Unsupervised reinforcement knowledge distillation

Abstract

Model compression techiniques are widly applied to large language models, especially for Pre-trained large language model, such as BERT (Devlin et al., 2019), those have improved the performance of many NLP tasks. However, the large language model has high requirements for computational expenses. To accelerate the inference and model size, two popular methods, weight pruning and knowledge distillation, are widely applied in the NLP area. We are going to focus on knowledge distillation (KD) (Hinton et al., 2015), specifically on Transformer-based ones. We use reinforcement learning (RL) to train a small language model, where the reward function is derived from a large language model. The reward derivation is based on previous work (Hao et al., 2022).

1 Introduction

Knowledge distillation (Hinton et al., 2015) is a very popular model compression technique. Applying KD on transformers are in favor of us researchers. The key of knowledge distillation is to pass the linguistic information from teacher model to student model. In our context, it is from pre-trained large language model (T0) to a small ones(T5-base). Unsupervised reinforcement learning trains the T5-base with pseudo-label generated by T0 guided by naturally designed prompt templates. The idea is to pass the knowledge from T0 to T5 using RL as knowledge distillation method.

2 Methodology

Classic-KD The concept of Knowledge distillation was first introduced (Hinton et al., 2015) where it emphasizes the knowledge are measured and passed through cross-entropy training with different loss functions which are designed to make the student model imitate the teacher model.

Sequence-KD Similar to the classic-KD, sequence-KD (Kim and Rush, 2016) focuses on passing the knowledge in sequence-level instead of word by word. The main contribution is it solved the intractability of combinations within a sequence which can be exponentially large.

Transformer-KD Transformer-KD (Jiao et al., 2020) based on transformer structure. It designed three different loss functions in order to capture as much linguistic knowledge as it can to pass to student models.

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Those are only three related work briefly introduced here. In the following part, a reading list is provided here to further improve the understanding.

Our Method The method we are going to use is to apply (Hao et al., 2022). to a large language model T0-3B, which will have 3 billion parameters, and confer its knowledge to the small-sized model T5-base which only has 220 million parameters. The RL algorithm will serve as a knowledge distillation method from our teacher to our student.

Evaluation The task we are currently applying is text generation in dialogue generation, and the metric to evaluate the performance is going to be the same as other papers, the BLEU scores.We are applying the models with cleaned datasets named dailydialogue and opensubtitles.However, there is no state of art paper in this specific area for us to compare currently, and more importantly all of the baselines we are applying is based on our own replication on this specific task and setting.

3 Importance of the work

While reading through those papers, there are some limitations and main contributions we would like to mention here.

For Transformer-based-KD, the key limitations are to design the loss function to capture the "knowledge". TinyBERT (Jiao et al., 2020), for example, only deal with encoder-only transformers and require a lot self-designed loss function. On the other hand, in an ideal scenario, our RL exploration would capture all information and works on any kind of transformers.

4 Reading list

This list [1] contains more than 20 papers related to knowledge distillation and including theory and best practices. We mark them in red and blue fonts, respectively.

References

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

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Yoon Kim and Alexander M. Rush. 2016. Sequence-level knowledge distillation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1317–1327, Austin, Texas. Association for Computational Linguistics.

[1] https://docs.google.com/document/d/17s3U2cWtjzbW_uiPb4yhxjiE-MUR63uPls7j0QD6dyw/edit