Multi-Task Pruning for Semantic Segmentation Networks

Xinghao Chen¹, Yunhe Wang¹, Yiman Zhang¹, Peng Du², Chunjing Xu¹, Chang Xu³
¹Noah’s Ark Lab, Huawei Technologies
²Huawei Technologies
³School of Computer Science, Faculty of Engineering, University of Sydney
{xinghao.chen,yunhe.wang,zhangyiman1,xuchunjing}@huawei.com
dp@zju.edu.cn, c.xu@sydney.edu.au

Abstract

This paper focuses on channel pruning for semantic segmentation networks. There are a large number of works to compress and accelerate deep neural networks in the classification task (e.g., ResNet-50 on ImageNet), but they cannot be straightforwardly applied to the semantic segmentation network that involves an implicit multi-task learning problem. To boost the segmentation performance, the backbone of semantic segmentation network is often pre-trained on a large scale classification dataset (e.g., ImageNet), and then optimized on the desired segmentation dataset. Hence to identify the redundancy in segmentation networks, we present a multi-task channel pruning approach. The importance of each convolution filter w.r.t. the channel of an arbitrary layer will be simultaneously determined by the classification and segmentation tasks. In addition, we develop an alternative scheme for optimizing importance scores of filters in the entire network. Experimental results on several benchmarks illustrate the superiority of the proposed algorithm over the state-of-the-art pruning methods. Notably, we can obtain an about $2 \times$ FLOPs reduction on DeepLabv3 with only an about $1\%$ mIoU drop on the PASCAL VOC 2012 dataset and an about $1.3\%$ mIoU drop on Cityscapes dataset, respectively.

1 Introduction

In recent years, convolutional neural networks (CNNs) have been the dominant methods for a variety of vision tasks such as image classification [14], object detection [29, 13, 9], pose estimation [1, 4] and semantic/instance segmentation [2, 3], etc. Despite its success, CNN suffers from large model sizes and huge computational resources, making it challenging to be deployed in mobile devices or embedded devices, e.g., cell phones and cameras.

Various approaches have been proposed to compress and accelerate CNNs, including channel pruning [24, 16, 26, 33], quantization [42, 25] and lightweight network design [30, 28, 10]. Among them channel pruning is one of the most popular methods to accelerate over-parameterized CNNs, since the pruned deep networks can be directly applied on any off-the-shelf platforms and hardware to obtain the online speed-up. However, most of existing channel pruning methods are dedicated to image classification task on a particular dataset, e.g., ThiNet [26] can reduce the computational complexity of the ResNet-50 on the ImageNet by a factor of 2.

Efficient semantic segmentation networks are of great importance for deployment on mobile devices. Nevertheless, there are only few works discussing the channel pruning for the semantic segmentation neural networks. Luo et al. [27] pruned filters in the backbone network on ImageNet and transferred it to the segmentation network. Besides, pruning methods designed over the classification task have been straightforwardly applied to segmentation neural networks [17, 35], but they rarely have a
Figure 1: The diagram of the proposed multi-task pruning for semantic segmentation networks. The scaling factor of each convolution filter in the given network will be simultaneously determined by the classification and segmentation tasks.

Table 1: The impact of ImageNet fine-tuning for pruned segmentation networks on PASCAL VOC 2012.

| Methods                                      | mIoU (%) |
|----------------------------------------------|----------|
| DeepLabV3 [2]                               | 77.27    |
| Slimming 0.5 × [24] w/o ImageNet finetuning  | 70.81    |
|Slimming 0.5 × [24] w/ ImageNet finetuning    | 74.91    |

Beyond the image classification, this paper focuses on the compression problem of semantic segmentation networks. The pruned architecture should be simultaneously determined by the classification and segmentation tasks, since the latent knowledge learned from the large-scale classification dataset is crucial for semantic segmentation as illustrated in Table 1. Specifically, each convolution filter in the given deep network will be assigned with an importance score and these scores will be optimized on both classification and segmentation datasets. An $\ell_1$-norm is introduced to shrink importance score vectors and thus redundant filters will be removed. In addition, we develop an effective alternative optimization scheme to solve the multi-task pruning problem as show in Figure 1. Extensive experiments conducted on several benchmark datasets demonstrate the significance of pruning segmentation networks through a multi-task scheme and the advantages of the proposed algorithm over existing methods.

2 Multi-task Pruning for Segmentation Networks

Generally, most of existing models for visual segmentation (semantic segmentation [3, 38] or instance segmentation [13, 23]) contain two training stages, i.e., pre-training and fine-tuning. In practice, the
We have proposed a multi-task pruning approach to produce lightweight segmentation networks, where we may be able to obtain a more optimal pruned architecture for segmentation. Specifically, we want to optimize the following formula to obtain a sparse model:

\[
\min_{W_1, W_2} \ell_{\text{cls}}(\mathcal{N}_1(W_1, X_1), Y_1) + \lambda \ell_{\text{seg}}(\mathcal{N}_2(W_1, W_2, X_2), Y_2) + \alpha_1 ||\gamma_1||_1 + \alpha_2 ||\gamma_2||_1,
\]

where \(\mathcal{N}_1\) is the backbone network (e.g., ResNet-50 \[14\] and VGGNet \[31\]), \(X_1\) is the classification training sample and \(Y_1\) is the corresponding ground-truth label, \(W_1\) denotes the parameters in \(\mathcal{N}_1\), and \(\ell_{\text{cls}}(\cdot)\) is the classification loss function.

Then, both the backbone and the decoder part (e.g., atrous spatial pyramid pooling, ASPP in DeepLabv3 \[2\]) are further optimized on the subsequent segmentation task as follows:

\[
W_1^+, W_2^* = \arg \min_{W_1, W_2} \ell_{\text{seg}}(\mathcal{N}_2(W_1, W_2, X_2), Y_2),
\]

where \(\mathcal{N}_2\) is the whole segmentation network including the backbone and decoder, \(W_2\) denotes the parameters for decoder part, \(X_2\) and \(Y_2\) are the training images and their corresponding ground-truth labels in the segmentation task, respectively. \(W_1\) is initialized with \(W_1^*\) solved from Eq. \((1)\), and \(\ell_{\text{seg}}(\cdot)\) is the loss function in the segmentation task. Note that decoder-encoder structure is widely used in segmentation network \[2, 3, 39\]. For DeepLabv3 \[2\], ASPP can be viewed as a vanilla decoder.

In this section, we proceed to introduce an optimization method to solve the proposed multi-task pruning problem.

Similarly, we can also directly utilize the above function to remove redundant parameters in the network \(\mathcal{N}_2\), in other words, applying traditional pruning methods (e.g., \[26, 24\]) on segmentation networks. However, some experimental evidences shown in Table 1 illustrate that the pruned backbone \(\mathcal{N}_1\) should be further tuned on the ImageNet dataset for maintaining the accuracy. This observation motivates us to design a new pruning scheme that simultaneously determines the pruned model via a multi-task method on the tasks of ImageNet classification and semantic segmentation. In this case, we may be able to obtain a more optimal pruned architecture for segmentation. Specifically, we want to optimize the following formula to obtain a sparse model:

\[
\min_{W_1, W_2} \ell_{\text{cls}}(\mathcal{N}_1(W_1, X_1), Y_1) + \lambda \ell_{\text{seg}}(\mathcal{N}_2(W_1, W_2, X_2), Y_2) + \alpha_1 ||\gamma_1||_1 + \alpha_2 ||\gamma_2||_1,
\]

where \(\lambda\) is the hyper-parameter for seeking the trade-off between the classification and the segmentation tasks, \(\alpha_2\) is the weight parameter for the sparsity of \(W_2\) and \(\gamma_2\) are scaling factors for channels in decoder. After minimizing Eq. \((4)\), we can obtain a sparse network and prune the unimportant channels for a lightweight semantic segmentation network.

### 3 Optimization

We have proposed a multi-task pruning approach to produce lightweight segmentation networks. In this section, we proceed to introduce an optimization method to solve the proposed multi-task pruning problem.

Eq. \((4)\) involves two sub-networks and two different tasks and datasets, which is hard to directly optimize. We first add an auxiliary variable for help:

\[
\min_{W_1, W_2, W_3} \ell_{\text{cls}}(\mathcal{N}_1(W_1, X_1), Y_1) + \lambda \ell_{\text{seg}}(\mathcal{N}_2(W_3, W_2, X_2), Y_2)
+ \alpha_1 ||\gamma_1||_1 + \alpha_2 ||\gamma_2||_1, \quad \text{s.t. } W_1 = W_3.
\]
By introducing $\mathcal{W}_3$, the above function can now be easily solved by exploiting the inexact augmented Lagrange multiplier [21]. We further introduce multipliers $\mu$ and $E$, the loss function of Eq. (5) can be formulated as

$$\mathcal{L}(W_1, W_2, W_3, \mu, E) = \ell_{cls}(N_1(W_1, X_1), Y_1) + \lambda \ell_{seg}(N_2(W_3, W_2, X_2), Y_2) + \frac{\mu}{2}||W_1 - W_3||^2_2 + <E, W_1 - W_3> + \alpha_1||\gamma_1||_1 + \alpha_2||\gamma_2||_1.$$  

(6)

Then, the optimal weights of the desired sparse segmentation network can be obtained by updating $W_1, W_2, W_3$, alternately.

**Solve $W_1$:** The loss function for optimizing $W_1$ is

$$\mathcal{L}_1(W_1, \mu, E) = \ell_{cls}(N_1(W_1, X_1), Y_1) + <E, W_1 - W_3> + \frac{\mu}{2}||W_1 - W_3||^2_2 + \alpha_1||\gamma_1||_1.$$  

(7)

which can be optimized using the backbone network $N_1$ on the classification dataset $X_1, Y_1$.

**Solve $W_2$:** The loss function of the weight in the decoder network can be written as

$$\mathcal{L}_2(W_2) = \lambda \ell_{seg}(N_2(W_3, W_2, X_2), Y_2) + \alpha_2||\gamma_2||_1.$$  

(8)

**Solve $W_3$:** The loss function w.r.t. the auxiliary variable $W_3$ is

$$\mathcal{L}_3(W_3, \mu, E) = \lambda \ell_{seg}(N_2(W_3, W_2, X_2), Y_2) + \frac{\mu}{2}||W_1 - W_3||^2_2 + <E, W_1 - W_3>,$$  

(9)

which can be only optimized on the segmentation dataset.

In addition, the multipliers are updated as:

$$E = E + \mu(W_1 - W_3), \quad \mu = \rho \mu,$$  

(10)

where $\rho > 1$ is a constant.

By optimizing the Eq. (7) - Eq. (10), we can obtain a sparse model that has small scaling factors in some channels. Eliminating channels with near-zero scaling factors results in a pruned and lightweight segmentation network. Given a predefined global percentile, the threshold of scaling factor values is calculated and all channels with scaling factors below the threshold will be pruned. Since the scaling factors in backbone and decoder network are optimized alternately, setting the same global threshold for both the backbone and decoder is inappropriate. Therefore, we instead use two independent thresholds for these two parts of the segmentation network. Specifically, if we want to prune a certain percentile (denote as $p\%$, i.e., $p = 50$) of all channels, we set the threshold for the backbone (denote as $\tau_1$) so that $p\%$ of all channels in backbone have smaller scaling factors than $\tau_1$. Similarly, the threshold for decoder $\tau_2$ is set to eliminate $p\%$ of channels in decoder network. To further recover the performance drop of the pruned model, we fine-tune the models for a few epochs on ImageNet and segmentation dataset. The proposed multi-task pruning procedure for semantic segmentation network is summarized as shown in Algorithm 1.

**Algorithm 1 Multi-task Pruning (MTP).**

**Input:** A segmentation network including the backbone part $N_1$ and the decoder part $N_2$ and their initial weights $W_1$ and $W_2$. Training datasets and ground-truth $X_1, X_2, Y_1$, and $Y_2$, respectively, parameters $\lambda, \alpha_1, \alpha_2, \rho$.

1: **Training a sparse model:**
2: repeat
3: \hspace{1em} Optimize $W_1$ according to Eq. (7)
4: \hspace{1em} Optimize $W_2$ according to Eq. (8)
5: \hspace{1em} Optimize $W_3$ according to Eq. (9)
6: \hspace{1em} Update $E$ and $\mu$ according to Eq. (10)
7: until convergence
8: **Pruning and Fine-tuning:**
9: \hspace{1em} Calculate scaling factors $\gamma_1$ and $\gamma_2$ from the parameters $W_1$ and $W_2$ of sparse model.
10: \hspace{1em} Prune the model according to $\gamma_1$ and $\gamma_2$.
11: \hspace{1em} Fine-tune the pruned model $\tilde{N}$ on ImageNet and target segmentation dataset sequentially.

**Output:** The pruned model $\tilde{N}$.

4 Experiments

In this section we first conduct experiments on several challenging benchmarks (including PASCAL VOC 2012 [7], Cityscapes [5] and ADE20K [41]). We apply the proposed multi-task pruning method on several competitive semantic segmentation models, including DeepLabv3 [2], PSPNet [39] and a real-time model BiSeNet [37]. We then further introduce more ablation analysis on the proposed method to better understand the effectiveness of different components.
Table 2: Comparisons of our proposed method with state-of-the-arts pruning methods on Pascal VOC 2012 val set. OS: output stride. †Image size 513 × 513.

| DeepLabV3-R101 (OS=16) [2] | 77.27 | 58.04 | 71.52 | 39.67 |
|----------------------------|-------|-------|-------|-------|
| Uniform [21]               | 75.09 | 40.18 | 71.52 | 49.70 |
| Slimming [24]              | 76.64 | 43.11 | 71.52 | 52.93 |
| **MTP (Ours)**             | **77.28** | **44.32** | **71.52** | **54.89** |

| 0.75× ThiNet [26]          | 74.71 | 32.88 | 71.52 | 39.55 |
| Slimming [24]              | 74.91 | 28.61 | 71.52 | 35.96 |
| **MTP (Ours)**             | **76.29** | **30.33** | **71.52** | **38.87** |

| PSPNet-R50 [39]            | 77.05 | 46.71 | 190.43 | 73.62 |
| PSANet-R50 [40]            | 77.25 | 50.81 | 205.98 | 62.09 |

4.1 Datasets

**PASCAL VOC 2012** [7] is a popular benchmark for semantic segmentation and it has 20 foreground object classes and one background class. Following the common protocol, the original training set is augmented with extra annotations provided by [11]. In total, the dataset contains 10,582 training samples (trainaug), 1,449 validation samples (val) and 1,456 testing samples (test).

**Cityscapes** [5] contains high quality pixel-level annotations of 5000 images, which are split into train_fine set (2975 images), val set (500 images) and test set (1525 images) respectively. In addition, it has about 20000 images (coarse) that are coarsely annotated. There are totally 19 semantic labels for evaluation.

**ADE20K** [41] dataset contains 20,210 images for training, 2000 and 3352 samples for validation and testing, respectively. There are totally 150 semantic classes on ADE20K.

4.2 Pruning DeepLabv3 on PASCAL VOC 2012

We choose DeepLabv3 [2] as our baseline for its competitive performance on different benchmarks. DeepLabv3 employs Atrous Spatial Pyramid Pooling (ASPP) as the decoder to predict segmentation results. We use ResNet-101 as the backbone of DeepLabv3 with multi_grid=(1,1,1) and the output stride is 16.

The experimental results of our proposed method on PASCAL VOC 2012 val set are shown in Table 2. The baseline DeepLabv3 with ResNet-101 as backbone achieves mIoU of 77.27%. When pruning 25% of channels, our proposed method (MTP 0.75×) suffers no performance drop while reducing the number of parameter and FLOPs to 77%. In contrast, the model whose number of channels in each layer are uniformly set to 75% of original model (denoted as Uniform 0.75×) achieves only 75.09% mIoU, which is 2.19% worse than our proposed method. This demonstrates the effectiveness of our proposed pruning method for segmentation network.

We also compare our method with some of prior pruning methods, including ThiNet [26] and network slimming [24]. These pruning methods are originally proposed for classification task. We adapt these methods for pruning semantic segmentation networks. For example, we apply the method of network slimming to DeepLabv3, i.e., add sparse constraints to the scaling factors of each channel and train the DeepLabv3 on PASCAL VOC 2012. Then we eliminate channels with small scaling factors to prune the model and fine-tune it on ImageNet and PASCAL VOC 2012 sequentially. As shown in Table 2, Slimming [24] achieves 76.64% mIoU when pruning 25% of channels, which is worse than our proposed method by 0.62%.

Similarly, we compare our method with ThiNet [26]. ThiNet achieves the performance of 74.71% when pruning 50% channels and is outperformed by our method with a margin of 1.66%. Our method reduces the number of parameters and FLOPs to about 50% when suffering from only less than 1% mIoU drop. Most importantly, our pruned model achieves actual speedup and reduce the inference time on GPU to 79%. The consistent improvement of our proposed method over prior pruning methods demonstrates effectiveness of multi-task pruning.

1We use the implementation of DeepLabv3 at [https://github.com/chenxil16/DeepLabv3.pytorch](https://github.com/chenxil16/DeepLabv3.pytorch)
We also compare our pruned models with some state-of-the-art segmentation networks, including UperNet101 [24] and Our MTP 0.5x as shown in Table 2. The pruned model obtained by our method achieves better mIoU than PSPNet-R50 [39] while having significant fewer FLOPs and higher speed. When compared with PSANet-R50 [40], our model achieves similar mIoU and runs about 1.8× faster.

Qualitative results of baseline DeepLabv3, Slimming 0.5× [24] and Our MTP 0.5× are shown in Figure 6. Note that our proposed method obtains better segmentation results than Network Slimming [24].

### 4.3 Pruning DeepLabv3 on Cityscapes

As shown in Table 3. The baseline DeepLabv3 with ResNet-101 backbone achieves the mIoU of 78.65% on Cityscapes val set. When pruning 25% of all channels, network slimming [24] has mIoU of 78.37% and suffers from performance drop of 0.28%. In contrast, our proposed method boosts the performance of pruned model and has insignificant accuracy drop. When the pruning rate is higher, the superiority of our method over state-of-the-art pruning methods becomes more significant. Specifically, when the model size and FLOPs are reduced to about 50%, our pruned model only has

---

**Table 3: Comparisons of our proposed method with state-of-the-arts on Cityscapes val set.** All models are trained on train_fine set without pretraining on COCO. OS: output stride. †Image size 2048 × 1024.

| Model            | mIoU (%) | #Params (M) | FLOPs (G)† | GPU Speed (ms)† |
|------------------|----------|-------------|------------|-----------------|
| DeepLabV3-R101 (OS=16) [2] | 78.65    | 58.04       | 201.88     | 183.07          |
| 0.75× Slimming [24] MTP (Ours) | 78.37±0.28 | 44.43±0.77× | 155.08±0.77× | 164.58±0.86× |
| 0.5× Slimming [24] MTP (Ours) | 76.94±1.71 | 29.74±0.51× | 106.02±0.53× | 132.98±0.67× |
| BiSeNet-R18 [37] | 74.83    | 12.89       | 104.27     | 29.11           |
| 0.75× Slimming [24] FPGM [15] MTP (Ours) | 72.99±1.84 | 9.23±0.72× | 86.22±0.83× | 25.58±0.88× |
| 0.5× Slimming [24] FPGM [15] MTP (Ours) | 71.98±2.85 | 5.90±0.46× | 73.65±0.71× | 23.61±0.81× |
| 0.25× MTP (Ours) | 70.22±4.61 | 3.09±0.24× | 58.93±0.57× | 21.26±0.57× |

---

https://github.com/hszhao/semseg
Table 4: Ablation results about different pruning strategies on Pascal VOC 2012 val set. The postfix *Ind* means using independent pruning thresholds for backbone and encoder, while *Uni* means using a unified threshold for the whole network. *Image size 1080 × 720.*

| Image size | mIoU (%) | #Params (M) | FLOPs (G) |
|------------|----------|-------------|-----------|
| † DeepLabV3 [2] | 77.27 | 58.039 | 201.86 |
| 0.75× Ours-Uni | 77.65↑ | 46.650 | 161.58 |
| Ours-Ind | 77.28↑ | 44.319 | 154.98 |
| 0.5× Slimming-Uni [24] | 73.77↓ | 36.937 | 125.86 |
| Slimming-Ind [24] | 74.91 | 28.607 | 101.59 |
| Ours-Uni | 75.33↑ | 37.636 | 131.13 |
| Ours-Ind | 76.29↑ | 30.332 | 109.88 |

Table 5: Evaluation of the pruned backbone networks on ImageNet val set.

| Acc (%) | Uniform | Slimming [24] | MTP (Ours) | Slimming [24] | MTP (Ours) |
|---------|---------|---------------|------------|---------------|------------|
| Top1    | 75.51   | 75.04         | 76.03      | 71.07         | 73.15      |
| Top5    | 92.35   | 92.44         | 92.98      | 90.24         | 91.15      |

1.26% performance drop, 0.45% less than network slimming [24]. MTP 0.5× achieves mIoU of 77.39% and reduces the latency to only 69% of original one.

We also evaluate our method on Cityscapes test set. The baseline DeepLabv3 achieves mIoU of 78.42% and MTP 0.5× obtains mIoU of 77.41%, suffering from accuracy drop of only 1% while having around 2× reduction of FLOPs.

### 4.4 Pruning BiSeNet on Cityscapes

We further conduct experiments for pruning on lightweight semantic segmentation networks, e.g., BiSeNet [37], to demonstrate the scalability of our proposed method. Note that pruning a lightweight model is much more challenging since it contains less redundancy. As shown in Table 3, the baseline BiSeNet with ResNet-18 achieves the mIoU of 74.83% on Cityscapes val set with 104.27 GFLOPs. Our method obtains mIoU of 73.46% when keeping 75% channels, which leads to 1.37% mIoU drop. Nevertheless, our method still outperforms prior pruning methods, e.g., network slimming [24] and FPGM [15] by 0.47% and 0.36%, respectively. Moreover, MTP-0.5× achieves 28% FLOPs reduction with 2.38% mIoU drop and consistently performs better than prior pruning methods.

### 4.5 Pruning PSPNet on ADE20K

Here we explore the performance of our proposed method on a more challenging scene parsing benchmark, i.e., ADE20K dataset [41]. As shown in Figure 2, our method suffers only 0.58 mIoU drop when pruning 25% channels, which is 0.24% better than network slimming [24]. Pruning more channels leads to slightly worse mIoU but consistently outperforms prior method. We also compare our pruned models with state-of-the-art semantic segmentation models, as shown in Figure 3. Our models (MTP-0.75× and MTP-0.5×) achieve a better trade-off between accuracy and model size. Specifically, MTP-0.5× has higher mIoU and fewer parameters than PSPNet-R18 [39]. MTP-0.75× obtains similar accuracy with UperNet50 [34] and RefineNet-R101 [20] but with 47% and 71% fewer parameters, respectively.

### 4.6 Ablation Study

**Impact of fine-tuning epochs.** Here we explore how the number of fine-tuning epochs on ImageNet and PASCAL VOC 2012 impact the performance of pruned models. As shown in Figure 4, when we fine-tune the pruned model on PASCAL VOC 2012 for more epochs, the performance improves and becomes stable at around epoch 50. More importantly, the performance is highly competitive even in epoch 20, which demonstrates that the superior performance of our method isn’t purely attributed to extra training budgets in fine-tuning. We can also observe that more fine-tuning epochs on ImageNet...
Figure 4: Impact of different fine-tuning epochs on ImageNet and PASCAL VOC 2012.

Figure 5: Visualization of pruned channels for DeepLabv3 on PASCAL VOC 2012.

Figure 6: Qualitative results of different methods on PASCAL VOC 2012 val set. From left to right are input images, ground truth, results of baseline DeepLabv3, Network Slimming 0.5× and Our method 0.5× respectively.

don’t necessarily improve the performance a lot, as shown in Figure 4. We fine-tuned the pruned models on ImageNet for 20 epochs for a tradeoff between training budget and performance.

**Unified vs. Independent pruning thresholds.** As described in Section 3, since the scaling factors in backbone and decoder network are optimized alternately, we instead use two independent pruning thresholds for backbone and decoder of the segmentation network. The ablation results of this strategy are shown in Table 4. These results show that the proposed pruning strategy of using independent thresholds for backbone and decoder boosts the performance of the pruned models of our proposed method and Network Slimming [24], obtaining higher mIoU with a slightly fewer number of parameters and FLOPs.

**Visualization of Pruned Channels.** We visualize the number of channels in each layer for the pruned model obtained by our method on PASCAL VOC 2012 dataset, as shown in Figure 5. Channels in red rectangle belong to decoder (ASPP in DeepLabv3) and others belong to backbone (ResNet-101). It can be observed that our method tends to keep more channels in the last residual block of the backbone network. We attribute it to the fact that features in the last block have lower resolution and thus may need more channels to capture the semantic information.

**Performance on Classification Task.** Since the proposed method simultaneously discovers the pruned architecture on classification and segmentation tasks, it is expected that our pruned models also have a good performance on image classification. We evaluate the pruned backbone network of DeepLabv3 on ImageNet val set. As shown in Table 5, the pruned models obtained by our proposed method consistently outperform Network Slimming [24] and uniformly pruned baseline at different pruning ratios, which demonstrates the advantage of the proposed multi-task pruning scheme.
5 Conclusions

In this paper we propose a novel multi-task channel pruning method to obtain a lightweight semantic segmentation network. We first excavate the relationship between the pre-training of the backbone model and the segmentation performance, and then establish an end-to-end multi-task filter pruning approach. The new method simultaneously identifies the redundant filters in both two datasets. Therefore, the produced lightweight segmentation network can greatly maintain the segmentation performance. Extensive experimental results on several benchmark datasets demonstrate that our method outperforms state-of-the-art pruning methods for generating lightweight segmentation networks.

6 Appendix

6.1 Experimental Settings

DeepLabv3 on PASCAL VOC 2012. For training baseline DeepLabv3 [2] with ResNet-101 on PASCAL VOC 2012, we use initial learning rate of 0.007 and poly learning rate scheduler where the learning rate is multiplied by \((1 - \frac{\text{iter}}{\text{iter}_{\text{max}}})^{0.9}\). We apply data augmentation including random horizontal flip, random scaling ranging from 0.5 to 2.0 and random crop of 513 \times 513 during training. We train the model for 50 epochs with batch size of 16 in a Nvidia V100 GPU.

For multi-task pruning, we set \(\alpha_1 = 0.001\) and \(\alpha_2 = 0.001\). The batch size for ImageNet is 256. The initial learning rate for ImageNet is 0.001 and linear learning rate scheduler is adopted. Since we are using post-activation variant of ResNet, we only prune the first two convolutional layers in each residual block. For fine-tuning, we set the initial learning rate as 0.0007 and also use poly learning rate policy. The pruned model is fine-tuned on ImageNet for 20 epochs and then fine-tuned on PASCAL VOC 2012 for another 50 epochs. All inference speeds for different models are evaluated on one Nvidia P100 GPU.

DeepLabv3 on Cityscapes. We use initial learning rate of 0.01 and poly learning rate policy for training baseline DeepLabv3 with ResNet-101 on Cityscapes. We train the model for 480 epochs, with data augmentation of random flip, random scaling (from 0.5 to 2) and random crop with the crop size of 1024 \times 512. The batch size for training is 32 and 8 Nvidia V100 GPUs are used.

For multi-task pruning, we set \(\alpha_1 = 0.001\) and \(\alpha_2 = 0.001\). The batch size for ImageNet is 256. The initial learning rate for ImageNet is 0.001 and linear learning rate scheduler is adopted. For fine-tuning, we set the initial learning rate as 0.0005 and also use poly learning rate policy. The pruned model is fine-tuned on ImageNet for 20 epochs and then fine-tuned on Cityscapes for another 240 epochs. We employ multi-scale testing of \([0.5, 0.75, 1.0, 1.25, 1.5, 1.75]\). When evaluating on test set, we train the model on \(\text{train}_\text{fine}\) and \(\text{val}_\text{fine}\) set. No coarse data is used and we do not employ COCO pre-training.

BiSeNet on Cityscapes. BiSeNet-R18 [37] is trained with initial learning rate of 0.01, poly learning rate policy and batch size of 32 on Cityscapes for 80 epochs with 8 GPUs. Data augmentations including random flip, random scaling (from 0.75 to 2) and random crop with the crop size of 1536 \times 768 are utilized.

For multi-task pruning, we set \(\alpha_1 = 0.0001\) and \(\alpha_2 = 0.0001\). The batch size for ImageNet is 512. The initial learning rate for ImageNet is 0.001 and linear learning rate scheduler is adopted. For fine-tuning, we set the initial learning rate as 0.001 and also use poly learning rate policy. The pruned model is fine-tuned on ImageNet for 50 epochs and then fine-tuned on Cityscapes for another 80 epochs. Since BiSeNet is devoted for real-time segmentation, no multi-scale testing is adopted in evaluation.

PSPNet on ADE20K. PSPNet-R50 [39] is trained for 120 epochs on ADE20K, with initial learning rate of 0.01 and batch size of 32 on 8 GPUs. Data augmentations of random flip, random scaling (from 0.5 to 2) and random crop with the crop size of 480 \times 480 are adopted.

For multi-task pruning, we set \(\alpha_1 = 0.0001\) and \(\alpha_2 = 0.0001\). The batch size for ImageNet is 128. The initial learning rate for ImageNet is 0.001 and linear learning rate scheduler is adopted. For fine-tuning, we set the initial learning rate as 0.0005 and also use poly learning rate policy. The

---

3We use the implementation of BiSeNet at [https://github.com/ycszen/TorchSeg](https://github.com/ycszen/TorchSeg).
pruned model is fine-tuned on ImageNet for 50 epochs and then fine-tuned on ADE20K for another 120 epochs. We employ multi-scale testing of [0.5, 0.75, 1.0, 1.25, 1.5, 1.75] for evaluation.

6.2 Detailed Quantitative Results

We provide more detailed results including per-category mIoU of different methods on PASCAL VOC 2012 val set and Cityscapes val set, as shown in Table 6 and Table 7 respectively. On PASCAL VOC 2012, the pruned models obtained by our proposed method achieve better mIoU for most categories. On Cityscapes dataset, our method obtains better overall mIoU when the pruning ratio is relatively low (e.g., keeping about 75% of channels).

| Model               | bg | aero | bike | bird | boat | bottle | bus | car | cat | chair | cow | table | dog | horse | mbike | person | plant | plane | train | tv    | mean  |
|---------------------|----|------|------|------|------|--------|-----|-----|-----|------|-----|-------|-----|-------|-------|--------|-------|-------|-------|------|-------|
| DeepLabv3 [2]       |    |      |      |      |      |        |     |     |     |      |     |       |     |       |       |        |       |       |       |      |       |
| 94.05               | 87.41 | 61.62 | 88.98 | 71.23 | 92.35 | 83.96 | 89.35 | 83.93 | 57.71 | 89.10 | 86.69 | 94.15 | 85.05 | 59.68 | 87.93 | 49.15 | 85.32 | 76.82 | 77.27 |
| Uniform 0.75        |    |      |      |      |      |        |     |     |     |      |     |       |     |       |       |        |       |       |       |      |       |
| 93.50               | 86.66 | 61.31 | 87.12 | 71.05 | 84.63 | 82.51 | 84.06 | 83.56 | 38.22 | 81.07 | 47.84 | 87.75 | 81.37 | 78.9 | 83.02 | 66.29 | 90.54 | 84.35 | 75.00 |
| Slimming 0.75 × [24]|    |      |      |      |      |        |     |     |     |      |     |       |     |       |       |        |       |       |       |      |       |
| 93.82               | 88.94 | 61.71 | 88.91 | 73.63 | 80.29 | 92.37 | 87.85 | 92.51 | 41.83 | 83.63 | 60.64 | 87.15 | 84.7 | 83.52 | 82.27 | 90.41 | 87.85 | 74.71 | 75.20 |
| MTP 0.75 × (Ours)   |    |      |      |      |      |        |     |     |     |      |     |       |     |       |       |        |       |       |       |      |       |
| 93.91               | 88.92 | 62.13 | 90.70 | 75.71 | 88.69 | 85.42 | 87.61 | 94.46 | 46.85 | 86.46 | 40.81 | 89.31 | 87.86 | 84.01 | 85.70 | 61.41 | 94.07 | 86.76 | 77.53 |
| ThiNet 0.5 × [26]   |    |      |      |      |      |        |     |     |     |      |     |       |     |       |       |        |       |       |       |      |       |
| 93.57               | 87.51 | 60.47 | 89.88 | 70.82 | 84.65 | 93.32 | 85.85 | 92.79 | 37.05 | 86.13 | 48.59 | 87.07 | 84.02 | 82.86 | 83.66 | 52.22 | 84.86 | 44.02 | 83.18 |
| Slimming 0.5 × [24] |    |      |      |      |      |        |     |     |     |      |     |       |     |       |       |        |       |       |       |      |       |
| 93.35               | 88.94 | 60.61 | 88.46 | 69.15 | 76.36 | 91.85 | 86.35 | 92.26 | 38.21 | 84.86 | 47.72 | 86.29 | 84.85 | 83.88 | 87.07 | 66.29 | 84.64 | 48.63 | 83.78 |
| MTP 0.5 × (Ours)    |    |      |      |      |      |        |     |     |     |      |     |       |     |       |       |        |       |       |       |      |       |
| 93.68               | 88.45 | 59.81 | 89.51 | 92.2 | 77.61 | 95.83 | 87.67 | 95.57 | 39.00 | 86.63 | 49.18 | 86.76 | 90.42 | 92.31 | 94.77 | 64.62 | 94.69 | 48.63 | 85.08 |

| Model               | road | sidewalk | bld | wall | fence | pole | light | sign | vgttn | terrain | sky | person | rider | car | truck | bus | train | meaning |
|---------------------|------|-----------|-----|------|-------|------|-------|------|------|---------|-----|--------|-------|-----|-------|-----|-------|----------|
| DeepLabv3 [2]       |      |           |     |      |       |      |       |      |      |         |     |        |       |     |       |     |       | 98.06   |
| 98.06               | 84.32 | 92.47 | 80.81 | 61.94 | 58.55 | 69.06 | 95.13 | 92.70 | 84.18 | 81.09 | 64.07 | 94.95 | 81.74 | 89.66 | 81.41 | 30.17 | 77.20 |
| Slimming 0.5 × [24] |      |           |     |      |       |      |       |      |      |         |     |        |       |     |       |     |       | 98.19   |
| 98.19               | 85.55 | 92.40 | 80.67 | 62.17 | 63.83 | 68.28 | 77.05 | 92.27 | 67.36 | 94.31 | 80.92 | 63.56 | 94.70 | 70.97 | 89.93 | 77.05 | 76.11 |
| MTP 0.5 × (Ours)    |      |           |     |      |       |      |       |      |      |         |     |        |       |     |       |     |       | 98.27   |
| 98.27               | 85.08 | 92.45 | 62.76 | 62.17 | 68.68 | 68.24 | 79.10 | 92.12 | 65.59 | 94.80 | 80.87 | 63.24 | 94.82 | 74.84 | 91.24 | 82.34 | 78.93 |

6.3 Qualitative results

Here we provide more qualitative results of baseline DeepLabv3 [2], Network Slimming 0.5 × [24] and Our method 0.5 × on PASCAL VOC 2012 val set, as shown in Figure 7. Note that our proposed method obtains better segmentation results than Network Slimming [24]. More qualitative results on Cityscapes val set are shown in Figure 8. Qualitative results of baseline PSPNet-R50 [39], Slimming 0.5 × and MTP 0.5 × are shown in Figure 9.
Figure 7: Qualitative results of different methods on PASCAL VOC 2012 val set. From left to right are input images, ground truth, results of baseline DeepLabv3 [2], Network Slimming $0.5 \times$ [24] and Our method $0.5 \times$ respectively.
Figure 8: Qualitative results of different methods on Cityscapes val set. From left to right are input images, ground truth, results of baseline DeepLabv3, Network Slimming 0.5×, and Our method 0.5× respectively.
Figure 9: Qualitative results of different methods on ADE20K val set. From left to right are input images, ground truth, results of baseline PSPNet-R50 [2], Slimming 0.5× [24] and Our method 0.5× respectively.
References

[1] Z. Cao, G. H. Martinez, T. Simon, S.-E. Wei, and Y. A. Sheikh. Openpose: Realtime multi-person 2d pose estimation using part affinity fields. TPAMI, 2019.

[2] L.-C. Chen, G. Papandreou, F. Schroff, and H. Adam. Rethinking atrous convolution for semantic image segmentation. arXiv preprint arXiv:1706.05587, 2017.

[3] L.-C. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In ECCV, pages 801–818, 2018.

[4] X. Chen, G. Wang, H. Guo, and C. Zhang. Pose guided structured region ensemble network for cascaded hand pose estimation. Neurocomputing, 395:138–149, 2020.

[5] M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, R. Benenson, U. Franke, S. Roth, and B. Schiele. The cityscapes dataset for semantic urban scene understanding. In CVPR, pages 3213–3223, 2016.

[6] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. Imagenet: A large-scale hierarchical image database. In CVPR, pages 248–255. Ieee, 2009.

[7] M. Everingham, L. Van Gool, C. K. Williams, J. Winn, and A. Zisserman. The pascal visual object classes (voc) challenge. IJCV, 88(2):303–338, 2010.

[8] J. Fu, J. Liu, H. Tian, Y. Li, Y. Bao, Z. Fang, and H. Lu. Dual attention network for scene segmentation. In CVPR, pages 3146–3154, 2019.

[9] J. Guo, K. Han, Y. Wang, C. Zhang, Z. Yang, H. Wu, X. Chen, and C. Xu. Hit-detector: Hierarchical trinity architecture search for object detection. In CVPR, pages 11405–11414, 2020.

[10] K. Han, Y. Wang, Q. Tian, J. Guo, C. Xu, and C. Xu. Ghostnet: More features from cheap operations. In CVPR, pages 1580–1589, 2020.

[11] B. Hariharan, P. Arbeláez, L. Bourdev, S. Maji, and J. Malik. Semantic contours from inverse detectors. In ICCV, pages 991–998. IEEE, 2011.

[12] K. He, R. Girshick, and P. Dollár. Rethinking imagenet pre-training. In ICCV, 2019.

[13] K. He, G. Gkioxari, P. Dollár, and R. Girshick. Mask r-cnn. In ICCV, pages 2961–2969, 2017.

[14] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In CVPR, pages 770–778, 2016.

[15] Y. He, P. Liu, Z. Wang, Z. Hu, and Y. Yang. Filter pruning via geometric median for deep convolutional neural networks acceleration. In CVPR, pages 4340–4349, 2019.

[16] Y. He, X. Zhang, and J. Sun. Channel pruning for accelerating very deep neural networks. In ICCV, pages 1389–1397, 2017.

[17] Q. Huang, K. Zhou, S. You, and U. Neumann. Learning to prune filters in convolutional neural networks. In WACV, pages 709–718. IEEE, 2018.

[18] S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In ICML, pages 448–456, 2015.

[19] X. Li, Y. Zhou, Z. Pan, and J. Feng. Partial order pruning: for best speed/accuracy trade-off in neural architecture search. In CVPR, 2019.

[20] G. Lin, A. Milan, C. Shen, and I. Reid. Refinenet: Multi-path refinement networks for high-resolution semantic segmentation. In CVPR, pages 1925–1934, 2017.

[21] Z. Lin, M. Chen, and Y. Ma. The augmented lagrange multiplier method for exact recovery of corrupted low-rank matrices. arXiv preprint arXiv:1009.5055, 2010.

[22] C. Liu, L.-C. Chen, F. Schroff, H. Adam, W. Hua, A. Yuille, and L. Fei-Fei. Auto-deeplab: Hierarchical neural architecture search for semantic image segmentation. In CVPR, 2019.

[23] S. Liu, L. Qi, H. Qin, J. Shi, and J. Jia. Path aggregation network for instance segmentation. In CVPR, pages 8759–8768, 2018.

[24] Z. Liu, J. Li, Z. Shen, G. Huang, S. Yan, and C. Zhang. Learning efficient convolutional networks through network slimming. In ICCV, pages 2755–2763, 2017.

[25] Z. Liu, B. Wu, W. Luo, X. Yang, W. Liu, and K.-T. Cheng. Bi-real net: Enhancing the performance of 1-bit cnns with improved representational capability and advanced training algorithm. In ECCV, pages 722–737, 2018.

[26] J.-H. Luo, J. Wu, and W. Lin. Thinet: A filter level pruning method for deep neural network compression. In ICCV, pages 5058–5066, 2017.

[27] J.-H. Luo, H. Zhang, H.-Y. Zhou, C.-W. Xie, J. Wu, and W. Lin. Thinet: Pruning CNN filters for a thinner net. TPAMI, 2018.
[28] N. Ma, X. Zhang, H.-T. Zheng, and J. Sun. Shufflenet v2: Practical guidelines for efficient cnn architecture design. In ECCV, pages 116–131, 2018.
[29] S. Ren, K. He, R. Girshick, and J. Sun. Faster R-CNN: Towards real-time object detection with region proposal networks. In NIPS, 2015.
[30] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In CVPR, pages 4510–4520, 2018.
[31] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. In ICLR, 2015.
[32] Z. Tian, T. He, C. Shen, and Y. Yan. Decoders matter for semantic segmentation: Data-dependent decoding enables flexible feature aggregation. In CVPR, 2019.
[33] Y. Wang, C. Xu, J. Qiu, C. Xu, and D. Tao. Towards evolutionary compression. In KDD, pages 2476–2485. ACM, 2018.
[34] T. Xiao, Y. Liu, B. Zhou, Y. Jiang, and J. Sun. Unified perceptual parsing for scene understanding. In ECCV, pages 418–434, 2018.
[35] K. Yamamoto and K. Maeno. Peas: Pruning channels with attention statistics for deep network compression. In BMVC, 2019.
[36] J. Ye, X. Lu, Z. Lin, and J. Z. Wang. Rethinking the smaller-norm-less-informative assumption in channel pruning of convolution layers. In ICLR, 2018.
[37] C. Yu, J. Wang, C. Peng, C. Gao, G. Yu, and N. Sang. Bisenet: Bilateral segmentation network for real-time semantic segmentation. In ECCV, pages 325–341, 2018.
[38] H. Zhao, X. Qi, X. Shen, J. Shi, and J. Jia. Icnet for real-time semantic segmentation on high-resolution images. In ECCV, pages 405–420, 2018.
[39] H. Zhao, J. Shi, X. Qi, X. Wang, and J. Jia. Pyramid scene parsing network. In CVPR, pages 2881–2890, 2017.
[40] H. Zhao, Y. Zhang, S. Liu, J. Shi, C. Change Loy, D. Lin, and J. Jia. Psanet: Point-wise spatial attention network for scene parsing. In ECCV, pages 267–283, 2018.
[41] B. Zhou, H. Zhao, X. Puig, S. Fidler, A. Barriuso, and A. Torralba. Scene parsing through ade20k dataset. In CVPR, 2017.
[42] S. Zhou, Y. Wu, Z. Ni, X. Zhou, H. Wen, and Y. Zou. Dorefa-net: Training low bitwidth convolutional neural networks with low bitwidth gradients. arXiv preprint arXiv:1606.06160, 2016.
[43] R. Zhu, S. Zhang, X. Wang, L. Wen, H. Shi, L. Bo, and T. Mei. Scratchdet: Training single-shot object detectors from scratch. In CVPR, 2019.