Meta-learning for downstream aware and agnostic pretraining

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Abstract

Neural network pretraining is gaining attention due to its outstanding performance in natural language processing applications. However, pretraining usually leverages predefined task sequences to learn general linguistic clues. The lack of mechanisms in choosing proper tasks during pretraining makes the learning and knowledge encoding inefficient. We thus propose using meta-learning to select tasks that provide the most informative learning signals in each episode of pretraining. With the proposed method, we aim to achieve better efficiency in computation and memory usage for the pretraining process and resulting networks while maintaining the performance. In this preliminary work, we discuss the algorithm of the method and its two variants, downstream-aware and downstream-agnostic pretraining. Our experiment plan is also summarized, while empirical results will be shared in our future works.

1 Introduction and related works

Recently neural network pretraining, such as BERT (Devlin et al., 2019), OpenAI GPT (Radford et al., 2018), XLNet (Yang et al., 2019), and ELECTRA (Clark et al., 2019) has yielded significant performance improvement for various downstream applications in natural language processing. Usually, semantic and syntactic information is implicitly learned from the co-occurrence of words and sentences in datasets and encoded in the networks for general purposes. The entire networks or part of their layers are then finetuned for the downstream usage. To better leverage training corpora and discover all valuable information, ERNIE 2.0 (Sun et al., 2020) proposes a sequential multitask pretraining framework containing a variety of word-, structure-, and semantic-aware pretraining tasks. Although increasing the diversity of pretraining tasks continually improves model performance accuracy, the lack of mechanisms in selecting and scheduling tasks makes the training process, model serving, and memory footprint bulky. The model expressivity has to grow accordingly to encode information from all the tasks generally.

To address the challenge, we propose a framework using meta-learning to schedule tasks and make pretraining more efficient in this preliminary paper. Meta-learning is commonly used in learning model architectures, hyperparameters, or learning algorithms that are generalizable across tasks through episodic training (Finn et al., 2017; Vinyals et al., 2016; Snell et al., 2017; Luo et al., 2020; Li et al., 2021). Hence, we leverage meta-learning to formulate each pretraining batch as an episode, and select the pretraining task offering the most helpful training signals in the episode, instead of following predefined or sequential order of tasks, to update the model parameters. With the formulation, we explore two variants, downstream-aware and downstream-agnostic pretraining, that utilize loss evaluating training signals with or without labels in downstream applications. The episodic task selection is expected to encode lexical, syntactic, and semantic information across various tasks more efficiently. In this preliminary work, we introduce the detailed algorithm, implementation challenges and corresponding solutions, and experiment settings. We will share empirical results later.

2 Method and experiment plan

To make multitask pretraining more efficient, we propose a framework of utilizing meta-learning to schedule tasks used for network pretraining. We summarize the framework step-by-step in Algo-
Algorithm 1 Meta-learning based network pretraining

**Inputs:** Set of all source and target tasks \( S, T \); data distribution over each source and target task \( p^s(\tau), p^t(\tau); L_\tau \), the loss function evaluated on a subtask \( \tau \) sampled from \( p^s(\tau) \) or \( p^t(\tau) \); learning rates \( \alpha, \lambda \), number of batches \( M, N \).

**Output:** Optimized network parameters \( \theta \).

1. Initialize \( \theta \);
2. **while** not done **do**
   3. Sample \( M = |T| \) target subtasks (i.e., batches) \( \tau_T = \bigcup_{t=1}^M \tau_t \), where \( \tau_j \sim p^t(\tau) \) and \( j = 1...M \);
   4. **for** \( s \in S \) **do**
     5. Sample \( M \) subtasks \( \tau_s \sim p^s(\tau) \), \( i = 1...M \);
     6. \( u(s) = 0 \);
     7. **for all** \( \tau_s \) **do**
       8. Compute gradient for fast adaptation:
       9. \( \theta' = \theta - \alpha \nabla_\theta \tau_s(f(\theta)) \);
       10. Evaluate updated parameters on target subtasks: \( u(s) \leftarrow scorer(\theta', \tau_s) \)
       11. \( \hat{s} = \arg\max u(s) \)
     12. Sample \( N \) subtasks \( \tau_s \sim p^s(\tau) \), \( i = 1...N \);
     13. **for all** \( \tau_s \) **do**
       14. Compute gradient and update parameters:
       15. \( \theta = \theta - \lambda \nabla_\theta L_{\tau_s}(f(\theta)) \);

3. We will focus on four applications for the downstream tasks and the target pretraining tasks in the downstream-aware setting: relation extraction, semantic role labeling, general language and sentence understanding, and machine reading comprehension. In this setting, additional prediction heads will be added to the backbone network separately for different tasks. These heads are pretrained (in the downstream-aware setting) and finetuned (in both downstream-aware and downstream-agnostic settings) for evaluation. We will employ CoNLL04 (Roth and Yih, 2004), CoNLL-2005 (Carreras and Márquez, 2004), CoNLL-2004 (Sun et al., 2020) as the work provides good coverage of tasks for word-, structure-, and semantic-aware pretraining signals. Masked passage retrieval (Glass et al., 2020), text generation, and unsupervised question answering (Luo et al., 2021) tasks will also be investigated to provide generation and passage level pretraining losses.

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1Similar to approaches in reinforcement learning, the epsilon-greedy algorithm can be used to choose between exploration and exploitation randomly.
In this work, we propose a meta-learning-based downstream-aware and downstream-agnostic pre-training method, where pretraining tasks are selected episodically from a list of candidate tasks to improve pretraining efficiency while maintaining the performance. We summarize the algorithm and our experiment plan. Empirical results will be shared in our future works.

3 Conclusion

In this work, we propose a meta-learning-based downstream-aware and downstream-agnostic pre-training method, where pretraining tasks are selected episodically from a list of candidate tasks to improve pretraining efficiency while maintaining the performance. We summarize the algorithm and our experiment plan. Empirical results will be shared in our future works.

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