Large Margin Mechanism and Pseudo Query Set on Cross-Domain Few-Shot Learning

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Abstract—In recent years, few-shot learning (FSL) has received a lot of attention due to difficulties and costs of data collection for many real-world problems. Conventional approaches focus on single-domain FSL where the base classes and novel classes are mostly from the same domain. We study a more challenging yet practical task, cross-domain few-shot learning (CD-FSL), which aims to recognize classes that are not only unseen but also from a different domain. We propose a novel large margin fine-tuning method (LMM-PQS), which enables models pre-trained on a single domain to be adaptable to various different domains with only a few labeled target samples. Our LMM-PQS centers on three novel components. (1) Pseudo query set (PQS): we generate more data to solve the problem that the query set is not available during fine-tuning. (2) Prototypical triplet loss (PT loss): it is a modified triplet loss integrating with the prototype concept which is commonly used in few-shot models. (3) Large margin cosine loss (LMCL): we treat CD-FSL problem as a near-open-set problem, and thus the large margin cosine loss is applied. Our LMM-PQS significantly outperforms competitive baselines on various different target domains, which demonstrates promising effectiveness on challenging CD-FSL problem. Most importantly, we provide a practical solution for CD-FSL with only a few data available.

Index Terms—cross-domain few-shot learning, large margin mechanism, pseudo query set.

I. INTRODUCTION

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eral deep neural networks (DNNs) [1] for computer vision and multimedia problems heavily rely on a large amount of labeled training data and need to be re-trained or fine-tuned when encountering different tasks. Besides, the generalization ability of these networks is highly correlated with the diversity and the size of the training set. However, collecting adequate amounts of data for practical problems is usually difficult and high-cost. Therefore, learning to characterize different classes with a few labeled samples, known as few-shot learning, is necessary. The problem is usually set under the meta-learning setting, which contains meta-training and meta-testing phases. In the first phase, models are trained with classification tasks where data composed of labeled samples, known as support sets, and unlabeled samples, known as query sets, both sampled from base classes. In the second phase, tasks sampled from novel classes are used for evaluating the model performance. Note that base classes and novel classes are disjoint, and thus quick adaptation from base classes to novel classes is indispensable and challenging.

The objective of FSL problem is to categorize the query set leveraging given support set in the meta-testing phase. Myriads of few-shot learning approaches [2], [3], [4], [5], [6] try designing different metrics to recognize the relationship between two sets. However, a recent work [7] claims that a general DNN, denoted as Baseline, trained under a standard practice shows competitive results with several fine-tuning iterations.

In the training procedure, the biggest difference between general DNNs (e.g., Baseline) and few-shot methods is that the former trains and updates parameters with batch data at every iteration, whereas the latter makes inference based on support sets (a few labeled data) and updates parameters with loss over query sets. As mentioned above, general DNNs need to be fine-tuned before solving novel tasks. Moreover, the query set is reserved for evaluation in the meta-testing phase, which means only support set can be used for fine-tuning. Consequently, general DNNs can fine-tune using data sliced from support set and adapt to novel tasks. On the other hand, few-shot methods infer the query set directly without fine-tuning. The reasons why few-shot methods don’t apply fine-tuning are (1) both support set and query set are needed for updating their parameters, and (2) they are trained to learn the relationship between support set and query set rather than how to classify query set, therefore, they should be flexible to adapt to novel tasks. From the literature, general DNNs show similar results with common few-shot models under conventional few-shot learning problem [7].

Moreover, some few-shot models also conduct experiments under the cross-domain setting where a domain shift exists between base classes and novel classes (cf. Figure 1(b)), such as meta-training on mini-ImageNet [2] and meta-testing on CUB dataset [8]. However, compared to human’s ability and daily experience of dealing with problems dissimilar from one’s knowledge, these two datasets, as both contain common objects, only demonstrate machines’ capability in a limited scenario. Even more interesting is few shot methods without further fine-tuning show inferior performance compared to general DNNs under cross-domain setting in [9].

Therefore, in this work, we further investigate the cross-domain few-shot learning problem (CD-FSL), especially when huge difference lies between domains of base classes and novel classes. We hypothesize that few-shot methods still need to fine-tune when a huge domain shift existed, and thus we propose a fine-tuning method for few-shot models which generates pseudo query images as an alternative and without access to the query set during fine-tuning. With the pseudo
problem as a near-open-set problem. Moreover, we handle the CD-FSL is consistence in both phases, which is the most important style as in the meta-training phase. The parameter updating query set, few-shot models can fine-tune using the same task. For example, base classes are sampled from common object images, and novel classes are sampled from satellite images. (cf. Section III-A)

The CD-FSL problem is not a open-set problem because the labeled support set is given in the meta-testing phase. The parameter updating query set, few-shot models can fine-tune using the same task. For example, base classes are sampled from common object images, and novel classes are sampled from satellite images. (cf. Section III-A)

query set, few-shot models can fine-tune using the same style as in the meta-training phase. The parameter updating is consistence in both phases, which is the most important contribution of our work. Moreover, we handle the CD-FSL problem as a near-open-set problem and large margin mechanism is widely used in open-set problems, so we leverage two large margin mechanisms to improve the performance, consisting of a novel prototypical triplet loss and large margin cosine loss (motivated by open-set face recognition models [10]). It is worth noting that we deal with CD-FSL problems under agnostic setting, which means that the information of query set (including features and label) is not used during fine-tuning. We need to infer the query set immediately when first accessing them.

Our main contributions are fourfold:

- **Pseudo query set.** To get out of the predicament that few-shot methods can’t fine-tune, we propose the pseudo query set and analyze its importance.
- **Prototypical triplet loss.** In order to make the model more suitable in the FSL problem, we modify the triplet and propose a novel prototypical triplet loss.
- **Large margin cosine loss.** Inspired by the similarity between open-set and cross-domain few-shot learning problem, the large margin cosine loss is applied.
- **Detailed comparison and visualization results.** We conduct a comprehensive comparison between general DNNs and few-shot models on CD-FSL problem, and provide several visualization results to elaborate the robustness of proposed LMM-PQS method.

The rest of this paper is organized as follows. Section II reviews studies from multiple related research area. Section III elaborates the CD-FSL problem and proposed LMM-PQS method. Experiment results are illustrated in Section IV. Moreover, we provide a further discussion in Section V, and the conclusion is made in Section VI.

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**II. RELATED WORK**

**A. Few-shot classification**

Few-shot classification is a task to recognize novel classes with only a few labeled examples, and usually formulated as a meta-learning problem. Before solving the novel tasks, methods can learn knowledge from base classes. There are two main factions of meta-learning approaches for addressing the few-shot classification problem, including optimization based and metric-learning based methods.

1) **Optimization based methods:** Optimization based methods aims to learn a good initial configuration (a set of neural parameters) for fine-tuning on few-shot problems. Given a network architecture, MAML [11] meta-learns the network initialization parameters and fine-tunes the network on current task with single fine-tuning iteration. Then, the gradient is calculated to update the initial parameters. Besides, Reptile [12] is a first-order approximation of MAML. By ignoring second-order derivatives, Reptile has a faster execution speed.

2) **Metric-learning based methods:** Metric-learning based methods try to learn a general feature space and use various metric to categorize unlabeled samples. MatchingNet [2] applies a bi-directional recurrent network and a weighted nearest neighbor classifier to recognize the samples. ProtoNet [3] selects euclidean distance as the evaluation metric. It calculates the class prototypes by the mean of the embedding of labeled samples and compares the distance between unlabeled samples with prototypes. In addition, RelationNet [4] is based on the same concept and introduces a learnable similarity metric. Many few-shot approaches belong to this faction due to its simplicity and effectiveness.

Conventional few-shot image classification is well studied. In fact, many few-shot approaches are designed to solve not only classification problems but also various real-world applications [13], [14], [15]. We study a more challenging task, the cross-domain few-shot learning, which is still scarcely investigated but urgently needed by many practical applications.
In the early years, triplet loss [17] made a huge success. Many approaches from various research fields utilize triplet loss as one of the loss functions, also including the method in few-shot learning problem [20]. Recently, CosFace [10] and ArcFace [19] are two representative models. These two models attempt to classify classes by the cosine similarity between normalized feature vector and normalized weight vector. Although they add the margin according to different considerations, both their goals are to make the model effectively distinguish between different categories.

We consider that cross-domain few-shot learning problem has similar property with the open-set problem. Both of their approaches need to deal with the unseen samples in the testing phase. The similarity between these two problems is described in Section III-E. Intuitively, CD-FSL problem is more difficult rather than traditional open-set problems. For open-set problems, although the classes in the test phase are unseen during training, they are still similar classes (classes are from adjacent domains). In CD-FSL, the novel classes might be extremely dissimilar with base classes. We are interested that if large margin mechanisms can assist few-shot models to solve CD-FSL problems, and thus we take two mechanisms in our proposed LMM-PQS and investigate the performance.

III. METHODOLOGY

A. Cross-Domain Few-Shot Learning Problem

In general few-shot scenario, a model \( f_\theta : \mathcal{X} \to \mathcal{Y} \) with parameters \( \theta \) is meta-trained on the tasks sampled from base classes data and meta-tested on the tasks from novel classes data. In practice, base classes and novel classes usually are two subsets from a large datasets. Furthermore, a task contains a support set \( S = \{ x_i, y_i \}^{N \times K}_{i=1} \) and a query set \( Q = \{ x_i, y_i \}^{N \times M}_{i=1} \). This is known as an “N-way K-shot” few-shot learning problem, as the support set has \( N \) classes and each class contains \( K \) labeled samples. In addition, the query set is used to evaluate the models inference performance, but the inference results can be used to help model training during the meta-training phase.

To formalize the cross-domain few-shot learning problem, we follow the definition in [9]. The domain is defined as

B. Cross-domain few-shot learning

Cross-domain few-shot learning is a new branch of few-shot learning, where base and novel classes are sampled from different domains. In nowadays, the cross-domain few-shot learning problem has not been well discussed yet, but we consider that it deserves a further investigation due to its connection to real world problems. Compared to general few-shot learning problem, Cross-domain few-shot learning is more challenging and laborious. Also, we can make use of these data of different domains to measure the robustness and generalization of few-shot approaches.

Tseng et al. [16] propose a feature-wise transformation layer to generalize image features for simulating different domains. By applying Gaussian distribution after each BatchNorm layer, they try to mimic the features coming from various domains. Moreover, the parameters \( \gamma \) and \( \beta \) of the Gaussian distribution are trained with pseudo tasks generated by same or other datasets, depending on the problem setting. Experiment results show that few-shot models with the feature-wise transformation layer can achieve a higher performance. Besides, Guo et al. [9] propose a new benchmark for this problem. In this benchmark, methods are trained on single domain dataset and meta-tested on various domain datasets. Moreover, a detailed comparison between several classifiers is provided.

In order to overcome the domain shift between the base class and the novel class in CD-FSL problem, we propose the pseudo query set to let few-shot models can be fine-tuned. Moreover, compared to previous works, we treat CD-FSL problem as a near-open-set problem, and the large margin mechanism is popular in the open-set problem. Consequently, the novel PT loss and large margin cosine loss are applied to improve the performance.

C. Large margin mechanism

Large margin mechanism is popular in the open-set problem. These approaches aim to recognize unseen classes with sufficient margin during testing. How to set the margin is the focus of these series of researches. Many models [17], [18], [10], [19] apply this mechanism to learn highly discriminative features by maximizing the inter-class margin.
Fig. 3. Pseudo query set (PQS). We use support samples (solid circles) to generate the pseudo query samples (hollow circles) by several digital image processing operations (cf. Section III-C). With PQS, we can discover more feature space with a few target data and learn more knowledge. Most importantly, few-shot models with PQS can fine-tune their parameter using the same way as in the meta-training phase. PQS has a benefit to assist few-shot models adapt to novel tasks.

Fig. 4. Illustration of PT loss. In PT loss, a sample $s_i$ (anchor) is pulled toward its class prototype $p_{c_{s_i}}$ (positive) and pushed away from other class prototypes $p_j$ (negative). Compared to triplet loss [17], we can obtain a more comprehensive margin between each classes, because the sample is operated with prototypes (cf. Section III-D).

a joint probability distribution $P$ over the input space $\mathcal{X}$ and label space $\mathcal{Y}$. The pair $(x, y)$ represents a sample $x$ and its corresponding label $y$ sampled from $P$. We denote the marginal distribution of $\mathcal{X}$ as $P_X$. The base classes data are sampled from the source domain $(\mathcal{X}_s, \mathcal{Y}_s)$ with joint probability distribution $P_{s}$, and novel classes data are sampled from the target domain $(\mathcal{X}_t, \mathcal{Y}_t)$ with joint probability distribution $P_{t}$, and specially $P_{X_t} \neq P_{X_s}$. A practical example is that models meta-train on a common object dataset (source domain) and meta-test on medical dataset (target domain). These two domains are not only disjoint but also far away from each other (domain shift). In the meta-testing phase, models are allowed to be fine-tuned before inferring query samples. During the fine-tuning, models adapt to the task by training with support set. After that, using the accuracy of inferring the category of query samples to evaluate the models performance. Notably, both the input space and the label space of the source domain and the target domain are disjoint in the cross-domain few shot learning problem.

B. Overviews

Our motivation is to solve the problem that few-shot models cannot update their parameters by inferring the query set during fine-tuning (query set is reserved for performance evaluation). Thus, we propose the pseudo query set (PQS). By generating pseudo query set during fine-tuning, few-shot models can be executed the same as in the meta-training phase and also have the adaptation ability.

In addition, we try fine-tuning the models in a different way, inspired by [7], [9]. In [7], Baseline model is trained under a standard way. Then its trained backbone is extracted and concatenated with a new linear classifier in the meta-testing phase, using the support set to fine-tune the backbone and train the classifier. Furthermore, Guo et al. [9] concatenates the backbone with various classifiers, such as cosine similarity or mean-centroid classifier. We are curious whether the backbone from different models have different performance, and thus we apply proposed LMM-PQS to backbones from various models.

In the training phase, we train the Baseline model and meta-train the ProtoNet, respectively. And LMM-PQS is applied in the meta-testing phase. This phase consists of two stages, fine-tuning and inference. The process of LMM-PQS is illustrated in Fig 2. First, the trained backbone from Baseline or ProtoNet is extracted and used as a feature extractor at both stages. During fine-tuning, we generate the pseudo query set (PQS) and fine-tune the backbone with prototypical triplet loss (PT loss) and large margin cosine loss (LMCL) several iterations. When inferring, a cosine mean-centroid classifier is applied to predict the category of query samples. More precisely, the backbone computes the feature embeddings of each (pseudo) query and support sample, which is the $s_i$ and $q_i$ in Figure 2 respectively. And the class prototype is the mean value of $s_i$ which belong to the same class. Besides, the LMCL and PT loss (see Section III-D) assist the backbone in adapting to the task. At the inferring stage, the classifier compares the cosine similarities between the embeddings of query samples and class prototypes to make inference about the category. About the PT loss, we integrate the “prototype” concept which is commonly used in many few-shot models and the triplet loss [17], proposing this novel loss function. On the other hand, the large margin cosine loss is inspired by the similarity between the few-shot learning problem and open-set problem. The detailed explanation is given in the following sections.

C. Pseudo Query Set (PQS)

As previously stated, few-shot models need both support sets and query sets to update their parameters. But the query set is reserved for the performance evaluation in the meta-testing phase, inferring the query set is prohibited during fine-tuning. To solve the problem that few-shot models can’t be fine-tuned due to the lack of the necessary components, we leverage support sets and a sequence of digital image processing operations to generate pseudo query sets. Those operations consist of gamma correction, random erasing with
mean RGB values, color channel shuffle, flip and rotation. The applying probability of gamma correction and color channel shuffle is 0.3, and the probability of rest operations is 0.5.

As shown in Figure 3, these operations are randomly applied, and each support image may be used to generate single or multiple pseudo query images according to the number of support images, detailed number is demonstrated in the experiment section. With pseudo query sets, few-shot models can update the parameters during the fine-tuning stage, as they do with normal query sets in the meta-training phase.

We can see the benefit when applying PQS to fine-tune few-shot models form Section IV-B and Table II.

D. Prototypical Triplet Loss (PT loss)

We propose a loss function which is an assemble of prototypes and triplet loss [17], named prototypical triplet loss. This loss function pulls support samples of each class closer to their prototype and push away from prototypes of other classes. Compared to triplet loss, PT loss can obtains a more complete margin between each classes. Because the anchor is operated with class prototypes, the ability to move toward the center of the category will be stronger than original triplet loss. To be more specific, we first calculate the prototypes for each class within the support set. Then, each support sample (anchor) and its class prototype (positive) are paired with prototypes of all other classes (negative). Subsequently, the original triplet loss is applied. Because there are \( N \) classes in the support set, each sample get \( N-1 \) triplet loss values. Afterwards, we loop over the samples and sum up all the values as the PT loss, which can be formalized as:

\[
PTloss = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} (c_{si} \neq j) \text{triplet}(s_i, p_{c_{si}}, p_j)
\]

where \( i \) is the sample index and \( j \) is the class index, respectively, and \( c_{si} \) is the class index of sample \( s_i \). The function \( \text{triplet()} \) is the original triplet loss, and \( p_{c_{si}} \) is the prototype of the class of \( s_i \), \( p_j \) is the prototype from other classes. Figure 4 is the schematic diagram of PT loss. The support sample \( s_i \) is closer to its class prototype \( p_{c_{si}} \) after applying PT loss and is far away from other prototypes. After fine-tuning the backbone with PT loss, we expect that it can recognize different categories more easily. This loss function belongs to the large margin mechanism introduced in Section II-C.

E. Large Margin Cosine Loss (LMCL)

When solving a problem, models are usually evaluated under closed-set setting or open-set setting. For the closed-set setting, all testing classes are predefined in the training data, which means the label space of test classes is as same as the label space of training classes. Hence, it can be regard as a general classification problem. On the other hand, under the open-set setting, the test classes and the training classes are usually disjoint. Thus, models need to learn how to recognize the unseen category in the testing phase. From this perspective, we argue that the cross-domain few-shot learning problem is similar to the open-set problem and treat it as near-open-set problem. Consequently, those large margin mechanisms should also work in the cross-domain few-shot learning problem.

In open-set problems, many models [17], [10], [19] apply large margin mechanisms to promote their performance. Motivated by these approaches, we apply large margin cosine loss (LMCL) as one of the losses during the fine-tuning stage, helping the model to recognize different novel categories. In our LMCL, we replace the normalized weight vector with each class prototype’s embedding. As illustrated in Figure 5 when we categorizing \( s_i \) using cosine value between normalized embedding of \( s_i \) and normalized embedding of class prototype
If \( s_i \) belongs to class 1 (red class), and the angle between \( s_i \) and class prototype \( p_1 \) is \( \theta_1 \), then LMCL subtracts the cosine value \( \cos \theta_1 \) with a margin, the subtracted cosine value still need to be the maximum, or the classification is failed. Hence, LMCL can squeeze the class space, because each sample is required to approach their prototype for a larger cosine value. Thus, the margin between classes is enlarged after applying LMCL.

IV. EXPERIMENTS

A. Experiment Setting

We use the benchmark proposed in \([9]\) to evaluate LMM-PQS performance. In this benchmark, models need to be trained or meta-trained on mini-ImageNet dataset and meta-tested on various domains datasets, including CropDisease, EuroSAT, ISIC and ChestX datasets, which contains plant disease images, satellite images, dermoscopic images of skin lesions and X-ray images, respectively. The sequence of four test datasets are listed from similar to dissimilar compared to mini-ImageNet. For few-shot learning problem, this benchmark reflect several practice cases in real world since collecting sufficient data from aforementioned domains are usually difficult and costly. Moreover, this benchmark brings the challenge to the few-shot models, since there is a huge domain shift between training and testing domains. How to adapt the trained model to the test tasks is critical. This domain shift include from perspective to no perspective, from color images to grayscale images and from natural photo to medical images.

All rules in the benchmark are followed, we train the Baseline and meta-train the few-shot models, respectively. Moreover, hyper-parameters used in the training phase are the same in \([9]\), except the number of tasks for few-shot models is changed from 100 to 300. In the meta-testing phase, models are evaluated on three different settings, including 5-way 5-shot, 5-way 20-shot, and 5-way 50 shot for each dataset. Besides, same 600 random tasks are sampled from each dataset. Models are evaluated on these tasks, and the average accuracy with 95\% confidence interval are reported. For the hyper-parameters used in the meta-testing phase, we illustrate all values in Table I. All experiments are conducted on a 64-bits Linux machine with Intel I9-9900K CPU and two Nvidia RTX 2080ti GPU cards.

We select Adam optimizer to train and fine-tune the models. Moreover, the backbone architecture is ResNet10 \([21]\) in all experiments for fair comparison. Meanwhile, we also provide results with other backbones. The size of pseudo query set differs in different evaluation setting. For 5-shot, each support sample generates 4 pseudo query images, and the size of the pseudo query set is 100. For 20-shot, each support sample produces 2 pseudo query images, and the size of the pseudo query set is 200. Finally, for the 50-shot, we select 40 support samples from each class and each sample generates 1 pseudo query image, and thus the size of the pseudo query set is also 200. In addition, the transductive inference mentioned in \([9]\) are applied in all experiments, which means BatchNorm layers can learn the implicit information from query set when inferring.

B. Few-shot Models with PQS Results

In this section, we discuss the importance of the pseudo query set. The results of three few-shot models are shown in Table I including MatchingNet \([2]\), ProtoNet (PN) \([3]\) and RelationNet (RN) \([4]\). The check mark in the PQS columns indicates that the model is fine-tuned with pseudo query set or infer the query set directly.

Every models with PQS can increase the performance 10\% – 20\% in first two datasets. In addition, it is not surprised that the performance margin w/ and w/o pseudo query set is relatively small in last two dataset, according to larger domain shifts from training dataset. But, it is still obvious that few-shot models fine-tuning with pseudo query set gets better performance rather than inferring the task directly. When comparing between few-shot models with PQS, ProtoNet get highest accuracy in three datasets. On the other hand, MatchingNet and RelationNet get competitive results.

C. Ablation Study

In this part, we are going to discuss the impact of each components in proposed LMM-PQS. Since that the performance of 5-shot varies a lot than other settings, and the 50-shot setting costs too much time. Hence, we conduct the ablation study on the 20-shot setting.

As previous stated, we start the ablation study with PQS due to the few-shot style fine-tuning. Table II shows the results. We can see that either adding PT loss or LMCL can slightly increase the performance. Additionally, adding PT loss can improve more than LMCL. In most cases, adding both large margin methods will have the highest accuracy. Furthermore, Figure 6 shows the visualization result about latent vectors of support set (dark colors) and query set (light colors). It is obvious that when implementing our core techniques, the model aggregates the data from the same classes closer and separates the data from different classes farther, especially in CropDisease and EuroSAT. More precisely, either implementing PT loss or LMCL, the difference between the intra-class and inter-class distance of support sets increase.

To sum up, in first three datasets, adding PT loss and LMCL will improve the accuracy, which also reflect on the result of T-SNE. However, in ChestX dataset, although the accuracy slightly improved after adding PT loss, the query set in visualization still cannot be separated well.

D. Comparison with Previous Methods

We compare LMM-PQS with several classifiers evaluated in \([9]\) and illustrate the results in Table IV. Moreover, we also measure the performance of different backbone resources (Baseline or ProtoNet) or architectures (ResNet10 or ResNet18). And the result of classifiers with * in the column classifier is produced in \([9]\). The linear, linear-T, mean and cosine term represents linear classifier, linear classifier with
Fig. 6. t-SNE results of support set and query set conducted on the 5-way 20-shot setting (four different domains). The circles (dark colors) represent support sets and the triangles (light colors) stand for query sets. The five different colors indicate five classes. Adding PT loss and LMCL can aggregate the data from the same classes closer and separate the data from different classes farther (best see in color, cf. Section IV-C).

TABLE II

The importance of pseudo query set (PQS). The results of three common few-shot models w/ and w/o pseudo query set are listed. Evidently, few-shot model fine-tuning with PQS obtain higher performance. In general, the accuracy of few-shot models with PQS can increase 3%-20%, depending on difference datasets. The reason why the accuracy improvements are significant is that few-shot models with PQS are able to adapt to tasks from novel domains. See Section IV-B for detailed discussion.

| backbone models | PQS | 5-way 5-shot | CropDiseases | EuroSAT | ISIC | ChestX |
|-----------------|-----|-------------|--------------|---------|------|--------|
| MatchingNet     | ✓   | 97.46% (0.71) | 76.28% (0.67) | 37.88% (0.52) | 23.45% (0.39) |
| ProtoNet        | ✓   | 90.91% (0.47) | 81.85% (0.61) | 44.20% (0.58) | 25.12% (0.41) |
| RelationNet     | ✓   | 90.50% (0.48) | 81.18% (0.63) | 45.56% (0.58) | 25.83% (0.41) |

TABLE III

Ablation study of the proposed LMM-PQS. In most cases, adding both large margin methods will have the highest accuracy. We conduct the experiment started with PQS, because we can’t apply fine-tuning in a few-shot style without PQS. See comprehensive discussion in Section IV-C.

| backbone models | PQS | PT loss | LMCL | 5-way 20-shot | CropDiseases | EuroSAT | ISIC | ChestX |
|-----------------|-----|---------|------|---------------|--------------|---------|------|--------|
| ResNet10 Baseline | ✓  | ✓       | ✓    | 97.48% (0.24) | 92.15% (0.32) | 61.13% (0.58) | 32.74% (0.47) |
|                 | ✓  | ✓       | ✓    | 97.50% (0.22) | 92.55% (0.32) | 64.73% (0.58) | 33.14% (0.47) |
|                 | ✓  | ✓       | ✓    | 97.47% (0.22) | 92.29% (0.33) | 64.71% (0.56) | 32.42% (0.46) |
|                 | ✓  | ✓       | ✓    | 97.51% (0.23) | 92.59% (0.31) | 64.88% (0.58) | 32.58% (0.47) |
The results of baseline methods and LMM-PQS. We have several observations: (1) LMM-PQS suppress other classifiers in most cases. (2) LMM-PQS with Baseline (ResNet10 backbone) get higher result on 5-shot and has competitive results on 20-shot or 50-shot when comparing to LMM-PQS with ProtoNet. (3) LMM-PQS with Baseline get better performance with ResNet18 rather than ResNet10. On the other hand, LMM-PQS with ProtoNet (ResNet18 backbone) reach higher accuracy in first two datasets and has a slightly performance drop in remain datasets. A detailed description is provided in Section IV-B.

| backbone | models | classifier       | 5-shot  | CropDiseases | 5-shot  | EuroSAT   |
|----------|--------|------------------|---------|--------------|---------|-----------|
|          |        |                  | 20-shot |              | 20-shot | 20-shot   |
|          |        |                  |         |              |         |           |
| ResNet10 | Baseline | linear*           | 89.25%  | 95.51%       | 97.68%  | 79.08%    |
|          |        | linear-T*         | 90.64%  | 95.91%       | 97.48%  | 81.76%    |
|          |        | mean*             | 87.61%  | 93.87%       | 94.77%  | 82.21%    |
|          |        | cosine*           | 89.15%  | 93.96%       | 94.27%  | 81.37%    |
| LMM-PQS  |        |                  | 93.14%  | 97.75%       | 98.63%  | 84.24%    |
| ProtoNet |        |                  | 93.52%  | 97.60%       | 98.24%  | 86.30%    |
| LMM-PQS  |        |                  | 94.24%  | 97.80%       | 98.76%  | 86.44%    |
| ResNet18 | Baseline | LMM-PQS           | 94.24%  | 97.98%       | 99.08%  | 93.17%    |
|          |        |                  | 93.71%  |             |         |           |
|          |        | ProtoNet          | LMM-PQS |              |         |           |
| LMM-PQS  |        |                  | 94.24%  | 97.98%       | 99.08%  | 93.17%    |
| ProtoNet |        |                  | 93.71%  |             |         |           |
|          |        |                  | 5-shot  | ISIC         | 5-shot  | ChestX    |
|          |        |                  | 20-shot |              | 20-shot | 20-shot   |
|          |        |                  |         |              |         |           |
| ResNet10 | Baseline | linear*           | 48.11%  | 59.31%       | 66.48%  | 25.97%    |
|          |        | linear-T*         | 49.68%  | 61.09%       | 67.20%  | 26.09%    |
|          |        | mean*             | 47.16%  | 56.40%       | 61.57%  | 26.31%    |
|          |        | cosine*           | 48.01%  | 58.13%       | 62.03%  | 26.95%    |
| LMM-PQS  |        |                  | 51.88%  | 64.88%       | 69.46%  | 26.10%    |
| ProtoNet |        |                  | 50.57%  | 63.58%       | 69.70%  | 26.07%    |
| LMM-PQS  |        |                  | 52.26%  | 65.84%       | 72.98%  | 26.54%    |
| ResNet18 | Baseline | LMM-PQS           | 50.60%  | 62.72%       | 68.21%  | 26.44%    |
|          |        |                  | 50.60%  |             |         |           |

transductive inference, mean-centroid classifier and cosine similarity classifier, respectively. Besides, LMM-PQS contains all components introduced in Section III.

First, we observe that LMM-PQS outperforms other classifiers with significant improvement in most cases, except for the ChestX 5-shot. This result demonstrates LMM-PQS has the powerful ability to assist backbones in adapting to novel tasks. Then, we compare the performance of backbones from different resources. Overall, LMM-PQS with Baseline gets higher performance in most cases on the 5-shot setting, but there is no significant difference in the results on 20-shot or 50-shot setting. Moreover, we further investigate the performance from different backbone architectures. For the LMM-PQS with Baseline, it is not surprising that ResNet18 obtains higher accuracy against ResNet10 in general. But, the result of the LMM-PQS with ProtoNet is interesting. It can get the best performance in first two datasets, but the ResNet18’s result is even worse than the ResNet10’s results in last two datasets. Therefore, in the cross-domain few-shot learning, it isn’t satisfied that using deeper network architecture will get better performance in common computer vision problems.

V. DISCUSSIONS

In this section, we want to compare which part of the image the Baseline model with linear classifier and LMM-PQS focus on. Thus we generate a task from ISIC dataset and let both models to solve the task. Meanwhile, we apply Grad-Cam to visualize the focal point (red region means higher gradient) of the query images. In Figure 7, we demonstrate four different inference result cases of this task. For the case which both model can infer correctly, both models can focus on the important region. For other three cases, the Grad-cam results of Baseline model are mess. Compared to Baseline model, our LMM-PQS can still stick on the foremost area even if the inference is failure. It reveals that LMM-PQS is...
more robust and has the ability to focus on the critical part of the images.

Why our LMM-PQS still make wrong inference even the model had focused on the important region? We speculate that this is because samples from the classes in the ISIC dataset are similar to each other in many cases. For example, the initial symptoms of many skin diseases look the same, so even LMM-PQS focus on the critical region, it still has the chance to infer the sample to similar but wrong category.

VI. CONCLUSION

In this paper, we tackle the cross-domain few-shot learning problem and propose pseudo query set to solve the problem that few-shot models can’t infer query set during fine-tuning. We observe that few-shot models can get outstanding results after several fine-tuning iterations. According to the results, it shows that few-shot models still need appropriate fine-tuning when there is a large domain shift between the domains of base classes and novel classes. In addition, we try fine-tuning the backbones extracted from the models with large margin mechanisms, including PT loss and LMCL, and surprisingly found that the backbone performance from Baseline and few-shot models are competitive under same network architecture. We conclude that the backbone trained in a standard way has robustness. Even if the parameter updating switched to the few-shot style, the backbone can still adapts to the tasks rapidly. Experiment results illustrate LMM-PQS has a significant performance improvement compared to the baseline methods. Moreover, how to improve the performance on ChestX dataset needs further investigation.

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