Studying BatchNorm Learning Rate Decay on Meta-Learning Inner-Loop Adaptation

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Abstract

Meta-learning for few-shot classification has been challenged on its effectiveness compared to simpler pretraining methods and the validity of its claim of “learning to learn”. Recent work has suggested that MAML-based models do not perform “rapid-learning” in the inner-loop but reuse features by only adapting the final linear layer. Separately, BatchNorm, a near ubiquitous inclusion in model architectures, has been shown to have an implicit learning rate decay effect on the preceding layers of a network. We study the impact of BatchNorm’s implicit learning rate decay on feature reuse in meta-learning methods and find that counteracting it increases change in intermediate layers during adaptation. We also find that counteracting this learning rate decay sometimes improves performance on few-shot classification tasks.

1 Introduction

Meta-learning [2] offers a compelling promise of machine learning generalization. A model “learns to learn” by solving a collection of different tasks in an episodic training objective. By optimizing this challenging bi-level objective, the model learns to adapt its weights to new tasks at test time through a few simple gradient descent steps. The updates usually aim to update large portions, if not the entire network, to suit each task.

This is in contrast to pretraining methods [14] that learn a single flexible representation to solve an entire distribution of tasks by adding and training a single layer linear classifier during test-time. These approaches have been shown to effectively tackle few-shot learning tasks and are simpler to train than meta-learning methods. A natural question is to explore why meta-learning is outperformed by these pretraining techniques. [12] uncovers that while meta-learning methods perform gradient descent updates to the entire network, the inner loop updates only change the final linear layer, leaving the majority of the weights unchanged. This suggests that meta-learning methods are not actually adapting their representations for each task. Intuitively, this weakens its distinction from pre-training methods as full-network adaptability is often considered one of the strengths of meta-learning [10].

Separately, it has been shown that the usage of BatchNorm modules in neural networks causes an implicit learning rate decay proportional to weight norm of the preceding layer. As many meta-learning models make use of the 4-block convolutional architecture used in [2], they may all be subject to this decay phenomenon. This is particularly in line with ANIL [12] where only the final layer, which is not followed by a BatchNorm layer, sees substantial adaptation.

In our work, we aim to answer the question, does BatchNorm’s implicit learning rate decay negatively impact model adaptation and lead to feature reuse? We find evidence that counteracting this decay increases learning in intermediate layers and improves performance on existing few-shot classification tasks.

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benchmarks. We also find that enabling this increased adaptation lead to notable performance gains over other methods for tasks sampled from a different distribution.

2 Related Work

**Representation adaptation in meta-learning** MetaOptNet [8] is the first method to meta-learn a fixed representation and then only adapt a final convex classification layer during task-specific training. ANIL [12] studies rapid-learning vs. feature reuse in meta-learning by studying individual layer adaptation. They demonstrate that representations hardly change during inner loop optimization for MAML [2] and that training only the final layer during the inner-loop preserves most of the method’s performance. More recently, BOIL [10] does the opposite of ANIL and only optimizes the body of the network and also proposes evaluating a model on different test-time datasets. [1] proposes a method of creating few-shot tasks that are more challenging and observe improved performance of full-model adaptation methods over ANIL and pretraining approaches.

**Normalization and learning rate decay** [4] first identifies that in CNNs, the norm of the weight vectors grows logarithmically with the number of gradient descent steps. [16] then identifies that the usage of normalization schemes influences the effective learning rate based on the magnitude of the layer weights that precede and normalization module. [9] then proposes an exponentially growing learning rate for neural network training to improve model performance.

3 Studying the Inner-Loop Adaptation Procedure

3.1 Implicit Learning Rate Decay in Inner-Loop Adaptation

We observe that all layers except for the final Dense layer in the 4-block convolutional architecture is affected by BatchNorm and its implicit learning rate decay. This was previously studied in [16] and we reference [3] in our explanation below. This is due to the scale invariance of functions from BatchNorm and other normalization schemes. We focus on BatchNorm as it is the most prevalent normalization method. Due to the operation being scale invariant, the network function and cost are also scale invariant when viewed from the incoming weights $w_j$. If a function $g(x)$ is scale invariant with respect to $x$ with any scale $\gamma$, the following holds true:

$$g(\gamma x) = g(x)$$
$$\nabla g(\gamma x) = \gamma^{-1} \nabla g(x)$$

We crucially observe that while the function value is now unaffected by scale due to BatchNorm, the gradient of the function is not. We can study the dynamics this has on training by looking at our stochastic gradient descent update. Because the scale of $w_j$ is invariant, we canonicalize $w_j$ to the unit vector $\hat{w}_j = w_j/||w_j||$ to use as a reference point to calculate an effective learning rate. The gradient update is approximated as:

$$w_j^{(k+1)} = w_j^{(k)} - \alpha \nabla J(w_j^{(k)}) = \frac{w_j^{(k)} - \alpha \nabla J(w_j^{(k)})}{||w_j^{(k)}||}$$

From this equation, we can interpret $\hat{\alpha} = \alpha ||w_j^{(k)}||^{-2}$ as the effective learning rate. Thus, the learning rate for each layer is downscaled by the square of the norm of its weights. We note that as the final Dense layer is not succeeded by BatchNorm, it does not experience any decay effect. It is also important to note that as training progresses, the weight norm $||w_j^{(k)}||$ will also increase, resulting in a further gradual decrease of learning rate. This is shown empirically in Figure 1 with the mathematical explanation in Appendix A.3.

3.2 Counteracting Implicit Learning Rate Decay

We aim to study the effect that implicit learning rate decay has on model adaptation by counteracting this effect during the inner-loop training procedure. We present two solutions – Scaled learning rate
update and Unit norm weight update. For each method, we outline the update rule and the resulting
new effective learning rate and include a toy example demonstrating each in Appendix A.2.

**Scaled learning rate update** multiplies the inner-loop learning rate for each layer except for the
classification head by its squared weight norm.

**Update rule:** We apply the following gradient update (with changes shown in color):

\[
\mathbf{w}_j^{(k+1)} = \mathbf{w}_j^{(k)} - \alpha ||\mathbf{w}_j^{(k)}||^2 \nabla J(\mathbf{w}_j^{(k)})
\]  

(4)

**Effective learning rate:**

\[
\mathbf{w}_j^{(k+1)} = \frac{\mathbf{w}_j^{(k)} - \alpha ||\mathbf{w}_j^{(k)}||^2 \nabla J(\mathbf{w}_j^{(k)})}{||\mathbf{w}_j^{(k)}|| - \alpha ||\mathbf{w}_j^{(k)}||^2 \nabla J(\mathbf{w}_j^{(k)})} = \mathbf{w}_j^{(k)} - \alpha \nabla J(\mathbf{w}_j^{(k)})
\]  

(5)

As seen above, the effects of BatchNorm’s implicit learning rate decay have been counteracted by our
scaled learning rate update. Note that our weights are not actually normalized, rather this update is to
correct the learning rate scaling from the perspective of a normed weight vector.

**Unit norm weight update** ensures that all the weights for each layer in the network other than the
classification head have a weight norm of 1 throughout training.

**Update rule:** We normalize each layer by its norm after every step of gradient descent, such that
\[||\mathbf{w}_j^{(k)}|| = 1\] for all \(k\). We apply the following gradient update (with changes shown in color).

\[
\mathbf{w}_j^{(k+1)} = \frac{\mathbf{w}_j^{(k)} - \alpha \nabla J(\mathbf{w}_j^{(k)})}{||\mathbf{w}_j^{(k)}|| - \alpha \nabla J(\mathbf{w}_j^{(k)})}
\]  

(6)

**Effective learning rate:** As seen below, the effects of BatchNorm’s implicit learning rate decay have
been counteracted by our unit norm weight update.

\[
\mathbf{w}_j^{(k+1)} = \mathbf{w}_j^{(k+1)} \approx \frac{\mathbf{w}_j^{(k)} - \alpha ||\mathbf{w}_j^{(k)}||^{-1} \nabla J(\mathbf{w}_j^{(k)})}{||\mathbf{w}_j^{(k)}||} = \mathbf{w}_j^{(k)} - \alpha \nabla J(\mathbf{w}_j^{(k)})
\]  

(7)

4 Experiments

4.1 Experimental setup

We perform our experiments on several classification benchmarks for few-shot learning. We use the
miniImageNet dataset proposed by [13]. We also perform experiments on the Caltech-UCSD
Birds 200 (CUB) dataset [17] which is a fine-grained classification task for birds and on the Fewshot-
CIFAR100 (FC-100) dataset [11], which is based on the widely-used CIFAR100 dataset.

For all experiments, we use the standard Conv4 architecture for meta-learning outlined by [2]. We
use 64 filters per layer and max-pooling, as was done previously for the miniImageNet benchmark. We
perform 5-way classification with 1 or 5 shots denoted as 5x1 and 5x5 classification, respectively.

We show results from MAML [2], ANIL [12] and our two methods. We also include a simple baseline
in several experiments, labelled “3X LR update”, which refers to the Vanilla MAML algorithm with
the inner loop learning rate scaled by a factor of 3. This is used to test whether rapid adaptation in the
network can occur simply with an increased learning rate.

We provide details on hyperparameter settings for our experiments in Appendix A.1.
### Table 1: Accuracy Results on the miniImageNet.

<table>
<thead>
<tr>
<th></th>
<th>5-way 1-shot</th>
<th>5-way 5-shot</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAML</td>
<td>47.8±1.0</td>
<td>63.9±1.0</td>
</tr>
<tr>
<td>MAML 3X</td>
<td>48.6±0.9</td>
<td>62.9±1.1</td>
</tr>
<tr>
<td>ANIL</td>
<td>47.3±0.9</td>
<td>61.0±0.8</td>
</tr>
<tr>
<td>Scaled LR Update</td>
<td>49.6±0.9</td>
<td>67.2±1.0</td>
</tr>
<tr>
<td>Unit Norm Update</td>
<td>35.8±0.7</td>
<td>49.6±1.0</td>
</tr>
</tbody>
</table>

4.2 Evaluation Metrics

In addition to reporting accuracies, we are interested in measuring the layer-wise similarity between the slow weights, the weights of the network prior to performing the inner-loop optimization, and the fast weights, the weights of the network after the inner-loop optimization.

We use the centered kernel alignment (CKA) metric [5], which is also used to motivate ANIL in [12]. CKA measures the similarity between two neural network representations by comparing the neuron activations over a set of data. We use the output activations of each convolutional layer in the Conv4 network and the final dense linear layer for our comparisons.

4.3 Weight norm throughout training

![Figure 1: Weight norms layers, conv1-4 and dense layer throughout training on miniImageNet 5x1 task](image)

We visualize how the weight norm changes throughout the training process across the learning algorithms in [1]. The growth in the weight norm confirms that learning rate decay occurs and begins quite early in training. We also see that the 3x learning rate method follows a similar weight norm trajectory compared to vanilla MAML updates. This suggests that increasing the learning rate does not change the weight trajectory. Curiously, we see that the Scaled LR norm increases dramatically in the Conv4 block, though the underlying mechanism behind this change requires further study.

4.4 Feature reuse due to batch normalization

![Figure 2: CKA Similarity for miniImageNet 5x1](image)

In Figure [2] we display the CKA similarity between the fast and slow weights per layer in the Conv4 network on the miniImageNet 5x1 tasks. This is performed after training the network for 60k iterations. Here, the feature reuse phenomenon of MAML can be observed, as the dense layer is the only one that changes meaningfully after inner loop optimization. ANIL has similar behaviour by construction, as its earlier layers do not perform any weight updates. We also see that the 3x Learning Rate only has significant updates in the last layer, which suggests that this effect is not due to the inner loop learning rate being too small.

Interestingly, we see that the unit norm weight update and scaled learning rate update have different behaviours, despite the results in Section 3.2 showing their equivalence. We see that the Unit weight update deviates significantly from its slow weights in the 2nd and 4th layers, while the scaled learning rate update drops off at the 3rd layer of the network.

From these plots, it is evident that our update methods behave differently when applied to MAML’s bi-level optimization. Furthermore, we see that the unit norm weight update counteracts the feature...
We wish to verify how batch normalization affects MAML’s performance in more diverse settings. To see considerable adaptation over all datasets trained using our two update methods.

MiniMAML continues to re-use features and surprisingly performs even less adaptation on the transfer CUB task than the model trained on CUB. This could be explained with further hyperparameter tuning in future work.

Lastly, in Figure 3 we see that the CKA similarity metrics do not change significantly throughout the training process for each learning rule, implying that the feature phenomenon occurs very quickly into the training procedure.

Figure 3: CKA similarity over model training on miniImageNet 5x1

4.5 Feature reuse and batch normalization in diverse tasks

We wish to verify how batch normalization affects MAML’s performance in more diverse settings. To test this, we measure the CKA metric on the CUB, and Fewshot-CIFAR100 datasets, as well as the miniImageNet dataset, Figure 4. As in Section 4.4 we train models using unit norm weight update, scaled learning rate update and the vanilla MAML algorithm.

In Figure 4, we observe that feature reuse continues to occur across most datasets for the vanilla MAML algorithm as CKA does not register any changes other than the final layer. Comparatively, we see considerable adaptation over all datasets trained using our two update methods.

Figure 4: CKA similarity for the CUB, FC-100, and miniImageNet datasets.

4.6 Novel Dataset Generalization

To further study how meta-learning behaves in different data settings, we draw tasks from different datasets during test time. Changing class domains and image settings may demand more adaptation from the model. Here, we evaluate our miniImageNet5x1 model on two downstream tasks of CUB and FC-100, in addition to its training set, miniImageNet as a baseline comparison. We present a single-graph comparing our different methods trained on miniImageNet and tested on FC-100 in Figure 5. We also show Figure 6 showing CKA results for each method across different datasets. MAML continues to re-use features and surprisingly performs even less adaptation on the transfer CUB task than the model trained on CUB. This could be
We present accuracy evaluations in Table 2, we notice similar trends in the CUB evaluation as in the miniImageNet evaluation - we observe improvements in accuracy for the model with scaled learning rate update as compared to vanilla MAML and a general decrease in accuracy in the unit norm weight update case. Interestingly, in the FC-100 evaluations, the unit norm weight update shows surprisingly competitive results, performing similarly to the scaled learning rate update and MAML in both 5 way-1 shot and 5 way-5 shot. Furthermore, in Figure 5, we see that the 3X learning rate update performs similarly to the Vanilla MAML and ANIL updates, and fails to update the intermediate layers significantly. This again reinforces the point that the underlying effect we are studying is not caused by a small learning rate.

Figure 6: CKA similarity for vanilla MAML, scaled learning rate and unit norm weight update trained on miniImageNet and evaluated on the CUB, FC-100, miniImageNet datasets

5 Conclusion and future work

As previous works have noted, meta-learning methods often do not “adapt” to new tasks and instead train a single-layer network to re-use a meta-learned representation. In our work, we study the impact of implicit learning rate decay due to batch normalization on model adaptation within the test time inner loop. Using CKA as our metric for model adaptation at each layer of the network, we find that counteracting the batch norm learning rate decay increases intermediate layer representation change throughout the entirety of meta-learning training. This suggests that there is increased model adaptation to each new task.

One of our methods does also show some modest improvement in classification accuracy for some tasks and settings. The normed weights approach, struggles, but we expect this to improve and require entirely new hyperparameter tuning compared to unnormalized weight vectors. Furthermore, we believe that the minor gain could be due to existing benchmarks being relatively simple. Other future work would include testing on more challenging tasks with greater class diversity or different image statistics to observe any possible benefits. Diverse tasks from Meta-Dataset or artificially generated ones from ATG may benefit from this increased adaptability and capacity to learn.
References

A Appendix

A.1 Hyperparameter Details

We train a single model for each N-way K-shot problem and test it on all 3 datasets (miniImageNet, CUB and FC-100). The MAML baseline uses the same hyperparameters as [2], making the 3x inner-loop learning rate variation use a rate of 0.03 for both training and validation. For the 5x1 setting, our methods used a batch size of 4, 6 inner-loop steps and an inner-loop learning rate of 0.005 and outer loop 0.0005. For our 5x5 setting, our methods used a batch size of 2 and 6 inner loops steps. Our scaled learning rate update used 0.001 for both inner and outer learning rates while our the unit norm weight update used 0.005 and 0.0005 respectively.

A.2 Unit weights vs. layer-wise learning rate update

We perform a simple toy experiment to confirm the parity between our two methods of scaling the learning rate for each layer as well as normalizing layer weights. We implement both methods and train the same convolutional model as discussed in Section 4.1. This is in a regular supervised learning (not meta-learning) problem where we train the model to classify CIFAR10 [7]. We see in Figure 7 that the unit weight and scaled learning rate methods are roughly the same. While not identical, this could be due to the approximation described in equation 5.

A.3 Mathematical Explanation of Increasing Weight Norm during Training

We reference our math from [16] and [3]. If the function $g(x)$ is homogeneous of degree $k$ with respect to $x$ with any scale $\gamma$, the following holds true:

$$g(\gamma x) = \gamma^k g(x) \quad (8)$$

$$\nabla g(\gamma x) = \gamma^{k-1} \nabla g(x) \quad (9)$$

The function $g(x)$ is said to be scale-invariant if this holds for the degree $k = 0$. One corollary required for Equation 9, which we left out for brevity in the main text, is that if the function $g$ is scalar-valued (which in our case holds true), Euler’s homogeneous function theorem tells us that:

$$x^T \nabla g(x) = kg(x) \quad (10)$$

In the scale invariant case where $k = 0$, then $x$ is orthogonal to $\nabla g(x)$. Using Pythagorean’s Theorem, we can now derive the update for our weight norm:

$$||w_j^{(k+1)}||^2 = ||w_j^{(k)} - \alpha \nabla J(w_j^{(k)})||^2 = ||w_j^{(k)}||^2 + \alpha^2 ||\nabla J(w_j^{(k)})||^2 \quad (11)$$

As shown in the equation, our weight norm increases monotonically according to $||J(w_j^{(k)})||^2$. 

Figure 7: Validation of our methods