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Master Thesis Exposé

A Review on State-of-the-art Text-To-SQL Solutions

presented by

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0.1 Introduction

Data retrieval in databases is typically done using SQL (Structured Query Language). Text-to-SQL machine learning models are a recent development in state-of-the-art research. The technique is an attractive alternative for many natural language problems, including complex queries and extraction tasks. The text is converted into a SQL query that can be executed on the database. This technique can save time and effort for both developers and end-users by enabling them to interact with databases through natural language queries. With the help of machine learning and knowledge-based resources, text language to SQL conversion is facilitated.

Semantic parsing is a natural language processing that extracts the meaning from text. Text-to-SQL, a type of Semantic Parsing, is a task that converts natural language problems into SQL query statements. This is achieved using machine learning and natural language processing algorithms, and this research is conducted to study different solutions and practices which has been taken by researchers to tackle this problem.

Text-to-SQL allows the elaboration of structured data with information about the natural language text in several domains, such as healthcare, customer service, and search engines. It can be used by data analysts, data scientists, software engineers, and end users who want to explore and analyze their data without learning SQL. It can be used in a variety of ways:

- 1) Data analysts can use it to generate SQL queries for specific business questions, such as "What are the top ten products sold this month?"
- 2) Data scientists can use it to generate SQL queries for machine learning experiments, such as "How does the price of these products affect their sales?"
- 3) Businesses can use this technique to automate data extraction and improve efficiency.
- 4) End-users who want to explore and analyze their data without learning SQL can use it by clicking on a button on any table or chart in a user interface.

Although these models may not solve this problem entirely and perfectly, humans can still struggle with the task. For example, people involved in database migration projects often have to work on schema that they have never seen before.

This research study will review some of the most commonly used NLP technologies relevant to converting text language into Structured Query Language (SQL), and representative models and datasets in the recent solutions for this challenge and their technical implementation.

0.2 Motivation and State of the Art

Representative datasets for Text-to-SQL include the WikiSQL[ZXS] dataset and the SPIDER[YZY⁺] dataset, which contains more complex SQL queries. We will also take a shallow look at older datasets and why they are not in use anymore in Text-to-SQL studies. The former case consists of Single Table - Multiple Question and the latter case Multiple Table - Multiple Question. The top models available for Text-To-SQL will be studied, and the implementation of a couple of currently best methods will be reviewed and discussed in this study.

In this thesis, we will review the Text-to-SQL Challenges and datasets and structure of existing datasets and difference between them. Datasets to be covered are: ATIS, GeoQuery, IMDb, Advising, WikiSQL, Spider.

Datasets

ATIS (Air Travel Information System) Dataset

A relational schema is used to organize data from the official airline guide in the ATIS corpus. There are 25 tables containing information about fares, airlines, flights, cities, airports, and ground services. All questions related to this dataset can be answered using a single relational query. The relational database uses shorter tables for this dataset to answer queries intuitively.

GeoQuery Dataset

United States geography is represented in the Geoquery dataset. About 800 facts are expressed in Prolog. State, city, river, and mountain information can be found in the database. Geographic and topographical attributes such as capitals and populations make up the majority of the attributes.

IMDb Dataset

The IMDb dataset contains 50K reviews from IMDb. There is a limit of 30 reviews per movie[MDP⁺11]. Positive and negative reviews are equally represented in the dataset. The dataset creators considered a negative review with a score of 4 out of 10 and a positive review with a score of 7 out of 10. When creating the dataset, neutral reviews are not taken into account. Furthermore, Training and testing datasets are equally divided.

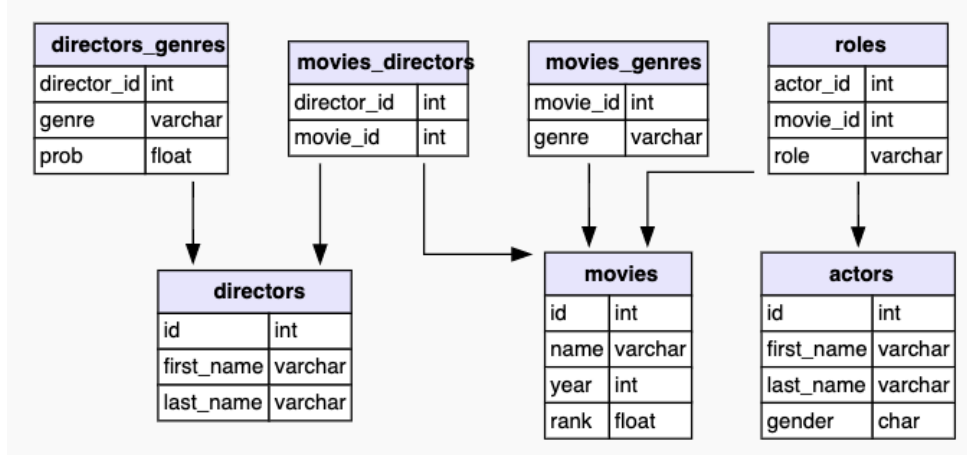


Figure 1: Database Structure of IMDb dataset

Advising Dataset

The Advising dataset was created in order to propose improvements in text2SQL systems. The creators of the dataset compare human-generated and automatically generated questions, citing properties of queries that relate to real-world applications. Dataset consists of questions from university students about courses that lead to particularly complex queries. The database contains fictional student records. The dataset includes student profile information, such as recommended courses, grades, and previous courses. In an academic advising meeting, students were asked to formulate questions they would ask if they knew the database. Many of the queries in this dataset were the same as those in ATIS, GeoQuery, and Scholar.

Advising Dataset

Advisor: "Hello Mingyang! Are you doing well?"

Student: "Hi advisor. I'm doing alright. I would like some advice on which courses to take next semester."

Student: "My interested area is Software Development and Intelligent system."

Advisor: "you have three choices namely, EECS481 Software Engineering, EECS492 Introduction to Artificial Intelligence, and EECS381 Object Oriented and Advanced Programming."

Student: "how many difficulty levels do these classes have?"

Correct Response: "EECS381 is not easy"

Examples of incorrect responses in the dataset:

| | |
|-------------------------------------|---|
| "It is highly rated in clarity." | "Which classes would you like to take?" |
| "Hey, its no problem!" | "Glad I was of help" |
| "Is it okay if the class is large?" | "EECS 494 is class to consider." |

Figure 2: Example from Advising dataset [VR19]

WikiSQL Dataset

WikiSQL consists of 80K+ natural language questions and corresponding SQL queries on 24K+ tables extracted from Wikipedia. Neither the train nor development sets contain the database in the test set. Databases and SQL queries have simplified the dataset’s creators’ assumptions. This dataset consists only of SQL labels covering a single SELECT column and aggregation and WHERE conditions. Furthermore, all the databases contain only one table.

The database does not include complex queries involving advanced operations like JOIN, GROUP BY, ORDER BY, etc. Prior to the release of SPIDER, this dataset was considered to be a benchmark dataset. Using WikiSQL has been the subject of a great deal of research. WikiSQL’s ”WHERE” clause has been recognized as one of the most challenging clauses to parse semantically, and SQLNet and SyntaxSQL were previous state-of-the-art models.

Table:

| Player | Country | Points | Winnings (\$) |
|-------------------|---------------|--------|---------------|
| Steve Stricker | United States | 9000 | 1260000 |
| K.J. Choi | South Korea | 5400 | 756000 |
| Rory Sabbatini | South Africa | 3400 | 4760000 |
| Mark Calcavecchia | United States | 2067 | 289333 |
| Ernie Els | South Africa | 2067 | 289333 |

Question: What is the points of South Korea player?

SQL: SELECT Points WHERE Country = South Korea

Answer: 5400

Figure 3: Example from WikiSQL dataset[?]

Spider Dataset

Yale University students created this dataset. The SPIDER database contains 10K questions and 5K+ complex SQL queries covering 138 different domains across 200 databases. As opposed to previous datasets (most of which used only one database), this one incorporates multiple datasets. Creating this corpus was primarily motivated by the desire to tackle complex queries and generalize across databases without requiring multiple interactions.

Creating a dataset involves three main aspects: SQL pattern coverage, SQL consistency, and question clarity. Several databases from WikiSQL are included in the dataset. The table is complex as it links several tables with foreign keys. In SPIDER, SQL queries include: SELECT with multiple columns and aggregations, WHERE, GROUP BY, HAVING, ORDER BY, LIMIT, JOIN, INTERSECT, EXCEPT, UNION, NOT IN, OR, AND, EXISTS, LIKE.

SPIDER’s exact matching accuracy was 12.4% compared to existing state-of-the-art models. As a result of its low accuracy, SPIDER presents a strong research challenge. Current SPIDER accuracy is around 75.5% with an exact set match without values (refers to values in the WHERE clause) and around 72.6% with values.

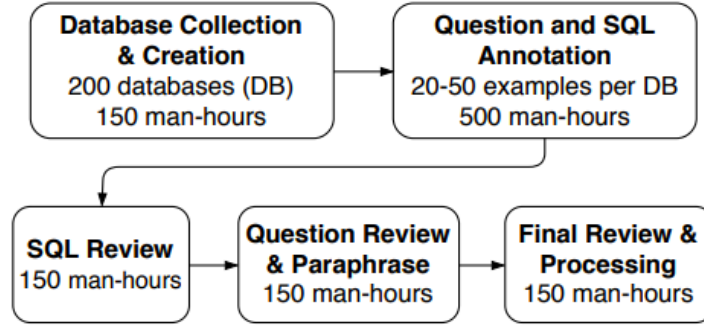


Figure 4: Example from Spider dataset[YZY⁺]

Complex question What are the name and budget of the departments with average instructor salary greater than the overall average?

Complex SQL

```

SELECT T2.name, T2.budget
FROM instructor as T1 JOIN department as
T2 ON T1.department_id = T2.id
GROUP BY T1.department_id
HAVING avg(T1.salary) >
(SELECT avg(salary) FROM instructor)
  
```

Figure 5: Example of Question-Query set from SPIDER[YZY⁺]

Models

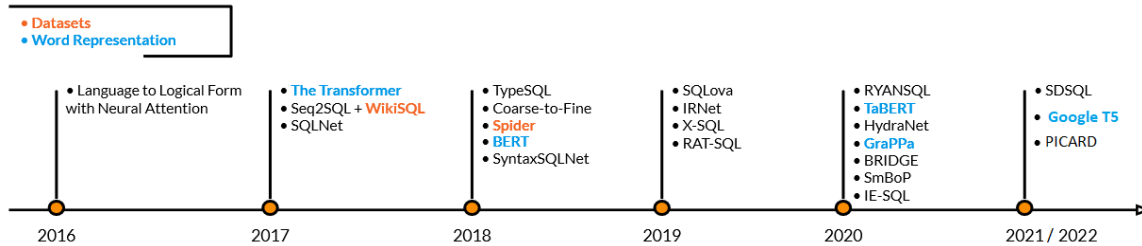


Figure 6: An overview of the deep learning process for Text-to-SQL.

An efficient text-to-SQL solution requires state-of-the-art natural language processing techniques. As a result of the neural network’s ability to handle only numerical inputs and not raw text, word embedding has been used to represent numerical words.

Aside from that, in the past few years, language models have become increasingly popular as a solution for increasing performance in natural language processing tasks.

Assuming that words have numerical representations that differ from those of other words, word embeddings aim to map each word to a multidimensional vector, incorporating valuable information about the word. In addition to the brute-force creation of one-hot embeddings, researchers have developed highly efficient methods for creating representations that

convey a word’s meaning and relationships with other words. In most, if not all, Text-to-SQL systems, word embedding techniques such as Word2Vec[Ron14], GloVe, and WordPiece embeddings[WSC⁺16] are used.

Recently Language models have been shown to excel at NL tasks as a new type of pre-trained neural network. It is important to note that language models are not a replacement for word embeddings since they are neural networks and need a way to transform words into vectors.

Depending on the specific problem they want to solve, researchers can adapt the pre-trained model’s inputs and outputs and train it for an additional number of epochs on their dataset. Thus, we can achieve state-of-the-art performance without complex architectures [DCLT18]. Recent neural network architectures, like the Transformer[VSP⁺17], have been used to achieve such performance by these models, which excel at handling NL and sequences of NL that are characterized by connections between words. Several language models have been used to handle the text-to-SQL task, including BERT [DCLT18] and MT-DNN [LHCG19], while new models pre-trained specifically for structured data tasks are emerging, such as TaBERT[YNYR20] and GraPPa [YWL⁺20].

The research section will assess the best state-of-the-art research in this field, starting from Seq2SQL[ZXS] study in 2017 with the hype in WikiSQL challenge and we will continue with SQLova[?] SQLNet[XLS] and introduction of transformers and BERT with focus on RAT-SQL[WSL⁺] (2019), BRIDGE[LSX] with BERT, HydraNet[LCH⁺20] (2020), and the most recent solution with Google T5[RSR⁺], PICARD[SSB] in SPIDER (2021).

After reviewing the research papers on these models, we will study the implementation steps of these models. Moreover, evaluation methods and approaches to compare these models in accuracy for different datasets and if they are usable and reliable enough for our usage.

Most of these studies have excellent documentation regarding their implantation. Execution of these studies will be documented and published on Github. Nonetheless, In case of old and impractical implementation instructions, we will skip the implementation and continue with the top models available.

Seq2SQL

An output of a sequence-to-sequence approach is a sequence of SQL tokens and schema elements, with that sequence being used to predict SQL queries or at least a significant portion of them. An NLQ sequence is transformed into a SQL sequence by these programs. There is no doubt that this approach is the simplest, but it is also the most error-prone. Seq2SQL[ZXS], one of the first deep-learning systems, used this approach, but later, systems avoided it. sequence-to-sequence architectures have the major disadvantage of not taking the strict grammar rules of SQL into account when generating queries.

As part of this model, its authors released the WikiSQL dataset, which ushered in a new era of text-to-SQL deep learning research. GloVe embeddings represent the inputs in the network architecture, which combines LSTM and linear layers. With a seq-to-seq network, the system predicts the aggregation function and the column for the SELECT clause. Its major drawback is that it generates parts of the query that can lead to syntactic errors.

SQLNet

The model was designed to demonstrate that reinforcement learning should be limited in Text2SQL tasks. Until SQLNet[XLS], all previous models used reinforcement learning to improve the decoder results when it generated appropriate serializations.

In cases where order is irrelevant, SQLNet avoids the seq2seq structure. For making predictions, the model uses a sketch-based approach consisting of a dependency graph that allows previous predictions to be taken into account. To improve the results, the model also incorporates column attention (weights assigned to significant words and phrases in sentences). According to the flowchart below, SQLNet employs three phases to generate SQL queries for WikiSQL tasks.

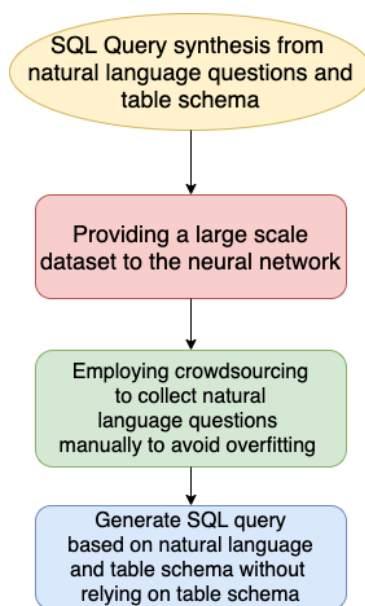


Figure 7: SQLNet

Sketch-based query synthesis

The token with the \$ sign represents an empty slot, and the token name represents the type of prediction. Tokens in bold represent SQL keywords such as **SELECT**, **WHERE**, etc. \$AGG can be filled with either an empty token or one of the aggregation operators, such as SUM or MAX. Fill in the \$COLUMN and \$VALUE slots with the column name and substring of the question, respectively. The \$OP slot can be a value between {=, >, <}. The notion ...* uses a regular expression to indicate zero or more AND clauses.

Column attention for sequence-to-set prediction

Instead of producing a sequence of column names, sequence-to-set prediction predicts the names of the columns of interest. Based on column names, column attention is part of the generic attention mechanism for computing the feature attention map on a question.

Predicting WHERE and SELECT clause

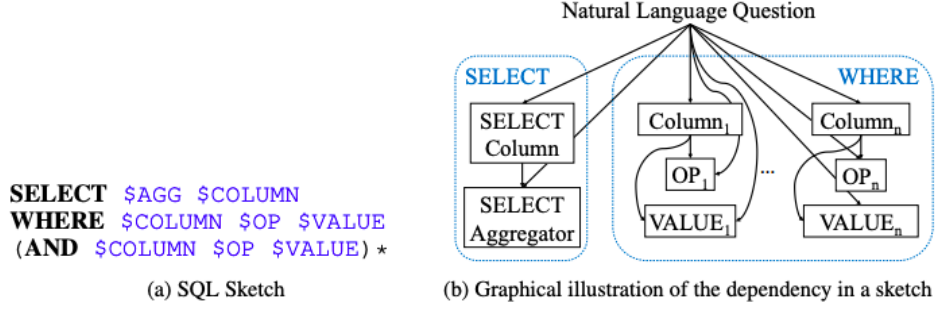


Figure 8: Sketch-based query synthesis

One of the most challenging tasks in Text2SQL is predicting the WHERE clause. According to SQL sketch, SQLNet finds the columns that appear in the WHERE clause and predicts the OP slots and value for each column.

It is predicted that the OP slot will be filled with one of the three classes $\{i, i, =\}$, and the VALUE slot will be filled with the substring from the natural language question. In SELECT clauses, columns are named, and aggregator functions are specified, such as count, sum, max, etc. There is only one difference between SELECT and WHERE: the column name. There is only one column selected in SELECT.

In the WikiSQL test set, SQLNet accuracy is 64.4%, and in the SPIDER test set, it is around 12.4%.

| Table | | | | | | Question: | |
|---------------|--------|---------------|----------------|------------------|------------------|---|----------|
| Player | No. | Nationality | Position | Years in Toronto | School/Club Team | Who is the player that wears number 42? | |
| Antonio Lang | 21 | United States | Guard-Forward | 1999-2000 | Duke | | |
| Voshon Lenard | 2 | United States | Guard | 2002-03 | Minnesota | | |
| Martin Lewis | 32, 44 | United States | Guard-Forward | 1996-97 | Butler CC (KS) | | |
| Brad Lohaus | 33 | United States | Forward-Center | 1996 | Iowa | | |
| Art Long | 42 | United States | Forward-Center | 2002-03 | Cincinnati | | |
| | | | | | | SQL: | Result: |
| | | | | | | SELECT player | Art Long |
| | | | | | | WHERE no. = 42 | |

Figure 9: An example of a query executed by SQLNet on WikiSQL

SyntaxSQLNet

- The main goal of developing the SyntaxSQLNet model was to generate complex SQL queries with multiple clauses and generalize them to new databases.
- The model is based on a syntax tree network to address complex and cross-domain queries. The encoders are table-aware, and the decoders have a history of the SQL generation path.
- With a massive 7.3% improvement in accuracy, SyntaxSQLNet outperformed previous models, such as SQLNet, on the SPIDER dataset.

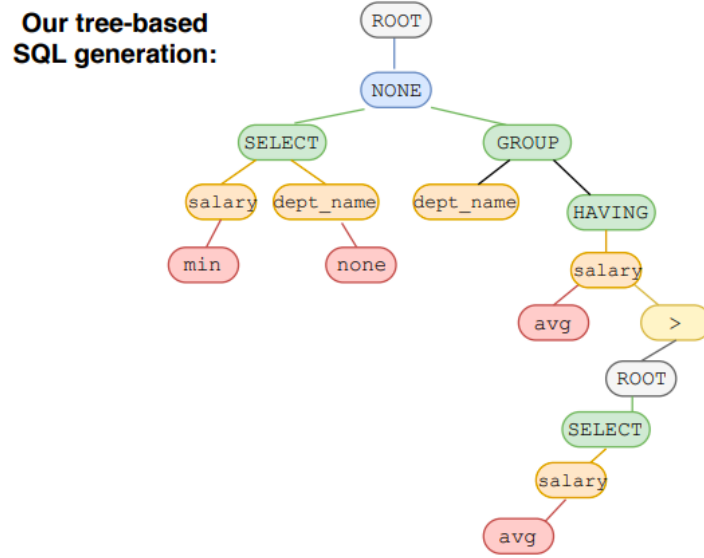


Figure 10: Tree-based SQL generator in SyntaxSQLNet

- A cross-domain data augmentation technique further improves accuracy by generating more variance during training.
- Below is a chart showing the various modules and their functions.

SQL Grammar and Attention Mechanism

- In order to enable the decoder to handle complex queries, SQL grammar is used. At each step of recursive decoding, it determines which module to invoke.
- Predicting the next SQL token is also based on the history of SQL path generation and current SQL tokens.
- The attention mechanism is also used to encode the question representation. Attention also applies to SQL path history encoding.

Data Augmentation

- Despite SPIDER’s large dataset, it lacks complex queries.
- For proper generalization, cross-domain datasets are used for data augmentation.
- Various training databases of the SPIDER dataset are used to prepare a list of patterns for natural language questions and corresponding SQL queries.

The SPIDER model using syntaxSQLNet decoding history reaches 27.2% accuracy.

Compared to previous models, such as SQLNet, the accuracy increased by 15%.

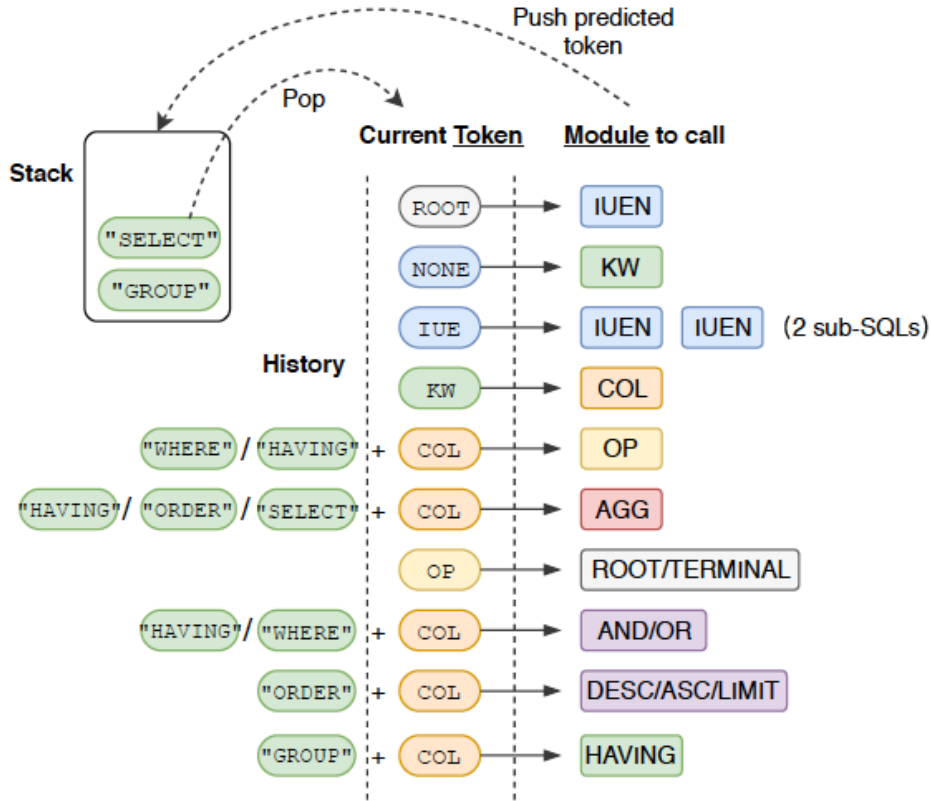


Figure 11: Modules defined in SyntaxSQLNet model

GrammarSQL

Sequence-to-sequence models for neural text-to-SQL typically perform token-level decoding and do not consider generating SQL hierarchically.

- [XLS] proposes a grammar-based model for reducing the complexity of text2SQL tasks involving hierarchical grammars.
- The authors introduce schema-dependent grammar with minimal over-generation.
- The grammar developed in [XLS] covers 98% of the instances in ATIS and SPIDER datasets.

SQL Grammar

- The shallow parsing expression grammar aims to capture as little SQL as possible to cover most instances in the dataset.
- In order to ensure consistency of table, column, and value references in SQL, the authors added non-terminals to context-free grammar.
- They use runtime constraints during decoding to ensure that only valid programs can be used to join different tables in DB together using a foreign key.

Few details on the proposed model

- As an input, the proposed model takes an utterance of natural language, a database, and grammar about that utterance.
- String matching heuristics are applied after taking the input to link words in the input to identifiers or tokens in the database.
- Afterward, the bidirectional LSTM receives a concatenated string of the learned word and the link embeddings for each token.
- Using the attention mechanism, the decoder builds up the SQL query iteratively on the input sequence.
- Database identifiers in natural language questions and SQL queries are also anonymized.

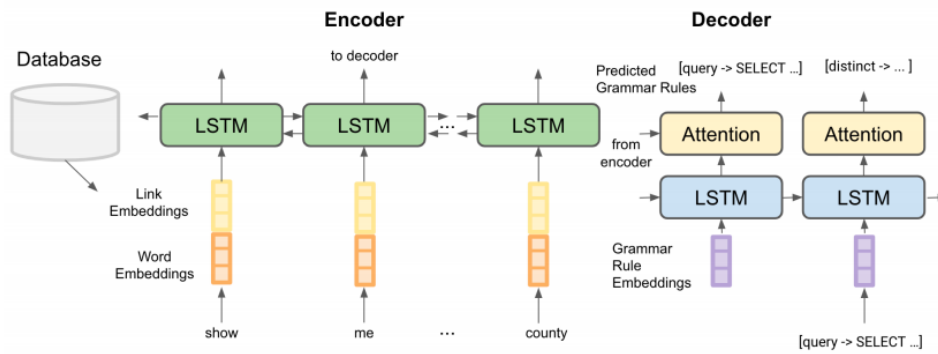


Figure 12: Structure of the proposed model

On ATIS and SPIDER datasets, the GrammarSQL model was evaluated. By 14%, it outperformed SyntaxSQLNet, the previous SOTA model.

IRNet

- In Text2SQL tasks, the Intermediate Representation Network (IRNet) addresses two main challenges.
- Among the challenges are mismatches between natural language intents and predicting columns resulting from a more significant number of out-of-domain words.
- Instead of synthesizing SQL queries end-to-end, IRNet decomposes natural language into three phases.
- Schema linking is performed over a database schema and a question during the first phase.
- IRNet uses SemQL to bridge the gap between SQL and natural language.
- It includes a Natural Language (NL) encoder, a Schema Encoder, and a Decoder.

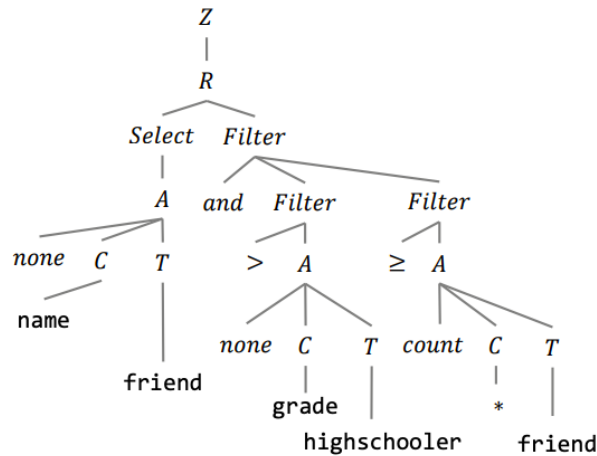


Figure 13: An illustrative example of SemSQL from [GZG⁺19]

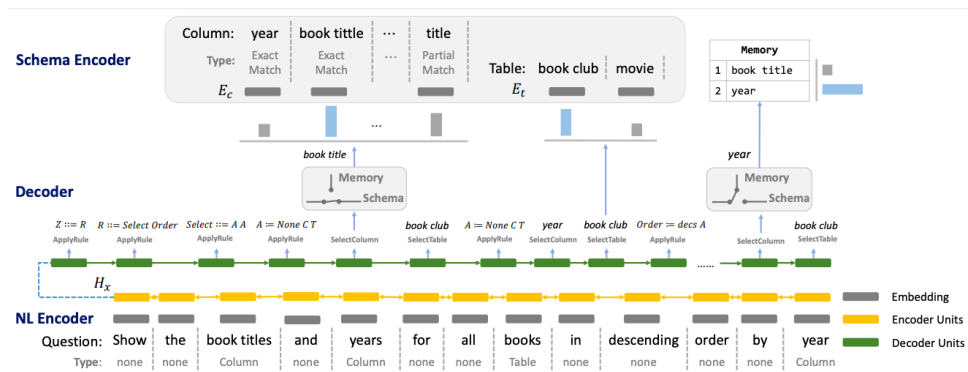


Figure 14: An overview of the neural model proposed in [GZG⁺19]

- The model provides different functions to accomplish Text2SQL tasks.
- Natural language is encoded into an embedding vector by the NL encoder. By using a bi-directional LSTM, these embedding vectors are used to construct hidden states.
- A schema encoder takes a database schema as input and outputs representations for columns and tables.
- Using a context-free grammar, the decoder synthesizes SemQL queries.
- On the SPIDER dataset, IRNet performs 46.7% better than previous benchmark models by 19
- The accuracy of 54.7% is achieved by combining IRNet with BERT.

EditSQL

- EditSQL focuses on text-to-SQL tasks that are context-dependent across domains.

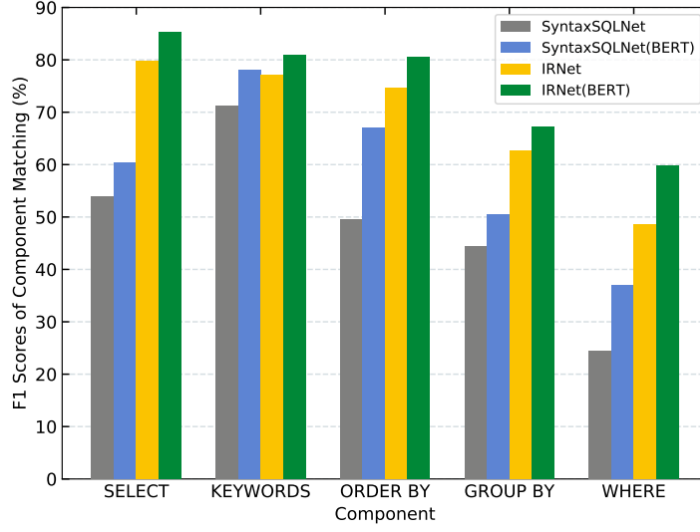


Figure 15: F1 scores of component matching of SyntaxSQLNet, SyntaxSQLNet $BERT$, IRNet and IRNet $BERT$ on the test set from [GZG⁺19]

- It exploits the fact that adjacent natural language questions are dependent on one another and that corresponding SQL queries overlap.
- To improve the generation quality, they edit the previously predicted query.
- The editing mechanism reuses generation results at the token level based on SQL input sequences.
- An utterance-table encoder and a table-aware decoder are utilized to incorporate the context of the natural language and the schema when dealing with complicated tables in different domains.

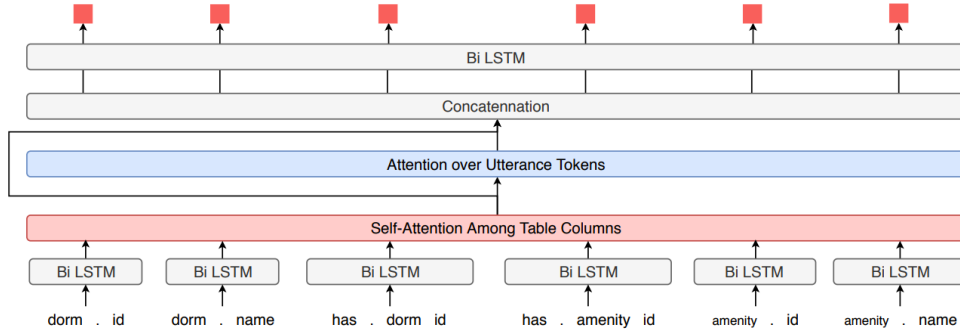


Figure 16: The model architecture of EditSQL from [ZYE⁺19a]

- User utterances and table schemas are encoded by the utterance-table encoder. Tokens of utterances are encoded using a bi-LSTM.
- To determine the most relevant columns, Attention weighed an average of column header embedding is applied to each token.

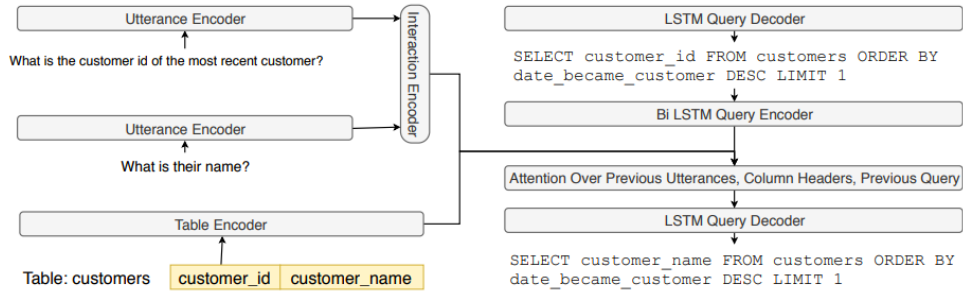


Figure 17: An example of user utterance and column headers and Utterance Encoder from [ZYE⁺19a]

- To capture the relationship between table schema and utterance, an attention layer is incorporated.
- The utterance-level encoder is built on top of an interaction-level decoder in order to capture information across utterances.
- LSTM decoding is used to generate SQL queries by incorporating interaction history, table schema, and user utterances.

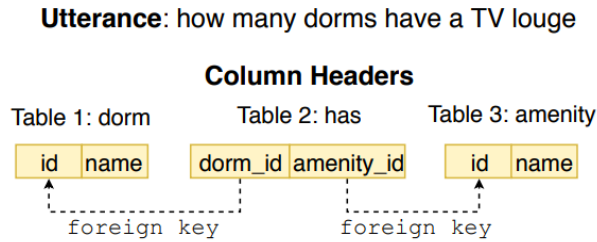


Figure 18: Table Encoder from [ZYE⁺19a]

- The model is evaluated on the SPaRC dataset, a large cross-domain context-dependent semantic parsing dataset derived from SPIDER.
- In both SPIDER and SPaRC, the model outperforms the previous state of the art model, IRNet.
- In cross-domain text2SQL generation, the model achieves 32.9% accuracy. A 53.4% improvement in accuracy can be achieved by using BERT embedding.

RAT-SQL

- A major challenge in translating natural language queries into SQL queries is generalizing them to unknown database schemas.
- As part of the generalisation, it is necessary to encode database relations in an accessible way and model alignment between relevant database columns in the query.

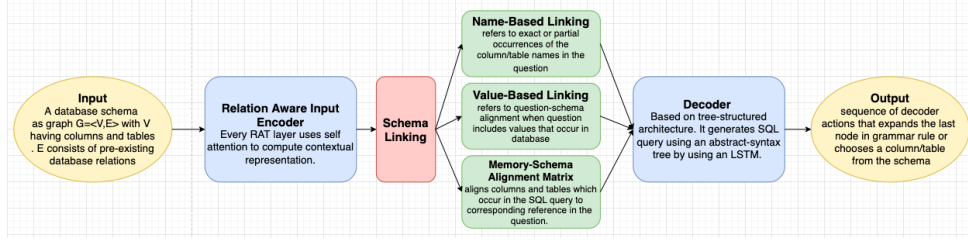


Figure 19: A flow chart of RAT-SQL model

- Within a text2SQL encoder, the proposed framework leverages the relation-aware self-attention mechanism to encode address schemas, represent features, and link schemas.
- Check out the flow chart below for an overview of RAT-SQL’s encoder-decoder structure.

| Model | Dev | Test |
|---|-------------|-------------|
| IRNet (Guo et al., 2019) | 53.2 | 46.7 |
| Global-GNN (Bogin et al., 2019b) | 52.7 | 47.4 |
| IRNet V2 (Guo et al., 2019) | 55.4 | 48.5 |
| RAT-SQL (ours) | 62.7 | 57.2 |
| <i>With BERT:</i> | | |
| EditSQL + BERT (Zhang et al., 2019) | 57.6 | 53.4 |
| GNN + Bertrand-DR (Kelkar et al., 2020) | 57.9 | 54.6 |
| IRNet V2 + BERT (Guo et al., 2019) | 63.9 | 55.0 |
| RYANSQL V2 + BERT (Choi et al., 2020) | 70.6 | 60.6 |
| RAT-SQL + BERT (ours) | 69.7 | 65.6 |

Figure 20: Accuracy on the Spider development and test sets, compared to the other approaches at the top of the dataset leaderboard as of May 1st, 2020 from [WSL⁺]

On the SPIDER dataset, RAT-SQL achieves 57.2% accuracy, an improvement of 8.7% over previous benchmark models.

| Split | Easy | Medium | Hard | Extra Hard | All |
|-----------------------|------|--------|------|------------|------|
| <i>RAT-SQL</i> | | | | | |
| Dev | 80.4 | 63.9 | 55.7 | 40.6 | 62.7 |
| Test | 74.8 | 60.7 | 53.6 | 31.5 | 57.2 |
| <i>RAT-SQL + BERT</i> | | | | | |
| Dev | 86.4 | 73.6 | 62.1 | 42.9 | 69.7 |
| Test | 83.0 | 71.3 | 58.3 | 38.4 | 65.6 |

Figure 21: Accuracy on the Spider development and test sets, by difficulty from [WSL⁺]

With RAT-SQL, 65.6% accuracy can be achieved by combining BERT with RAT-SQL.

BRIDGE

Seq-to-seq approaches such as Bridge[LSX] have been rare in recent times. Additionally, it implements schema-consistency-guided decoding to avoid errors at prediction time, incorporating BERT for better NL processing and fuzzy string matching for schema linking. For instance, the system is forced to predict SQL keywords in a specific order. If the table name has not already been generated, it will not be able to generate column names.

Picard

Picard[[SSB](#)] stands for "Parsing Incrementally for Constrained Auto-Regressive Decoding". It can be used with any existing language model decoder or vocabulary based on auto-regressive language modeling.

As an optional feature, Picard can be enabled at inference time and is absent from pre-training or fine-tuning. In the case of text-to-SQL translation, Picard operates directly on the output of the language model. Picard demonstrates state-of-the-art performance on challenging Spider and CoSQL text-to-SQL translation tasks.

Picard warps model prediction scores and integrates trivially with existing greedy and beam search algorithms. In addition to the token ids of the current hypothesis, the model's language modeling head also predicts the log-softmax scores for each vocabulary token. Additionally, Picard has access to SQL schema information, including table and column names and which column resides in which table.

0.3 Outline

1. Introduction

Description

Applications

2. Related Works and Motivation

3. Datasets

Datasets and Challenges

WikiSQL Benchmark

CoSQL Benchmark

SPIDER Benchmark

4. Models and State of the Art approaches

Theoretical background and the review of world literature

Natural Language Processing Concepts

Transformers and Google T5 [[RSR⁺20](#)]

Evaluation Metrics [[VR19](#)]

Study Different Researches in Text-to-SQL Challenges

Seq2SQL [[ZXS](#)]

SQLNet [[XLS](#)]

SyntaxSQLNet [[YYY⁺18](#)]

EditSQL [[ZYE⁺19b](#)]

RAT-SQL [[WSL⁺](#)]

RYANSQL [[CSKS](#)]

HydraNet [[LCH⁺20](#)]

BRIDGE [[LSX](#)]

T5 - PICARD [[SSB](#)]

Alternative approaches

Challenges and Research Opportunities

5. Results and Discussion

6. Implementation

Implementation Details

Implementation Online Applications of a Model

7. Summary and Future Work

Implement and test on private dataset

Discussion of the Results

Effect on other researches, like Text-to-SPARQL

Conclusions

8. Bibliography

0.4 Timeline

The timeline for the project will be broken down into four phases: literature review, establishing the theoretical framework and research implementation, using some datasets on a state-of-the-art model, and finally, documenting our study.

| Phase | Date | Description |
|--------------------|--------------------------------------|---|
| Phase Zero | July, 2022 | Working on Expose: Background research and preparing proposal |
| Phase One | August September October, 2022 | Literature Review: The first phase will be a review of any literature considering Text-to-SQL solutions and challenges. It includes examining how other researchers have approached the topic and discussing challenges around this research problem. Many considerations need to be addressed in this phase, such as the goal, the data, and how researchers find solutions for such a task. Each week I will try to focus on one state-of-the-art technique. |
| Phase Two | November, 2022 | Theoretical Framework and Research implementation: The second phase is where A theoretical framework of a model will be established and implemented. In order to do this, a variety of different approaches will be explored, which are possible to implement with our hardware and legal license limitations. |
| Phase Three | December, 2022 | Using private data on our model: Here, the previously collected dataset will be used to test our model and validate the accuracy of the final result. It is planned to have an online web application that can showcase Text-To-SQL scenarios with custom input from a user. |
| Phase Four | January, 2023 | Documenting our study: It will be planned to finish a draft regarding our study and our outcome in a month, and getting prepared for thesis defense and presentation. |

Bibliography

- [CSKS] DongHyun Choi, Myeong Cheol Shin, EungGyun Kim, and Dong Ryeol Shin. RYANSQL: Recursively applying sketch-based slot fillings for complex text-to-SQL in cross-domain databases. version: 1.
- [DCLT18] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805, 2018.

- [GZG⁺19] Jiaqi Guo, Zecheng Zhan, Yan Gao, Yan Xiao, Jian-Guang Lou, Ting Liu, and Dongmei Zhang. Towards complex text-to-sql in cross-domain database with intermediate representation. *CoRR*, abs/1905.08205, 2019.
- [LCH⁺20] Qin Lyu, Kaushik Chakrabarti, Shobhit Hathi, Souvik Kundu, Jianwen Zhang, and Zheng Chen. Hybrid ranking network for text-to-SQL. 2020.
- [LHCG19] Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. Multi-task deep neural networks for natural language understanding. *CoRR*, abs/1901.11504, 2019.
- [LSX] Xi Victoria Lin, Richard Socher, and Caiming Xiong. Bridging textual and tabular data for cross-domain text-to-SQL semantic parsing.
- [MDP⁺11] Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. Learning word vectors for sentiment analysis. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 142–150, Portland, Oregon, USA, June 2011. Association for Computational Linguistics.
- [Ron14] Xin Rong. word2vec parameter learning explained. *CoRR*, abs/1411.2738, 2014.
- [RSR⁺] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer.
- [RSR⁺20] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67, 2020.
- [SSB] Torsten Scholak, Nathan Schucher, and Dzmitry Bahdanau. PICARD: Parsing incrementally for constrained auto-regressive decoding from language models.
- [VR19] Jesse Vig and Kalai Ramea. In *Comparison of Transfer-Learning Approaches for Response Selection in Multi-Turn Conversations*, 2019.
- [VSP⁺17] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. *CoRR*, abs/1706.03762, 2017.
- [WSC⁺16] Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Lukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, and Jeffrey Dean. Google’s neural machine translation system: Bridging the gap between human and machine translation. *CoRR*, abs/1609.08144, 2016.
- [WSL⁺] Bailin Wang, Richard Shin, Xiaodong Liu, Oleksandr Polozov, and Matthew Richardson. RAT-SQL: Relation-aware schema encoding and linking for text-to-SQL parsers.

- [XLS] Xiaojun Xu, Chang Liu, and Dawn Song. SQLNet: Generating structured queries from natural language without reinforcement learning.
- [YNYR20] Pengcheng Yin, Graham Neubig, Wen-tau Yih, and Sebastian Riedel. Tabert: Pre-training for joint understanding of textual and tabular data. *CoRR*, abs/2005.08314, 2020.
- [YWL⁺20] Tao Yu, Chien-Sheng Wu, Xi Victoria Lin, Bailin Wang, Yi Chern Tan, Xinyi Yang, Dragomir R. Radev, Richard Socher, and Caiming Xiong. Grappa: Grammar-augmented pre-training for table semantic parsing. *CoRR*, abs/2009.13845, 2020.
- [YYY⁺18] Tao Yu, Michihiro Yasunaga, Kai Yang, Rui Zhang, Dongxu Wang, Zifan Li, and Dragomir R. Radev. Syntaxsqlnet: Syntax tree networks for complex and cross-domain text-to-sql task. *CoRR*, abs/1810.05237, 2018.
- [YZY⁺] Tao Yu, Rui Zhang, Kai Yang, Michihiro Yasunaga, Dongxu Wang, Zifan Li, James Ma, Irene Li, Qingning Yao, Shanelle Roman, Zilin Zhang, and Dragomir Radev. Spider: A large-scale human-labeled dataset for complex and cross-domain semantic parsing and text-to-SQL task.
- [ZXS] Victor Zhong, Caiming Xiong, and Richard Socher. Seq2sql: Generating structured queries from natural language using reinforcement learning. version: 6.
- [ZYE⁺19a] Rui Zhang, Tao Yu, Heyang Er, Sungrok Shim, Eric Xue, Xi Victoria Lin, Tianze Shi, Caiming Xiong, Richard Socher, and Dragomir R. Radev. Editing-based SQL query generation for cross-domain context-dependent questions. *CoRR*, abs/1909.00786, 2019.
- [ZYE⁺19b] Rui Zhang, Tao Yu, Heyang Er, Sungrok Shim, Eric Xue, Xi Victoria Lin, Tianze Shi, Caiming Xiong, Richard Socher, and Dragomir R. Radev. Editing-based SQL query generation for cross-domain context-dependent questions. *CoRR*, abs/1909.00786, 2019.