Evolving parametrized Loss for Image Classification Learning on Small Datasets

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Abstract

This paper proposes a meta-learning approach to evolving a parametrized loss function, which is called Meta-Loss Network (MLN), for training the image classification learning on small datasets. In our approach, the MLN is embedded in the framework of classification learning as a differentiable objective function. The MLN is evolved with the Evolutionary Strategy algorithm (ES) to an optimized loss function, such that a classifier, which optimized to minimize this loss, will achieve a good generalization effect. A classifier learns on a small training dataset to minimize MLN with Stochastic Gradient Descent (SGD), and then the MLN is evolved with the precision of the small-dataset-updated classifier on a large validation dataset. In order to evaluate our approach, the MLN is trained with a large number of small sample learning tasks sampled from FashionMNIST and tested on validation tasks sampled from FashionMNIST and CIFAR10. Experiment results demonstrate that the MLN effectively improved generalization compared to classical cross-entropy error and mean squared error.

1 Introduction

Deep learning task is always defined as $\theta^* = \arg\min_{\theta \in \Theta} \text{Loss}(f(\theta))$, which means that searching the parameters in the solution space $\theta \in \Theta$ to minimize the objective function $\text{Loss}(f(\theta))$[1]. And the gradient descent is the most common optimization method, which is shown in Formula 1.

$$
\theta_{t+1} = \theta_t - \alpha_t \times \frac{\partial \text{Loss}(f(\theta_t))}{\partial f(\theta_t)} \times \frac{\partial f(\theta_t)}{\partial \theta_t}
$$

(1)

Objective function plays an important role in the optimization process based on gradient descent, but the traditional loss function can’t guarantee the effect of convex optimization on the unseen data. Therefore, the large amounts of training data are necessary in the optimization process with traditional objective functions to guarantee the generalization ability of models. However, it is difficult to obtain the labeled datasets in some research fields, such as medicine and aerospace. Therefore, it is a matter of cardinal significance that researching on the parametrized objective function for small datasets.
We propose a parametrized objective function learning method based on meta learning. The traditional objective function is replaced by an artificial neural network called Meta-Loss Network (MLN) and the architecture of our method is shown in figure 1.

![Figure 1. The architecture of proposed method. Our method consists of two optimization loops. In the inner loop, a classifier is trained to solve a Classification task by MLN. In the outer loop, the parameters of MLN are adjusted with Evolution Strategy (ES) to obtain the best fitness.](image)

Our contributions include the following: 1) Formulating a meta-learning approach that learns a differentiable loss function for classification tasks; 2) Optimizing the parameter of MLN via ES, which overcoming the challenge that there is no explicit expression between loss function and generalization ability; 3) Demonstrating that it can train classifier faster than traditional objective functions, such as Cross Entropy(CE) and Mean Square Error(MSE); 4) Showing that the trained MLN can generalize to out-of-distribution test tasks. 5) Proposing a new idea of objective function construction, which combined with meta-knowledge. So that the objective function can ensure the ability of optimization and generalization.

### 2 Related work

At present, there are more and more researchers pay attention to Meta-Learning Method and apply it to different research fields, which can be divided into 3 categories: Model-based,
The method of providing prior knowledge for the model to adapt to new tasks quickly is called model-based method, which can be divided into pre-training neural network \([2]-[9]\) and generating the parameter of network with meta learner \([10], [11]\). \([2]-[9]\) These approaches are widely used for few-shot learning where target problems can be learned without over-fitting using few examples, given such a carefully chosen initial condition. \([10]\) MetaNet learns to fast parameterize underlying neural networks for rapid generalizations by processing a higher order meta information, resulting in a flexible AI model that can adapt to a sequence of tasks with possibly distinct input and output distributions. The goal of \([11]\) is to generate \(w\) that generalizes well from these few training examples i.e., to make \(w\) as close as to the desired \(w^*\), which indicate the corresponding underlying classifier learned from a large set of annotated samples of the same category.

The method of designing metric function with parametrized models to improve the optimization effect is called metric-based method. \([12]\) aims to learn a loss function \(L_\phi\) that outperforms the usual policy gradient surrogate loss. The learned loss function consists of temporal convolutions over the agent’s recent history. The loss could perform a form of system identification, inferring environment parameter and adapting how it guides the agent as a function of these parameter (e.g., by adjusting the effective learning rate of the agent). The loss function parameter \(\Phi\) are evolved through \(\text{ES}\) and the loss trains an agent’s policy \(\pi_\theta\) in an on-policy fashion via stochastic gradient descent. The task of \([13]\) is that finding and optimizing loss function can be framed as a functional regression problem. Genetic Loss-function Optimization accomplishes this through the following high-level steps: (1) loss function discovery: using approaches from genetic programming, a genetic algorithm builds new candidate loss functions, and (2) coefficient optimization: to further optimize a specific loss function, a covariance-matrix adaptation evolutionary strategy (CMA-ES) is leveraged to optimize coefficients. \([14], [15], [16]\) consists of two modules: an embedding module \(f_\phi\) and a relation module \(g_\phi\). Samples \(x_j\) in the query set \(Q\), and samples \(x_i\) in the sample set \(S\) are fed through the embedding module \(f_\phi\), which produces feature maps \(f_\phi(x_i)\) and \(f_\phi(x_j)\). The feature maps \(f_\phi(x_i)\) and \(f_\phi(x_j)\) are compared with operator \(C(f_\phi(x_i), f_\phi(x_j))\). The combined feature map of the sample and query are fed into the
relation module $g_{\phi}$, which eventually produces a scalar in range of 0 to 1 representing the similarity between $x_j$ and $x_i$, which is called relation score.

The method of providing prior knowledge for optimizer is called optimization based. The optimization algorithms with learnable parameter are proposed in [17], [18] firstly that they can adjust the structure of optimizer automatically according to the tasks. In [19]-[22], neural networks is used to replace the traditional optimizers to update the task network. And it is mentioned in [19],[21],[22],[23] that the input of parametrized optimizer must be transformed with some complex nonlinear functions in order to make the optimizer converge, and the parametrized optimizer is proved better than the traditional optimizers.

3 Method

We aim at obtaining a parametrized objective function, which is better than the traditional loss function on the ability of generalization. The parameters of MLN $\phi$ is evolved through ES and MLN trains a classifier $C(\theta^*)$ with stochastic gradient descent (SGD).

In addition, we need to explain the dataset structure of meta learning method, which is split into Meta-training and Meta-validation. And the structure of Meta-Learning dataset is shown in figure 2. The Meta-training dataset and Meta-testing dataset is randomly sampled from classification dataset. It includes a set of training data and validation data in an episode. In order to simulate the task of learning on small dataset, we set the number of training data is very small and the number of validation data is very large. Such that the task of learning on small dataset requires the MLN to learn that how to make the classifier, which is trained with the MLN and small dataset, have better generalization ability.
Figure 2. The structure of Meta-Learning dataset. The training data is used in the inner loop to update a classifier and the validation data is used in the outer loop to evaluate the generalization of the optimized classifier.

### 3.1 Meta-Learning Objective

We assume access to a distribution \( p(M) \) over classification tasks. Given a sampled classification task \( M \), the inner loop optimization problem is to minimize the loss \( MLN_\phi \) with the classifier \( C_\theta \):

\[
\theta^* = \arg\min_{\theta} \mathbb{E}_{M \sim p(M)} \left[ MLN_\phi (C_\theta, M) \right]
\]

Note that this is similar to usual supervised objective, except that we are aiming at training a parametrized loss \( MLN_\phi \) rather than directly optimizing the classifier. The outer loop objective is to learn \( MLN_\phi \) such that a classifier \( C_\theta \) trained with loss function achieves high precision in validation datasets \( \text{val} \):

\[
\phi^* = \arg\max_{\phi} \mathbb{E}_{M \sim p(M)} \mathbb{E}_{\text{val} \sim M, MLN_\phi} \left[ \text{precision(\text{val})} \right]
\]

### 3.2 Architecture

The MLN is parametrized using a dual-channel deep neural network with observation the classification probabilities \( \hat{y} \) and labels \( y \). As such, it can handle \( \hat{y} \) and \( y \) separately in different function forms. For example, the cross-entropy Loss uses \( \log(\hat{y}) \) and \( -y \) to process the different information, or mean square error uses \( \hat{y} \) and \( y \) directly. But in MLN, the parametrized processing functions of MLN for \( \hat{y} \) and \( y \) are evolved, which ensures the flexibility and robustness of the function form.

In addition to parametrized processing functions, the MLN also includes a parametrized block to integrate the two kinds of processed information. In the MLN, these two kinds of information tensors are concatenated into a 2-channel matrix. Then they are converted into loss by convolution layers in integration block. The architecture is depicted in Figure 3.
3.3 Algorithm

In order to ensure the consistency between loss function and the accuracy, we set the classification accuracy as the optimization objective. Thus, we cannot use gradient-based methods to solve Eq. (2). In our approach, MLN is optimized with evolution strategies in outer loop, which is summarized in Algorithm 1.

| Algorithm 1: Evolved MLN |
|-------------------------|
| **[Outer Loop]**        |
| **Initialize** $MLN_{1,\ldots,T}$ |
| Fitness = []            |
| **Initialize** mutation strength $\sigma_{1,\ldots,T}$ |
| **for** episode = 1, \ldots, E do |
| $MLN_{1,\ldots,2T}, \sigma_{1,\ldots,2T} = \text{MakeKid}(MLN_{1,\ldots,T}, \sigma_{1,\ldots,T})$ |
| **[Inner Loop]**        |
| **for** worker = 1, \ldots, 2T do |
| **Initialize** classifier C |
| **Random sample**: MetaTraining([train_x, train_y), (validation_x, validation_y)] |
| **for** step = 1, \ldots, N do |
| prediction = C(train_x) |
| Loss = $MLN_i(prediction, train_y)$ |
As shown in Algorithm 1, at the start of each episode in the outer loop, we initialize T MLN and generate T mutation strength σ with the same dimension as the loss function parameter \( \phi \). As such, T MLN will produce T progeny according to \( (\mu + \lambda) \) ES.

Given a loss function \( MLN_{i}, i \in \{1, ..., 2T\} \), from the outer loop, each inner loop worker \( \omega \) samples a random Meta-training dataset from the task distribution \( M_{i} \sim p(M) \) and random initializes a classifier \( C_{\theta} \). The \( MLN_{i} \) then trains the classifier \( C_{\theta} \) in \( M_{i} \) over N steps of SGD.

\[
\theta = \theta - \alpha \times \nabla_{\theta}MLN_{i}(C_{\theta}, M_{i})
\]  
(4)

At the end of the inner loop training, each MLN returns the final precision of validation dataset in \( M_{i} \) as fitness to the outer loop. And the outer loop selects T MLN and mutation strength σ. Algorithm 1 outputs a learned loss function \( MLN_{\phi} \) after E episodes of ES updates.

4 Experiment

To evaluate the proposed methods, we apply our method to FashionMnist[24], CIFAR10[25]. Due to the limitation of the MLN’s architecture, our method is only experimented on 10 categories tasks currently. The classifiers we used in experiments are multilayer perceptron (MLP), which includes 3 fully connection layers. And the optimization algorithm of any classification task is stochastic gradient descent in experiments.

4.1 Results

Figure 4 shows the learning curves of the MLN, CE and MSE. The results in each task are averaged over 10 test-time training curves in the left and the mean precision of 10 test-time validation curves in the right. In addition, the number of iterations in inner loop is set to 20. The summary results for all tasks are shown in Table 1.
Figure 4 (1). Meta-testing dataset is sampled from FashionMnist randomly. MLN vs CE and MSE. The left is the mean of 10 training curves and the right is the mean of 10 validation curves.

Figure 4 (2). Meta-testing dataset is sampled from CIFAR10 randomly. MLN vs CE and MSE. The left is the mean of 10 training curves and the right is the mean of 10 validation curves.

Table 1. comparison of classification losses on different datasets, including FashionMnist, and CIFAR10.

| Dataset     | Cross-Entropy Loss | Mean Square Error | MLN       |
|-------------|--------------------|------------------|-----------|
| FashionMnist| 0.5922 ± 0.0474    | 0.4807 ± 0.0451  | 0.646 ± 0.0392 |
| CIFAR10     | 0.1771 ± 0.0241    | 0.1263 ± 0.0284  | 0.1935 ± 0.0328 |

The results of experiments showcased that our proposed method was able to substantially improve the performance across all FashionMnist and CIFAR10 tasks. Compared with CE and MSE, our method achieves higher precision on the unseen data with fewer iterations.

Conclusion
In this paper, we propose a meta-learning approach to evolving a parametrized loss function for training the image classification learning on small datasets. In our experiments, we found that such a Meta-Loss Network can improve the performance of classification tasks, which is compared with the Cross-Entropy Loss and Mean Square Error. We aim at

However, there are still some unsolved problems in our method. Firstly, due to the limitation of deep neural network’s architecture, our method can only be applied to 10 categories datasets currently. Secondly, in order to improve the evolution speed of MLN, we use one set of validation data to estimate the performance of MLN, which causes the fluctuation of MLN. Therefore, we have to rely on the Meta-Testing datasets to select the best MLN. Thirdly, we found that although the MLN is better than Cross-Entropy loss and Mean Square Error, its stability is much worse on the unseen datasets.

In the next research, we need to design a better architecture of MLN to adapt any classification tasks. In addition, the evolution of MLN needs to be further optimized, so that we could find the best MLN during the meta training process accurately. Furthermore, we need also research that how to improve the robustness of MLN on unseen data.

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