Beyond Self-Supervision: A Simple Yet Effective Network Distillation Alternative to Improve Backbones

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Abstract

Recently, research efforts have been concentrated on revealing how pre-trained model makes a difference in neural network performance. Self-supervision and semi-supervised learning technologies have been extensively explored by the community and are proven to be of great potential in obtaining a powerful pre-trained model. However, these models require huge training costs (i.e., hundreds of millions of images or training iterations). In this paper, we propose to improve existing baseline networks via knowledge distillation from off-the-shelf pre-trained big powerful models. Different from existing knowledge distillation frameworks which require student model to be consistent with both soft-label generated by teacher model and hard-label annotated by humans, our solution performs distillation by only driving prediction of the student model consistent with that of the teacher model. Therefore, our distillation setting can get rid of manually labeled data and can be trained with extra unlabeled data to fully exploit capability of teacher model for better learning. We empirically find that such simple distillation settings perform extremely effective, for example, the top-1 accuracy on ImageNet-1k validation set of MobileNetV3-large and ResNet50-D can be significantly improved from 75.2% to 79% and 79.1% to 83%, respectively. We have also thoroughly analyzed what are dominant factors that affect the distillation performance and how they make a difference. Extensive downstream computer vision tasks, including transfer learning, object detection and semantic segmentation, can significantly benefit from the distilled pretrained models. All our experiments are implemented based on PaddlePaddle and a series of improved pretrained models with ssld suffix are available in PaddleClas.

1. Introduction

Convolutional Neural Network (CNN) has been developing rapidly in recent years. It has been proven to be the best practice for many computer vision tasks, including image recognition, semantic segmentation, object detection and so on. The success of CNN majorly comes along with both the prevalence of modern parallel computing devices such as GPUs and the availability of numerous annotated datasets. The former fact makes fast inference of CNNs practical while the later one makes training large CNN models possible. How to further improve performances of backbone CNNs without heavy extra computation cost or without massive manually data annotations then becomes key research topics.

Toward these topics, there exist multiple solutions. One of the hot directions is to design (or search) better network
architectures [13, 54, 14, 24, 16], which can obtain backbones with better efficiency-effectiveness trade-off. The natural question we may raise is how can we further improve the performance of existing off-the-shelf backbones with limited labeling cost, regardless whether they are manually designed with human insights or found by searching from huge network space. Reviewing the literature, a possible answer is to get better pre-trained weights without extra labeling efforts by self-supervision [29, 12] or semi-supervised training [42, 1, 53, 42, 40]. Though effective, these methods have to leverage predefined pretext tasks or huge amount of data to obtain a satisfying pre-trained backbone, and the cost of training phase is very expensive due to the huge training corpus consumption as well as the multiple training stages in need. For instances, Noisy Student [40] requires up to 81M unique unlabeled images for self-training and it also requires a iterative training process to get more and more robust pseudo labels for unlabeled data; [42] consumes up to 1 billion images for semi-supervised learning and it also has to perform multiple stages such as teacher-student model pre-training and student model fine-tuning.

In this paper, we also concentrate our efforts on developing technologies for improving off-the-shelf backbones. The following three questions will be answered in this work. First of all, we challenge whether existing self-supervision solutions are the ultimate choices. Is there any simpler yet effective alternative training paradigm? The second one we would like to study is whether we really need hundreds of millions of unlabeled images to train the backbone. Finally, we will answer whether our proposed alternative, which is much simpler and cheaper, generalizes well to downstream tasks, including transfer learning, object detection and semantic segmentation.

Specifically, we have developed a simple yet effective network distillation framework for this task. Knowledge distillation can directly result in student models for image recognition task. Different from other distillation frameworks [15, 21, 44] which force the student prediction to align with manually labeled one-hot hard-label (or its smoothed version), in our framework, student is only required to be consistent with soft-labels predicted by teacher model. One of motivations for this design choice is the fact that images can contain multiple objects, thus manually labeled one-hot hard-label cannot well describe such a nature. The other one is that soft-label can get rid of annotations and unlabeled data can be directly utilized for fully exploit the knowledge learned by the teacher model. Inspired by theoretical conclusions drawn in the literature, we also find a way to successfully obtain plausible backbone models using much less unlabeled data than existing state-of-the-arts, as can be seen from Figure 1. In more detail, top-1 classification accuracy of 79.0% and 83% can be achieved by MobileNetV3-large [16] and ResNet50-D [13] with only 4 million extra unlabeled images. We also conduct extensive experiments on downstream tasks, and the results show that the distilled backbones can be leveraged to consistently improve the performances remarkably on transfer learning, object detection and semantic segmentation.

In short, we emphasize that this work mainly aims at providing a comprehensive perspective on pushing the limit of existing backbones instead of proposing new ones. The contributions are summarized as follows:

- We proposed a simple yet effective distillation framework to improve existing backbones with unlabeled data;
- Empirical analysis on how such important factors as teacher model, unlabeled data volume, weight-decay setting etc. make a difference are conducted;
- A large variety of models can be significantly improved with only 4M extra unlabeled data and many downstream tasks can remarkably benefit from the resulted backbones.

2. Related Works

Our work focuses on developing technologies to improve existing backbones, and it is closely related to previous works which make such attempts on this tasks, including network distillation solutions and model pre-training under semi-supervised learning settings or self-supervision settings.

**Knowledge Distillation** Knowledge distillation has been originally proposed in [15] to distill knowledge in an ensemble of models into one single model. [32] used not only the final output but also intermediate hidden layer values of the teacher network to train the student network and showed that using these intermediate layers can improve the performance of deeper and thinner student networks. In [43] FSP (Flow of Solution Procedure) matrix is proposed to inherit the relationship between features from two layers. There are also other attempts aiming at improving knowledge distillation from perspectives of label-smoothing regularization [44], presence of noisy label [40] and role-wise data augmentation [9] and so on. There are a plenty of follow up works on knowledge distillation improvement and its applications. A detailed survey can be found from [11]. The referred knowledge distillation jobs always follow the conventional setting where the prediction of student model should be consistent with the labeled groundtruth. In our work, we simply require the student to be well aligned with the teacher model in terms of final prediction. This enables us to fully distill knowledge of teacher using unlabeled data.

**Semi-Supervised Learning** Supervised learning is verified to be effective, however it is bottlenecked by labor...
cost of data annotation. Semi-supervised learning (SSL), which can leverage unlabeled data to help model training, has demonstrated great potential. Recently, SSL has been successfully applied in deep learning area. Mean-teacher [35], Mix-Match [1], UDA [39] and Fix-Match [33] are the recent state-of-the-arts, where unsupervised data augmentation strategies are designed for obtaining regularization from unlabeled data as training signals, thus improving the performance of backbone networks. The methods listed above are usually verified on small datasets such as CIFAR-100 [20] or small networks. When it comes to big models or large scale datasets, semi-supervised learning is also proved to be effective. In [42], by leveraging 1 billion unlabeled images, top-1 accuracy of ResNet-50 on ImageNet benchmark is largely boosted to 81.2%. This work have concluded with quite many recommended best practices on web-scale semi-supervised learning. In this paper, we further explore how to eliminate the data consumption for saving training costs. Recently, Noisy student [40] is proposed to extend self-training and distillation with the use of equal-or-even-larger student model, and an iterative training procedure is designed to obtain state-of-the-art models using 81 million unique unlabeled data. In our work, iterative training is not in need and we can achieve state-of-the-art recognition performance using about 4 million unlabeled data.

3. Proposed Method

3.1. Overview

The overall solution is depicted in Figure 2. Our distillation framework tries to transfer knowledge learned by a teacher model $Q$ to a student model $P$, with the training dataset $T$ and a carefully collected unlabeled dataset $U$, which is a subset of a much larger unlabeled image gallery $X_U$. In more detail, the teacher model can be any of well trained off-the-shelf ImageNet classification models which are more powerful than the student model. The teacher model is also leveraged to perform unlabeled data filtering in our solution. The filtering step is designed to make sure that 1) valuable unlabeled data is selected to help the distillation process; 2) the selected data is quite different from the validation dataset $V$, ensuring fairness of our comparisons with other solutions as well as the reliability of our experimental results. Both the training set $T$ and the unlabeled set $U$ are used for knowledge distillation. Different from many state-of-the-art solutions where the annotations of $T$ are still used to supervise the predictions of student model, we only force that predictions of the student model and teacher model are well aligned. Such a constraint is achieved by minimizing the Jensen–Shannon divergence.

3.2. Problem Formulation

We denote the training set and validation set of ImageNet-1k [8] as $T = \{ (x_i, y_{x_i}) \}$ and $V = \{ (x_i, y_{x_i}) \}$, respectively, where $x_i$ means a input image and $y_{x_i}$ is the corresponding label. Besides, we have an extra unlabeled dataset $U = \{ x_i \}$. Our teacher model $Q^*$ is parameterized by $\theta_{Q^*}$, where $\theta_{Q^*}$ is obtained by:

$$\theta_{Q^*} = \min_{\theta_{Q}} \sum_{(x_i, y_{x_i}) \in T} L(y_{x_i}, \pi_{Q}(x_i|\theta_{Q})) + \alpha ||\theta_{Q}||_2^2, \quad (1)$$

where $\pi_{Q}(x_i|\theta_{Q})$ is the classification probability of $x_i$ generated by teacher model $Q$, $L$ is the cross-entropy loss function and $\alpha$ is the weight decay factor. Our assumption here
is that the teacher model is well trained and its generalization error $R_Q^*$ of is bounded by a small number $R_0$, i.e.,

$$R_Q = \sum_{(x_i, y_{x_i}) \in V} L(y_{x_i}, Q(x_i|\theta_Q^*)) \leq R_0,$$  \hspace{6mm} (2)

Under our distillation setting, the objective is to obtain an optimal student model $P$ parametered by $\theta_P$ from $Q^*$ by solving the following problem:

$$\theta_P^* = \min_{\theta_P} \sum_{(x_i) \in U \cup T} L(Q^*(x_i|\theta_Q^*), P(x_i|\theta_P)) + \beta ||\theta_P||_2,$$  \hspace{6mm} (3)

where $\beta$ is the weigh decay factor for student model $P$.

### 3.3. Design Choices

In this section, we will analysis and explain our design choices in detail, including the selection of teacher model, our choice of using soft-label, our insights in weight decay factor and the way we collecting unlabeled data.

#### 3.3.1 Teacher Model

Teacher model plays a central role in our framework. Intuitively, the more powerful the teacher model is, the better the student will be. For a thorough evaluation purpose, we choose to improve a series of backbones (student models) whose target deploy platform ranges from mobile devices to powerful modern GPU devices. In our current implementation, when we aim at improving relatively larger models, the teacher model is ResNeXt101-32x16d [41] which is well trained with nearly 1 billion images and its top-1 accuracy (denoted as top-1 acc in the following) is 84.8% [42]. When the student model is a lightweight one, such as MobileNet series [17] [16], the teacher model we use is a ResNet50-D [14] improved with our proposed distillation framework and its top-1 acc is as high as 83%. The reason we use ResNet50-D to improve lightweight models are two-fold: 1) Compared to its students, its accuracy and capacity is sufficiently high, so it is qualified to teach student models; 2) the computation intensity of ResNet50-D is much smaller than other big models, it is very efficient for distillation.

#### 3.3.2 Soft-label v.s. Hard-label

When knowledge distillation was first proposed [15], both soft-label generated by teacher model and hard-label annotated with human intelligence were used as supervision information. Follow up works also adopt this paradigm. To improve the performance, many distillation method introduced a hyper-parameter termed as temperature $\tau$ when generating soft-labels. However, if we want to get the best results, the temperature should be well tuned according to different teacher models, respectively. Therefore, obtaining a global optimal $\tau$ is very difficult.

In this work, we find that very competitive results or even better performance can be achieved using only soft-labels without the parameter $\tau$. In addition, since the student model only cares about the output of the teacher model in our solution, we can use any data we want to improve performance without introducing any labeling labor. Another motivation of merely using the soft-labels is inspired by the properties of natural images. Specifically, natural images can have multiple tags, for example, a cow on the grass can be tagged as "cow" or "grass", most of popular datasets provides only a single label for each image and such hard-label is not sufficient to describe the information of the image. Meanwhile, soft-label predicted by a well-trained model can generate a probability distribution over the tag system. Entropy of soft-labels can be larger than hard-labels, meaning that more information can be provided.

#### 3.3.3 Weight-Decay

Regularization in the optimization of deep neural networks is often critical to avoid undesirable over-fitting. One of the most popular regularization algorithms is to impose L2 penalty on the model parameters as shown in Eq.3 called weight-decay.

Appropriately reducing the value of $\beta$ can result in smaller training loss. Potentially, the validation accuracy can be improved when the training loss is reduced without heavy over-fitting. Intuitively, because in our framework the student model is required to fit a much more complex mapping, where image to soft-label which has much larger entropy than hard-label, reducing weight decay to some extent would not result in sever over-fitting.

According to [10], the model generalization error scales (with high probability) as:

$$O \left( \frac{B^2 4! d^4 \Pi_{j=1}^d \| M_F(j) \|}{\sqrt{m}} \right),$$  \hspace{6mm} (4)

where $d$ is network depth, $m$ is number of training samples, $M_F(j)$ is Frobenius norms of weight parameter matrix at the $j^{th}$ layer and $B$ is a constant. Recall that our framework can get rid of annotations, so we can have sufficiently large $m$. From this formula, we can see that, our solution can also have very small over-fitting risk due to the increasing of $m$ can be as large as we want, although reducing weight decay can result in increased $M_F(j)$’s. In the ablation experiment, we also further illustrate the importance of reducing $\beta$ in knowledge distillation through experiments.

#### 3.3.4 Unlabeled Data Collection

For labeled data, we use the full training data of ImageNet-1K, which has a total of 1.2M images. In order to improve performance, we need to collect an unlabeled dataset in our
framework. In detail, the unlabeled data gallery $X_U$ we use is the ImageNet-22K, from which 4M images are selected to form $U$ with the help of the teacher model of ResNeXt101-32x16d [42].

The filtering procedure is performed as follows: First of all, we filter out images that are visually similar with validation images of ImageNet-1K from the ImageNet-22K. In this step, the well-known SIFT [27] is used to match similar image pairs from the two image sets. The purpose of this step is to prevent training the student model on images similar to the validation set and keep the evaluation results fair enough. Then, we use the teacher model to obtain prediction results for the images of ImageNet-22k. Finally, we sort the images within each category according to their score and take the top k images of each category to form the final unlabeled data $U$. Currently, k is empirically set to 4000, so our unlabeled data has a total of 4M images and in total 5.2M images are used for distillation.

4. Experiment

4.1. Datasets and Evaluation Metrics

In this paper, we use ImageNet 2012 ILSVRC dataset [8] to evaluate our method and compare with other state-of-the-arts. The dataset consists of 1000 categories and 1.28 million training images in total, which is considered to be the most convincing one in the field of image classification. It is also the most preferred dataset to pre-train models for downstream tasks in the computer vision community. Analog to most image classification scenarios, we report top-1 accuracy on the validation partition as the evaluation metric.

4.2. Implementation Details

When training on ImageNet, we follow standard practice and perform data augmentation with random-size cropping to $224 \times 224$ pixels and random horizontal flipping. Optimization is performed using SGD with momentum 0.9 and a mini-batch size of 256. Weight decay is empirically set to 4e-5 for large student models and 1e-5 for small student models and initial learning rate is 0.1. As commonly known that bigger models need more regularization, we also use AutoAugment [7] on large student models. For declining learning rate, we use a cosine learning rate schedule with the first 5 epochs reserved for warm-up. The training epoch of distillation training with labeled and unlabeled data in the first stage is 360, and for further improvement, we finetune the student with only labeled data for extra 30 epochs.

4.3. Comparison with State-of-the-Arts

We first compare our proposed method with state-of-the-arts [42, 40] on the ImageNet dataset as commonly done in previous works. As shown in Table 1, our algorithm performs consistently better than other variants of ResNet50 backbone, such as using auto-augment strategies including cutout [7], mixup [1], etc. Specifically, Without finetuning, our method improves ResNet50-D from 79% to 82.2%. Finetuning brings an extra gain of 0.8%. When ResFix [36] which is proposed to fix the training-test resolution discrepancy is further adopted, top-1 acc will be boosted up to 84%, which is significantly higher than 79.1% reported in [14]. Note that the remarkable improvement comes at the cost of only 4M extra unlabeled data, consuming 5.2M images in total.

Moreover, our method outperforms Billion-scale [42] by an absolute gain of 1.8%, which demands huge training cost for semi-supervised learning 940M of unlabeled images on the training phase. As for Noisy Student [40], it uses a unlabeled dataset 81M images for iteratively training. Considering that the inference latency is comparable with ResNet50-D on a T4 GPU, here we report the performance of EfficientNet-B0 for comparison and top-1 acc of Noisy Student is 78.5%. To illustrate the strong performance of our method, we also compared the performance of EfficientNet-B1, whose latency is 1.5 times that of ResNet50-D. On the contrary, our solution need requires 4M extra unlabeled data to exploit the knowledge learned by the teacher model, which is the overall distillation is much computational efficient.

| Method                           | Training Data Volume | Top-1 Acc(%) |
|----------------------------------|----------------------|--------------|
| ResNet50                         | 1.2M                 | 76.5         |
| +cutout                          | 1.2M                 | 77.1         |
| +mixup                           | 1.2M                 | 77.4         |
| +cutmix                          | 1.2M                 | 78.6         |
| +gridmask                        | 1.2M                 | 78.7         |
| +cutmix+label-smooth             | 1.2M                 | 79.0         |
| ResNet50-D+mixup+label-smooth    | 1.2M                 | 79.1         |
| ResNet50(Billion-scale)          | 940M                 | 81.2         |
| EfficientNet-B0(Noisy-Student)   | 81M                  | 78.8         |
| EfficientNet-B1(Noisy-Student)   | 81M                  | 81.5         |
| Ours(ResNet50-D) w/o finetune    | 5.2M                 | 82.2         |
| Ours(ResNet50-D) w finetune      | 5.2M                 | 83.0         |
| Ours(ResNet50-D+ResFix)          | 5.2M                 | 84.0         |

Table 1. Comparison of top-1 acc with state of the art methods.

4.4. Performance of different models

In order to provide a more comprehensive understanding, we provide results of different backbones, including models designed for mobile devices and GPU servers, improved using our proposed distillation solution. The experimental results are summarized in Table 2. In this table, the baseline top-1 acc reported is achieved by following the
standard ImageNet-1K training procedure. It is clear that our solution can consistently increase model accuracy by a very large margin, no matter it is a lightweight mobile model or it is a very powerful model as big as ResNet200-D. Especially, our method can boost the performance of MobileNetV3-large from 75.3% to 79% and such a performance is comparable with the ResNet50-D baseline, meaning that using our distillation framework, equivalent accuracy can be achieved with much cheap models. Meanwhile, ResNet200-D is improved by an absolute gain of 4.1%, it further validates that our solution is robust and will not saturate when the student model gets larger.

### 4.5. Ablation Study

Here we study what factors will influence the distillation performance in our framework and how they make a difference. Experiments are conducted using the mobile settings, i.e., the teacher is ResNet50-D and the student is MobileNetV3, because larger models are too time-consuming to complete all the below experiments.

**Impact of different teacher models** We evaluate the performance of different teacher models using MobileNetV3-large as the student. Intuitively, a better teacher model tends to guide a student. This intuition does not heavily conflict with our experiment result shown in Table 3. However, when the accuracy of the teacher model exceeds a certain range, the student model will not be further improved. From the table, we can see that MobileNetV3-large can achieve top-1 accuracy of 76.8% and 78.4% when using ResNet50-D as teacher whose top-1 acc of 79.1% and 83%, respectively. When the accuracy of the teacher model is further improved, the accuracy of MobileNetV3-large will no longer increase. This result also makes sense, because the capacity of student model is limited, its performance upper bound is also limited. Such experimental result also suggest an appropriate teacher model is important to our framework in terms of accuracy-efficiency trade-off, especially when computational resources are a central concern.

**Convergence** We study the convergence of our framework by evaluating top-1 acc of student network at different training iterations. In this experiment, the teacher model we select is ResNet50-D with top-1 accuracy of 83%, while the student network is MobileNetV3-large. We fix the weight decay of 1e-5. Generally, the observation is, the more epochs the better. As seen in Table 4, when the number of training epoch increases from 50 to 200, the top-1 accuracy improves gradually meanwhile when it reaches 360, the performance improvement becomes very marginal especially when an extra 30 epochs of finetuning is carried out on ImageNet-1K, showing that 360 epochs can ensure the knowledge of teacher is sufficiently exploited.

### Table 3. The accuracy of MobileNetV3-large under different teacher models, the number of distilled training epoch is 120, weight-decay is 1e-5.

| Teacher Model | Teacher Model Top-1 Acc(%) | Student Model Top-1 Acc(%) |
|---------------|----------------------------|---------------------------|
| ResNet50-D    | 79.1                       | 76.8                      |
| ResNet50-D (ours) | 83.0                     | 78.4                      |
| ResNet101-D   | 83.7                       | 78.4                      |
| ResNet200-D   | 85.0                       | 78.4                      |

### Table 4. Top-1 Acc of student network at different epochs.

| epochs | Top-1 Acc(%) | Top-1 Acc(%) (finetune) |
|--------|--------------|-------------------------|
| 50     | 76.98        | 77.58                   |
| 100    | 77.77        | 78.29                   |
| 200    | 78.29        | 78.75                   |
| 300    | 78.42        | 78.90                   |
| 360    | **78.54**    | **79.00**               |
| 400    | 78.56        | 79.01                   |
tor of 4e-5 is also empirically tuned and determined when distilling ResNeXt101-32x16d into larger student models such as ResNet50-D, HRNet-18W-C [37] and HRNet with squeeze-and-excitation [18] etc.

Figure 3. Convergence curves of different distillation experiments with various weight decay factors.

| weight-decay | Top-1 Acc(%) | Top-1 Acc(%) (finetune) |
|--------------|--------------|-------------------------|
| 3e-5         | 77.11        | 77.63                   |
| 2e-5         | 77.40        | 77.95                   |
| 1e-5         | **77.88**    | **78.36**               |

Table 5. Top-1 Acc of student network under different weight-decay. The number of distilled training epochs is 120.

4.6. Improvements in Downstream Tasks

We also conduct experiments on several downstream tasks, including image classification, object detection and semantic segmentation, to verify the effectiveness of our distilled model as initialization.

**Classification** We first investigate generalization of the proposed distilled model and performs transfer learning experiments on several image classification datasets, including FGVC-Aircraft-2013b [28], CIFAR-100 [19], DTD [5] and SUN397 [38].

We finetune the entire network using the weights of the pre-trained network as initialization. For each dataset, we search the best hyper-parameters with ResNet50-D baseline on validation set to ensure fair comparison. Note that for all experiments, after searching, we use the same hyper-parameters and strategies for training, except for changing the pre-trained model.

Table 7 summaries the comparison results with baseline ResNet50-D model in terms of top-1 classification accuracy. As can be seen, our method beats ResNet50-D baseline on all datasets with considerable margins, demonstrating that our distilled model can be well generalized in these downstream tasks. An interesting finding is that, the lower the baseline accuracy is, the larger our model improves. For example, for the SUN397 dataset, we outperform baseline by a margin of 4.34%. While for FGVC-Aircraft-2013b, the baseline accuracy is high enough (88.98%), our method achieves an improvement of 1.02%.

Table 7. Comparison of the acc1 of the ordinary ResNet50-D pre-trained model and the distilled version on different datasets, except for replacing the pre-trained model, we use the same training strategy.

| Dataset              | Baseline Top-1 Acc(%) | Ours Top-1 Acc(%) |
|----------------------|-----------------------|-------------------|
| FGVC-Aircraft-2013b  | 88.98                 | **90.00 (+1.02)** |
| CIFAR-100            | 86.50                 | **87.58 (+1.04)** |
| DTD                  | 76.48                 | **77.71 (+1.23)** |
| SUN397               | 64.02                 | **68.36 (+4.34)** |

Object Detection In this experiment, we compare our distilled models with baseline ResNet50-D on object detection tasks based on PaddleDetection. All experiments are conducted on the commonly used MS-COCO2017 [23] dataset, which involves 80 object categories. Following the standard COCO metric, we report the average mAP at IoU of 0.5:0.05:0.95. The official train/val split is used for training and validation. As for the detection framework, we select two-stage, one-stage and anchor-free methods, i.e.,

3https://github.com/PaddlePaddle/PaddleDetection
Faster-RCNN-FPN [31], YOLOv3 [30] and TTFNet [26], to prove the widely effectiveness of our distilled backbone.

Table 8 demonstrates the experiment results on COCO minival2017, results are obtained by single-scale training/testing mechanism. With our improved backbone, object detection performance can be consistently increased, regardless of what kind of detector is used. Our backbone can increase mAP@[0.5,0.95] of Faster-RCNN-FPN, YOLOv3, TTFNet and RetinaNet by 1.5%, 1.1%, 2.1% and 1.1%, respectively. Besides, our distillation solution is also complementary for deformable convolutional, adding deformable convolutional v2 (DCNv2) [47] on the basis of ResNet50-D(ours)-YOLOv3 can still gain by 1.2%. This suggests that pre-trained backbone obtained from our distillation solution can well improve object detection tasks.

| Model            | Backbone    | Baseline mAP(%) | Ours mAP(%) |
|------------------|-------------|-----------------|-------------|
| Faster-RCNN-FPN  | ResNet50-D  | 34.8            | **36.3 (+1.5)** |
| RetinaNet        | ResNet50-D  | 37.0            | **38.1 (+1.1)** |
| TTFNet           | ResNet50-D  | 33.2            | **35.3 (+2.1)** |
| YOLOv3           | ResNet50-D  | 37.4            | **38.5 (+1.1)** |
| YOLOv3-DCNv2     | ResNet50-D  | 39.1            | **40.3 (+1.2)** |

Table 8. Comparison of the detection mAP on MS COCO dataset between ordinary ResNet50-D pretrained model and its distilled version with our solution.

Semantic Segmentation. We also report the semantic segmentation results on Cityscapes dataset [6]. It contains 5000 high-quality labeled images, among which 2,975 images consists of the training set and 500 images form the validation set.

We implemented it based on PaddleSeg [4]. We follow the same training protocol of [46] and following prior work [4] [45] to report mIoU evaluated on the validation set for comparison. Table 9 provides the detailed results of different semantic segmentation heads with different pretrain models. With different semantic segmentation heads, our improved backbone models has consistently shown great advantages compared to their baseline counterparts. Even on a state-of-the-art head like OCRNet, we can still have an obvious improvement.

| Model       | Backbone      | Baseline mIoU(%) | Ours mIoU(%) |
|-------------|---------------|------------------|-------------|
| FCN         | HRNetV2-W18   | 78.83            | **80.38 (+1.55)** |
| FCN         | ResNet50-D    | 74.87            | **77.03 (+2.16)** |
| Deeplabv3+  | ResNet50-D    | 78.06            | **79.51 (+1.45)** |
| OCRNet      | HRNetV2-W18   | 80.12            | **80.44 (+0.32)** |

Table 9. mIoU values of different semantic segmentation heads using different pre-train models.

that of the teacher model, thus unlabeled data can be easily leveraged to support fully exploitation of the knowledge learned by the teacher. In this paper, we also answer that it is possible to use only 4M unlabeled data to get backbone models significantly improved. Extensive experiments are conducted to offer empirically guidance on our design choices and effectiveness are validated on multiple computer vision tasks.

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