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Fakultät für Informatik und Automatisierung

Master Thesis

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

presented by

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Dedication

Dedicated to my family and friends for their support and encouragement throughout my academic journey.

I dedicate this thesis to the brave and heroic Iranian women who have stood up against oppression and fought for their rights and freedoms. These women, often at significant personal risk, have courageously spoken out against the injustices they have faced and have worked tirelessly to bring about positive change in their country.

Their tireless efforts and dedication to the cause of gender equality and social justice have inspired me and countless others worldwide. I am deeply grateful for their unwavering commitment to making the world a better place for all.

This thesis is also dedicated to the memory of those who have lost their lives in the struggle for equality and justice. Their sacrifice will never be forgotten, and their legacy will inspire future generations to fight for a more just and equitable world.

Also, I express my love to my parents, who have always been my biggest supporters and have believed in me throughout my academic journey. Their love, guidance, and encouragement have been invaluable to me.

I am immensely grateful to my advisors, Prof. Patrick Mäder and also Martin Hofmann, who has been excellent mentor and guide throughout the process of writing this thesis. Their expertise and support have been instrumental in helping me to complete this work.

Contents

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. Machine learning and knowledge-based resources aid in converting text language to SQL.

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:

- Data analysts can use it to generate SQL queries for specific business questions, such as ”What are the top ten products sold this month?”
- 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?”
- Businesses can use this technique to automate data extraction and improve efficiency.
- 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 Text-to-SQL models may provide a partial solution to this complex problem, humans still have challenges to overcome. Even experienced database administrators and developers can need help with the task of dealing with unfamiliar schema when working on database migration projects. This is often due to the fact that they have never seen the schema before and therefore need to learn how to read and interpret it correctly. Furthermore, it can take time to determine how to make the necessary changes in order to migrate the data from one database to another successfully. In spite of these challenges, it is possible to successfully complete a database migration project with the help of a text-to-SQL model, as long as the model is carefully implemented and the proper steps are taken.

This research study will examine the various natural language processing (NLP) technologies that have been utilized in recent years to convert text language into Structured Query Language (SQL). Specifically, it will explore and compare the most commonly used NLP technologies and review their effects on the effectiveness of the conversion process. Moreover, this study will also analyze the representative datasets and evaluation metrics that are utilized in the current solutions for this challenging task. By doing so, it is our hope that this research study will provide valuable insights into how NLP technologies can be effectively and efficiently utilized in the conversion of text language into SQL.

Additionally, we will undertake a comprehensive study of the SEOSS (Software Engineering Dataset for Text-to-SQL and Question Answering Tasks) dataset from our esteemed researchers at the university. We will then evaluate the execution of this dataset using the most advanced Text-to-SQL model currently available. This will enable us to understand the capabilities of the SEOSS dataset better and help us to make informed decisions.

1.1 Challenges

Text-to-SQL is an intricate task, given the complexity and diversity of natural language and the structure and regulations of SQL. One of the most challenging aspects is to decipher the intent and significance of the natural language input, as it can be ambiguous or have varied interpretations. This can result in mistakes when building the corresponding SQL query, like selecting the incorrect table or columns or not recognizing the conditions for filtering or sorting the data. Additionally, the natural language input may contain typos or unknown words, which can complicate the mapping process. Moreover, the query generated may not be in the optimal form, as it has to take into account the various data types, operations, and constraints of the underlying database. Therefore, it is crucial to develop models and algorithms that can accurately map natural language to SQL queries.

Another challenge is dealing with the diverse and dynamic nature of databases, as the schema and data may change over time, and there may be variations in naming conventions and conventions across different databases. This can make it difficult for the model to correctly map the natural language input to the appropriate SQL elements, such as table and column names, and to handle variations in the structure of the SQL queries generated. Additionally, many real-world scenarios require integration with external knowledge bases and ontologies, which can be challenging to handle, especially when the external knowledge needs to be completed or consistent. Furthermore, the system must be robust to different types of user input, such as colloquial or informal language or input that needs to be completed or clarified. Additionally, Text-to-SQL systems must be able to handle errors in the input, such as typos, as well as rare edge cases that may not have been encountered during the training process. Finally, Text-to-SQL systems must be robust to the presence of out-of-vocabulary words and rare edge cases, which can be challenging to handle without significant amounts of labeled data, as well as the need to make accurate predictions with limited training data.

1.2 Thesis Outline

In this section, we provide an outline of our thesis.

- Chapter 1 of the thesis provides an introduction to the topic of Text-to-SQL and discusses the challenges and contributions of the research.
- Chapter 2 provides technical background on Text-to-SQL, including early approaches, recent approaches, and important terminologies such as LSTM, encoder, decoder, transformers, BERT, semantic parsing, baseline model and incremental decoding.
- Chapter 3 describes the benchmark datasets used for evaluating Text-to-SQL methods, including the ATIS, GeoQuery, IMDb, Advising, WikiSQL, and Spider datasets.
- Chapter 4 presents an overview of SOAT Text-to-SQL solutions, including Seq2SQL, SQLNet, SyntaxSQLNet, IRNet, EditSQL, RAT-SQL, BRIDGE, and PICARD.
- Chapter 5 explains the evaluation metrics used to assess the performance of Text-to-SQL systems, including exact string matching, exact set matching, and distilled test suites.
- Chapter 6 presents an experiment and case study using the SEOSS dataset and the T5 PICARD model, with a focus on the metrics and evaluation results. The thesis also includes a section on EZ-PICARD and its Microservices practices.
- Chapter 7 concludes the thesis by summarizing the findings and exploring emerging challenges such as conversational Text-to-SQL.

2 Technical Background

In this chapter, we provide background information about the technical concepts related to the main topics of this thesis, which focus on natural language understanding and text generation. We focus on early and recent approaches and the terminology needed to understand the basics of this thesis.

The text-to-SQL problem, or NL2SQL, is defined as the following: Given a Natural Language Query (NLQ) on a Relational Database (RDB), produce a SQL query equivalent to the NLQ. Several challenges include ambiguity, schema linking, vocabulary gaps, and user errors. It has been a holy grail for the database community for over 30 years to translate user queries into SQL.

Early approaches to Text-to-SQL relied on rule-based and template-based methods, while recent approaches use neural networks and machine learning techniques. This allows them to handle a wide range of natural language inputs and generate more accurate SQL queries, which we will discuss further.

2.1 Early Approaches

Early approaches to Text-to-SQL focused on rule-based methods and template-based methods. These approaches relied on predefined templates and a set of predefined rules to generate SQL queries. These methods were based on the idea that a fixed set of templates and rules could be used to generate SQL queries for a wide range of natural language inputs. However, these methods were limited by their reliance on predefined templates and were not able to handle a wide range of natural language inputs.

In the case of rule-based methods, a set of predefined rules were used to map the natural language input to the corresponding SQL query. These rules were based on predefined grammar and were used to identify the SQL constructs present in the input text. These methods were able to generate simple SQL queries, but they were not able to handle more complex queries or handle variations in natural language inputs.

Template-based methods, on the other hand, relied on predefined templates to generate SQL queries. These templates were based on a predefined set of SQL constructs and were used to map the natural language input to the corresponding SQL query. These methods were able to handle a limited set of natural language inputs, but they were not able to handle variations in the input or generate more complex queries.

Early research in Text-to-SQL includes work by researchers such as Warren and Pereira in 1982[WP82], who proposed a rule-based method for generating SQL queries from natural language text. Their system used a set of predefined rules to map natural language constructs to SQL constructs and was able to generate simple SQL queries. Another example of a rule-based method is the work by Zelle and Mooney in 1996, who proposed CHILL parser[ZM96] a system that used a predefined grammar to identify the SQL constructs present in the input text and generate the corresponding SQL query. In the case of template-based methods, one of the very first systems that used predefined templates to map natural language inputs to SQL queries was able to handle a limited set of natural language inputs.

In summary, early approaches to Text-to-SQL were limited by their reliance on predefined templates and rules, which made them unable to handle a wide range of natural language inputs and generate complex SQL queries.

2.2 Recent Approaches

Recent approaches to Text-to-SQL have focused on using neural networks and machine learning techniques to generate SQL queries. These methods use large amounts of training data to learn the relationship between natural language and SQL and can generate SQL queries for a wide range of inputs. These methods are able to handle a wide range of natural language inputs and are not limited by predefined templates or rules. Additionally, recent approaches leverage pre-trained models such as BERT, GPT-2, and T5, which have been pre-trained on a large corpus of text, to fine-tune text-to-SQL tasks, which enables them to understand the natural language inputs better and generate more accurate SQL queries.

One popular approach is the use of encoder-decoder architecture, which uses an encoder to encode the natural language input and a decoder to generate the corresponding SQL query. The encoder is a pre-trained language model such as BERT, which is fine-tuned on the task of text-to-SQL, and the decoder is a neural network that generates the SQL query. This architecture has been shown to be effective in generating accurate SQL queries for a wide range of natural language inputs.

Another recent approach is the use of reinforcement learning to generate SQL queries, where a neural network generates a sequence of SQL tokens and is trained using a reward signal based on the quality of the generated query. This approach has been shown to be adequate in generating more complex SQL queries and handling variations in natural language inputs.

In recent years, the Transformer architecture has had a significant impact on natural language processing and machine learning, including in the field of Text-to-SQL. The Transformer architecture, presented in the paper ”Attention Is All You Need” by Vaswani et al. in 2017, is a neural network architecture that uses self-attention mechanisms to process sequences of data, such as natural language text.

One of the key advantages of the Transformer architecture is its ability to handle long-term dependencies in sequences of data, making it well-suited for tasks such as natural language understanding and text generation. This has led to the development of pre-trained Transformer models, such as BERT, GPT-2, and T5, that have been trained on a large corpus of text and can be fine-tuned on specific tasks such as Text-to-SQL.

The use of pre-trained Transformer models such as BERT in Text-to-SQL has shown to be effective in improving the performance of the models. The pre-trained models have a good understanding of the natural language, which enables them to understand the input text better and generate more accurate SQL queries. The Transformer architecture and pre-trained models such as BERT have had a significant impact on recent studies in the field of Text-to-SQL. The ability of the Transformer architecture to handle long-term dependencies in sequences of data and the pre-trained models’ good understanding of natural language has made it possible to generate more accurate SQL queries for a wide range of natural language inputs.

In summary, recent approaches to Text-to-SQL leverage neural networks and machine learning techniques, such as the use of encoder-decoder architecture and reinforcement learning. These approaches use large amounts of training data and pre-trained models such as BERT to generate accurate SQL queries for a wide range of natural language inputs.

2.3 Terminology

Here is an updated list of key terminology and vocabulary that you may need to know before studying Text-to-SQL language models:

2.3.1 Natural Language Processing (NLP)

The field of study focused on the interaction between human language and computers, which ranges from understanding spoken language to generating natural language text.

2.3.2 Tokenization

The process of breaking up a sentence into individual words or phrases, that is necessary for tasks such as machine translation and text summarization.

2.3.3 Word2Vec

X[Ron14]

2.3.4 WordPiece embeddings

X[WSC+16]

2.3.5 Encoder-Decoder Architecture

A powerful neural network architecture that utilizes an encoder[CvMG+14] to transform the input data into a compact and meaningful representation and a decoder to generate the desired output from that representation. This architecture has been widely used in many applications such as language translation, image captioning, and text summarization to produce high-quality results. Furthermore, the encoder-decoder architecture has the advantage of being able to learn complex relationships between input and output, making it a suitable tool for many challenging tasks.

2.3.6 Transformers

The architecture introduced in the paper "Attention Is All You Need" by Vaswani et al. in 2017[VSP+17a], known as Transformers, is a revolutionary breakthrough in the way sequences of data are processed. By utilizing self-attention mechanisms, the model is able to achieve improved efficiency and accuracy, while also being much simpler to implement and deploy. This makes it particularly appealing for a wide range of applications, from natural language processing to computer vision. Furthermore, due to their scalability, Transformers are able to accommodate large data sets, enabling them to be used to tackle more complex tasks. As such, Transformers are becoming increasingly popular in the field of machine learning and artificial intelligence, with more and more research being done to further explore its capabilities.

There were many excellent works around 2015 on learning word vectors to continuous representations for words where the identity of a word was mapped to a fixed-length vector which ideally encoded some meaning about the word in a continuous space and for a long time.

That has been an essential part of the NLP pipeline, especially for deep learning models where these pre-trained word vectors were used, typically trained using an unsupervised objective, and new models were fed and trained on top of them.

An important paper in 2017 that helped researchers change their way of thinking towards the transfer learning paradigm was the unsupervised sentiment neuron paper from people at OpenAI [RJS17], which essentially showed that by just training a language model on a purely unsupervised objective, the model could learn concepts that were potentially useful for downstream tasks.

In 2018, the NLP community had a couple of super important papers,
including the ULMFiT[HR18], which took the recipe from semi-supervised sequence learning, added some tweaks, figured out how to get it working better, and got some noble results with a similar pipeline, pre-training a language model, fine-tuning on a downstream task.

And then, ELMo[HR18] showed that we could get significantly better performance by using a bi-directional language model.

Then GPT1 [RN18] came along, saying that instead of using analyst TM, we can get good performance by using a transformer with a language model.

Finally, in 2018, BERT [DCLT19] showed that a bi-directional transformer could get outstanding performance, and by the end of 2018, many researchers were convinced that this was the path forward given all of the impressive results that these papers and a few others showed.

Following these researches, there has been a burst of work on transfer learning for NLP, working on various methods, different pre-training ideas, datasets, and different benchmark tasks.

In Google T5, it is tried to use all the new studies in transfer learning and combine the best selection of these studies to achieve state-of-the-art results on many benchmarks covering summarization, classification, question answering, and more.

2.3.7 Self-attention

Self-attention[VSP+17a] is a mechanism used in the transformer architecture that enables the model to identify the significance of different elements of the input sequence, so as to be able to generate an output that is more accurate and effective. This mechanism allows the model to take into account the relationships between different parts of the input sequence and to factor those relationships into its output. Additionally, self-attention allows the model to capture patterns from the input sequence and to use those patterns to generate more meaningful output. It is this combination of factors that makes self-attention such an important tool for deep learning models.

2.3.8 Pre-training and Fine-tuning

Pre-training refers to training a model on a large dataset and then fine-tuning it on a smaller dataset for a specific task, which helps to improve the model's performance on the specific task.

2.3.9 Long Short-Term Memory (LSTM)

A type of recurrent neural network that has been designed to store information over a longer period of time than traditional neural networks, allowing it to better capture long-term dependencies[HS97]. This makes it especially well-suited for tasks such as language modeling and text generation, where it can take into account the context of the text in order to generate more accurate outputs. In addition, LSTM networks are able to identify patterns in the data that would be difficult for traditional networks to capture. This makes them ideal for tasks such as sequence prediction and classification, where they can identify patterns that would otherwise be too subtle for traditional networks to detect.

2.3.10 Bidirectional Encoder Representations from Transformers(BERT)

A pre-trained Transformer model that has been trained on a large corpus of text, with the primary aim of pre-training language representations for use in natural language processing tasks[DCLT19]. This pre-training helps to give BERT a strong understanding of the language structure and helps in faster training times for downstream tasks. BERT can be fine-tuned for various applications, such as Text-to-SQL, where it can provide better performance than non-specialized models. By leveraging the already learned representations from the pre-trained model, BERT is able to quickly adjust to the task at hand, resulting in faster training times.

2.3.11 SQL Constructs

The elements of SQL language such as SELECT, FROM, WHERE, JOIN, are used to build queries and retrieve data from a database.

2.3.12 Evaluation Metrics

Measures used to evaluate the performance of Text-to-SQL models, such as accuracy, F1-score, and Exact Match score, are used to compare different models and determine the best-performing model.

2.3.13 Baseline Model

A model that serves as a reference point or starting point for comparison, providing a baseline for performance against which other models can be evaluated.

2.3.14 Incremental decoding

A decoding strategy where the model generates a sequence of tokens one at a time, at each step conditioned on the previous tokens, the input, and the context of the sentence. This approach allows for a more dynamic and flexible generation of output, as it takes into account a variety of factors when making decisions about the next token. This strategy also helps the model avoid repeating itself, providing more diverse and unique outputs. Furthermore, incremental decoding helps the model to better capture the nuance of the language as it is able to build upon previous decisions and refine its output as it progresses[HM10].

2.3.15 Semantic parsing

Semantic parsing[KDG17] is an area of natural language processing that involves extracting the meaning or intent from text. One type of Semantic Parsing, Text-to-SQL, involves the conversion of natural language problems into SQL query statements. This is a challenging task, one that requires the use of advanced machine learning and natural language processing algorithms. As such, the research conducted in this field seeks to explore the various solutions and practices that have been employed by researchers in order to effectively tackle this problem. Furthermore, it is also important to note that this problem is not just limited to the conversion of natural language into SQL query statements, as there are other applications of Semantic Parsing that have been explored, such as Natural Language Generation (NLG). Overall, by understanding the various techniques used for Semantic Parsing, we can gain a better understanding of the complexities involved in this task and how best to approach it.

3 Benchmark Dataset

Datasets play a crucial role in developing and evaluating Text-to-SQL models for semantic parsing of natural language phrases. A variety of benchmark datasets are available, each with unique characteristics and features. Examples of early datasets include ATIS[DBB+94], GeoQuery[TM01], and Yelp[YWDD17], which focus on a single topic and database. More recent datasets, such as WikiSQL[ZXS] and Spider[YZY+18], are larger and cover a broader range of domains.

Additionally, new datasets include more advanced queries to assess the generalization capabilities of models. These benchmark datasets provide a standardized testbed for evaluating the performance of Text-to-SQL models and are widely used in the research community. They vary in complexity, size, and annotation, allowing researchers to evaluate models' performance at different levels and under different scenarios. This chapter will review the top benchmark datasets used in the Text-to-SQL Semantic Parsing community and discuss their significance for the research community.

3.1 Single-Domain

3.1.1 ATIS (Air Travel Information System) and GeoQuery

ATIS (Air Travel Information System)[DBB+94] and GeoQuery[TM01] are two datasets that are frequently utilized for semantic parsing, a technique for converting natural language inquiries into a structured meaning representation. The ATIS dataset consists of audio recordings and hand transcripts of individuals using automated travel inquiry systems to search for information regarding flights. It is structured using a relational schema to organize data from the official airline guide, with 25 tables containing information concerning fares, airlines, flights, cities, airports, and ground services. All questions concerning this dataset can be answered using a single relational query. This makes it an ideal choice for training deep learning models, as it is designed for a specific domain and the queries are relatively straightforward.

Furthermore, the questions in the ATIS dataset are mainly limited to select and project queries. On the other hand, GeoQuery is made up of seven tables from the US geography database and 880 natural languages to SQL pairings. It includes geographic and topographical characteristics such as capitals, populations, and landforms. While both datasets are regularly employed to train deep learning models, GeoQuery is more comprehensive and provides a wider range of queries than ATIS. This includes join and nested queries, as well as grouping and ordering queries, which are absent in the ATIS dataset. As a result, GeoQuery is better equipped to answer more complex queries, making it a better choice for training AI models.

3.1.2 IMDb Dataset

The IMDb dataset is a well-known dataset in the machine learning community. It contains 50,000 reviews from IMDb and has a limit of 30 reviews per movie[MDP+11]. It is noteworthy that the dataset is balanced in terms of positive and negative reviews, which are equally represented. When creating the dataset, reviews with a score of 4 out of 10 were considered negative and those with a score of 7 out of 10 were considered positive. Neural reviews were excluded to maintain the quality of the dataset. The dataset is divided into training and testing datasets, each with an equal portion. To ensure fairness and accuracy in the results, the dataset creators have taken special care to keep the training and testing datasets balanced.

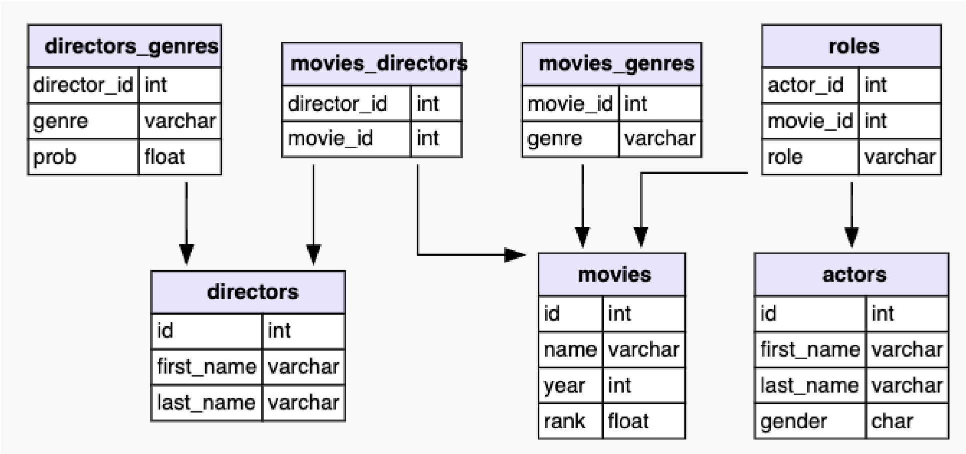


Figure 1: Database Structure of IMDb dataset

3.1.3 Advising Dataset

The Advising dataset[FDKZ+18] was created in order to propose improvements in Text-to-SQL systems. The creators of the dataset compare human-generated and automatically generated questions, citing properties of queries that relate to real-world applications. The dataset consists of questions from the University of Michigan students about courses that lead to particularly complex queries. The data is obtained from a fictional student database which includes student profile information such as recommended courses, grades, and previous courses. Moreover, in order to obtain the data for the dataset, academic advising meetings were conducted where students were asked to formulate questions they would ask if they knew the database. After obtaining the questions, the creators of the dataset compared the query results with those from other datasets such as ATIS, GeoQuery, and Scholar. Many of the queries in the Advising dataset were the same as those found in the other datasets.

3.1.4 MAS (Microsoft Academic Search)

MAS, or Microsoft Academic Search[RCM+13], is a database of academic and social networks and a collection of queries. It has a total of 17 tables in its database, as well as 196 natural languages to SQL pairs. MAS can handle join, grouping, and nested queries but does not support ordering queries.

There are a few limitations to be aware of when using natural language queries within MAS. Firstly, all-natural language questions must begin with the phrase ”return me” and can not include an interrogative statement or a collection of keywords. Additionally, all queries must follow the proper grammatical conventions.

3.2 Large Scale Cross-Domain

3.2.1 WikiSQL

WikiSQL[HYPS19] consists of 80,654 natural language questions and corresponding SQL queries on 24,241 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 datasets in the test set are not present in the train or development sets in the WikiSQL problem definition. Further, the task needs to accept input from several table schemas. The model must therefore be generalized to new databases. However, they used oversimplified assumptions about the SQL queries and databases in order to generate questions and SQL pairings for 24241 databases. They provide WHERE conditions, a single SELECT column, and aggregation in their SQL labels. Additionally, each database only has one table, with no mention of JOIN, GROUP BY, or ORDER BY.

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.

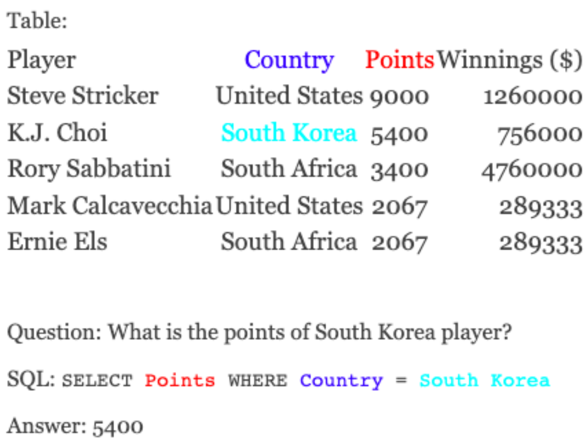


Table:

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 2: Example from WikiSQL dataset[HYPS19]

One example of a state-of-the-art Text-to-SQL solution in the WikiSQL benchmark is the Seq2SQL model, which uses a sequence-to-sequence learning framework to map natural language input to SQL queries. The model uses an attention mechanism to align the input and output sequences and a pointer network to handle SQL queries with complex structural dependencies. We will discuss this model in more detail in the next section.

3.2.2 SPIDER

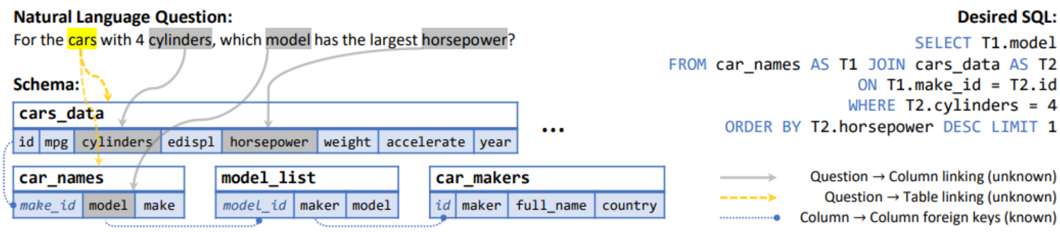


Figure 3: A difficult text-to-SQL task from the Spider dataset.[WSL+]

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 dataset took 11 Yale University students, 1,000 man-hours in total.

Spider contains queries with a lot of intricate SQL elements. In comparison to the sum of the previous Text-to-SQL datasets, Spider comprises around twice as many nested queries and ten times as many ORDER BY (LIMIT) and GROUP BY (HAVING) components.

Creating this corpus was primarily motivated by the desire to tackle complex queries and generalize across databases without requiring multiple interactions.

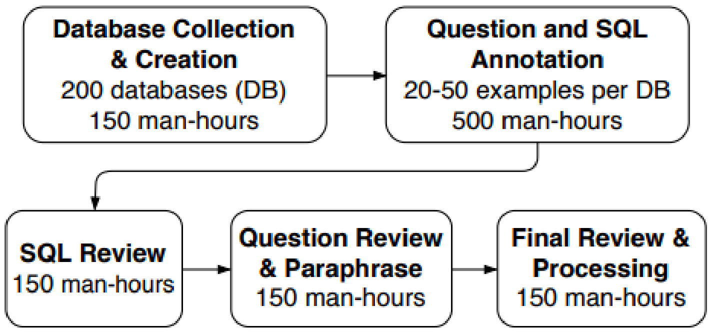


Figure 4: Process of creating SPIDER dataset[YZY+18]

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.

The complexity of the dataset increases and the accuracy of solutions drops as the number of foreign keys in the database increases. This is mainly due to the difficulty in selecting the relevant column and table names from a complex database schema. Furthermore, complex database schemas present a major challenge for the model to accurately capture the relationship between different tables which involve foreign keys. SQL queries with a higher number of foreign keys tend to join more tables, suggesting a need for more effective methods to encode the connection between tables with foreign keys.

SQL Hardness Criteria

In order to gain a better understanding of how the model performs on different queries, we have divided SQL queries into four difficulty levels: easy, medium, hard, and extra hard. This classification is based on the number of SQL components, selections, and conditions. Queries that contain multiple SQL keywords (e.g., GROUP BY, ORDER BY, INTERSECT, nested subqueries, column selections, aggregators) are generally considered more complex. For example, a query is considered hard if it includes more than two SELECT columns, more than two WHERE conditions, and GROUP BY two columns, or contains EXCEPT or nested queries. If it contains even more additions on top of that, it is considered extra hard.

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+18]

SPIDER's exact matching accuracy5 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 above 75.5% with an exact set match without values (refers to values in the WHERE clause) and above 72.6% with values using PICARD4.7.

The SPIDER challenge is a research competition dedicated to developing cutting-edge Text-to-SQL and Semantic Parsing solutions. In this challenge, participants strive to develop algorithms that can automatically generate structured SQL queries from natural language input, to improve the performance and accuracy of Text-to-SQL models.

In this challenge, numerous state-of-the-art Text-to-SQL solutions have been proposed, such as the Spider model. This model uses a combination of recurrent and convolutional neural networks to learn the mapping between natural language and SQL queries. This model also has a hierarchical structure, which allows it to process the natural language input more effectively, thereby allowing it to handle complex queries and variations in language with greater precision and accuracy. This model successfully generates accurate and efficient SQL queries from natural language inputs.

One difference between the SPIDER and WikiSQL challenges is the specific dataset that is used for evaluation. The SPIDER challenge uses a dataset of complex SQL queries and natural language questions derived from real-world databases, while the WikiSQL challenge uses a dataset of more straightforward SQL queries and natural language questions derived from Wikipedia articles. This difference in the dataset can affect the performance and accuracy of the models on the different tasks.

Another difference is in the evaluation metrics used. The SPIDER challenge evaluates the models using execution accuracy and natural language understanding metrics, while the WikiSQL challenge evaluates the models using only execution accuracy. This difference in the evaluation metrics can affect how the models are trained and their performance on the tasks. We will discuss the evaluation metrics used in the SPIDER challenge in more detail in the next section5.

3.2.3 SEDE

Stack Exchange Data Explorer (SEDE)[HMB21] is a popular online question-and-answer platform with more than 3 million questions, and it recently released a benchmark dataset of SQL queries containing 29 tables and 211 columns. This dataset comprises real-world questions from the Stack Exchange website, such as published posts, comments, votes, tags, and awards.

Although these datasets contain a variety of real-world challenges, they still need to be more tricky to parse semantically due to the complexity of the questions they contain. After further analysis of the 12,023 questions (clean) asked on the platform, a total of 1,714 have been verified by humans, which makes it an ideal choice for training and validating the model. This benchmark dataset is highly valuable and helpful for research in natural language processing, as it provides an extensive list of real-world challenges that have rarely been seen in other semantic parsing datasets.

3.2.4 SEOSS

SEOSS dataset is a compilation of natural language expressions with seven alternative phrasings, each linked to a single SQL query. In total, 166 questions (expressions) were organized. The natural language expressions were mainly obtained from existing literature and modified to match the data identified in the issue tracking system (ITS) and version control system (VCS) of an existing software project (namely Apache Pig). This data was extracted and saved into an SQLite database by Rath et al. [RM19].

Expressions are labeled into two different tags, development and research. Eighty-one queries with a focus on software needs of stakeholders and developers or from typical use cases' queries of issue tracking systems were labeled as 'development,' and 63 queries containing issue tracking systems information or version control systems were labeled as 'research.' Also, 22 records were generated from the content in questions stakeholders asked within the comment sections of issues of type bug, enhancement/improvement, new feature/feature request, and tasks of 33 open-source Apache projects, which were extracted and stored into databases by Rath and Mäder[RM19].

In SEOSS-Queries[THM22] research, they experienced RatSQL and SQLNet methods on the SEOSS dataset and released their evaluation steps. In this research, we will use the same dataset to evaluate state-of-the-art models currently available in the literature and used in SPIDER for this dataset.

In this chapter, we have reviewed various datasets widely used in the Text-to-SQL Semantic Parsing community. These datasets vary in complexity, size, and annotation, providing a standardized testbed for evaluating the performance of Text-to-SQL models. We have discussed their unique characteristics and features from early datasets such as ATIS and GeoQuery to more recent datasets such as WikiSQL and Spider. The datasets discussed in this chapter are a valuable resource for the research community to evaluate the progress and performance of

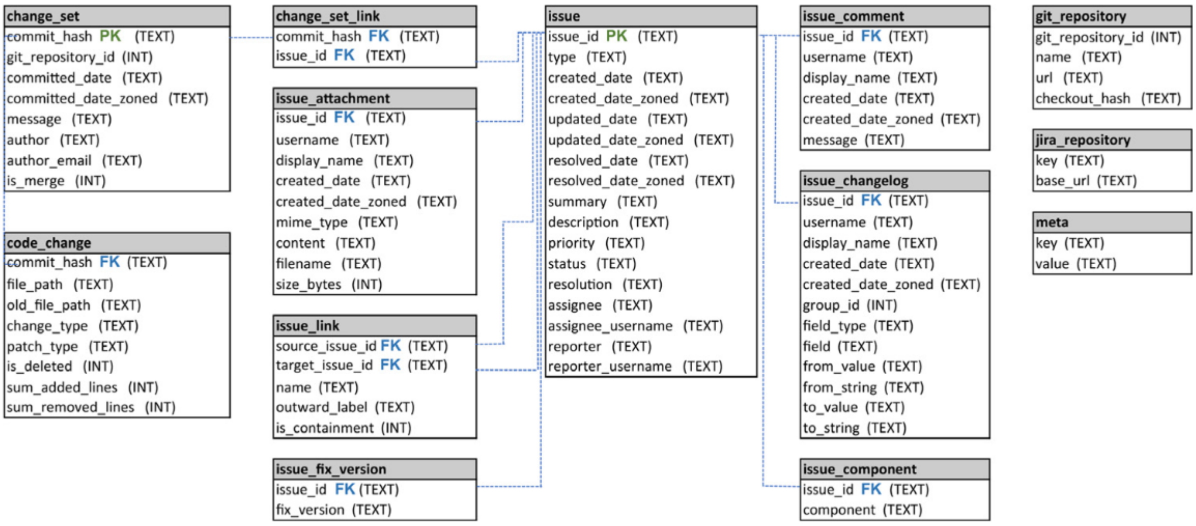


Figure 6: Database Schema of the PIG Database [THM22]

Text-to-SQL models. The continued development and improvement of these datasets will be necessary for advancing the field of Text-to-SQL Semantic Parsing. The table1 below provides an overview of the datasets mentioned in this chapter, including the number of queries and questions sorted by year.

Dataset	Year	DBs	Tables	Utterances	Queries	Domain
ATIS	1994	1	32	5280	947	Air Travel Information
GeoQuery	2001	1	6	877	247	US geography database
Academic	2014	1	15	196	185	Microsoft Academic Search
IMDB	2015	1	16	131	89	Internet Movie Database
Scholar	2017	1	7	817	193	Academic Publications
Yelp	2017	1	7	128	110	Yelp Movie Website
WikiSQL	2017	26.521	26,521	80,654	77,840	Wikipedia
Advising	2018	1	10	3,898	208	Student Course Information
Spider	2018	200	1,020	10,181	5,693	138 Different Domains
SEDE	2021	1	29	12,023	11,767	Stack Exchange
SEOSS	2022	1	13	1,162	116	Project ITS and VSC

Table 1: Comparison of datasets (Sort by Year)

4 State-of-the-art Text-To-SQL Methods

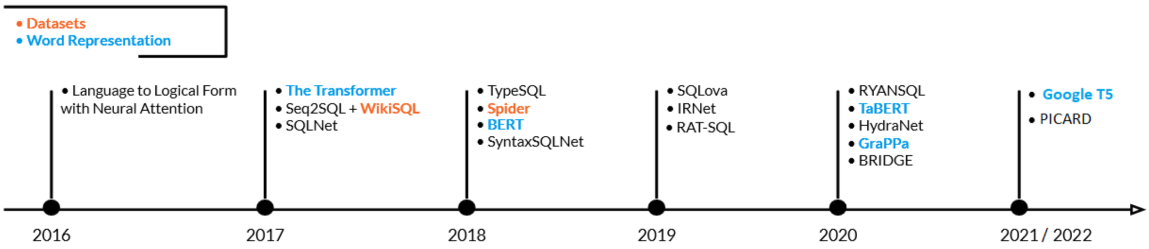


Figure 7: Timeline of the deep learning process for Text-to-SQL.

This section will discuss existing cross-domain state-of-the-art (SOTA), text-to-SQL models, beginning with a broad overview and moving on to individual modules. This will provide a clear picture of the progress made in text-to-SQL research. Experiments have shown that pre-trained embeddings improve models because they construct better schema linking and a more accurate SQL structure.

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], 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+17b], 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]. BERT is a pre-trained language model that has been shown to achieve state-of-the-art performance in a variety of NLP tasks. BERT is a Transformer-based model that uses a bidirectional encoder to learn the representation of a word based on the context in which it appears. BERT has been used in several text-to-SQL models, such as BRIDGE [LSX] and RAT-SQL [WSL+].

4.1 Sequence-to-SQL

4.1.1 Seq2Seq

The seq2seq model[SVL14] is a type of neural network architecture that has revolutionized the field of natural language processing. It generates meaningful sequences from input data, such as translating one language into another or summarizing text. The primary components of the seq2seq model are an encoder and decoder, which work together to learn how to map inputs onto outputs in a way that preserves their meaning.

The encoder takes raw input data and converts it into a series of numerical vectors known as embeddings. These embeddings represent each word or phrase in the input sequence with its unique vector representation so that it can be understood by the decoder for further processing. The decoder then uses these representations and other parameters like attention weights and recurrent layers to generate output sequences based on what was learned during training time from previous examples given by humans or machines alike.

Seq2Seq models can be trained using techniques such as supervised learning, which is trained on a dataset of input-output pairs, or unsupervised learning, where the model is trained to reconstruct the input sequence. Attention mechanisms, such as the attention mechanism used in the Transformer model, can also be incorporated into Seq2Seq models to improve their performance by allowing the decoder to focus selectively on certain parts of the input sequence.

Finally, once appropriately trained on large datasets containing millions of examples across multiple languages (or even within just one), this powerful tool can be used for tasks such as machine translation between two different languages; automatically generating summaries; question-answering systems; voice recognition software; among many others! Seq2Seq models have become increasingly popular due to their ability to quickly process large volumes of information while still maintaining accuracy and efficiency when compared to traditional methods like rule-based algorithms. However, one of the significant challenges of Seq2Seq models is the risk of generating irrelevant or nonsensical outputs, known as the ”exposure bias” problem. Researchers have proposed various solutions to this problem, such as using beam search during decoding.

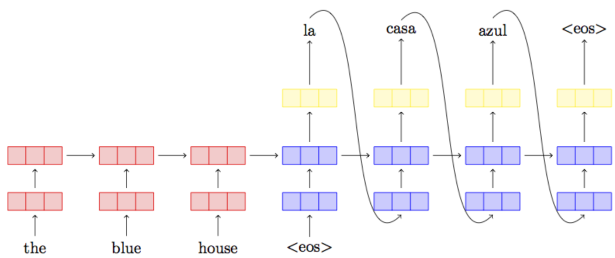


Figure 8: Example of Seq2Seq model in translating a sentence from English to French.

4.1.2 Seq2SQL

Seq2SQL [ZXS] is a deep-learning system based on a straightforward concept: similar to Seq2Seq[SVL14], it takes an input sentence or phrase, breaks it down into its components, and maps them onto a SQL query structure. Seq2SQL was one of the first deep-learning systems to employ this approach. However, later systems opted for different approaches due to the significant disadvantage of this approach: it does not consider the strict grammar rules of SQL when generating queries, making it the most error-prone. On the other hand, sequence-to-sequence architectures may have the potential to provide more accurate results but require more complex architectures to be implemented.

As part of this model, its authors released the WikiSQL dataset, which ushered in a new era of text-to-SQL deep learning research. 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.

4.2 SQLNet

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

In cases where the 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. The model also incorporates column attention (weights assigned to significant words and phrases in sentences) to improve the results. According to the flowchart below, SQLNet employs three phases to generate SQL queries for WikiSQL tasks.

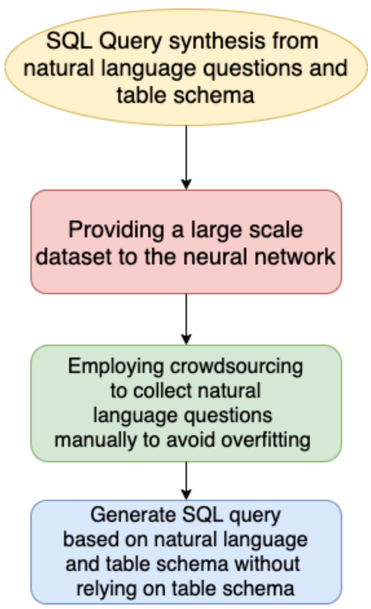


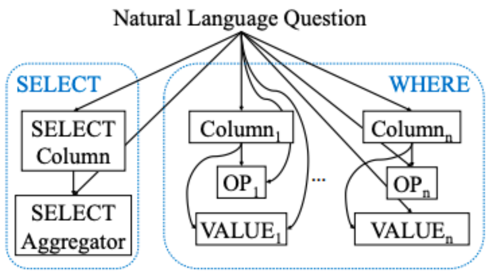
Figure 9: SQLNet

4.2.1 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.

```
SELECT $AGG $COLUMN
WHERE $COLUMN $OP $VALUE
(AND $COLUMN $OP $VALUE)*
```

(a) SQL Sketch



(b) Graphical illustration of the dependency in a sketch

Figure 10: Sketch-based query synthesis

Column attention for sequence-to-set prediction

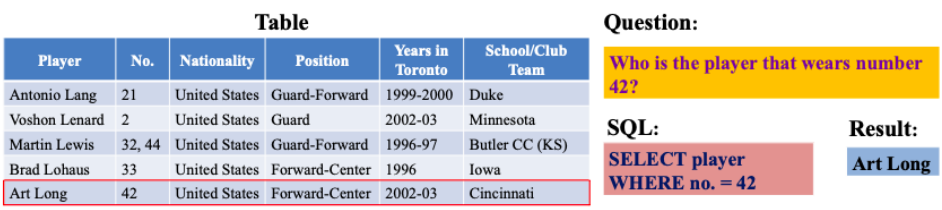
Instead of producing a sequence of column names, sequence-to-set prediction predicts the names of the columns of interest. Based on column names, column attention is part of the generic attention mechanism for computing the feature attention map on a question.

Predicting WHERE and SELECT clause

One of the most challenging tasks in Text-to-SQL 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 {¡,¿,=}, 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

Player	No.	Nationality	Position	Years in Toronto	School/Club Team
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

Figure 11: An example of a query executed by SQLNet on WikiSQL

4.3 SyntaxSQLNet

The main[YYY+18] goal of developing the SyntaxSQLNet model was to generate complex SQL queries with multiple clauses and generalize them to new databases. This was achieved through the use of a syntax tree network, which is capable of addressing complex and cross-domain queries. As is evident in the chart below, the SyntaxSQLNet model is composed of several components, each with its unique function and purpose in generating complex SQL queries. The encoders are table-aware, while 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. A cross-domain data augmentation technique was employed to improve accuracy further to generate more variance during training, allowing for a greater degree of accuracy and robustness.

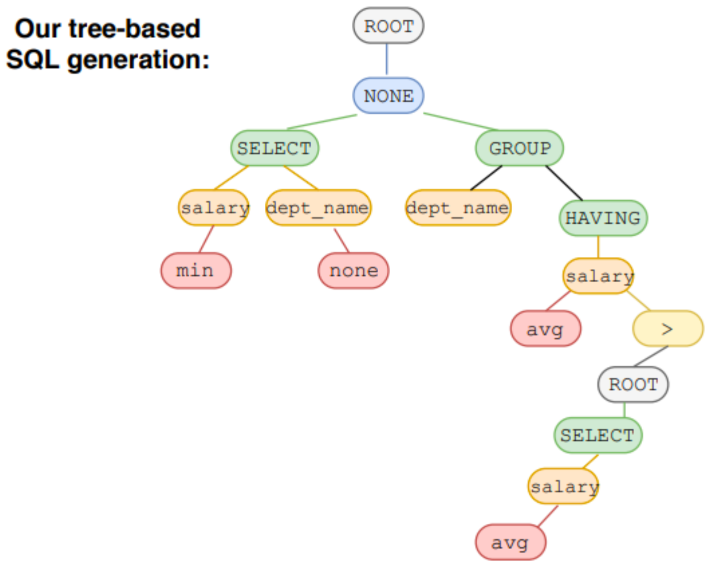


Figure 12: Tree-based SQL generator in SyntaxSQLNet

SQL Grammar and Attention Mechanism

To enable the decoder to handle complex queries, SQL grammar is employed in order to allow the decoder to make decisions at each step of recursive decoding. This allows the decoder to determine which module to invoke for the prediction of the following SQL token, taking into account the history of SQL path generation, the current SQL tokens, and the attention mechanism. The attention mechanism is used to encode the question representation, which is then applied to the SQL path history encoding. This is advantageous as it allows for a more detailed representation of the query to be created, which in turn leads to more efficient and accurate responses.

Data Augmentation

Despite SPIDER's large dataset, it lacks complex queries. To achieve proper generalization, cross-domain datasets are used for data augmentation. The SPIDER dataset is used to prepare

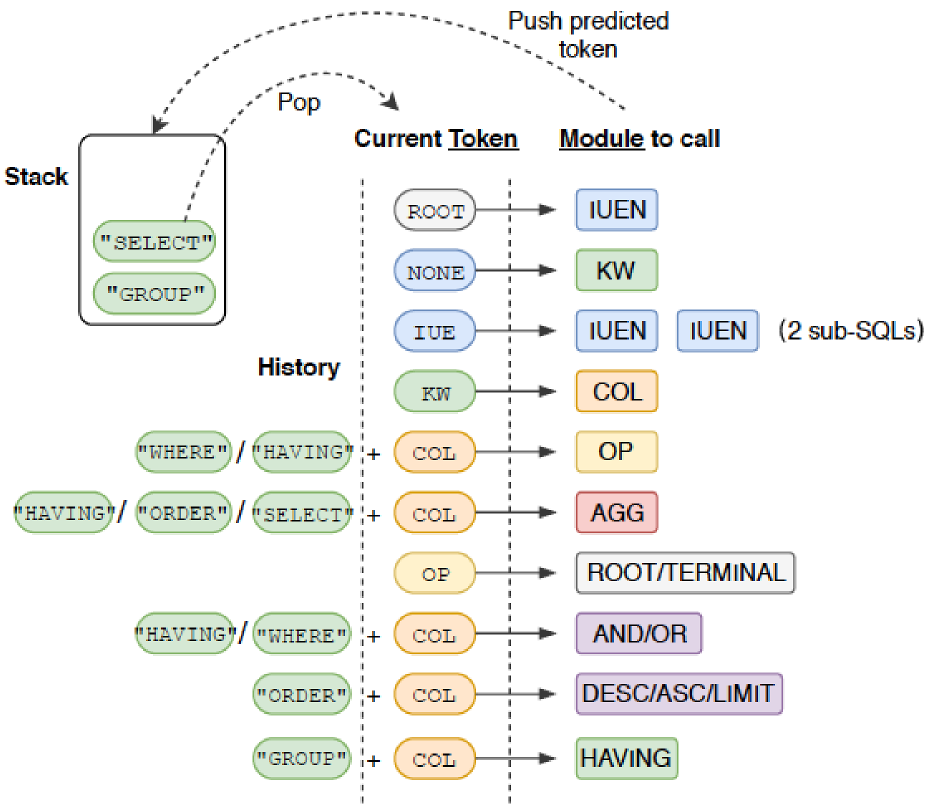


Figure 13: Modules defined in SyntaxSQLNet model[YYY+18]

a list of patterns for natural language questions and corresponding SQL queries. The SPIDER model, using syntaxSQLNet decoding history, reaches 27.2% accuracy, an increase of 12.4% compared to previous models such as SQLNet.

4.3.1 TypeSQL

TypeSQL [YLZ+18], proposed by Yu et al. (2018), is an enhanced version of SQLNet. It introduces a new training process and uses types obtained from knowledge graphs or table content to help the model better understand the entities and numbers in question. This process helps the model comprehend the semantics of the query and effectively use the context information of the database. In our experiment, we extracted question type info from database content and extended the modules to include ORDER BY and GROUP BY components. This makes TypeSQL the only model incorporating database content, providing a more complete and accurate understanding of the query. With these enhanced features, TypeSQL can better understand the query and produce more accurate results.

In contrast, SQLNet and TypeSQL that utilize SQL structure information to guide the SQL generation process significantly outperform other Seq2Seq models. While they can produce valid queries, however, they are unable to generate nested queries or queries with keywords such as EXCEPT and INTERSECT because they limit possible SQL outputs in some fixed pre-defined SQL structures.

4.4 IRNet

In Text-to-SQL tasks, the Intermediate Representation Network (IRNet)[GZG+19] 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 (NL encoder, a schema encoder and a decoder). 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.

SemQL(Semantic Query Language)[LB99] is a query language designed explicitly for text-to-SQL tasks. It is a simplified version of SQL that is more human-readable and intuitive, making it easier for a model to generate SQL queries from natural language input. SemQL can be adapted to operate with various databases, letting users query whatever data source they need. This makes SemQL a flawless language for data-driven applications and analytics.

```
select * from Restaurants
where
    ServedCuisine.Name='Sushi'
and Location.City = 'New York'
and any PersonsThatLiked have (
    any Person.Friends have (
        Friend.Name = 'Philip'
    )
)
```

Figure 14: SemQL query example[20118]

The IRNet model provides different functions to accomplish Text-to-SQL 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 context-free grammar, the decoder synthesizes SemQL queries.

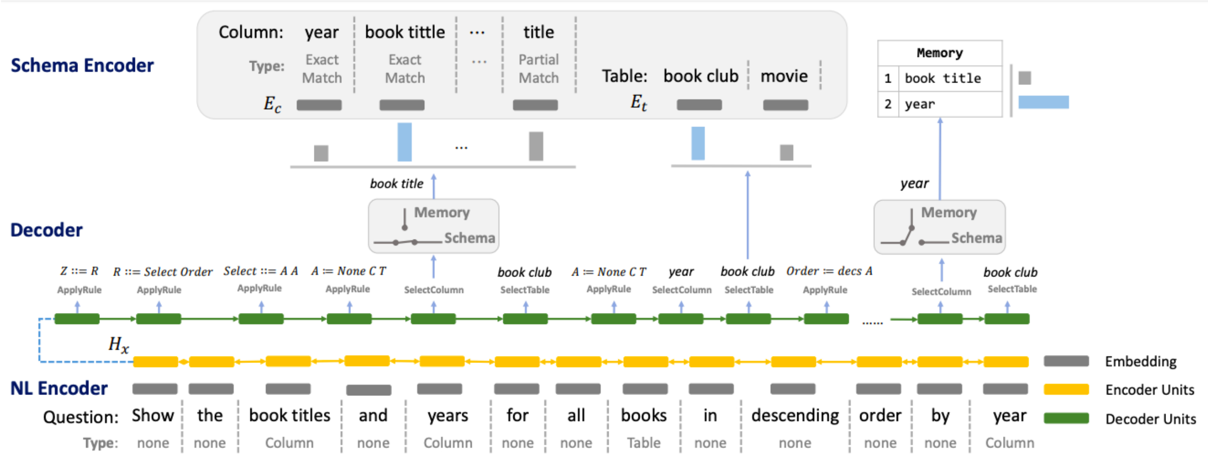


Figure 15: An overview of the neural model to synthesize SemQL queries[GZG+19]

They leverage BERT (Devlin et al., 2018) to encode questions, database schemas, and schema-linking results. The decoder stays the same. Notably, the sequence of spans in the question is concatenated with all the different column names in the schema. Each column name is divided with a unique token [SEP]. BERT takes the concatenation as input.

On the SPIDER dataset, IRNet performs 46.7% better than previous benchmark models by 19%. The accuracy of 54.7% is achieved fine-tuneing BERT for IRNet.

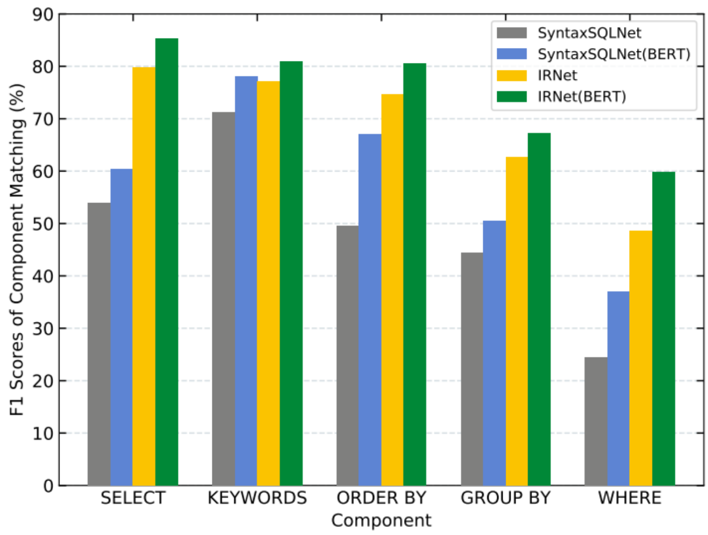


Figure 16: F1 scores of component matching of SyntaxSQLNet and IRNet on the test set from [GZG+19]

4.5 EditSQL

EditSQL[ZYE+19] focuses on text-to-SQL tasks that are context-dependent across domains. 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.

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.

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.

The SPIDER dataset was used to evaluate the model, which outperformed the previous state-of-the-art model, such as IRNet. The model achieved a 32.9% accuracy, and by using BERT embedding, a 57.9% improvement in accuracy was achieved.

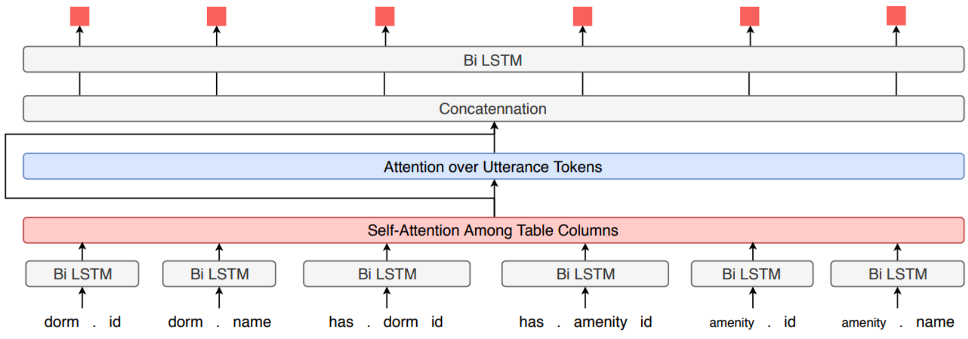


Figure 17: The model architecture of EditSQL [ZYE+19]

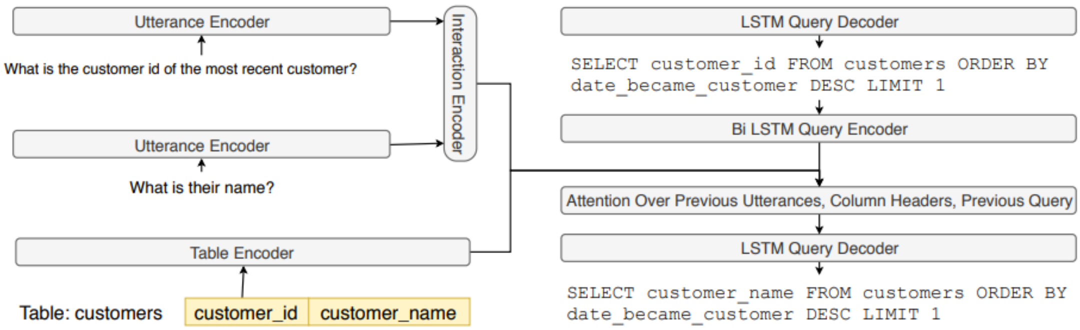


Figure 18: An example of user utterance and column headers and Utterance Encoder [ZYE+19]

4.6 RAT-SQL

RAT-SQL, or Relation-Aware Schema Encoding and Linking[WSL+], is a method used in text-to-SQL parsers to improve the accuracy of SQL generation. A significant issue in transforming natural language queries into SQL queries is generalizing them to unfamiliar database schemas. As part of the generalization process, it is crucial to represent database relations comprehensibly and to model the alignment between pertinent database columns in the query. Within a Text-to-SQL encoder, the proposed framework employs a relation-aware self-attention mechanism to encode schemas, illustrate features, and connect schemas.

On the SPIDER dataset, RAT-SQL achieved a 57.2% accuracy score, which is 8.7% higher than the accuracy of prior benchmark models. Combining BERT with RAT-SQL further increased the accuracy to 65.6%.

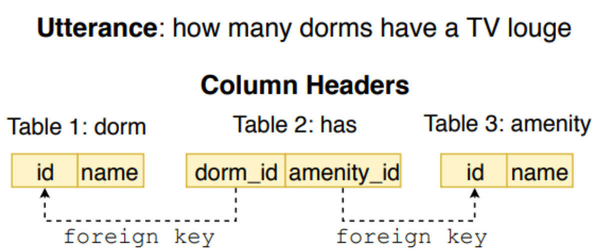


Figure 19: Table Encoder [ZYE+19]

4.7 T5 + PICARD

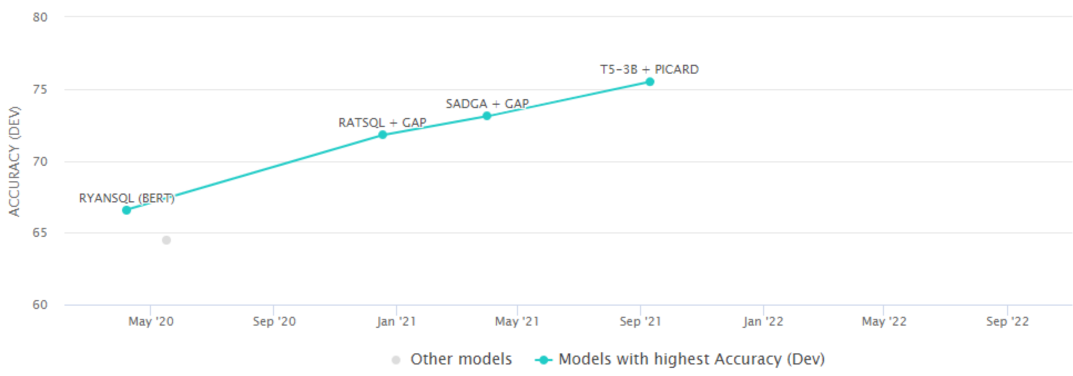


Figure 20: SPIDER Benchmark until 2022

After the release of Google T5, researchers have been using it to improve the accuracy of text-to-SQL models instead of BERT. New solutions have been released, such as the PICARD with T5-3B model, that significantly improved the SPIDER challenge's accuracy and are motivating researchers to use T5 in their work with innovative approaches since 2021.

4.7.1 T5

In Transfer Learning, we start by training our model in an unsupervised fashion on unlabeled data. Then fine-tuning it on a labeled dataset some tasks that we care about, which we call the downstream tasks. For instance, in our unsupervised free training task, we take some text, drop out some of the words, and train the model to predict the missing words. Next, we will fine-tune it on a supervised task like sentiment analysis classifying movie reviews as a given label. This way of training has become an incredible recipe for natural language processing.

T5 Model implemented by Raffel et al. (2020)[RSR+19] uses the BERT encoder-decoder architecture proposed by Vaswani et al. (2017) [DCLT19] and they showed in their studies that it will outperform decoder-only language models. Originally T5 was introduced with five pre-trained models — Small (60 million parameters), Base(220 million parameters), Large(770 million parameters), 3B(3 billion parameters), and 11B(11 billion parameters)[RSR+19].

Model	Parameters	# layers	d_{ff}
Small	60M	6	2048
Base	220M	12	3072
Large	770M	24	4096
3B	3B	24	16384
11B	11B	24	65536

Figure 21: T5 models with their Nr. of parameters, layer and feed-forward parameters[RSR+19]

To pre-train the T5 model, we start with clean text and drop some words to corrupt the text. Each dropped-out span will be replaced with a unique sentinel token, so if multiple words in a row get dropped out, they will be replaced with a single token. The words are dropped out independently uniformly at random so for an inviting get replaced by a single Sentinel token. Then the model is trained to output Sentinel tokens to delineate the dropped-out text corresponding to the text that was dropped out in the input and then each span of dropped-out text.

This method is pretty similar to the span BERT objective. It tried to come up with an objective that was not too different from standard practice.

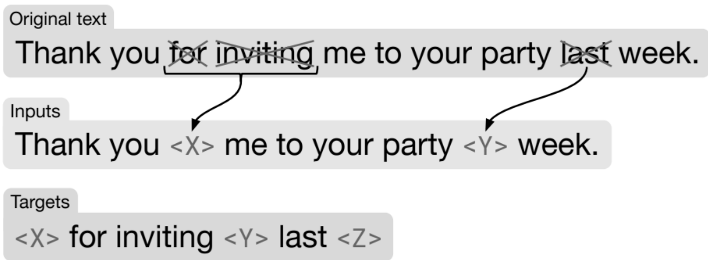


Figure 22: Pre-training by Replace Corrupted Spans [RSR+19]

Google T5's basic idea is that it models every NLP problem and every text problem as a text-to-text task that takes the text as input and produces text as output.

So fundamentally, it is in a sequence-to-sequence framework; hence, T5 is perfectly suitable for transfer learning machine translation. T5 can handle various tasks, and it can be fine-tuned for different NLP tasks, such as summarization, COLA (Corpus on linguistic acceptability), classification, multiple text translation, also regression problems like STSB that predict how similar two sentences are. And in our case Text-to-SQL.

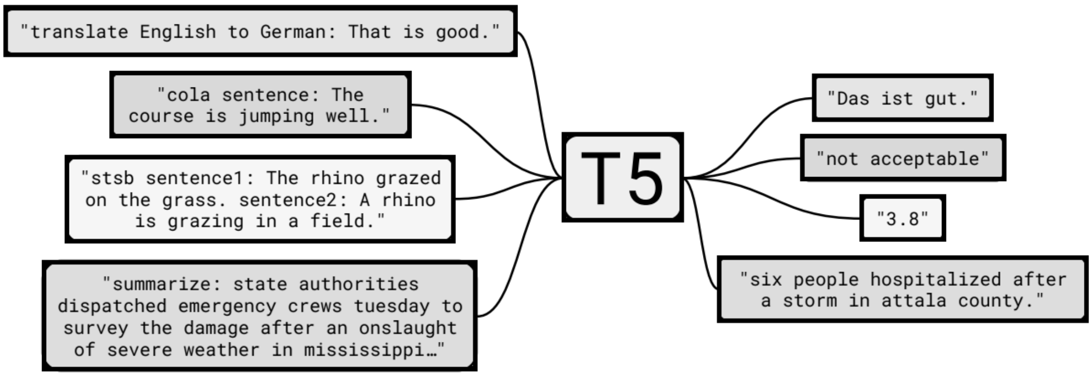


Figure 23: Each task uses text as input in the model and generates target text. In this way, the same model, loss function, and hyper-parameters are used across various diverse tasks, including translation. [RSR+19]

Further, because the same model is used for many tasks, the model understands which tasks to perform by prepending a prefix that will also be text. Therefore, By the end of fine-tuning, T5 will have "n" different models where "n" is the number of tasks. It starts with the same base pre-trained model, and then it is fine-tuned on task A, and then separately, on task B and task C. In our work, we are essentially adding another task to the T5 to handle SQL translation.

C4 (Colossal Clean Crawled Corpus)

The T5 model is pre-trained on C4 Dataset[RSR+19], so its results are quite realistic. The C4 is an unlabeled dataset gathered and filtered from Common Crawl Dataset, a non-commercial crawler that saves snapshots of the web every month. And web content is dumped out on the order of 20 terabytes.

The cleaning process included deduplication, discarding incomplete sentences, and removing offensive or noisy content. The filtering led to more reliable results on downstream tasks, and the added size let the model size grow without over-fitting when pre-training. C4 is about 750 gigabytes of clean-ish data and is accessible in Tensorflow Datasets Library.

Beam Search

Before understanding the PICARD, let us first understand the concept of Beam Search:

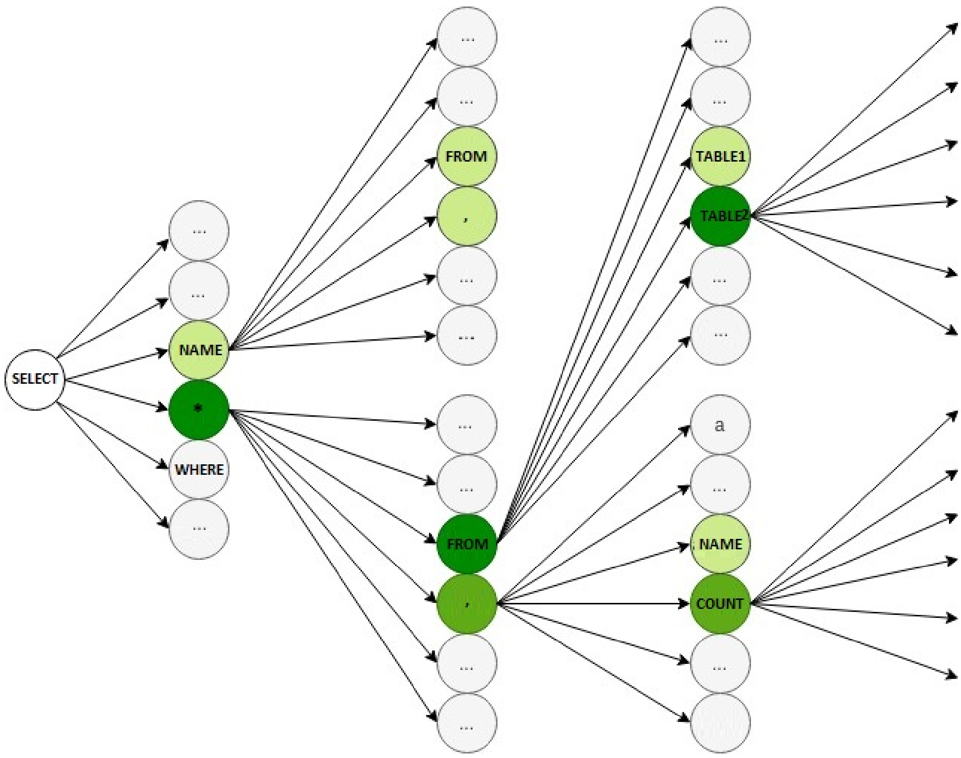


Figure 24: Beam Search

Beam search is a widely used search algorithm in natural language processing and machine learning. It is beneficial in sequence-to-sequence (seq2seq) models, which generate output sequences based on input sequences. Beam search is used to find the most likely sequence of output words given an input sequence.
The basic idea behind beam search is to maintain a set of the most likely sequences at each step of the decoding process. This set of sequences, called the "beam," is initially set to the starting point of the decoding process, and at each step, new sequences are generated by considering all the following possible words. The new sequences are then ranked based on their likelihood, and the highest-ranking sequences are added to the beam. The process is repeated until a stopping

criterion is met [MLGftADNI19]. Beam search is handy in seq2seq models because it allows the model to generate multiple output sequences rather than just a single sequence. This is important because, in many cases, there may be multiple valid outputs for a given input sequence. By generating multiple outputs, beam search allows the model to explore the space of possible outputs and find the most likely sequences.
One of the critical advantages of beam search is that it is computationally efficient. Because it only considers a small number of sequences at each step, it can quickly find the most likely sequences without exploring the entire space of possible outputs. This makes it well-suited for use in applications with limited computational resources, such as on mobile devices or in real-time systems. Another advantage of beam search is that it can be used with other techniques, such as attention mechanisms, to improve the performance of seq2seq models. Attention mechanisms allow the model to focus on specific parts of the input sequence when generating the output, which can help to improve the quality of the generated sequences.
In conclusion, Beam Search is a robust algorithm widely used in natural language processing and machine learning, particularly in the context of sequence-to-sequence (seq2seq) models. It allows the model to generate multiple output sequences rather than just a single sequence and is computationally efficient, making it well-suited for use in applications where computational resources are limited. Additionally, it can be combined with other techniques, such as attention mechanisms, to improve the performance of seq2seq models.

4.7.2 PICARD

PICARD[SSB21], short for "Parsing Incrementally for Constrained Auto-Regressive Decoding," is a method that can be used in conjunction with any language model decoder or vocabulary that utilizes auto-regressive language modeling.

PICARD is a technique that utilizes standard beam search, commonly used in natural language processing, to generate executable code by ensuring the output of the language model is both syntactically and semantically correct. It works by expanding a beam of hypotheses step by step and discarding any tokens that are not valid at each decoding step. This method can be applied to any language model that generates a sequence of tokens, including character, subword, and word-level models, without requiring unique recovery methods.

It effectively improves the performance of existing models and achieves state-of-the-art performance on tasks such as text-to-SQL translation. Warps model prediction scores and integrates trivially with existing greedy and beam search algorithms used in auto-regressive decoding from language models.

At each generation step, Picard first restricts prediction to the top-k highest probability tokens and then assigns a score of negative infinity to those that fail Picard's numerous checks.

PICARD has four modes that control the level of comprehensiveness of its checking process: off, lexing, parsing without guards, and parsing with guards, with the latter being the most comprehensive. In lexing mode, PICARD checks if the current token is a valid keyword or identifier. In parsing guard mode, it checks if the current token is a valid keyword or identifier, a valid SQL keyword, and a valid SQL identifier.

Picard can detect spelling errors in keywords or reject table and column names that are invalid for the given SQL schema. "Out-of-distribution compositional generalization and natural language variation" refers to the ability of a natural language processing (NLP) system to handle novel combinations of words and phrases that it has not seen before while also being able to handle variations in language usage. Compositional generalization refers to the ability of an NLP system to understand and generate novel combinations of words and phrases by using its knowledge of the meanings and relationships of individual words and phrases. This is an essential aspect of NLP because it allows the system to understand and generate language flexibly and adaptively.

The concept of natural language variation refers to the multiple ways people can express the same ideas or concepts using natural language. This can include variations in dialect, style, or tone, which can make it difficult for NLP systems to understand and generate language accurately.

Together, out-of-distribution compositional generalization and natural language variation represent fundamental challenges in the field of NLP. They require NLP systems to handle a wide range of language input and output in order to be effective.

PICARD can be applied as an optional feature during inference but is not necessarily included in pre-training or fine-tuning, and for text-to-SQL translation, it works directly on the output of the language model. PICARD has been shown to have state-of-the-art performance on complex Spider text-to-SQL translation tasks, achieving an accuracy of 75.1%.

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.

Motivated by the success of Shaw et al. (2021)[SCPT21], who demonstrated that a pre-trained T5-Base or T5-3B model could effectively learn the text-to-SQL task, generalize to never-before-seen databases, and even rival the state-of-the-art methods of Choi et al. (2021)[CSKS21] without any modifications to the model itself, the researchers opted to use T5 as the baseline for all their experiments. The results from Shaw et al. (2021)[SCPT21] suggest that T5-based models had the potential to improve the field of natural language processing significantly. Therefore, the researchers sought to take advantage of the capabilities of T5 in order to gain new insights into how natural language can be effectively utilized to solve complex tasks.

5 Evaluation Metrics

The F1 score is a metric used to evaluate the performance of many machine learning tasks. It is computed as the harmonic mean of precision and recall, where precision is the ratio of true positive (TP) predictions to the total positive predictions, and recall is the ratio of true positive predictions to the total actual positive values. The F1 score is between 0 and 1, with higher values representing better performance. Precision indicates the accuracy of the classifier's prediction of the positive class. It is calculated by taking the number of correct positive predictions (True Positive) and dividing it by the total number of positive predictions (True Positive and False Positive). A higher precision value means that the classifier is less likely to identify a negative instance as a positive incorrectly. Recall measures the classifier's ability to identify all positive instances. It is determined by dividing the number of True Positive predictions by the total number of positive predictions (True Positive and False Negative). A higher recall value indicates that the classifier is less likely to miss a positive instance.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F1 = \frac{2 * (Precision * Recall)}{Precision + Recall} \tag{3}$$

Text-to-SQL tasks are usually evaluated by multiple methods such as Component Matching, Accurate matching rate and Execution accuracy rate. Predicted SQL statements are compared with standard statements to determine how accurate the match is. By splitting the predicted SQL statement and definitive statement into multiple clauses according to keywords, we can solve the problem of matching errors caused by the order of the where clause. The matching is successful as long as the elements in both sets are the same.

$$Accuracy = \frac{Successful\ matching\ of\ predicted\ SQL\ statements}{totalnumber\ of\ questions} \tag{4}$$

When using the correct predicted SQL statements, the correct execution rate refers to the proportion of questions that can receive the correct answers from the database.

5.1 Exact Matching

Exact Matching[XLS], a popular metric for assessing the effectiveness of Text-to-SQL models, has drawbacks because it can yield erroneous negative results when the semantic parser can produce innovative syntactic structures. The predicted SQL query is compared against the corresponding reference SQL query. The model is considered to have produced the proper SQL query and is given a score of 1.0 if the predicted query is an exact duplicate of the reference query. The model is deemed to have generated an invalid query and obtains a score of 0.0 if the predicted query does not match the reference query. This metric aids in evaluating the overall syntactic and semantic accuracy of the generated query, but it ignores the query's constituent parts. This measure is a reliable evaluation technique because it verifies the entire SQL query. It is, therefore, a more stringent evaluation metric because it only deems a query correct if it exactly matches the reference question, down to the capitalization, spacing, and word order.

5.2 Exact Set Matching

Exact Set Matching compares the set of predicted SQL queries with the set of corresponding reference SQL queries, regardless of the elements' order, to assess the performance of a model. If every element from the set of predicted queries is included in the reference query, it returns a score of 1.0; otherwise, it returns a score of 0.0.

Generally, Exact Set Matching is more forgiving than Exact Matching, as the former does not take the order of elements or capitalization into account. On the other hand, Exact Matching is more stringent as it requires a perfect match including the order of words, capitalization and spaces, thus making it a reliable evaluation method.

5.3 Component Matching

Component matching[YZY+18] involves comparing the elements of the generated SQL query (e.g., the specified columns and tables) to the elements of the reference SQL query. Evaluation is based on the number of components that match correctly between the produced and reference queries, with a higher amount indicating improved performance. This metric assists in measuring the precision of the model's capability to create the correct SQL query components, but it does not factor in the full syntactic or semantic correctness of the query. Furthermore, it is utilized to assess the performance of various models on the same dataset.

5.4 Execution Accuracy

The execution accuracy metric[YZY+18] is a commonly used measure to evaluate the performance of text-to-SQL models. It determines the percentage of correctly generated SQL queries that can be successfully executed on the relevant database. In other words, it evaluates how well a model can convert text written in natural language into a SQL query that can successfully access the desired data from a database.

Execution accuracy is typically reported as a percentage, and higher values denote better performance. It is also important to remember that this metric only considers how correctly the generated SQL queries are syntactically and semantically and ignores how relevant or comprehensive the information is that is returned. Consequently, it is frequently combined with other metrics, such as informativeness, which assesses the accuracy and completeness of the retrieved data.

6 Experiments

Since SEOSS Dataset[RM19] was only evaluated and trained with SQLNet and RatSQL in this section, we decided to investigate further by experimenting with this dataset using state-of-the-art solutions currently proposed for the SPIDER challenge. In order to determine the effectiveness of these methods, we compared the results obtained with those of SQLNet4.2 and RatSQL4.6 from the SEOSS-Queries research paper[THM22]. The results of these experiments are presented in the following section, and they will demonstrate the potential of modern solutions for solving the SPIDER task.

6.1 Limitations

Our experiment requires a lot of computational resources as we mainly leverage the T5 model. We used a single Nvidia RTX 3070 16GB GPU with 40GB Memory for our experiment, which unfortunately limited us to smaller models with more restrictions. Despite these limitations, we were still able to achieve excellent results. If we had used a larger T5 model, such as T5-3B, we would have been able to reach much higher scores. Therefore, investing in a more powerful GPU for our experiment is something that we must consider in order to maximize our results.

6.2 SEOSS + T5 PICARD Experiment

After studying the SEOSS dataset, we decided to experiment with the PICARD model4.7 to evaluate its performance against that of SQLNet and RatSQL. We decided to use the T5Base model for our experiment, as it is smaller than the T5-3B and T5-11B models used by most state-of-the-art studies. To ensure a fair comparison between the models, we used two beam sizes of 2 and 4 and the same evaluation metrics as SEOSS-SQLNet and SEOSS-RatSQL, which is ”exact matching accuracy”. We wanted to see if the PICARD model could achieve similar results to those of SQLNet and RatSQL, so we conducted our experiment with our findings. The results of our experiment are discussed in the following section and can be used to compare the performance of the PICARD model to the models used in the SEOSS study. [1]

Model	Picard Mode	Beams	**Exact Matching Accuracy**	**Execution Accuracy**
T5-base	parse with guards	2	0.3297	0.3576
T5-base	lex	4	0.3071	0.3039
T5-base	parse with guards	4	0.3286	0.3512
T5-large	parse with guards	4	0.4274	0.4822

Table 2: Expermiment Accuracy Results

The table shows the results of various configurations of T5-base and T5-large models for natural language processing tasks. The configurations are differentiated by the Picard mode parse with guards or lex and the number of beams used in the beam search process 2 or 4.

Comparing the results, we can observe that:

[1] Link to the Github Page: https://github.com/yazdipour/text-to-sql-seoss-t5

- The T5-large model generally performs better than the T5-base model in both exact matching accuracy and execution accuracy.
- The parse with guards Picard mode performs better than the lex Picard mode in both models.
- Using four beams instead of 2 in the beam search process improves the performance for both models and Picard modes.
- The highest exact matching accuracy is achieved by the T5-large model with parse with guards Picard mode and four beams 0.4274.
- The highest execution accuracy is also achieved by the T5-large model with parse with guards Picard mode and four beams 0.4822.
- Increasing beam size does not have a significant effect compared to changing the model and mode.

Exact Match Accuracy	easy 392	medium 378	hard 77	extra hard 84	all 931
SQLNet	0.023	0.000	0.000	0.000	0.010
RatSQL + Glove	0.309	0.214	0.091	0.000	0.224
RatSQL + Bert	0.161	0.201	0.065	0.012	0.156
PICARD + T5Base + 4Beam	0.446	0.254	0.182	0.012	0.307
PICARD + T5Large + 4Beam	0.571	0.410	0.182	0.060	0.427

Table 3: Comparison between Exact Match Accuracy

The table compares the exact match accuracy of various models that are not fine-tuned for our dataset. The models are evaluated on five difficulty levels: easy, medium, hard, extra hard, and all.

Comparing the results, we can observe that:

- The PICARD + T5Large + 4Beam model has the highest exact match accuracy among all models and difficulty levels, with a maximum value of 0.571; this shows that this model is more generalized and can handle unseen databases quite well compared to other solutions.
- The PICARD + T5Base + 4Beam model performs better than the other models, with a maximum value of 0.446.
- The RatSQL models with Glove and Bert embeddings perform similarly, with a maximum value of 0.309 and 0.201, respectively.
- The SQLNet model performs the worst among all models, with a maximum value of 0.023.
- The extra hard and all difficulty levels generally have lower exact match accuracy values compared to the easy and medium levels. Amazingly T5 PICARD was still able to solve complex problems with a low percentage, yet better than the other models.

- Research in[THM22] shows that the trained RatSQL were able to achieve a high exact match accuracy. This is a good sign that the PICARD model can achieve high accuracy with a little fine-tuning.

6.3 Recall and F1 Scores

Here, we can observe the Recall and F1 scores of each SQL Keyword for the PICARD T5-Large 4-Beam experiment on the SEOSS dataset. We can see that PICARD has managed to attain a very impressive F1 score for the SEOSS dataset without even having to be specifically trained for our dataset. This is a very encouraging result and indicates that the model is able to generalize accurately across different domains. Moreover, it is essential to note that the F1 score obtained by the PICARD model was obtained without any additional fine-tuning. This is a testament to the robustness and capability of the model and further highlights its ability to generalize to different datasets.

We experimented with a variety of different parameters, including beam size, modes and model sizes, and spent multiple hours for each evaluation. These experiments have been carefully documented in the Appendix8 of this thesis, where you can find the results in detail.

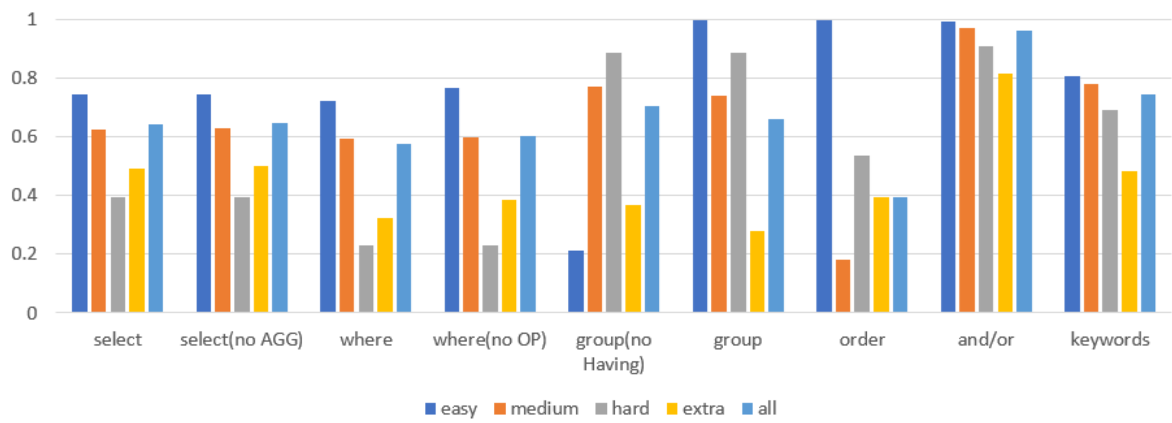


Figure 25: F1 Scores of Component Matching - PICARD T5-Large 4-Beam

6.4 EZ-PICARD - Microservices Practices

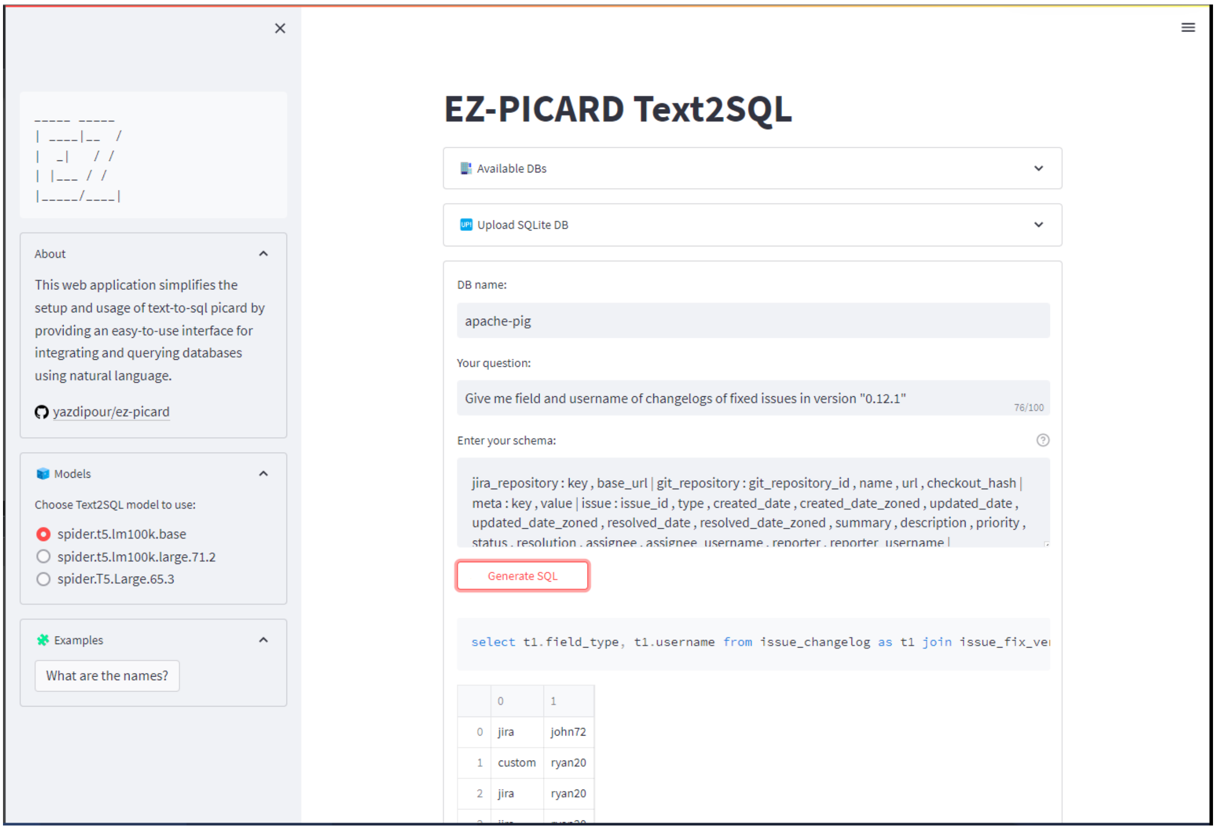


Figure 26: EZ-PICARD Web Application

For software engineering practices and to make PICARD setup easier for engineers, researchers, and users, a microservice web service with a web application has been created and open-sourced to the community[1]. This application consists of a web user interface that gives users the ability to upload their databases and enter their natural language questions and receive queries from our model with values from the database if available. Additionally, a REST API exists for further expansion and usage within the application, providing users with a more versatile and powerful tool for their needs. This web service and application is designed to make the usage of PICARD easier and more accessible for everyone and to allow for the development of new applications and services that utilize its powerful capabilities.

PICARD is a method for constrained inference on top of an existing model, but it is not a model itself. Currently, the PICARD parser and the supporting software are not supported for PostgreSQL, MySQL and others, which would require changes to the PICARD parser, translation of Spider databases and text-to-SQL data, and retraining models to produce MSSQL code. To use the Picard Method, a complex toolchain of Haskell code is built with CABAL and requires a complicated toolchain for the Facebook Thrift library.

The thrift library is used for communication between the parser and the beam search algorithm. The parser, written in the efficient and powerful Haskell programming language, is

[1]Link to the Github Page: https://github.com/yazdipour/ez-picard/

used in combination with the hf transformers, which is a Python package. To further expand the scope of the system, new SQL engines can be supported by adding a parser for each one.

These parsers also need to be written in Haskell, as the existing SQLite parser is of limited use in this regard, as it has been written to work best on Spider's subset of SQLite and only supports part of the SQLite specification. This means that more advanced parsers must be created to maximize the system's capabilities. Additionally, these parsers need to be written with a high level of precision in order to ensure that the system can effectively communicate with various engines and databases.

With EZ-PICARD, we can have an adapter layer between SQLite DB and any other database engine, such as MySQL. This layer can be implemented independently from PICARD itself using Python instead of Haskell and can provide a wide range of features, such as automatically translating queries from SQLite to the target database engine and mirroring the schema to the SQLite DB. This adapter layer can provide further advantages by allowing developers to use the same codebase to support multiple database engines, thus reducing the need for additional development and maintenance costs.

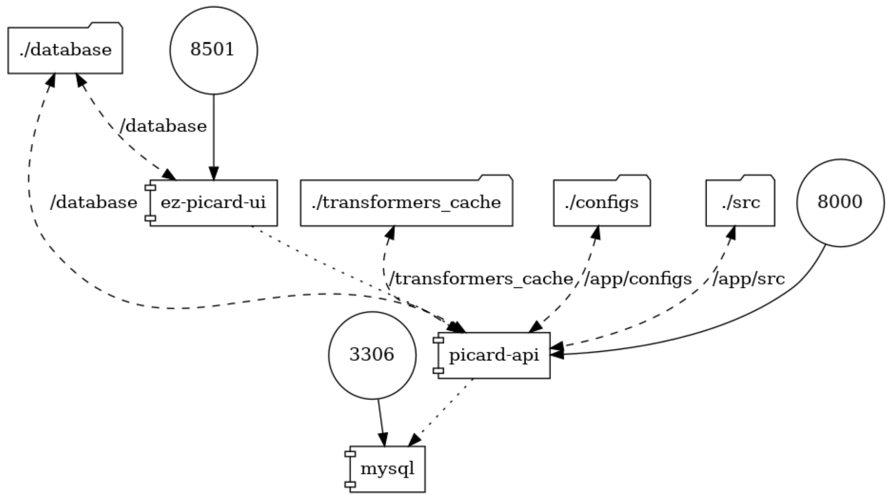


Figure 27: EZ-PICARD Architecture

7 Conclusion

In this thesis, we discussed the state-of-the-art text-to-SQL solutions from a cross-domain perspective, providing a comprehensive overview of the current progress in the field. We demonstrated the effectiveness of pre-trained embeddings in improving schema linking and SQL structure accuracy through experimental results. We hope this study will shed light on the key similarities as well as differences between older models and more recent approaches.

We also explored the impact of the dataset on the performance of the text-to-SQL models. We showed that the Spider dataset is a challenging benchmark for the text-to-SQL task. We also demonstrated the challenging SEOSS dataset and worked on some experiments on it with state-of-the-art models. Our comparison of different models for Text-to-SQL tasks shows that the PICARD + T5 model is a promising choice. However, the potential for even better results exists through fine-tuning the PICARD + T5 model. This process could lead to even more accurate results, but it would likely require access to high-end computing resources. These results demonstrate the importance of considering both model architecture and computational resources when evaluating the performance of NLP models.

Investigating new solutions and the need for more robust evaluation metrics now need to be addressed and further explored in future research. Additionally, with the growth of research in the transformer and language models field, new challenges, such as the Conversation-to-SQL task, have emerged and warrant further research directions.

In conclusion, text-to-SQL has witnessed significant progress over the past few years due to the development of cutting-edge datasets, models, and evaluation metrics. This field offers a wide variety of possibilities for ongoing research and technological advancement.

8 Appendix

- T5 base
- Mode: Lex
- maximum tokens to check: 2
- number of beams: 2

	easy	medium	hard	extra	all
select	0.873	0.624	0.469	0.500	0.717
select(no AGG)	0.873	0.642	0.469	0.500	0.724
where	0.882	0.824	0.308	0.421	0.780
where(no OP)	0.958	0.833	0.308	0.474	0.825
group(no Having)	0.238	0.841	0.969	0.778	0.789
group	0.000	0.805	0.969	0.556	0.726
order	0.000	0.409	0.469	0.400	0.431
and/or	1.000	0.929	0.896	0.598	0.927
keywords	0.885	0.867	0.672	0.455	0.829

Table 4: PARTIAL MATCHING ACCURACY

	easy	medium	hard	extra	all
select	0.597	0.373	0.390	0.131	0.447
select(no AGG)	0.597	0.384	0.390	0.131	0.451
where	0.756	0.429	0.229	0.104	0.477
where(no OP)	0.821	0.434	0.229	0.117	0.504
group(no Having)	0.714	0.543	0.886	0.167	0.533
group	0.000	0.520	0.886	0.119	0.490
order	0.000	0.321	0.429	0.095	0.267
and/or	0.992	1.000	0.986	0.961	0.993
keywords	0.834	0.513	0.506	0.119	0.545

Table 5: PARTIAL MATCHING RECALL

	easy	medium	hard	extra	all
select	0.709	0.467	0.426	0.208	0.551
select(no AGG)	0.709	0.480	0.426	0.208	0.556
where	0.814	0.564	0.262	0.167	0.592
where(no OP)	0.885	0.570	0.262	0.188	0.626
group(no Having)	0.357	0.660	0.925	0.275	0.636
group	1.000	0.632	0.925	0.196	0.585
order	1.000	0.360	0.448	0.154	0.329
and/or	0.996	0.963	0.939	0.737	0.959
keywords	0.859	0.644	0.578	0.189	0.658

Table 6: PARTIAL MATCHING F1

- T5 base
- Mode: parse with guards
- maximum tokens to check: 2
- number of beams: 2

	easy	medium	hard	extra	all
select	0.873	0.624	0.469	0.500	0.717
select(no AGG)	0.873	0.642	0.469	0.500	0.724
where	0.882	0.824	0.308	0.421	0.780
where(no OP)	0.958	0.833	0.308	0.474	0.825
group(no Having)	0.238	0.841	0.969	0.778	0.789
group	0.000	0.805	0.969	0.556	0.726
order	0.000	0.409	0.469	0.400	0.431
and/or	1.000	0.929	0.896	0.598	0.927
keywords	0.885	0.867	0.672	0.455	0.829

Table 7: PARTIAL MATCHING ACCURACY

select	0.597	0.373	0.390	0.131	0.447
select(no AGG)	0.597	0.384	0.390	0.131	0.451
where	0.756	0.429	0.229	0.104	0.477
where(no OP)	0.821	0.434	0.229	0.117	0.504
group(no Having)	0.714	0.543	0.886	0.167	0.533
group	0.000	0.520	0.886	0.119	0.490
order	0.000	0.321	0.429	0.095	0.267
and/or	0.992	1.000	0.986	0.961	0.993
keywords	0.834	0.513	0.506	0.119	0.545

Table 8: PARTIAL MATCHING RECALL

	easy	medium	hard	extra	all
select	0.709	0.467	0.426	0.208	0.551
select(no AGG)	0.709	0.480	0.426	0.208	0.556
where	0.814	0.564	0.262	0.167	0.592
where(no OP)	0.885	0.570	0.262	0.188	0.626
group(no Having)	0.357	0.660	0.925	0.275	0.636
group	1.000	0.632	0.925	0.196	0.585
order	1.000	0.360	0.448	0.154	0.329
and/or	0.996	0.963	0.939	0.737	0.959
keywords	0.859	0.644	0.578	0.189	0.658

Table 9: PARTIAL MATCHING F1

- T5 base
- Mode: Lex
- maximum tokens to check: 2
- number of beams: 4

	easy	medium	hard	extra	all
select	0.858	0.623	0.483	0.571	0.713
select(no AGG)	0.858	0.643	0.483	0.571	0.721
where	0.863	0.804	0.333	0.474	0.771
where(no OP)	0.950	0.814	0.333	0.526	0.820
group(no Having)	0.192	0.842	0.968	0.750	0.759
group	0.000	0.812	0.968	0.500	0.699
order	0.000	0.391	0.484	0.444	0.431
and/or	1.000	0.921	0.870	0.602	0.921
keywords	0.836	0.833	0.673	0.476	0.797

Table 10: PARTIAL MATCHING ACCURACY

	easy	medium	hard	extra	all
select	0.538	0.341	0.377	0.143	0.409
select(no AGG)	0.538	0.352	0.377	0.143	0.414
where	0.714	0.418	0.229	0.117	0.460
where(no OP)	0.786	0.423	0.229	0.130	0.489
group(no Having)	0.714	0.486	0.857	0.143	0.486
group	0.000	0.469	0.857	0.095	0.448
order	0.000	0.321	0.429	0.095	0.267
and/or	0.995	1.000	0.971	0.980	0.994
keywords	0.789	0.462	0.481	0.119	0.505

Table 11: PARTIAL MATCHING RECALL

	easy	medium	hard	extra	all
select	0.661	0.441	0.423	0.229	0.520
select(no AGG)	0.661	0.455	0.423	0.229	0.526
where	0.782	0.550	0.271	0.188	0.576
where(no OP)	0.860	0.557	0.271	0.208	0.613
group(no Having)	0.303	0.616	0.909	0.240	0.593
group	1.000	0.594	0.909	0.160	0.546
order	1.000	0.353	0.455	0.157	0.329
and/or	0.997	0.959	0.918	0.746	0.956
keywords	0.812	0.595	0.561	0.190	0.618

Table 12: PARTIAL MATCHING F1

- T5 base
- Mode: parse with guards
- maximum tokens to check: 2
- number of beams: 4

	easy	medium	hard	extra	all
select	0.757	0.537	0.417	0.469	0.618
select(no AGG)	0.757	0.559	0.417	0.469	0.627
where	0.779	0.746	0.250	0.433	0.695
where(no OP)	0.812	0.811	0.250	0.467	0.738
group(no Having)	0.044	0.678	0.971	0.478	0.588
group	0.000	0.658	0.971	0.391	0.561
order	0.000	0.269	0.457	0.526	0.407
and/or	1.000	0.910	0.883	0.619	0.919
keywords	0.742	0.785	0.667	0.422	0.729

Table 13: PARTIAL MATCHING ACCURACY

	easy	medium	hard	extra	all
select	0.653	0.442	0.390	0.274	0.511
select(no AGG)	0.653	0.460	0.390	0.274	0.519
where	0.690	0.464	0.171	0.169	0.475
where(no OP)	0.720	0.505	0.171	0.182	0.504
group(no Having)	0.286	0.589	0.971	0.262	0.579
group	0.000	0.571	0.971	0.214	0.552
order	0.000	0.250	0.457	0.238	0.314
and/or	0.992	0.997	1.000	1.000	0.995
keywords	0.823	0.605	0.571	0.226	0.610

Table 14: PARTIAL MATCHING RECALL

	easy	medium	hard	extra	all
select	0.701	0.485	0.403	0.346	0.560
select(no AGG)	0.701	0.505	0.403	0.346	0.568
where	0.732	0.572	0.203	0.243	0.564
where(no OP)	0.763	0.623	0.203	0.262	0.599
group(no Having)	0.077	0.630	0.971	0.338	0.584
group	1.000	0.612	0.971	0.277	0.556
order	1.000	0.259	0.457	0.328	0.355
and/or	0.996	0.951	0.938	0.765	0.956
keywords	0.780	0.684	0.615	0.295	0.665

Table 15: PARTIAL MATCHING F1

- T5 large
- Mode: parse with guards
- maximum tokens to check: 2
- number of beams: 4

	easy	medium	hard	extra	all
select	0.781	0.672	0.400	0.552	0.684
select(no AGG)	0.781	0.678	0.400	0.567	0.688
where	0.739	0.689	0.269	0.396	0.642
where(no OP)	0.783	0.696	0.269	0.472	0.673
group(no Having)	0.143	0.786	0.865	0.522	0.719
group	0.000	0.756	0.865	0.391	0.675
order	0.000	0.250	0.528	0.542	0.462
and/or	1.000	0.947	0.831	0.699	0.937
keywords	0.796	0.846	0.735	0.574	0.792

Table 16: PARTIAL MATCHING ACCURACY

	easy	medium	hard	extra	all
select	0.709	0.585	0.390	0.440	0.608
select(no AGG)	0.709	0.590	0.390	0.452	0.611
where	0.708	0.520	0.200	0.273	0.523
where(no OP)	0.750	0.526	0.200	0.325	0.548
group(no Having)	0.429	0.754	0.914	0.286	0.691
group	0.000	0.726	0.914	0.214	0.649
order	0.000	0.143	0.543	0.310	0.343
and/or	0.987	0.997	1.000	0.983	0.992
keywords	0.823	0.725	0.649	0.417	0.704

Table 17: PARTIAL MATCHING RECALL

	easy	medium	hard	extra	all
select	0.743	0.625	0.395	0.490	0.644
select(no AGG)	0.743	0.631	0.395	0.503	0.647
where	0.723	0.593	0.230	0.323	0.576
where(no OP)	0.766	0.599	0.230	0.385	0.604
group(no Having)	0.214	0.770	0.889	0.369	0.705
group	1.000	0.741	0.889	0.277	0.661
order	1.000	0.182	0.535	0.394	0.393
and/or	0.994	0.971	0.908	0.817	0.964
keywords	0.809	0.781	0.690	0.483	0.746

Table 18: PARTIAL MATCHING F1

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