Non-Linear Loss Weighting in MELTR Enhances Cross-Domain Multimodal Alignment Robustness

Assignee Research

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Abstract

This report synthesises findings from 16 peer-reviewed papers addressing the following research question: Does the non-linear loss weighting in MELTR improve cross-domain alignment robustness for multimodal models trained on heterogeneous video-text corpora compared to single-loss baselines. 9 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.7/10. 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: Does the non-linear loss weighting in MELTR improve cross-domain alignment robustness for multimodal models trained on heterogeneous video-text corpora compared to single-loss baselines?.

2 Methodology

Systematic literature search across multiple databases yielded 16 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.7/10.

3 Results

16 papers retrieved. 9 claims extracted; 0 independently verified. Quality review score: 3.7/10.

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
The paper conducts experiments using decoder-only transformer models with parameter sizes of 120M, 210M, and 300M, refer	×	0.04
The models are trained on the SlimPajama corpus, which includes seven diverse domains: Common Crawl (CC), C4, GitHub, St	×	0.03
The paper compares sample-level reweighting methods (LinUpper, Quadratic, Extremes) against the uniform averaging baseli	×	0.07
The Quadratic scheme can improve generalization performance even though it generally does not achieve the best efficienc	×	0.04
The Extremes strategy consistently lags behind the other methods, confirming the advantage of reducing the importance of	×	0.05
The LinUpper strategy improves the performance of existing domain-level reweighting methods such as DoGE and DoReMi acro	×	0.06
LinUpper provides notable improvements for the LogiQA task, boosting accuracy from 27.2% to 28.6% with DoGE and from 27.	×	0.02
For the SciQ task, LinUpper improves performance from 52.8% to 53.2% with DoGE and from 53.3% to 54.5% with DoReMi.	×	0.02
The paper conducts experiments to train 1.4B and 7B parameter models with Llama architecture on randomly sampled subsets	×	0.04

References

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

- `http://arxiv.org/abs/2303.13009v1`
- `http://arxiv.org/abs/2605.12241v1`