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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.

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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, 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.

2.1.1 Rule-based methods

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.

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. However, these rule-based methods were limited by their reliance on predefined templates and grammar rules, making them incapable of handling complex natural language inputs.

2.1.2 Template-based methods

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. 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. The system was called LUNAR and was developed by Woods et al. in 1972[**?**]. 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. The rule-based and template-based methods were two of the most common early approaches used in Text-to-SQL, each with their own strengths and limitations.

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 is necessary for tasks such as machine translation and text summarization.

2.3.3 WordPiece embeddings

WordPiece[WSC+16] is a tokenization approach used in natural language processing (NLP) to break down words into smaller units, also known as pieces. It is an extension of the original word2vec parameter learning algorithm and is used to address out-of-vocabulary (OOV) words, which are words that did not appear in the training data. This technique divides each word into a series of subword units learned during the training phase based on their frequency and consistency within words. These subword units are stored in a shared vocabulary, dubbed the WordPiece vocabulary, and can be used for multiple words. This system can represent rare or unseen words as a combination of more common subword units, which are more likely to be in the vocabulary. As a result, the model can handle OOV words more efficiently and reduce the vocabulary size, leading to a more economical representation of the language. In NLP models, words are usually portrayed as dense vectors referred to as word embeddings. WordPiece embeddings extend this representation by breaking words down into subword units and representing each piece as a dense vector. These subword embeddings are then combined to represent the whole word. The use of WordPiece embeddings has various advantages in NLP models. Firstly, it enables the model to treat OOV words more effectively by representing them as a combination of more common subword units. Secondly, it decreases the vocabulary size, resulting in a more succinct representation of the language. Finally, it enhances the model's capability to learn fine-grained representations of words and their meanings, resulting in improved performance in NLP tasks.

2.3.4 Word2Vec

Word2Vec[Ron14] is a well-known word embedding approach in NLP that encodes words as dense vectors in an unending, high-dimensional area. This technique is designed to capture the significance and context of words, providing an improved representation of words compared to classic one-hot encoding. The fundamental concept behind Word2Vec is to train a neural network to anticipate the context words about a target word, given the target word. As the model is trained, the weights of the neural network are adjusted in such a way that the dot

product of the input layer (representing the target word) and the output layer (representing the context words) closely estimate the probability distribution of the context words given the target word. Word2Vec can be trained to utilize two different algorithms: Continuous Bag-of-Words (CBOW) and Skip-gram. CBOW predicts the target word given the context words, while Skip-gram predicts the context words given the target word. The algorithm selection relies on the particular NLP task and the data available for training.

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 order 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.

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.

3.1.5 SEDE

Stack Exchange Data Explorer (SEDE)[HMB21] is from 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.

3.1.6 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].

```
Q: Return the issue ids of issues of type Bug
SQL (Easy):
SELECT issue_id FROM issue
WHERE type = 'Bug'

Q: Return the issue id, type, description of issues that have component "impl"
SQL (Medium):
SELECT T1.issue_id, T1.type, T1.description FROM issue AS T1
JOIN issue_component AS T2 ON T1.issue_id = T2.issue_id
WHERE T2.component = "impl"

Q: In which fix version were most issues fixed
SQL (Hard):
SELECT fix_version FROM issue_fix_version
GROUP BY fix_version
ORDER BY Count(*) DESC LIMIT 1

Q: Return  the maximum number of file paths of modified files which can be
associated with issue ids of issues of type 'Improvement'
SQL (Extra Hard):
SELECT Count(file_path) FROM code_change AS T1
JOIN change_set_link AS T2 ON T1.commit_hash = T2.commit_hash
JOIN issue AS T3 ON T2.issue_id = T3.issue_id WHERE T3.type = 'Improvement'
GROUP BY T3.issue_id
ORDER BY Count(file_path) DESC LIMIT 1
```

Figure 1: Examples of queries with different levels of complexity in SEOSS-Queries [THM22]

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.

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

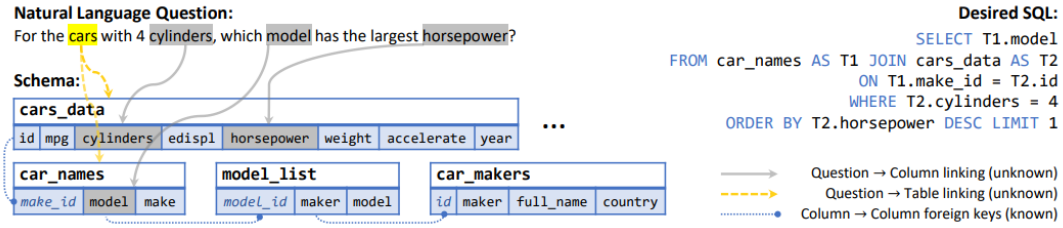

Figure 3: A difficult text-to-SQL task from the Spider dataset.[WSL+]

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.

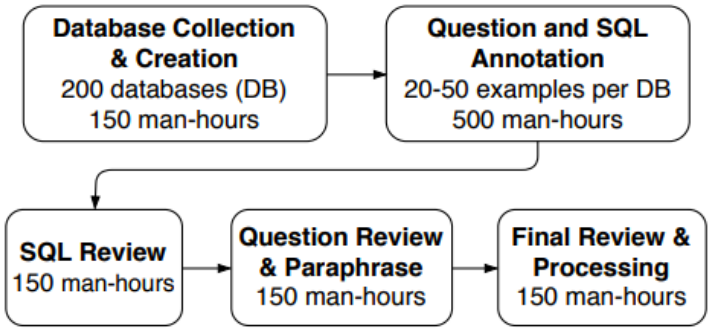

Figure 4: Process of creating SPIDER dataset[YZY+18]

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 accuracy9 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 PICARD**??**.

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 section9.

3.2.3 Multi-Lingual Large Scale Datasets

In this study, we are only focusing on English datasets. Nevertheless, Researchers have produced several large-scale text-to-SQL datasets in diverse languages, such as CSpider[MSZ19], TableQA Sun et al. [SYL20], DuSQL Wang et al. (2020c) [WZW+20] in Chinese, ViText2SQL Tuan Nguyen et al. [TNDN20] in Vietnamese, and PortugueseSpider José and Cozman in Portuguese[JC21]. Human specialists primarily annotate these datasets based on the English Spider dataset, given that human translation is more accurate than machine translation Min et al. (2019a)[MSZ19]. As such, these datasets have the potential to evolve into valuable resources in multi-lingual text-to-SQL studies.

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 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

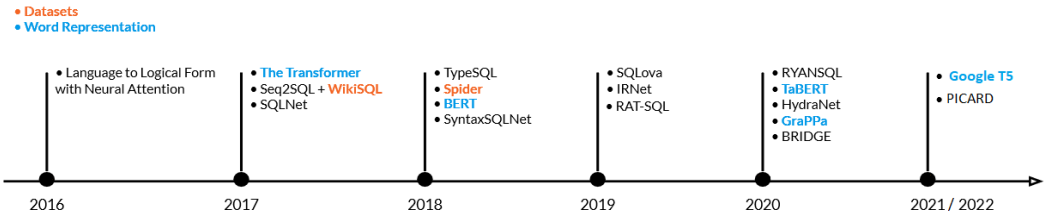

Figure 6: Timeline of the deep learning process for Text-to-SQL.

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+].

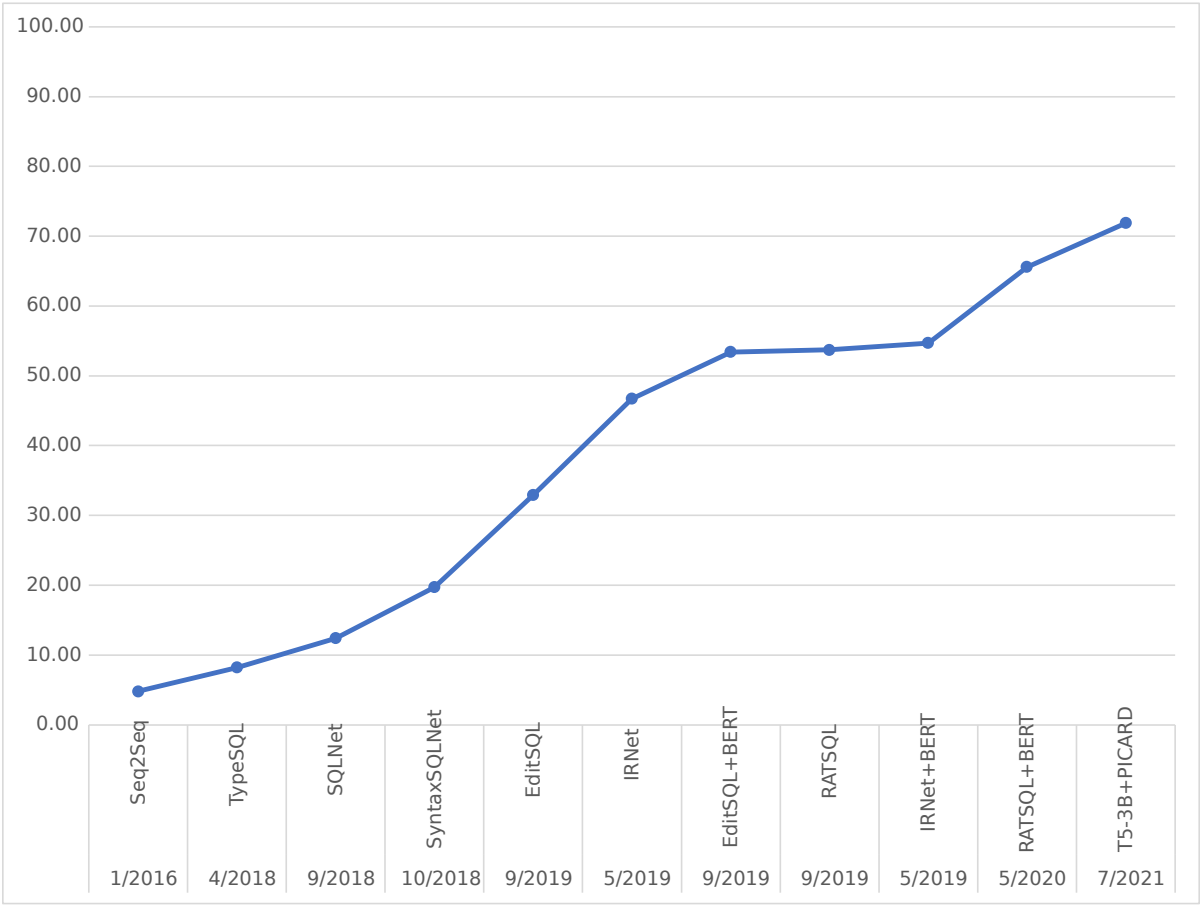

Figure 7: SPIDER benchmark Exact Match Results in 2022

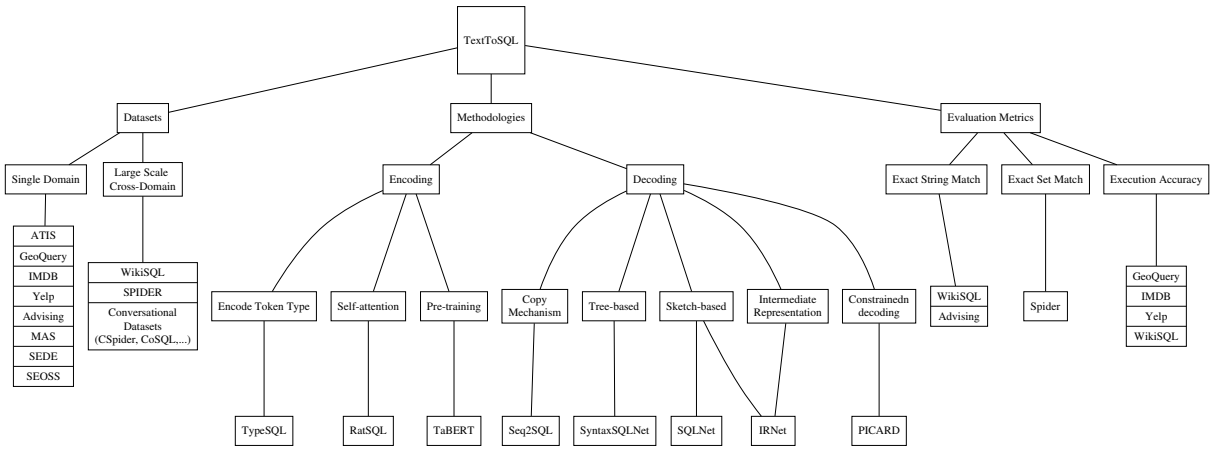

Figure 8: Text-to-SQL state-of-the-art Topology

5 Data Augmentation

Data augmentation has emerged as a valuable method to enhance the performance of text-to-SQL models by helping them tackle complex or previously unseen questions (Zhong et al., 2020b; Wang et al., 2021b), achieve state-of-the-art results with less supervised data (Guo et al., 2018), and attain robustness towards different question types (Radhakrishnan et al., 2020).

Common data augmentation strategies include paraphrasing questions and using pre-defined templates to increase data diversity. Iyer et al. (2017) utilized the Paraphrase Database (PPDB) (Ganitkevitch et al., 2013) to generate paraphrased training questions. Additionally, researchers have used neural models to create natural utterances for sampled SQL queries, thus expanding the available data. For instance, Li et al. (2020a) fine-tuned the pre-trained T5 model (Raffel et al., 2019) on WikiSQL. They used the SQL query as input to predict natural utterances and then synthesized SQL queries from WikiSQL tables to generate corresponding natural utterances with the tuned model.

The quality of augmented data is crucial, as low-quality data can negatively impact model performance (Wu et al., 2021). Various techniques have been employed to improve augmented data quality. Zhong et al. (2020b) used an utterance generator to produce natural utterances and a semantic parser to convert these utterances into SQL queries, filtering out low-quality data by retaining only instances with generated SQL queries that matched the sampled ones. Wu et al. (2021) adopted a hierarchical SQL-to-question generation process to obtain high-quality data, decomposing SQL queries into clauses, translating each clause into a sub-question, and combining the sub-questions into a complete question.

To further diversify augmented data, Guo et al. (2018) added a latent variable to their SQL-to-text model to promote question diversity. Radhakrishnan et al. (2020) improved the WikiSQL dataset by simplifying and compressing questions to mimic the colloquial query behavior of end-users. Wang et al. (2021b) used a probabilistic context-free grammar (PCFG) to explicitly model the composition of SQL queries, which fostered the sampling of compositional SQL queries. These data augmentation techniques collectively contribute to the improvement of text-to-SQL models, enabling them to better handle a wider range of questions and adapt to previously unseen data.

6 Encoders

Several approaches have been explored to address the challenges of representing the meaning of questions, capturing the structure of database schemas, and establishing connections between database content and questions in the text-to-SQL domain. These methods play a crucial role in facilitating the understanding of the complex relationships between natural language questions and their corresponding SQL queries.

One of the main challenges in text-to-SQL research is effectively representing the meaning of questions. Various encoding methods have been used to capture the semantics of natural language questions, ranging from traditional word embeddings like Word2Vec and GloVe to more advanced contextualized representations like BERT and its variants. These encoding techniques aim to produce meaningful vector representations of questions that models can use to understand and generate accurate SQL queries.

Another important aspect is representing database schemas, which serve as blueprints for organizing and structuring databases. Researchers have used various strategies to encapsulate database schema information, such as graph-based, tree-structured, and sequence-based encodings. These approaches enable text-to-SQL models to understand the hierarchical relationships and dependencies among various database elements. This allows for more accurate and efficient query generation.

Linking database content to questions is a vital task for text-to-SQL systems. It involves the identification and mapping of relevant entities and attributes from the question to the database schema. To achieve this, various methods have been employed, including attention mechanisms, entity-linking techniques, and schema-agnostic encodings. These approaches help models identify relevant portions of the database schema and generate SQL queries that accurately reflect the intended meaning of the natural language questions.

Encoding methods and encoders play a crucial role in addressing the challenges of representing question semantics, encapsulating database schema structures, and linking database content to questions in the text-to-SQL domain. The exploration of diverse encoding techniques has led to significant advancements in the development of more accurate and efficient text-to-SQL models, furthering the field's understanding of the complex relationships between natural language questions and SQL queries.

Methods	Adopted by	Applied datasets	Addressed challenges
Encode token type	TypeSQL	WikiSQL	Representing question meaning
Graph-based	GNN	Spider	Representing question and DB schemas in a structured way and Schema linking
	Global-GCN	Spider	
	IGSQL	Sparc, CoSQL	
	RAT-SQL	Spider	
	LEGSQL	Spider	
	SADGA	Spider	
	ShawdowGNN	Spider	
	S2SQL	Spider	
Self-attention	X-SQL	WikiSQL	Representing question and DB schemas in a structured way and Schema linking
	SQLova	WikiSQL	
	RAT-SQL	Spider	
	DuoRAT	Spider	
	UnifiedSKG	WikiSQL, Spider	
Adapt PLM	X-SQL	WikiSQL	Leveraging external data to represent question and DB schemas
	SQLova	WikiSQL	
	Content Enhanced	WikiSQL	
	HydraNet	WikiSQL	
Pre-training	TaBERT	Spider	Leveraging external data to represent question and DB schemas
	GraPPA	Spider	
	GAP	Spider	

Table 2: Methods used for encoding in text-to-SQL.

6.1 Encode Token Types

6.2 Graph-based Methods

6.3 Self-attention

6.4 Adapt PLM

6.5 Pre-training

6.6 Ranking-enhanced Encoder

7 Decoders

7.1 Tree-based

7.2 Sketch-based

7.3 Bottom-up

7.4 Attention Mechanism

7.5 Copy Mechanism

7.6 Intermediate Representations

7.7 Prevent Invalid Tokens

7.8 Skeleton-aware Decoder

Schema linking is a component of text-to-SQL models that helps map natural language phrases to elements of a database schema. Skeleton parsing is a component of text-to-SQL models that helps generate the structure of an SQL query based on a natural language question. It focuses on generating the pure skeleton of an SQL query (i.e., SQL keywords).

Methods	Adopted by	Applied datasets	Addressed challenges
Tree-based	Seq2Tree Seq2AST SyntaxSQLNet	- - Spider	Hierarchical decoding
Sketch-based	SQLNet IRNet RYANSQL	WikiSQL WikiSQL Spider Spider	Hierarchical decoding
Bottom-up	SmBop	Spider	Hierarchical decoding
Self-Attention	Seq2Tree Seq2SQL	- WikiSQL	Synthesizing information
Bi-attention	SmBop	Spider	Synthesizing information
Structured attention	SmBop	Spider	Synthesizing information
Relation-aware Self-attention	SmBop	Spider	Synthesizing information
Copy Mechanism	Seq2AST Seq2SQL SeqGenSQL	- WikiSQL WikiSQL WikiSQL	Synthesizing information
Intermediate Representation	IncSQL IRNet ? ? ? ?	WikiSQL WikiSQL Spider Spider GeoQuery, ATIS Spider	Bridging the gap between natural language and SQL query
Constrained decoding	UniSAr PICARD	WikiSQL, Spider Spider, CoSQL	Fine-grained decoding
Execution-guided	SQLova ?	WikiSQL WikiSQL	Fine-grained decoding
Discriminative re-ranking	Global-GCN ?	 Spider	SQL Ranking
Constrained decoding	SQLNet ? ?	WikiSQL WikiSQL Spider	Easier decoding
BPE	UniSAr	WikiSQL, Spider	Easier decoding
Link gating	SmBop	Spider	Synthesizing information

Table 3: Methods used for encoding in text-to-SQL.

8 Learning Techniques

8.1 Fully Supervised

Active learning (Ni et al., 2020) Interactive/Imitation learning (Yao et al., 2019) (Yao et al., 2020) Meta-learning (Huang et al., 2018) (Wang et al., 2021a) (Chen et al., 2021a) Multi-task learning (Chang et al., 2020) (Xuan et al., 2021) (Hui et al., 2021b) (Shi et al., 2021) (McCann et al., 2018) (Xie et al., 2022)

8.2 Weakly Supervised

Reinforcement learning (Zhong et al., 2017) (Liang et al., 2018) Meta-learning and Bayesian optimization (Agarwal et al., 2019) (Min et al., 2019b)

9 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.

Evaluation Setup

The evaluation methods for Text-to-SQL systems have advanced over time to assess different aspects of model performance and adaptability. Early datasets generally used a standard train/dev/test split to randomly divide question-SQL pairs across sets as proposed by Iyer et al. (2017), which provided a baseline for evaluation but did not specifically target model generalization capabilities.

To assess the ability of models to generalize to new SQL query structures within a given domain, Finegan-Dollak et al. (2018) introduced the SQL query split method. This method

ensures that SQL queries are only present in one set among the train, dev, and test sets, offering a better understanding of how well models can adapt to new query structures. This approach allows researchers to more accurately evaluate the robustness of their models when faced with novel SQL queries.

In addition to the SQL query split, Yu et al. (2018c) proposed a database split method, which aims to evaluate the generalization capabilities of Text-to-SQL models across different databases. By withholding databases in the test set from the training phase, this method assesses the ability of models to handle unseen databases, emphasizing the importance of real-world adaptability in Text-to-SQL systems.

Other splitting methods have also been proposed to support various research objectives. For example, Shaw et al. (2021) and Chang et al. (2020) have introduced alternative evaluation setups to address specific challenges and research questions in the Text-to-SQL domain. These methods, along with the standard train/dev/test split, SQL query split, and database split, contribute to the diverse range of evaluation strategies employed in Text-to-SQL research, enabling a more comprehensive understanding of model performance and generalization capabilities.

9.1 Naiive Execution Accuracy

Naïve Execution Accuracy (NEA) has become a popular evaluation metric for Text-to-SQL systems because it can measure the accuracy of generated SQL queries in a way that considers both syntax and meaning. Unlike other metrics that mainly focus on the syntax of the queries, NEA examines the practical impact of the queries by evaluating their execution results. Therefore, it provides a more complete view of a model's performance, allowing researchers to better understand how well their algorithms perform in real-world situations.

By applying NEA to commonly used datasets like GeoQuery, IMDB, Yelp, and WikiSQL, researchers can gain a more nuanced understanding of their models' strengths and weaknesses. For instance, GeoQuery is a dataset that contains geographical questions and corresponding SQL queries. By using NEA to evaluate this dataset, researchers can determine not only whether their model generates syntactically correct SQL queries but also whether these queries return the correct geographical data when executed.

Similarly, NEA provides valuable insight into the performance of Text-to-SQL models when generating queries related to movie and business information in the context of the IMDB and Yelp datasets, respectively. By measuring the accuracy of the execution results, NEA helps researchers identify potential improvement areas, whether in the natural language understanding component or the SQL generation process.

The WikiSQL dataset is another significant example where NEA has been used as an evaluation metric. WikiSQL is a massive dataset derived from Wikipedia's SQL-like tables and contains over 24,000 questions and corresponding SQL queries. Evaluating the performance of Text-to-SQL models on WikiSQL can be challenging due to the dataset's size and complexity. However, NEA enables researchers to assess the performance of their models more, accounting for both the syntax of the generated queries and the accuracy of the data they return when executed.

In summary, the adoption of Naïve Execution Accuracy as an evaluation metric for Text-to-SQL systems has proven to be valuable in recent studies involving datasets such as GeoQuery,

IMDB, Yelp, and WikiSQL. By evaluating the practical impact of generated SQL queries, NEA provides a more comprehensive understanding of a model's performance than traditional metrics that concentrate solely on syntax. Consequently, NEA enables researchers to identify potential improvement areas more effectively, ultimately advancing Text-to-SQL technology.

9.2 Exact String Matching

Exact Matching[XLS], a popular metric for assessing the effectiveness of Text-to-SQL models, but it 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.

9.3 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.

9.4 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.

9.5 Test Suite Accuracy (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.

10 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 SQLNet**??** and RatSQL**??** 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.

10.1 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.

10.2 SEOSS + T5 PICARD Experiment

After studying the SEOSS dataset, we decided to experiment with the PICARD model**??** 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 4: 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 5: 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.

10.3 F1 Scores

Here, we can observe the 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 Appendix13 of this thesis, where you can find the results in detail.

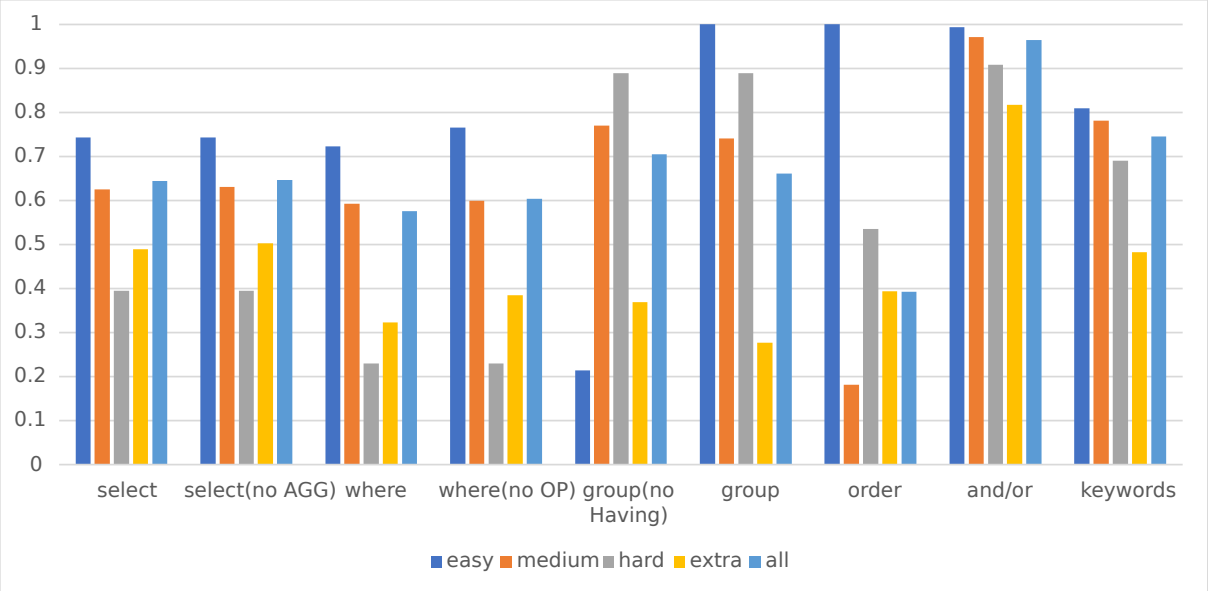

Figure 9: F1 Scores of Component Matching - PICARD T5-Large 4-Beam

10.4 EZ-PICARD - Microservices Practices

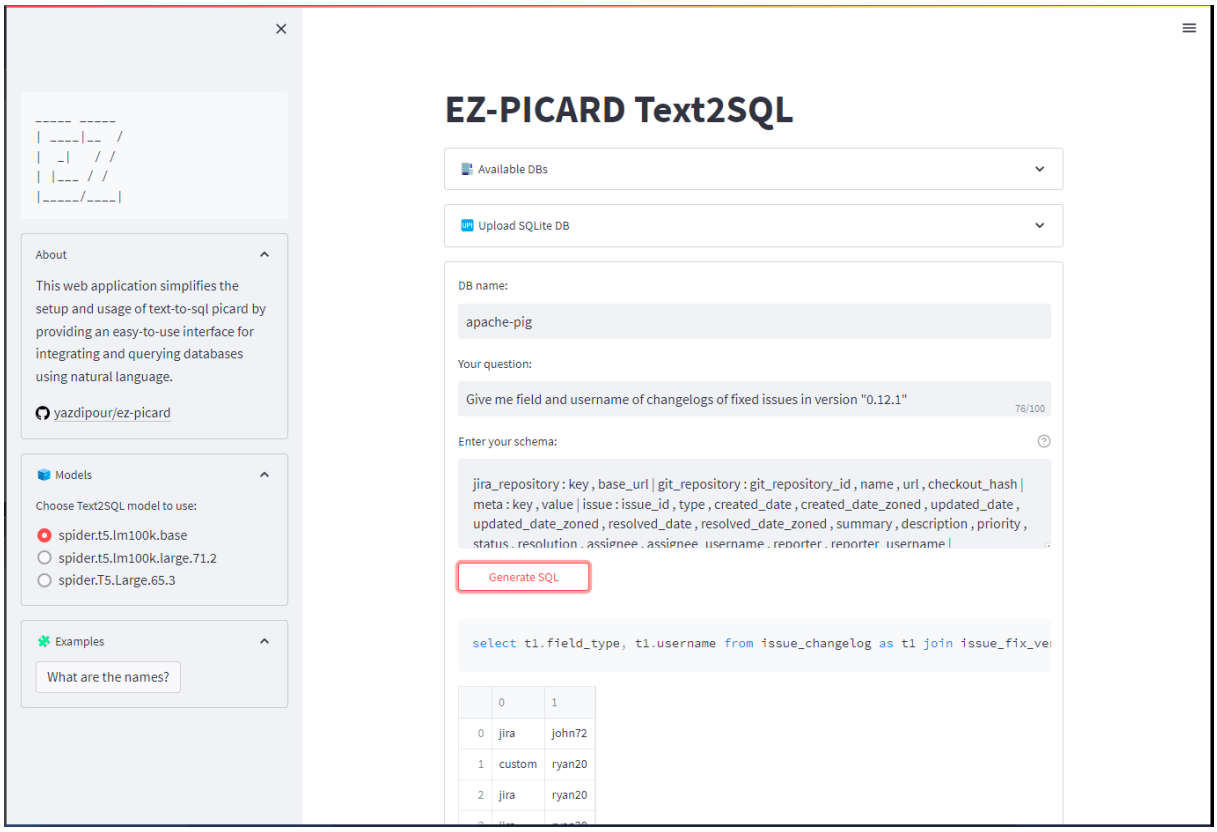

Figure 10: EZ-PICARD Web Application

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.

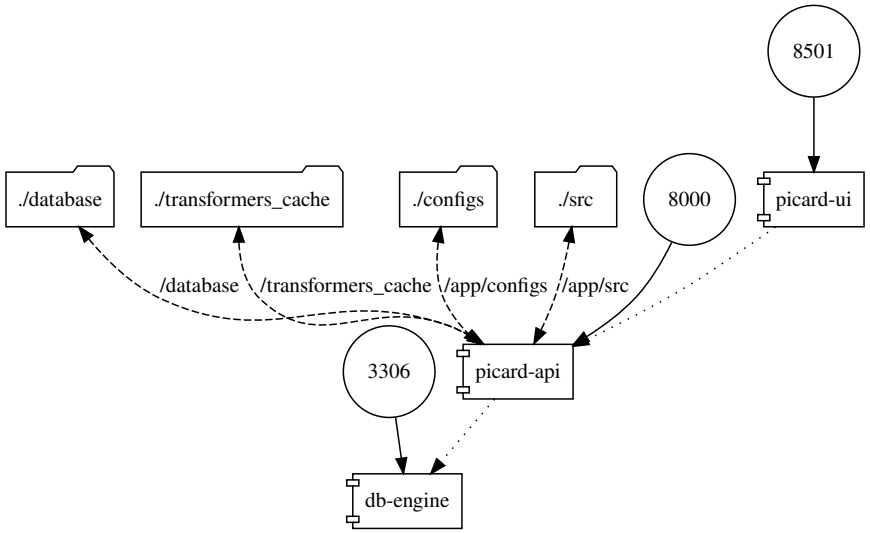

Figure 11: EZ-PICARD Architecture

11 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.

12 Discussion and Future Directions

The field of text-to-SQL is a rapidly growing area of research, with numerous systems and approaches proposed to generate SQL queries from natural language text. However, there are still several areas that require further exploration and improvement.

A promising avenue for further research is cross-domain text-to-SQL. Incorporating domain-specific knowledge into models trained on existing datasets would enable them to be more adaptable and applicable in different domains. Furthermore, this would facilitate their capacity to handle scenarios where the tables are corrupted or unavailable. In addition, advanced handling of user inputs that are different from the existing datasets and providing database administrators with the ability to manage database schemas and update content are key real-world applications of text-to-SQL. Additionally, multilingual text-to-SQL and creating a database interface for the disabled are noteworthy directions for future research.

Incorporating Text-to-SQL into a broader range of research areas, such as constructing a question-answering system for databases or a dialog system with knowledge from databases, could promote progress in the field. Investigating the interconnection between SQL and other logical forms, as well as generalized semantic parsing, would yield a more comprehensive comprehension of the topic and facilitate the development of more adjustable and generalizable systems.

Regarding more focused strategies, prompt learning could be utilized to improve the robustness of text-to-SQL, and existing text-to-SQL systems could be evaluated and compared to identify their advantages and disadvantages.

In sum, the domain of text-to-SQL has much potential for growth and progress, with numerous significant realistic applications and prospects for integration with related fields.

13 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 6: 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 7: 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 8: 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 9: 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 10: 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 11: 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 12: 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 13: 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 14: 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 15: 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 16: 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 17: 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 18: 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 19: 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 20: PARTIAL MATCHING F1

Bibliography

[CvMG+14] Kyunghyun Cho, Bart van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using RNN encoder–decoder for statistical machine translation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1724–1734, Doha, Qatar, October 2014. Association for Computational Linguistics.

[DBB+94] Deborah A. Dahl, Madeleine Bates, Michael Brown, William Fisher, Kate Hunicke-Smith, David Pallett, Christine Pao, Alexander Rudnicky, and Elizabeth Shriberg. Expanding the scope of the ATIS task: The ATIS-3 corpus. In *Human Language Technology: Proceedings of a Workshop held at Plainsboro, New Jersey, March 8-11, 1994*, 1994.

[DCLT18] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805, 2018.

[DCLT19] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics.

[FDKZ+18] Catherine Finegan-Dollak, Jonathan K. Kummerfeld, Li Zhang, Karthik Ramanathan, Sesh Sadasivam, Rui Zhang, and Dragomir Radev. Improving text-to-SQL evaluation methodology. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 351–360, Melbourne, Australia, July 2018. Association for Computational Linguistics.

[HM10] Liang Huang and Haitao Mi. Efficient incremental decoding for tree-to-string translation. In *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*, pages 273–283, Cambridge, MA, October 2010. Association for Computational Linguistics.

[HMB21] Moshe Hazoom, Vibhor Malik, and Ben Bogin. Text-to-sql in the wild: A naturally-occurring dataset based on stack exchange data. *CoRR*, abs/2106.05006, 2021.

[HR18] Jeremy Howard and Sebastian Ruder. Fine-tuned language models for text classification. *CoRR*, abs/1801.06146, 2018.

[HS97] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Computation*, 9:1735–1780, 1997.

[HYPS19] Wonseok Hwang, Jinyeung Yim, Seunghyun Park, and Minjoon Seo. A comprehensive exploration on wikisql with table-aware word contextualization. *CoRR*, abs/1902.01069, 2019.

[JC21] Marcelo Archanjo José and Fábio Gagliardi Cozman. mrat-sql+gap: A portuguese text-to-sql transformer. *CoRR*, abs/2110.03546, 2021.

[KDG17] Jayant Krishnamurthy, Pradeep Dasigi, and Matt Gardner. Neural semantic parsing with type constraints for semi-structured tables. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 1516–1526, Copenhagen, Denmark, September 2017. Association for Computational Linguistics.

[LSX] Xi Victoria Lin, Richard Socher, and Caiming Xiong. Bridging textual and tabular data for cross-domain text-to-SQL semantic parsing.

[MDP+11] Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. Learning word vectors for sentiment analysis. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 142–150, Portland, Oregon, USA, June 2011. Association for Computational Linguistics.

[MSZ19] Qingkai Min, Yuefeng Shi, and Yue Zhang. A pilot study for Chinese SQL semantic parsing. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3652–3658, Hong Kong, China, November 2019. Association for Computational Linguistics.

[RCM+13] Senjuti Basu Roy, Martine De Cock, Vani Mandava, Swapna Savanna, Brian Dalessandro, Claudia Perlich, William Cukierski, and Ben Hamner. The microsoft academic search dataset and kdd cup 2013 - workshop for kdd cup 2013. ACM - Association for Computing Machinery, August 2013.

[RJS17] Alec Radford, Rafal Józefowicz, and Ilya Sutskever. Learning to generate reviews and discovering sentiment. *CoRR*, abs/1704.01444, 2017.

[RM19] Michael Rath and Patrick Mäder. The seoss 33 dataset — requirements, bug reports, code history, and trace links for entire projects. *Data in Brief*, 25:104005, 2019.

[RN18] Alec Radford and Karthik Narasimhan. Improving language understanding by generative pre-training. 2018.

[Ron14] Xin Rong. word2vec parameter learning explained. *CoRR*, abs/1411.2738, 2014.

[SYL20] Ningyuan Sun, Xuefeng Yang, and Yunfeng Liu. Tableqa: a large-scale chinese text-to-sql dataset for table-aware SQL generation. *CoRR*, abs/2006.06434, 2020.

[THM22] Mihaela Todorova Tomova, Martin Hofmann, and Patrick Mäder. Seoss-queries - a software engineering dataset for text-to-sql and question answering tasks. *Data in Brief*, 42:108211, 2022.

[TM01] Lappoon R. Tang and Raymond J. Mooney. Using multiple clause constructors in inductive logic programming for semantic parsing. In Luc De Raedt and Peter Flach, editors, *Machine Learning: ECML 2001*, pages 466–477, Berlin, Heidelberg, 2001. Springer Berlin Heidelberg.

[TNDN20] Anh Tuan Nguyen, Mai Hoang Dao, and Dat Quoc Nguyen. A pilot study of text-to-SQL semantic parsing for Vietnamese. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 4079–4085, Online, November 2020. Association for Computational Linguistics.

[VSP+17a] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need, 2017.

[VSP+17b] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. *CoRR*, abs/1706.03762, 2017.

[WP82] David H. D. Warren and Fernando C Pereira. An efficient easily adaptable system for interpreting natural language queries. *Am. J. Comput. Linguistics*, 8:110–122, 1982.

[WSC+16] Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Lukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, and Jeffrey Dean. Google's neural machine translation system: Bridging the gap between human and machine translation. *CoRR*, abs/1609.08144, 2016.

[WSL+] Bailin Wang, Richard Shin, Xiaodong Liu, Oleksandr Polozov, and Matthew Richardson. RAT-SQL: Relation-aware schema encoding and linking for text-to-SQL parsers.

[WZW+20] Lijie Wang, Ao Zhang, Kun Wu, Ke Sun, Zhenghua Li, Hua Wu, Min Zhang, and Haifeng Wang. DuSQL: A large-scale and pragmatic Chinese text-to-SQL dataset. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 6923–6935, Online, November 2020. Association for Computational Linguistics.

[XLS] Xiaojun Xu, Chang Liu, and Dawn Song. SQLNet: Generating structured queries from natural language without reinforcement learning.

[YWDD17] Navid Yaghmazadeh, Yuepeng Wang, Isil Dillig, and Thomas Dillig. Sqlizer: Query synthesis from natural language. *Proc. ACM Program. Lang.*, 1(OOPSLA), oct 2017.

[YZY+18] Tao Yu, Rui Zhang, Kai Yang, Michihiro Yasunaga, Dongxu Wang, Zifan Li, James Ma, Irene Li, Qingning Yao, Shanelle Roman, Zilin Zhang, and Dragomir

Radev. Spider: A large-scale human-labeled dataset for complex and cross-domain semantic parsing and text-to-SQL task. 2018.

[ZM96] John M. Zelle and Raymond J. Mooney. Learning to parse database queries using inductive logic programming. In *AAAI/IAAI, Vol. 2*, 1996.

[ZXS] Victor Zhong, Caiming Xiong, and Richard Socher. Seq2sql: Generating structured queries from natural language using reinforcement learning. version: 6.