TinyML Workshop

Building Efficient AI for the Edge.

Obed Mogaka | obed.mogaka@mdu.se

HERO Lab, Malardalens University

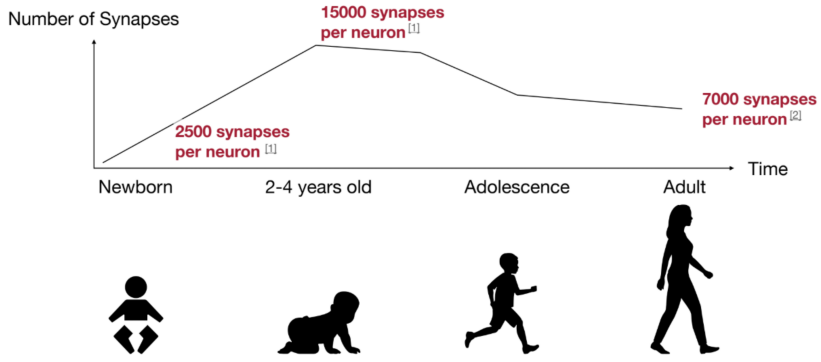
November 24, 2025

Overview

1. **Introduction to Pruning**
   - What is pruning?
   - How to formulate pruning.
2. **How and when to prune?**
   - Pruning Granularity.
   - Pruning Criterion.
   - Pruning Ratio.
   - Train/Fine-tune
3. **Hands-on**

Introduction to Pruning

Pruning in the Human Brain

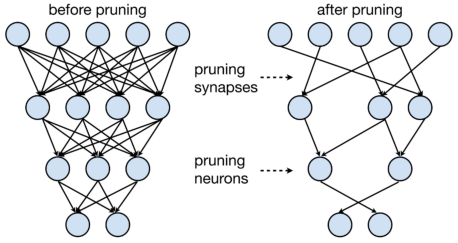


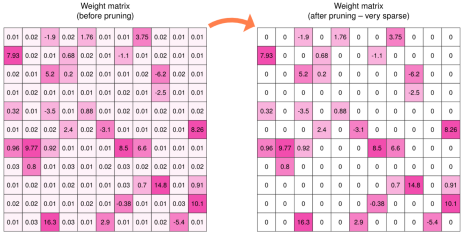
Sources: [1],[2], Alila Medical Media

[1] Drachman, David A. "Do we have brain to spare?." Neurology 64.12 (2005): 2004-2005.
[2] Walsh, Christopher A. "Peter Huttenlocher (1931–2013)." Nature 502.7470 (2013): 172-172.

Pruning makes a neural network smaller by removing synapses and neurons[3]

It removes unnecessary/redundant parameters from the model while maintaining predictive performance.

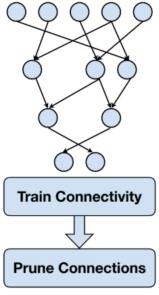


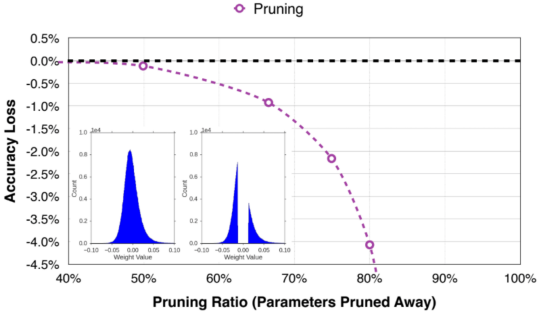


[3] Han, Song, et al. "Learning both weights and connections for efficient neural network." Advances in neural information processing systems 28 (2015).

Neural Network Pruning

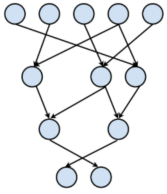
- When we train a NN, we are learning the connections.
- To make the NN smaller and efficient we prune redundant connections

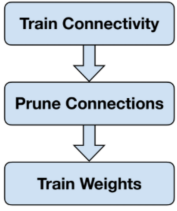


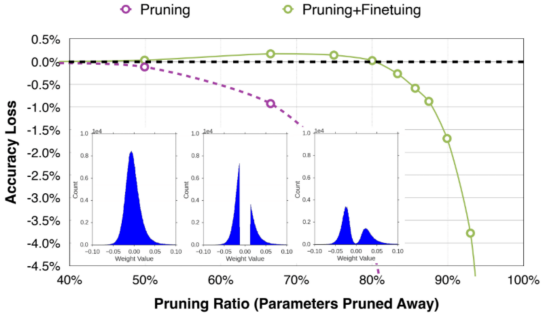


Aggressive pruning leads to accuracy loss!

Pruning with Fine-tuning







Effect of Pruning

Table 1: Effect of pruning: parameter counts and MACs for common CNNs. Reductions are shown as multiples relative to the unpruned models.[4]

Neural Network	#Parameters			MACs
	Before Pruning	After Pruning	Reduction	Reduction
AlexNet	61 M	6.7 M	**9** ×	3 ×
VGG-16	138 M	10.3 M	**12** ×	5 ×
GoogleNet	7 M	2.0 M	**3.5** ×	5 ×
ResNet50	26 M	7.47 M	**3.4** ×	6.3 ×
SqueezeNet	1 M	0.38 M	**3.2** ×	3.5 ×

[4] Han, Song. Efficient methods and hardware for deep learning. Diss. Stanford University, 2017.

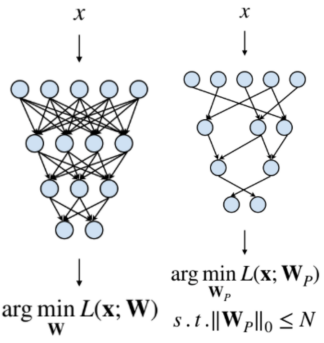
Formulating Pruning

Pruning can be formalized as an optimization problem.
Given a trained model with parameters W, we seek a sparse version W_P that retains only the most important parameters.

- The objective is defines as follows:

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

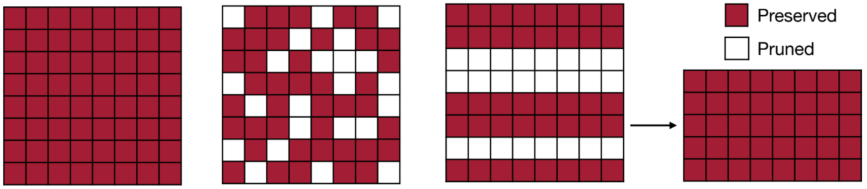
- L represents the objective function for neural network training;
- $\mathbf{x}$ is the input, $\mathbf{W}$ is the original weights, and $\mathbf{W_p}$ is the pruned weights;
- $\|\mathbf{W_p}\|_0$ calculates the number of nonzero elements in $\mathbf{W_p}$, and N is the target number of nonzeros.



How to Prune

Pruning Granularity

In what pattern should we prune the neural network?
Pruning can be performed at different granularities, from structured to non-structured.



Fine-grained/Unstructured

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

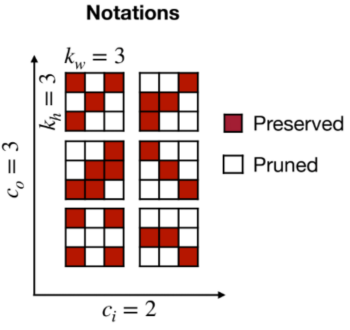
Course-grained/Structured

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

The case of convolutional layers

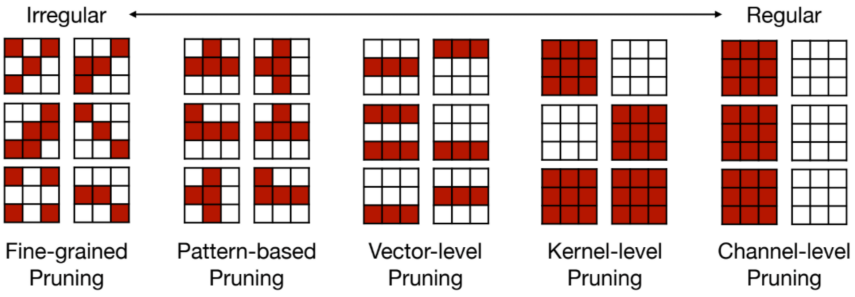
- The weights of convolutional layers have 4 dimensions $[c_o, c_i, k_h, k_w]$:
  - c_i: input channels (or channels)
  - c_o: output channels (or filters)
  - k_h: kernel size height
  - k_w: kernel size weight

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



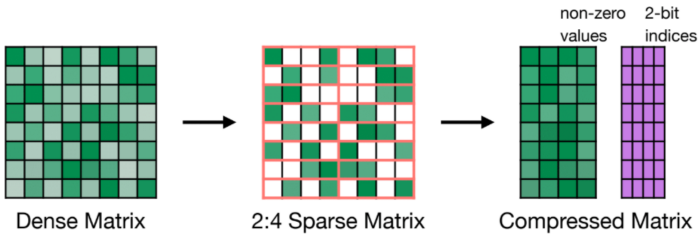
Pruning at Different Granularities

Some of the commonly used pruning granularities



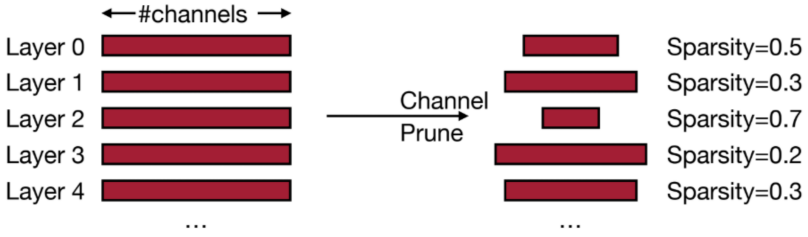
Looking into some cases

- **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)
  - Supported by NVIDIA's Ampere GPU Architecture, which delivers up to 2x speed up



Looking into some cases

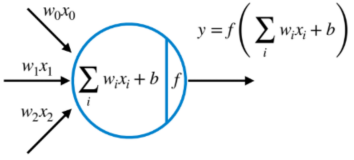
- **Channel Pruning**
  - Pro: Direct speed up due to reduced channel numbers (leading to an NN with fewer channels)
  - Con: smaller compression ratio



Pruning Criterion

What synapses and neurons should we 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.



Example

$f(\cdot) = \text{ReLU}(\cdot), \quad W = [10, -8, 0.1]$

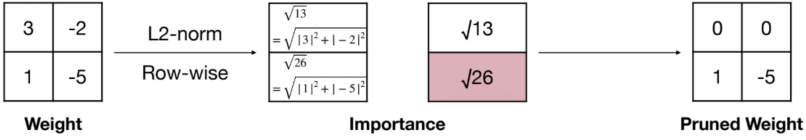
➡ $y = \text{ReLU}(10x_0 - 8x_1 + 0.1x_2)$

- If one weight will be removed, which one?

Magnitude-based Pruning

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, $||W^{(S)}||_p = (\sum_{i \epsilon s} |w_i|^p)$, where $W^{(S)}$ is a structural set of parameters

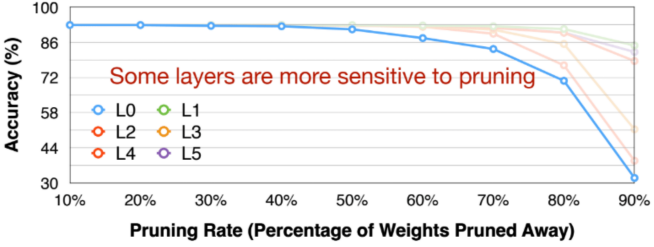


Other Pruning Criteria

- **Filter pruning using scaling factors**
- **Second-Order-based pruning:** Minimize the error on loss function introduces by pruning synapses.
- **Percentage-of-Zero-based pruning:** A measure of the importance of the neurons.
- **Regression-based Pruning:** Minimize reconstruction error of the corresponding layer's outputs.
- **One-shot Pruning:** removes multiple architectural components in a single step, followed by an extensive fine-tuning phase to recover model accuracy.

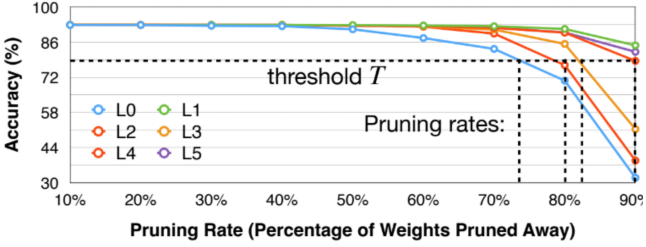
Analyse the sensitivity of each layer

- 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 $r \epsilon \{0, 0.1, 0.2..., 0.9\}$ (or other strides)
    - Observe the accuracy degrade ΔAcc_r^i for each pruning ratio
  - Repeat the process for all layers

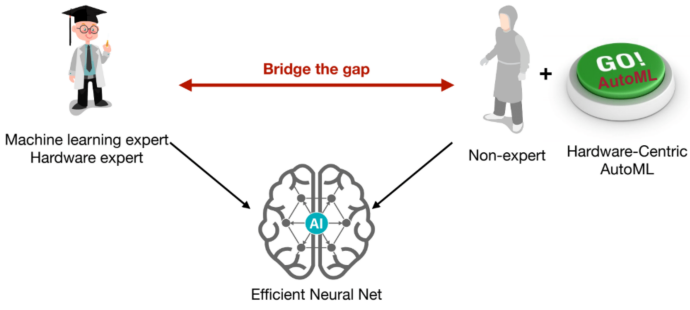


Analyse the sensitivity of each layer

- 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 $r \epsilon \{0, 0.1, 0.2..., 0.9\}$ (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

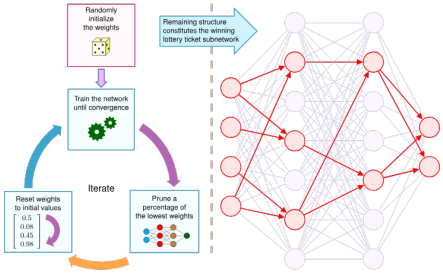


Can we have a push-the-button solution?



Lottery Ticket Hypothesis

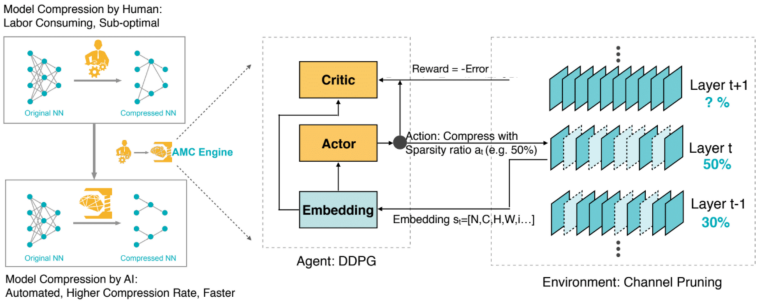
- **Core Idea:** Large neural networks contain small, sparse subnetworks called "winning tickets."
- These "winning tickets" can be trained in isolation from the start to achieve the same (or better) accuracy as the full, dense network.
- LTH reframes pruning not just as compression, but as a discovery mechanism to find these inherently efficient subnetworks.[5]



- **LTH challenges overparameterization**: It suggests that massive models may not be necessary for training, but rather to ensure a "winning ticket" exists at initialization.
- Practical Example: A 90% pruned BERT-base (a "winning ticket") can retain 97% of its performance and train 5-8x faster.

[5] Frankle, Jonathan, and Michael Carbin. "The lottery ticket hypothesis: Finding sparse, trainable neural networks." arXiv preprint arXiv:1803.03635 (2018).

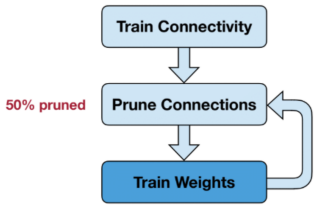
Pruning as a reinforcement learning problem[6]

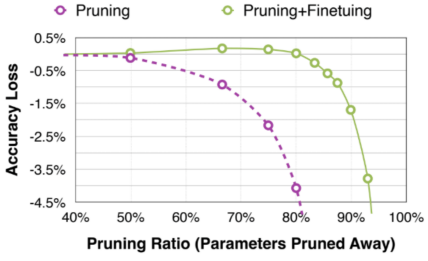


[6] He, Yihui, et al. "AMC: Automl for model compression and acceleration on mobile devices." Proceedings of the European conference on computer vision (ECCV). 2018.

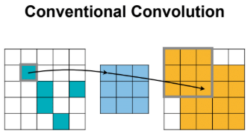
Fine-tuning Pruned Neural Networks

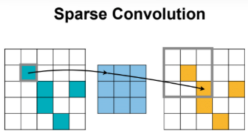
- After pruning, the model may decrease, especially for larger pruning ratio.
- Fine-tuning the pruned neural networks will help recover the accuracy and push the pruning ratio higher.
- Consider pruning followed by a fine-tuning is one iteration.
- **Iterative Pruning:** gradually increases the target sparsity in each iteration.





Sparse convolution computation





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, $W_{-1,1}$)
(P_0, Q_9, $W_{-1,0}$)
(P_0, Q_{10}, $W_{-1,-1}$)

9 matrix multiplications

No compute
No compute
No compute
No compute
(P_0, Q_6, $W_{0,0}$)
No compute
No compute
No compute
(P_0, Q_1, $W_{-1,-1}$)

2 matrix multiplications

Hands-on

“Talk is cheap. Show me the code.”

— Linus Torvalds

Github Repository.