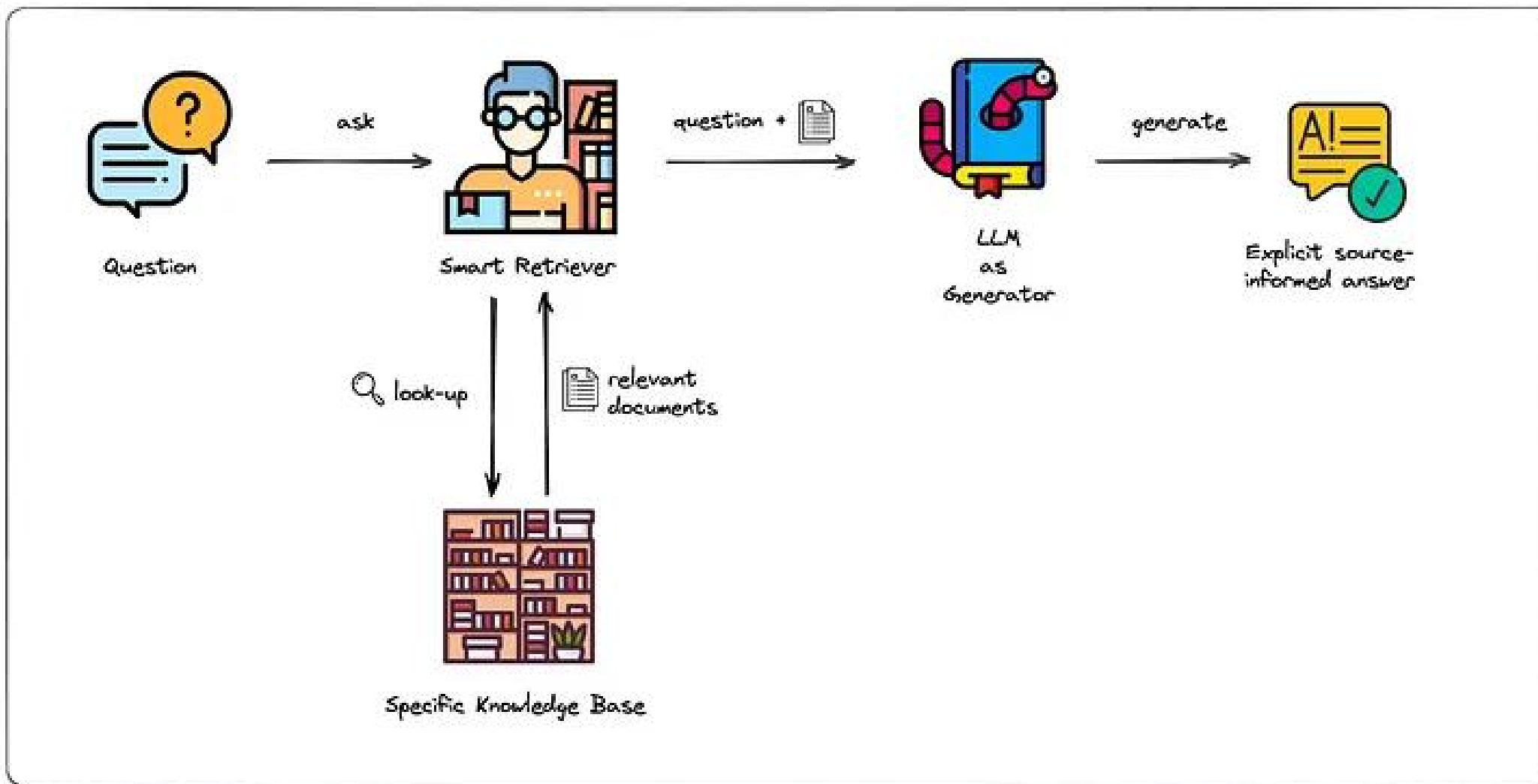


LLM-as-a-Judge在RAG及合成数据中的价值与应用

讲解人：徐铨晋 博士 深圳市特聘专家（B类）

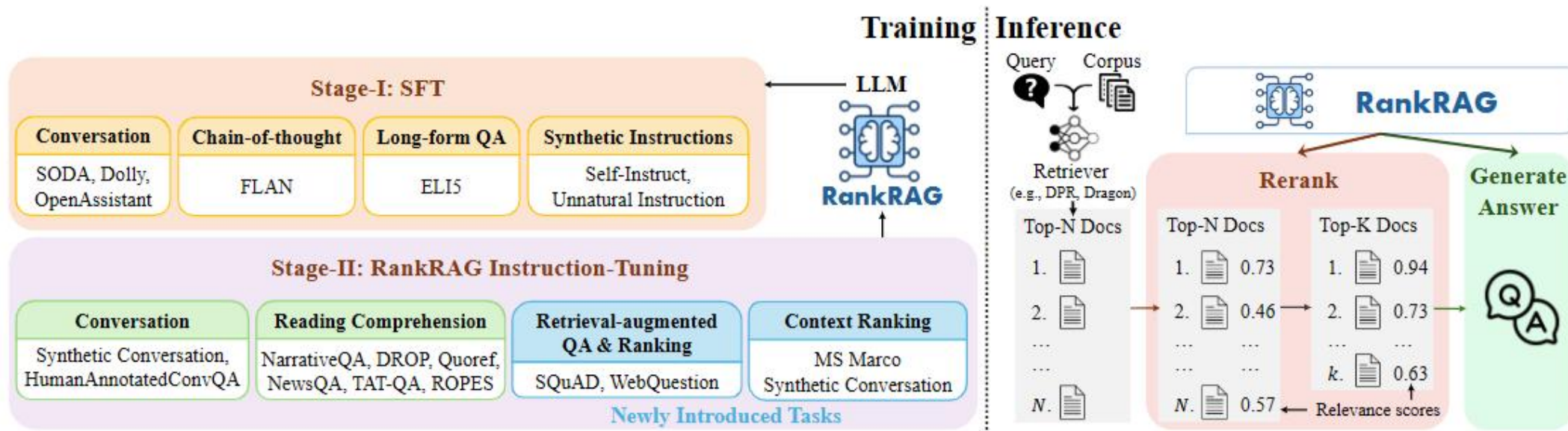
IDEA研究院AI研究科学家
DataArc联合创始人&CTO

检索增强生成 (LLM-as-a-generator)



1. 检索信息和问题足够相关吗 (Reranker)
2. 检索信息是否足够回答问题 (Critic)
3. 回答是否和检索信息一致 (Verifier)
4. 对回答质量进行评估 (Evaluator)





System: This is a chat between a user and an artificial intelligence assistant. The assistant gives helpful, detailed, and polite answers to the user's questions based on the context. The assistant should also indicate when the answer cannot be found in the context.

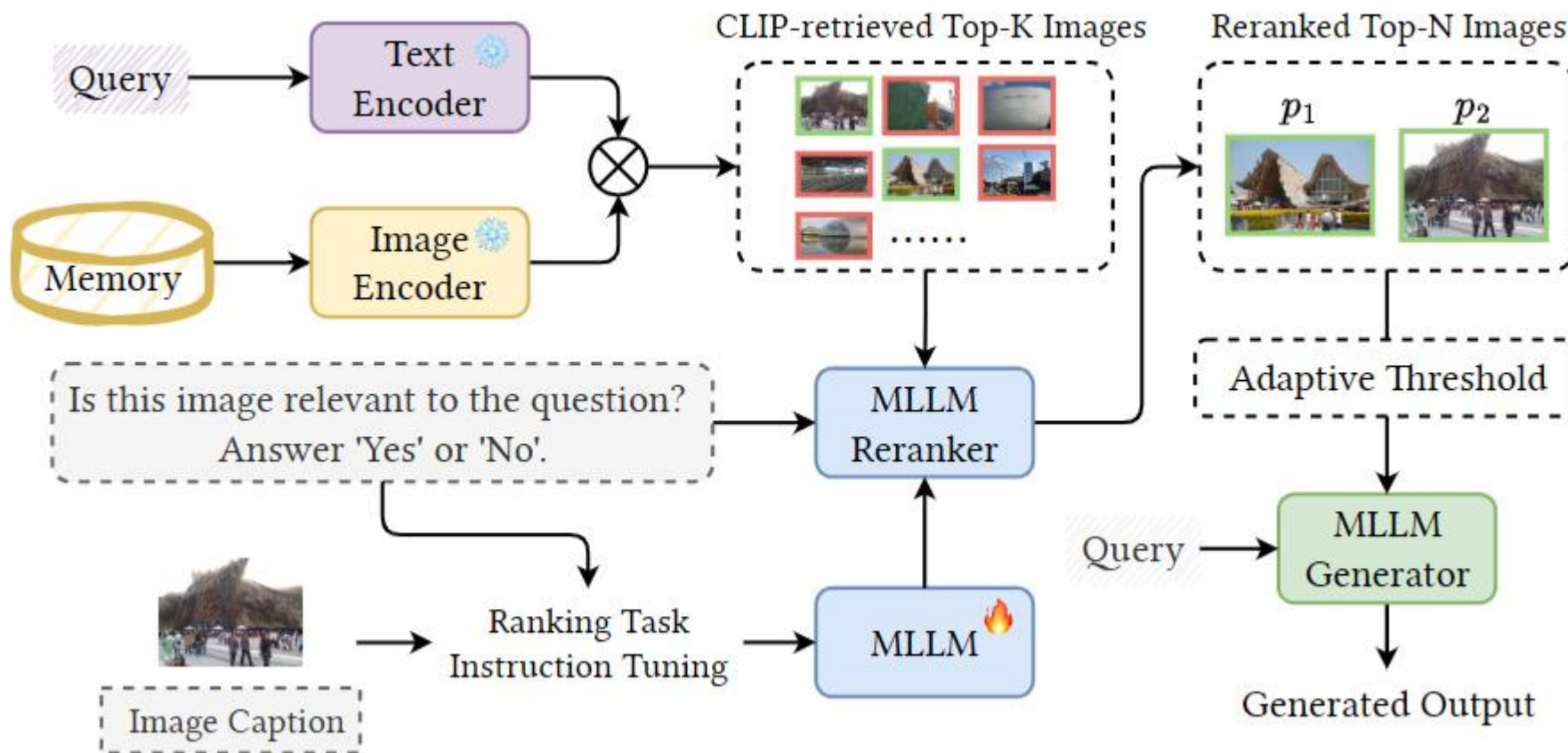
Passage 1: {(Shuffled) Passage 1}

Passage 2: {(Shuffled) Passage 2}

Passage 3: {(Shuffled) Passage 3}

User: {For the question <question>, access whether the above passages are relevant to the question. Return all the relevant passage id. }

Assistant:



论文: MLLM is a strong reranker: Advancing multimodal retrieval-augmented generation via knowledge-enhanced reranking and noise-injected training

Methods	MultimodalQA			WebQA		
	R@1	R@5	R@10	R@2	R@5	R@10
CLIP-ViT-L/14-336px	84.78	94.35	95.65	57.10	71.96	84.86
<i>w/ SFT</i>	83.04	94.35	94.78	55.09	73.23	81.94
Vis-BGE-base	49.57	74.78	82.61	28.78	43.62	54.56
Vis-BGE-m3	43.48	66.52	72.17	26.69	40.75	51.14
InternVL-C	82.17	95.65	96.96	64.90	81.22	88.09
InternVL-G	82.17	95.22	97.39	64.90	80.23	88.28
<i>Reranking Top-K from CLIP-ViT-L/14-336px</i>						
LLaVA-v1.5-13B	72.61	90.87	95.22	45.35	65.87	80.56
<i>w/ caption-aware IT</i>	98.26	98.26	98.26	79.74	88.14	89.77
mPLUG-Owl2	67.83	87.39	93.91	43.26	63.80	79.38
<i>w/ caption-aware IT</i>	90.87	96.09	97.39	71.27	85.08	88.97
Qwen-VL-Chat	68.26	89.57	92.61	47.64	67.22	80.42
<i>w/ caption-aware IT</i>	91.30	95.65	97.39	80.12	88.53	89.96
InternVL2-1B	47.39	84.78	93.91	34.99	57.49	74.72
<i>w/ caption-aware IT</i>	98.26	98.26	98.26	82.00	88.78	89.94
InternVL2-2B	66.52	88.70	93.91	42.79	62.48	77.97
<i>w/ caption-aware IT</i>	98.26	98.26	98.26	81.91	88.94	89.94
<i>Reranking Top-K from Different Retrievers</i>						
LLaVA-v1.5-13B						
<i>w/ Vis-BGE-base</i>	88.70	88.70	88.70	59.61	64.71	65.70
<i>w/ Vis-BGE-m3</i>	84.78	84.78	84.78	57.57	62.26	63.03
<i>w/ InternVL-C</i>	98.70	98.70	98.70	82.08	90.79	92.72
<i>w/ InternVL-G</i>	97.83	97.83	97.83	81.91	90.24	92.31

Input: Write an essay of your best summer vacation

Output: My best summer vacation was a magical escape to the coastal town of Santorini. The azure waters, charming white-washed building are unforgettable.

Augmented Output: No Retrieval My best summer vacation was a magical escape to the coastal town of Santorini. No Retrieval The azure waters, charming white-washed building are unforgettable experience. Util: 5

Input: How did US states get their names?

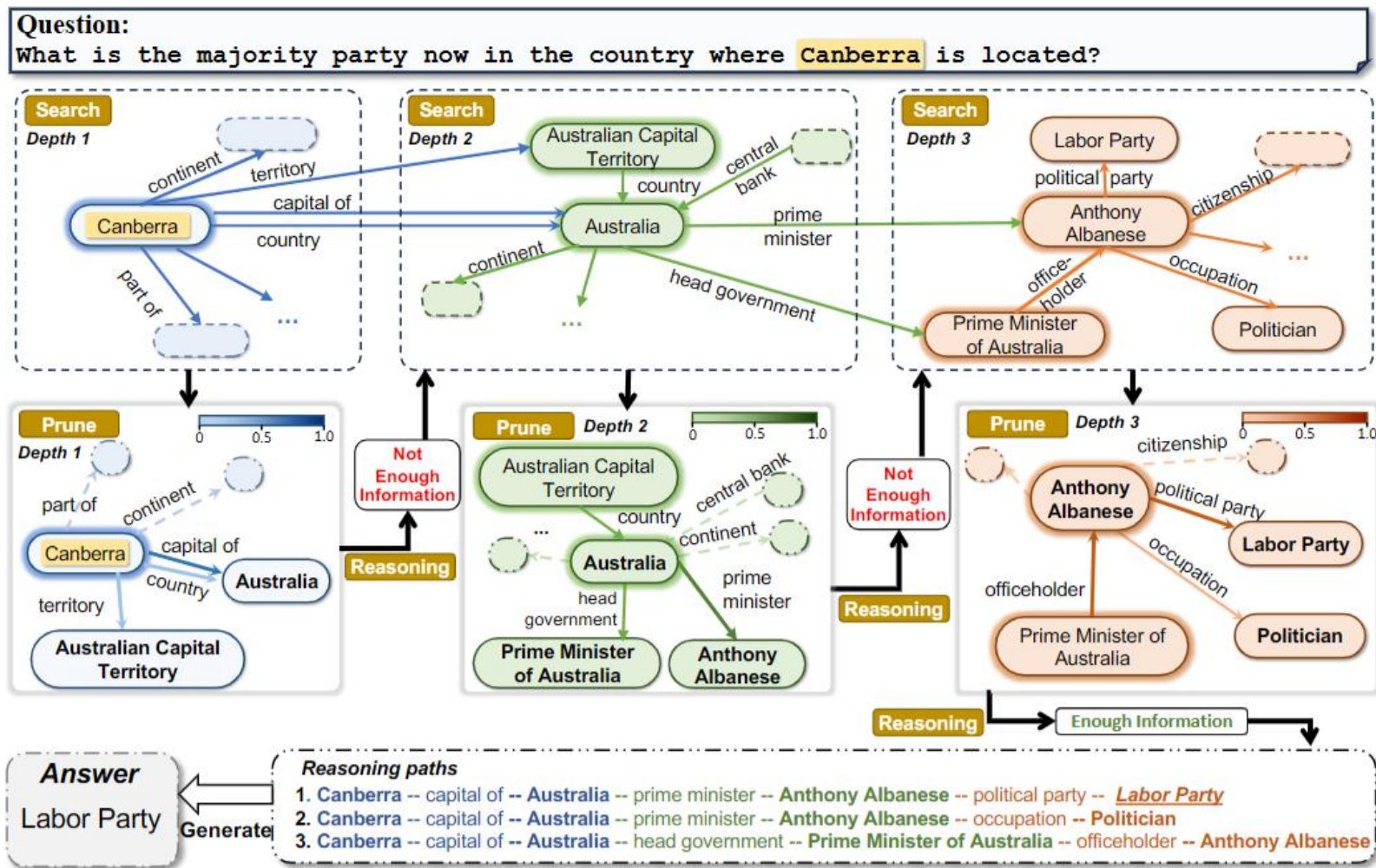
Output: 1 of 50 states names come from persons. For instance, Louisiana was named in honor of King Louis XIV of France and Georgia was named after King George II.



Type	Input	Output	Definitions
Retrieve	$x / x, y$	{yes, no, continue}	Decides when to retrieve with \mathcal{R}
ISREL	x, d	{ relevant , irrelevant}	d provides useful information to solve x .
ISSUP	x, d, y	{ fully supported , partially supported, no support}	All of the verification-worthy statement in y is supported by d .
ISUSE	x, y	{ 5 , 4, 3, 2, 1}	y is a useful response to x .

论文: Self-rag: Learning to retrieve, generate, and critique through self-reflection (ICLR 2024)

Critic: 是否需要检索



论文: Think-on-Graph: Deep and responsible reasoning of large language model on knowledge graph (ICLR 2024)

Think-on-Graph 2.0: Deep and Faithful Large Language Model Reasoning with Knowledge-guided Retrieval Augmented Generation

Verifier: 回答是否和检索信息一致

Question

What year was the Argentine actor who directed El Tio Disparate born?

(a) Chain of Thought & Self-Consistency

Rationales: First, the Argentine actor who directed El Tio Disparate is Fernando Birri.
Second, Fernando Birri was born in 1925.
The answer is 1925.

(b) Retrieval-Based Methods (Verify-and-Edit)

Verifying questions: Who directed El Tio Disparate?
When was Fernando Birri born?
Retrieved & Edit once: Palito Ortega directed El Tio Disparate. Fernando Birri was born in 1925.
The answer is 1925.

Error propagation

(c) Chain-of-Knowledge with Dynamic Knowledge Adapting

Identified domains: factual (Wikidata, Wikipedia)

Rationale 1: First, the Argentine actor who directed El Tio Disparate is Fernando Birri.

Retrieve (Wikidata) 1: SELECT ?answer WHERE { wd:El Tio Disparate wdt:director ?answer . } -> Palito Ortega

Retrieve (Wikipedia) 1: Who directed El Tio Disparate? -> El Tio Disparate is directed by Palito Ortega.

Corrected rationale 1: the Argentine actor who directed El Tio Disparate is Palito Ortega.

Rationale 2: Second, Palito Ortega was born in 1941.

Retrieve (Wikidata) 2: SELECT ?answer WHERE { wd:Palito Ortega wdt:date of birth ?answer . } -> 8 March 1941

Retrieve (Wikipedia) 2: When was Palito Ortega born? -> Palito Ortega was born in 8 March 1941.

Corrected rationale 2: Palito Ortega was born in 8 March 1941.

Corrected rationales: First, the Argentine actor who directed El Tio Disparate is Palito Ortega. Second, Palito Ortega was born in 8 March 1941.

The answer is 1941.

论文: Chain-of-Knowledge: Grounding Large Language Models via Dynamic Knowledge Adapting over Heterogeneous Sources (ICLR 2024)

Evaluator: 回答是否和标准答案一致

Query: 谁赢得了2024年的美国总统选举?

Context: 唐纳德·川普在2024年总统大选中取得令人瞩目的胜利, 于11月6日击败副总统卡玛拉·哈里斯....

Response: 唐纳德·川普

Golden Answer: 唐纳德·特朗普

Exact Match: **False**

LLM Eval: True

---Role---

You are an expert tasked with evaluating two answers to the same question based on four criteria: **Comprehensiveness**, **Diversity**, and **Empowerment**.

---Goal---

You will evaluate two answers to the same question based on four criteria: **Comprehensiveness**, **Diversity**, and **Empowerment**.

- **Comprehensiveness**: How much detail does the answer provide to cover all aspects and details of the question?
- **Diversity**: How varied and rich is the answer in providing different perspectives and insights on the question?
- **Empowerment**: How well does the answer help the reader understand and make informed judgments about the topic?

For each criterion, choose the better answer (either Answer 1 or Answer 2) and explain why. Then, select an overall winner based on these three categories.

Evaluation Instruction Prompt

Here is the question: {query}

Here are the two answers: **Answer 1**: {answer1}; **Answer 2**: {answer2}

Evaluate both answers using the three criteria listed above and provide detailed explanations for each criterion.

Output your evaluation in the following **JSON format**:

```
{{
  "Comprehensiveness": {{ "Winner": "[Answer 1 or Answer 2]", "Explanation": "[Provide explanation here]" }},
  "Diversity": {{ "Winner": "[Answer 1 or Answer 2]", "Explanation": "[Provide explanation here]" }},
  "Empowerment": {{ "Winner": "[Answer 1 or Answer 2]", "Explanation": "[Provide explanation here]" }},
  "Overall Winner": {{ "Winner": "[Answer 1 or Answer 2]", "Explanation": "[Summarize why this answer is the overall winner based on the three criteria]" }}
}}
```

Evaluation Input Prompt

论文: Lightrag: Simple and fast retrieval-augmented generation

石油



BP《世界能源统计年鉴》(BP Statistical Review of World Energy)，基于已探明石油储量与年产量的比例，**原油将在至少50年后才可能被耗尽**[1]

[1] BP. (2023). BP Statistical Review of World Energy 2023.
<https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html>.

数据 多久被耗尽?

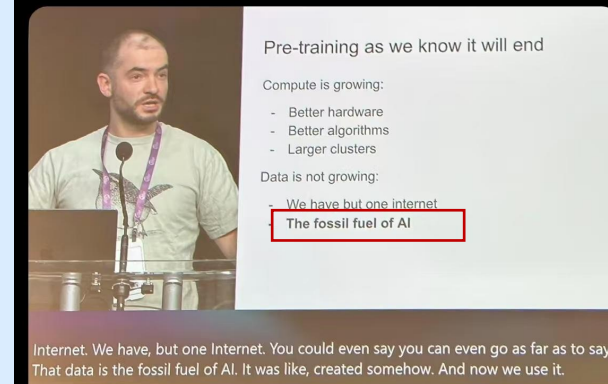
关于数据的数据 Data about Data

GPT 3: 2T
GPT 4: 20T
GPT 5: 200T?



互联网40年积累的数据 为了一AI时刻?

“Pre-training will end” - Dr. Ilya Sutskever at NeurIPS 2024



破局点：合成数据

是什么：通过算法和数学模型构建，模拟真实数据中的统计属性和关系。

如果把数据比作AI的“石油”，那么合成数据就是AI的“可再生能源”。



英伟达开源3400亿参数大模型使用**98%**合成数据训练。

(Adler B, Agarwal N, Aithal A, et al. Nemotron-4 340B Technical Report[J]. arXiv preprint arXiv:2406.11704, 2024.)



OpenAI CEO **Sam Altman**曾公开表达他相信很快所有数据都会是合成数据。

(The promise and perils of synthetic data., Kyle Wiggers Oct 13, 2024)



ScaleAI CEO **Alexandr Wang**指出合成数据的生成需要像对待芯片生产一样看待。

(A16Z: Unlocking AI's Future: Alexandr Wang on the Power of Frontier Data David George and Alexandr Wang)

Synthetic Data & LLM-as-a-judge



Synthetic
Data

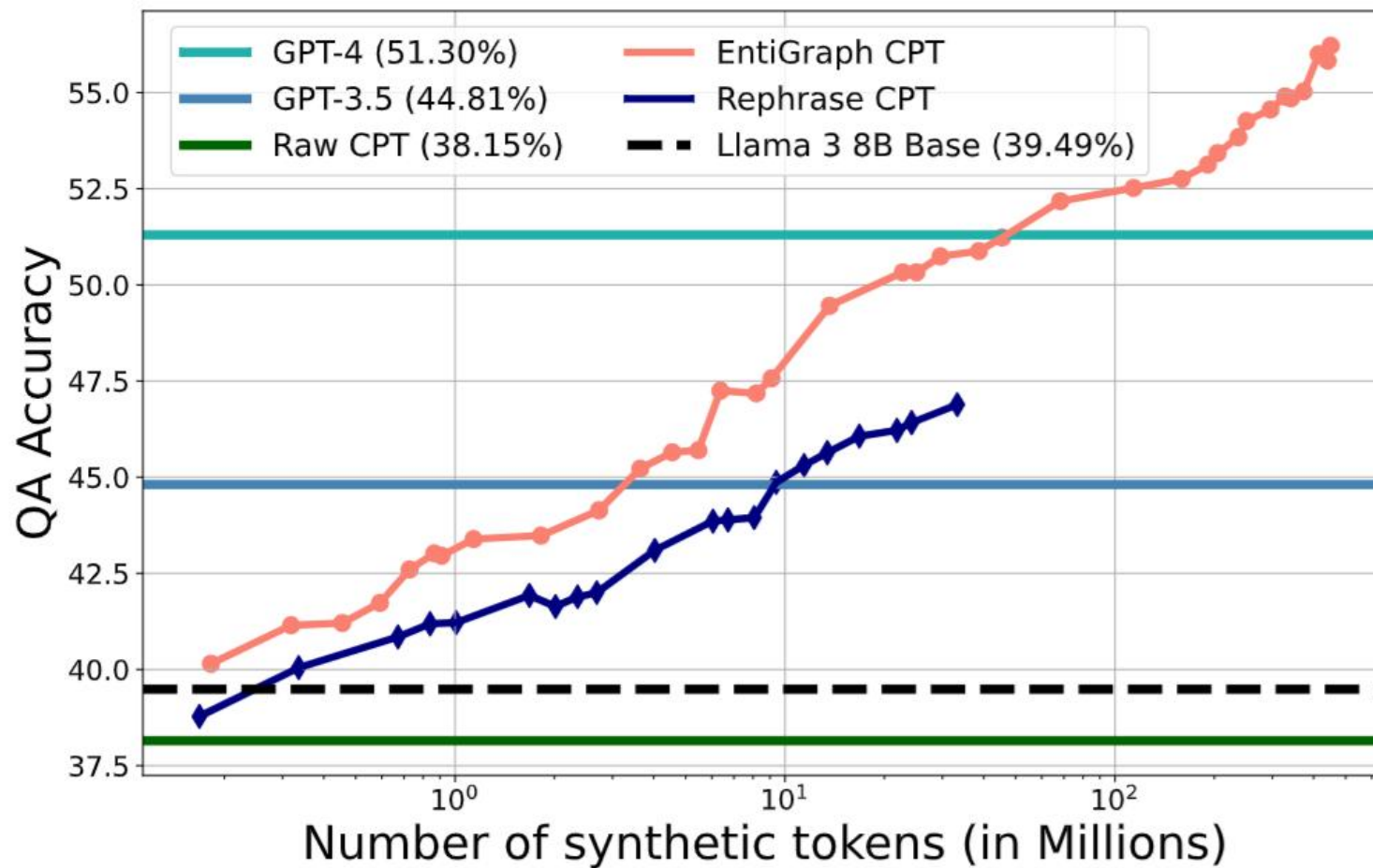


Indicator	Notation	Explanation
Length	Len	The average length of every response in the dataset.
Reward score	Rew	The average reward model inference score of every pair in the dataset. (Köpf et al., 2023)
Perplexity	PPL	The exponentiated average negative log-likelihood of response.
MTLD	$MTLD$	Measure of Textual Lexical Diversity McCarthy and Jarvis (2010)
KNN-i	KNN_i	Distance to approximate i^{th} -nearest neighbors (Dong et al., 2011) in SentenceBERT(Reimers and Gurevych, 2019) embedding space.
Unieval-naturalness	Nat	The score of whether a response is like something a person would naturally say, provided by the UniEval (Zhong et al., 2022) dialogue model.
Unieval-coherence	Coh	The score of whether this response serves as a valid continuation of the previous conversation, provided by the UniEval (Zhong et al., 2022) dialogue model.
Unieval-understandability	Und	The score of whether the response is understandable, provided by the UniEval (Zhong et al., 2022) dialogue model.

Table 1: Natural language indicators for instruction quality evaluation. Every data example is viewed as a pair of instruction(input) and response(output). Unless otherwise specified, the indicator value on a dataset is the average value of each sample on the indicator.

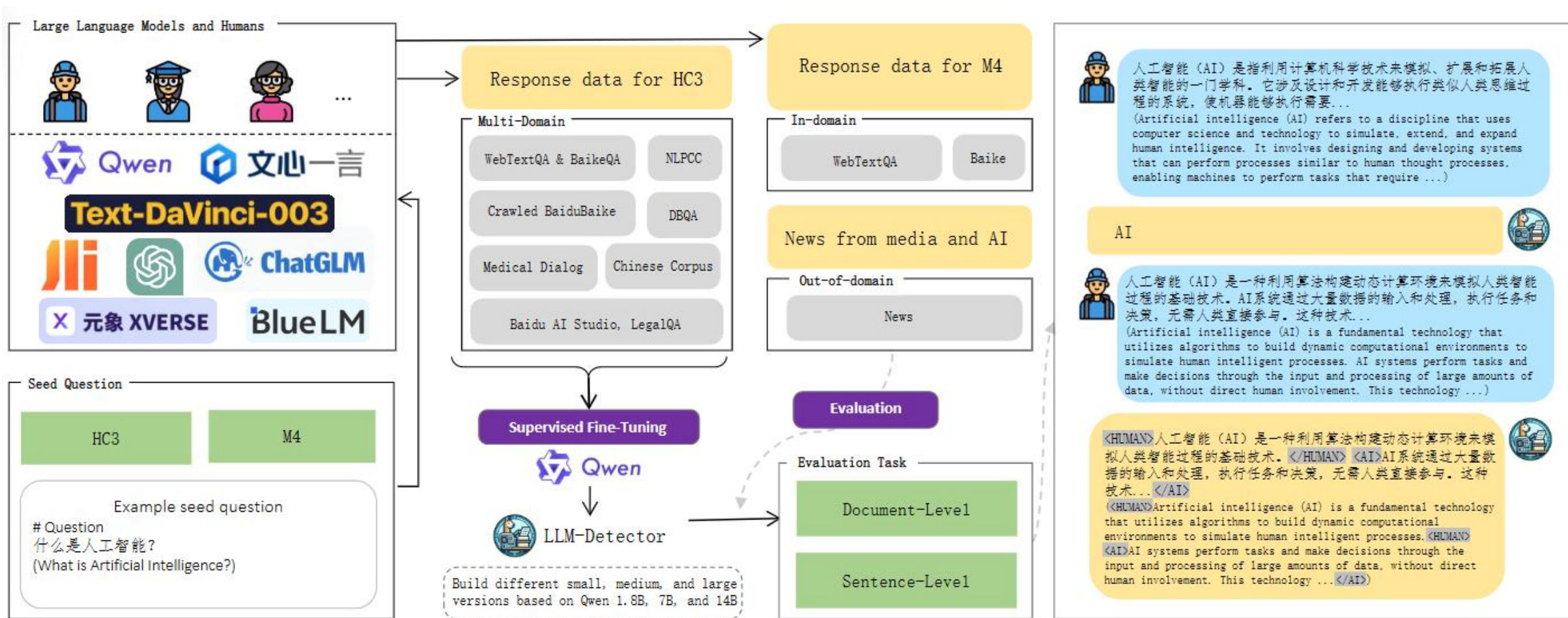
论文: Instruction Mining: High-Quality Instruction Data Selection for Large Language Models

Judge: 通过模型训练的效果评估合成数据质量



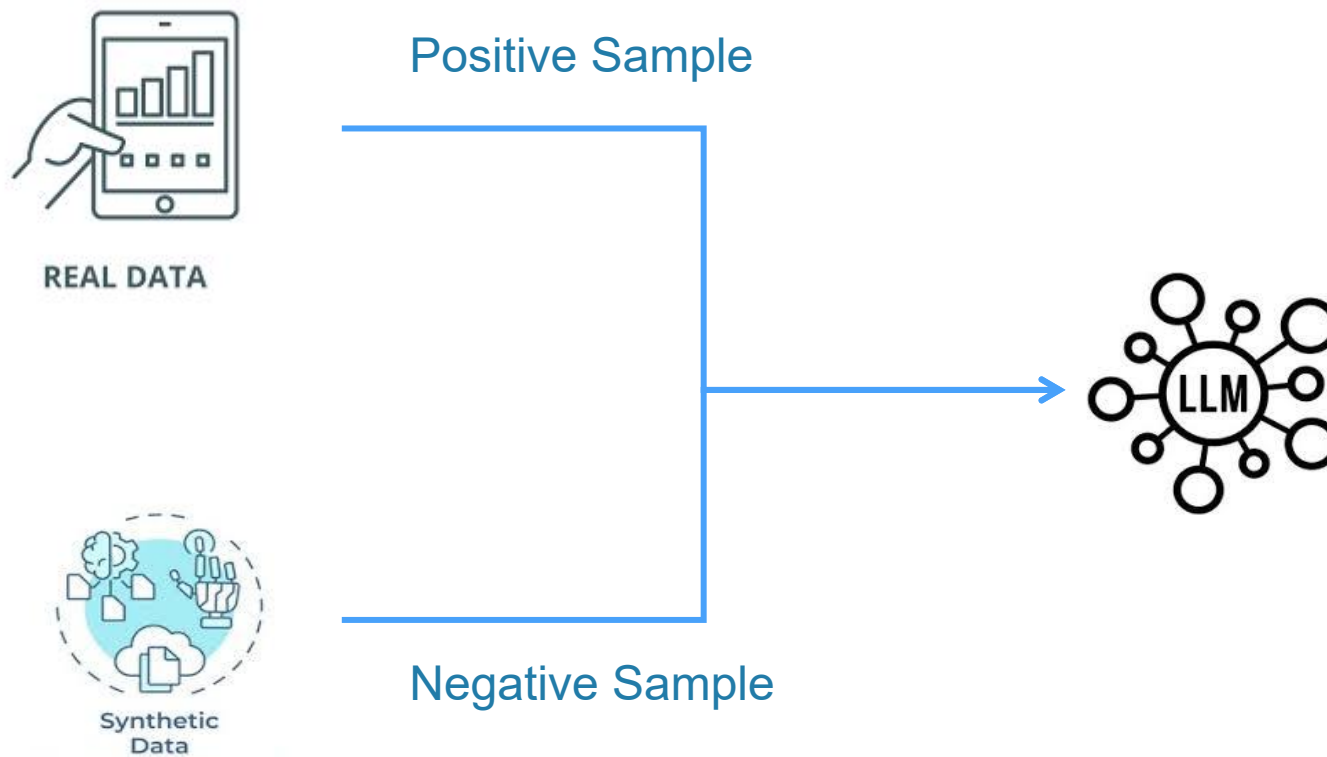
论文: Synthetic Continued Pretraining

Judge: 通过模型分辨真实数据和合成数据



论文: LLM-Detector: Improving AI-Generated Chinese Text Detection with Open-Source LLM Instruction Tuning

用合成数据训练LLM-as-a-judge: 蒸馏



用合成数据训练LLM-as-a-judge: 蒸馏



Positive Sample



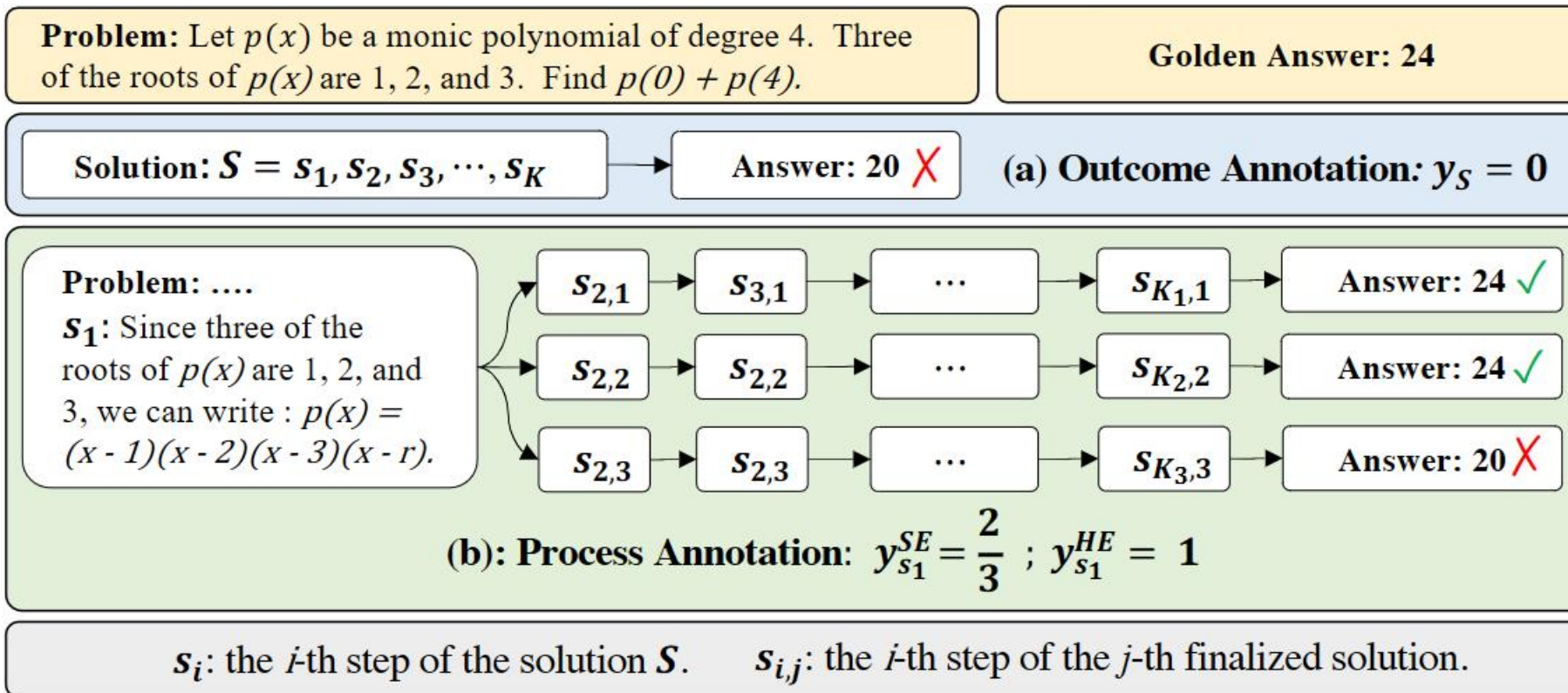
Negative Sample



用合成数据训练LLM-as-a-judge: 蒸馏



用合成数据训练LLM-as-a-judge: 蒙特卡洛 inspired by AlphaGo



论文: MATH-SHEPHERD: VERIFY AND REINFORCE LLMS STEP-BY-STEP WITHOUT HUMAN ANNOTATIONS

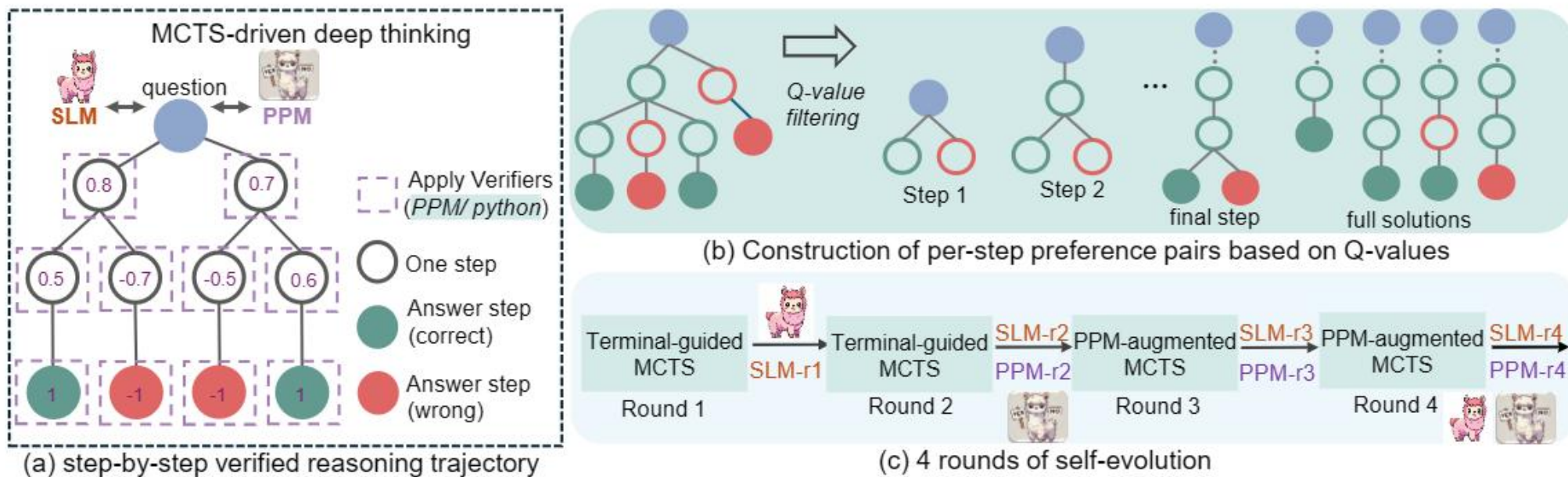
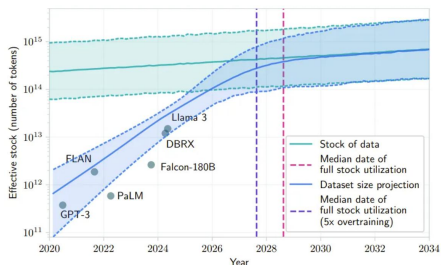


Figure 1: The overview of rStar-Math.

论文: rStar-Math: Small LLMs Can Master Math Reasoning with Self-Evolved Deep Thinking

Why 合成数据&LLM-as-a-judge?

1. 大模型Scaling Law困局，合成数据重要性将逐渐成为共识



但似乎我们不必等到 2028 年了。昨天，The Information 发布了一篇独家报道《随着 GPT 提升减速，OpenAI 改变策略》，其中给出了一些颇具争议的观点：

- OpenAI 的下一代旗舰模型的质量提升幅度不及前两款旗舰模型之间的质量提升；
- AI 产业界正将重心转向在初始训练后再对模型进行提升；
- OpenAI 已成立一个基础团队来研究如何应对训练数据的匮乏。

GPT-5?



2. 数据层面先发优势：合成数据积累 + 流程标准化



scale

3. 国内缺少具备对应能力与技术的企业，市场蓝海



谢谢!

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