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Hierarchical Self-Supervised Representation Learning for Movie Understanding

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Movie understanding

- Movies are:
 - a lot more complex than short YouTube videos (e.g., Kinetics)
 - a lot fewer (MovieClips: 3k vs Kinetics 650k)
 - classic video action models are not enough (e.g., SlowFast, I3D, etc.)
 - require reasoning at many levels

[From MovieNet dataset]

From simple low-level actions \rightarrow

Hugging

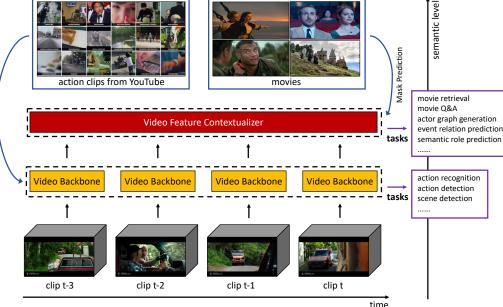


To high-level semantic narratives ightarrow

The actors are sad because the boat is sinking and they don't know if they will survive

Recent advances on movie understanding

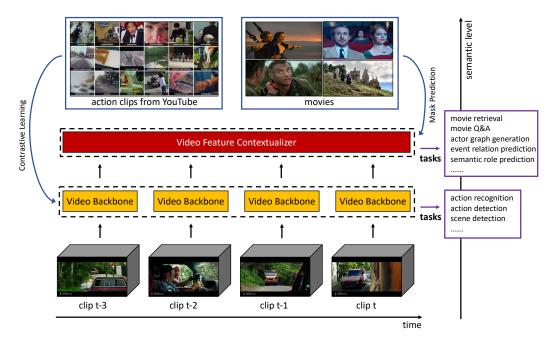
- VidSitu's hierarchical movie model [1]
 - Low-level video backbone encoder
 - Higher-level transformer contextualizer
 - Fully-supervised learning
- Challenges:
 - Extremely difficult to annotate large-scale movie datasets
- Our solution:
 - Self-Supervised pre-training



This paper

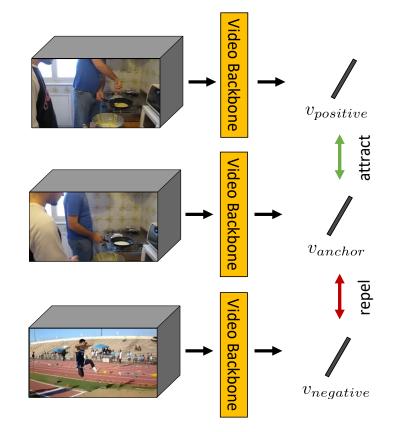
- Sequentially pretrain

 a low-level backbone and
 a high-level contextualizer
 in a self-supervised manner
- Benefits:
 - Each level can specialize better
 - Reduces data needs \rightarrow Each level can be trained on its own dataset
 - SOTA performance



This paper: Low-level backbone

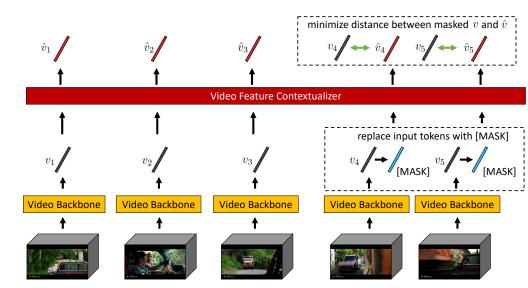
- Extracts low-level appearance and motion cues for people, objects and scenes from raw pixels
- High capacity
- Trained on a large amount of YouTube videos (e.g., Kinetics)
- Trained using contrastive learning objective



contrastive learning for video feature backbone

This paper: High-Level Contextualizer

- Learn to contextualize the neighboring low-level visual tokens
- Low capacity
- Trained on a small amount of movie data with stronger semantic and topporal structures (e.g., VidSitu, LV
- Trained using mask prediction objective



mask prediction for video feature contextualizer

Results on VidSitu: Semantic Role Prediction

• Goal: predict various semantic role labels for each verb. For example, the agent ("person") and the patient ("ball") of the verb ("throw"), as well as other attributes like the scene where the verb is happening ("a gym")

Model	Pre-training		CIDEr
	Backbone	Contextualizer	
VidSitu paper [1]	Fully-Supervised (K400)	None	47.06
This paper	Self-Supervised (K400)	Self-Supervised (VS)	60.34 <i>(+13.28)</i>
This paper	Self-Supervised (K400)	Self-Supervised (LVU)	61.18 <i>(+14.12)</i>

Results on VidSitu: Event Relation Prediction

• Goal: 4-way classification problem between four relation types: "A is enabled by B", "A is a reaction to B", "A causes B", and "A is unrelated to B"

Model	Pre-training		Top1-Acc
	Backbone	Contextualizer	
VidSitu paper [1]	Fully-Supervised (K400)	None	39.91
This paper	Self-Supervised (K400)	Self-Supervised (VS)	41.62 <i>(+1.71)</i>

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Thank you!



