**Spirit Distillation: A Model Compression Method with Multi-domain Knowledge Transfer**

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**Abstract.** Recent applications pose requirements of both cross-domain knowledge transfer and model compression to machine learning models due to insufficient training data and limited computational resources. In this paper, we propose a new knowledge distillation model, named Spirit Distillation (SD), which is a model compression method with multi-domain knowledge transfer. The compact student network mimics out a representation equivalent to the front part of the teacher network, through which the general knowledge can be transferred from the source domain (teacher) to the target domain (student). To further improve the robustness of the student, we extend SD to Enhanced Spirit Distillation (ESD) in exploiting a more comprehensive knowledge by introducing the proximity domain which is similar to the target domain for feature extraction. Results demonstrate that our method can boost mIOU and high-precision accuracy by 1.4% and 8.2% respectively with 78.2% segmentation variance, and can gain a precise compact network with only 41.8% FLOPs.

**Keywords:** Knowledge Transfer, Knowledge Distillation, Multi-domain, Model Compression, Few-shot Learning.

## 1 Introduction

Recent applications, such as self-driving cars and automated delivery robots, present the requirement of light-weight models due to limited computational resources as well as the real-time demand for recognition. At the same time, such applications often suffer from inadequate training data [22,3], the introduction of cross-domain knowledge is urgently needed. Model compression [20,31,8], which compress the formed network in the back-end at the cost of a low loss of accuracy, and few-shot learning [10,25,33], which reduces the dependence of

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models on data through prior knowledge transfer, are presented to address these problems.

Among the various approaches, knowledge distillation and Fine-tuning-based Transfer Learning (FFT) are respectively considered as the most commonly used techniques for model compression and few-shot learning, and remarkable progress has been made in recent years [15,24,32,18,33]. However, these methods can only solve one of these two problems, and so far there has been no study to combine them.

In our work, we pioneer cross-domain knowledge transfer under the framework of feature-based knowledge distillation [29], and introduce the Spirit Distillation (SD). Different from previous approaches, SD adopts the teacher and the student networks that address problems in different domains (source and target domain, respectively). The performance of the student network is improved by exploiting the potential to extract general features with cumbersome backbone discarded through general knowledge transfer from the source domain. In addition, a more comprehensive general features extraction knowledge is transferred by extending SD to Enhanced Spirit Distillation (ESD). By introducing extra data from the proximity domain which is similar to the target domain as general feature extraction materials, the student network can learn richer and more complete knowledge and achieve a more stable performance after fine-tuning.

In general, our contributions can be summarized as follows:

– We apply knowledge distillation to both model compression and few-shot learning and propose the Spirit Distillation (SD). Through general feature extraction knowledge transfer, the compact student network is able to learn an effective representation based on the front part of the teacher network.
– We extend SD to Enhanced Spirit Distillation (ESD). By introducing the proximity domain to achieve richer supervised intermediate representation, more complete knowledge can be learned by the student network, so that robustness of the student network can be significantly boosted.
– Experiments on Cityscapes [7] semantic segmentation with the prior knowledge transferred from COCO2017 [17] and KITTI [11] demonstrate that:
  • Spirit Distillation can significantly improve the performance of the student network (by 1.8% mIOU enhancement) without enlarging the parameter size.
  • Enhanced Spirit Distillation can reinforce the robustness of the student network (8.2% high-precision accuracy boosting and 21.8% segmentation variance reduction) with comparable segmentation results attained.

2 Related Work

2.1 Knowledge Distillation

Knowledge distillation researches on the technical means of training compact student network with the prompt of cumbersome teacher network. Previous works can be mainly classified into logit-based distillation [15,21,28] and feature-based
distillation [14,18,19,24], which transfer the knowledge from different stages of the teacher network to improve the performance of the student network. Pioneering works on knowledge distillation bases on logits transfer [15], which adopt a weighted average of soft and hard labels as supervisory information for student network training. Subsequent works begin to focus on transferring intermediate representation of the teacher network, like FitNet stage-wise training [24], knowledge adaptation [14], and structured knowledge distillation [18], hoping that the student network learns an effective representation based on the front part of the teacher with much fewer FLOPs.

2.2 Few-shot Learning

Few-shot learning provides a solution to the problems in scenarios with insufficient data, utilizing prior knowledge like understanding of the dataset or models trained on other datasets to reduce the dependence of machine learning models on data [30]. Existing few-shot learning methods based on data augmentation [12,6,5], metric learning [26,27,2], and initialization [10,25,23] ameliorate the models in terms of supervised empirical growth, hypothesis space reduction, and initial parameter setting, respectively, so as to enhance the generalization ability of the models under the premise of inadequate training data.

2.3 Fine-tuning-based Transfer Learning

Fine-tuning-based transfer learning [33] proposes to splice the problem-specific feature analysis part to the first few layers of a heavy network pretrained on a large-scale dataset, and train the constructed network under the condition of freezing the weights of the front part and do further fine-tuning. Since the layers transfered from the cubersome network are able to extract features with universal properties (i.e. general features), the trained-out network tends to be of great generalization capabilities.

3 Approach

3.1 Framework of Spirit Distillation

The basic framework of SD is similar to feature-based knowledge distillation [29], which introduces both the teacher network ($T$) and the student network ($S$) in the training procedure, as shown in Fig. 1. The teacher network adopts state-of-art architecture with pre-trained weights, and the student is compact and efficient. This scheme of knowledge distillation allows the student to optimize by minimizing the distillation losses ($L_D$) between the hidden layer output features of the teacher ($F_T$) and the student ($F_S$), through which the student can learn a rich teacher-based intermediate representation. The optimization objective is defined as:

$$W_{S}^{front} \leftarrow \arg \min L_D(F_T, F_S)$$

(1)
Fig. 1. Framework of Spirit Distillation. The teacher network is pretrained on the source domain \((D_s)\), while the student network is used to solve the problem on the target domain \((D_t)\), which is with insufficient data. Three main steps are conducted: (1) Construct the student network by compact modules substitution and designing compact SH. (2) Learn a teacher-front-based representation utilizing feature-based knowledge distillation. (3) Perform constrained optimization on the student network.

thereout, we learn the weights of the front part of the student \((W_S^{\text{front}})\) from its teacher.

Unlike previous knowledge distillation methods, the teacher network and the student network in this paper are solving problems in different domains. Our teacher is pretrained on the source domain \((D_s)\), and the student is trained on
the target domain \((D_t)\). Just as there is a huge gap in sample size and scenarios between \(D_t\) and \(D_s\), our goal is to improve the performance of \(S\) on \(D_t\) to the greatest extent, with powerful knowledge transferred from the representation of \(T\) learned from \(D_s\). As shown in Fig. 1, \(SD\) is conducted according to the following three steps:

- Construct the student network by compact modules substitution and designing compact \(SH\).
- Learn a teacher-front-based representation utilizing feature-based knowledge distillation.
- Perform constrained optimization on the student network.

Moreover, \(ESD\) introduces the proximity domain \((D_p)\) that is similar to \(D_t\) and adopts data in \(D_p\) as feature extraction materials, providing richer knowledge to enhance the distillation effect.

### 3.2 Spirit Distillation

**Student Network Construction** Given a bulky pretrained teacher network \(T\), we divide it into two parts according to the deviation between \(D_s\) and \(D_t\). In this way, we gain the activation map generator \((AMG)\) which is the first part, and the teacher head \((TH)\) to be the second one. Obtaining the \(S\)'s feature extractor \((FE)\) by replacing the convolutional layers of \(AMG\) with compact modules (e.g. group convolution [16]) to prepare the ground for efficient feature extraction. By designing the efficient feature analysis part for \(S\) (i.e., student head, denoted as \(SH\)) and stacking the part after \(FE\), the final \(S\) is obtained. As such, the inference cost of \(S\) is much cheaper than that of \(T\), and \(FE\) has the potential to extract general features just like \(AMG\) with even stronger generalization capability due to the smaller parameter size.

**Feature-based Distillation** We input images of \(D_t\) into \(AMG\) and gain their general features (i.e., the output of the \(AMG\), denoted as \(y^{AMG}\)). Suppose that the general features extracted by \(AMG\) are “spirit” of the \(T\)'s representation for general feature extraction. These general features are less relevant to a specific domain and a particular network architecture compared with the hidden layer output of bulky networks converged on only the \(D_t\)'s training data. The rich semantic information of “spirit” for supervision is helpful knowledge to guide \(FE\) to optimize toward extracting useful features for \(D_t\). As a result, we take \(y^{AMG}\) as the optimization objective of the feature extractor \((FE\), whose output is denoted as \(y^{FE}\)) and transfer the “spirit” by minimizing the distillation loss \((L_D)\).

**Constrained Optimization** After transferring the knowledge from the teacher network, further optimization is required for precise prediction. We first train \(S\) (training loss function denoted as \(L_P\)) with a frozen \(FE\), followed by a small learning rate optimization for the overall weights, to preserve the prior knowledge in the representation of \(FE\) to the greatest extent.
3.3 Enhanced Spirit Distillation

Since the dataset of $D_t$ is largely undersampled from real scenes, the required diversity general features cannot be fully obtained by simply reinterpreting the images of $D_t$, which leads to the incomplete nature of the knowledge transferred.

Fortunately, feature representation knowledge learned from a particular dataset tends to work well for similar domains. Therefore, introducing a large-scale dataset of $D_p$ for feature extraction can prevent the feature extractor from over-fitting to the little general features of $D_t$. Moreover, $D_p$ may implicitly provide richer information of scenarios, and can compensate for the problem of insufficient data on $D_t$.

Based on the assumptions above, we extend SD in terms of data inputting by shuffling $D_t$ and $D_p$ images together, extracting their features, and allowing the student network to imitate. This method, shown in Fig. 2, expects to be executed in substitution with the input of $D_t$ images during the feature-based distillation process, and we name the newly integrated transferring and training scheme Enhanced Spirit Distillation ($ESD$).

3.4 Formal Description of Enhanced Spirit Distillation

Algorithm 1 provides a formal description of the overall procedure of Enhanced Spirit Distillation. The algorithm takes the weights of pre-trained teacher network $W^T$ (whose weights of $AMG$ part corresponds to $W^{AMG}$), the weights of randomly initialized student network $W^S$ (whose weights of $FE$ and $SH$ parts correspond to $W^{FE}$ and $W^{ST}$), the distillation loss $L_D$, the prediction loss $L_P$, the target domain dataset $D_t$, the proximity domain dataset $D_p$, and the optimizer $\text{optimizer}_i$ of the $i^{th}$ stage of training (with hyper settings) as inputs, and takes trained $W^S$ as output. Define $W_1, W_2, ...W_k$ as the weights of layers $\{W_1, W_2, ...W_k\}$, $\{W_1, W_2, ...W_k\}^X$ as the output of data $X$ (whose label is denoted as $y^X$) after the transformation operation of each layer, and $W^k_s$ as the result of a certain iteration update of $W^k$. 
Algorithm 1: Enhanced Spirit Distillation

**Input:** $W^T(W^{AMG}), W^S(W^{FE}, W^{ST}), L_D, L_P, D_t, D_p, \text{optimizer}_i$

**Output:** Trained $W^S$

**Stage 1: Feature-based Distillation**

```java
while FE not convergence do
    $X_1 \leftarrow \text{shuffle, select}(D_p, D_t)$;
    $W^{FE*} \leftarrow W^{FE} - \text{optimizer}_1(\nabla L_D(\{W^{AMG}\}^{X_1}, \{W^{FE}\}^{X_1}))$;
end
```

**Stage 2: Frozen Training**

```java
while SH not convergence do
    $X_2, y^{X_2} \leftarrow \text{random, choice}(D_t)$;
    $W^{SH*} \leftarrow W^{SH} - \text{optimizer}_2(\nabla L_P(\{W^{S}\}^{X_2}, y^{X_2}))$;
end
```

**Stage 3: Fine-tuning**

```java
while S not convergence do
    $X_3, y^{X_3} \leftarrow \text{random, choice}(D_t)$;
    $W^{S*} \leftarrow W^{S} - \text{optimizer}_3(\nabla L_P(\{W^{S}\}^{X_3}, y^{X_3}))$;
end
```

| Dataset            | Volume   | Resolution | Scenario       | Domain     | Preprocess |
|--------------------|----------|------------|----------------|------------|------------|
| COCO2017 [17]      | 100K+    | -          | Common Objects | Source     | -          |
| Cityscapes-64 [7]  | 64       | 2048*1024  | Road Scenes    | Target     | RC, RHF, MP |
| KITTI [11]         | 15K      | About 1224*370 | Proximity     | RZ, RC, RHP, MP |

Table 1. The main properties, roles, and preprocessing methods of the datasets adopted in this paper. RC, RHF, MP, RZ in the table are abbreviations of random cropping, random horizontal flipping, maximum pooling and resizing, respectively.

4 Experiments

4.1 Datasets

We introduce COCO2017 [17], Cityscapes [7] and KITTI [11] in our experiments, whose main properties, roles, and preprocessing methods are shown in Table 1. The subset of COCO2017 that contains the same class as Pascal VOC [9] is used to pretrain the teacher network\(^1\). Only the first 64 images of Aachen in Cityscapes (denoted as Cityscapes-64) is chosen for feature-based distillation and constrained optimization. What’s more, the images in KITTI are randomly shuffled with Cityscapes-64 ones in the feature-based distillation process when ESD is adopted.

\(^1\) The pretrained weights of the teacher network are downloaded from download.
pytorch.org/models/deeplabv3_resnet50_coco-cd0a2569.pth
4.2 Network Architecture

We adopt DeepLabV3 [4] (resnet-50 [13] backbone, pretrained on COCO2017) as the teacher network. To construct the feature extractor, we adopt the teacher’s backbone with all of the convolutional layers replaced by group convolutions [16], each group being the greatest common factor of the number of input and output channels. The student head is constructed by replacing the ASPP and subsequent layers with a SegNet-like [1] decoder structure, i.e., two groups of $3 \times (Conv + BN + ReLU)$ stack with bilinear up-sampling modules to achieve resolution increment and pixel-level classification. The convolution layers of the decoder also adopt group convolutions in the same setup as that adopted in the construction of $FE$.

4.3 Implement Details

Basic Setup Experiments on binary segmentation on Cityscapes-64 are conducted to distinguish roads and backgrounds. Mean square error and pixel-average cross-entropy are taken as $L_D$ and $L_P$, respectively.

Metrics We adopt mean intersection over union (mIOU) as the index to measure the segmentation effect, the size of parameters and floating point operations in measuring the compactness and inference efficiency of the network; the prediction variance and high-precision segmentation accuracy (considered to be segmented properly when $mIOU \geq 75\%$, denoted as (HP-Acc)) in evaluating the robustness of the model.

Hyper-parameter Settings We take a comparison experiment on whether or not to adopt SD method. We also employ the FTT on the network that stacks $AMG$ and the $SH$ (denoted as constructed teacher network (CT)), and the former part is frozen in the first training stage. We directly train the student network using stochastic gradient descent (SGD) with momentum 0.9 and learning rate $10^{-2}$. For distillation process, a learning rate of $3 \times 10^{-3}$ and a momentum of 0.99 are adopted until convergence. Constrained optimization requires freezing weights of $FE$. The training of the remaining portion adopts a momentum of 0.9 with a learning rate of $10^{-2}$. Further fine-tuning sets the learning rate of the entire network to $5 \times 10^{-5}$ and the momentum to 0.99. L2 weight penalty is adopted in all cases, with a decay constant of $3 \times 10^{-3}$. Moreover, a data enhancement scheme with random cropping ($512 \times 512$) and random horizontal flipping is adopted, with max pooling (kernel size=2) adopted before input. To validate ESD, we set up a series of different scales to control the ratio $r$ that the number of input $D_t$ images to that of $D_p$ during distillation, and conduct the experiments separately. The $D_t$ images are preprocessed in the same way adopted for SD, except that they were previously resized to $2448 \times 740$ before cropping. All the preprocessing schemes for images in different datasets are shown in Table 1.
Table 2. The performance on the Cityscapes dataset in comparison with regular training and FTT. All the networks are trained only on the first 64 images of Cityscapes.

| Method                | GFLOPs | Param(M) | mIOU(%) | HP-Acc(%) |
|-----------------------|--------|----------|---------|-----------|
| CT (FFT [33], without fine-tuning) | 405.7  | 23.6     | 62.6    | 1.4       |
| CT (FFT [33], with fine-tuning)      | 405.7  | 23.6     | 58.9    | 2.6       |
| S                                   | 169.4  | 9.5      | 81.7    | 81.2      |
| Ours: S (SD)                      | 169.4  | 9.5      | 83.5    | 84.6      |

Table 3. Comparison of the results on regular training, Spirit Distillation, and Enhanced Spirit Distillation with different r values adopted.

| Method          | mIOU(%) | HP-Acc(%) | Var(10^{-4}) |
|-----------------|---------|-----------|--------------|
| S               | 81.7    | 81.2      | 5.77         |
| Ours: S (SD)    | 83.5    | 84.6      | 5.70         |
| r=10.0          | 82.2    | 85.4      | 5.12         |
| r=5.0           | 81.9    | 85.6      | 5.20         |
| r=3.0           | 82.2    | 84.6      | 5.21         |
| Ours: S (ESD)   | 82.3    | 84.2      | 4.52         |
| r=1.0           | 83.3    | 89.2      | 4.71         |
| r=0.5           | 82.8    | 89.0      | 4.48         |
| r=0             | 83.1    | 89.4      | 4.51         |

4.4 Results

We display the segmentation results of the student network (S) trained with SD along with the results of that trained follows regular training scheme and FTT in Table 2. To validate the effectiveness of ESD, we respectively train S under different r settings and obtain the results shown in Table 3. We also plot the comparison of mIOU-GFLOPs, Var-(HP-Acc), and mIOU-r with different training settings, and calculated the distribution of segmentation effects when regular training, SD, and ESD are adopted. (see Fig. 3)

The following conclusions can be drawn from Tables 2, 3 and Fig 3, 4.

- The S using SD outperforms normally trained S as well as the fine-tune-transferred CT. In addition, with inference efficiency significantly improved, SD also prevents the final network from over-fitting due to the large network size as well as under-fitting for the sake of freezing weights. (Table 2, Fig. 3(a))
- The segmentation effect of S is improved with either SD or ESD adopted. The S trained with ESD can perform splendid predictions in more cases, and the proportion of very poor results is significantly reduced. Hence, ESD can improve the robustness of S to a great extent. (Fig. 3(b))
- The effectiveness of introducing D_t is easily demonstrated as the final obtained S tends to gain a higher HP-Acc as well as mIOU when the value of
r is set small, i.e., the proximity domain accounts for a larger proportion of the images used for feature extraction. (Table 2, Fig. 3(c))

- **ESD** effectively improves the **HP-Acc** while keeping the variances small numbers. The comprehensive learning of the general features extracted from T helps prevent unstable prediction and enhances robustness. (Fig. 3(d))

- The validity of our methods in cross-domain knowledge transfer and robustness improvement under complex scenarios is easily confirmed, as the comparison shown in Fig. 4. The obvious finding is that the segmentation results of the undistilled S are rather unsatisfactory for the shadow parts of the images. After adopting **SD**, the new S has improved the segmentation results of these parts, which is able to distinguish the road scene from the shadows partially. Adopting the **ESD** method on top of this, the S would capture the global representation for shadow segmentation more completely.
Fig. 4. Comparison of segmentation results on Cityscapes-64. (1) Input images. (2) Ground truth. (3) The segmentation results of the student network. (4) The segmentation results of the student network that adopts Spirit Distillation. (5) The result of the student network that adopts Enhanced Spirit Distillation, with $r$ value set to be 0.5.

and can distinguish the road part with shadows of the images more as a whole. (Fig. 4)

5 Conclusion

In order to introduce cross-domain knowledge while acquiring compressed models, a novel knowledge distillation method is proposed, which allows student networks to simulate part of the teacher’s representation by transferring general knowledge from the large-scale source domain to the student network. To further boost the robustness of the student network, we introduce the proximity domain as the source of general feature extraction knowledge during feature-based distillation process. Experiments demonstrate that our methods can effectively achieve cross-domain knowledge transfer and significantly boost the performance of compact models even with insufficient training data.

Future works will include extending our approach to other visual applications and conducting domain transformation to feature extraction materials using approaches like conditional generative adversarial network training.

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