Natural Language to SQL: State of the Art and Open Problems

Yuyu Luo, Nan Tang
HKUST(GZ)

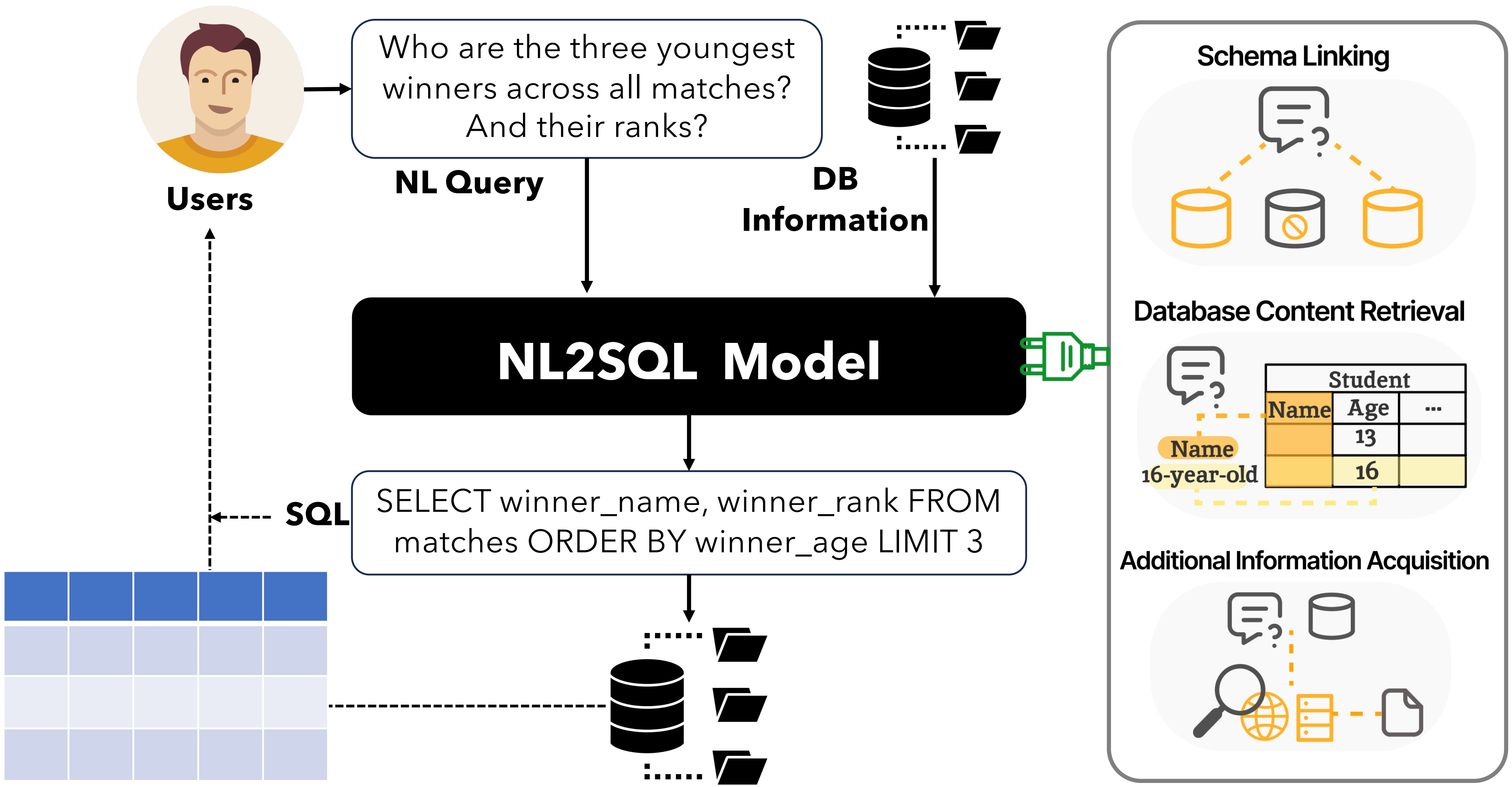
Guoliang Li
Tsinghua University

Ju Fan
Renmin Univ. of China

Chengliang Chai
Beijing Institute of Tech.

https://github.com/HKUSTDial/NL2SQL_Handbook
https://github.com/HKUSTDial/awesome-data-agents
yuyuluo@hkust-gz.edu.cn

NL2SQL (Text-to-SQL): Bridges Humans and Databases



Task Challenges

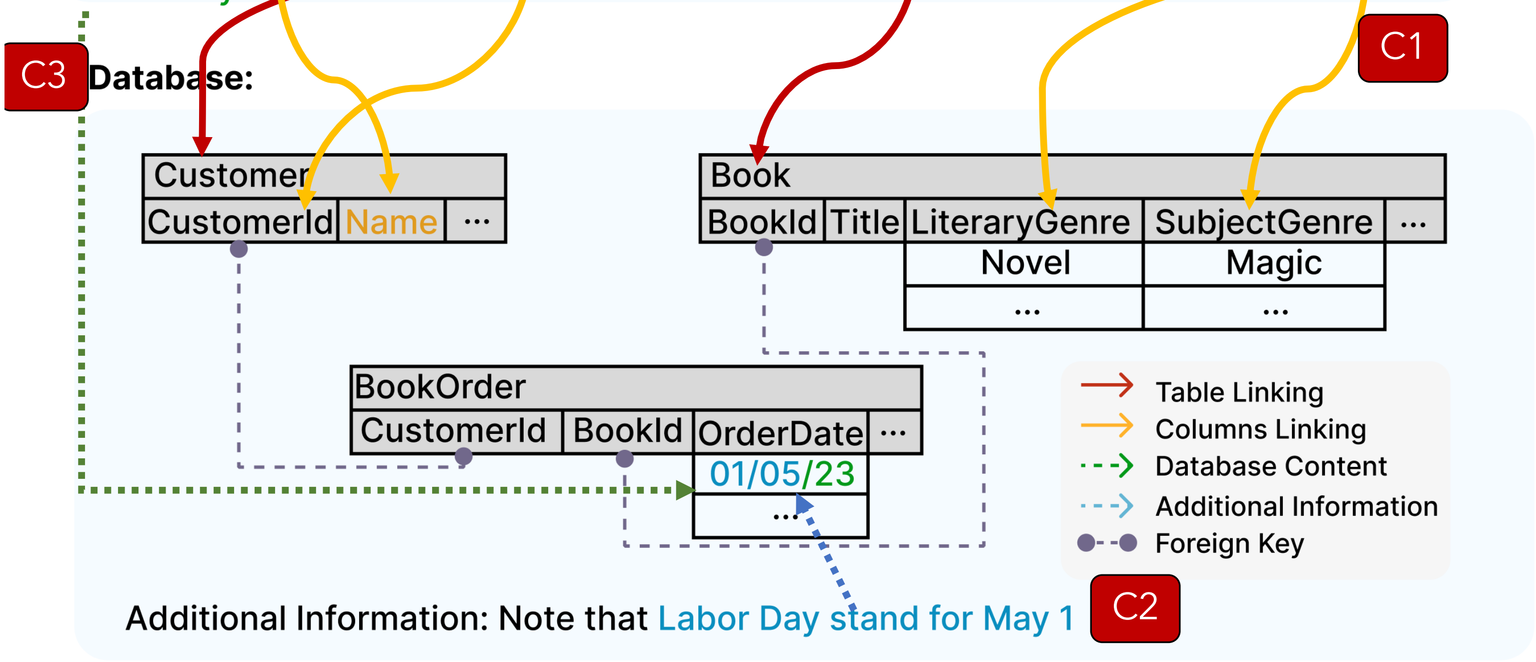
C1. Ambiguous NL Query

C2. Requiring Domain Knowledge

C3. Complex Database Schema

Natural Language Query:

Find the names of all customer who checked out books on exactly 3 different genres on Labor Day in 2023.



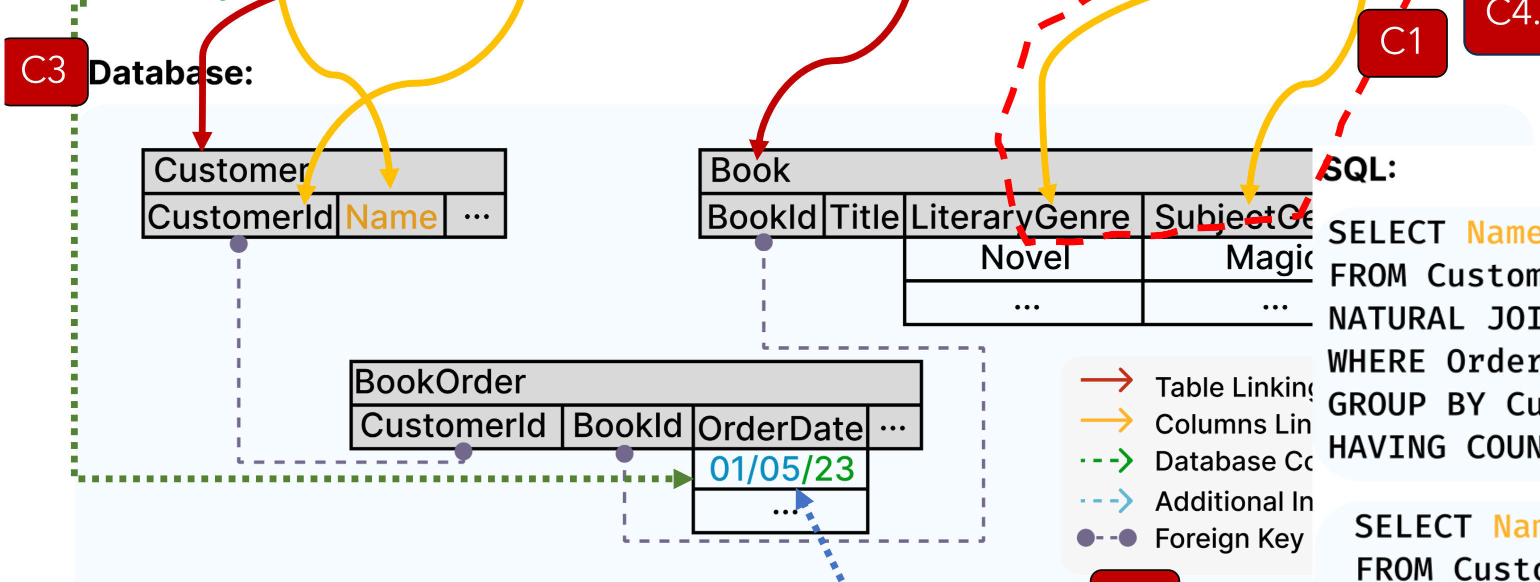
Task Challenges

- C1. Ambiguous NL Query
- C2. Requiring Domain Knowledge
- C3. Complex Database Schema
- C4. Multiple Possible SQL Queries

Natural Language Query:

Find the names of all customer who checked out books on exactly 3 different genres on Labor Day in 2023.

Database:



Additional Information: Note that Labor Day stand for May 1

C2

SQL:

```
SELECT Name
FROM Customer
NATURAL JOIN BookOrder NATURAL JOIN Book
WHERE OrderDate = '01/05/23'
GROUP BY CustomerId, Name
HAVING COUNT(DISTINCT SubjectGenre) = 3;
```

LiteraryGenre

C1

```
SELECT Name
FROM Customer
WHERE CustomerId = (SELECT CustomerId
FROM BookOrder NATURAL JOIN Book
WHERE OrderDate = '01/05/23'
GROUP BY CustomerId
HAVING COUNT(DISTINCT SubjectGenre)=3);
```

LiteraryGenre

Task Challenges

Natural Language Query:

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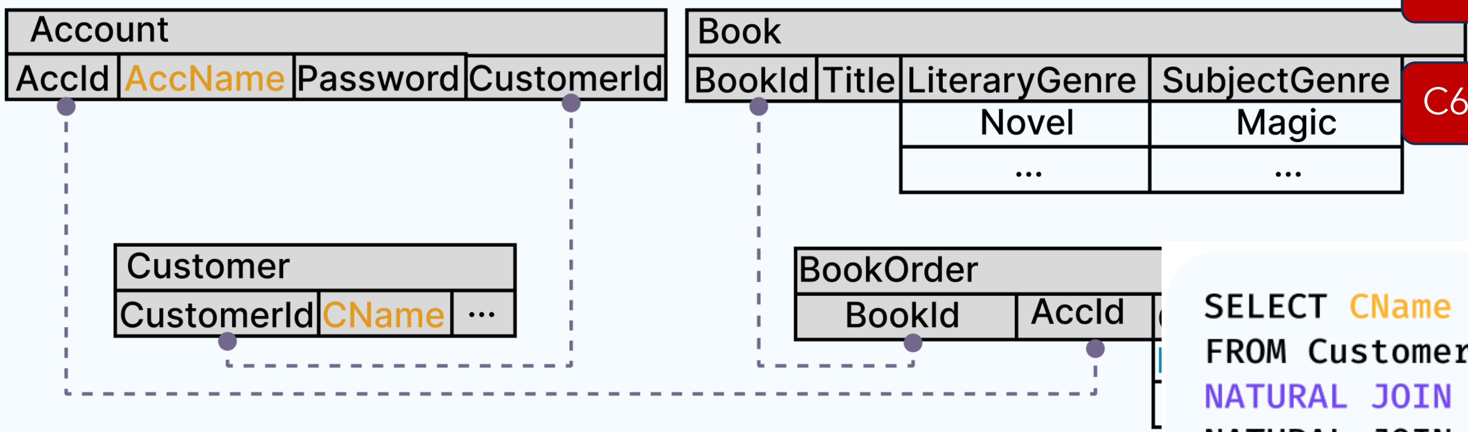


Additional Information: Note that Labor Day stand for May 1

```
SELECT CName
FROM Customer
NATURAL JOIN Account
NATURAL JOIN BookOrder
NATURAL JOIN Book
WHERE OrderDate = 'May 1st 2023'
GROUP BY CustomerId, CName
HAVING COUNT(DISTINCT SubjectGenre) = 3;
```

C1. Ambiguous NL Query

C2. Requiring Domain Knowledge

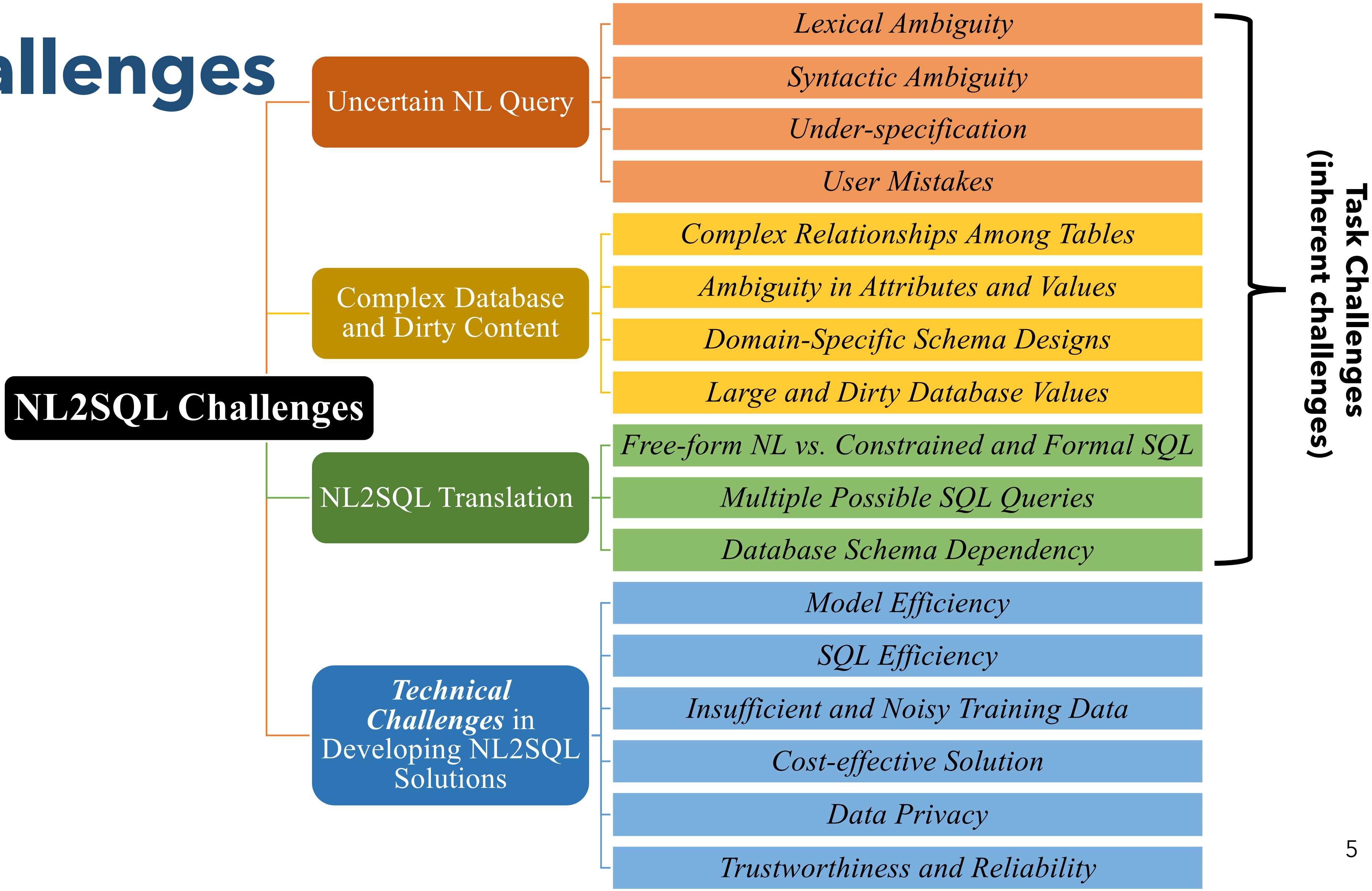
C3. Complex Database Schema

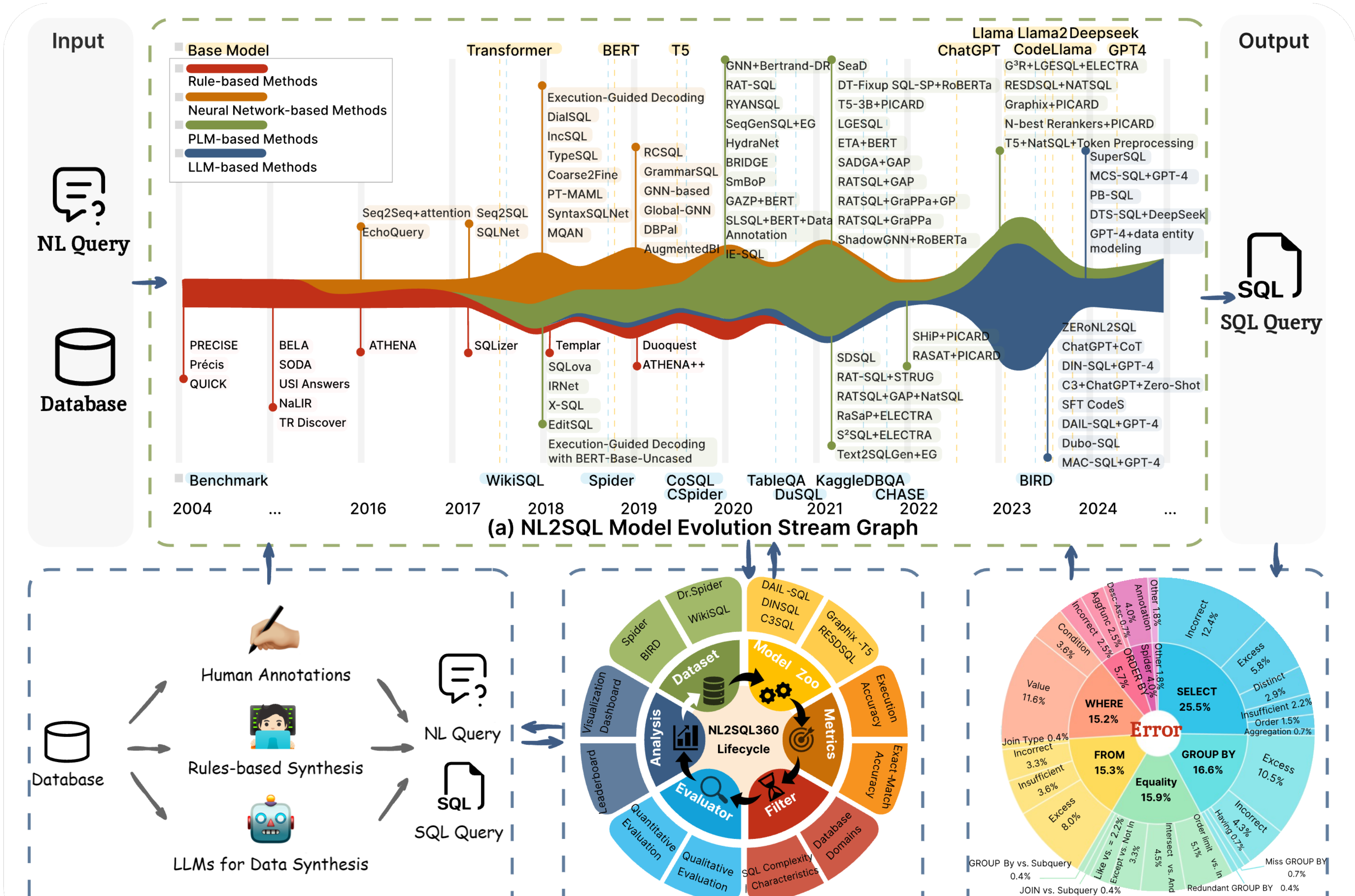
C4. Multiple Possible SQL Queries

C5. Database Schema Dependency

C6. Database Domain Adaption

Challenges


NL2SQL Challenges
Uncertain NL Query
Lexical Ambiguity
Syntactic Ambiguity
Under-specification
User Mistakes
Complex Database and Dirty Content
Complex Relationships Among Tables
Ambiguity in Attributes and Values
Domain-Specific Schema Designs
Large and Dirty Database Values
NL2SQL Translation
Free-form NL vs. Constrained and Formal SQL
Multiple Possible SQL Queries
Database Schema Dependency
Technical Challenges in Developing NL2SQL Solutions
Model Efficiency
SQL Efficiency
Insufficient and Noisy Training Data
Cost-effective Solution
Data Privacy
Trustworthiness and Reliability
Task Challenges (inherent challenges)



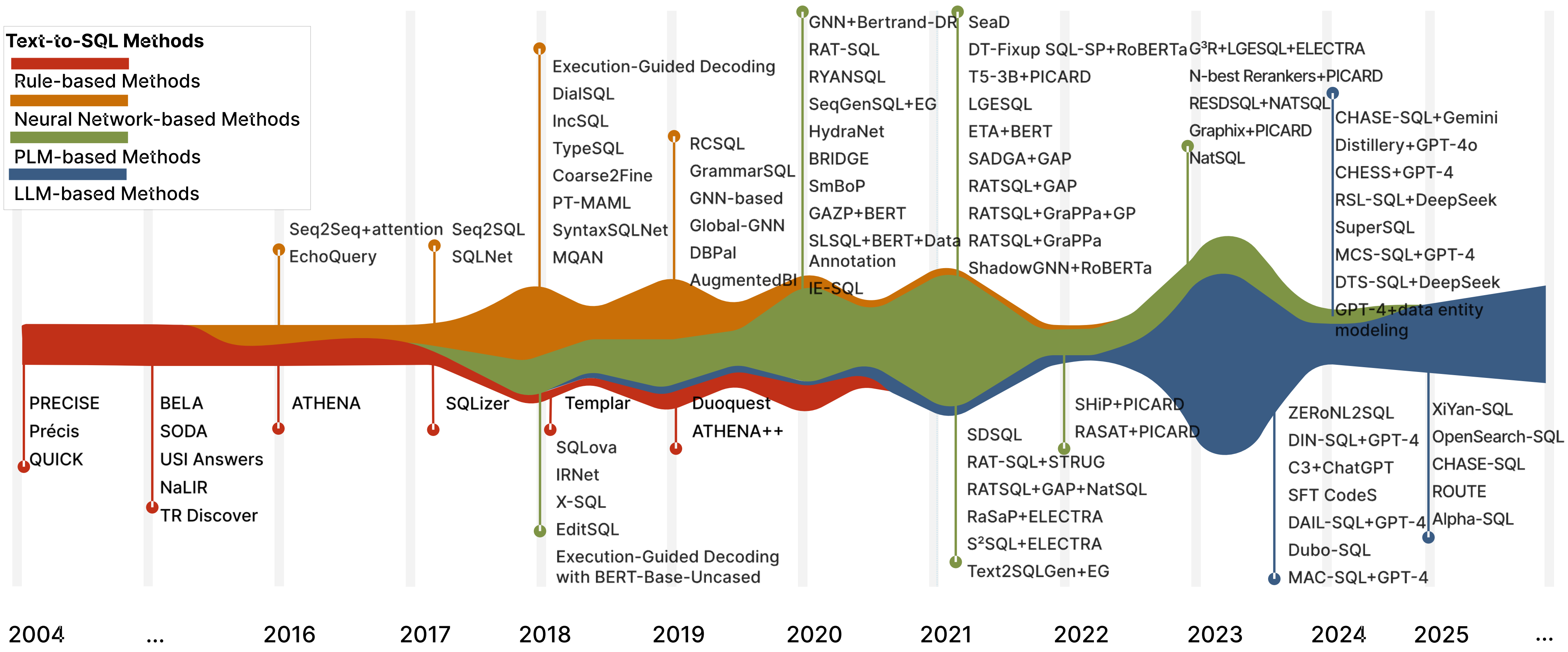
(a) NL2SQL Model Evolution Stream Graph

(b) Benchmarks and Training Data Synthesis

(c) NL2SQL Evaluation

(d) NL2SQL Error Analysis

Where Are We?

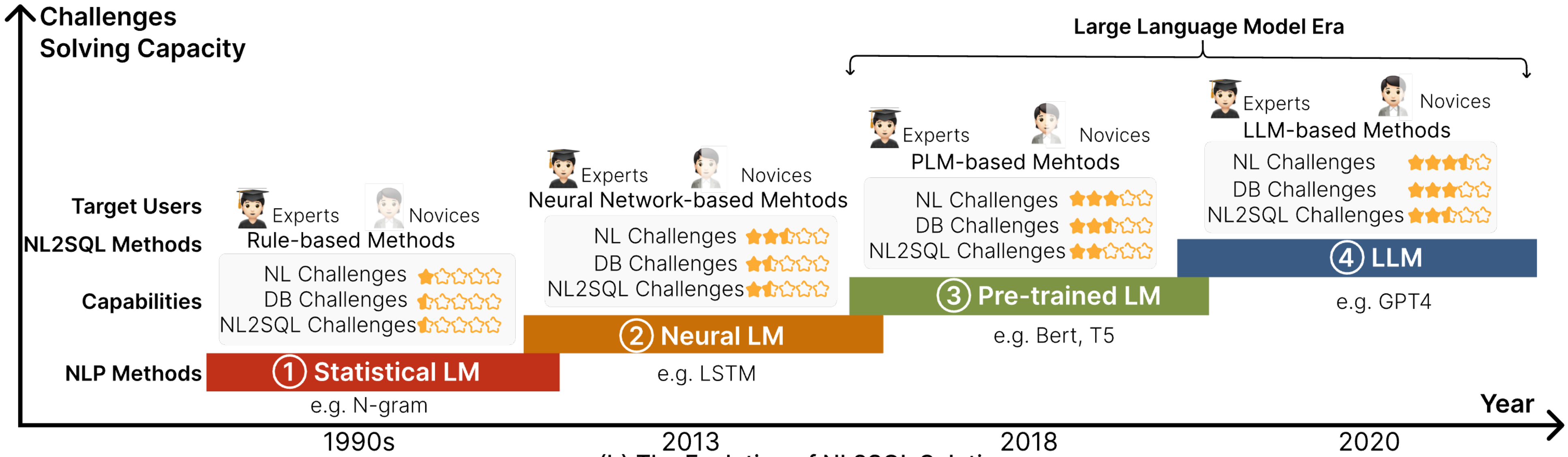


https://github.com/HKUSTDial/NL2SQL_Handbook

Where Are We?

Type \ Level	★	★★	★★★	★★★★	★★★★★
NL Challenges	Token-level Recognition	Synonym Recognition	Semantic Understanding	Domain Knowledge Query Recognition	Multi-turn Dialogues
DB Challenges	Single-table Queries	Simple Multiple Tables	Multiple Tables with Complex Schema	Massive Tables and Values	Real-world Databases
NL2SQL Challenges	Single-table SQL	Multi-table SQL	Advanced SQL Feature Support	Adapting to Changed Schema	Efficient SQL Generation

(a) The Definition of Challenges Levels



(b) The Evolution of NL2SQL Solutions

Figure: The Evolution of NL2SQL Solutions from the Perspective of Language Models.

An Overview of NL2SQL Benchmarks

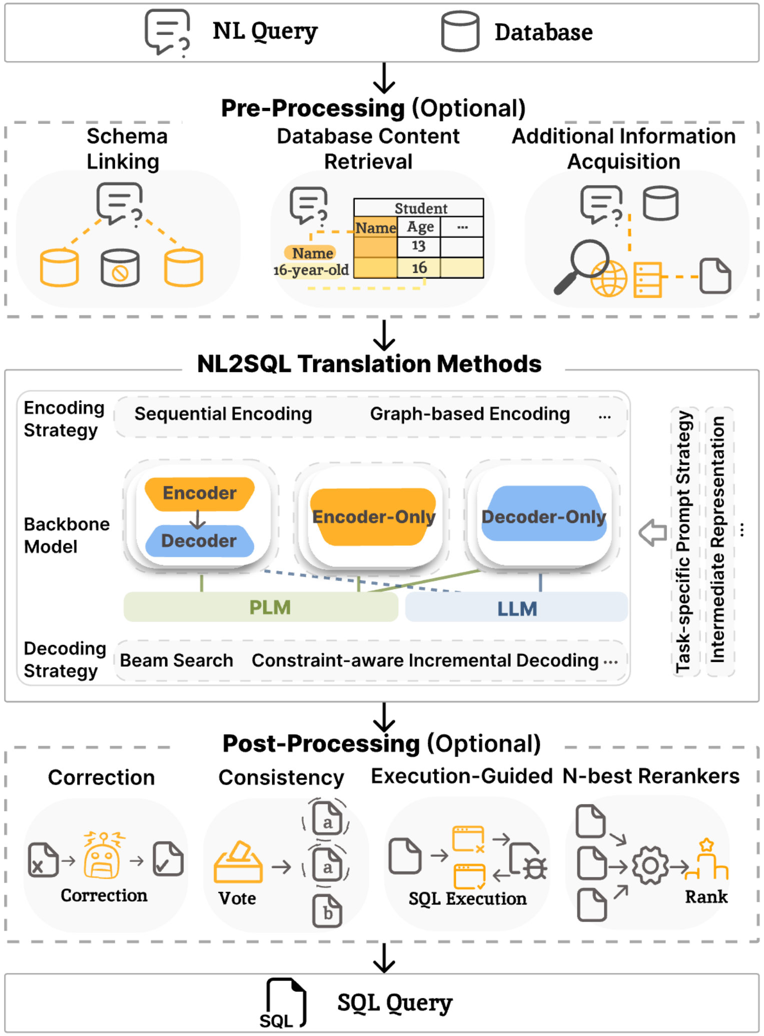
✍️ Human Annotations · 🧑‍💻 Rules-based Synthesis · 🤖 LLMs for Data Synthesis

Milestone \ Timeline	Before 2017	2017	2018	2019	2020	2021	2022	2023	2024
Single-domain	✍️ATIS ✍️GeoQuery ✍️Restaurant ✍️Academic	✍️IMDb ✍️Yelp ✍️Scholar	✍️Advising		🧑‍💻✍️MIMISQL ✍️FIBEN	✍️SEDE			🧑‍💻✍️ScienceBenchmark ✍️BULL ✍️BookSQL
Cross-domain		✍️WikiSQL	✍️Spider	✍️SParC ✍️CoSQL ✍️CSpider	✍️SQLUALL ✍️ViText2SQL 🧑‍💻✍️DuSQL	✍️CHASE ✍️Spider-Syn 🧑‍💻MT-TEQL ✍️KaggleDBQA ✍️Spider-DK ✍️Spider-Realistic 🧑‍💻✍️PortugueseSpider	✍️PAUQ ✍️knowSQL	✍️BIRD 🧑‍💻✍️Dr.Spider 🤖✍️AmbiQT	✍️Archer
Multi-turn				✍️SParC ✍️CoSQL		✍️CHASE			
Robustness						✍️Spider-Syn ✍️Spider-Realistic		🧑‍💻✍️Dr.Spider	
Knowledge						✍️KaggleDBQA ✍️Spider-DK		✍️BIRD	✍️Archer
Efficiency								✍️BIRD	
Ambiguity								🤖✍️AmbiQT	

NL2SQL Benchmark Discussion & Insights

- **From the Redundancy Measure perspective**
  - We observe a trend from early datasets to recent ones where datasets have grown in size, including increases in the number of questions and unique queries.
- **From the Database Complexity perspective**
  - The number of databases (and tables) in datasets correlates with the tasks (e.g., Single-domain vs. Robustness) they serve.
- **From the Query Complexity perspective**
  - Recent datasets show a growing emphasis on Scalar Functions and Mathematical Computations in SQL queries, which introduces challenges in SQL generation structure not seen in earlier datasets.

Tutorial Roadmap



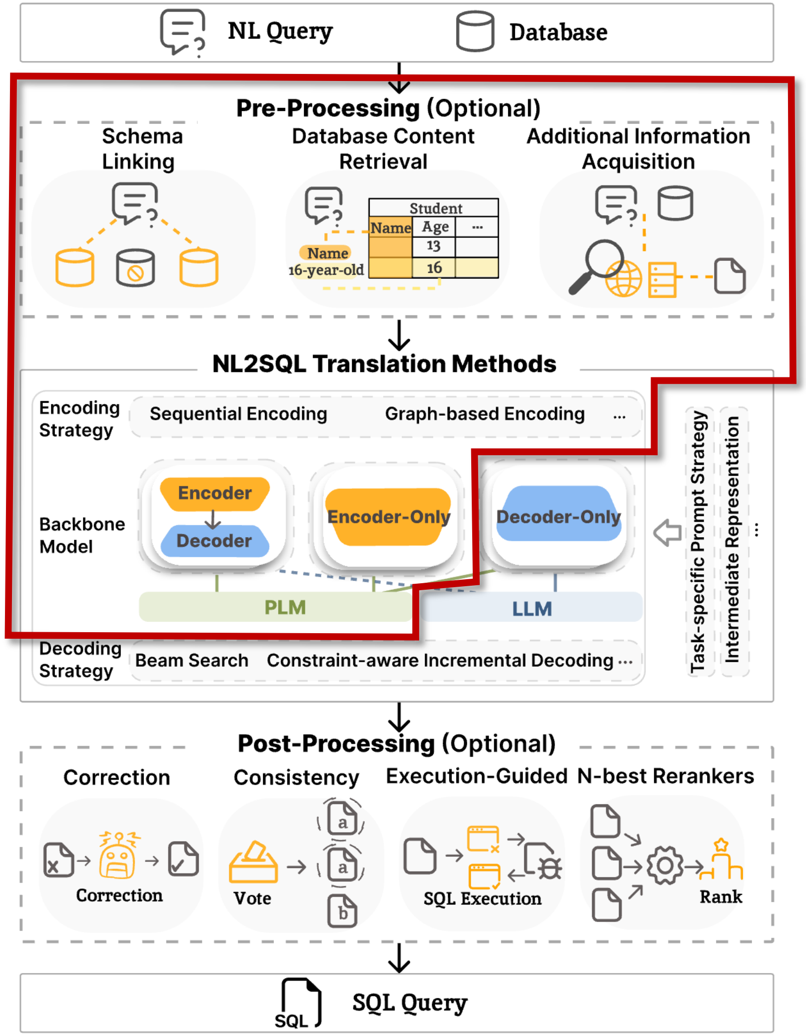
Tutorial Roadmap

NL2SQL Solutions with PLMs and LLMs

Q1: How to design prompts and train PLMs/LLMs for NL2SQL?

- Prompt Settings: Few-shot/Zero-shot
- Training: SFT / RL

Q2: How effective are the core pre-processing techniques?



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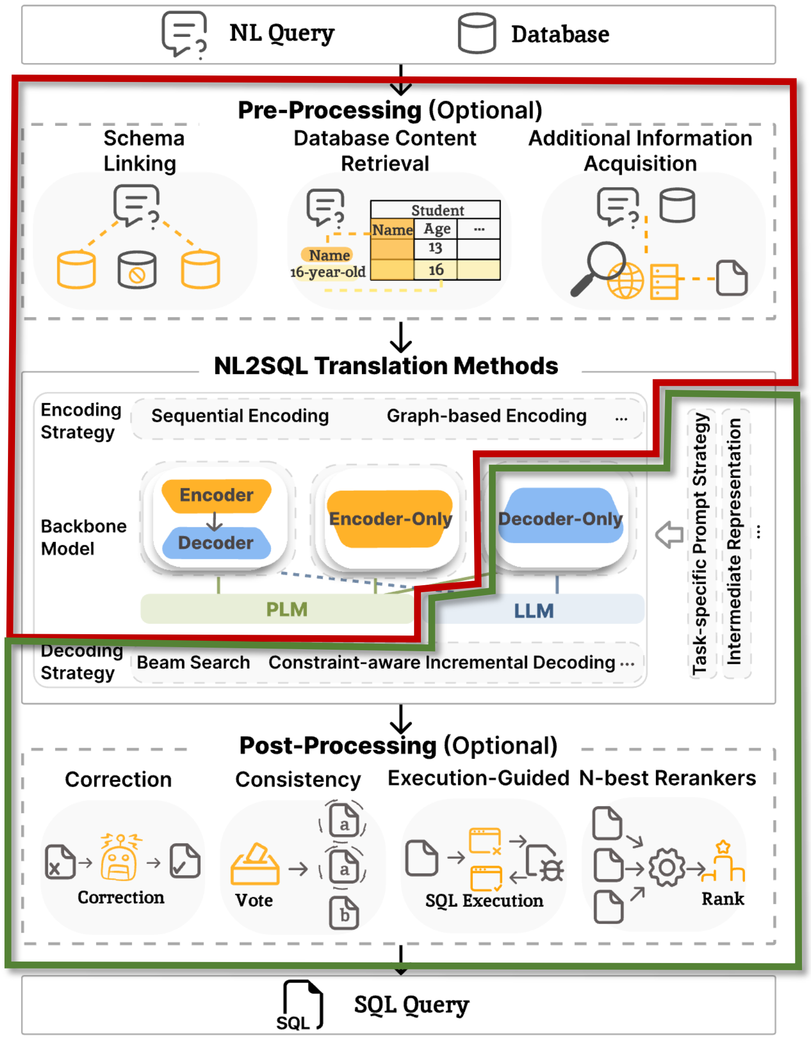


Q3: How can we build a robust NL2SQL Agent with LLMs?

Q4: From NL2SQL Agents to Data Agents: Where are we going?

NL2SQL Solutions with (LLM) Agents

Tutorial Outline

- Problem Definition, Preliminaries, Benchmarks
- **NL2SQL Solutions with PLMs and LLMs**
- NL2SQL Solutions with LLM Agents
- Open Problems

NL2SQL Solutions with PLMs and LLMs

- Rather than categorizing existing solutions by the specific PLMs or LLMs they employ, we classify them according to the practical considerations of different applications.

- **Consideration #1:** The resources or costs required to develop NL2SQL
  - Computational resources (e.g., GPUs) for training
  - The monetary cost of calling LLMs (e.g., GPT) APIs

Model	Resources
RESDSQL + NatSQL	A100*1
CodeS	A800*8
Granite-20B-Code	A100*8+H100*8

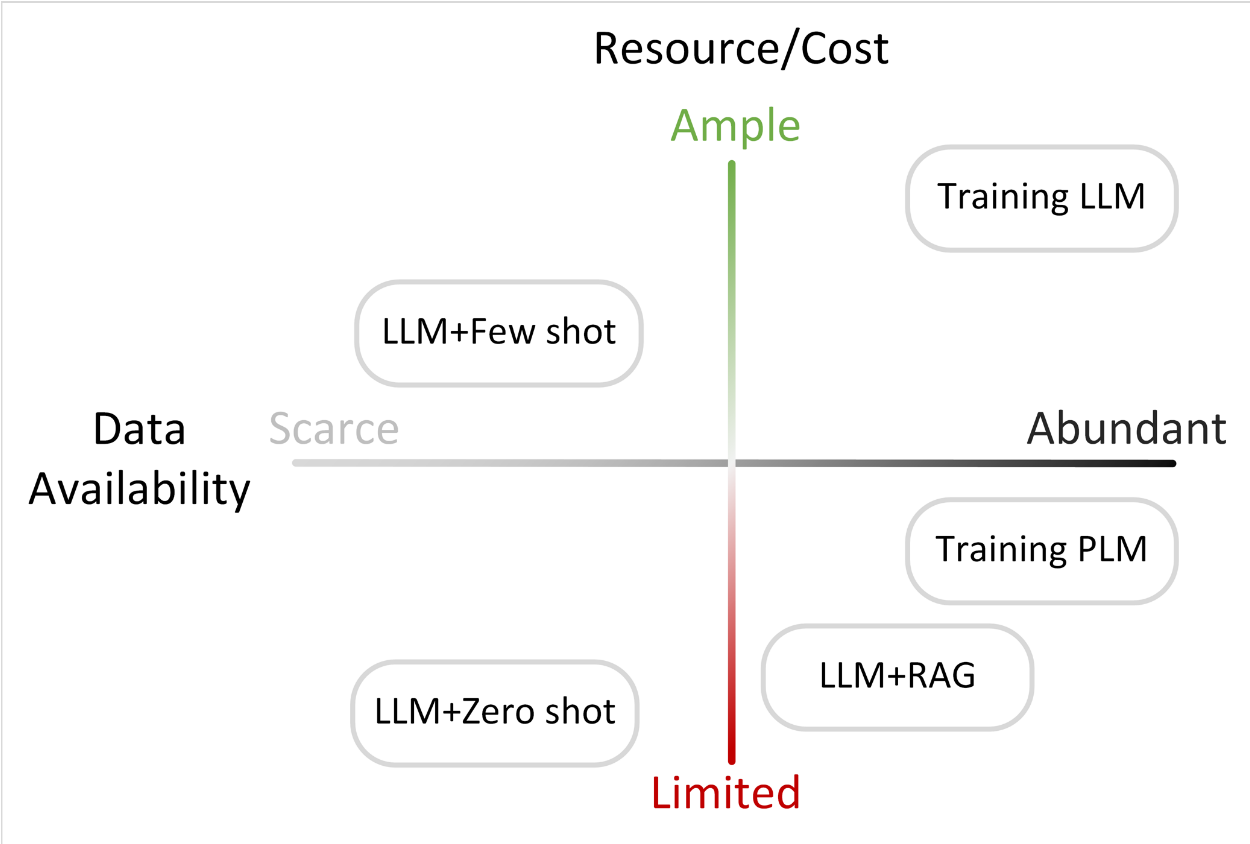
Model	Input	Output
GPT-3.5-turbo	$0.50 / 1M tokens	$0.50 / 1M tokens
gpt-4o	$5 / 1M tokens	$15 / 1M tokens

NL2SQL Solutions with PLMs and LLMs

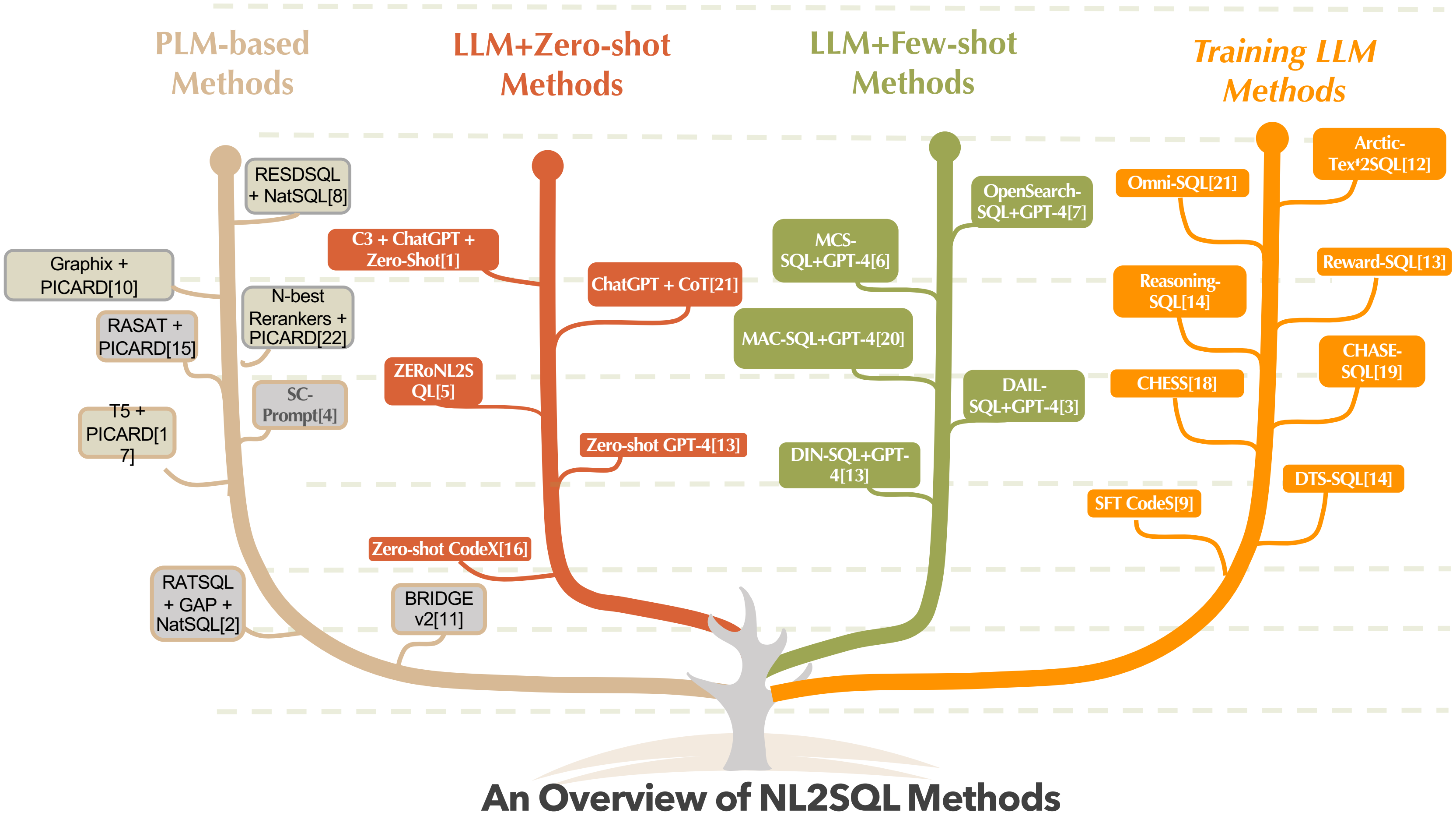
- Rather than categorizing existing solutions by the specific PLMs or LLMs they employ, we classify them according to the practical considerations of different applications.
- **Consideration #2:** The amount of data required for training NL2SQL
  - E.g., the CodeS model collects:
    - SQL-related data (11GB), NL-to-code data (6GB), and NL-related data (4.5GB)
  - E.g., the existing benchmarks paid much efforts to collect annotated data
    - Spider has 10,181 NL-SQL pairs
    - BIRD has 12,751 NL-SQL pairs

Categorization of Existing Studies

- We categorize the existing studies of NL2SQL Solutions with PLMs and LLMs based on two dimensions: (1) **Resources/Cost; (2) Data availability**



Categorization of Existing Studies



Few-Shot NL2SQL

- **Basic Idea**
  - Utilizing the **in-context learning** capability of LLMs to generate SQL queries from a few **demonstration examples**.
- **Key Characteristics**
  - Requirement of a handful of examples → Reduction of annotation costs
- **Technical Challenges**
  - How to represent the structure of the underlying database
  - How to select and organize the demonstration examples

Few-Shot NL2SQL

- **DAIL-SQL**, by Alibaba
  - **Database Representation:** representing database schema as CREATE TABLE statements with complete primary/foreign key information
  - **Example Selection:** combining question similarity and SQL query similarity, prioritizing examples with both similar questions and similar SQL structures
  - **Example Organization:** only preserving question-to-SQL mappings while removing token-expensive database schema from examples

```
Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request.

### Instruction:
Write a sql to answer the question "How many continents are there?"

### Input:
continents(ContId, Continent)
countries(CountryId, CountryName, Continent)

### Response:
SELECT
```

```
/* Some example questions and corresponding SQL queries are provided based on similar problems: */
/* Answer the following: How many authors are there? */
SELECT count(*) FROM authors

/* Answer the following: How many farms are there?. */
SELECT count(*) FROM farm

${TARGET_QUESTION}
```

Gao, Dawei, et al. "Text-to-sql empowered by large language models: A benchmark evaluation." PVLDB, 17(5): 1132-1145, 2024.

Zero-shot NL2SQL

- **Zero-shot NL2SQL**
  - A practical scenario for NL2SQL is that oftentimes, for a new test environment, **annotated NL-SQL pairs** are time-consuming and labor-intensive to acquire, and thus is not available

- Existing approaches may not perform well in this zero-shot NL2SQL setting, as the new test environments may be very different
  - **New databases:** an NL2SQL model trained on the Spider benchmark may not perform well for domain-specific (e.g., academic or financial) databases
  - **New linguistic phenomena:** varying linguistic phenomena (e.g., abbreviations, synonyms, etc.) in the test environments

Can we have a NL2SQL model generalizable to new test environments

Limitation of Existing Solutions

- The LM-based approaches to NL2SQL fall into two categories
  - **Pre-trained language models (PLMs)** such as BART and T5
  - **Large language models (LLMs)** such as GPT and PaLM
- PLM-based methods (e.g., T5) may have limited *generalizability* in natural language reasoning in the zero-shot setting

(a) A Text Question Q

Which course has the highest score for the student named timothy ward?

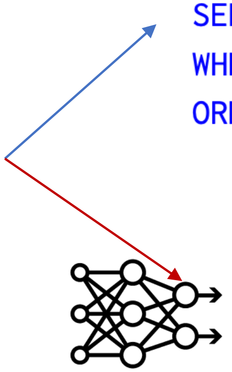
(b) Snippets of a Database D

Course

id	course	teacher
001	math	jordy wu
…	…	…

Student

id	given_name	last_name	score	course
1	timmy	ward	92	math
…	…	…	…	…



(c) The Ground-truth SQL Query S w.r.t. Q

```
SELECT course FROM Student
WHERE given_name = 'timmy' AND last_name = 'ward'
ORDER BY score LIMIT 1;
```

(d) An SQL query S' translated by an SLM

```
SELECT course FROM Student
WHERE given_name = 'timothy ward'
ORDER BY score LIMIT 1;
```

Limitation of Existing Solutions

- The LM-based approaches to NL2SQL fall into two categories
  - **Pre-trained language models (PLMs)** such as BART and T5
  - **Large language models (LLMs)** such as GPT and PaLM
- LLMs (e.g., gpt-3.5-turbo-0613) are capable of NL reasoning, but may not achieve precise alignment on schema and data value due to "hallucination"

(a) A Text Question Q

Which course has the highest score for the student named timothy ward?

(b) Snippets of a Database D

Course

id	course	teacher
001	math	jordy wu
…	…	…

Student

id	given_name	last_name	score	course
1	timmy	ward	92	math
…	…	…	…	…

(c) The Ground-truth SQL Query S *w.r.t.* Q

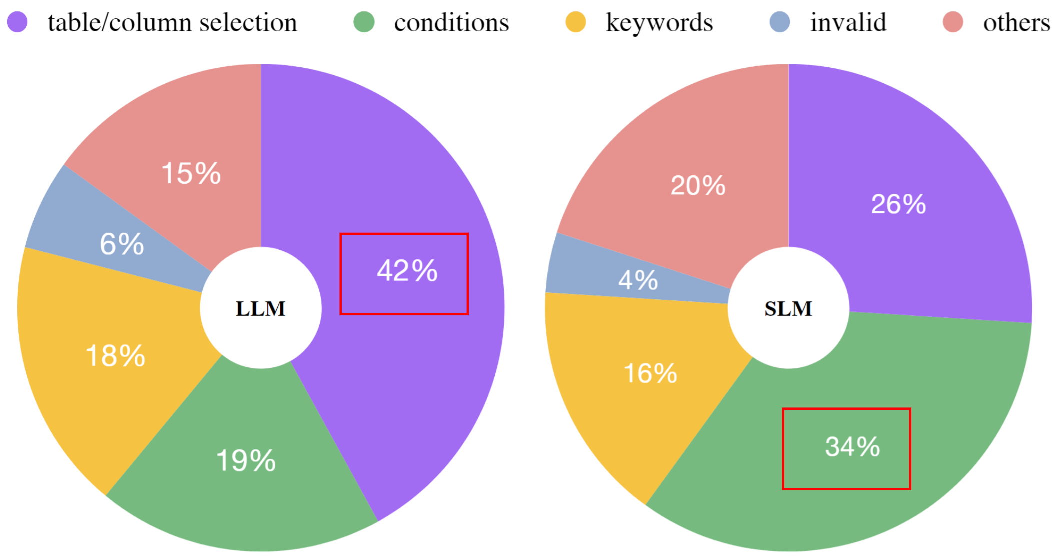
```
SELECT course FROM Student
WHERE given_name = 'timmy' AND last_name = 'ward'
ORDER BY score LIMIT 1;
```

(e) An SQL query S'' translated by an LLM

```
SELECT Course.course, Student.score
FROM Student JOIN Course ON Student.id = Course.id
WHERE given_name = 'timothy' AND last_name = 'ward'
ORDER BY score LIMIT 1;
```

Limitations of Existing Solutions

- A systematic **error analysis** that illustrates insights into limitations of the fine-tuned T5 and vanilla GPT-3.5



(a) The error distribution of LLMs

(b) The error distribution of SLMs

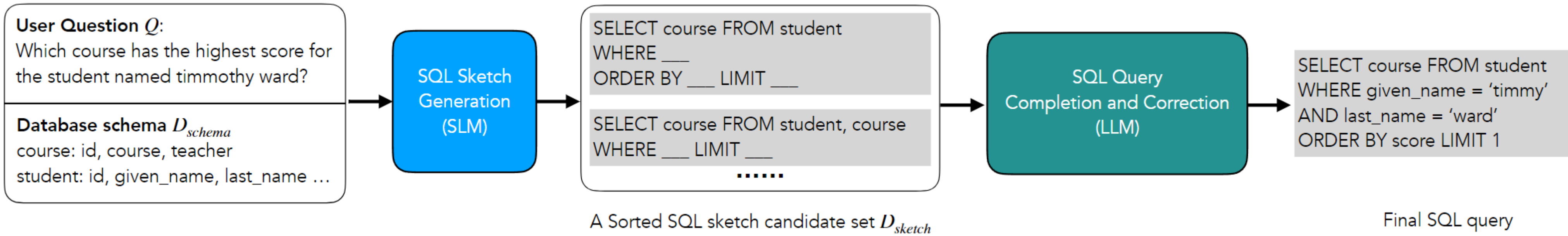
200 error examples sampled from Dr.Spider (GPT-3.5 and T5 respectively)

	LLMs	PLMs
👍	Complex NL Reasoning	Schema Alignment
👎	Schema Alignment	Complex NL Reasoning

Can we combine PLMs and LLMs to solve Zero-shot NL2SQL?

The ZeroNL2SQL Framework

- ZeroNL2SQL breaks down the NL2SQL task into smaller sub-tasks
- **Sub-task 1: SQL Sketch Generation**
  - Utilizing PLMs to generate a SQL sketch, with attributes to SELECT, tables in FROM, and necessary keywords (e.g., ORDER BY) for composing the SQL query
- **Sub-task 2: SQL Query Completion and Correction**
  - Utilizing LLMs to complete the missing information in the SQL sketch and generate complete SQL queries, e.g., aligning with data values from the database



Zihui Gu, **Ju Fan**, Nan Tang, Songyue Zhang, Yuxin Zhang, Zui Chen, Lei Cao, Guoliang Li, Sam Madden, Xiaoyong Du: Combining Pre-Trained Language Models and Large Language Models for Zero-Shot NL2SQL Generation. **VLDB 2024**.

Training LLMs for NL2SQL

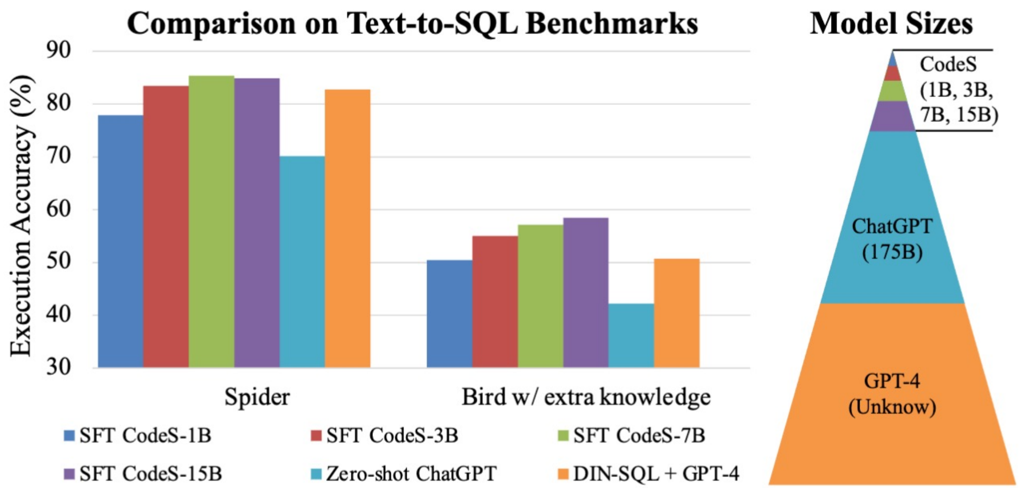
- **Basic Idea**
  - Training LLMs in two stages: (1) performing continual pre-training (**CPT**) on SQL-related corpora to strengthen SQL knowledge, and (2) conducting supervised fine-tuning (**SFT**) on curated NL2SQL datasets to specialize in SQL geneartion.

- **Key Characteristics**
  - **Enhanced SQL domain knowledge:** CPT injects rich understanding of SQL syntax and semantics.
  - **Superior reasoning capabilities:** SFT enables models to gain stronger ability to parse complex natural language and map it to SQL queries.

Training LLMs for NL2SQL

- **CodeS** proposes to develop a new text-to-SQL model built on **open-source** models.

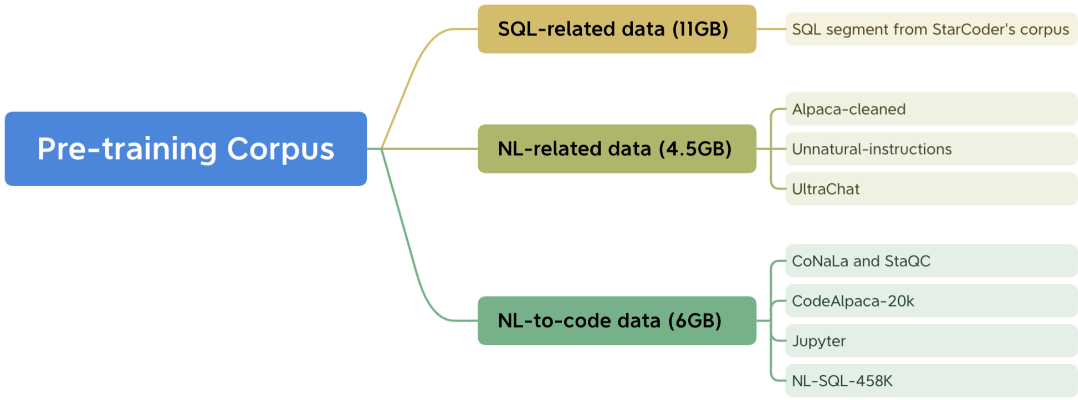
- **Solution Overview:**
  - CodeS introduces a series of open-source language models (ranging from 1B to 15B parameters) specifically tailored for text-to-SQL tasks
  - Built on top of StarCoder, CodeS is further enhanced through CPT and SFT on a curated 21.5GB SQL-centric corpus.



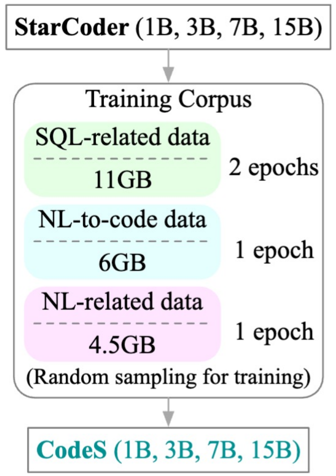
Li, Haoyang, Jing Zhang, Hanbing Liu, Ju Fan, Xiaokang Zhang, Jun Zhu, Renjie Wei, Hongyan Pan, Cuiping Li, and Hong Chen. "Codes: Towards building open-source language models for text-to-sql." Proceedings of the ACM on Management of Data 2, no. 3 (2024): 1-28.

Data Collection for CPT and SFT

- **Curated CPT corpus:** 11GB SQL-related data, 6GB NL-to-code data, and 4.5GB NL-related data
- **SFT corpus:** NL-SQL-458K, containing 458K SQL queries paired with corresponding natural language questions
- **Enhanced capabilities:** improvements in both SQL generation and natural language understanding



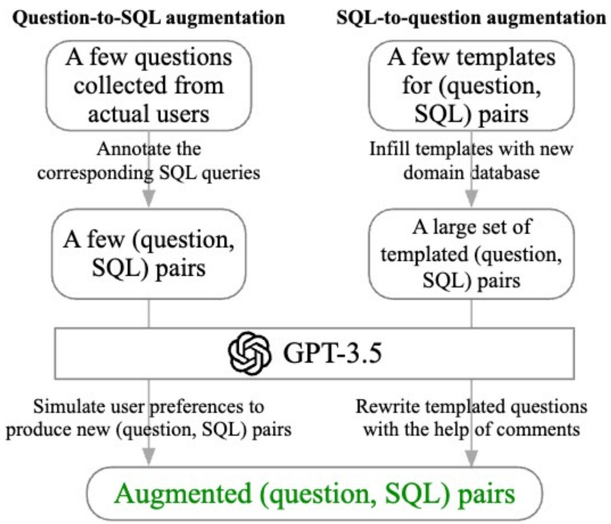
Step 1: Collect SQL-related corpus



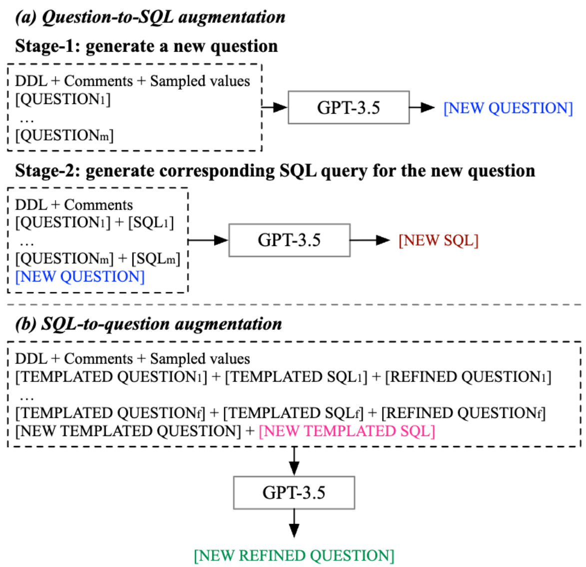
Step 2: Incremental pre-training

Data Augmentation for SFT

- **Question-to-SQL:** starting from real user questions, manually annotate, and expanding using GPT-3.5
- **SQL-to-Question:** leveraging Spider-style templates, populating with new domain schemas, and refining via GPT-3.5
- **Enhanced capabilities:** rapid domain adaptation with minimal annotation effort



Bi-directional augmentation



Prompt formats used in data augmentation.

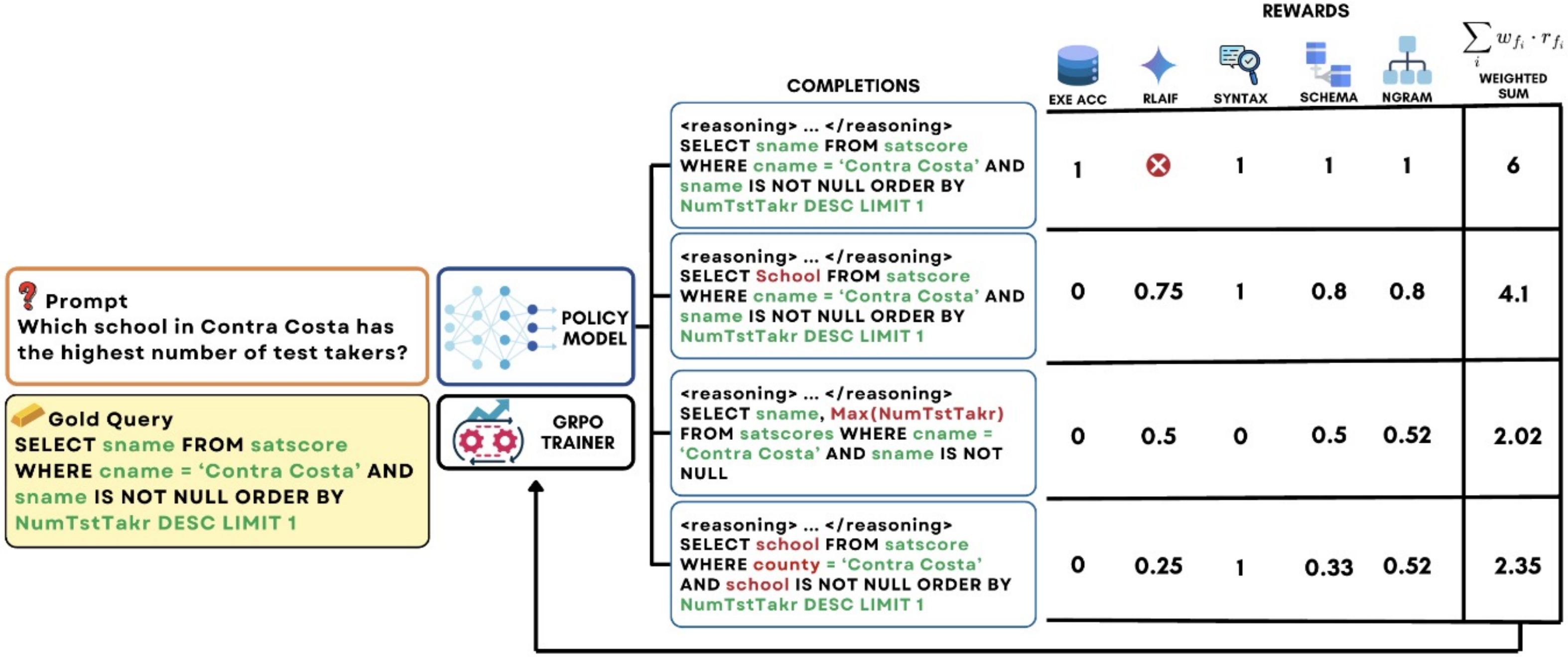
RL-based Training for NL2SQL

- Reinforcement learning based training for NL2SQL leverages execution feedback and reasoning signals, and applies techniques such as DPO, GRPO, and reward-based optimization to generate SQL queries.

- **Key Characteristics:**
  - **Stronger Reasoning:** RL fosters structured, step-by-step reasoning for better SQL generation
  - **Richer Feedback:** dedicated rewards overcome sparsity, guiding models more effectively
  - **Higher Accuracy & Generalization:** outperform larger models across benchmarks at lower cost

RL-based Training for NL2SQL

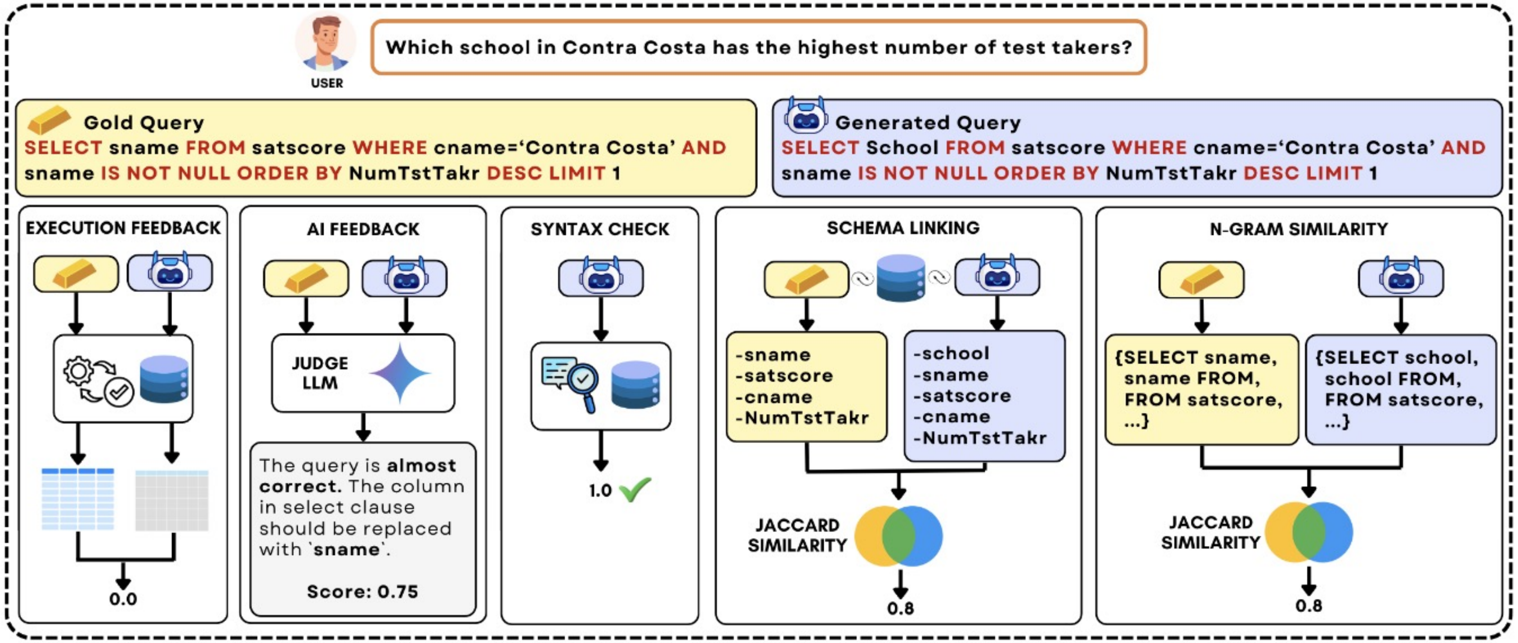
- **Reasoning-SQL**, RL-Enhanced NL2SQ with ***Partial Rewards***
  - Introducing the first RL-based framework for optimizing reasoning in LLMs for NL2SQL
  - Leveraging Group Relative Policy Optimization (GRPO) for efficient and stable training
  - Employing a novel suite of partial rewards to address the reward sparsity problem



Pourreza, Mohammadreza, Shayan Talaei, Ruoxi Sun, Xingchen Wan, et al. "Reasoning-sql: Reinforcement learning with sql tailored partial rewards for reasoning-enhanced text-to-sql." arXiv preprint arXiv:2503.23157 (2025).

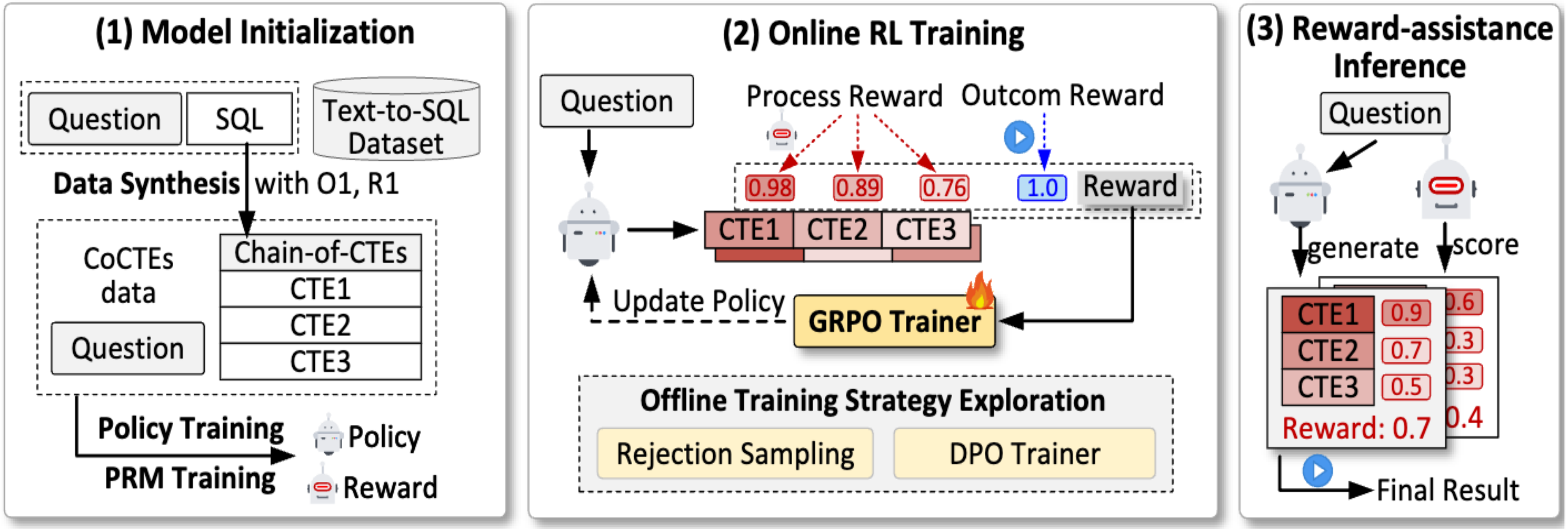
A Suite of Partial Rewards

- **Execution Accuracy Reward (RLEF):** Binary reward for correct SQL execution
- **LLM-as-a-Judge Reward (RLAIF):** AI feedback for queries with zero execution accuracy
- **Syntax Check Reward:** Positive score for syntactically valid and executable queries
- **Schema Linking Reward:** Jaccard similarity between schema items in candidate vs. gold queries
- **N-gram Similarity Reward:** Token-level overlap measurement using Jaccard similarity



Process-Supervised Rewards for NL2SQL

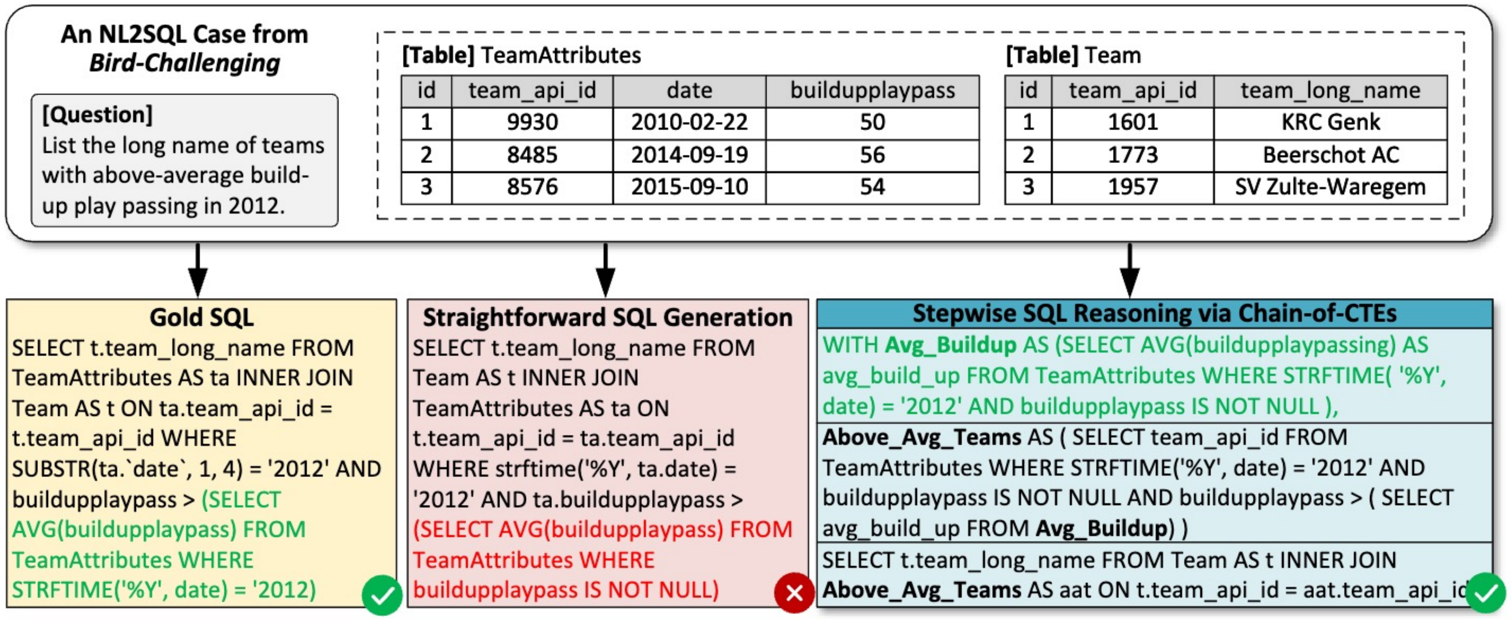
- **Reward-SQL:** introducing Process Reward Models (PRMs) for NL2SQL
  - **PRM-Enhanced Test-Time Scaling:** Adopting PRMs for test-time scaling for NL2SQL
  - **GRPO-Integrated Training:** Incorporating PRMs into training via Group Relative Policy Optimization to further enhance reasoning capabilities



Zhang, Yuxin, Meihao Fan, Ju Fan, Mingyang Yi, Yuyu Luo, Jian Tan, and Guoliang Li. "Reward-sql: Boosting text-to-sql via stepwise reasoning and process-supervised rewards." arXiv preprint arXiv:2505.04671 (2025).

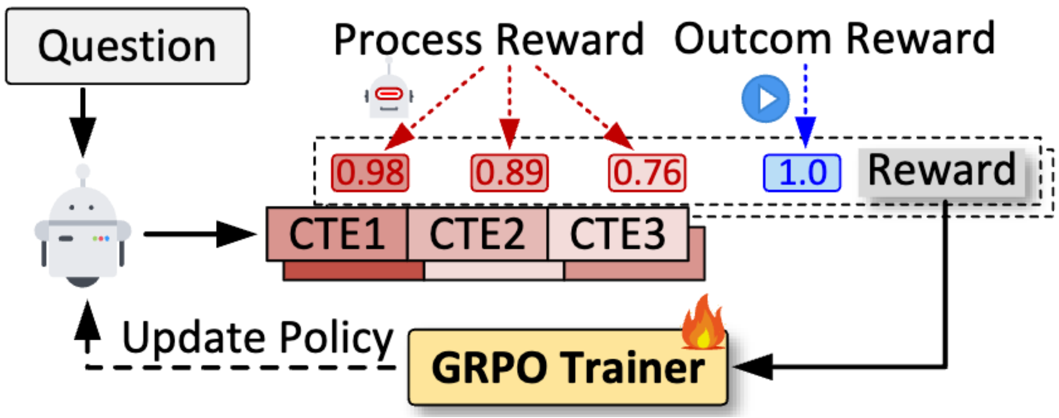
Process-Supervised Rewards for NL2SQL

- **SQL Query Decomposition**: Breaks complex queries into step-by-step Common Table Expressions (CTEs)
- **Step-Level Executability**: Each CTE produces concrete, verifiable intermediate results
- **PRM-Compatible Structure**: Enables fine-grained evaluation at each reasoning step



PRM-Involved GRPO Training

- **GRPO Model Update**: Leveraging GRPO to update the model with PRM preferences, maintaining consistency between training and inference distributions to further enhance test-time scaling capabilities.
- **Combined Reward Structure**: Process Reward (PR) + Outcome Reward (OR) for comprehensive feedback
- **Fine-Grained Advantages**: Step-level advantages reflecting both solution quality and internal step variations



Online GRPO Training

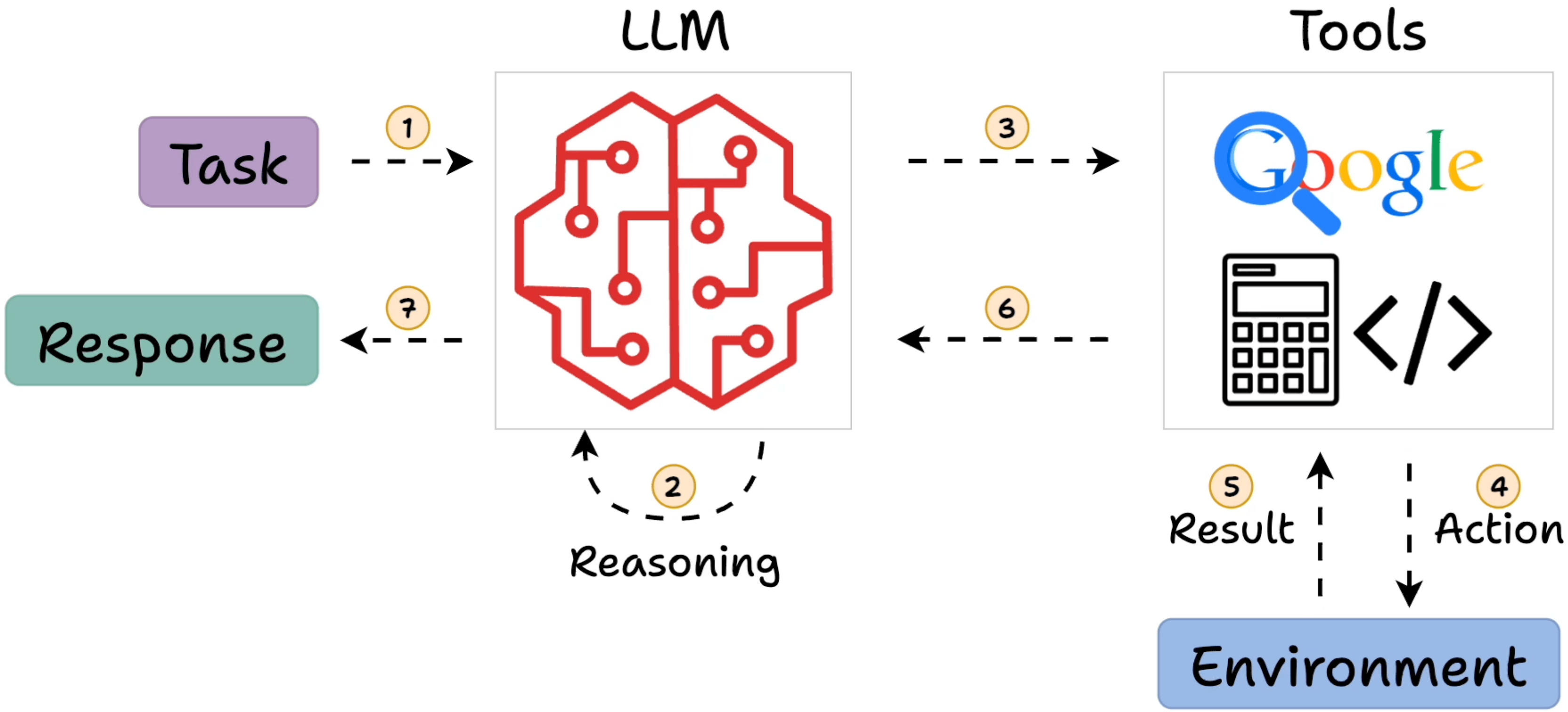
Takeaways

- **Architectural Simplification:** Text-to-SQL has evolved from complex multi-stage PLM pipelines to streamlined end-to-end training, with RL-based frameworks eliminating auxiliary components while achieving superior performance.
- **Escalating Data Demands:** Simplified architectures paradoxically require exponentially more training data, making synthetic data generation critical while demanding unprecedented quality and diversity for robust generalization.
- **Performance-Cost Trade-off:** State-of-the-art methods introduce substantial computational overhead, creating fundamental tensions between model performance and practical deployment in resource-constrained environments.

Tutorial Outline

- Problem Definition, Preliminaries, Benchmarks
- NL2SQL Solutions with PLMs and LLMs
- **NL2SQL Solutions with LLM Agents**
- Open Problems

What is the (Reasoning) Agent?

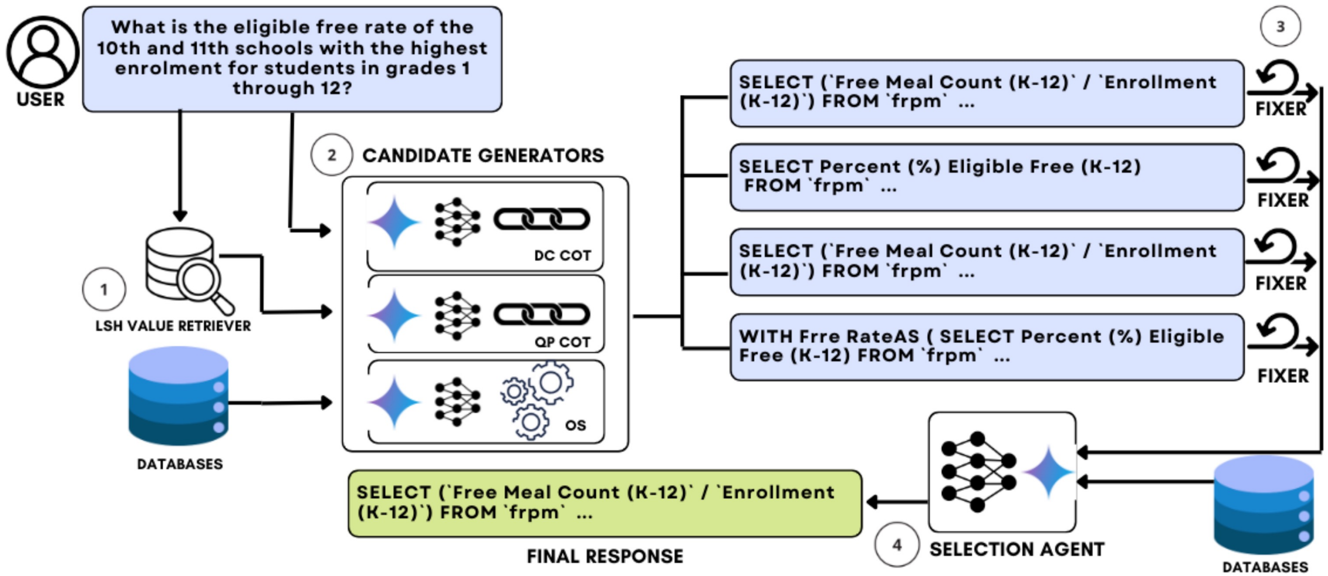


https://blog.dailydoseofds.com/p/intro-to-react-reasoning-and-action

Where Are We?

Closed-source LLMs

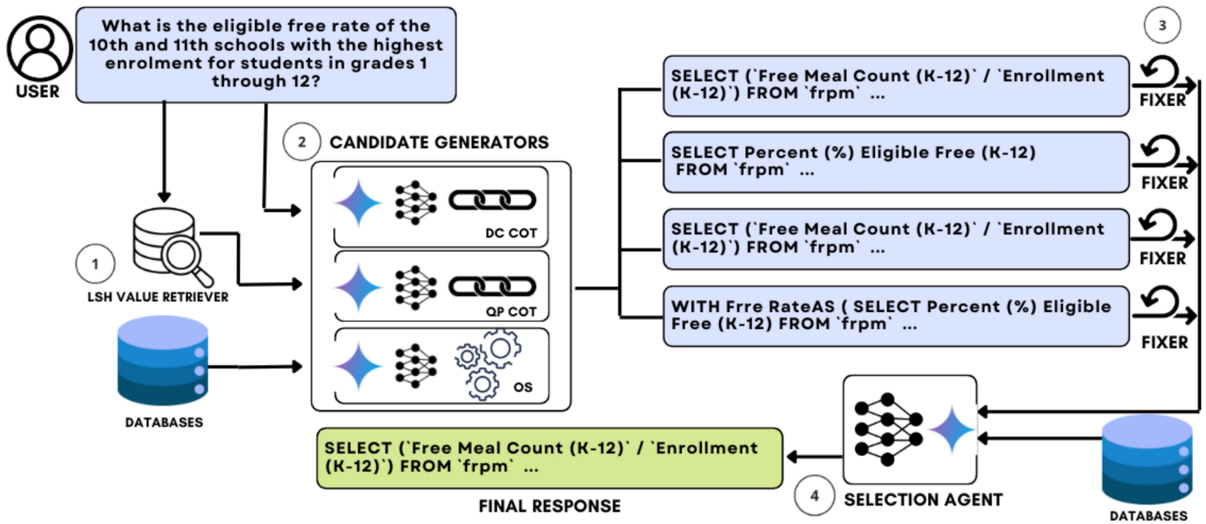
- **CHASE-SQL** (*ICLR 2025, Google Cloud and Stanford*)
  - Utilizes the **MinHash LSH** to search for values related to the user query
  - Multiple prompting strategies to **generate various candidate SQL queries** using LLMs, and corrects SQL queries with execution errors through prompting LLMs.
  - Employs an **SQL selection agent** fine-tuned specifically for the database to select the final SQL from multiple candidates.



Where Are We?

Closed-source LLMs

- **CHASE-SQL (***ICLR 2025, Google Cloud and Stanford***)**



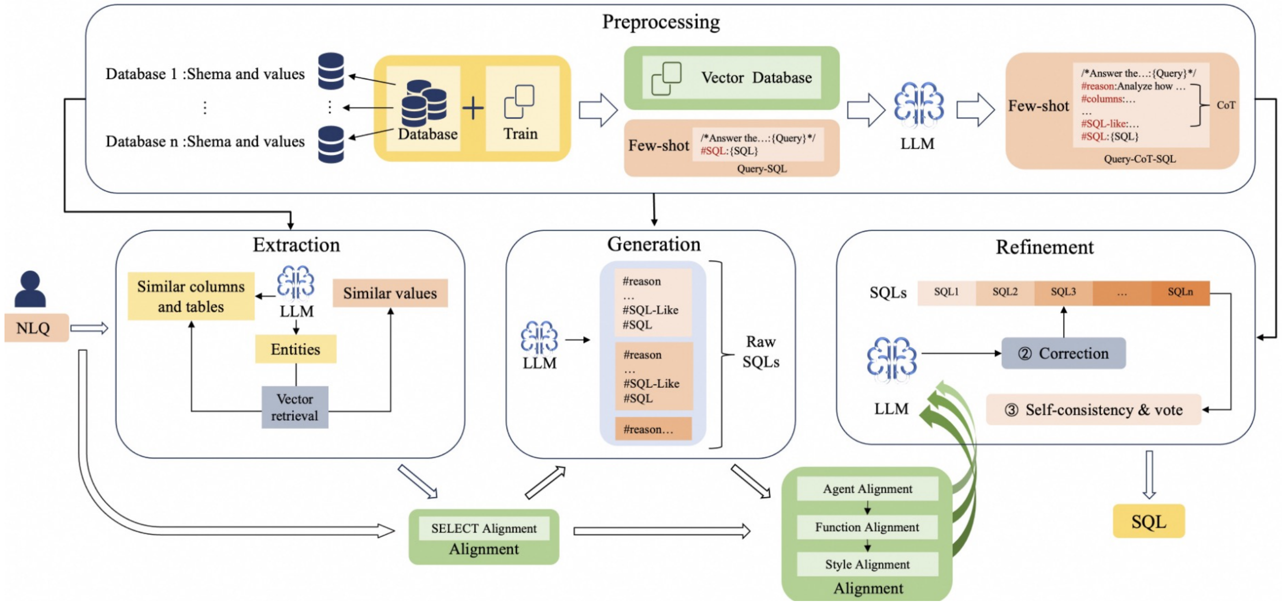
Key Limitations:

- **Reliance on closed-source large models**
  - High cost (**0.6 USD/query**), making it difficult to widely deploy in real-world industrial scenarios.
- **SQL selection agent requires fine-tuning**
  - The *Google* team *fine-tuned* the *Gemini-1.5-Flash* model specifically.
  - Limited flexibility due to reliance on domain-specific data.
- **Predefined and Fixed Reasoning Workflows**

Where Are We?

Closed-source LLMs

- **OpenSearch** (*SIGMOD 25, Alibaba*)
  - **Modular Architecture**: Divides the task into four stages (Preprocessing, Extraction, Generation, and Refinement) and adds an Alignment module to ensure consistency between steps.
  - **Intermediate Language:** A custom language named SQL-Like is designed to structure the model's reasoning process.



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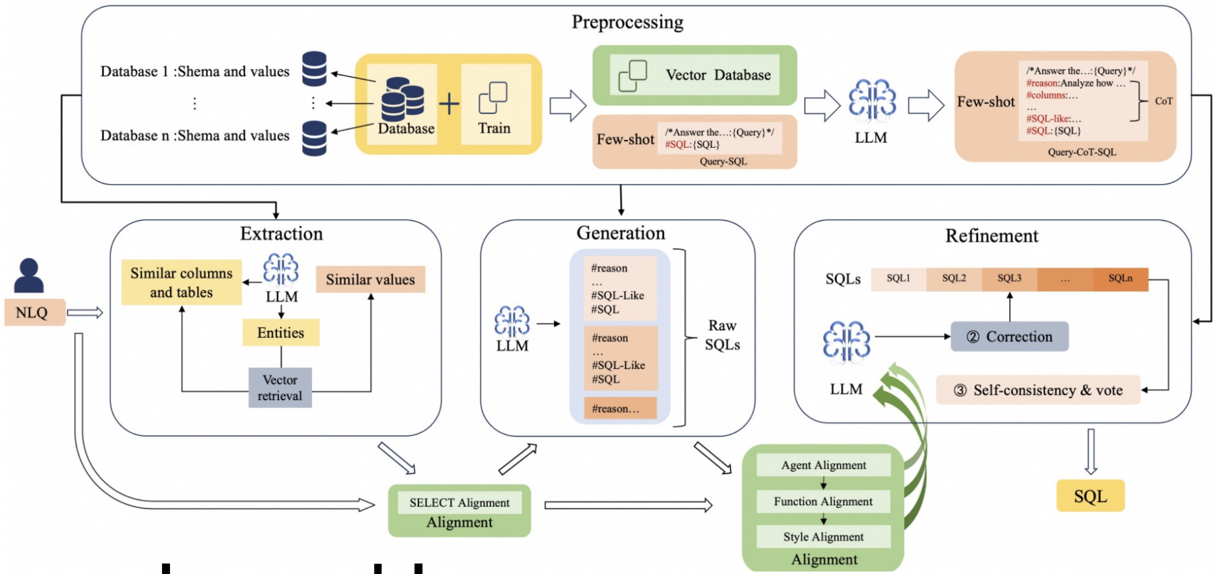
Closed-source LLMs



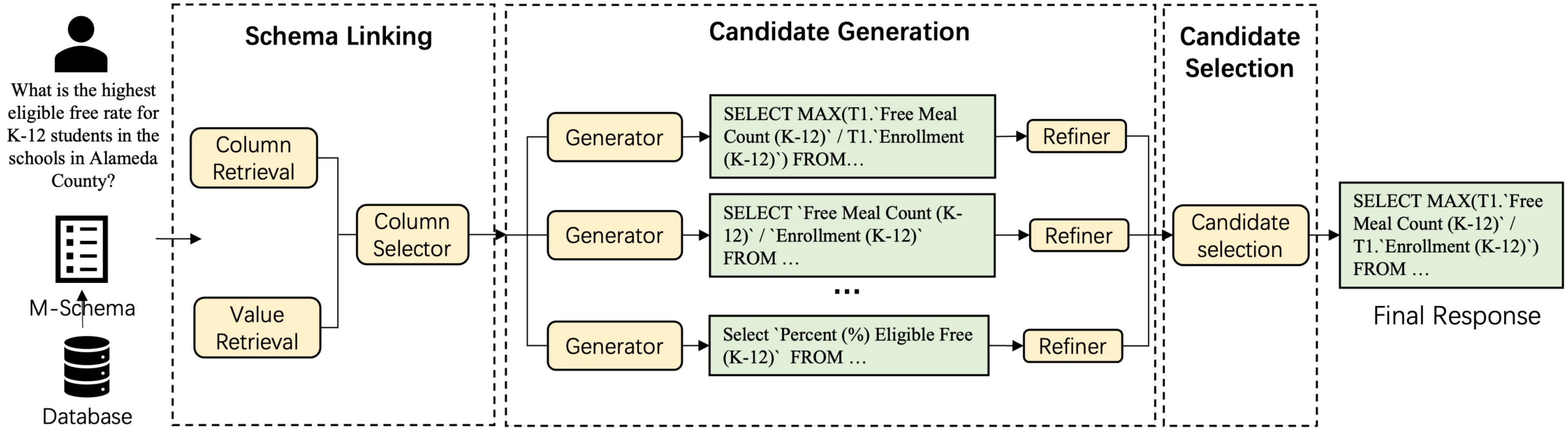
Key Limitations:

- **Reliance on closed-source large models**
  - Privacy Risks
- **Rigidity of the Alignment Module**:
  - The alignment mechanism enforces consistency but risks over-constraining SQL generation and limiting adaptability across scenarios.
- **Predefined and fixed reasoning workflows**

Where Are We?

Open-source LLMs

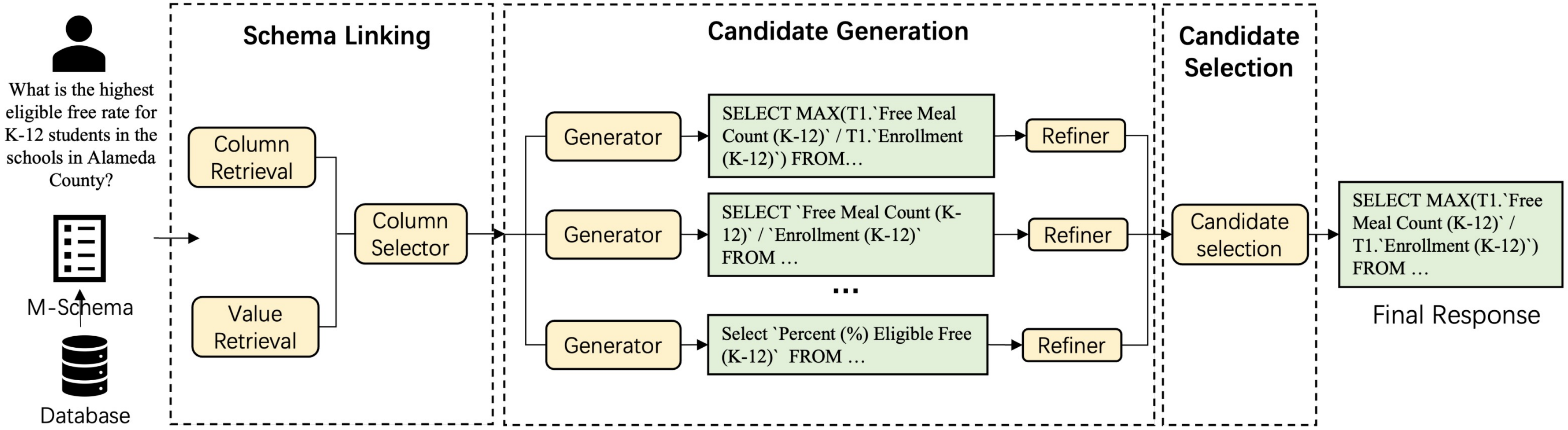
- **XiYan-SQL** (*SIGMOD 25, Alibaba*)
  - **M-Schema**: Uses column and value retrieval to select relevant schema items from DBs.
  - **Fine-tunes a base LLM** on SQL-specific data, then **creates multiple specialized SQL-generation** models by fine-tuning with diverse Text-to-SQL syntax datasets.
  - Employs a **fine-tuned SQL selection** model to choose the best SQL from predictions made by multiple generators.



Where Are We?

- **XiYan-SQL** (*SIGMOD 25, Alibaba*)

Open-source LLMs



Key Limitations:

- High dependency on extensive **domain-specific data**.
- Significant **costs** associated with **fine-tuning** multiple models.
- **Difficulty** in rapid **adaptation** and **generalization** across varied scenarios.
- **Predefined and Fixed Reasoning Workflows**.

Key Takeaways

Closed-source LLMs for Text-to-SQL:

- High inference API cost limits practical deployments.
- Potential data privacy concerns for sensitive applications.

Open-source LLMs for Text-to-SQL:

- Dependence on extensive domain-specific data for model fine-tuning.
- Limited generalization capability across different use cases.

Common Limitations in Existing Solutions:

- Predefined and fixed reasoning workflows restrict adaptability.
- Domain adaptation and generalization across DB and text queries

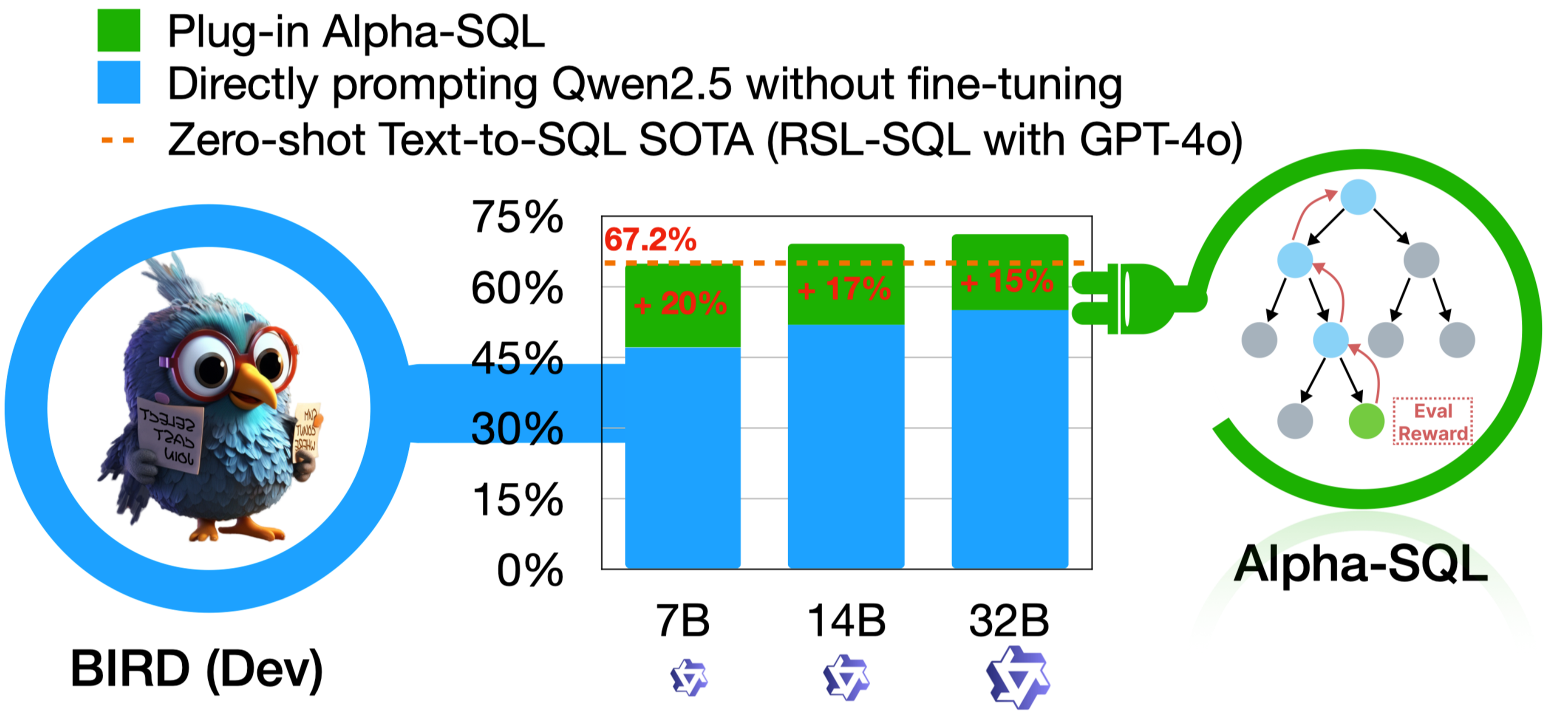
Where Are We Going?

Challenges		Key Idea
High Inference API Cost	→	**Open-source LLMs** Lower deployment cost and improved flexibility
Expensive fine-tuning	→	**Training-free Paradigm** Zero-shot reasoning without additional tuning
Fixed Reasoning	→	**Dynamic Reasoning** Adaptive reasoning workflows guided by task

Our Goal

Reasoning Agents based on Open-source LLMs

Alpha-SQL:
A Plug-and-Play NL2SQL Reasoning Framework



Open-source LLMs

Training-free Paradigm

Dynamic Reasoning

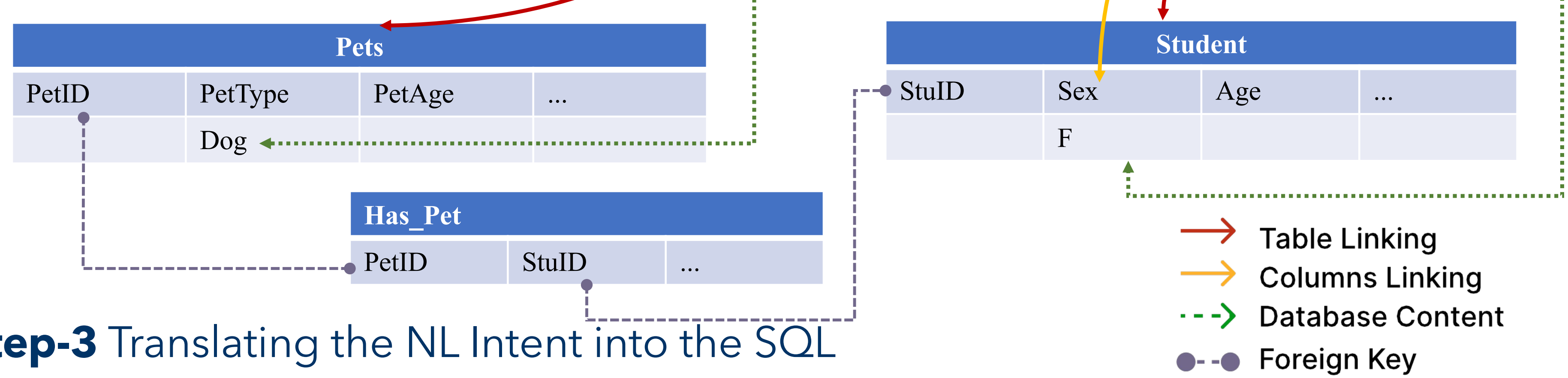
Boyan Li, Yuyu Luo, Alpha-SQL: Zero-Shot Text-to-SQL using Monte Carlo Tree Search, **ICML** 2025.
https://github.com/HKUSTDial/Alpha-SQL

NL2SQL Human Workflow

Step-1 NL Understanding

Find the number of dog pets that are raised by female student

Step-2 Schema Linking and Database Content Retrieval

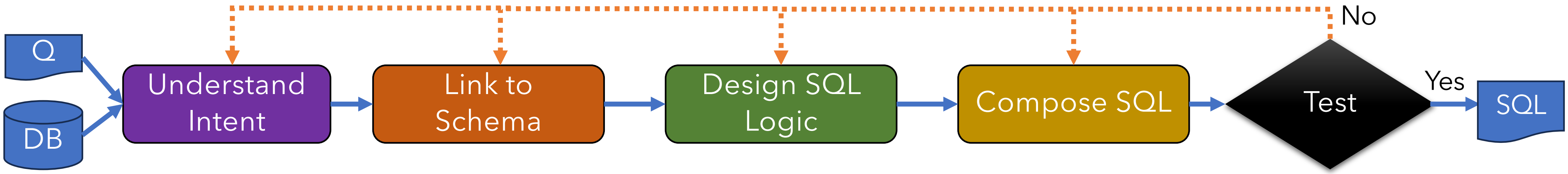


Step-3 Translating the NL Intent into the SQL

Select count(*) *FROM* student *AS* T1 *JOIN* has_pet *AS* T2 *ON* T1.stuid=T2.stuid *JOIN* pets *AS* T3 *ON* T2.petid=T3.petid *WHERE* T1.sex='F' *AND* T3.pettype='Dog'

Task Formulation: Mimic Human Experts

- Human Expert Workflow for Text-to-SQL



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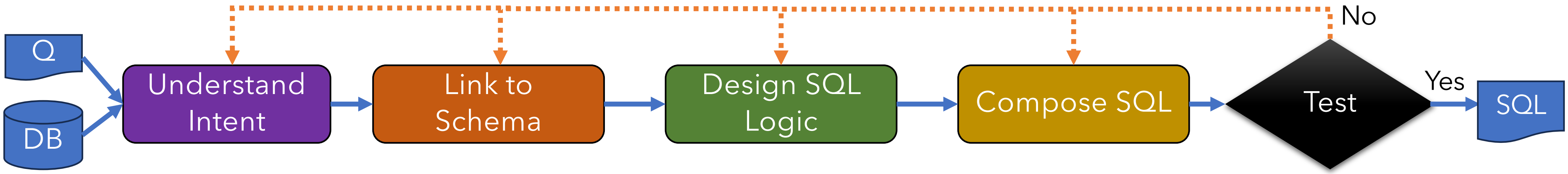
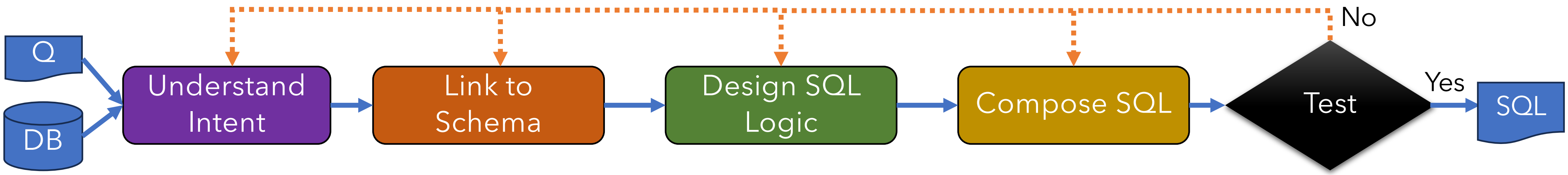


- From ***Human Actions*** to ***Agent Actions***

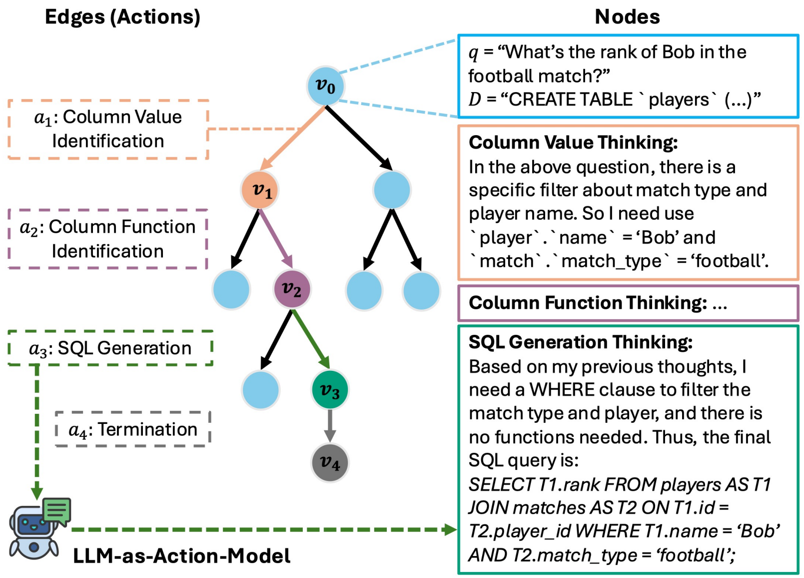
Human Actions	Agent Actions	
Understand Intent	**Question Rephrasing**	(Revise, clarify ambiguities, rephrasing)
Link to Schema	**Schema Selection** **Cell Value Selection**	(decides which tables / columns / values)
Design SQL Logic	**Column Function**	(joins, aggregations, functions)
Compose SQL	**SQL Generation**	(assemble an initial executable query)
Validate & Iter.	**SQL Revision**	(iteratively test, debug, and optimize the query)

Task Formulation: Mimic Human Experts

- Human Expert Workflow for Text-to-SQL



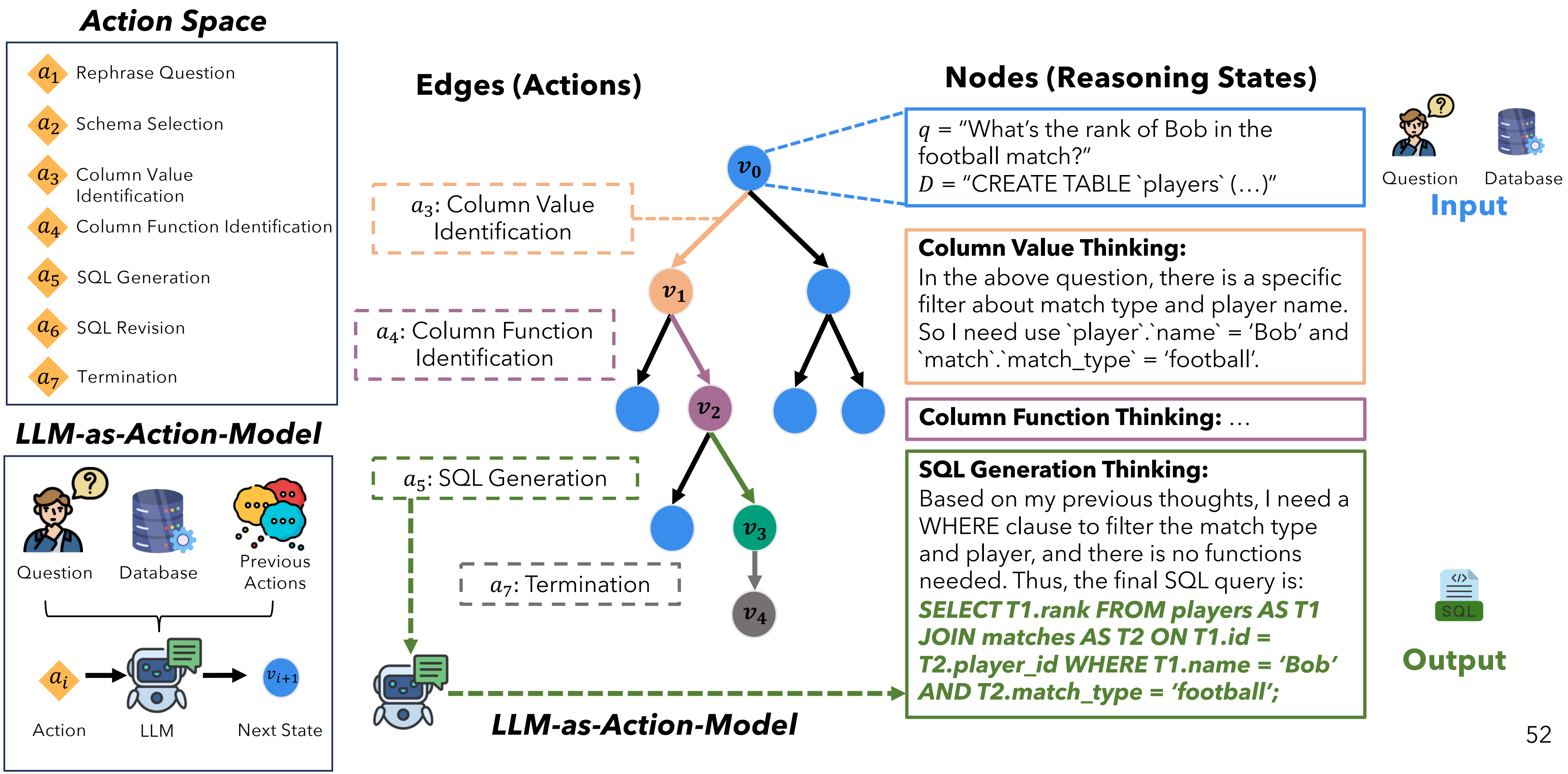
- From the ***Fixed*** Action to ***Dynamic*** Actions



Tree-based Search:

- Each ***edge*** corresponds to an ***agentic action*** in the query construction process,
- Each ***node*** represents a ***reasoning state*** at a specific step, and
- Each ***path*** corresponds ***to a sequence of SQL construction actions*** for Text-to-SQL task.

Text-to-SQL as a Tree-based Search Problem



Text-to-SQL as a Tree-based Search Problem

- **Q1**: How to select the next action (edge)?
- **Q2**: How to effectively navigate the vast search space?
- **Q3**: How to evaluate the quality of the candidate SQL queries?

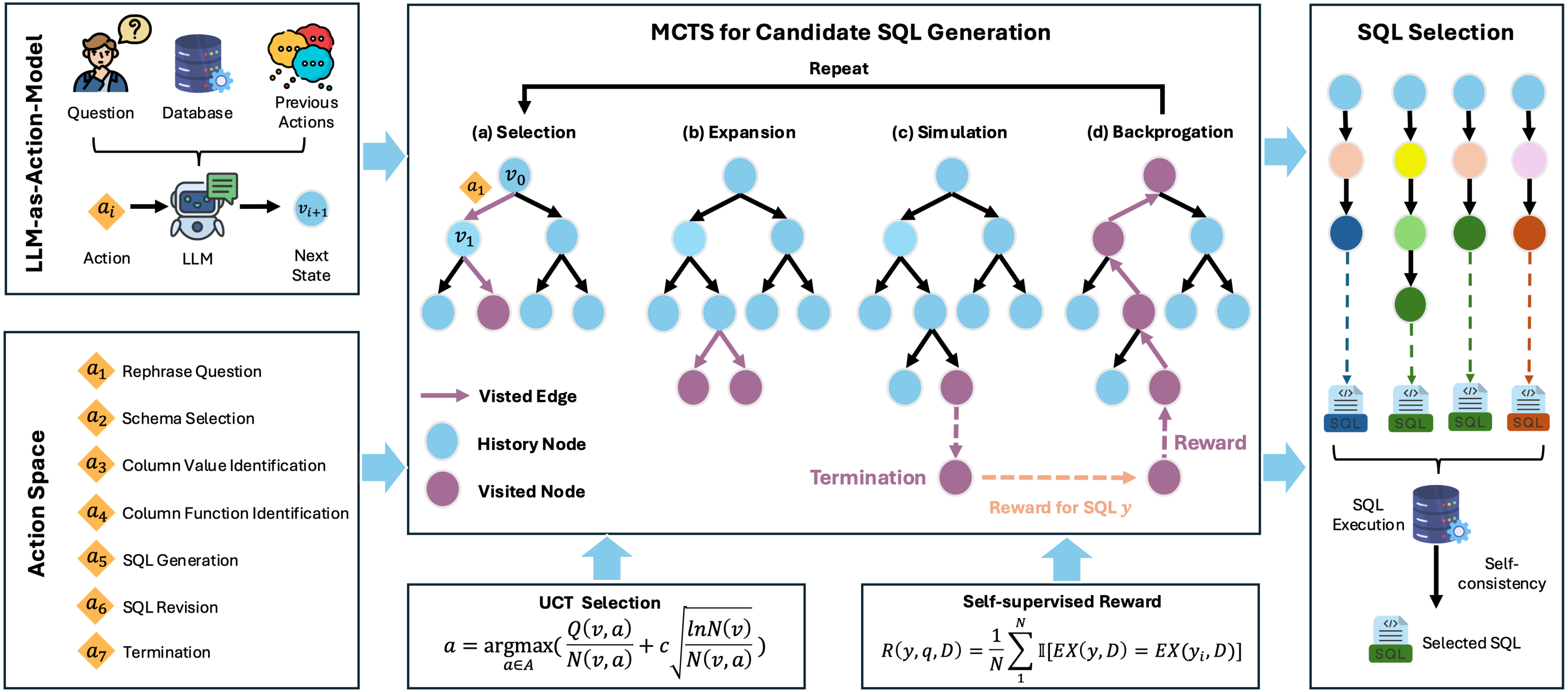
Q1 & Q2

- Monte Carlo Tree Search (MCTS) addresses this by balancing *exploration* (testing *uncertain* actions) and *exploitation* (choosing actions *likely to yield good* results)

Q3

- We need a *self-supervised* reward function since our goal is to avoid reliance on labeled data
- Resampling the LLMs M times to compute the self-consistent scores

Alpha-SQL Solution Overview



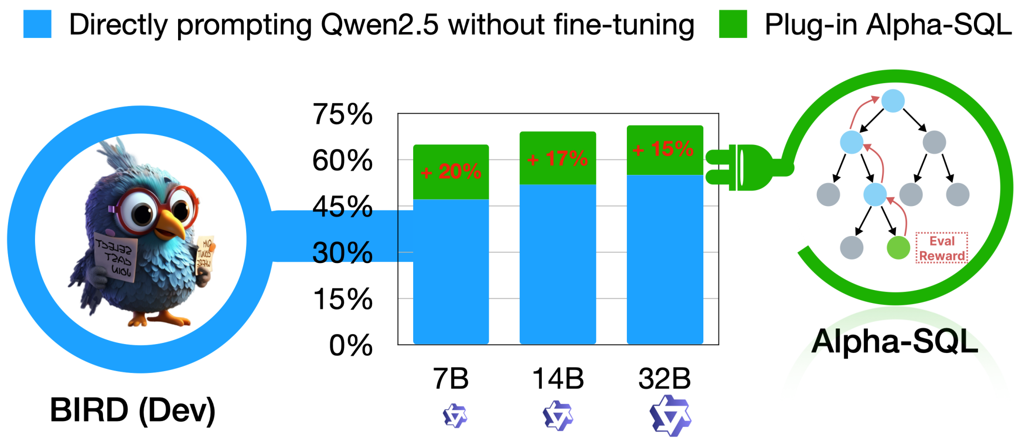
Boyan Li, Yuyu Luo, Alpha-SQL: Zero-Shot Text-to-SQL using Monte Carlo Tree Search, **ICML** 2025.

https://github.com/HKUSTDial/Alpha-SQL

Alpha-SQL: Plug-and-Play Capabilities

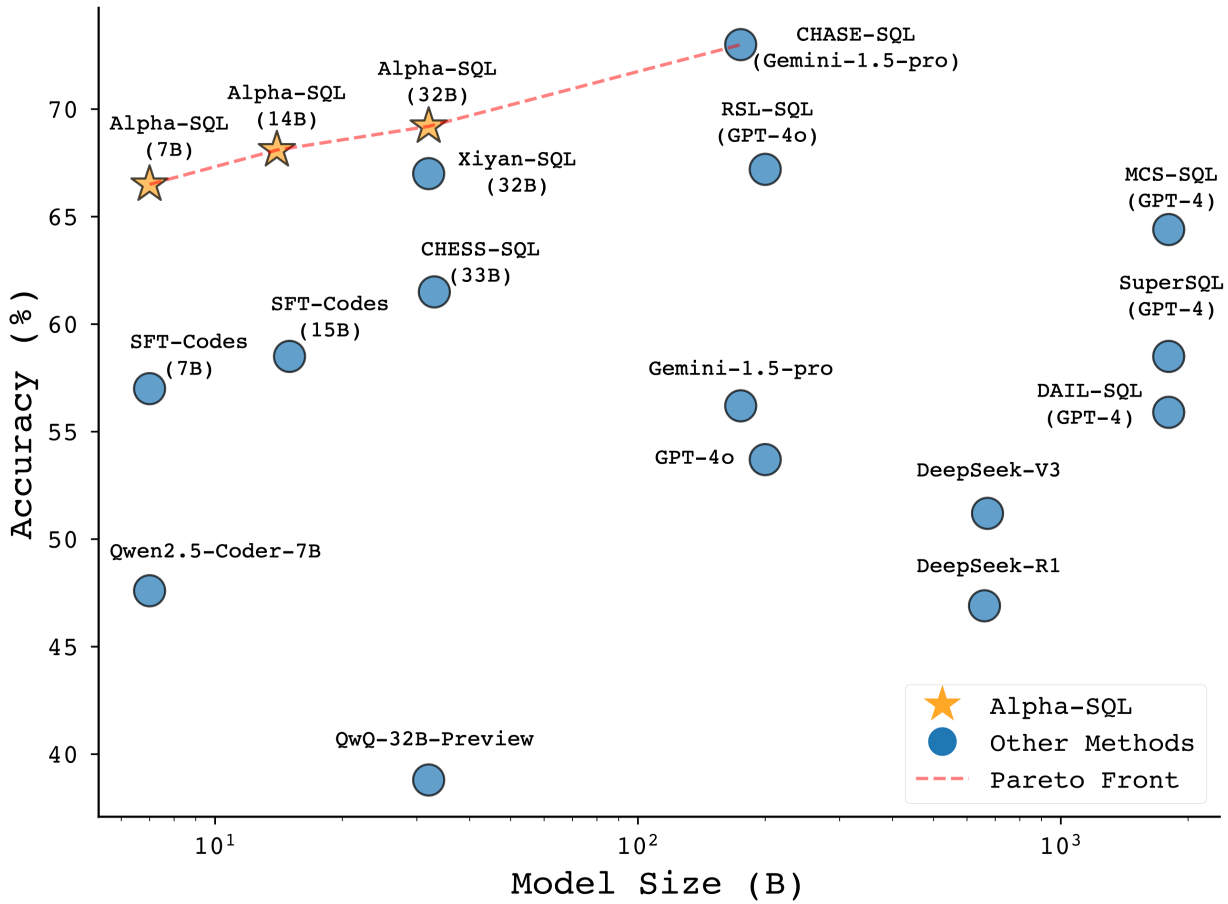
Table 4. Comparison with Baseline LLMs on the SDS dataset.

Model	Accuracy (%)
Deepseek-V3	51.2
GPT-4o	53.7
Gemini-1.5-Pro	56.2
QwQ-32B-Preview	38.8
DeepSeek-R1	50.3
Gemini-2.0-Flash-Thinking-Exp	60.8
Qwen2.5-Coder-7B	47.6
+ Alpha-SQL (Ours)	**64.6 (↑ 17.0)**
Phi-4	43.5
+ Alpha-SQL (Ours)	**60.0 (↑ 16.5)**



Performance-Scale Trade-off Analysis

Agents: Small LLMs, Big Gains



Tutorial Outline

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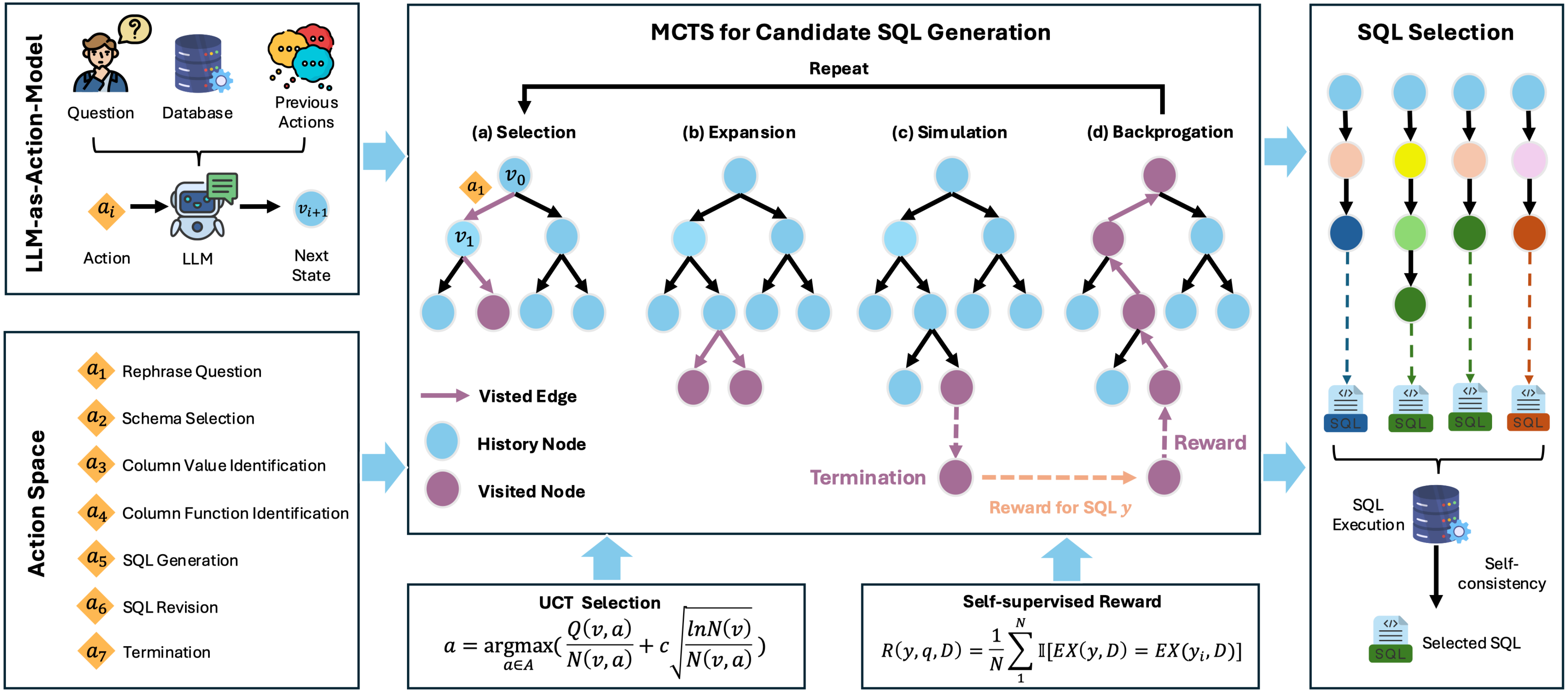
Rethinking: Limitations of NL2SQL Agent



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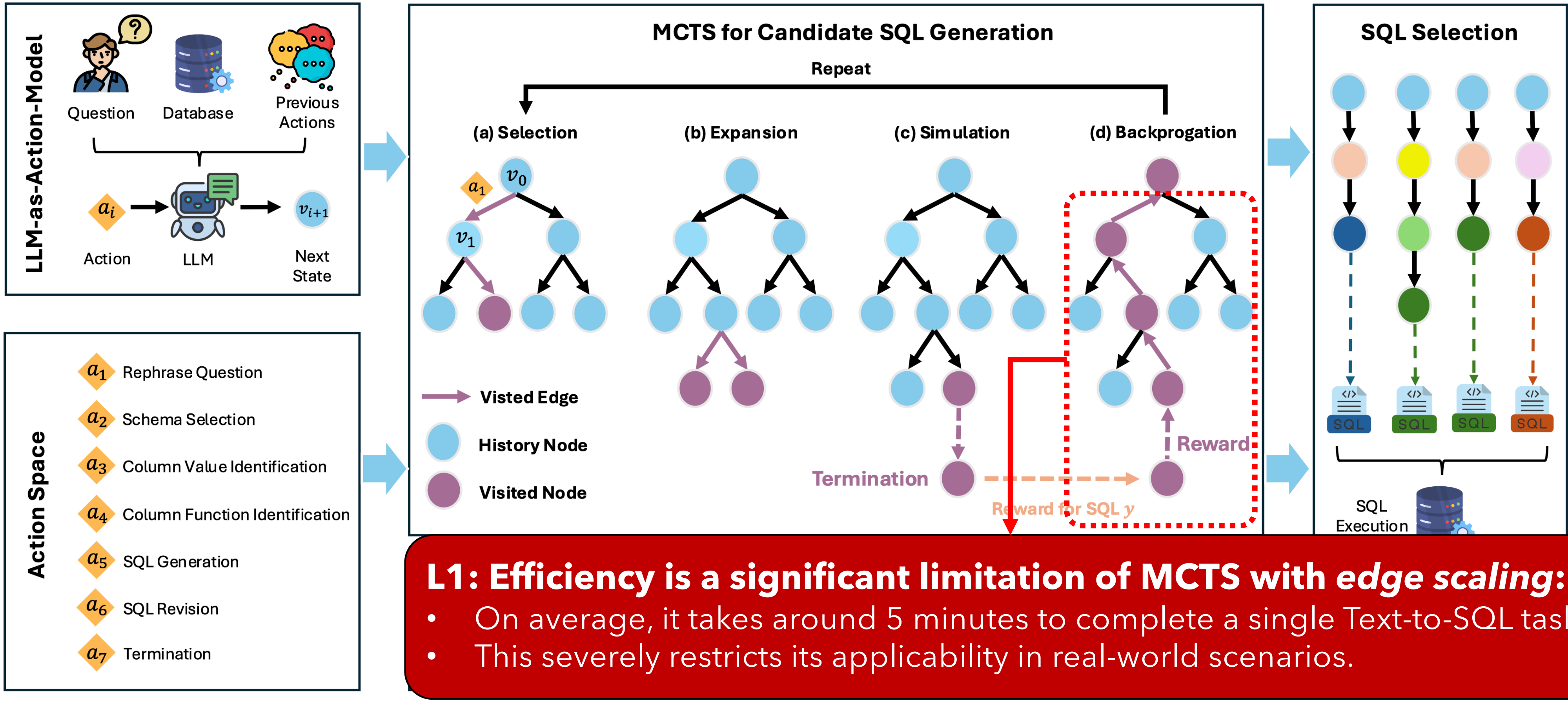

L1: Efficiency is a significant limitation of MCTS with *edge scaling*:

- On average, it takes around 5 minutes to complete a single Text-to-SQL task.
- This severely restricts its applicability in real-world scenarios.

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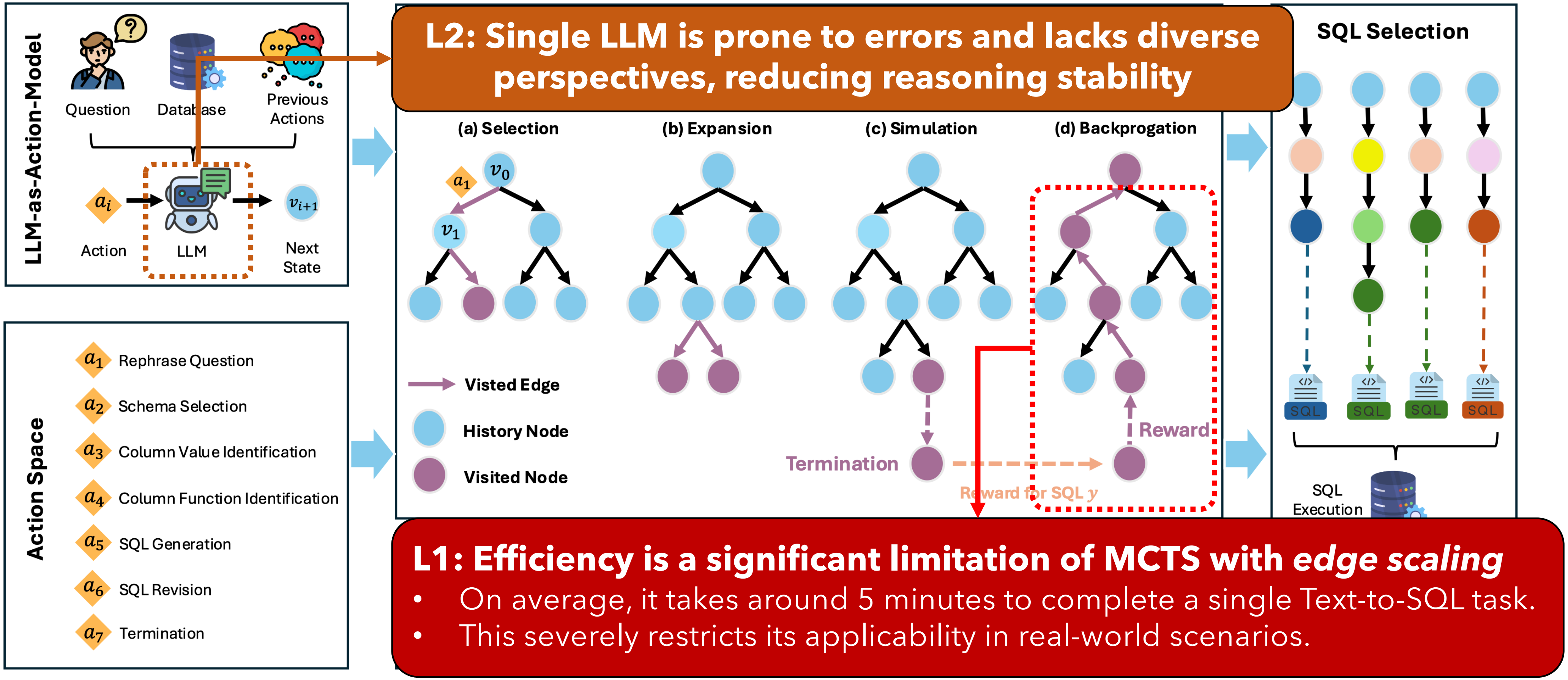

L2: Single LLM is prone to errors and lacks diverse perspectives, reducing reasoning stability

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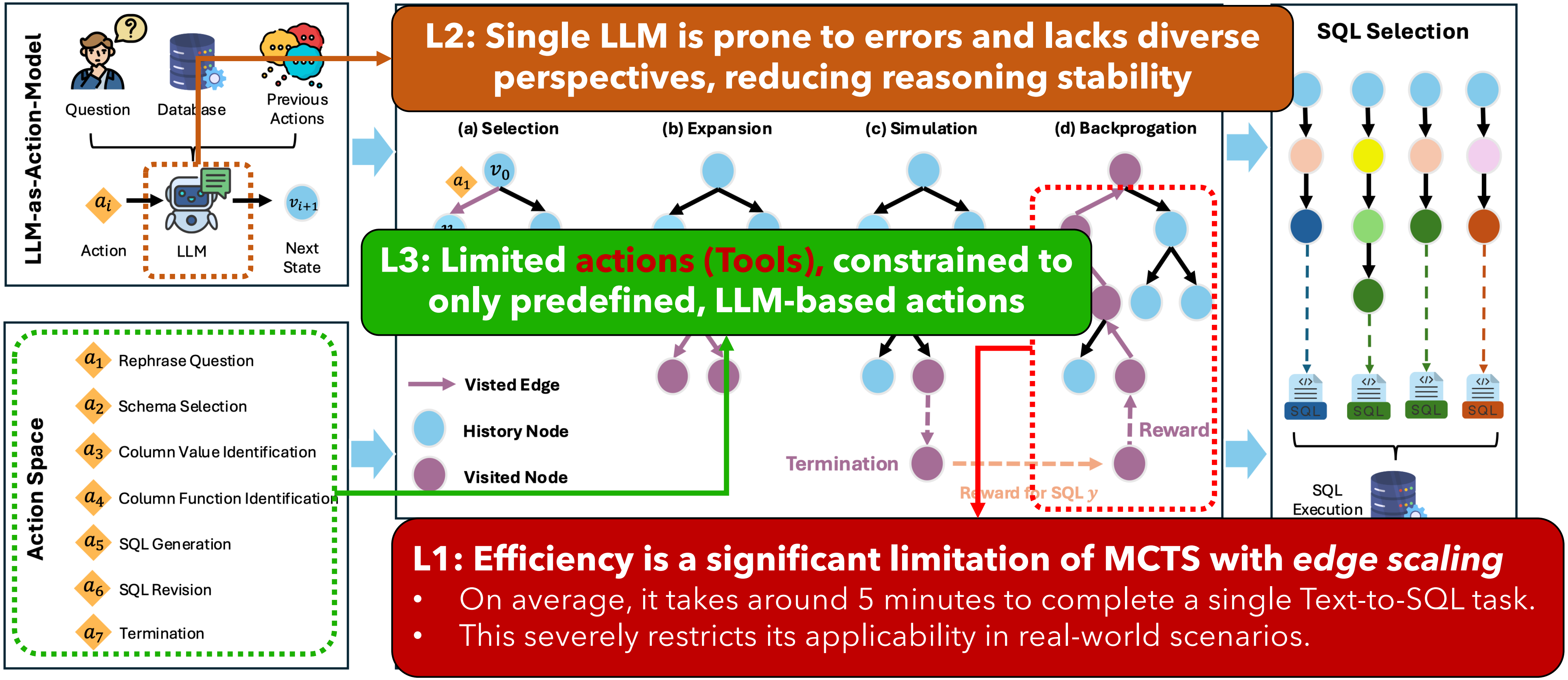
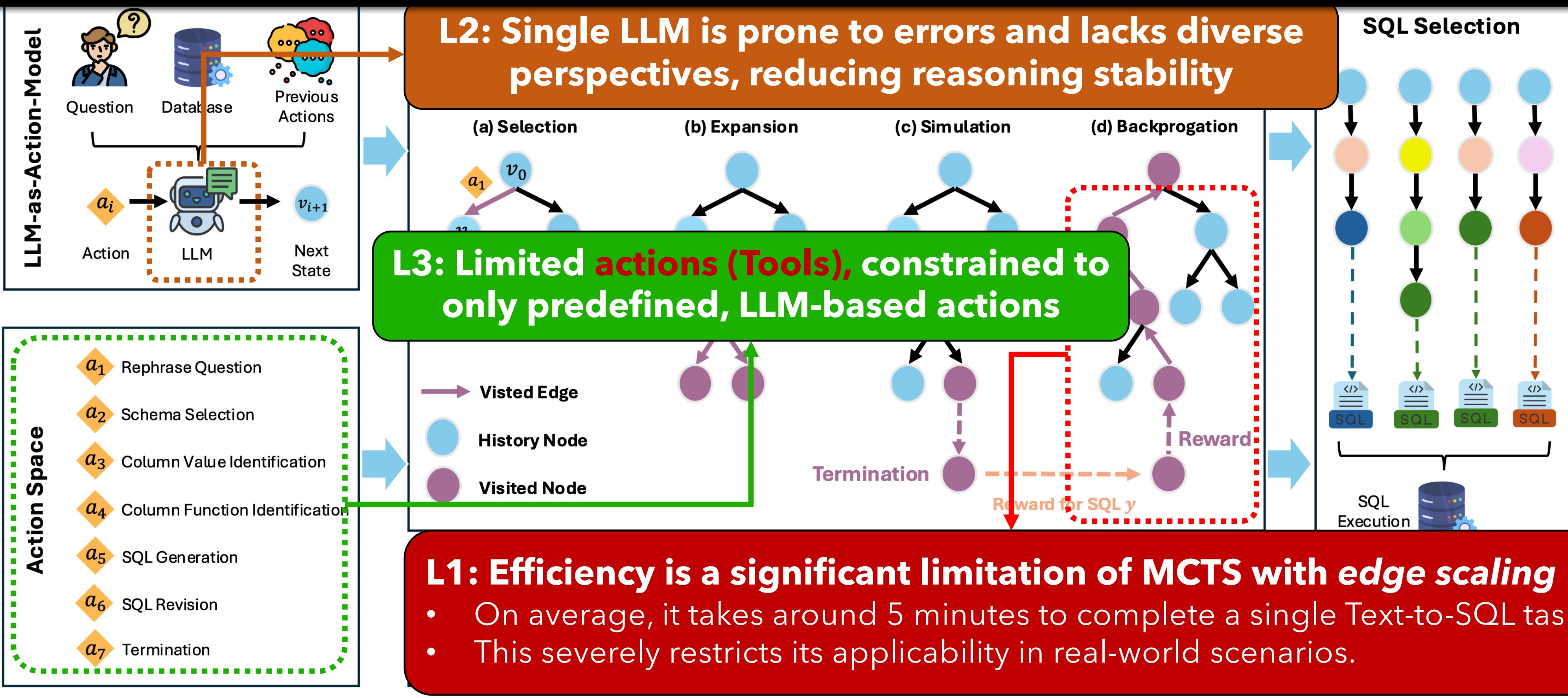


Boyan Li, Yuyu Luo, Alpha-SQL: Zero-Shot Text-to-SQL using Monte Carlo Tree Search, **ICML** 2025.
https://github.com/HKUSTDial/Alpha-SQL

These limitations highlight the need for more diverse actions, efficient reasoning, and richer memory



L2: Single LLM is prone to errors and lacks diverse perspectives, reducing reasoning stability

L3: Limited actions (Tools), constrained to only predefined, LLM-based actions

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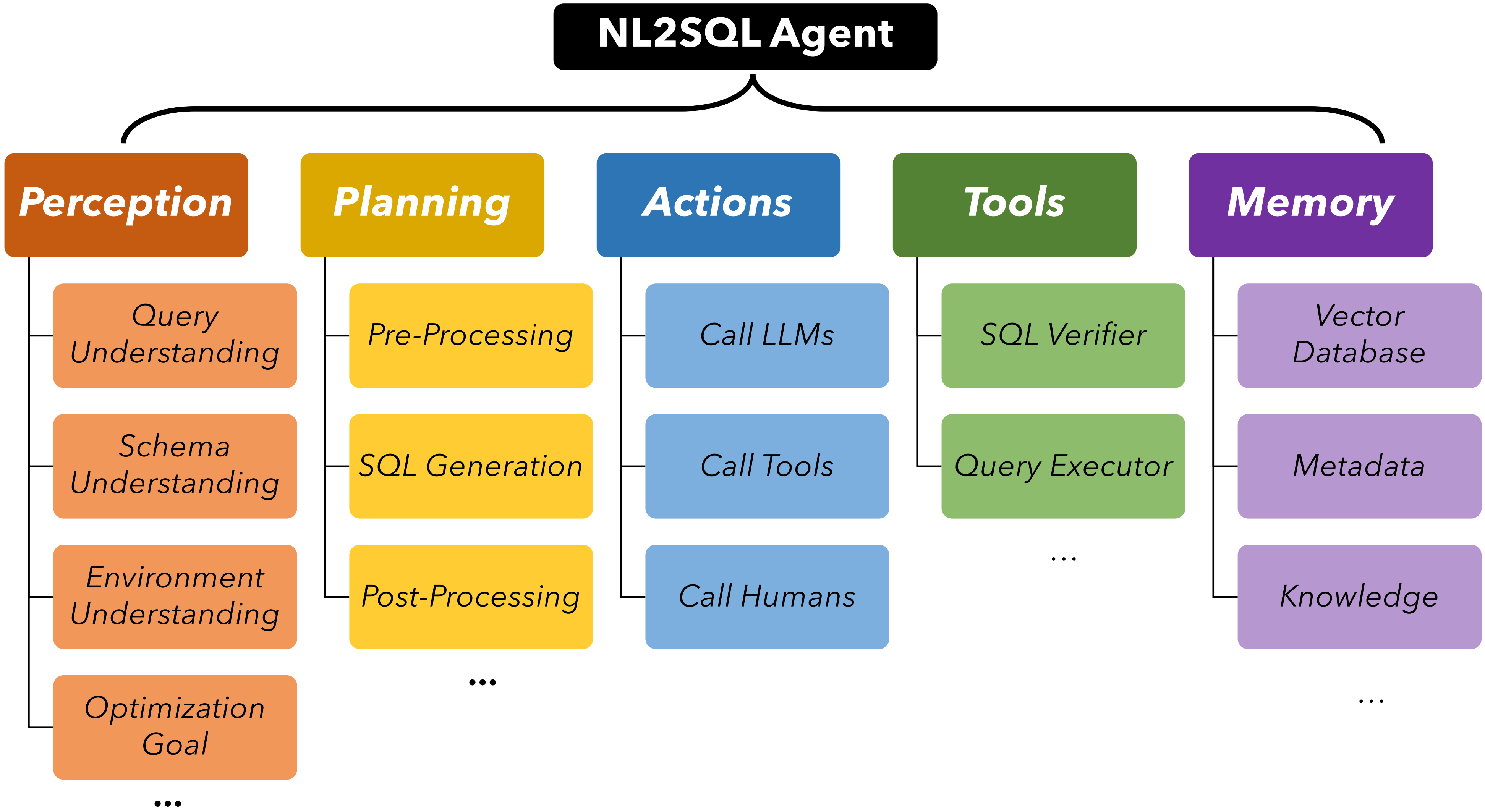
What Alpha-SQL Reveals About NL2SQL Agents

(Alpha-SQL) Limitation	Opportunity Axis	Design Lever (what to change)
L1. Efficiency bottleneck (MCTS is slow)	**Planning**	Adaptive search budgets, routing by query difficulty, test-time compute allocation
	Tools	Early pruning via validators / partial execution; cost-aware candidates
	Memory	Cache schema/context/results; reuse prior plans
L2. Reasoning instability / low diversity	**Actions**	Multi-agent/committee, self-consistency, *human-as-an-agent* for disambiguation
	Perception	Better query & schema understanding (scope detection, value grounding)
L3. Limited actions & tool use	**Tools**	Add retrievers, value lookups, execution-guided rewrite, SQL checkers
	Memory	(1) Long context + vector memory for task state & user prefs; (2) Metadata Management and Schema Interpretation

Opportunities for NL2SQL Agents: Five Key Aspects



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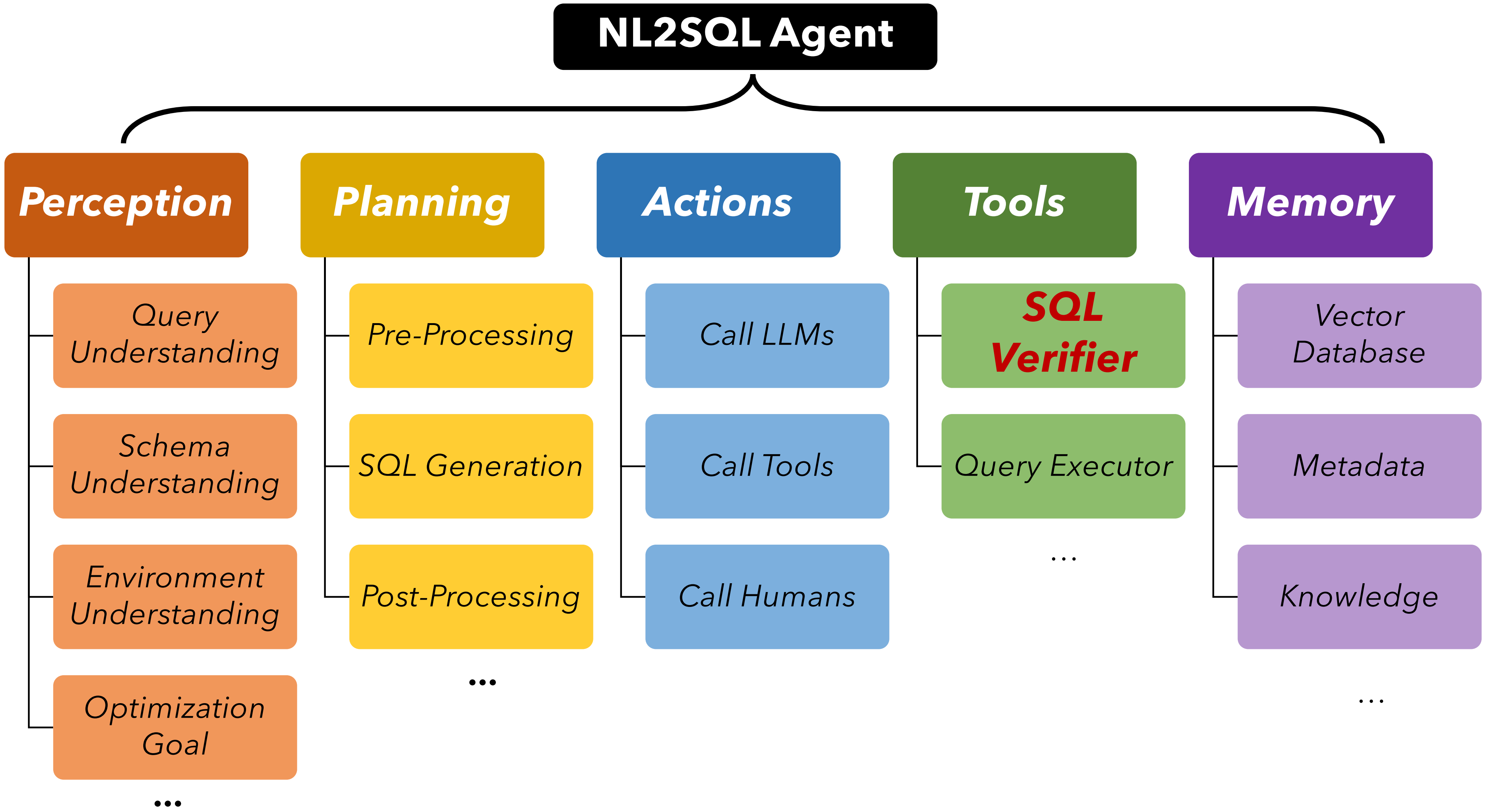
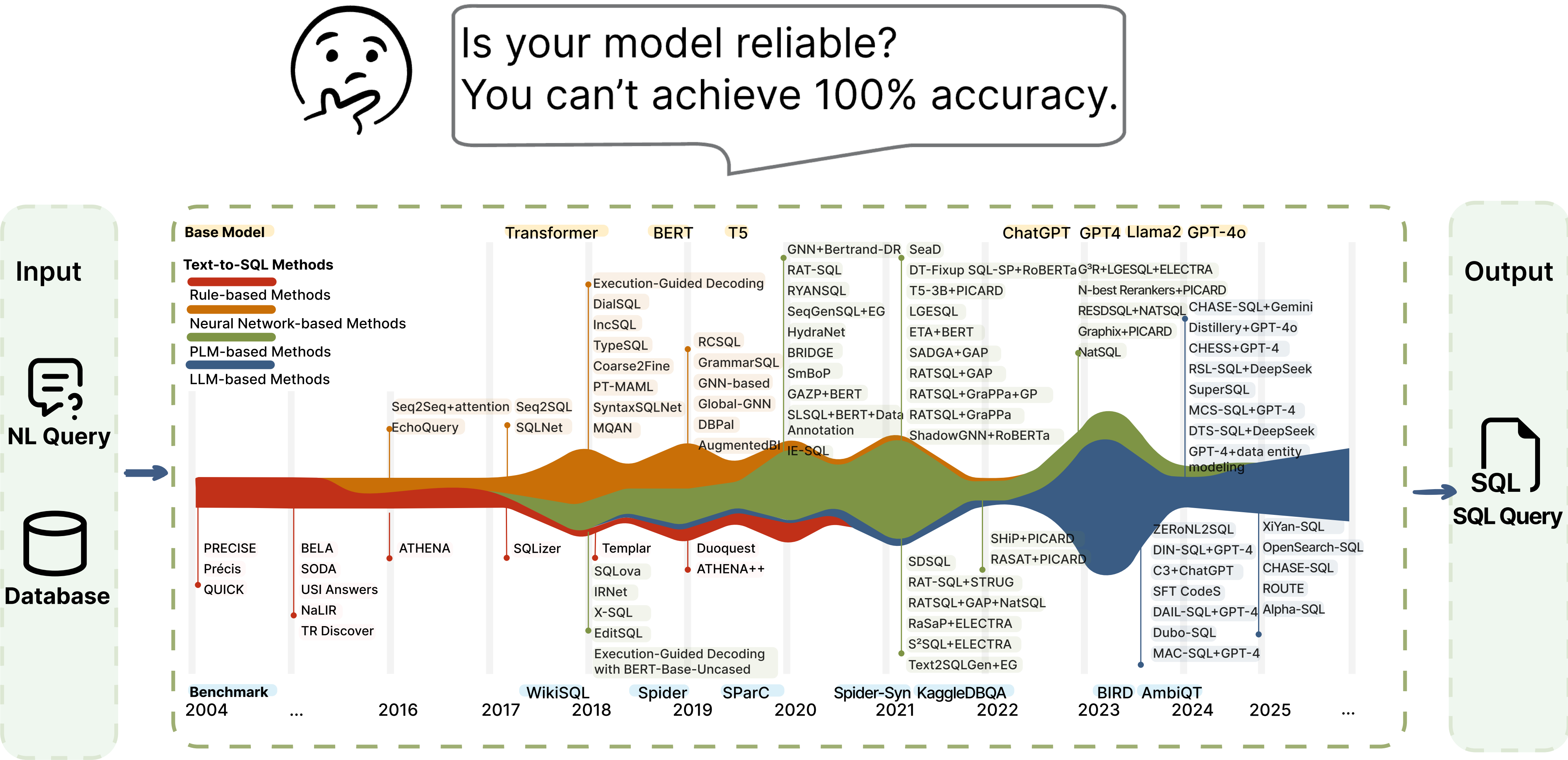
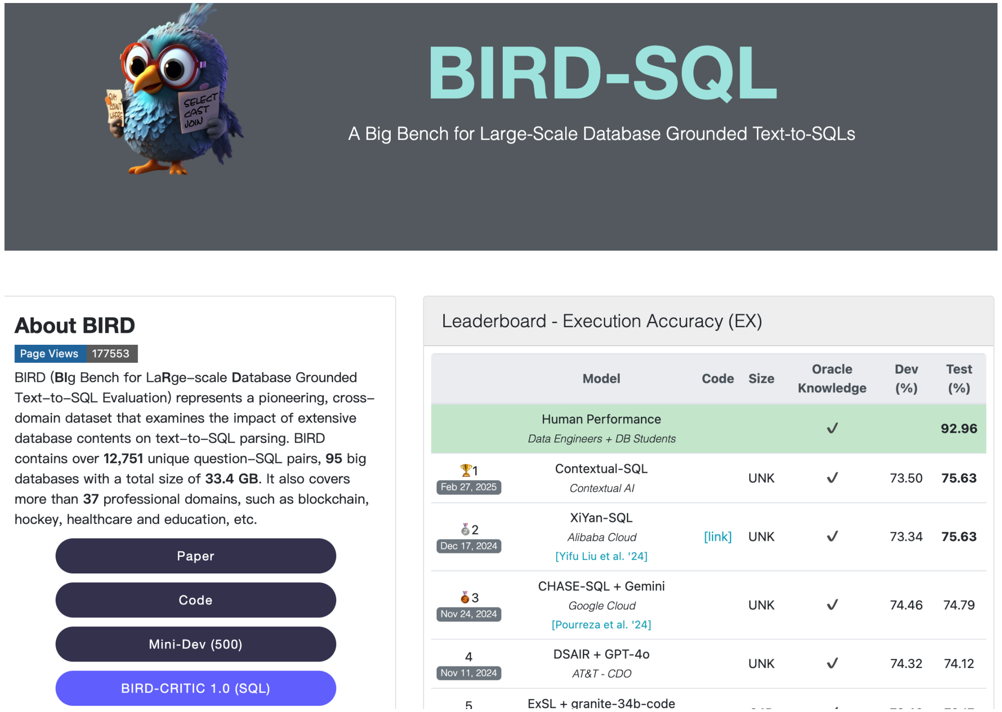


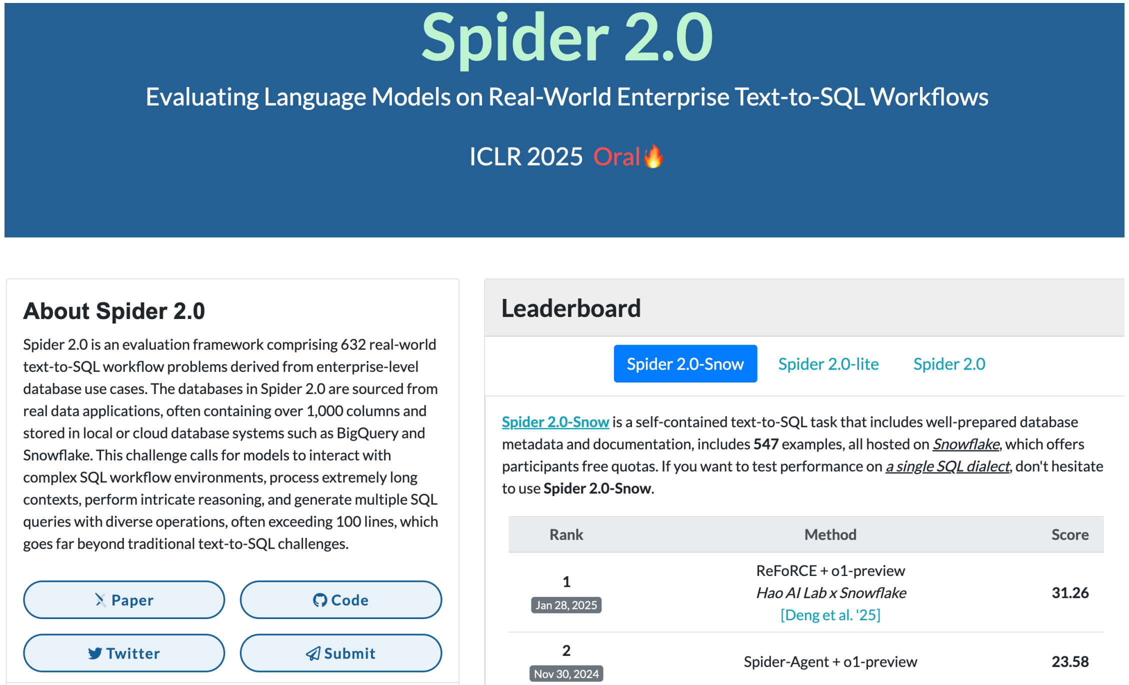

Is your model reliable?
You can't achieve 100% accuracy.
Input
NL Query
Database
Output
SQL
SQL Query
Base Model
Transformer
BERT
T5
ChatGPT
GPT4
Llama2
GPT-4o
Text-to-SQL Methods
Rule-based Methods
Neural Network-based Methods
PLM-based Methods
LLM-based Methods
PRECISE
Précis
QUICK
BELA
SODA
USI Answers
NaLIR
TR Discover
ATHENA
Seq2Seq+attention
EchoQuery
Seq2SQL
SQLNet
SQLizer
Execution-Guided Decoding
DialSQL
IncSQL
TypeSQL
Coarse2Fine
PT-MAML
SyntaxSQLNet
MQAN
Templar
SQLova
IRNet
X-SQL
EditSQL
Execution-Guided Decoding with BERT-Base-Uncased
RCSQL
GrammarSQL
GNN-based
Global-GNN
DBPal
AugmentedBI
Duoquest
ATHENA++
GNN+Bertrand-DR
RAT-SQL
RYANSQL
SeqGenSQL+EG
HydraNet
BRIDGE
SmBoP
GAZP+BERT
SLSQL+BERT+Data Annotation
IE-SQL
SeaD
DT-Fixup SQL-SP+RoBERTa
T5-3B+PICARD
LGESQL
ETA+BERT
SADGA+GAP
RATSQL+GAP
RATSQL+GraPPa+GP
RATSQL+GraPPa
ShadowGNN+RoBERTa
SDSQL
RAT-SQL+STRUG
RATSQL+GAP+NatSQL
RaSaP+ELECTRA
S²SQL+ELECTRA
Text2SQLGen+EG
SHiP+PICARD
RASAT+PICARD
G³R+LGESQL+ELECTRA
N-best Rerankers+PICARD
RESDSQL+NATSQL
Graphix+PICARD
NatSQL
CHASE-SQL+Gemini
Distillery+GPT-4o
CHESS+GPT-4
RSL-SQL+DeepSeek
SuperSQL
MCS-SQL+GPT-4
DTS-SQL+DeepSeek
GPT-4+data entity modeling
ZERoNL2SQL
DIN-SQL+GPT-4
C3+ChatGPT
SFT CodeS
DAIL-SQL+GPT-4
Dubo-SQL
MAC-SQL+GPT-4
XiYan-SQL
OpenSearch-SQL
CHASE-SQL
ROUTE
Alpha-SQL
Benchmark
WikiSQL
Spider
SParC
Spider-Syn
KaggleDBQA
BIRD
AmbiQT
2004
...
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025
...

😔 Execution ACC ～75%



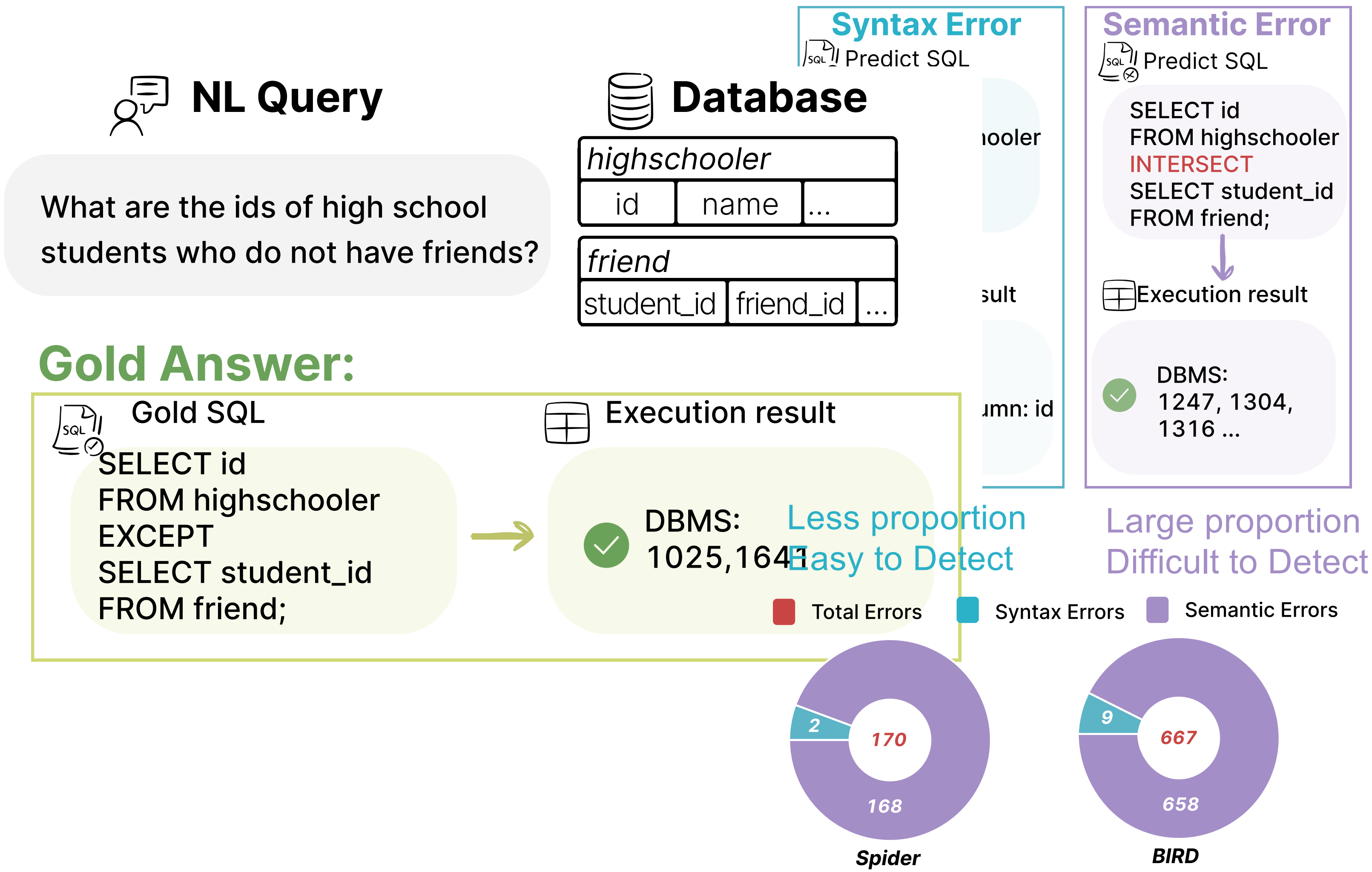
https://bird-bench.github.io/

😔Execution ACC ～30%

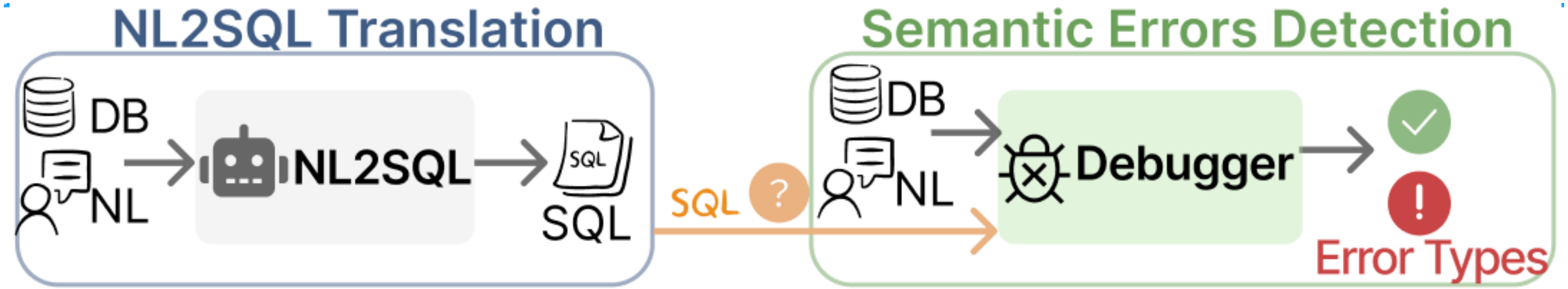


https://spider2-sql.github.io/

Types of Errors That Require Verification



Semantic Errors Detection



Question:

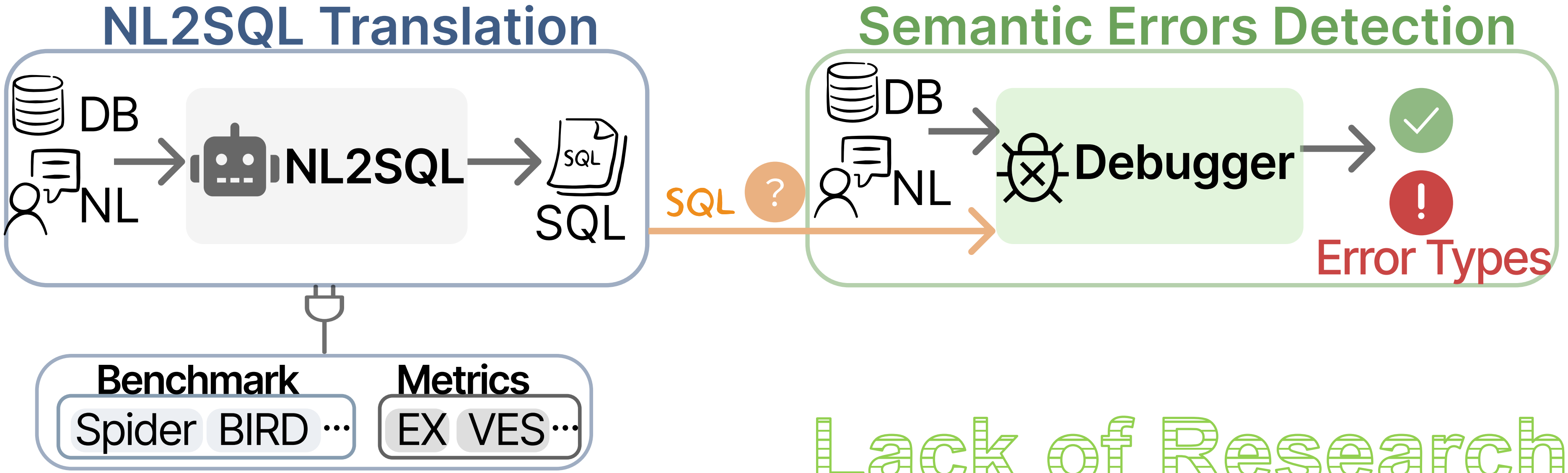
List all students and their course grades. (including students who haven't taken any courses)

Predicted SQL by NL2SQL methods:

```
SELECT s.name, e.grade
FROM student s
INNER JOIN enrollment e
ON s.id = e.id
```

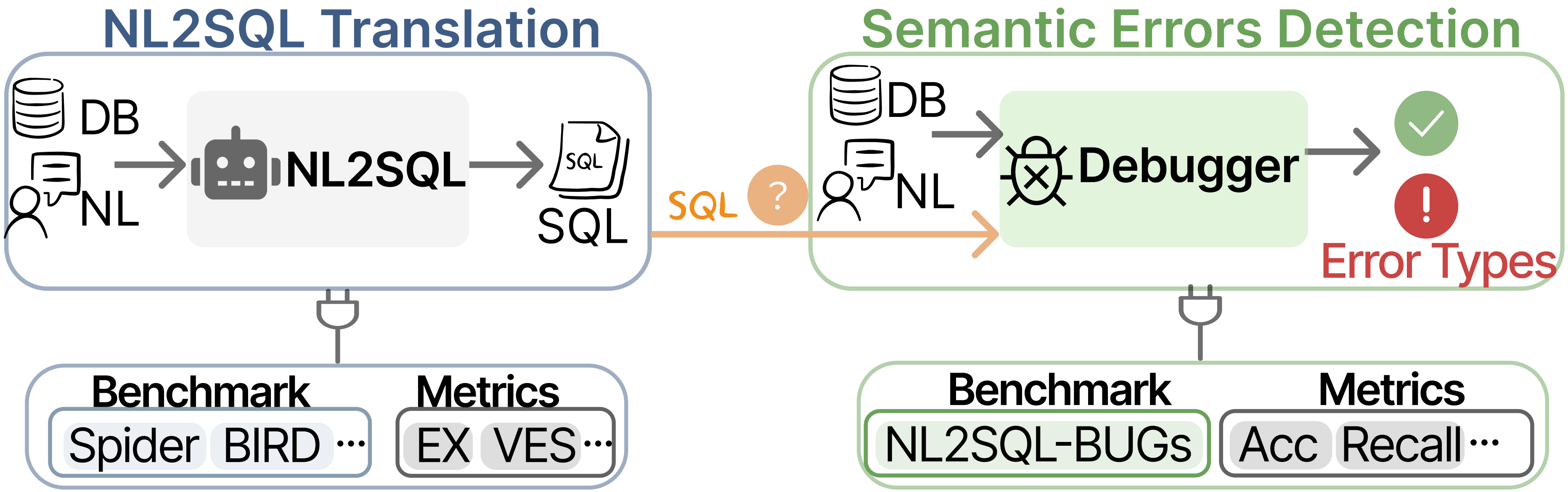
This SQL is incorrect. *The join type is mismatched, and the foreign key connection is incorrect.*

Research Gap: Lack of Robust Verifiers



Lack of Research

NL2SQL-BUGs Benchmark for Verifier



Xinyu Liu, Shuyu Shen, Boyan Li, Nan Tang, Yuyu Luo: NL2SQL-BUGs: A Benchmark for Detecting Semantic Errors in NL2SQL Translation. SIGKDD 2025

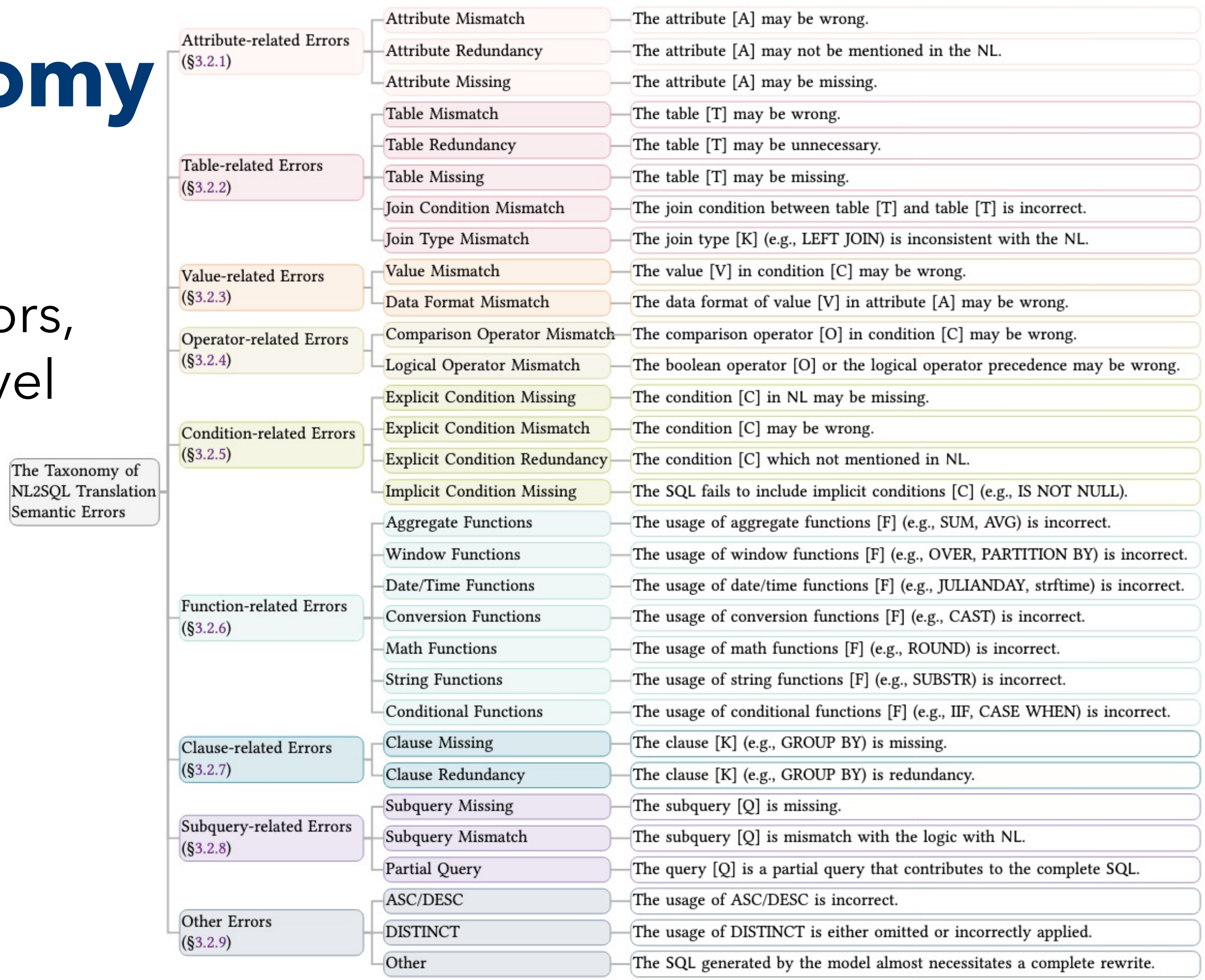
Error Taxonomy

To systematically analyze semantic errors, we propose a two-level taxonomy with

9 main type

31 subtype

to analysis semantic errors in NL2SQL translation.



SQL

```
SELECT Fname, Sex
FROM Student
WHERE StuID IN (
SELECT StuID
FROM Has_Pet
GROUP BY StuID
HAVING count(PetID) > 1)
```

NL

Find the first name and gender of student who have more than one pet.

DB

pets_1

Label

True

Matching case structure

SQL

```
SELECT DISTINCT
model_list.Model
FROM model_list
JOIN cars_data ON
model_list.ModelId =
cars_data.Id
WHERE cars_data.Year > 1980
```

NL

Which distinct car models are the produced after 1980?

DB

car_1

Label

False

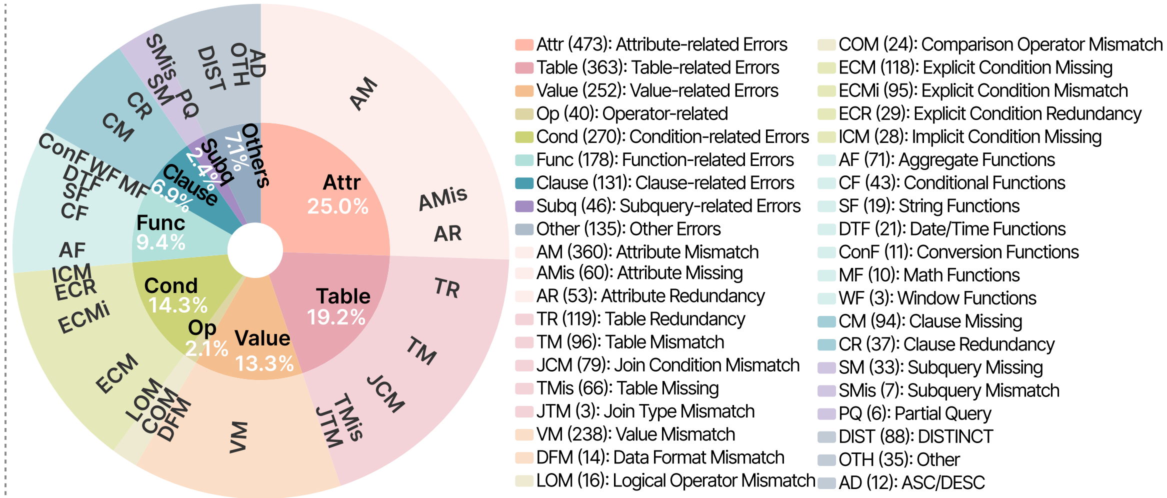
Error Type

```
{ "MainType": "Table Error",
 "SubType": "Condition Error"},
{ "MainType": "Table Error",
 "SubType": "Table Missing"}
```

Mismatched case structure

(a) Data Structure of NL2SQL-BUGs

NL2SQL-BUGs Benchmark



(b) Proportion of error types in NL2SQL-BUGs

2,018 expert-annotated examples, 1,019 correct examples, 999 incorrect examples

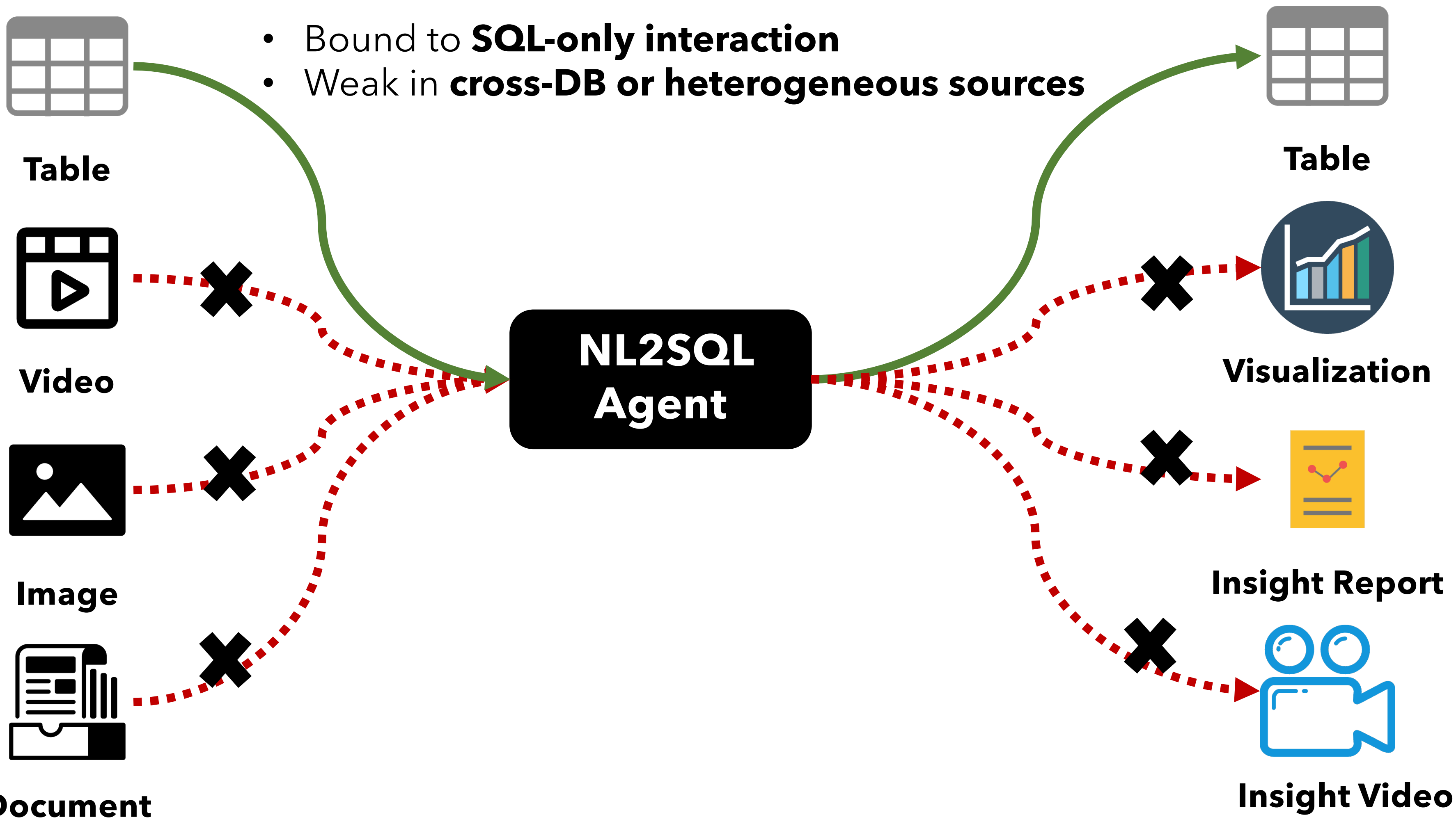
Xinyu Liu, Shuyu Shen, Boyan Li, Nan Tang, Yuyu Luo: NL2SQL-BUGs: A Benchmark for Detecting Semantic Errors in NL2SQL Translation. SIGKDD 2025

Opportunities: NL2SQL Agents

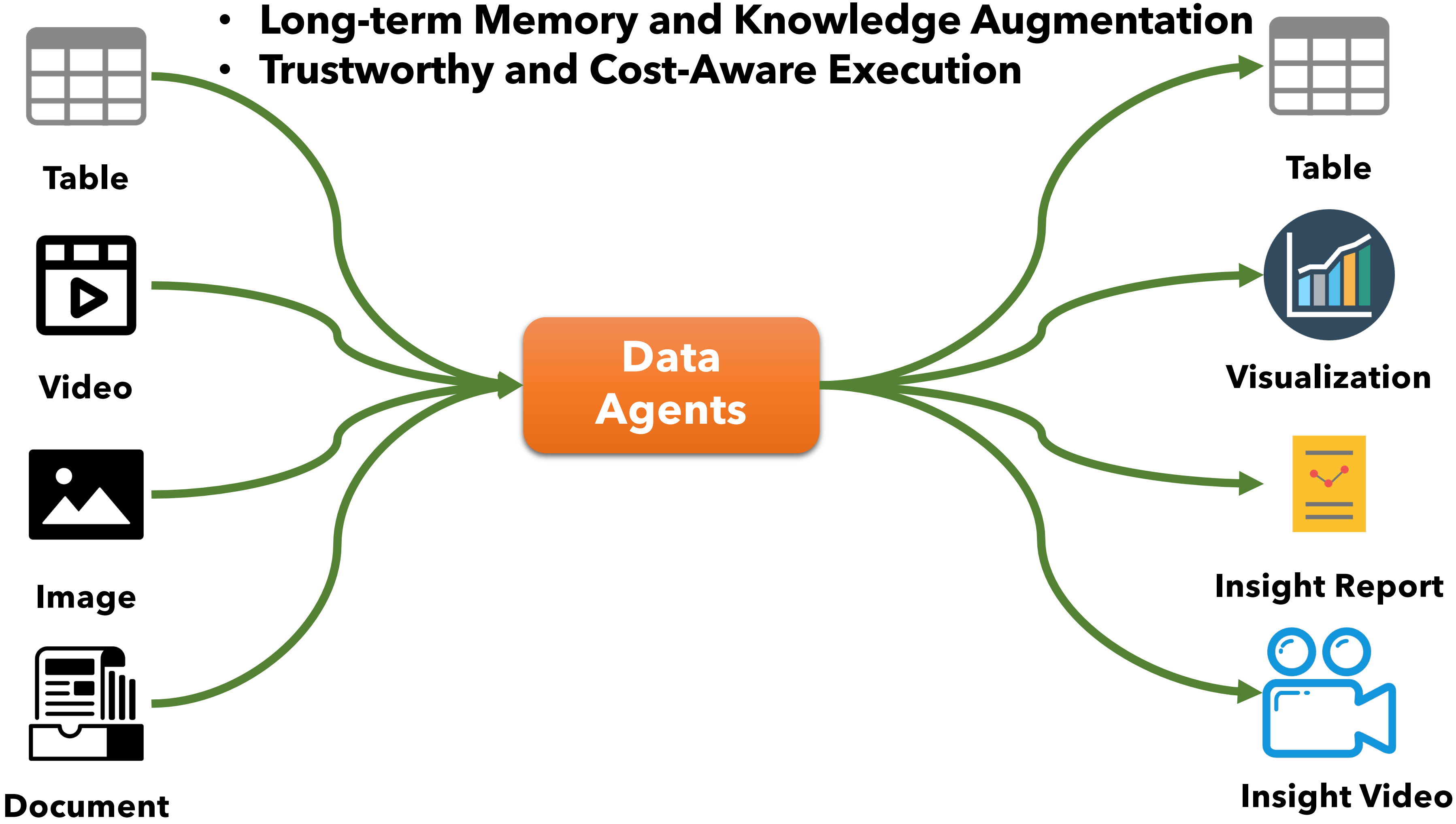
- **Human-as-an-Agent and Human-in-the-Reasoning-Loop**
  - How can we dynamically *integrate human experts into the reasoning loop* to address complex tasks beyond LLM agents' current capabilities and clarify the question ambiguities?
- **Explainable and Interpretable SQL Reasoning Agents**
  - Users typically require explanations for the reasoning steps and decisions underlying SQL generation (i.e., knowing both "what" and "why").
  - How can we design reasoning agents that transparently communicate their thought processes, decisions, and final SQL statements to improve system transparency and foster user trust?
- **Metadata Management and Schema Interpretation**
  - Real-world databases commonly feature complex schemas, detailed metadata (e.g., column annotations, table descriptions, foreign key constraints, data types).
  - How can we enable *data agents* to effectively extract, manage, and utilize this metadata to generate more accurate semantic mappings, informed reasoning processes, and precise SQL generation?

Are NL2SQL Agents Enough?

- Bound to **SQL-only interaction**
- Weak in **cross-DB or heterogeneous sources**

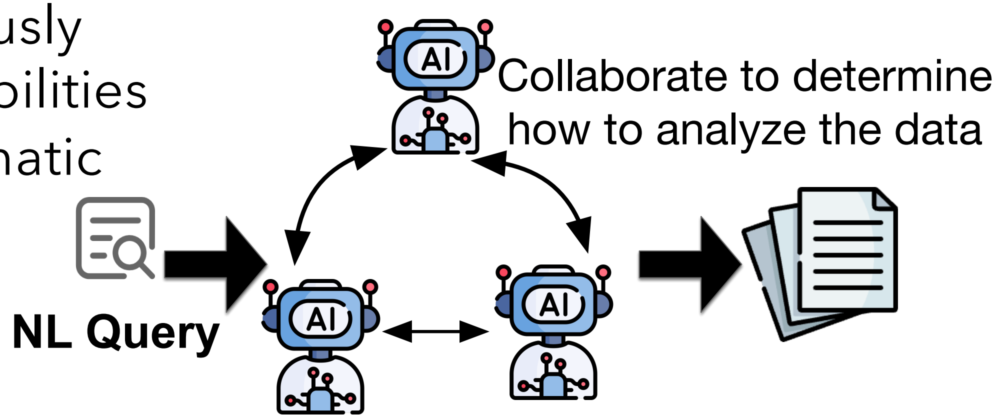


- **Unified Query Interface:** SQL → Semantic Operators
- **Multimodal Data Analysis**
- **Adaptive Reasoning and Orchestration**
- **Long-term Memory and Knowledge Augmentation**
- **Trustworthy and Cost-Aware Execution**



Data Agent

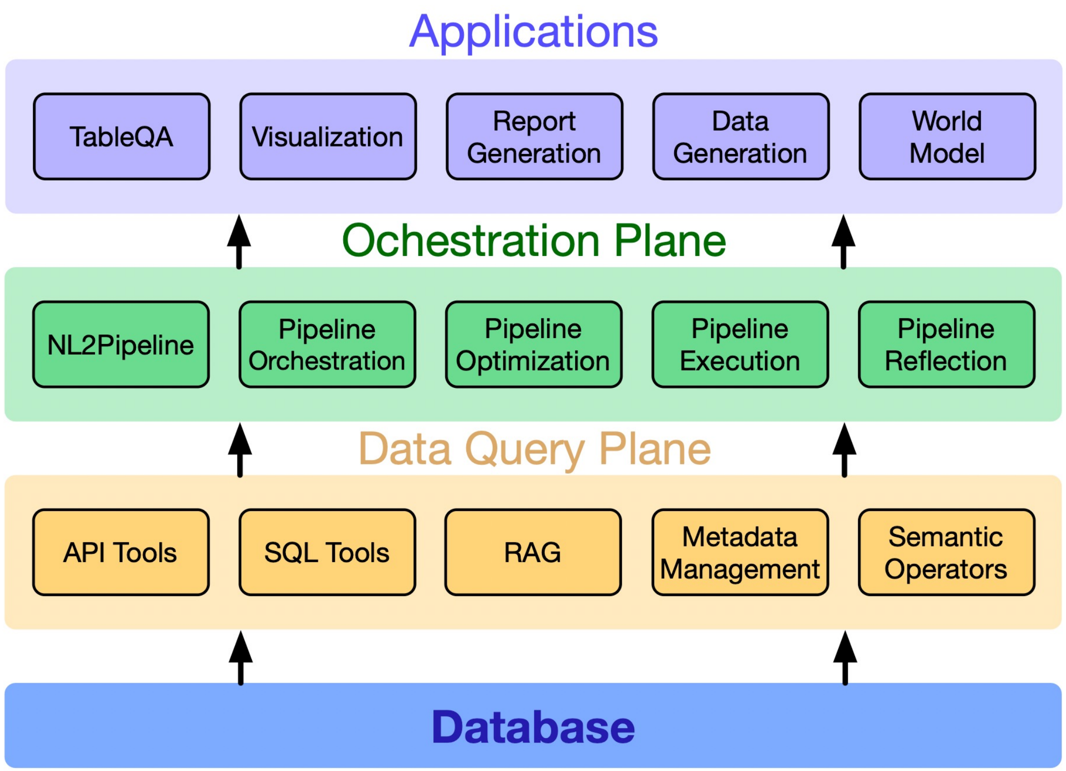
- ❑ **Data Agent:** designed to autonomously carry out data-related tasks with capabilities for knowledge comprehension, automatic planning, and self-reflection of LLMs

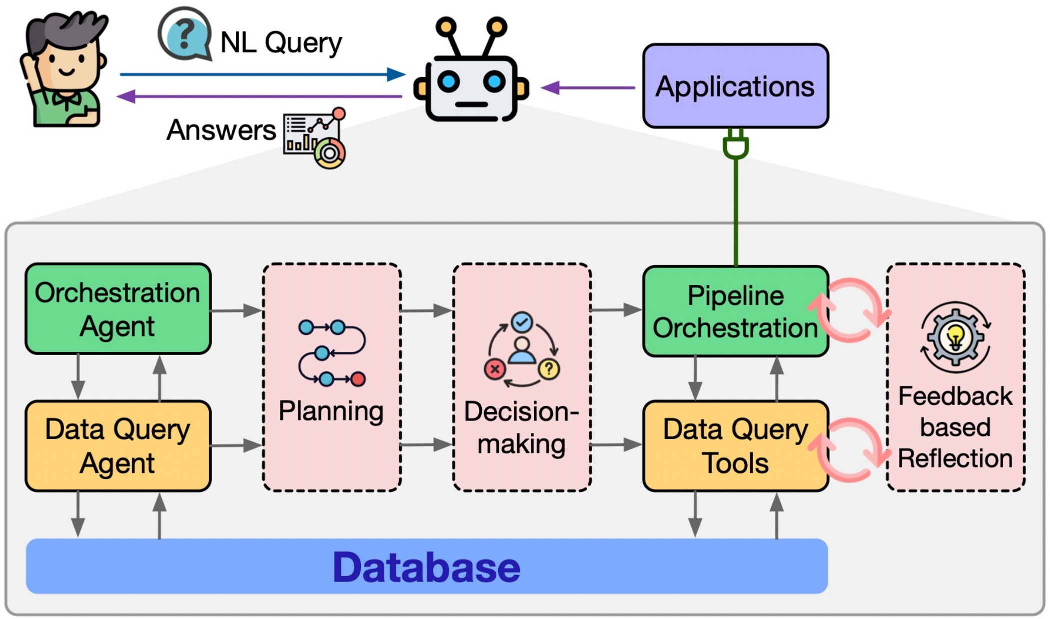


- ❑ **Challenges:**
  - How can data agents **understand** queries, data, other agents, and tools?
  - How can data agents **orchestrate** effective and efficient pipelines to bridge the gaps between user requirements and underlying heterogeneous data?
  - How to **schedule and coordinate** agents/tools to improve effectiveness?

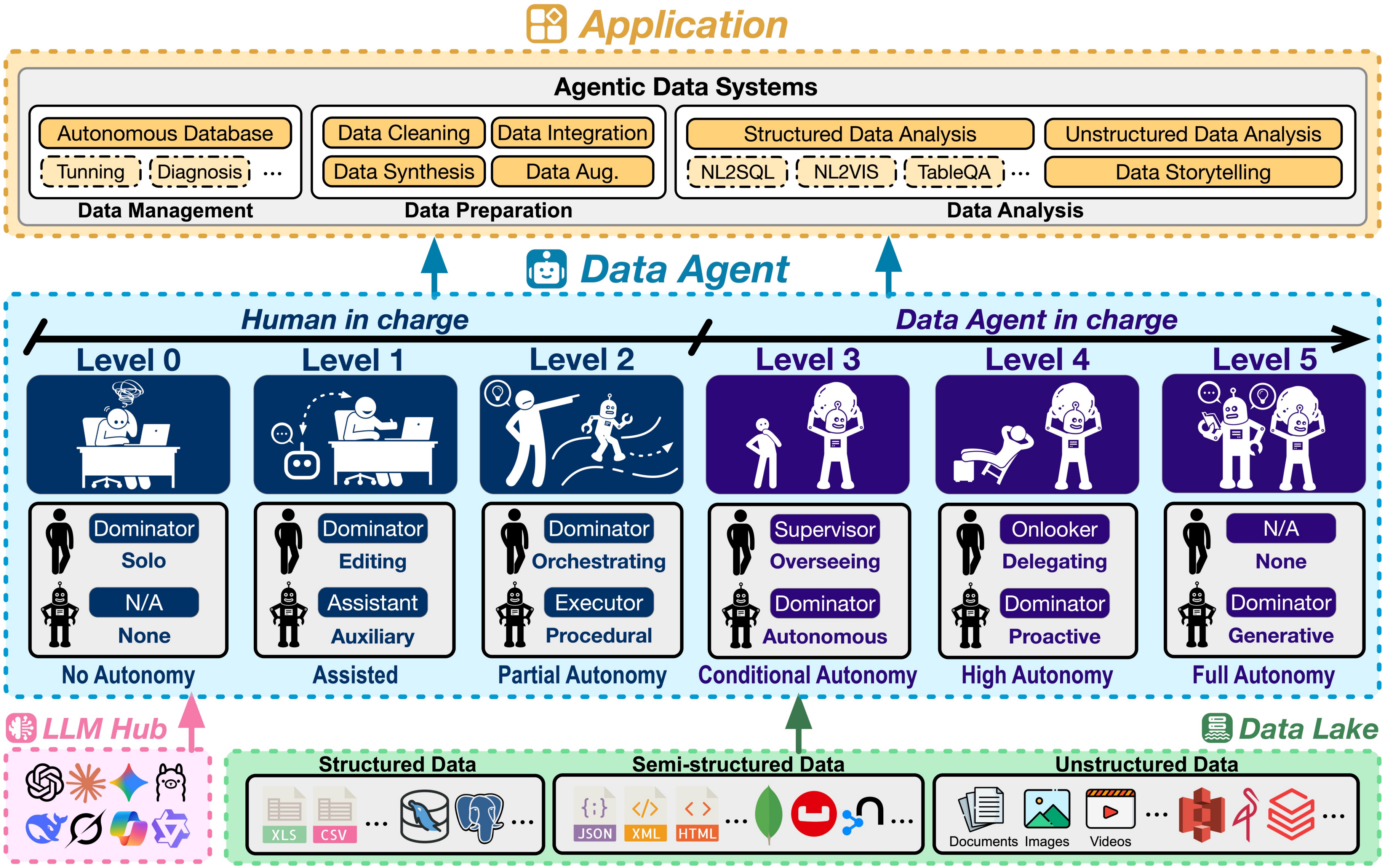
Guoliang Li et al. Data+AI: LLM4Data and Data4LLM. SIGMOD 2025
https://dbgroup.cs.tsinghua.edu.cn/ligl/papers/SIGMOD2025-Data+LLM.pdf

Data Agent: A High-level View





https://github.com/HKUSTDial/DataAgents_Handbook

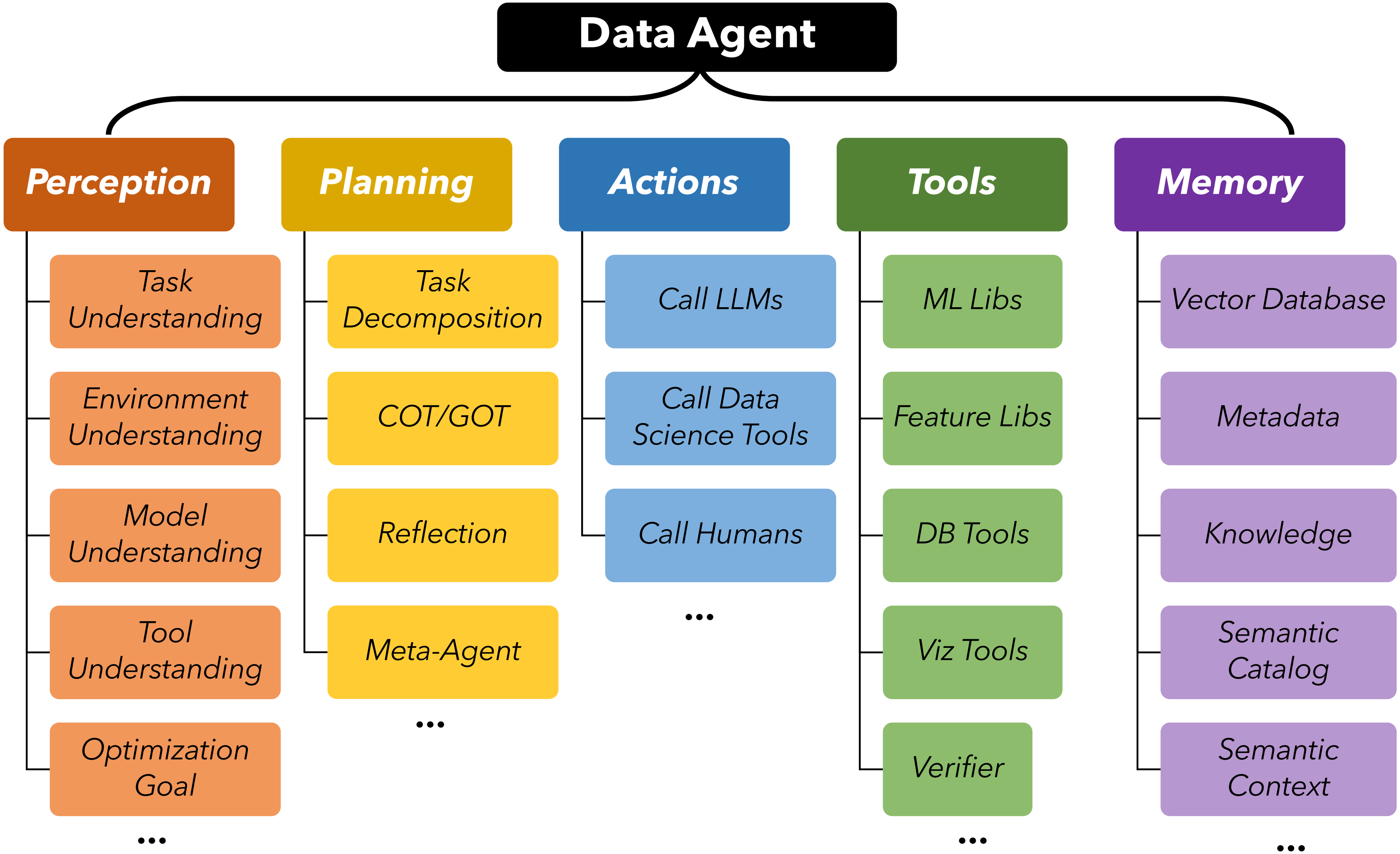


https://github.com/HKUSTDial/DataAgents_Handbook

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Name	Platform	Year_of_Release	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales	User_Count	Rating	Critic_Score	Critic_Count	User_Score
2	Wii Sports	Wii	2006	Sports	Nintendo	41.36	28.96	3.77	8.45	82.53	322	E	76	51	8
3	Mario Kart Wii	Wii	2008	Racing	Nintendo	15.68	12.76	3.79	3.29	35.52	709	E	82	73	8.3
4	Wii Sports Resort	Wii	2009	Sports	Nintendo	15.61	10.93	3.28	2.95	32.77	192	E	80	73	8
5	New Super Mario Bros.	DS	2006	Platform	Nintendo	11.28	9.14	6.5	2.88	29.8	431	E	89	65	8.5
6	Wii Play	Wii	2006	Misc	Nintendo	13.96	9.18	2.93	2.84	28.92	129	E	58	41	6.6
7	New Super Mario Bros. Wii	Wii	2009	Platform	Nintendo	14.44	6.94	4.7	2.24	28.32	594	E	87	80	8.4
8	Mario Kart DS	DS	2005	Racing	Nintendo	9.71	7.47	4.13	1.9	23.21	464	E	91	64	8.6
9	Wii Fit	Wii	2007	Sports	Nintendo	8.92	8.03	3.6	2.15	22.7	146	E	80	63	7.7
10	Kinect Adventures!	X360	2010	Misc	Microsoft Game Studios	15	4.89	0.24	1.69	21.81	106	E	61	45	6.3
11	Wii Fit Plus	Wii	2009	Sports	Nintendo	9.01	8.49	2.53	1.77	21.79	52	E	80	33	7.4
12	Grand Theft Auto V	PS3	2013	Action	Take-Two Interactive	7.02	9.09	0.98	3.96	21.04	3994	M	97	50	8.2
13	Grand Theft Auto: San Andreas	PS2	2004	Action	Take-Two Interactive	9.43	0.4	0.41	10.57	20.81	1588	M	95	80	9
14	Brain Age: Train Your Brain in Minutes a Da	DS	2005	Misc	Nintendo	4.74	9.2	4.16	2.04	20.15	50	E	77	58	7.9
15	Grand Theft Auto V	X360	2013	Action	Take-Two Interactive	9.66	5.14	0.06	1.41	16.27	3711	M	97	58	8.1
16	Grand Theft Auto: Vice City	PS2	2002	Action	Take-Two Interactive	8.41	5.49	0.47	1.78	16.15	730	M	95	62	8.7
17	Brain Age 2: More Training in Minutes a Day	DS	2005	Puzzle	Nintendo	3.43	5.35	5.32	1.18	15.29	19	E	77	37	7.1
18	Gran Turismo 3: A-Spec	PS2	2001	Racing	Sony Computer Entertainment	6.85	5.09	1.87	1.16	14.98	314	E	95	54	8.4
19	Call of Duty: Modern Warfare 3	X360	2011	Shooter	Activision	9.04	4.24	0.13	1.32	14.73	8713	M	88	81	3.4
20	Call of Duty: Black Ops	X360	2010	Shooter	Activision	9.7	3.68	0.11	1.13	14.61	1454	M	87	89	6.3
21	Call of Duty: Black Ops II	PS3	2012	Shooter	Activision	4.99	5.73	0.65	2.42	13.79	922	M	83	21	5.3
22	Call of Duty: Black Ops II	X360	2012	Shooter	Activision	8.25	4.24	0.07	1.12	13.67	2256	M	83	73	4.8
23	Call of Duty: Modern Warfare 2	X360	2009	Shooter	Activision	8.52	3.59	0.08	1.28	13.47	2698	M	94	100	6.3
24	Call of Duty: Modern Warfare 3	PS3	2011	Shooter	Activision	5.54	5.73	0.49	1.57	13.32	5234	M	88	39	3.2
25	Grand Theft Auto III	PS2	2001	Action	Take-Two Interactive	6.99	4.51	0.3	1.3	13.1	664	M	97	56	8.5
26	Super Smash Bros. Brawl	Wii	2008	Fighting	Nintendo	6.62	2.55	2.66	1.01	12.84	1662	T	93	81	8.9
27	Mario Kart 7	3DS	2011	Racing	Nintendo	5.03	4.02	2.69	0.91	12.66	632	E	85	73	8.2
28	Call of Duty: Black Ops	PS3	2010	Shooter	Activision	5.99	4.37	0.48	1.79	12.63	1094	M	88	58	6.4
29	Grand Theft Auto V	PS4	2014	Action	Take-Two Interactive	3.96	6.31	0.38	1.97	12.61	2899	M	97	66	8.3
30	Animal Crossing: Wild World	DS	2005	Simulation	Nintendo	2.5	3.45	5.33	0.86	12.13	242	E	86	57	8.7
31	Halo 3	X360	2007	Shooter	Microsoft Game Studios	7.97	2.81	0.13	1.21	12.12	4100	M	94	86	7.8
32	Gran Turismo 4	PS2	2004	Racing	Sony Computer Entertainment	3.01	0.01	1.1	7.53	11.66	272	E	89	74	8.5
33	Super Mario Galaxy	Wii	2007	Platform	Nintendo	6.06	3.35	1.2	0.74	11.35	2147	E	97	73	8.9
34	Grand Theft Auto IV	X360	[illegible]	Action	Take-Two Interactive	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	2951	M	98	86	7.9
35	Gran Turismo	PS	1997	Racing	Sony Computer Entertainment	4.02	3.87	2.54	0.52	[illegible]	138	E	96	16	8.7
36	Super Mario 3D Land	3DS	2011	Platform	Nintendo	4.89	3	2.14	0.78	10.81	921	E	90	82	8.4

This is game sales data for market analysis

Opportunities for Data Agents: Five Key Aspects



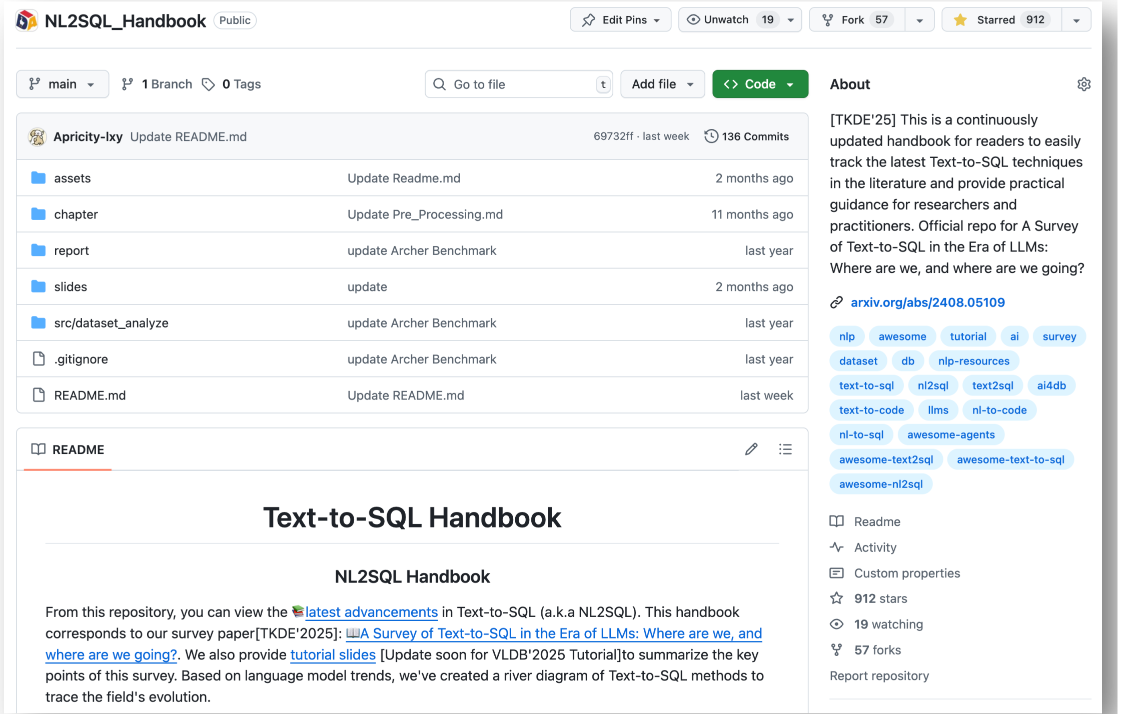
From NL2SQL Agents to Data Agents

- **Cross-DB & heterogeneous orchestration**
  - Plan over multiple stores/APIs with join-path inference and result fusion; measure success beyond single-DB EM
- **Semantic operator layer**
  - Lift from raw SQL to semantic operators that unify tabular, text, image, and report generation tasks—support *table*→*viz*→*insight report/video* workflows
- **Meta-planning & reflection**
  - A **meta-agent** that decomposes tasks, schedules tools/agents, and reflects with feedback loops
- **Memory & Semantic Catalog**
  - Unified task-specific+ long-term memory;
  - Auto-induce units, constraints, keys, value normalizations, synonyms, KPI definitions, policies, lineage from DDL/docs/logs/queries;

https://github.com/HKUSTDial/awesome-data-agents

NL2SQL:
Paper List & Slides

Data Agents:
Paper List



https://github.com/HKUSTDial/NL2SQL_Handbook

https://github.com/HKUSTDial/awesome-data-agents

Thanks!

http://luoyuyu.vip

yuyuluo@hkust-gz.edu.cn