Few-Shot Image Recognition by Predicting Parameters from Activations

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Abstract

In this paper, we are interested in the few-shot learning problem. In particular, we focus on a challenging scenario where the number of categories is large and the number of examples per novel category is very limited, i.e. 1, 2, or 3. Motivated by the close relationship between the parameters and the activations in a neural network associated with the same category, we propose a novel method that can adapt a pre-trained neural network to novel categories by directly predicting the parameters from the activations. Zero training is required in adaptation to novel categories, and fast inference is realized by a single forward pass. We evaluate our method by doing few-shot image recognition on the ImageNet dataset, which achieves state-of-the-art classification accuracy on novel categories by a significant margin while keeping comparable performance on the large-scale categories.

1 Introduction

Recent years have witnessed rapid advances in deep learning [1], with a particular example being visual recognition [2] [3] [4] on large-scale image datasets, e.g., ImageNet [5]. Despite their great performance on benchmark datasets, the machines exhibit clear difference with people in the way they learn concepts. Deep learning methods typically require huge amounts of supervised training data per concept, and the learning process could take days using specialized hardware, i.e. GPUs. In contrast, children are known to be able to learn novel visual concepts almost effortlessly with a few examples after they have accumulated enough past knowledge [6]. This phenomenon motivates computer vision research on the problem of few-shot learning, i.e., the task to learn novel concepts from only a few examples for each category [7] [8].

Formally, in the few-shot learning problem [9] [10] [11], we are provided with a large-scale set \( D_{\text{large}} \) with categories \( C_{\text{large}} \) and a few-shot set \( D_{\text{few}} \) with categories \( C_{\text{few}} \) that do not overlap with \( C_{\text{large}} \). \( D_{\text{large}} \) has sufficient training samples for each category whereas \( D_{\text{few}} \) has only a few examples (< 4 in this paper). The goal is to achieve good classification performances, either on \( D_{\text{few}} \) or on both \( D_{\text{few}} \) and \( D_{\text{large}} \). We argue that a good classifier should have the following properties: (1) It achieves reasonable performance on \( C_{\text{few}} \). (2) Adapting to \( C_{\text{few}} \) does not degrade the performance on \( C_{\text{large}} \) significantly (if any). (3) It is fast in inference and adapts to few-shot categories with little or zero training, i.e., an efficient lifelong learning system [12] [13].

Both parametric and non-parametric methods have been proposed for the few-shot learning problem. However, due to the limited number of samples in \( D_{\text{few}} \) and the imbalance between \( D_{\text{large}} \) and \( D_{\text{few}} \), parametric models usually fail to learn well from the training samples [9]. On the other hand, many non-parametric approaches such as nearest neighbors can adapt to the novel concepts easily without severely forgetting the original classes, but this requires careful design of the distance metrics [14], which can be difficult and sometimes empirical. To remedy this, some previous work instead adapts feature representation to the metrics by using siamese networks [10] [15]. As we will show later through experiments, these methods do not fully satisfy the properties mentioned above.
In this paper, we present an approach that meets the desired properties well. Our method starts with a pre-trained deep neural network on $D_{\text{large}}$. The final classification layers (the fully connected layer and the softmax layer) are shown in Figure 1. We use $w_y \in \mathbb{R}^n$ to denote the parameters for category $y$ in the fully connected layer, and use $a(x) \in \mathbb{R}^n$ to denote the activations before the fully connected layer of an image $x$. Training on $D_{\text{large}}$ is standard; the real challenge is how to re-parameterize the last fully connected layer to include the novel categories under the few-shot constraints, i.e., for each category in $C_{\text{few}}$ we only have a few examples. Our proposed method addresses this challenge by directly predicting the parameters $w_y$ (in the fully connected layer) using the activations belonging to that category, i.e., $A_y = \{a(x) | x \in D_{\text{large}} \cup D_{\text{few}}, Y(x) = y\}$, where $Y(\cdot)$ denotes the category of the image.

This parameter predictor stems from the tight relationship between the parameters and activations. Intuitively in the last fully connected layer, we want $w_y \cdot a_y$ to be large, for all $a_y \in A_y$. Let $\bar{a}_y \in \mathbb{R}^n$ be the mean of the activations in $A_y$. Since it is known that the activations of images in the same category are spatially clustered together [17], a reasonable choice of $w_y$ is to align with $\bar{a}_y$ in order to maximize the inner product, and this argument holds true for all $y$. To verify this intuition, we use t-SNE [16] to visualize the neighbor embeddings of the activation statistic $\bar{a}_y$ and the parameters $w_y$ for each category of a pre-trained deep neural network, as shown in Figure 2. Comparing them and we observe a high similarity in both the local and the global structures. More importantly, the semantic structures [18] are also preserved in both activations and parameters, indicating a promising generalizability to unseen categories.

These results suggest the existence of a category-agnostic mapping from the activations to the parameters given a good feature extractor $a(\cdot)$. More generally, we could allow the input to $\phi$ to be a statistic representing the activations of category $y$. Note that we use the same mapping function for all categories $y \in C_{\text{large}}$, because we

2 Model

The key component of our approach is the category-agnostic parameter predictor $\phi : \bar{a}_y \rightarrow w_y$ (Figure 3). More generally, we could allow the input to $\phi$ to be a statistic representing the activations of category $y$. Note that we use the same mapping function for all categories $y \in C_{\text{large}}$, because we
believe the activations and the parameters have similar local and global structure in their respective space. Once this mapping has been learned on \( D_{\text{large}} \), because of this structure-preserving property, we expect it to generalize to categories in \( C_{\text{few}} \).

### 2.1 Learning Parameter Predictor

Since our final goal is to do classification, we learn \( \phi \) from classification supervision. Specifically, we can learn \( \phi \) from \( D_{\text{large}} \) by minimizing the classification loss (with a regularizer \( ||\phi|| \)) defined by

\[
L(\phi) = \sum_{(y,x) \in D_{\text{large}}} \left( -\phi(\bar{a}_y) a(x) + \log \sum_{y' \in C_{\text{large}}} e^{\phi(a_{y'}) a(x)} \right) + \lambda ||\phi||
\]

Eq. [1] models the parameter prediction for categories \( y \in C_{\text{large}} \). However, for the few-shot set \( C_{\text{few}} \), each category only has a few activations, whose mean value is the activation itself when each category has only one sample. To model this few-shot setting in the large-scale training on \( D_{\text{large}} \), we allow both individual activations and mean activation to represent a category. Concretely, let \( s_y \in A_y \cup \bar{a}_y \) be a statistic for category \( y \). Let \( S_{\text{large}} \) denote a statistic set \( \{s_1, \ldots, s_{|C_{\text{large}}|}\} \) with one for each category in \( C_{\text{large}} \). We sample activations \( s_y \) for each category \( y \) from \( A_y \cup \bar{a}_y \) with a probability \( p_{\text{mean}} \) to use \( \bar{a}_y \) and \( 1 - p_{\text{mean}} \) to sample uniformly from \( A_y \). Now, we learn \( \phi \) to minimize the loss defined by

\[
L(\phi) = \sum_{(y,x) \in D_{\text{large}}} E_{S_{\text{large}}} \left[ -\phi(\bar{a}_y) a(x) + \log \sum_{y' \in C_{\text{large}}} e^{\phi(s_{y'}) a(x)} \right] + \lambda ||\phi||
\]

### 2.2 Inference

During inference we include \( C_{\text{few}} \), which calls for a statistic set for all categories \( S = \{s_1, \ldots, s_{|C|}\} \), where \( C = C_{\text{large}} \cup C_{\text{few}} \). Each statistic set \( S \) can generate a set of parameters \( \{\phi(s_1), \ldots, \phi(s_{|C|})\} \) that can be used for building a classifier on \( C \). Since we have more than one possible set \( S \) from the dataset \( D = D_{\text{large}} \cup D_{\text{few}} \), we can do classification based on all the possible \( S \). Formally, we compute the probability of \( x \) being in category \( y \) by

\[
P(y|x) = \frac{e^{\mathbb{E}_S[\phi(s_y)a(x)]}}{\sum_{y' \in C} e^{\mathbb{E}_S[\phi(s_{y'})a(x)]}}
\]

However, classifying images with the above equation is time-consuming since it computes the expectations over the entire space of \( S \) which is exponentially large. We show in the following that if we assume \( \phi \) to be a linear mapping, then this expectation can be computed efficiently.

In the linear case \( \phi \) is a matrix \( \Phi \). The predicted parameter for category \( y \) is

\[
\hat{w}_y = \Phi \cdot s_y
\]

The inner product of \( x \) before the softmax function for category \( y \) is

\[
h(s_y, a(x)) = \hat{w}_y \cdot a(x) = \Phi \cdot s_y \cdot a(x)
\]

If \( a(x) \) is always normalized, then by setting \( \Phi \) as the identity matrix, \( h(s_y, a(x)) \) is equivalent to the cosine similarity between \( s_y \) and \( a(x) \). Essentially, by learning \( \Phi \), we are learning a more general
similarity metric on the activations \(a(x)\) by capturing correlations between different dimensions of the activations. We will show more comparisons between the learned \(\Phi\) and identity matrix in §4.5.

Because of the linearity of \(\phi\), the probability of \(x\) being in category \(y\) simplifies to

\[
P(y|x) = e^{a(x) \cdot \phi(E_S[s_y])} / \left( \sum_{y' \in C} e^{a(x) \cdot \phi(E_S[s_{y'}])} \right) = e^{a(x) \cdot \Phi \cdot E_S[s_y]} / \left( \sum_{y' \in C} e^{a(x) \cdot \Phi \cdot E_S[s_{y'}]} \right)
\]

(6)

Now \(E_S[s_y]\) can be pre-computed which is efficient. Adapting to novel categories only requires updating the corresponding \(E_S[s_y]\). Although it is ideal to keep the linearity of \(\phi\) to reduce the amount of computation, introducing non-linearity could potentially improve the performance. To keep the efficiency, we still push in the expectation and approximate Eq. (3) as in Eq. (6).

When adding categories \(y \in C_{\text{few}}\), the estimate of \(E_S[s_y]\) may not be reliable since the number of samples is small. Besides, Eq. (2) models the sampling from one-shot and mean activations. Therefore, we take a mixed strategy for parameter prediction, i.e., we use \(E_S[s_y]\) to predict parameters for category \(y \in C_{\text{large}}\), but for \(C_{\text{few}}\) we treat each sample as a newly added category. The probability of \(y \in C_{\text{few}}\) is the maximization of the probabilities of all the categories originally belonging to \(y\).

### 2.3 Training Strategy

The objective of training is to find \(\phi\) that minimizes Eq. (2). There are many methods to do this. We approach this by using stochastic gradient decent with weight decay and momentum. Figure 4 demonstrates the training strategy of the parameter predictor \(\phi\). We train \(\phi\) on \(D_{\text{large}}\) with categories \(C_{\text{large}}\). For each batch of the training data, we sample \(|C_{\text{large}}|\) statistics \(s_y\) from \(A_y \cup a_y\) to build a statistic set \(S\) with one in each category \(y\) in \(C_{\text{large}}\). Next, we sample a training activation set \(T\) from \(D_{\text{large}}\) with one for each category in \(C_{\text{large}}\). In total, we sample \(2|C_{\text{large}}|\) activations. The activations in the statistic sets are fed to \(\phi\) to generate parameters for the fully connected layer. With the predicted parameters for each category in \(C_{\text{large}}\), the training activation sets then is used to evaluate their effectiveness by classifying the training activations. At last, we compute the classification loss with respect to the ground truth, based on which we calculate the gradients and back-propagate them in the path shown in Figure 4. After the gradient flow passes through \(\phi\), we update \(\phi\) according to the gradients.

### 2.4 Implementation Details

Our experiments are conducted on ILSVRC 2015 [5]. ILSVRC 2015 is a large-scale image dataset with 1000 categories, each of which has about 1300 images for training, and 50 images for validation. For the purpose of studying both the large-scale and the few-shot settings at the same time, ILSVRC 2015 is split to two sets by the categories. The training data from 900 categories are collected into \(D_{\text{large}}\), while the rest 100 categories are gathered as set \(D_{\text{few}}\).

We first train a 50-layer ResNet [4] on \(D_{\text{large}}\). We use the outputs of the global average pooling layer as the activation \(a(x)\) of an image \(x\). For efficiency, we compute the activation \(a(x)\) for each image \(x\) before the experiments as well as the mean activations \(\bar{a}_y\). Following the training strategy shown in §2.3, for each batch, we sample 900 activations as the statistic set and 900 activations as the training activation set. We compute the parameters using the statistic set, and copy the parameters into the fully connected layer. Then, we feed the training activations into the fully connected layer, calculate the loss and back-propagate the gradients. Next, we redirect the gradient flow into \(\phi\). Finally, we update \(\phi\) using stochastic gradient descent. The learning rate is set to 0.0005 and the momentum is set to 0.9. We train \(\phi\) on \(D_{\text{large}}\) for 300 epochs, each of which has 250 batches. \(\mu_{\text{mean}}\) is set to 0.9.
For the parameter predictor, we implement three different $\phi$: $\phi^1$, $\phi^2$ and $\phi^2\ast$. $\phi^1$ is a one-layer fully connected model. $\phi^2$ is defined as a sequential network with two fully connected layers in which each maps from 2048 dimensional features to 2048 dimensional features and the first one is followed by a ReLU non-linearity layer [19]. The final outputs are normalized to unity in order to speed up training and ensure generalizability. By introducing non-linearity, we observe slight improvements on the accuracies for both $C_{\text{large}}$ and $C_{\text{few}}$. To demonstrate the effect of minimizing Eq. 2 instead of Eq. 1, we train another $\phi^2\ast$ which has the same architecture with $\phi^2$ but minimizes Eq. 1. As we will show later through experiments, $\phi^2\ast$ has strong bias towards $C_{\text{large}}$.

3 Related Work

3.1 Large-scale Image Recognition

We have witnessed an evolution of image datasets over the last few decades. The sizes of the early datasets are relatively small. Each dataset usually collects images on the order of tens of thousands. Representative datasets include Caltech-101 [7], Caltech-256 [20], Pascal VOC [21], and CIFAR-10/100 [22]. Nowadays, large-scale datasets are available with millions of detailed image annotations, e.g. ImageNet [5] and MS COCO [23]. With datasets of this scale, machine learning methods that have large capacity start to prosper, and the most successful ones are convolutional neural network based [2, 3, 4, 24, 25].

3.2 Few-Shot Image Recognition

Unlike large-scale image recognition, the research on few-shot learning has received limited attention from the community due to its inherent difficulty, thus is still at an early stage of development. As an early attempt, Fei-Fei et al. proposed a variational Bayesian framework for one-shot image classification [7]. A method called Hierarchical Bayesian Program Learning [26] was later proposed to specifically approach the one-shot problem on character recognition by a generative model. On the same character recognition task, Koch et al. developed a siamese convolutional network [10] to learn the representation from the dataset and modeled the few-shot learning as a verification task. Later, Matching Network [11] was proposed to approach the few-shot learning task by modeling the problem as a $k$-way $m$-shot image retrieval problem using attention and memory models. Following this work, Ravi and Larochelle proposed a LSTM-based meta-learner optimizer [27]. Although they show state-of-the-art performances on their few-shot learning tasks, they are not flexible for both large-scale and few-shot learning since $k$ and $m$ are fixed in their architectures.

3.3 Unified Approach

Learning a metric then using nearest neighbor [10, 15, 28] is applicable but not necessarily optimal to the unified problem of large-scale and few-shot learning since it is possible to train a better model on the large-scale part of the dataset using the methods in §3.1. Mao et al. proposed a method called Learning like a Child [9] specifically for fast novel visual concept learning using hundreds of examples per category while keeping the original performance. However, this method is less effective when the training examples are extremely insufficient, e.g. < 4 in this paper.

4 Results

In this section we describe our experiments and compare our approach with other strong baseline methods. As stated in §1, there are three aspects to consider in evaluating a method: (1) its performance on the few-shot set $D_{\text{few}}$, (2) its performance on the large-scale set $D_{\text{large}}$, and (3) its computation overhead of adding novel categories and the complexity of image inference. In the following subsections, we will cover the settings of the baseline methods, compare the performances on the large-scale and the few-shot sets, and discuss their efficiencies.

4.1 Baseline Methods

The baseline methods must be able to be applied to both large-scale and few-shot learning settings. We compare our method with a fine-tuned 50-layer ResNet [4], Learning like a Child [9] with a pre-trained 50-layer ResNet as the starting network, Siamese-Triplet Network [10, 15] using three 50-layer ResNets with shared parameters, and the nearest neighbor using the pre-trained 50-layer ResNet convolutional features. We will elaborate individually on how to train and use them.
As mentioned in §2.4, we first train a 900-category classifier on $\mathcal{D}_{\text{large}}$. We will build other baseline methods using this classifier as the starting point. For convenience, we denote this classifier as $\mathcal{R}_{\text{large}}^{\text{pt}}$, where $\text{pt}$ stands for "pre-trained". Next, we add the novel categories $\mathcal{C}_{\text{few}}$ to each method. For the 50-layer ResNet, we fine tune $\mathcal{R}_{\text{large}}^{\text{pt}}$ with the newly added images by extending the fully connected layer to generate 1000 classification outputs. Note that we will limit the number of training samples of $\mathcal{C}_{\text{few}}$ for the few-shot setting. For Learning like a Child, however, we fix the layers before the global average pooling layer, extend the fully connected layer to include 1000 classes, and only update the parameters for $\mathcal{C}_{\text{few}}$ in the last classification layer. Since we have full access to $\mathcal{D}_{\text{large}}$, we do not need Baseline Probability Fixation [9]. The nearest neighbor with cosine distance can be directly used for both tasks given the pre-trained deep features.

The other method we compare is Siamese-Triplet Network [10, 15]. Siamese network is proposed to approach the few-shot learning problem on Omniglot dataset [29]. In our experiments, we find that its variant Triplet Network [15, 28] is more effective since it learns feature representation from relative distances between positive and negative pairs instead of directly doing binary classification from the feature distance. Therefore, we use the Triplet Network from [15] on the few-shot learning problem, and upgrade its body net to the pre-trained $\mathcal{R}_{\text{large}}^{\text{pt}}$. We use cosine distance as the distance metric and fine-tune the Triplet Network. For inference, we use nearest neighbor with cosine distance.

4.2 Oracles

Here we explore the upper bound performance on $\mathcal{C}_{\text{few}}$. In this setting we have all the training data for $\mathcal{C}_{\text{large}}$ and $\mathcal{C}_{\text{few}}$ in ImageNet. For the fixed feature extractor $\mathcal{a}(\cdot)$ pre-trained on $\mathcal{D}_{\text{large}}$, we can train a linear classifier on $\mathcal{C}_{\text{large}}$ and $\mathcal{C}_{\text{few}}$, or use nearest neighbor, to see what are the upper bounds of the pre-trained $\mathcal{a}(\cdot)$. Table 1 shows the results. The performances are evaluated on the validation set of ILSVRC 2015 [5] which has 50 images for each category. The feature extractor pre-trained on $\mathcal{D}_{\text{large}}$ demonstrates reasonable accuracies on $\mathcal{C}_{\text{few}}$ which it has never seen during training for both parametric and non-parametric methods.

4.3 Few-Shot Accuracies

Let us now go back to the few-shot setting where we only have several training examples for $\mathcal{C}_{\text{few}}$. Specifically, we study the performances of different methods when $\mathcal{D}_{\text{few}}$ has for each category 1, 2, and 3 samples. It is worth noting that our task is much harder than the previously studied few-shot learning: we are evaluating top predictions from 1000 candidate classes, i.e., 1000-way accuracies while previous work is mostly interested in 5-way or 20-way accuracies [10, 11, 15, 27, 28].

With the pre-trained $\mathcal{R}_{\text{large}}^{\text{pt}}$, the training samples in $\mathcal{D}_{\text{few}}$ are like invaders to the activation space for $\mathcal{C}_{\text{large}}$. Intuitively, there will be a trade-off between the performances on $\mathcal{C}_{\text{large}}$ and $\mathcal{C}_{\text{few}}$. This is true especially for non-parametric methods. Table 2 shows the performances on the validation set of ILSVRC 2015 [5]. The second column is the percentage of data of $\mathcal{D}_{\text{large}}$ in use, and the third column is the number of samples used for each category in $\mathcal{D}_{\text{few}}$. Note that fine-tuned ResNet [4] and Learning like a Child [9] require fine-tuning while others do not.

Triplet Network is designed to do few-shot image inference by learning feature representations that adapt to the chosen distance metric. It has better performance on $\mathcal{C}_{\text{few}}$ compared with the fine-tuned ResNet and Learning like a Child when the percentage of $\mathcal{D}_{\text{large}}$ in use is low. However, its accuracies on $\mathcal{C}_{\text{large}}$ are sacrificed a lot in order to favor few-shot accuracies. We also note that if full category supervision is provided, the activations of training a classifier do better than that of training a Triplet Network. We speculate that this is due to the less supervision of training a Triplet Network which uses losses based on fixed distance preferences. Fine-tuning and Learning like a Child are training based, thus are able to keep the high accuracies on $\mathcal{D}_{\text{large}}$, but perform badly on $\mathcal{D}_{\text{few}}$ which does not have sufficient data for training. Compared with them, our method shows state-of-the-art accuracies on $\mathcal{C}_{\text{few}}$ without compromising too much the performances on $\mathcal{C}_{\text{large}}$.

### Table 1: Oracle 1000-way accuracies of the feature extractor $\mathcal{a}(\cdot)$ pre-trained on $\mathcal{D}_{\text{large}}$.

| Feature Extractor | Classifier | Top-1 $\mathcal{C}_{\text{large}}$ | Top-5 $\mathcal{C}_{\text{large}}$ | Top-1 $\mathcal{C}_{\text{few}}$ | Top-5 $\mathcal{C}_{\text{few}}$ |
|-------------------|------------|-----------------------------------|-----------------------------------|---------------------------------|---------------------------------|
| ResNet-50         | NN + Cosine| 70.25%                            | 89.98%                            | 52.46%                          | 87.58%                          |
| ResNet-50         | Linear     | 75.20%                            | 92.38%                            | 60.50%                          | 87.58%                          |
Table 2: Comparing 1000-way accuracies with feature extractor $a(\cdot)$ pre-trained on $D_{\text{large}}$. For different $D_{\text{few}}$ settings, red: the best few-shot accuracy, and blue: the second best.

| Method             | $D_{\text{large}}$ | $D_{\text{few}}$ | FT | Top-1 $C_{\text{large}}$ | Top-5 $C_{\text{large}}$ | Top-1 $C_{\text{few}}$ | Top-5 $C_{\text{few}}$ |
|--------------------|---------------------|-------------------|----|--------------------------|--------------------------|------------------------|------------------------|
| NN + Cosine        | 100%                | 1                 | N  | 71.54%                   | 91.20%                   | 1.72%                  | 5.86%                  |
| NN + Cosine        | 10%                 | 1                 | N  | 67.68%                   | 88.90%                   | 4.42%                  | 13.36%                 |
| NN + Cosine        | 1%                  | 1                 | N  | 61.11%                   | 85.11%                   | 10.42%                 | 25.88%                 |
| Triplet Network    | 100%                | 1                 | N  | 70.47%                   | 90.61%                   | 1.26%                  | 4.94%                  |
| Triplet Network    | 10%                 | 1                 | N  | 66.64%                   | 88.42%                   | 3.48%                  | 11.40%                 |
| Triplet Network    | 1%                  | 1                 | N  | 60.09%                   | 84.83%                   | 8.84%                  | 22.24%                 |
| Fine-Tuned ResNet  | 100%                | 1                 | Y  | 76.28%                   | 93.17%                   | 2.82%                  | 13.30%                 |
| Learning like a Child | 100%           | 1                 | Y  | 76.71%                   | 93.24%                   | 2.90%                  | 17.14%                 |

| Ours-$\phi_1$      | 100%                | 1                 | N  | 72.56%                   | 91.12%                   | 19.88%                 | 43.20%                 |
| Ours-$\phi_2$      | 100%                | 1                 | N  | 74.17%                   | 91.79%                   | 21.58%                 | 45.82%                 |
| Ours-$\phi_2$*     | 100%                | 1                 | N  | 75.63%                   | 92.92%                   | 14.32%                 | 33.84%                 |
| NN + Cosine        | 100%                | 2                 | N  | 71.54%                   | 91.20%                   | 3.34%                  | 9.88%                  |
| NN + Cosine        | 10%                 | 2                 | N  | 67.66%                   | 88.89%                   | 7.60%                  | 19.94%                 |
| NN + Cosine        | 1%                  | 2                 | N  | 61.04%                   | 85.04%                   | 15.14%                 | 35.70%                 |
| Triplet Network    | 100%                | 2                 | N  | 70.47%                   | 90.61%                   | 2.34%                  | 8.30%                  |
| Triplet Network    | 10%                 | 2                 | N  | 66.63%                   | 88.41%                   | 6.10%                  | 17.46%                 |
| Triplet Network    | 1%                  | 2                 | N  | 60.02%                   | 84.74%                   | 13.42%                 | 32.38%                 |
| Fine-Tuned ResNet  | 100%                | 2                 | Y  | 76.27%                   | 93.13%                   | 10.32%                 | 30.34%                 |
| Learning like a Child | 100%           | 2                 | Y  | 76.68%                   | 93.17%                   | 11.54%                 | 37.68%                 |

| Ours-$\phi_1$      | 100%                | 2                 | N  | 71.94%                   | 90.62%                   | 25.54%                 | 52.98%                 |
| Ours-$\phi_2$      | 100%                | 2                 | N  | 73.43%                   | 91.13%                   | 27.44%                 | 55.86%                 |
| Ours-$\phi_2$*     | 100%                | 2                 | N  | 75.44%                   | 92.74%                   | 18.70%                 | 49.76%                 |
| NN + Cosine        | 100%                | 3                 | N  | 71.54%                   | 91.20%                   | 4.58%                  | 12.72%                 |
| NN + Cosine        | 10%                 | 3                 | N  | 67.65%                   | 88.88%                   | 9.86%                  | 24.96%                 |
| NN + Cosine        | 1%                  | 3                 | N  | 60.97%                   | 84.95%                   | 18.68%                 | 42.16%                 |
| Triplet Network    | 100%                | 3                 | N  | 70.47%                   | 90.61%                   | 3.22%                  | 11.48%                 |
| Triplet Network    | 10%                 | 3                 | N  | 66.62%                   | 88.40%                   | 8.52%                  | 22.52%                 |
| Triplet Network    | 1%                  | 3                 | N  | 59.97%                   | 84.66%                   | 17.08%                 | 38.06%                 |
| Fine-Tuned ResNet  | 100%                | 3                 | Y  | 76.25%                   | 93.07%                   | 16.76%                 | 39.92%                 |
| Learning like a Child | 100%          | 3                 | Y  | 76.55%                   | 93.00%                   | 18.56%                 | 50.70%                 |

| Ours-$\phi_1$      | 100%                | 3                 | N  | 71.56%                   | 90.21%                   | 28.72%                 | 58.50%                 |
| Ours-$\phi_2$      | 100%                | 3                 | N  | 72.98%                   | 90.59%                   | 31.20%                 | 61.44%                 |
| Ours-$\phi_2$*     | 100%                | 3                 | N  | 75.34%                   | 92.60%                   | 22.32%                 | 49.76%                 |

Table 2 also compares $\phi_2$ and $\phi_2^*$, which are trained to minimize Eq. 2 and Eq. 1, respectively. Since during training $\phi_2^*$ only mean activations are sampled, it shows a bias towards $C_{\text{large}}$. However, it still outperforms other baseline methods on $C_{\text{few}}$. In short, modeling using Eq. 2 and Eq. 1 shows a tradeoff between $C_{\text{large}}$ and $C_{\text{few}}$.

### 4.4 Efficiency Analysis

We briefly discuss the efficiencies of each method including ours on adding novel classes and image inference. For adding novel classes, fine-tuned ResNet and Learning like a Child require re-training the neural networks, in which Learning like a Child is faster and more efficient since it only updates parts of the parameters. Our method only needs to predict the parameters for the novel categories using $\phi$ and add them to the original neural network. Siamese-Triplet Network and nearest neighbor require no operations for adapting to novel categories. For image inference, Siamese-Triplet Network and nearest neighbor are very slow since they will look over the entire dataset. Fine-tuned ResNet, Learning like a Child and our method are very fast since at the inference stage, these three methods are just normal deep neural networks. In a word, compared with other methods, our method is fast and efficient in both novel category adaptation and image inference.

### 4.5 Comparing Activation Impacts

In this subsection we investigate what $\phi_1$ has learned that helps it perform better than the cosine distance, which is a special solution for one-layer $\phi$ by setting $\phi$ to the identity matrix $I$. We first visualize the matrix $\phi_{ij}$ in log scale as shown in the left image of Figure 5. Due to the space limit, we

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*Table 2 also compares $\phi_2$ and $\phi_2^*$, which are trained to minimize Eq. 2 and Eq. 1, respectively. Since during training $\phi_2^*$ only mean activations are sampled, it shows a bias towards $C_{\text{large}}$. However, it still outperforms other baseline methods on $C_{\text{few}}$. In short, modeling using Eq. 2 and Eq. 1 shows a tradeoff between $C_{\text{large}}$ and $C_{\text{few}}$.**
In this paper, we study a novel problem: can we develop a unified approach that works for both large-scale and few-shot learning. Our motivation is based on the observation that in the final classification layer of a pre-trained neural network, the parameter vector and the activation vector have highly similar structures in space. This motivates us to learn a category-agnostic mapping from activations to parameters. Once this mapping is learned, the parameters for any novel category can be predicted by a simple forward pass, which is significantly more convenient than re-training used in parametric methods or enumeration of training set used in non-parametric approaches.

We experiment our novel approach on the challenging ImageNet dataset, both because of the large number of categories (1000) and the very limited number (< 4) of training samples for $C_{new}$. We show promising results, achieving state-of-the-art classification accuracy on novel categories by a significant margin while maintaining comparable performance on the large-scale classes. We further visualize and analyze the learned parameter predictor, as well as demonstrate the similarity between the predicted parameters and those of the classification layer in the pre-trained deep neural network in terms of the activation impact.

\section{Conclusion}

For a fixed activation space, we define the \textit{impact} of its $j$-th channel on mapping $\phi$ by $I_j(\phi) = \sum_i |\phi_{ij}|$. Similarly, we define the activation impact $I_j(\cdot)$ on $w_{pt}^{large}$ which is the parameter matrix of the last fully connected layer of $R_{pt}^{large}$. For cosine distance, $I_j(1) = 1$, $\forall j$. Intuitively, we are evaluating the impact of each channel of $a$ on the output by adding all the weights connected to it. For $w_{pt}^{large}$ which is trained for the classification task using large-amounts of data, if we normalize $I(w_{pt}^{large})$ to unity, the mean of $I(w_{pt}^{large})$ over all channel $j$ is $2.13e^{-2}$ and the standard deviation is $5.83e^{-3}$. $w_{pt}^{large}$ does not use channels equally, either.

In fact, $\phi^1$ has a high similarity with $w_{pt}^{large}$. We show this by comparing the orders of the channels sorted by their impacts. Let top-$k(S)$ find the indexes of the top-$k$ elements of $S$. We define the top-$k$ similarity of $I(\phi)$ and $I(w_{pt}^{large})$ by

\begin{equation}
    OS(\phi, w_{pt}^{large}, k) = \frac{\text{card} \left( \text{top}-k(I(\phi)) \cap \text{top}-k(I(w_{pt}^{large})) \right)}{k}
\end{equation}

where \text{card} is the cardinality of the set. The right image of Figure 5 plots the two similarities, from which we observe high similarity between $\phi$ and $w_{pt}^{large}$ compared to the random order of $1$. From this point of view, $\phi^1$ outperforms the cosine distance due to its better usage of the activations.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure5.png}
\caption{Visualization of the upper-left $256 \times 256$ submatrix of $\phi^1$ in log scale (left) and top-$k$ similarity between $\phi^1$, $1$ and $w_{pt}^{large}$ (right). In the right plotting, red and solid lines are similarities between $\phi^1$ and $w_{pt}^{large}$, and green and dashed lines are between $1$ and $w_{pt}^{large}$ only show the upper-left $256 \times 256$ submatrix. Not surprisingly, the values on the diagonal dominates the matrix. We observe that along the diagonal, the maximum is 0.976 and the minimum is 0.744, suggesting that different from $1$, $\phi^1$ does not use each activation channel equally. We speculate that this is because the pre-trained activation channels have different distributions of magnitudes and different correlations with the classification task. These factors can be learned by the last fully connected layer of $R_{pt}^{large}$, with large amounts of data but are assumed equal for every channel in cosine distance. This motivates us to investigate the impact of each channel of the activation space.

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