Abstract

Meta-learning enables a model to learn from very limited data to undertake a new task. In this paper, we study the general meta-learning with adversarial samples. We present a meta-learning algorithm, ADML (ADversarial Meta-Learner), which leverages clean and adversarial samples to optimize the initialization of a learning model in an adversarial manner. ADML leads to the following desirable properties: 1) it turns out to be very effective even in the cases with only clean samples; 2) it is model-agnostic, i.e., it is compatible with any learning model that can be trained with gradient descent; and most importantly, 3) it is robust to adversarial samples, i.e., unlike other meta-learning methods, it only leads to a minor performance degradation when there are adversarial samples. We show via extensive experiments that ADML delivers the state-of-the-art performance on two widely-used image datasets, MiniImageNet and CIFAR100, in terms of both accuracy and robustness.

1 Introduction

Deep learning has made tremendous successes and emerged as a de facto approach to many learning tasks, which, however, depends heavily on huge amounts of labeled training data. The goal of meta-learning is to enable a model (especially a Deep Neural Network (DNN)) to learn from only a small number of data samples to undertake a new task, which is critically important to machine intelligence but turns out to be very challenging. Currently, a common approach to learning is to train a model to undertake a task from scratch without making use of any previous experience. Specifically, a model is initialized randomly and then updated slowly using gradient descent with a large number of training samples. This kind of time-consuming and data-hungry training process is quite different from the way how a human learns quickly from only a few samples and obviously cannot meet the requirement of meta-learning. Several methods have been proposed in recent works [1, 2] to address meta-learning by fixing the above issue. For example, a recent work [1] presents a novel meta-learning algorithm called MAML (Model-Agnostic Meta-Learning), which trains a model’s initial parameters carefully such that it has the maximal performance on a new task after its parameters are updated through one or just a few gradient steps with a small amount of new data. This method is claimed to be model-agnostic since it can be directly applied to any learning model that can be trained with a gradient descent procedure.

Robustness is another major concern for machine intelligence. It has been shown by [3] that learning models can be easily fooled by adversarial manipulation of actual training data to cause incorrect classifications. Therefore, adversarial samples pose a serious security threat to learning tasks, which need to be properly and effectively handled by learning models and training algorithms. We also show via experiments that existing meta-learning algorithms (such as MAML [1] and Matching Networks [2]) are also vulnerable to adversarial samples (Section 4.2), i.e., adversarial samples can lead to a significant performance degradation for meta-learning. To the best of our knowledge, none of
existing works on meta-learning have well addressed adversarial samples, which, however, are the main focus of this paper.

In this paper, we extend meta-learning to a whole new dimension by studying how to quickly train a model (especially a DNN) for a new task using a small dataset with both clean and adversarial samples. Since both meta-learning and adversarial learning have been studied recently, a straightforward solution is to simply combine an existing meta-learning method (e.g., MAML [1]) with adversarial training (e.g., [4]). However, we show such an approach does not work well by our experimental results in Section 4.2. We present a novel ADversarial Meta-Learner (ADML), which utilizes antagonistic correlations between clean and adversarial samples to let the inner gradient update arm-wrestle with the meta-update (Section 3) to obtain a good and robust initialization of model parameters. Hence, “adversarial” in ADML refers to not only adversarial samples but also the way of updating the learning model. The design of ADML leads to several desirable properties. First, it turns out to be very effective even in the cases with only clean samples. Second, just like MAML, ADML is model-agnostic since it is compatible with any model that can be trained with gradient descent. Most importantly, unlike other meta-learning methods [1, 2], ADML is robust to adversarial samples since it only suffers from a minor performance degradation when encountering adversarial samples. We conducted a comprehensive empirical study for performance evaluation using two widely-used image datasets, MiniImageNet [2] and CIFAR100 [5]. Experimental results well justify the effectiveness and superiority of the proposed ADML in terms of both accuracy and robustness.

We organize the rest of the paper as follows: We discuss related work in Section 2. We describe the meta-learning problem and present the proposed ADML in Section 3. Experiments setup and results are presented in Section 4. We conclude the paper in Section 5.

2 Related Work

In this section, we review related works on meta-learning and adversarial learning.

2.1 Meta-Learning

Research on meta-learning has a long history, which can be traced back to some early works [6, 7]. Meta-learning and few-shot learning have recently attracted extensive attention due to its potential on achieving human-level intelligence. Several specialized neural network models [2, 8, 9] have been proposed for meta-learning, particularly for one or few-shot classification, by comparing similarity among data samples. Specifically, Koch et al. [8] leveraged a Siamese neural network to rank similarity between input samples and predict if two samples belong to the same class. In [2], Vinyals et al. presented a neural network model, Matching Networks, which learn an embedding function and use the cosine distance in an attention kernel to measure similarity. Snell et al. [9] employed a similar approach to few-shot classification but used the Euclidean distance with their embedding function.

Another popular approach to meta-learning is to develop a meta-learner to optimize key parameters (e.g., initialization) of the learning model. Specifically, Finn et al. [1] presented a model-agnostic meta-learner, MAML, to optimize the initialization of a learning model with the objective of maximizing its performance on a new task after updating its parameters with a small number of samples. Several other methods [11, 12, 13] utilize an additional neural network, such as LSTM, to serve as the meta-learner. In a seminal work [10], Andrychowicz et al. showed how the design of an optimization algorithm (such as a training algorithm) can be cast as a learning problem. They developed a meta-learner based on LSTMs, which has been shown to outperform generic and hand-designed competitors, and also generalize well to new tasks with similar structures. Ravi et al. [11] proposed another LSTM-based meta-learner to learn a proper parameter update and a general initialization for the learning model, allowing for quick convergence of training for a new task. Compared to LSTM, a memory-augmented neural network (such Neural Turing Machine (NTM) [14]) is equipped with a large external memory and thus has a much higher capacity, which has also been leveraged for meta-learning [12]. A very recent work [13] presented a class of simple and generic meta-learners that use a novel combination of temporal convolutions and soft attention.
2.2 Adversarial Learning

DNN models have been shown to be vulnerable to adversarial samples. Particularly, Szegedy et al. [3] showed that they can cause a DNN to misclassify an image by applying a certain hardly perceptible perturbation, and moreover, the same perturbation can cause a different network (trained on a different subset of the dataset) to misclassify the same input. It has also been shown by [15] that injecting adversarial samples during training can increase the robustness of DNN models. Rozsa et al. [16] conducted experiments on various adversarial sample generation methods with multiple deep Convolutional Neural Networks (CNNs), and found that adversarial samples are mostly transferable across similar network topologies, and better learning models are less vulnerable. Huang et al. [17] proposed a method, learning with a strong adversary, which learns robust classifiers from supervised data by generating adversarial samples as an intermediate step. Papernot et al. [18] introduced the first practical demonstration of a black-box attack controlling a remotely hosted DNN without either the model internals or its training data. In another work [19], Papernot introduced a defensive mechanism called defensive distillation to reduce the effectiveness of adversarial samples on DNNs. They analytically investigated its generalizability and robustness properties; and showed via experiments that the defensive distillation can reduce the effectiveness of sample creation from 95% to less than 0.5% on a DNN. More recently, Kurakin et al. [4] studied adversarial learning at scale by proposing an algorithm to train a large scale model, Inception v3, on the ImageNet dataset, which has been shown to significantly increase the robustness against adversarial samples. In addition, Miyato et al. [20] extended adversarial training to the text domain by applying perturbations to word embeddings in an RNN rather than to the original input itself, which has been shown to achieve the state-of-the-art results on multiple benchmark semi-supervised and purely supervised tasks.

To the best of our knowledge, meta-learning has not been studied in the setting of adversarial samples. We not only show a straightforward solution does not work well but also present a novel and effective method, ADML.

3 Adversarial Meta-Learning

In this section, we first describe the adversarial meta-learning problem and then present the proposed Adversarial Meta-Learner (ADML).

3.1 Problem Statement

The regular machine learning problem seeks a model that maps observations $x$ to output $y$; and a training algorithm optimizes the parameters of the model with a training dataset, whose generalization is then evaluated on a testing dataset. While in the setting of meta-learning, the learning model is expected to be trained with limited data to be able to adapt to a new task quickly. Meta-learning includes meta-training and meta-testing. In the meta-training, we use a set $T$ of $T$ tasks, each of which has a loss function $L_i$, and a dataset $D_i$ (with limited data) that is further split into $D_i$ and $D_i'$. For example, in our experiments, each task is a 5-way classification task.

We aim to develop a meta-learner (i.e., a learning algorithm) that takes as input the datasets $D = \{D_1, \cdots, D_T\}$ and returns a model with parameters $\theta$ that maximizes the average classification accuracy on the corresponding testing sets $D' = \{D_1', \cdots, D_T'\}$. Note that here these testing data are also used for meta-training. In the meta-testing, we evaluate the generalization of the learned model with parameters $\theta$ on new tasks, whose corresponding training and testing datasets may include adversarial samples. The learned model is expected to learn quickly from just one (1-shot) or $K$ ($K$-shot) training samples of a new task and deliver highly-accurate results on its testing samples. An ideal meta-learner is supposed to return a learning model that can deal with new tasks with only clean samples; and suffers from only a minor performance degradation for new tasks with adversarial samples. Note that we only consider classification here since so far only classification has been addressed in the context of adversarial learning [4]. We believe the proposed ADML can be easily extended to other scenarios as long as adversarial samples can be properly generated.
3.2 Adversarial Meta-Learner (ADML)

We formally present the proposed ADML as Algorithm 1 for meta-training. We consider a model \( f_\theta \) parameterized by \( \theta \), which is updated iteratively. Here, an updating episode includes an inner gradient update process (Line 5–Line 9) and a meta-update process (Line 11). Unlike MAML, for each task, additional adversarial samples are generated and used to enhance the robustness for meta-training. Note that our algorithm is not restricted to any particular adversarial sample generation method. We used the Fast Gradient Sign Method (FGSM) \cite{goodfellow2014explaining} in our implementation and experiments. The key idea behind ADML is to utilize antagonistic correlations between clean and adversarial samples to let the inner gradient update and the meta-update arm-wrestle with each other to obtain a good initialization of model parameters \( \theta \), which is robust to adversarial samples.

Specifically, in the inner gradient update, we compute the new model parameters (updated in two directions) \( \theta_{\text{adv}} \) and \( \theta_{\text{clean}} \) based on generated adversarial samples \( D_{\text{adv}} \) and clean samples \( D_{\text{clean}} \) in training set \( D_i \) of task \( T_i \) respectively using gradient descent (Line 7). In the meta-update process, we update the model parameters \( \theta \) by optimizing the losses \( L_i(f_{\theta_{\text{adv}}}) \) and \( L_i(f_{\theta_{\text{clean}}}) \) of the model with updated parameters \( \theta_{\text{adv}} \) and \( \theta_{\text{clean}} \) with respect to \( \theta \) based on the clean samples \( D_{\text{clean}} \) in testing set \( D_i \) of task \( T_i \) and the corresponding adversarial samples \( D_{\text{adv}} \), respectively:

\[
\begin{align*}
\min_{\theta} \sum_{T_i \sim \mathcal{D}} L_i(f_{\theta_{\text{adv}}}, D_{\text{clean}}) &= \min_{\theta} \sum_{T_i \sim \mathcal{D}} L_i(f_{\theta - \alpha_1 \nabla_\theta L_i(f_{\theta_{\text{adv}}}, D_{\text{adv}})}, D_{\text{clean}}); \\
\min_{\theta} \sum_{T_i \sim \mathcal{D}} L_i(f_{\theta_{\text{clean}}}, D_{\text{adv}}) &= \min_{\theta} \sum_{T_i \sim \mathcal{D}} L_i(f_{\theta - \alpha_2 \nabla_\theta L_i(f_{\theta_{\text{clean}}}, D_{\text{clean}})}, D_{\text{adv}}).
\end{align*}
\]

Note that in the meta-update, \( \theta \) is optimized in an adversarial manner: the gradient of the loss of the model with \( \theta_{\text{adv}} \) (updated using adversarial samples \( D_{\text{adv}} \)) is calculated based on clean samples \( D_{\text{clean}} \), while the gradient of the loss of the model with \( \theta_{\text{clean}} \) (updated using \( D_{\text{clean}} \)) is calculated based on adversarial samples \( D_{\text{adv}} \). The arm-wrestling between the inner gradient update and the meta-update brings an obvious benefit: the model adapted to adversarial samples (through the inner gradient update using adversarial samples) is made suitable also for clean samples through the optimization of \( \theta \) in the meta-update based on the clean samples, and vice versa. So “adversarial” in ADML refers to not only adversarial samples but also the way of meta-training.

\begin{algorithm}
\caption{Adversarial Meta-Learner (ADML)}
\begin{algorithmic}[1]
\Require \( \alpha_1/\alpha_2 \) and \( \beta_1/\beta_2 \): The step sizes for inner gradient update and meta-update respectively
\Require \( \mathcal{D} \): The datasets for meta-training
\Ensure \( \mathcal{L}_i(\cdot) \): The loss function for task \( T_i \), \( \forall i \in \{1, \ldots, T\} \)
1: Randomly initialize \( \theta \);
2: while not done do
3: \hspace{1em} Sample batch of tasks \( \mathcal{R}_i \) from task set \( \mathcal{R} \);
4: \hspace{1em} for all \( T_i \) do
5: \hspace{2em} Sample \( K \) clean samples \( \{(x_c^1, y_c^1), ..., (x_c^K, y_c^K)\} \) from \( D_i \);
6: \hspace{2em} Generate \( K \) adversarial samples \( \{(x_{\text{adv}}^1, y_{\text{adv}}^1), ..., (x_{\text{adv}}^K, y_{\text{adv}}^K)\} \) based on the clean samples from \( D_i \) to form a dataset \( D_i^\prime := \{D_{\text{adv},i}, D_{\text{clean}}\} \) for the inner update, containing \( K \) adversarial samples and \( K \) clean samples;
7: \hspace{2em} Compute updated model parameters with gradient descent respectively:
8: \hspace{2.5em} \( \theta_{\text{adv}} := \theta - \alpha_1 \nabla_\theta \mathcal{L}_i(f_{\theta}, D_{\text{adv}}) \); \( \theta_{\text{clean}} := \theta - \alpha_2 \nabla_\theta \mathcal{L}_i(f_{\theta}, D_{\text{clean}}) \);
9: \hspace{2em} Sample \( k \) clean samples \( \{(x_c^1, y_c^1), ..., (x_c^k, y_c^k)\} \) from \( D_i^\prime \);
10: \hspace{2em} Generate \( k \) adversarial samples \( \{(x_{\text{adv}}^1, y_{\text{adv}}^1), ..., (x_{\text{adv}}^k, y_{\text{adv}}^k)\} \) based on the clean samples from \( D_i^\prime \) to form a dataset \( D_i^\prime := \{D_{\text{adv},i}, D_{\text{clean}}\} \) for the meta-update, containing \( k \) adversarial samples and \( k \) clean samples;
11: \hspace{2em} Update \( \theta := \theta - \beta_1 \nabla_\theta \sum_{T_i \sim \mathcal{D}} \mathcal{L}_i(f_{\theta_{\text{adv}}}, D_{\text{clean}}^\prime) \);
12: \hspace{2em} Update \( \theta := \theta - \beta_2 \nabla_\theta \sum_{T_i \sim \mathcal{D}} \mathcal{L}_i(f_{\theta_{\text{clean}}}, D_{\text{adv}}^\prime) \);
end for
end while
\end{algorithmic}
\end{algorithm}
The meta-update of the model parameters $\theta$ is performed as the last step of each episode (Line 11). Through the arm-wrestling between the inner gradient update and the meta-update in the meta-training process, $\theta$ will be updated to a certain point, such that the average loss given by both adversarial samples and clean samples of all the tasks is minimized. In addition, we set the step sizes $\alpha_1 = \alpha_2 = 0.01$, $\beta_1 = \beta_2 = 0.001$, and set $L_i(\cdot)$ of each classification task $T_i$ to be the cross-entropy loss. $K$ and $k$ are task-specific, whose settings are discussed in the next section. It can be easily seen that ADML preserves the model-agnostic property of MAML because both the inner gradient update and the meta-update processes are fully compatible with any learning model that can be trained by gradient descent.

As mentioned before, a rather straightforward solution to the above adversarial meta-learning problem is to simply combine a meta-learner (e.g., MAML [1]) with adversarial training (e.g., [4]). Specifically, we can mix adversarial and clean samples to form both $D_i$ (used in the inner gradient update) and $D'_i$ (used in the meta-update), which are then used to calculate $\theta'_i$ and update $\theta$ using the following two equations (just like MAML) respectively:

$$\theta'_i = \theta - \alpha \nabla_\theta L_i(f_\theta, D_i);$$  \hspace{1cm} (2)

$$\theta \leftarrow \theta - \beta \nabla_\theta \sum_{T_i \sim T} L_i(f_{\theta'}, D'_i).$$  \hspace{1cm} (3)

We call this method MAML-AD, which was used as a baseline for performance evaluation. However, it has been shown by our experimental results (in the next section) that MAML-AD produces a model that still suffers from a significant performance degradation for new tasks with adversarial samples. This finding shows that simply involving adversarial samples during the meta-training does not necessarily enhance the model’s robustness; and well justify that our idea of doing the inner gradient update and the meta-update in an adversarial way is necessary.

4 Performance Evaluation

The goal of our evaluation is to test and verify three properties of ADML: 1) ADML can learn quickly from limited data via a few gradient updates for a new task, and it is effective even in the cases with only clean samples; 2) ADML suffers from a minor performance degradation and yields much better performance than other meta-learning methods when encountering adversarial samples; and 3) ADML maintains stable performance when the perturbation of adversarial samples (i.e., $\epsilon$) escalates. In this section, we first introduce the experimental setup, and then present and analyze the results.

4.1 Experimental Setup

In our experiments, we employed two commonly-used image benchmarks, MiniImageNet [2], and CIFAR100 [5]. MiniImageNet is a benchmark for few-shot learning, which includes 100 classes and each of them has 600 samples. CIFAR100 was created originally for object recognition tasks, whose data are actually very suitable for meta-learning since just like MiniImageNet, it has 100 classes, each of which contains 600 images. Similar as in [1], we considered 1-shot and 5-shot 5-way classification tasks. Five samples per class were used for the inner gradient update during meta-training of a 5-shot learning model (one for 1-shot learning model). Thus $K$ in ADML was set to 25 for 5-shot learning and 5 for 1-shot learning. Fifteen samples per class were used for the meta-update, thus we set $k = 75$. During the meta-testing, the learning model was trained using samples of 5 unseen classes, then we tested it by using it to classify new instances into these 5 classes. MiniImageNet was divided into 64, 16 and 20 classes for training, validation (for tuning hyperparameters) and testing respectively. We randomly sampled 5 classes from them to form each classification task. Since CIFAR100 has not been used for meta-learning before, we created the meta-learning version of CIFAR100, which has the same settings as MiniImageNet.

In addition, we used the Fast Gradient Sign Method (FGSM) [15] to generate adversarial samples in our experiments. The parameter $\epsilon$ of FGSM specifies the size of perturbation (the larger the $\epsilon$, the higher the perturbation) in the adversarial sample generation, which was set to 2 when generating adversarial samples for the meta-training, and was set to 2 and 0.2 for the meta-testing.
We compared ADML against two recent and representative methods for meta-learning, including MAML [1] and Matching Networks [2]. We chose these two as baselines since MAML represents a state-of-the-art meta-learner and Matching Networks is a well-known similarity-based method. Moreover, for fair comparisons, we also compared ADML with another adversarial meta-learner MAML-AD (introduced in the last section), which can be considered as a rather straightforward extension of MAML.

For the implementation of ADML, we followed the architecture used by [1] for image embedding, which contains 4 convolutional layers, each of which is $3 \times 3$ convolutions and 32 filters, followed by batch normalization, a ReLU non-linearity and $2 \times 2$ max-pooling. In our experiments, we used the implementation provided at [21] for MAML; and the Full Contextual Embeddings (FCE) version and the corresponding implementation provided at [22] for Matching Networks.

### 4.2 Experimental Results

To fully test the effectiveness of ADML, we conducted a comprehensive empirical study, which covers various possible cases. The experimental results on MiniImageNet are presented in Tables 1 and 2; and the results on CIFAR100 are presented in Tables 3 and 4. The best results for each test case are marked in bold.

From these tables, we can see the experiments were conducted in six different test scenarios (combinations): "Clean-Clean", "Clean-Adversarial", "Adversarial-Clean", "Adversarial-Adversarial", "40%-Clean" and "40%-Adversarial". The first part of each combination corresponds to a row of a table and the training data used in the gradient update of each class during the meta-testing, while the second part corresponds to a column of a table and the corresponding testing data for evaluation. "Clean" means clean samples only; "adversarial" means adversarial samples only; and "40%" means that 40% samples are adversarial and the rest 60% are clean, which represents intermediate cases. Note that two combinations, "40%-Clean" and "40%-Adversarial", do not exist for 1-shot learning since there is only one sample per class.

Each entry in these tables gives the average classification accuracy (with 95% confidence intervals) of the corresponding test case. Based on the results in Tables 1–4, we can make the following observations:

| Meta-learning Method | Meta-testing | $\epsilon = 2$ | $\epsilon = 0.2$ |
|----------------------|--------------|----------------|-----------------|
|                      | Clean        | Adversarial    | Clean           | Adversarial     |
| MAML [1]             | Clean        | 48.47 ± 1.78%  | 28.63 ± 1.54%   | 48.47 ± 1.78%   | 42.13 ± 1.75%   |
|                      | Adversarial  | 28.93 ± 1.62%  | 30.73 ± 1.66%   | 42.23 ± 1.85%   | 40.17 ± 1.76%   |
| MAML-AD              | Clean        | 43.13 ± 1.88%  | 32.33 ± 1.74%   | 43.13 ± 1.88%   | 36.80 ± 1.76%   |
|                      | Adversarial  | 32.47 ± 1.60%  | 37.87 ± 1.74%   | 37.63 ± 1.64%   | 37.13 ± 1.75%   |
| ADML (Ours)          | Clean        | 48.00 ± 1.87%  | 43.00 ± 1.88%   | 48.00 ± 1.87%   | 43.20 ± 1.70%   |
|                      | Adversarial  | 40.10 ± 1.73%  | 40.70 ± 1.74%   | 44.00 ± 1.83%   | 41.20 ± 1.75%   |
| Matching Nets [2]    | Clean        | 41.87 ± 0.41%  | 30.02 ± 0.39%   | 43.88 ± 0.48%   | 36.14 ± 0.40%   |
|                      | Adversarial  | 30.45 ± 0.44%  | 30.80 ± 0.43%   | 36.58 ± 0.49%   | 35.03 ± 0.39%   |
Table 2: Average classification accuracies on MiniImageNet (5-way, 5-shot)

| Meta-learning Method | Meta-testing | \( \epsilon = 2 \) | \( \epsilon = 0.2 \) |
|----------------------|--------------|---------------------|---------------------|
|                      | Clean        | Adversarial         | Clean               | Adversarial         |
| MAML \[1\]           | Clean        | 61.45 ± 0.1%        | 56.74 ± 0.9%        | 41.49 ± 0.9%        |
|                      | Adversarial  | 41.49 ± 0.9%        | 56.74 ± 0.9%        | 41.49 ± 0.9%        |
| MAML-AD               | Clean        | 57.13 ± 0.96%       | 54.07 ± 0.91%       | 42.13 ± 0.91%       |
|                      | Adversarial  | 57.13 ± 0.96%       | 54.07 ± 0.91%       | 42.13 ± 0.91%       |
| ADML (Ours)           | Clean        | 59.38 ± 0.99%       | 59.40 ± 0.99%       | 59.40 ± 0.99%       |
|                      | Adversarial  | 59.38 ± 0.99%       | 59.40 ± 0.99%       | 59.40 ± 0.99%       |
| Matching Nets \[2\]   | Clean        | 55.99 ± 0.47%       | 55.55 ± 0.44%       | 44.91 ± 0.40%       |
|                      | Adversarial  | 49.88 ± 0.45%       | 52.72 ± 0.45%       | 45.65 ± 0.42%       |

Table 3: Average classification accuracies on CIFAR100 (5-way, 1-shot)

| Meta-learning Method | Meta-testing | \( \epsilon = 2 \) | \( \epsilon = 0.2 \) |
|----------------------|--------------|---------------------|---------------------|
|                      | Clean        | Adversarial         | Clean               | Adversarial         |
| MAML \[1\]           | Clean        | 57.67 ± 1.76%       | 57.67 ± 1.76%       | 43.30 ± 1.68%       |
|                      | Adversarial  | 57.67 ± 1.76%       | 57.67 ± 1.76%       | 43.30 ± 1.68%       |
| MAML-AD               | Clean        | 52.70 ± 1.89%       | 52.70 ± 1.89%       | 39.17 ± 1.82%       |
|                      | Adversarial  | 37.27 ± 1.72%       | 37.27 ± 1.72%       | 37.27 ± 1.72%       |
| ADML (Ours)           | Clean        | 55.70 ± 2.00%       | 50.90 ± 1.84%       | 49.30 ± 1.76%       |
|                      | Adversarial  | 55.70 ± 2.00%       | 50.90 ± 1.84%       | 49.30 ± 1.76%       |
| Matching Nets \[2\]   | Clean        | 47.94 ± 0.56%       | 47.68 ± 0.52%       | 49.30 ± 0.51%       |
|                      | Adversarial  | 24.82 ± 0.46%       | 27.72 ± 0.43%       | 27.72 ± 0.43%       |

Table 4: Average classification accuracies on CIFAR100 (5-way, 5-shot)

| Meta-learning Method | Meta-testing | \( \epsilon = 2 \) | \( \epsilon = 0.2 \) |
|----------------------|--------------|---------------------|---------------------|
|                      | Clean        | Adversarial         | Clean               | Adversarial         |
| MAML \[1\]           | Clean        | 74.03 ± 0.89%       | 68.99 ± 0.94%       | 54.15 ± 1.00%       |
|                      | Adversarial  | 33.34 ± 0.90%       | 53.15 ± 0.93%       | 53.15 ± 0.93%       |
| MAML-AD               | Clean        | 67.71 ± 0.96%       | 67.71 ± 0.96%       | 67.71 ± 0.96%       |
|                      | Adversarial  | 36.61 ± 0.86%       | 56.61 ± 0.86%       | 56.61 ± 0.86%       |
| ADML (Ours)           | Clean        | 65.26 ± 0.96%       | 65.26 ± 0.96%       | 65.26 ± 0.96%       |
|                      | Adversarial  | 65.26 ± 0.96%       | 65.26 ± 0.96%       | 65.26 ± 0.96%       |
| Matching Nets \[2\]   | Clean        | 62.95 ± 0.46%       | 62.95 ± 0.46%       | 62.95 ± 0.46%       |
|                      | Adversarial  | 54.39 ± 0.48%       | 54.39 ± 0.48%       | 54.39 ± 0.48%       |

1) ADML is indeed an effective meta-learner since it leads to quick learning from a small amount of new data for a new task. In the "Clean-Clean" cases, ADML delivers desirable results, which are very close to the state-of-the-art given by MAML and consistently better than those of MAML-AD and Matching Networks. For example, in the case of 5-way 1-shot classification with \( \epsilon = 2 \), ADML gives an average classification accuracy of 48.00%, which is very close to that given by MAML (i.e., 48.47%), and it performs better than MAML-AD (43.13%) and Matching Networks (43.87%). Note that here "Clean-Clean" means no adversarial samples in the meta-testing. However, ADML was still trained with adversarial samples during the meta-training. So it produced models different from those given by MAML, which give different classification accuracies.

2) ADML is robust to adversarial samples since it only suffers from a minor performance degradation when encountering adversarial samples. For example, for the 5-way 5-shot classification with
\( \epsilon = 2 \), ADML gives classification accuracies of 57.03%, 58.06%, 55.27%, 58.12% and 55.22% in the five test cases respectively. Compared to the corresponding "Clean-Clean" case where its accuracy is 59.38%, the performance degradation is only 4.16% in the worst-case and 2.64% on average.

3) ADML significantly outperforms all the other meta-learning methods in the test cases with adversarial samples. The classification accuracies given by all the other meta-learning methods, including MAML-AD, drop substantially when there are adversarial samples. For example, in the cases of 5-way 5-shot learning with \( \epsilon = 2 \), for MAML, the accuracy drops from 61.45% ("Clean-Clean") to 36.65% ("Clean-Adversarial") when injecting adversarial samples for actual testing, which represents a significant degradation of 24.80%; similarly, for MAML-AD, the accuracy drops from 57.13% to 41.65%, which represents a noticeable degradation of 15.48%; and for Matching Networks, the accuracy drops from 55.99% to 33.73%, representing a substantial degradation of 22.26%. However, for ADML, there is only a minor degradation of 2.35%. Moreover, we can see that ADML consistently brings significant or noticeable improvements over MAML, MAML-AD, and Matching Networks in these five test cases with adversarial samples. This observation clearly shows the ineffectiveness of the straightforward adversarial meta-learner MAML-AD and well justifies the superiority of the adversarial meta-training procedure of the proposed ADML.

4) When the perturbation of adversarial samples escalates, ADML maintains stable performance. For example, for 5-way 1-shot learning, when \( \epsilon \) increases from 0.2 to 2, ADML only leads to minor degradations of 0.2%, 3.9% and 0.5% in the corresponding three cases involving adversarial samples. However, much more significant degradations can be observed when the other methods are applied. For instance, the accuracies of MAML suffer from 13.50%, 13.30% and 9.44% drops in these three cases when increasing \( \epsilon \) from 0.2 to 2.

5) As expected, the classification accuracy increases dramatically when going from 1-shot to 5-shot learning. Particularly, when \( \epsilon = 2 \), if we do 5-shot learning with ADML, we can achieve classification accuracies of 59.38%, 57.03%, 58.06% and 55.27% in the four corresponding test cases respectively, which represent 11.38%, 14.03%, 17.96% and 14.57% improvements over 1-shot learning. This observation shows that more training samples (even if they may be adversarial samples) lead to better classification accuracies. We can see similar trends for the other three methods.

6) Similar observations can be made for the results corresponding to CIFAR100 (i.e., Tables 3-4). In general, compared to MiniImageNet, there are noticeable improvements on CIFAR100 in terms of the classification accuracy. For instance, for 5-way 1-shot learning with \( \epsilon = 2 \), ADML achieves classification accuracies of 55.70%, 50.90%, 54.50% and 50.60% on CIFAR100 in the corresponding four test cases respectively, which are 7.70%, 7.90%, 14.40% and 9.90% higher than those on MiniImageNet.

In addition, we show how the loss changes during the meta-testing in Figure 4. Specifically, this figure shows when ADML, MAML and MAML-AD are applied, how the losses of the learning models drop with the gradient update step during meta-testing in the cases of "Clean-Clean", "Clean-Adversarial", "Adversarial-Clean", "Adversarial-Adversarial" for 5-way 1-shot learning with \( \epsilon = 2 \). We observe that, in all of these test cases, the losses of the models learned with ADML drop sharply after only several gradient updates, and stabilize at small values during meta-testing, which are generally lower than those of the other two methods. This observation further confirms that ADML is suitable for meta-learning since it can quickly learn and adapt from small data for a new task though only several gradient updates. Note that same as in 4, the model learned using each of these three methods was updated for 5 steps and 10 steps in the meta-training and the meta-testing respectively in these experiments.

5 Conclusions

In this paper, we proposed a novel and model-agnostic method called ADML (ADversarial Meta-Learner) for meta-learning with adversarial samples, which features an adversarial way for optimizing model parameters \( \theta \) during meta-training through the arm-wrestling between inner gradient update and meta-update using both clean and adversarial sample. A comprehensive empirical study has been conducted for performance evaluation using two widely-used image datasets, MiniImageNet and CIFAR100. The extensive experimental results have showed that 1) ADML is an effective meta-learner even in the cases with only clean samples; 2) a straightforward adversarial
meta-learner, namely, MAML-AD, does not work well with adversarial samples; and most importantly, 3) ADML is robust to adversarial samples and delivers the state-of-the-art performance on adversarial meta-learning tasks.
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