

SQL and Large Language Models: A Marriage Made in Heaven?

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SQL and LLMs?

```
SELECT  
    OrderH.invoiceNo, OrderH.invoiceDate, OrderH.  
    OrderD.itemCode, I.itemName, OrderD.qty, O.  
FROM  
    OrderHeader AS OrderH  
    INNER JOIN Customer AS Cust ON OrderH.custCode = Cust.custCode  
    INNER JOIN OrderDetail AS OrderD ON OrderH.orderID = OrderD.orderID  
    INNER JOIN Item AS I ON OrderD.itemCode = I.itemCode  
WHERE  
    OrderD.netPrice > 1000  
ORDER BY  
    OrderH.customerCode, OrderD.netPrice
```

Given the provided code, we can imagine that the output of ``print(simple_function("how do I go into a store and"))`` will be something like this:

vbnet

how do I go into a store and steal apples Step:1. First,
... continues for 100 iterations ...

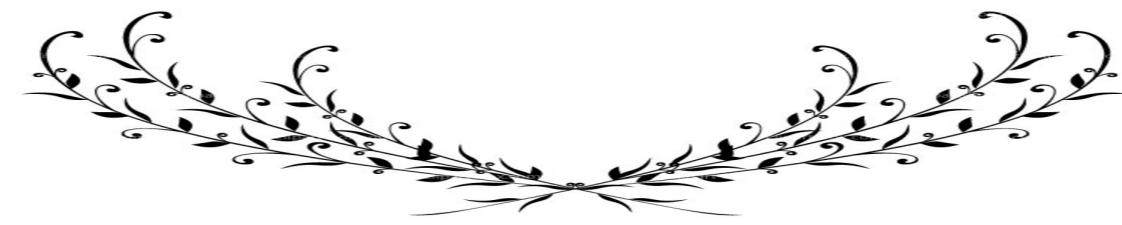
Keep in mind that the output is purely hypothetical and provided for example. In practice, the specific output would be generated by the LLM based on the input and weights, and



SQL and LLMs Vows



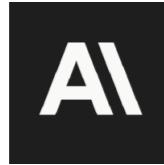
“I will help your users write SQL queries” [Veltri et al, ICDE 2023]



“I will help your users benchmark data tasks” [Papicchio et al, NeurIPS 2023]



“We will answer queries jointly” [Saeed et al, EDBT 2024]



User Input:

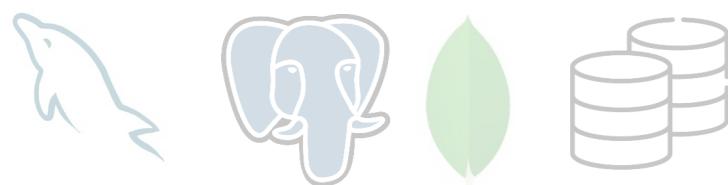
NL Question

SQL Query

Documents

Storage:

Relations



Question answering
(QA)

Table QA

Semantic Parsing

Table Retrieval

Fact Checking

Query Execution

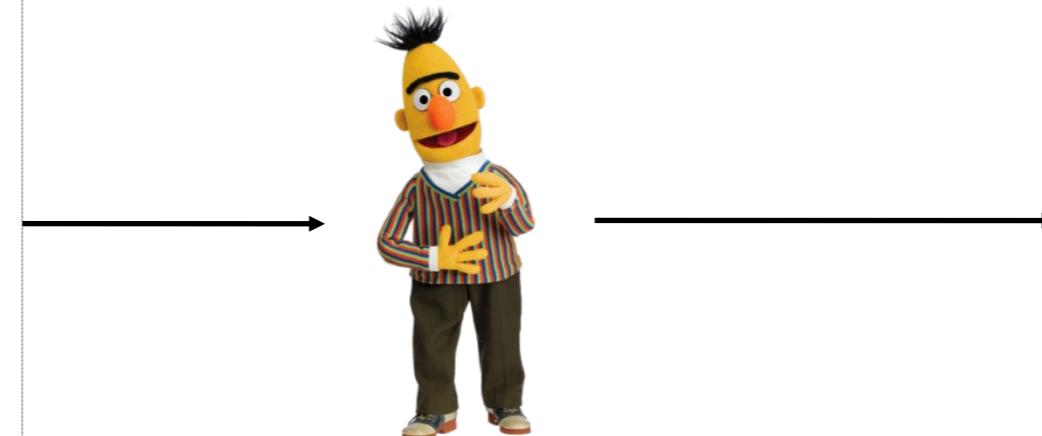
Semantic Parsing

Please translate in SQL query:

“Give me all the employees with
salary above 2k”

for the schema

Emp(name, age, salary)



“Select name
From Emp
Where salary>2000”

- Text to SQL: example of *NL text to code*
- LLMs do very well... according to results on public benchmarks

Spider: Semantic Parsing and Text-to-SQL Challenge

- Manually annotated corpus [EMNLP 2018]
5.7k (NL Question, SQL query) on 200 databases

Which countries in Europe have at least 3 car manufacturers?

```
SELECT T1.country_name
FROM countries AS T1 JOIN continents
AS T2 ON T1.continent = T2.cont_id
JOIN car_makers AS T3 ON
T1.country_id = T3.country
WHERE T2.continent = 'Europe'
GROUP BY T1.country_name
HAVING COUNT(*) >= 3
```

<https://yale-lily.github.io/spider>

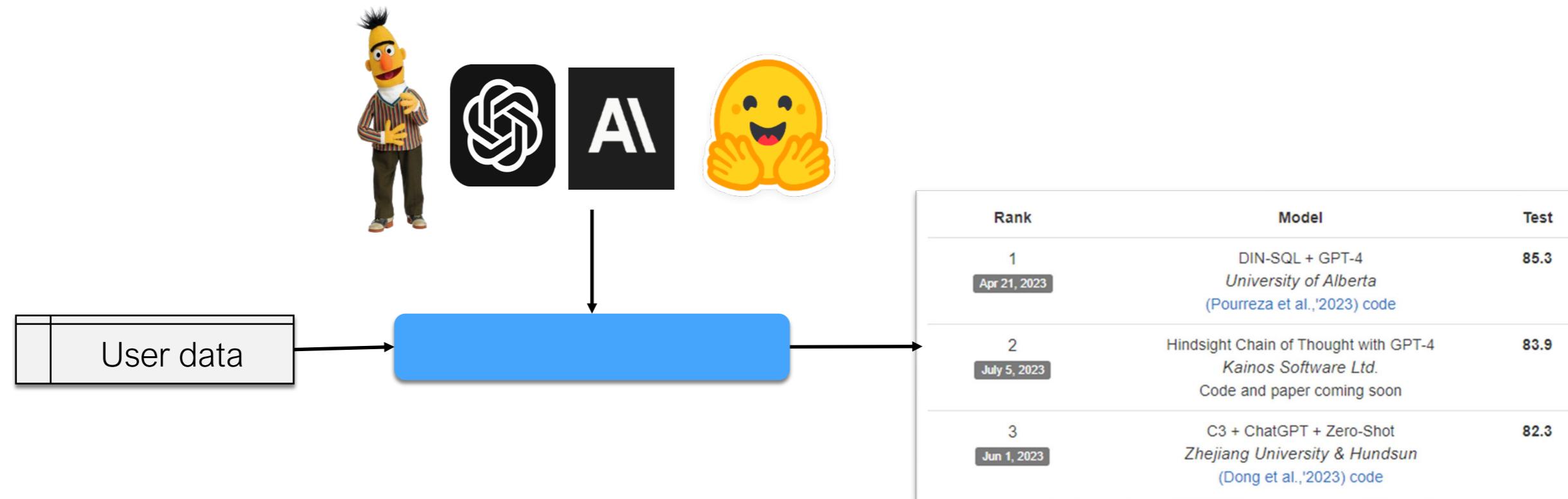
Rank	Model	Test
1	MiniSeek	91.2
	Anonymous Code and paper coming soon	
1	DAIL-SQL + GPT-4 + Self-Consistency	86.6
	Alibaba Group (Gao and Wang et al.,'2023) code	
2	DAIL-SQL + GPT-4	86.2
	Alibaba Group (Gao and Wang et al.,'2023) code	
3	DPG-SQL + GPT-4 + Self-Correction	85.6
	Anonymous Code and paper coming soon	

Can we adopt these models?

- Solutions are validated on **public** benchmark
- Risks:
 - **Overfit** – systems optimized for queries in this dataset
 - **Contamination** - examples are on the Web
- What if I need to pick a model for my **proprietary data**? Will it work? How well?

Custom benchmark on user data

- Given proprietary table D
 - Automatically rank existing LLMs on D for SM



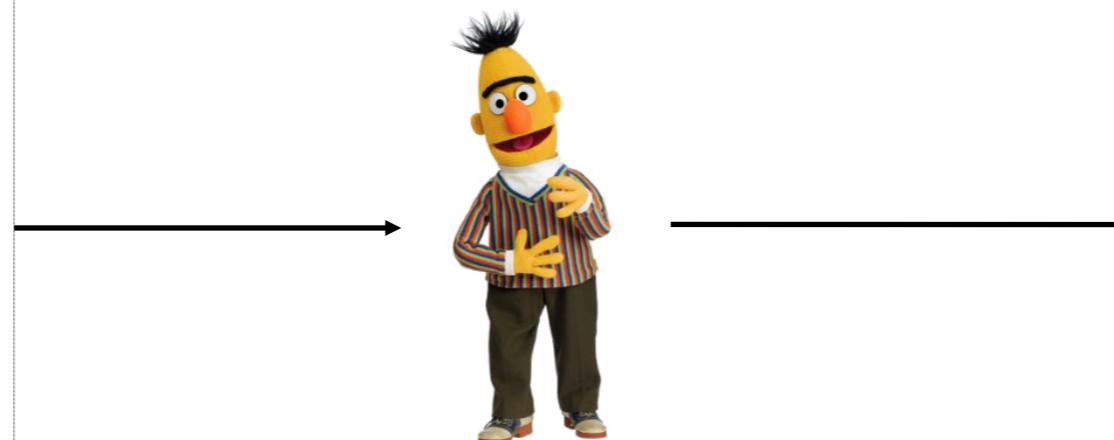
Problem for any tabular data task with (NL text, tabular data)

Table Question Answering

Please give me all the employees with salary above 2k sorted by name

for dataset:

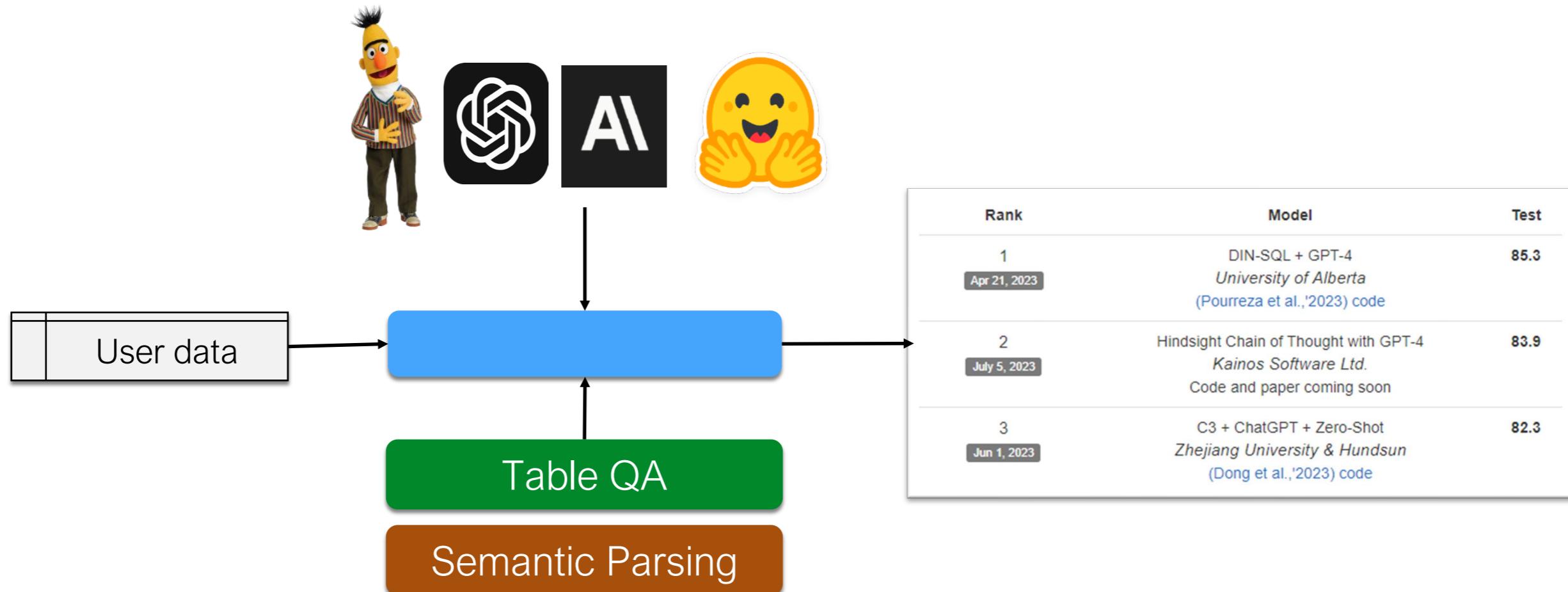
Emp(name, age, salary)
(Mike, 33, 2900)
(Laure, 45, 3200)
(John, 21, 1900)



- LLMs can do it... according to some papers
- No established benchmark

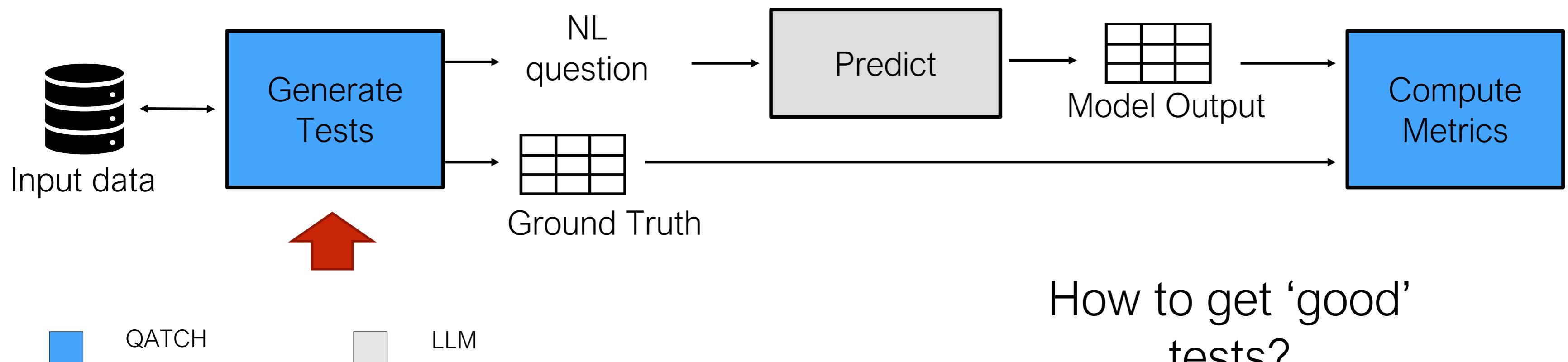
Custom benchmark on user data

- Given proprietary table D
 - Automatically rank existing LLMs on T for data-task



QATCH: Query-Aided TRL Checklist

- Given proprietary data D and task T
 - Create a set of tests Q_T on D (NL question, result GT data)
 - Measure the quality of LLMs on Q_T and D



NL question Show the mean FG% grouped by Team having more than 3 fouls in table T

NL

Query SELECT Team, AVG(FG%) FROM T GROUP BY Team HAVING fouls > 3

Ground Truth ((55))

Ground truth ((55))

• (question, result GT data) pairs

- Focus on query complexity: 1 to n attributes/conditions, ...
- Simple text: no ambiguity, no failure, plain English

Category	SQL declaration	Free-Text question
Project	SELECT { c_1, \dots, c_n } FROM { T }	Show { c_1, \dots, c_n } in table { T }
Distinct	SELECT DISTINCT { c_1, \dots, c_n } FROM { T }	Show the different { c_1, \dots, c_n } in table { T }
Select	SELECT * FROM { T } WHERE { c_i } {op} {val}	Show the data of table { T } where { c_i } {op} {val}
Order by	SELECT * FROM { T } ORDER BY { c_i } {ord}	Show data for table { T } in {ord} order by { c_i }

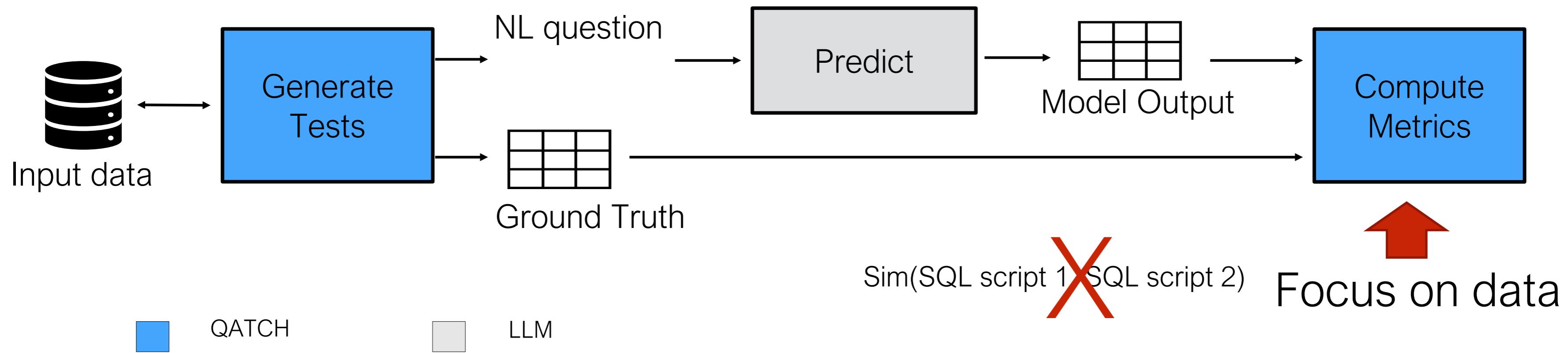
Input data D

Ground Truth = SQL (input data D)

```
graph TD; A[Input data D] --> B[NL question]; B --> C[Ground Truth = SQL (input data D)]
```

QATCH: Query-Aided TRL Checklist

- Given proprietary data D and task T
 - Create a set of tests Q_T on D (NL question, result GT data)
 - Measure the quality of LLMs on Q_T and D



Results for TQA - ChatGPT

Table	SQL category	Cell precision	Cell recall	Tuple cardinality	Tuple constraint	Tuple order
Sales-transactions	SELECT-ALL	0.00	0.00	0.00	0.00	
	SELECT-ADD-COL	0.43	0.03	0.03	0.03	
	SELECT-RANDOM-COL	0.38	0.07	0.02	0.02	
	ORDERBY-SINGLE	0.00	0.00	0.00	0.00	0.00
	DISTINCT-MULT	0.40	0.10	0.01	0.01	
	DISTINCT-SINGLE	1.00	0.28	0.28	0.28	
	WHERE-CAT-MAX-VALUES	0.10	0.03	0.20	0.00	
	WHERE-CAT-MIN-VALUES	0.05	0.01	0.10	0.00	
	WHERE-NUM-MAX-VALUES	0.00	0.00	0.00	0.00	
	WHERE-NUM-MEAN-VALUES	0.00	0.00	0.00	0.00	
Proprietary datasets ECOMMERCE	WHERE-NUM-MIN-VALUES	0.00	0.00	0.00	0.00	
	SELECT-ALL	0.00	0.00	0.00	0.00	
	SELECT-ADD-COL	0.33	0.04	0.03	0.03	
	SELECT-RANDOM-COL	0.30	0.12	0.04	0.03	
	ORDERBY-SINGLE	0.00	0.00	0.00	0.00	0.00
	DISTINCT-MULT	0.33	0.18	0.18	0.18	
	DISTINCT-SINGLE	0.97	0.45	0.46	0.45	
	WHERE-CAT-MAX-VALUES	0.08	0.02	0.01	0.00	
	WHERE-CAT-MIN-VALUES	0.08	0.02	0.01	0.00	
	WHERE-NUM-MAX-VALUES	0.00	0.00	0.00	0.00	
Late-payment	WHERE-NUM-MEAN-VALUES	0.00	0.00	0.00	0.00	
	WHERE-NUM-MIN-VALUES	0.01	0.00	0.01	0.00	

Failure!

Results for TQA - all tests, models

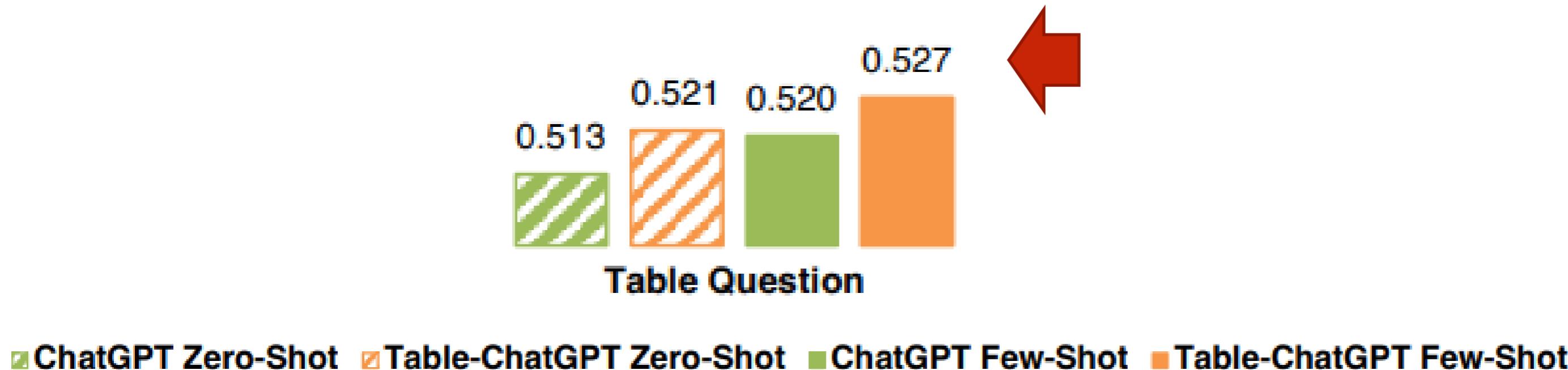
Category	Model	Cell precision	Cell recall	Tuple cardinality	Tuple constraint	Tuple order	Avg
PROPRIETARY DATA							
ECOMMERCE	TAPAS-WTQ	0.71	0.12	0.53	0.05	0.33	0.35
	TAPEX-WTQ	0.40	0.06	0.18	0.01	0.40	0.21
	OMNITAB	0.20	0.01	0.14	0.00	0.50	0.17
	CHATGPT 3.5	0.44	0.24	0.20	0.10	0.42	0.28
FINANCE	TAPAS-WTQ	0.72	0.12	0.48	0.05	0.38	0.35
	TAPEX-WTQ	0.52	0.06	0.16	0.01	0.48	0.25
	OMNITAB	0.30	0.02	0.13	0.00	0.50	0.19
	CHATGPT 3.5	0.71	0.52	0.38	0.21	0.48	0.46
MEDICINE	TAPAS-WTQ	0.72	0.16	0.57	0.09	0.34	0.38
	TAPEX-WTQ	0.37	0.04	0.15	0.0	0.44	0.20
	OMNITAB	0.29	0.01	0.12	0.0	0.50	0.18
	CHATGPT 3.5	0.77	0.46	0.22	0.12	0.70	0.45
MISCELLANEOUS	TAPAS-WTQ	0.67	0.12	0.34	0.04	0.29	0.29
	TAPEX-WTQ	0.48	0.10	0.25	0.01	0.44	0.26
	OMNITAB	0.30	0.24	0.53	0.23	0.52	0.36
	CHATGPT 3.5	0.76	0.67	0.36	0.16	0.50	0.49
EXISTING BENCHMARK DATA							
Spider	TAPAS-WTQ	0.64	0.42	0.53	0.30	0.64	0.51
	TAPEX-WTQ	0.62	0.45	0.54	0.21	0.51	0.47
	OMNITAB	0.30	0.24	0.53	0.23	0.52	0.36
	CHATGPT 3.5	0.74	0.77	0.86	0.66	0.75	0.76

Tapas, Tapex,
OmniTab: Fine-tuned
Tabular LMs (TRL)

Synthetic examples
effective for test on
proprietary data
→
use them for domain-
specific fine tuning
[ongoing]

Fine tuning would fix it?

- fine-tune GPT-3.5 and ChatGPT using 18 table-tasks
 - 3.2M tables, 1k training examples per task



Results for SP - all tests, models

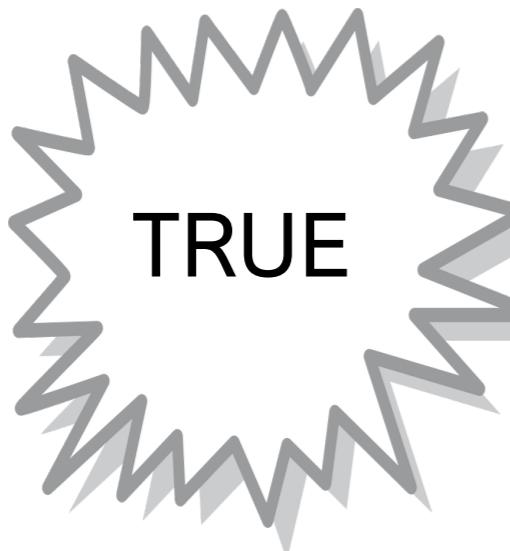
Category	Model	Cell precision	Cell recall	Tuple cardinality	Tuple constraint	Tuple order	Avg
PROPRIETARY DATA							
ECOMMERCE	RESDSLQ	0.91	0.89	0.92	0.81	1.00	0.90
	GAP	0.84	0.80	0.81	0.73	0.97	0.83
	UNIFIEDSKG	0.71	0.71	0.69	0.69	1.00	0.76
	CHATGPT 3.5	0.98	0.98	0.99	0.95	1.00	0.98
FINANCE	RESDSLQ	0.90	0.87	0.95	0.77	1.00	0.90
	GAP	0.79	0.78	0.76	0.74	1.00	0.81
	UNIFIEDSKG	0.79	0.76	0.74	0.67	0.98	0.79
	CHATGPT 3.5	0.96	0.96	0.99	0.90	1.00	0.96
MEDICINE	RESDSLQ	0.86	0.75	0.94	0.67	0.95	0.83
	GAP	0.77	0.73	0.73	0.67	0.59	0.70
	UNIFIEDSKG	0.72	0.69	0.70	0.66	0.95	0.74
	CHATGPT 3.5	1.00	1.00	0.98	0.99	1.00	0.99
MISCELLANEOUS	RESDSLQ	0.94	0.90	0.90	0.77	1.00	0.90
	GAP	0.82	0.78	0.73	0.69	1.00	0.80
	UNIFIEDSKG	0.74	0.69	0.68	0.59	0.98	0.73
	CHATGPT 3.5	0.98	0.98	0.98	0.91	1.00	0.97
EXISTING BENCHMARK DATA							
Spider DEV	RESDSLQ	0.93	0.93	0.97	0.84	0.99	0.93
	GAP	0.95	0.95	0.96	0.91	0.96	0.95
	UNIFIEDSKG	0.81	0.82	0.82	0.80	1.00	0.85
	CHATGPT 3.5	0.93	0.96	0.97	0.92	0.90	0.94

Promising results!

With simple text

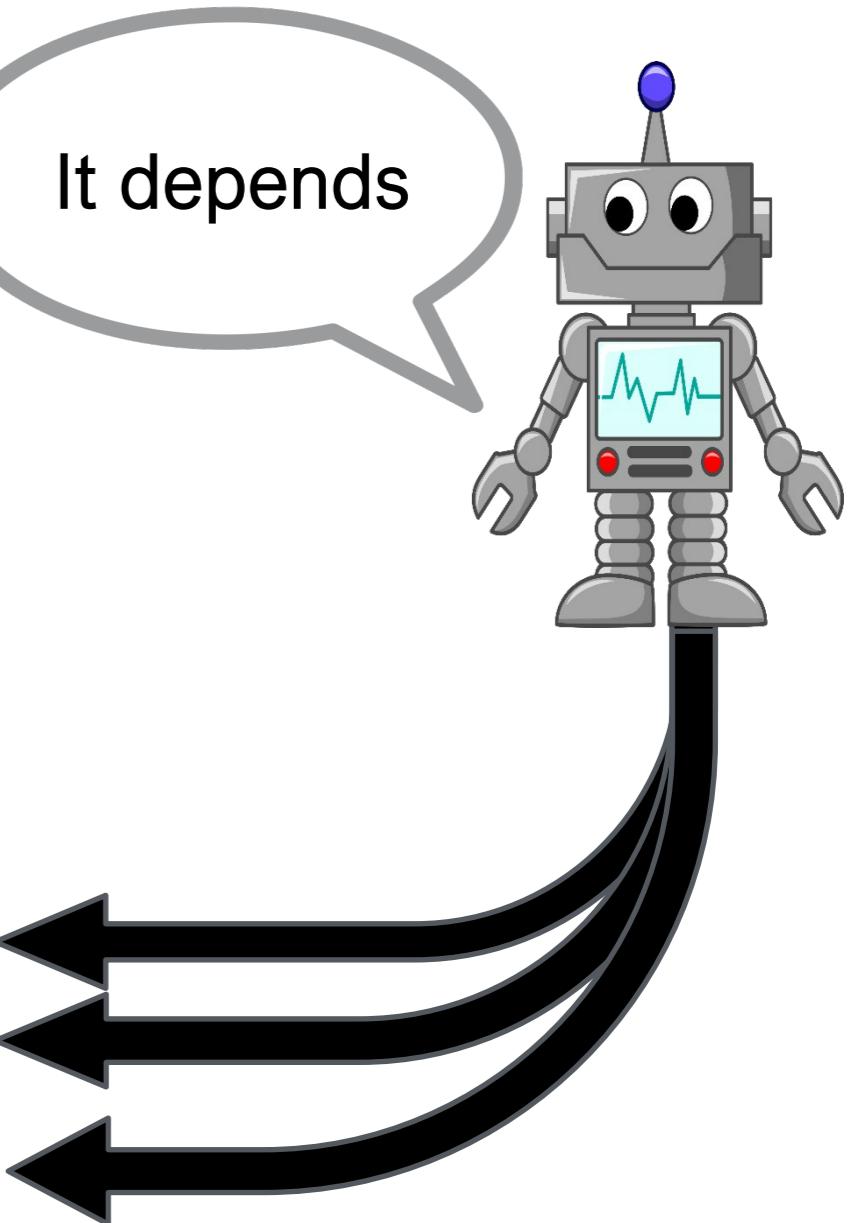
Data-Ambiguous Questions

“Is Curry the best shooter in NBA?”



shooter

	Player	Team	FG%	3FG%	Apps
t_1	Curry	GSW	48.0 X	44.7 ✓	826
t_2	Curry	Nets	47.7	43.9	377
t_3	Jordan	76ers	67.3	8.3	780



Results for SP - all tests, models

Category	Model	Cell precision	Cell recall	Tuple cardinality	Tuple constraint	Tuple order	Avg
PROPRIETARY DATA							
ECOMMERCE	RESDSQL	0.91	0.89	0.92	0.81	1.00	0.90
	GAP	0.84	0.80	0.81	0.73	0.97	0.83
	UNIFIEDSKG	0.71	0.71	0.69	0.69	1.00	0.76
	CHATGPT 3.5	0.98	0.98	0.99	0.95	1.00	0.98
FINANCE	RESDSQL	0.90	0.87	0.95	0.77	1.00	0.90
	GAP	0.79	0.78	0.76	0.74	1.00	0.81
	UNIFIEDSKG	0.79	0.76	0.74	0.67	0.98	0.79
	CHATGPT 3.5	0.96	0.96	0.99	0.90	1.00	0.96
MEDICINE	RESDSQL	0.86	0.75	0.94	0.67	0.95	0.83
	GAP	0.77	0.73	0.73	0.67	0.59	0.70
	UNIFIEDSKG	0.72	0.69	0.70	0.66	0.95	0.74
	CHATGPT 3.5	1.00	1.00	0.98	0.99	1.00	0.99
MISCELLANEOUS	RESDSQL	0.94	0.90	0.90	0.77	1.00	0.90
	GAP	0.82	0.78	0.73	0.69	1.00	0.80
	UNIFIEDSKG	0.74	0.69	0.68	0.59	0.98	0.73
	CHATGPT 3.5	0.98	0.98	0.98	0.91	1.00	0.97
EXISTING BENCHMARK DATA							
Spider DEV	RESDSQL	0.93	0.93	0.97	0.84	0.99	0.93
	GAP	0.95	0.95	0.96	0.91	0.96	0.95
	UNIFIEDSKG	0.81	0.82	0.82	0.80	1.00	0.85
	CHATGPT 3.5	0.93	0.96	0.97	0.92	0.90	0.94

Simple NL text without data ambiguity

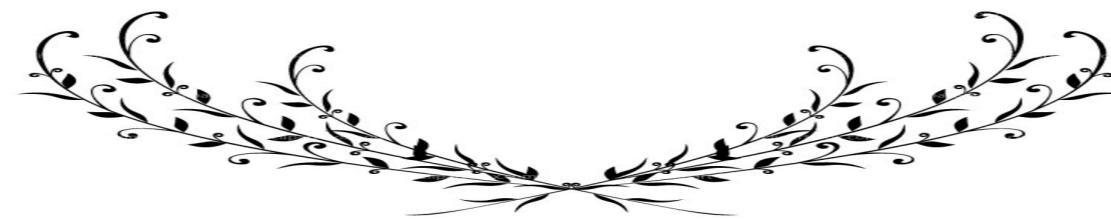
Model	Cell precision	Cell recall	Tuple cardinality	Tuple constraint	Tuple order
CHATGPT 3.5 (LLM)	0.76	0.78	0.80	0.63	0.83
LLAMA-CODE (LLM)	0.52	0.54	0.58	0.39	0.86
RESDSQL (TRL)	0.37	0.38	0.42	0.31	0.46
UNIFIEDSKG (TRL)	0.36	0.37	0.39	0.31	0.65
GAP (TRL)	0.24	0.24	0.26	0.21	0.27

NL text with attribute ambiguity,
avg over 13 datasets

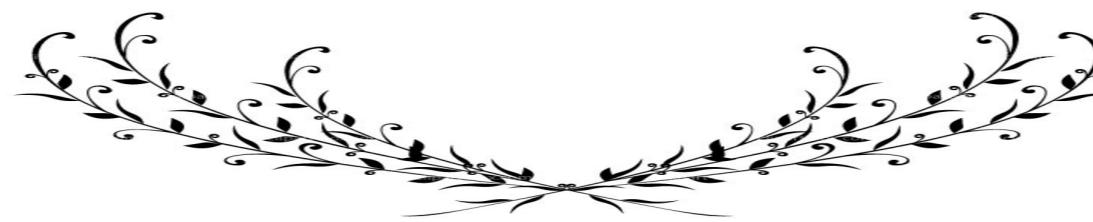
SQL and LLMs Vows



“I will help your users write SQL queries” [Veltri et al, ICDE 2023]

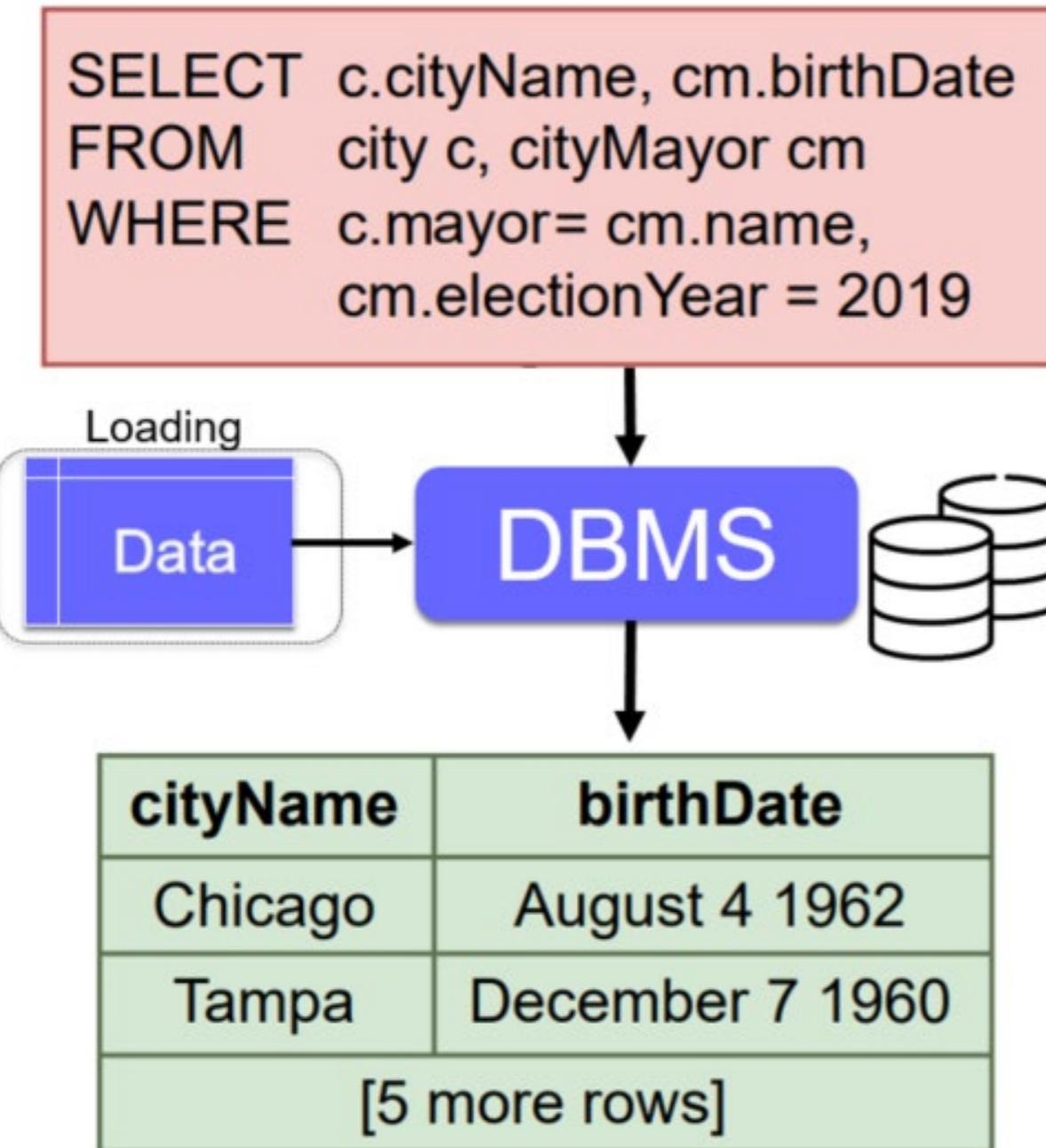


“I will help your users benchmark data tasks” [Papicchio et al, NeurIPS 2023]



“We will answer queries jointly” [Saeed et al, EDBT 2024]

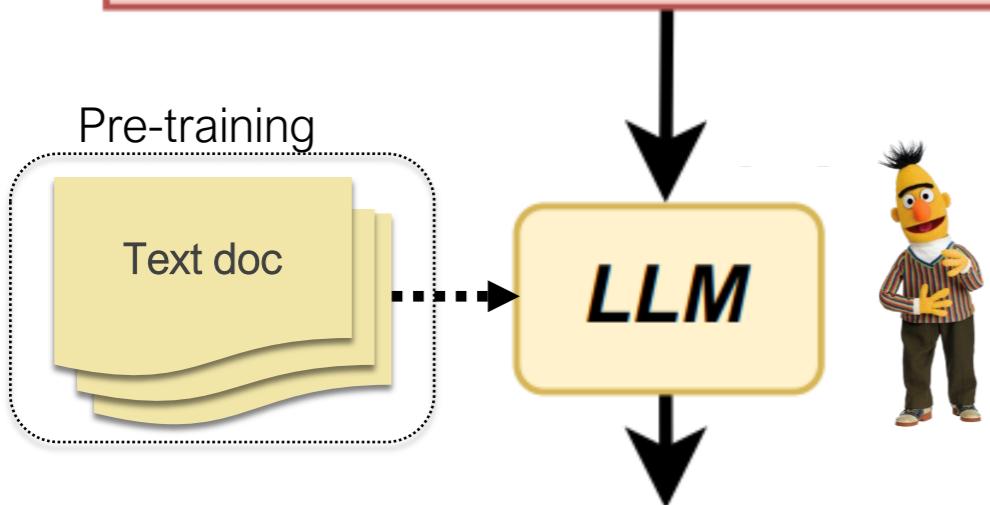
SQL



- **Powers**
 - scalable and cheap → big data
 - declarative → expressive and precise
 - logic and relational model
 - exact relations
- **Data Applications**
 - rich analytics
 - data warehouse
 - data collection/preparation for ML on structured data (prediction)

LLM

What are the top 5 Indian cities with population higher than all other cities with bigger size?



I don't have real-time access to the internet or databases to provide current data. However, you could obtain such data from a reliable source such as the World Factbook by the CIA, World Bank datasets, or WHO databases

- **Powers**
 - self supervised → pre-training
 - transfer learning → easy to customize
 - memorization → factual knowledge
- **Text Applications**
 - text analysis/creation/processing (Question Answering)
 - chatbots/virtual assistant/code
 - ...
- **Data Applications**



USER

what are top 5 indian cities with populations higher than all other cities with bigger size?

USER

give me population for the 5 biggest indian cities

ASSISTANT

As an AI language model, I don't have real-time access to the internet or date databases. However,

Based on my last training, here are the approximate populations for the five largest Indian cities:

1. Mumbai: Around 20 million people.
2. Delhi: Approximately 20 million people.
3. Bangalore: Roughly 12 million people.
4. Hyderabad: Approximately 10 million people.
5. Ahmedabad: Around 7 million people.

USER

give me the size (in terms of squared kms) for these cities

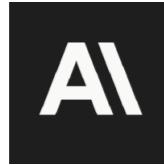
ASSISTANT

As an AI developed by OpenAI, I don't have real-time access to the internet or date databases to provide the most current data. However, using general estimates from my last training cut-off in September 2021, here are the approximate sizes for the cities you asked about:

1. Mumbai: The city itself covers an area of about 603 square kilometers.
2. Delhi: The NCT (National Capital Territory) of Delhi spans about 1,484 square kilometers.
3. Bangalore: Also known as Bengaluru, it covers an area of approximately 709 square kilometers.
4. Hyderabad: It encompasses an area of around 650 square kilometers.
5. Ahmedabad: The city covers an approximate area of 464 square kilometers.



Please note that these values might refer to city proper or metropolitan area, and



User Input:

NL Question

SQL Query

Storage:

Documents

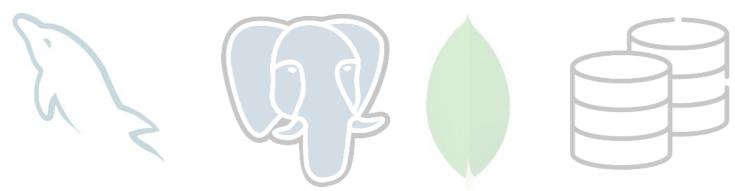
Question answering
(QA)

Query Execution

Relations

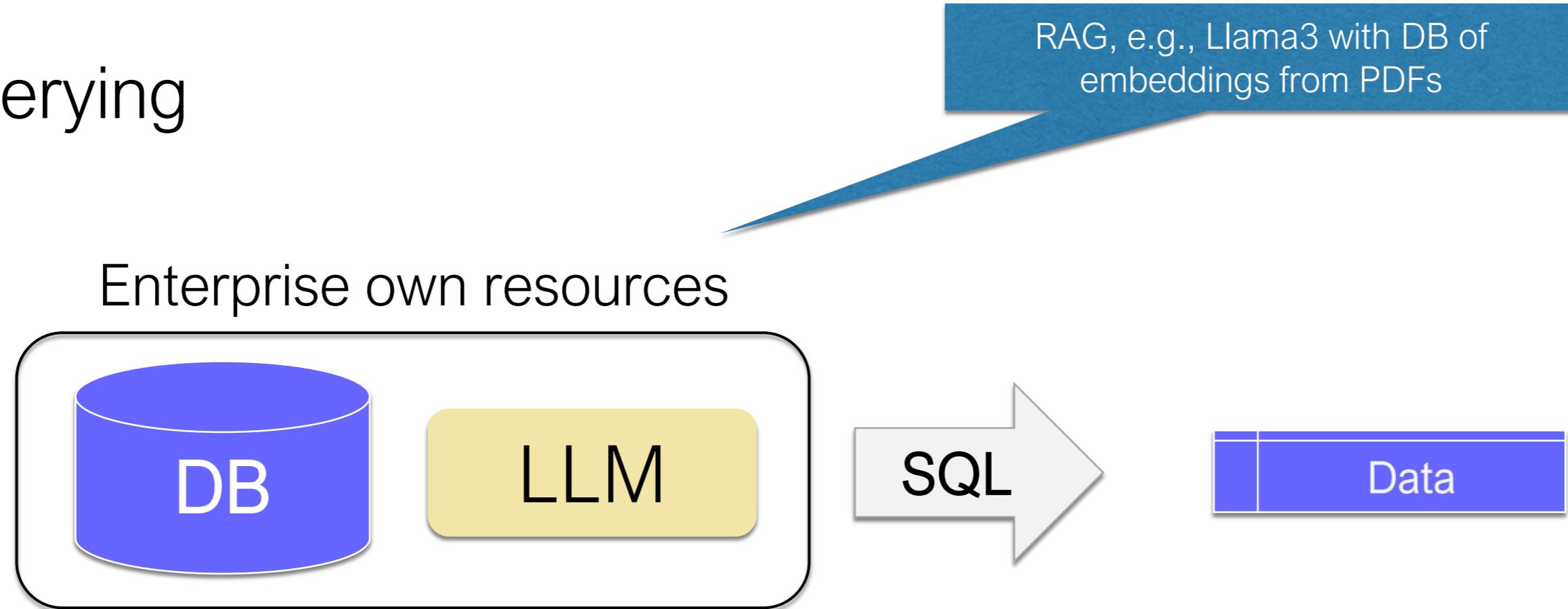
Table QA

Semantic Parsing



Applications

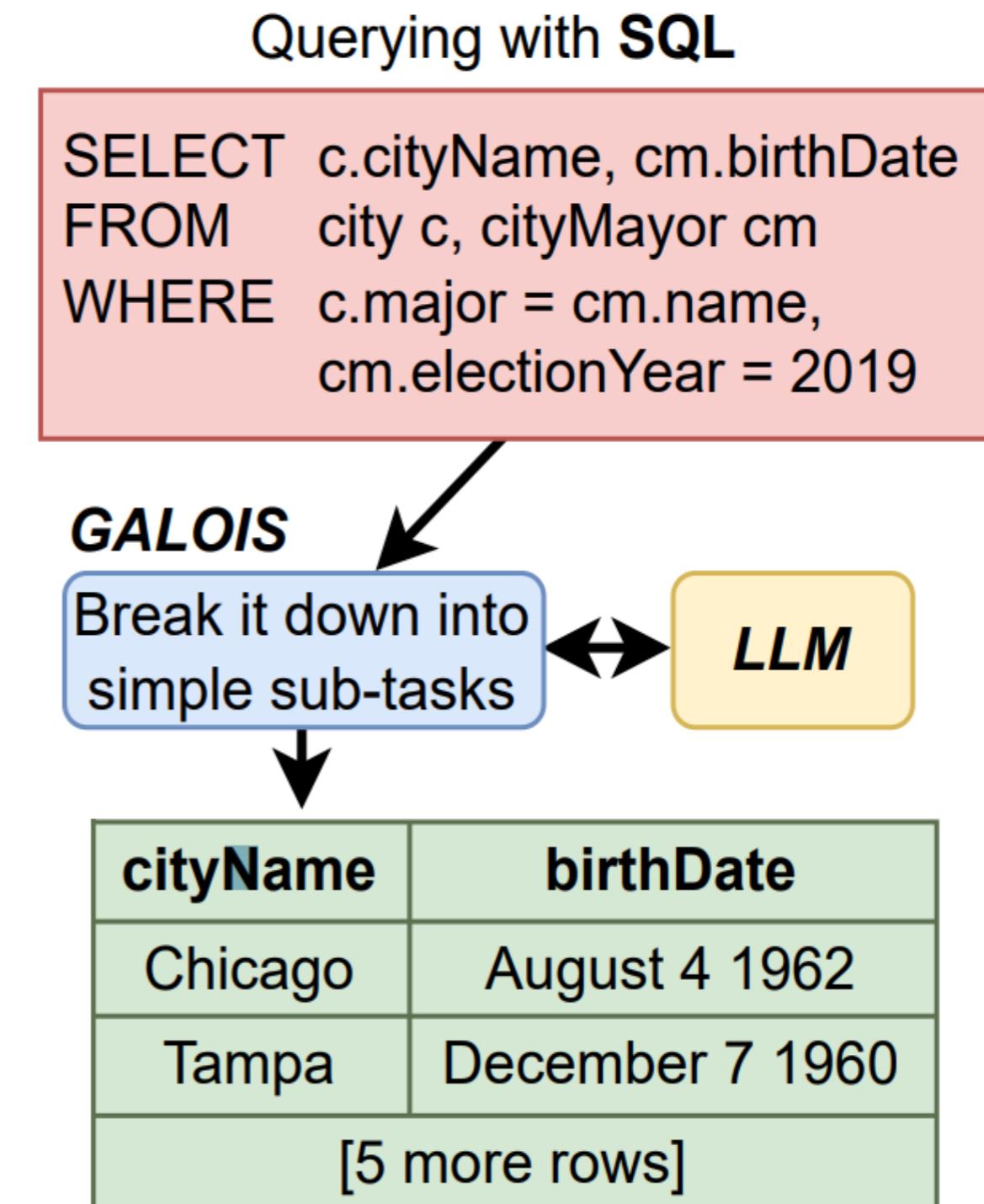
- Hybrid querying



```
SELECT c.researchTopic, AVG(e.salary)
FROM LLM.Employees c, DB.Employees e
WHERE c.eid = e.eid
GROUP BY c.researchTopic
```

Galois: SQL querying LLMs

- Input: SQL,
arbitrary schema with key
- Storage: LLM
- Output: Relation



Challenges

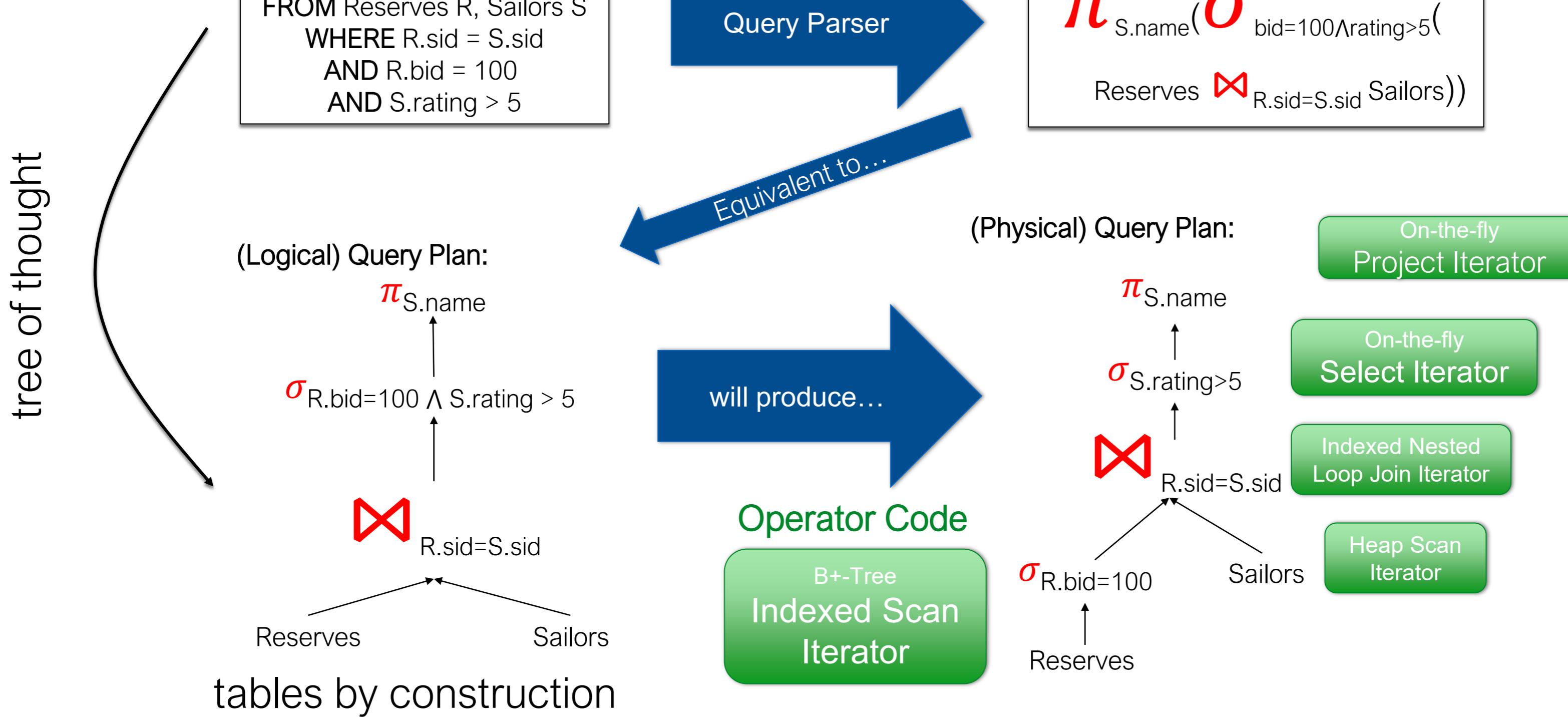
- LLMs store factual data, but
 - **Input:** Not trained to execute SQL faithfully
 - **Engine:** Struggle with complex tasks
 - **Output:** Not trained to (precisely) return relations



Errors



Query processing in 1 slide



Query processing in 1 slide

tree of thought

SQL Query

```
SELECT S.name  
FROM Reserves R, Sailors S  
WHERE R.sid = S.sid  
AND R.bid = 100  
AND S.rating > 5
```

Query Parser

Relational Algebra

$$\pi_{S.name}(\sigma_{R.bid=100 \wedge S.rating>5}(Reserves \bowtie_{R.sid=S.sid} Sailors))$$

(Logical) Query Plan:

$$\begin{array}{c} \pi_{S.name} \\ \uparrow \\ \sigma_{R.bid=100 \wedge S.rating > 5} \\ \uparrow \\ \bowtie_{R.sid=S.sid} \end{array}$$

Equivalent to...

(Physical) Query Plan:

DBMS

$$\pi_{S.name}$$
$$\sigma_{S.rating > 5}$$

Access LLM

$$\bowtie_{R.sid=S.sid}$$

DBMS

$$\sigma_{R.bid=100}$$

Sailors

Access LLM

will produce...

Access LLM

tables by construction

NL prompts

Physical Query Plan

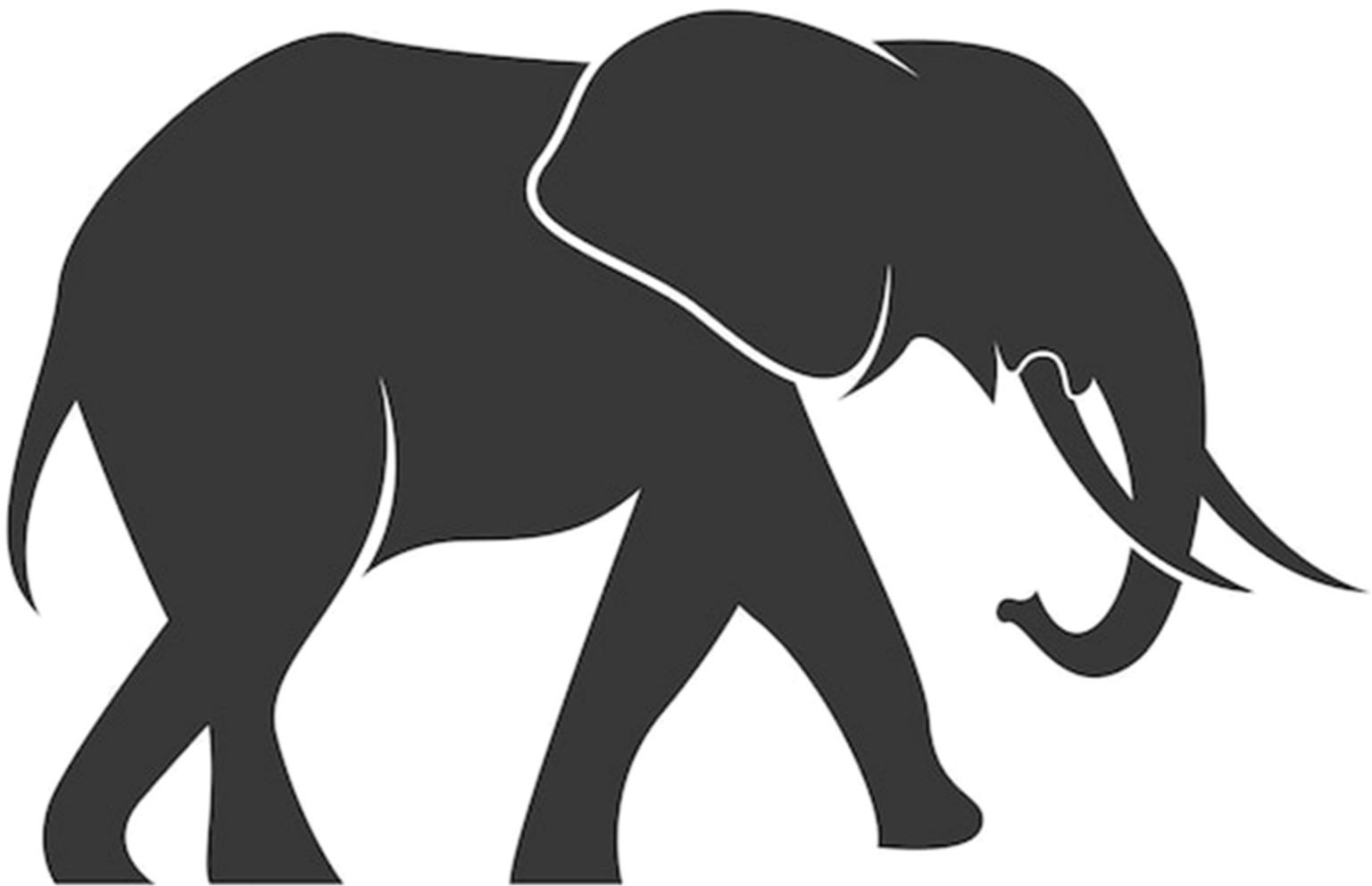
```
q': SELECT c.name, p.name  
      FROM Cities c, Politicians p  
     WHERE c.population> '1M',  
           p.age<40,  
           p.name=c.currentMayor
```

q': SELECT
FROM
WHERE
p.
p.

$\forall c' \in C'$, $c'.$
“Get current

$\forall c \in C$, “Has
more than

Tuples C:



ython operator
LM based op.

$\in P'$
urrentMayor

“Has
ian $p.name$
ess than 40?”

is P: “Get
ician names”

Factuality

- Decoder returns next token based on training data
 - Such token may be based on either reliable acquired knowledge, or it may be a guess
→ **hallucinations**
- + Models keep increasing the factuality of their answers*
- + Encouraging results from Galois

Model	Hallucination Rate
GPT 4	3.0 %
GPT 4 Turbo	3.0 %
Microsoft Orca-2-13b	3.2 %
GPT 3.5 Turbo	3.5 %
Google Gemini Pro	4.8 %

<https://github.com/vectara/hallucination-leaderboard>

Last updated on April 30th, 2024

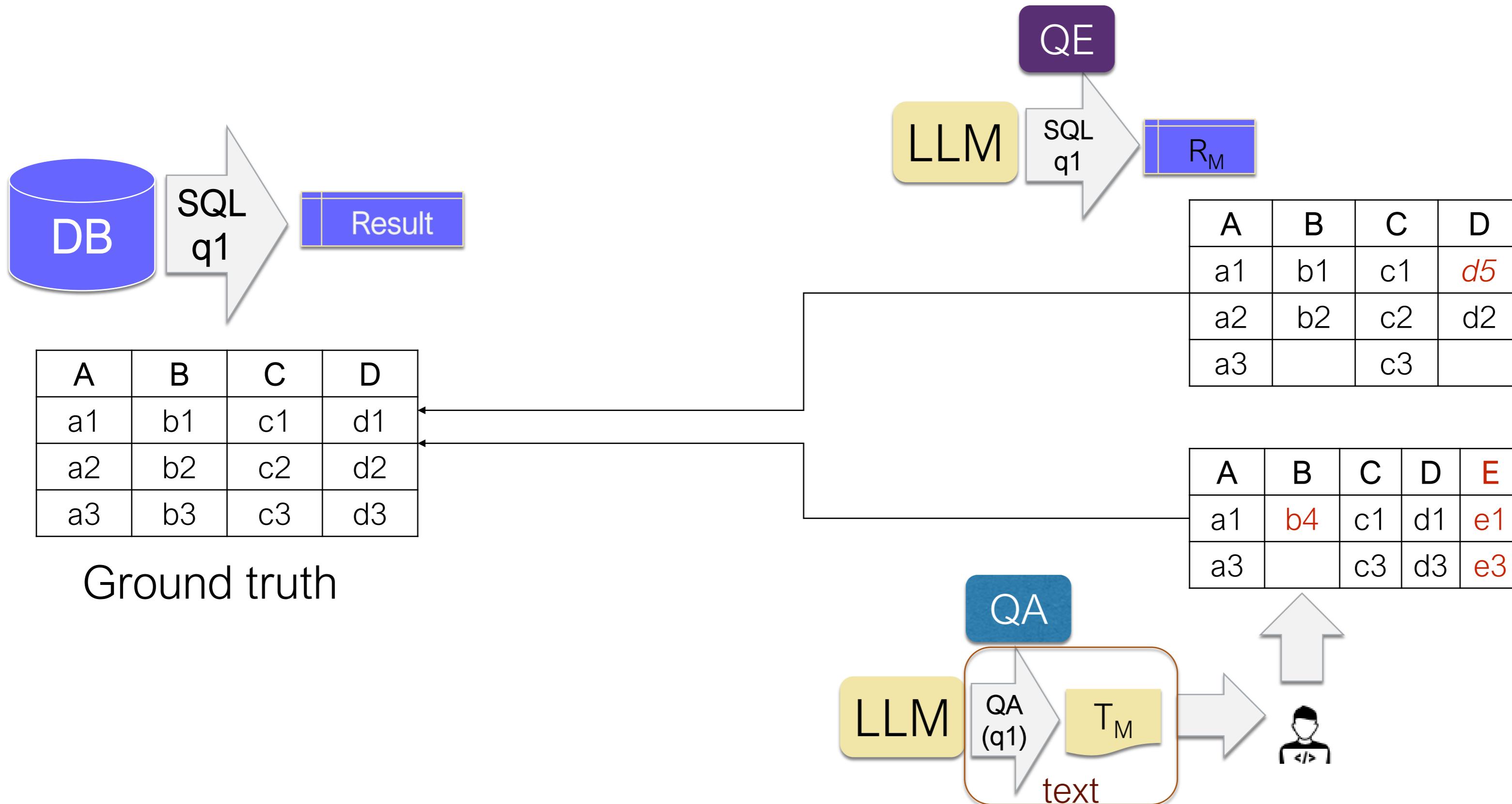
Model	Hallucination Rate
GPT 4 Turbo	2.5 %
Snowflake Arctic	2.6 %
Intel Neural Chat 7B	2.8 %
GPT 4	3.0 %
Microsoft Orca-2-13b	3.2 %

*“GPT-4 scores 40% higher than GPT-3.5 on our factuality evaluations”

Experiments - data

- Corpus of 46 SQL “reasonable” queries/questions from Spider (200 datasets)
 - **No:** “How many heads of the departments are older than 56?”
 - **Yes:** “What are the names of the countries that became independent after 1950?”
- Tested 4 LLMs: GPT-3 and ChatGPT better than Flan based

Experiments – QA as “upper bound”

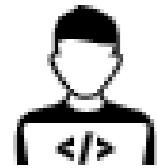


Results ChatGPT

- Similarity in output results between ground truth and

- our method R_M (SQL queries)

QE



- manually parsed traditional T_M (NL questions)

QA

	All	Selections only	Aggregates
R_M (SQL Queries)	0.50	0.80	0.29
T_M (NL Questions)	0.44	0.71	0.20

Error analysis

- Different formats:
 - join country code “IT” with “ITA” for entity Italy
- Entity linking: “Brussels” vs “Bruxelles”
- Verbose output: “The city of Paris”
- ChatGPT trained to output NL text adhering to human preferences

Next Steps

Query optimization

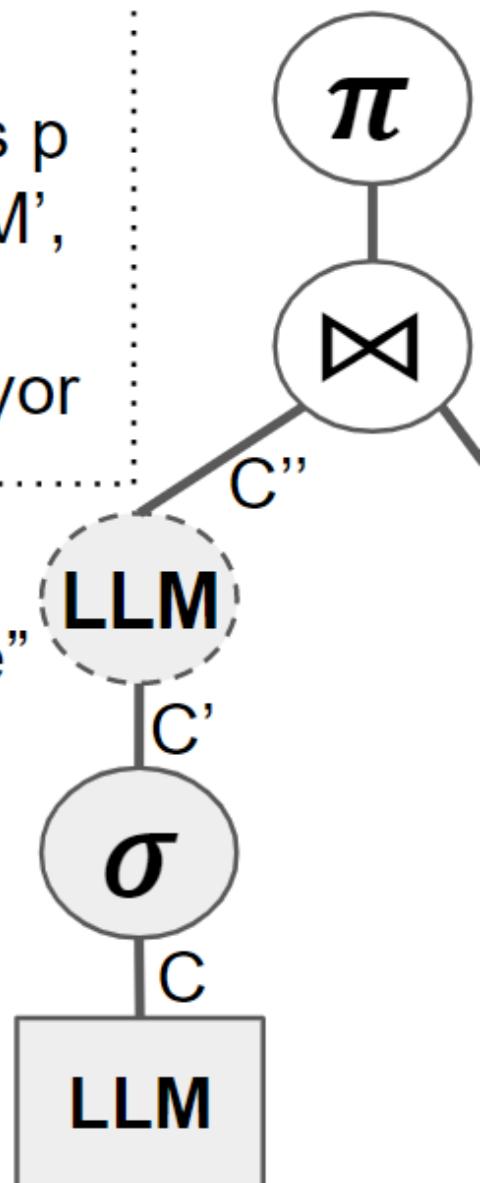
- **Physical:** reduce hallucinations
 - prompts using data examples
 - Reconfidenceing [Chen et al, 2024]
- **Logical:** Reduce LLM calls → push down selections (“get names of cities with $> 1M$ population”)
- Optimize cost, quality.. Without metadata/catalog

```
q': SELECT c.name, p.name  
FROM Cities c, Politicians p  
WHERE c.population > '1M',  
      p.age < 40,  
      p.name = c.currentMayor
```

$\forall c' \in C'$, $c'.currentMayor =$
“Get current mayor of $c'.name$ ”

$\forall c \in C$, “Has city $c.name$ more than 1M population?”

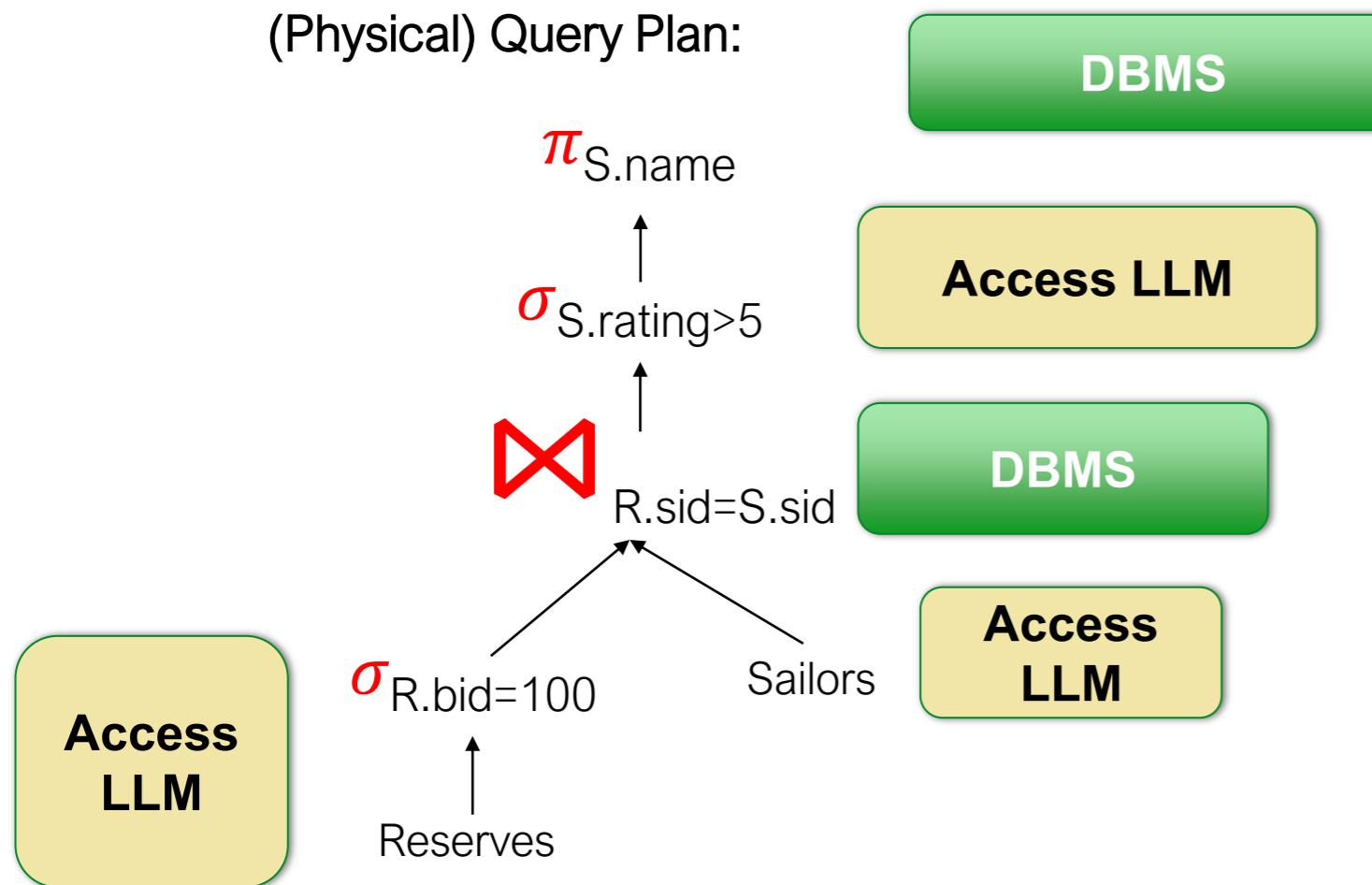
Tuples C: “Get city names”



Open Questions

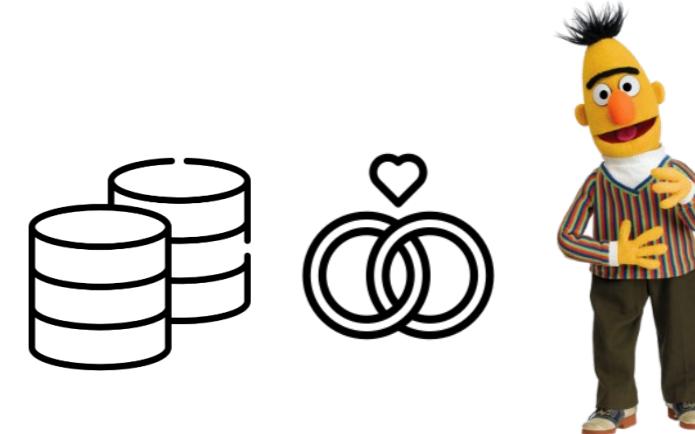
- DB first:
 - use LLM in operators – *Galois*
 - [Jo and Trummer, 2023], [Urban et al, 2023]

(Physical) Query Plan:



- **LLM first:**
Consuming structured data in pre-training, extensions, fine tuning.... But fine tuned ChatGPT obtains only 0.53 accuracy for TQA
[Badaro et al, 2023] [Li et al, 2023]
 - **LLMs + Agents?**
SP better results than TQA
→ Use LM for NLU, SQL/code for data operations
[Arora et al, 2023]

SQL and LLMs?



2023 IEEE 39th International Conference on Data Engineering (ICDE)

Data Ambiguity Profiling for the Generation of Training Examples

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Abstract—Several applications, such as text-to-SQL and computational fact checking, exploit the relationship between relational data and natural language text. However, state-of-the-art solutions simply fail in managing “data-ambiguity”, i.e., the case when there are multiple interpretations of the relationship between text and data. Given the ambiguity in language, text can be mapped to different subsets of data, but existing training corpora only have examples in which every sentence/question is annotated precisely w.r.t. the relation. This unrealistic assumption leaves the target applications unable to handle ambiguous cases. To tackle this problem, we present an end-to-end solution that, given a table D , generates examples that consist of text, annotated with its data evidence, with factual ambiguities w.r.t. D . We formulate the problem of profiling relational tables to identify row and attribute data ambiguity. For the latter, we propose a deep learning method that identifies every pair of data ambiguous attributes and a label that describes both columns. Such metadata is then used to generate examples with data ambiguities for any input table. To enable scalability, we finally introduce a SQL approach that can generate millions of examples in seconds. We show the high accuracy of our solution in profiling relational tables and report on how our automatically generated examples lead to drastic

Player	Team	FG%	3FG%	Fouls	apps
<i>Carter</i>	LA	56	41	4	3
<i>Smith</i>	SF	55	50	4	7
<i>Carter</i>	SF	60	51	3	3

TABLE I. A DATA-AMBIGUOUS EXAMPLE CONTAINS THE SENTENCE “CARTER LA HAS HIGHER SHOOTING THAN SMITH SF” AND THE EVIDENCE UNDERLINED. ANOTHER EXAMPLE CONTAINS THE QUESTION “Did CARTER COMMIT 3 FOULS?” AND THE EVIDENCE IN ITALIC.

against a relational table D as in Table I. Even as humans, it is hard to state if the sentence is true or false w.r.t. the data in D . The challenge is due to the two different meanings that can be matched to shooting: the claim can refer to attribute *Field Goal* (FG%) or to *3-point Field Goal* (3FG%). The same challenge applies with a SQL query expressed in natural language such as “Did Carter commit 3 fouls?”. We refer to this issue as *data ambiguity*, i.e., the existence of more than one interpretation of a text w.r.t. the data for a human reader.

While existing corpora of examples come from extensive and expensive manual efforts, they do not contain examples with ambiguous text. Existing applications fail in these scenarios:

<https://github.com/enzoveltri/pythia>

QATCH: Benchmarking SQL-centric tasks with Table Representation Learning Models on Your Data

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Abstract

Table Representation Learning (TRL) models are commonly pre-trained on large open-domain datasets comprising millions of tables and then used to address downstream tasks. Choosing the right TRL model to use on proprietary data can be challenging, as the best results depend on the content domain, schema, and data quality. Our purpose is to support end-users in testing TRL models on proprietary data in two established SQL-centric tasks, i.e., Question Answering (QA) and Semantic Parsing (SP). We present QATCH (Query-Aided TRL Checklist), a toolbox to highlight TRL models’ strengths and weaknesses on relational tables unseen at training time. For an input table, QATCH automatically generates a testing checklist tailored to QA and SP. Checklist generation is driven by a SQL query engine that crafts tests of different complexity. This design facilitates inherent portability allowing the checks to be used by alternative models. We also introduce

<https://github.com/spapicchio/QATCH>

Vision Paper

Querying Large Language Models with SQL

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ABSTRACT

In many use-cases, information is stored in text but not available in structured data. However, extracting data from natural language (NL) text to precisely fit a schema, and thus enable querying, is a challenging task. With the rise of pre-trained Large Language Models (LLMs), there is now an effective solution to store and use information extracted from massive corpora of text documents. Thus, we envision the use of SQL queries to cover a broad range of data that is not captured by traditional databases (DBs) by tapping the information in LLMs. This ability would enable the hybrid querying of both LLMs and DBs with the SQL interface, which is more expressive and precise than NL prompts. To show the potential of this vision, we present one possible direction to ground it with a traditional DB architecture using physical operators for querying the underlying LLM. One promising idea is to execute some operators of the query plan with prompts that retrieve data from the LLM. For a large class of SQL queries, querying LLMs returns well structured relations, with encouraging qualitative results. We pinpoint several research challenges that must be addressed to build a DBMS that jointly exploits LLMs and DBs. While some challenges call for new contributions from the NLP field, others offer novel research avenues for the DB community.

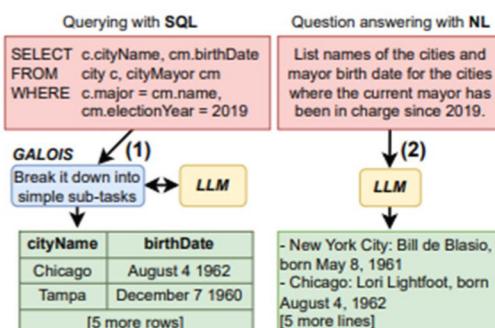


Figure 1: Querying a pre-trained LLM with SQL is different from question answering (QA). We assume a user SQL query as input. GALOIS executes the query, and obtains relations, by retrieving data from a LLM (1). The corresponding QA task consumes and produces natural language text (2). complex questions in a closed-book fashion [46] (example (2))

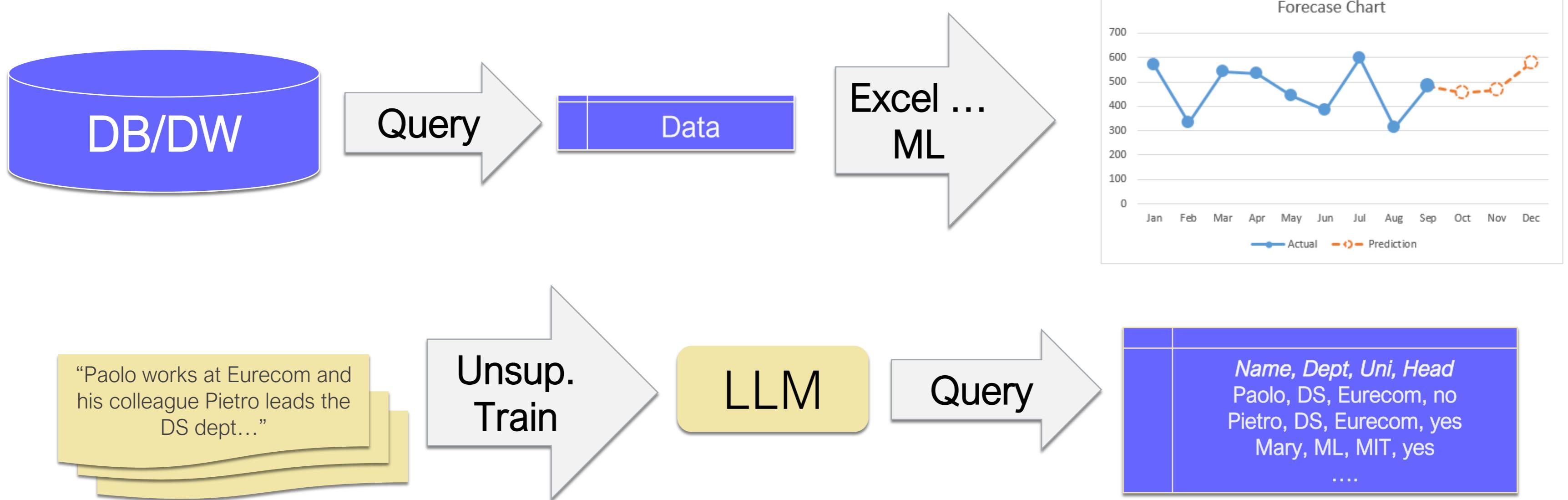
<https://gitlab.eurecom.fr/saeedm1/galois>

Solution

- LLMs store factual data, but
- Input: Not trained to execute SQL faithfully
→ use simple NL prompts to get data
- Engine: Struggle with complex tasks
→ chain of thought* with simple tasks
- Output: Not trained to return relations
→ tables by construction as in DBMS

* breaking a problem down into intermediate reasoning steps increases LLM abilities

If only LLMs had SQL powers...



Data applications: we could immediately query text documents!

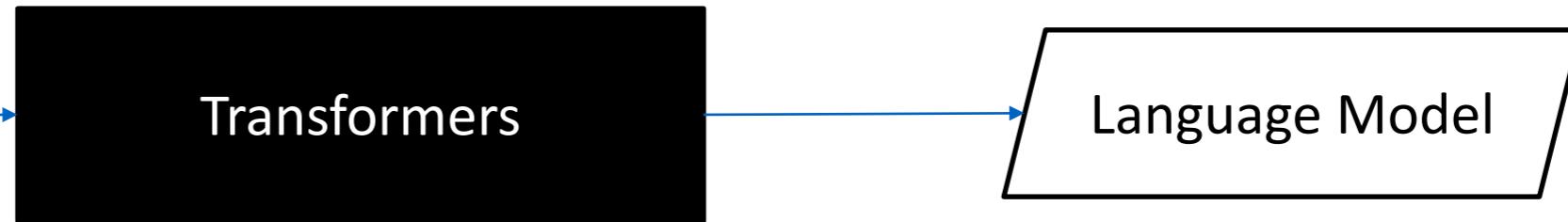
Evaluate on output data

1. Benchmark multiple tasks: QA output is data
2. Data comparison enables accurate metrics for SP: execute correct SQL and generated SQL on D, compare data outputs

		Cell precision	Cell recall	Tuple cardinality	Tuple constraint	Tuple order
Target	SELECT DISTINCT "emailisfree" FROM "fraud"					
Prediction	SELECT "emailisfree", "income" FROM "fraud"	0.5	1.0	0.2	0.0	-
Target	SELECT "emailisfree" FROM "fraud" ORDERBY ASC					
Prediction	SELECT "emailisfree" FROM "fraud" ORDERBY DESC	1.0	1.0	1.0	1.0	0.0
Target	SELECT * FROM "fraud"					
Prediction	SELECT "emailisfree" FROM "fraud"	1.0	0.10	1.0	0.0	-

How do LLMs work? Big Picture

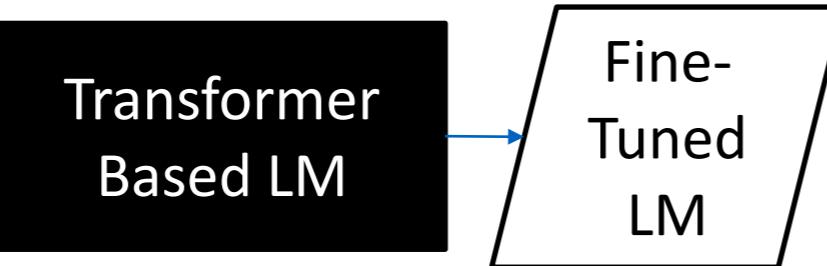
1- Develop LM through *pre-training* using large unlabeled text corpora



2- *Fine-tune* LM using (small) labeled training data for target application

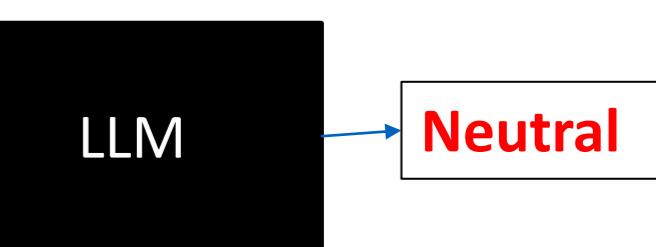
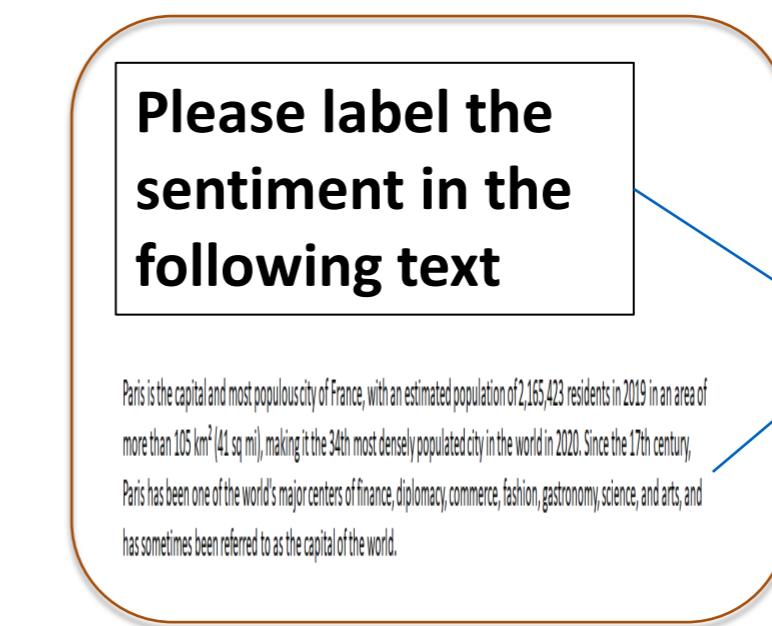
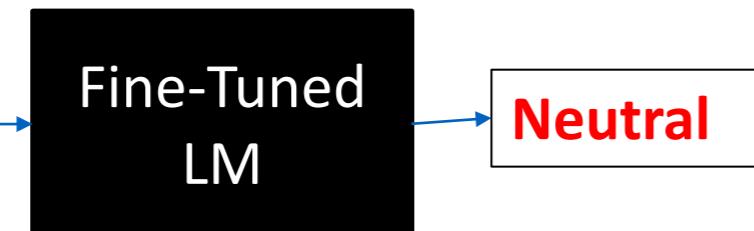
Sydney is the capital city of the state of New South Wales, and the most populous city in Australia and Oceania. Located on Australia's east coast, the metropolis surrounds Port Jackson and extends about 70 km (43.5 mi) on its periphery towards the Blue Mountains to the west, Hawkesbury to the north, the Royal National Park to the south and Macarthur to the south-west. Sydney is made up of 658 suburbs, spread across 33 local government areas. Residents of the city are known as "Sydneysiders". As of June 2020, Sydney's estimated metropolitan population was 5,361,466, meaning the city is home to approximately 66% of the state's population. Nicknames of the city include the 'Emerald City' and the 'Harbour City.'

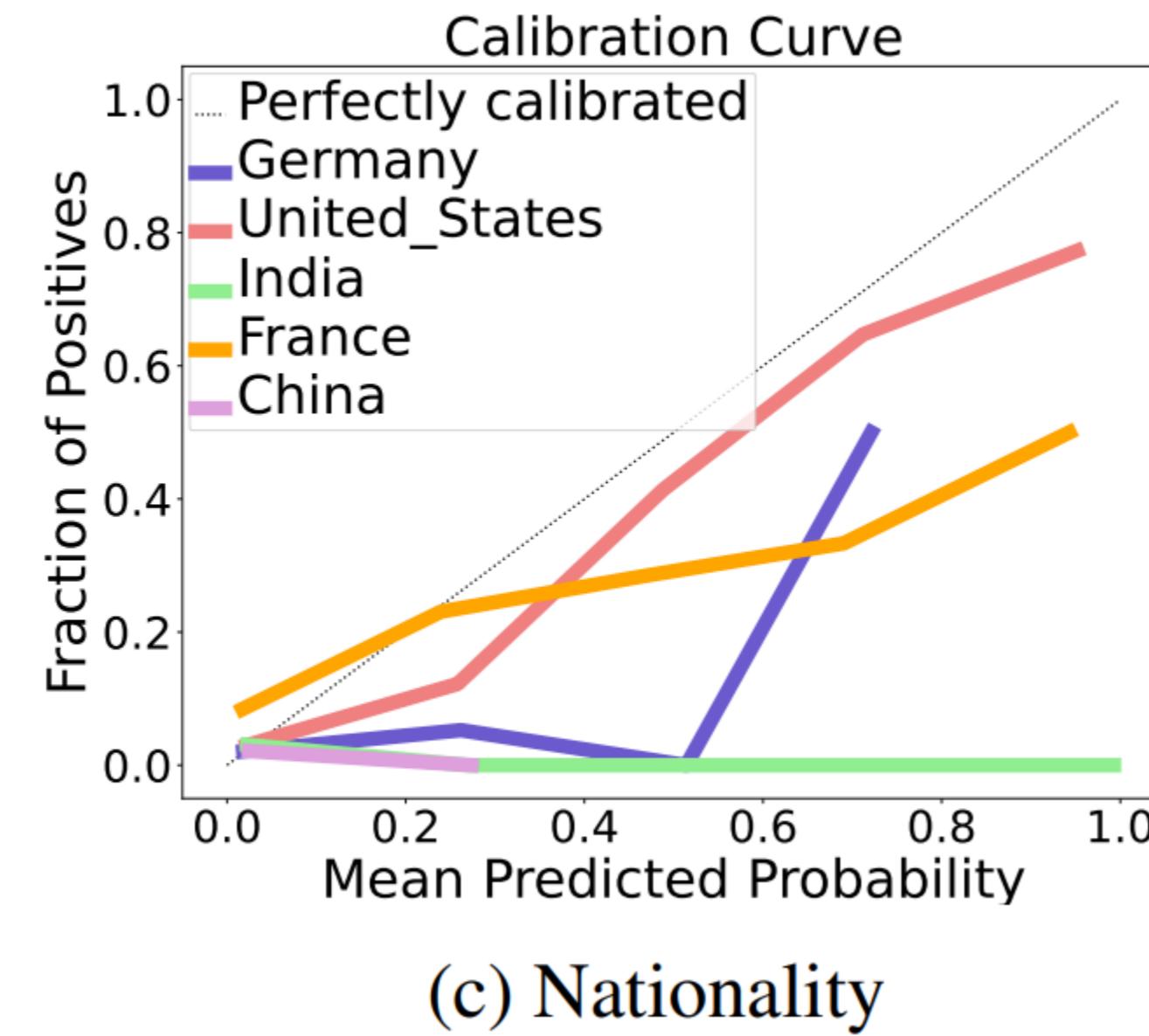
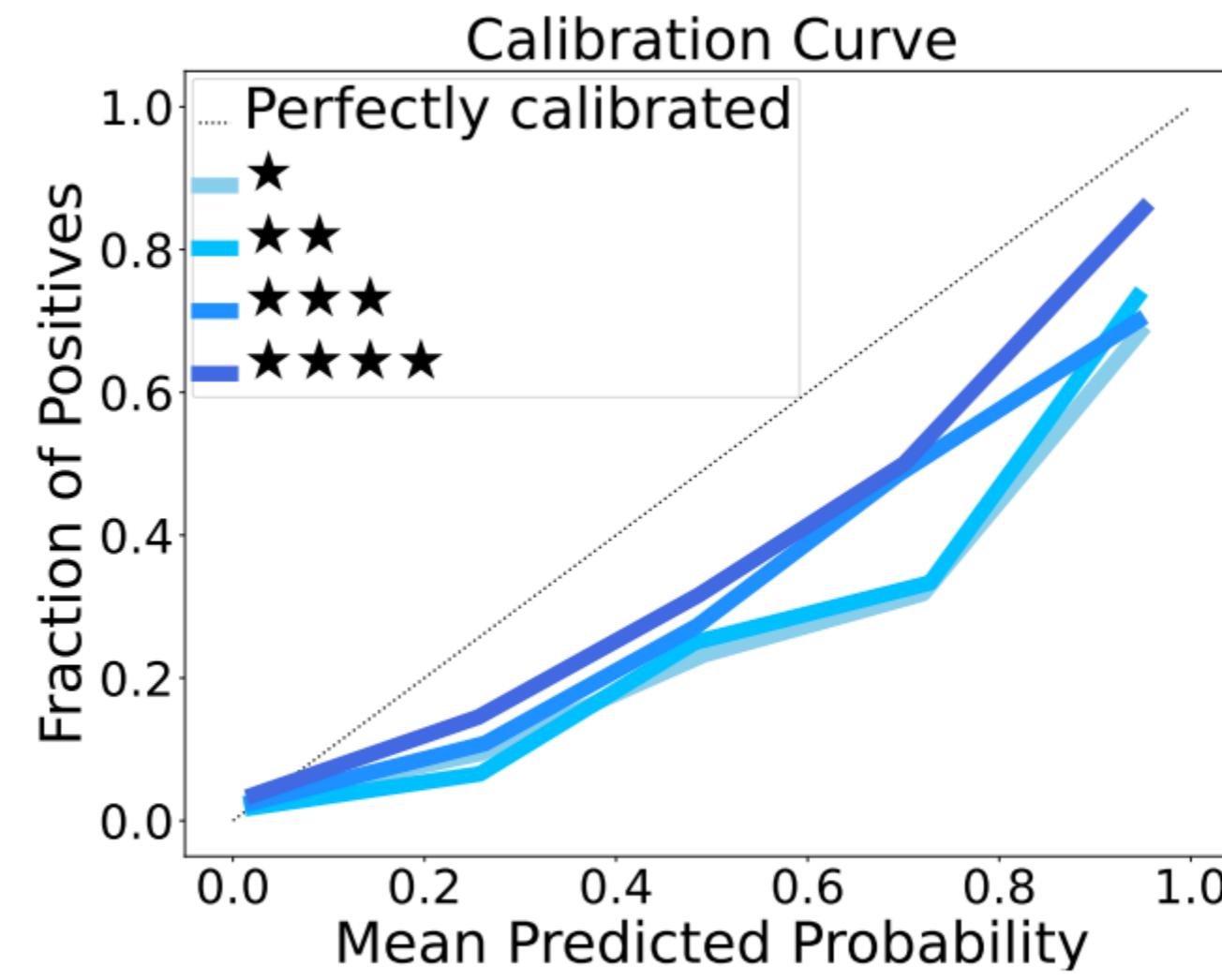
Neutral



3- Given a new paragraph, predict sentiment

Paris is the capital and most populous city of France, with an estimated population of 2,165,423 residents in 2019 in an area of more than 105 km² (41 sq mi), making it the 34th most densely populated city in the world in 2020. Since the 17th century, Paris has been one of the world's major centers of finance, diplomacy, commerce, fashion, gastronomy, science, and arts, and has sometimes been referred to as the capital of the world.





Background

Query LLM with *SQL queries*. Different from

- SP : translate NL questions to SQL
- TQA on tabular data: querying a relation with NL questions
- Neural DBs: textual facts encoded with a transformer and NL questions [Thorne et al., 2020] QA

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- Badaro et al. Transformers for Tabular Data Representation: A Survey of Models and Applications TACL 2023

SQL and LLMs Vows



“I will help your users write SQL queries”



“I will help your users benchmark data tasks”

[Papicchio et al, NeurIPS 2023]



“We will answer queries jointly”

[Saeed et al, EDBT 2024]

