TheoremExplainAgent: Towards Video-based Multimodal Explanations for LLM Theorem Understanding

     

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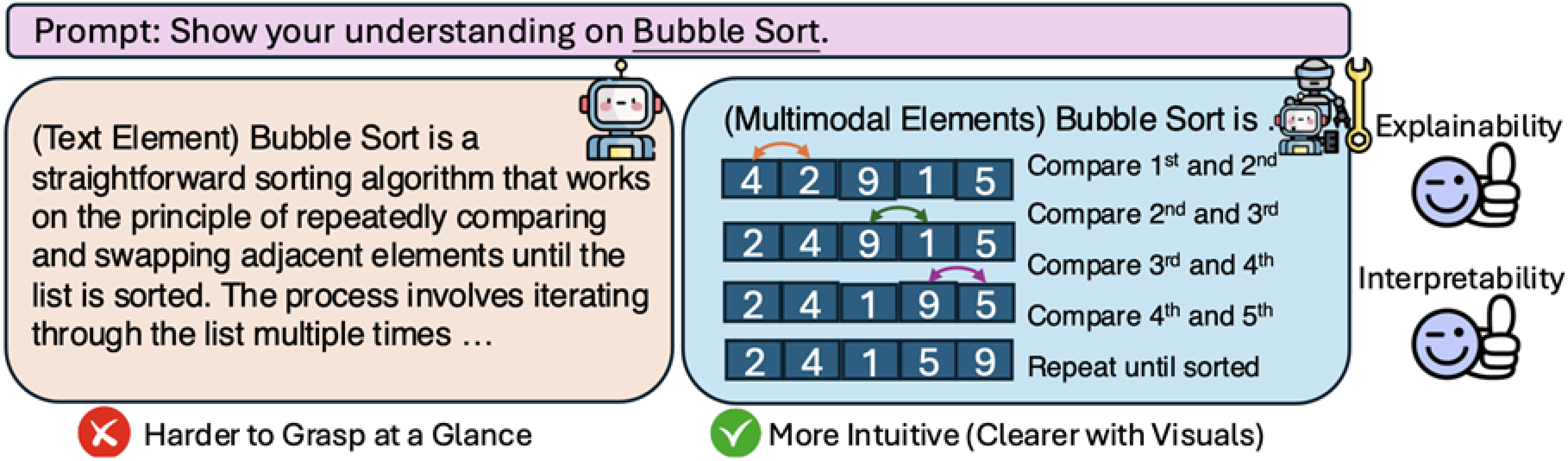
ACL 2025 Oral

Paper ID: #733

Background: What is Multimodal Explanations?

Definition: Combining text, visuals (animations), and narration to explain a concept.

- Humans often rely on visual scaffolding to explain abstract concepts
  - e.g. drawing figures on a papers, lecture videos with slides, etc.



Why Multimodal Explanation Matters

Is textual QA enough to test AI model understanding?

Models can exploit superficial cues in text-based tests (answer order, etc.), potentially overestimating true understanding

- Real-world concepts are often inherently spatial and hard to describe with solely text
- Text-only outputs can hide reasoning errors (e.g., hallucinated logic)
- Visual explanations expose flaws in logic and flow

Multimodal Explanations for LLM Theorem Understanding

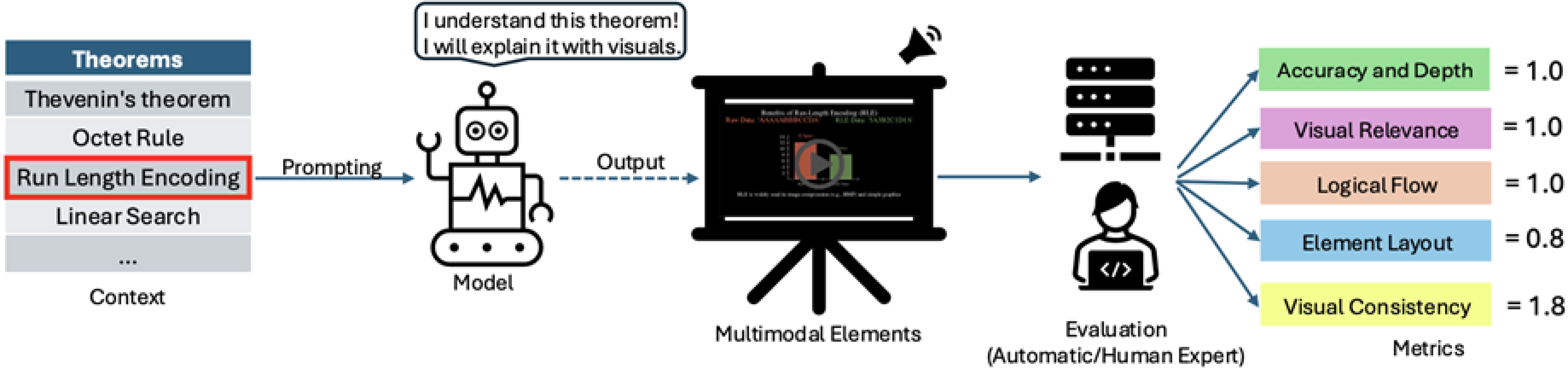
Problem Definition:

Generate >1 min video that explains a given theorem

- Long-form narrative (sound/text)
- Visual coherent structure (visual)
- Procedural accuracy (logic)
- Domain knowledge (understanding)

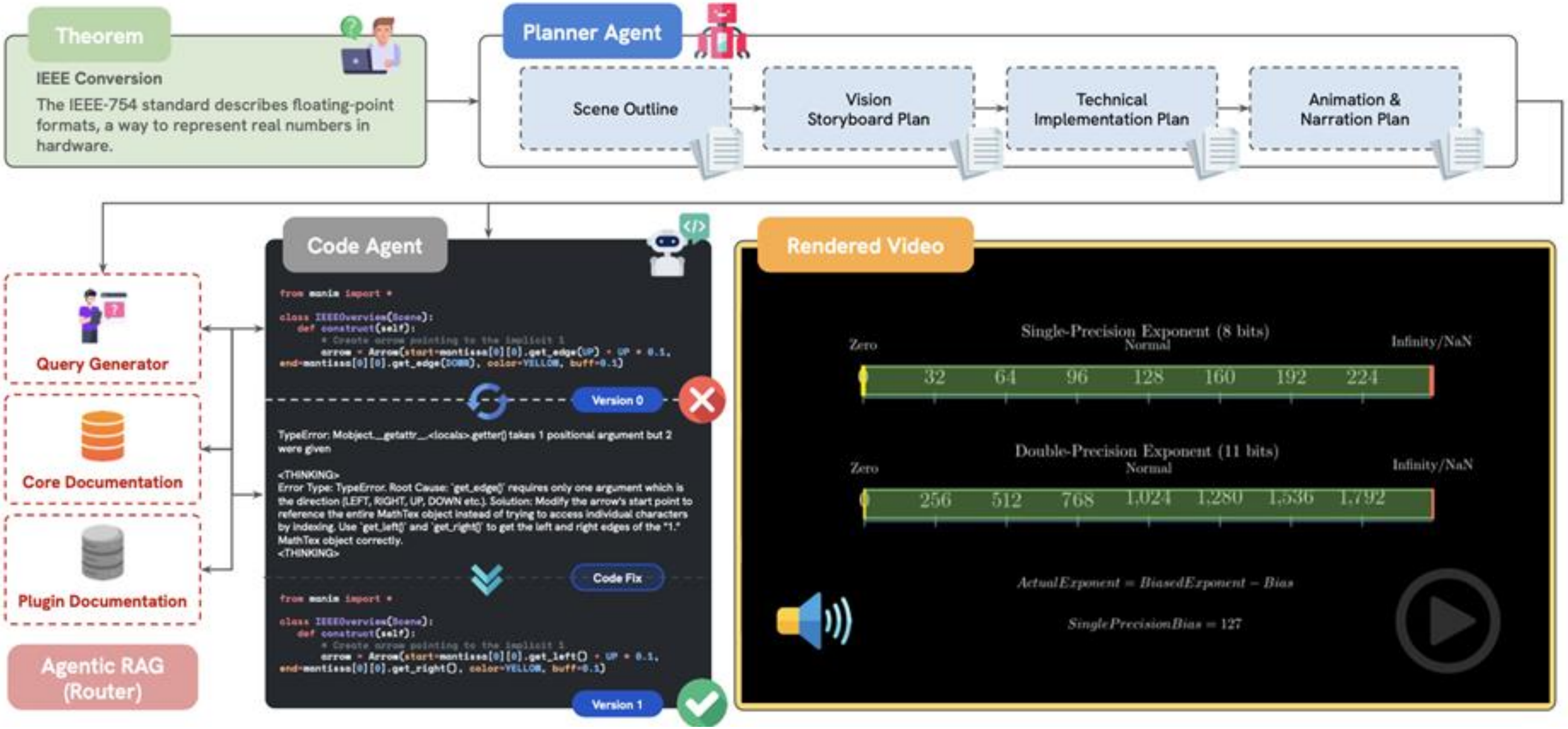
This is hard with current AI models,
and we present TheoremExplainAgent as the first attempt.

TheoremExplainAgent Framework



- **Input**: Theorem + Context
- **Process**: Agent(s) plan and generate multimodal elements (animations, narration).
- **Output**: Explanatory Video
- **Evaluation**: Assessed using automated metrics.

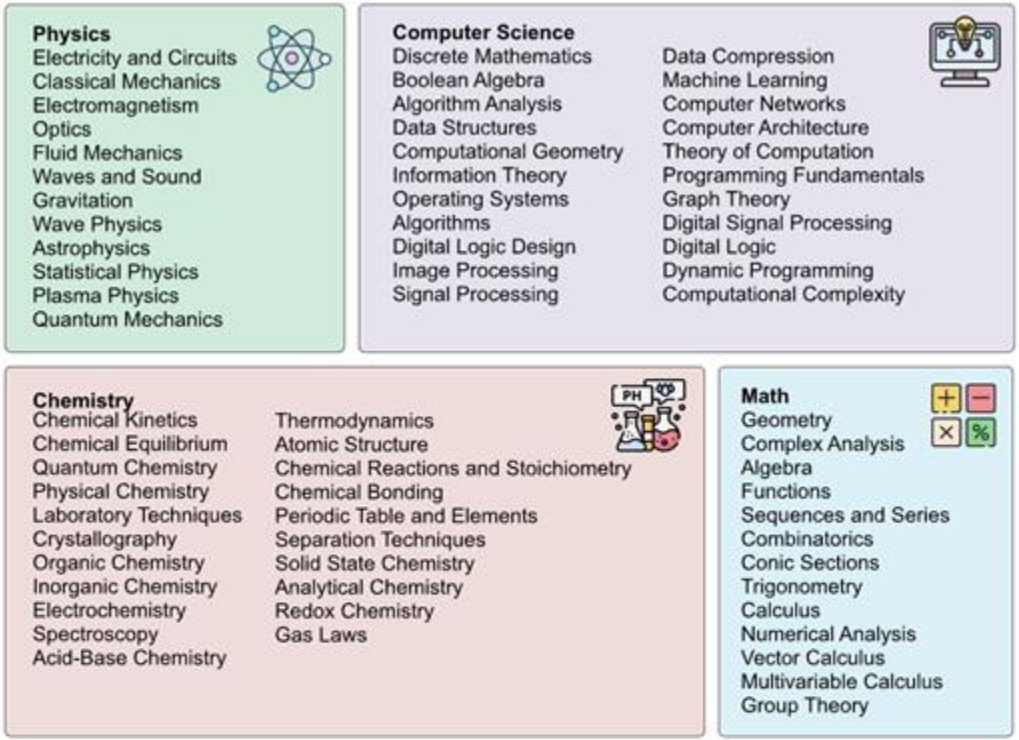
TheoremExplainAgent (TEA)



TheoremExplainBench (TEB) Dataset

A standardized benchmark to evaluate multimodal explanations.

- 240 theorems across 4 STEM disciplines
- Sourced from OpenStax, LibreTexts.
- 3 Difficulty Levels: Easy (HS), Medium (UG), Hard (Grad) - 80 each.
- 5 Metrics on explanations video quality.



Experimental Setup

Models Tested

GPT-4o, Claude 3.5 Sonnet v1, Gemini 2.0 Flash, o3-mini (medium).
Used for both Planner and Coder roles.

Evaluation

Among all 240 theorems in TEB:
1) Whether models can write proper visualization code to generate the video?
2) How effective are the multimodal explanations?
Against actual human-made Manim videos ?
3) Case studies to show visual explanations can expose flaws in logic and flow.

Results: Video Generation Success Rate

Agent	Easy	Medium	Hard	Math	Phys	CS	Chem	Overall
GPT-4o	61.3%	57.5%	46.2%	61.7%	55.0%	58.3%	45.0%	55.0%
GPT-4o + RAG	42.5%	57.5%	37.5%	70.0%	40.0%	41.7%	31.7%	45.8%
Claude 3.5-Sonnet v1	2.5%	1.2%	2.5%	1.7%	1.7%	1.7%	3.3%	2.1%
Claude 3.5-Sonnet v1 + RAG	18.8%	13.8%	11.2%	23.3%	10.0%	20.0%	5.0%	14.6%
Gemini 2.0-Flash	20.0%	11.2%	12.5%	16.7%	8.3%	21.7%	11.7%	14.6%
Gemini 2.0-Flash + RAG	23.8%	21.2%	16.2%	26.7%	15.0%	20.0%	20.0%	20.4%
o3-mini (medium)	**93.8%**	**91.2%**	**96.2%**	**95.0%**	**93.3%**	**93.3%**	**93.3%**	**93.8%**
o3-mini (medium) + RAG	83.8%	82.5%	80.0%	81.7%	90.0%	88.3%	68.3%	82.1%

- **o3-mini** consistently outperforms others (93.8% overall success)
- **GPT-4o** is moderate, struggles with complexity. **Gemini 2.0 Flash** struggles most.
- **Math** has highest success; **Chemistry** is most challenging (complex object rendering).
- **RAG slightly decreased** success rates in most cases (potential noise/distraction).

Results: Video Quality Scores

(on successful videos)

Agent	Accuracy and Depth	Visual Relevance	Logical Flow	Element Layout	Visual Consistency	Overall Score
GPT-4o	0.79	0.79	**0.89**	0.59	0.87	0.78
GPT-4o + RAG	0.75	0.77	0.88	0.57	0.86	0.76
Claude 3.5-Sonnet v1	0.75	**0.87**	0.88	0.57	**0.92**	**0.79**
Claude 3.5-Sonnet v1 + RAG	0.67	0.79	0.69	0.65	0.87	0.71
Gemini 2.0 Flash	**0.82**	0.77	0.80	0.57	0.88	0.76
Gemini 2.0 Flash + RAG	0.79	0.75	0.84	0.58	0.87	0.76
o3-mini (medium)	0.76	0.76	**0.89**	0.61	0.88	0.77
o3-mini (medium) + RAG	0.75	0.75	0.88	0.61	0.88	0.76
Human-made Manim Videos	0.80	0.81	0.70	**0.73**	0.87	0.77

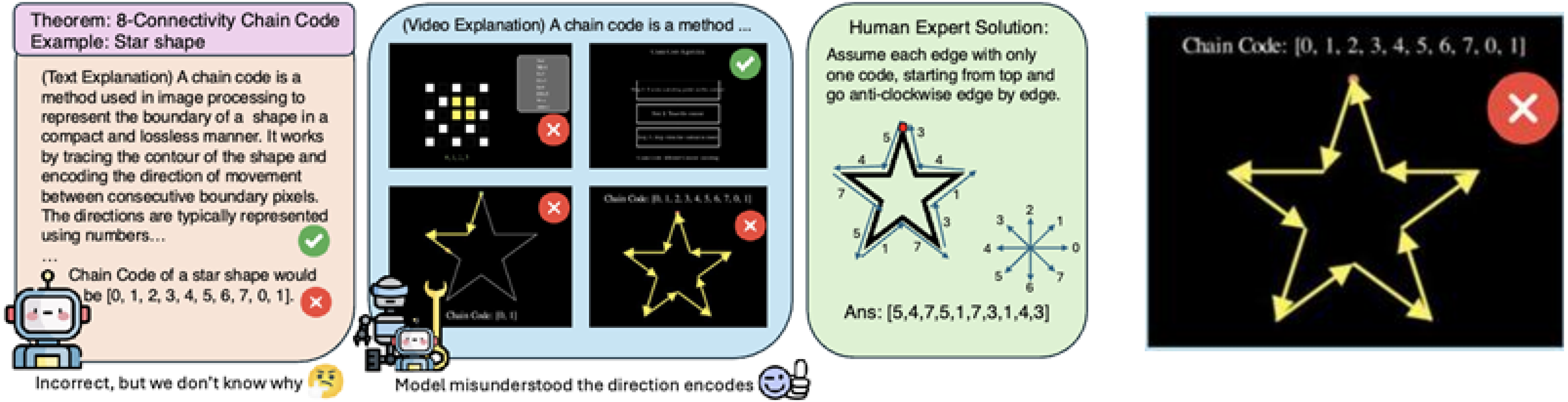
Insights

MLLM as judge:
Human videos excel at Element Layout & Visual Relevance.
Element Layout is a common challenge for AI models (avg ~0.6).

o3-mini (0.77) and GPT-4o (0.78) achieve good overall scores, comparable to human-made videos (0.77). Claude 3.5 Sonnet v1 (0.79) slightly higher but low success rate.

Case Study: Visual Error Diagnosis

Multimodal explanations expose deeper reasoning flaws.

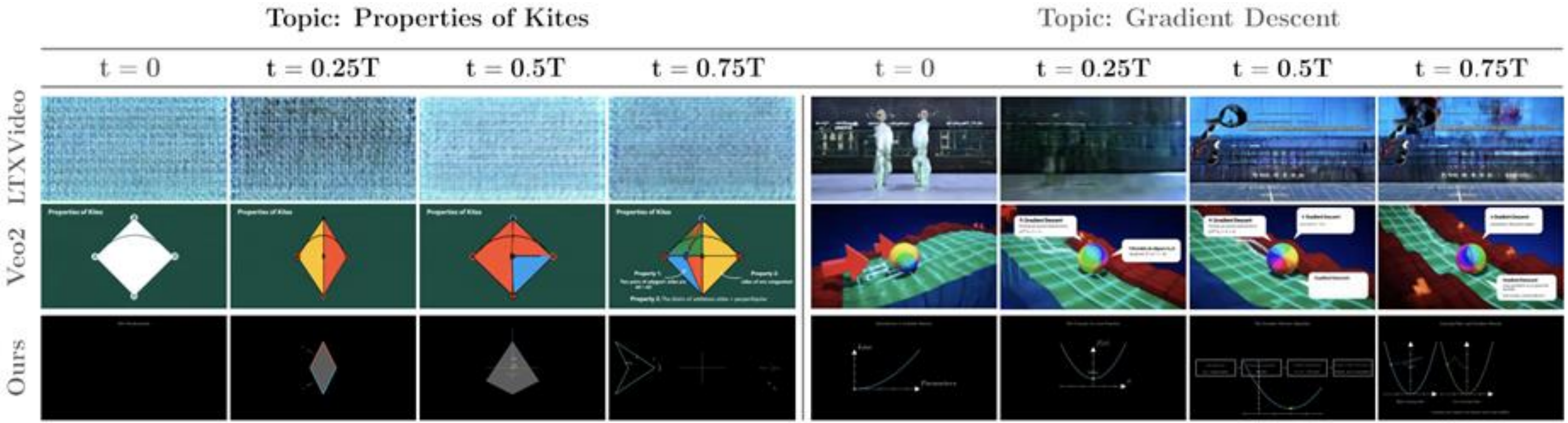


Example: 8-Connectivity Chain Code

Text Explanation:
Might show the final answer is wrong, but why is unclear. Model seems to "understand" the definition but applies it incorrectly.

Video Explanation:
Clearly shows the model misunderstanding direction encoding (wrong arrows, incorrect path tracing). Makes the reasoning error explicit and diagnosable.

Can Video Models be an alternative solution?



Findings:
Video models lack reasoning/planning to produce explanatory videos. However, recent video model development shows promising direction to serve as the visual (and even audio) component in the future, replacing the coding agent role.

Conclusion

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We contributed TEA (agentic system for multimodal theorem explanation videos) & TEB (benchmark/metrics).

Agentic planning is crucial for long-form coherent videos. o3-mini shows strong generation capability.

We demonstrated that Multimodal explanations are vital for deep understanding and effective error diagnosis.

However Visual element layout remains a key challenge for existing approaches, and the evaluation effectiveness is unexplored.

Thank you!

Project Page (tiger-ai-lab.github.io/TheoremExplainAgent/), Code Available