CIPS-SMP 2024 大模型时代的AI+

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The Twelfth China National Conference on Social Media Processing

SMP2024 博士论坛

大模型工具学习与垂直领域应用的一些思考

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About Me

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About Me

I am a Ph.D. student at the School of Information, Renmin University of China, under supervision of Jing Zhang. At the same time, I'm an intern at THUKEG and ZHIPU.AI, under supervision of Jifan Yu. Previous to that, I graduated from Honors College of Northwestern Polytechnical University, where I majored in Computer Science and Technology.

Currently, my research focuses on **Tool Intelligence of LLMs** and **AI for Education**. Besides, I love soccer⚽, photography📷, and snowboarding🏂. I also keep training for triathlon races 🏊 🚴 🏃. Feel free to contact me for our shared interests whether in research or life.

Selected Publications:

- **Tool Intelligence of LLMs**
  - SoAy: A Solution-based LLM API-using Methodology for Academic Information Seeking
  - R-Eval: A Unified Toolkit for Evaluating Domain Knowledge of Retrieval Augmented Large Language Models
- **AI for Education**
  - From MOOC to MAIC: Reshaping Online Teaching and Learning through LLM-driven Agents

https://wangyc-99.github.io/

LLM Specific Domain Application

Currently, the common requirement of LLM specific domain application is **domain QA**.

Challenge of the directly deployment of LLMs into a specific domain:

Hallucination in General-purpose LLMs:

- Lack of command of Domain Knowledge
- Difficult in Information updating

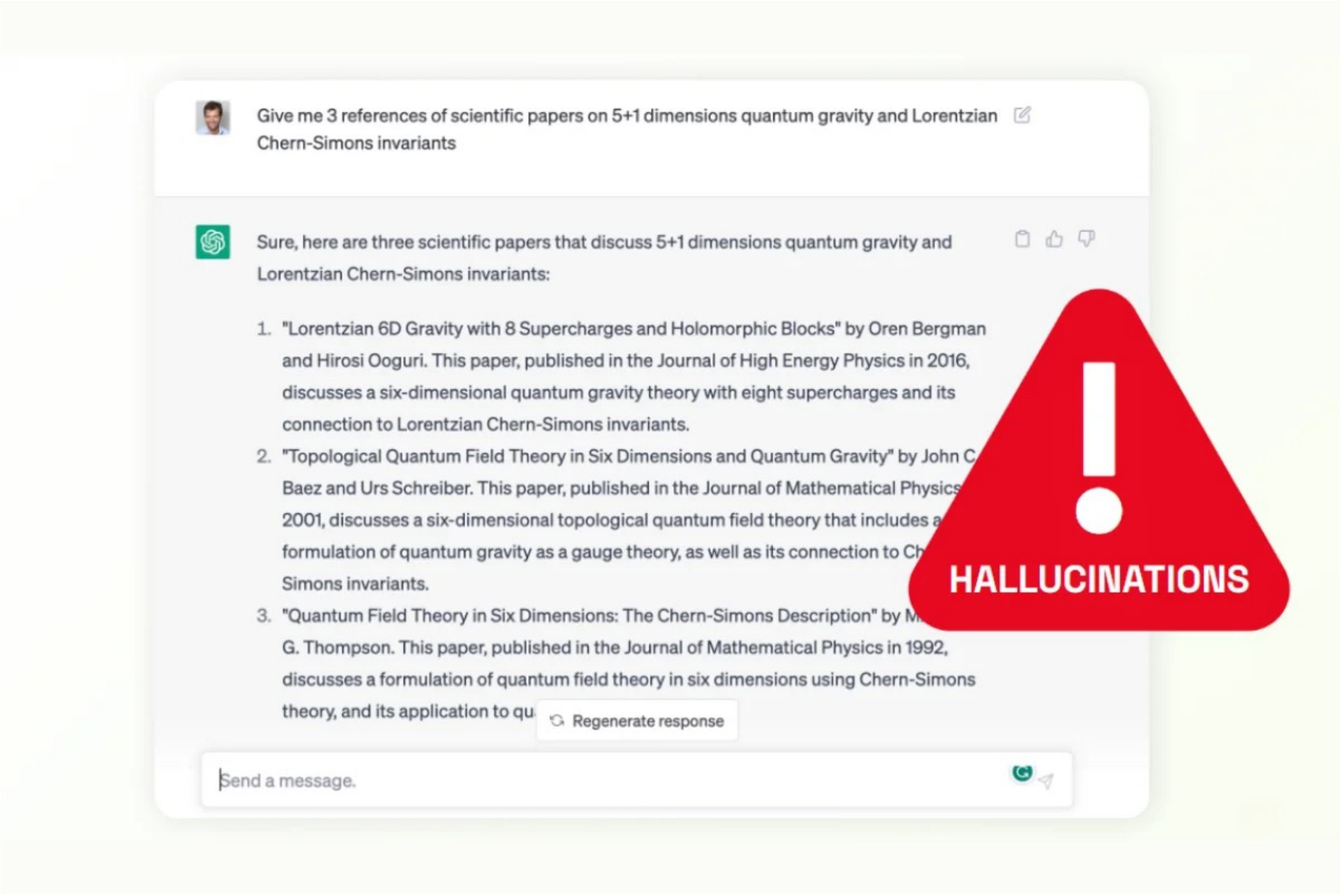


Fig.1 ChatGPT hallucinates on providing scientific reference.

https://kili-technology.com/large-language-models-llms/building-domain-specific-llms-examples-and-techniques

LLM Specific Domain Application

Methods of apply LLM into specific domain:

- Training on collected domain dataset.
    - High cost of data collecting.
    - Still difficult in information updating
- Text2SQL
- Retrieval-augmented Generation

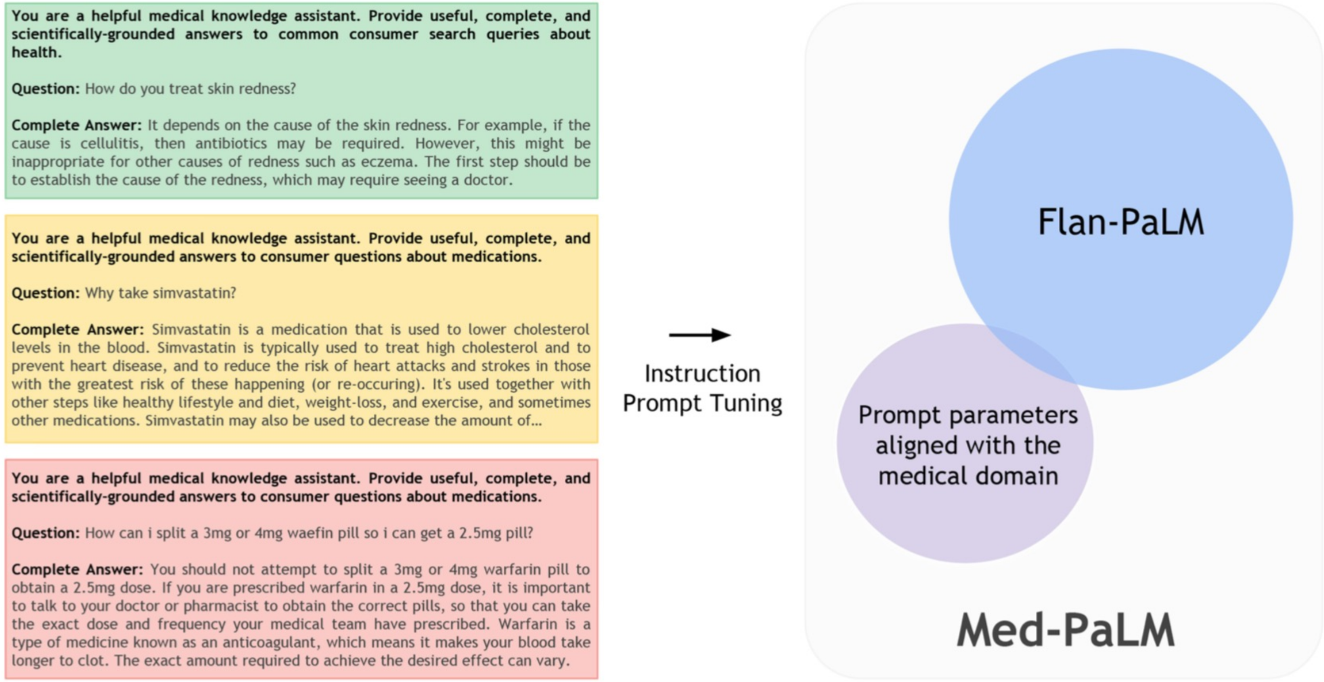


Fig.2 Flan-PaLM into Med-PaLM: Training on medical data.

Med-PaLM. Google Research. Nature (https://www.nature.com/articles/s41586-023-06291-2)

LLM Specific Domain Application

Methods of apply LLM into specific domain:

- Training on collected domain dataset.
- Text2SQL
  - Limited on specific SQL Language.
  - Safety concerns about interaction directly with DB.
- Retrieval-augmented Generation

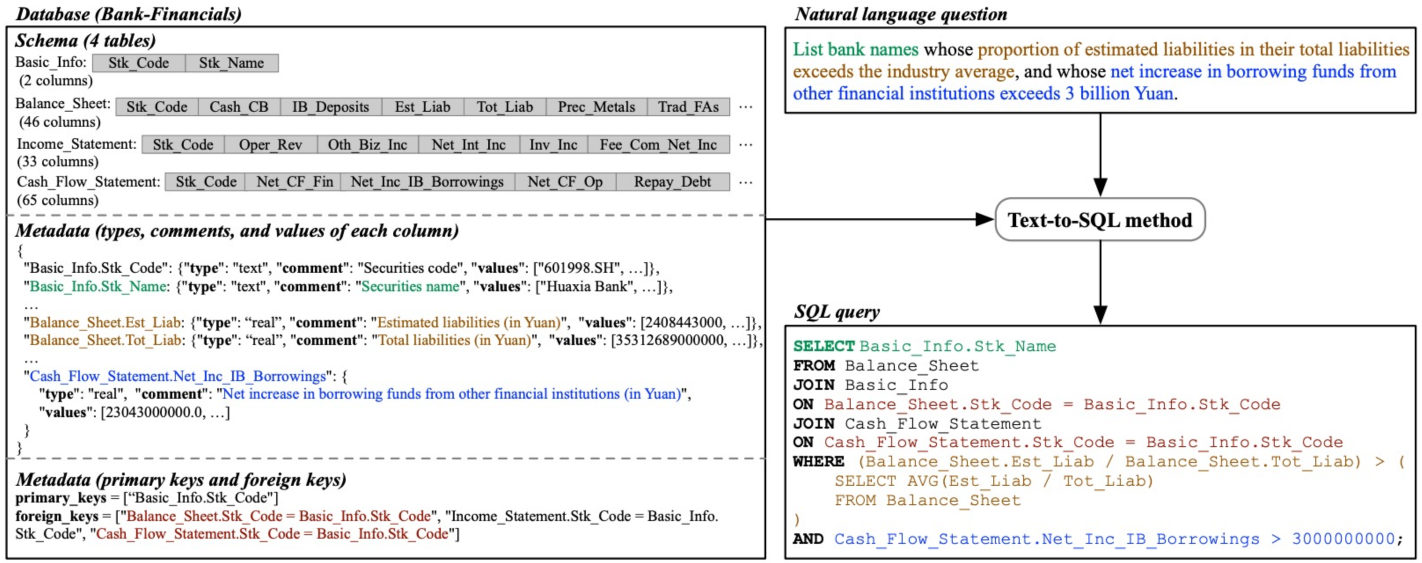


Fig.3 LLM interaction with domain KB through SQL query.

CodeS: Towards Building Open-source Language Models for Text-to-SQL. Haoyang Li, Jing Zhang, etc. (SIGMOD'24)

LLM Specific Domain Application

Methods of apply LLM into specific domain:

- Training on collected domain dataset.
- Text2SQL
- Retrieval-augmented Generation
    - Through Retriever
    - Through External Tools (Tool Learning)

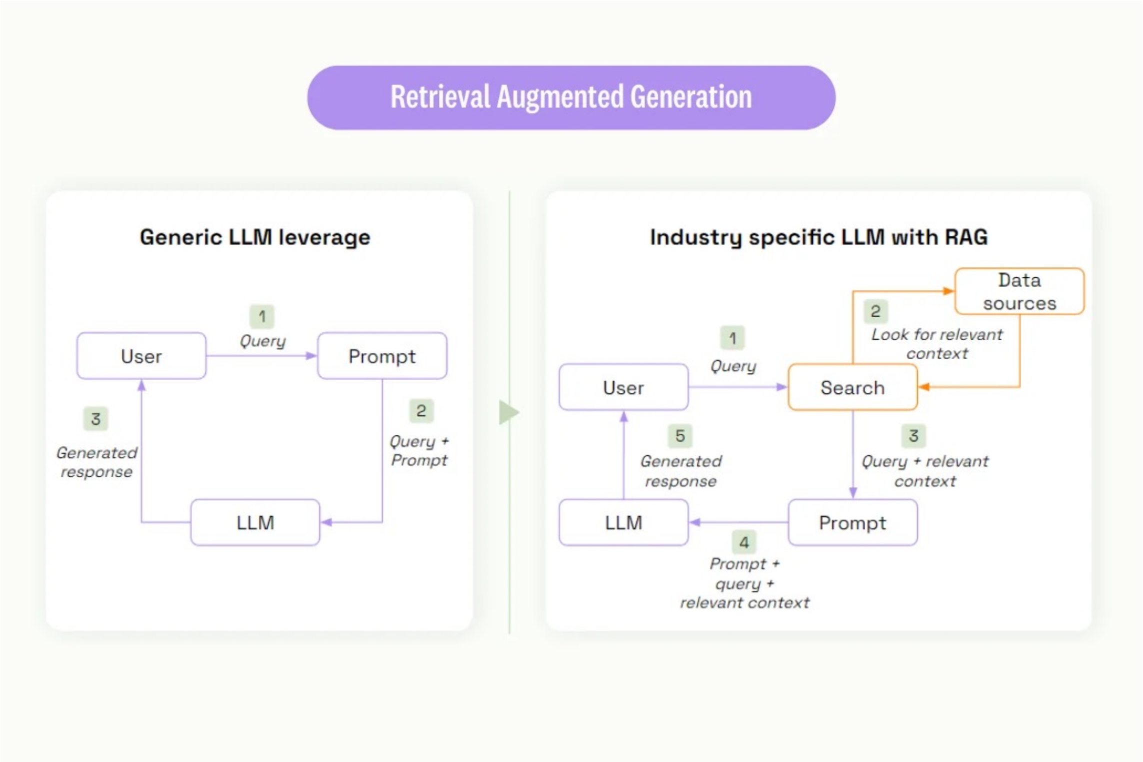


Fig.4 LLM specific domain application through RAG.

https://kili-technology.com/large-language-models-llms/building-domain-specific-llms-examples-and-techniques

LLM Tool Learning

LLMs can use tools to interact with external environment, including **web news**, **calculator**, real-world **agent scene**, and **domain knowledge**...

- How to teach LLMs to use IR tools to get domain knowledge?
- How to evaluate the ability of the LLM domain tool using?

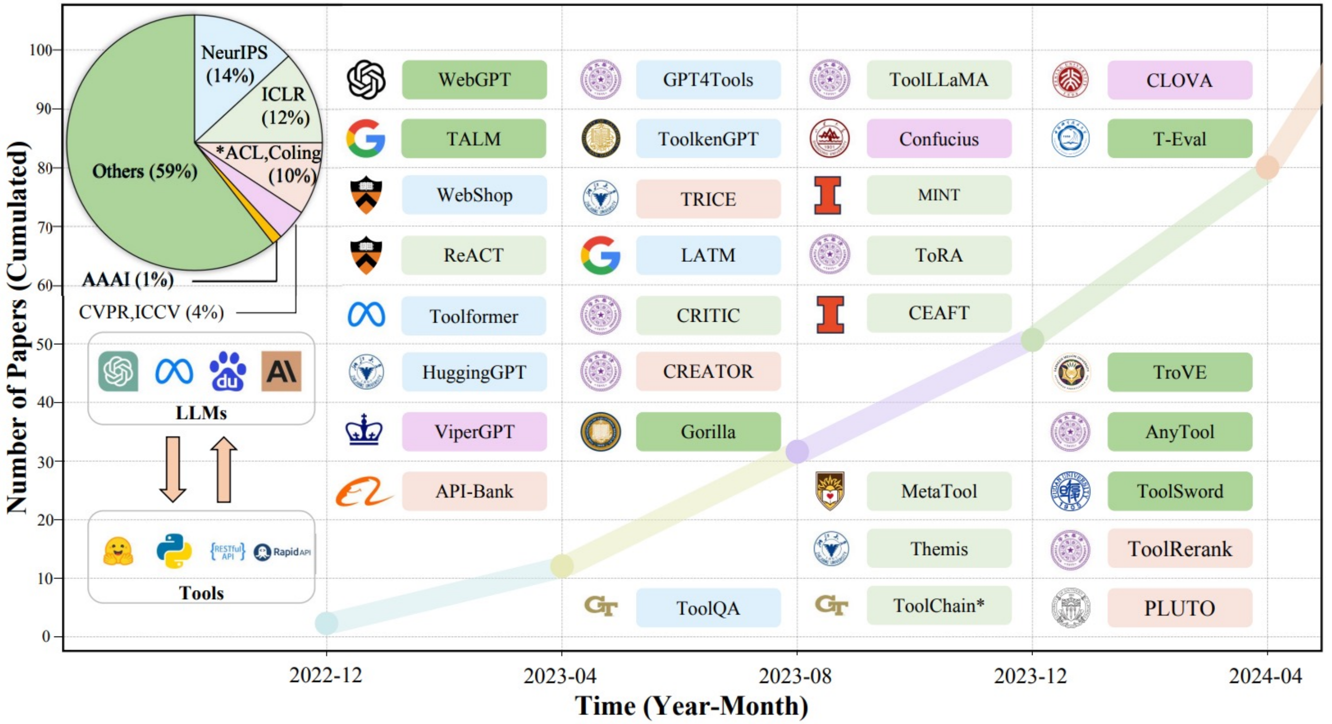


Fig.5 LLM specific domain application through Tool Learning.

Survey: Tool Learning with Large Language Models. Changle Qu, Sunhao Dai, etc. (Arxiv)

SoAy: A Solution-based LLM API-using Methodology for Academic Information Seeking

Yuanchun Wang[†*], Jifan Yu[§*], Zijun Yao[§], Jing Zhang[†], Yuyang Xie[§], Shangqing Tu[§]
Yiyang Fu[†], Youhe Feng[†], Jinkai Zhang[†], Jingyao Zhang[◇], Bowen Huang[◇], Yuanyao Li[◇]
Huihui Yuan[◇], Lei Hou[§], Juanzi Li[§] and Jie Tang[§]
[†]Renmin University of China [§]Tsinghua University [◇]Zhipu AI

[Paper] https://arxiv.org/pdf/2405.15165

[Code] https://github.com/RUCKBReasoning/SoAy

[System] https://soay.aminer.cn/

[Model] https://huggingface.co/frederickwang99/soayllama_v2_7b

[Benchmark & Dataset] https://huggingface.co/datasets/frederickwang99/SoAyBench

Seeking Academic Metadata

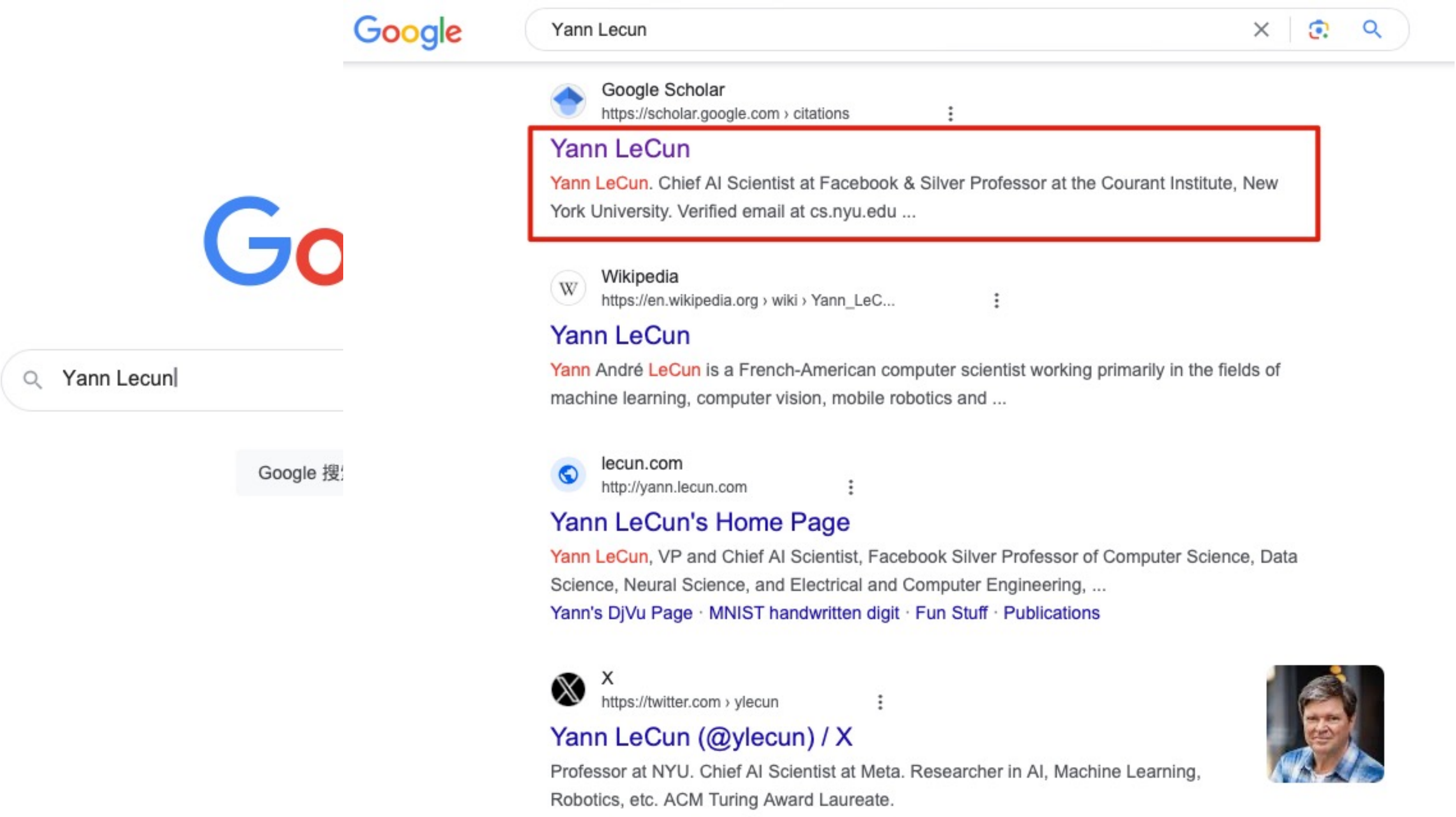
Query: How many times has New York University's Yann LeCun's most cited publication been cited?

Step 1: Typing Keywords in the searching box

Seeking Academic Metadata

Query: How many times has New York University's Yann LeCun's most cited publication been cited?

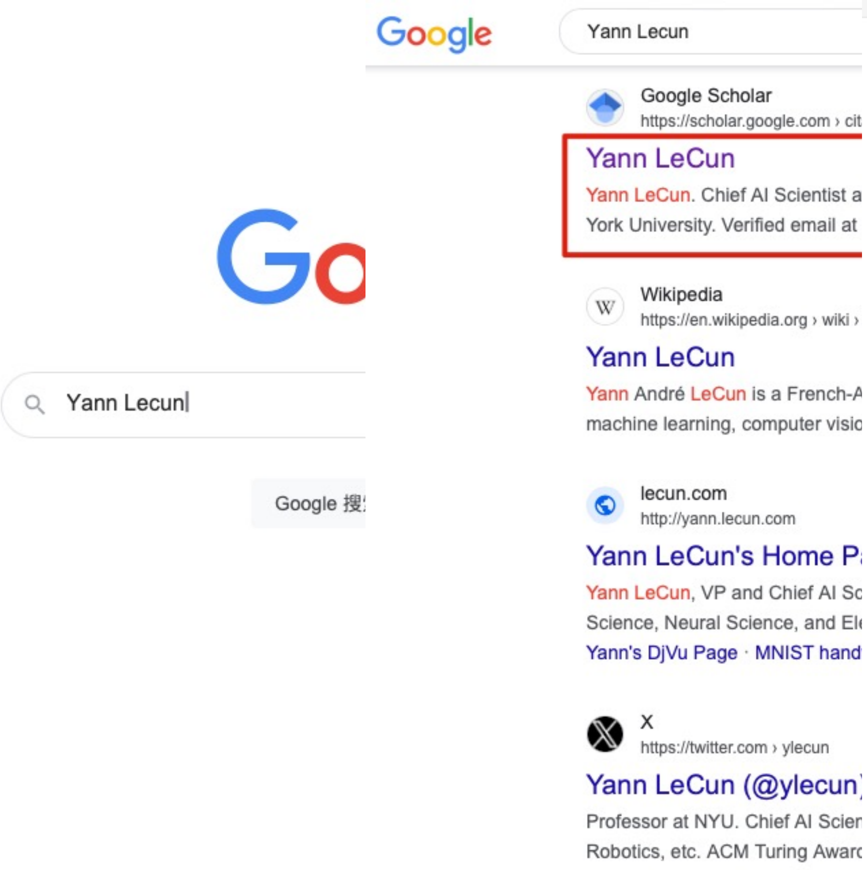
Step 2: Find the probable item in the results list.

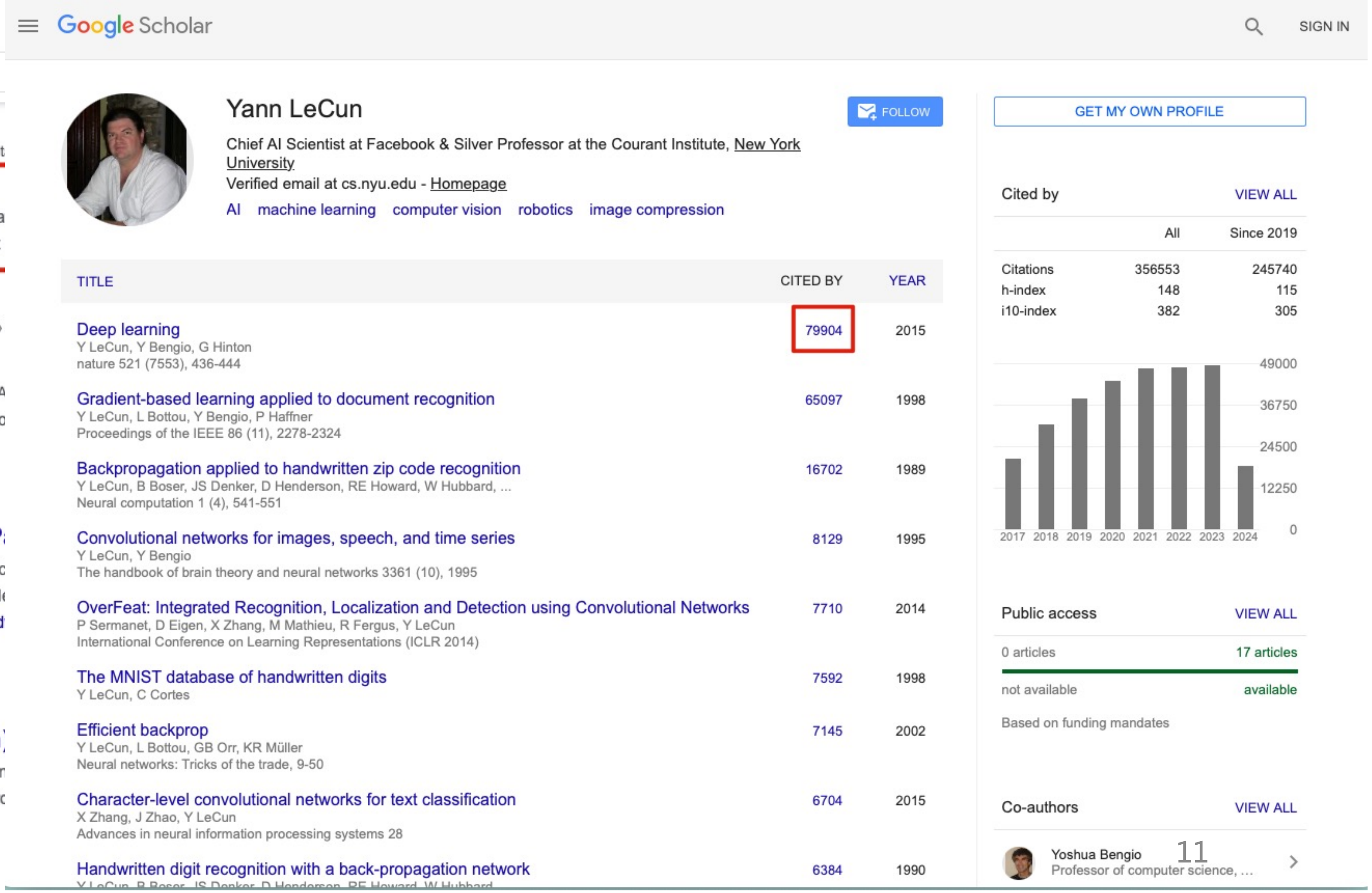


Seeking Academic Metadata

Query: How many times has New York University's Yann LeCun's most cited publication been cited?

Step 3: Seek the target information on the page





Academic Information Systems API Calling

Query: How many times has New York University's Yann LeCun's most cited publication been cited?

ID	API name	Type	Parameter(s)	Return
1	searchPerson	fuzzy	name, organization, interest	[person_id, name, num_citation, interest, num_pubs, organization]
2	searchPublication	fuzzy	publication_info	[pub_id, title, year]
3	getCoauthors	exact	person_id	[id, name, relation]
4	getPersonInterest	exact	person_id	list of interests
5	getPublication	exact	pub_id	abstract, author_list, num_citation
6	getPersonBasicInfo	exact	pub_id	person_id, name, gender, organization, position, bio, education_experience, email
7	getPersonPubs	exact	person_id	[authors_name_list, pub_id, title, num_citation, year]

Yann LeCun, NYU ➤ searchPerson ➤ [{ person_id: ec0f***jsk, person_name: Yann LeCun, ... }]

ec0f***jsk ➤ getPersonPubs ➤ [{ pub_id : al4k***8fa, ...}, { pub_id : 79pa***rjk, ...}, { pub_id : q2f4***n3c, ...}...]

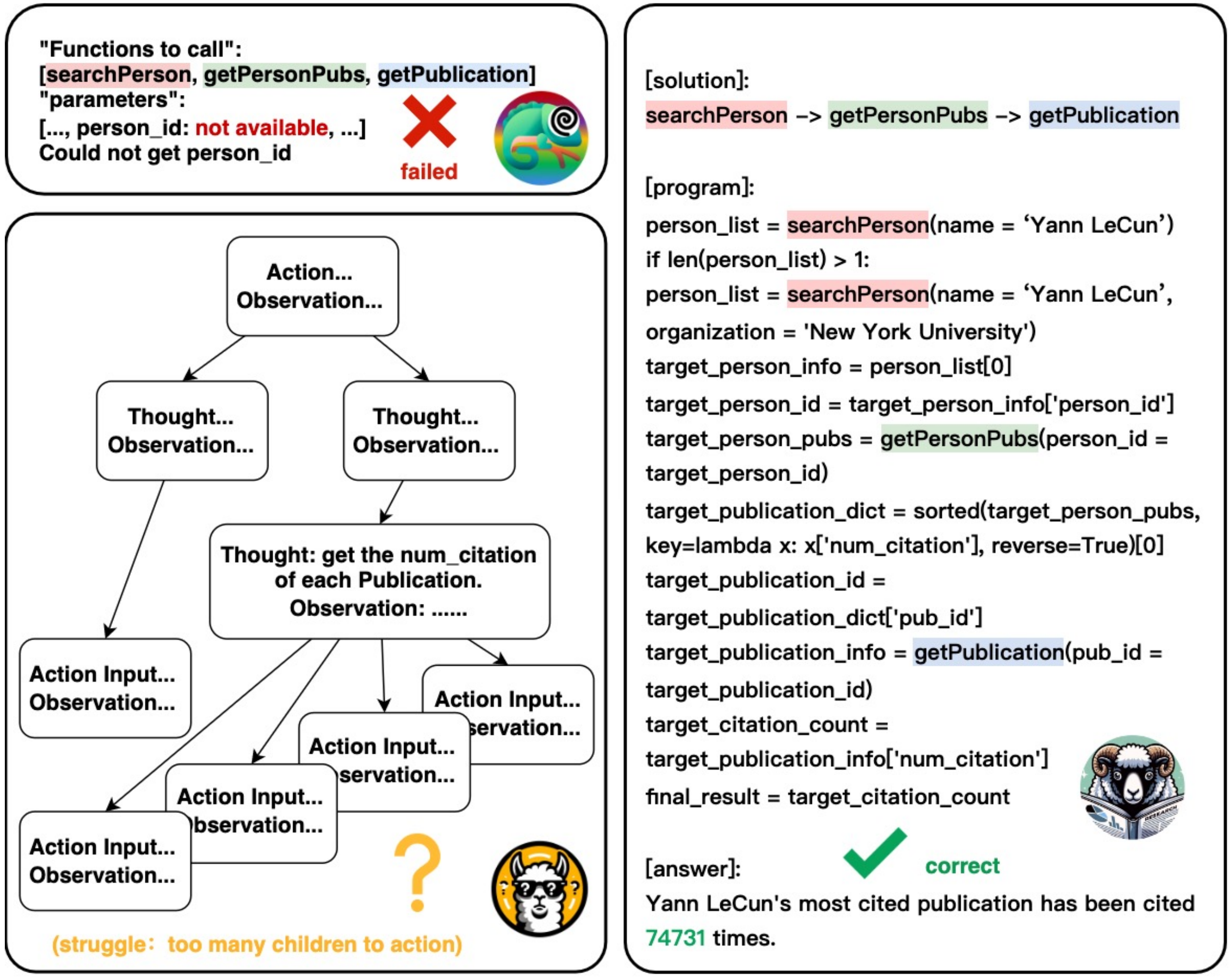
al4k***8fa
79pa***rjk
q2f4***n3c
➤ getPublication ➤ [{ title: Efficient Backprop, citation: 7145}, { title: Deeplearning, citation: 79904}, { title: The Minist Database, citation: 7592}...]

LLM API-Using

Query: How many times has New York University's Yann LeCun's most cited publication been cited?

Retrieval & Execution:
Failed to handle
API Coupling

DFSDT Reasoning:
Could not meet
the Efficiency needs



SoAy:

Pre-defined Solution
&
Solution-based Program Generation

Fig.6 Different API-using sturctures facing the same academic question.

SoAy: SoAPIs Applying Framework

Query: How many times has New York University's Yann LeCun's most cited publication been cited?

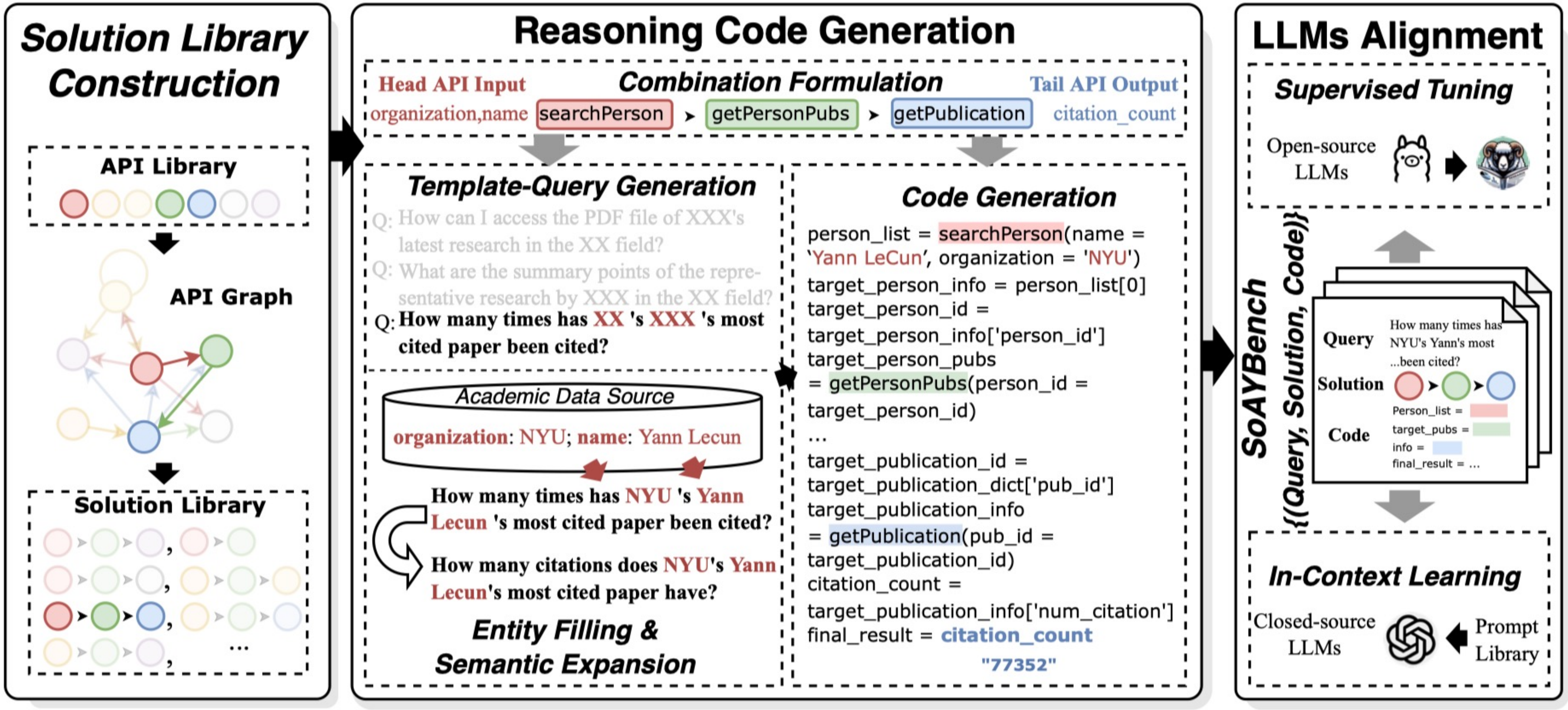


Fig.7 SoAy Framework.

SoAyBench

To assess API utilization capabilities, it is essential to publish the foundational APIs of AMiner for LLMs to invoke and provide a test set composed of academic {Query, Code, Answer} triplets for evaluation.

However, given the dynamic nature of academic data, with scholar and publication information rapidly changing, maintaining a test set with static answers proves challenging.

To address this challenge, **we clone AMiner's SoAPIs at a specific point in time** to create a static service, from which we generate a corresponding static test set.

SoAyBench now are open-sourced at : 🤗 Hugging Face:
https://huggingface.co/datasets/frederickwang99/SoAyBench

Question statistics in SoAyBench.

Question Type	One-hop	Two-hop	Three-hop	**Total**
Scholar	540	1,800	540	2,980
Publication	180	180	720	1,080
Total	720	1,980	1,230	**3,960**

SoAyEval

We outline five types of evaluation metrics.

* EM: Both the retrieved solution and answer **E**xactly **M**atch the ground truth.
* DS: The answer is correct, but a **D**ifferent **S**olution is retrieved compared to the ground truth.
* WS: The answer is wrong due to a **W**rong **S**olution.
* WP: The solution is correct but the answer is wrong, due to a **W**rong **P**rogram generated for the solution, which can be executed but yields the wrong answer.
* EE: **E**xecution **E**rror, which may by caused by the generation of a nonexecutable program or network errors during the APIs request.

$$\mathrm{ACC} = \mathrm{EM} + \mathrm{DS}$$

$$\mathrm{Score} = \frac{w_1 \cdot \mathrm{ACC}_1 + w_2 * \cdot \mathrm{ACC}_2 + w_3 \cdot \mathrm{ACC}_3}{w_1 + w_2 + w_3}$$

Results on SoAyBench - Part I

Results on SoAyBench. DS, WS, WP and EE are differenct types of error, ACC denotes a accurate answer, EM means exact match, not only the answer but also the solution. Score is a weighted sum of the ACC score on different question types.

Method	Version	Question Type	Error Rate↓ DS(%)	WS(%)	WP(%)	EE(%)	EM(%)	ACC(%)	Score
ToolLLaMA	7B	one-hop	12.50±8.00	24.31±13.26	1.39±0.00	54.17±16.01	7.64±5.20	20.14	16.72
		two-hop	10.10±4.10	47.22±12.28	0.76±2.27	38.13±9.62	3.79±2.92	13.89	
		three-hop	11.51±6.53	38.10±14.27	1.19±3.57	43.25±13.07	5.95±4.59	17.46	
GPT-DFSDT	3.5	one-hop	55.56±21.06	15.28±7.80	4.86±0.00	21.53±10.67	2.78±0.00	58.33	43.22
		two-hop	29.55±11.47	34.34±9.23	4.29±3.64	25.76±8.65	6.06±4.11	35.61	
		three-hop	38.10±15.09	28.57±11.35	3.17±2.50	25.00±8.87	5.16±6.19	43.25	
	3.5-16k	one-hop	25.69±10.91	9.72±5.00	2.78±0.00	22.92±9.47	38.89±15.60	64.58	43.67
		two-hop	16.92±7.76	15.91±6.05	3.28±1.31	46.97±7.13	16.92±4.99	33.84	
		three-hop	18.65±7.37	15.48±5.63	2.78±0.00	38.49±10.43	24.60±8.53	43.25	
	4	one-hop	27.78±9.60	2.08±0.00	4.17±5.00	28.47±6.82	37.50±10.91	65.28	58.16
		two-hop	26.26±8.89	9.60±4.88	17.93±5.40	15.15±5.39	31.06±9.12	57.32	
		three-hop	22.22±8.65	7.54±4.46	17.06±6.96	19.05±6.45	34.13±9.87	56.35	
GPT-SoAY	3.5	one-hop	27.78±8.70	15.97±7.73	3.47±0.00	13.19±7.80	39.58±9.12	67.36	67.30
		two-hop	33.84±4.94	9.60±4.75	6.06±2.81	13.13±7.12	37.37±5.06	71.21	
		three-hop	22.22±6.43	12.70±5.91	9.52±4.42	13.10±6.72	42.46±6.00	64.68	
	3.5-16k	one-hop	28.47±11.67	15.28±6.12	1.39±0.00	17.36±7.78	37.50±9.07	65.97	66.76
		two-hop	35.86±6.01	7.32±3.41	5.30±2.18	15.91±7.16	35.61±4.65	71.46	
		three-hop	23.02±7.16	10.32±4.99	8.33±3.42	17.46±7.37	40.87±6.26	63.89	
	4	one-hop	0.00±0.00	0.00±0.00	1.39±0.00	2.78±0.00	95.83±5.70	95.83	86.57
		two-hop	15.91±4.71	1.26±0.00	9.34±1.07	2.02±1.69	71.46±3.74	87.37	
		three-hop	6.75±0.00	0.40±0.00	14.68±1.68	1.98±0.00	76.19±3.25	82.94	

Results on SoAyBench - Part II

Results on SoAyBench. DS, WS, WP and EE are differenct types of error, ACC denotes a accurate answer, EM means exact match, not only the answer but also the solution. Score is a weighted sum of the ACC score on different question types.

GPT-SoAY	3.5	one-hop	27.78±8.70	15.97±7.73	3.47±0.00	13.19±7.80	39.58±9.12	67.36	67.30
		two-hop	33.84±4.94	9.60±4.75	6.06±2.81	13.13±7.12	37.37±5.06	71.21	
		three-hop	22.22±6.43	12.70±5.91	9.52±4.42	13.10±6.72	42.46±6.00	64.68	
	3.5-16k	one-hop	28.47±11.67	15.28±6.12	1.39±0.00	17.36±7.78	37.50±9.07	65.97	66.76
		two-hop	35.86±6.01	7.32±3.41	5.30±2.18	15.91±7.16	35.61±4.65	71.46	
		three-hop	23.02±7.16	10.32±4.99	8.33±3.42	17.46±7.37	40.87±6.26	63.89	
	4	one-hop	0.00±0.00	0.00±0.00	1.39±0.00	2.78±0.00	95.83±5.70	95.83	86.57
		two-hop	15.91±4.71	1.26±0.00	9.34±1.07	2.02±1.69	71.46±3.74	87.37	
		three-hop	6.75±0.00	0.40±0.00	14.68±1.68	1.98±0.00	76.19±3.25	82.94	
SoAYLLaMA	Chat-7B	one-hop	0.00±0.00	0.00±0.00	0.00±0.00	0.69±0.00	99.31±2.94	99.31	85.76
		two-hop	0.00±0.00	0.00±0.00	20.20±3.84	2.53±1.97	77.27±2.70	77.27	
		three-hop	0.00±0.00	0.00±0.00	9.92±3.56	3.17±2.50	86.90±2.72	86.90	
	Code-7B	one-hop	0.69±0.00	0.00±0.00	0.69±0.00	5.56±4.37	93.06±7.50	93.75	88.95
		two-hop	0.25±0.00	3.28±0.00	7.07±2.75	4.80±3.69	84.60±5.18	84.85	
		three-hop	0.40±0.00	0.00±0.00	4.76±2.14	5.16±4.57	89.68±6.54	90.08	
	Code-13B	one-hop	0.00±0.00	0.00±0.00	1.39±0.00	0.00±0.00	98.61±4.03	98.61	**92.74**
		two-hop	0.00±0.00	2.27±0.00	14.14±2.14	0.51±0.00	83.08±3.32	83.08	
		three-hop	0.00±0.00	0.00±0.00	2.38±2.86	0.40±0.00	97.22±4.28	97.22	

Efficiency & Online Evaluation

To evaluate how efficient are SoAy, we compare the average response time of different methods (second).

Method	7B	13B	3.5	3.5-16k	4
ToolLLaMA	45.10	/	/	/	/
GPT-DFSDT	/	/	39.12	53.73	70.92
SoAyGPT	/	/	6.15	6.40	26.05
SoAyLLaMA-Code	1.12	1.35	/	/	/

To test weather SoAy could meet the need of real-world user requirement, we implement SoAy as an online application, gather 56 real user demands from the logs, and invite 10 annotators to conduct human evaluation.

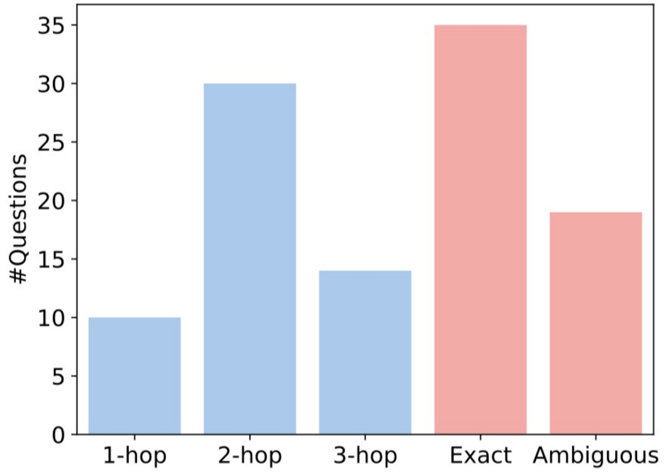


Fig.8 Online Gathered Question statistics.

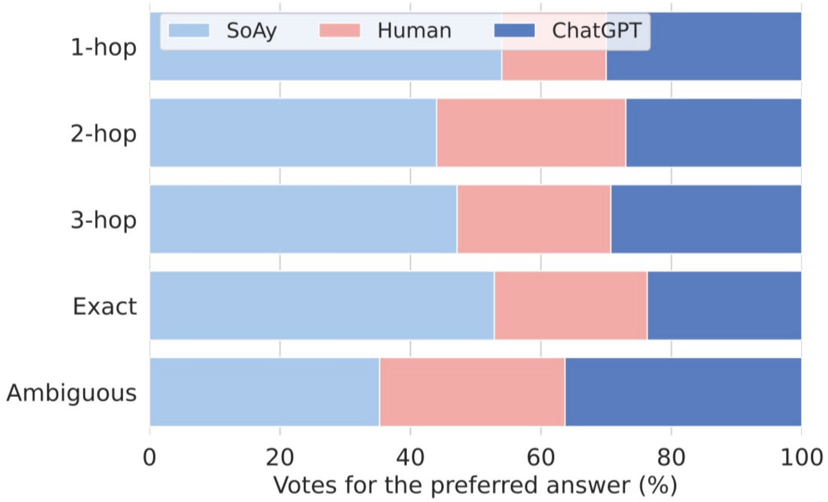


Fig.9 Results of Online Human Evaluation

Results on SoAyBench - Weak to Strong Supervision

A Small Model trained on Data generated by GPT-4 can outperform GPT-4, and also more efficient.

SoAyGPT	3.5	one-hop	27.78±8.70	15.97±7.73	3.47±0.00	13.19±7.80	39.58±9.12	67.36	67.30
		two-hop	33.84±4.94	9.60±4.75	6.06±2.81	13.13±7.12	37.37±5.06	71.21	
		three-hop	22.22±6.43	12.70±5.91	9.52±4.42	13.10±6.72	42.46±6.00	64.68	
	3.5-16k	one-hop	28.47±11.67	15.28±6.12	1.39±0.00	17.36±7.78	37.50±9.07	65.97	66.76
		two-hop	35.86±6.01	7.32±3.41	5.30±2.18	15.91±7.16	35.61±4.65	71.46	
		three-hop	23.02±7.16	10.32±4.99	8.33±3.42	17.46±7.37	40.87±6.26	63.89	
	4	one-hop	0.00±0.00	0.00±0.00	1.39±0.00	2.78±0.00	95.83±5.70	95.83	86.57
		two-hop	15.91±4.71	1.26±0.00	9.34±1.07	2.02±1.69	71.46±3.74	87.37	
		three-hop	6.75±0.00	0.40±0.00	14.68±1.68	1.98±0.00	76.19±3.25	82.94	
SoAyLLaMA	Chat-7B	one-hop	0.00±0.00	0.00±0.00	0.00±0.00	0.69±0.00	99.31±2.94	99.31	85.76
		two-hop	0.00±0.00	0.00±0.00	20.20±3.84	2.53±1.97	77.27±2.70	77.27	
		three-hop	0.00±0.00	0.00±0.00	9.92±3.56	3.17±2.50	86.90±2.72	86.90	
	Code-7B	one-hop	0.69±0.00	0.00±0.00	0.69±0.00	5.56±4.37	93.06±7.50	93.75	88.95
		two-hop	0.25±0.00	3.28±0.00	7.07±2.75	4.80±3.69	84.60±5.18	84.85	
		three-hop	0.40±0.00	0.00±0.00	4.76±2.14	5.16±4.57	89.68±6.54	90.08	
	Code-13B	one-hop	0.00±0.00	0.00±0.00	1.39±0.00	0.00±0.00	98.61±4.03	98.61	**92.74**
		two-hop	0.00±0.00	2.27±0.00	14.14±2.14	0.51±0.00	83.08±3.32	83.08	
		three-hop	0.00±0.00	0.00±0.00	2.38±2.86	0.40±0.00	97.22±4.28	97.22	

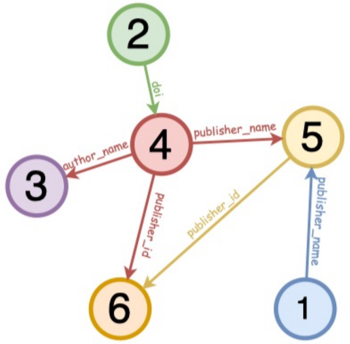
Method	7B	13B	3.5	3.5-16k	4
ToolLLaMA	45.10	/	/	/	/
GPT-DFSDT	/	/	39.12	53.73	70.92
SoAyGPT	/	/	6.15	6.40	26.05
SoAyLLaMA-Code	1.12	1.35	/	/	/

Deployment on other Academic Platforms

AMiner APIs are NOT the only that face the coupling challenges.
We also deployment SoAy on two other open-sourced scenarios: OpenLibrary and CrossRef

ID	API name	Type	Parameter(s)	Return
1	searchPublisherBySubject	fuzzy	subject	[publisher_name, doi_count]
2	searchWorksByTitle	fuzzy	work_title	[type, author, doi, publisher]
3	searchWorksByAuthor	fuzzy	author_name	[works_title, works_doi]
4	getWorksByDoi	exact	doi	[author_name, work_title, publisher_name, type, reference_count]
5	getPublisherBasicInfo	exact	publisher_name	[publisher_id, current_dois, backfile_dois, total_dois, doi_prefix]
6	getPublisherWorks	exact	publisher_id	[works_title, doi, works_author]

(a) CrossrefAPI Library



(b) CrossrefAPI Graph

Solution	Parameter(s)	Return	Question Template
searchPublisherBySubject	subject	publisher_name	Please list some publishers in the XXX field.
searchPublisherBySubject → getPublisherBasicInfo	subject	publisher_id	Please give me some publishers' id of crossref about the field of XXX.
seachPublisherBySubject → getPublisherBasicInfo → getPublisherWorks	subject	doi	Can you list some articles' DOI numbers in the field of XXX?
searchWorksByTitle	work_title	type	I want to know the type of work XXX.

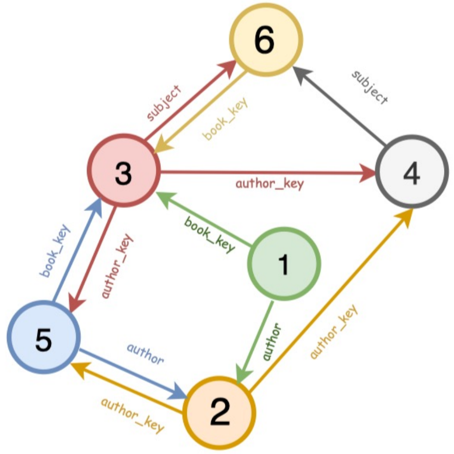
(c) Solution Library (partly shown)

ID	API name	Type	Parameter(s)	Return
1	searchBook	fuzzy	book_info	[book_key, title, author_name, year]
2	searchAuthor	fuzzy	author_info	[author_key, name, list of alternate_names]
3	getBook	exact	book_key	description, list of author, title, first_publish, list of subjects
4	getAuthorBasicInfo	exact	author_key	name, list of alternate_names, birth_date, work_count, top_work, top_subjects
5	getAuthorWorks	exact	author_key, amount	[book_key, title, subjects]
6	searchSubject	fuzzy	subject	[book_key, title]

(a) SoAPI Library

Solution	Parameter(s)	Return	Question Template
searchSubject	subject	list of books	Please list some books on XXX topic.
searchAuthor→getAuthorWorks	author_info	list of books	Which works were written by XXX?
searchBook→getBook	book_info	book_description	Introduce some information about XXX.
searchBook→getBook→getAuthorWorks	book_info	list of books	What other books has the author of XXX written?

(c) Solution Library (partly shown)



(b) SoAPI Graph

Challenges of the SoAyBench & SoAyEval

There's still some challenges on the evaluation part of specific-domain tool using.

- The benchmark or evaluation set is limited on the Academic domain.
- The complexity of testing on the combination of the **LLMs**, Tool-using **Workflows** and the **domains**.

Method	7B	13B	3.5	3.5-16k	4
ToolLLaMA	45.10	/	/	/	/
GPT-DFSDT	/	/	39.12	53.73	70.92
SoAyGPT	/	/	6.15	6.40	26.05
SoAyLLaMA-Code	1.12	1.35	/	/	/

R-Eval: A Unified Toolkit for Evaluating Domain Knowledge of Retrieval Augmented Large Language Models

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[Paper] Accepted by KDD'24 (ADS track), under camera ready preparation.

[Code & Toolkit] https://github.com/THU-KEG/R-Eval

Background - Component Selection

Given a Specific Domain, which LLM and which RAG Workflow to choose?

Shortcomings of exsisting evaluations:

- Insufficient exploration of combinations between LLMs and RAG workflows.
- Lack comprehensive mining of the domain knowledge.

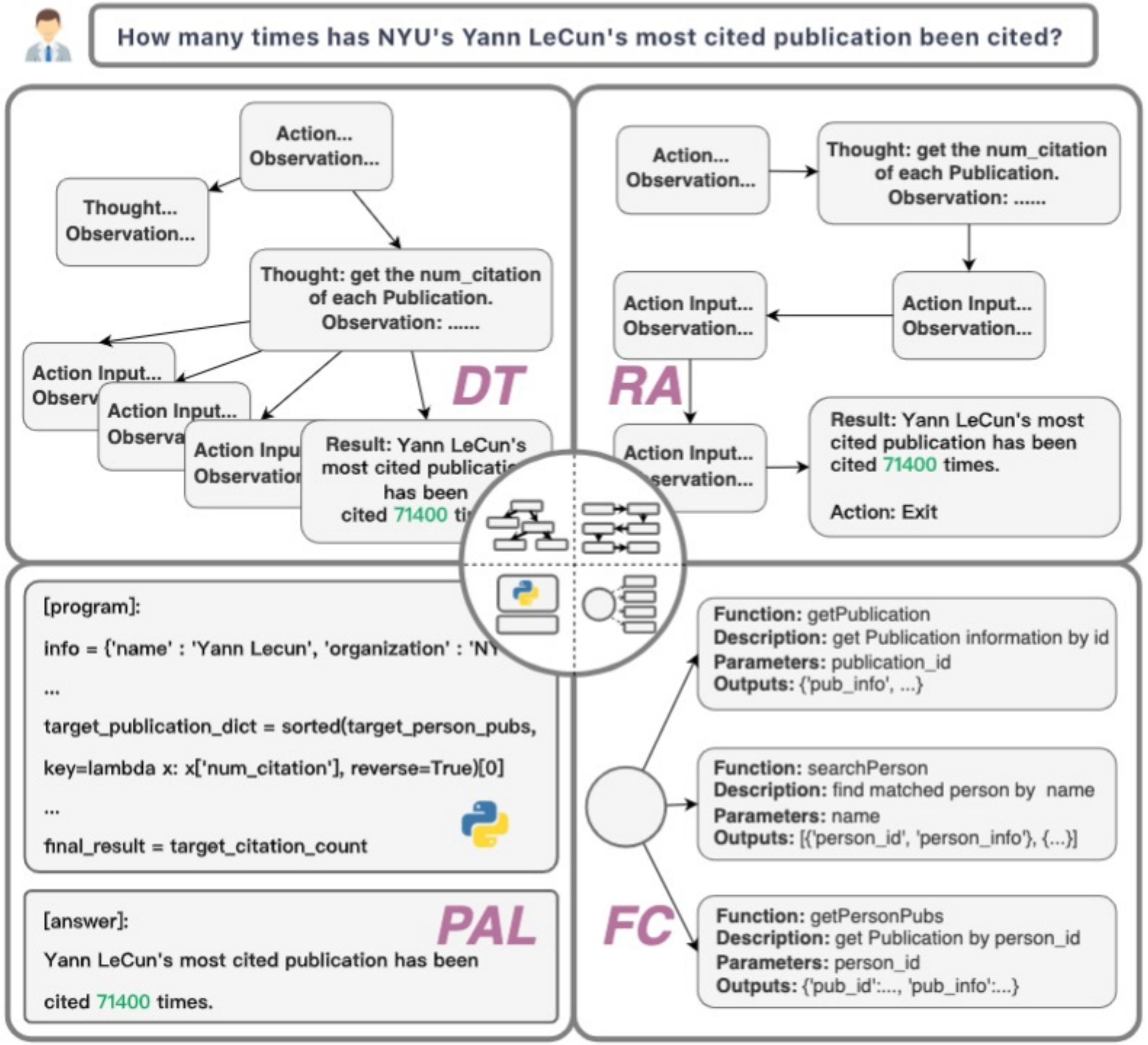
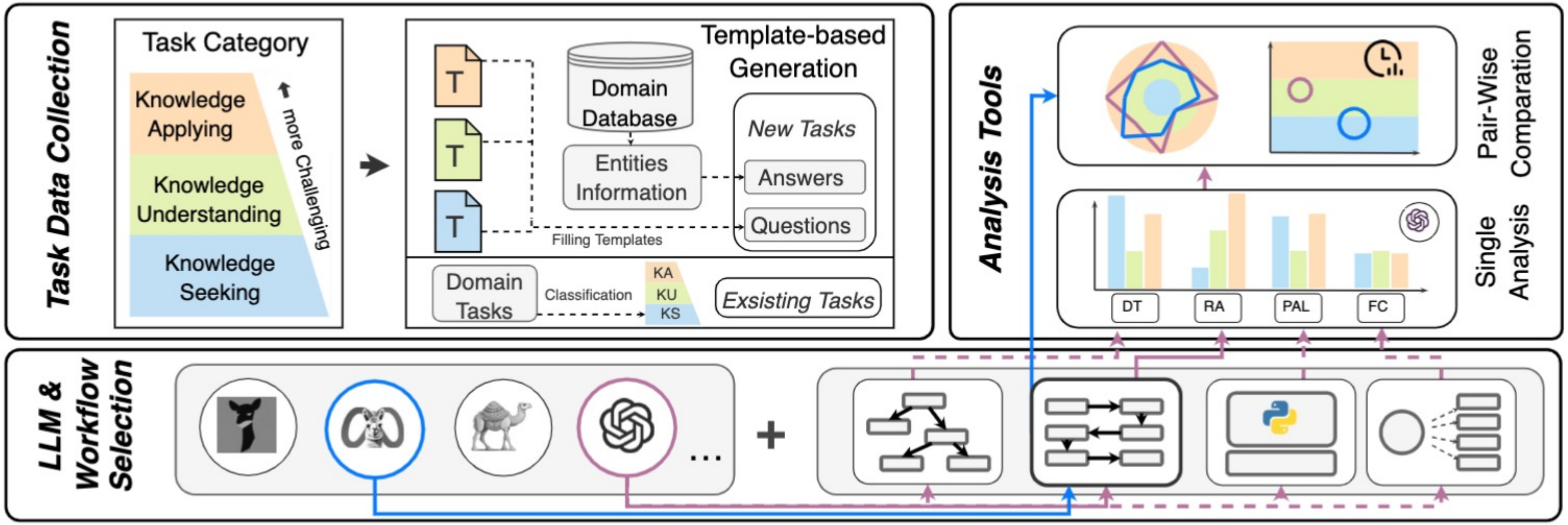


Fig.10 Four Popular RAG Workflows.

Evaluation Framework

Inspired by KoLA and SoAy, We propose R-Eval, a Python toolkit designed to streamline the evaluation of different RAG workflows in conjunction with LLMs on a specific domain's task.

- A easy-to-use evaluation of the combination between RAG Workflows and LLMs
- Customized testing data in specific domains through template-based question generation



KoLA: https://iclr.cc/virtual/2024/poster/19238
SoAy: https://arxiv.org/pdf/2405.15165

Fig.11 Framework of R-Eval.

Evaluation Result - Performance Ranking

Workflow	LLM	aminer KS		aminer KU		aminer KA		Overall Average (Level 1, 2, 3)					
		1-3	Rank	2-4	Rank	3-5	Rank	wiki	Rank	aminer	Rank	all	Rank
ReAct	gpt-4-1106	89.7	1st	46.7	3rd	57.7	1st	38.8	1st	64.7	1st	45.3	1st
PAL	gpt-3.5-turbo	80.1	3rd	50.7	2nd	54.9	2nd	19.9	6th	61.9	2nd	30.4	2nd
PAL	gpt-4-1106	59.3	4th	56.8	1st	52.7	3rd	20.3	5th	56.2	3rd	29.2	3rd
ReAct	llama2-7b-chat	45.2	5th	36.5	6th	21.5	6th	23.8	3rd	34.4	5th	26.4	4th
PAL	llama2-13b	25.3	6th	36.4	7th	20.3	7th	25.2	2nd	27.3	6th	25.7	5th
ReAct	gpt-3.5-turbo	84.6	2nd	4.0	14th	33.0	4th	19.6	7th	40.6	4th	24.9	6th
ReAct	vicuna-13b	19.9	10th	6.0	13th	7.1	16th	20.7	4th	11.0	17th	18.2	7th
PAL	tulu-7b	9.1	15th	26.8	9th	11.5	12th	18.9	8th	15.8	9th	18.1	8th
PAL	vicuna-13b	4.5	17th	40.9	4th	2.3	20th	16.7	9th	15.9	8th	16.5	9th
ReAct	llama2-13b	16.7	13th	0.7	19th	23.2	5th	15.0	10th	13.5	12th	14.6	10th
PAL	llama2-7b-chat	18.7	12th	2.8	15th	16.1	8th	12.4	11th	12.5	14th	12.4	11th
PAL	codellama-13b	4.4	18th	38.3	5th	8.1	14th	10.0	14th	16.9	7th	11.7	12th
PAL	toolllama2-7b	1.6	20th	24.4	10th	4.6	18th	12.2	12th	10.2	18th	11.7	13th
ReAct	tulu-7b	4.0	19th	27.8	8th	7.9	15th	10.3	13th	13.2	13th	11.0	14th
DFSDT	gpt-4-1106	20.6	9th	9.6	12th	11.8	11th	9.9	15th	14.0	11th	10.9	15th
FC	gpt-4-1106	24.7	7th	10.9	11th	10.2	13th	8.2	18th	15.3	10th	9.9	16th
FC	gpt-3.5-turbo	19.0	11th	1.0	17th	15.9	9th	8.8	16th	12.0	15th	9.6	17th
ReAct	toolllama2-7b	15.0	14th	2.2	16th	5.7	17th	8.3	17th	7.6	19th	8.1	18th
DFSDT	gpt-3.5-turbo	20.7	8th	0.2	20th	13.8	10th	4.8	20th	11.6	16th	6.5	19th
ReAct	codellama-13b	0.2	21th	0.8	18th	0.7	21th	7.0	19th	0.6	21th	5.4	20th
DFSDT	toolllama2-7b	7.1	16th	0.0	21th	2.3	19th	3.5	21th	3.1	20th	3.4	21th

Fig.12 Evaluation Results of R-Eval on AMiner, wiki and overall ranking.

Evaluation Result - Performance Ranking

The same Workflow + LLM,

Same Domain Task

Differenct Level

Workflow	LLM	aminer KS		aminer KU		aminer KA		Overall Average (Level 1, 2, 3)					
		1-3	Rank	2-4	Rank	3-5	Rank	wiki	Rank	aminer	Rank	all	Rank
ReAct	gpt-4-1106	89.7	1st	46.7	3rd	57.7	1st	38.8	1st	64.7	1st	45.3	1st
PAL	gpt-3.5-turbo	80.1	3rd	50.7	2nd	54.9	2nd	19.9	6th	61.9	2nd	30.4	2nd
PAL	gpt-4-1106	59.3	4th	56.8	1st	52.7	3rd	20.3	5th	56.2	3rd	29.2	3rd
ReAct	llama2-7b-chat	45.2	5th	36.5	6th	21.5	6th	23.8	3rd	34.4	5th	26.4	4th
PAL	llama2-13b	25.3	6th	36.4	7th	20.3	7th	25.2	2nd	27.3	6th	25.7	5th
ReAct	gpt-3.5-turbo	84.6	2nd	4.0	14th	33.0	4th	19.6	7th	40.6	4th	24.9	6th
ReAct	vicuna-13b	19.9	10th	6.0	13th	7.1	16th	20.7	4th	11.0	17th	18.2	7th
PAL	tulu-7b	9.1	15th	26.8	9th	11.5	12th	18.9	8th	15.8	9th	18.1	8th
PAL	vicuna-13b	4.5	17th	40.9	4th	2.3	20th	16.7	9th	15.9	8th	16.5	9th
ReAct	llama2-13b	16.7	13th	0.7	19th	23.2	5th	15.0	10th	13.5	12th	14.6	10th
PAL	llama2-7b-chat	18.7	12th	2.8	15th	16.1	8th	12.4	11th	12.5	14th	12.4	11th
PAL	codellama-13b	4.4	18th	38.3	5th	8.1	14th	10.0	14th	16.9	7th	11.7	12th
PAL	toolllama2-7b	1.6	20th	24.4	10th	4.6	18th	12.2	12th	10.2	18th	11.7	13th
ReAct	tulu-7b	4.0	19th	27.8	8th	7.9	15th	10.3	13th	13.2	13th	11.0	14th
DFSDT	gpt-4-1106	20.6	9th	9.6	12th	11.8	11th	9.9	15th	14.0	11th	10.9	15th
FC	gpt-4-1106	24.7	7th	10.9	11th	10.2	13th	8.2	18th	15.3	10th	9.9	16th
FC	gpt-3.5-turbo	19.0	11th	1.0	17th	15.9	9th	8.8	16th	12.0	15th	9.6	17th
ReAct	toolllama2-7b	15.0	14th	2.2	16th	5.7	17th	8.3	17th	7.6	19th	8.1	18th
DFSDT	gpt-3.5-turbo	20.7	8th	0.2	20th	13.8	10th	4.8	20th	11.6	16th	6.5	19th
ReAct	codellama-13b	0.2	21th	0.8	18th	0.7	21th	7.0	19th	0.6	21th	5.4	20th
DFSDT	toolllama2-7b	7.1	16th	0.0	21th	2.3	19th	3.5	21th	3.1	20th	3.4	21th

Fig.12 Evaluation Results of R-Eval on AMiner, wiki and overall ranking.

Evaluation Result - Performance Ranking

The same Workflow + LLM,

Different Domain

Workflow	LLM	aminer KS		aminer KU		aminer KA		Overall Average (Level 1, 2, 3)					
		1-3	Rank	2-4	Rank	3-5	Rank	wiki	Rank	aminer	Rank	all	Rank
ReAct	gpt-4-1106	89.7	1st	46.7	3rd	57.7	1st	38.8	1st	64.7	1st	45.3	1st
PAL	gpt-3.5-turbo	80.1	3rd	50.7	2nd	54.9	2nd	19.9	6th	61.9	2nd	30.4	2nd
PAL	gpt-4-1106	59.3	4th	56.8	1st	52.7	3rd	20.3	5th	56.2	3rd	29.2	3rd
ReAct	llama2-7b-chat	45.2	5th	36.5	6th	21.5	6th	23.8	3rd	34.4	5th	26.4	4th
PAL	llama2-13b	25.3	6th	36.4	7th	20.3	7th	25.2	2nd	27.3	6th	25.7	5th
ReAct	gpt-3.5-turbo	84.6	2nd	4.0	14th	33.0	4th	19.6	7th	40.6	4th	24.9	6th
ReAct	vicuna-13b	19.9	10th	6.0	13th	7.1	16th	20.7	4th	11.0	17th	18.2	7th
PAL	tulu-7b	9.1	15th	26.8	9th	11.5	12th	18.9	8th	15.8	9th	18.1	8th
PAL	vicuna-13b	4.5	17th	40.9	4th	2.3	20th	16.7	9th	15.9	8th	16.5	9th
ReAct	llama2-13b	16.7	13th	0.7	19th	23.2	5th	15.0	10th	13.5	12th	14.6	10th
PAL	llama2-7b-chat	18.7	12th	2.8	15th	16.1	8th	12.4	11th	12.5	14th	12.4	11th
PAL	codellama-13b	4.4	18th	38.3	5th	8.1	14th	10.0	14th	16.9	7th	11.7	12th
PAL	toolllama2-7b	1.6	20th	24.4	10th	4.6	18th	12.2	12th	10.2	18th	11.7	13th
ReAct	tulu-7b	4.0	19th	27.8	8th	7.9	15th	10.3	13th	13.2	13th	11.0	14th
DFSDT	gpt-4-1106	20.6	9th	9.6	12th	11.8	11th	9.9	15th	14.0	11th	10.9	15th
FC	gpt-4-1106	24.7	7th	10.9	11th	10.2	13th	8.2	18th	15.3	10th	9.9	16th
FC	gpt-3.5-turbo	19.0	11th	1.0	17th	15.9	9th	8.8	16th	12.0	15th	9.6	17th
ReAct	toolllama2-7b	15.0	14th	2.2	16th	5.7	17th	8.3	17th	7.6	19th	8.1	18th
DFSDT	gpt-3.5-turbo	20.7	8th	0.2	20th	13.8	10th	4.8	20th	11.6	16th	6.5	19th
ReAct	codellama-13b	0.2	21th	0.8	18th	0.7	21th	7.0	19th	0.6	21th	5.4	20th
DFSDT	toolllama2-7b	7.1	16th	0.0	21th	2.3	19th	3.5	21th	3.1	20th	3.4	21th

Fig.12 Evaluation Results of R-Eval on AMiner, wiki and overall ranking.

Evaluation Result - Performance Ranking

The same LLM & Domain

Different Workflow

Workflow	LLM	aminer KS		aminer KU		aminer KA		Overall Average (Level 1, 2, 3)					
		1-3	Rank	2-4	Rank	3-5	Rank	wiki	Rank	aminer	Rank	all	Rank
ReAct	gpt-4-1106	89.7	1st	46.7	3rd	57.7	1st	38.8	1st	64.7	1st	45.3	1st
PAL	gpt-3.5-turbo	80.1	3rd	50.7	2nd	54.9	2nd	19.9	6th	61.9	2nd	30.4	2nd
PAL	gpt-4-1106	59.3	4th	56.8	1st	52.7	3rd	20.3	5th	56.2	3rd	29.2	3rd
ReAct	llama2-7b-chat	45.2	5th	36.5	6th	21.5	6th	23.8	3rd	34.4	5th	26.4	4th
PAL	llama2-13b	25.3	6th	36.4	7th	20.3	7th	25.2	2nd	27.3	6th	25.7	5th
ReAct	gpt-3.5-turbo	84.6	2nd	4.0	14th	33.0	4th	19.6	7th	40.6	4th	24.9	6th
ReAct	vicuna-13b	19.9	10th	6.0	13th	7.1	16th	20.7	4th	11.0	17th	18.2	7th
PAL	tulu-7b	9.1	15th	26.8	9th	11.5	12th	18.9	8th	15.8	9th	18.1	8th
PAL	vicuna-13b	4.5	17th	40.9	4th	2.3	20th	16.7	9th	15.9	8th	16.5	9th
ReAct	llama2-13b	16.7	13th	0.7	19th	23.2	5th	15.0	10th	13.5	12th	14.6	10th
PAL	llama2-7b-chat	18.7	12th	2.8	15th	16.1	8th	12.4	11th	12.5	14th	12.4	11th
PAL	codellama-13b	4.4	18th	38.3	5th	8.1	14th	10.0	14th	16.9	7th	11.7	12th
PAL	toolllama2-7b	1.6	20th	24.4	10th	4.6	18th	12.2	12th	10.2	18th	11.7	13th
ReAct	tulu-7b	4.0	19th	27.8	8th	7.9	15th	10.3	13th	13.2	13th	11.0	14th
DFSDT	gpt-4-1106	20.6	9th	9.6	12th	11.8	11th	9.9	15th	14.0	11th	10.9	15th
FC	gpt-4-1106	24.7	7th	10.9	11th	10.2	13th	8.2	18th	15.3	10th	9.9	16th
FC	gpt-3.5-turbo	19.0	11th	1.0	17th	15.9	9th	8.8	16th	12.0	15th	9.6	17th
ReAct	toolllama2-7b	15.0	14th	2.2	16th	5.7	17th	8.3	17th	7.6	19th	8.1	18th
DFSDT	gpt-3.5-turbo	20.7	8th	0.2	20th	13.8	10th	4.8	20th	11.6	16th	6.5	19th
ReAct	codellama-13b	0.2	21th	0.8	18th	0.7	21th	7.0	19th	0.6	21th	5.4	20th
DFSDT	toolllama2-7b	7.1	16th	0.0	21th	2.3	19th	3.5	21th	3.1	20th	3.4	21th

Fig.12 Evaluation Results of R-Eval on AMiner, wiki and overall ranking.

Evaluation Result - Performance Ranking

The same Workflow & Domain

Different LLM

Workflow	LLM	aminer KS		aminer KU		aminer KA		Overall Average (Level 1, 2, 3)					
		1-3	Rank	2-4	Rank	3-5	Rank	wiki	Rank	aminer	Rank	all	Rank
ReAct	gpt-4-1106	89.7	1st	46.7	3rd	57.7	1st	38.8	1st	64.7	1st	45.3	1st
PAL	gpt-3.5-turbo	80.1	3rd	50.7	2nd	54.9	2nd	19.9	6th	61.9	2nd	30.4	2nd
PAL	gpt-4-1106	59.3	4th	56.8	1st	52.7	3rd	20.3	5th	56.2	3rd	29.2	3rd
ReAct	llama2-7b-chat	45.2	5th	36.5	6th	21.5	6th	23.8	3rd	34.4	5th	26.4	4th
PAL	llama2-13b	25.3	6th	36.4	7th	20.3	7th	25.2	2nd	27.3	6th	25.7	5th
ReAct	gpt-3.5-turbo	84.6	2nd	4.0	14th	33.0	4th	19.6	7th	40.6	4th	24.9	6th
ReAct	vicuna-13b	19.9	10th	6.0	13th	7.1	16th	20.7	4th	11.0	17th	18.2	7th
PAL	tulu-7b	9.1	15th	26.8	9th	11.5	12th	18.9	8th	15.8	9th	18.1	8th
PAL	vicuna-13b	4.5	17th	40.9	4th	2.3	20th	16.7	9th	15.9	8th	16.5	9th
ReAct	llama2-13b	16.7	13th	0.7	19th	23.2	5th	15.0	10th	13.5	12th	14.6	10th
PAL	llama2-7b-chat	18.7	12th	2.8	15th	16.1	8th	12.4	11th	12.5	14th	12.4	11th
PAL	codellama-13b	4.4	18th	38.3	5th	8.1	14th	10.0	14th	16.9	7th	11.7	12th
PAL	toolllama2-7b	1.6	20th	24.4	10th	4.6	18th	12.2	12th	10.2	18th	11.7	13th
ReAct	tulu-7b	4.0	19th	27.8	8th	7.9	15th	10.3	13th	13.2	13th	11.0	14th
DFSDT	gpt-4-1106	20.6	9th	9.6	12th	11.8	11th	9.9	15th	14.0	11th	10.9	15th
FC	gpt-4-1106	24.7	7th	10.9	11th	10.2	13th	8.2	18th	15.3	10th	9.9	16th
FC	gpt-3.5-turbo	19.0	11th	1.0	17th	15.9	9th	8.8	16th	12.0	15th	9.6	17th
ReAct	toolllama2-7b	15.0	14th	2.2	16th	5.7	17th	8.3	17th	7.6	19th	8.1	18th
DFSDT	gpt-3.5-turbo	20.7	8th	0.2	20th	13.8	10th	4.8	20th	11.6	16th	6.5	19th
ReAct	codellama-13b	0.2	21th	0.8	18th	0.7	21th	7.0	19th	0.6	21th	5.4	20th
DFSDT	toolllama2-7b	7.1	16th	0.0	21th	2.3	19th	3.5	21th	3.1	20th	3.4	21th

Fig.12 Evaluation Results of R-Eval on AMiner, wiki and overall ranking.

Visilization of the performance

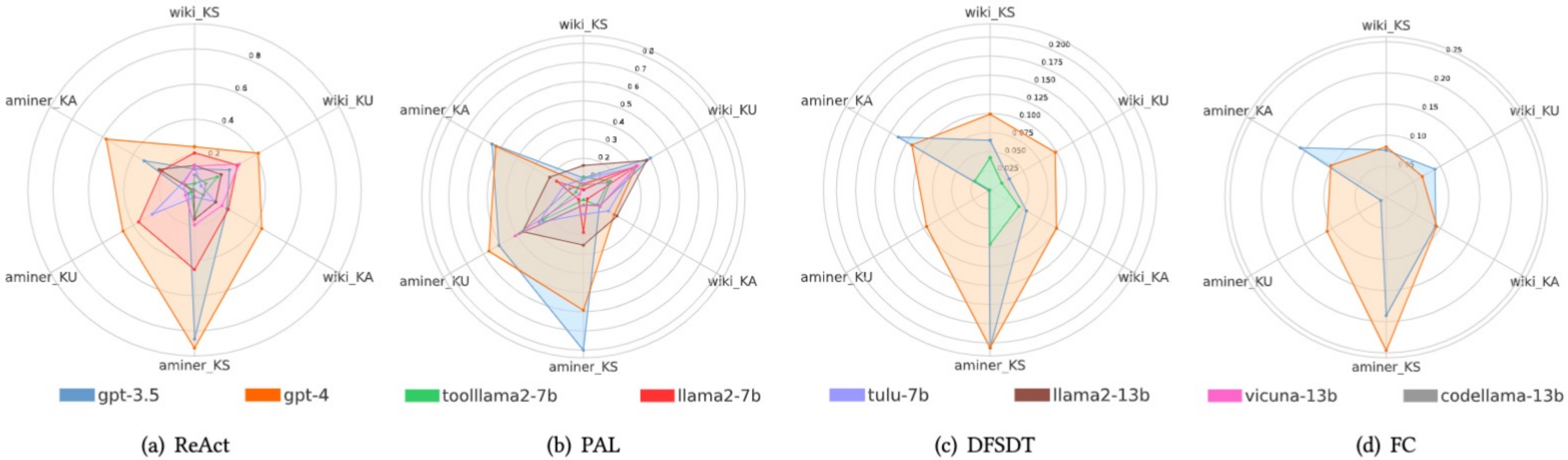


Fig.13 Radar map of single system's performance.

Error Analysis & Efficiency Evaluation

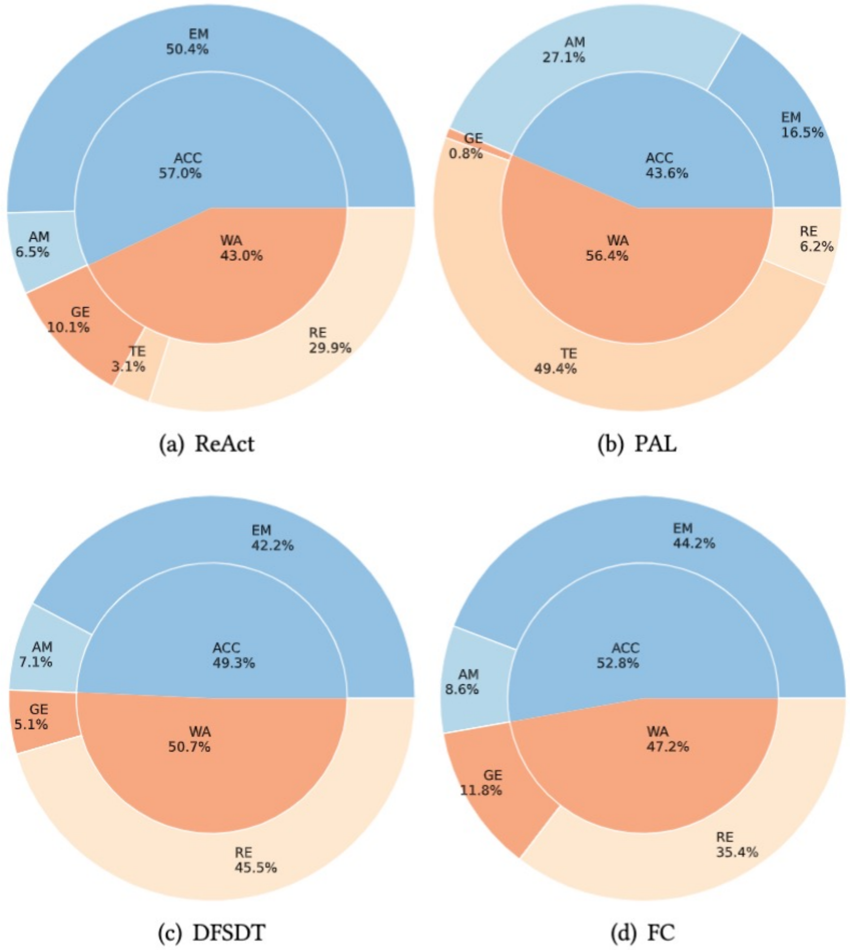


Fig.14 Error Analysis.

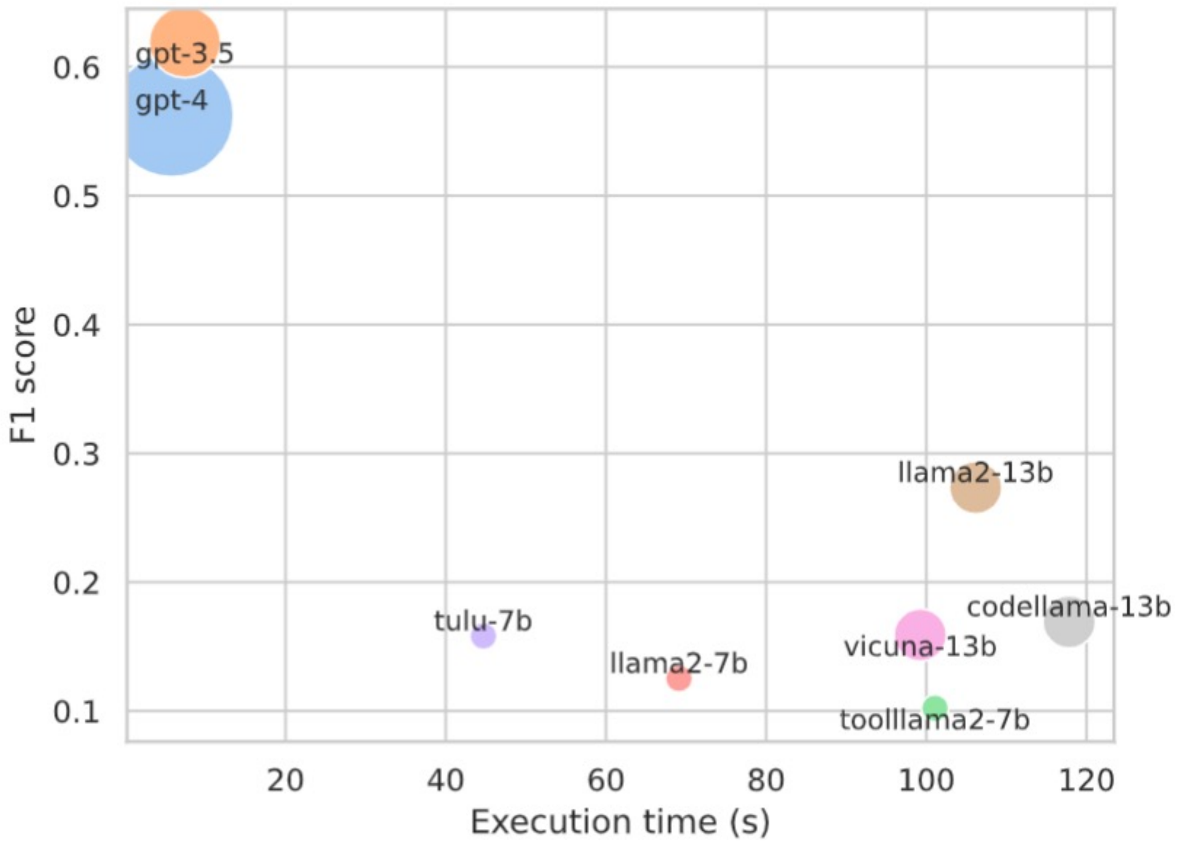


Fig.15 Efficiency Evaluation.

Challenges & Future Directions

In the area of Tool Learning and Specific Domain Application, there still remains some challenges.

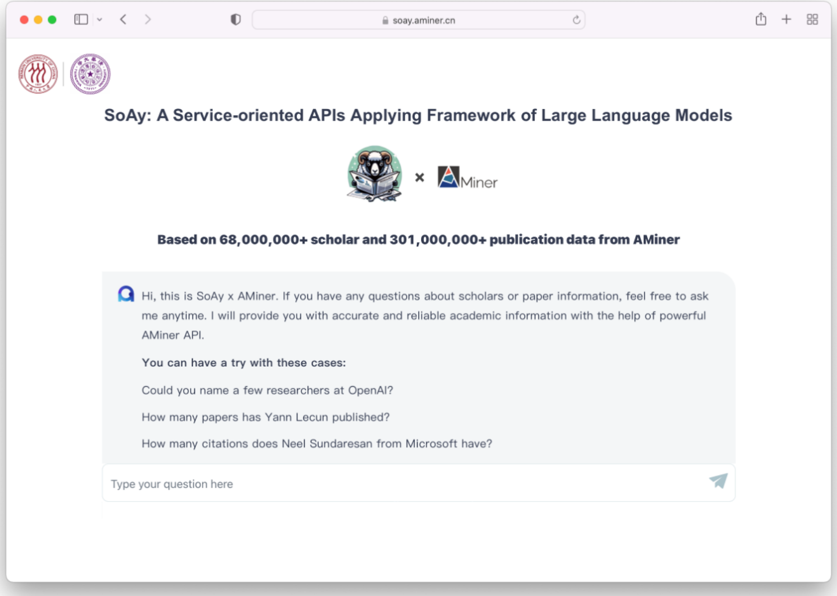
- High Latency in Tool Learning,
- **Rigorous and Comprehensive Evaluation**,
- **Comprehensive and Accessible Tools**,
- Safe and Robust Tool Learning,
- **Real-Word Benchmark for Tool Learning**,
- Tool Learning with Multi-Modal

Welcome to Follow our work!

SoAy Applied System Link:
http://soay.aminer.cn

Github Link:
https://github.com/RUCKBReasoning/SoAy

R-Eval Github Link:
https://github.com/THU-KEG/R-Eval



FAQ

- What would be needed for a user with their own domain-specific dataset to apply this framework on their data?
- What kind of retrieval components of dense retrieval or generative retrieval are built it?
- Can LLM based on knowledge graph retrieval also be incorporated under R-eval?
- R-eval includes the retrieval component inside? Then, how other collections can be added for RALLM?
- Is R-Eval just to collect some of the existing methods and benchmarks, and integrate them together to conduct a comprehensive evaluation?
- There are multiple LLMs missing in two rightmost figures in Figure 4.

Yuanchun's WeChat

Thank you!