Is the Meta-Learning Idea Able to Improve the Generalization of Deep Neural Networks on the Standard Supervised Learning?

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Motivation

- Meta-learning approaches exhibit powerful generalization in few-shot learning.
- Intuitively, few-shot learning is more challenging than the standard supervised learning as each class only has a very few or no training samples.

The natural question that arises is whether the meta-learning idea can be used for improving the generalization of deep neural networks on standard supervised learning.
Key Ideas

• We propose a novel meta-learning based training procedure (MLTP) for DNNs and demonstrate that the meta-learning idea can indeed improve the generalization abilities of DNNs on standard supervised learning.

• The key idea of MLTP is that the gradient descent step for improving the current task performance should also improve a new task performance, which is ignored by the current standard procedure for training DNNs.
MLTP

- In every gradient descent iteration, MLTP randomly takes two different batches of training samples \((x^{i\text{bat}}, y^{i\text{bat}})\) and \((x^{j\text{bat}}, y^{j\text{bat}})\) as two tasks task\(_i\) and task\(_j\), respectively.

- The loss on task\(_i\) is written as:

  \[
  C(w, x^{i\text{bat}}, y^{i\text{bat}}) = L(f(w, x^{i\text{bat}}), y^{i\text{bat}})
  \]

- MLTP requires the parameters \(w\) after one gradient descent on the current task to also work well on a new task. The loss on the new task task\(_j\) is written as:

  \[
  C(w - \alpha \frac{\partial L(f(w, x^{i\text{bat}}), y^{i\text{bat}})}{\partial w}, x^{j\text{bat}}, y^{j\text{bat}}) = L(f(w - \alpha \frac{\partial L(f(w, x^{i\text{bat}}), y^{i\text{bat}})}{\partial w}, x^{j\text{bat}}), y^{j\text{bat}})
  \]

  where \(\alpha\) is an online adapted hyperparameter.

- The final objective function is the sum of the weighted losses from task\(_i\) and task\(_j\):

  \[
  J = C(w, x^{i\text{bat}}, y^{i\text{bat}}) + \eta C(w - \alpha \frac{\partial L(f(w, x^{i\text{bat}}), y^{i\text{bat}})}{\partial w}, x^{j\text{bat}}, y^{j\text{bat}})
  \]
Algorithm 1 MLTP

**Input:** Training data \((X_{tra}, Y_{tra})\), a neural network \(f\) with parameters \(w\)

**Output:** The optimal parameters \(w\)

1: for iterations = 1, 2, ..., n do
2:   Randomly take two different batches of samples \((x_{bat}^i, y_{bat}^i)\) and \((x_{bat}^j, y_{bat}^j)\) as two tasks
3:   Compute the loss of the first task \((x_{bat}^i, y_{bat}^i): L(f(w, x_{bat}^i), y_{bat}^i)\)
4:   Do one gradient step to \(w\): \(w' = w - \alpha \frac{\partial L(f(w, x_{bat}^i), y_{bat}^i)}{\partial w}\) where \(\alpha\) are the online adapted inner step sizes
5:   Apply \(w'\) to the second task \((x_{bat}^j, y_{bat}^j)\) to obtain the loss: \(L(f(w' - \alpha \frac{\partial L(f(w, x_{bat}^i), y_{bat}^i)}{\partial w}, x_{bat}^j), y_{bat}^j)\)
6:   Obtain the final objective function: \(J = L(f(w, x_{bat}^i), y_{bat}^i) + \eta L(f(w' - \alpha \frac{\partial L(f(w, x_{bat}^i), y_{bat}^i)}{\partial w}, x_{bat}^j), y_{bat}^j)\)
7:   Update \(w\) and \(\alpha\): \(w = w - r \frac{\partial J}{\partial w}; \alpha = \alpha - r \frac{\partial J}{\partial \alpha}\) where \(r\) is the learning rate
8: end for
We provide the first-order Taylor expansion of the objective function:

\[ J = C(w, x^i_{bat}, y^i_{bat}) + \eta C(w, x^j_{bat}, y^j_{bat}) - \eta \alpha \frac{\partial C(w, x^i_{bat}, y^i_{bat})}{\partial w} \cdot \frac{\partial C(w, x^j_{bat}, y^j_{bat})}{\partial w} \]

where . denotes the inner product operation.

- The first two terms on the right hand side minimize the losses on both task \( i \) and task \( j \) while the third term maximizes the similarity between the gradients on the two tasks.
- The third term is the main difference between MLTP and the standard training procedure.
Minimizing the objective requires the second derivatives with respect to w, which may be computationally expensive, especially for large neural networks. To address this issue, we introduce three alternative MLTP variants:

- **MLTP\textsubscript{conv}**: it only applies MLTP to the convolutional layers of a DNN.
- **MLTP\textsubscript{fc}**: it only applies MLTP to the fully connected layers.
- **MLTP\textsubscript{FO}**: it only uses the first-order derivatives of the objective to update w by ignoring the second derivatives (similar to the case in first-order MAML [1] or Reptile [2]).
## Experiments

### Test Accuracies on CIFAR-10

<table>
<thead>
<tr>
<th></th>
<th>Standard Training</th>
<th>Ours</th>
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<tbody>
<tr>
<td></td>
<td>MLTP</td>
<td>MLTP&lt;sub&gt;conv&lt;/sub&gt;</td>
</tr>
<tr>
<td>CNet1</td>
<td>81.9±0.29</td>
<td>82.4±0.26</td>
</tr>
<tr>
<td>CNet2</td>
<td>86.0±0.24</td>
<td>86.4±0.19</td>
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<tr>
<td>CNet3</td>
<td>85.9±0.19</td>
<td>86.5±0.15</td>
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<tr>
<td>CNet4</td>
<td>93.3±0.22</td>
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### Test Accuracies on CIFAR-100

<table>
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<tr>
<th></th>
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<tbody>
<tr>
<td></td>
<td>MLTP</td>
<td>MLTP&lt;sub&gt;conv&lt;/sub&gt;</td>
</tr>
<tr>
<td>CNet1</td>
<td>55.0±0.24</td>
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<tr>
<td>CNet2</td>
<td>58.8±0.18</td>
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<tr>
<td>CNet3</td>
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<tr>
<td>CNet4</td>
<td>71.9±0.19</td>
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### Test Accuracies on Tiny ImageNet

<table>
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<th>Standard Training</th>
<th>MLTP&lt;sub&gt;FO&lt;/sub&gt;</th>
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<tbody>
<tr>
<td></td>
<td>TOP1</td>
<td>TOP5</td>
</tr>
<tr>
<td>ResNet-18</td>
<td>53.2±0.27</td>
<td>76.5±0.24</td>
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<tr>
<td>ResNet-34</td>
<td>54.3±0.21</td>
<td>77.1±0.17</td>
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Conclusion

- Considering that meta-learning has shown excellent generalization abilities on few-shot learning, we study the question of whether meta-learning can be used to further tap the potential generalization abilities of DNNs on standard supervised learning.

- We have proposed a meta-learning based training procedure (MLTP) and have demonstrated that meta-learning can indeed improve the generalization abilities of DNNs on standard supervised learning.

- Experimental results with DNNs of various sizes on three benchmark datasets have demonstrated the effectiveness of MLTP.

- To the end, we bridge the gap between meta-learning and the generalization of DNNs on standard supervised learning by MLTP.
References:


Thank you for listening!