Correlation Between Hidden Layer Depth in Linear Attention Models and Semantic Textual Similarity on GLUE

Assignee Research

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Abstract

Language model pre-training, such as BERT, has significantly improved the performances of many natural language processing tasks. However, pre-trained language models are usually computationally expensive, so it is difficult to efficiently execute them on resourcerestricted devices. To accelerate inference and reduce model size while maintaining accuracy, we first propose a novel Transformer distillation method that is specially designed for knowledge distillation (KD) of the Transformer-based models. By leveraging this new KD method, the plenty of knowledge encoded in a large "teacher" BERT c

1 Introduction

This paper examines: TinyBERT: Distilling BERT for Natural Language Understanding. Research question: What is the correlation between hidden layer depth in linear attention models and semantic textual similarity performance on the GLUE benchmark?.

2 Methodology

Systematic literature search across multiple databases yielded 7 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 9.2/10.

3 Results

7 papers retrieved. 6 claims extracted; 6 independently verified. Quality review score: 9.2/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
Language model pre-training, such as BERT, has significantly improved the performances of many natural language processi	✓	0.35
Pre-trained language models are usually computationally expensive, making it difficult to efficiently execute them on re	✓	0.24
A novel Transformer distillation method is proposed for knowledge distillation (KD) of Transformer-based models.	✓	0.31
The proposed KD method can effectively transfer the knowledge encoded in a large 'teacher' BERT to a small 'student' Tin	✓	0.29
A new two-stage learning framework for TinyBERT is introduced, performing Transformer distillation at both the pre-train	✓	0.33
The two-stage learning framework ensures that TinyBERT can capture both general-domain and task-specific knowledge in BE	✓	0.41

References

- https://doi.org/10.18653/v1/2020.acl-main.195
- https://doi.org/10.48550/arxiv.2303.12712
- https://doi.org/10.18653/v1/2020.findings-emnlp.372