

UVE: Are MLLMs Unified Evaluators for AI- Generated Videos?

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Motivation

□ Challenge of Al-Generated Video Evaluation:

□ Current studies rely on **specialized evaluators** for individual aspects (e.g., video-text alignment, aesthetic quality), which is **incomprehensive and hard to scale**.

□ Opportunity:

Modern MLLMs exhibit general vision-language understanding ability in open domain scenarios.

■ Key question:

Can MLLMs be utilized as a unified evaluator for AI-Generated videos?



Method: Unified Video Evaluation Framework

Specialized Evaluators video-text dynamic aesthetic appearance alignment consistency degree quality **ViCLIP** DINO **RAFT** DOVER Single Video **Text Prompt** Video Pair A man in the desert, mountain in background **MLLM** dynamic video-text appearance aesthetic customized alignment consistency degree quality aspect

Unified Evaluator



Method: Unified Video Evaluation Framework

Specialized Evaluators video-text dynamic aesthetic appearance consistency quality alignment degree **ViCLIP** DINO **RAFT** DOVER Single Video Video Pair **Text Prompt** A man in the desert, mountain in background MLLM dynamic aesthetic customized video-text appearance consistency quality alignment degree aspect **Unified Evaluator**

Single Video Rating

<video>

Watch the above frames of an AI-generated video and evaluate aspect-specific description

Complete your evaluation by answering this question:

<aspect-specific question>? <answer prompt>

Video Pair Comparison

The first video: <video>

The second video: <video>

Watch the above two AI-generated videos and evaluate <aspect-specific description>

Complete your evaluation by answering this question:

Which video is <aspect-specific question>?

You should make your judgment based on the following rules:

<instructions on how to make the choice>

Now give your judgment:



Method: Unified Video Evaluation Framework

Specialized Evaluators appearance video-text dynamic aesthetic alignment consistency degree quality **VICLIP** DINO RAFT DOVER Single Video **Text Prompt** Video Pair A man in the desert, mountain in background **MLLM** video-text dvnamic aesthetic customized appearance alignment consistency degree quality aspect

Unified Evaluator

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Complete your evaluation by answering this question:

Which video is <aspect-specific question>?

You should make your judgment based on the following rules:

<instructions on how to make the choice>

Now give your judgment:

single video rating

$$\mathcal{S} = \frac{P_{\theta}(t_{\text{pos}}|\mathcal{V}, \mathcal{T}, \mathcal{G}_a)}{P_{\theta}(t_{\text{pos}}|\mathcal{V}, \mathcal{T}, \mathcal{G}_a) + P_{\theta}(t_{\text{neg}}|\mathcal{V}, \mathcal{T}, \mathcal{G}_a)}$$

video pair comparison

$$C = f_{\theta}(\mathcal{V}_1, \mathcal{V}_2, \mathcal{T}_1, \mathcal{T}_2, \mathcal{G}_a) \in \mathbf{O}$$

 $\{"\mathcal{V}_1 \text{better"}, "\mathcal{V}_2 \text{better"}, "\text{same good"}, "\text{same bad"}\},$



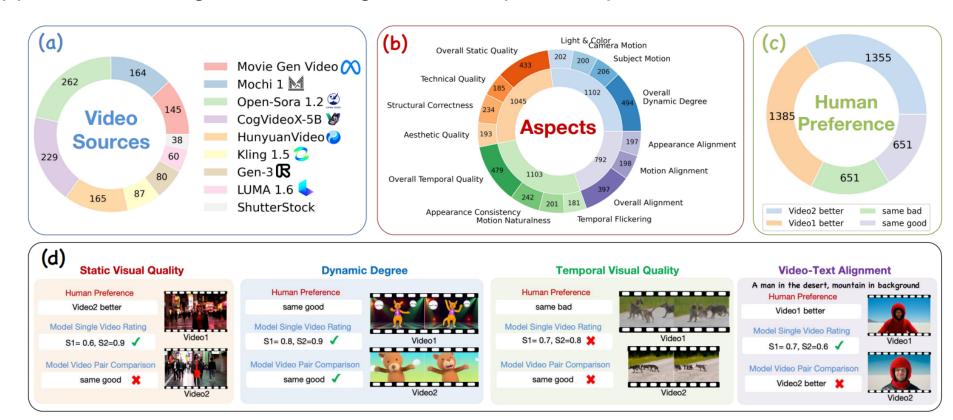
UVE-Bench: A benchmark to assess AIGV evaluators

(a): 1,230 videos generated by 8 SOTA T2V models and real-world videos from ShutterStock

(b): 15 fine-grained AIGV evaluation aspects

(c): Human pairwise preference annotation as ground-truth

(d): Support of both single video rating and video pair comparison





Performance of MLLMs as Unified Video Evaluator

- Unified evaluators outperforms specialized evaluators
- Good Aspects: Dynamic Degree, Technical/Aesthetic Quality, Appearance Alignment
- Bad Aspects: Structural Correctness, Temporal Quality, Motion Alignment

Single Video

Rating

Method	Model Size	Overall Dynamic	SM	CM	LC	Overall Static	TQ	SC	AQ	Overall Temporal	AC	MN	TF	Overall Alignment	MA	AA	AVG
Random	-	48.8	49.5	48.9	49.8	49.2	47.6	49.0	48.1	49.0	48.6	48.2	46.2	48.4	48.6	48.3	48.6
Specialized Evaluators																	
VideoScore-v1.1	8B	57.4	-	-	-	40.1	30.4	47.7	41.9	-	43.1	36.1	-	38.9	-	-	-
VBench	-	87.8	-	-	-	-	62.5	-	75.6	-	54.0	50.2	-	54.4	-	-	-
UMTScore	-	-	-	-	-	-	-	-	-	-	-	-	-	66.4	-	-	-
VIDEOCON-PHYSICS	7B	-	-	-	-	-	-	-	-	-	-	53.4	-	68.7	-	-	-
DOVER	58M	-	-	-	-	-	69.2	-	80.3	-	-	-	-	-	-	-	-
Unified Evaluators																	
Video-LLaVA	7B	52.4	74.8	63.4	47.6	47.8	66.1	44.5	63.4	44.1	51.3	55.5	48.6	59.4	54.9	66.8	54.5
LongVA-DPO	7B	59.8	76.2	69.9	57.5	62.4	74.9	56.2	72.0	56.0	47.3	40.7	54.3	68.7	63.9	71.6	61.6
ShareGPT4Video	8B	77.5	81.0	77.1	82.5	59.4	68.7	54.1	69.4	54.4	48.1	42.6	60.9	62.7	54.3	70.3	63.9
VideoLLaMA2.1	7B	72.1	80.5	67.1	77.2	61.4	78.7	47.5	72.6	46.1	50.9	50.2	61.8	72.6	65.7	77.7	64.4
mPLUG-Owl3	7B	78.6	84.8	77.8	79.9	76.0	83.1	55.6	80.0	59.8	59.5	42.0	72.0	80.4	75.2	87.6	72.6
VideoChat2-Mistral	7B	83.1	92.2	89.6	74.9	68.1	76.2	53.8	74.1	58.7	58.3	52.8	85.6	75.6	78.0	80.9	72.6
MiniCPM-V-2.6	8B	81.4	86.3	80.3	88.8	70.9	75.0	52.9	80.6	61.1	59.4	51.7	70.9	82.1	74.3	90.8	73.4
LLaVA-OneVision	7B	81.0	87.6	83.2	84.9	70.7	78.2	50.6	83.1	62.9	60.4	41.5	85.9	79.3	66.9	86.7	73.0
LLaVA-OneVision	72B	82.3	87.8	78.4	88.2	71.3	77.6	60.2	81.5	64.6	61.9	39.9	86.8	84.4	71.7	93.5	75.0
LLaVA-Video	7B	80.4	85.5	80.9	81.5	66.2	74.2	49.5	75.7	58.3	58.2	39.3	82.3	80.5	69.9	90.0	71.0
LLaVA-Video	72B	82.8	86.1	82.9	86.9	70.2	80.0	55.4	77.7	60.1	59.2	40.4	83.5	84.8	73.7	94.6	74.0
Qwen2-VL	7B	84.6	89.7	94.2	79.7	64.6	67.3	50.7	70.6	51.1	51.3	48.0	62.7	85.4	78.7	92.2	70.9
Qwen2-VL	72B	86.5	92.6	92.7	86.0	70.6	76.9	60.2	83.4	52.5	58.0	48.9	71.0	89.0	81.8	95.0	75.4
InternVL-2.5-MPO	8B	81.3	86.1	80.4	88.0	68.1	77.9	53.6	77.5	60.9	54.9	50.9	72.5	80.6	73.2	90.5	72.6
InternVL-2.5-MPO	78B	84.3	86.6	82.4	91.6	72.8	84.0	67.2	82.3	61.5	65.2	61.8	88.4	87.4	79.3	95.5	78.2
GPT-4o	-	79.0	84.3	74.9	81.8	74.0	81.6	65.2	84.2	70.0	79.8	54.0	58.6	80.8	77.2	89.6	75.7
Seed1.5-VL	20B Act.	83.2	91.2	83.7	89.5	82.4	82.9	66.8	88.8	70.5	78.6	59.5	70.1	84.2	79.0	94.2	80.0



Performance of MLLMs as Unified Video Evaluator

- □ Good Aspects: Dynamic Degree, Technical/Aesthetic Quality, Appearance Alignment
- Bad Aspects: Structural Correctness, Temporal Quality, Motion Alignment
- □ There is still a notable gap between MLLM evaluators and humans

Video Pair Comparison

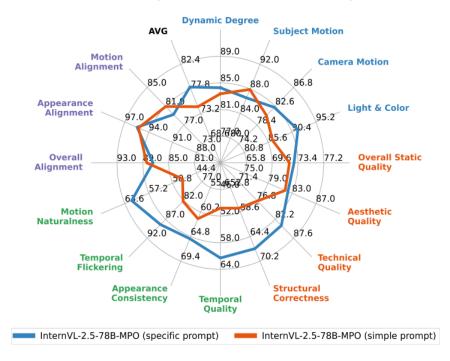
Method	Model Size	Overall Dynamic	SM	CM	LC	Overall Static	TQ	SC	AQ	Overall Temporal	AC	MN	TF	Overall Alignment	MA	AA	AVG
Random	-	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0
Unified Evaluators																	
LLaVA-OneVision	7B	44.2	52.6	40.0	38.5	35.8	35.2	25.7	51.0	37.4	23.9	29.1	52.0	43.1	39.7	43.4	38.6
LLaVA-OneVision	72B	36.5	55.1	40.0	53.8	37.0	51.4	22.2	54.1	25.6	43.3	34.5	45.7	63.0	58.9	69.7	44.3
LLaVA-Video	7B	37.0	52.6	37.5	44.9	44.4	43.8	38.9	62.2	33.7	28.9	31.1	57.5	43.1	39.7	46.9	41.1
LLaVA-Video	72B	42.5	57.7	32.5	56.4	41.6	55.2	31.2	60.2	32.6	41.1	27.7	55.9	60.3	53.0	66.2	46.1
Qwen2-VL	7B	46.4	56.4	43.8	39.7	42.8	38.1	20.8	54.1	29.8	24.4	29.7	42.5	54.9	50.3	57.9	41.1
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InternVL-2.5-MPO	8B	42.5	51.3	33.8	43.6	38.3	31.4	40.3	55.1	35.1	32.2	27.0	44.9	53.5	50.3	53.8	41.8
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GPT-4o	-	42.0	48.7	38.8	59.0	53.5	54.3	41.0	71.4	44.9	38.9	31.8	59.8	58.9	57.0	61.4	50.2
Seed1.5-VL	20B Act.	52.5	56.4	47.5	61.5	51.0	52.4	44.4	62.2	48.6	36.7	35.8	65.4	56.9	53.6	61.4	51.6
Gemini2.5-Flash	-	55.8	60.3	45.0	59.0	55.6	50.5	43.1	64.3	50.8	41.7	38.5	60.6	65.0	62.3	66.2	54.6
Human	-	87.3	85.3	87.3	85.3	90.0	92.0	88.0	91.3	88.0	90.0	78.7	92.0	88.0	84.7	92.0	88.0



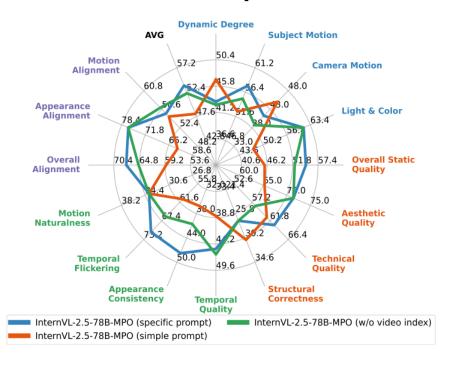
Key Design Choices: Prompting Strategy

- Aspect-specific prompting is essential
- Removing video order index does not significantly impact performance.

Single Video Rating



Video Pair Comparison





Key Design Choices: Scoring Strategy

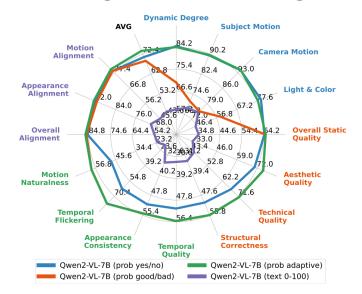
Single Video Rating

- Probability-based scoring outperforms directly generating discrete rating score (0-100)
- Yes/no and good/bad excel at different aspects, adaptive strategy is more effective

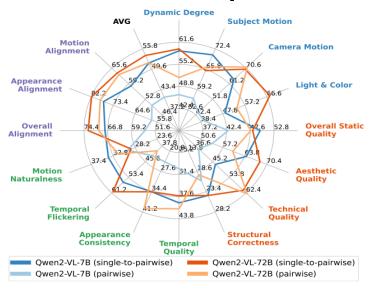
Video Pair Comparison

Adapting from single video rating outperforms direct video pair comparison for 7B-scale models

Single Video Rating



Video Pair Comparison





Summary of Contributions

■ UVE Framework

We introduce a unified approach to evaluate any aspect of AIGV using pre-trained MLLMs.

UVE-Bench

We propose UVE-Bench, a comprehensive benchmark to assess the capability of unified AIGV evaluation.

Experiments and Analysis

- We demonstrate that unified MLLM evaluators substantially outperforms existing specialized evaluators.
- We conduct in-depth analysis on the pros and cons of MLLMs in unified AIGV evaluation and the key design choices that impact their performance.





Thank you!



Code: https://github.com/bytedance/UVE
Data: https://huggingface.co/datasets/lyx97/UVE-Bench

