🍅 TOMATO: Assessing Visual Temporal Reasoning Capabilities in Multimodal Foundation Models

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Ai2

Do Multimodal Foundation Models truly understand videos or just individual frames?

Motivation

Existing benchmarks do not mandate the video modality.

Existing Benchmarks

Video ID: 7966

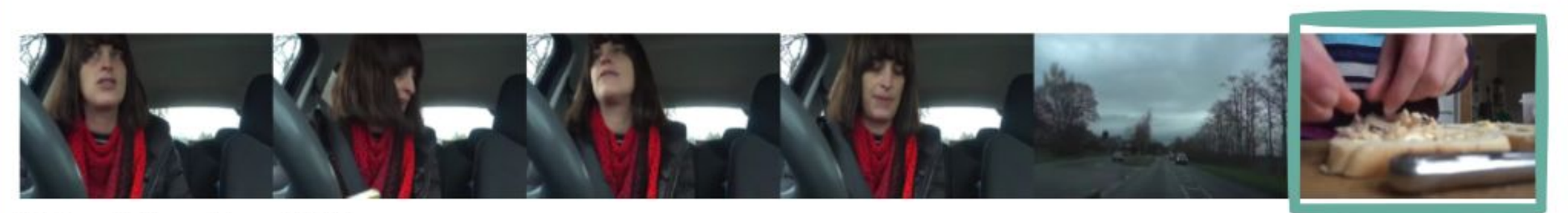
VITATECS (Li et al., 2023):
Which of the following best describes the content of the video?
A. Cheese is being spread B. Cheese is being sliced

Video ID: friends_s05e10_seg02_clip_11_3.52_37.14

MVBench (Li et al., 2024):
What is behind Monica when she is in the chair talking to Ross?
A. A television B. Joey's white dog sculpture
C. An American flag D. A Christmas tree E. A basket of laundry

Video ID: 1034736653

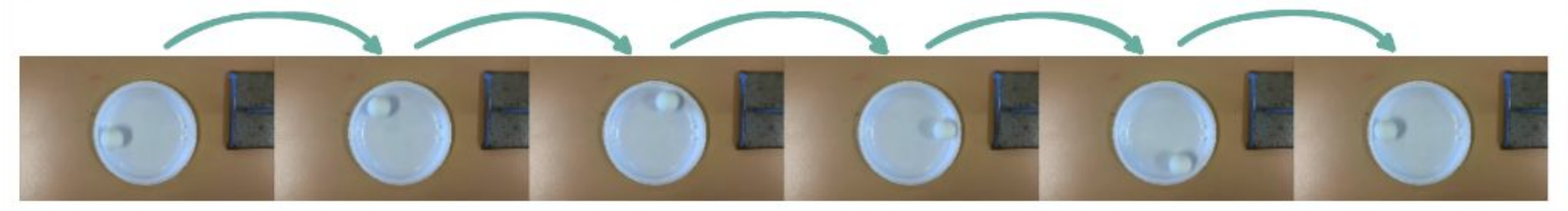
TempCompass (Liu et al., 2024):
What are the woman athletes doing?
A. Cycling B. Swimming C. Running D. Dancing



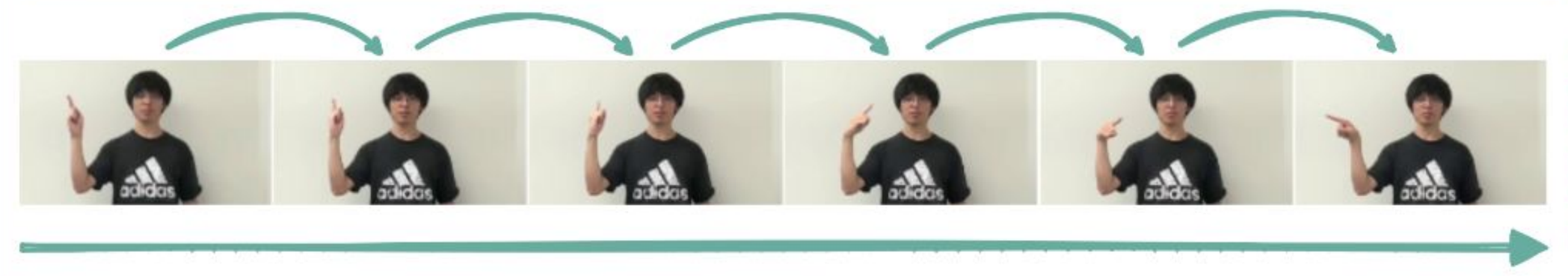
Video ID: qvh_val368

ReXTime (Chen et al., 2024):
Why is the woman preparing ingredients and utensils?
A. To make herself a sandwich B. To cook dinner for her family
C. To bake a cake D. To prepare a salad

🍅 TOMATO (Ours)



In which direction(s) does the Ping Pong ball rotate?
A. Clockwise throughout B. Counter-clockwise then clockwise
C. Counter-clockwise throughout D. Clockwise then counter-clockwise



What directional command is this person trying to convey?
A. Move to the left B. Move to the right
C. Move up D. Turn around

Our Benchmark: 🍅 TOMATO

- **1,484** human-annotated questions applied to **1,417** videos—including **805** self-recorded and generated videos, **398** YouTube videos, and **214** videos from existing datasets
- **6 reasoning types**: *rotation, direction, velocity & frequency, shape & trend, visual cues, action count*
- **3 scenarios**: *human-centric, real-world, simulated*

ICLR International Conference On Learning Representations

arXiv

Dataset

Benchmarking Principles

Our 3 principles aim to enforce visual temporal reasoning.

1. Multi-Frame Gain

$$\kappa = \frac{Acc(m \text{ frames}) - Acc(1 \text{ frame})}{Acc(1 \text{ frame}) + \epsilon}$$

*How much **better** does a model perform using multiple frames compared to one?*

A **higher κ** value on TOMATO indicates a necessity to reason across multiple frames, and the question cannot be accurately answered using a single frame.

	VITATECS			MVBench			TempCompass			ReXTime			TOMATO		
# Frames	1	16	κ ↑	1	16	κ ↑	1	16	κ ↑	1	16	κ ↑	1	16	κ ↑
Average	70.7	87.2	23.4	47.1	62.7	33.3	51.3	75.3	47.1	62.8	80.0	27.4	20.9	37.8	**81.0**
# Frames	1[H]	16	κ ↑	1[H]	16	κ ↑	1[H]	16	κ ↑	1[H]	16	κ ↑	1[H]	16	κ ↑
Average	86.0	87.2	1.5	58.8	62.7	6.7	64.0	75.3	17.6	86.1	80.0	-7.1	22.8	37.8	**66.3**

2. Frame-Order Sensitivity

$$\tau = \frac{Acc(m \text{ frames}) - Acc(\text{shuffled } m \text{ frames})}{Acc(\text{shuffled } m \text{ frames}) + \epsilon}$$

*How much does performance **increase** when we put shuffled frames back in the correct order?*

A **higher τ** value on TOMATO suggests a stronger reliance on the frames' correct order, and the question cannot be accurately answered using out-of-order frames.

	VITATECS			MVBench			TempCompass			ReXTime			TOMATO		
# Frames	16[S]	16	τ ↑	16[S]	16	τ ↑	16[S]	16	τ ↑	16[S]	16	τ ↑	16[S]	16	τ ↑
Average	84.5	87.2	3.2	59.3	62.7	5.8	61.5	75.3	22.3	79.7	80.0	0.3	28.5	37.8	**34.1**

3. Frame-Information Disparity

$$\rho = \frac{Acc(\text{handpicked 1 frame}) - Acc(\text{random-sampled 1 frame})}{Acc(\text{random-sampled 1 frame}) + \epsilon}$$

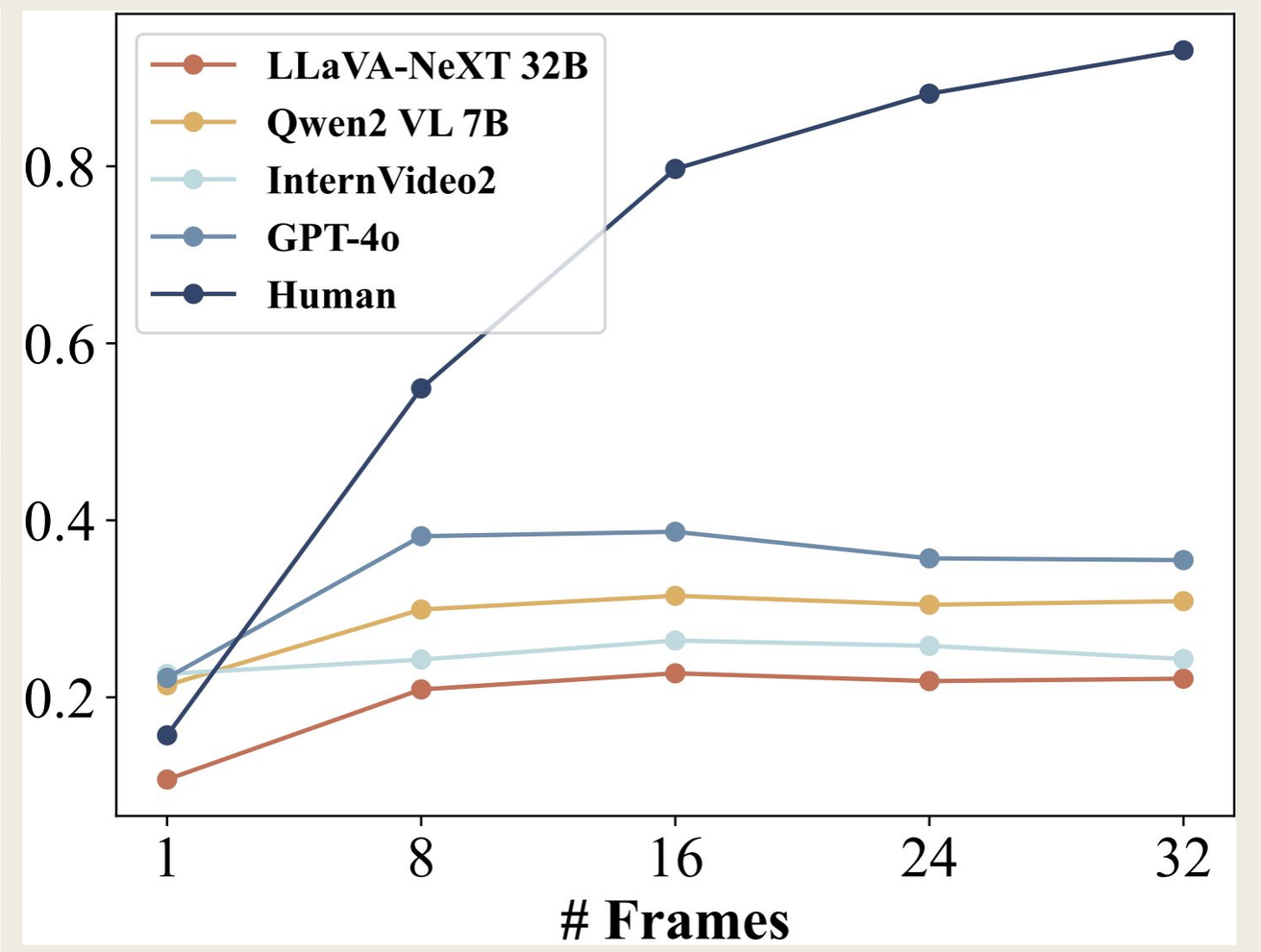
*How much does performance **drop** when we replace the most informative frame with a random one?*

A **lower ρ** value on TOMATO indicates a more even distribution of informativeness across the multiple frames, and the question cannot be more accurately answered by a handpicked 1 frame compared to a random 1 frame.

	VITATECS			MVBench			TempCompass			ReXTime			TOMATO (200)		
# Frames	1[R]	1[H]	ρ ↓	1[R]	1[H]	ρ ↓	1[R]	1[H]	ρ ↓	1[R]	1[H]	ρ ↓	1[R]	1[H]	ρ ↓
Average	70.7	86.0	21.6	47.1	58.8	25.0	51.3	64.0	24.9	62.8	86.1	37.2	21.8	22.8	**4.6**

Main Results

Model	Score
Baselines	
Human (Videos)	95.2
Human (Frames)	79.7
Random (GPT-4o)	23.1
Proprietary Multimodal Foundation Models (MFMs)	
GPT-4o	**37.7**
Gemini 1.5 pro ‡	36.1
Claude 3 Opus	28.2
Claude 3.5 Sonnet	27.8
Open-Source Multimodal Foundation Models (MFMs)	
Qwen2-VL-72B	**37.9**
Qwen2-VL-7B	31.5
Video-CCAM-v1.1 14B	30.7
InternVL 2 40B	29.0
LLaVA-Video-72B	28.2
Video-CCAM-v1.1 9B	27.0
InternVideo 2 8B	26.4

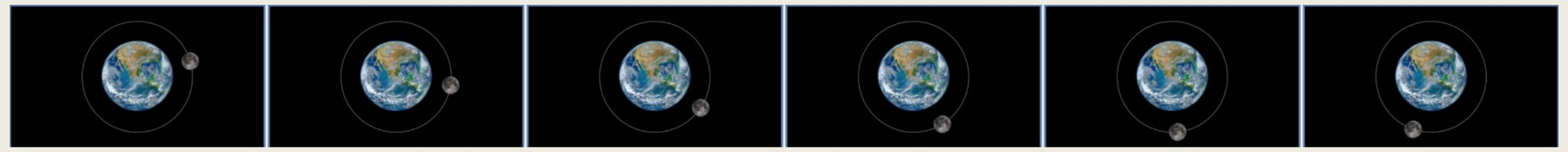


1. **Significant gap** between human and SOTA model performance.

2. **Narrowing gap** between proprietary and open-source models.

Analysis

1. SOTA Models Cannot Interpret Frames as a Continuous Sequence



GPT-4o: … the sequential positions of the moon as it moves from the **right** side of the Earth, **downwards**, to the **left** side, and then **upwards**…
Therefore, the most possible answer based on the frames is:
`A`: Counter-clockwise throughout.

✓ correct description
✗ wrong conclusion

2. SOTA Models are Over-Reliant on Common Sense

GPT-4o: … the object (a cup with liquid) is **initially moving downward and then upward**…the object seems to be **accelerating** as it moves downward due to gravity and **then decelerating** as it is caught or swung back up…
Therefore, the most plausible answer based on the frames is:
`Option D`: Accelerating.

✗ wrong description
✗ wrong conclusion