# Language as the Medium:

# Multimodal Video Classification through Text only

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## Introduction

**Hypothesis**: Can we use textual descriptions alone as the medium to convey visual and audio information to an LLM?

#### Motivation:

- Leverage the general knowledge of LLMs for better contextual video understanding
- Plug & play different perception or reasoning models
- No training needed

### **Contributions**

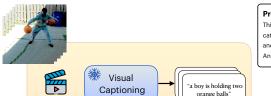
1. We introduce a new multimodal zero-shot video classification approach consisting of: a. a "perception" phase where specialised models act as sensory proxies

b. a "reasoning" phase where an LLM is used to analyse these multimodal textual clues in order to classify a video.



2. We demonstrate that LLMs can use these multimodal textual clues as proxies for "sight" or "hearing" and classify videos in-context.

# **Method**



Prompt: hink step by step what the most likel ategory is given this video infor and these categories {LABELS}. wer with the five most likely categories

Here are 5 action categories from the list that ost likely to match this video Dribbling basketball - The perso nd picking up orange balls, likel

# **Experiments**

Comparing different levels of context using Claude-instant-1

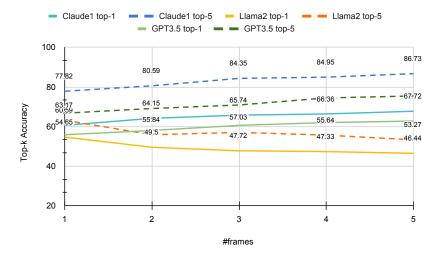
Tr uitary

	UCF-101 Kinetics400		(subset)	
Model	Тор-1 Асс.	Top-5 Acc.	Тор-1 Асс.	Тор-5 Асс.
BLIP2(FlanT5-XXL)+Claude-1(caps)	63.01	85.35	38.90	54.20
BLIP2(FlanT5-XXL)+Claude-1(caps, speech)	67.06	86.13	41.20	57.00
BLIP2(FlanT5-XXL)+Claude-1(caps, speech, audio)	67.13	86.15	41.20	57.35

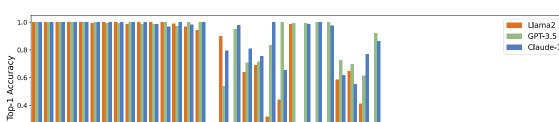
#### Comparing varying LLMs on the UCF101 test set

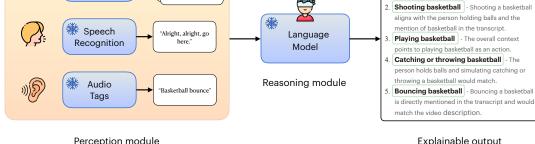
Model	Top-1 Acc.	Тор-3 Асс.	Top-5 Acc.
BLIP2(FlanT5-XXL)+Llama2-13B	49.56	56.70	58.51
BLIP2(FlanT5-XXL)+GPT3.5	66.37	79.27	82.04
BLIP2(FlanT5-XXL)+Claude-1	63.01	81.49	85.35

#### Varying number of frames per video



#### Best and worst performing UCF101 classes





Explainable output

#### **Perception models**

Video: We extract visual captions from video frames, with BLIP-2 [1]. Audio:

- We use Faster Whisper [2] to obtain audio transcripts.
- We leverage ImageBind [3] to get audio embeddings and compute the similarity with the textual embeddings of the AudioSet labels.

#### **Reasoning models**

- GPT3.5-turbo
- Claude-instant-1
- Llama2 Llama-2-13b-chat variant (13B parameters) [4]

#### **Structured Output**

To convert free-flowing natural language outputs to 5 ranked class names:

- GPT API: JSON Schema feature
- Claude: ask for the results to be returned as JSON
- LLama2: Parse the observed numbered list in the output

# bine cterror

## **Discussion and Future Work**

#### Limitations:

- 1. Separate models for vision and speech might not capture inter-modal interactions.
- Frame-by-frame image analysis doesn't account for temporal relationships 2. or persistent identities.
- Generative models can produce hallucinations and unreliable outputs. 3.
- 4. Performance not yet on par with state-of-the-art zero-shot benchmarks.

#### Future work:

- Leveraging additional video context, such as user comments 1.
- Try a chat-based approach where the "reasoning" module can ask the 2. "perception" module for clarification to get more information

#### <u>References</u>

- 1. Junnan, et al. "Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models." arXiv:2301.12597 (2023)
- 2. Radford, Alec, et al. "Robust speech recognition via large-scale weak supervision." ICML, 2023.
- 3. Girdhar, Rohit, et al. "Imagebind: One embedding space to bind them all." IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023
- 4. Touvron, Hugo, et al. "Llama 2: Open foundation and fine-tuned chat models." arXiv:2307.09288 (2023).