Learning by Examples Based on Multi-level Optimization

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Abstract

Learning by examples, which learns to solve a new problem by looking into how similar problems are solved, is an effective learning method in human learning. When a student learns a new topic, he/she finds out exemplar topics that are similar to this new topic and studies the exemplar topics to deepen the understanding of the new topic. We aim to investigate whether this powerful learning skill can be borrowed from humans to improve machine learning as well. In this work, we propose a novel learning approach called Learning By Examples (LBE). Our approach automatically retrieves a set of training examples that are similar to query examples and predicts labels for query examples by using class labels of the retrieved examples. We propose a three-level optimization framework to formulate LBE which involves three stages of learning: learning a Siamese network to retrieve similar examples; learning a matching network to make predictions on query examples by leveraging class labels of retrieved similar examples; learning the "ground-truth" similarities between training examples by minimizing the validation loss. We develop an efficient algorithm to solve the LBE problem and conduct extensive experiments on various benchmarks where the results demonstrate the effectiveness of our method on both supervised and few-shot learning.

1 Introduction

Learning by examples is a broadly used technique in human learning. For example, in course learning, given a new topic for students, students will find out exemplar topics that are similar to this new topic and study the exemplar topics to deepen the understanding of the new topic. The study in [20, 21, 54] shows that learning by examples is a powerful tool for helping people learn new things.

Inspired by this examples-driven learning technique of humans, we are interested in investigating whether this methodology can be helpful for improving the abilities of machine learning as well. We propose a novel learning framework called learning by examples (LBE). In this framework, the model is trained to retrieve a set of training examples that are similar to the query examples and predict labels for query examples by using the class labels of the retrieved examples. The model consists of a Siamese network and a matching network. The Siamese network is trained to retrieve similar examples and the matching network is trained to make predictions on query examples by leveraging retrieved similar examples. Our framework is formulated as a three-level optimization problem that involves three learning stages. In the first learning stage, we train a Siamese network $T^*$ by minimizing the cross-entropy loss between predicted similarity by $T$ and the ground-truth similarity.

In this stage, the ground-truth similarities are fixed. They will be updated at a later stage. The optimal solution $T^*(A)$ is a function of $A$ since $T^*(A)$ is a function of the cross-entropy loss and the cross-entropy loss is a function of $A$. In the second stage, we use the Siamese network $T^*(A)$ trained in the first stage to retrieve a subset of training examples $B$ similar to each query example. Then
we train the matching network $S$ to predict labels for query examples using the labels of retrieved examples $B$. Note that the optimal solution $S^*(T^*(A))$ is a function of $T^*(A)$ since $S^*(T^*(A))$ is a function of the cross entropy loss and the cross entropy loss is a function of $T^*(A)$. In the third stage, we apply $S^*(T^*(A))$ to make predictions on the validation set and update $A$ by minimizing the validation loss. The three stages are performed jointly end-to-end, where different stages influence each other. Experiments on various benchmarks demonstrate the effectiveness of our method.

The major contributions of this paper are summarized as follows:

- Inspired by the examples-driven learning technique of humans, we propose a novel machine learning approach called learning by examples (LBE). Our approach automatically retrieves a set of training examples that are similar to query examples and predicts labels for query examples by using the class labels of the retrieved ones.
- We propose a multi-level optimization framework to formulate LBE which involves three stages of learning: learning to retrieve similar examples by a Siamese network; learning to make predictions using retrieved examples by a matching network; learning the "ground-truth" similarity matrix between training examples by minimizing the validation loss.
- We develop an efficient optimization algorithm to solve the LBE problem.
- Experiments on various benchmarks demonstrate the effectiveness of our method on supervised and few-shot learning.

The rest of the paper is organized as follows. Section 2 and 3 present the method and experiments respectively. Section 4 reviews related works. Section 5 concludes the paper.

## 2 Method

In this section, we propose a framework called learning by examples (LBE) and develop an optimization algorithm for solving the LBE problem in Figure 2. The solid arrows denote the process of making predictions and calculating losses. The dotted arrows denote the process of updating learnable parameters by minimizing corresponding losses. To easy reading, we summarize the notations in Table 1.

**Figure 1:** Illustration of learning by examples. The Retriever (a Siamese network $T$) and the Kernel density estimator (a matching network $S$) are used to make predictions for Validation examples. The similarity matrix $A$ of training examples is updated by minimizing corresponding losses of Validation performance.

**Figure 2:** Learning by examples.

**Table 1:** Notations in learning by examples.

| Notation | Meaning |
|----------|---------|
| $N$      | the number of training examples |
| $M$      | the number of validation examples |
| $x_i$, $x_j$ | two training examples $i$ and $j$ |
| $y_i$, $y_j$ | the groundtruth label of $x_i$ and $x_j$ |
| $u_i$  | a validation example $i$ |
| $t$    | the groundtruth label of $u_i$ |
| $A$    | the similarity matrix between training examples |
| $A_{i,j}$ | the similarity matrix between training examples $i$ and $j$ |
| $T$    | the parameters of Siamese network |
| $S$    | the parameters of matching network |
| $D^{(tr)}$ | training dataset |
| $D^{(val)}$ | validation dataset |
2.1 Learning by Examples

Learning from examples is a broadly used human learning technique. When a student learns a new topic, he/she finds out exemplary topics that are similar to this new topic and studies the exemplary topics to deepen the understanding of the new topic. We aim to leverage this human learning skill to help with machine learning. Given a query example, we first retrieve a set of training examples that are similar to the query. Then we use the class labels of the retrieved examples to predict the label of the query.

Without loss of generality, we assume the end task is image classification while noting that our framework can be applied to other tasks as well. Let $N$ be the number of training examples. Let $A$ be a $N \times N$ learnable matrix, where $A_{ij} \in [0, 1]$ indicates the similarity between training example $i$ and $j$. A larger $A_{ij}$ indicates more similarity. Let $f(x_i, x_j; T)$ be a Siamese network with network weights $T$. $f(x_i, x_j; T)$ takes two images $x_i$ and $x_j$ as inputs and outputs a probability indicating how similar $x_i$ and $x_j$ are. Our framework involves three inter-dependent learning stages. In the first stage, we train $T$ by solving the following optimization problem:

$$T^*(A) = \min_T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} -A_{ij} \log f(x_i, x_j; T)$$

where $A_{ij}$ is treated as the “ground-truth” similarity between example $i$ and $j$. The Siamese network is trained to match the “ground-truth”. In the second stage, for each training example $x_i$, we use the Siamese network trained in the first stage to retrieve a subset of training examples $B$ that are similar to $x_i$. Then we train a matching network parameterized by $S$. The matching network predicts the label $\hat{y}_i$ for $x_i$ in the following way:

$$\hat{y}_i = \sum_{x_j \in B} c(x_i, x_j; S)y_j$$

where $c(x_i, x_j; S)$ calculates the similarity between $x_i$ and $x_j$. $y_j$ is the groundtruth label of $x_j$. Eq. (2) can be relaxed to

$$\hat{y}_i = \sum_{j=1}^{N} f(x_i, x_j; T^*(A))c(x_i, x_j, S)y_j$$

We learn $S$ by solving the following optimization problem:

$$S^*(T^*(A)) = \min_S \sum_{i=1}^{N} -y_i \log(\sum_{j=1}^{N} f(x_i, x_j; T^*(A))c(x_i, x_j, S)y_j)$$

where $y_i$ is the ground-truth label of $x_i$. Given the trained Siamese network and matching network, we perform prediction on the validation examples and get the following validation loss

$$\sum_{i=1}^{M} -t_i \log(\sum_{j=1}^{N} f(u_i, x_j; T^*(A))c(u_i, x_j, S^*(T^*(A)))y_j)$$

where $M$ is the number of validation examples, $u_i$ is a validation example and $t_i$ is its class label. We learn the matrix $A$ by minimizing this loss. Putting these pieces together, we get the following overall formulation.

$$\min_A \sum_{i=1}^{M} -t_i \log(\sum_{j=1}^{N} f(u_i, x_j; T^*(A))c(u_i, x_j, S^*(T^*(A)))y_j)$$

s.t. $S^*(T^*(A)) = \min_S \sum_{i=1}^{N} -y_i \log(\sum_{j=1}^{N} f(x_i, x_j; T^*(A))c(x_i, x_j, S)y_j)$

$$T^*(A) = \min_T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} -A_{ij} \log f(x_i, x_j; T)$$

3
Note that there are multiple notations of similarity in this formulation. The Siamese network calculates similarities between the query and all training examples for retrieving similar training examples. The matching network calculates similarities between query and retrieved examples to predict the class label for the query. The similarity in $A$ is the “ground-truth” similarity between training examples.

### 2.2 Optimization Algorithm

In this section, we derive an optimization algorithm for solving the LBE problem defined in Eq. (6). To explain how to solve the optimization problem, we denote the above formulation simply as

$$
\min_A L(T^*(A), S^*(T^*(A)), D^{(\text{val})})
$$

subject to

$$
S^*(T^*(A)) = \min_S L(T^*(A), S, D^{(\text{tr})})
$$

where $D^{(\text{tr})}$ and $D^{(\text{val})}$ denote the training data and validation data. Inspired by [37], we approximate $T^*(A)$ using one-step gradient descent update of $T$ with respect to $L(A, T, D^{(\text{tr})})$, then plug in $T^*(A)$ into $L(T^*(A), S, D^{(\text{tr})})$ to approximate $S^*(T^*(A))$ using one-step gradient descent update of $S$ with respect to its objective. Then we plug in these two approximations into $L(T^*(A), S^*(T^*(A)), D^{(\text{val})})$ and perform gradient-descent update of $A$ with respect to this approximated objective. In the sequel, we use $\nabla^2_{X,Y} f(X,Y)$ to denote $\frac{\partial^2 f(X,Y)}{\partial X \partial Y}$.

Approximating $T^*(A)$ using $T' = T - \xi_T \nabla_T L(A, T, D^{(\text{tr})})$ where $\xi_T$ is a learning rate, we can calculate the approximated gradient of $L(T^*(A), S, D^{(\text{tr})})$ w.r.t $S$ as:

$$
\nabla_S L(T^*(A), S, D^{(\text{tr})}) \approx \nabla_S L(T', S, D^{(\text{tr})})
$$

Then we can approximate $S^*(T^*(A))$ using $S' = S - \xi_S \nabla_S L(T', S, D^{(\text{tr})})$ where $\xi_S$ is also a learning rate. We can approximate $T^*(A)$ and $S^*(T^*(A))$ using the following one-step gradient descent update of $T$ and $S$ respectively:

$$
T' = T - \xi_T \nabla_T L(A, T, D^{(\text{tr})}), \quad S' = S - \xi_S \nabla_S L(T', S, D^{(\text{tr})})
$$

where $\xi_T$ and $\xi_S$ are learning rates. Plugging in these approximations into the objective function $L(T^*(A), S^*(T^*(A)), D^{(\text{val})})$, we can learn $A$ by minimizing the objective $L(T', S', D^{(\text{val})})$ using gradient methods. The derivative of this objective with respect to $A$ can be calculated as:

$$
\nabla_A L(T', S', D^{(\text{val})}) = \frac{\partial T'}{\partial A} \nabla_T L(T', S', D^{(\text{val})}) + \frac{\partial S'}{\partial A} \nabla_S L(T', S', D^{(\text{val})})
$$

where

$$
\frac{\partial T'}{\partial A} = -\xi_T \nabla^2_{A,T} L(A, T, D^{(\text{tr})}), \quad \frac{\partial S'}{\partial A} = -\xi_S \nabla^2_{T,S} L(T', S, D^{(\text{tr})})
$$

$\nabla^2_{A,T} L(A, T, D^{(\text{tr})}) \nabla_T L(T', S', D^{(\text{val})})$ involves expensive matrix-vector product. We can reduce the computational complexity by a finite difference approximation:

$$
\nabla^2_{A,T} L(A, T, D^{(\text{tr})}) \nabla_T L(T', S', D^{(\text{val})}) \approx \frac{1}{2\alpha_T} \left( \nabla_A L(A, T^+, D^{(\text{tr})}) - \nabla_A L(A, T^-, D^{(\text{tr})}) \right)
$$

where $T^\pm = T \pm \alpha_T \nabla_T L(T', S', D^{(\text{val})})$, and $\alpha_T$ is a small scalar that equals to $0.01/\|\nabla_T L(T', S', D^{(\text{val})})\|_2$.

Similar to Eq. (12), using finite difference approximation to calculate

$$
\nabla^2_{T,S} L(T', S, D^{(\text{tr})}) \nabla_S L(T', S', D^{(\text{val})}) \approx \frac{1}{2\alpha_S} \left( \nabla_T L(T', S^+, D^{(\text{tr})}) - \nabla_T L(T', S^-, D^{(\text{tr})}) \right)
$$

we have:

$$
\nabla^2_{T,S} L(T', S, D^{(\text{tr})}) \nabla_S L(T', S', D^{(\text{val})}) \approx \frac{1}{2\alpha_S} \left( \nabla_T L(T', S^+, D^{(\text{tr})}) - \nabla_T L(T', S^-, D^{(\text{tr})}) \right)
$$
where \( S^\pm = S \pm \alpha_S \nabla_S L(T', S', D^{(\text{val})}) \), and \( \alpha_S \) is a small scalar that equals to \( 0.01/\|\nabla S' L(T', S', D^{(\text{val})})\|_2 \).

The overall algorithm for solving the LBE problem is summarized in Algorithm 1.

**Algorithm 1** Optimization algorithm for learning by examples

```plaintext
while not converge do
    1. Update the matrix \( A \) by descending the gradient calculated in Eq. (10-13)
    2. Update the the matching network parameters \( S \) by descending the gradient in Eq. (9)
    3. Update the weights \( T \) of the Siamese network by descending the gradient in Eq. (9)
end while
```

### 2.3 Fast Retrieval & Matching

When the training dataset is large, performing retrieval on a large number of training examples during test time is computationally inefficient. To address this problem, we design the retrieval network \( T \) in a way that facilitates fast retrieval. Given two images \( x_i \) and \( x_j \), we first encode them using a CNN to get their encodings \( e_i \) and \( e_j \). In the encoding vector, the value of each dimension is in \([0, 1]\) (after applying sigmoid). Then we transform these two encoding vectors into binary vectors \( h_i \) and \( h_j \), where elements in binary vectors are either 0 or 1. The transformation is as follows: for each dimension in an encoding vector where the value of this dimension is \( p \), we define a Bernoulli distribution parameterized by \( p \); then we sample a binary variable from this Bernoulli distribution.

Given these two binary vectors \( h_i \) and \( h_j \), we calculate the similarity of the two images by taking the Hamming distance between \( h_i \) and \( h_j \). The similarity is denoted by \( f(x_i, x_j; T) \). The rest of Eq. (6) remains the same. The binary vectors are not end-to-end differentiable. To address this problem, we use the Gumbel-softmax \([26]\) trick. Hamming distance between binary vectors can be calculated very efficiently, which facilitates fast retrieval. There are three variants of the vanilla LBE model for fast retrieval: (1) LBE-fast-\( T \), where we apply hash codes for \( T \) and continuous representations for \( S \); (2) LBE-fast-\( S \), where we apply hash codes for \( S \) and continuous representations for \( T \); (3) LBE-fast-\( TS \), where we apply hash codes for both \( T \) and \( S \).

### 3 Experiments

#### 3.1 Datasets

We used four datasets in the experiments: CIFAR-10, CIFAR-100, ImageNet \([10]\), and Tiny-ImageNet \([63]\). The CIFAR-10 dataset contains 50K training images and 10K testing images, from 10 classes (the number of images in each class is equal). We split the original 50K training set into a new 45K training set and a 5K validation set. In the sequel, when we mention “training set”, it always refers to the new 45K training set. The CIFAR-100 dataset contains 50K training images and 10K testing images, from 100 classes (the number of images in each class is equal). Similar to CIFAR-10, the 50K training images are split into a 45K training set and 5K validation set. The usage of the new training set and validation set is the same as that for CIFAR-10. The ImageNet dataset contains a training set of 1.2M images and a validation set of 50K images, from 1000 object classes. The validation set is used as a test set for architecture evaluation. The Tiny-ImageNet dataset is a modified subset of the original ImageNet dataset, where there are 200 different classes instead of 1000 classes of the ImageNet dataset, with 100K training examples and 10K validation examples. The usage of the validation set is the same as that for the ImageNet dataset.

For few-shot experiments, we use Omniglot \([33]\), miniImageNet \([10]\) and tiredImageNet \([10]\). We closely follow previous methods \([61]\) and compare our LBE framework against strong baselines. All of our experiments revolve around the same basic task: an \( N \)-way \( k \)-shot learning task. During the meta-training stage, we use \( N \) classes and \( k \) samples per class in the support set. Then we predict the label for the tested batch set which has the same classes as the support set. In our LBE framework, we take this support set as the training set \( D^{(tr)} \) and the batch set as the validation set \( D^{(val)} \). Then we do the three-level optimization task in the LBE framework. During the meta-test stage, we apply the same setting as the training stage and provide a support set \( (N \) classes and \( k \) samples per class) from unseen classes. We compared a number of alternative models, as baselines, to our LBE framework.
3.2 Baselines

For experiments on CIFAR-10, CIFAR-100, ImageNet [10], and Tiny-ImageNet [65], we compare with the supervised learning method as our baseline to validate the rationality of learning by examples. We also implement state-of-the-art ResNet [22] series models (ResNet-18, ResNet-34, ResNet-50, ResNet-101, ResNet-152, ResNeXt-50, ResNeXt-101, wide ResNet-50, wide ResNet-101) as the backbone for comprehensive comparison. In order to prove the effectiveness of learning by examples on the few-shot setting, we also apply previous few-shot learning methods [61, 49, 15, 60, 54, 42, 46, 35, 63, 27, 7] as our baselines for a comprehensive comparison.

3.3 Experiment Settings

The Siamese and matching network weights are optimized using SGD with a momentum of 0.9 and a weight decay of 3e-4. The initial learning rate is set to 0.01 with a cosine decay scheduler. The similarity matrix is optimized with the Adam [29] optimizer with a learning rate of 1e-3 and a weight decay of 1e-3. The network is trained for 1000 epochs with a batch size of 32 (for both CIFAR-10 and CIFAR-100). The experiments are performed on a single Tesla v100. For ImageNet and Tiny-ImageNet, the network is trained for 1000 epochs with a batch size of 64 on one Tesla v100 GPU. Each experiment on LBE is repeated ten times with the random seed to be from 1 to 10. We report the mean and standard deviation of results obtained from 10 runs using different random seeds.

3.4 Results

3.4.1 Supervised Settings

Table 2: Comparison results on the CIFAR-10.

| Backbone       | Supervised | LBE |
|----------------|------------|-----|
| ResNet-18      | 92.95±0.11 | 99.25±0.08 |
| ResNet-34      | 93.23±0.12 | 99.43±0.07 |
| ResNet-50      | 93.41±0.13 | 99.54±0.09 |
| ResNet-101     | 93.69±0.11 | 99.61±0.04 |
| ResNet-152     | 93.62±0.11 | 99.58±0.02 |
| ResNeXt-50     | 96.21±0.13 | 99.85±0.02 |
| ResNeXt101     | 96.36±0.09 | 99.85±0.02 |
| wide_ResNet50  | 95.83±0.13 | 99.56±0.05 |
| wide_ResNet101 | 96.11±0.12 | 99.79±0.05 |

Table 3: Comparison results on the CIFAR-100.

| Backbone       | Supervised | LBE |
|----------------|------------|-----|
| ResNet-18      | 75.61±0.11 | 93.05±0.05 |
| ResNet-34      | 76.76±0.13 | 93.37±0.04 |
| ResNet-50      | 77.39±0.12 | 93.96±0.03 |
| ResNet-101     | 77.88±0.14 | 94.39±0.04 |
| ResNet-152     | 77.69±0.13 | 94.19±0.05 |
| ResNeXt-50     | 80.07±0.12 | 94.96±0.04 |
| ResNeXt101     | 82.86±0.10 | 95.01±0.03 |
| wide_ResNet50  | 80.75±0.11 | 94.73±0.05 |
| wide_ResNet101 | 81.34±0.12 | 94.85±0.04 |

Table 4: Comparison results on the ImageNet.

| Backbone       | Supervised | LBE |
|----------------|------------|-----|
| ResNet-18      | 69.57±0.18 | 89.24±0.08 |
| ResNet-34      | 73.27±0.16 | 91.26±0.07 |
| ResNet-50      | 75.99±0.17 | 92.98±0.07 |
| ResNet-101     | 77.56±0.15 | 93.79±0.06 |
| ResNet-152     | 77.84±0.16 | 93.84±0.07 |
| ResNeXt-50     | 77.78±0.16 | 93.91±0.07 |
| ResNeXt101     | 78.77±0.15 | 94.28±0.06 |
| wide_ResNet50  | 78.08±0.17 | 93.97±0.08 |
| wide_ResNet101 | 78.29±0.16 | 94.08±0.07 |

Table 5: Results on the Tiny-ImageNet.

| Backpack       | Supervised | LBE |
|----------------|------------|-----|
| ResNet-18      | 58.55±0.16 | 78.95±0.07 |
| ResNet-34      | 61.34±0.15 | 79.62±0.06 |
| ResNet-50      | 61.12±0.15 | 79.32±0.06 |
| ResNet-101     | 62.45±0.14 | 80.87±0.05 |
| ResNet-152     | 61.86±0.15 | 79.58±0.04 |
| ResNeXt-50     | 62.67±0.15 | 80.95±0.05 |
| ResNeXt101     | 63.01±0.14 | 81.13±0.05 |
| wide_ResNet50  | 62.13±0.15 | 79.95±0.06 |
| wide_ResNet101 | 62.34±0.15 | 80.36±0.04 |

Table 2 shows the top-1 and top-5 classification accuracy (%) of supervised learning and LBE on CIFAR-10 dataset. From this table, we make the following observations. First, our method achieves competitive performance compared to the supervised learning baseline in 7 out of the 9 backbones and achieves a smaller standard deviation of averaged top-1 and top-5 accuracy than the baselines. This demonstrates the effectiveness of our method. Our method learns to retrieve a set of training examples that are similar to the query examples and predicts labels for query examples by using the class labels of the retrieved ones. The Siamese network calculates similarities between the query and all training examples for retrieving similar training examples. The matching network calculates the similarity between the query and retrieved examples to predict the class label for the query. The most important similarity matrix is updated to generate “ground truth” similarity between training examples. Instead of using the specific similarity between examples, the supervised learning method is just using the general class label of training examples to train the network, which might cause the trained model to overfit the training set easily and harder to generalize well to new data. Second, our method achieves the best performance using the ResNeXt101 backbone, which further demonstrates the effectiveness of LBE in driving the frontiers of image classification forward.
Table 4 shows the top-1 and top-5 classification accuracy (%) of supervised learning and LBE on ImageNet and Tiny-ImageNet datasets. Applying our proposed LBE method to each backbone, we can achieve comparable, even better classification performance on the test set compared to the baselines. Especially when we use the ResNeXt101 backbone, our method achieves the best performance among all backbones. This further demonstrates the effectiveness of learning by examples.

### 3.4.2 Omniglot & miniImageNet & tieredImageNet

We closely follow the few-shot setting same as [61] and report the accuracy of 5-way 1-shot, 5-way 5-shot, 20-way 1-shot, and 20-way 5-shot experiments on the Omniglot dataset in Table 6. As can be seen, we make two observations: First, under the same-way setting, our LBE can achieve comparable performance in the 1-shot setting and perform better results in terms of the 5-shot case. Second, under the same-shot setting, given more classes, the increasing gap between our LBE and MatchingNet becomes larger, which demonstrates the advantage of our LBE on retrieving a set of examples automatically from the given support set that is similar to the query examples in the tested batch set. Table 7 report the five-way classification results on miniImageNet dataset using various networks. In the 5-way 5-shot setting using WRN-28-10, our LBE (81.78%) outperforms MatchingNet [61] (76.32%) by a large margin, i.e., 5.46%. And our LBE also can achieve comparable results with SimpleShot [63], although we do not need any feature normalization tricks used in SimpleShot. This also validates the rationality of our LBE on retrieving a set of examples from the given support set that are similar to the query examples in the tested batch set.

For the few-shot setting on the tieredImageNet dataset, we also implement the same network architecture (ResNet-18, MobileNet, WRN-28-10) as SimpleShot [63] in our Siamese and matching network. The results are reported in Table 10. Our LBE framework outperforms most baselines in both few-shot settings using those above networks. Note that when using WRN-28-10, our LBE can outperform the SimpleShot by 1.28%, in terms of the 5-way 1-shot setting. This infers the importance of the Siamese and matching network in our LBE framework for the few-shot learning.

### 3.4.3 Visualizations

To better analyze the “ground-truth” similarity matrix learned in our proposed LBE framework, we select 20 random training examples and visualize their similarity matrix at three epochs (0, 500, 1000) during the training process. As can be seen in Figure 3, our proposed LBE framework captures the “ground-truth” similarity between training examples, which is consistent with the class label of

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**Table 6: Results on the Omniglot dataset.**

| Model         | 1-shot (%) | 5-way (%) | 20-way (%) |
|---------------|------------|-----------|------------|
| MANN [53]     | 82.80      | 94.90     |            |
| Siamese Net [30] | 97.30      | 98.40     | 88.10      | 97.00 |
| MAML [15]     | 98.70      | 99.90     | 95.80      | 98.90 |
| VAMPIRE [44]  | 96.27      | 98.77     | 86.60      | 96.14 |
| ProtoNet [57] | 98.80      | 99.70     | 96.00      | 98.90 |
| RelationNet [59] | 99.60      | 99.80     | 97.60      | 99.10 |
| MAML++ [13]   | 99.47      |           | 97.65      | 99.33 |
| MatchingNet [61] | 98.10      | 98.90     | 93.80      | 98.50 |
| LBE (w/o weight tying) | 98.93 (0.83) | 99.35 (1.45) | 97.07 (13.27) | 99.01 (10.51) |
| LBE (w. weight tying) | **99.23 (+1.13)** | **99.61 (+0.71)** | **97.25 (+13.45)** | **99.22 (+0.72)** |

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**Table 7: Results on the miniImageNet dataset for five-way classification using various networks.**

| Method            | Network       | 1-shot (%) | 5-shot (%) | Method            | Network       | 1-shot (%) | 5-shot (%) |
|-------------------|---------------|------------|------------|-------------------|---------------|------------|------------|
| Quo et al. [48]   | WRN-28-10     | 59.60±0.41 | 73.74±0.19 | SimpleShot [63]   | (UN)          | MobileNet  | 55.70±0.20 | 77.46±0.15 |
| MatchingNet [61]  | WRN-28-10     | 64.03±0.20 | 76.32±0.16 | SimpleShot [63]   | (L2N)         | MobileNet  | 59.43±0.20 | 78.00±0.15 |
| LEO [51]          | WRN-28-10     | 61.76±0.08 | 77.59±0.12 | SimpleShot [63]   | (CL2N)        | MobileNet  | 61.30±0.20 | 78.37±0.15 |
| ProtoNet [57]     | WRN-28-10     | 62.60±0.20 | 79.97±0.14 | LBE (w/o weight tying) | MobileNet | 62.68±0.20 | 79.73±0.14 |
| FEAT [47]         | WRN-28-10     | 65.10±0.20 | 81.11±0.14 | LBE (w. weight tying) | MobileNet | 62.81±0.19 | **80.04±0.13** |
| SimpleShot [63]   | (UN)          | WRN-28-10  | 57.26±0.21 | 78.99±0.14 | SimpleShot [63] | (UN)         | DenseNet  | 57.81±0.21 | 80.43±0.15 |
| SimpleShot [63]   | (L2N)         | WRN-28-10  | 61.22±0.21 | 81.05±0.14 | SimpleShot [63] | (L2N)        | DenseNet  | 61.49±0.20 | 81.48±0.14 |
| SimpleShot [63]   | (CL2N)        | WRN-28-10  | 63.50±0.20 | 80.35±0.14 | SimpleShot [63] | (CL2N)       | DenseNet  | 64.29±0.20 | 81.50±0.14 |
| Dhillon et al. [11] | WRN-28-10     | 65.73±0.68 | 78.40±0.52 | LBE (w/o weight tying) | DenseNet | 66.36±0.18 | 82.74±0.12 |
| SIB [49]          | WRN-28-10     | 70.08±0.60 | 79.20±0.40 | LBE (w. weight tying) | DenseNet | 66.82±0.17 | **83.91±0.11** |
| BD-CSRN [55]     | WRN-28-10     | 70.31±0.93 | 81.89±0.60 | LBE (w/o weight tying) | WRN-28-10 | 72.92±0.18 | 83.45±0.12 |
| EPNet [60]        | WRN-28-10     | 70.74±0.85 | 84.34±0.53 | LBE (w. weight tying) | WRN-28-10 | **73.23±0.17** | **83.78±0.12** |
Table 8: Results on the minImageNet dataset for five-way classification using Conv-4 network.

| Model                | Network | 1-shot | 5-shot |
|---------------------|---------|--------|--------|
| MAML                | Conv-4  | 51.67±1.81 | 70.10±0.08 |
| MatchingNet [61]    | Conv-4  | 48.97±0.21 | 66.47±0.21 |
| SimpleShot [63]     | Conv-4  | 51.02±0.20 | 68.96±0.18 |
| LBE (w/o weight tying) | Conv-4  | 51.85±0.18 | 70.39±0.16 |
| LBE (w: weight tying) | Conv-4  | 52.43±0.16 | 71.06±0.15 |
| Meta SGD [65]       | WRN-28-10 | 62.95±0.03 | 79.34±0.06 |
| FEAT [67]           | WRN-28-10 | 70.41±0.23 | 84.38±0.16 |
| LEO [51]            | WRN-28-10 | 66.33±0.05 | 81.44±0.09 |
| SimpleShot [63] (CL2N) | WRN-28-10 | 63.85±0.21 | 84.17±0.15 |
| LBE (w: weight tying) | WRN-28-10 | 73.12±0.18 | 86.17±0.13 |

Table 9: Results on the minImageNet dataset for five-way classification using ResNet-18/15/12.

| Model                | Network | 1-shot | 5-shot |
|---------------------|---------|--------|--------|
| MAML                | ResNet-18 | 49.61±0.92 | 65.72±0.77 |
| MatchingNet [61]    | ResNet-18 | 51.87±0.77 | 75.68±0.63 |
| RelationNet [59]    | ResNet-18 | 52.48±0.86 | 69.83±0.68 |
| Meta SGD [65]       | ResNet-18 | 55.45±0.89 | 70.13±0.68 |
| RelationNet [59]    | ResNet-18 | 51.71±0.99 | 68.88±0.92 |
| LBE (w/o weight tying) | ResNet-18 | 56.30±0.40 | 73.90±0.30 |
| SimpleShot [63] (CL2N) | ResNet-18 | 56.88±0.62 | 71.94±0.57 |
| LBE (w: weight tying) | ResNet-18 | 58.50±0.30 | 76.70±0.30 |
| LBE (w: weight tying) | ResNet-18 | 59.23±0.99 | 72.35±0.71 |
| LBE (w: weight tying) | ResNet-18 | 62.35±0.66 | 74.53±0.54 |
| LBE (w: weight tying) | ResNet-18 | 68.25±0.20 | 80.02±1.04 |
| LBE (w: weight tying) | ResNet-18 | 64.26±0.18 | 81.23±0.12 |
| LBE (w: weight tying) | ResNet-18 | 64.48±0.16 | 81.41±0.11 |

Table 10: Results on the tiredImageNet dataset for five-way classification using various networks.

| Method               | Network | 1-shot | 5-shot |
|---------------------|---------|--------|--------|
| MAML [15]           | Conv-4  | 51.67±1.81 | 70.10±0.08 |
| MatchingNet [61]    | Conv-4  | 48.97±0.21 | 66.47±0.21 |
| SimpleShot [63]     | Conv-4  | 51.02±0.20 | 68.96±0.18 |
| LBE (w/o weight tying) | Conv-4  | 51.85±0.18 | 70.39±0.16 |
| LBE (w: weight tying) | Conv-4  | 52.43±0.16 | 71.06±0.15 |
| Meta SGD [65]       | WRN-28-10 | 62.95±0.03 | 79.34±0.06 |
| FEAT [67]           | WRN-28-10 | 70.41±0.23 | 84.38±0.16 |
| LEO [51]            | WRN-28-10 | 66.33±0.05 | 81.44±0.09 |
| SimpleShot [63] (CL2N) | WRN-28-10 | 63.85±0.21 | 84.17±0.15 |
| LBE (w: weight tying) | WRN-28-10 | 73.12±0.18 | 86.17±0.13 |

A larger similarity between the two examples means that the bigger probability that they are from the same class. The similarity between examples from different classes is smaller than 0.1, which means that our LBE framework is capable of retrieving a set of training examples that are from the same class. This will help our proposed LBE framework automatically retrieve a set of training examples that are similar to the query examples and predict labels for query examples by using the class labels of the retrieved examples. Given a query image, we report the top 10 retrieved images from MatchingNet [61], SimpleShot [63], and our LBE in Figure 4. There exist no false positives retrieved from our LBE, which further demonstrates the effectiveness of our LBE framework.

Figure 3: Visualization of the “groundtruth” similarity matrix between training examples by using LBE through the training process, where we select 20 random training examples with their class label (noted on x, y axis). The similarity value \( \alpha \in [0,1] \), and larger value indicates more similarity between two examples.

3.5 Ablation Study

In this section, we perform extensive ablation studies on fast retrieval & matching, weight tying of \( T \) and \( S \), and the temperature parameter in \( T \).

Fast retrieval & matching. Table 11 reports the results of the ablation study on applying hash codes to our LBE framework on the CIFAR-10 and ImageNet datasets. For training and inference speed per batch, our LBE-fast-T model can achieve 50.57% and 38.38% faster than the vanilla LBE, validating
Weight tying. Table 12 (Top rows) explores the effect of weight tying between the Siamese network and matching network on the final performance score. As can be seen, applying weight tying to each backbone can boost the top-1 classification accuracy further. To analyze the comprehensive contribution of the Siamese and matching network, we also apply different backbones to the Siamese and matching network, as shown in Table 12 (Bottom rows). We can observe that the Siamese network with a better backbone achieves larger improvements over the matching network. This
Temperature. Using the ResNet-18 backbone, we also explore the effect of the temperature parameter broadly applied for neural architecture search [37], data reweighting [56], hyperparameter tuning [14], and top-5 classification accuracy of our LBE framework. We can observe that larger temperature, the top-1 accuracy will decrease a lot. This further demonstrates the rationality of the Siamese network in our proposed LBE framework.

| train | val | Supervised top-1 | Supervised top-5 | LBE top-1 | LBE top-5 |
|-------|-----|-----------------|-----------------|----------|----------|
| 500   | 50  | 83.65±0.11      | 97.13±0.08      | 82.52±0.09 | 96.82±0.04 |
| 800   | 80  | 88.25±0.09      | 97.74±0.07      | 87.68±0.08 | 97.14±0.04 |
| 1000  | 100 | 90.82±0.10      | 98.52±0.06      | 89.03±0.07 | 97.58±0.03 |
| 2000  | 200 | 91.92±0.08      | 99.02±0.05      | 91.05±0.06 | 98.05±0.03 |
| 3000  | 300 | 91.95±0.08      | 99.04±0.06      | 91.65±0.05 | 98.43±0.04 |
| 4000  | 400 | 92.51±0.09      | 99.16±0.07      | 91.16±0.07 | 98.56±0.05 |
| 4500  | 500 | 92.95±0.11      | 99.25±0.08      | 92.03±0.06 | 98.83±0.03 |

Number of examples. Table 14 explores the effect of the number of training and validation examples on the final score of LBE. As can be seen, retrieving a set of training examples that are similar to the query examples in a bigger training and validation examples pool further help the matching network predict the class label for the query examples by using the “ground-truth” label from retrieved examples. Our LBE framework achieves competitive top-1 and top-5 accuracy compared to the supervised learning methods.

Batch size. As shown in Table 15 we also ablate the effect of the batch size on the performance of our proposed LBE framework and the supervised learning method. We can observe that the top-1 and top-5 classification accuracy of our LBE framework decreases with the increase of batch size by a smaller margin compared to the supervised approach. This validates the robustness of our LBE framework to the choice of batch size, which will save us memories given limited GPU resources.

4 Related Work

Learning similarities. Learning similarities plays a crucial role in the supervised machine learning literature. The aim of similarity learning is to learn a siamese network that measures how similar or associative two objects are. Generally, there are four common types of similarity and metric distance learning, including classification [61, 30, 52], regression [28, 47], ranking [6, 62] and locality sensitive hashing [8, 25]. In this work, we focus on classification similarity learning, i.e., learning a similarity function to classify other objects given the class of one object.

Leveraging data similarity for classification. Previous works [61, 30, 41] in metric learning achieves remarkable progress in few-shot-classification, where the model is trained to learn a mapping function that maps examples belonging to the same class close together while pulling separate classes apart. Similarities between features of samples from the support set and query set are computed to perform classification. Several approaches have been proposed for learning by examples. Common supervised learning approaches (AlexNet [32], ResNet [22], etc) use a bi-level optimization framework to update the network weights by matching the “ground-truth” class label of training examples directly.

Similar to learning similarity between examples in our LBE framework, metric learning ([19, 40, 31]) is an approach based directly on a distance metric that aims to establish similarity or dissimilarity between objects. The main purpose of metric learning is to learn a new metric to reduce the distances between samples of the same class and increase the distances between the samples of different classes. The methods in [61, 30, 41] perform similarity learning in the training and validation dataset separately. As a result, the validation performance of the model cannot be used to guide similarity learning. These works only focus on learning by examples using a bi-level optimization framework while our work aims to retrieve a set of training examples that are similar to the query examples using a three-level optimization framework.

Bi-level optimization. Our framework is based on bi-level optimization (BLO) [9]. BLO has been broadly applied for neural architecture search [57], data reweighting [56], hyperparameter tuning [14],
meta learning [16], learning rate tuning [4], label correction [69], etc. BLO involves two levels of optimization problems where the lower level learns model weights while the upper level learns meta parameters. BLO has been extended to multi-level optimization (MLO) which involves more than two levels of optimization problems. MLO has been applied for data generation [58], interleaving multi-task learning [2], data reweighting in domain adaptation [68], explainable learning [23], human-inspired learning [66], curriculum evaluation [13], mutual knowledge distillation [12], end-to-end knowledge distillation [55], etc.

5 Conclusions

In this paper, we propose a novel machine learning approach – learning by examples (LBE), inspired by the examples-driven learning technique of humans. Our LBE framework automatically retrieves a set of training examples that are similar to the query examples and predicts labels for query examples by using the class labels of the retrieved ones. We propose a multi-level optimization framework to formalize LBE which involves three learning stages: a Siamese network is trained to retrieve similar examples; a matching network is learned to make predictions on query examples by leveraging class labels of retrieved examples; the “ground-truth” similarities are updated by minimizing the validation loss calculated using the trained Siamese and matching network. Experiments on various benchmarks demonstrate the effectiveness of our method on both supervised and few-shot learning.

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