CSN: Component-Supervised Network for Few-Shot Classification

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Abstract—The few-shot classification (FSC) task has been a hot research topic in recent years. It aims to address the classification problem with insufficient labeled data on a cross-category basis. Typically, researchers pre-train a feature extractor with base data, then use it to extract the features of novel data and recognize them. Notably, the novel set only has a few annotated samples and has entirely different categories from the base set, which leads to that the pre-trained feature extractor can not adapt to the novel data flawlessly. We dub this problem as Feature-Extractor-Maladaptive (FEM) problem. Starting from the root cause of this problem, this paper presents a new scheme, Component-Supervised Network (CSN), to improve the performance of FSC. We believe that although the categories of base and novel sets are different, the composition of the sample’s components is similar. For example, both cat and dog contain leg and head components. Actually, such entity components are intra-class stable. They have fine cross-category versatility and new category generalization. Therefore, we refer to WordNet, a dictionary commonly used in natural language processing, to collect component information of samples and construct a component-based auxiliary task to improve the adaptability of the feature extractor. We conduct experiments on two benchmark datasets (mini-ImageNet and tiered-ImageNet), the improvements of 0.9%-5.8% compared with state-of-the-arts have evaluated the efficiency of our CSN.

Index Terms—Few-shot classification (FSC), Feature-Extractor-Maladaptive (FEM) problem, Component-Supervised Network (CSN), WordNet

I. INTRODUCTION

In a traditional classification task, Convolutional Neural Network (CNN) based methods have achieved fantastic performance, such as [1]–[3]. Their successes are inseparable from the support of rich and accessible labeled data. However, collecting labeled data is a heavy-priced work or even impractical. Therefore, a new investigation – Few-Shot Classification (FSC), targets to address this problem with scarce labeled samples, has attracted growing attention in recent years. In a standard FSC task, the employed data includes two parts, i.e., base set and novel set. There are many labeled samples in the base set, but very few in the novel set (typically, for the general FSC setting, each category only has 1 or 5 labeled samples). We need to pre-train a feature extractor through the base set, then employ it to extract features of novel data, and finally design a classifier to recognize the novel data's category. Notably, the categories contained in the base set are entirely different from those in the novel set.

From the setting of FSC, we observe that one of the essential factors affecting the performance is that: the pre-trained feature extractor (based on base data) can not adapt to the novel data flawlessly due to the different categories between base set and novel set. Precisely, the feature extractor captures the novel feature according to the focus trend on the base data, which causes the novel feature to have weak discrimination. We dub this problem as Feature-Extractor-Maladaptive (FEM) problem.

Sound like fine-tuning the pre-trained network for novel data is a suitable way to deal with the challenge. But unfortunately, [4] has demonstrated that this strategy with few labeled samples easily causes the overfitting problem. Hence, it usually provides limited improvements for FSC or even negatively affects the results. Thus researchers usually give up fine-tuning and choose the decoupled paradigm, i.e., freezing the feature extractor after pre-training and directly extracting novel features.

As for the other recent proposed classical algorithms, such as metric-learning based methods [5], [6], self-supervision based methods [7], [8], graph based methods [9], [10], they have not focused on this particular issue. Therefore, it is necessary to develop a dedicated approach for the specific FEM problem.

In this paper, we attempt to address the FEM problem from the root cause, that is, assigning the same labels to different components. And this assumption is the key point of our proposed method.

Fig. 1: An example to show the composition of different categories of samples. Obviously, cat, dog, and camel are made of the similar components. And this assumption is the key point of our proposed method.
Algorithm 1: How to use WordNet

Input: Label Semantics: airplane
Output: Component Labels: accelerator, wing, windshield, navigation_light, etc.

1. from nltk.corpus import wordnet as wn
2. for synset in wn.synsets("airplane")
3. print(synset.part_meronyms())

sets. How to achieve this purpose? In nature, if we decompose some objects, it’s not hard to find that the components that make up different objects usually have many similarities. For example, suppose dogs are in the base set, and cats are in the novel set. Although their categories are different, they all have some same components, such as head, body, and leg. We illustrate an example in Figure 1. Motivated by this assumption, we propose Component-Supervised Network (CSN). It constructs a component-supervised auxiliary task for FSC, which generates component-based multi-labels for the base set and introduces multi-label classification loss as the auxiliary loss to update the network.

While, how to generate discriminative component-based multi-labels? This is a very critical issue. If we need to consume a lot of manpower and material resources to obtain component labels, then this work will lose most of its meaning. Fortunately, we find a simple-but-effective approach, that is, to call it when using it. Inputting the label semantics (e.g., airplane), then outputting the new component labels (e.g., accelerator, wing, windshield). We give an example in Algorithm 1. The complete process only takes no more than 2 seconds in our Intel(R) Core(TM) i7-8700 CPU @ 3.20GHz 3.19 GHz. Compared with the related approaches that rely on the annotated multi-labels, such as [13] [14], our strategy is extremely flexible which can be easily applied in reality (we discuss the details in Section II-B).

Besides, in order to control the impact of multi-label accuracy in the paper, we introduce an empirical parameter for our component-supervised auxiliary loss. We believe that when the accuracy of generated-multi-label is sufficiently high, this parameter should be scaled large for larger loss weight and conversely small. We evaluate the influence of the parameter in Section IV-E. Furthermore, to improve the final performance, we introduce some tricks, including rotation-based self-supervision [15] and self-training [16]. A flowchart is illustrated in Figure 2. Note that, like most methods, our method also has some limitations, that is, when the difference between the base class and the novel class is too small or too large, the effect of our component-supervised auxiliary task will be greatly reduced. Because, in both two cases, WordNet can’t get valid component labels, so that can’t establish the ideal connection between base and novel sets by this way.

In summary, the main contributions focus on:

- We point out that the feature-extractor-maladaptive (FEM) problem is one of the core issues that affect the few-shot classification (FSC). In response, we put forward a new point of view: the components that make up different categories are similar. Inspired by this assumption, we design the Component-Supervised Network (CSN) to improve the adaptability of the feature extractor.
- In order to construct discriminative component-based multi-labels, we introduce WordNet as a dictionary to query the components of the target. Besides, to balance
the influence of multi-label accuracy, we add an empirical parameter to the loss function.

- We evaluate our CSN on two benchmark datasets (mini-ImageNet, tiered-ImageNet) and achieve significant improvements of at least 0.9%-5.8% compared with other state-of-the-art methods, which has demonstrated the efficiency of our method. In addition, we design experiments to analyze our method and evaluate that our CSN is a simple, easy to implement, and easy to understand method.

II. RELATED WORK

A. Few-Shot Classification

The work of few-shot classification (FSC) is one of the most concerning issues at present. Researchers usually pay efforts from two perspectives to solve it. On the one hand, hoping the designed feature extractor is robust enough to achieve a feature extracting process on cross-category situation. Many classical strategies have been proposed, for examples, [17] and [8] introduce knowledge distillation; [18] and [7] introduce self-supervision; [19] and [10] introduce manifold learning; [20], [21] introduce meta-learning. On the other hand, strengthening the final classifier and make it ignore the influence of inaccurate feature representation to some extent, as examples, [22], [23] introduce distribution calibration; [24], [25] introduce self-training; [15], [26] introduce multi-view fusion. Our CSN can be viewed as focusing on the first point. We introduce component-based multi-labels to make our feature extractor more adaptable for novel data. For the final classifier, we just employ one of the simplest one, shown in the following section.

B. Label-Semantics-Related Few-Shot Classification

Some recent works also use the label semantics information, such as [14], [27]–[32]. The similarity between our method with them is that: they all use the label semantic information. But on (1) the way of application, and (2) the way to obtain label semantics are very different from each other. (1) On the way of application: These methods all need to design an extra word2vector network to convert the label semantic information into label embedding, and then splits it with visual embedding. While our CSN directly uses the label semantics, no need for additional networks, only need to design a multi-class loss in the pre-train network. (2) On the way to obtain label semantics: In the comparison methods, each sample has a variety of labels. These labels are manually annotated, which are very accurate but difficult to obtain. Therefore, these methods lack universality. While in our CSN, we use the existing toolkit WordNet [11] to generate new labels for samples of the same category. The accuracy of the generated multi-labels is definitely far from the manually annotated labels, but it greatly reduces the labor cost and makes our method more practical.

C. Component Information

The composition of an object can be visually decomposed into textures, structures, etc. Some related few-shot learning works attempt to introduce attention mechanisms to employ some extra texture-based or structure-based information to strengthen the robustness of the network, such as [33], [34]. However, as that visual information differs greatly among individuals of the same class, such as a curly hair dog and a straight hair dog, it is not suitable to represent the characteristics of one class of data. Fortunately, the physical components of a class is stable, for example, an airplane consists of window, wheel, wing, etc. And the window, wheel also belong to the car, and train. Based on this phenomenon, we adopt additional component information to construct auxiliary tasks. In this paper, we refer to the hierarchy dictionary, WordNet [11] to obtain the base data’s component information. Specifically, we input a name of target, such as airplane, then output the components, like accelerator, window, door, mirror, buffer, etc, finally construct multi-labels.

III. METHODOLOGY

In this section, we first introduce the setting of few-shot classification and split the complete framework into two phases, pre-training and meta-testing; then propose our Component-Supervised Network (CSN) as the feature extractor for pre-training; finally introduce the to-be-used classifier in meta-testing phase for few-shot classification.

A. Problem Setup

In the few-shot classification (FSC) task, we have two kinds of datasets, i.e., base set \(D_b = \{(x_i, y_i)\}_{i=1}^{N_b}\) and novel set \(D_n = \{(x_j, y_j)\}_{j=1}^{N_n}\), where \(x\) and \(y\) indicate the sample and corresponding label; \(N_b\) and \(N_n\) denote the total number of base data and novel data; \(C_b\) and \(C_n\) denote the base category and novel category. Besides, \(C_b \cap C_n = \emptyset\). Note that there exist a large number of labeled images in \(D_b\) and only a few labeled images in \(D_n\).

The FSC task consists of two phases: (1) Pre-training. Researchers employ the base data \(D_b\) to pre-train a CNN-based model, which consists of feature extractor \(\mathcal{F}\) and base classifier \(\mathcal{M}_b(\cdot)\). (2) Meta-testing. We freeze the pre-trained feature extractor and utilise it to extract the feature of novel data \(\mathcal{D}_n = \{S, \mathcal{U}, \mathcal{Q}\}\), where \(S\), \(\mathcal{U}\) and \(\mathcal{Q}\) denote support set (labeled training samples), unlabeled set (unlabeled training samples) and query set (to-be-classified testing samples). \(S \cap \mathcal{U} = \emptyset\), \(S \cap \mathcal{Q} = \emptyset\), \(\mathcal{Q} \cap \mathcal{U} = \emptyset\). According to whether using the unlabeled data when constructing the novel classifier \(\mathcal{M}_n(\cdot)\) to recognize categories of query data, we split the FSL into two settings: supervised setting and semi-supervised setting. Section III-C show more details. In classification stage, we follow the standard paradigm with C-way-K-shot per episode as [24], where C-way denotes C classes, and K-shot indicates K samples per class. The reported results are the average of accuracies of all the episodes with 95% confidence intervals.
Feature-Extractor-Maladaptive (FEM) problem, we design a component-supervised auxiliary loss, and integrate it with a standard classification loss and self-supervised auxiliary loss. We illustrate a flowchart in Figure 2 and introduce the details as follows.

1) Standard Classification Task: Assume we have a base image \( x \). Input it to the pre-trained feature extractor \( \mathcal{F}(\cdot) \) and achieve the feature vector \( x = \mathcal{F}(x) \in \mathbb{R}^{\text{dim}} \), where \( \text{dim} \) denotes the dimension of the feature vector. Next, input the feature into the base classifier \( \mathcal{M}_b(\cdot) \) to predict the soft label. There are lots of choices, such as Support Vector Machine [6], Nearest Neighbor [5], Softmax [24]. In the standard classification task, we select the softmax activation function as our classifier. Specifically, we project the feature vector into a label space, i.e., \( x \rightarrow z^{sc} \), where \( z^{sc} = [z^{sc}_1, z^{sc}_2, \ldots, z^{sc}_{C_b}] \in \mathbb{R}^{C_b}, C_b \) denotes the number of base category. Then transform it to the probability distribution by:

\[
y^{sc}_c = \frac{e^{z^{sc}_c}}{\sum_{c=1}^{C_b} e^{z^{sc}_c}}
\]

where \( y^{sc} = [y^{sc}_1, y^{sc}_2, \ldots, y^{sc}_{C_b}] \in \mathbb{R}^{C_b} \) can be viewed as the predicted soft label of sample \( x \) in the standard classification task. Introduce categorical cross entropy function \( \mathcal{L}_{	ext{cce}} \) to calculate the standard classification loss \( \mathcal{L}^{sc} \) as:

\[
\mathcal{L}^{sc}(x, ̂y^{sc}) = \mathcal{L}_{	ext{cce}}(\mathcal{M}_b(\mathcal{F}(x)), ̂y^{sc})
\]

where \( ̂y^{sc} = [ ̂y^{sc}_1, ̂y^{sc}_2, \ldots, ̂y^{sc}_{C_b}] \in \mathbb{R}^{C_b} \) denotes the one-hot truth label vector of \( x \) in the standard classification task.

2) Component-Supervised Auxiliary Task: As described before, the novel set \( \mathcal{D}_n \) has totally different categories with the base set \( \mathcal{D}_b \). Therefore, the pre-trained feature extractor \( \mathcal{F}(\cdot) \) (based on base set) is not applicable for the novel set. But fortunately, the components that make up samples of different categories are similar, just like both dogs and cats have legs, body, head (some examples are shown in Figure 1). Inspired by this assumption, we construct new component-based labels for the base set. Since each sample has multiple components, the problem can be diverted to be a multi-label classification task.

From WordNet [11], we collect \( C_m \) components and generate the multi-labels. Each sample belongs to a part of the multi-labels. In this component-supervised auxiliary task, we choose the sigmoid activation function as the classifier for base data. Similar as the standard classification task, we project the feature vector into a component-based label space, e.g., \( x \rightarrow z^{cs} \), where \( z^{cs} = [z^{cs}_1, z^{cs}_2, \ldots, z^{cs}_{C_m}] \in \mathbb{R}^{C_m}, \) then transform it to the binomialial distribution by:

\[
y^{cs}_c = \frac{1}{1 + e^{-z^{cs}_c}}
\]

where \( y^{cs} = [y^{cs}_1, y^{cs}_2, \ldots, y^{cs}_{C_m}] \in \mathbb{R}^{C_m} \) can be regarded as the predicted soft multi-label of sample \( x \). Then compute the component-supervised auxiliary loss \( \mathcal{L}^{cs} \) by introducing binary cross entropy function \( \mathcal{L}_{	ext{bce}} \), which can be formulated as:

\[
\mathcal{L}^{cs}(x, ̂y^{cs}) = \mathcal{L}_{	ext{bce}}(\mathcal{M}_b(\mathcal{F}(x)), ̂y^{cs})
\]

3) Self-Supervised Auxiliary Task: Besides the two tasks described above, we attempt to enforce rotation invariance for the network. Inspired by [10] and [35], we introduce self-supervised learning to our model. Self-supervision is helpful to capture general features without labels. Specifically, we rotate the base set to 4 degrees, i.e., \( \{0^\circ, 90^\circ, 180^\circ, 270^\circ\} \), then use the softmax activation function to predict the image rotations. We map the base data (after rotation) to rotation-based label space, e.g., \( x \rightarrow z^{ss} \), where \( z^{ss} = [z^{ss}_1, z^{ss}_2, z^{ss}_3, z^{ss}_4] \in \mathbb{R}^4 \), then employ Equation 1 to achieve the rotation-based probability distribution \( \hat{y}^{ss} = [\hat{y}^{ss}_1, \hat{y}^{ss}_2, \hat{y}^{ss}_3, \hat{y}^{ss}_4] \in \mathbb{R}^4 \). Next, introduce categorical cross entropy function \( \mathcal{L}_{	ext{cce}} \) to compute the self-supervised auxiliary loss \( \mathcal{L}^{ss} \) by:

\[
\mathcal{L}^{ss}(x, ̂y^{ss}) = -\sum_{c=1}^{4} \hat{y}^{ss}_c \log(y^{ss}_c)
\]

4) Overall Loss Function: Finally, we achieve the resultant loss for our Component-Supervised Network, which can be simply formulated as:

\[
\mathcal{L} = \mathcal{L}^{sc} + \alpha \mathcal{L}^{cs} + \mathcal{L}^{ss}
\]

where \( \alpha \) is an empirical parameter to control the influence of Component-Supervised Auxiliary loss. It is determined by the accuracy of component-based multi-label. For more discussions, please refer to the Section IV-E.

C. Few-Shot Classification

Through Equation 6, the feature extractor \( \mathcal{F}(\cdot) \) is more suitable for the novel data than before. Send the novel data to \( \mathcal{F}(\cdot) \) and achieve novel feature \( V = \mathcal{F}(\mathcal{D}_n) \), where \( V = [V_s, V_u, V_q] \). \( V_s = \mathcal{F}(S) \in \mathbb{R}^{\text{dim} \times N_s} \) denotes the support feature, \( V_u = \mathcal{F}(U) \in \mathbb{R}^{\text{dim} \times N_u} \) denotes the unlabeled feature, \( V_q = \mathcal{F}(Q) \in \mathbb{R}^{\text{dim} \times N_q} \) denotes the query feature, \( N_s, N_u \) and \( N_q \) indicate the number of support, unlabeled and query data, \( \text{dim} \) represents the dimension of samples. Next, we try to construct a novel classifier \( \mathcal{M}_n(\cdot) \), which includes two paradigms.
Algorithm 2: Supervised Few-Shot Classification

Input: Base set $D_{\text{base}}$, Novel set $D_{\text{novel}} = \{S, U, Q\}$
Output: Query label

1. Design the feature extractor $\mathcal{F}(\cdot)$ through $D_{\text{base}}$
2. Obtain novel data’ feature by $V_s = \mathcal{F}(S)$, $V_q = \mathcal{F}(Q)$.
3. repeat
   4. Train or update a basic classifier $W$ by Equation 8.
   5. Predict the query data by Equation 9.
   6. Select the most confidence sample and expand it to the support set by Equation 10.
4. until the performance of to-be-learned classifier is stable.
5. Utilize the optimal classifier to predict the query label by Equation 9.

1) Supervised Few-Shot Classification: In this case, researchers don’t consider the unlabeled feature when constructing the classifier $\mathcal{M}_n(\cdot)$. Multiple kinds of traditional classifiers are suitable, such as support vector machine, linear regression, logistic regression. Here, we select the linear regression as the example to introduce our method. We formulate the objective function as:

$$\arg \min_W \|Y_s - WV_s\|_F^2 + \beta \|W\|_F^2$$  (7)

where $\|\cdot\|_F$ represents $(\cdot)$’s Frobenius-norm; $Y_s \in \mathbb{R}^{C_n \times N_s}$ denotes the truth one-hot label matrix of support data, $C_n$ denotes the number of novel categories; $W \in \mathbb{R}^{C_n \times \text{dim}}$ represents the to-be-learned classifier. We directly optimize the objective function and obtain the $W$ as:

$$W = Y_sV_s^T(V_sV_s^T + \beta I)^{-1}$$  (8)

where $I$ denotes the diagonal matrix. Besides, to further improve the performance, we refer to [25], introduce a self-training strategy to construct a more robust classifier. That is, we use the $W$ to classify the category of $V_q$ by:

$$Y_q = WV_q$$  (9)

where $Y_q \in \mathbb{R}^{C_n \times N_q}$ is the generated soft label matrix of query samples. Then selecting one most confident sample $v_{\text{select}}$ through the $Y_q$ without putting back, the corresponding one-hot pseudo label is denoted as $y_{\text{select}}$. Then, expand it to the support data by:

$$\begin{cases} V_s = [V_s, v_{\text{select}}] \\ Y_s = [Y_s, y_{\text{select}}] \end{cases}$$  (10)

Repeat the above process until the performance of classifier is stable. Finally, employ the optimal classifier to predict the query label by Equation 9. We illustrate the process in Algorithm 2.

2) Semi-Supervised Few-Shot Classification: In semi-supervised FSC, researchers use the unlabeled samples to correct the distribution. In our paper, we also use the self-training strategy. It is similar as the supervised case when training the basic classifier. The difference between the two cases lies in that: supervised FSC use the query feature $V_q$ to update the classifier, while the semi-supervised FSC employ the unlabeled feature $V_u$ to complete this process.

IV. EXPERIMENTS

This section introduces the benchmark datasets briefly and demonstrates the experimental implementation in detail. Then, we demonstrate the experimental results and discuss them. Next, we design ablation experiments to analyze the performance influence factors. Finally, we discuss about how to further improve our CSN. All experiments are conducted on a Tesla-V100 GPU with 32G memory.

A. Dataset

We evaluate our methods on two FSC benchmark datasets, i.e., mini-ImageNet [48], tiered-ImageNet [52]. Both of them are the subset of ImageNet dataset [56]. For the mini-ImageNet, it consists of 100 classes and each class has 600 images with the size of $84 \times 84$. In experiments, we split the datasets as [24], and use 64, 16, 20 classes as the base set, validation set, novel set for mini-ImageNet, respectively. For the tiered-ImageNet, it has 608 classes and each class contains 1,281 images on average. Same as mini-ImageNet, the images are resized to $84 \times 84$. In the experiment, 351, 97, and 160 classes are selected as the base set, validation set, and novel set, respectively. Besides, researchers grouped the tiered-ImageNet dataset into 34 high-level categories, and each one has unbalanced classes, and the base, validation, and novel set come from different high-level categories.

B. Implementation Details

In most experiments, we follow the general setup and select ResNet12 [24] as the backbone on mini-ImageNet and tiered-ImageNet. Unlike traditional ResNet architecture [57], Dropblock regularizer (dropblock size = 2) [58] is applied here. For the optimizer, we select the stochastic gradient descent (SGD) with Nesterov momentum (0.9) and introduce StepLR. For the learning rate, we employ a weight decay of $1e-4$ with the initial value of 0.05. In the pre-training stage, the training epochs are set to 120. In the meta-testing stage, it includes 600 episodes and tests 15 query samples per class for all the episodes. In the few-shot classification, the selected classifier follows the default implementation of scikit-learn [12]. Besides, this classification step has no fine-tuning process. For other detailed settings, such as the number of filters, the data pre-processing method, and the data augmentation method, please refer to [24].

C. Experimental Results

1) Comparison Results with Supervised State-of-The-Art Methods: In this section, we first compare our CSN with
TABLE I: Comparison results with state-of-the-art methods in supervised case. The reported accuracies are in 95% confidence intervals over 600 episodes. The top two results are shown in **bold** and **underline**, respectively.

| Method        | Backbone | mini-ImageNet | tiered-ImageNet |
|---------------|----------|---------------|-----------------|
|               |          | 5-way 1-shot  | 5-way 5-shot    | 5-way 1-shot  | 5-way 5-shot    |
| TapNet [36]   | ResNet12 | 61.65 ± 0.15  | 76.36 ± 0.10    | 63.08 ± 0.15  | 80.26 ± 0.12    |
| MetaOpt [6]   | ResNet12 | 62.66 ± 0.61  | 78.63 ± 0.46    | 65.99 ± 0.72  | 81.56 ± 0.53    |
| TEAM [37]     | ResNet12 | 60.07 ± 0.63  | 75.90 ± 0.52    | -              | -               |
| DSN-MR [38]   | ResNet12 | 64.60 ± 0.72  | 79.51 ± 0.50    | 67.39 ± 0.82  | 82.85 ± 0.56    |
| ICI [24]      | ResNet12 | 66.80         | 79.26           | **80.79**     | 87.92           |
| MABAS [39]    | ResNet12 | 64.21 ± 0.82  | 81.01 ± 0.57    | -              | -               |
| EPNet [10]    | ResNet12 | 66.50 ± 0.89  | 81.06 ± 0.60    | 76.53 ± 0.87  | 87.32 ± 0.64    |
| MELR [40]     | ResNet12 | 67.40 ± 0.43  | 83.40 ± 0.28    | 72.14 ± 0.51  | 87.01 ± 0.35    |
| ODE [8]       | ResNet12 | 67.76 ± 0.46  | 82.71 ± 0.51    | 71.89 ± 0.52  | 85.96 ± 0.35    |
| Meta-Base [41]| ResNet12 | 63.17 ± 0.23  | 79.26 ± 0.17    | 68.62 ± 0.27  | 83.74 ± 0.18    |
| ConstellationNet [42] | ResNet12 | 64.89 ± 0.23  | 79.95 ± 0.17    | -              | -               |
| SNAIL [43]    | ResNet12 | 55.71 ± 0.99  | 68.88 ± 0.92    | -              | -               |
| SLA-AG [44]   | ResNet12 | 62.93 ± 0.63  | 79.63 ± 0.47    | -              | -               |
| CAN [45]      | ResNet12 | 63.85 ± 0.48  | 79.44 ± 0.34    | 69.89 ± 0.51  | 84.23 ± 0.37    |
| Distill [17]  | ResNet12 | 64.82 ± 0.60  | 82.14 ± 0.43    | 71.52 ± 0.69  | 86.03 ± 0.40    |
| DSN [38]      | ResNet12 | 62.64 ± 0.66  | 78.83 ± 0.45    | 66.22 ± 0.75  | 82.79 ± 0.48    |
| DeepEMD [46]  | ResNet12 | 65.91 ± 0.82  | 82.41 ± 0.56    | 71.16 ± 0.87  | 86.03 ± 0.58    |
| TPMN [47]     | ResNet12 | 67.64 ± 0.63  | 83.44 ± 0.43    | 72.24 ± 0.70  | 86.55 ± 0.63    |
| MatchingNet   | ResNet18 | 52.91 ± 0.88  | 68.88 ± 0.69    | -              | -               |
| ProtoNet [5]  | ResNet18 | 54.16 ± 0.82  | 73.68 ± 0.65    | -              | -               |
| MAML [4]      | ResNet18 | 49.61 ± 0.92  | 65.72 ± 0.77    | -              | -               |
| RelationNet [49]| ResNet18| 52.48 ± 0.86  | 69.83 ± 0.68    | -              | -               |
| CL [50]       | ResNet18 | 51.75 ± 0.80  | 74.27 ± 0.63    | -              | -               |
| CL++ [59]     | ResNet18 | 51.87 ± 0.77  | 75.68 ± 0.63    | -              | -               |
| CTM [51]      | ResNet18 | 62.05 ± 0.55  | 78.63 ± 0.06    | 64.78 ± 0.11  | 81.05 ± 0.52    |
| S2M2 [7]      | ResNet18 | 64.06 ± 0.18  | 80.58 ± 0.12    | -              | -               |
| CSN           | ResNet12 | **73.57 ± 1.26** | **84.30 ± 0.60** | **81.03 ± 1.12** | **88.96 ± 0.61** |
| CSN           | ResNet18 | 66.86 ± 1.19  | 79.09 ± 0.67    | 76.03 ± 0.81  | 85.19 ± 0.74    |

TABLE II: Comparison results with state-of-the-art methods in semi-supervised case. The reported accuracies are in 95% confidence intervals over 600 episodes. All the methods are based on the ResNet12 backbone. The top two results are shown in **bold** and **underline**, respectively.

| Method      | Backbone | mini-ImageNet | tiered-ImageNet |
|-------------|----------|---------------|-----------------|
|             |          | 5-way 1-shot  | 5-way 5-shot    | 5-way 1-shot  | 5-way 5-shot    |
| MSK [32]    | ResNet12 | 62.10         | 73.60           | 68.60         | 81.00           |
| TPN [53]    | ResNet12 | 62.70         | 74.20           | 72.10         | 83.30           |
| ICI [34]    | ResNet12 | 71.41         | 81.12           | **85.44**     | 89.12           |
| LST [23]    | ResNet12 | 70.10 ± 1.90  | 78.70 ± 0.80    | 77.70 ± 1.60  | 85.20 ± 0.80    |
| EPNet [10]  | ResNet12 | **75.30 ± 1.01** | **84.07 ± 0.60** | 81.79 ± 0.97  | 88.45 ± 0.61    |
| TransMatch   | ResNet12 | 63.02 ± 1.07  | 81.19 ± 0.59    | -              | -               |
| PLCM [55]   | ResNet12 | 72.06 ± 1.08  | 83.71 ± 0.63    | 84.78 ± 0.96  | 90.11 ± 0.57    |
| CSN         | ResNet12 | **78.80 ± 0.96** | **86.43 ± 0.76** | **85.03 ± 1.12** | **90.67 ± 0.90** |

other state-of-the-art methods in the supervised case, which is shown in Table I. All the methods are based on the ResNet12 or ResNet18 backbone. Obviously, whatever in 5-way 1-shot case or 5-way 5-shot case, our CSN achieves outstanding performances compared with others. Specifically, in mini-ImageNet, CSN achieves significant improvements of 5.8%-17.9% in 5-way 1-shot case, and 0.9%-15.4% in 5-way 5-shot case. In tiered-ImageNet, CSN can exceed others 0.3%-18.0% in 5-way 1-shot case, and 1.0%-8.7% in 5-way 5-shot case.

Compared with the algorithms also employ self-supervised loss, including S2M2 [7], EPNet [10], ODE [8], our CSN also obtain the best performance. In mini-ImageNet, CSN exceeds them at least 5.8% in 5-way 1-shot case, and 1.6% in 5-way 5-shot case. In tiered-ImageNet, CSN outperforms them at least 4.5% in 5-way 1-shot case, and 0.6% in 5-way 5-shot case. For more details about the efficiency of the self-supervised term, please see Table III.

2) Comparison Results with Semi-Supervised State-of-The-Art Methods: Table II shows the comparison results with recently proposed semi-supervised few-shot classification methods. These approaches use the unlabeled samples to correct the distribution. Our CSN also can be extended to the semi-supervised case through self-training strategy and outperform others a lot. Specifically, in mini-ImageNet, CSN exceeds others 3.4%-16.7% in 1-shot case, and 2.4%-12.9% in 5-shot case; in tiered-ImageNet, CSN is slightly lower than ICI about 0.4% in 1-shot case, but outperforms others 0.25%-16.4% in 1-shot case, and 1.2%-10.3% in 5-shot case. In our method, it adopts the 100 unlabeled samples, and we discuss more details in Section IV-D3 and Figure 5.
Table IV: Comparison results with other methods which also use label information. All the methods are based on the ResNet12 backbone. The top two results are shown in bold and underline, respectively.

| Method          | Backbone | mini-ImageNet          |
|-----------------|----------|------------------------|
|                 |          | 5-way 1-shot 5-way 5-shot |
| AM3 [27]        | ResNet12 | 65.30 ± 0.49 78.10 ± 0.36 |
| COMMET [14]     | ResNet12 | 69.11 ± 0.67 81.21 ± 0.80 |
| HSIC [28]       | ResNet12 | 64.43 ± 1.02 76.50 ± 0.64 |
| GPN [39]        | ResNet12 | 70.14 ± 0.17 80.00 ± 0.45 |
| KTCH [30]       | ResNet12 | 69.64 ± 0.95 80.67 ± 1.20 |
| KGDN [31]       | ResNet12 | 68.71 ± 1.06 79.87 ± 1.13 |
| S2M2 with MAGR [32] | ResNet12 | 66.93 ± 0.65 83.35 ± 0.53 |
| LEO with MAGR [32] | ResNet12 | 60.93 ± 0.19 76.33 ± 0.17 |
| CSN             | ResNet12 | 73.57 ± 1.26 84.30 ± 0.60 |

Table V: Comparison results of incorporating component-supervised auxiliary task. Baseline denotes the network without the component-supervised auxiliary task, and CSN represents the Baseline + Component-Supervision.

| Dataset         | Method | Base | Novel |
|-----------------|--------|------|-------|
|                 |        | 1-shot | 5-shot |
| mini-ImageNet   | Baseline | 95.62 | 56.06 | 75.70 |
|                 | CSN increase | 95.69 | 63.72 | 77.47 |
|                 |         | 7.66 | 1.77 |
| tiered-ImageNet | Baseline | 70.22 | 69.02 | 85.37 |
|                 | CSN increase | 70.31 | 73.69 | 86.01 |
|                 |         | 4.67 | 0.64 |

D. Ablation Studies

To my best knowledge, any mature method has the experience of predecessors in it, that is to say, in addition to its own innovative parts, it will also learn from the effective parts of other people’s methods, and so do we. This section split our complete model into four parts and analyse them in detail. The intuitive results are shown in Table III. Our baseline denotes the composition of ICI based feature extractor and logistic regression based classifier.

1) The Influence of Component-Supervision: From Table III, comparing ① with ②, ③ with ④, ⑤ with ⑥ and ⑦ with ⑧, we observe that our proposed component-supervision helps a lot for the method. So intuitively, our method is very effective. We discuss the α (Equation 6) in the Section IV-E. And next, it’s necessary to think about why the method we designed can achieve such an effect.

The ultimate goal of designing the component-supervised auxiliary task is to enable the pre-trained model (based on base data) more applicable to data in the novel set. It is interesting to find out if the model has achieved the purpose. Here, we research this question from three views.

(i) We compare the impact of component-supervised auxiliary task on the base set and the impact on the novel set, which is shown in Table V. Baseline denotes the network without the component-supervised auxiliary task, and CSN represents the Baseline + Component-Supervision. From this table, we find that whatever in mini-ImageNet or tiered-ImageNet, the component-supervised auxiliary task has little influence on classifying the base data, but contributes a lot when recognizing the novel data on both 1-shot case and 5-shot case. This phenomenon verifies that our CSN is available for the cross-category task.

(ii) Following, to further analyze the impact of component-supervised auxiliary task on our goal, we construct t-SNE [59] visualization to observe the feature distribution of base and novel data. We show the results of mini-ImageNet and tiered-ImageNet with random selection of 5 categories on Figure 4. Through watching the Figure 4(a) and 4(c), we find that both CSN and Baseline obtain satisfactory feature distribution of base data. Then observing Figure 4(b) and 4(d), our CSN

3) Comparison Results with Methods also Use Label Semantics: Our CSN employs the label semantics to generate hierarchical component information, so that it is necessary to compare it with recently proposed methods which also use this kind of extra information. The experiments are conducted in the mini-ImageNet with supervised case and all the backbones are ResNet12. The comparison results are presented in the Table IV. We can see that, our CSN outperforms others at least 3.4% in the 1-shot case and 1.0% in the 5-shot case.
Fig. 3: The visualization results of the pre-trained network on novel data.

![Image](image1.png)  
**Fig. 3:** The visualization results of the pre-trained network on novel data.

(iii) While, why CSN based feature distribution is more discriminative? We guess that the component-supervised auxiliary task allows the pre-trained network to pay more attention on the important information of the sample when extracting novel class features. In order to verify this conjecture, we refer to [60] to visualize the performance of the network. Observation results are listed in Figure 3. Obviously, our CSN outperforms the baseline method a lot.

2) The Influence of Self-Supervision: Looking at the comparison results of ① and ③, ② and ④, ⑥ and ⑦, ⑧ and ⑩ in Table III, obviously, the generally employed self-supervised strategy yields positive influence to our CSN. It also verifies that the self-supervised strategy is compatible with our method. However, self-supervision is not our highlight, just a general auxiliary method to help our model more complete. Therefore, instead of employing some recent proposed self-supervised methods, we only introduce the most basic, simple but effective rotation based self-supervision strategy to enhance our model.

3) The Influence of Self-Training: Self-training is a crucial trick in our method. Comparing ① and ③, ② and ④, ⑥ and ⑦, ⑧ and ⑩ in Table III, we observe that it can improve the performance a lot. Besides, self-training can extend the standard supervised FSL to semi-supervised case. Here, we show the impact of the number of unlabeled samples on the results, which is listed in Figure 5. The performance of the proposed method is increasing with the unlabeled instances. And it becomes to be saturation after 100 unlabeled samples.
Fig. 5: Comparison results of semi-supervised CSN with varied unlabeled samples.

Fig. 6: The comparison results with different $\alpha$ (x-axis) on mini-ImageNet. CSN denotes the multi-label constructed from the WordNet. CSN with noised multi-label indicates that we introduce some noise to the multi-label matrix.

Fig. 7: An example to show that the same category of images have different component information.

E. Discussion about How to Further Improve Our CSN

From Equation 6, we know $\alpha$ is a key parameter to our method, which is used to control the influence of the component-supervised auxiliary task. We list the results of mini-ImageNet with different $\alpha$ in Figure 6. Look at the CSN based line (red line). The result first rises then declines with the increase of $\alpha$, achieving the best performance when $\alpha = 0.3$.

How to explain this phenomenon?

As described above, the $\alpha$ is an empirical value. It is determined by the accuracy of component-based multi-label, comes from the WordNet [11]. However, multi-labels obtained in this way are sometimes inaccurate. Because the angle of image acquisition is different, and the image is only two-dimensional, in many cases, part information of a certain type cannot be fully reflected in the image. For example, look at the Figure 7, both the two images are dogs, but the left dog only includes the head, ear and eye components, the right dog has the head, eye, ear, leg, body and tail components. Indeed, this is a challenge of our method in application, but if we think from another angle, if we can solve this problem, it will be beneficial to the performance improvement for our method. We believe that adjusting the $\alpha$ can solve this problem to a certain extent.

Specifically, to balance the impact, we should assert a large value when the multi-label is accurate, and it is the opposite if the multi-label is confused. To evaluate it, we deliberately add some noise to the multi-label of samples and show the final results in Figure 6. Observe the yellow line, the performances of the red line are higher than the yellow one, but the $\alpha$ corresponded to the best result on the yellow line is lower than that on the red one (i.e., $\alpha_1 = 0.2 < \alpha_2 = 0.3$). It is demonstrated that the $\alpha$ is capable of influence the component-supervised auxiliary task.

V. Conclusion

Few-shot classification (FSC) exists a fundamental problem, i.e., Feature-Extractor-Maladaptive (FEM) problem. To solve it, this paper proposes a novel Component-Supervised Network (CSN). We believe that different category targets have similar component information and design a component-supervised auxiliary task. The outstanding performances have evaluated the efficiency of our method. For future work, we are committed to addressing the limitation (introduced in the Section I) in CSN to make the network more robust.

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