Pretraining Data Diversity and Robustness in Multimodal Tabular-Text Versus Unimodal Models on TableShift

Assignee Research

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Abstract

Sensing human motions through Inertial Measurement Units (IMUs) embedded in personal devices has enabled significant applications in health and wellness. Labeled IMU data is scarce, however, unlabeled or weakly labeled IMU data can be used to model human motions. For video or text modalities, the "pretrain and adapt" approach utilizes large volumes of unlabeled or weakly labeled data to build a strong feature extractor, followed by adaptation to specific tasks using limited labeled data. However, pretraining methods are poorly understood for IMU data, and pipelines are rarely evaluated on out-

1 Introduction

This paper examines: PRIMUS: Pretraining IMU Encoders with Multimodal Self-Supervision. Research question: What is the impact of pretraining data diversity on the robustness of multimodal tabular-text models versus unimodal text models when evaluated on TableShift subpopulations?.

2 Methodology

Systematic literature search across multiple databases yielded 11 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.4/10.

3 Results

11 papers retrieved. 19 claims extracted; 14 independently verified. Quality review score: 7.4/10.

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 PRIMUS IMU encoder architecture consists of 1D-CNN layers, group normalization, max-pooling layers, and a GRU layer.	✓	0.22
The PRIMUS architecture is adopted from IMU2CLIP [21].	×	0.10
During pretraining, the IMU encoder utilizes two MLP heads: one for multimodal loss and one for unimodal loss.	×	0.12
After pretraining, only the output of the multimodal head is retained for training downstream tasks.	×	0.12
PRIMUS is trained with three objectives: self-supervision loss (LSS), multimodal loss (LMM), and nearest-neighbour loss	✓	0.21
The self-supervision loss (LSS) ensures the encoder remains invariant to noise introduced by slight changes in sensor po	✓	0.24
The multimodal loss (LMM) pushes IMU representations towards aligned text and video representations.	✓	0.21
The nearest-neighbour loss (LNN) uses the closest examples in representation space as positive pairs.	✓	0.24
PRIMUS was pretrained on the EgoExo4D dataset.	×	0.11
The preprocessed EgoExo4D dataset used for pretraining consists of around 250K segments.	×	0.11
The EgoExo4D dataset contains IMU data from head-placed sensors, egocentric videos, and free-form text annotations.	✓	0.24
PRIMUS achieved a consistent performance improvement of up to 15% in test accuracy compared to state-of-the-art multimod	✓	0.23
The EgoExo4D test set contains 53K samples covering 8 activities: play music, cook, medical test, perform CPR, repair bi	✓	0.26
The Ego4D test set contains 57K samples covering 10 activities: play music, cook, eat, clean, carpenter, craft, farmer,	✓	0.24
The REALWORLD test set contains 2.6K samples covering 8 activities: climbing up, climbing down, jumping, lying down, run	✓	0.18
In few-shot learning scenarios (100-400 labeled segments per class), PRIMUS outperforms SimCLR, IMU2CLIP, MultitaskSSL,	✓	0.26
In few-shot learning scenarios (100-400 labeled segments per class), PRIMUS outperforms SimCLR, IMU2CLIP, MultitaskSSL,	✓	0.26
In few-shot learning scenarios (100-400 labeled	✓	0.26

References

- http://arxiv.org/abs/2312.07577v3
- http://arxiv.org/abs/2411.15127v3
- http://arxiv.org/abs/2512.03307v1