
Formatting instructions for NeurIPS 2018

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Abstract

The abstract paragraph should be indented $\frac{1}{2}$ inch (3 picas) on both the left- and right-hand margins. Use 10 point type, with a vertical spacing (leading) of 11 points. The word **Abstract** must be centered, bold, and in point size 12. Two line spaces precede the abstract. The abstract must be limited to one paragraph.

1 Introduction

Modern neural networks tend to be immensely large with several millions of connections and weights. The memory and energy requirements for deploying such networks is significant, and constantly growing with the complexity of state-of-the-art networks. Although having a large number of trainable parameters is beneficial to network accuracy, it was shown by Han et al. (2015), LeCun et al. (1990) and Hassibi et al. (1993) that the impact of some parameters is negligible in comparison with others. Successful identification and removal (“pruning”) of such parameters would lead to smaller and faster networks, which in turn would significantly reduce the computational cost at test time. The goal of most pruning algorithms is to achieve this computational advantage without an appreciable impact on accuracy.

and gained initial popularity due to LeCun et al. (1990) and Hassibi et al. (1993). Since then, pruning has been applied in various forms and continues to be an area of research, and more recently by Liu et al. (2019).

However, these weights can only be identified either after Han et al. (2015), or during LeCun et al. (1990); Hassibi et al. (1993); Prechelt (1995) training. The process of identifying and removing these weights has been shown to provide significant savings in memory and energy consumption Han et al. (2015), and is known as pruning. Furthermore, architectures obtained as a result of pruning may show superior efficiency and generalizability relative to the full architecture, regardless of the weights Liu et al. (2019).

A variety of pruning algorithms have been proposed, many of which apply to convolutional neural networks. Some remove individual weights (leading to sparse weight matrices) while others remove entire filters, channels or layers. Units may be removed based on many criteria, including their magnitude, their contribution to the final loss (approximated through their gradients), and information criteria such as entropy Han et al. (2015); Molchanov et al. (2016a); Luo and Wu (2017); Liu

Algorithm 1 Meta-pruning for weights

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1:  $\theta \leftarrow \text{Random initialization}$ 
2: for all  $D$  in collection of datasets  $\mathcal{D}$  do
3:    $T \leftarrow \text{Sample tasks from dataset } D$ 
4:   for all  $i$  in  $T$  do
5:      $G_i \leftarrow \nabla_{\theta,i} \mathcal{L}(f_{\theta,i})$ 
6:      $\theta_i \leftarrow \theta_i - \beta G_i$ 
7:    $\theta \leftarrow \text{Pruned and fine-tuned } \theta$ 
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Algorithm 2 Meta-pruning for architecture

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1: for all  $D$  in collection of datasets  $\mathcal{D}$  do
2:    $\theta \leftarrow \text{Random initialization}$ 
3:    $T \leftarrow \text{Sample tasks from dataset } D$ 
4:   for all  $i$  in  $T$  do
5:      $G_i \leftarrow \nabla_{\theta,i} \mathcal{L}(f_{\theta,i})$ 
6:      $\theta_i \leftarrow \theta_i - \beta G_i$ 
7:    $\theta \leftarrow \text{Pruned } \theta$ 
```

et al. (2017). Pruning may be applied towards a human-defined architecture (e.g. removing a certain proportion of weights in each layer) Yu et al. (2017) or help determine the final architecture autonomously Luo et al. (2017).

2 Goals

In previous works referenced above, pruning has been applied with respect to a particular training set. Pruning can lead to better generalization to related datasets (transfer learning) Molchanov et al. (2016b), but the actual process of pruning has only been applied to one training set at a time. In this project, we propose to extend existing pruning algorithms to make them data-agnostic, at least for related datasets, and improve generalizability. A meta-learning algorithm has already been proposed Finn et al. (2017) to initialize training parameters in a data-agnostic way. We propose to combine the idea of meta-learning with pruning, to obtain a pruning algorithm that is data-agnostic. We refer to this concept as "meta-pruning". The basic algorithm is provided below:

After each dataset sample, only connections that survive pruning and thus contribute to the final loss will be retained. At the beginning of each dataset sample, weights will be initialized with the value of the updated weights in the previous sample. We hypothesize that this approach will result in weights that are important for a broad set of related tasks.

It has been suggested Liu et al. (2019) that pruning can also improve algorithm efficiency by virtue of the resulting architecture, rather than just the resulting weights. Therefore, we will also assess a modified meta-pruning algorithm that only retains the architecture, and not the weights, across datasets:

We hypothesize that this approach will result in architectures that are more generalizable and efficient than the full model. Comparing the two approaches in algorithms 1 and 2 will illuminate the relative contributions of the weights and the architecture to the value of pruning for generalizability.

3 Methods

We will first select a relatively simple pruning algorithm that can be adapted to the meta-pruning approach described above, as a proof of concept. Since pruning studies to date have largely focused on convolutional neural networks, we will develop our algorithm in the context of image recognition, initially working with the CIFAR-100 data. For the initial model, we will use VGGNet due to its simple architecture and expand to ResNet if time allows. To assess our algorithms' baseline

performance, we will use test images which have the same categories as the training images. We will then assess our algorithms’ capacity to generalize using a test set that contains a distinct set of categories from the training set. We will use cross entropy loss and assess the algorithms’ performance by comparing its classification accuracy to the accuracy of the full model, as well as a reduced model with the same number of connections but where connections are randomly dropped. We will also compare the training time, memory requirements, and the number of retained parameters to assess the algorithms’ efficiency and quantify the amount of compression achieved.

An important consideration in the proposed algorithms is the consequence of pruning to backpropagation. Particularly in algorithm 1, depending on the order in which operations are applied, special care must be taken to ensure that gradients are computed correctly for the pruned model, at each outer iteration. One way to circumvent the issue is to recompute gradients every time the model is updated via pruning. However, it may be possible to do this more intelligently by applying advanced techniques for gradients of discrete problems. This will be an area to explore, if time permits.

4 Nice-to-haves

There are several additional analyses we can incorporate if time allows:

- To ensure our results are not specific to a particular pruning method, we can test meta-pruning using several pruning algorithms that span a range of approaches.
- Explore how to modify the meta-pruning approach to preserve connections that are retained in most, but not all training sets.
- Leverage the meta-learning framework to learn how to prune Han et al. (2015).
- Explicitly incorporate transfer learning into the meta-learning framework by assessing loss on a pseudo-test validation set with different categories Li et al. (2017).
- Apply meta-pruning to a more complex real-world dataset in a transfer learning context.

Acknowledgments

Use unnumbered third level headings for the acknowledgments. All acknowledgments go at the end of the paper. Do not include acknowledgments in the anonymized submission, only in the final paper.

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