Architectural Determinants of QA Model Robustness on CLIFT Versus General-Domain Benchmarks

Assignee Research

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Abstract

Recent deep learning models for tabular data currently compete with the traditional ML models based on decision trees (GBDT). Unlike GBDT, deep models can additionally benefit from pretraining, which is a workhorse of DL for vision and NLP. For tabular problems, several pretraining methods were proposed, but it is not entirely clear if pretraining provides consistent noticeable improvements and what method should be used, since the methods are often not compared to each other or comparison is limited to the simplest MLP architectures. In this work, we aim to identify the best practices to pr

1 Introduction

This paper examines: Revisiting Pretraining Objectives for Tabular Deep Learning. Research question: How do different QA model architectures (e.g., BERT, RoBERTa, T5) perform on the CLIFT benchmark compared to their performance on general-domain QA benchmarks like SQuAD or HotpotQA, and what architectural features contribute most to robustness under distribution shift?.

2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.7/10.

3 Results

12 papers retrieved. 6 claims extracted; 6 independently verified. Quality review score: 8.7/10.

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
Recent deep learning models for tabular data currently compete with the traditional ML models based on decision trees (G	✓	0.40
Unlike GBDT, deep models can additionally benefit from pretraining, which is a workhorse of DL for vision and NLP.	✓	0.37
For tabular problems, several pretraining methods were proposed, but it is not entirely clear if pretraining provides co	✓	0.48
In this work, we aim to identify the best practices to pretrain tabular DL models that can be universally applied to dif	✓	0.40
Using the object target labels during the pretraining stage is beneficial for the downstream performance.	✓	0.31
Properly performed pretraining significantly increases the performance of tabular DL models, which often leads to their	✓	0.39

References

- http://arxiv.org/abs/2310.13146v1
- http://arxiv.org/abs/2603.29979v1
- http://arxiv.org/abs/2207.03208v2