

ReXTime: A Benchmark Suite for Reasoning-Across-Time in Videos

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Introduction

- QA with Reasoning-Across-Time
 - Question and answer each belongs to different time spans.

Conventional QA

A: To sharpen the knife on the bottom of the plate.

Q: Why do we hold up a knife?



Reasoning Across Time

A: Hold up a plate and sharpen the knife with the bottom of plate.

Q: How can we cut up the tomato efficiently?



GPT-4o



Gemini

You can use the unglazed bottom rim of a ceramic plate to sharpen it.

It demonstrates using a plate or flat surface to help guide the knife and cut the tomato into even slices.

The video does not provide any information on how to cut tomatoes more efficiently.

Human Performance: 88.0%

73.7%

68.7%

68.0%

ReXTime Benchmark



Reasoning Across Time

A: Hold up a plate and sharpen the knife with the bottom of plate.

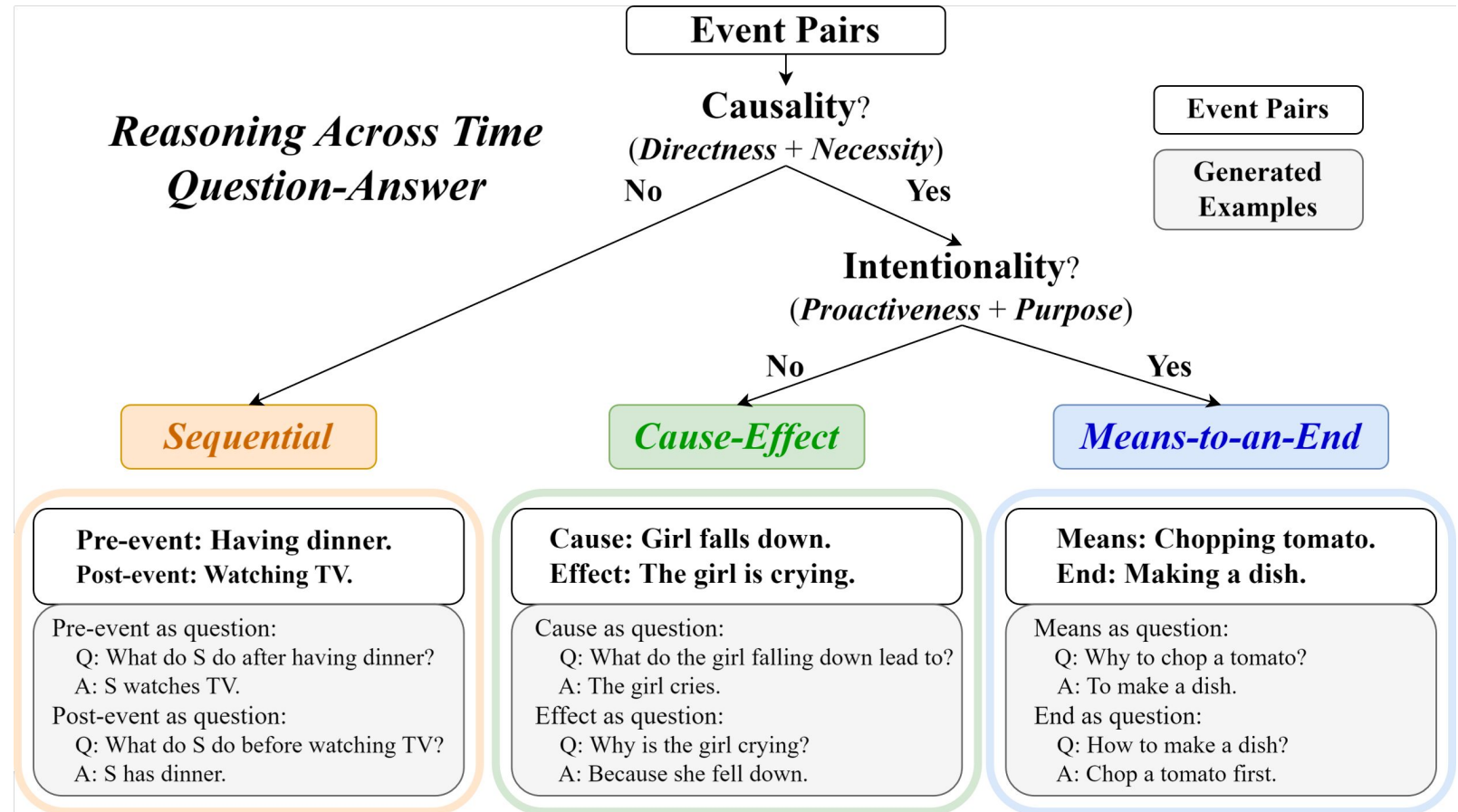
Q: How can we cut up the tomato efficiently?

- Grounding-VQA data pairs:

- Sequential
- Cause-Effect
- Means-to-an-End

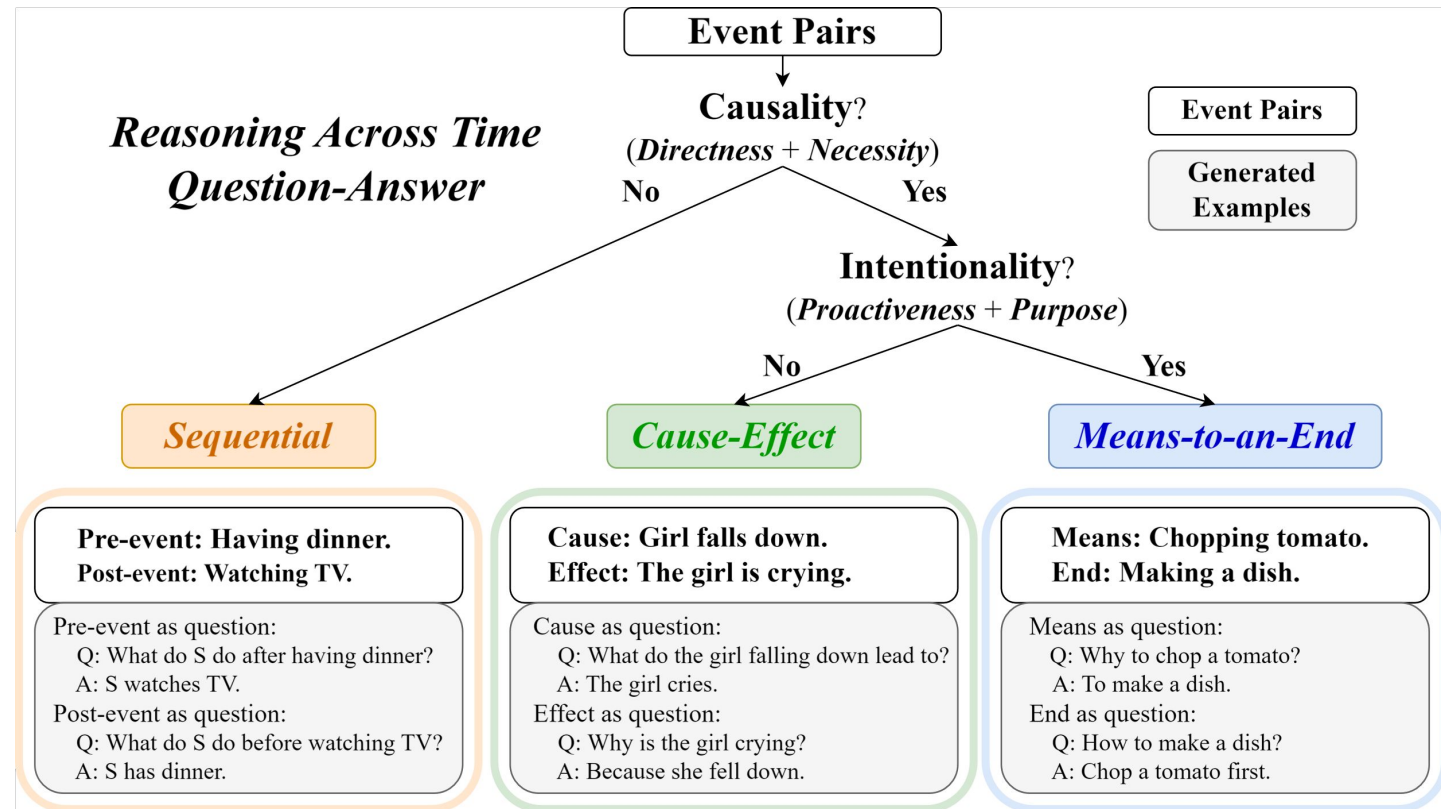
- ReXTime tasks:

- Multi-choice VQA
- Moment localization



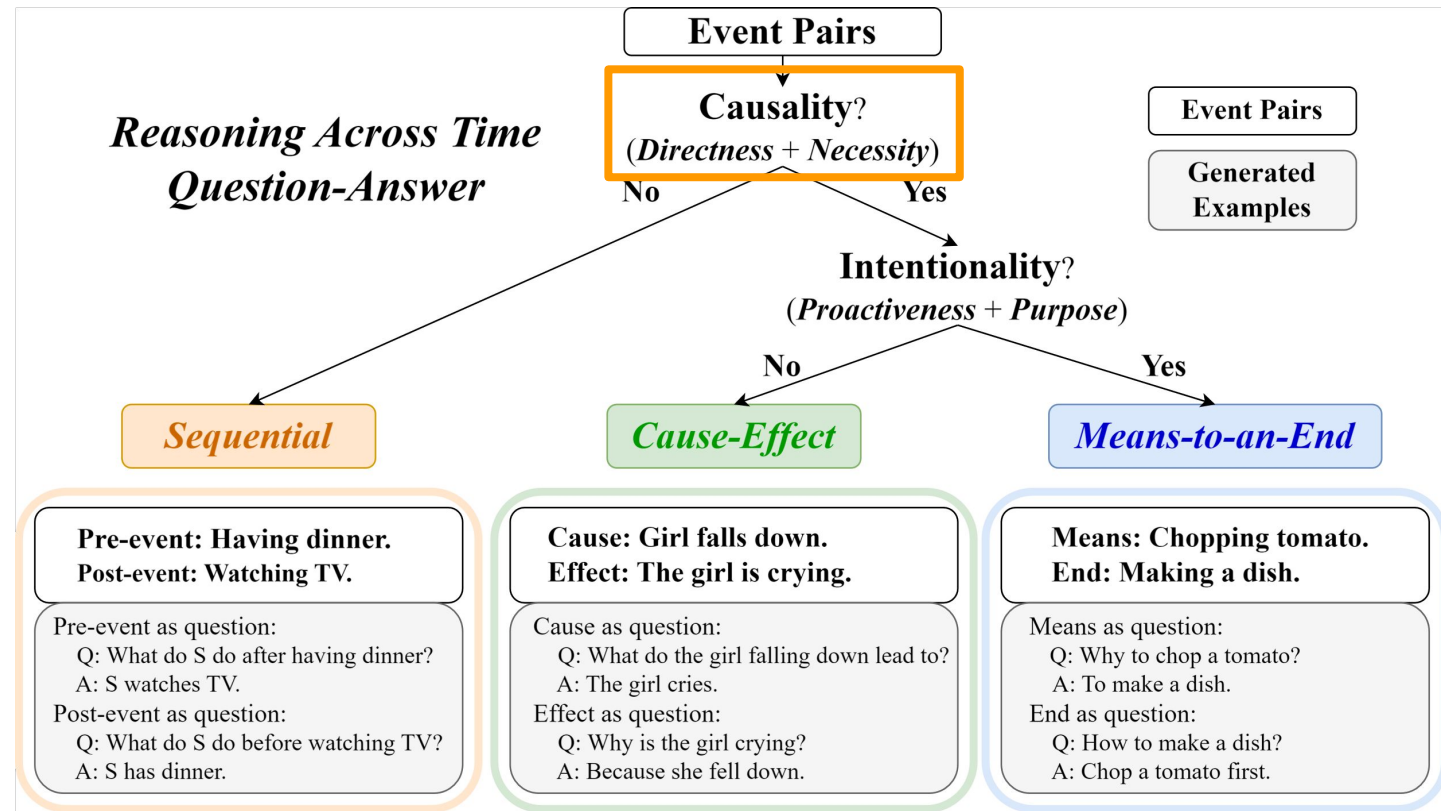
Grounding-VQA Classification Criteria

- ❑ **Directness:** This criterion assesses the directness of the causal link between events.
- ❑ **Necessity:** This criterion measures whether the second event is inevitable due to the first.
- ❑ **Proactiveness:** This evaluates whether an event is carried out with deliberate intention.
- ❑ **Purpose:** This evaluates whether the intention has been fulfilled.



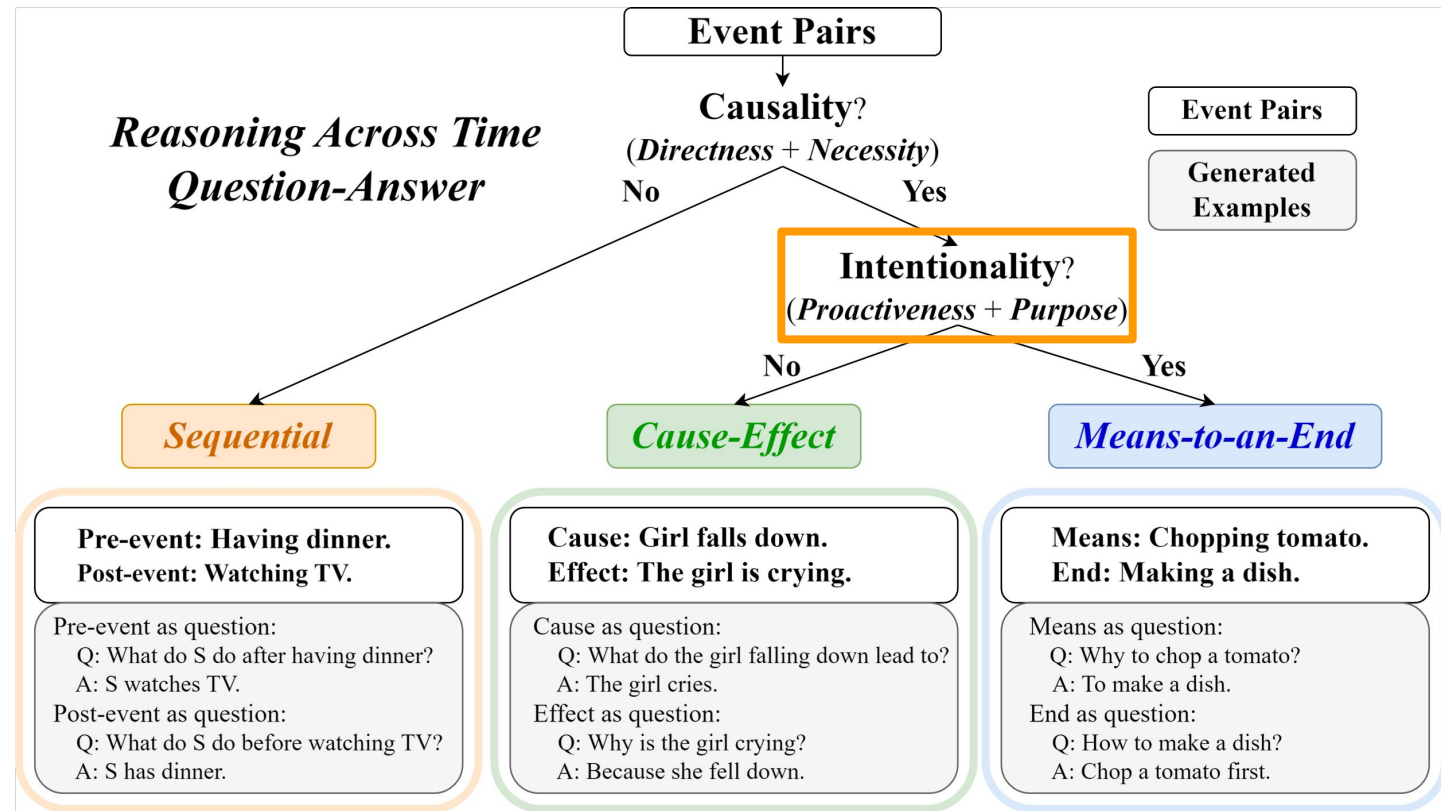
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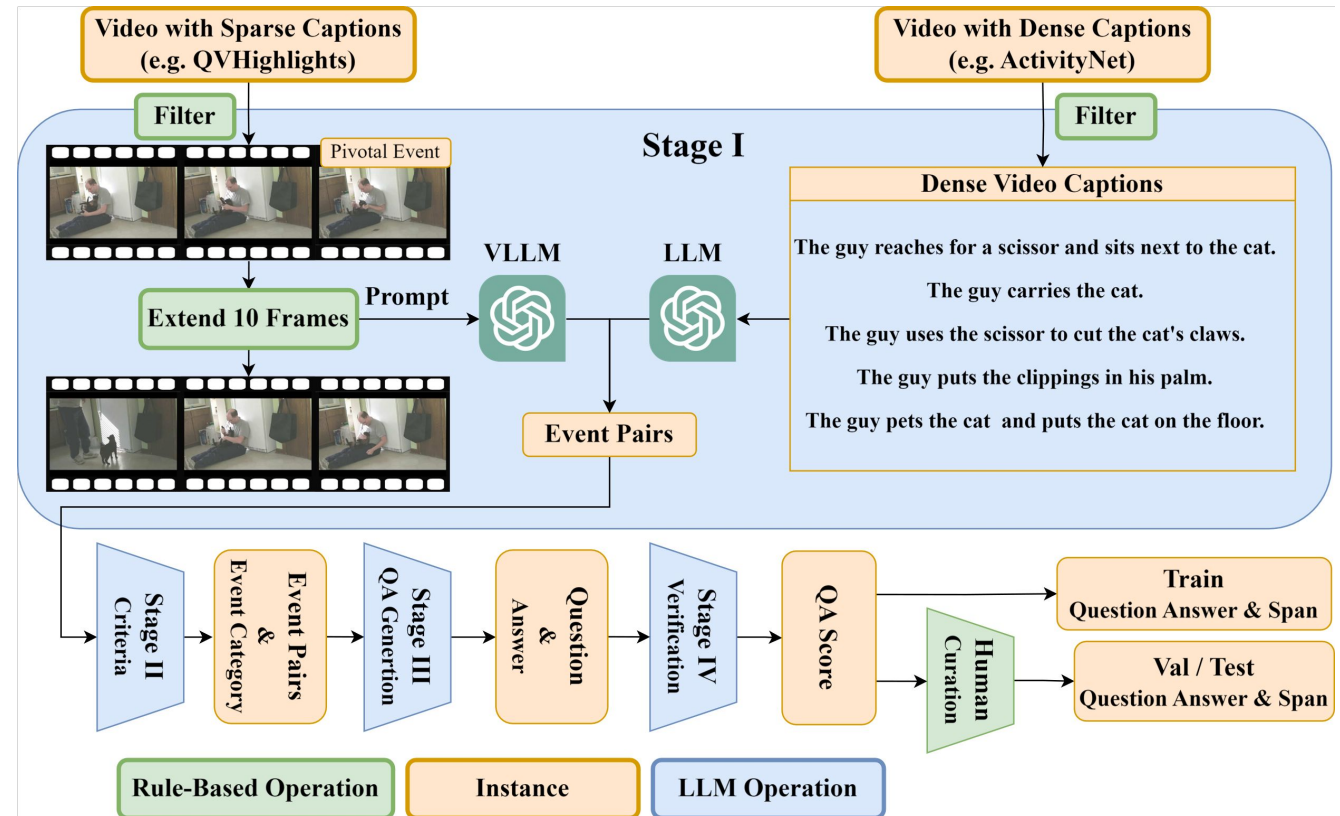
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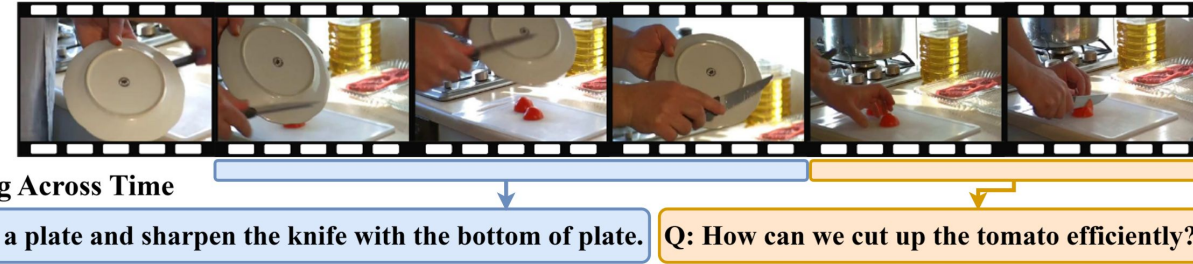


Performances on ReXTime

- Dataset sources:
 - ActivityNet [1], QVHighlights [2]
- Machine generated / verified
- Human verified validation / test set
- Reduce about 55% of overall cost



ReXTime Evaluation



- QA-IoU
 - ❑ Question-Answer Intersection over Union
- Lower QA-IoU indicates:
 - ❑ Less overlapping between the question span and the answer span.
 - ❑ More challenging for temporal reasoning.

Datasets	# of Reasoning Across Time Samples			C.L. (s) ↑	QA-mIoU (%) ↓
	Train	Val	Test		
Ego4D-NLQ	2,212 [†]	775 [†]	705 [†]	5.2	85.5
NExTGQA	–	1,403 [†]	2,301 [†]	11.7	66.1
ReXTime (Ours)	9,695	921	2,143	66.0	15.5

Table: Frontier Models' Performances

Results of Frontier Models on ReXTime

- Moment localization
 - ❑ mIoU, R@1 (IoU=0.3), R@1 (IoU=0.5)
- VQA / Grounding VQA
 - ❑ Accuracy
 - ❑ Acc@IoU>0.5
- Human evaluation
 - ❑ 3 testers per question

Models	Moment Localization			VQA	
	mIoU	R@1 (IoU=0.3)	R@1 (IoU=0.5)	Accuracy(%)	Accuracy(%) @IoU ≥ 0.5
Human	61.11	74.30	62.85	87.98	58.51
GPT-4o	36.28	45.33	34.00	73.67	28.67
Claude3-Opus	23.61	30.67	17.67	68.67	13.67
Gemini-1.5-Pro	28.43	35.67	25.00	68.00	18.33
GPT-4V	26.74	33.33	22.00	63.33	16.67
Reka-Core	27.95	36.33	24.00	59.67	17.00

Table: Frontier MLLMs' Performances on ReXTime

Results of the Fine-tuned Performance

- Fine-tuned on ReXTime generated training data
- Performance boost after fine-tuned with our generated training data

Models	Moment Localization			VQA	
	mIoU	R@1 (IoU=0.3)	R@1 (IoU=0.5)	Accuracy(%)	Accuracy(%) @ IoU \geq 0.5
UniVTG (Zero-shot)	28.17	41.34	26.88	—	—
UniVTG (Finetuned)	34.63 (+6.46)	53.48 (+12.14)	34.53 (+7.65)	—	—
CG-DETR (Zero-shot)	23.87	31.31	16.67	—	—
CG-DETR (Finetuned)	26.53 (+2.66)	39.71 (+8.40)	22.73 (+6.06)	—	—
VTimeLLM (Zero-shot)	20.14	28.84	17.41	36.16	—
VTimeLLM (Finetuned)	29.92 (+9.78)	43.69 (+14.85)	26.13 (+8.72)	57.58 (+21.42)	17.13
TimeChat (Zero-shot)	11.65	14.42	7.61	40.04	—
TimeChat (Finetuned)	26.29 (+14.64)	40.13 (+25.71)	21.42 (+13.81)	49.46 (+9.42)	10.92

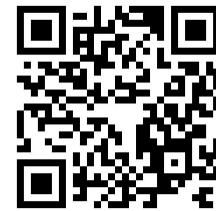
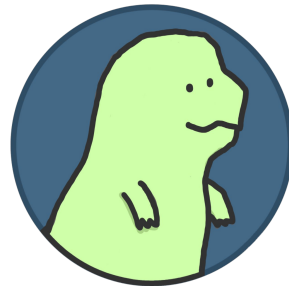
Conclusion

- Reasoning across time remains a challenge for current MLLMs.
- ReXTime is the first benchmark for reasoning-across-time with 2143 test samples
- ReXTime generated data is effective in enhancing reasoning across time.

- Thank you for your listening!



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