



A Survey of NL2SQL with Large Language Models: Where are we, and where are we going?

Acknowledgement

- The slides accompany our recent NL2SQL survey^[1] and handbook^[2]. I would like to extend my gratitude to my students and collaborators for their valuable contributions.
- **All materials in the slides, including the figures, are available for distribution and use for educational and research purposes.** If you find any resources in our survey, handbook, or slides helpful, *please feel free to cite it in your work^[3].*
- As NL2SQL is an emerging area, we appreciate your informing us of any significant work we may have overlooked in our survey, so we can address it in future updates.

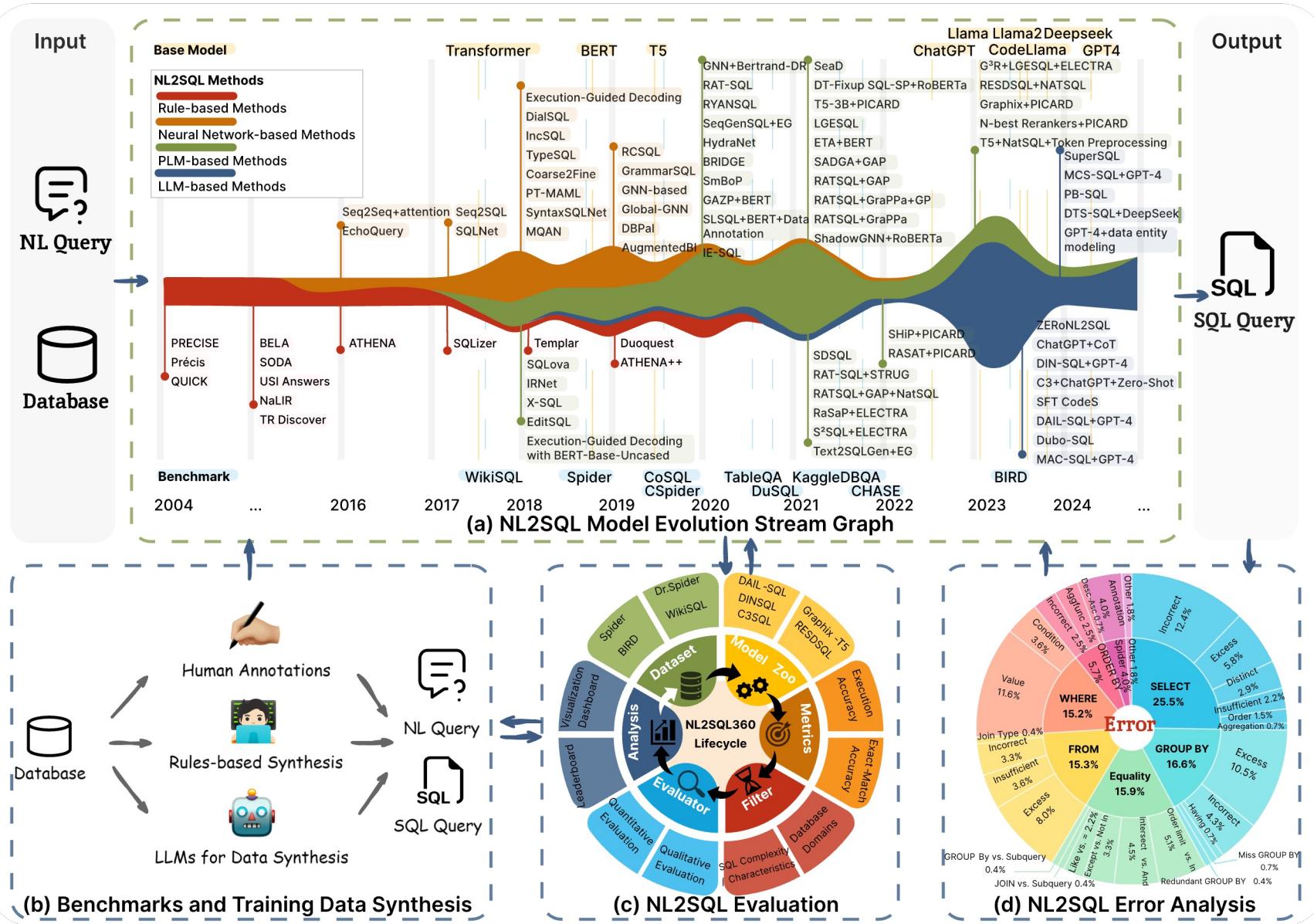
[1] Liu, Xinyu, et al. "A Survey of NL2SQL with Large Language Models: Where are we, and where are we going?." arXiv preprint arXiv:2408.05109 (2024).

[2] NL2SQL Handbook: https://github.com/HKUSTDial/NL2SQL_Handbook

[3]

```
@misc{liu2024surveynl2sqllargelanguage,
  title={A Survey of NL2SQL with Large Language Models: Where are we, and where are we going?},
  author={Xinyu Liu and Shuyu Shen and Boyan Li and Peixian Ma and Runzhi Jiang and Yuyu Luo and Yuxin Zhang and Ju Fan and Guoliang Li and Nan Tang},
  year={2024},
  eprint={2408.05109},
  archivePrefix={arXiv},
  primaryClass={cs.DB},
  url={https://arxiv.org/abs/2408.05109},
}
```

An Overview of the Survey: the entire lifecycle of NL2SQL



(a) NL2SQL Model Evolution Stream Graph

- Recent advances in NL2SQL solutions, driven by pre-trained language models (PLMs) and large language models (LLMs)

(b) Benchmarks and Training Data Synthesis

- How to collect high-quality training data
 - How to synthesize high-quality training data

(c) NL2SQL Evaluation

- Multi-angle evaluation
 - Scenario-based evaluation

(d) NL2SQL Error Analysis

- provide a taxonomy to summarize typical errors produced by NL2SQL methods

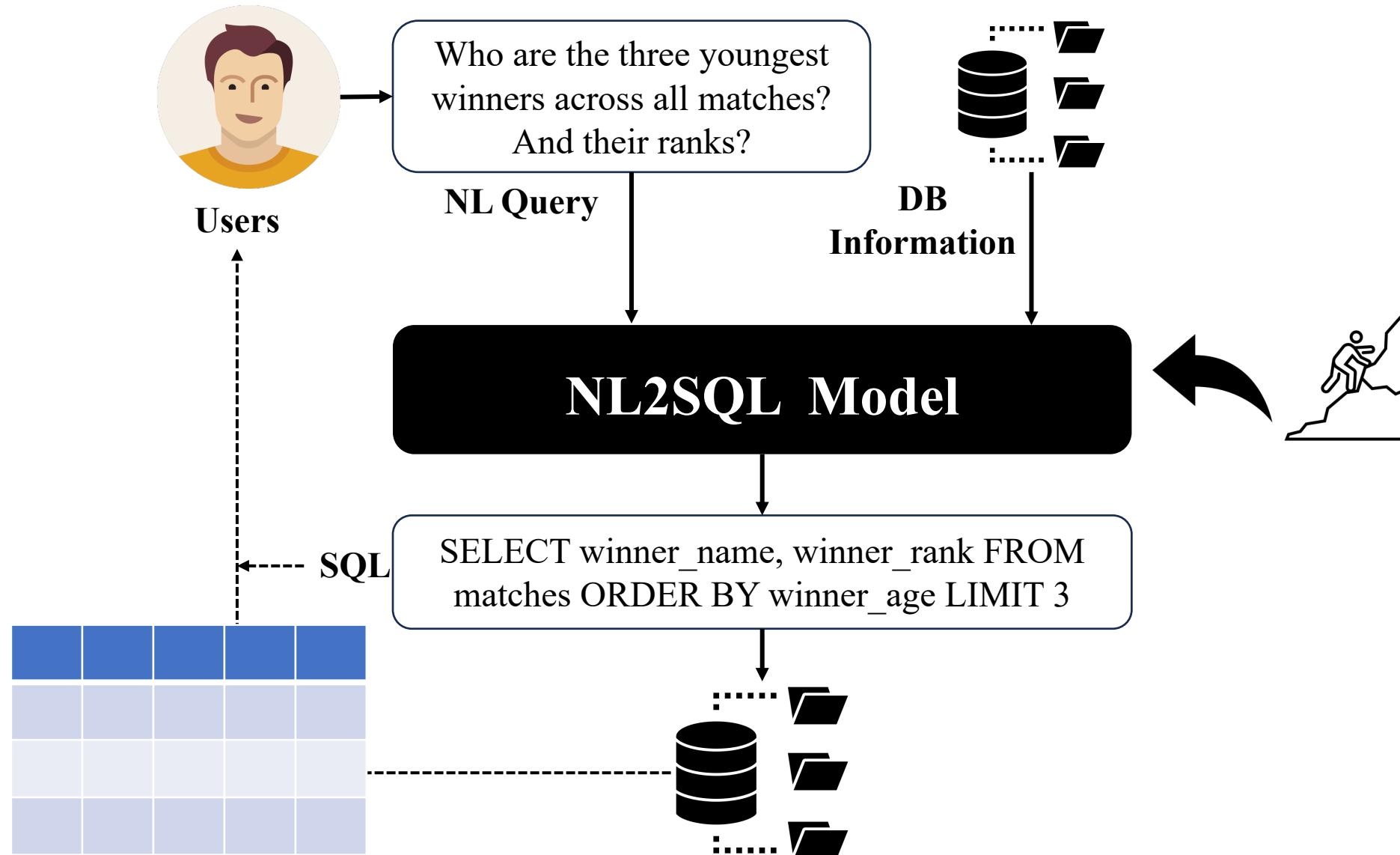
Outline

- NL2SQL Problem and Background
- Language Model-Powered NL2SQL Solutions
- NL2SQL Benchmarks
- Evaluation and Error Analysis
- Practical Guidance for Developing NL2SQL Solutions
- Open Problems

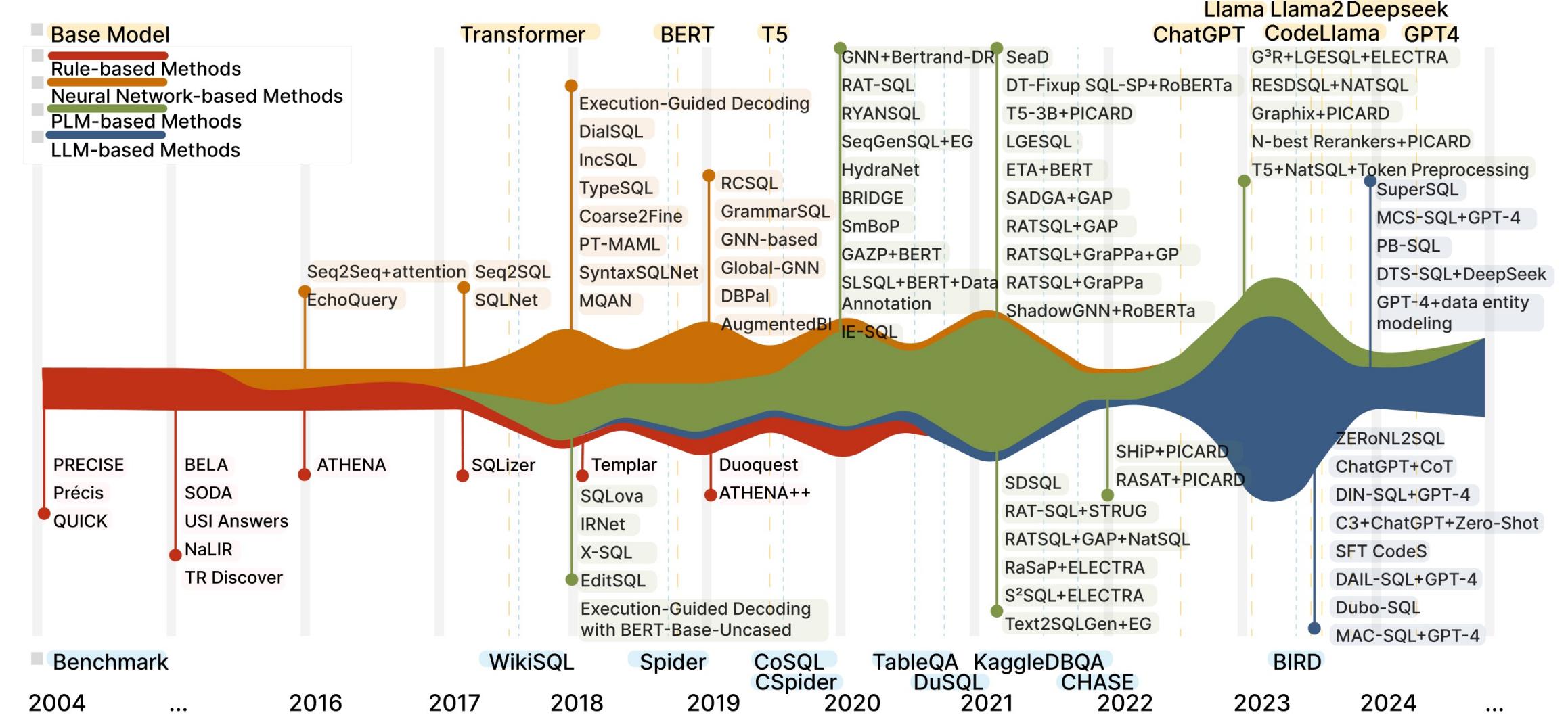
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- NL2SQL Problem and Background
 - Problem Formulation
 - NL2SQL Human Workflow
 - NL2SQL Task Challenges
 - Challenges Solving with Large Language Models
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What is Natural Language to SQL (NL2SQL)?



NL2SQL Model Evolution Stream Graph



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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

Pets			
PetID	PetType	PetAge	...
	Dog		

Student			
StuID	Sex	Age	...
	F		

Has_Pet		
PetID	StuID	...

- Table Linking
- Columns Linking
- Database Content
- Foreign Key

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'
```

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NL2SQL Task Challenges

C1. Ambiguous NL Query

C2. Requiring Domain Knowledge

C3. Complex Schema



Natural Language Query:

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

C3 Database:

Customer		
CustomerId	Name	...
1	John Doe	...

Book				
BookId	Title	LiteraryGenre	SubjectGenre	...
1	The Great Gatsby	Novel	Magic	...
2	1984	Science Fiction	Dystopian	...
3	To Kill a Mockingbird	Novel	Social Commentary	...

BookOrder			
CustomerId	BookId	OrderDate	...
1	1	2023-05-01	01/05/23
1	2	2023-05-02	02/05/23

- Table Linking
- Columns Linking
- Database Content
- Additional Information
- Foreign Key

Additional Information: Note that **Labor Day stand for May 1**

C2

NL2SQL Task Challenges



Natural Language Query:

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

C3 Database:

Customer		
CustomerId	Name	...
1	John Doe	...

Book			
BookId	Title	LiteraryGenre	SubjectGenre
1	The Great Gatsby	Novel	Mystery
2	1984	Novel	Science Fiction
3	To Kill a Mockingbird	Novel	Classic
4	The Catcher in the Rye	Novel	Young Adult
5	Pride and Prejudice	Novel	Romance
6	War and Peace	Novel	Historical
7	The Brothers Karamazov	Novel	Philosophical
8	The Idiot	Novel	Satire
9	The Master and Margarita	Novel	Mythological
10	The Brothers Karamazov	Novel	Philosophical
11	The Idiot	Novel	Satire
12	The Brothers Karamazov	Novel	Philosophical
13	The Idiot	Novel	Satire
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BookOrder			
CustomerId	BookId	OrderDate	...
1	1	01/05/23	...
2	2	01/05/23	...

Additional Information: Note that **Labor Day stand for May 1**

C1. Ambiguous NL Query

C2. Requiring Domain Knowledge

C3. Complex Schema

C4. Multiple Possible SQL Queries

- Table Linking
- Columns Linking
- Database Connection
- Additional Information
- Foreign Key

C2

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

NL2SQL Task Challenges



Natural Language Query:

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

C1. Ambiguous NL Query

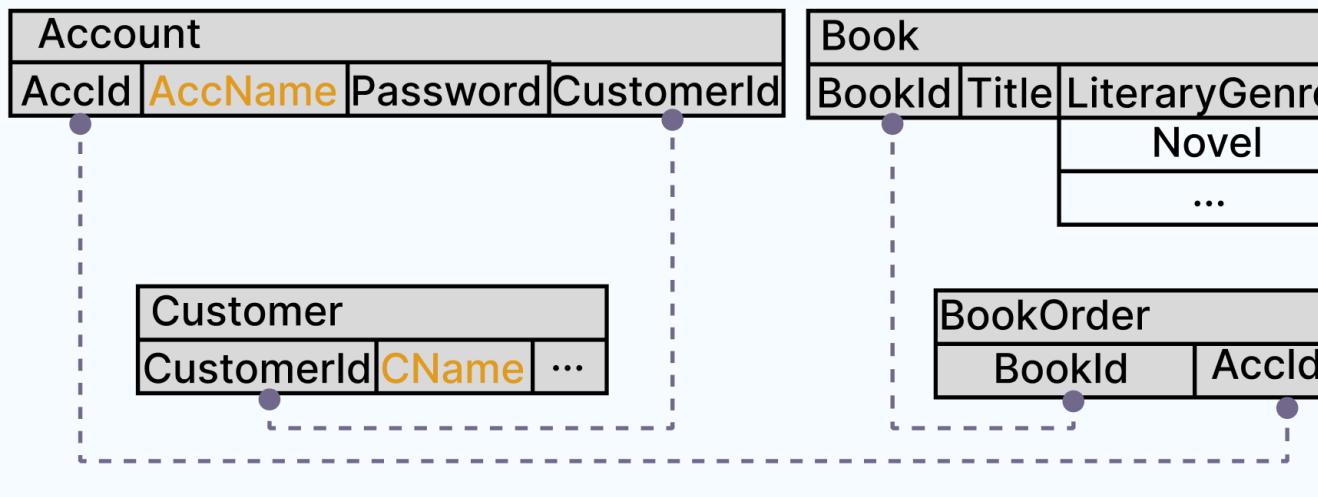
C2. Requiring Domain Knowledge

C3. Complex Schema

C4. Multiple Possible SQL Queries

C5. Database Schema Dependency

C6. Database Domain Adaption

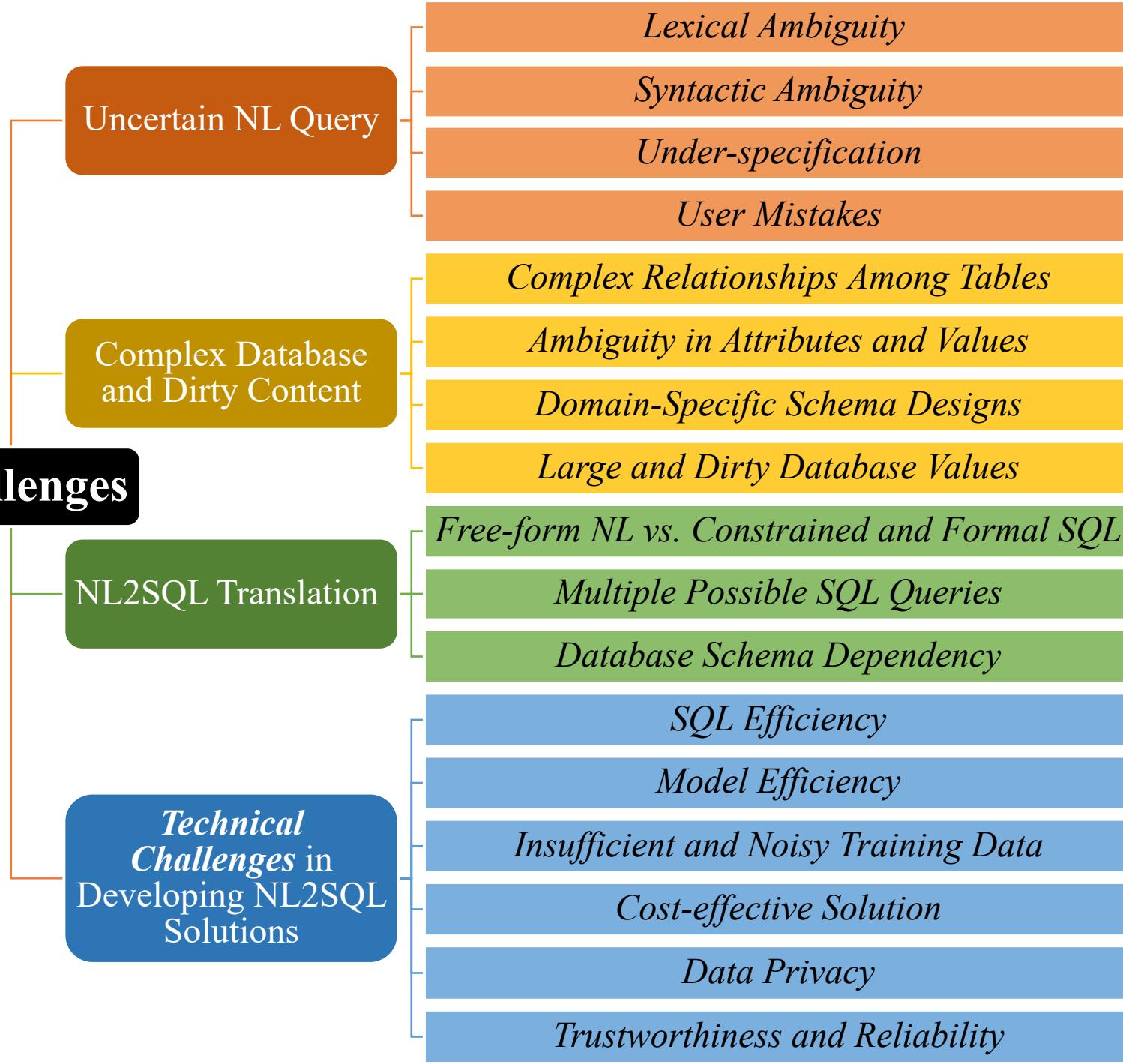


Additional Information: Note that **Labor Day** stand for May 1

```
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;
```

Challenges

NL2SQL Challenges



Task Challenges
(inherent challenges)

Uncertain NL Query

Type	Explanation	Example
Lexical Ambiguity	A single word with multiple meanings	<ul style="list-style-type: none">The word “bat” can refer to: 1) <i>an animal</i>, 2) <i>a baseball bat</i>, or 3) <i>the action of swinging</i>
Syntactic Ambiguity	A sentence can be parsed in multiple ways	<ul style="list-style-type: none">Mary [saw [the man [with the telescope]]]Mary [saw [the man]] [with the telescope]
Under-specification	Linguistic expressions lack sufficient detail to convey specific intentions or meanings clearly	<ul style="list-style-type: none">Labor Day in 2023 refers to September 4th in the US but May 1st in China
User Mistakes	Spelling mistakes and grammatical errors	<ul style="list-style-type: none">calendar → calender

Complex Database and Dirty Content

Type	Explanation	Example
Complex Relationships Among Tables	Databases often contain hundreds of tables with complex interrelationships.	<ul style="list-style-type: none">The <i>FIBEN</i> Benchmark^[1] has 152 tables per database.
Ambiguity in Attributes and Values	Attributes and values within a database can be ambiguous, making it difficult for NL2SQL systems to determine the correct context.	<ul style="list-style-type: none">An attribute or value named “status” could refer to an order’s shipping status in the shipping table, while in the payment table, it might represent the payment status.
Large and Dirty Database Values	In large databases, efficiently handling vast data volumes is critical, and data values may sometimes be inaccurate or “dirty”.	<ul style="list-style-type: none">In BI scenario, the database may contain thousands of tables.Missing values, duplicates, or inconsistencies.
Domain-Specific Schema Designs	Different domains often have unique database designs and schema patterns. The variations in schema design across domains make it difficult to develop a one-size-fits-all solution.	<ul style="list-style-type: none">Healthcare databases may include complex relational structures including patient records, medical history, and treatment plans, requiring specialized joins and query patterns.

[1] Jaydeep Sen, Chuan Lei, Abdul Quamar, Fatma Özcan, Vasilis Eftymiou, Ayushi Dalmia, Greg Stager, Ashish R. Mittal, Diptikalyan Saha, Karthik Sankaranarayanan: ATHENA++: Natural Language Querying for Complex Nested SQL Queries. Proc. VLDB Endow. 13(11): 2747-2759 (2020)

NL2SQL Translation

Challenge 1: Free-form NL vs. Constrained and Formal SQL

Natural language is flexible, while SQL queries must follow strict syntax rules.

Challenge 2: Multiple Possible SQL Queries

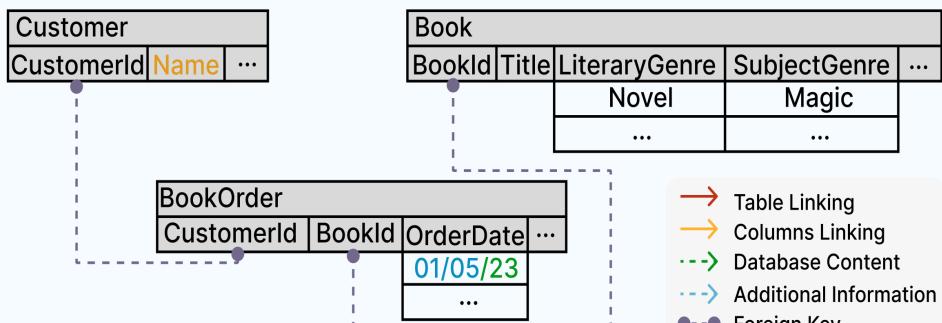
A single NL query can correspond to multiple SQL queries that fulfill the query intent, leading to ambiguity in determining appropriate SQL translation.



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

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;
```

```
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);
```

Example

NL2SQL Translation

Challenge 3: Database Schema Dependency

The NL2SQL translation process is highly dependent on the database schema it interacts with.

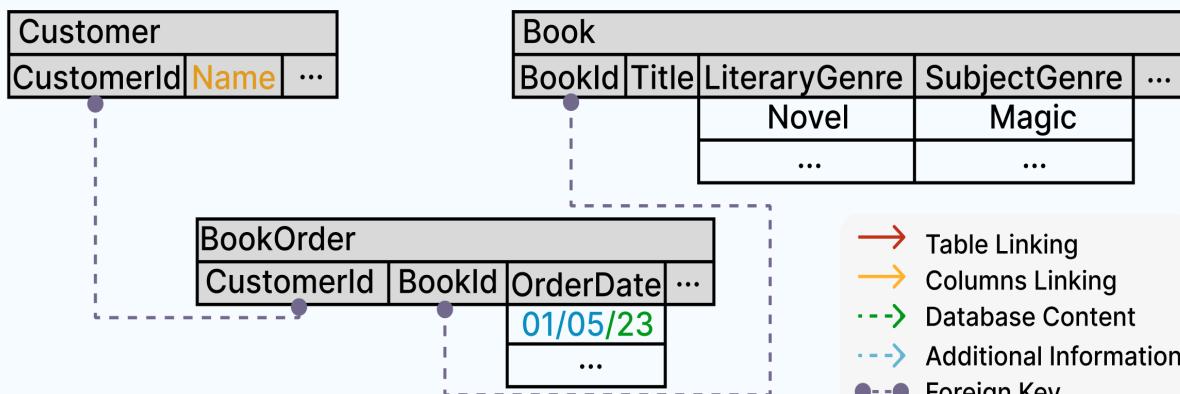
- Example: The same user intent can result in different SQL queries for different database schemas**



Natural Language Query:

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NL2SQL Translation

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- Example: The same user intent can result in different SQL queries for different database schemas

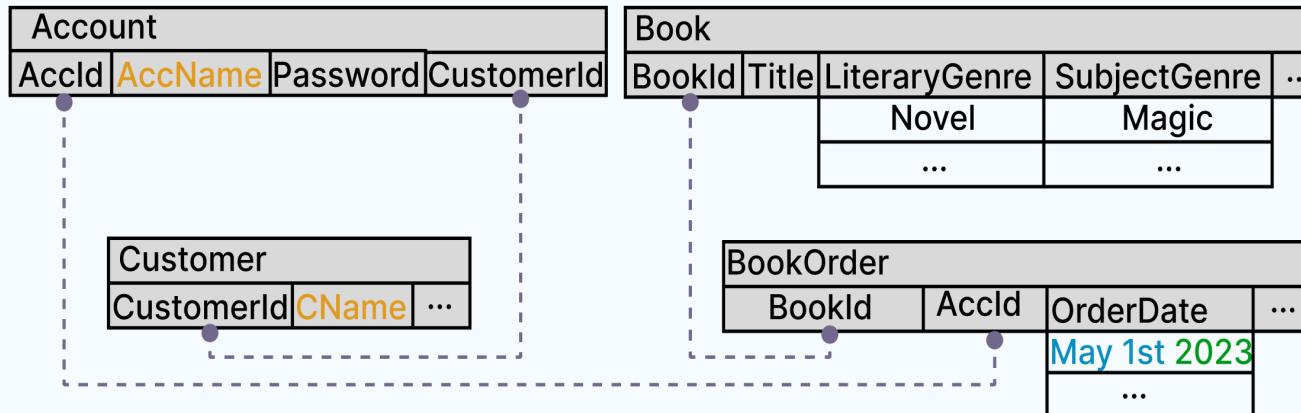


Natural Language Query:

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

Database:

The update in the DB schema



```
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;
```

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Technical Challenges in Developing Solutions

<i>Type</i>	<i>Explanation</i>
SQL Efficiency	The SQL generated by NL2SQL models must be both correct and optimized for the SQL execution efficiency.
Model Efficiency	There is often a trade-off between model performance and efficiency, as larger models generally deliver better results due to scaling laws but suffer from high latency.
Insufficient and Noisy Training Data	Acquiring high-quality NL2SQL training data is challenging. The limited publicly available datasets are often insufficient for training robust models, and noisy annotations further compromise their quality.

Technical Challenges in Developing Solutions

<i>Type</i>	<i>Explanation</i>
Cost-effective Solution	Deploying NL2SQL models, especially those powered by large language models, requires substantial resources, including hardware and API costs.
Data Privacy	Data privacy is crucial for NL2SQL systems, especially when the databases contain sensitive data.
Trustworthiness and Reliability	For NL2SQL models to be widely used, they must be trustworthy and reliable, consistently delivering accurate results across various datasets and use cases. Trustworthiness also requires that the model's decisions are transparent.

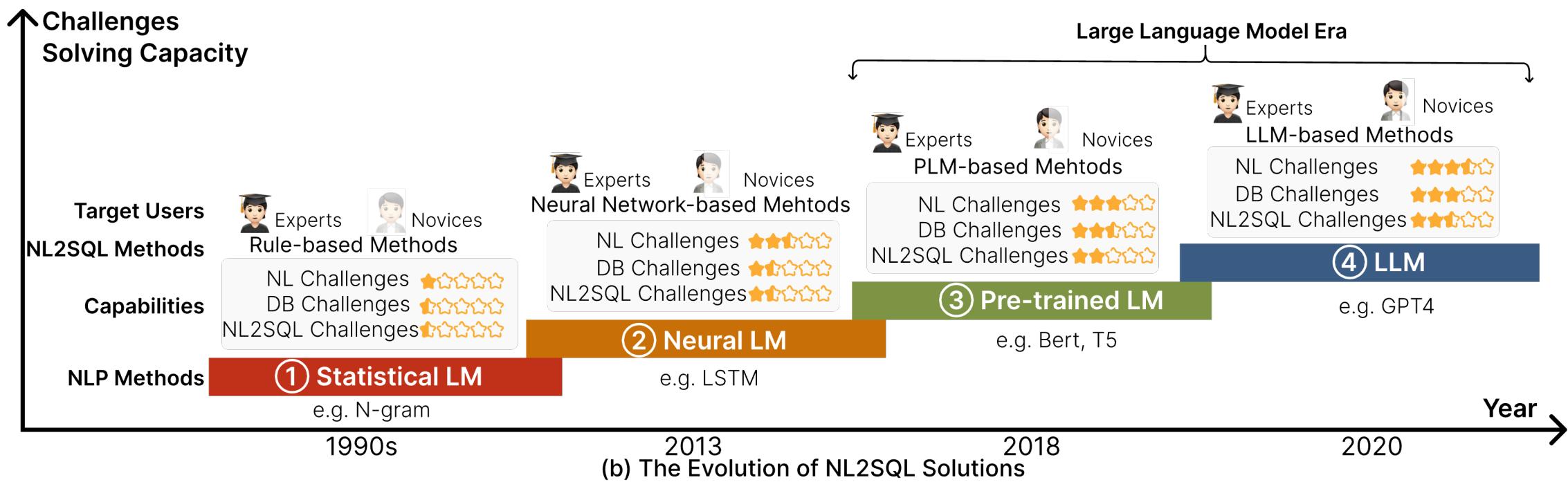
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Challenges Solving with Language Models

Type	Level	★	★★	★★★	★★★★	★★★★★
NL Challenges	Token-level Recognition	Synonym Recognition	Semantic Understanding	Domain Knowledge Query	Multi-turn Dialogues	Recognition
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

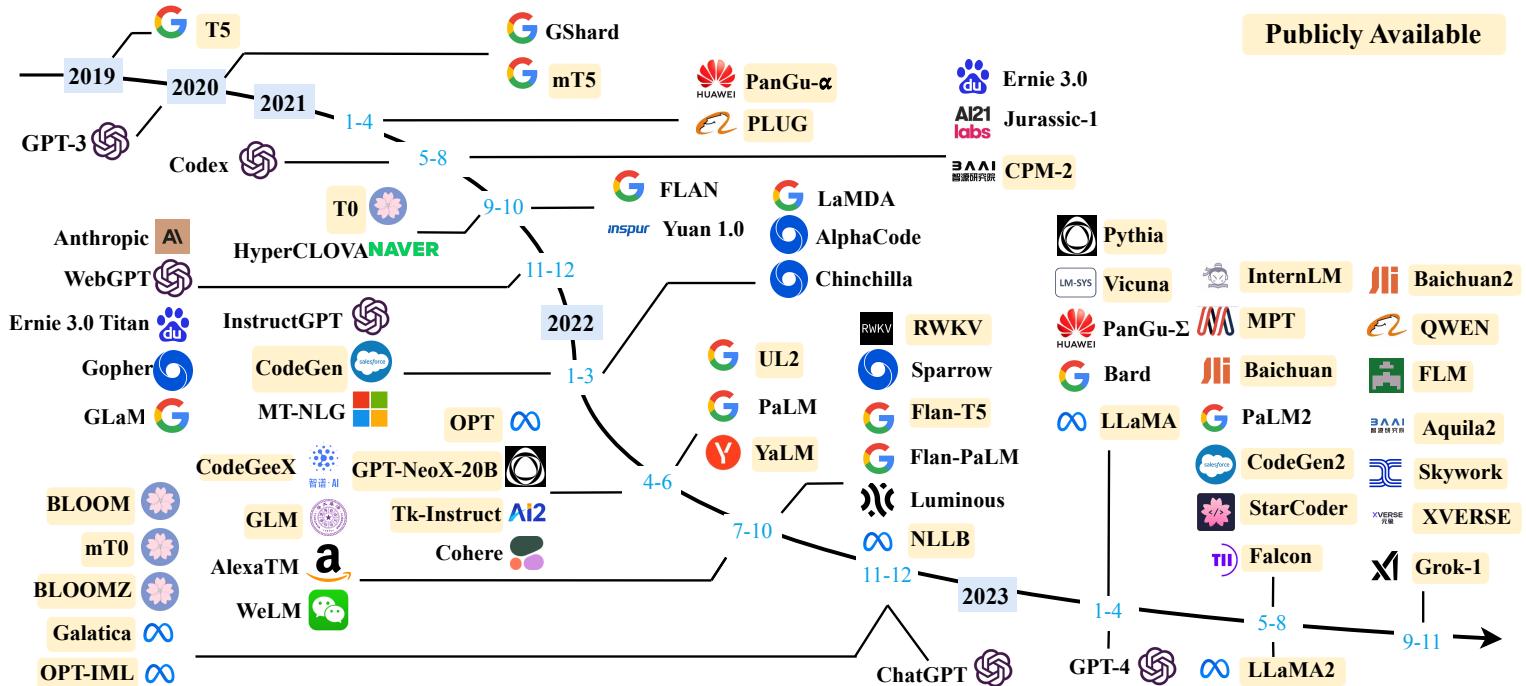
Recap: LLM vs. PLM

PLMs (Pre-trained Language Models):

- Trained on large text corpora
- General language understanding
- Examples: BERT, T5

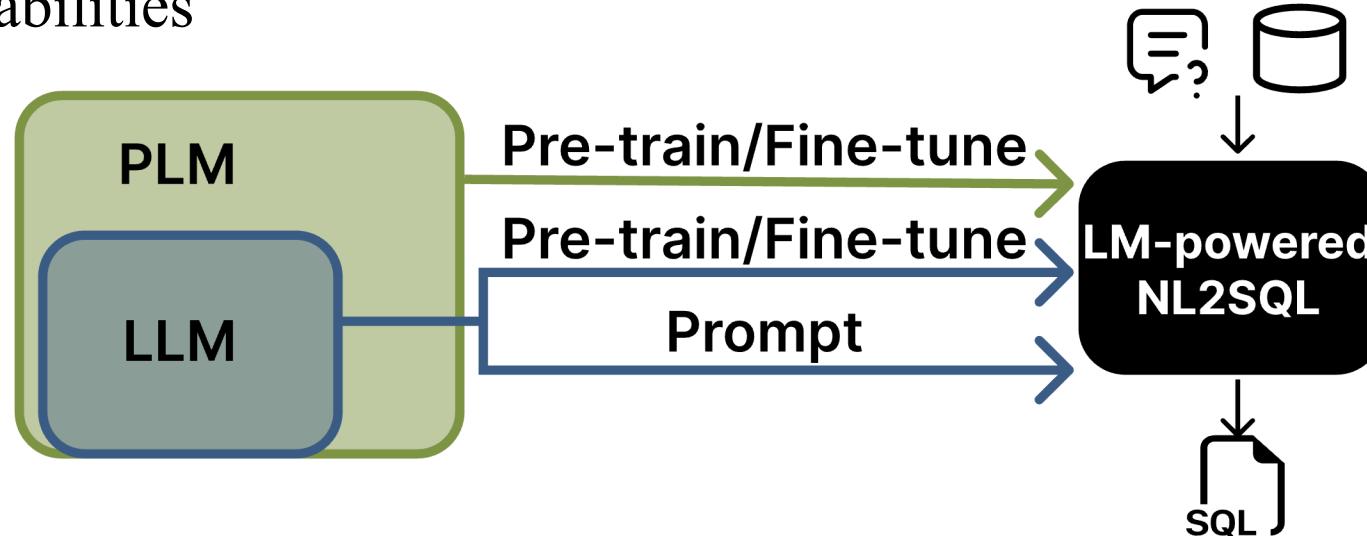
LLMs (Large Language Models):

- A subset of PLMs with larger size and more training data
- Superior language understanding and emergent capabilities
- Examples: GPT-4, LLama2



How to adapt LLM/PLM to NL2SQL?

- The LLMs are a type of PLMs characterized by superior language understanding and emergent capabilities



Steps for applying PLMs to downstream tasks:

1. Pre-training: Training a model on large-scale data to learn general knowledge.
2. Fine-tuning: Adapting a pre-trained model to a specific task using specialized data.

Steps for applying LLMs to downstream tasks:

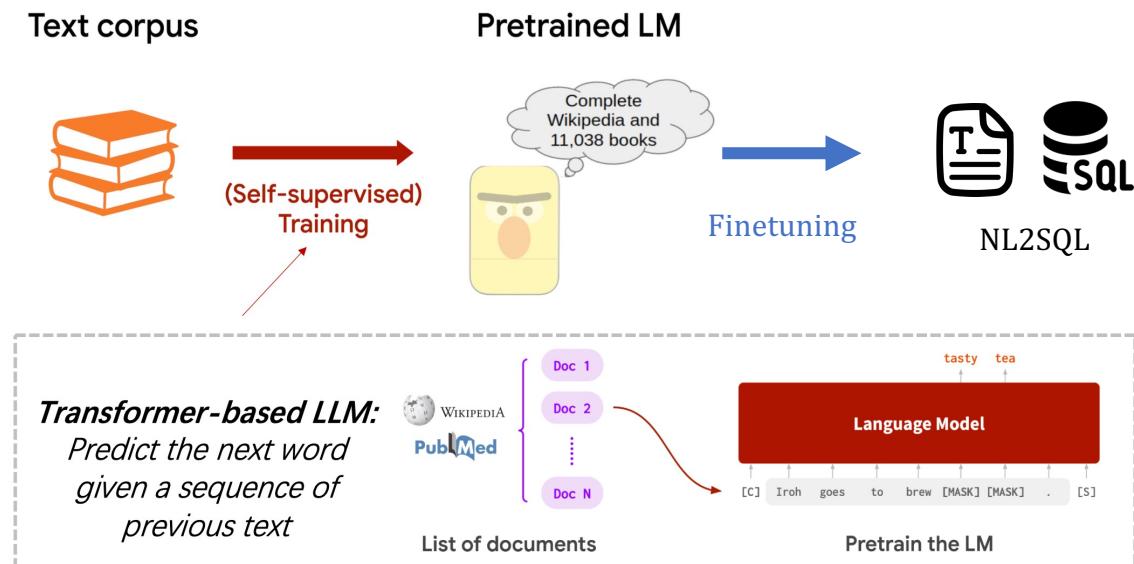
1. Pre-training (optional)
2. Fine-tuning (optional)
3. Prompt the LLMs with different strategies (e.g, In-context learning)

NL2SQL Solution in the Era of LLMs

Pre-train and Fine-tune LLMs for NL2SQL:

$$\text{LLM}^* = \mathcal{F}_{\text{fine-tune}}(\mathcal{F}_{\text{pre-train}}(\text{LLM}, \mathcal{D}_p), \mathcal{D}_f)$$

- Diverse datasets (D_p) include a broad range of linguistic patterns and domain-general knowledge, enabling the model to develop robust understanding capabilities.
- Specialized datasets (D_f) are closely aligned with the NL2SQL task.



You can get more idea from Section Practical Guidance for Developing NL2SQL Solutions (click it)

NL2SQL Solution in the Era of LLMs

In-Context Learning for NL2SQL:

The goal is to optimize the prompt function P to guide the LLMs.

$$\mathcal{F}_{\text{LLM}}(P \mid \text{NL}, \text{DB}, \text{K}) \rightarrow \text{SQL},$$

- K denotes additional information or domain-specific knowledge related to NL or DB.
- P is a prompt function that transforms the input (NL, DB, K) into a suitable textual prompt for the LLMs.

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

### Example ####
/* 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

### DB ####
/* Given the following database schema : */
CREATE TABLE continents (
ContId int primary key ,
Continent text ,
foreign key ( ContId ) references countries ( Continent )
);

### NL ####
/* Answer the following : How many continents are there ?*/
SELECT
```

Example: In-context learning for NL2SQL

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 - NL2SQL Translation Methods
 - Post-Processing
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An Overview of Language Model-Powered NL2SQL

- **Pre-Processing**
 - Schema Linking
 - Database Content Retrieval
 - Additional Information Acquisition
- **NL2SQL Translation Methods**
 - Encoding Strategy
 - Decoding Strategy
 - Task-specific Prompt Strategies
 - Intermediate Representation
- **Post-Processing**
 - Correction
 - Consistency
 - Execution- Guided
 - N-best Rerankers

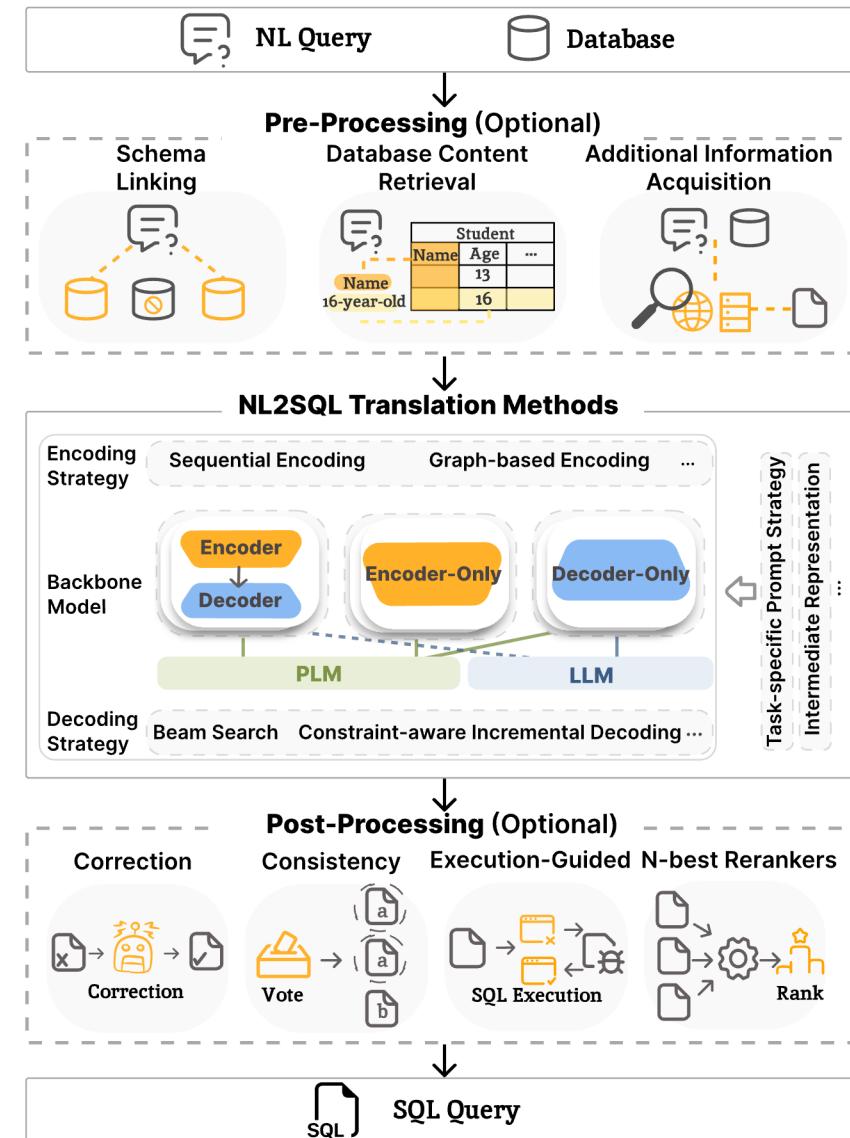


Figure: An Overview of NL2SQL Methods in the LM Era

TABLE I: Comparisons of Existing NL2SQL Solutions.

Methods	Years	Finetuning	Pre-Processing			NL2SQL Translation Methods					Post-Processing			
			Schema Linking	DB Content Retrieval	Additional Information Acquisition	Backbone Model	Encoding Strategy	Intermediate Representation	Task-specific Prompt Strategy	Decoding Strategy	Correction	Consistency	Execution Guided	N-best Rerankers
CHESS [51]	2024	-	✓	✓	✓	Decoder-Only	Sequential Encoding	-	COT	Greedy Search	✓	✓	✓	-
CodeS [46]	2024	-	✓	✓	-	Decoder-Only	Sequential Encoding	-	-	Greedy Search	-	-	✓	-
SFT CodeS [46]	2024	✓	✓	✓	✓	Decoder-Only	Sequential Encoding	-	-	Greedy Search	-	-	✓	-
FinSQL [47]	2024	✓	✓	-	✓	Decoder-Only	Sequential Encoding	-	-	Greedy Search	✓	✓	-	-
DTS-SQL [52]	2024	✓	✓	-	-	Decoder-Only	Sequential Encoding	-	-	Greedy Search	-	-	-	-
TA-SQL [53]	2024	-	✓	-	-	Decoder-Only	Sequential Encoding	Sketch Structure	COT	Greedy Search	-	-	-	-
SuperSQL [45]	2024	-	✓	✓	✓	Decoder-Only	Sequential Encoding	-	-	Greedy Search	-	✓	-	-
ZeroNL2SQL [44]	2024	✓	-	-	-	Encoder-Decoder	Sequential Encoding	Sketch Structure	Decomposition	Beam Search	✓	-	✓	-
PET-SQL [54]	2024	✓	✓	-	✓	Decoder-Only	Sequential Encoding	-	-	Greedy Search	-	✓	-	-
CoE-SQL [55]	2024	-	-	-	✓	Decoder-Only	Sequential Encoding	-	CoT	Greedy Search	✓	-	-	-
PURPLE [56]	2024	-	✓	-	✓	Decoder-Only	Sequential Encoding	-	-	Greedy Search	✓	✓	✓	-
MetaSQL [57]	2024	-	✓	-	✓	Decoder-Only	Sequential Encoding	-	Decomposition	Greedy Search	-	-	-	✓
DEA-SQL [58]	2024	-	✓	-	✓	Decoder-Only	Sequential Encoding	-	Decomposition	Greedy Search	✓	-	-	-
DIN-SQL [5]	2023	-	✓	-	✓	Decoder-Only	Sequential Encoding	Syntax Language	Decomposition	Greedy Search	✓	-	-	-
DAIL-SQL [6]	2023	-	-	-	✓	Decoder-Only	Sequential Encoding	-	-	Greedy Search	-	✓	-	-
C3-SQL [59]	2023	-	✓	-	-	Decoder-Only	Sequential Encoding	-	COT	Greedy Search	-	✓	-	-
RESDSLQ [7]	2023	✓	✓	✓	-	Encoder-Decoder	Sequential Encoding	Syntax Language	Decomposition	Beam Search	-	-	-	-
T5-3B+NatSQL+Token Preprocessing [60]	2023	✓	✓	✓	-	Encoder-Decoder	Sequential Encoding	Syntax Language	-	Greedy Search	-	-	-	-
ACT-SQL [61]	2023	-	✓	-	✓	Decoder-Only	Sequential Encoding	-	CoT	Greedy Search	-	-	-	-
ODIS [62]	2023	-	-	-	✓	Decoder-Only	Sequential Encoding	-	-	Greedy Search	-	-	-	-
MAC-SQL [63]	2023	-	✓	-	-	Decoder-Only	Sequential Encoding	-	Decomposition	Greedy Search	✓	-	✓	-
SC-Prompt [64]	2023	✓	-	-	-	Encoder-Decoder	Separate Encoding	Sketch Structure	-	Beam Search	✓	-	-	-
CatSQL [65]	2023	✓	-	-	-	Encoder-Only	Sequential Encoding	Sketch Structure	-	Beam Search	✓	-	-	-
SQLFormer [66]	2023	✓	✓	-	-	Encoder-Decoder	Graph-based Encoding	-	-	Beam Search	-	-	-	-
G ³ R [67]	2023	✓	✓	✓	-	Encoder-Only	Graph-based Encoding	-	COT	Beam Search	-	-	-	✓
Graphix-T5 [43]	2022	✓	✓	✓	-	Encoder-Decoder	Graph-based Encoding	-	-	Constraint-aware Incremental	-	-	-	-
SHiP [68]	2022	✓	-	✓	-	Encoder-Decoder	Graph-based Encoding	-	-	Constraint-aware Incremental	-	-	-	-
N-best List Rerankers [69]	2022	✓	✓	✓	-	Encoder-Decoder	Sequential Encoding	-	-	Constraint-aware Incremental	-	-	-	✓
RASAT [70]	2022	✓	-	✓	-	Encoder-Decoder	Graph-based Encoding	-	-	Constraint-aware Incremental	-	-	-	-
PICARD [71]	2022	✓	-	✓	-	Encoder-Decoder	Sequential Encoding	-	-	Constraint-aware Incremental	-	-	-	-
TKK [72]	2022	✓	-	✓	-	Encoder-Decoder	Separate Encoding	Sketch Structure	Decomposition	Constraint-aware Incremental	-	-	-	-
S ² SQL [73]	2022	✓	✓	✓	-	Encoder-Only	Graph-based Encoding	-	-	Greedy Search	-	-	-	-
RAT-SQL [74]	2021	✓	✓	✓	-	Encoder-Only	Graph-based Encoding	Syntax Language	-	Beam Search	-	-	-	-
SmBoP [75]	2021	✓	-	✓	-	Encoder-Only	Graph-based Encoding	-	-	Beam Search	-	-	-	-
RaSaP [76]	2021	✓	✓	✓	-	Encoder-Only	Graph-based Encoding	-	-	Beam Search	-	-	-	-
BRIDGE [77]	2020	✓	-	✓	-	Encoder-Only	Sequential Encoding	-	-	Others	-	-	-	-

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- Open Problems

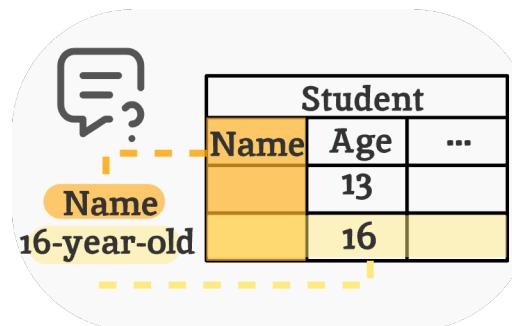
Pre-Processing

Motivation:

- The pre-processing ensures the accurate mapping and processing of key information within the limited input, by identifying the tables and columns related to the given NL query.
- The pre-processing serves as an **enhancement** to the model's inputs in the NL2SQL translation.



Schema Linking



Database Content Retrieval



Additional Information Acquisition

Schema Linking

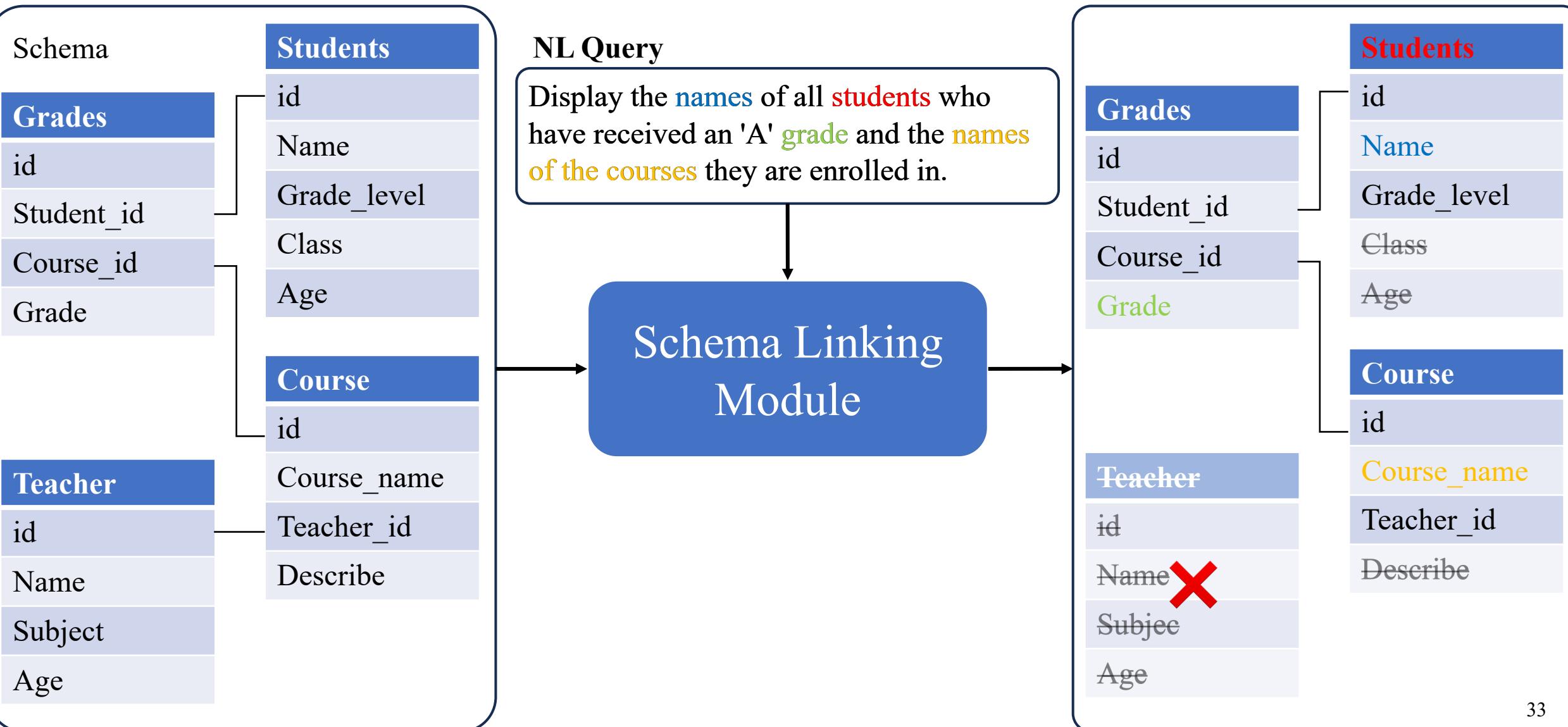
Motivation:

- Schema complexity and presence of irrelevant tables with NL in database.
- The model has input limitations, e.g., the input limit of ChatGPT is 4096 tokens.

Goal:

- Identify the tables and columns related to the given NL.

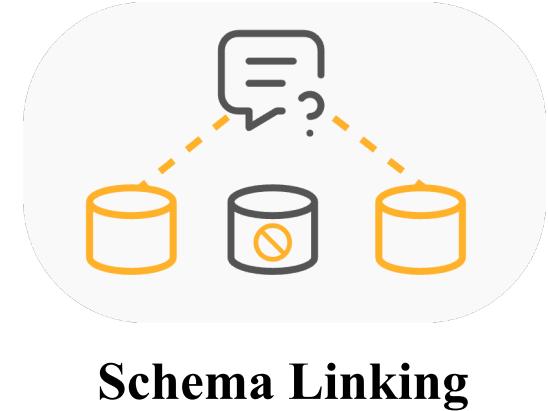
Workflow of Schema Linking



Method Classification of Schema Linking

Method classification:

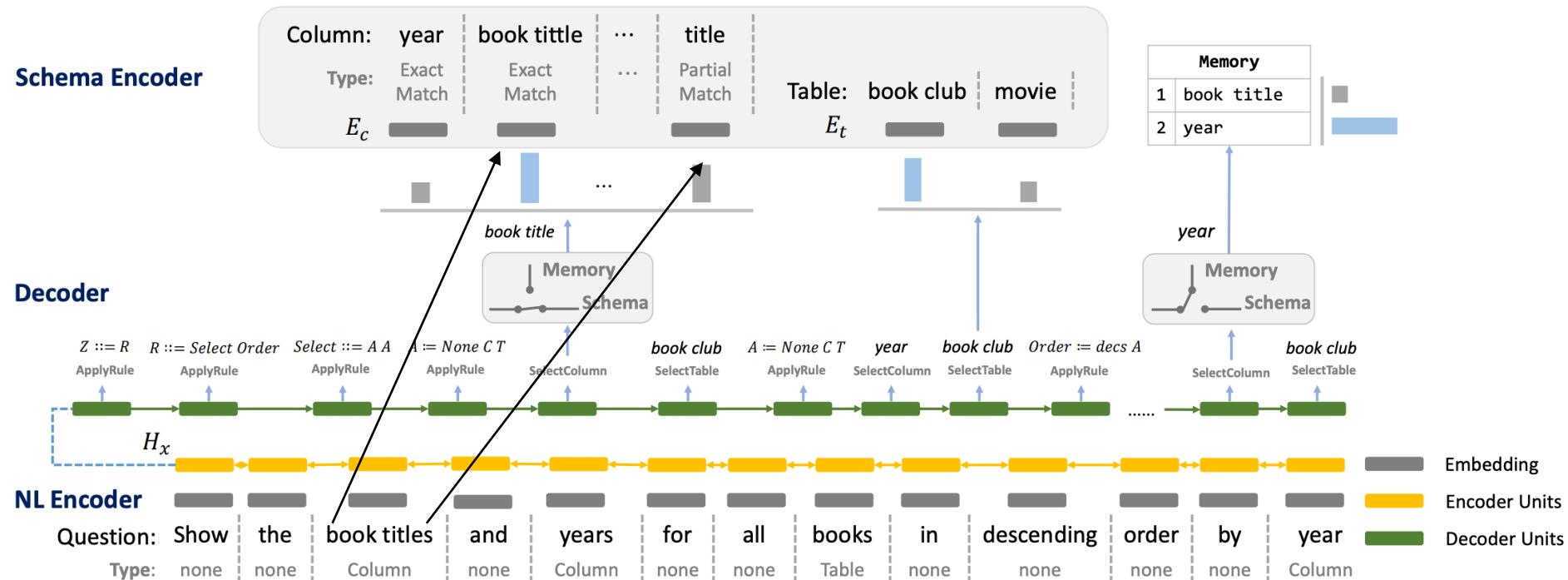
- String Matching-based Schema Linking
- Neural Network-based Schema Linking
- In-Context Learning for Schema Linking



String Matching-based Schema Linking

IRNet designs string-based schema linking and an intermediate representation called SemQL.

- It uses n-grams (1-6 length) extracted from user queries as **query candidates**
- It evaluates the string-level similarity between the **query candidates** and the database schema, then classifies them as **Exact** or **Partial** matches.



String Matching-based Schema Linking

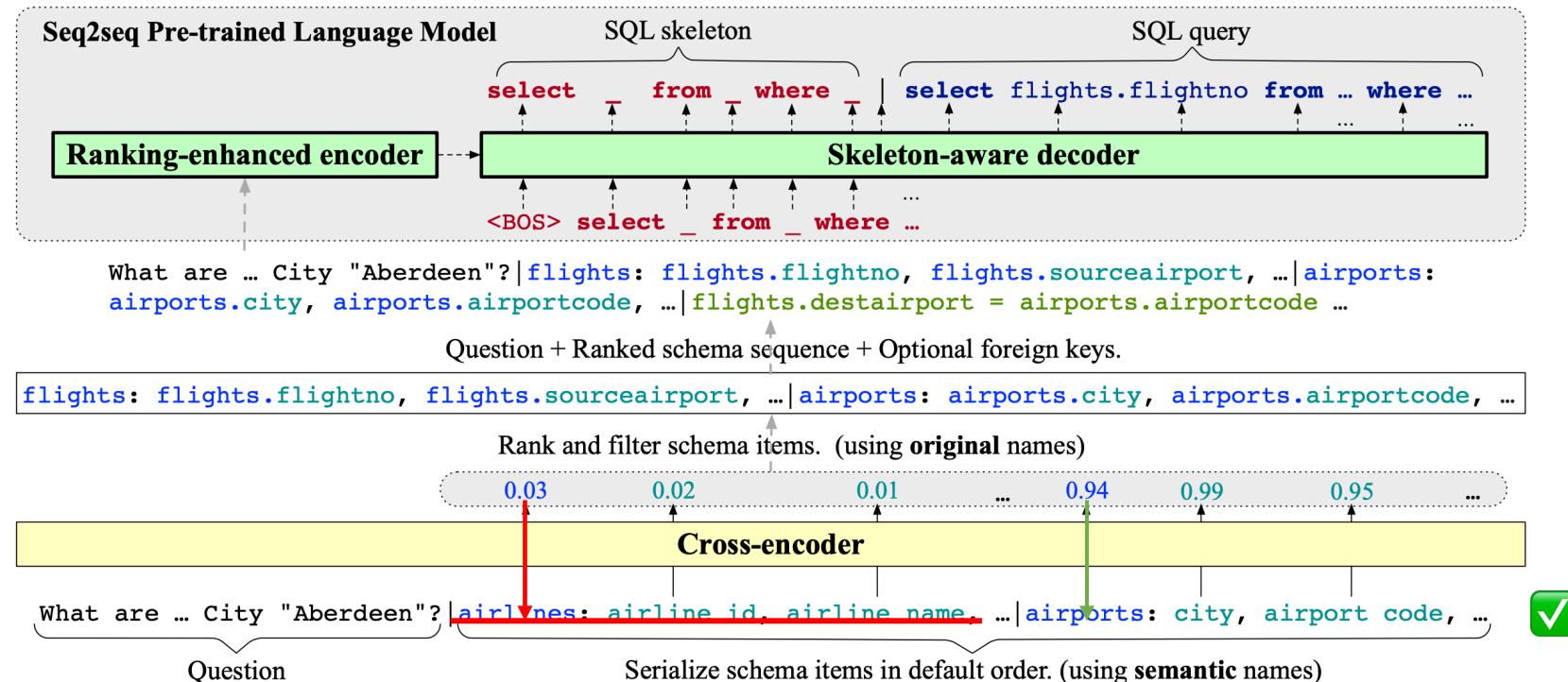
Limitations:

- False positives when candidates share common words.
- Lack the ability to handle synonyms.

Neural Network-based Schema Linking

RESDSQL proposes a ranking-enhanced encoding and skeleton-aware decoding framework.

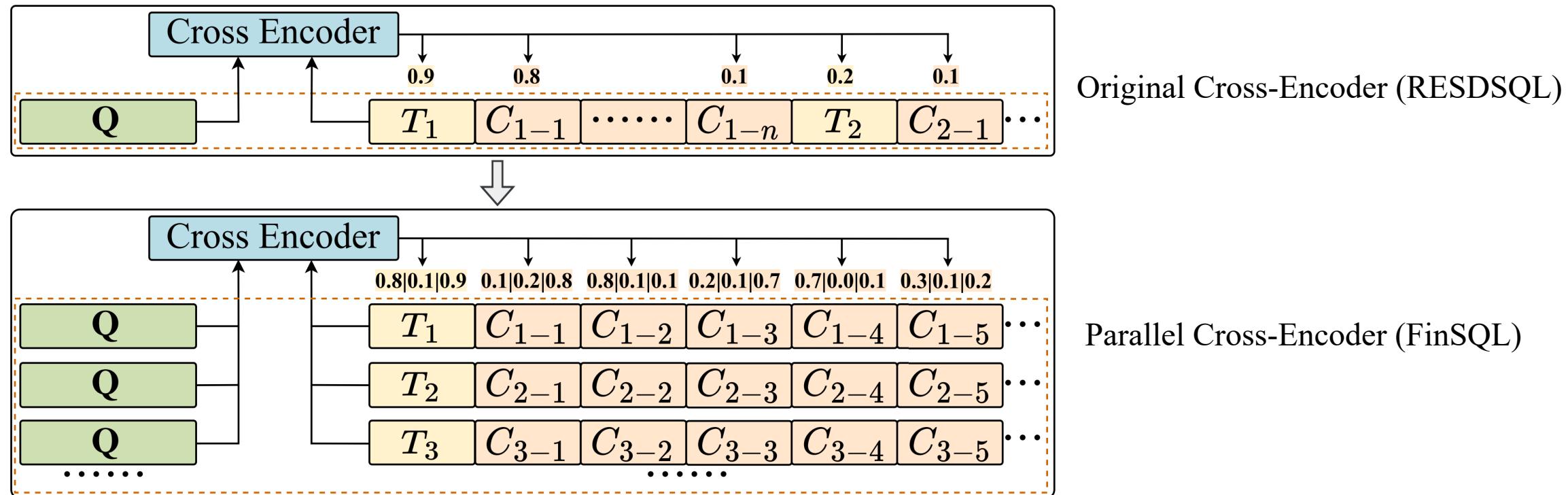
- A **cross-encoder** is trained to classify tables and columns based on the input query.



Neural Network-based Schema Linking

FinSQL, a model-agnostic LLMs-based NL2SQL framework for financial analysis.

- Organizing the tables into a **batch**
- Devising a **Parallel Cross-Encoder** to retrieve relevant tables and columns from hundreds of schema items



Neural Network-based Schema Linking

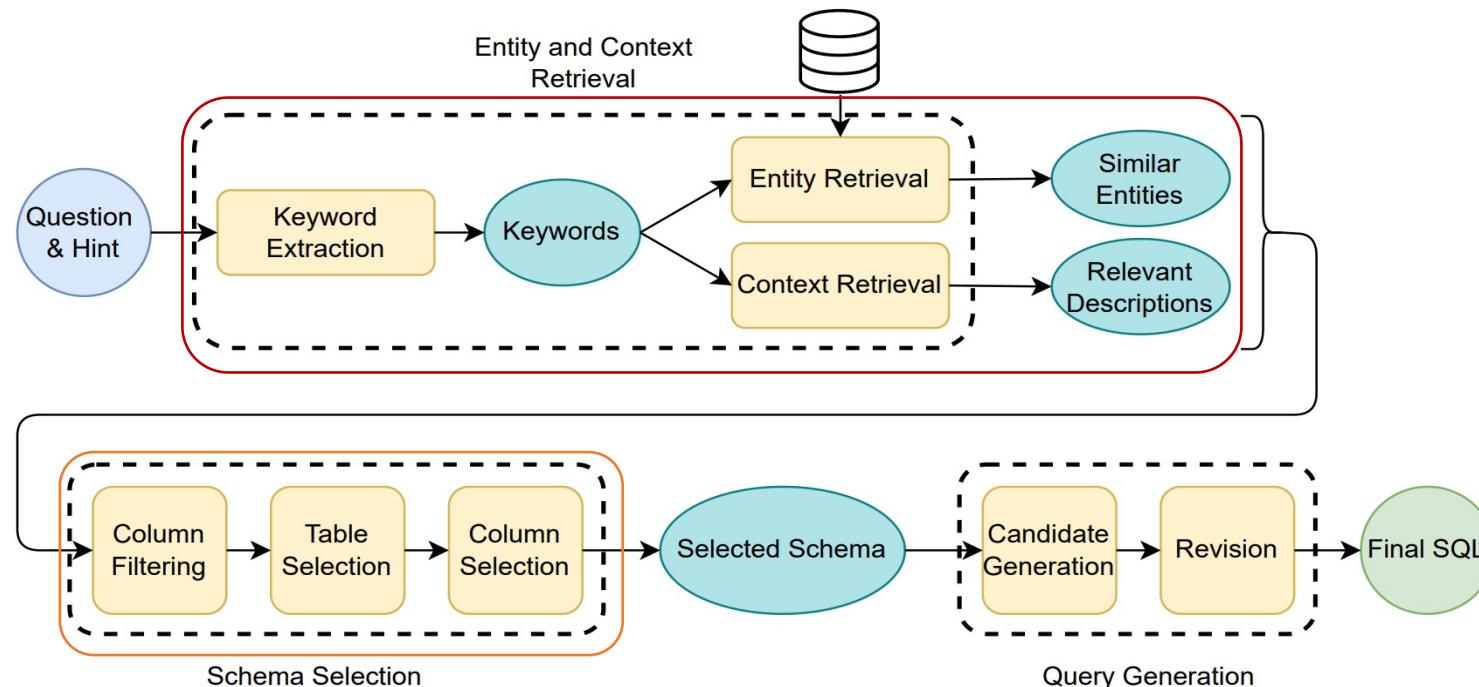
Limitations:

- Highly rely on the quantity and quality of training data
- Struggle to generalize effectively across databases with new schemas or domains

In-Context Learning for Schema Linking

CHESS breaks down the NL2SQL task into a 3-staged pipeline, including entity and context retrieval, schema selection, and query generation.

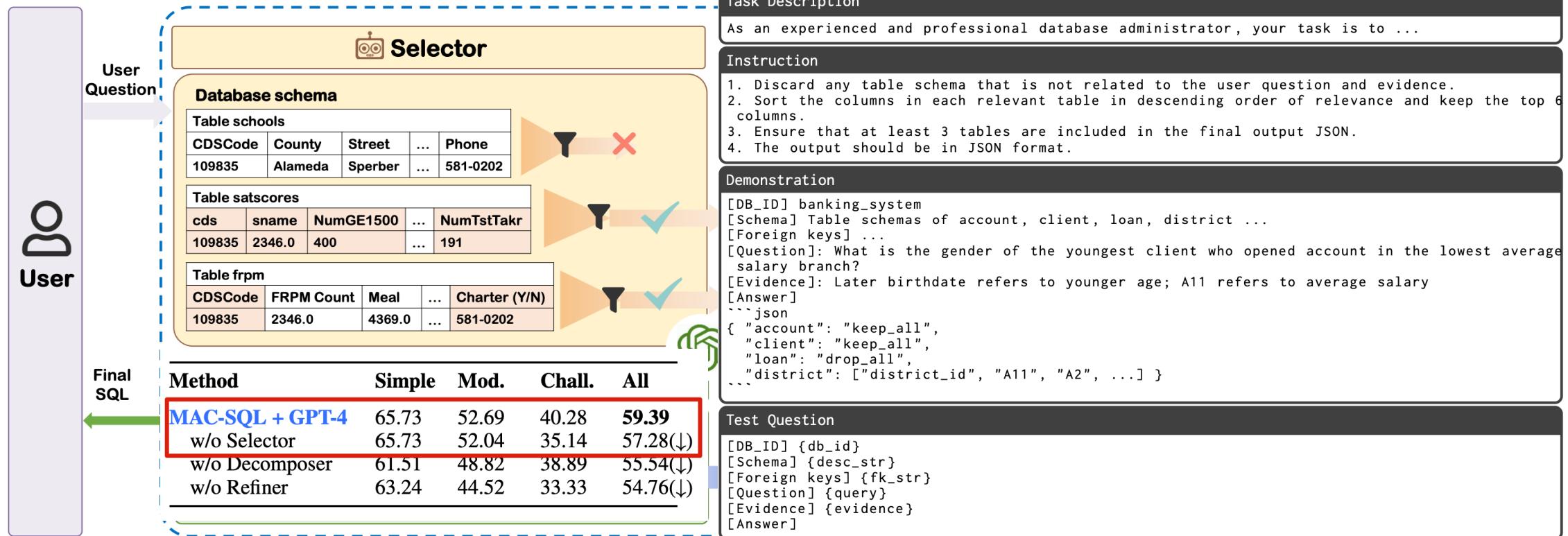
- Utilizing GPT-4 to **extract keywords** from both NL and Hint.
- It implements an efficient **three-stage** schema selection with different prompts.



In-Context Learning for Schema Linking

MAC-SQL is a multi-agent collaborative framework for NL2SQL.

- The **Selector agent** performs the schema linking task.
- The Selector is activated only when the length of the database schema prompt exceeds a specified threshold.



In-Context Learning for Schema Linking

Limitations:

- Large schema may exceed context length limitation
- Highly rely on the quality of the prompt
- High API cost

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Database Content Retrieval

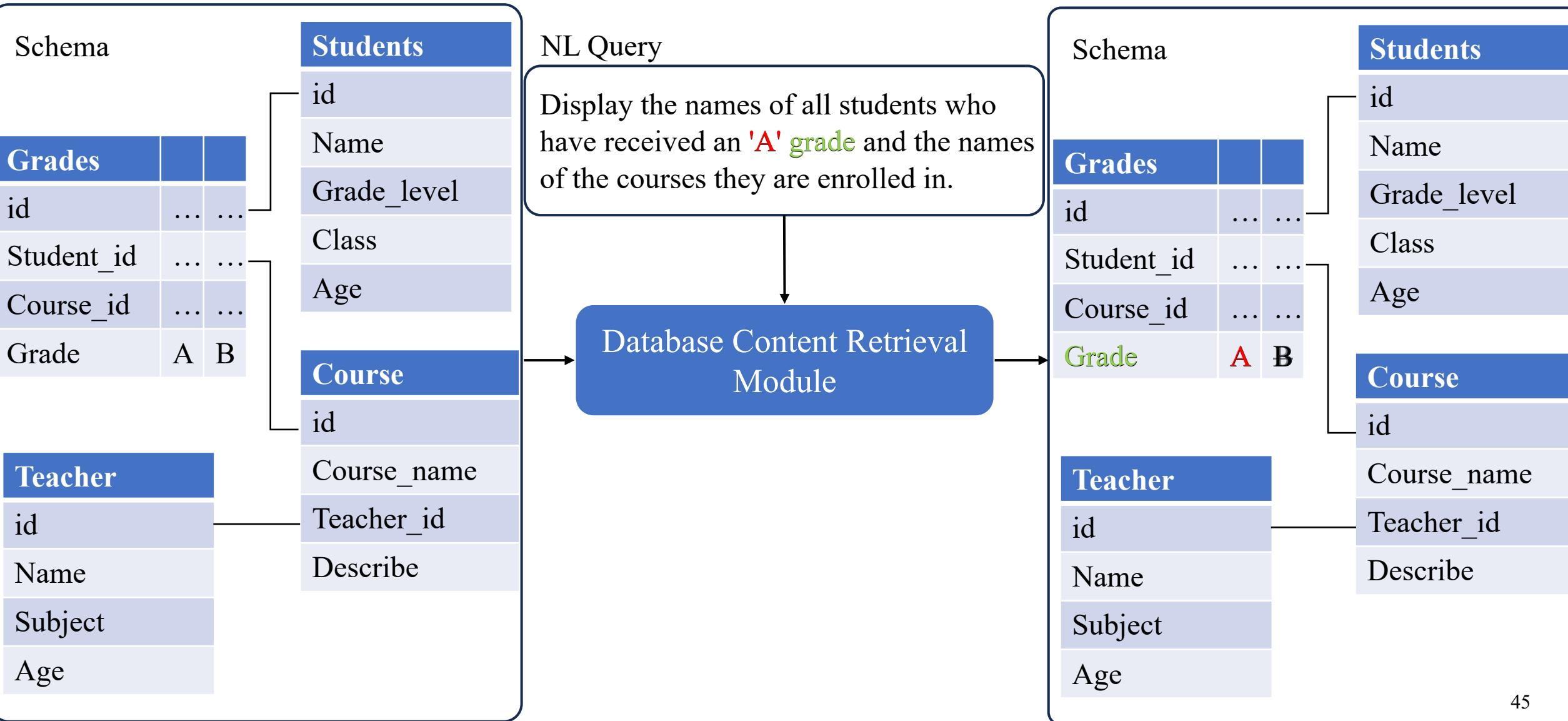
Motivation:

- Due to the large databases and input limitations of the model, retrieving cell values is resource-intensive.
- Effectively handle some SQL clauses such as WHERE and JOIN .

Goal:

- **Efficiently retrieve cell values** related to the given NL.

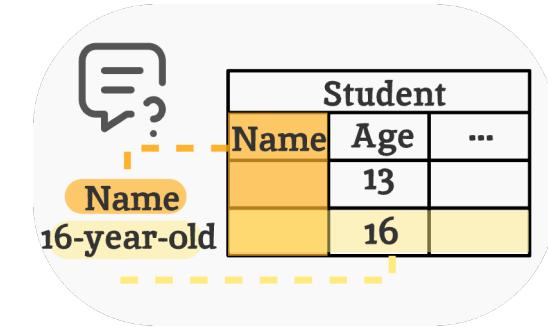
Workflow of Database Content Retrieval



Method Classification of DB Content Retrieval

Method classification:

- String Matching-based Database Content Retrieval
- Neural Network-based Database Content Retrieval
- Index Strategy for Database Content Retrieval

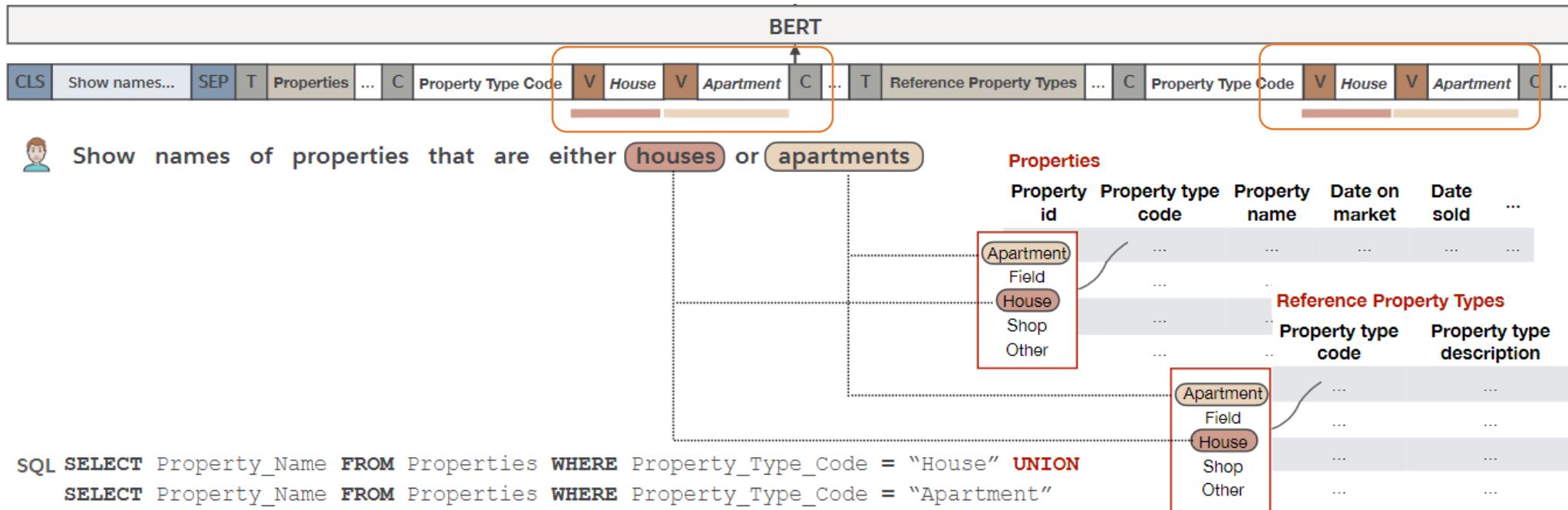


Database Content Retrieval

String Matching-based Database Content Retrieval

BRIDGE designs an anchor text matching to automatically extract cell values mentioned in the NL.

- It uses a heuristic method to calculate the maximum sequence match between the problem and the cell values to determine the matching boundary.



String Matching-based Database Content Retrieval

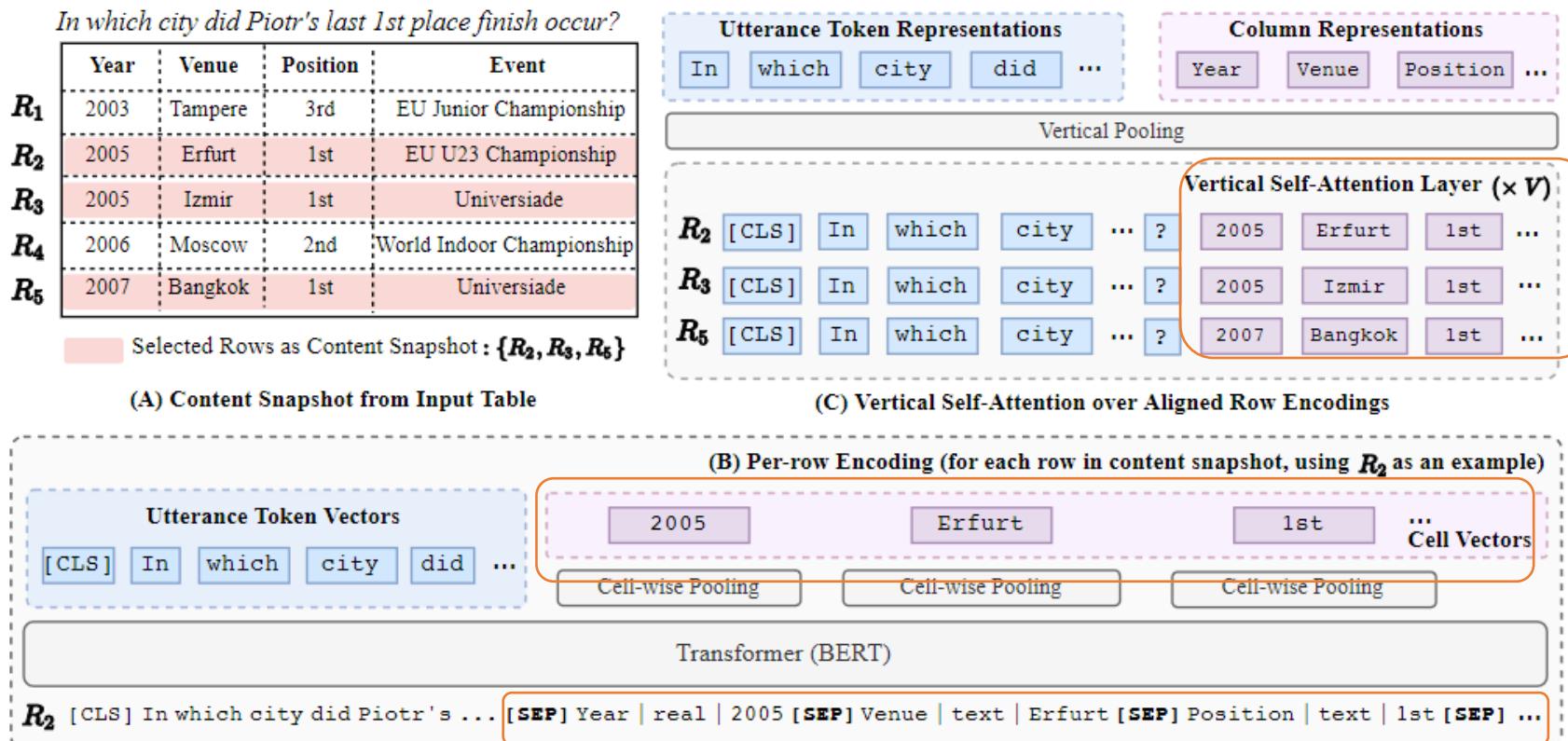
Limitations:

- Struggles with synonyms
- High computational cost for large databases

Neural Network-based Database Content Retrieval

TABERT uses a method called **database content snapshots**.

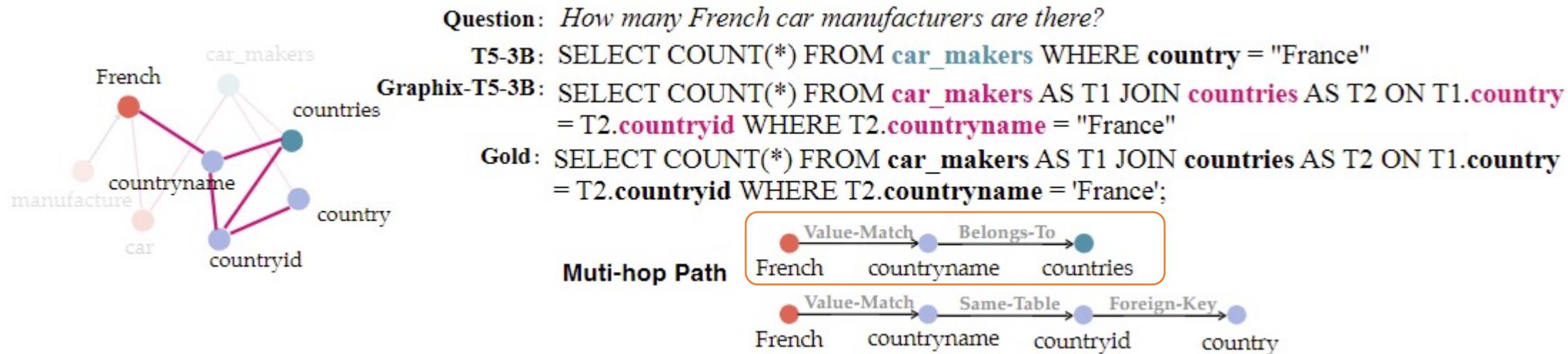
- It uses an attention mechanism to manage information between **cell values** across different rows.



Neural Network-based Database Content Retrieval

Graphix-T5 improves structural reasoning capabilities by **modeling the relationship** between cell values and the NL query.

- it uses **a value-match relation** that defines the relationship between cell values and questions.



Question	Column	VALUE-MATCH	x is part of the candidate cell values of column y.
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Neural Network-based Database Content Retrieval

Limitations:

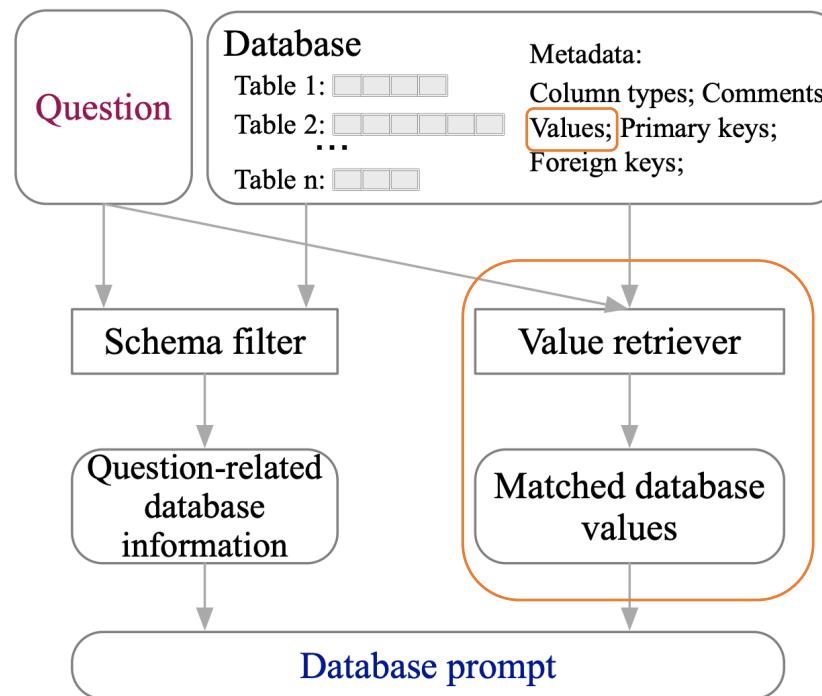
- Lead to the misinterpretation of ambiguous or context-sensitive queries.
- Require significant computing resources.

Index Strategy for Database Content Retrieval

CodeS introduces a **coarse-to-fine cell value matching approach**.

- It builds the index for all values using BM25.
- The index identifies candidate values that are relevant to NL.

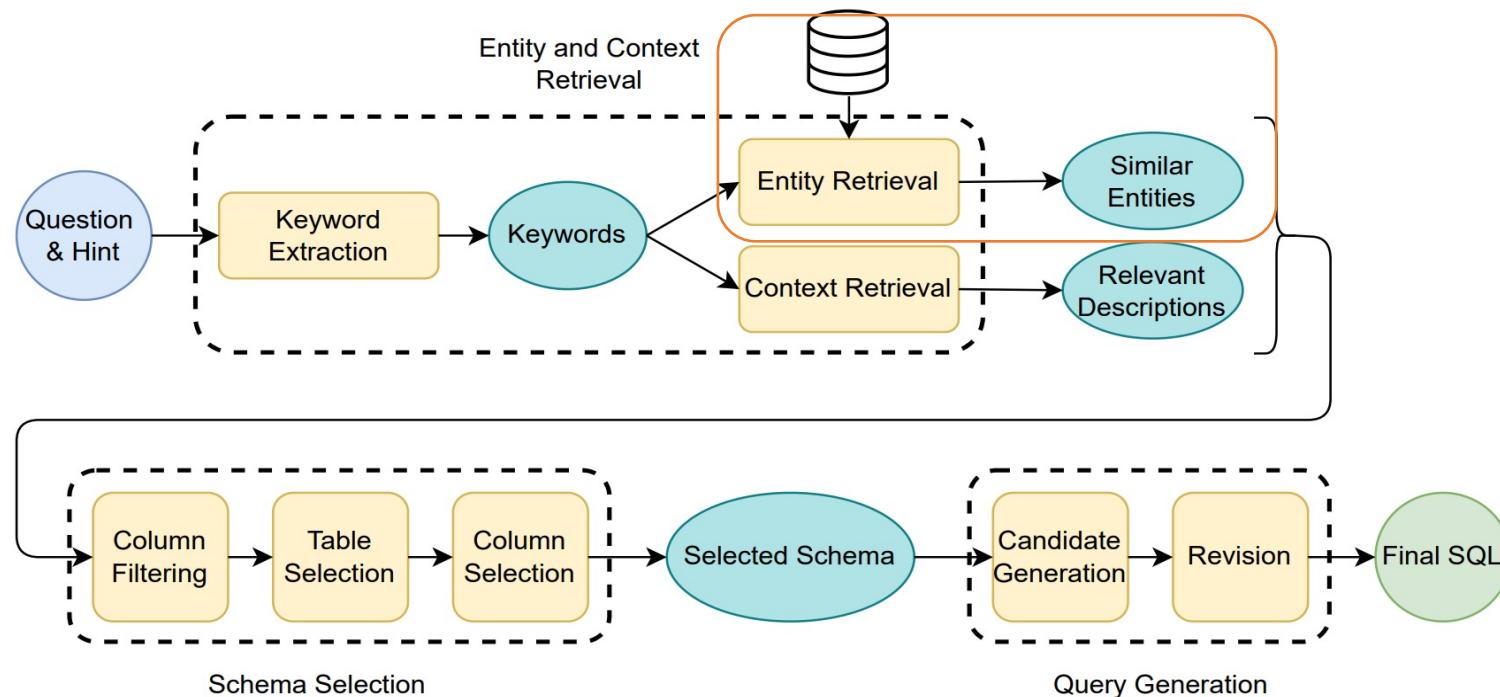
(b) Database prompt construction



Index Strategy for Database Content Retrieval

CHESS uses a **Locality-sensitive Hashing algorithm** for approximate nearest neighbor searches.

- It indexes unique cell values to quickly identify the top similar values related to the NL query.



Index Strategy for Database Content Retrieval

Limitations:

- Time-consuming to build.
- Requires frequent updates for dynamic databases, which increases inference overhead.

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Additional Information Acquisition

Motivation:

- Incorporate additional information (e.g., domain knowledge) to improve the comprehension capabilities of NL2SQL models for understanding the NL query, performing the schema linking, and benefiting the NL2SQL translation.



Additional Information
Acquisition

Goal:

- To retrieve useful information such as Demonstration examples, Specific domain knowledge, Formulaic Evidence, and Format Information for the NL2SQL backbone model or specific modules.

Method Classification?

Method classification:

- Sample-based Methods
- Retrieval-based Methods

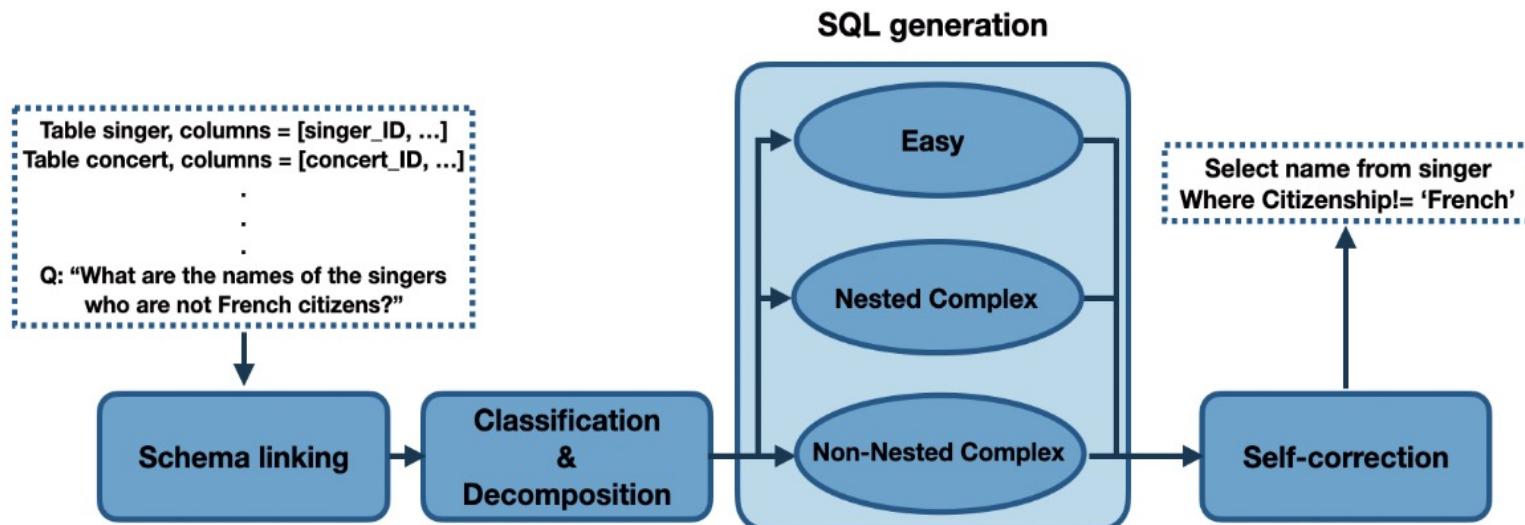


**Additional Information
Acquisition**

Sample-based Methods

DIN-SQL inserts additional information through few-shot learning across multiple stages of the workflow.

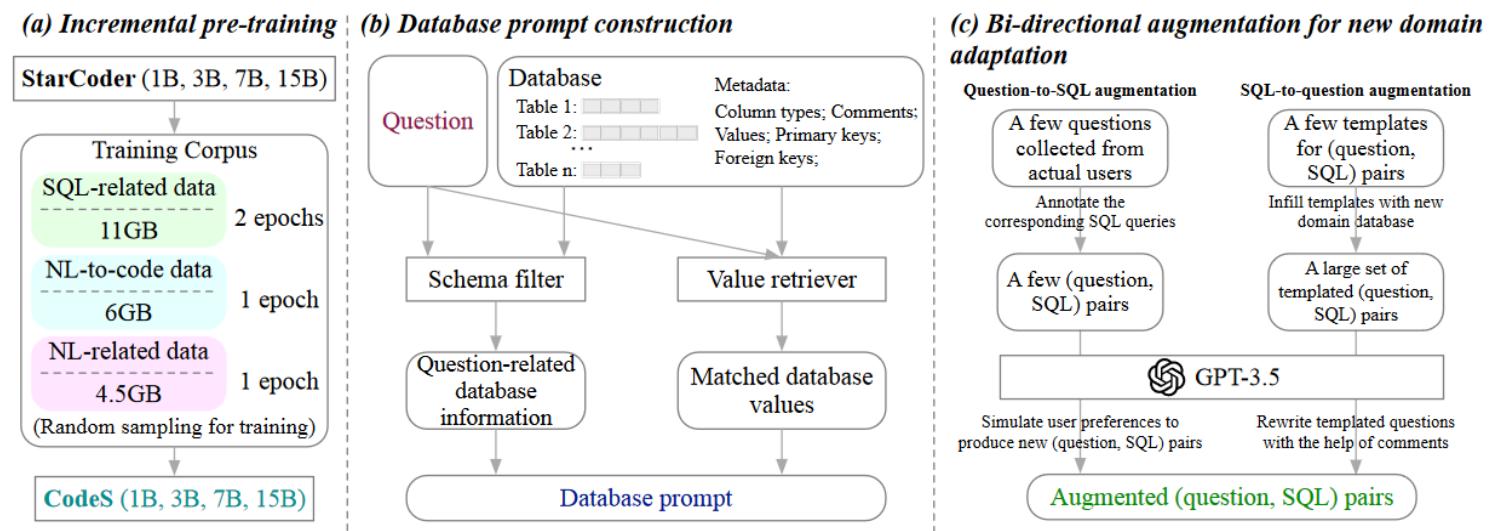
- These stages comprise schema linking, query classification, task decomposition, and self-correction.
- It allows DIN-SQL to effectively tackle various challenges, including the complexity of schema links, identification of multiple table joins, and handling of nested queries.



Sample-based Methods

CodeS utilizes metadata examples of cross-domain databases as the main additional information, including data types and annotation text, which help the model resolve potential ambiguity issues and understand entity relationships

- This extracted information is transformed into coherent text and concatenated with the question query to form the final input context.



Sample-based Methods

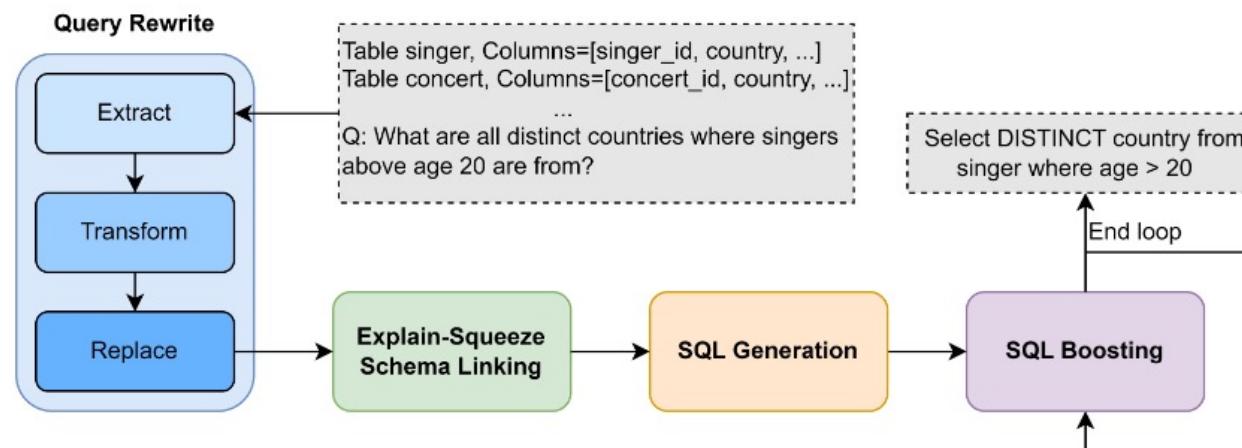
Limitations:

- Increasing computational cost
- Potential hallucination caused by low-quality samples or wrong knowledge

Retrieval-based Methods

ReBoost engages with the LLMs model using the Explain-Squeeze Schema Linking mechanism.

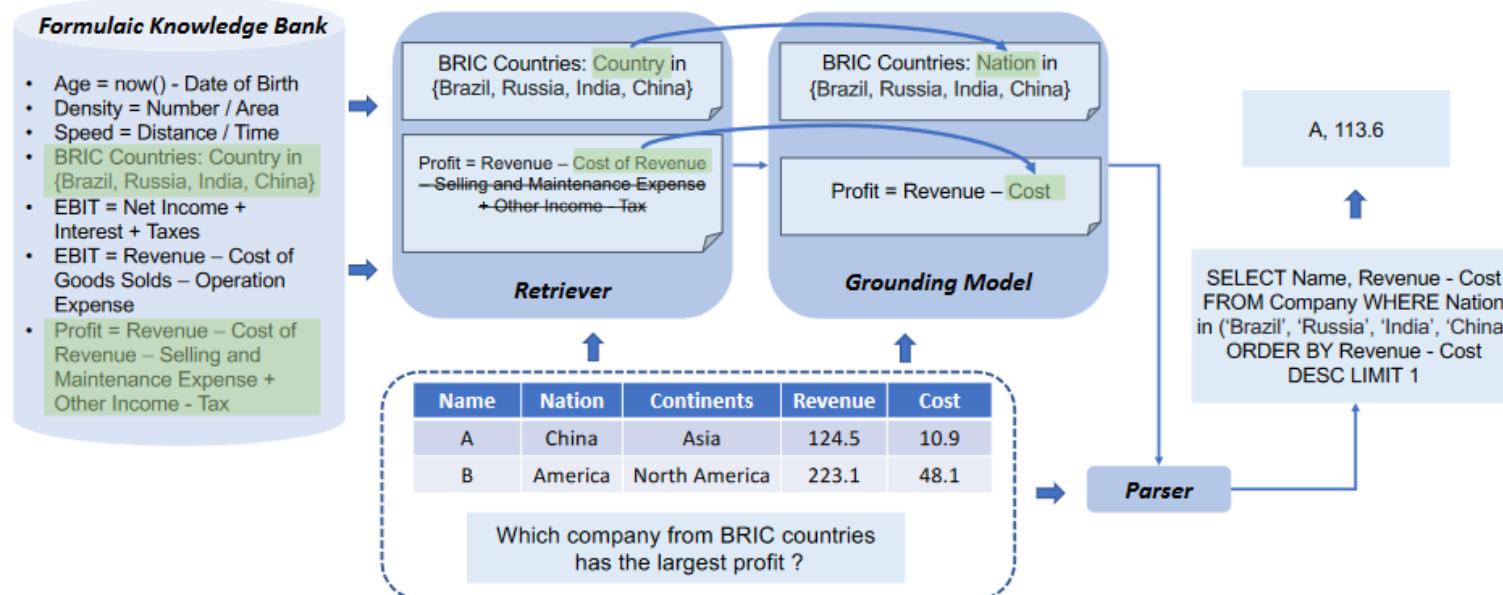
- This mechanism is a two-phase strategy. Initially, it presents a generalized schema to the LLMs to establish a foundational understanding.
- Subsequently, it employs targeted prompting to elicit detailed associations between query phrases and specific database entities, thereby enhancing accuracy in mapping queries to database structures without incurring excessive token cost.



Retrieval-based Methods

REGROUP constructs a formulaic knowledge base encompassing various domains, such as finance, real estate, and transportation.

- It leverages a Dense Passage Retriever (DPR) to compute similarity scores for the retrieval results from the formulaic knowledge base.
- Subsequently, an Erasing-Then-Awakening (ETA) model is used to integrate the entities in these formulaic items with the entities in NL and schema.



Retrieval-based Methods

Limitations:

- Insufficient exploration of retrieving formulated or structured domain knowledge bases
- Computational cost of retrieving and embedding additional information

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Encoding Strategy

Motivation:

- Converts unstructured and semi-structured data into a form that can be processed for generating SQL queries.
- The encoding process captures the semantic meaning of the NL input and the structural information of the database schema, enabling the model to understand and map the user's intent to the corresponding SQL query.

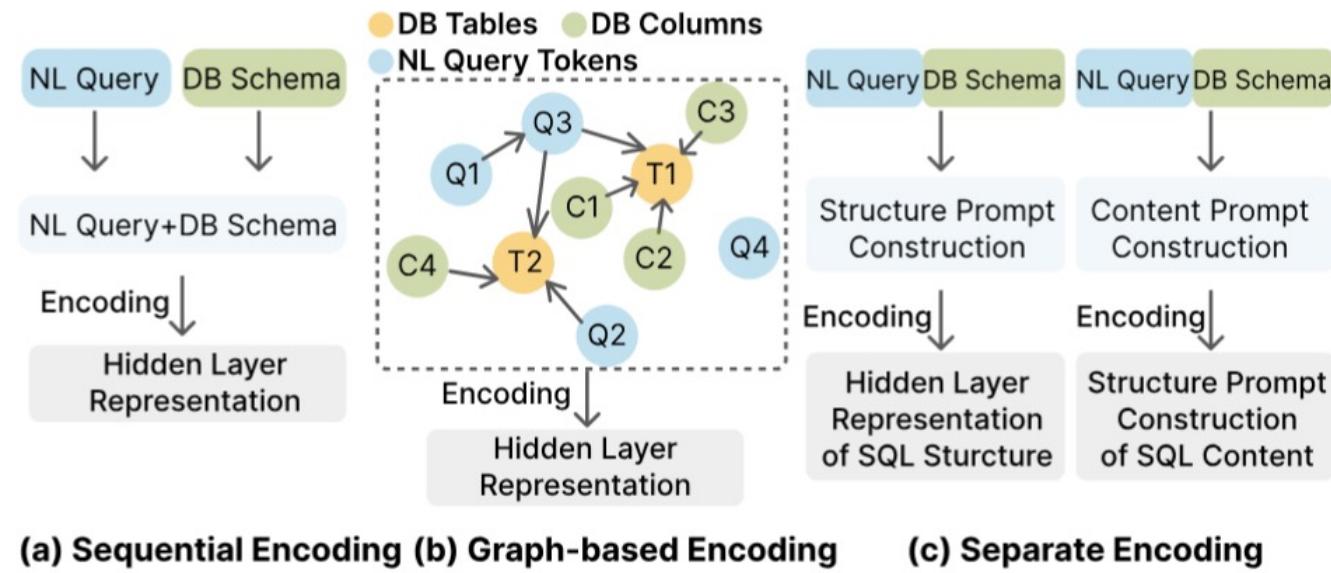
Goal:

- Transform NL and database schema into a structured format that can be effectively utilized by a language model.

Method classification of Encoding Strategy

Method classification:

- Sequential Encoding Strategy
- Graph-based Encoding Strategy
- Separate Encoding Strategy

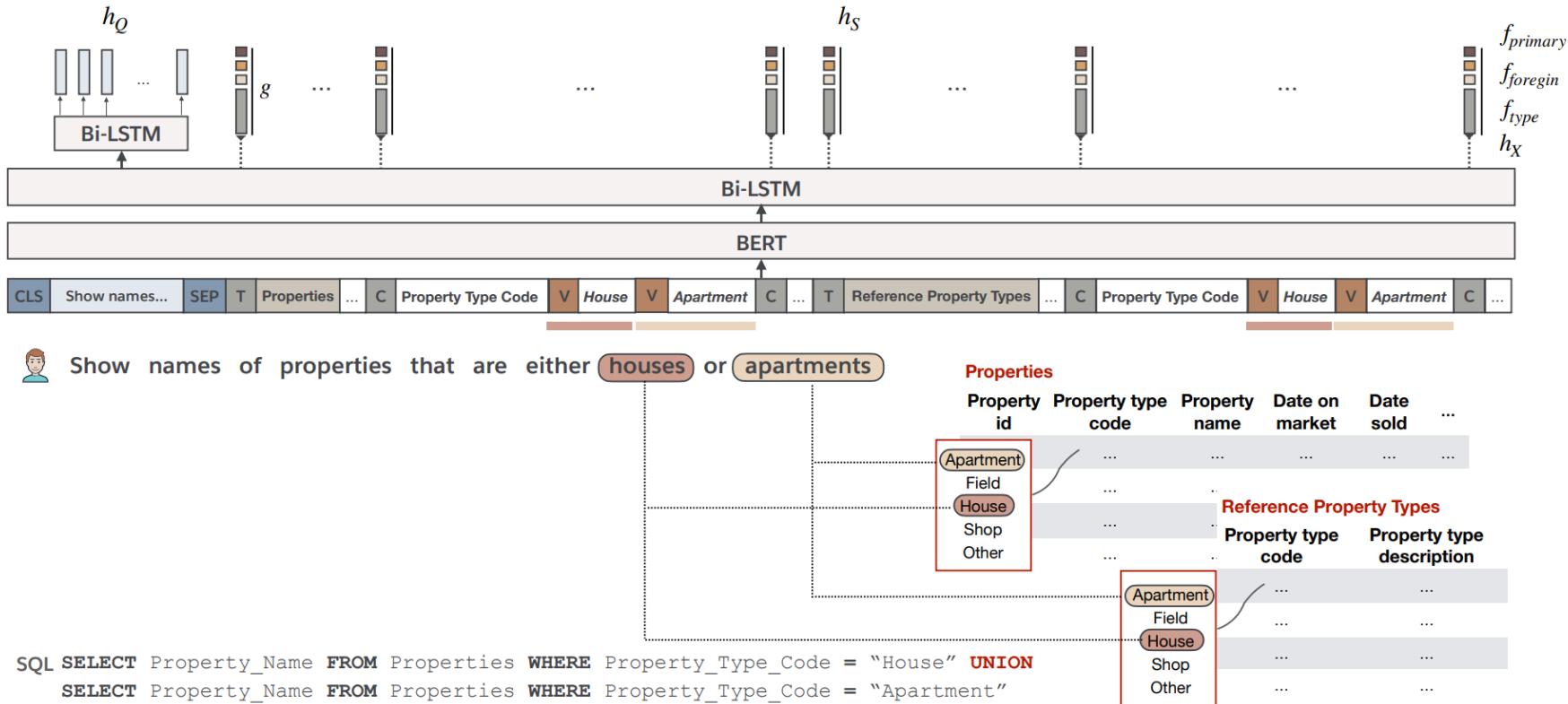


An Overview of the Encoding Strategies

Sequential Encoding Strategy

BRIDGE enhances the alignment between text and the database schema.

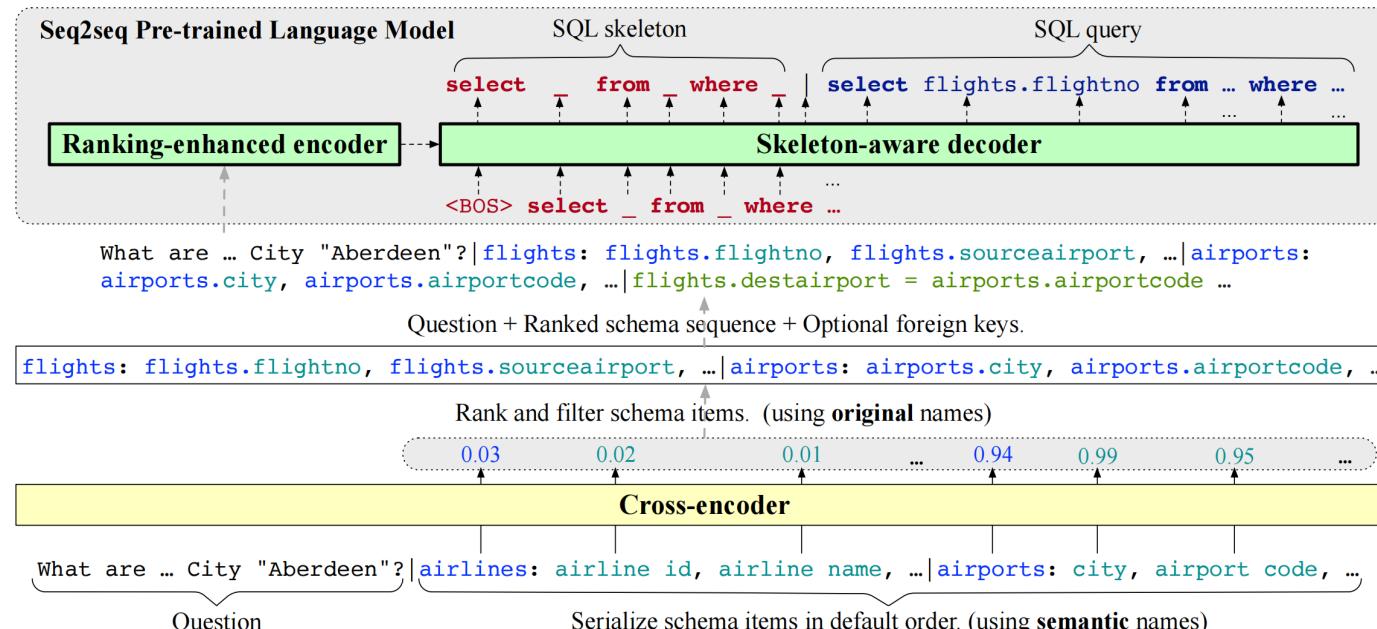
- It represents the NL question and database schema as a tagged sequence.
- It inserts matched database cell values (anchor texts) after the corresponding fields.



Sequential Encoding Strategy

RESDSQL uses a ranking-enhanced encoder to sort and filter schema items, thereby reducing the complexity of schema linking during encoding.

- This method ensures that the most relevant schema items are prioritized, improving the overall efficiency of the encoding process.



Sequential Encoding Strategy

Limitations:

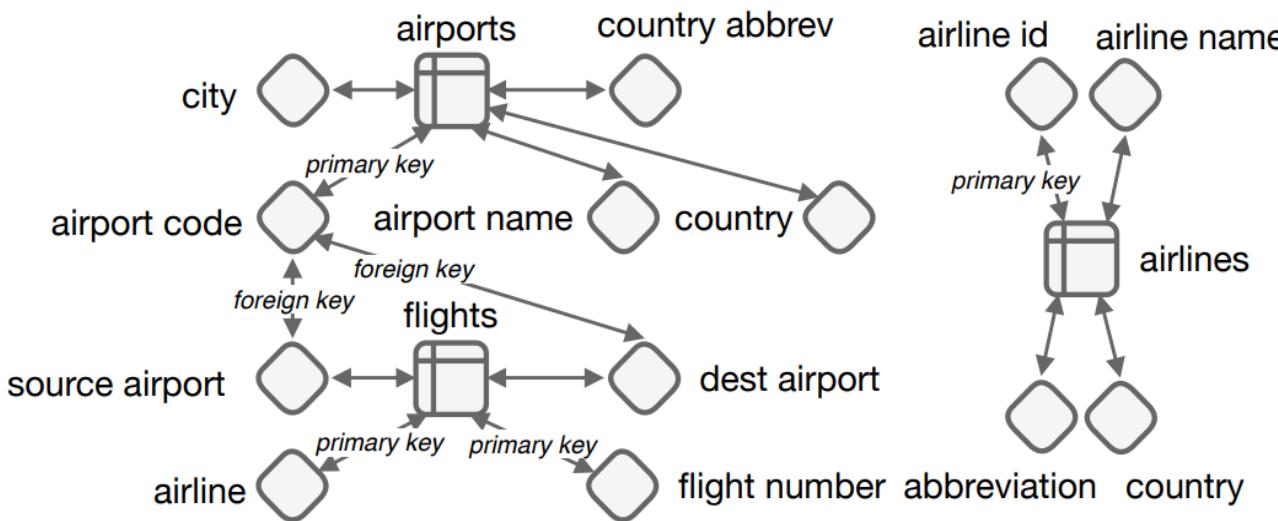
- Its linear approach, which treats all inputs as sequences of tokens, may fail to fully capture the complex relationships between the database schema and NL query.
- This can affect the model's ability to understand and generate complex queries.

Graph-based Encoding Strategy

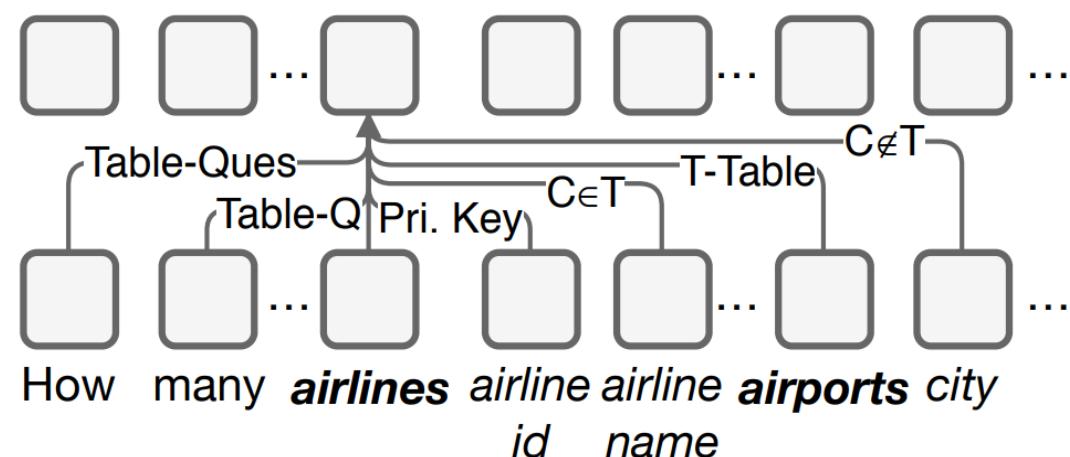
RAT-SQL introduces a relation-aware self-attention mechanism.

- It allows the model to explicitly consider and utilize predefined relational information when jointly encoding the question and the database schema.
- These relationships are represented as a graph structure, and it can more effectively capture the structural information in the schema and its alignment with the NL query.

An illustration of an example schema as a graph G



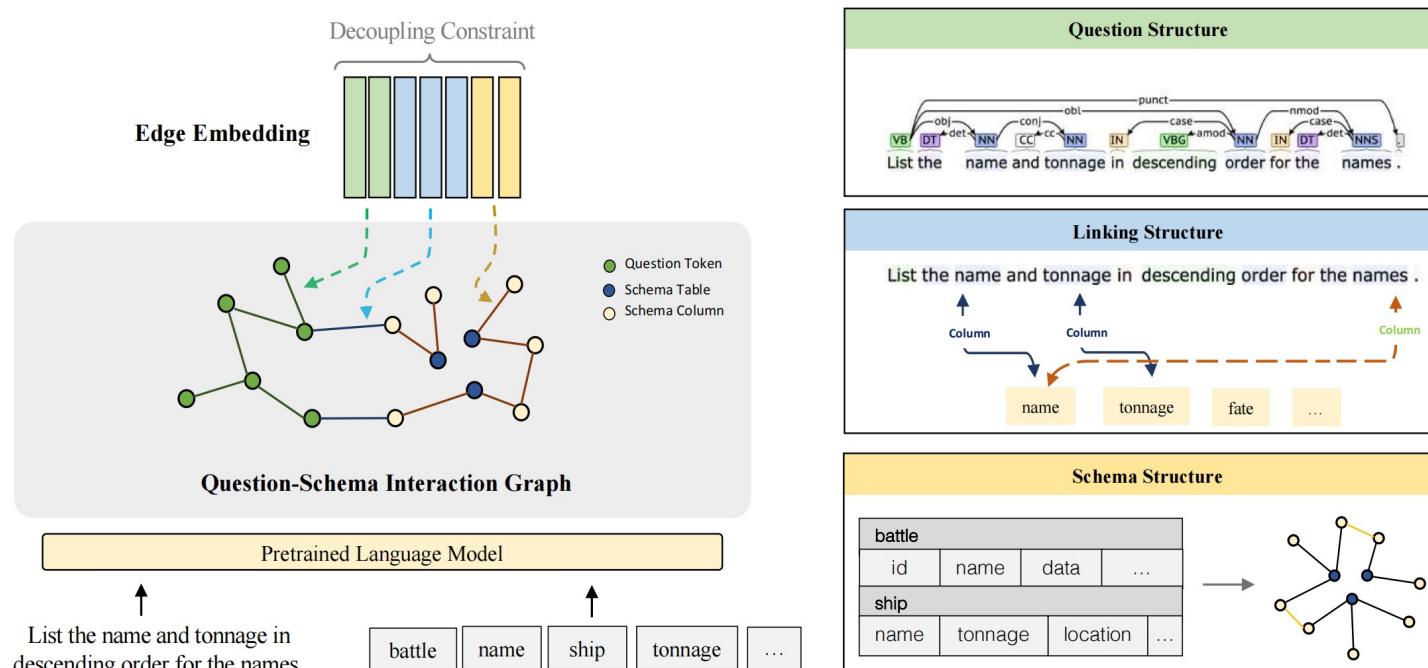
One RAT layer in the schema encoder.



Graph-based Encoding Strategy

S²SQL uses ELECTRA as its pre-trained language model.

- It enhances encoding by injecting syntactic structure information at the encoding stage, improving the semantic understanding and generation of models.

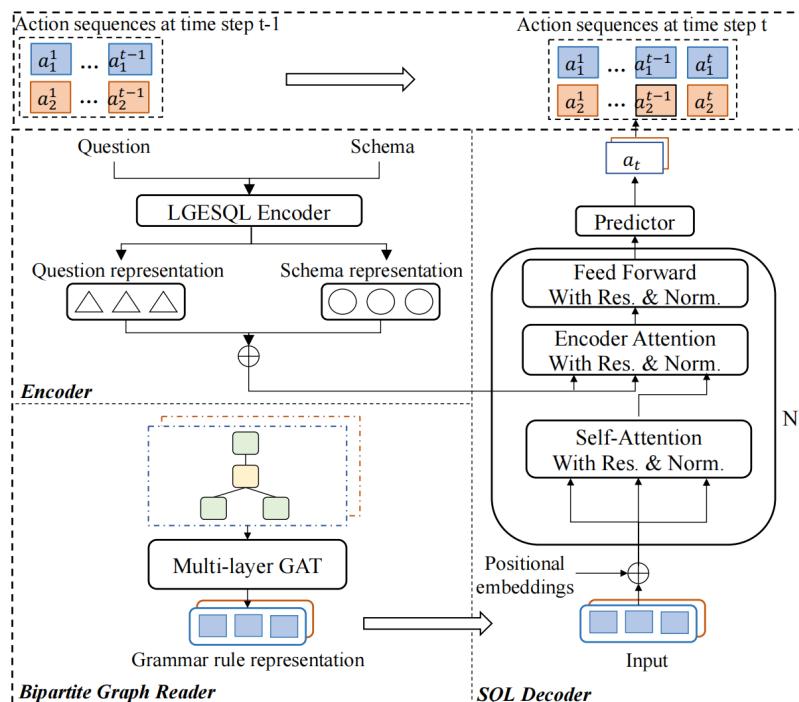


An overview
of S²SQL framework.

Graph-based Encoding Strategy

G³R introduces the LGESQL encoder.

- It captures and integrates multisource heterogeneous information by constructing and utilizing a heterogeneous graph and a Graph Attention Network (GAT) , thereby enhancing the representation capability for NL and database schema.



An overview of the architecture of G³R framework.

Graph-based Encoding Strategy

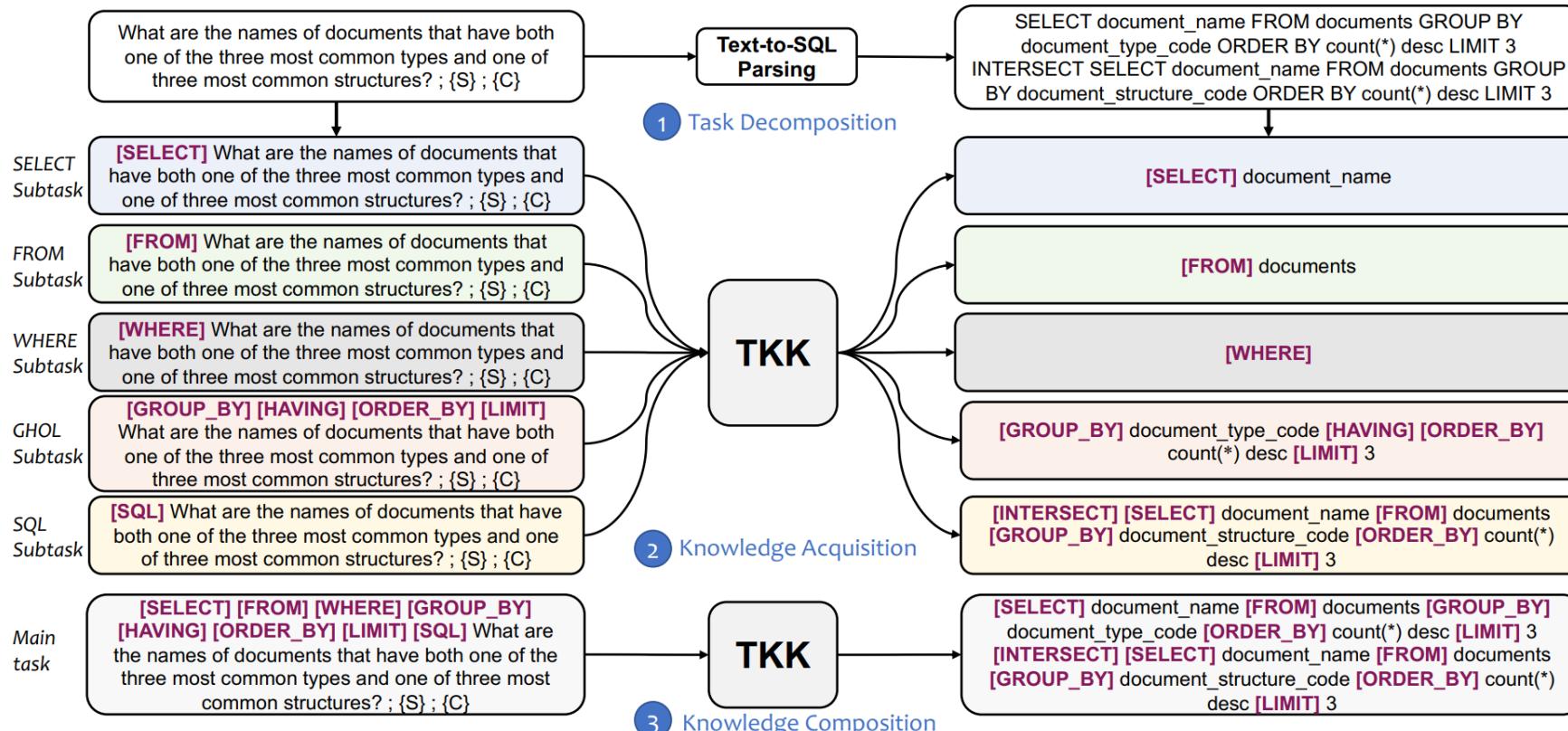
Limitation:

- Require more sophisticated algorithms for constructing and processing graph structures.
- Need a large amount of training data to fully leverage its structural advantages.

Separate Encoding Strategy

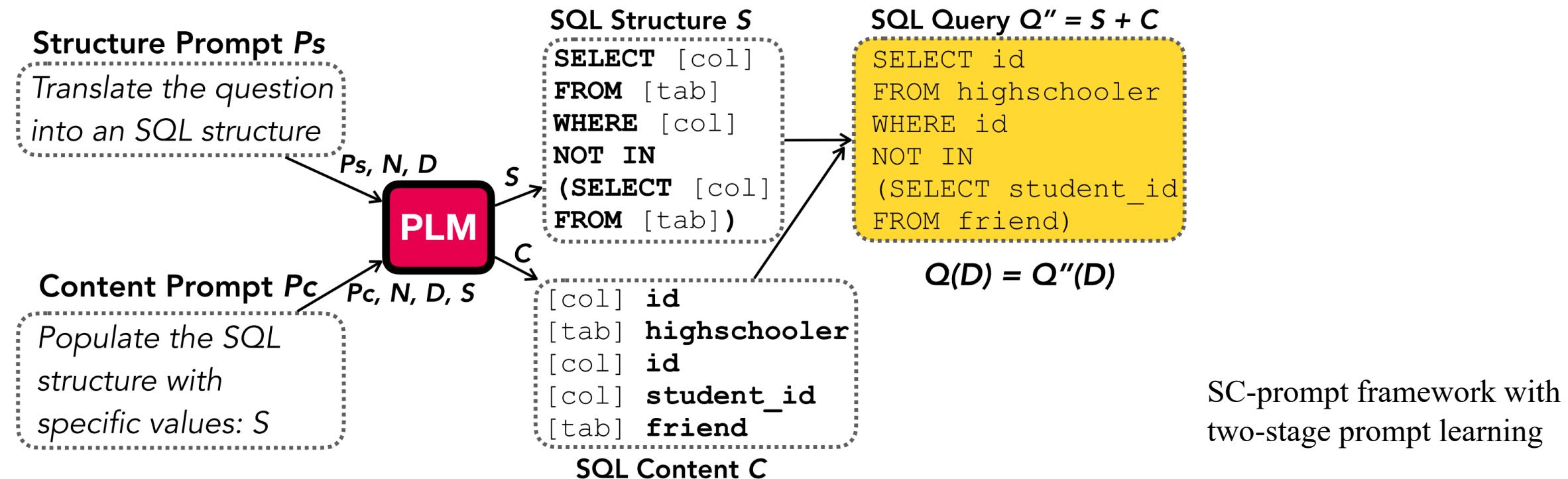
TKK employs task decomposition and multi-task learning strategies in encoding.

- It breaks down the complex NL2SQL task into multiple subtasks.
- In this way, it can progressively acquire and combine knowledge.



Separate Encoding Strategy

SC-Prompt divides text encoding into two stages: the structure stage and the content stage, with each stage being encoded separately.



Separate Encoding Strategy

Limitations:

- Require multiple processing of input data
- May extend the training and inference time of the model

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Decoding Strategy

Motivation:

- The choice of decoding strategy directly affects the quality and performance of the generated SQL queries.
- An excellent decoding strategy not only produces syntactically correct SQL queries but also ensures that the semantics of the SQL queries align with the NL and can even optimize the execution efficiency of the queries.

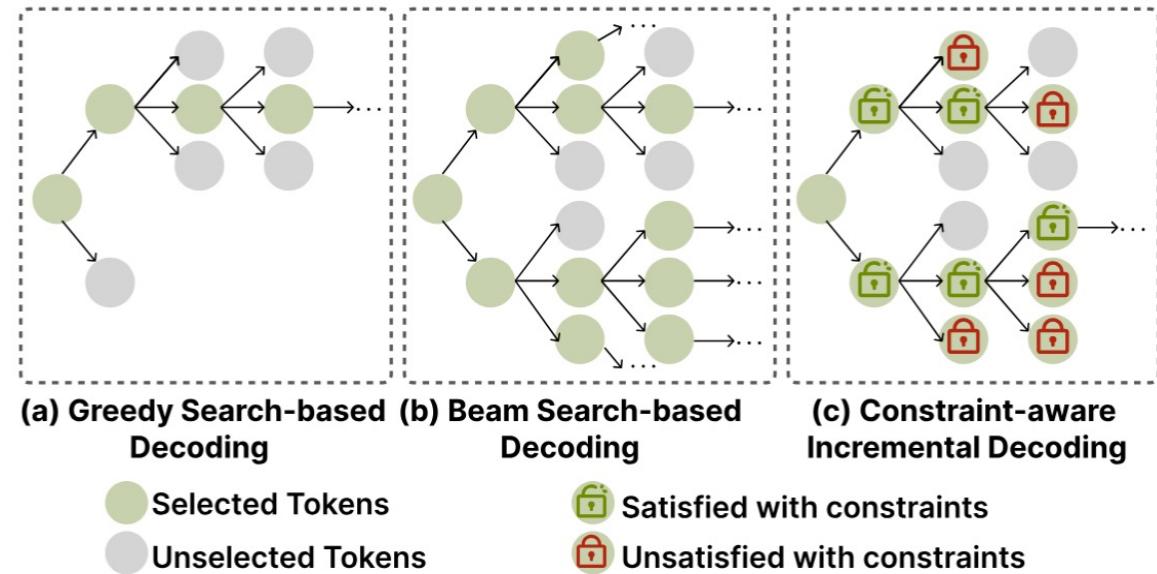
Goal:

- Convert the representations generated by the encoder into the target SQL queries.

Method classification of Decoding Strategy

Method classification:

- Greedy search-based decoding strategy
- Beam search-based decoding strategy
- Constraint-aware incremental decoding strategy

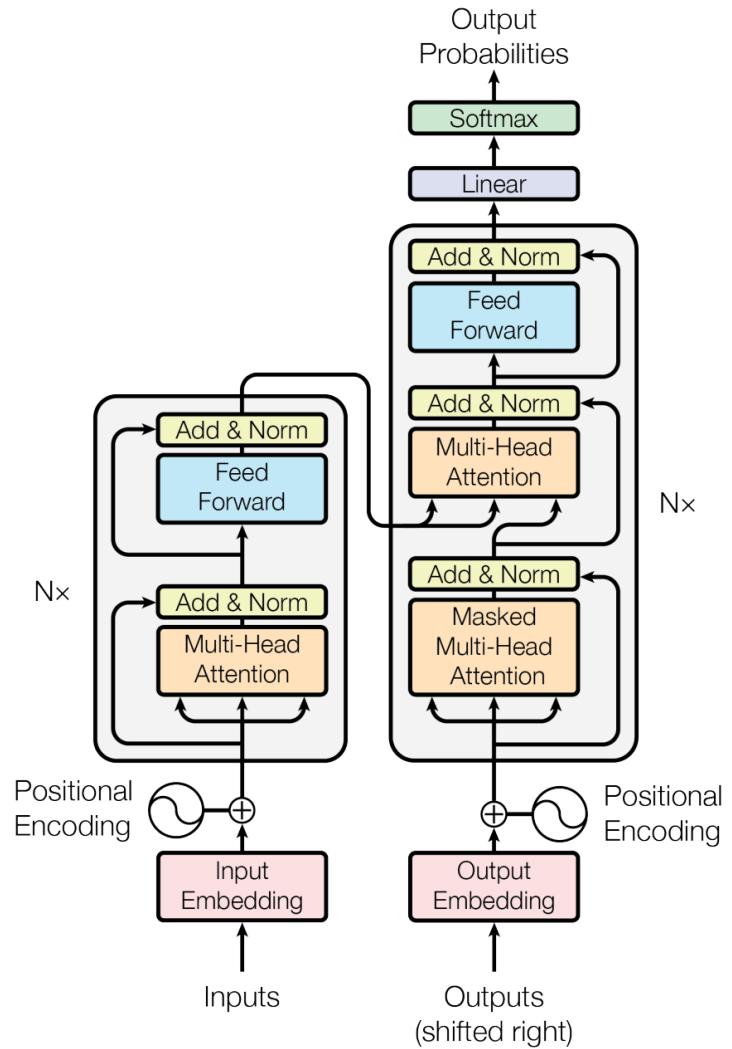


An Overview of the Decoding Strategies

Greedy Search-based Decoding Strategy

The greedy search-based decoding strategy is a simple and fast approach for decoding.

- At each decoding step, greedy search selects the token with the highest current probability as the output.
- This strategy builds the final output sequence by continuously choosing the locally optimal solution.
- Since the default decoding strategy of GPT series models (e.g., GPT-4) is greedy search-based decoding, NL2SQL solutions based on GPT fall into this category.



The Transformer-Model Architecture

Greedy Search-based Decoding Strategy

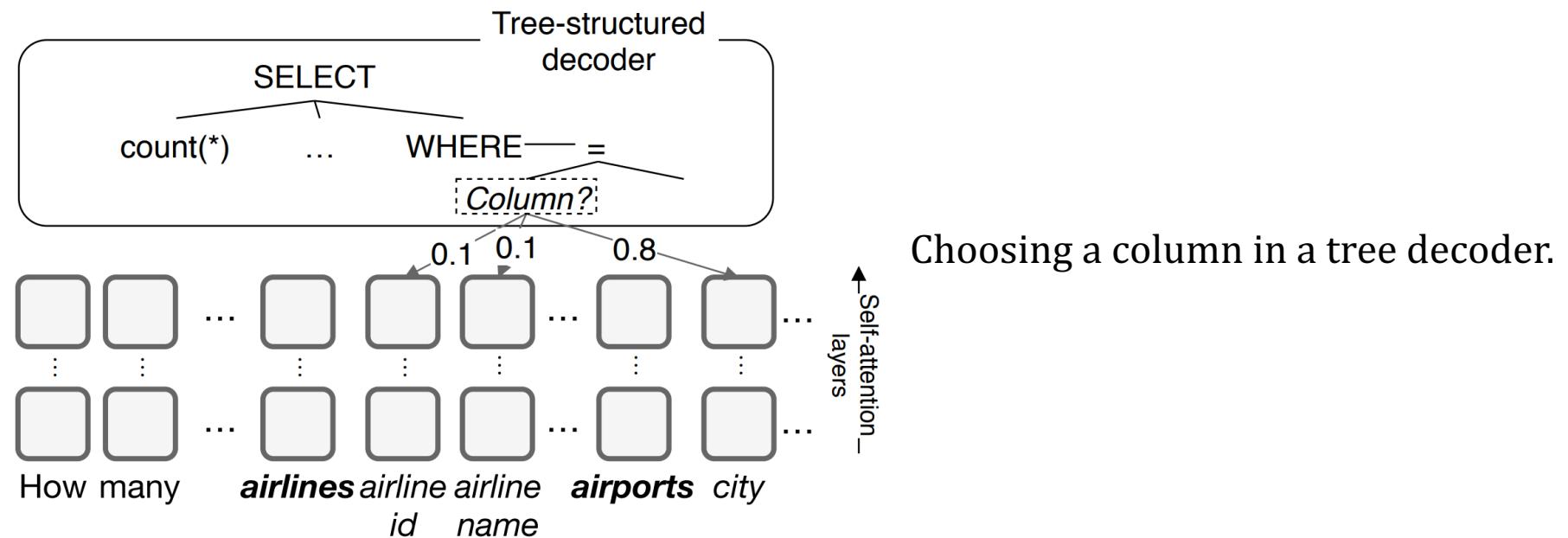
Limitations:

- Greedy search only considers the optimal solution at the current step, ignoring long-term dependencies and overall optimal solutions.
- May result in the generation of SQL queries that are not globally optimal.
- Errors at each step could lead to biases in decision-making in subsequent steps, potentially accumulating errors throughout the decoding process, especially when handling complex queries.

Beam Search-based Decoding Strategy

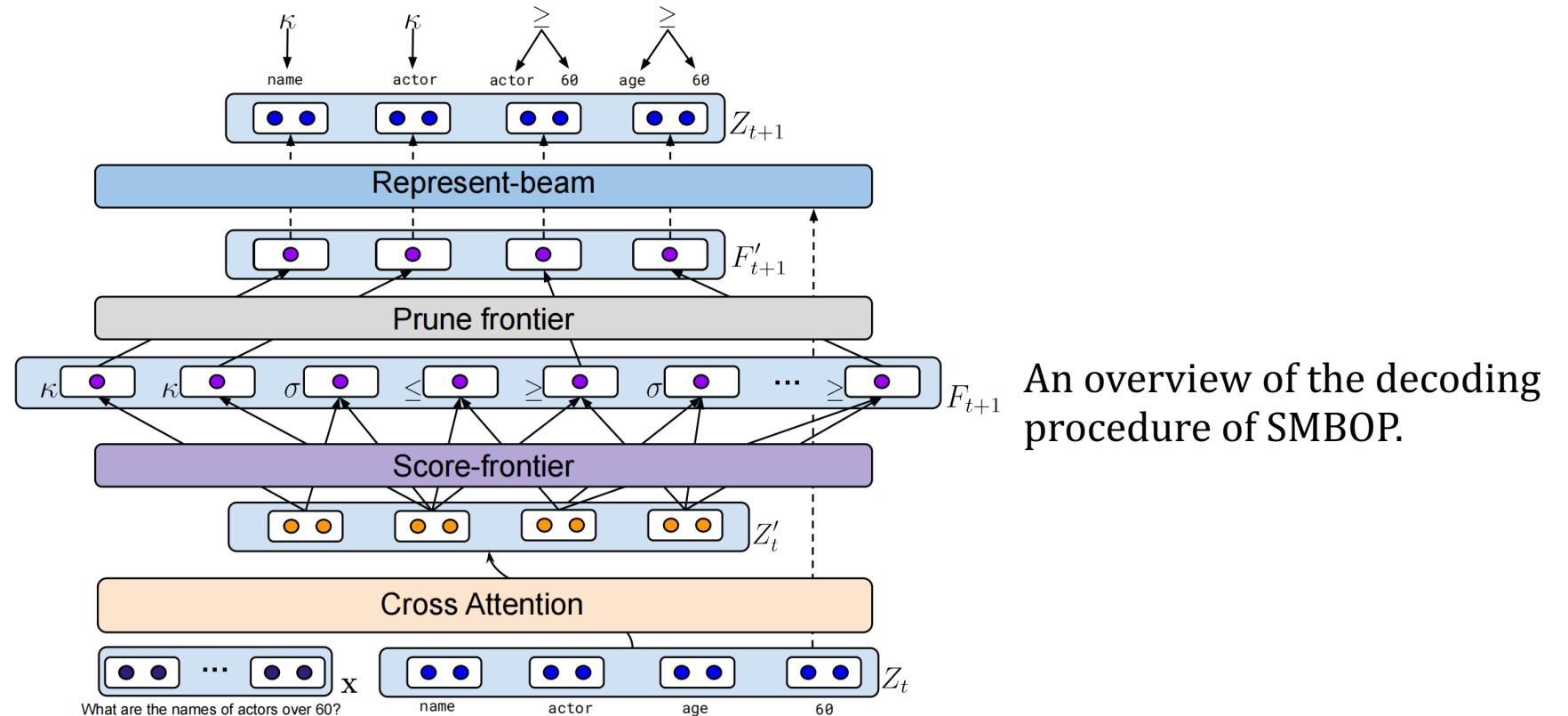
RAT-SQL combines relation-aware graph structure encoding and generation techniques.

- During the decoding process, RAT-SQL uses beam search to generate multiple candidate SQL queries
- These queries are then reranked, and the optimal query is selected based on graph structure information.



Beam Search-based Decoding Strategy

SmBoP uses a semi-autoregressive bottom-up decoding approach, improving decoding efficiency by parallelizing the construction and scoring of sub-trees, achieving logarithmic time complexity.



Beam Search-based Decoding Strategy

Limitations:

- More data needs to be processed at each decoding step.
- This significantly increases the demand for memory and computational resources and results in slower decoding speeds than greedy search.

Constraint-aware Incremental Decoding Strategy

PICARD (Parsing Incrementally for Constrained Auto-Regressive Decoding) introduces the constraint-aware incremental decoding strategy.

- The constraint-aware incremental decoding strategy is specifically designed for NL2SQL tasks.
- This strategy aims to ensure the generation of syntactically correct SQL queries by incorporating constraints during the decoding process.

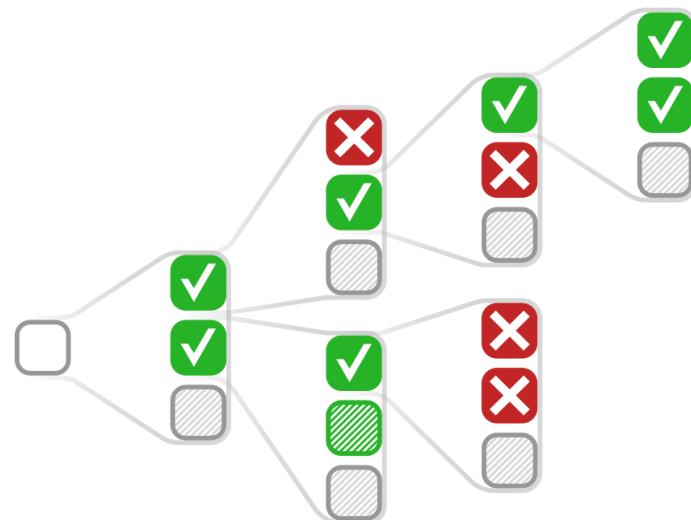
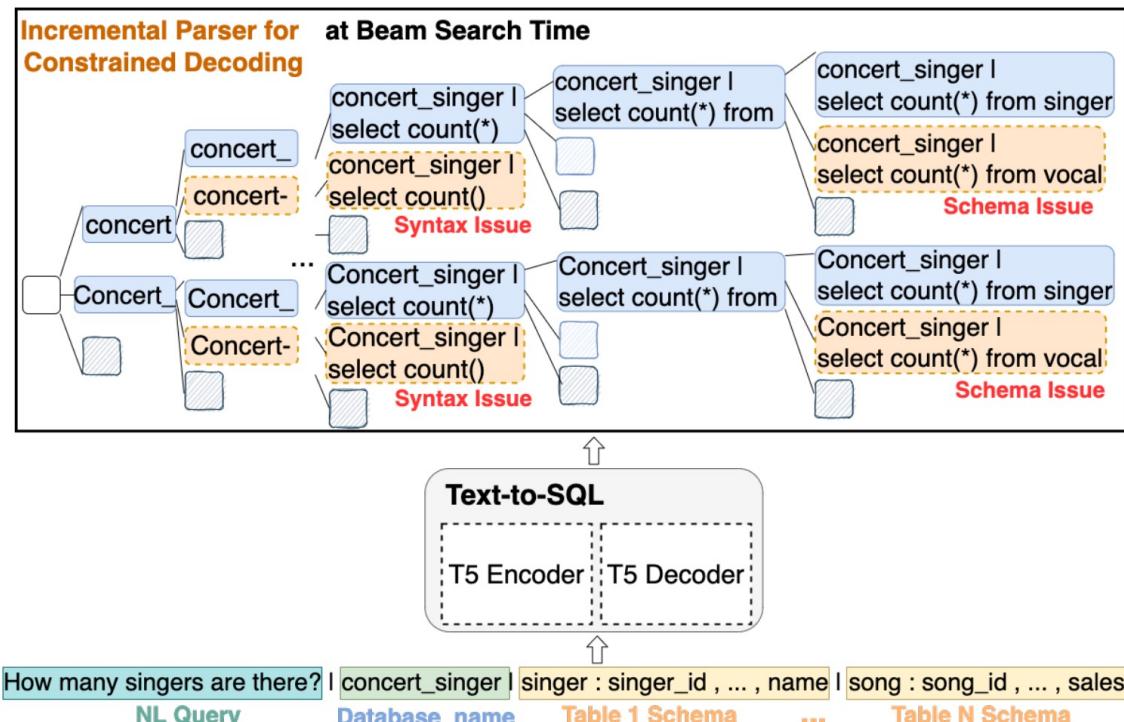


Illustration of constrained beam search with beam size 2 and PICARD.

Constraint-aware Incremental Decoding Strategy

Due to its ability to improve the accuracy of SQL generation, PICARD has been adopted as a decoding strategy by several models, such as **N-best List Rerankers**.

- Compared to versions without PICARD, these models have shown improved accuracy.



PICARD explained by an example. The prediction pattern is “⟨Database name⟩ | ⟨pred SQL⟩”.

Constraint-aware Incremental Decoding Strategy

Limitations:

- Incremental decoding and progressively adding constraints may require more computational resources and processing time.

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Task-Specific Prompt Strategy

Motivation:

- Instruct the LLMs to optimize the SQL query generation process according to task-specific rules.

Goal:

- Improve the accuracy of translating complex semantic NL query into the corresponding SQL query.

Task-Specific Prompt Strategy

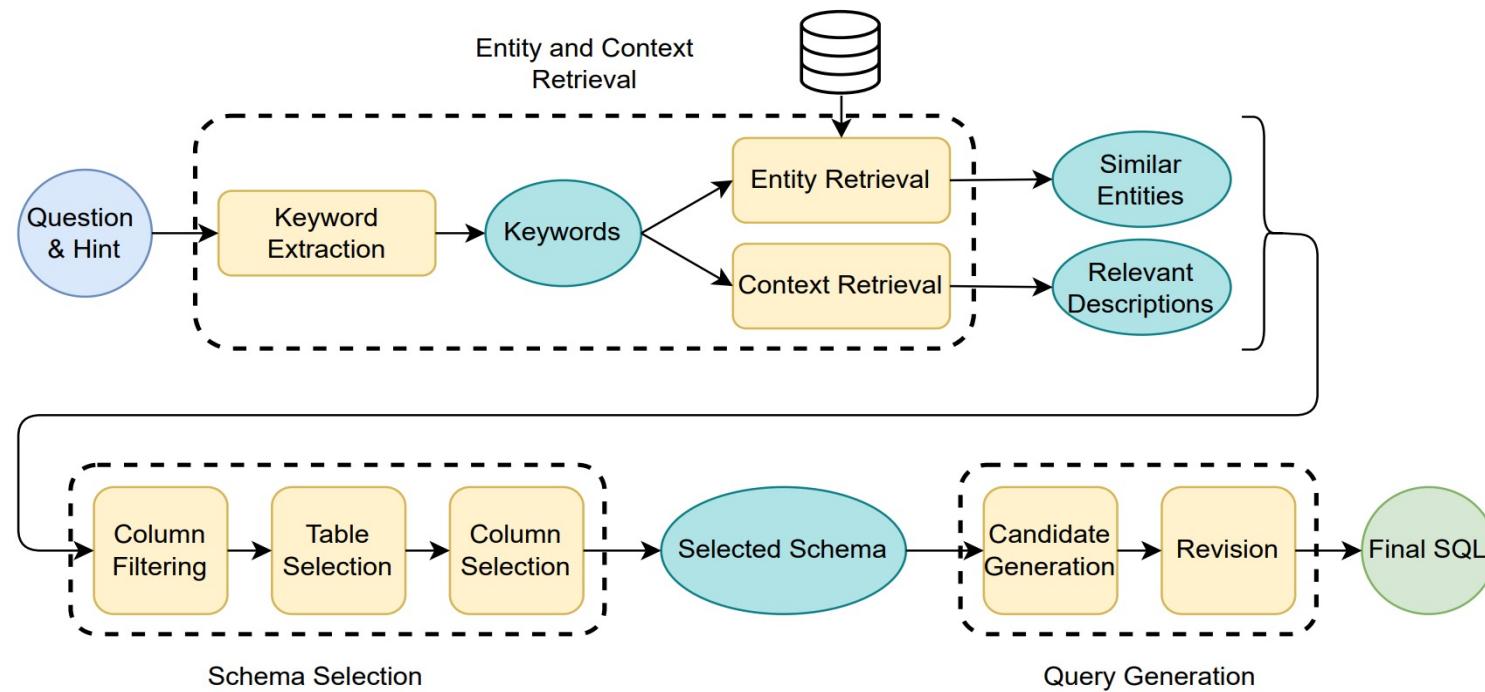
Method classification:

- Chain-of-Thought
- Task Decomposition

Chain-of-Thought

CHESS transforms NL into SQL statements using a streamlined pipeline that relies on LLMs and CoT.

- This CoT process comprises entity and context retrieval, schema selection, SQL generation, and revision.



Chain-of-Thought

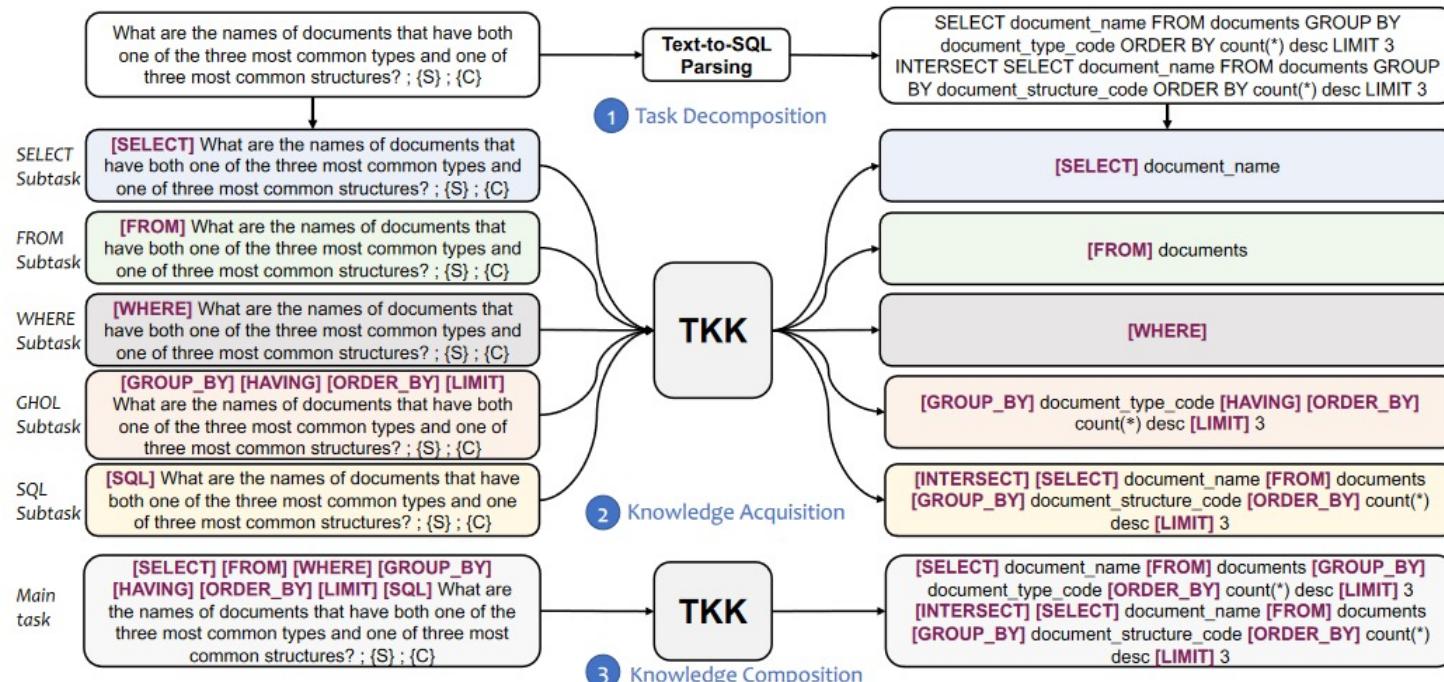
Limitations:

- Hallucination caused by unknown domain knowledge
- Hard to control the output of key components

Decomposition

TKK divides the initial NL2SQL parsing tasks into various small individual subtasks, with each corresponding to the mapping of the NL query to one or more clauses of the SQL query.

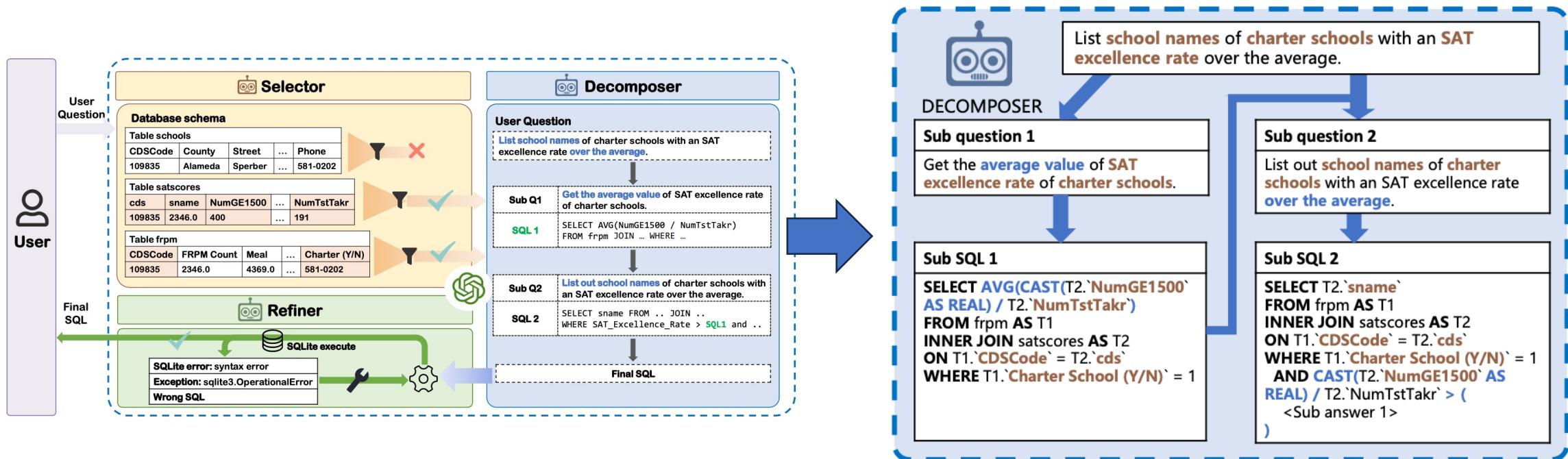
- This decomposition approach allows the model to concentrate on learning the generation of each clause, thereby compelling the model to understand the problem, the database schema, and the alignment between each SQL clause.



Decomposition

MAC-SQL incorporates a *Decomposer* agent designed to break down the user's original problem into several subproblems.

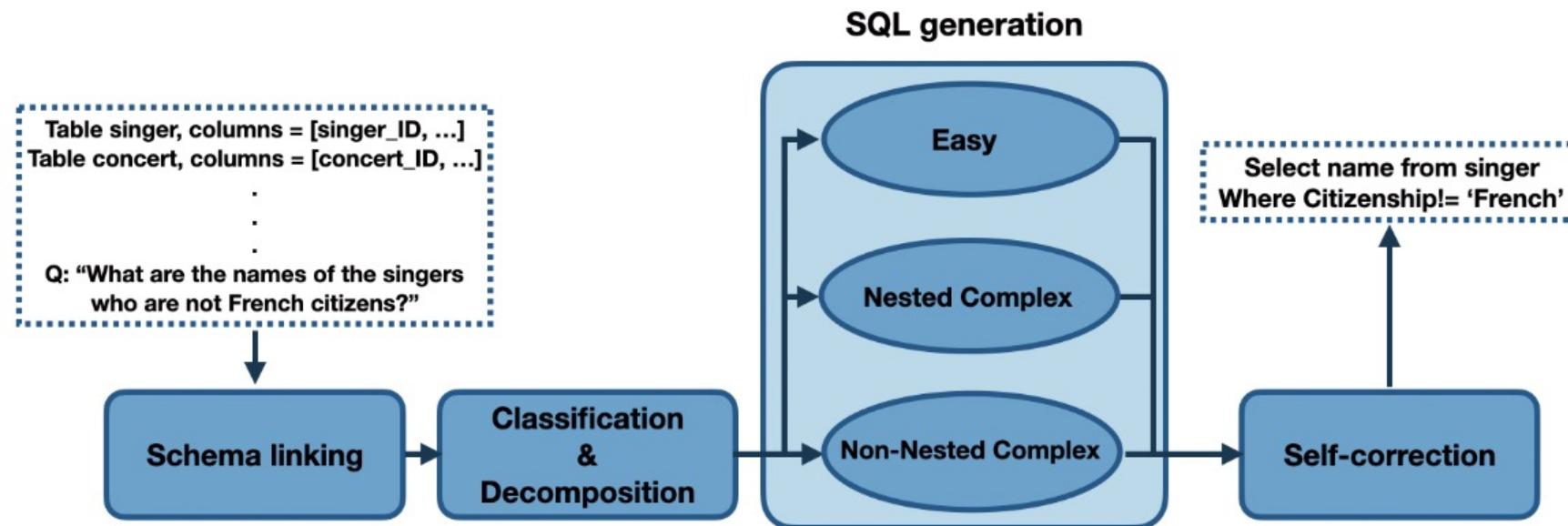
- This decomposition process aims to lessen the complexity of the origin question, enabling the generation of simpler SQL queries to solve each individual subproblem.



Decomposition

DIN-SQL employs a sophisticated categorization module for decomposition.

- It classifies queries into distinct complexity groups: Easy, Non-Nested Complex, and Nested Complex, with the reference of NL and database schema.
- By strategically identifying and separating schema linking, join conditions, and nested structures, the module facilitates a structured generation of SQL queries and amplifies the accuracy of translating complex the NL query into executable SQL.



Decomposition

Limitations:

- Increasing computational cost
- Lowering efficiency because the model need to finish more sub-tasks

Outline

- NL2SQL Problem and Background
- Language Model-Powered NL2SQL Solutions
 - Pre-Processing
 - NL2SQL Translation Methods
 - Encoding Strategy
 - Decoding Strategy
 - Task-specific Prompt Strategies
 - ★ • Intermediate Representation
 - Post-Processing
- NL2SQL Benchmarks
- Evaluation and Error Analysis
- Practical Guidance for Developing NL2SQL Solutions
- Open Problems

Intermediate Representation

Motivation:

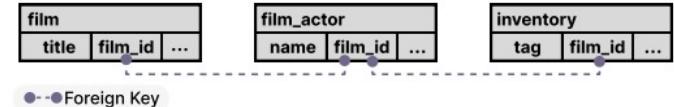
- Design a grammar-free intermediate representation compared to SQL as the bridge between the "free-form" NL query and the "constrained and formal" SQL query.

Goal:

- Capture the essential components and relationships of an NL query without the strict syntax rules of SQL.

NL Query:

Which film has more than 5 actors and less than 3 in the inventory?



Intermediate Representation:

SQL-like Syntax Language
(e.g. NATSQL)

```
SELECT film.title  
WHERE count(film_actor.*)>5 And count(inventory.*)<3
```

SQL-like Sketch Structure
(e.g. SC-Prompt)

```
SELECT [column] [column] title  
FROM [table] [table] film  
JOIN [table] [table] film_actor  
ON [table].[column] [table].[column] film.film_id  
=[table].[column] [table].[column] film_actor.film_id  
GROUP BY [column] [column] film_id  
HAVING count([column]) > n [column] * [n] 5  
INTERSECT  
(SELECT [column] [column] title  
FROM [table] [table] film  
JOIN [table] [table] inventory  
ON [table].[column] [table].[column] film.film_id  
=[table].[column] [table].[column] inventory.film_id  
GROUP BY [column] [column] film_id  
HAVING count([column]) < n [column] * [n] 3
```

SQL:

```
SELECT T1.title  
FROM film AS T1 JOIN film_actor AS T2 ON T1.film_id = T2.film_id  
GROUP BY T1.film_id HAVING count(*) > 5  
INTERSECT  
SELECT T1.title  
FROM film AS T1 JOIN inventory AS T2 ON T1.film_id = T2.film_id  
GROUP BY T1.film_id HAVING count(*) < 3
```

Method Classification of Intermediate Representation

Method classification:

- SQL-Like Syntax Language
- SQL-Like Sketch Structure

NL Query:

Which film has more than 5 actors and less than 3 in the inventory?

film	film_actor	inventory
title	name	tag
film_id	film_id	film_id

--- Foreign Key

Intermediate Representation:

SQL-like Syntax Language
(e.g. NATSQL)

```
SELECT film.title  
WHERE count(film_actor.*)>5 And count(inventory.*)<3
```

SQL-like Sketch Structure
(e.g. SC-Prompt)

```
SELECT [column] [column] title  
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ON [table].[column] [table].[column] film.film_id  
=[table].[column] [table].[column] film_actor.film_id  
GROUP BY [column] [column] film_id  
HAVING count([column]) > n [column] * [n] 5  
INTERSECT  
(SELECT [column] [column] title  
FROM [table] [table] film  
JOIN [table] [table] inventory  
ON [table].[column] [table].[column] film.film_id  
=[table].[column] [table].[column] inventory.film_id  
GROUP BY [column] [column] film_id  
HAVING count([column]) < n) [column] * [n] 3
```

SQL:

```
SELECT T1.title  
FROM film AS T1 JOIN film_actor AS T2 ON T1.film_id = T2.film_id  
GROUP BY T1.film_id HAVING count(*) > 5  
INTERSECT  
SELECT T1.title  
FROM film AS T1 JOIN inventory AS T2 ON T1.film_id = T2.film_id  
GROUP BY T1.film_id HAVING count(*) < 3
```

Intermediate Representation

NatSQL is a widely recognized SQL-like syntax language that eliminates SQL statement operators, keywords, set operators, and other elements seldom found in user problem descriptions.

- It enhances schema linking by minimizing the necessary number of schema items.

Question :

Which film has more than 5 actors and less than 3 in the inventory?

SQL :

```
SELECT T1.title FROM film AS T1 JOIN film_actor AS T2 ON T1.film_id = T2.film_id GROUP BY T1.film_id HAVING count(*) > 5 INTERSECT SELECT T1.title FROM film AS T1 JOIN inventory AS T2 ON T1.film_id = T2.film_id GROUP BY T1.film_id HAVING count(*) < 3
```

The IR of RAT-SQL : (Remove the JOIN ON Clause)

```
SELECT title FROM film, film_actor GROUP BY film_id HAVING count(*) > 5  
INTERSECT SELECT title FROM film, inventory GROUP BY film_id HAVING count(*) < 3
```

The IR of SyntaxSQL : (Remove the JOIN ON and FROM Clause)

```
SELECT film.title GROUP BY film.film_id HAVING count(*) > 5 INTERSECT  
SELECT film.title GROUP BY film.film_id HAVING count(*) < 3
```

SemQL : (Remove the JOIN ON, FROM and GROUP BY Clause. Merge the HAVING and WHERE clause)

```
SELECT film.title WHERE count(film_actor.*) > 5 INTERSECT  
SELECT film.title WHERE count(inventory.*) < 3
```

NatSQL : (Further remove the set operators based on SemQL)

```
SELECT film.title WHERE count(film_actor.*) > 5 and count(inventory.*) < 3
```

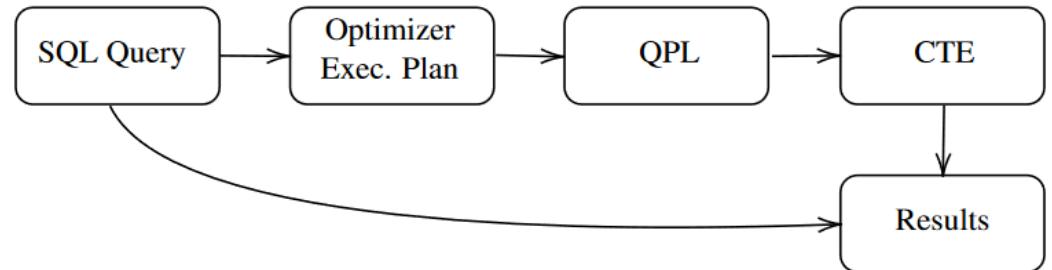
SQL-Like Syntax Language

QPL leverages the problem decomposition strategy to improve the parsing of intricate SQL queries.

- By breaking down a SQL query into modularized sub-queries, the complexity of the original query is reduced.
- This approach mitigates parsing difficulties associated with complex problems and cross-domain complex queries.

Operator	Description
Scan	Scan all rows in a table with optional filtering predicate
Aggregate	Aggregate a stream of tuples using a grouping criterion into a stream of groups
Filter	Remove tuples from a stream that do not match a predicate
Sort	Sort a stream according to a sorting expression
TopSort	Select the top-K tuples from a stream according to a sorting expression
Join	Perform a logical join operation between two streams based on a join condition
Except	Compute the set difference between two streams of tuples
Intersect	Compute the set intersection between two streams of tuples
Union	Compute the set union between two streams of tuples

Table 2: Description of QPL Operators



SQL-Like Syntax Language

QDMR decomposes the original question into a number of atomic questions

- Each atomic question serves as an intermediate representation of the original question and can be translated into a set of small-scale formal operations involving tasks such as selecting entities, retrieving attributes, or aggregating information.

QDMR Step	Phrase-DB Linking	SQL
1. ships	1. SELECT (ship.id)	SELECT ship.id FROM ship;
2. injuries	2. SELECT (death.injured)	SELECT death.injured FROM death;
3. number of #2 for each #1	3. GROUP (count, #2, #1)	SELECT COUNT(death.injured) FROM ship, death WHERE death.caused_by_ship_id = ship.id GROUP BY ship.id;
4. #1 where #3 is highest	4. SUPER. (max, #1, #3)	SELECT ship.id FROM ship, death WHERE death.caused_by_ship_id = ship.id GROUP BY ship.id ORDER BY COUNT(death.injured) DESC LIMIT 1;
5. the name of #4	5. PROJECT (ship.name, #4)	SELECT ship.name FROM ship, death WHERE death.caused_by_ship_id = ship.id AND ship.id IN (#4);

SQL-Like Syntax Language

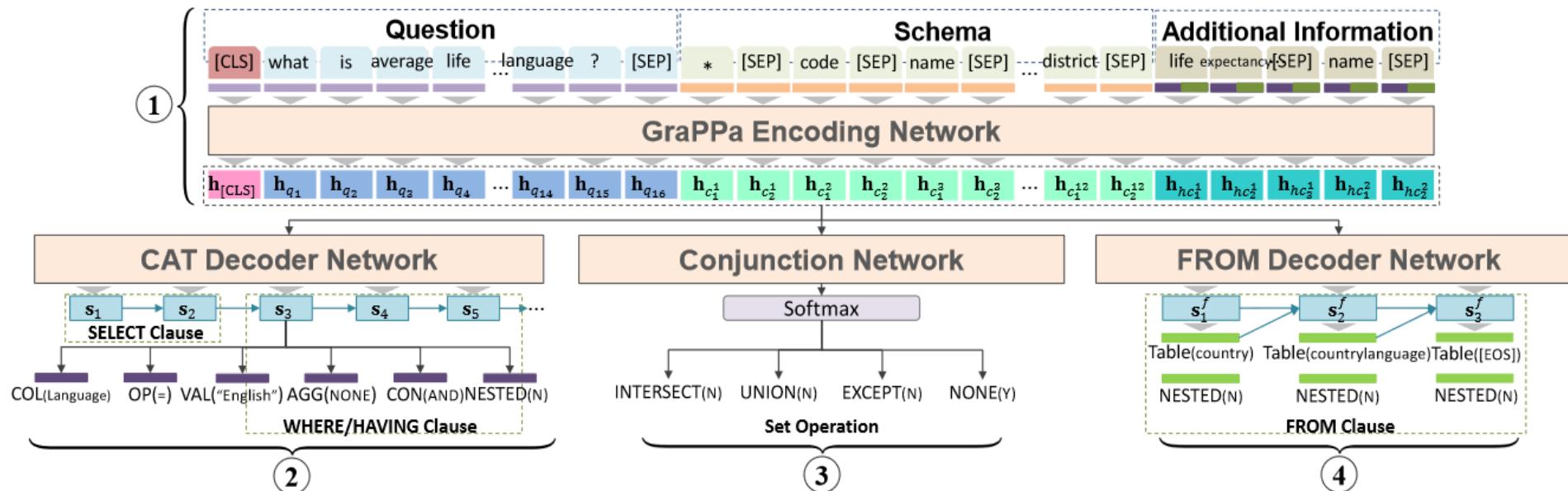
Limitations:

- High complexity and inadequate coverage of database structures
- Cost of manual design and deployment

SQL-Like Sketch Structure

CatSQL constructs a general template sketch with slots serving as initial placeholders.

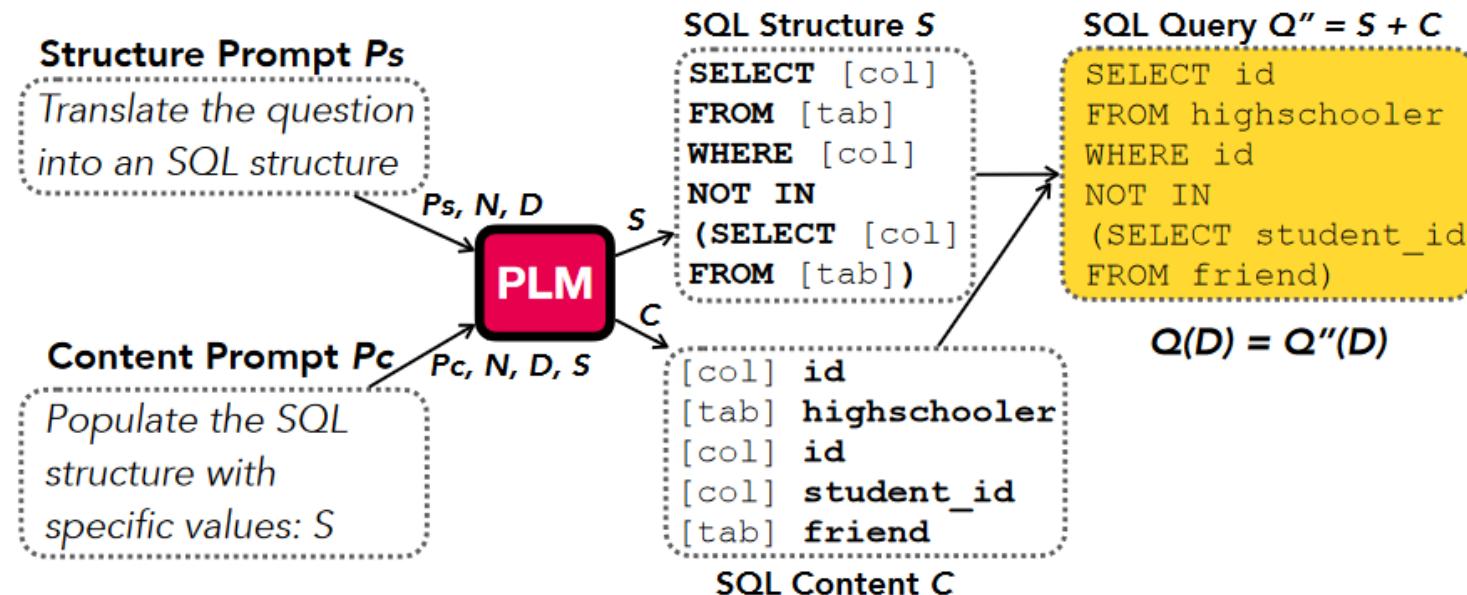
- Its base model focus on the parsing of user queries to fill these placeholders, consequently decreasing the computational resource cost.
- It implements a novel semantic correction algorithm to assess the semantic accuracy of the resulting SQL queries and rectify any semantic issues detected in the generated queries.



SQL-Like Sketch Structure

SC-prompt utilizes a two-stage divide and conquer method for NL2SQL parsing

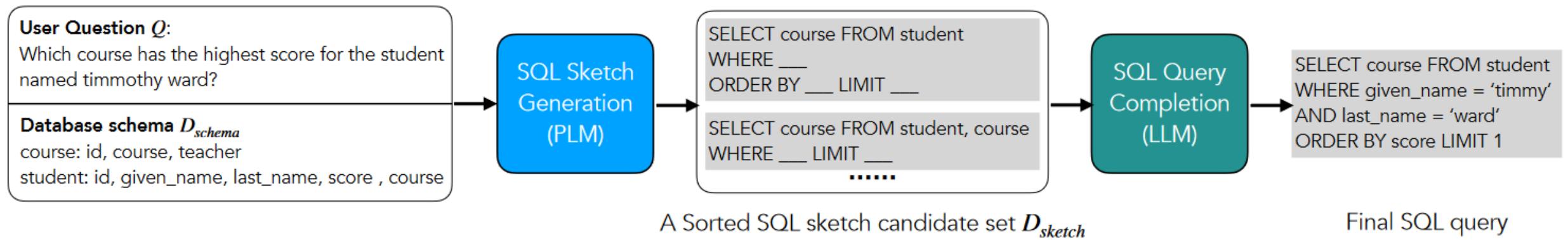
- It instructs PLM to generate specific SQL structures.
- In the subsequent phase, it directs the PLM to generate SQL structures containing actual values to fill the previously provided placeholders.



SQL-Like Sketch Structure

ZeroNL2SQL integrates the schema alignment capabilities of PLM with the complex reasoning capabilities of LLMs.

- Initially, it utilizes PLM to produce SQL sketches for achieving schema alignment and subsequently employs LLMs to execute complex content reasoning for populating missing information.
- Additionally, it also proposes a predicate calibration method for guiding the design of language models for SQL sketches based on database instances and selecting the optimal SQL query.



SQL-Like Sketch Structure

Limitations:

- High computational cost
- Hard to construct accurate sketch when the query is much more complex

Outline

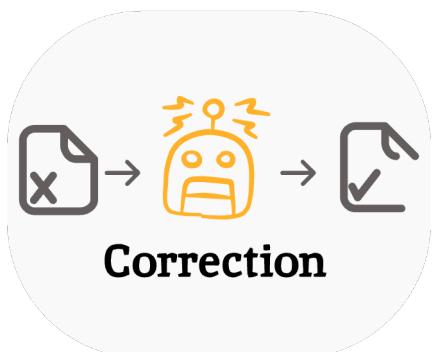
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Post Processing

Motivation:

- Post-processing is a crucial step to refine the generated SQL queries, ensuring they meet user expectations more accurately.
- This involves enhancing the initial SQL output using various strategies.

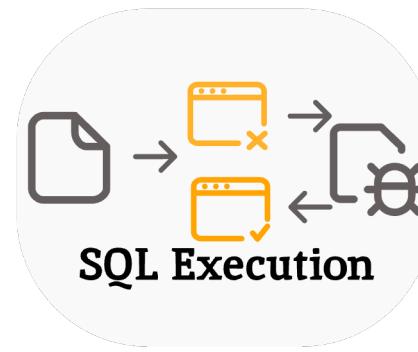
Correction



Consistency



Execution-Guided



N-best Rerankers



SQL Correction Strategies



Motivation:

- The SQL generated by the model may sometimes contain syntax errors.
- SQL Correction Strategies aim to prompt LLMs to correct syntax errors in SQL.

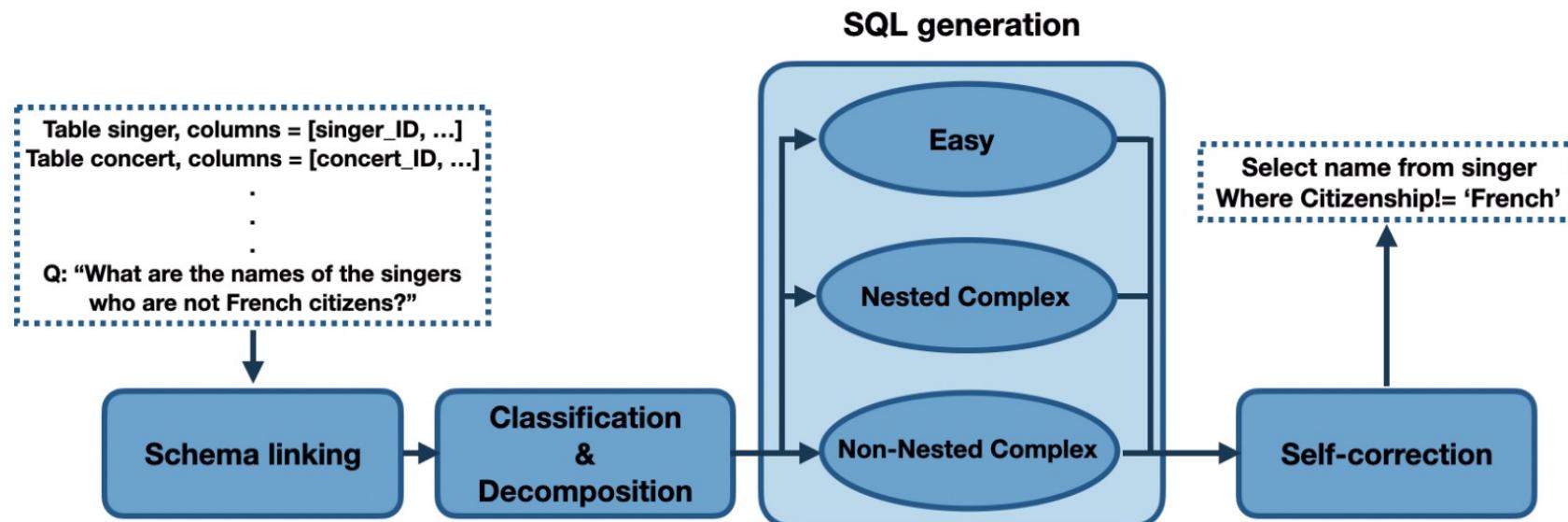
Goal:

- Convert the buggy SQL query into the correct SQL queries.

SQL Correction Strategies

DIN-SQL introduces a self-correction module for refining SQL queries generated by NL-to-SQL models, addressing issues like redundant keywords or missing functions.

Two prompts are used: a general prompt for the CodeX model, which explicitly asks to identify and fix errors in the “BUGGY SQL,” and a milder prompt for GPT-4, which simply asks the model to point out potential issues without assuming the presence of errors.

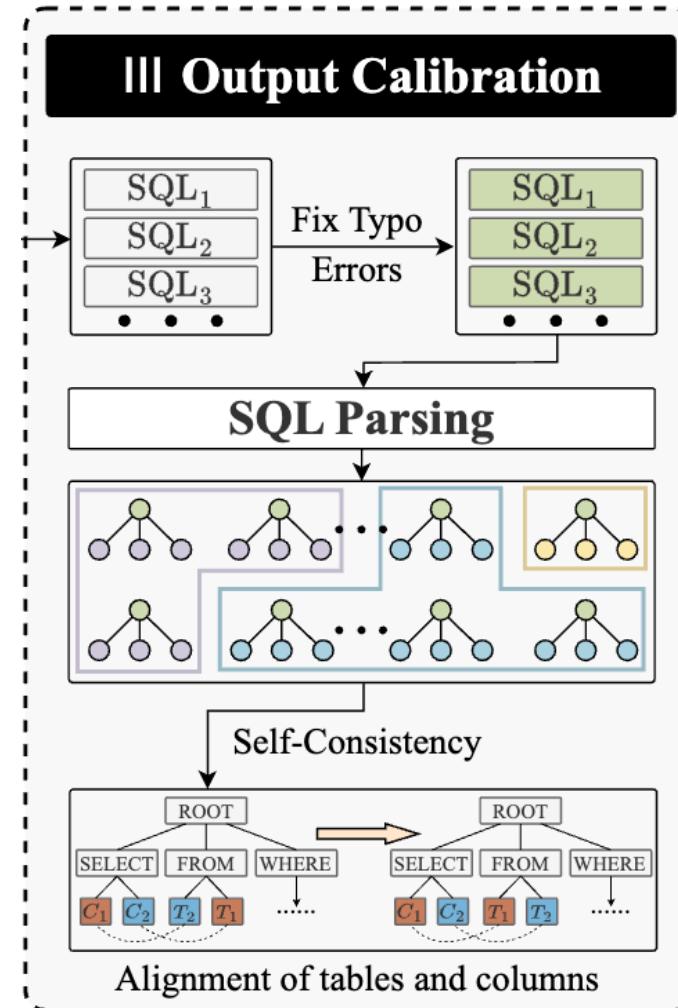


SQL Correction Strategies

Fin-SQL introduces an output calibration algorithm to avoid executing time-consuming SQL queries on large financial databases.

Fin-SQL corrects spelling errors, performs fuzzy matching for invalid columns, and ensures that all tables containing referenced columns are included in the FROM clause.

This approach helps improve SQL query accuracy without actual query execution.



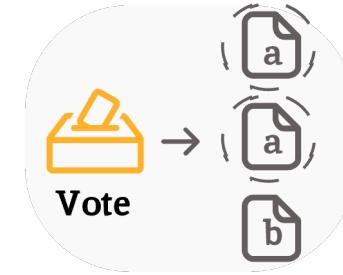
SQL Correction Strategies

Limitations:

- Primarily focus on specific syntax errors correction
- Lack of generalized error correction for other SQL errors

Output Consistency

Consistency



Motivation:

- In complex reasoning problems, there are multiple reasoning paths that can lead to a unique correct answer. It first samples multiple different reasoning paths and then selects the most consistent answer to significantly improve the quality of the output.
- In the NL2SQL task, being similar to reasoning tasks, can also have multiple ways to write SQL queries that express the same meaning.

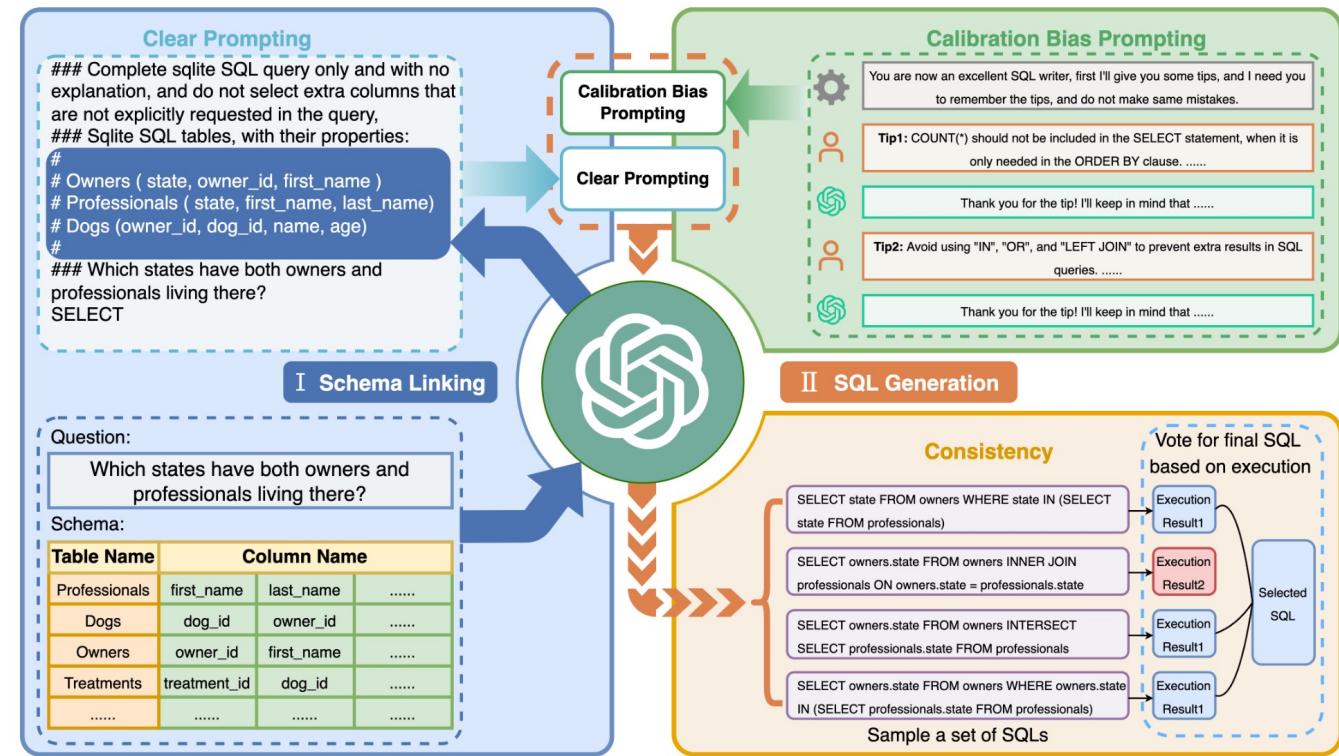
Goal:

- Vote to determine the final SQL to enhance the consistency of model outputs.

Output Consistency

C3-SQL incorporates the Consistency Output (CO) component to enhance the reliability of SQL queries generated by large language models, addressing their inherent randomness.

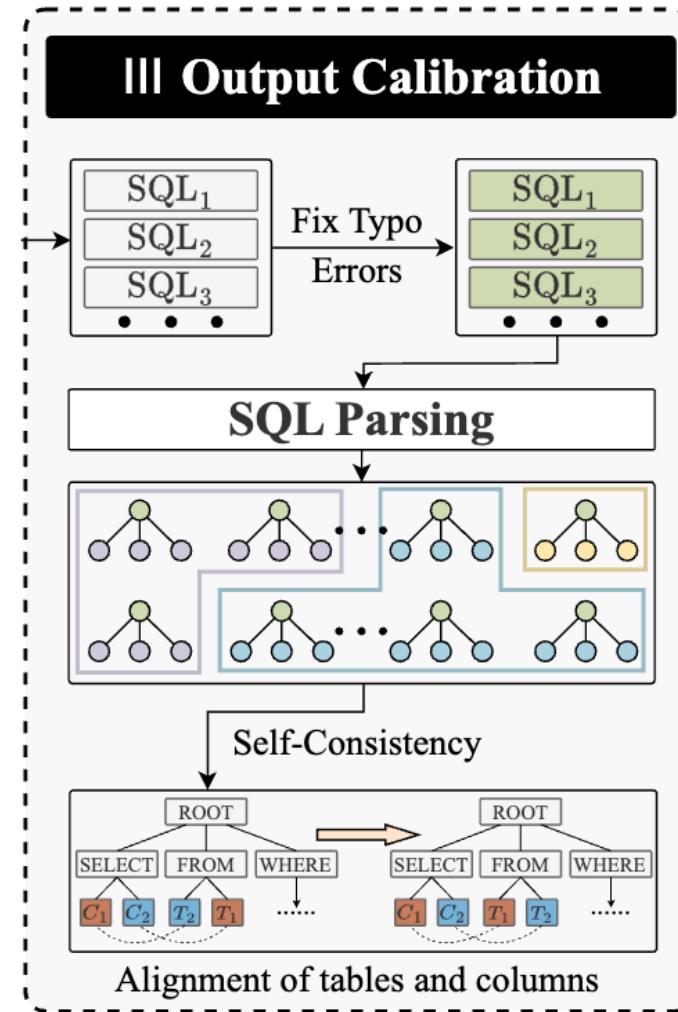
CO samples multiple reasoning paths to generate different SQL queries, executes them, and uses a voting mechanism to select the most consistent result after removing errors.



Output Consistency

Fin-SQL addresses the randomness of LLM outputs by generating multiple candidate SQL queries in parallel. It evaluates the equivalence of these queries based on keyword consistency and clusters them accordingly.

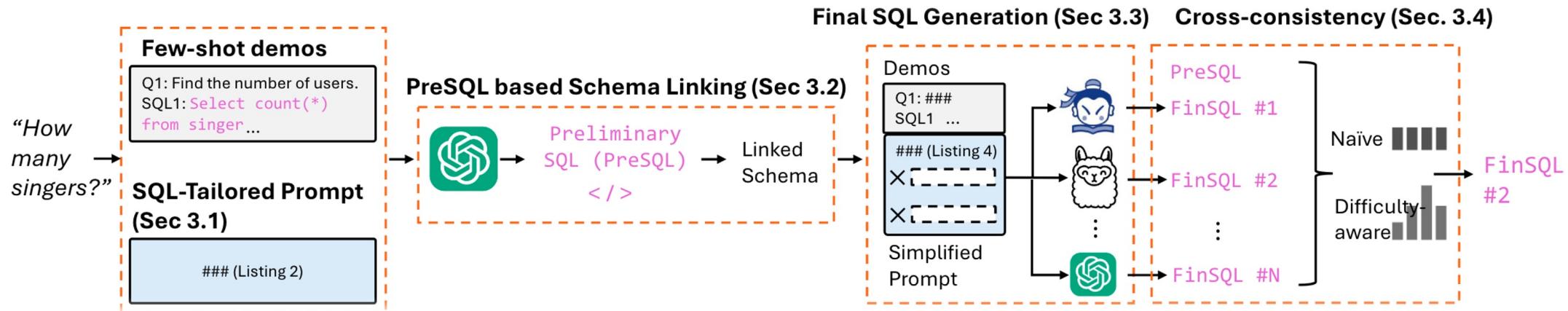
The final query is selected from the largest cluster, improving the consistency and reliability of SQL query generation.



Output Consistency

The self-consistency method for LLMs uses high temperatures to create diverse outputs but may suffer from performance degradation due to increased hallucinations.

PET-SQL addresses this by employing a cross-consistency strategy where multiple LLMs generate SQL queries at lower temperatures and select results through execution-based voting. This approach enhances query diversity while preserving LLM performance at lower temperatures.



Output Consistency

Limitations:

- Increased inference cost and time
- Reliance on multiple queries may not address all types of errors
- Effectiveness may decrease as LLM capabilities improve

Execution-Guided Strategies



Motivation:

- The execution result of an SQL query is a crucial piece of information, as it may indicate the quality of the query itself. For instance, if the query execution results in errors or NULL values, it might indicate an issue with the SQL query.

Goal:

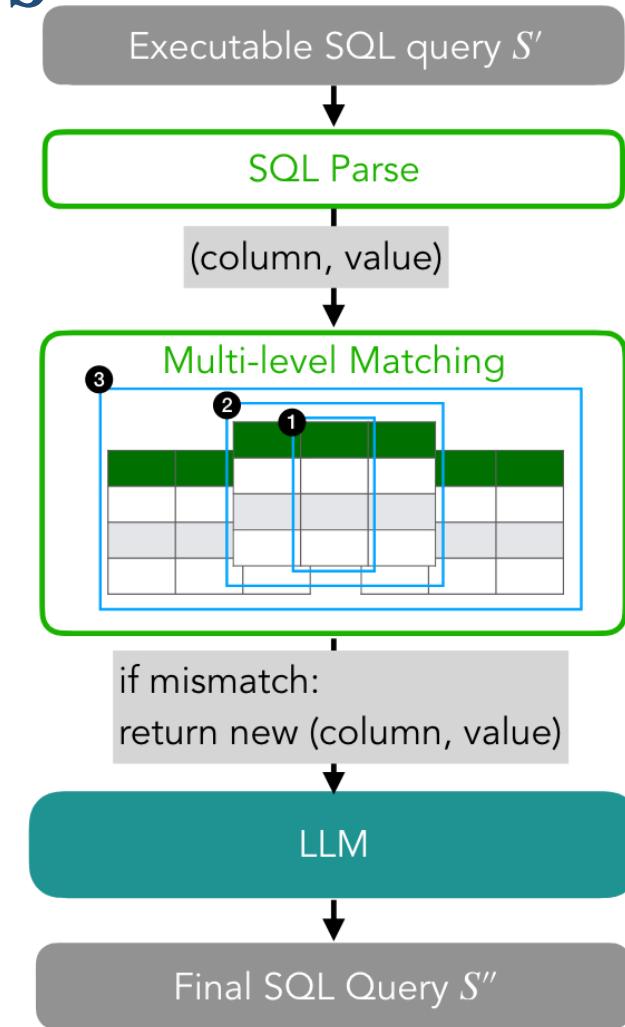
- Incorporating the results of SQL queries to guide subsequent processing of the SQL.

Execution-Guided Strategies

ZeroNL2SQL generates SQL queries iteratively by checking the executability of multiple candidate SQL sketches.

It provides error feedback to the LLMs, refining the query until a feedback limit is reached, at which point the current sketch is discarded.

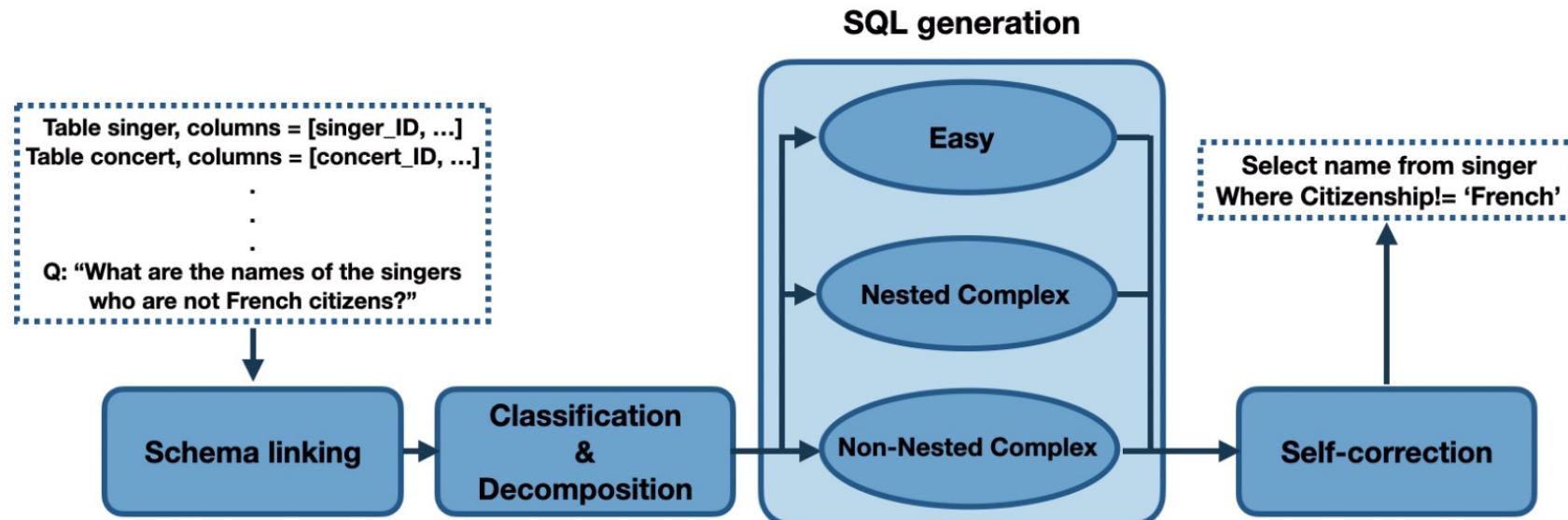
This process continues until the LLMs generate an optimal, executable SQL query as the final output.



Execution-Guided Strategies

MAC-SQL introduces a Refiner agent that detects and corrects SQL errors in a multi-agent collaboration framework.

The agent evaluates SQL queries for syntactic correctness, execution feasibility, and whether they retrieve non-empty results from the database. If errors are found, it uses feedback or guidance to correct the SQL, enhancing the model's self-diagnosis and overall



Execution-Guided Strategies

Limitations:

- Increased SQL generation time, especially with large databases
- Dependency on execution results may not address logical errors
- Limited scalability for complex or extensive databases



N-best Rankers Strategies

Motivation:

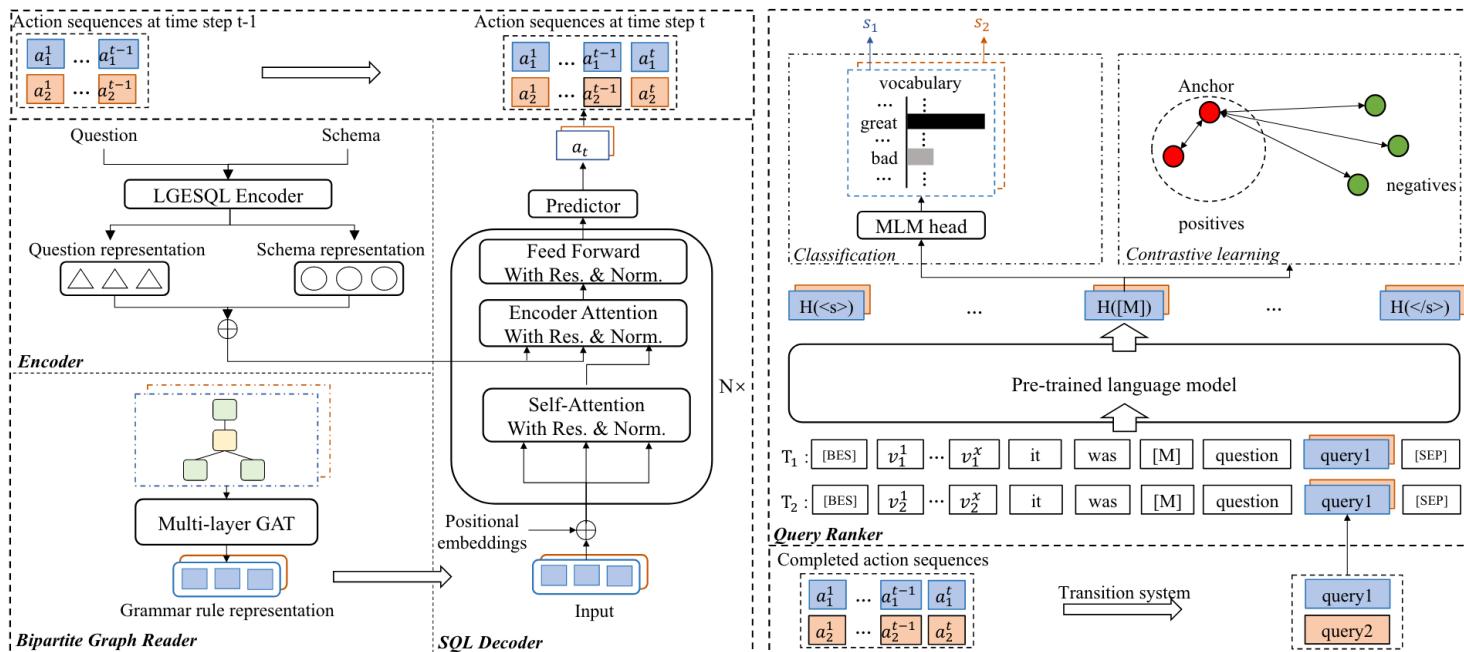
- In cross-domain scenarios, the generated SQL queries may exhibit subtle variances in both structure and semantics.
- We can reranking the generated SQL by larger model or using additional knowledge.

Goal:

- Reordering the top n results from the original model using a larger model or incorporating additional knowledge sources.

N-best Rankers Strategies

G³R addresses the issue of unstable and dependent on threshold settings by introducing a feature-enhanced SQL Reranker based on pre-trained language models with hybrid prompt tuning, allowing it to bridge domain gaps without adding extra parameters.



N-best Rankers Strategies

Limitations:

- Limited applicability to LLMs with stronger inference capabilities
- Reduced effectiveness as LLMs increase in size and sophistication
- Reliance on additional models or knowledge for effective filtering

Outline

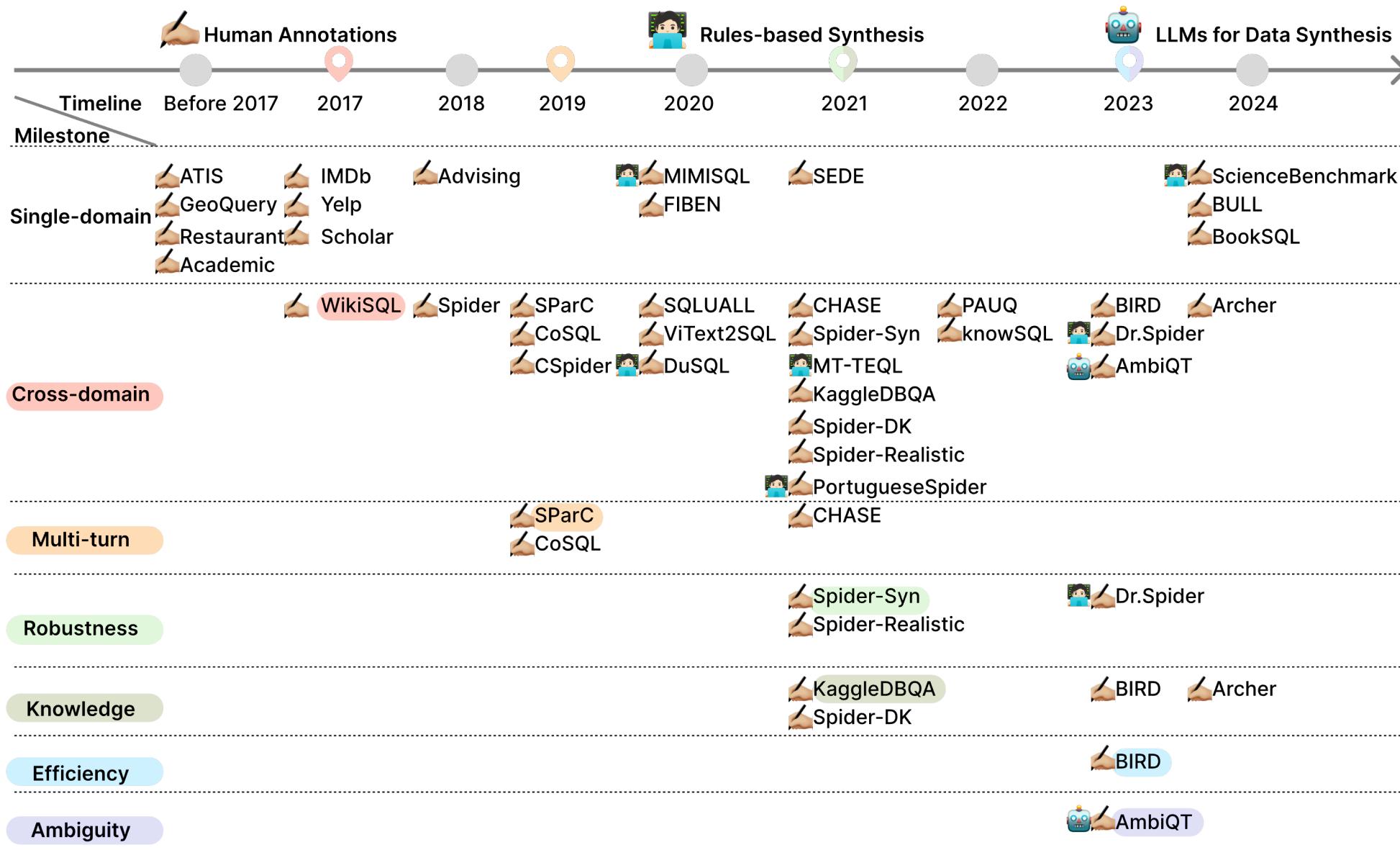
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Why We Need Benchmark?

Motivation:

- To **quantify the performance** of NL2SQL models
- To **provide sufficient data** for training NL2SQL models
- To **simulate the challenges** in real-world application scenarios

An Overview of NL2SQL Benchmarks



Single-domain Dataset

Motivation:

- Early NL2SQL datasets focused on specific domains, often featuring simple SQL query structures
- Recent single-domain datasets feature more complex databases and SQL queries specific to particular scenarios

Question:

Which funds have a fund establishment size exceeding 1 billion?
And what is their three-year annualized return rate?

SQL Query:

```
SELECT a.secuabbr, a.annualizedrrinthreeyear  
FROM mf_netvalueperformancehis as a JOIN mf_fundarchives as b  
ON a.innercode = b.innercode  
Where b.foundedsize > 1000000000;
```

Table Name & Column Name

mf_netvalueperformancehis

secuabbr

annualizedrrinthreeyear

mf_fundarchives

foundedsize

Table and Column Description

Latest range performance of public fund net value

Fund abbreviation

Three-year annualized return rate (%)

Public fund overview

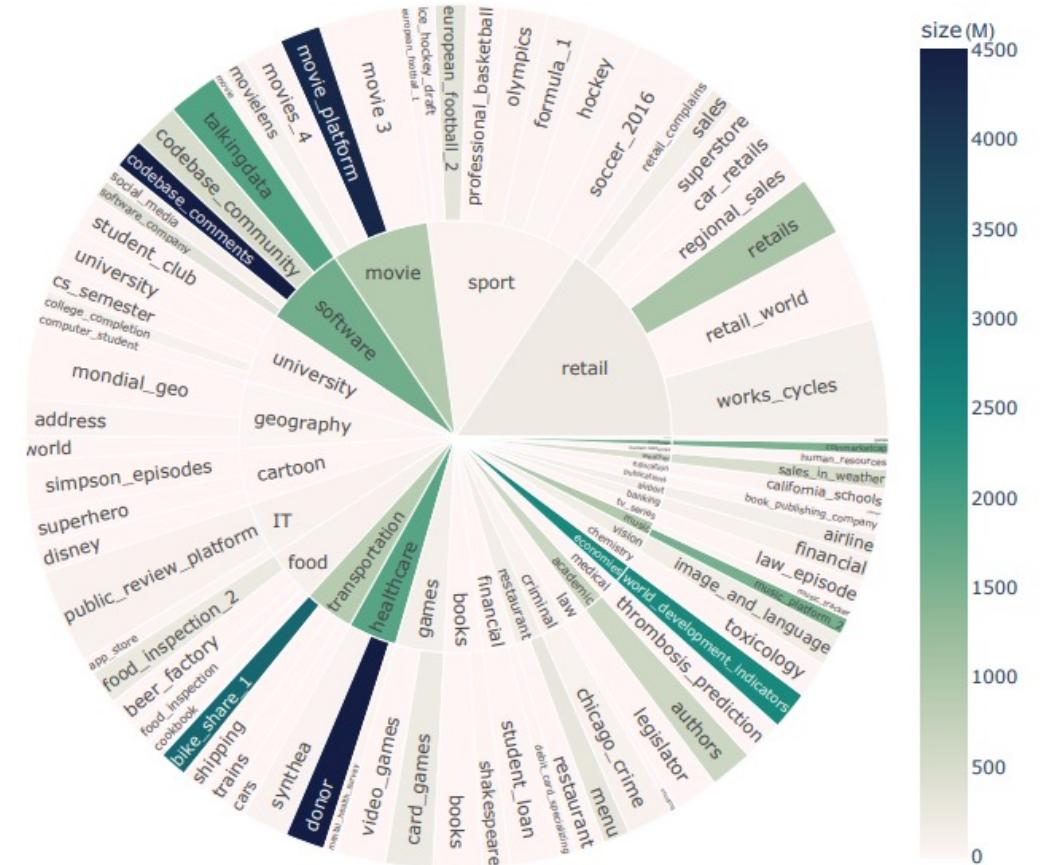
Fund establishment size (units)

An example in BULL dataset

Cross-domain Dataset

Motivation:

- Cross-domain datasets challenge the generalization capabilities of NL2SQL systems across different domains, requiring these systems to generalize not only to new SQL queries but also to new databases.



Multi-turn Dataset

Motivation:

- In a real-world setting, users tend to ask a sequence of thematically related questions to learn about a particular topic or to achieve a complex goal.

D_1 : Database about student dormitory containing 5 tables.

C_1 : Find the first and last names of the students who are living in the dorms that have a TV Lounge as an amenity.

Q_1 : How many dorms have a TV Lounge?

S_1 : `SELECT COUNT(*) FROM dorm AS T1 JOIN has_amenity AS T2 ON T1.dormid = T2.dormid JOIN dorm_amenity AS T3 ON T2.amenid = T3.amenid WHERE T3.amenity_name = 'TV Lounge'`

Q_2 : What is the total capacity of these dorms?

S_2 : `SELECT SUM(T1.student_capacity) FROM dorm AS T1 JOIN has_amenity AS T2 ON T1.dormid = T2.dormid JOIN dorm_amenity AS T3 ON T2.amenid = T3.amenid WHERE T3.amenity_name = 'TV Lounge'`

Q_3 : How many students are living there?

S_3 : `SELECT COUNT(*) FROM student AS T1 JOIN lives_in AS T2 ON T1.stuid = T2.stuid WHERE T2.dormid IN (SELECT T3.dormid FROM has_amenity AS T3 JOIN dorm_amenity AS T4 ON T3.amenid = T4.amenid WHERE T4.amenity_name = 'TV Lounge')`

Q_4 : Please show their first and last names.

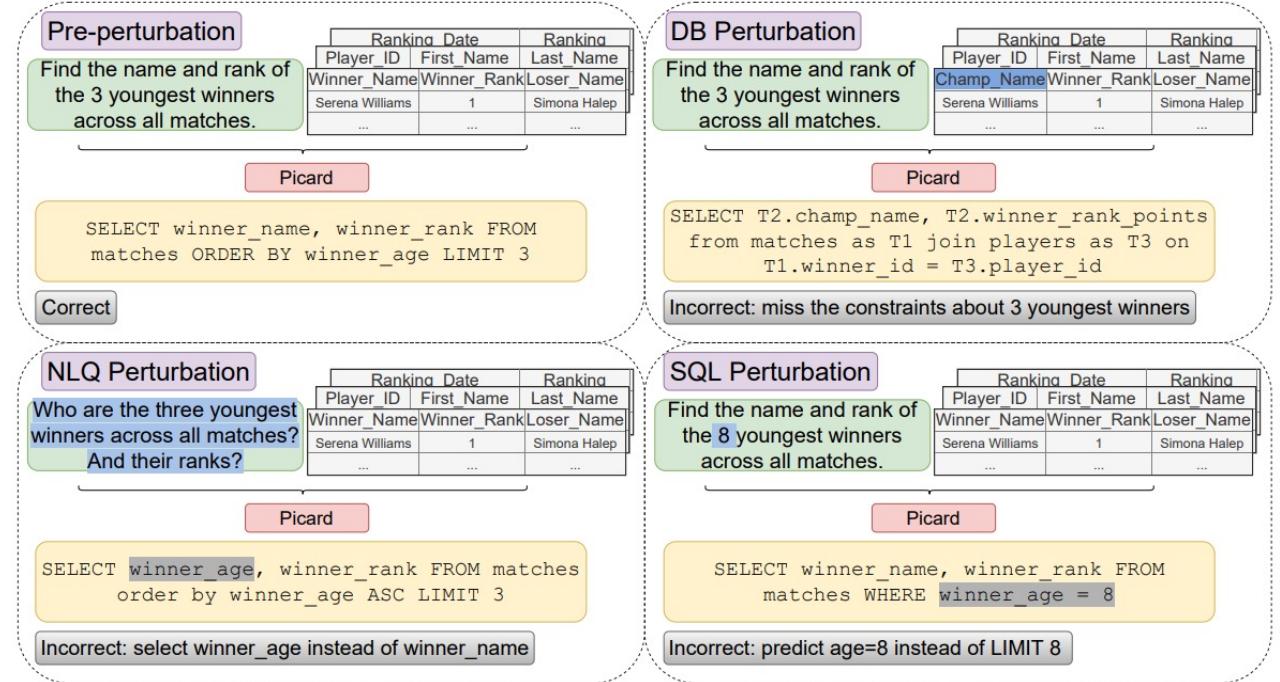
S_4 : `SELECT T1.fname, T1.lname FROM student AS T1 JOIN lives_in AS T2 ON T1.stuid = T2.stuid WHERE T2.dormid IN (SELECT T3.dormid FROM has_amenity AS T3 JOIN dorm_amenity AS T4 ON T3.amenid = T4.amenid WHERE T4.amenity_name = 'TV Lounge')`

An example in SParC dataset

NL2SQL Datasets: Considering Robustness

Motivation:

- In real-world applications, NL2SQL systems need to handle diverse user groups and various database domains, making robustness a growing focus within the community.

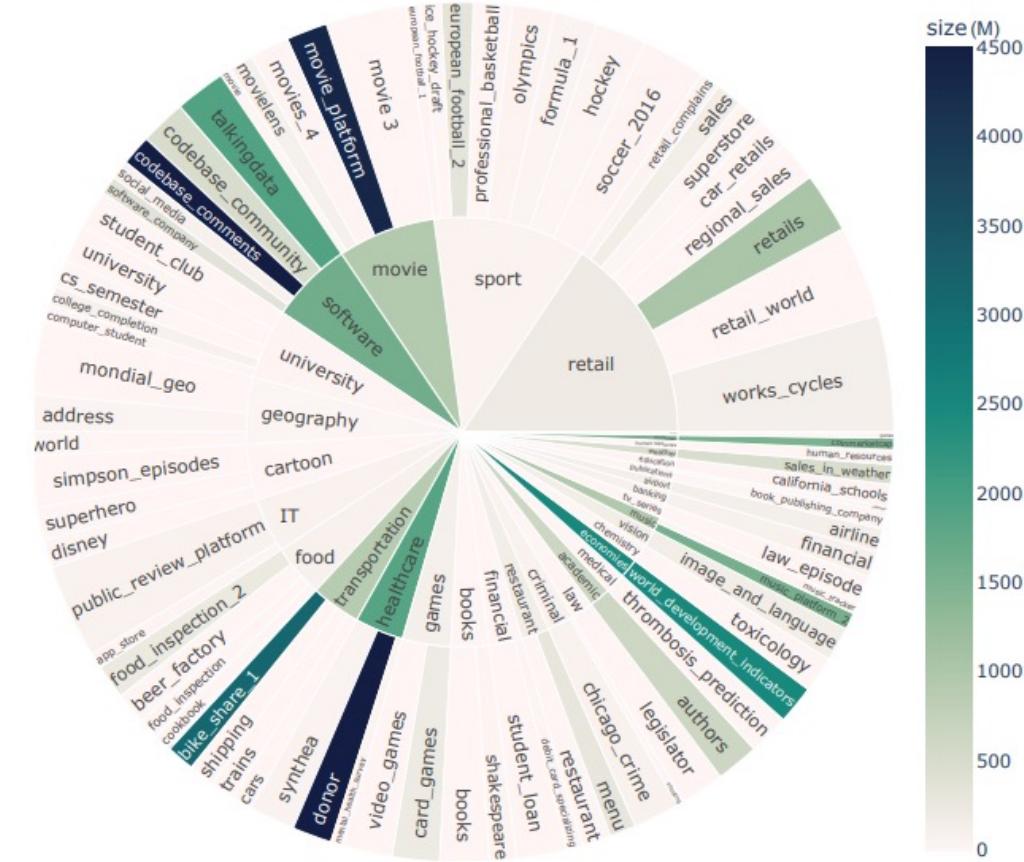


An example in Dr.Spider dataset

NL2SQL Datasets: Considering SQL Efficiency

Motivation:

- Databases in real-world scenarios often contain massive amounts of data, and a user question can be solved by multiple SQL queries.
 - These SQL queries can vary in execution efficiency, which has attracted attention from the community.

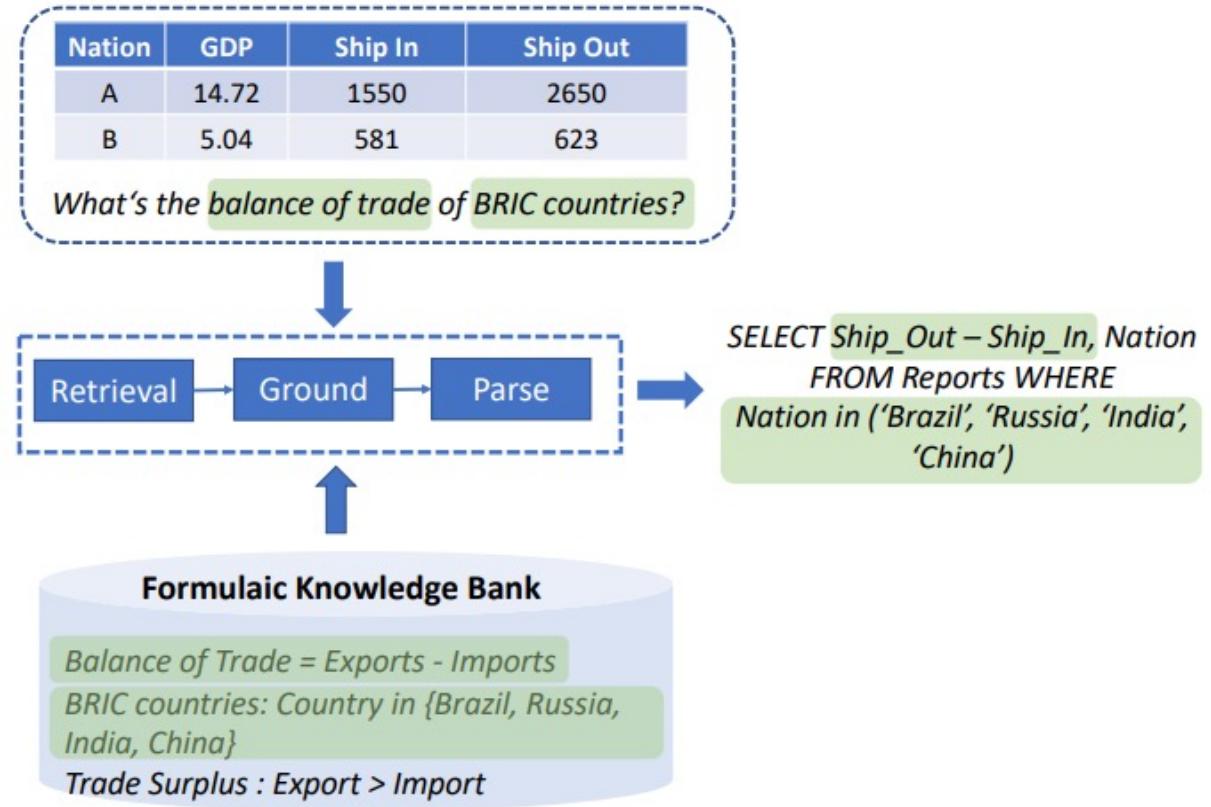


Database domain distribution with size in BIRD dataset

Knowledge-Augmented NL2SQL Datasets

Motivation:

- NL2SQL systems often require **domain-specific knowledge** to effectively perform the NL2SQL task in real-world applications within specific domains.



An example in KnowSQL

NL2SQL Datasets: Considering NL Ambiguity

Motivation:

- In real-world NL2SQL tasks, various ambiguities often arise, such as semantic ambiguities in NL and overlapping database schema.

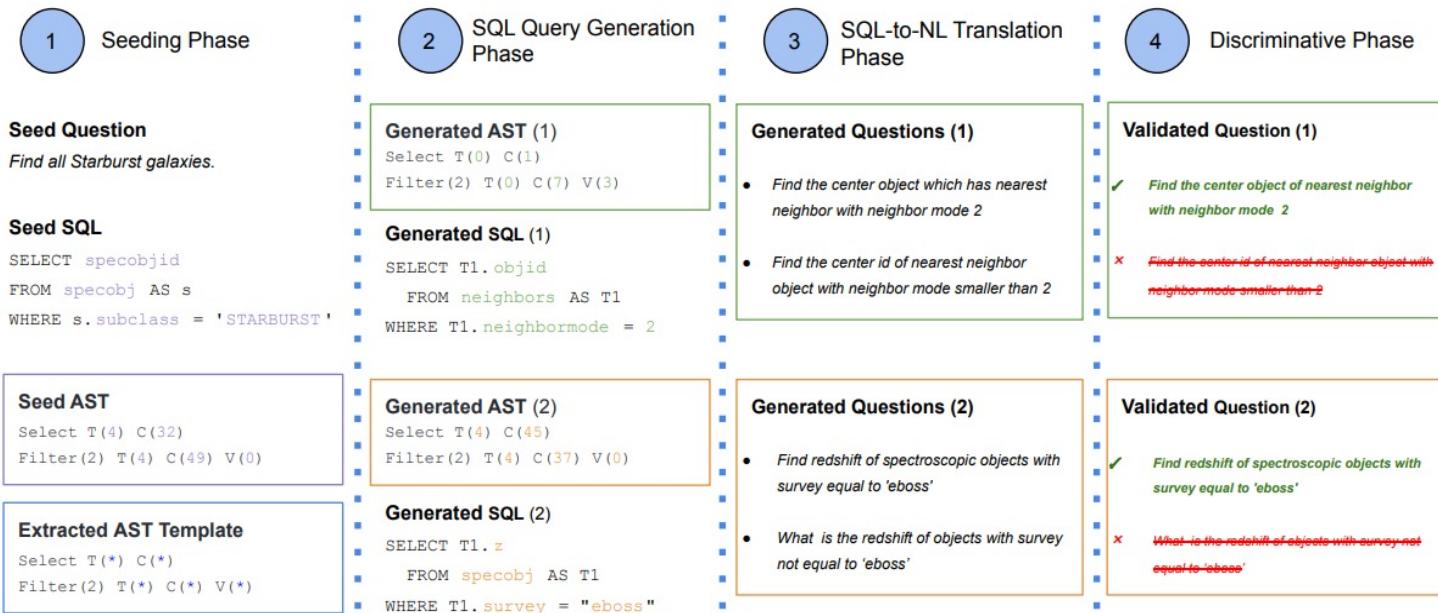
Kind of ambiguity	Count	Example		
		Question Text	SQL #1	SQL #2
Column Ambiguity (C)	1240	List the ids of all students.	SELECT roll_number FROM students	SELECT admission_number FROM students
Table Ambiguity (T)	1417	How many singers do we have?	SELECT COUNT(*) FROM artist	SELECT COUNT(*) FROM performer
Join Ambiguity (J)	288	What are the makers and models?	SELECT maker, model FROM model	SELECT t2.maker, t1.model FROM model AS t1 JOIN model_maker AS t2 ON t1.model_id = t2.model_id
Precomputed Aggregates (P)	101	Find the average weight for each pet type.	SELECT AVG(weight), pettype FROM pets GROUP BY pettype	SELECT avg_weight, pettype FROM pets_weight

An example in AmbiQT

Synthetic NL2SQL Datasets

Motivation:

- Despite the fact that many datasets have been manually annotated so far, the rapid development of LLMs in the NL2SQL field has led to a growing demand for NL2SQL data.



End-to-end architecture
for automatic training
data generation in
ScienceBenchmark

The Statistics of NL2SQL Benchmarks

TABLE II: Statistics of NL2SQL Benchmarks.

Dataset	Redundancy Measure			DB Complexity				Query Complexity					
	#-Questions	#-Unique Queries	#-Questions / #-Queries	#-DBs	#-Tables	#-Tables / DB	#-Cols / Table	#-Records / DB	Tables	Selects	Agg	Scalar Func	Math Comp
ATIS [118]	5280	947	5.6	1	25	25	5.24	162243	8.39	1.79	0.22	0	0
GeoQuery [119]	877	246	3.6	1	7	7	4.14	937	2.22	2.19	0.92	0	0.01
Restaurants [120]	378	23	16.4	1	3	3	4.00	19295	2.43	1.17	0.35	0	0
Academic [108]	196	185	1.1	1	17	17	3.12	58249674	3.48	1.04	0.54	0	0
IMDb [121]	131	89	1.5	1	17	17	3.94	40147386	2.91	1.01	0.30	0	0
Yelp [121]	128	110	1.2	1	8	8	5	4823945	2.41	1	0.45	0	0
Scholar [122]	817	193	4.2	1	10	10	2.50	147416275	3.38	1.02	0.68	0	0.02
WikiSQL [40]	80654	80257	1	26531	26531	1	6.34	17	1	1	0.28	0	0
Advising [123]	4387	205	21.4	1	15	15	7.40	332596	3.41	1.21	0.40	0	0.11
Spider [31]	11840	6448	1.8	206	1056	5.13	5.01	8980	1.83	1.17	0.54	0	0
SParC [124]	10228	8981	1.1	166	876	5.28	5.14	9665	1.58	1.10	0.44	0	0
CoSQL [125]	8350	8007	1	166	876	5.28	5.14	9665	1.54	1.11	0.42	0	0
CSpider [126]	11840	6408	1.8	206	1056	5.13	5.01	8980	1.83	1.17	0.54	0	0
MIMICSQL [127]	20000	10000	2	-	-	-	-	-	1.74	1	0.84	0	0
SQUALL [128]	11276	8296	1.4	2108	4028	1.91	9.18	71	1.22	1.29	0.40	0.03	0.16
FIBEN [129]	300	233	1.3	1	152	152	2.46	11668125	5.59	1.56	0.97	0	0.04
ViText2SQL [130]	9693	5223	1.9	166	876	5.28	5.14	9665	1.17	1.12	0.54	0	0
DuSQL [131]	25003	20308	1.2	208	840	4.04	5.29	20	1.49	1.25	0.73	0	0.30
PortugueseSpider [132]	9693	5275	1.8	166	876	5.28	5.14	9665	1.85	1.17	0.54	0	0
CHASE [133]	15408	13900	1.1	350	1609	4.60	5.19	4594	1.81	1.16	0.31	0	0
Spider-Syn [134]	1034	550	1.9	166	876	5.28	5.14	9665	1.68	1.17	0.59	0	0
Spider-DK [135]	535	283	1.9	169	887	5.25	5.14	9494	1.71	1.16	0.54	0	0
Spider-Realistic [136]	508	290	1.8	166	876	5.28	5.14	9665	1.79	1.21	0.50	0	0
KaggleDBQA [137]	272	249	1.1	8	17	2.12	10.53	595075	1.25	1.05	0.69	0	0.04
SEDE [138]	12023	11421	1.1	1	29	29	7.28	-	1.90	1.29	0.94	0.49	0.49
MT-TEQL [139]	489076	4525	108.1	489076	3279004	6.70	5.51	-	1.69	1.15	0.53	0	0
PAUQ [140]	9876	5497	1.8	166	876	5.28	5.14	9693	1.82	1.17	0.53	0	0
knowSQL [141]	28468	-	-	488	-	-	-	-	-	-	-	-	-
Dr.Spider [142]	15269	3847	4	549	2197	4	5.54	28460	1.81	1.19	0.52	0	0
BIRD [49]	10962	10840	1	80	611	7.64	7.14	4585335	2.07	1.09	0.61	0.20	0.27
AmbiQT [143]	3046	3128	1	166	876	5.28	5.14	9665	1.85	1.17	0.51	0	0.01
ScienceBenchmark [144]	5031	3654	1.4	-	-	-	-	-	1.45	1	0.24	0	0.07
BULL [47]	7932	5864	1.4	3	78	26	14.96	85631	1.22	1	0.18	0.42	0.05
BookSQL [145]	78433	39530	2	1	7	7	8.86	1012948	1.25	1.12	0.78	0.39	0.22
Archer [146]	518	260	2	10	68	6.8	6.81	31365.3	3.89	3.07	1.77	0.1	3.55

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

The Next For NL2SQL Benchmark

- Despite the growing number of datasets proposed by the NL2SQL community, we find that current datasets still exhibit a gap in SQL complexity compared to real-world scenarios
 - Recent datasets generally feature lower counts of SELECT keyword, indicating fewer nested SQL queries or complex set operations
 - Challenges related to Scalar Functions (e.g., ROUND) and Mathematical Computations (e.g., Addition) also need further attention

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 - Open Problems

NL2SQL Evaluation Metrics

- Accuracy
 - Execution Accuracy (EX)
 - String-Match Accuracy (SM)
 - Component-Match Accuracy (CM)
 - Exact-Match Accuracy (EM)
- Efficiency
 - Valid Efficiency Score (VES)
- Robustness
 - Query Variance Testing (QVT)

NL2SQL Evaluation Metrics

- **Accuracy**

- Execution Accuracy (EX)

$$EX = \frac{\sum_{i=1}^N 1(V_i = \hat{V}_i)}{N}$$

- N : the size of dataset
- V_i : the execution result set of the i -th ground-truth SQL query
- \hat{V}_i : the execution result set of the i -th predicted SQL query
- $1(\bullet)$: an indicator function that equals 1 if the condition inside is satisfied, and 0 otherwise

NL2SQL Evaluation Metrics

- **Accuracy**
 - String-Match Accuracy (SM)

$$SM = \frac{\sum_{i=1}^N 1(Y_i = \hat{Y}_i)}{N}$$

- N : the size of dataset
- Y_i : the i -th ground-truth SQL query
- \hat{Y}_i : the i -th predicted SQL query
- $1(\bullet)$: an indicator function that equals 1 if the condition inside is satisfied, and 0 otherwise

NL2SQL Evaluation Metrics

- **Accuracy**

- Component-Match Accuracy (CM)

$$CM^C = \frac{\sum_{i=1}^N 1(Y_i^C = \hat{Y}_i^C)}{N}$$

- N : the size of dataset
 - Y_i^C : the component of the i -th ground-truth SQL query Y_i
 - \hat{Y}_i^C : the component of the i -th predicted SQL query \hat{Y}_i
 - $1(\bullet)$: an indicator function that equals 1 if the condition inside is satisfied, and 0 otherwise

SQL Components:

- SELECT
- WHERE
- GROUP
-

NL2SQL Evaluation Metrics

- **Accuracy**

- Exact-Match Accuracy (EM)

$$EM = \frac{\sum_{i=1}^N 1 \left(\wedge_{C_k \in C} Y_i^{C_k} = \hat{Y}_i^{C_k} \right)}{N}$$

- N : the size of dataset
- C_k : the k -th component of SQL query (e.g., WHERE)
- $Y_i^{C_k}$: the k -th component of the i -th ground-truth SQL query
- $\hat{Y}_i^{C_k}$: the k -th component of the i -th predicted SQL query
- $1(\bullet)$: an indicator function that equals 1 if the condition inside is satisfied, and 0 otherwise

NL2SQL Evaluation Metrics

- **Efficiency**
 - Valid Efficiency Score (VES)

$$VES = \frac{\sum_{i=1}^N \mathbb{1}(V_i = \hat{V}_i) \cdot R(Y_i, \hat{Y}_i)}{N} \quad R(Y_i, \hat{Y}_i) = \sqrt{\frac{E(Y_i)}{E(\hat{Y}_i)}}$$

- N : the size of dataset
- V_i : the execution result set of the i -th ground-truth SQL query Y_i
- \hat{V}_i : the execution result set of the i -th predicted SQL query \hat{Y}_i
- $E(\bullet)$: measures the efficiency of specific SQL query, which can be refer to execution time

NL2SQL Evaluation Metrics

- **Robustness**

- Query Variance Testing (QVT)

$$QVT = \frac{1}{N} \left(\frac{\sum_{j=1}^{m_i} 1(\phi(Q_{ij}) = Y_i)}{m_i} \right)$$

- N : the size of dataset
- $\phi(Q_{ij})$: the predicted SQL query for the j -th NL variation of Y_i
- m_i : denotes the number of different NL variations for the SQL query Y_i

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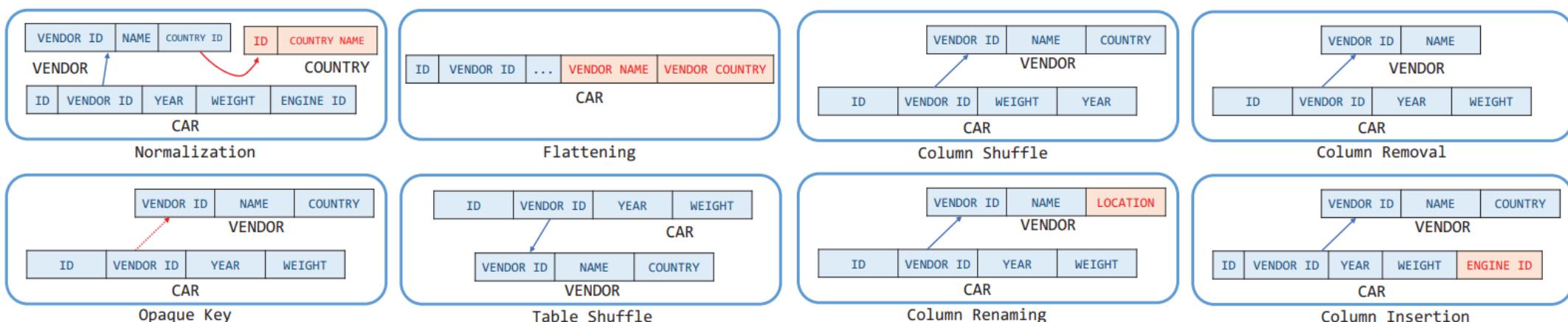


MT-TEQL

- MT-TEQL
 - NL Utterance Variations
 - Database Schema Variations

Type	Illustrative Examples
Common Interrogative Prefix	what is/are, which is/are
Common Declarative Prefix	tell me, return, find, list
Special Interrogative Prefix	when, where, how many
Special Declarative Prefix	count

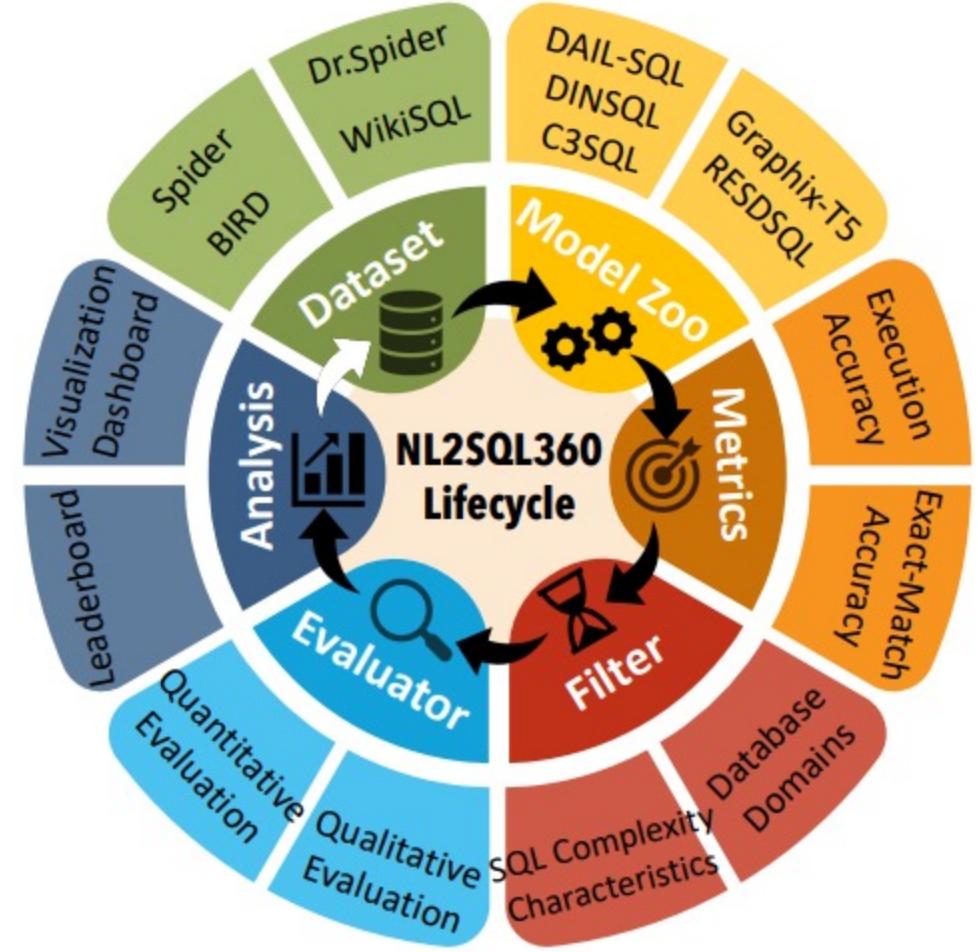
Categorizations of frequently-used prefixes in typical NLIDB utterances



Illustrative examples of schema-oriented MRs

NL2SQL360

- NL2SQL360
 - SQL Complexity
 - SQL Characteristics (e.g., JOIN)
 - Database Domain Adaption
 - NL Query Variance Testing
 - Economy
 - Efficiency
- Features
 - Multi-angle & Fine-grained Evaluation
 - Scenario-based Evaluation



NL2SQL360: User Interface



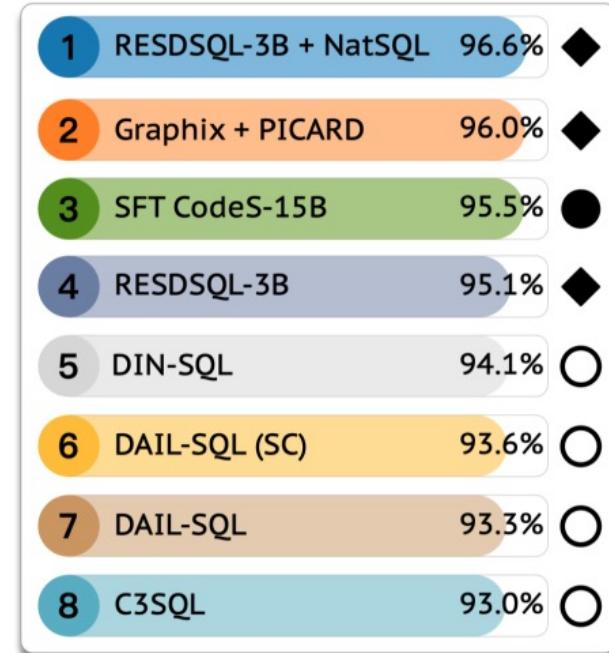
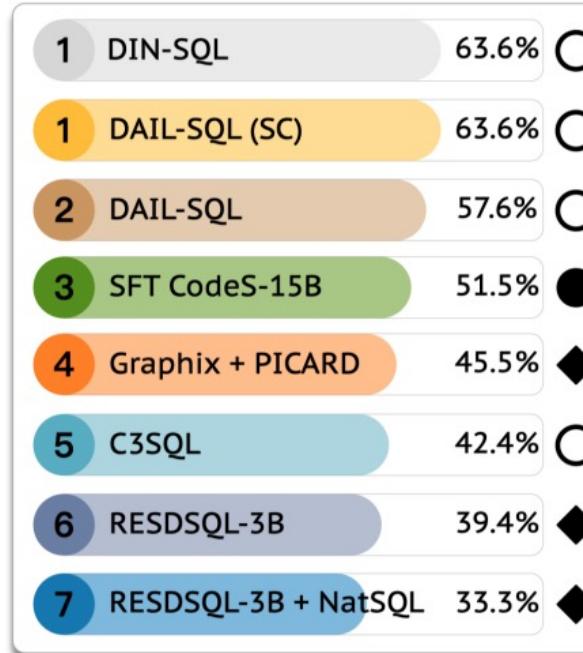
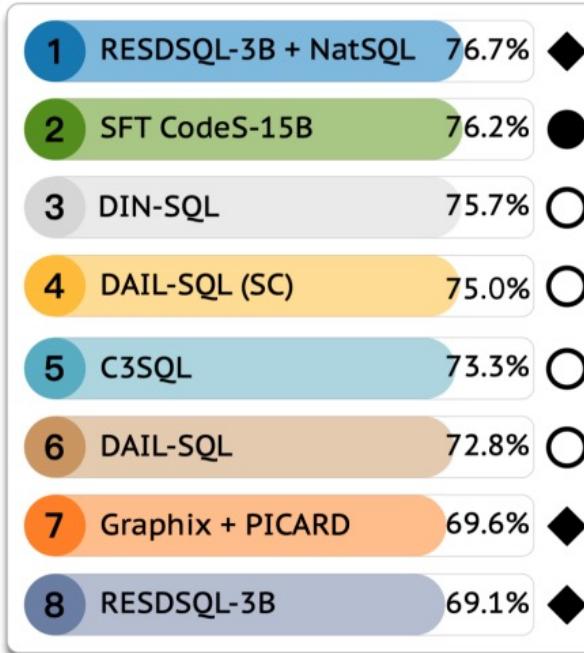
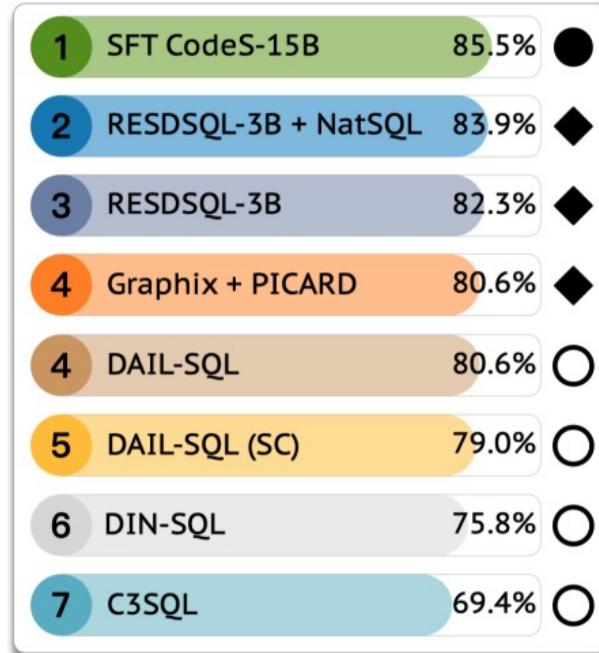
NL2SQL360: User Interface



NL2SQL360 Case Study

- Dataset: Spider
- Model:
 - LLM-based methods:
 - DAILSQ, DAILSQ(SC)
 - DINSQL
 - C3SQL
 - SFT CodeS-1B/3B/7B/15B
 - PLM-based methods:
 - RESDSQL-3B, RESDSQL-3B + NatSQL
 - Graphix + PICARD
- Metric:
 - Execution Accuracy (EX)
 - Exact-Match Accuracy (EM)
 - Valid Efficiency Score (VES)
 - Query Variance Testing (QVT)
- Multi-Angle:
 - SQL Characteristics
 - SQL Complexity
 - NL Variance
 - Database Domain Adaption
 - Efficiency
 - SQL Efficiency
 - Economy (Cost)

NL2SQL360: Leaderboard



(a) Test Results in Domain of Competition

(b) Test Results in SQL with JOIN

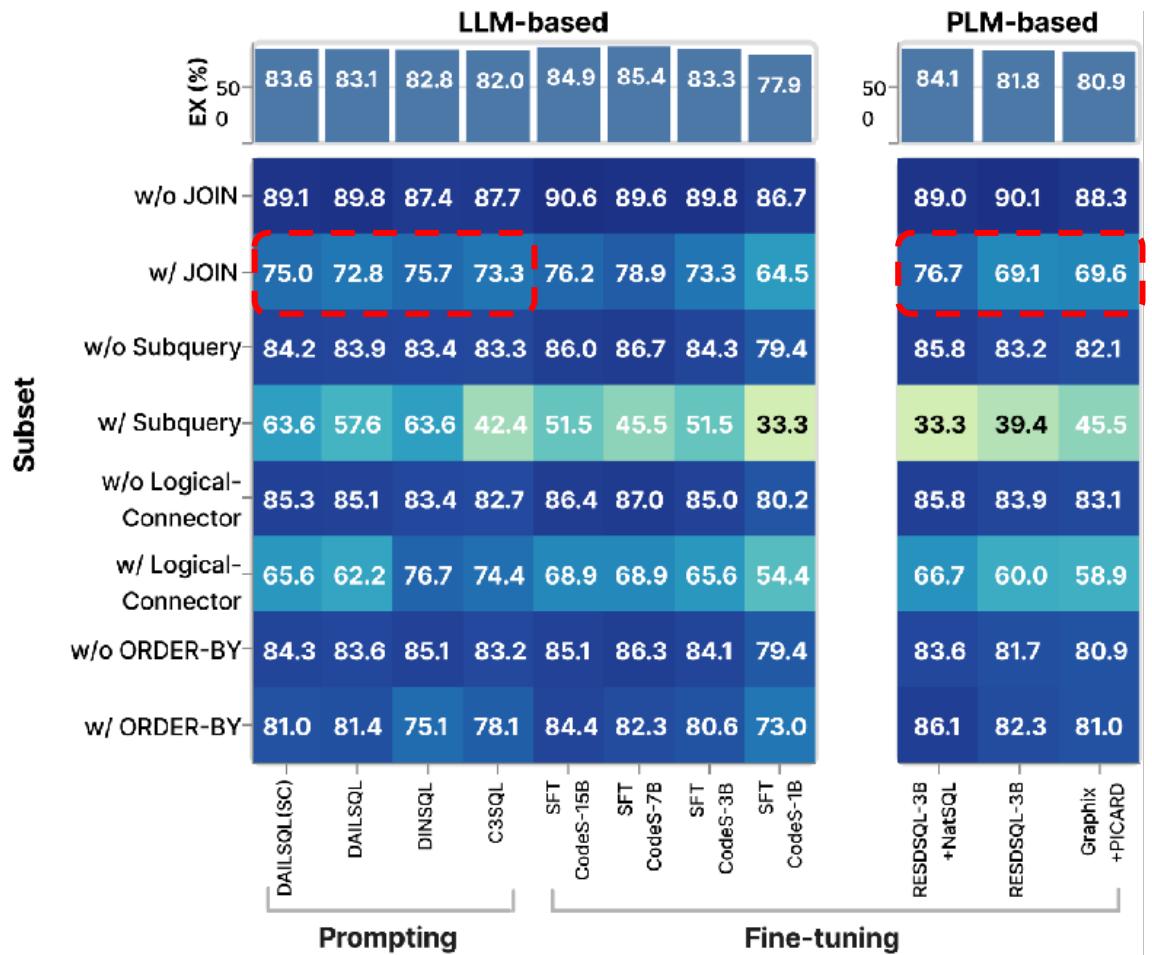
(c) Test Results in Nested SQL

(d) Test Results in Query Variance

Figure 3: NL2SQL Models on Spider from Different Angles (○: Prompting LLM, ●: Fine-tuning LLM, ♦: Fine-tuning PLM).

Leaderboard Link: <https://nl2sql360.github.io/>

NL2SQL360 Case Study – JOIN Finding



We find that:

DINSQL outperforms in LLMs with prompting.
RESDSQL + NatSQL outperforms in PLMs.

Commonality:

Both methods use **NatSQL** as the intermediate representation (IR) of SQL.

Finding:

Taking **NatSQL** reduces the complexity of predicting JOIN operations and potentially enhances the model performance.

Question :

Find the name of students who have a pet

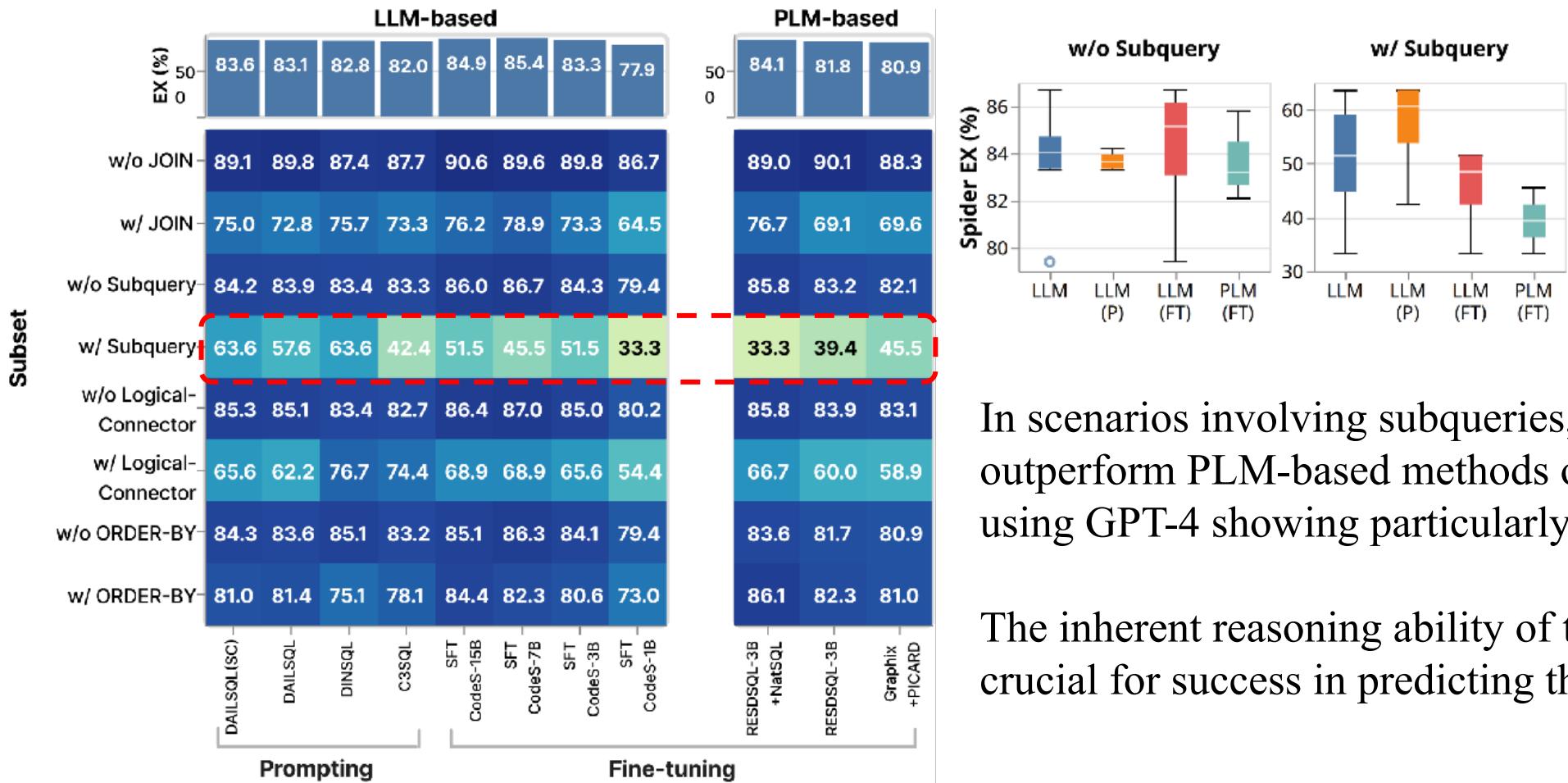
SQL :

```
SELECT T1.name FROM student AS T1
JOIN has_pet AS T2 ON T1.stuid=T2.stuid
```

NatSQL : (Extend FROM clause)

```
SELECT student.name FROM student, has_pet
```

NL2SQL360 Case Study – Subquery Finding



In scenarios involving subqueries, LLM-based methods outperform PLM-based methods overall, with methods using GPT-4 showing particularly better performance.

The inherent reasoning ability of these models is likely crucial for success in predicting the subqueries.

NL2SQL360 Case Study – QVT

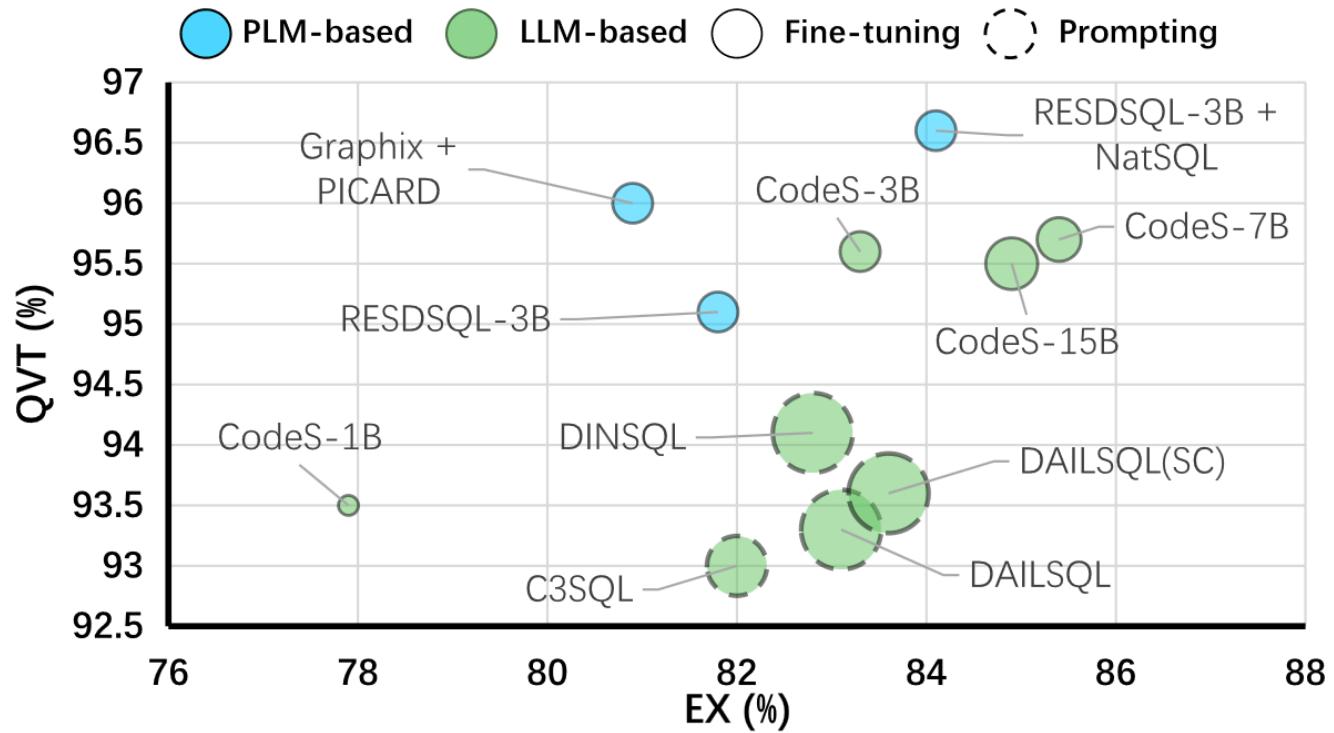
- To further evaluate the robustness and flexibility of NL2SQL solutions in handling variations in natural language queries, we propose a new metric called **Query Variance Testing (QVT)**. This metric assesses how well the models can adapt to different forms of NL queries.

Query Variance Testing (QVT): Given a SQL query Q_i , there typically exist multiple corresponding NL queries, denoted as pairs $\{(N_1, Q_i), (N_2, Q_i), \dots, (N_m, Q_i)\}$. The formula for computing QVT accuracy is defined as follows:

$$QVT = \frac{1}{M} \sum_{i=1}^M \left(\frac{\sum_{j=1}^{m_i} \mathbb{1}(\mathcal{F}(N_{ij}) = Q_i)}{m_i} \right)$$

- M is the total number of SQL queries in the test set.
- m_i is the number of natural language query variations corresponding to the SQL query Q_i .
- $\mathcal{F}(N_{ij})$ represents the SQL query generated by the model for the j -th natural language query variation of Q_i .

NL2SQL360 Case Study – QVT



- Fine-tuned LLMs generally exhibit higher QVT than prompting LLMs.
- Notably, although the Graphix+PICARD method underperforms in overall EX compared to all prompt-based LLMs, it surpasses them in QVT.
- **Fine-tuning the model with task-specific datasets may help stabilize its performance against NL variations.**

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Error Analysis

Motivation:

- Error Analysis provides valuable insights into the limitations and challenges faced by current models.

Goal:

- By systematically examining errors, researchers can identify specific areas for improvement, enhance model robustness, and develop more effective training strategies.

Existing Taxonomies for NL2SQL Errors

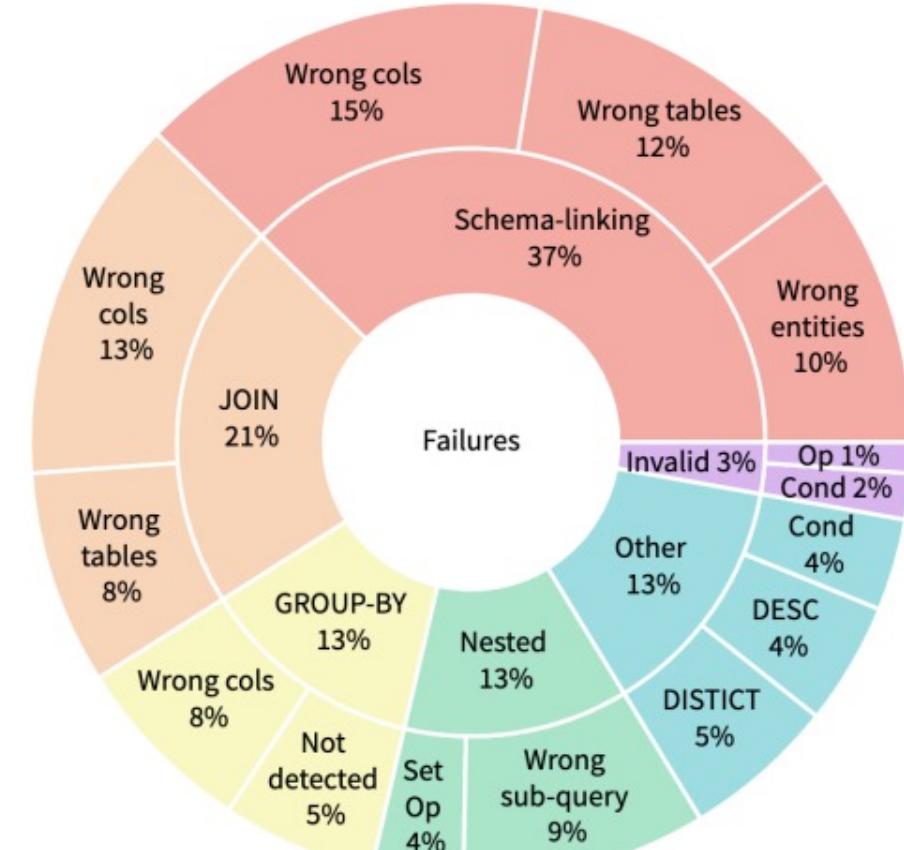
- Schema Linking
- Misunderstanding Database
- Misunderstanding Knowledge
- Reasoning
- Syntax-Related Errors
- Database related Errors



SQL-PaLM

Existing Taxonomies for NL2SQL Errors

- Schema Linking
- JOIN
- GROUP BY
- Queries with Nesting and Set Operations
- Invalid SQL
- Miscellaneous



DIN-SQL

Existing Taxonomies for NL2SQL Errors

Limitations:

- Designed for specific datasets
- Limited scalability
- Due to inconsistent taxonomies, the annotated data cannot be shared or compared between different studies

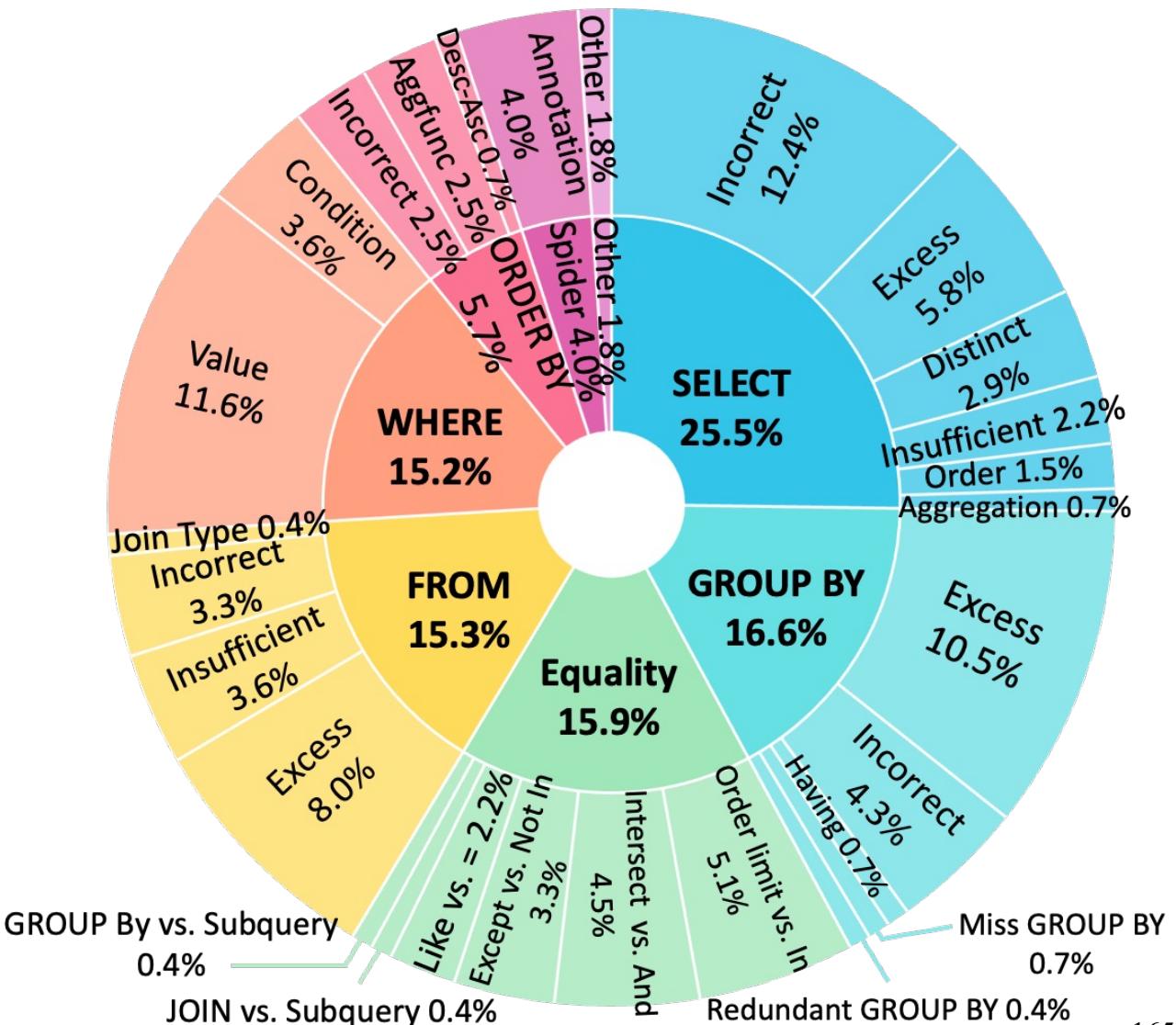
Therefore, it is imperative to develop **a standardized and effective taxonomy** for analyzing NL2SQL Errors

Principles for NL2SQL Errors Taxonomy

- **Comprehensiveness:** The taxonomy should encompass all potential errors that could occur during the NL2SQL conversion process.
- **Mutual Exclusivity:** Each error type should be clearly distinct with no overlap, to avoid ambiguity in error classification.
- **Extensibility:** The taxonomy should be adaptable to incorporate new error types as NL2SQL technologies and methodologies evolve.
- **Practicality:** The taxonomy should be practical and applicable in real-world settings, aiding developers in diagnosing and correcting errors effectively

Our Two-level Taxonomy

- **Error Localization:** Focus on identifying the specific parts of the SQL where errors occur
- **Cause of Error:** Focus on understanding why the model is wrong when generating SQL.



Outline

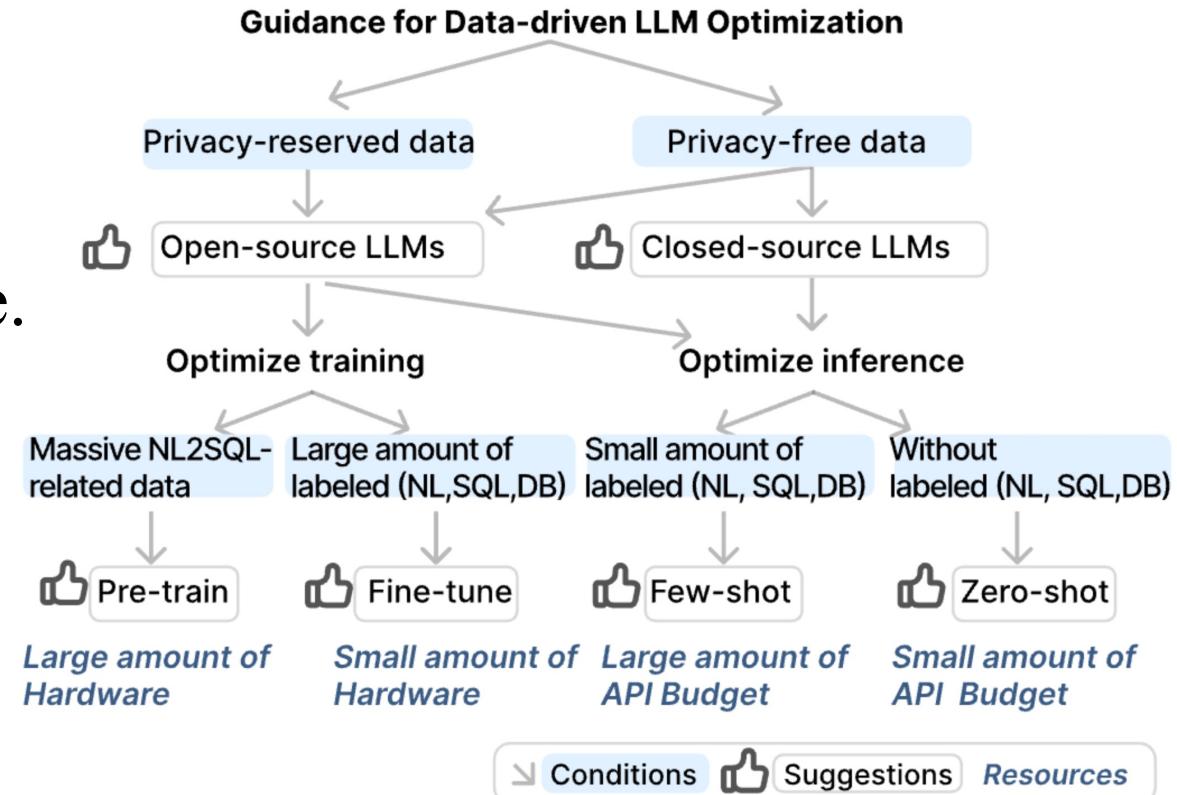
- NL2SQL Problem and Background
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 - Decision Flow of Selecting NL2SQL Modules
- Open Problems

A Roadmap of Optimizing LLMs for NL2SQL

Condition 1: Data Privacy.

Condition 2: Training Data Volume.

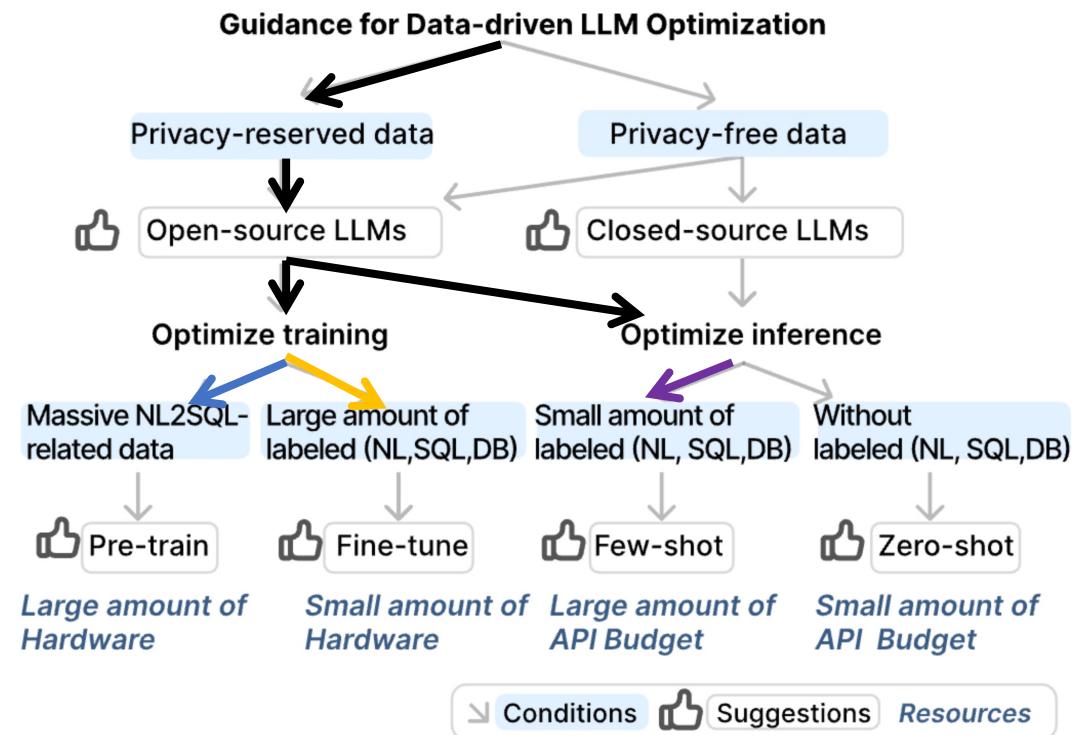
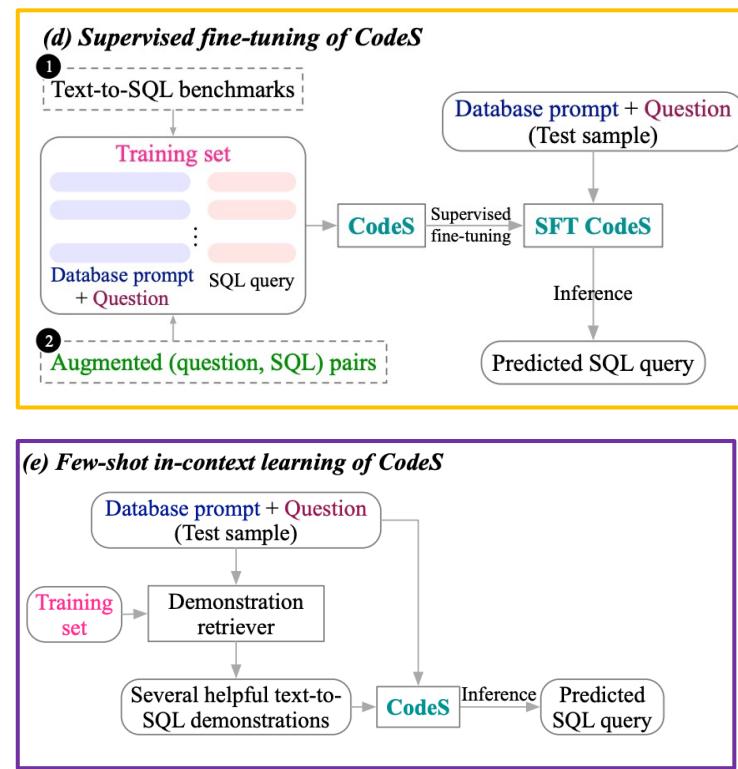
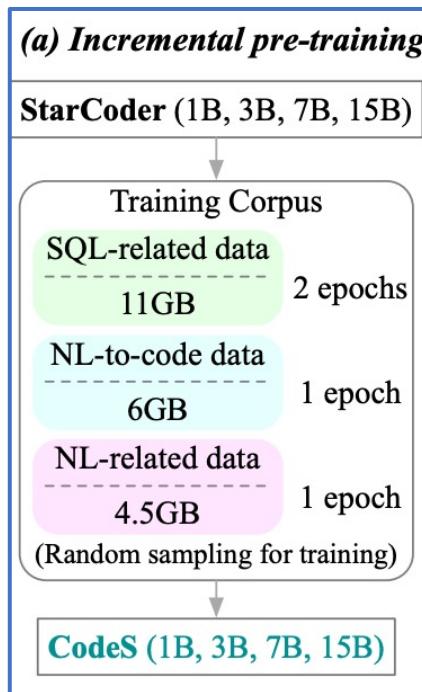
Note that also need consider hardware resources and API costs



A Roadmap of Optimizing LLMs for NL2SQL

A Case Study

CodeS designs open-source NL2SQL LLM to solve data privacy risks when using GPT-4

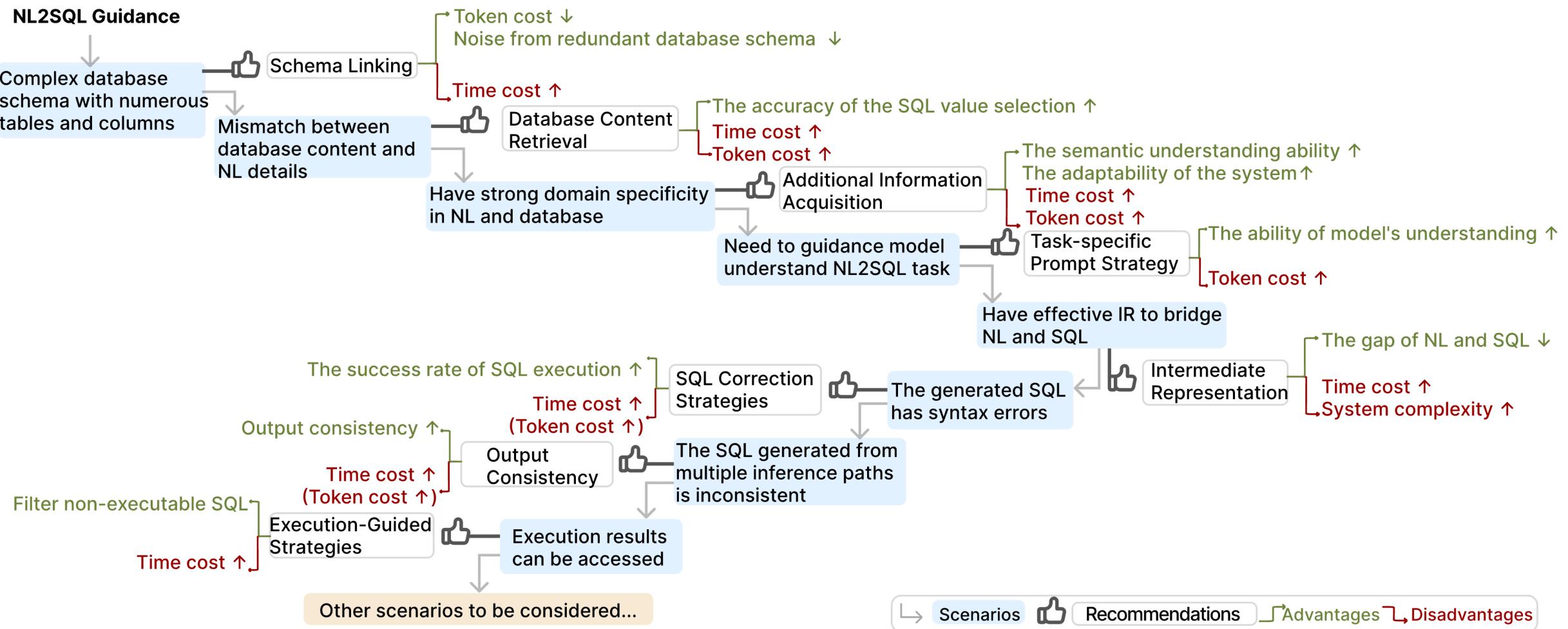


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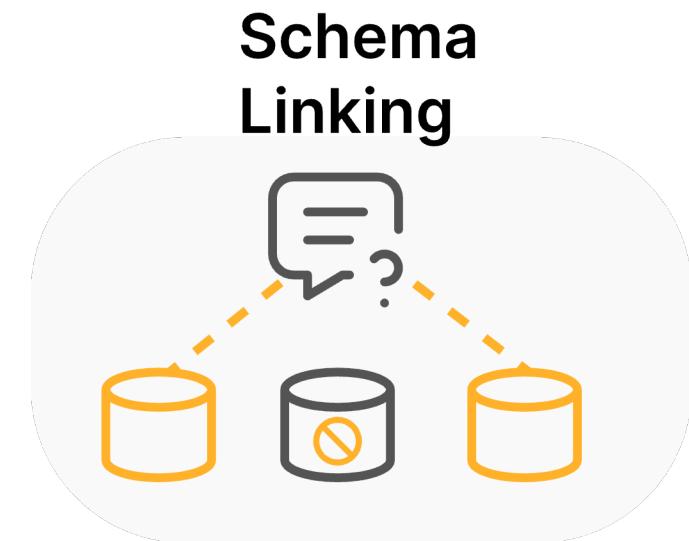


Decision Flow of Selecting Modules



Decision Flow of Selecting Modules

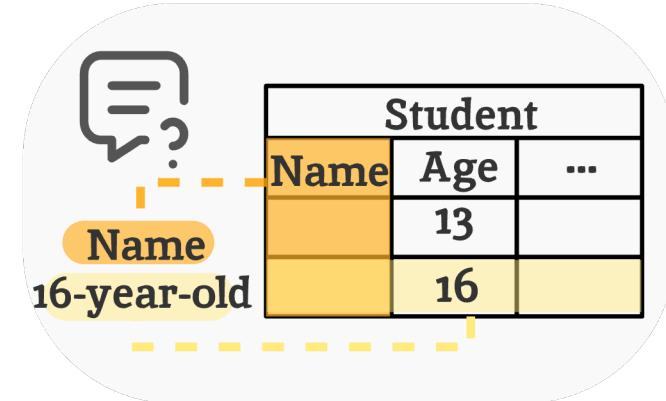
- **Scenario 1:**
 - Complex Database Schema with Numerous Tables and Columns.
- **Recommendation:**
 - Schema Linking.
- **Advantages:**
 - Reduced token costs.
 - Decreased noise from the redundant database schema.
- **Disadvantages:**
 - Increased time costs.



Decision Flow of Selecting Modules

- **Scenario 2:**
 - Mismatch between Database Content and NL.
- **Recommendation:**
 - Database Content Retrieval.
- **Advantages:**
 - Increased the accuracy of SQL value selection.
- **Disadvantages:**
 - Increased time costs.
 - Increased token costs.

Database Content Retrieval



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Open Problem- Open NL2SQL Problem

- **Problem & Goal:**
 - Open NL2SQL Problem: Querying Multiple Databases.
- **Motivation:**
 - In many real-world scenarios, such as government open data platforms, answering complex questions often requires querying multiple databases and aggregating results.
- **Key Idea:**
 - Database Retrieval
 - Handling Heterogeneous Schemas
 - Answer Aggregation
 - Domain Adaptation
 - Scalability and Efficiency
 - Evaluating and Benchmarking

Open Problem- Cost-effective NL2SQL Methods

- **Problem & Goal:**
 - Cost-effective NL2SQL Methods: Balancing Performance and Costs.
- **Motivation:**
 - LLM-based NL2SQL methods show potential but face challenges due to high token consumption, which impacts both costs and inference times. Conversely, PLM-based methods excel at complex SQL query processing and schema interpretation.
- **Key Idea:**
 - Modular NL2SQL Solutions
 - Multi-agent Framework

Open Problem- Trustworthy NL2SQL Solutions

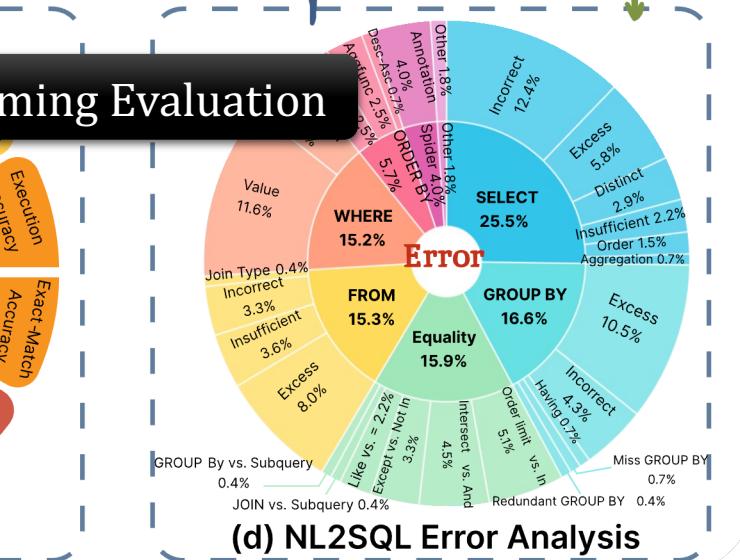
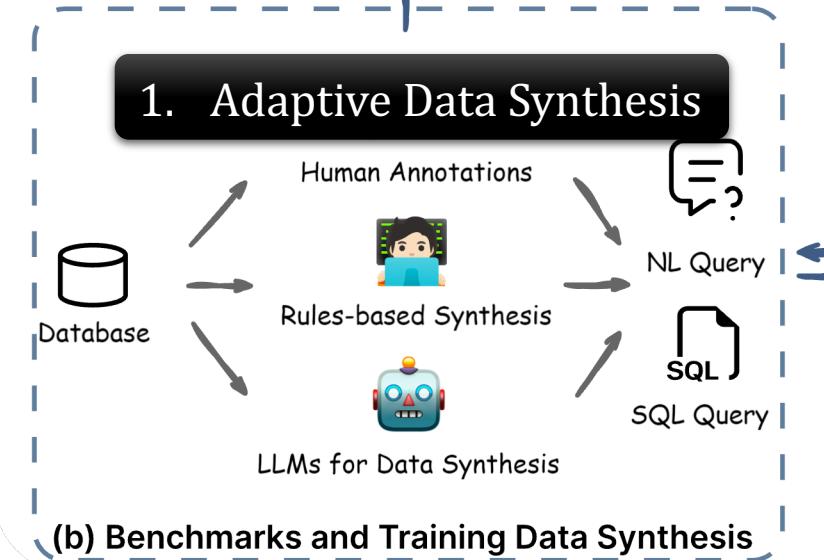
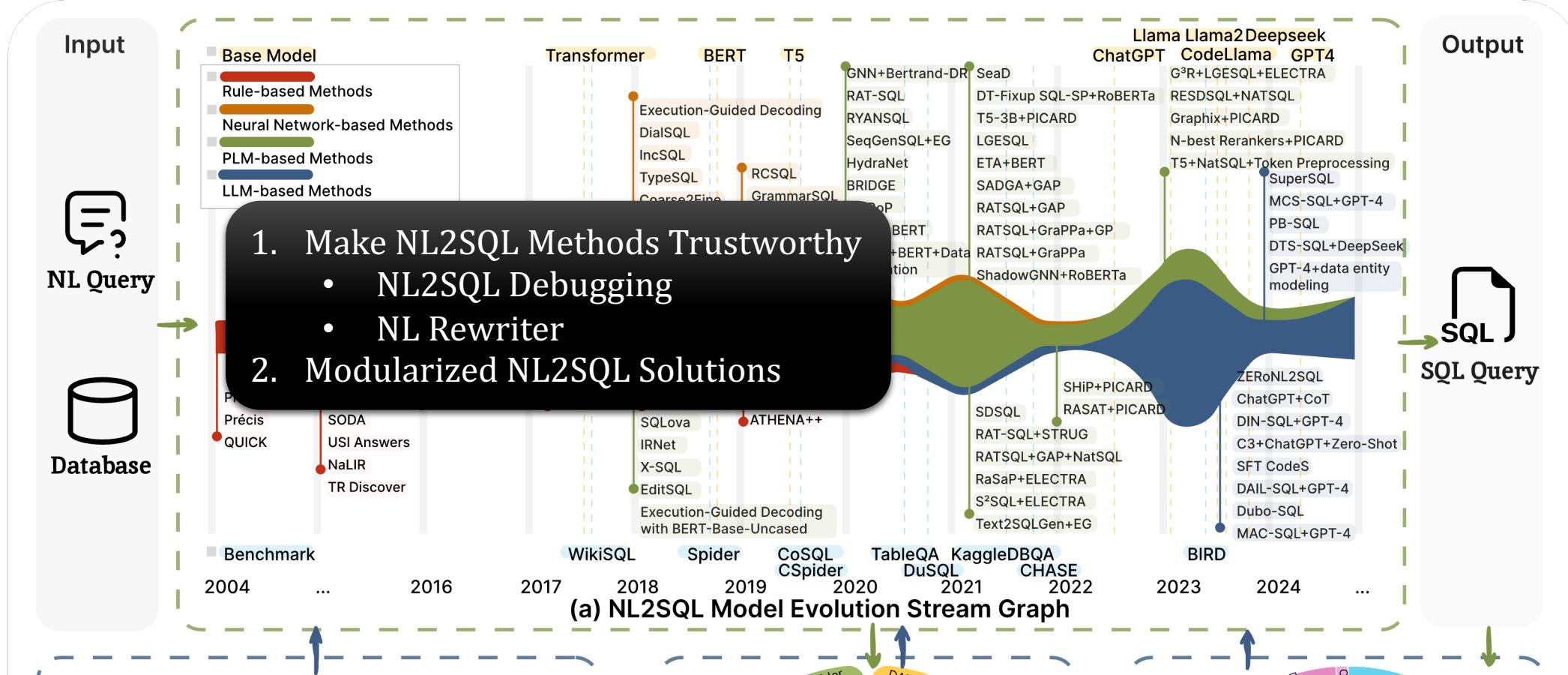
- **Problem & Goal:**
 - Trustworthy NL2SQL Solutions: Enhancing Accuracy and Reliability.
- **Motivation:**
 - Ensuring the accuracy and reliability of generated SQL queries is essential to reduce risks and minimize manual intervention.
- **Key Idea:**
 - Interpreting NL2SQL Solutions
 - Multi-agent Framework
 - NL2SQL Debugging Tools

Open Problem- NL2SQL with Ambiguous and Unspecified NL Queries

- **Problem & Goal:**
 - NL2SQL with Ambiguous and Unspecified NL Queries: Addressing Vague Inputs.
- **Motivation:**
 - Ambiguous or unspecified queries are common in real-world scenarios and pose challenges for NL2SQL systems.
- **Key Idea:**
 - NL Query Rewriter.
 - NL Query Auto-completion.
 - Training with Ambiguous Queries.

Open Problem- Adaptive Training Data Synthesis

- **Problem:**
 - Adaptive Training Data Synthesis: Improving Model Generalization.
- **Motivation:**
 - Learning-based NL2SQL methods often struggle with new domains and require high-quality, diverse training data for effective performance.
- **Key Idea:**
 - Adaptive Data Synthesis.
 - Incorporating Feedback.





Thanks!

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<https://arxiv.org/abs/2408.05109>

https://github.com/HKUSTDial/NL2SQL_Handbook