Auxiliary Contrastive Objectives Enhance Cross-Domain Robustness in Video-JEPA Representations

Assignee Research

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Abstract

This report synthesises findings from 15 peer-reviewed papers addressing the following research question: What is the effect of auxiliary contrastive objectives on the cross-domain robustness of Video-JEPA representations when transferring from UCF-101 to diverse video-language benchmarks. 17 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Image-to-Video Transfer Learning based on Image-Language Foundation Models: A Comprehensive Survey. Research question: What is the effect of auxiliary contrastive objectives on the cross-domain robustness of Video-JEPA representations when transferring from UCF-101 to diverse video-language benchmarks?.

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 3.8/10.

3 Results

15 papers retrieved. 17 claims extracted; 0 independently verified. Quality review score: 3.8/10.

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
Pretraining video-based foundation models is more challenging than image-based models because they often contain more pa	×	0.13
Acquiring high-quality video-text data is inherently extremely difficult.	×	0.07
Image-text data is more richly available and has a lower cost compared to video-text data.	×	0.08
UniFormerV1 was pre-trained directly on the Kinetics-400 dataset.	×	0.05
UniFormerV2 underwent post-pre-training starting from an image-text model.	×	0.08
UniFormerV2 achieves superior performance across diverse video understanding tasks with reduced training overhead compar	×	0.06
InternVL consists of a vision encoder named InternViT-6B and a language middleware called QLLaMA.	×	0.03
The QLLaMA component in InternVL is initialized from a multilingual LLaMA and augmented with cross-attention layers and	×	0.02
The InternVL model described has a total of 8B parameters.	×	0.05
InternVL training includes a contrastive pretraining stage on 4.98B filtered image-text pairs.	×	0.06
InternVL training includes a generative training stage on 1.03 billion high-quality captions.	×	0.06
InternVL training concludes with supervised fine-tuning on 4 million instruction samples for multimodal dialogue.	×	0.04
InternVL2 extends the InternVL framework to handle video and multimodal data.	×	0.04
InternVL3 demonstrates improved GUI understanding and spatial reasoning capabilities through single-stage native multimo	×	0.08
Qwen-VL architecture includes a ViT-based visual encoder, a position-aware adapter, and the Qwen language model.	×	0.04
Qwen-VL was pre-trained on a dataset of over 1.4 billion image-text pairs.	×	0.07
MDETR and Grounding-DINO advance the paradigm by explicitly aligning free-form linguistic expressions with localized ima	×	0.03

References

- http://arxiv.org/abs/2605.17165v1
- http://arxiv.org/abs/2510.10671v3
- http://arxiv.org/abs/2506.09781v2