Pruning neural networks

Efficient Deep Learning - Session 4

IMT Atlantique
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Course organisation

Sessions

1. Intro Deep Learning,
2. Data Augmentation and Self Supervised Learning,
3. Quantization,
4. Pruning,
5. Factorization,
6. Distillation,
7. Embedded Software and Hardware for DL,
8. Presentations for challenge.

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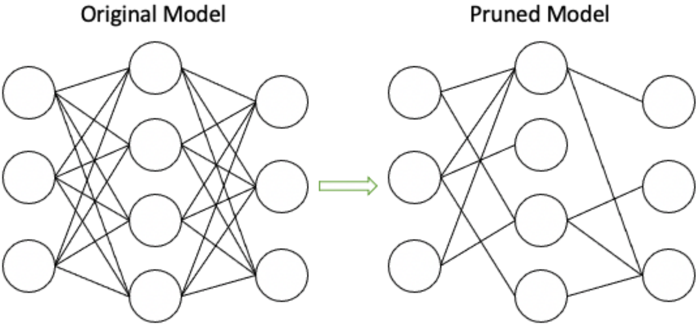
What is pruning?

Intuitive principle

Removing parts of the network to reduce its cost (in memory, computation power, etc.).



What does it involve?

The three big questions of pruning

1. What kind of part should I prune?
2. How to tell which parts can be pruned?
3. How to prune parts without harming the network?

⇒ **Pruning structure**: the kind of part you will remove, how it will affect the network's cost.

⇒ **Pruning criterion**: the metric to use to identify parts to prune.

⇒ **Pruning method**: the removal strategy and schedule, how to reduce the loss in performance, how to avoid some known pitfalls...

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Pruning structure (1/2)

Mainly two kinds of pruning:

- **“Unstructured" (weight) pruning**: removing individual weights
  - More straightforward to implement
  - More fine-grained
  - Allows better accuracy/parameters ratio
  - **But**, very hard to optimize: you not always get any speedup out of it! (cf. *Non-Structured DNN Weight Pruning – Is It Beneficial in Any Platform?*, by Ma et. al. 2019)
  - However good as a proof of concept
- **“Structured" (filter) pruning**: removing convolution filters (or neurons)
  - Watch out for dimensional consistency between layers!
  - More coarse-grained (watch out not to prune entire layers by accident!)
  - Produces a smaller network that allows real speedup on any framework
  - Lighter to run because of fewer feature maps

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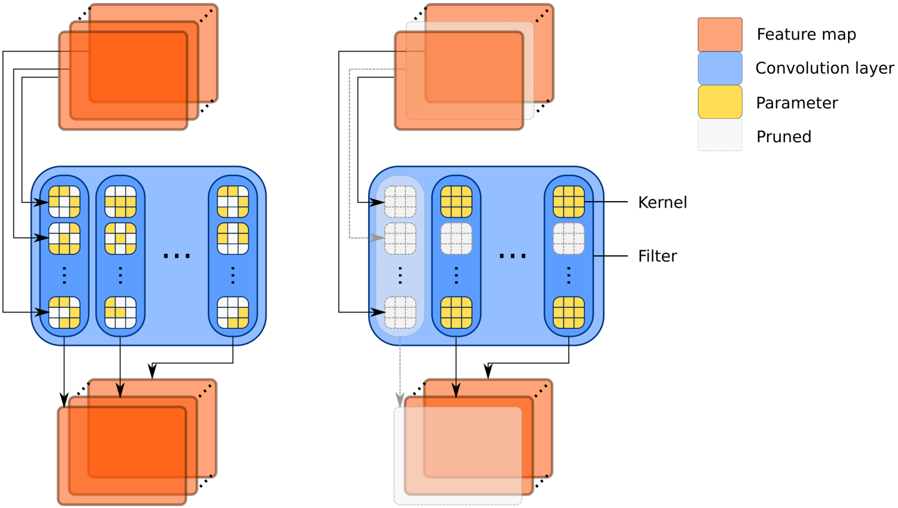

"Unstructured" : weight pruning

"Structured" : filter pruning

Pruning structure (2/2)

How to distribute pruning:

- **Local pruning**: remove the same proportion to each layer
  - A lot simpler to implement
  - Sub-optimal
- **Global pruning**: remove different proportions to each layer to reach a global target
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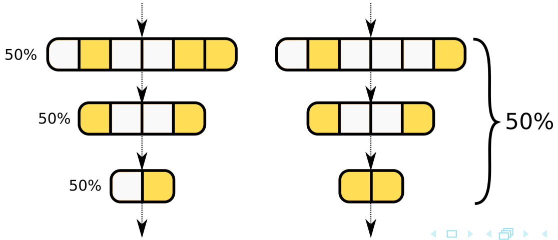

Pruning criteria (1/2)

Two widespread examples for individual weights:

- **Weight magnitude**: prune weights of least $\mathcal{L}_1$ norm
- **Weight gradient**: do a back-propagation over a minibatch and prune weights whose gradients are of least $\mathcal{L}_1$ norm

Things get more tricky in the case of structured pruning:

- $\mathcal{L}_1$, $\mathcal{L}_2$ of the filter or its gradient... (cf. *Pruning Filters for Efficient ConvNets*, by Li et. al. 2016)
- Magnitude of the batch-normalization layer's multiplicative parameter (cf. *Learning Efficient Convolutional Networks through Network Slimming*, by Liu et. al. 2017)
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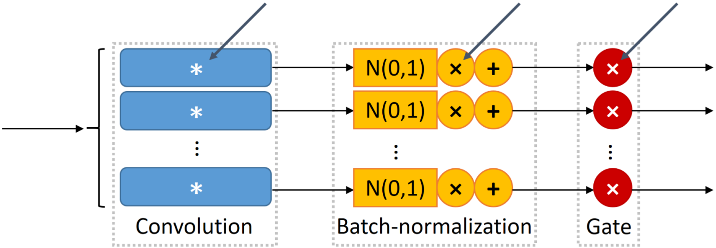

Pruning criteria (2/2)

Remarks:

1. Criteria reported previously are among the simplest: the literature has been very prolific on the topic of pruning criteria and include many complex ones. For example:
   - Filter identification through reinforcement learning (cf. *AMC: AutoML for Model Compression and Acceleration on Mobile Devices*, by He et. al. 2018)
   - Optimization through variational inference (cf. *Variational Dropout Sparsifies Deep Neural Networks*, by Molchanov et. al. 2017)
   - Computation of the network's second derivative (Hessian)... (cf. *Optimal Brain Damage*, by Le Cun et. al. 1989)
2. **Warning**, in the case of global pruning:
   - Some criteria may be unbalanced: for example, magnitude-based criteria tend to prune mostly the last layers.
   - There are risks to prune entire layers by accident, a.k.a. "**layer collapse**". (cf. *Pruning neural networks without any data by iteratively conserving synaptic flow*, by Tanaka et. al. 2020)

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- Two aspects that encompasses most simple ones:
  1. **Removal strategy**
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  1. **Removal strategy**
     - Set weights to prune to 0 definitely
     - Same but iterative with a growing pruning rate (cf. *Learning both Weights and Connections for Efficient Neural Networks*, by Han et. al. 2015)
     - Progressively all throughout pruning, until the target is reached (cf. *To prune, or not to prune: exploring the efficacy of pruning for model compression*, by Zhu et. al. 2017)
     - At each epoch, set targeted weights to 0 but let them train again until the end, a.k.a. “Soft pruning" (cf. *Soft Filter Pruning for Accelerating Deep Convolutional Neural Networks*, by He et. al. 2018)
  2. **Training schedule**

Pruning methods

- Many existing and very different methods in the literature...
- Two aspects that encompasses most simple ones:
  1. **Removal strategy**
  2. **Training schedule**
     - Train, prune and fine-tune once (or prune while training) (cf. *Learning Efficient Convolutional Networks through Network Slimming*, by Liu et. al. 2017)
     - Fine-tune after each pruning step (cf. *Learning both Weights and Connections for Efficient Neural Networks*, by Han et. al. 2015)
     - Train, prune, and wholly retrain, a.k.a. LR-Rewinding (cf. *Comparing Rewinding and Fine-tuning in Neural Network Pruning*, by Renda et. al. 2020)

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Remark 1

For the sake of convenience, many methods/paper count as pruned weights that are simply set to 0. Even though it does not produce any speedup, it allows measuring a parameters/performance ratio without worrying about dimensional discrepancies or efficiency issues.

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Remark 2

Iterative or progressive methods are more robust to layer-collapse, because values of remaining weights values may be updated so that they are less likely to be targeted afterward.

Some unstructured examples

- *Learning both Weights and Connections for Efficient Neural Networks*, by Han et. al. 2015
  - Structure: global individual weights
  - Criterion: weights magnitude
  - Method: train, then iterate between pruning and fine-tuning
- *To prune, or not to prune: exploring the efficacy of pruning for model compression*, by Zhu et. al. 2017
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Some unstructured examples

- *Learning both Weights and Connections for Efficient Neural Networks*, by Han et. al. 2015
- *To prune, or not to prune: exploring the efficacy of pruning for model compression*, by Zhu et. al. 2017
  - Structure: local individual weights
  - Criterion: weights magnitude
  - Method: train while pruning progressively the smallest weights, no fine-tuning
- *Comparing Rewinding and Fine-tuning in Neural Network Pruning*, by Renda et. al. 2020

Some unstructured examples

- *Learning both Weights and Connections for Efficient Neural Networks*, by Han et. al. 2015
- *To prune, or not to prune: exploring the efficacy of pruning for model compression*, by Zhu et. al. 2017
- *Comparing Rewinding and Fine-tuning in Neural Network Pruning*, by Renda et. al. 2020
  - Structure: global individual weights
  - Criterion: weights magnitude
  - Method: train, prune the lowest 20%, re-train and repeat until pruned enough
  - Remark: the principle of retraining, with its learning-rate schedule, instead of fine-tuning with the lowest learning-rate is the heart of *Learning Rate Rewinding*.

Some structured examples

- *Pruning Filters for Efficient ConvNets*, by Li et. al. 2016
  - Structure: local convolution filters and corresponding kernels in the following layer (with varying rates)
  - Criterion: $\mathcal{L}_1$ norm of filters
  - Method: train, then iterate between pruning and fine-tuning
- *Learning Efficient Convolutional Networks through Network Slimming*, by Liu et. al. 2017
- *Importance Estimation for Neural Network Pruning*, by Molchanov et. al. 2019

Some structured examples

- *Pruning Filters for Efficient ConvNets*, by Li et. al. 2016
- *Learning Efficient Convolutional Networks through Network Slimming*, by Liu et. al. 2017
  - Structure: global convolution filters
  - Criterion: magnitude of multiplicative parameter in batch-normalization layers
  - Method: train, prune and fine-tune once
  - Remark: applies a smooth-$\mathcal{L}_1$ penalty on multiplicative parameters in batch-normalization layers during training
- *Importance Estimation for Neural Network Pruning*, by Molchanov et. al. 2019

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  - Structure: global gates (or global individual weights)
  - Criterion: gradient magnitude
  - Method: train, then iterate between pruning and fine-tuning

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Advice

Refer to the original papers (available online) for more details on methods, implementation or eventual variants.

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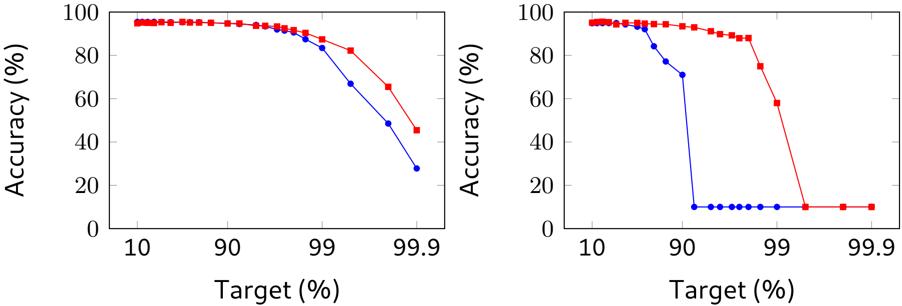
To go further:

- *Neural Network Pruning 101* on towardsdatascience.com.

Some results



(a) Unstructured pruning

(b) Structured pruning

Han et. al.

Han et. al. + LR-Rewinding

Liu et. al.

Liu et. al. + LR-Rewinding

Figure: Pruning rate/Accuracy tradeoff, ResNet-20 on CIFAR-10

Lab Session and Project

Lab Session

- Implement one of the pruning methods from this course
- Apply it on CIFAR10

Presentation at next session

Present your current explorations on CIFAR10 and / or CIFAR100 using the methods seen so far!