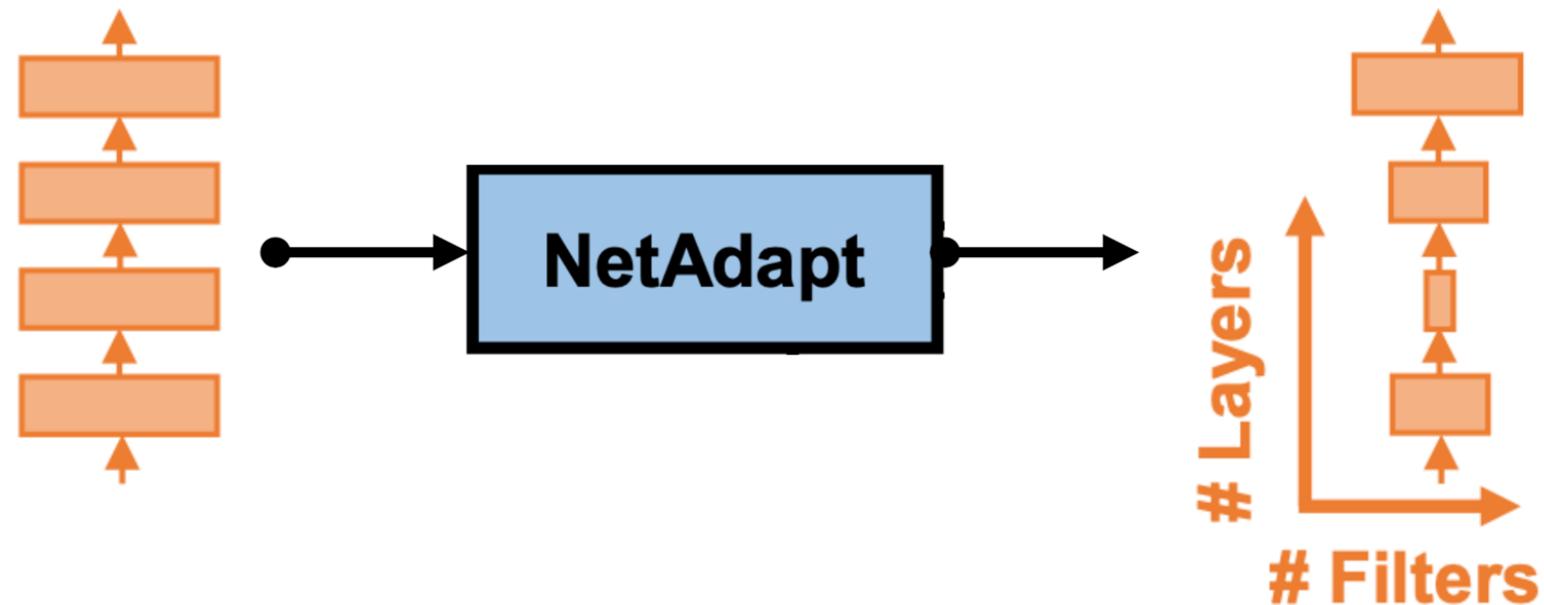
# AMC: AutoML for Model Compression

- The reinforcement learning agent automatically learns that 3x3 convolution has more redundancy than 1x1 convolution and can be pruned more



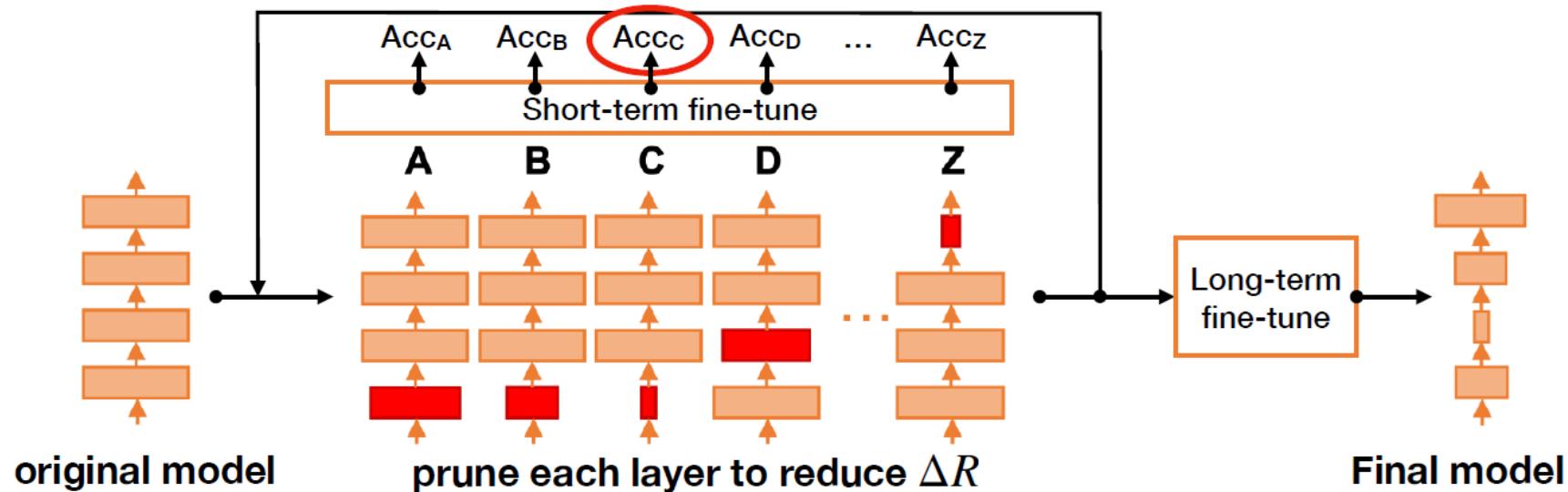
# NetAdapt

- 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



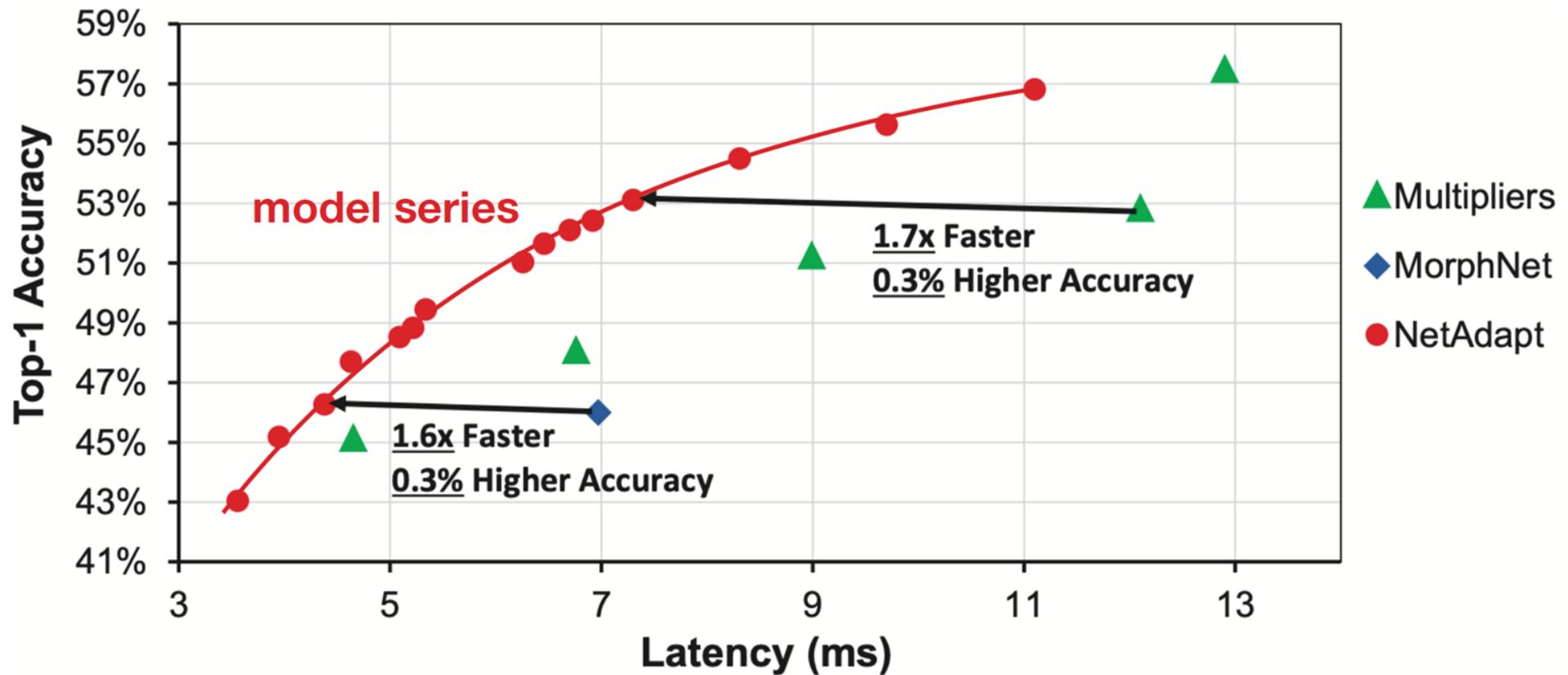
# NetAdapt

- For each iteration, we aim to reduce the latency by a certain amount  $\Delta R$  (manually defined)
  - For each layer  $L_k$  ( $k$  in A-Z in the figure)
    - Prune the layer s.t. the latency reduction meets  $\Delta R$  (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



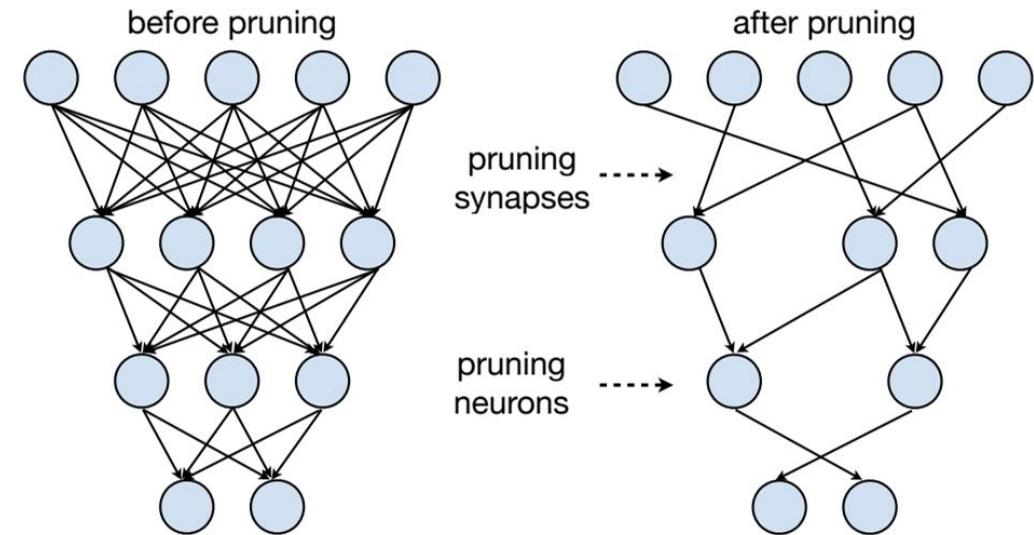
# NetAdapt

- The iterative nature allows us to obtain a serial of models with different costs
  - $\# \text{models} = \# \text{iterations}$



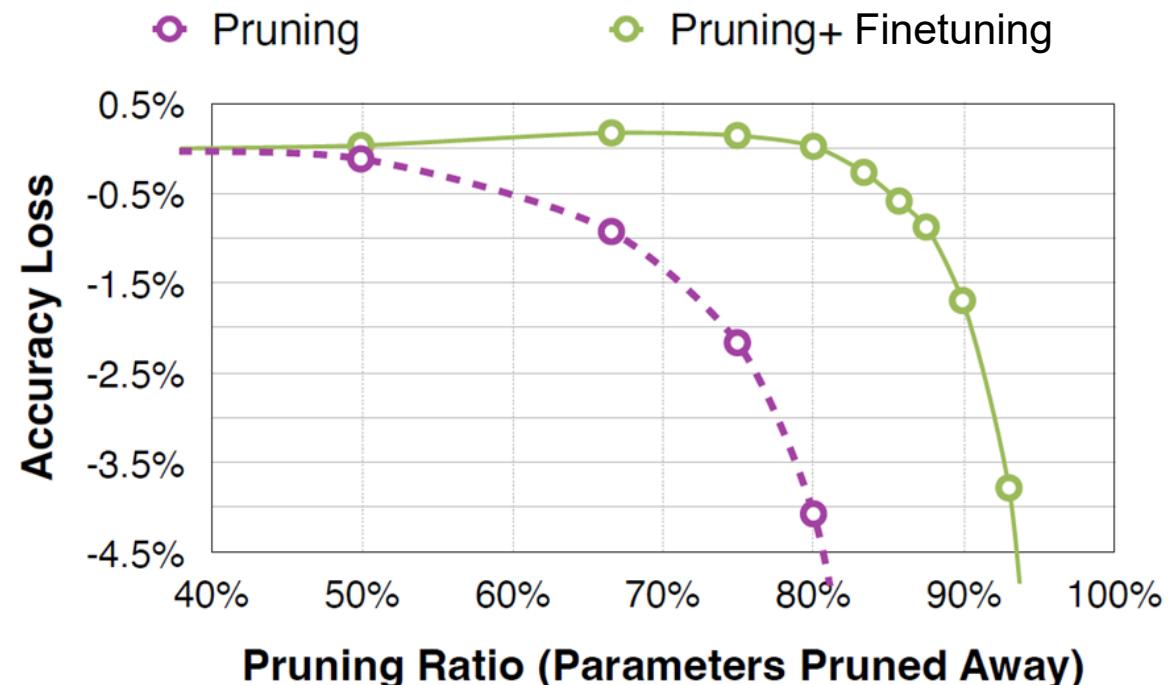
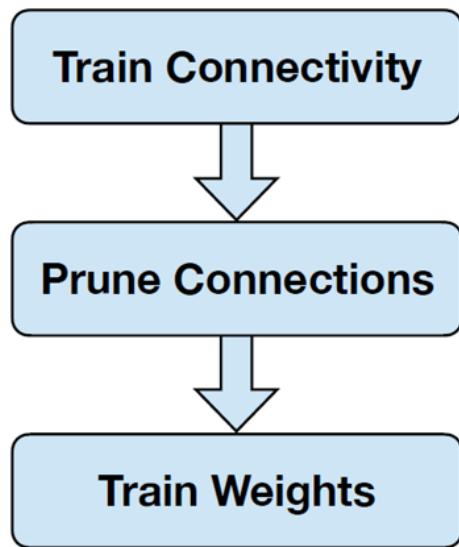
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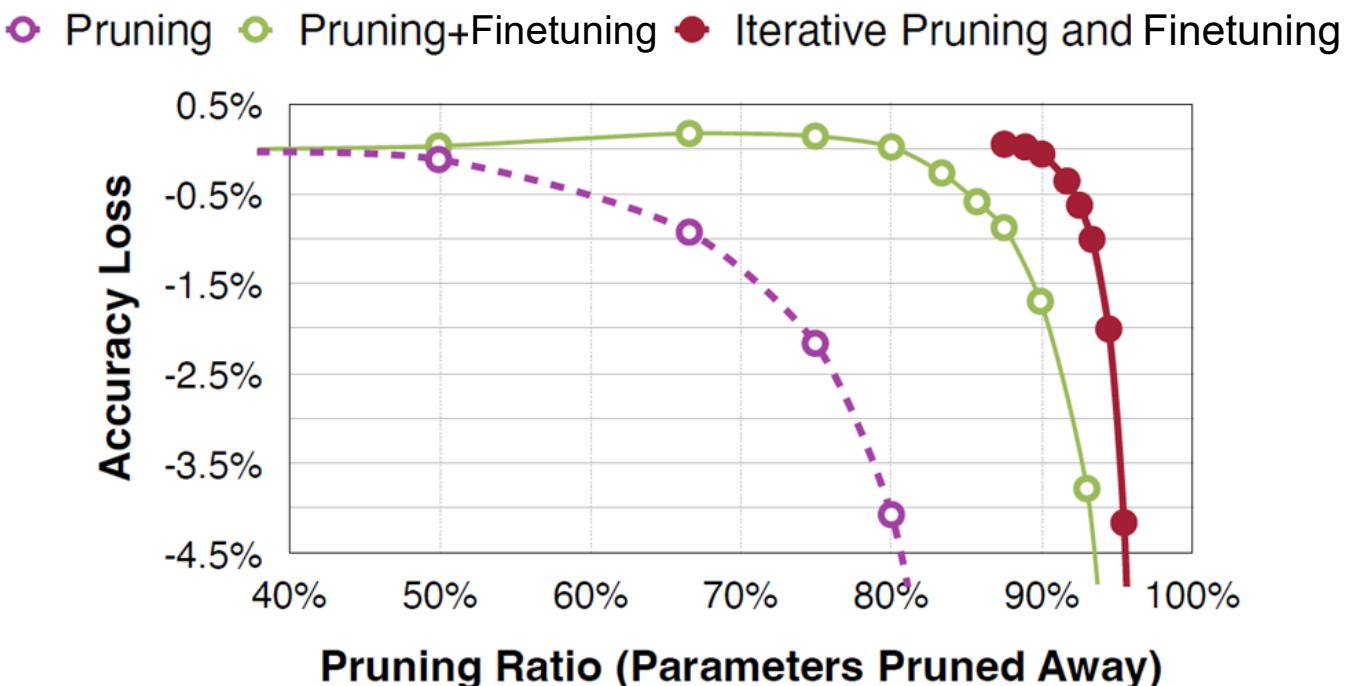
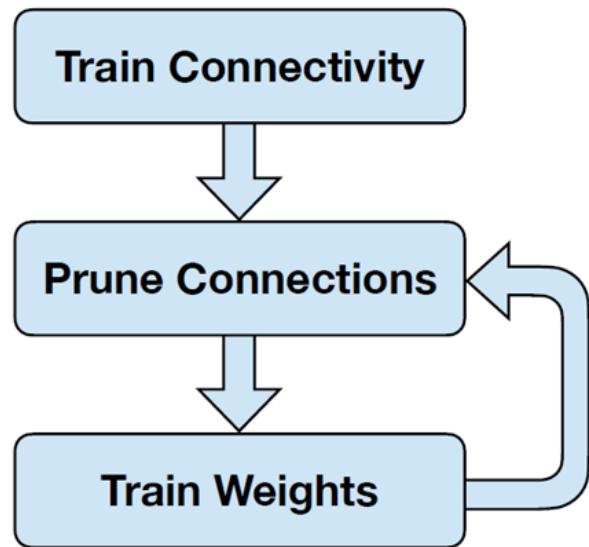
# Fine-tuning Pruned Neural Networks

- The model performance may decrease after pruning.
- Fine-tuning the pruned neural network will help recover the accuracy and enables a higher pruning ratio.



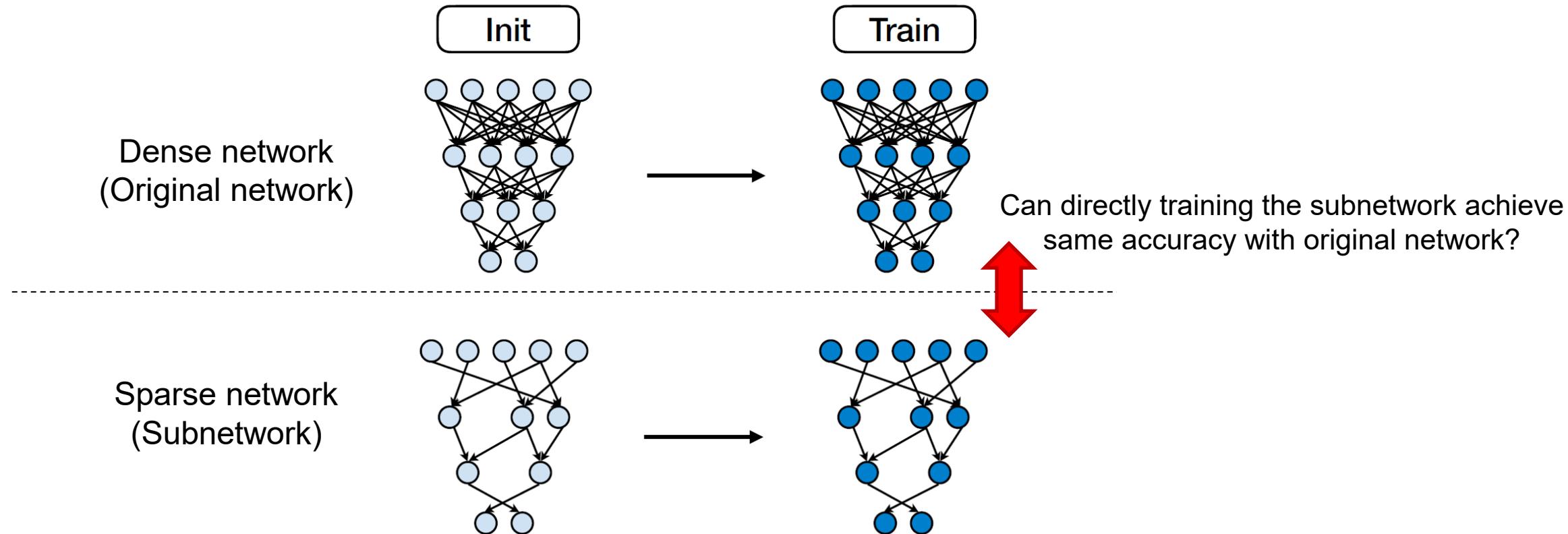
# Iterative Pruning

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



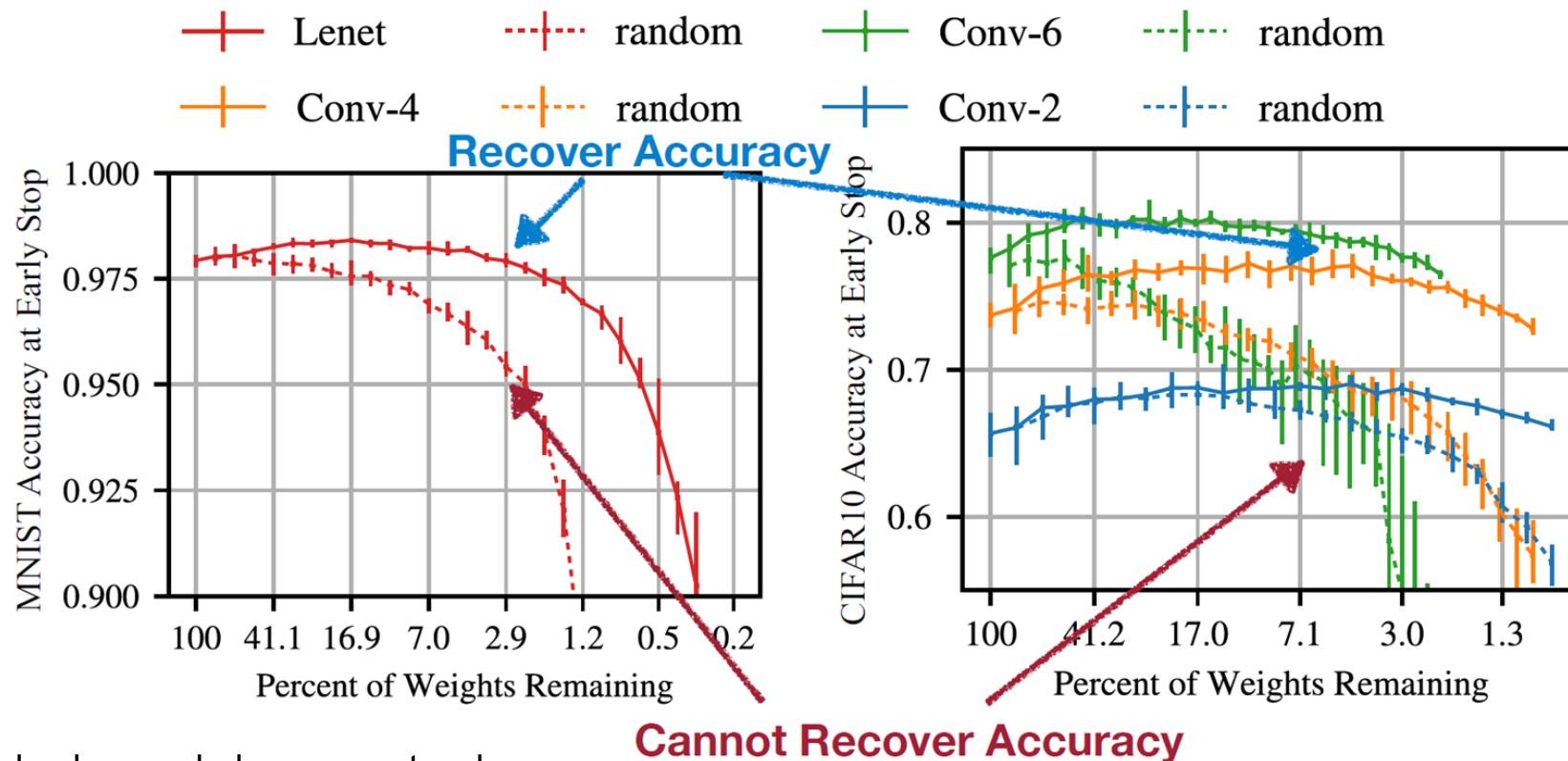
# Can we Train a Sparse Neural Network from Scratch?

- Neural network pruning shows that a neural network can be reduced in size.
- Question: Can we directly train this sparse network from scratch?



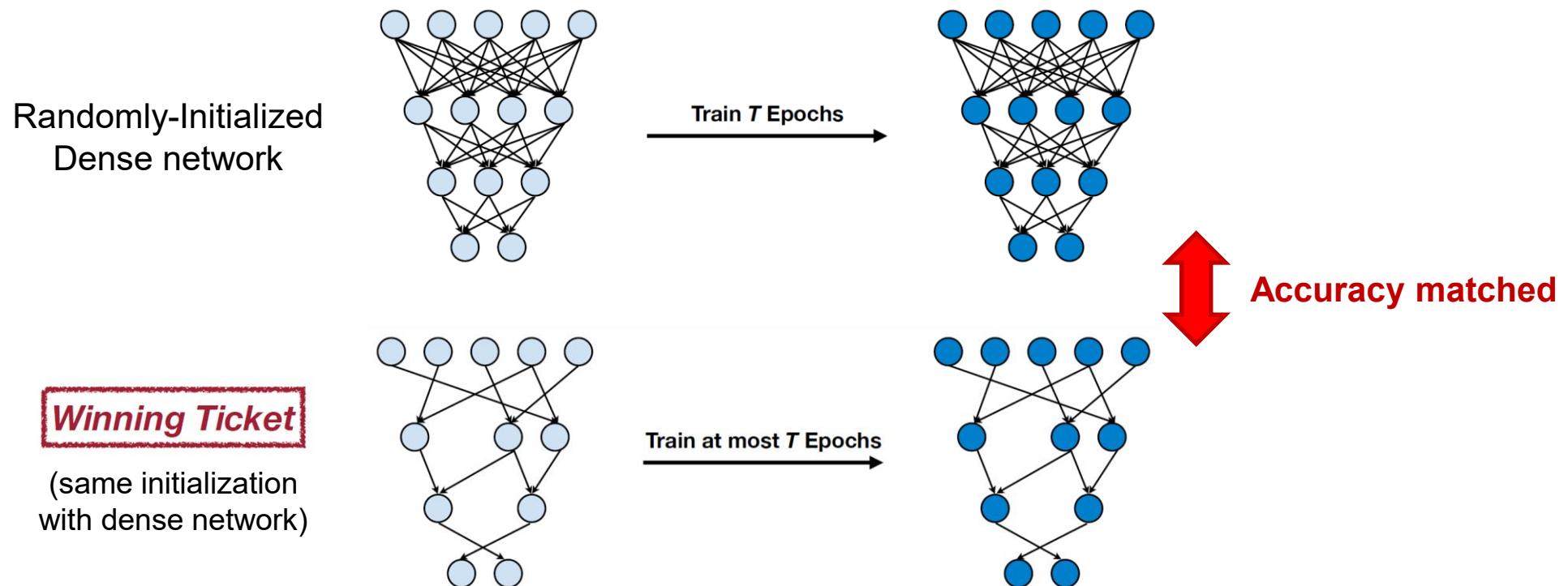
# Can we Train a Sparse Neural Network from Scratch?

- Experience tells us that the architectures uncovered by pruning are harder to train from the start reaching lower accuracy than the original networks.

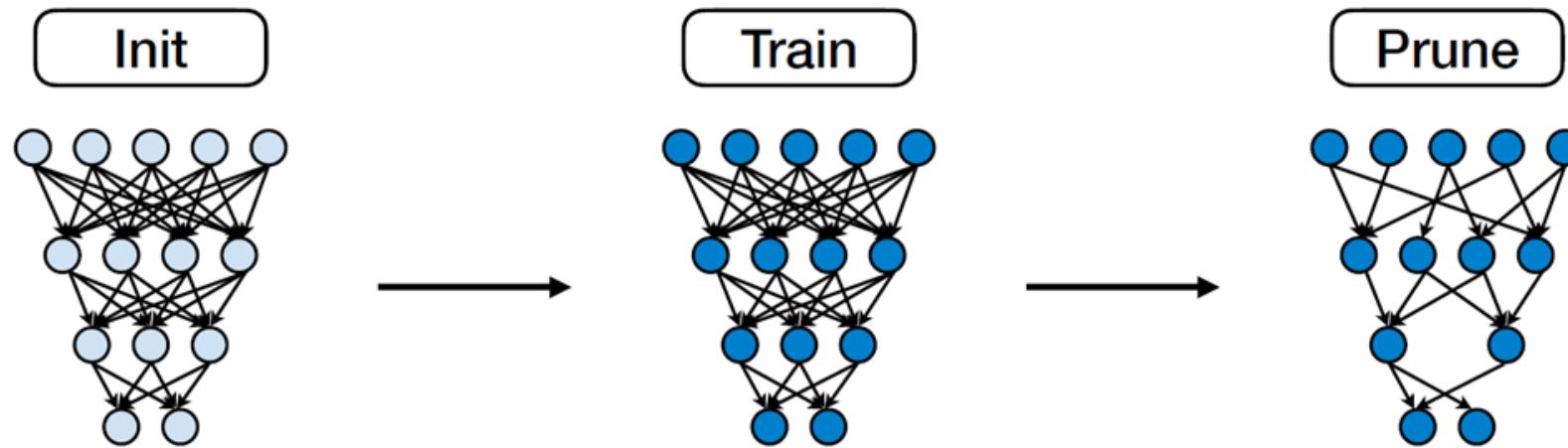


# Lottery Ticket Hypothesis

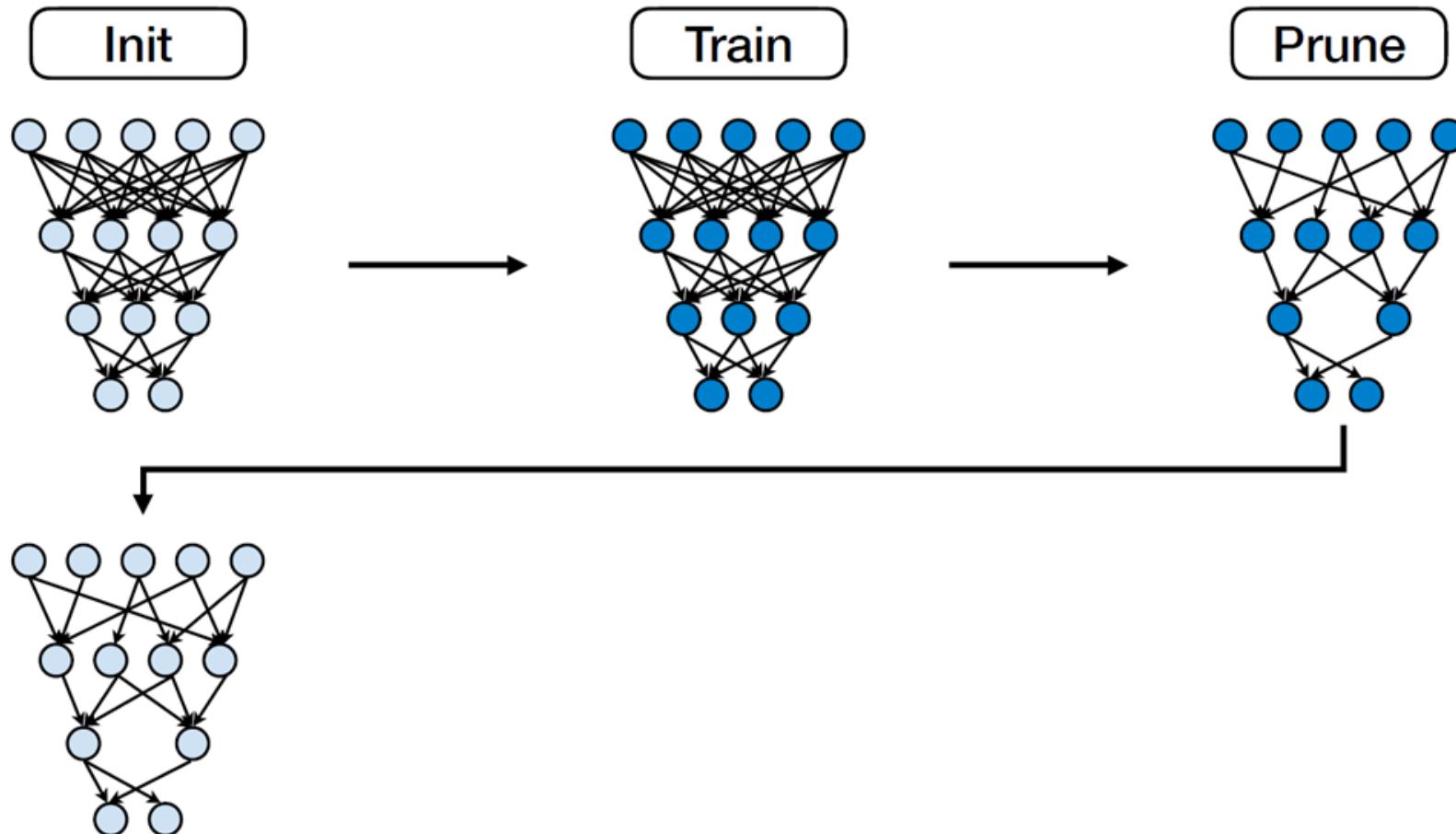
“A randomly initialized, dense neural network contains a **subnetwork** that is initialized such that—when **trained in isolation**—it can **match the test accuracy** of the original network after training for **at most the same number of iterations**.”



# Iterative Magnitude Pruning

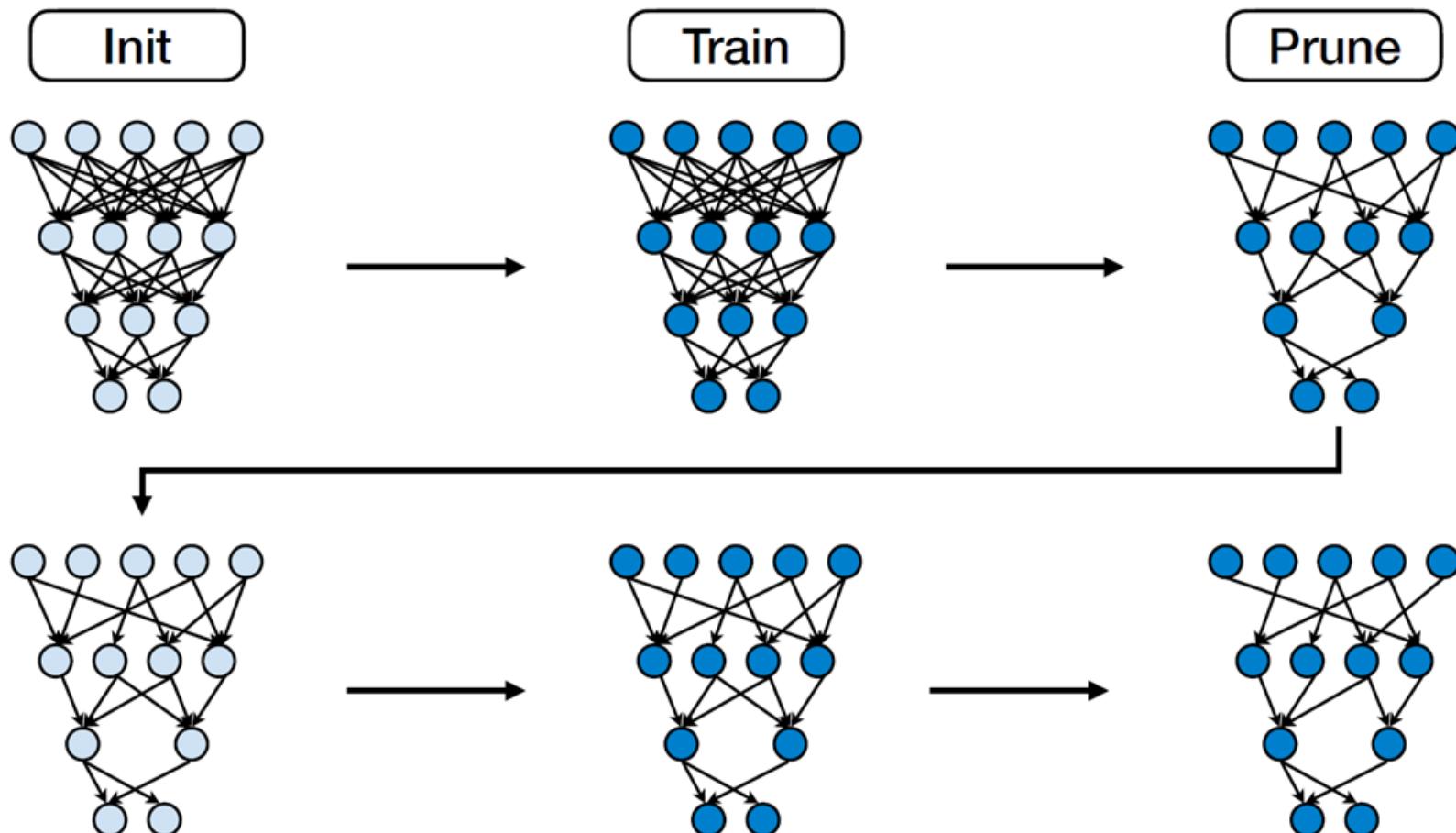


# Iterative Magnitude Pruning

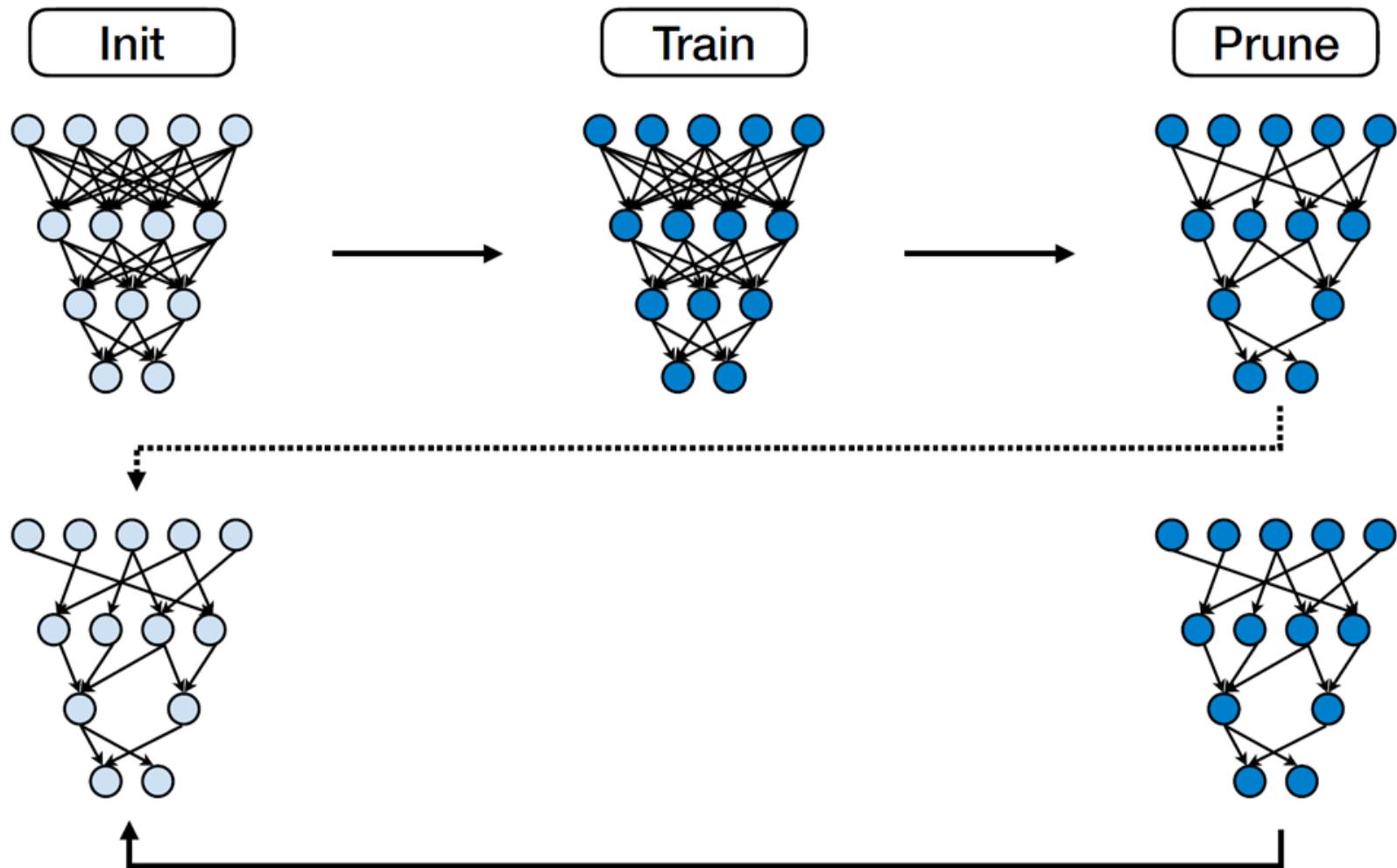


# Iterative Magnitude Pruning

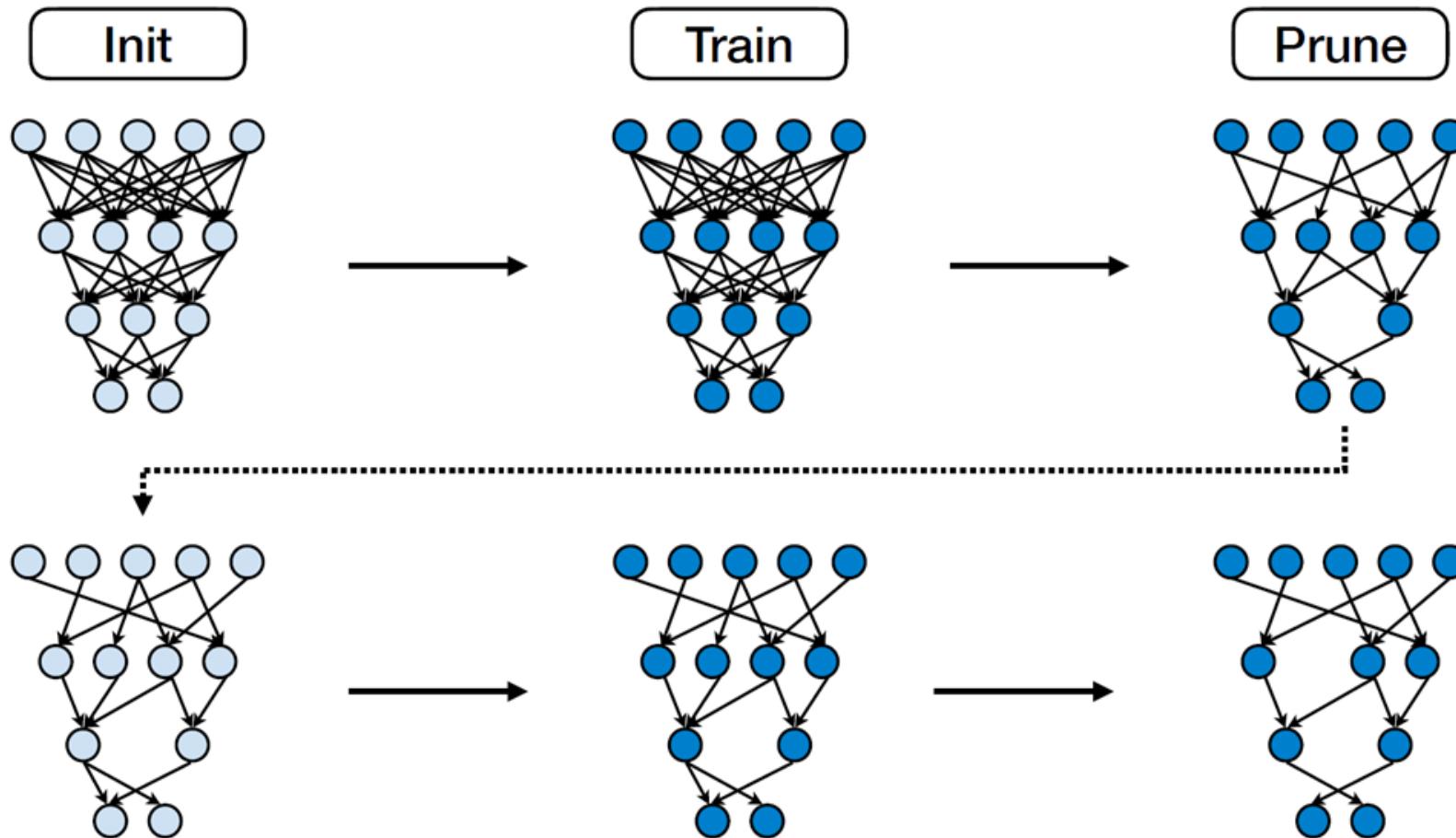
- Iterative Magnitude Pruning



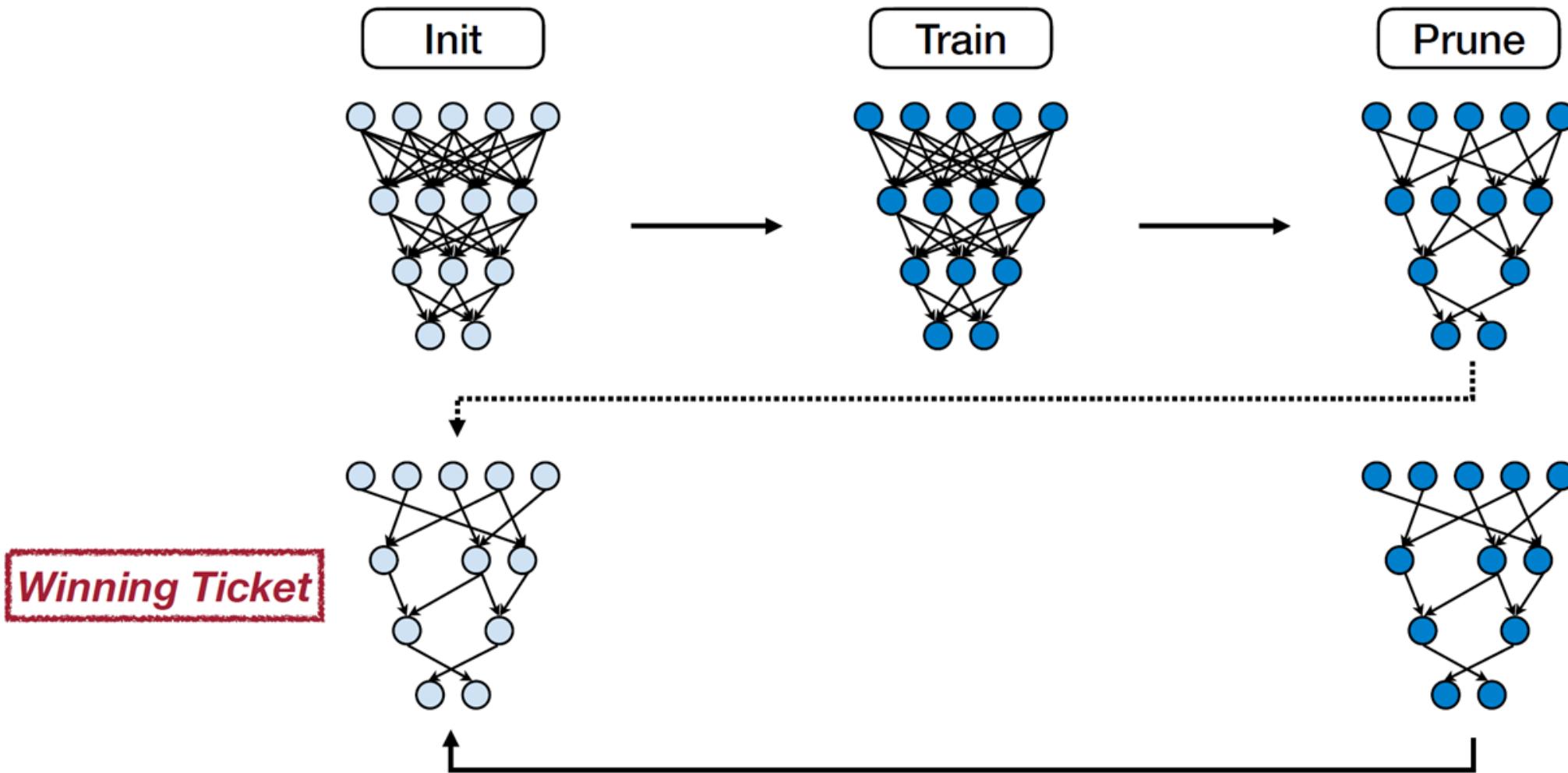
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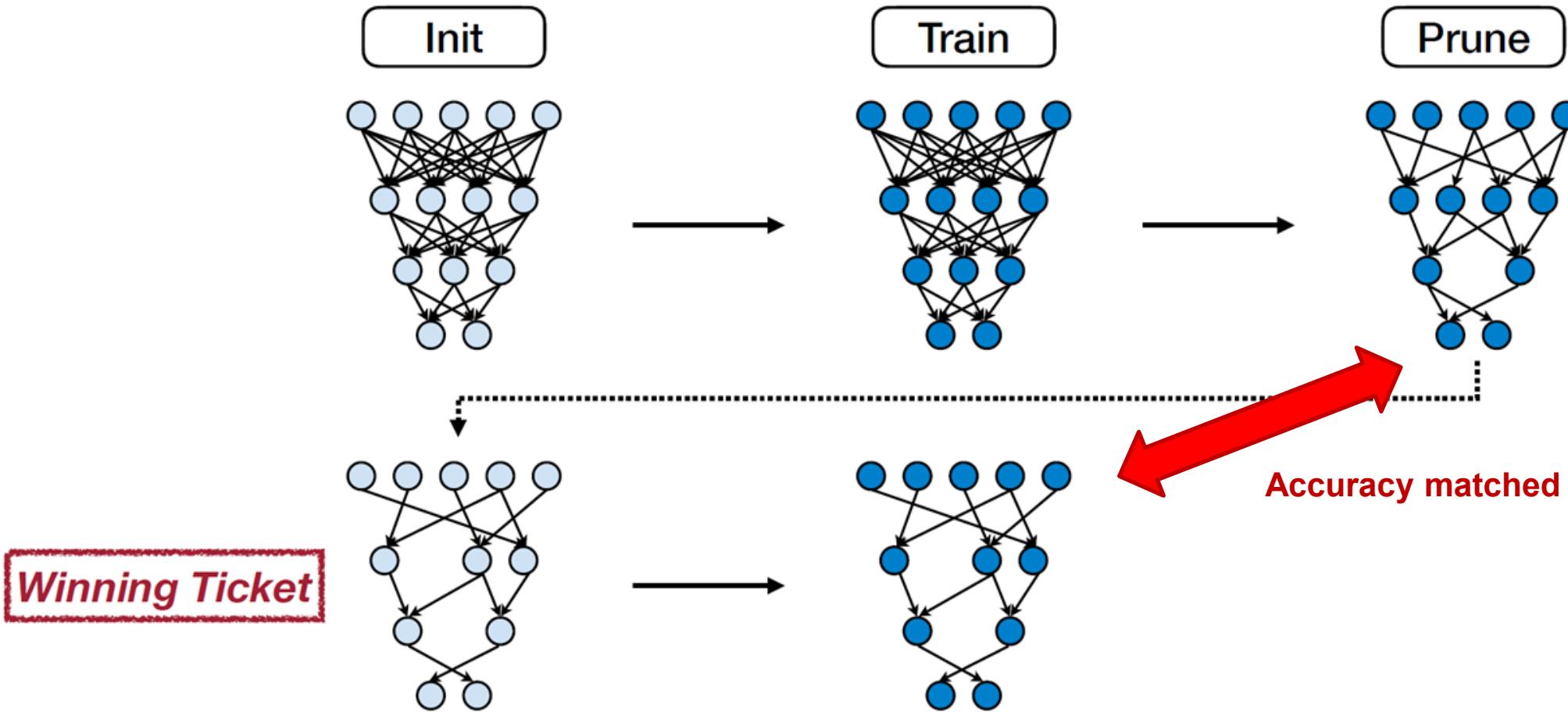
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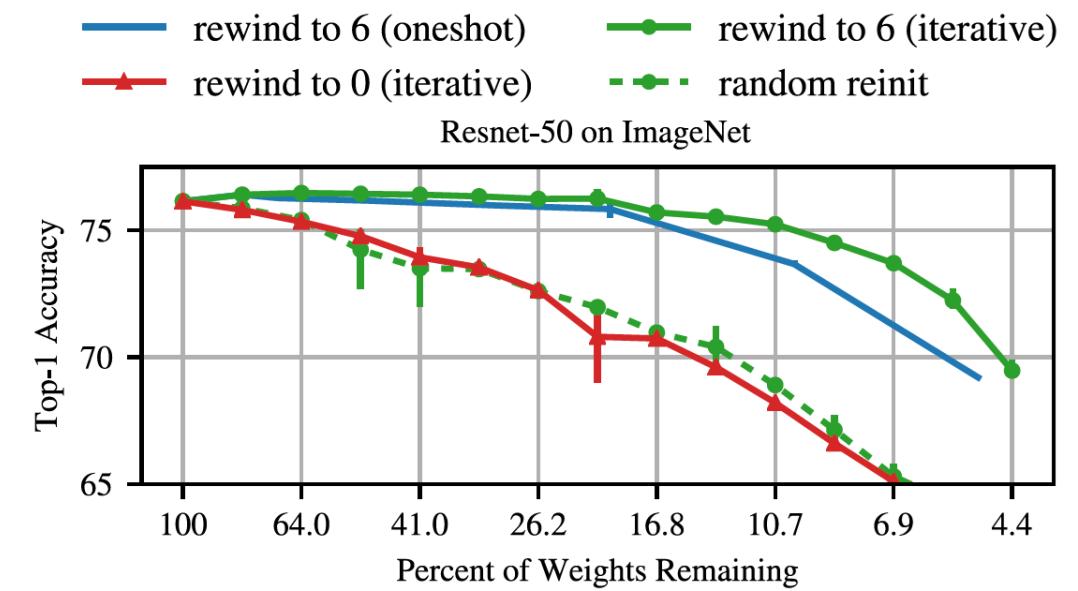
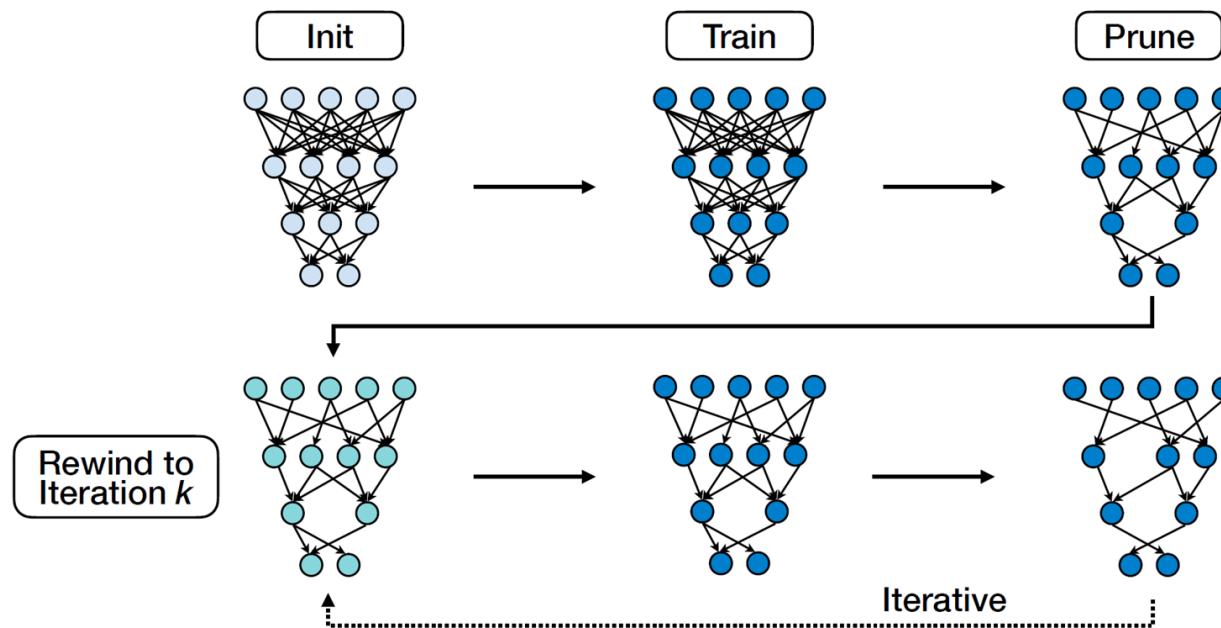


# Iterative Magnitude Pruning



# Iterative Magnitude Pruning

- Resetting the weights to the very initial value works for small-scale tasks (e.g., MNIST), but fails on deep networks.
- Instead, it is possible to robustly obtain pruned subnetworks by resetting the weights to the **values after a small number of k training iterations**.



# Summary

- In this lecture, we learned:
  - Each layer in neural network has different sensitivity to pruning
  - Automated ways to find pruning ratios
  - Performance improvement after pruning
  - Lottery ticket hypothesis