


Few Shot Learning via Multiple Teacher Knowledge Distillation

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Abstract: Machine learning enables computers to discover patterns in large datasets and use them for recognition or prediction. A model's performance typically depends on the amount of data available; sufficient training samples ensure good generalization. However, in many applications, acquiring large amounts of labeled data is costly and time-consuming, and in fields like healthcare or autonomous driving, labeled samples can be scarce. This raises the important challenge of training effective models with only a few samples. Few-shot learning addresses this challenge by aiming to perform tasks with very few training examples, learning and generalizing from just a few or even a single sample. The paper designs a novel method that combines Knowledge Distillation and Few-Shot Learning to improve model performance with limited data. By leveraging intermediate features from the teacher model and applying Multiple Teacher-Student Architecture, the paper's approach enhances feature extraction and adaptation in few-shot scenarios. This method achieves premier results on the various dataset, demonstrating the effectiveness of feature distillation in Few-Shot Learning tasks.

1 INTRODUCTION


In applications which require intensive data, Machine Learning is widely applied and achieved significant success. However, when the available dataset is small, model performance is often limited. In reality, obtaining large amounts of training samples is both difficult and expensive, making it crucial to study how to learn effectively under limited data conditions. Few-Shot Learning (FSL), which is a new learning method to train with limited supervised example was proposed (Fei-Fei et al., 2006; Fink, 2004). FSL's objective is to make it possible for models to fast adapt to new tasks using only a few samples. Current FSL approaches can be categorized into three types: non-episodic approaches that pre-train on base classes and then fine-tune on new classes (Dong et al., 2022), beta learning methods based on meta-learning, where the model learns how to learn (Finn et al., 2017), and metric-learning methods that categorize by directly analyzing the consistency of query images and support classes (Snell et al., 2017).

Additionally, Transfer learning has been extensively employed in image classification tasks as

a means of avoiding the need to train models from scratch. By leveraging models pre-trained on large datasets, transfer learning helps models significantly enhances the performance of few-shot learning (Sung et al., 2022; Mehrotra et al., 2020; Lotfollahi et al., 2022).

The paper proposes a novel method that combines Knowledge Distillation (KD) with few-shot learning. While most previous KD research has focused on logical distillation, which trains student models by reducing any KL divergence in the output probability distributions of the teacher and student models. However, feature distillation where intermediate teacher's features are used to guide the student model has been proved to outperform logical distillation in several tasks (Romero et al., 2014). Despite its superior performance, feature distillation has rarely been applied to few-shot learning. Therefore, the main contributions of the paper include:

1. Introducing feature distillation into few-shot learning. By leveraging the teacher model's logic distribution and intermediate features, the paper further improves the performance of the few-shot learning model.

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2. This method introduces multi-teacher distillation into few-shot learning tasks. By utilizing multiple teacher models, the student model is able to learn diverse and complementary information from different teachers, resulting in more robust feature representations. Unlike traditional single-teacher distillation, the multi-teacher setup allows for better capture of task diversity, thereby enhancing the student model's generalization ability.

3. The potential of combining feature distillation with few-shot learning is demonstrated through the best performance metrics in image classification tasks achieved by this method on various datasets.

2 RELATED WORKS

2.1 Knowledge Distillation

KD was first introduced by Hinton (2015), where a complex and excellent model (also called teacher model) trained to provide knowledge to a slim model (also called student model) through distillation training. It allows the knowledge of a complex teacher model to be transferred to a simpler student model with minimal performance loss. Hinton proposed the class probability with parameter T , also known as "soft targets." Soft targets carry more generalized information than hard targets. Initially, knowledge distillation only focused on learning from the teacher model's soft labels to produce a lightweight student model, but as teacher models grew deeper and more complex, learning solely from soft labels became insufficient.

Currently, knowledge distillation methods focus on two aspects: logical distillation (Komodakis & Zagoruyko, 2017; Benaim & Wolf, 2018) and feature distillation (Romero et al., 2014; Komodakis & Zagoruyko, 2017; Kim et al., 2018; Chen et al., 2021). The teacher model's knowledge can include more than just its logical output, features from intermediate layers, parameters, and even the connections between layers can be considered knowledge. Both final-layer outputs and intermediate outputs can teach student model to learn. Knowledge based on feature can complement response-based knowledge and is useful for training slim networks. FitNets introduced intermediate representations (Romero et al., 2014), selecting an intermediate layer from the teacher model to guide the hidden layer output of the student model. Inspired by (Romero et al., 2014), subsequent research proposed various methods to use teacher model intermediate layers (Komodakis & Zagoruyko, 2017; Kim et al., 2018; Chen et al., 2021). Zagoruyko

et al. proposed using attention maps to represent knowledge; Kim et al. introduced convolutional translators as more interpretable intermediate representations (Kim et al., 2018). Chen et al. proposed cross-layer KD, adaptively assigning layers in the student network to layers in the teacher network using attention mechanisms (Chen et al., 2021). Additionally, feature extraction-based methods often overlook the importance of logical distillation, which Zhao et al. emphasized by rephrasing classical KD loss to highlight logical distillation's importance (Zhao et al., 2022).

2.2 Few Shot Learning

Few-shot learning was proposed in (Fei-Fei et al., 2006; Fink, 2004) as a new machine learning paradigm for learning from limited supervised examples. One approach to FSL is data augmentation (Lake et al., 2015; Wang et al., 2019), which involves transformations such as translation, flipping, and shearing, or data synthesis and feature enhancement. These methods enlarge the dataset, but their design requires expert domain knowledge and high labor costs. Another category is meta-learning-based methods, where the model learns to learn. Finn et al. proposed a model-agnostic meta-learning framework (MAML) (Finn et al., 2017), which performs a few gradient updates across multiple tasks to find the optimal initialization parameters across all tasks. These allow the model to adapt quickly to new tasks with minimal gradient updates and achieve good performance. Other meta-learning-inspired methods like MetaDet use a meta-model to learn predict-class-specific parameters from few-shot data (Wang et al., 2019), enabling accurate object detection in new classes. Zhang et al. designed a new associated meta-learning strategy (Zhang et al., 2022), Meta-DETR, which use the association aggregation module (CAM) combined with task encoding to integrate the supported category information into the query features, and then encode and decode through the Transformer to adapt to new classes in few-shot tasks for efficient object detection.

Previous research has shown that transfer learning make model avoid training from scratch possible by adapting to new tasks fast (Sung et al., 2022; Mehrotra et al., 2020; Lotfollahi et al., 2022). Transferring learning has been widely proven to be effective through KD, where the teacher model instructs the student model. The core task of few-shot learning is enabling the model to fit on very few samples and generalize well. The dark knowledge provided by the teacher model's soft labels in KD are

crucial for FSL models with only a few hard targets, helping prevent overfitting and improving task generalization. Therefore, some recent studies have attempted to combine KD and FSL, typically by using the teacher model to augment the data (Rashid et al., 2020; Rajasegaran et al., 2020; Yoo et al., 2021). In contrast, the paper applies feature based distillation to FSL, fully utilizing the feature extraction capabilities of powerful teacher models to improve student model performance under few-shot conditions.

3 METHOD

3.1 Pre-Train

Typically, to perform few-shot learning, the model needs to be pre-trained on a source domain dataset $S_s = \{(x_1, y_1), \dots, (x_N, y_N)\}$, and then trained on the target domain dataset $S_D = \{(x_1, y_1), \dots, (x_N, y_N)\}$, (x_i, y_i) represents the i -th sample x_i and label y_i in the dataset. If only S_D is used for training, the model will struggle to converge. The pre-training phase involves mixing the source domain data with the target domain data, which has limited samples, to create a mixed domain dataset $S_C = S_s + S_D$, and train the teacher backbone using S_C . This allows the teacher model to better grasp the low-level feature representations, such as edge information and texture information, across different categories, preventing the model from overfitting. The student's ability to generalize well even with a few samples is greatly enhanced by the presence of a well-trained teacher backbone in the subsequent steps, which can transfer its low-level feature extraction capability to the student backbone through KD.

3.2 Attention-Weighted Distillation Loss

During the distillation process, the first step is to let the teacher model perform inference on the data, save the output prediction results (soft labels), and then train the smaller model. Soft labels differ from the hard labels typically used in model training and contain similar information between different classes. However, directly using soft labels to train the student model can easily ignore the relationships between different classes. This is because the output of the teacher model is typically a probability distribution calculated through the Softmax function. By default, the Softmax function tends to concentrate the output distribution on one or a few most likely categories, resulting in a sharp probability distribution, where

most categories have probabilities close to zero. However, by introducing a temperature coefficient T to the Softmax, the output probability distribution of Softmax becomes smoother (Hinton, 2015). The Softmax with the temperature parameter T can be represented as:

$$p_i = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)} \quad (1)$$

Where z_i is the unnormalized score (logit) for class i .

When $T > 1$, the probability distribution becomes smoother, and the differences between class probabilities decrease. The student model is better able to capture subtleties during training with a smooth probability distribution that provides more information about the similarities between different classes. After introducing the temperature coefficient T into the Softmax function, the output probability distribution is $P^t = \{P_1^t, \dots, P_N^t\}$, and the output of student's is $P^s = \{P_1^s, \dots, P_N^s\}$, P_i representing the probability of class i . The key to training with soft labels is the KL divergence. The loss is calculated to determine the disparity between the probability distribution of output in student and the soft labels from the teacher model.

$$\ell_{soft} = DK_{KL}(P^t || P^s) = \sum_{i=1}^C (P_i^t) (\log \frac{P_i^t}{P_i^s}) \quad (2)$$

In equation (2) C represents the number of classes.

The final distillation loss is obtained by combining KL divergence and task-specific loss:

$$\ell_{logic} = \alpha \ell_{soft} + \beta \ell_{task} \quad (3)$$

This method designed a feature loss to measure the differences in intermediate layers between the student and the teacher. Let the feature maps of the teacher model be denoted as $F_i^t \in \{F_1^t, F_2^t, \dots, F_N^t, P^t\}$ and the student model's are $F_i^s \in \{F_1^s, F_2^s, \dots, F_N^s, P^s\}$. The one-to-one matching method is defined as:

$$\ell_f = \sum_{i=1}^N D(F_i^t, F_i^s) \quad (4)$$

D is a function that calculate the distance used to determine the difference between the student and teacher models (such as Euclidean distance or other metrics)

Specifically, equation (4) assumes that channels in the feature maps that come from teacher and student model are the same. To map features into target representations, a transformation \mathbf{o} is necessary

for channels that differ, and equation (4) can be expressed as:

$$\ell_f = \sum_{i=1}^N D(o(F_i^t), o(F_i^s)) \quad (5)$$

The paper’s goal is to minimize ℓ_f . When the architecture of the teacher and student models differ significantly, or multi-layer information needs to be considered, a simple one-to-one matching might not be enough to effectively transfer knowledge. To better achieve knowledge distillation, it is usually necessary to combine multi-layer knowledge. After introducing multi-layer distillation, the loss in multi-layer can be defined as:

$$\ell_{multi} = \sum_{i=1}^N (\sum_{j=1}^i D(o(F_i^s), o(F_j^t))) \quad (6)$$

Different layers have different effects on the student’s learning based on the features of the teacher model. Some layers’ features are more important than others, and simply accumulating the features from all layers can lead to these important features being overlooked. By introducing attention weights, the model can adaptively assign different weights to the features of each layer, allowing the important features to receive more attention while the less important features are appropriately suppressed. Therefore, the paper designed **Attention-Weighted Distillation Loss (AWD)**, which balances multi-layer knowledge with dynamic weighting instead of simply accumulating it. AWD is defined as:

$$\ell_{AWD} = \sum_{i=1}^N D(o(F_i^s), \sum_{j=1}^i \alpha_{i,j} \cdot o(F_j^t)) \quad (7)$$

where $\alpha_{i,j}$ is the attention weight, and the definition of $\alpha_{i,j}$ is:

$$\alpha_{i,j} = \frac{\exp(F_i^s \cdot F_j^t)}{\sum_{k=1}^i \exp(F_i^s \cdot F_k^t)} \quad (8)$$

Finally, the paper define the overall loss function as:

$$\ell = \gamma \ell_{soft} + (1 - \gamma) \ell_{AWD} \quad (9)$$

3.3 Multiple Teacher-Student Architecture

Previous KD work has focused on the framework of single teacher-single students (Komodakis & Zagoruyko, 2017; Chen et al., 2021; Zhao et al., 2022). This is because, under conditions of limited computational resources and insufficient data, this method has shown relatively good performance, and it is easy to implement in practice. A single teacher model can provide strong supervision by transferring complex knowledge representations to a smaller student model, thus improving the student model’s learning ability. However, in FSL scenarios, the single teacher distillation method has certain limitations. Due to insufficient training data, the teacher model often fails to fully capture the diversity and fine-grained characteristics of the data, leading to insufficient transfer of knowledge and limiting the student’s ability to generalize.

This paper suggests a method called **MTKD** (multiple teacher-student) to address this issue. The student model can learn from diverse perspectives and dimensions in FSL scenarios when the multiple teacher models are combined. Each teacher model can provide diverse feature representations, helping the student model to achieve a more comprehensive learning process. Multiple teacher models generate various knowledge. Distilling with multiple teachers, which is different from a single teacher, the student model can better handle the diversity and complexity of tasks under few-shot conditions. The multiple teacher-student framework effectively enables the student model to build a stronger learning foundation in limited data settings, compensating for the shortcomings of a single teacher.

Table 1: Accuracy of teacher model on ImageNet Dataset.

Model	Dataset	Top-1(%)	Tok-5(%)
ResNet-50	ImageNet	77.6	93.2
DenseNet-121	ImageNet	76.2	92.6

Table 2: Accuracy of few-shot learning tasks in the 1-shot settings.

Model	Mini-ImageNet	Omniglot	CUB
MTKD(Ours)	67.40±0.18	97.74 ± 0.15	70.44 ± 0.25
MAML(Finn et al., 2017)	56.72±0.22	96.50 ± 0.30	61.52 ± 0.20
ProtoNet(Snell et al., 2017)	60.74±0.19	97.62 ± 0.20	65.31 ± 0.25
SAML(Hao et al., 2019)	61.61±0.20	97.30 ± 0.15	66.07 ± 0.20

MetaOptNet(Gong, 2023)	62.79±0.20	97.53 ± 0.15	66.49 ± 0.20
Transfer Learning+Finetune	65.95±0.20	98.45 ± 0.15	69.53 ± 0.20

Table 3: Accuracy of few-shot learning tasks in the 5-shot settings.

Model	Mini-ImageNet	Omniglot	CUB
MTKD(Ours)	81.83±0.20	98.64 ± 0.15	82.50 ± 0.21
MAML(Finn et al., 2017)	68.81±0.19	98.59 ± 0.22	74.21 ± 0.21
ProtoNet(Snell et al., 2017)	79.19±0.22	98.82 ± 0.15	77.50 ± 0.19
SAML(Hao et al., 2019)	78.91±0.17	98.72 ± 0.17	78.22 ± 0.22
MetaOptNet(Gong, 2023)	80.52±0.20	98.92 ± 0.17	79.39 ± 0.19
Transfer Learning+Finetune	79.77±0.22	99.25 ± 0.16	80.26 ± 0.21

4 EXPERIMENTS

4.1 Implementation Details

In experiments, the paper adopted ResNet-50 and DenseNet-121 as the teacher models, as these two architectures possess different feature learning abilities. ResNet-50, with its deeper hierarchical structure, excels at capturing global features, while DenseNet-121 enhances local feature extraction through inter-layer feature reuse. Combining both logics and features from these two teacher models, the paper performed distillation training on the student model, ResNet-18. The paper compared MTKD with a baseline model that did not use distillation and was directly trained on the small sample dataset, to validate the effectiveness of MTKD in few-shot learning scenarios.

In both the distillation and baseline training, the paper conducted 1-shot and 5-shot learning tasks. The teacher models were pre-trained on the full training dataset, while the student model was trained under one-shot and five-shot scenarios with guidance from the teacher models. Paper’s method combined soft-label distillation, hard-label supervision, and attention-weighted feature distillation loss functions. The student model was able to improve its feature representation and generalization capabilities by acquiring knowledge from both teacher models during the distillation process.

The train process experiment employed a SGD and use a baseline ResNet-18 model. Weight decay occurs at a rate of $4e-4$. Initially, the learning rate is lowered to 0.01. Models were trained directly on the one-shot and five-shot settings with different methods. In the experiments, the paper used accuracy as evaluation metrics.

4.2 Teacher Models on Source Dataset

The two teacher models performed exceptionally well on the ImageNet dataset, as shown in Table 1, indicating that they were able to capture key features and class information in large-scale image classification tasks. The Top-1 accuracy of ResNet-50 was 77.6% and the Top-5 accuracy was 93.2, while DenseNet-121 was 76.2% accurate in Top-1 and 92.6% in Top-5. Although ResNet-50 slightly outperformed DenseNet-121, the difference in Top-5 accuracy between the two models is minimal, indicating that both models have strong generalization capabilities and can accurately identify the correct class in most cases. This strong classification performance makes these two models well-suited as teacher models, providing effective supervision signals for the student model in few-shot learning tasks. Through these teacher models, the student model can learn from rich feature representations, overcoming the data scarcity issue in few-shot learning and improving the overall performance of the model.

4.3 Performance of Few Shot Learning

In Table 2, MTKD achieves higher accuracy across all datasets compared to other methods in the 1-shot learning tasks. On Mini-ImageNet and CUB, the improvement is particularly evident when compared to baseline methods like MAML and ProtoNet. This demonstrates that MTKD can effectively extract key features even with extremely limited data, regardless of the small number of training samples. Unlike MAML and ProtoNet, which tend to struggle with distinguishing subtle inter-class differences when sample sizes are small, MTKD, with the assistance of teacher models, can extract features more efficiently and generalize faster.

On the Omniglot dataset, MTKD also performs exceptionally well, with accuracy significantly higher

than other models. Although Omniglot is a relatively simple dataset, the stable performance of MTKD on this dataset further demonstrates its robustness. The results indicate that MTKD not only excels at learning from small amounts of data but is also adaptable to different types of datasets, including those with relatively simple or homogeneous classes. However, it is also evident from the results that while MTKD performs excellently on Omniglot, it does not achieve the best performance among all methods. The source dataset the teacher model used is ImageNet and it is quite different from handwritten character dataset, Omniglot. Obviously, there is a huge domain gap.

According to Table 3, when performing 5-shot learning tasks, the performance of all models improves as the number of training samples increases. However, MTKD continues to maintain its leading position, especially on the Mini-ImageNet and CUB datasets. This suggests that MTKD not only benefits from having more samples but also consistently maintains a significant performance gap compared to other methods. The improved accuracy with more samples further demonstrates MTKD's strong ability to utilize additional information, improve classification decisions, and reduce errors.

A key factor contributing to the enhanced performance of MTKD is the use of distillation from multiple teachers. By leveraging several teacher models, the student model can assimilate diverse and complementary insights from various sources, leading to stronger feature representations. This technique helps the student model improve its generalization abilities, especially in situations where the training data is limited or contains noise.

Although Transfer Learning + Finetune shows competitive performance on the Omniglot dataset, its performance is inconsistent across different datasets. This inconsistency suggests that while transfer learning helps leverage pre-trained knowledge, it may struggle to adapt effectively to new categories and tasks that differ from the source domain. In contrast, MTKD is specifically designed for few-shot learning tasks, making it more reliable and adaptable across various scenarios.

Furthermore, the success of MTKD can also be attributed to its ability to simultaneously learn both local and global features. This allows the model to capture fine details while also recognizing broader patterns, giving it a distinct advantage over models that focus predominantly on one aspect. This balanced feature-learning approach ensures that the model can adapt to a wide range of tasks, regardless of the complexity of the dataset.

5 CONCLUSION

This study proposed and validated a FSL approach based on KD. By utilizing ResNet50 and DenseNet-121 as teacher models and ResNet18 as the student model, the study effectively applied the principles of knowledge distillation. This allowed the student model, even with a limited amount of training data, to achieve performance surpassing other few-shot learning methods. Additionally, the paper designed a comprehensive loss function, combining soft-label loss, hard-label loss, and attention-weighted feature distillation, which further enhances the student model's feature learning capabilities while maintaining prediction accuracy.

The experimental results show that after thorough training of the teacher model on a large dataset, distillation to the student model not only reduced the model's parameter count and computational cost but also significantly improved the student model's generalization ability in few-shot tasks. Specifically, in One-Shot and Few-Shot scenarios, the student model achieved better performance after distillation training compared to training independently on small datasets and other few-shot learning methods. This approach fully validated the effectiveness of knowledge distillation in few-shot learning and demonstrated its high practical value, especially in resource-constrained applications. Future work will further explore more sophisticated distillation strategies, such as adaptive temperature parameter adjustment, to achieve more robust model performance across more tasks and datasets.

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