When does MAML Work the Best? An Empirical Study on Model-Agnostic Meta-Learning in NLP Applications

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Abstract

Model-Agnostic Meta-Learning (MAML) is successfully employed in Natural Language Processing applications including few-shot text classification and multi-domain low-resource language generation. Many impacting factors, including data quantity and data distribution, can affect the performance of MAML in NLP, but few works have thoroughly studied them. In this paper, we conduct an empirical study to investigate these impacting factors and conclude when MAML works the best based on the experimental results.

1 Introduction

In the field of Natural Language Processing (NLP), the abundance of training data plays a crucial role in the performance of deep learning models (Dodge et al., 2021). However, numerous NLP applications face a substantial challenge due to the scarcity of annotated data (Schick and Schütze, 2021). For example, in personalized dialogue generation, each user’s annotated data is limited, making it difficult to train a well-performing response generation model for each individual (Madotto et al., 2019; Song et al., 2020). Many techniques have been employed to address the issue of data scarcity, including self-supervised pre-training (Achiam et al., 2023; OpenAI, 2022), transfer learning (Gero et al., 2018; Kumar et al., 2022), and meta-learning (Madotto et al., 2019; Song et al., 2020; Zhao et al., 2022). Compared to other approaches, meta-learning focuses on designing models that learn to learn from small data sets, reducing the dependency on extensive pre-training data (Finn et al., 2017; Vilalta and Drissi, 2002). Therefore, meta-learning has been widely applied in low-resource NLP tasks.

Model-Agnostic Meta-Learning (MAML) (Finn et al., 2017) is one of the most popular meta-learning methods. It is trained on plenty of tasks (i.e. small data sets) to get a parameter initialization which is easy to adapt to target tasks with a few samples. As a model-agnostic framework, MAML is successfully employed in different NLP applications. Some works use MAML for few-shot text classification, such as relation classification (Obamuyide and Vlachos, 2019) and topic classification (Bao et al., 2020). Other works use MAML for multi-domain and low-resource language generation, such as few-shot dialogue system (Mi et al., 2019; Madotto et al., 2019; Qian and Yu, 2019; Song et al., 2020) and low-resource machine translation (Gu et al., 2018).

When applying MAML to NLP, several factors can influence the training strategy and performance of the model. Firstly, the data quantity within the datasets used as “tasks” varies across different applications, which can impact the effectiveness of MAML (Serban et al., 2015; Song et al., 2020). Secondly, while vanilla MAML assumes that the data distribution is the same across tasks, in real-world NLP tasks, the data distributions can differ significantly (Li et al., 2018; Balaji et al., 2018). For example, PAML (Madotto et al., 2019) regards each person’s dialogues as a task for MAML and they have different personal profiles. This variation manifests both between training tasks and between training and testing tasks, similarly affecting the performance of MAML. Few works have thoroughly studied these impact factors.

In this paper, we take an empirical approach to systematically investigating these impacting factors and finding when MAML works the best. We conduct extensive experiments over 4 datasets. We first

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study the effects of data quantity and distribution on the training strategy: \textbf{RQ1}. Since the parameter initialization learned by MAML can be seen as a general language model of training tasks, when the training and testing tasks have different data distributions, how can the general language model training affect the model’s task-specific adaptation ability? \textbf{RQ2}. How do the data distribution and data quantity affect our decision of fine-tuning epoch number? Then we study the effects of these factors on the model performance: \textbf{RQ3}. How do the data quantity and data distribution affect the performance of MAML?

The experimental results provide insights on MAML in NLP applications. Our conclusions help researchers to better develop meta-learning methods in NLP.

2 Preliminaries

2.1 Meta-learning Problem Definition

In meta-learning, we have multiple tasks \(T\) sampled from distribution \(p(T)\) \cite{Ravi2017, Andrychowicz2016, Santoro2016}. For each task \(T_i\), we train a base model \(f^\theta_i\) with parameter \(\theta_i\) on its training corpus \(D_{\text{train}}^i\) which only has a few samples, and evaluate the model on the testing corpus \(D_{\text{valid}}^i\). We divide the tasks into meta-training, meta-validation, and meta-testing. The goal of meta-learning is that after training on meta-training, we can quickly find \(f^\theta_i\) via fine-tuning (adaptation) with \(D_{\text{train}}^i\) for each task \(T_i\) in meta-testing.

2.2 Model-Agnostic Meta-Learning

Model-Agnostic Meta-Learning (MAML) \cite{Finn2017} pre-trains a parameter initialization \(\theta\) shared among tasks. At each training epoch, MAML samples a set of tasks \(T_i \sim p(T)\). For each task \(T_i\), MAML trains from the initialization \(\theta\) on \(D_{\text{train}}^i\) to get \(\theta_i\), then evaluates each \(\theta_i\) on \(D_{\text{valid}}^i\) and updates \(\theta\), which is,

\[
\theta_i = \theta - \alpha \nabla_{\theta} \mathcal{L}_{D_{\text{train}}^i}(\theta), \quad \theta = \theta - \beta \nabla_{\theta} \sum_{T_i \sim p(T)} \mathcal{L}_{D_{\text{valid}}^i}(\theta_i)
\]

where \(\mathcal{L}_{D_{\text{train}}^i}(\theta)\) and \(\mathcal{L}_{D_{\text{valid}}^i}(\theta_i)\) are the loss functions of \(\theta\) on \(D_{\text{train}}^i\) and \(\theta_i\) on \(D_{\text{valid}}^i\), \(\alpha\) and \(\beta\) are the learning rates. In fine-tuning stage, each task fine-tunes from the pre-trained initialization \(\theta\) on its \(D_{\text{train}}^i\).

3 Experimental Setup

3.1 Datasets

In Experiment I: Text Classification, we use FewRel \cite{Han2018} and Amazon \cite{He2016}. They are datasets for 5-way 5-shot classification, which means 5 classes are randomly sampled from the full dataset for each task, and each class has 5 samples. FewRel is a relation classification dataset with 65/5/10 tasks for meta-training/meta-validation/meta-testing. Amazon is a large customer review dataset with 24 product categories. We follow \cite{Bao2020} to sample 1000 reviews from each category and use 10/5/9 tasks for meta-training/meta-validation/meta-testing.

In Experiment II: Dialogue Generation, we use Persona \cite{Zhang2018} and Weibo, regarding building a dialogue model for a user as a task. Persona is a personalized dialogue dataset with 1137/99/100 users for meta-training/meta-validation/meta-testing. Each user has 121 utterances on average. Weibo is a personalized dialogue dataset collected from Weibo conversations with 371/40/38 users for meta-training/meta-validation/meta-testing. Each user has 1200 utterances on average.

3.2 Base Models and Settings

In each experiment, we use the same base model among the 2 datasets. In text classification experiments, we use the CNN proposed in \cite{Bao2020} as the base model and follow the hyperparameter settings. We use Transformer \cite{Vaswani2017} as the base model in dialogue generation experiment. In Persona, we use pre-trained Glove embedding \cite{Pennington2014}. In Weibo, we use Gensim \cite{Rehurek2010}. We follow the other hyperparameter settings in \cite{Madotto2019}.
3.3 Evaluation Metrics

In text classification experiment, we use accuracy (Acc) to evaluate the classification performance. In dialogue generation experiment, we evaluate the performance of MAML in terms of quality and personality. We use PPL and BLEU (Papineni et al., 2002) to measure the similarity between the reference and the generated response, and use C Score (Madotto et al., 2019) to measure the personality. In Persona we use a pre-trained natural language inference model to measure the response consistency with persona description for C Score. In Weibo, users do not have persona descriptions, so we pre-train a user classifier to classify the generated responses, and use the accuracy for C Score.

4 Results and Analysis

4.1 Trade-off Problem between General Language Model and Task-specific Adaptation

To answer RQ1, we compare the changing trend of the general language model and the task-specific adaptation ability during the training of MAML to find whether there is a trade-off problem. (Figure 1) We select the trained parameter initialization at different MAML training epochs and evaluate them directly on the meta-testing set before fine-tuning, using the quality performance (accuracy for classification and BLEU for generation) to evaluate the general language model. Then we use the personality performance (accuracy for classification and C Score for generation) after fine-tuning to measure each model’s ability to adapt to specific tasks.

When the training epochs increase, the model’s ability of task-specific adaptation reaches the peak earlier than the quality of its general language model does. In Persona, BLEU before fine-tuning reaches the peak at epoch 3000, but after epoch 1500, the final C Score drops. In Weibo, the changing trends are consistent with the results on Persona. In FewRel and Amazon, the general language model first becomes better and then over-fits to the training data, but the final accuracy decreases after epoch 1.

The finding suggests that parameter initialization at the late training stage has strong general language generation ability, but performs comparative poorly in task-specific adaptation. Although in the early training stage, the performance improves benefiting from the pre-trained general language model, if the language model becomes too “general”, it will lose the ability of adapting to specific tasks. It is noteworthy that the ”too general” problem is not the same as over-fitting, since the ”too general” model performs well before fine-tuning, which means it does not over-fit to the training data.

4.2 Impact of Data Quantity and Task Profile on Fine-tuning

To answer RQ2, we find the fine-tuning epochs for each task in Persona where its BLEU and C Score reaches the best respectively to find the impact of data quantity and the task profile (persona description) on fine-tuning. (Table 1) We cluster the tasks with similar best fine-tuning epoch number and calculate the average dialogue quantity and task profile similarity for each cluster. We define Jac Score of the persona descriptions to evaluate their task profile similarity as $Jac_{\text{Score}} = \frac{\sum_{i=1}^{N} Jac_i}{N} / (N Jac_{\text{whole}})$, where $Jac_i$ is the Jaccard similarity of the persona descriptions in cluster $i$, $Jac_{\text{whole}}$ is the Jaccard similarity of
| Cluster | Mean Fine-tuning Epochs | Task Similarity | Dialogue Quantity | Mean Fine-tuning Epochs | Task Similarity | Dialogue Quantity |
|---------|------------------------|-----------------|-------------------|------------------------|-----------------|-------------------|
| 1       | 0.22                   | 1.05            | 9.31              | 2.50                   | 1.00            | 9.05              |
| 2       | 1.16                   | 1.04            | 9.63              | 5.83                   | 1.06            | 9.89              |
| 3       | 2.07                   | 1.01            | 9.94              | 8.86                   | 1.09            | 10.05             |
| 4       | 3.68                   | 1.00            | 9.63              | 10.25                  | 1.05            | 9.16              |
| 5       | 5.38                   | 1.00            | 9.85              | 12.86                  | 1.00            | 10.24             |

Table 1: The average dialogue quantity and task profile similarity of the task clusters grouped by each task’s “best fine-tuning epochs” of BLEU and C (where its BLEU and C reaches the best) in Persona.

all the persona descriptions, and N is the number of clusters. If Jac Score is larger than 1, the persona descriptions are similar to each other in each cluster. Larger Jac Score means better similarity.

For both BLEU and C Score, Jac Score is around 1 in each cluster, which means the persona descriptions are not similar. The dialogue quantity also seems similar among different clusters. So we can conclude that data quantity and task profile does not have a major impact on the fine-tuning process.

4.3 Impact of Data Quantity and Task Similarity on the performance of MAML

To answer RQ3, we conduct experiments on different data quantity and task similarity settings. We compare two baselines with MAML: Transformer/CNN, which pre-trains the base model (Transformer/CNN) on the meta-training set and evaluates directly on the meta-testing set, and Transformer/CNN-F, which fine-tunes Transformer/CNN on each meta-testing task.

Data Quantity. In Persona, we evaluate Transformer/CNN, Transformer/CNN-F and MAML on 3 data quantity settings: 50/100/120-shot (each task has 50, 100, 120 utterances on average). In Weibo, FewRel and Amazon, the settings are 500/1000/1500-shot, 3/4/5-shot and 3/4/5-shot respectively (Table 2). When the data quantity is small, the advantage of MAML is more significant. In Persona, the C Score and BLEU of MAML outperform baselines on 50-shot and 100-shot settings, but on 120-shot setting, the BLEU of MAML is lower than Transformer-F. In Weibo, FewRel and Amazon, the percentages that MAML outperforms the baselines by also decrease as the data quantity increasing. This finding is in line with the mechanism of MAML. MAML finds a sensitive parameter initialization that can adapt with few data samples (Finn et al., 2017). When there are enough data samples, fine-tuning also performs well, so BLEU of Transformer-F in Persona on 120-shot setting is even better.

Task similarity. In Persona and Weibo, each task is a set of dialogues for one user, so tasks are different from each other. We shuffle the samples and randomly divide tasks to construct the setting that tasks are similar to each other. For a fair comparison, each task on this setting also has 120 and 1200 utterances on average in Persona and Weibo respectively. We train and evaluate Transformer-F and MAML on this setting. (Table 2). When tasks are similar to each other, MAML performs comparatively poorly. In Persona and Weibo, the performance of MAML is similar to that of Transformer-F, while MAML performs significantly better than Transformer-F when tasks are different. A possible explanation is that if there is no clear distinction between tasks, the meta-learning setting can be viewed as
a transfer learning setting, which only has a source domain and a target domain, and fine-tuning performs well in transfer learning. So if the tasks are similar to each other, we can simply use Transformer-F rather than MAML.

5 Conclusion

In this paper, we conduct an empirical study to investigate the impacting factors on the performance of MAML in NLP applications. We show that MAML works the best when the general language model is not fully trained by MAML, the data quantity of each task is small and tasks are dissimilar with each other. We also point out that it is unnecessary to customize the fine-tuning epoch number for each task according to the task profile or data quantity. Our work sheds light on the application of MAML in NLP.

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