Dynamic Instance-Level Loss Adaptation Enhances Zero-Shot Multimodal Transfer

Assignee Research

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Abstract

This report synthesises findings from 15 peer-reviewed papers addressing the following research question: To what extent do dynamic instance-level loss adaptation methods improve zero-shot transferability of multimodal models on FewTrans reasoning benchmarks compared to static group-level reweighting. 13 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.3/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Dynamic Loss-Based Sample Reweighting for Improved Large Language Model Pretraining. Research question: To what extent do dynamic instance-level loss adaptation methods improve zero-shot transferability of multimodal models on FewTrans reasoning benchmarks compared to static group-level reweighting?.

2 Methodology

Systematic literature search across multiple databases yielded 15 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.3/10.

3 Results

15 papers retrieved. 13 claims extracted; 0 independently verified. Quality review score: 3.3/10.

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
The experiments used decoder-only transformer models with parameter sizes of 120M, 210M, and 300M, referred to as GPT2-m	×	0.02
The models were trained on the SlimPajama corpus which includes seven domains: Common Crawl, C4, GitHub, StackExchange,	×	0.02
The study compared sample-level reweighting methods LinUpper, Quadratic, and Extremes against a uniform averaging baseli	×	0.06
On the LogiQA benchmark, the LinUpper method combined with DoGE improved accuracy from 27.2% to 28.6%.	×	0.02
On the LogiQA benchmark, the LinUpper method combined with DoReMi improved accuracy from 27.2% to 27.6%.	×	0.02
On the SciQ benchmark, the LinUpper method combined with DoGE improved accuracy from 52.8% to 53.2%.	×	0.04
On the SciQ benchmark, the LinUpper method combined with DoReMi improved accuracy from 53.3% to 54.5%.	×	0.04
The Extremes strategy consistently performed worse than the Uniform, LinUpper, and Quadratic methods.	×	0.01
Experiments were conducted training 1.4B and 7B parameter models using the Llama architecture on subsets of the FineWeb	×	0.05
For the GPT2-mini model, the Uniform baseline achieved a mean score of 3.32 across the tested domains.	×	0.03
For the GPT2-mini model, the LinUpper method achieved a mean score of 3.30 across the tested domains.	×	0.03
For the GPT2-small model, the Uniform baseline achieved a mean score of 3.15 across the tested domains.	×	0.03
For the GPT2-small model, the LinUpper method achieved a mean score of 3.13 across the tested domains.	×	0.03

References

- http://arxiv.org/abs/2502.06733v1
- http://arxiv.org/abs/2601.01982v1
- http://arxiv.org/abs/2409.03868v1