Exploiting Unsupervised Inputs for Accurate Few-Shot Classification

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Abstract. In few-shot classification, the aim is to learn models able to discriminate classes with only a small number of labelled examples. Most of the literature considers the problem of labelling a single unknown input at a time. Instead, it can be beneficial to consider a setting where a batch of unlabelled inputs are treated conjointly and non-independently. In this vein, we propose a method able to exploit three levels of information: a) feature extractors pretrained on generic datasets, b) few labelled examples of classes to discriminate and c) other available unlabelled inputs. If for a), we use state-of-the-art approaches, we introduce the use of simplified graph convolutions to perform b) and c) together. Our proposed model reaches state-of-the-art accuracy with a $6 - 11\%$ increase compared to available alternatives on standard few-shot vision classification datasets.

Keywords: Few-Shot Learning, Semi-supervised Learning, Transfer, Graph Convolutions

1 Introduction

Deep learning is the state-of-the-art solution for many problems in machine learning, specifically in the domain of computer vision. Relying on a huge number of tunable parameters, these systems are able to absorb subtle dependencies in the distribution of data in such a way that it can later generalize to unseen inputs. Numerous experiments in the field of vision suggest that there is a trade-off between the size of the model (for example expressed as the number of parameters \cite{29}) and its performance on the considered task. As such, reaching state-of-the-art performance often requires to deploy complex architectures. On the other hand, using large models in the case of data-thrifty settings would lead to a case of an underdetermined system. This is why few-shot and few-label settings are particularly challenging in the field.

In order to overcome this limitation of deep learning models, numerous works have proposed to artificially increase the number of examples used to train the systems. For example, many methods rely on the use of transfer \cite{31} or meta-learning \cite{30}, where typically very large datasets are used to pretrain feature extractors. Other methods propose to artificially augment the number of training
Fig. 1. Illustration of the proposed method. The proposed method is composed of two stages. During the pretraining stage, a classical backbone is trained using large datasets (step 1.). This trained backbone is then used to extract features of a novel dataset, comprising few supervised inputs. During adapting stage, first is built a similarity graph depending on the cosine similarity between extracted features of both labelled and unlabelled available data (step 2.). Then this graph is used to diffuse (i.e. interpolate) features of similar (neighbor) samples (step 3.). The obtained representations are used to train a simple fully connected layer (step 4.) using the supervised data. Finally, in step 5., the fully connected layer is used to perform predictions on unlabelled data.

examples [22,20]. Interestingly, few works [7,12,8,19] have considered using the query (unlabelled) inputs to increase accuracy of the system, and they do not necessarily achieve better results than standard counterparts.

As a matter of fact, in the case of batch predictions (i.e. when multiple unlabelled inputs are processed concurrently and non-independently), the amount of information contained in the queries can be significant with regards to that of the training (labelled) samples. In this work, we contribute a new method in that direction of research. Namely, we propose to combine transfer with small graph neural network models to solve few-label classification of input images. Here, we explicitly use the term few-label to point out that we consider given both supervised training samples and a batch of query inputs when performing decisions. This is in contrast with early classical few-shot settings where only one query input is processed at a time, independently from the others. The graph considered in this paper uses vertices to represent each sample of the batch, and its edges are weighted depending on the similarity of corresponding feature vectors. The graph is then used to diffuse features and thus share information between unlabelled and labelled inputs. In our work, we consider a fixed pretrained feature extractor (backbone), so that only the graph neural network parameters are trained using the considered few-label dataset. This work comes with the following claims:

- We introduce a novel method for few-label classification of input images that combines state-of-the-art transfer learning [20] with simplified graph convolutional [38] neural networks.
- We empirically demonstrate that the proposed method reaches state-of-the-art accuracy on standardized benchmarks in the field of few-shot learning.
We analyze the importance of each step of the method and discuss hyperparameters influence.

The paper is organized as follows. In Section 2 we present related works. In Section 3 we introduce our proposed methodology. In Section 4 we show experimental results on standard vision datasets and discuss hyperparameters influence. Finally, Section 5 is a conclusion. The code is available at https://github.com/yhu01/transfer-sgc.

2 Related Work

2.1 Optimization based methods

Recent work on few-shot classification contains a variety of approaches, one of which can be categorized as meta-learning where the goal is to train an optimizer that initializes the network parameters using a first generic dataset, so that the model is able to reach good performance with only a few more steps on actual considered data. The well-known MAML method trains on different tasks with a basic stochastic gradient decent optimizer and Meta-LSTM utilizes a LSTM-based meta-learner that is thus memory-augmented. Meta-learning can be thought of as a refined transfer method, where the few-shot setting is taken into consideration directly when training on the generic dataset. Although both MAML and Meta-LSTM achieve good performance with quick adaptation, this type of solution suffers from the domain shift problem as well as the sensitivity of hyperparameters.

2.2 Embedding based methods

Another popular approach aims at finding compact embedding for the input data by learning a metric that measures the distance in a low-dimensional way. Matching Nets and Proto Nets learn a nearest-neighbor classifier by comparing the distance between the query inputs and labelled inputs with a certain metric, while Relation Nets construct a new neural network that learns the metric itself. If some of these methods are able to outperform MAML, they mainly suffer from over-fitting and a lack of task specific information.

Therefore, ideas have been proposed to address these issues. For example in a plug network is added to find task-relevant features inside embeddings so that the model can tell the inter-class uniqueness and intra-class commonality for a specific task. In and the authors create a class-weight generator by training the model with a linear classifier (e.g. SVM) in order for the model to minimize generalization error across a distribution of tasks. More recently, the use of graph methods starts to gain momentum in the few-shot learning problems. For example, in the authors incorporate the idea of semi-supervised learning as a mean to benefit from the unlabelled query input data when solving a task, what we refer to as few-label settings. Our work can be considered following the same path.
The field of graph operators for deep learning is also very active recently. For example, in GCN [14], the authors introduce a graph convolution operator, that can be used in cascade to generate deep learning architectures. In GAT [32], the authors enrich GCN with additional learnable attention kernels. In SGC [38], the authors propose to simplify GCN by using only one-layer systems on powers of the adjacency matrix of considered graphs. Interestingly, they reach state-of-the-art accuracy with fewer hyperparameters.

2.3 Hallucination based methods

Other methods propose to augment the training sets by learning a generator that can hallucinate novel class data using data-augmentation techniques [3]. In [41], the authors extract labelled data into different components and then combine them using learned transformations, while in [4], the authors aim at constructively deforming original samples with new samples drawn from another dataset. However, these methods lack precision as in the way the data is generated, which results in coarse and low-quality synthesized data that can sometimes lead to insignificant gains in performance [37].

2.4 Transfer based methods

As in our work, transfer learning is another possible solution to solve few-shot and few-label classification problems. The main idea is to first train a feature extractor using a generic dataset [31,5], then process these features directly when solving the new task. In [3] a distance-based classifier is applied to train the backbone (i.e. the feature extractor), and in [20], the authors aims at improving the feature quality by adding self-supervised learning and data-augmentation techniques during training. These methods have been proven to perform generally well, yet the challenge remains to fine-tune using the limited amount of data.

In our work, we propose to combine multiple ingredients that have been introduced in this section. Namely, we use transfer with graph neural networks. We mainly use transfer to exploit information contained in massive generic datasets, and we use graph methods to leverage the additional information available in both labelled and unlabelled inputs. In a way, our proposed method can be considered as similar to [19], but contrary to their work, we only train the graph neural network model when facing the new few-shot task. Also, in contrast to their work, we make use of a very recently introduced graph neural network model, termed SGC, introduced in the previous subsection [38].

3 Methodology

3.1 Problem statement

Consider the following problem. We are given two datasets, termed $D_{\text{base}}$ and $D_{\text{novel}}$ with disjoint classes. The first one (called “base”) contains a large number
Exploiting Unsupervised Inputs for Accurate Few-Shot Classification of labelled examples from $K_b$ different classes. The second one (called “novel”) contains a small number of labelled examples, along with some unlabelled ones, all from $K_n$ new classes. Our aim is to accurately predict the class of the unlabelled inputs of the novel dataset. There are a few important parameters to this problem: the number of classes in the novel dataset $K_n$, the number of training samples $s$ for each corresponding class, and the total number of unlabelled inputs $Q$.

Note that in previous works [19], authors consider that there are exactly $q = Q/K_n$ unlabelled inputs for each class. We consider that this is non-practical, since in most applications there is no reason to think that this holds. We shall see in Section 4 that this has strong implications in terms of performance, especially when $q$ is small. Indeed, in practice the $Q$ unlabelled examples are drawn uniformly at random in a pool containing the same amount of unlabelled inputs for each class. So, when $Q$ is large, the central limit theorem tells us that the number of drawn inputs from each class should be similar, whereas it can be highly contrasted when $Q$ is small, leading to an imbalanced case.

### 3.2 Proposed solution

Our method is illustrated in Figure 1. We first train a backbone deep neural network able to discriminate inputs from the base dataset $D_{base} = \{(x'_1, \ell_1), ..., (x'_m, \ell_m)\}$, where $x'_i \in \mathbb{R}^d$ and $1 \leq \ell_i \leq K_b$. The proposed methodology builds upon using this pretrained architecture as a generic feature extractor, what is referred to as transfer in the literature [31]. Usually, a common way to extract features is to process data belonging to the novel dataset using the penultimate activation layer. Here, we obtain the extractor $f_\varphi : \mathbb{R}^d \rightarrow \mathbb{R}^h$, where $\varphi$ are the learnable parameters trained using only the base dataset.

We then directly make use of the transferred representations $f_\varphi(D_{novel}) = \{f_\varphi(x), x \in D_{novel}\}$. Based on these, we build a $k$ nearest neighbor graph using cosine similarity:

$$\cos(f_\varphi(x), f_\varphi(y)) = \frac{f_\varphi(x)^\top f_\varphi(y)}{\|f_\varphi(x)\|_2 \|f_\varphi(y)\|_2}.$$ (1)

This graph contains as many vertices as the total number of inputs in the novel dataset (both labelled and unlabelled ones). Then, we train a simplified graph convolution model, that is supervised only for labelled inputs.

The rationale behind this method is twofold: 1) the pretrained backbone should be able to find good discriminative features since it is trained on a sufficiently large labelled dataset 2) the graph neural network should be able to benefit from both the supervised inputs and the unlabelled ones when trained, resulting in significant gains in accuracy when compared to methods that would ignore the unlabelled data.

We show in the experiments that this method is also able to outperform other methods that use the unlabelled data especially when the number of labelled inputs is very limited. The details of the proposed method are provided in the following paragraphs, first the pre-training stage (i.e. training the generic


backbone) then the adapting stage (i.e. training the graph neural network based model on novel classes).

**Pre-training stage:** We follow the methodology introduced in [20]. In more details the feature extractor \( f_\varphi \) and a distance-based classifier \( D_{W_b} \) (parametrized by \( W_b \)) [21] are trained on \( D_{\text{base}} \), where we compute the cosine distance between an input feature \( f_\varphi(x'_i) \) and each weight vector in \( W_b \) in order to reduce the intra-class variations [3]. The training process consists of two sub-stages: the first sub-stage utilizes rotation-based self-supervised learning technique [9] where each input image is randomly rotated by a multiple of 90 degrees. We then co-train a linear classifier to tell which rotation was applied. Therefore, the total loss function of this sub-stage is given by:

\[
L_A = L_{\text{class}} + L_{\text{rotation}}.
\]  

(2)

The second sub-stage fine-tunes the model with Manifold Mixup [33] technique for a few more epochs, where the outputs of hidden layers in the neural network are linearly combined to help the trained model generalize better. The total loss in this sub-stage is given by:

\[
L_B = L_{\text{ManifoldMixup}} + 0.5(L_{\text{class}} + L_{\text{rotation}}).
\]  

(3)

With this training process, we are able to obtain robust input representations that generalize well to novel classes.

**Adapting stage:** We consider fixed the pretrained parameters \( \varphi \) of \( f_\varphi \) in the backbone model and train a new classifier \( C_{W_n} \) on the transferred representations of the novel dataset. Instead of just training a linear classifier with extremely few labelled inputs [3], a simplified graph convolution layer [38] is used.

In details, we define a graph \( G_T(V, E) \) [14] where vertices matrix \( V \in \mathbb{R}^{(sK_n+Q+h) \times h} \) contains the stacked features of labelled and unlabelled inputs [7]. To build the adjacency matrix \( E \in \mathbb{R}^{(sK_n+Q) \times (sK_n+Q)} \), we first compute:

\[
S[i, j] = \begin{cases} 
\cos(V[i, :], V[j, :]) & \text{if } i \neq j \\
0 & \text{otherwise}
\end{cases},
\]  

(4)

where \( V[i, :] \) denotes the \( i \)-th row of \( V \). Note that in all backbone architectures we use in the experiments, the penultimate layers are obtained by applying a ReLU function, so that all coefficients in \( V \) are nonnegative. As a result, coefficients in \( S \) are nonnegative as well. Also, note that \( S \) is symmetric.

Then, we only keep the value \( S[i, j] \) if it is one of the \( k \) largest values on the corresponding row or on the corresponding column in \( S \). So, as soon as \( k \geq (sK_n + Q - 1) \), all values are kept. Otherwise, \( S \) contain many 0s.

Finally, we apply normalization on the resulting matrix:

\[
E = D^{-1/2} S D^{-1/2},
\]  

(5)
where $D$ is the degree diagonal matrix defined as:

$$D[i, i] = \sum_j S[i, j].$$ (6)

Therefore, the graph vertices represent all inputs (both labelled and unlabelled) of the novel dataset. Its nonzero weights are based on the cosine similarity between corresponding transferred representations.

We then apply feature propagation [38] to obtain new features for each vertex. The formula is:

$$V_{new} = (\alpha I + E)\kappa V,$$ (7)

in which $\kappa$ and $\alpha$ are both hyperparameters, and $I$ is the identity matrix. The role of $\kappa$ is important: providing $\kappa$ is too small, the new feature of a vertex will only depend on its direct neighbors in the graph. Using larger values of $\kappa$ allows to encompass for more indirect relationships. Using a too large value of $\kappa$ might drown out the information by averaging over all inputs. Similarly, $\alpha$ allows to balance between the neighbors representations and self-ones. In the next section, we shall discuss more in details the influence of both these hyperparameters.

Finally, a softmax classifier is trained using only the labelled vertices. We denote by $V_{new}^{labelled}$ the subset of $V_{new}$ corresponding to labelled vertices, then the predicted results $\hat{Y}$ can be written following this formula:

$$\hat{Y}^{labelled} = softmax(V_{new}^{labelled}W_n),$$ (8)

where $V_{new}^{labelled} \in \mathbb{R}^{(sK_n) \times h}$, $\hat{Y} \in \mathbb{R}^{(sK_n) \times K_n}$ and $\hat{Y}[i, j]$ denotes the probability of vertex $i$ being categorized as being in the $j$-th class. Prediction is performed using the same principle, but using unlabelled inputs instead: denote by $V_{new}^{unlabelled}$ the subset of $V_{new}$ corresponding to unlabelled inputs, then we have the decision:

$$\hat{Y}^{unlabelled}[i] = \arg \max_j ((V_{new}^{unlabelled}W_n)[i, j]).$$ (9)

In Table 1 we summarize the main parameters and hyperparameters of the considered problem and proposed solution.

4 Experimental Validation

4.1 Datasets

We perform our experiments on 3 standardized few-shot classification datasets: miniImageNet [34], CUB [35] and CIFAR-FS [1]. These datasets are split into two parts: a) $K_b$ classes are chosen to train the backbone, called base classes, b) $K_n$ classes are drawn uniformly in the remaining classes to form the novel dataset, called novel classes. Among the $K_n$ drawn novel classes, $s$ labelled inputs per class and a total of $Q$ unlabelled inputs are drawn uniformly at random. As in most related works and unless mentioned otherwise, all our experiments are
Table 1. Parameters and hyperparameters of the considered problem and proposed solution.

| Novel dataset parameters |     |     |
|--------------------------|-----|-----|
| **Notation**             | **Value** | **Description** |
| $K_n$                    | typically 5 | number of classes |
| $s$                      | typically 1 or 5 | number supervised inputs per class |
| $Q$                      | typically $\leq 100$ | total number of unsupervised inputs |

| Proposed method hyperparameters |     |     |
|---------------------------------|-----|-----|
| **Notation**                    | **Range** | **Description** |
| $k$                             | $1 \leq k < sK_n + Q$ | number of nearest neighbors to keep |
| $\kappa$                       | $\kappa \in \mathbb{N}^*$ | power of the diffusion matrix |
| $\alpha$                       | $0 \leq \alpha \leq 1$ | strength of self-representations |

performed using $K_n = 5$ and $Q/K_n = 15$. We run 10,000 random draws to obtain a mean accuracy score and indicate confidence scores (95%) when relevant.

**miniImageNet**: It consists of a subset of ImageNet [24] that contains 100 classes and 600 images of size $84 \times 84$ pixels per class. According to the standard [23], we use 64 base classes to train the backbone and 20 novel classes to draw the novel datasets from. So, for each run, 5 classes are drawn uniformly at random among these 20 classes, and $s$ labelled inputs are chosen uniformly at random among the corresponding classes.

**CUB**: The dataset contains 200 classes and has a total of 11,788 images of size $84 \times 84$ pixels. We split it into 100 base classes to train the backbone and 50 novel classes to draw the novel datasets from.

**CIFAR-FS**: This dataset has 100 classes, each class contains 600 images of size $32 \times 32$ pixels. We use the same numbers as for the miniImageNet dataset.

4.2 Backbone models and implementation details

In order to stress the genericity of our proposed method with regards to the chosen backbone architecture, we perform experiments using 2 different backbones as the structure of feature extractor $f_{\varphi}(x)$.

**Wide residual networks (WRN)**: We follow the settings in [20] by choosing a WRN [40] with 28 convolutional layers and a widening factor of 10. The output feature size $h$ is 640.

**Residual networks (ResNet18)**: Our ResNet18 [11] contains a total of 18 convolutional layers grouped into 8 blocks. Following the settings in [36], we remove the first two down-sampling layers and change the kernel size of the first convolutional layer to $3 \times 3$ pixels instead of $7 \times 7$ pixels. Contrary to WRN, the obtained representation is only comprising $h = 512$ dimensions.

**Implementation**: For the pre-training stage and miniImageNet, we train all backbones for a total of 470 epochs from scratch using Adam optimizer [13] and cross-entropy loss, including 400 epochs on the first sub-stage and 70 epochs on the second sub-stage. For the adapting stage, we train the SGC with the same optimizer and loss function for 1000 epochs with learning rate being $1e - 3$ and
weight decay being $5e-6$, which typically requires of the order of one second of computation on a modern GPU. Note that we observed that convergence usually occurs much quicker than the 1000 epochs.

In the In-Domain settings two stages are trained on the same dataset with base classes and novel classes respectively, while in the Cross-Domain settings we use these splits from two different datasets (e.g. base classes from miniImageNet and novel classes from CUB).

4.3 Comparison with state-of-the-art methods

As a first experiment, we compare the raw performance of the proposed method with state-of-the-art solutions. The results are presented in Table 2. We fixed $\alpha$, $k$ and $\kappa$ values using a grid search respectfully for $s = 1$ and $s = 5$. Note that the sensitivity of these parameters is discussed later in this section.

We first point out that the proposed method reaches state-of-the-art performance in the case of 1-shot classification, whatever the choice of the backbone and for all three considered datasets. The proposed method ranks in the top #2 in the case of 5-shot. The fact the performance is a bit lesser in the case of more labelled examples is not surprising, as the additional information from the unlabelled inputs is less prominent in that case.

4.4 Performance in Cross-Domain Settings

We then perform experiments where the backbone has been trained using the base classes of miniImageNet but the few-label task is performed using the novel classes of the CUB dataset. Results are presented in Table 3. We can draw conclusions very similar to the previous study, where the proposed method ranks first for this specific task.

4.5 Importance of SGC

In our work, we considered using SGC to diffuse features between inputs. As mentioned in the related work section, there are many alternatives. In the next experiment, we compare the accuracy of the method when using existing alternatives, namely GCN [14] and GAT [32]. Results are presented in Table 4. We note that the best results are obtained using SGC. The reasons why SGC performs better are not completely obvious, but we believe that it is mainly due to the fact SGC requires a very limited set of hyperparameters compared to the other methods, resulting in easier setup and optimization. SGC also has the interest of being many times faster to train. In our experiments, each run took about 0.65 seconds to train using SGC, 1.18 seconds using GCN and 22.42 seconds using GAT, though it led to the worst performance of our testbench.

It is worth pointing out that a drawback of the proposed method is that it requires to train an SGC model each time a batch prediction is required. In other words, it can be limiting in settings where predictions to make are streamed. However, the time required to train the SGC model remains very small in our experiments (less than one second).
Table 2. 1-shot and 5-shot accuracy of state-of-the-art methods in the literature, compared with the proposed solution. We present results using WRN or ResNet18 as a backbone. For the proposed solution, we use the hyperparameters $\alpha = 0.5$, $k = 10$ and $\kappa = 3$ for $s = 1$; $\alpha = 0.75$, $k = 15$ and $\kappa = 1$ for $s = 5$. FS stands for few-shot and FL for few-label (with $Q/K_n = 15$).

| Problem | Method          | Backbone | 1-shot       | 5-shot       |
|---------|-----------------|----------|--------------|--------------|
| FL      | GNN [7]         | Conv4    | 50.33 ± 0.36%| 66.41 ± 0.63%|
|         | TPN [19]        | Conv4    | 55.51 ± 0.86%| 69.86 ± 0.65%|
|         | wDAE-GNN [8]    | WRN      | 61.07 ± 0.15%| 76.75 ± 0.11%|
|         | ACC+Amphibian [27] | WRN | 64.21 ± 0.62%| 87.75 ± 0.73%|
|         | BD-CSPN [18]    | WRN      | 70.31 ± 0.93%| 81.89 ± 0.60%|
| FS      | MAML [6]        | ResNet10 | 54.69 ± 0.89%| 66.62 ± 0.83%|
|         | RelationNet [28] | ResNet10 | 52.19 ± 0.83%| 70.20 ± 0.66%|
|         | Baseline++ [3]  | ResNet10 | 53.97 ± 0.79%| 75.90 ± 0.61%|
|         | LEO [25]        | WRN      | 61.76 ± 0.08%| 77.59 ± 0.12%|
|         | Matching Networks [34] | WRN | 64.03 ± 0.20%| 76.32 ± 0.16%|
|         | ProtoNet [26]   | WRN      | 62.60 ± 0.20%| 79.97 ± 0.14%|
|         | FEAT [39]       | WRN      | 65.10 ± 0.20%| 81.11 ± 0.14%|
|         | SimpleShot [36] | DenseNet | 64.29 ± 0.20%| 81.50 ± 0.14%|
|         | S2M2_R [20]     | WRN      | 64.93 ± 0.18%| 83.18 ± 0.11%|
| FL      | Transfer+SGC(ours) | ResNet18 | 71.82 ± 0.24%| 82.92 ± 0.14%|
|         | Transfer+SGC(ours) | WRN      | 76.47 ± 0.23%| 85.23 ± 0.13%|

| Problem | Method          | Backbone | 1-shot       | 5-shot       |
|---------|-----------------|----------|--------------|--------------|
| FS      | Baseline++ [3]  | ResNet10 | 69.55 ± 0.89%| 85.17 ± 0.50%|
|         | MAML [6]        | ResNet10 | 71.29 ± 0.95%| 80.33 ± 0.70%|
|         | RelationNet [28] | ResNet10 | 68.65 ± 0.91%| 81.12 ± 0.63%|
|         | Matching Networks [34] | ResNet18 | 72.36 ± 0.90%| 83.64 ± 0.60%|
|         | ProtoNet [26]   | ResNet18 | 71.88 ± 0.91%| 87.42 ± 0.48%|
|         | S2M2_R [20]     | WRN      | 80.68 ± 0.81%| 90.85 ± 0.44%|
| FL      | Transfer+SGC(ours) | WRN      | 88.35 ± 0.19%| 92.14 ± 0.10%|

| Problem | Method          | Backbone | 1-shot       | 5-shot       |
|---------|-----------------|----------|--------------|--------------|
| FL      | ACC+Amphibian [27] | WRN | 73.10 ± 0.50%| 89.30 ± 0.90%|
|         | BD-CSPN [18]    | WRN      | 72.13 ± 1.01%| 82.28 ± 0.69%|
| FS      | MAML [6]        | ConvNet32 | 58.90 ± 1.90%| 71.50 ± 1.00%|
|         | RelationNet [28] | ConvNet256 | 55.50 ± 1.00%| 69.30 ± 0.80%|
|         | ProtoNet [26]   | ConvNet64 | 55.50 ± 0.70%| 72.00 ± 0.60%|
|         | R2D2 [1]        | ConvNet512 | 65.30 ± 0.20%| 79.40 ± 0.10%|
|         | MetaOptNet-SVM [16] | ResNet12 | 72.00 ± 0.70%| 84.20 ± 0.50%|
|         | S2M2_R [20]     | WRN      | 74.81 ± 0.19%| 87.47 ± 0.13%|

\* Results reported in [36].
**Table 3.** 1-shot and 5-shot accuracy of state-of-the-art methods when performing cross-domain few-label classification (training the backbone on miniImageNet and classifying inputs from the CUB dataset). We used the WRN backbone and the same hyperparameters as Table 2.

| Problem | Method                  | 1-shot               | 5-shot               |
|---------|-------------------------|----------------------|----------------------|
| FS      | Baseline++ [3]^         | 40.44 ± 0.75%        | 56.64 ± 0.72%        |
| FS      | MetaOptNet-SVM [16]^    | 44.79 ± 0.75%        | 64.98 ± 0.68%        |
| FS      | Rotation [9]^           | 48.42 ± 0.84%        | 68.40 ± 0.75%        |
| FS      | Manifold Mixup [33]^    | 46.21 ± 0.77%        | 66.03 ± 0.71%        |
| FS      | S2M2-R [20]             | 48.24 ± 0.84%        | 70.44 ± 0.75%        |
| FL      | Transfer+SGC(ours)      | 58.63 ± 0.25%        | 73.46 ± 0.17%        |

^: Results reported in [20].

**Table 4.** 1-shot and 5-shot accuracy on miniImageNet, when using the WRN backbone and various Graph Neural Networks for the adapting stage. We use the same hyperparameters as Table 2 and apply them to all methods when applicable.

| Method       | 1-shot       | 5-shot       |
|--------------|--------------|--------------|
| Transfer+SGC | 76.47 ± 0.23%| 85.23 ± 0.13%|
| Transfer+GCN | 75.88 ± 0.23%| 84.51 ± 0.13%|
| Transfer+GAT | 65.38 ± 0.89%| 76.00 ± 0.67%|

^*GAT is evaluated with 600 test runs.

### 4.6 Influence of Parameters

We then inquire the importance of various parameters of the task to the performance of the proposed method. We begin by varying the number of supervised inputs $s$, and consider two settings: one where we dispose of an average of $Q/K_n = 5$ unsupervised inputs for each class and one where we dispose of $Q/K_n = 100$ of them. Results are depicted in Figure 2. As we can see, the performance of the method is highly influenced by the number of supervised inputs, as expected. Interestingly, there is a significant gap in accuracy between $Q/K_n = 5$ and $Q/K_n = 100$ for 1-shot setting, even if this gap diminishes as the number of supervised inputs is increased.

In the next experiment, we draw in Figure 3 the evolution of the performance of the method as a function of the number of unsupervised inputs $Q$, for 1-shot, 3-shot and 5-shot settings. This curve confirms two observations: a) in the case of 5-shot setting, the influence of the number of unsupervised inputs is little, and the accuracy of the method quickly reaches its pick and b) in the case of 1-shot setting, the number of unsupervised inputs significantly influences accuracy up to a few dozens. It is worth pointing out that about the same accuracy is achieved for 5-shot using $Q = 1$ and 1-shot using $Q = 100$, suggesting that 100 unsupervised inputs bring about the same information as increasing $s$ by 4.
In the next experiment we look at the influence of the parameters $\kappa$ and $\alpha$ which respectively control to which power the diffusion matrix is taken and the importance of self-representations. In Figure 4, we draw the obtained mean accuracy as a function of $\kappa$, $\alpha$ and $k$. We use $s = 1$ and $Q/K_n = 15$.

There are multiple interesting conclusions to draw from this figure.

1. This curve justifies the previously mentioned choice of parameters, leading to the best performance in our testbench.
2. We observe that when $k$ is large and $\alpha$ is small, it is better not to use powers of the diffusion matrix. This is the only setting where this statement holds, emphasizing the fact that if the graph is not sparse and self-importance is low, powers of the diffusion matrix are likely to over-smooth the representations.
3. When $k$ is small (here: $k = 5$ or $k = 10$), there is little sensitivity to both $\alpha$ and $\kappa$ (for $\kappa \leq 3$). This is an asset as it makes it simpler to find good hyperparameters in practice.
4. The best results are achieved for smaller values of $k$, suggesting that cosine similarity between distant representations can be noisy and damaging to the performance of the method.
5. Note that in this experiment $s + Q/K_n = 16$. So using $k = 15$ would ideally select exactly 15 neighbors of the same class for each input. Interestingly,
this choice of $k$ does not lead to the best performance, showing the graph structure is not perfectly aligned with classes.

It is often disregarded the impact of class imbalance in the context of few-shot learning. As a matter of fact, since we only consider very few labelled examples, it does not make much sense to consider such a scenario. But in the context of few-label, it is highly probable that unlabelled inputs are imbalanced between classes. So we perform the next experiment by varying the number of examples chosen in two random classes from miniImageNet. We always make sure that the total number of queries to classify remains the same, that is 100. But we select $q_1$ of them in class 1 and $100 - q_1$ of them in class 2.

In Figure 5 we depict the evolution of the accuracy of the proposed method, as a function of $q_1$. As one can clearly see from this figure, there is an important influence of class imbalance towards the performance of the proposed method. This is expected as the generated graphs will have imbalanced communities as a consequence. However, this could be problematic to some application domains where such imbalance is expected to happen in considered datasets, as there is no direct way of correcting it. Obviously, if one has insights about the relative distribution between classes, simple data augmentation or sampling could be used for balancing this negative effect.

Finally, in Figure 6 we draw a representation of a typical graph obtained with the miniImageNet dataset, using Laplacian embedding. On this figure, we colored vertices depending on which class they belong to. Interestingly, this figure shows that some classes are easily separated in the graph, whereas others are much harder to discriminate. We believe that the main reason why these graphs
Fig. 5. Accuracy of 2-ways classification with unevenly distributed query data for each class, where the total number of query inputs remains constant. When \( q_1 = 1 \), we obtain the most imbalanced case, whereas \( q_1 = 50 \) corresponds to a balanced case. We use \( \alpha = 0.5 \), \( \kappa = 3 \) and \( k = 10 \).

are not perfectly segregating classes is because some dimensions obtained using the backbone are specialized on features completely irrelevant for the novel task.

Fig. 6. Visualisation of a graph obtained using miniImageNet. Colors represent various classes. Vertices are placed close if they share many connections.

5 Conclusion

In this paper we introduced a novel method to solve the few-label classification problem. It consists in combining two steps: a pretrained transfer and a graph neural network based model trained on both labelled and unlabelled available data for the considered task. By performing experiments on standardized vision datasets, we obtained state-of-the-art results, with the most important gains in the case of 1-shot classification.

Interestingly, the proposed method requires to tune few hyperparameters, and these have a little impact on accuracy. We thus believe that it is an applicable solution to many practical problems.

There are still open questions to be addressed, such as the case of imbalanced classes, or settings where prediction must be performed on streaming data, one input at a time, which requires retraining a model at each step.
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