Investigating Meta-Learning Algorithms for Low-Resource Natural Language Understanding Tasks

Zi-Yi Dou, Keyi Yu, Antonios Anastasopoulos
Language Technologies Institute, Carnegie Mellon University

Introduction

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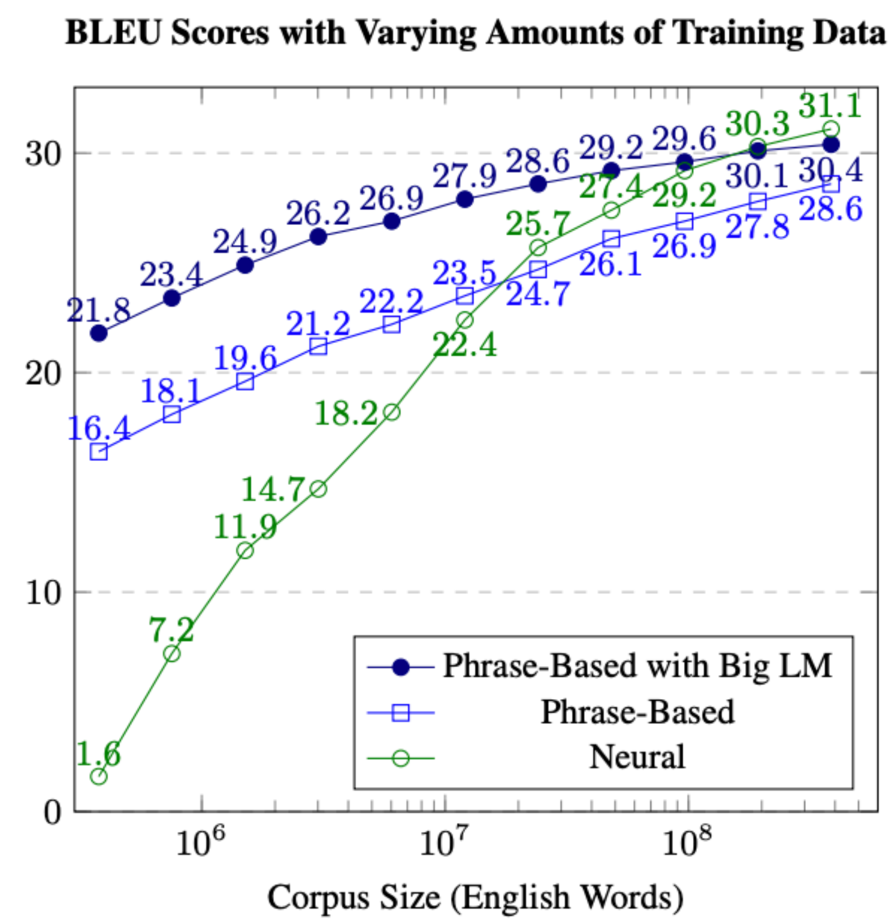

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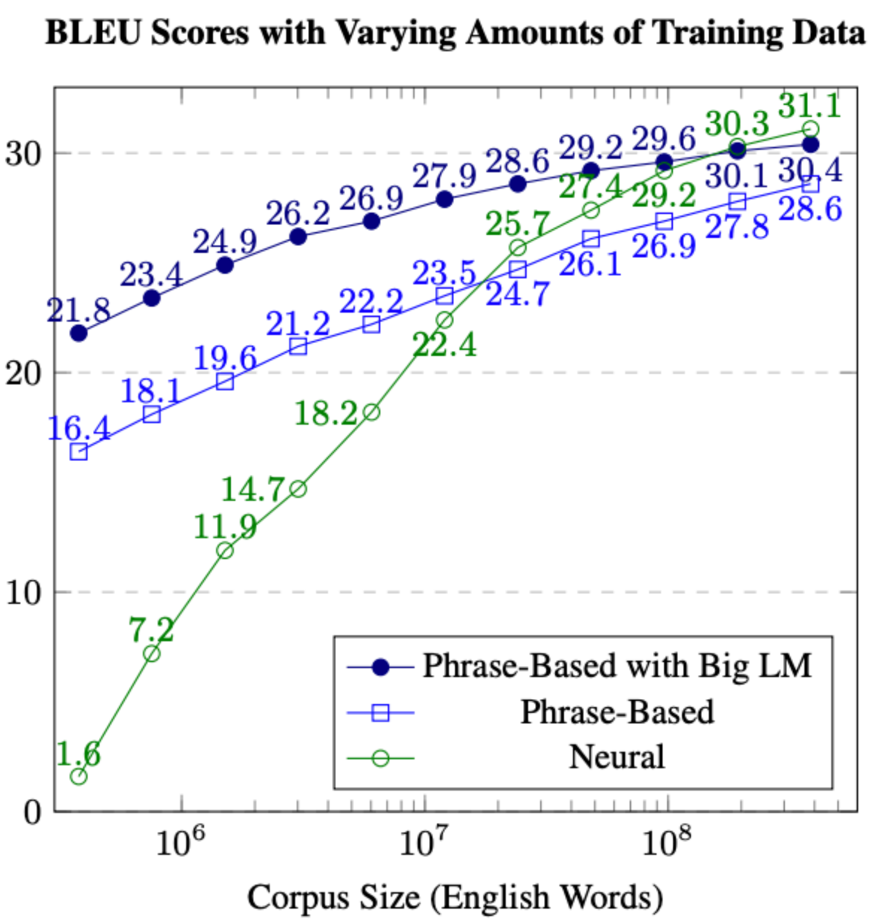

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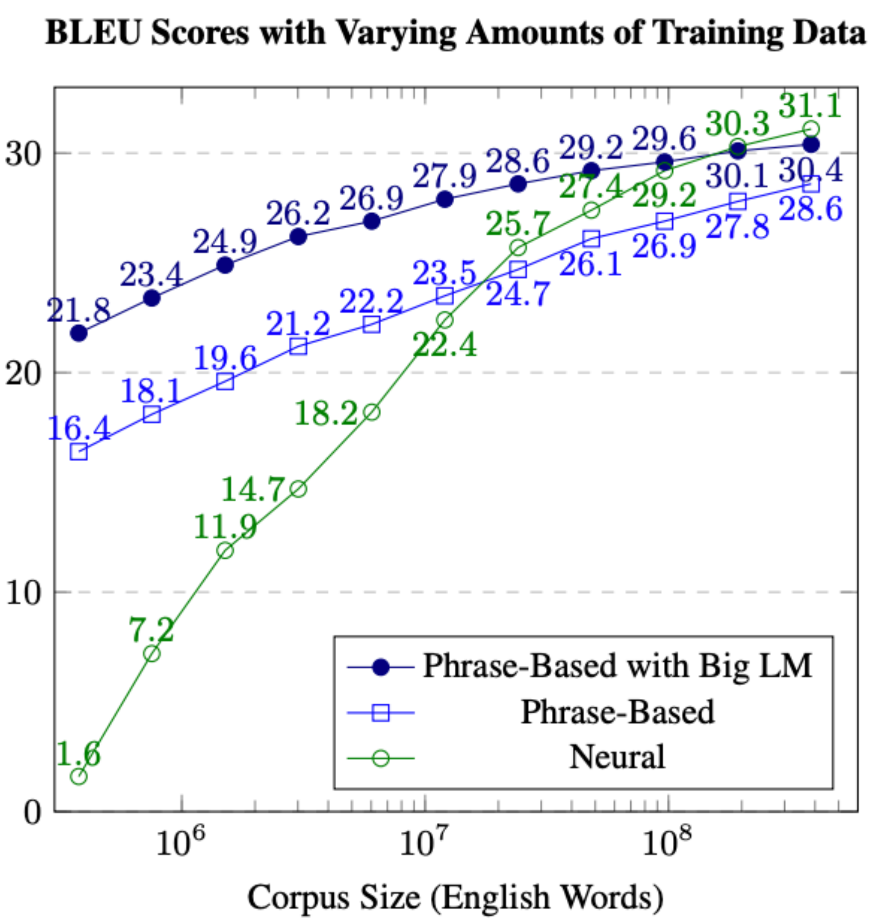
- It is essential to develop ways to tackle the scarcity of fully-annotated data



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- In this paper, we adapt several *optimization-based meta-learning algorithms* to NLU tasks
- We first adopt language model pre-training techniques to learn dense representations of texts, then continue to meta-learn robust representations

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for all T_i **do**
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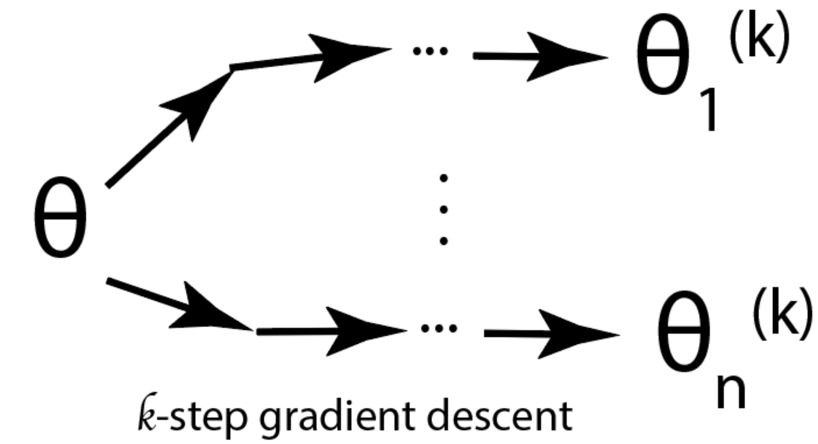

Inner loop

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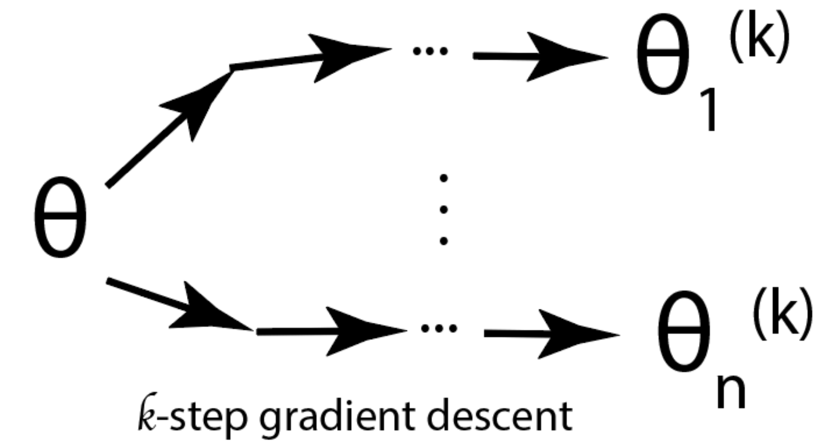

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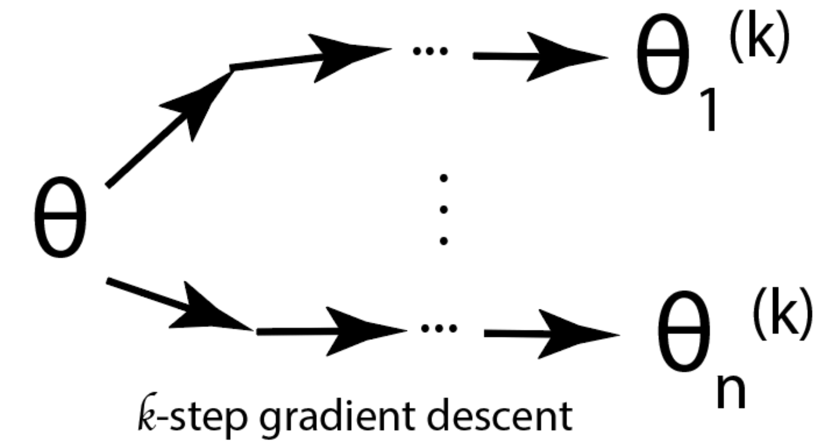

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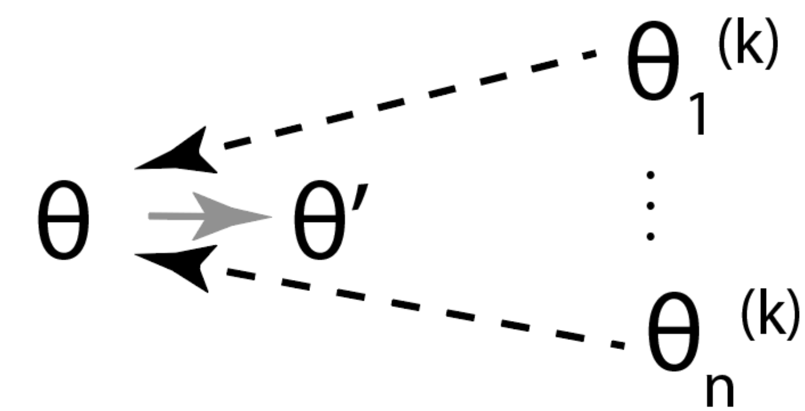

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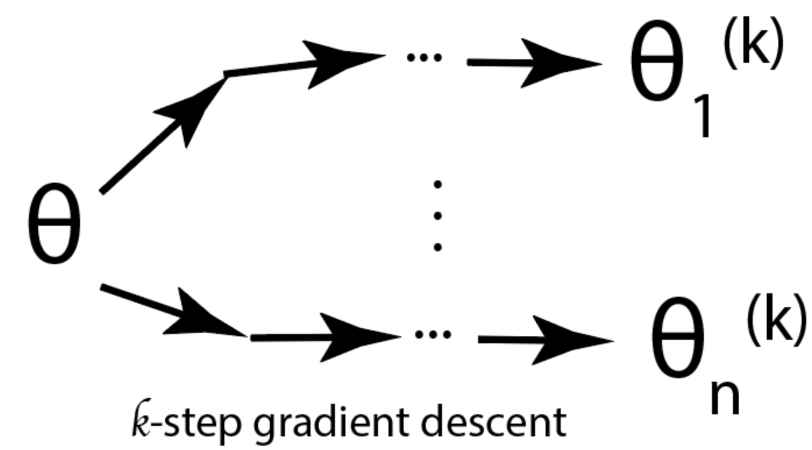

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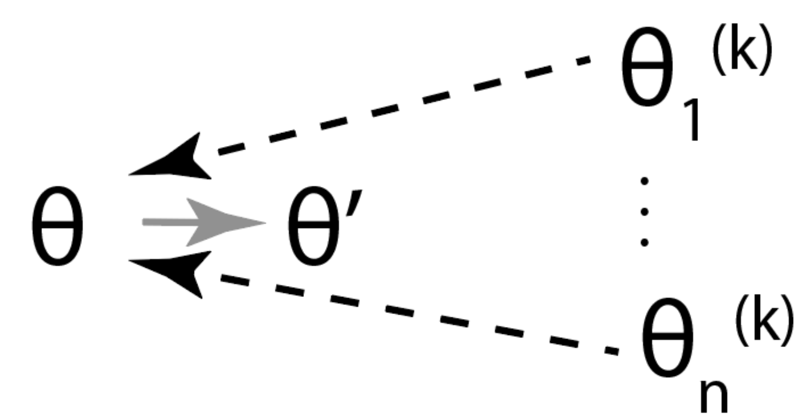

MetaUpdate

The meta-learning algorithms used in this paper just differ in the MetaUpdate step.

MAML

- Model-agnostic Meta Learning (MAML; Finn et al., 2017)
    - Objective function

$$\min_{\theta} \sum_{T_i \sim p(T)} L_i(f_{\theta_i^{(k)}})$$

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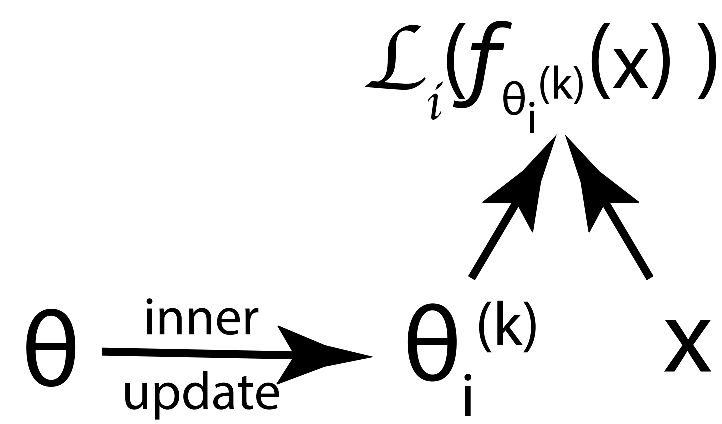

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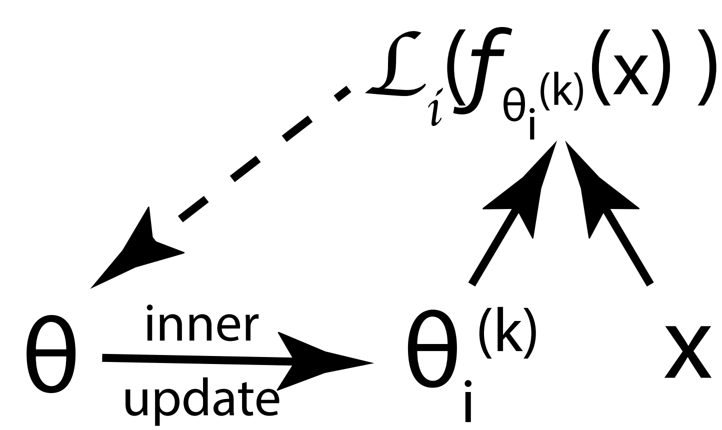

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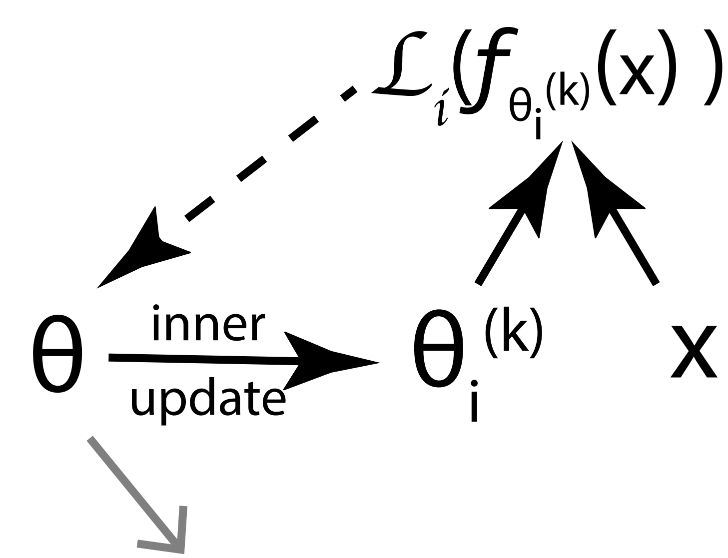

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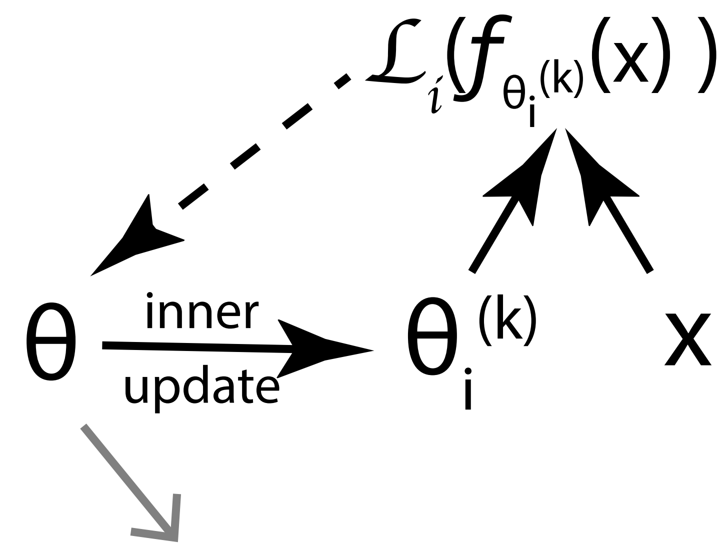

Involve computing second-order derivatives

First-order MAML

- Computing second-order derivatives can be computationally and memory intensive
- First-order MAML
  - The MetaUpdate Step

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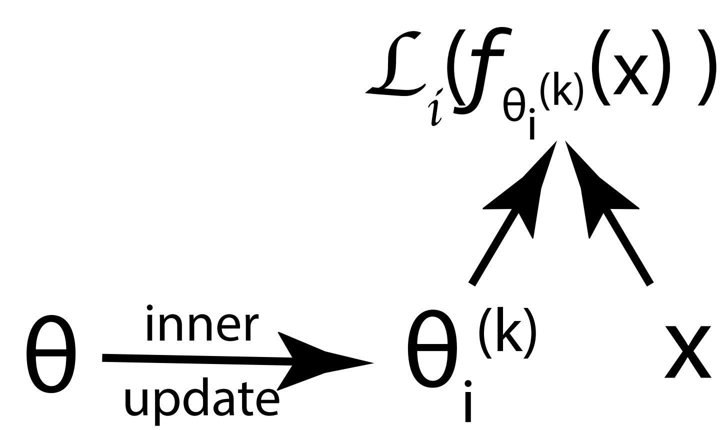

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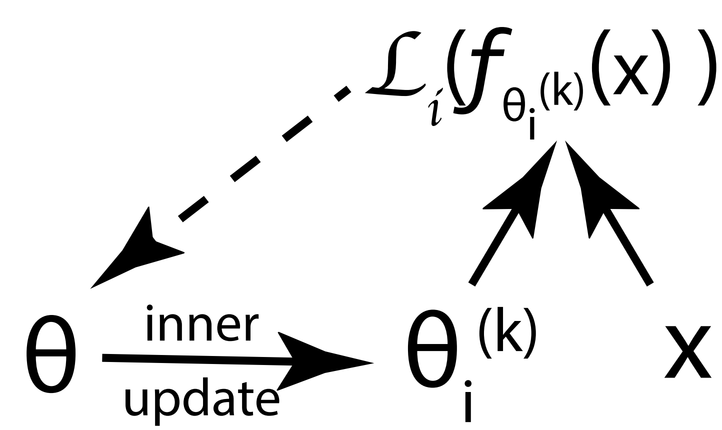

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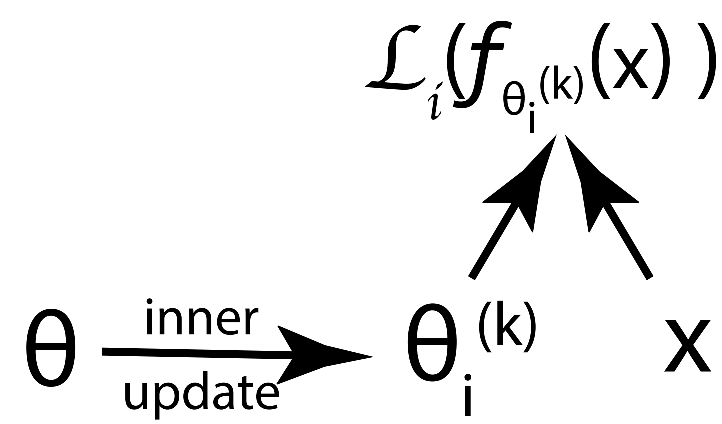

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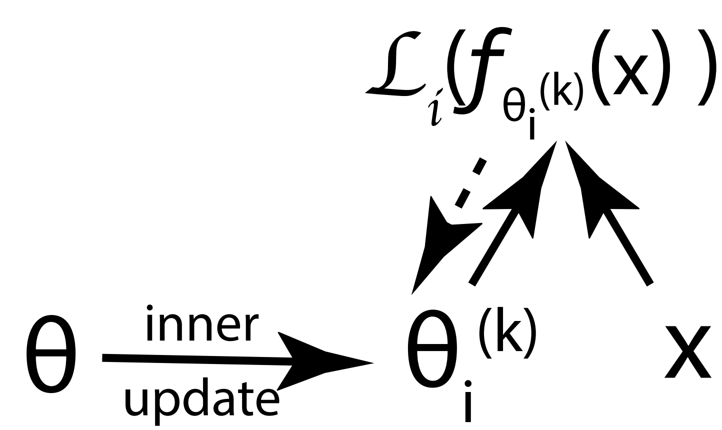

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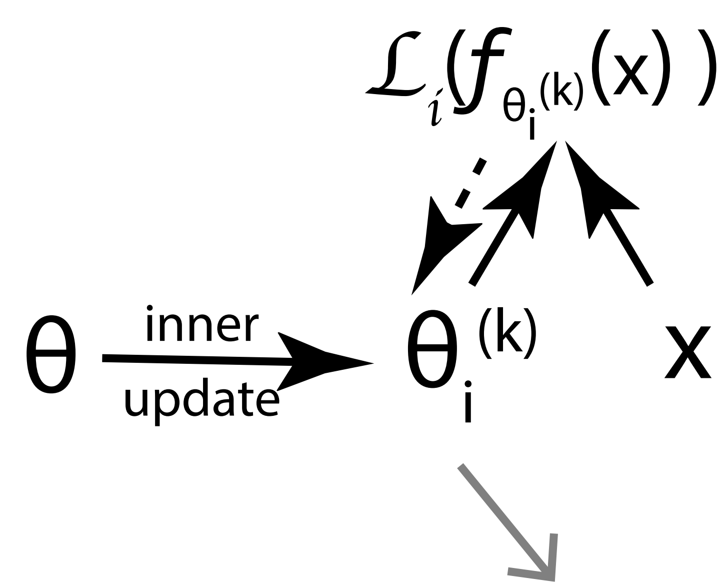

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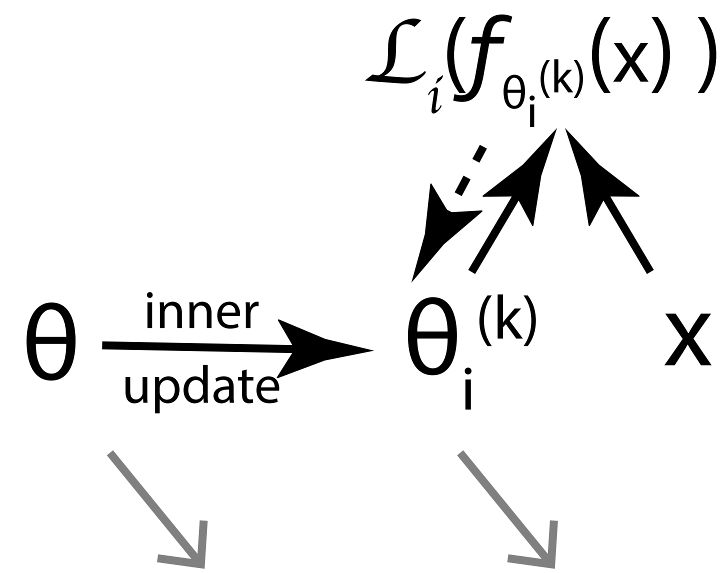

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Reptile

- Reptile (Nichol et al., 2018)
  - Another first-order algorithm
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Similar to joint training

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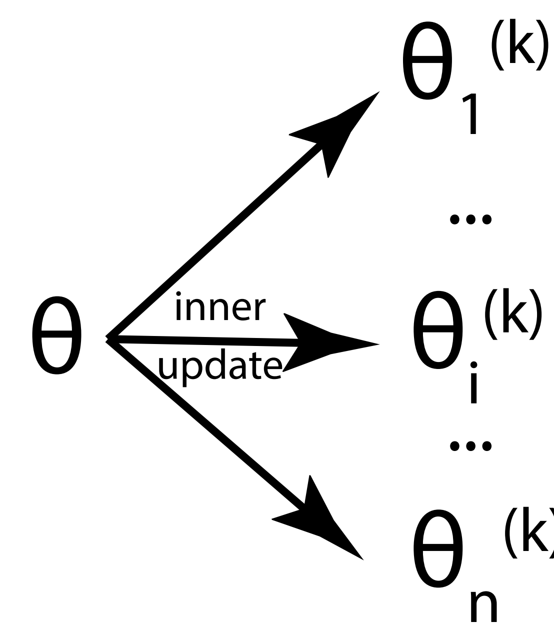

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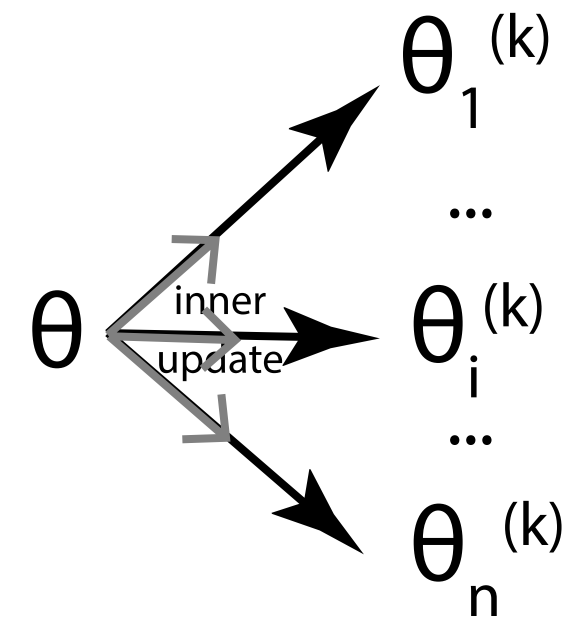

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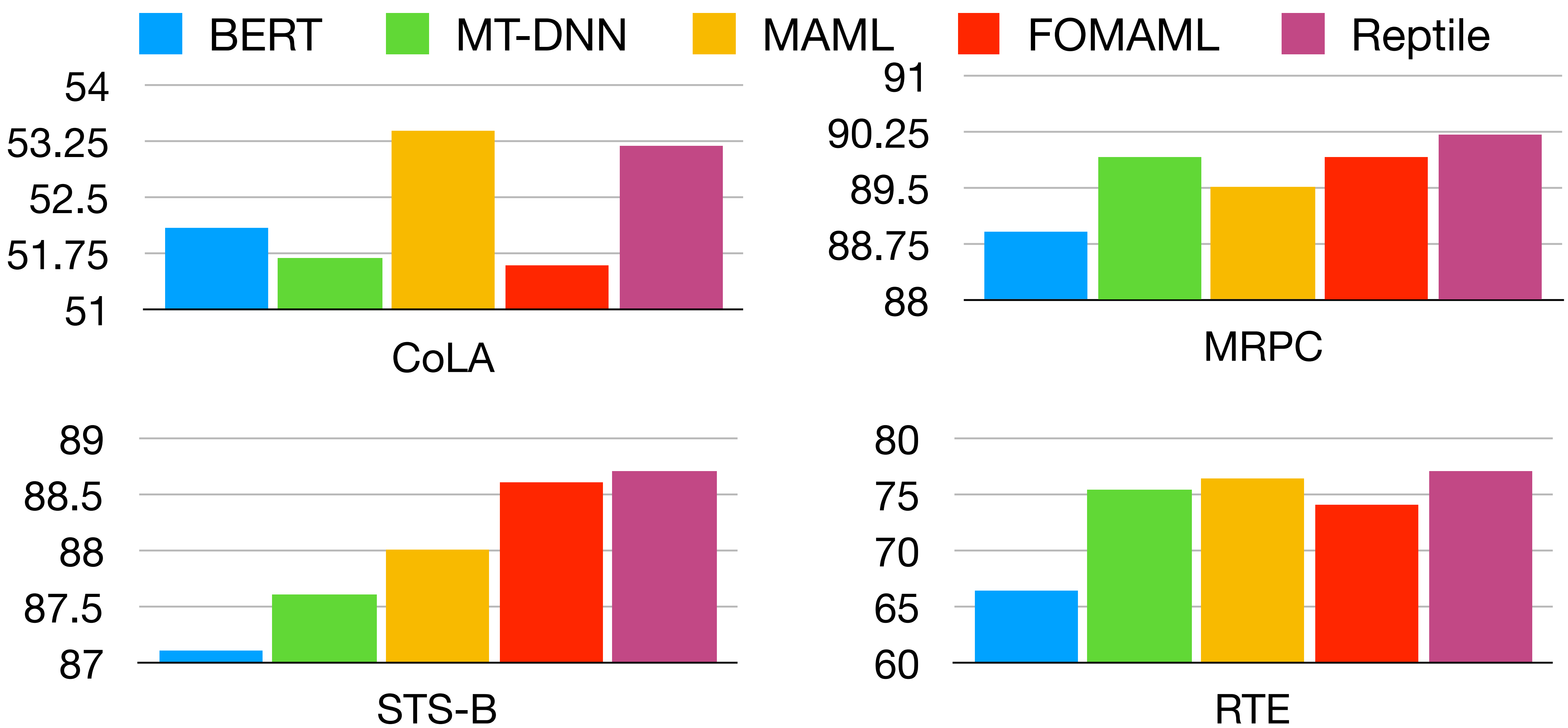
Experiment

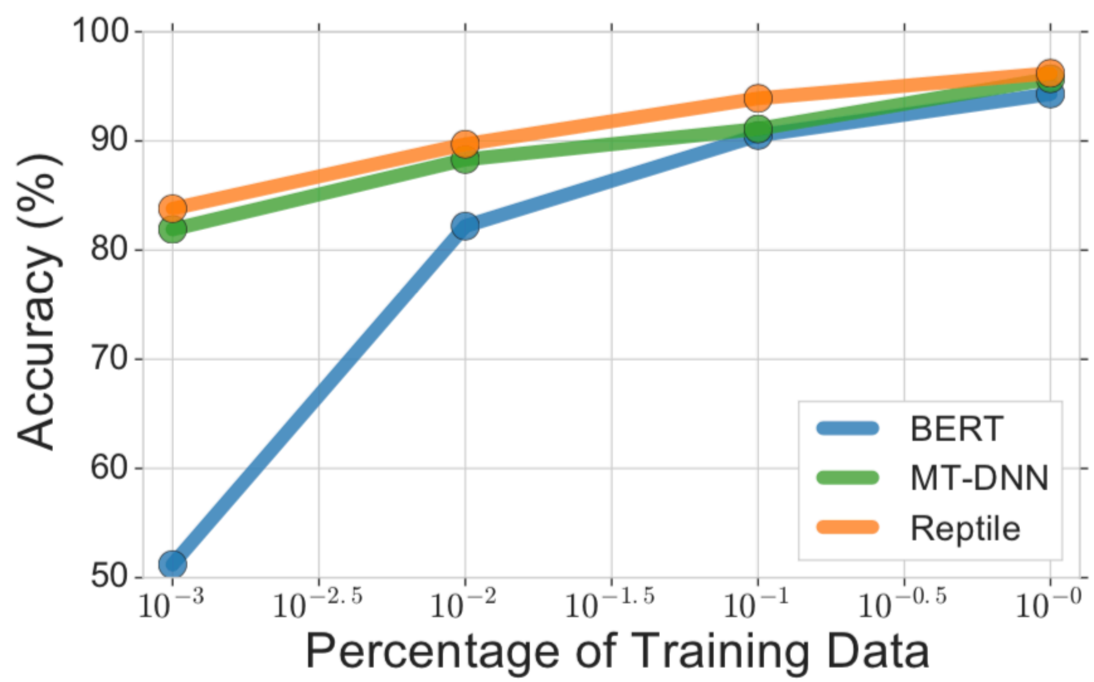
- Datasets
  - GLUE benchmark (Wang et al., 2019)
    - Auxiliary tasks: SST-2, QQP, MNLI, QNLI
    - Target Tasks: CoLA, MRPC, STS-B, RTE
  - SciTail dataset (Khot et al., 2018)
- Baselines
  - BERT (Devlin et al., 2019)
  - MT-DNN (Liu et al., 2019)

Results



- Generally, the meta-learning algorithms achieve better performance than the baselines
- Reptile performs better than MAML and FOMAML

Fast Adaptation



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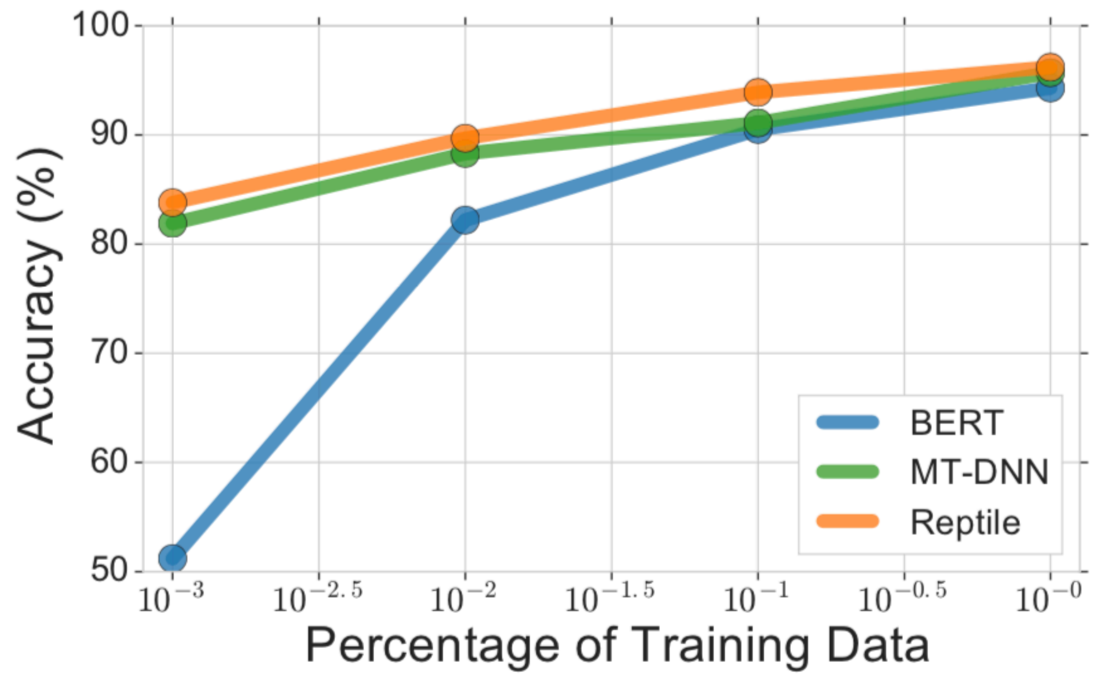

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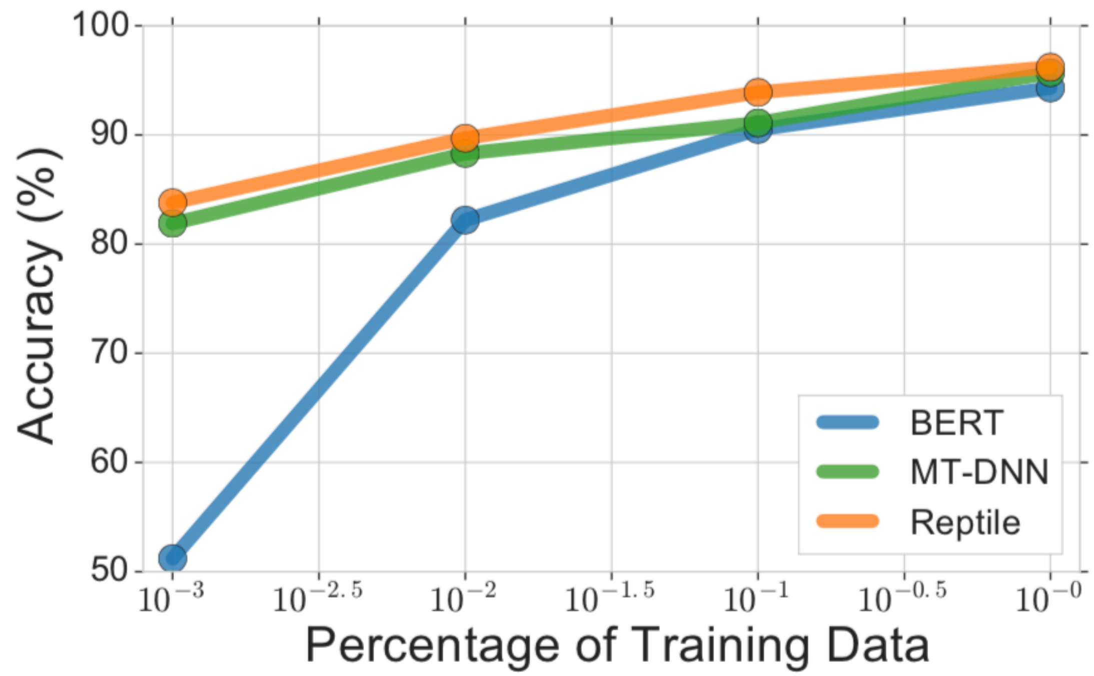

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- The meta-learned representations can be adapted to new tasks more *efficiently* compared with other baselines

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- In the future, we want to take the performance of the adapted parameters into consideration during the meta-learning stage

Thank you!