

DocThinker: Explainable Multimodal Large Language Models with Rule-based Reinforcement Learning for Document Understanding

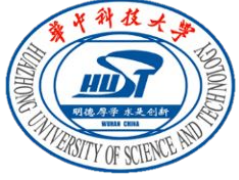
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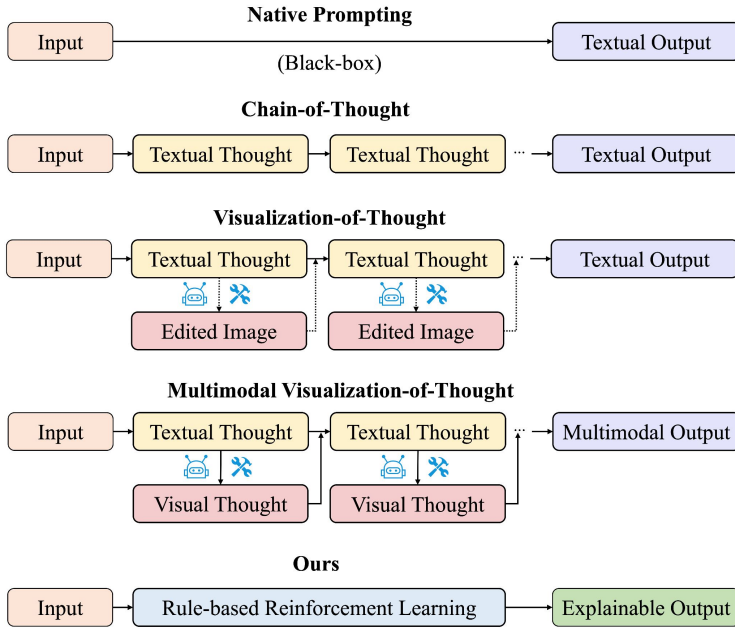
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Introduction:

- Multimodal Large Language Models (MLLMs) have demonstrated remarkable capabilities in document understanding. However, their reasoning processes remain largely black-box, making it difficult to ensure reliability and trustworthiness, especially in high-stakes domains such as legal, financial, and medical document analysis.
- Existing methods use fixed Chain-of-Thought (CoT) reasoning with supervised fine-tuning (SFT) but suffer from catastrophic forgetting, poor adaptability, and limited generalization across domain tasks.

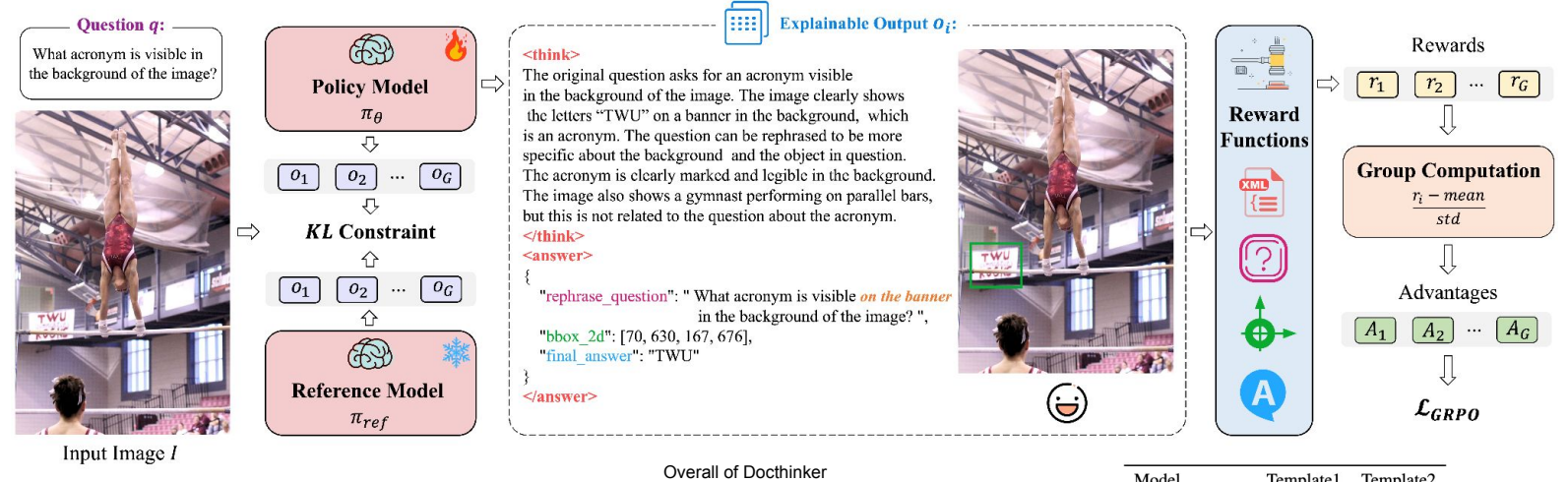


Comparison of different approaches for improving model's explainability and transparency in MLLM-based document understanding.

- We propose Docthinker, a rule-based Reinforcement Learning (RL) framework for dynamic inference-time reasoning.

Methods:

- Instead of relying on static CoT templates, our model autonomously refines reasoning strategies via policy learning, generating explainable intermediate results, including structured reasoning processes, rephrased questions, regions of interest (RoI) supporting the answer, and the final answer. By integrating multi-objective rule-based rewards and KL-constrained optimization, our method mitigates catastrophic forgetting and enhances both adaptability and transparency.



Experiments:

- DocThinker significantly improves generalization while producing more explainable and human-understandable reasoning steps.

MLLM	Res.	Data	Str.	Document-oriented Understanding						General Multimodal Understanding					
				Doc/Text				Chart		General VQA		Relation Reasoning			
				DocVQA	TextCaps	TextVQA	DUDE	SROIE	InfoQA	F30k	V7W	QQA	OI	VS	VSR
LLaVA-1.5-7B [22]	336 ²	-	SFT	0.244	0.597	0.588	0.290	0.136	0.400	0.581	0.575	0.534	0.412	0.572	
LLaVA-1.5-13B [22]	336 ²	-	SFT	0.268	0.615	0.617	0.287	0.164	0.426	0.620	0.580	0.571	0.413	0.590	
SPHINX-13B [18]	224 ²	-	SFT	0.198	0.551	0.532	0.000	0.071	0.352	0.607	0.558	0.584	0.467	0.613	
VisCoT-7B [35]	224 ²	438k	SFT	0.355	0.610	0.719	0.279	0.341	0.356	0.671	0.580	0.616	0.833	0.682	
VisCoT-7B [35]	336 ²	438k	SFT	0.476	0.675	0.775	0.386	0.470	0.324	0.668	0.558	0.631	0.822	0.614	
Qwen2.5VL-7B ¹ [1]	336 ²	-	-	0.350	0.642	0.735	0.202	0.472	0.325	0.603	0.556	0.455	0.347	0.616	
Qwen2.5VL-7B ¹ [1]	1536 ²	-	-	0.773	0.710	0.792	0.492	0.708	0.663	0.685	0.604	0.457	0.371	0.603	
Qwen2.5VL-7B* [1]	336 ²	4k	SFT	0.355	0.658	0.740	0.215	0.489	0.334	0.624	0.563	0.467	0.405	0.619	
Qwen2.5VL-7B* [1]	1536 ²	4k	SFT	0.784	0.725	0.801	0.498	0.714	0.674	0.680	0.609	0.472	0.427	0.624	
DocThinker-3B	336 ²	4k	RL	0.460	0.663	0.746	0.213	0.486	0.335	0.664	0.572	0.486	0.485	0.625	
DocThinker-3B	1536 ²	4k	RL	0.751	0.691	0.762	0.469	0.735	0.566	0.682	0.583	0.490	0.517	0.637	
DocThinker-7B	336 ²	4k	RL	0.579	0.682	0.802	0.408	0.495	0.347	0.674	0.580	0.546	0.542	0.656	
DocThinker-7B	1536 ²	4k	RL	0.795	0.738	0.827	0.515	0.806	0.689	0.701	0.625	0.694	0.686	0.721	
DocThinker-7B	1536 ²	8k	RL	0.802	0.757	0.836	0.568	0.814	0.697	0.734	0.641	0.737	0.784	0.768	

Conclusion

- This paper introduced DocThinker, a reinforcement learning-based framework designed to enhance explainability, adaptability, and reasoning ability in multimodal document understanding. DocThinker achieves state-of-the-art or highly competitive performance on standard benchmarks

Model	Template	
	Template1	Template2
Specialist Models		
TransVG [6]	50.1	54.0
MAttNet [48]	52.3	60.5
QRNet [45]	52.7	59.1
MDETR [14]	54.4	63.3
TAMN [9]	77.8	80.8
DocThinker-7B	82.4	