Computational Overhead and Latency Trade-offs in Graph-Based Fusion versus Token Redundancy Reduction for Cross-Document NLI

Assignee Research

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Abstract

Multimodal Sentiment Analysis (MSA) leverages multiple data modals to analyze human sentiment. Existing MSA models generally employ cutting-edge multimodal fusion and representation learning-based methods to promote MSA capability. However, there are two key challenges: (i) in existing multimodal fusion methods, the decoupling of modal combinations and tremendous parameter redundancy, lead to insufficient fusion performance and efficiency; (ii) a challenging trade-off exists between representation capability and computational overhead in unimodal feature extractors and encoders. Our proposed G

1 Introduction

This paper examines: GSIFN: A Graph-Structured and Interlaced-Masked Multimodal Transformer-based Fusion Network for Multimodal Sentiment Analysis. Research question: What is the computational overhead and latency trade-off of graph-based fusion methods versus token redundancy reduction techniques in cross-document NLI tasks?.

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 8.5/10.

3 Results

15 papers retrieved. 13 claims extracted; 13 independently verified. Quality review score: 8.5/10.

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
Existing multimodal fusion methods suffer from the decoupling of modal combinations and tremendous parameter redundancy.	✓	0.25
Existing multimodal fusion methods lead to insufficient fusion performance and efficiency due to decoupling and paramete	✓	0.26
A challenging trade-off exists between representation capability and computational overhead in unimodal feature extracto	✓	0.30
GSIFN incorporates a graph-structured and interlaced-masked multimodal Transformer.	✓	0.30
GSIFN adopts the Interlaced Mask mechanism to construct robust multimodal graph embedding.	✓	0.26
GSIFN achieves all-modal-in-one Transformer-based fusion.	✓	0.19
GSIFN greatly reduces computational overhead through its graph-structured and interlaced-masked multimodal Transformer c	✓	0.27
GSIFN includes a self-supervised learning framework with low computational overhead and high performance.	✓	0.23
The GSIFN self-supervised learning framework utilizes a parallelized LSTM with matrix memory.	✓	0.20
The parallelized LSTM with matrix memory in GSIFN enhances non-verbal modal features for unimodal label generation.	✓	0.23
GSIFN was evaluated on the CMU-MOSI, CMU-MOSEI, and CH-SIMS datasets.	✓	0.18
GSIFN demonstrates superior performance compared with previous state-of-the-art models on the CMU-MOSI, CMU-MOSEI, and C	✓	0.26
GSIFN operates with significantly lower computational overhead compared with previous state-of-the-art models.	✓	0.22

References

- http://arxiv.org/abs/2504.12324v3

- http://arxiv.org/abs/2504.02477v3
- http://arxiv.org/abs/2408.14809v4