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International Journal of Artificial Intelligence and Machine Learning
Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

Automating Foundation Model Adaptation Through Gradient-Based Meta-Optimization Strategies

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Abstract

Foundation models can induce natural language processing and computer vision capabilities via generalized representations pre-trained on massive corpora. But tuning such large foundation models to downstream tasks is both computationally intractable and inefficient with standard fine-tuning procedures. In this work, introduce Gradient-Based Meta-Optimization Architecture (GB-MOA), a method that automates the adaptation process by building meta-learning into a second-order gradient optimization loop. GB-MOA employs a hypernetwork conditioned on the task-specific adapter weights, as well as a curriculum-driven bi-level optimization approach, which co-minimizes inner loop task losses and outer loop generalization loss. This study shows on GLUE, SuperGLUE, and few-shot classification benchmarks that model reaches 91.8% accuracy on a held-out composite GLUE benchmark with just 80 inner loop update steps, exceeding all baselines (including full fine-tuning, LoRA, and MAML variants), by updating less than 1.5% parameters. Ablation studies on various components of architecture support design choices.

Keywords Foundation Models, Meta-Learning, Gradient-Based Optimization, Parameter-Efficient Adaptation, Bilevel Optimization, Hypernetworks, few-Shot Learning.

1. Introduction

The rise of large-scale foundation models such as BERT [1] and GPT-4 [2] and their successors has changed the nature of applied machine learning. Pre-trained on internet-scale data, capture rich semantic and structural knowledge that is transferable to a wide variety of downstream tasks. Full fine-tuning training of all model parameters on each new task, however, has two main drawbacks: it is memory-intensive, requires separate training on every task, and may suffer from catastrophic forgetting. Parameter-efficient fine-tuning methods such as adapter tuning [3] and Low-Rank Adaptation (LoRA) [4] mitigate some of these limitations by tuning only a few parameters, while prompting [5] further reduces the size of the learned component to a small set of input tokens. These approaches, however, operate in a single task manner and typically ignore task similarities. Also demand task-specific hyperparameter tuning. Meta-learning (or "learning to learn") [6], by contrast, aims to find initializations or adaptation procedures that quickly generalize to new tasks; MAML [7] optimizes an initialization by taking a few gradient steps on new tasks. Applying MAML to billion-parameter foundation models, however, is computationally intractable, since calculating second-order meta-gradients over these models involves a massive number of parameters.

In this paper, develop a framework that addresses both the needs of efficient adaptation and effective meta-learning. Specifically, restrict second-order meta-gradient computation to a low-dimensional adapter subspace determined by a hypernetwork, incorporate task identity through a small task embedding network, and use a curriculum of tasks to speed up meta-training. This enables a fully automated adaptation procedure that is simultaneously memory-efficient, fast-adapting, and broadly generalizing. Contributions are (1) propose GB-MOA, the first framework for bilevel meta-learning on top of parameter-efficient foundation models, and (2) demonstrate its effectiveness on a variety of tasks. (2) propose a hypernetwork prior that restricts meta-gradients to a low-dimensional manifold of adapter parameters. (3) propose a task curriculum that accelerates meta-convergence. (4) perform extensive experiments on GLUE, SuperGLUE, and few-shot benchmarks, which confirm approach achieves state-of-the-art results with much less computational effort.

2. Related Work

2.1 Parameter-Efficient Fine-Tuning

There have been substantial efforts to efficiently fine-tune pretrained language models. Adapter layers [3] inject thin bottleneck modules between the transformer blocks and reach nearly the performance of full fine-tuning by modifying only <5% parameters. LoRA [4] drastically shrinks the modification area to just low-rank factors of weight updates, making fine-tuning possible in a computationally cheap manner for both text and vision models. Parameter-efficient prefix tuning [8] and prompt tuning [5] work by adding learnable virtual tokens to the input and require no parameter modification of the original model. These techniques work on individual tasks separately and fail to capture the underlying cross-task structure.

2.2 Meta-Learning for NLP

The application of meta-learning to NLP has mainly been in the few-shot paradigm. MAML [7] fine-tunes initial parameters of a model that allows for fast adaptation on new tasks, while Reptile [9] approximates it using first-order updates. ProtoNets [10] and relation networks learn distance metrics over samples for few-shot classification tasks. More recently, meta-learning has been coupled with pre-trained language models, though second-order optimisation across massive models is computationally intractable. Mitigate this by constraining the meta-gradients to a small adapter subspace parameterised by a hypernetwork to perform bilevel optimisation in a tractable way.

3. Proposed Methodology: GB-MOA

3.1 Problem Formulation

Let $T = \{\tau_1, \tau_2, \ldots, \tau N\}$ denote a distribution over tasks, each comprising a support set S_i and a query set Q_i. Given a foundation model $f\theta$ with parameters θ, seek a meta-initialization θ_0 and an adaptation function A such that for each task τ_i, the task-adapted parameters $\theta_i * = A(\theta_0, S_i)$ minimize the expected query loss $L(f\theta_i *, Q_i)$. The bilevel optimization objective is:

$$min\_\theta_0 \ \Sigma_i \, L(f\_\{A(\theta_0, S_i)\}, Q_i) \ \ subject\ to \ \ A(\theta_0, S_i) = \theta_0 - \alpha \nabla\_\theta \, L(f\theta, S_i)$$

Rather than updating all of θ, restrict adaptation to a set of lightweight adapter parameters $\varphi \subset \theta$ generated by a hypernetwork H conditioned on a task embedding $e_i = E(S_i)$, where E is a task encoder network.

3.2 Hypernetwork-Conditioned Adapter Prior

The hypernetwork $H: \mathbb{R}^d \rightarrow \mathbb{R}|\varphi|$ maps a task embedding e_i of dimension d to adapter weight values φ_i. This establishes a structured prior over the space of possible adapter configurations, constraining meta-gradient computation to the low-dimensional input space of H rather than the full parameter space of $f\theta$. Adapter modules are inserted after each transformer attention and feed-forward sublayer as in [3], but their weights are no longer task-independently initialized generated by H.

3.3 Bilevel Gradient Optimization

The inner loop updates adapter parameters φ for k steps on the support set: $\varphi_i' = \varphi_i - \alpha\nabla\_\varphi L(f\_\{\theta;\varphi_i\}, S_i)$. The outer loop then computes the meta-gradient with respect to the hypernetwork parameters ψ (weights of H) using query set loss: $\nabla\_\psi \Sigma_i L(f\_\{\theta;\varphi_i'\}, Q_i)$. Second-order gradients are computed through the inner loop using implicit differentiation, reducing memory overhead compared to full MAML unrolling.

3.4 Curriculum-Based Task Sampling

For more stable meta-convergence, adopt a curriculum scheduler C, which sorts tasks according to their difficulty in the meta-training process. Task difficulty is measured by the entropy of the model's output distribution on the support examples. In the early stage of meta-training, mostly easy tasks are drawn and, as meta-training proceeds, harder tasks are more frequently sampled. This process is analogous to the teaching strategy that orderly exposure to challenging environments fosters a more robust generalization.

4. Experiments

4.1 Datasets and Baselines

Evaluate GB-MOA on three benchmark suites: (i) GLUE [1], which consists of nine diverse English natural language understanding tasks; (ii) SuperGLUE, a difficult counterpart that tasks more complicated problems with multiple reasoning steps; and (iii) proposed few-shot classification suite constructed from the CrossFit benchmark. Compare GB-MOA with a set of full fine-tuning methods, namely full fine-tuning, adapter tuning [3], LoRA [4], prompt tuning [5], and MAML-FT [7]. Always use a pretrained RoBERTa-large backbone (355M parameters) as the base model and train all methods using 4 NVIDIA A100 GPUs. The learning rate is chosen via grid search among $\{1e-5, 5e-5, 1e-4\}$.

4.2 Implementation Details

For the GB-MOA adapter modules, use the 64 bottleneck dimension in all transformer layers (a total of 24 layers). The hypernetwork H consists of 2 linear layers with ReLU activations, projecting the 128-dimensional task embedding into adapter weights. The task encoder E is a mean-pooling transformer, operating over support examples. The inner loop runs for $k = 5$ gradient steps with $\alpha = 0.01$. The outer loop uses AdamW with $\beta = 5e-5$ and weight decay 0.01. Curriculum progression follows a cosine schedule over meta-training epochs.

5. Results

5.1 Main Performance Comparison

Table 1 shows an overview of the results of GB-MOA compared to all baseline methods on the combined GLUE metric. With 91.8% accuracy and 0.914 F1, GB-MOA exceeds the second-highest score (MAML-FT) in accuracy by 4.4 percentage points and F1 by 0.046. Significantly, GB-MOA achieved this with only 80 inner-loop adaptions, a 5x reduction from MAML-FT's 150, and a 12x reduction from the fully fine-tuned methods. Even with the best accuracy, GB-MOA updates 1.4% of the model parameters, while fully fine-tuning or MAML-FT updates 100% of the parameters. It also reports the fastest wall-clock adaptation time per task (97.3 sec), showing how meta-learned adaptor initialization minimizes redundant gradient computations. LoRA, while parameter-efficient, does not provide cross-task generalization from meta-optimization and is outperformed by GB-MOA by 5.6 points. Prompt tuning achieves the poorest accuracy: this is in line with its limitations regarding expressive compositional reasoning.

Table 1: Performance comparison on GLUE composite benchmark. bold indicates best result

Method	Accuracy (%)	F1-Score	Avg. Adapt. Steps	Params Updated (%)	Wall Time (s)
Full Fine-Tuning	84.3	0.831	1000	100.0	412.6
Adapter Tuning [3]	85.7	0.849	600	3.2	189.4
LoRA [4]	86.2	0.856	500	0.8	154.2
Prompt Tuning [5]	83.1	0.819	800	0.1	143.8
MAML-FT [7]	87.4	0.868	150	100.0	278.5
GB-MOA (Ours)	**91.8**	**0.914**	**80**	**1.4**	**97.3**

5.2 Ablation Study

Table 2 shows an ablation study comparing the benefit of each component of GB-MOA on GLUE, SuperGLUE, and few-shot accuracy metrics. Forgetting the second-order gradient computations (using first-order FOMAML-style updates instead) drops the GLUE score by 3.7 points, demonstrating the utility of curvature for fast task adaptation. The hypernetwork prior (replacing it with a random initialization of the adapters) yields a cost of 2.5 GLUE points, confirming that it is indeed a useful structured prior for out-of-distribution (cold start) generalization. Removing the task embedding (using an initial adapter state that does not depend on the task) has the greatest individual benefit, increasing the GLUE score by 4.2 points; the initial adapter becomes task-agnostic, failing to discriminate between tasks of different semantics. The curriculum schedule provides a gain of 1.9 points to the GLUE score, although in the one-shot accuracy, gains are 3.1 points; curricula prove more beneficial for very few shots. The first-order approximation is 1 point less accurate than the second-order formulation (last row) and is 1.3 times faster than it, which may provide benefits for deployment latency-sensitive applications.

Table 2: Ablation study of GB-MOA components. Each row removes one component from the full model

Configuration	GLUE Avg.	SuperGLUE Avg.	5-Shot Acc. (%)	1-Shot Acc. (%)
Full GB-MOA	**91.8**	**88.4**	**87.6**	**79.3**
w/o Second-Order Grad.	88.1	84.9	83.2	74.1
w/o Hypernet Prior	89.3	85.7	84.5	75.8
w/o Task Embedding	87.6	83.4	81.9	72.4
w/o Curriculum Schedule	89.9	86.3	85.1	76.2
First-Order Approx. Only	88.7	85.2	83.8	74.9

6. Discussion

Overall, these results suggest that GB-MOA is a principled way to automate foundation model adaptation. By limiting the adaptation manifold to adapter subspaces from the hypernetwork, GB-MOA manages to combine the theoretical benefits of second-order MAML and the limitations from deploying large models in practice. The task embedding mechanism has had a surprising and substantial effect, suggesting that explicit task representation is an under-investigated, yet fundamental part of task automation. Perhaps surprisingly, the curriculum schedule is beneficial mostly for the few-shot case, and task difficulty ordering seems to perform as implicit data augmentation in low-resource situations. Future research should include exploring extensions of GB-MOA for multimodal foundation models, introducing uncertainty estimates for the task embeddings, and looking at the relationship between adapter dimensions and meta-gradient curvature.

7. Conclusion

This study, propose GB-MOA, a gradient-based meta-optimization architecture that automates large foundation models' adaptation to new tasks. By pairing hypernetwork-generated adapter priors with bilevel second-order optimization and task curriculum, GB-MOA can achieve state-of-the-art on GLUE, SuperGLUE, and few-shot task

adaptation with less than 1.5% parameters updated and 80 inner-loop steps per task. The ablation study proves each component is crucial, and the robustness performance across various data amounts demonstrates the generalization ability of the meta-optimization strategy. GB-MOA provides a promising route toward an automated and efficient adaptation process.

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