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Master Thesis

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

presented by

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Dedication

I am devoted to my family and friends for their support and encouragement throughout my academic journey.

I dedicate this thesis to brave and heroic Iranian women who have fought against oppression and 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 typically uses SQL (Structured Query Language). Machine learning and knowledge-based resources aid in converting text language to SQL. 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 transformed into a SQL query that can be executed on the database. This process can preserve developers' and end-users time and effort by enabling them to interact with databases through natural language queries.

Text-to-SQL allows structured data to evolve 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 forms:

- 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 forge SQL queries for machine learning experimentations, 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 a button on any table or chart in a user interface.

Although these Text-to-SQL models may partially solve this complex problem, humans still face challenges. 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 to migrate the data from one database to another successfully. Despite these challenges, it is possible to 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 used to convert text into Structured Query Language (SQL) in recent years. 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 utilized in the current solutions for this challenging task. By doing so, this research study will provide valuable insights into how NLP technologies can be effectively and efficiently utilized in converting text language into SQL.

Additionally, we will undertake a comprehensive study of the SEOSS 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 deciphering 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. The natural language input may also contain typos or unknown words, which can complicate the mapping process. Moreover, the query generated may not be optimal, as it has to consider the various data types, operations, and constraints of the underlying database. Therefore, developing models and algorithms that can accurately map natural language to SQL queries is crucial.

Another challenge is dealing with databases' diverse and dynamic nature, as the schema and data may change over time, and there may be variations in naming patterns and conventions across various databases. This can make it challenging for the model to accurately 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, numerous real-world scenarios demand integration with external knowledge bases and ontologies, which can be challenging to address, particularly 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 and rare edge cases that may not have been encountered during the training process. Finally, Text-to-SQL techniques must be robust to the existence 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 demand to make accurate predictions with biased training data.

1.2 Thesis Outline

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

- Introduction: This chapter presents the motivation, challenges, and goals of the thesis, setting the stage for the subsequent chapters.
- Technical Background: In this chapter, we discuss early and recent approaches to Text-to-SQL tasks. We also introduce essential terminology, concepts, and methods in the field of natural language processing. We will also cover Learning Techniques, the fully supervised and weakly supervised learning techniques used in Text-to-SQL models, exploring the advantages and drawbacks of each.
- Benchmark Dataset: This chapter provides an overview of single-domain and large-scale cross-domain benchmark datasets used for evaluating Text-to-SQL models.
- State-of-the-art Text-to-SQL Methods: We review the most recent and advanced methods for Text-to-SQL tasks, discussing various techniques for data augmentation, encoding, and decoding.
- Evaluation Metrics: In this chapter, we present the commonly used evaluation metrics for assessing the performance of Text-to-SQL models and discuss their limitations and benefits.
- Experiments: This chapter details the experiments conducted using SEOSS, GPT, and T5 PICARD on various benchmark datasets, as well as the implementation of the proposed EZ-PICARD method for microservices practices.
- Conclusion: We summarize the main findings of the thesis and highlight its contributions to the field of natural language processing and Text-to-SQL tasks.
- Discussion and Future Directions: This chapter provides a discussion on the implications of the results, identifies limitations, and suggests potential future research directions to advance the state of the art in Text-to-SQL methods.

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

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, 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 could handle a limited set of natural language inputs, but they could not 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 in 1972 [WKW72]. 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 its 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 can 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 [DCLT19], GPT-2 [RWC+19], and T5 [RSR+19], 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 favored strategy is using 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 effectively generates accurate SQL queries for various natural language inputs.

Another recent approach is using 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 is adequate for generating more complex SQL queries and handling variations in natural language inputs.

In recent years, the Transformer architecture has significantly impacted 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 in 2017 [VSP+17], is a neural network architecture that uses self-attention mechanisms to process data sequences, such as natural language text.

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 significantly impacted 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 outline, recent approaches in Text-to-SQL leverage neural networks and machine learning techniques, such as 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 focuses on the interaction between human language and computers, which ranges from understanding spoken language to generating natural language text.

2.3.2 Tokenization

Tokenization is a process in natural language processing that involves breaking up a piece of text into smaller units called tokens. These tokens can be words, subwords, or characters, and tokenization is a fundamental step in many NLP tasks. By breaking down text data into smaller units, tokenization simplifies the analysis and processing of text content. Several other tokenization techniques can be utilized, including word-level, subword-level, and character-level tokenization [KNNV22].

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 employ 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 robust 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 utilized 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 learning complex relationships between input and output, making it a suitable tool for many challenging tasks[KNNV22].

2.3.6 Transformers

The architecture introduced in the paper ”Attention Is All You Need” by Vaswani et al. in 2017[VSP+17], 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 explore its capabilities further.

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 essential 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 benchmark tasks.

Google T5 [RSR$^+$19] 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$^+$17] is a mechanism used in the transformer architecture that allows the model to determine the significance of various components of the input sequence to be able to generate an outcome that is more precise and sufficient. This mechanism allows the model to consider the relationships between different parts of the input sequence and to factor those relationships into its output. Further, self-attention lets the model capture patterns from the input sequence and use those patterns to generate more meaningful output. It is this combination of factors that makes self-attention such an essential 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 LSTM

A type of recurrent neural network designed to store information over a more extended period than traditional neural networks, allowing it to capture long-term dependencies better [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 can 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 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 adjust quickly 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, 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 capture the nuance of the language better 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 class of Semantic Parsing, Text-to-SQL, involves converting 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 employed by researchers to tackle this problem effectively. Furthermore, it is also important to note that this problem is not just limited to converting natural language into SQL query statements, as other applications of Semantic Parsing have been explored, such as Natural Language Generation (NLG). Overall, by understanding the various techniques used for Semantic Parsing, we can better understand the complexities involved in this task and how best to approach it.

2.4 Learning Techniques

The advancement of Text-to-SQL research has been driven by various learning techniques that address specific challenges in the field. We provide a comprehensive overview of these learning techniques, focusing on both fully supervised and weakly supervised methods.

2.4.1 Fully Supervised Learning Techniques

Fully supervised learning approaches depend on labeled data to train models. We explore various cutting-edge methods proposed to enhance Text-to-SQL generation.

2.4.1.1 Active Learning

Active learning aims to reduce the labeled data needed for training by selectively identifying the most informative examples. Ni et al.[NYN19] developed an active learning framework that uses uncertainty estimation to pinpoint samples that would gain the most from human annotations.

2.4.1.2 Interactive/Imitation Learning

Interactive or imitation learning concentrates on learning from demonstrations, with a model trying to replicate expert behavior. Yao et al. [YSSY19] presented an interactive learning method that integrates user feedback to improve the model's comprehension of intricate SQL queries.

2.4.1.3 Meta-learning

Meta-learning entails training models to learn how to learn effectively. Huang et al. [HWS+18] suggested a meta-learning strategy for Text-to-SQL tasks, enabling the model to swiftly adapt to new tasks or domains with limited labeled data.

2.4.1.4 Multi-task Learning

Multi-task learning consists of training a single model on multiple related tasks concurrently. Chang et al. [CGW+21] investigated a multi-task learning framework for Text-to-SQL generation, illustrating that sharing information across tasks can result in enhanced performance.

2.4.2 Weakly Supervised Learning Techniques

Weakly supervised learning approaches employ weak or noisy labels for training, often diminishing the need for extensive human annotation.

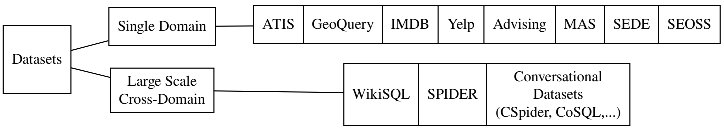
2.4.2.1 Reinforcement Learning

Reinforcement learning focuses on learning through trial and error, with models receiving feedback via rewards or penalties. Seq2SQL Zhong et al. [ZXS] applied reinforcement learning to Text-to-SQL generation, demonstrating that such a method can effectively learn from weak supervision, for instance, it allowed Seq2SQL to understand different orders of WHERE clauses in a query.

2.4.2.2 Meta-learning and Bayesian Optimization

Agarwal et al. [ALSN19] combined meta-learning and Bayesian optimization for weakly supervised Text-to-SQL tasks. This technique enables models to adapt more efficiently to new tasks while taking advantage of limited supervision, ultimately reducing the necessity for large amounts of labeled data.

3 Benchmark Dataset



Datasets are crucial in developing and evaluating Text-to-SQL models for semantic parsing of natural language phrases. Various 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.

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 scenarios. Additionally, new datasets include more advanced queries to assess the generalization capabilities of models. This chapter will review the complete 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 and GeoQuery

ATIS [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 [DBB+94] are mainly limited to select and project queries. On the other hand, GeoQuery [TM01] 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 [TM01] 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[DBB+94]. As a result, GeoQuery is better equipped to answer more complex queries, making it a better choice for training AI models.

Example of a complex IMDb SQL query

Utterance:

```
I would like a flight between BOSTON and ATLANTA on any day at one in the afternoon.
```

Query:

```
SELECT DISTINCT flight.FLIGHT_ID FROM AIRPORT_SERVICE AS airport_service , AIRPORT_SERVICE AS
airport_service2 , CITY AS city2 , CITY AS city , FLIGHT AS flight WHERE ( city.CITY_CODE
= airport_service2.CITY_CODE AND city.CITY_NAME = "ATLANTA" AND flight.DEPARTURE_TIME
= 1300 AND flight.TO_AIRPORT = airport_service2.AIRPORT_CODE ) AND city2.CITY_CODE =
airport_service.CITY_CODE AND city2.CITY_NAME = "BOSTON" AND flight.FROM_AIRPORT =
airport_service.AIRPORT_CODE ;
```

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.

Example of a complex IMDb SQL query

Utterance:

```
What year was the movie The Imitation Game produced?
```

Query:

```
SELECT MOVIEalias0.RELEASE_YEAR FROM MOVIE AS MOVIEalias0 WHERE MOVIEalias0.TITLE = 'The
Imitation Game' ;
```

3.1.3 Advising Dataset

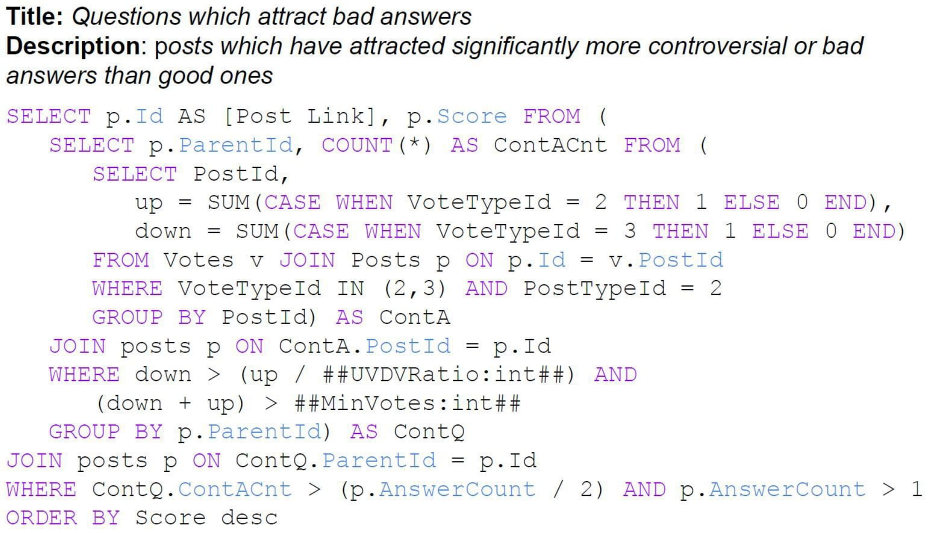
The Advising dataset[FDKZ+18] was created in order to propose improvements in Text-to-SQL systems. The creators of the dataset compare human-generated and automatically generated questions, citing properties of queries that relate to real-world applications. The dataset consists of questions from the 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 [3.1.1], 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



Title: *Questions which attract bad answers*
Description: *posts which have attracted significantly more controversial or bad answers than good ones*

```
SELECT p.Id AS [Post Link], p.Score FROM (
   SELECT p.ParentId, COUNT(*) AS ContACnt FROM (
      SELECT PostId,
         up = SUM(CASE WHEN VoteTypeId = 2 THEN 1 ELSE 0 END),
         down = SUM(CASE WHEN VoteTypeId = 3 THEN 1 ELSE 0 END)
      FROM Votes v JOIN Posts p ON p.Id = v.PostId
      WHERE VoteTypeId IN (2,3) AND PostTypeId = 2
      GROUP BY PostId) AS ContA
   JOIN posts p ON ContA.PostId = p.Id
   WHERE down > (up / ##UVDVRatio:int##) AND
      (down + up) > ##MinVotes:int##
   GROUP BY p.ParentId) AS ContQ
JOIN posts p ON ContQ.ParentId = p.Id
WHERE ContQ.ContACnt > (p.AnswerCount / 2) AND p.AnswerCount > 1
ORDER BY Score desc
```

Figure 1: An example of a Complex query from the SEDE dataset.[HMB21]

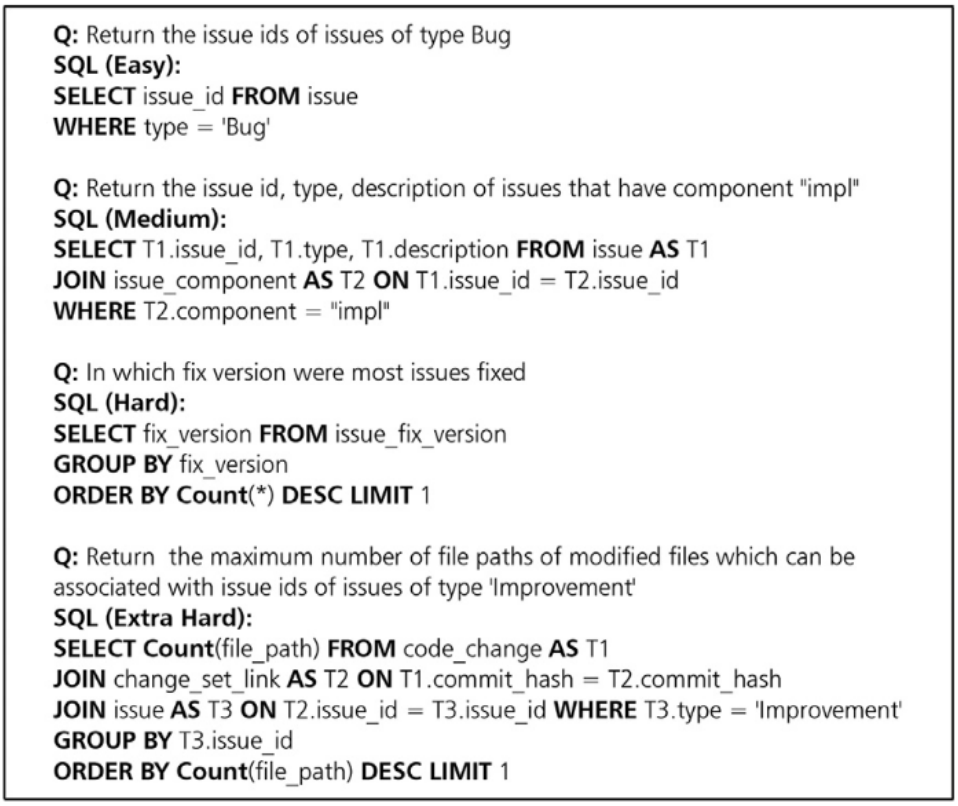
Stack Exchange Data Explorer (SEDE) [HMB21] is from a popular online question-and-answer platform with more than 3 million questions, and it recently released a benchmark dataset of SQL queries containing 29 tables and 211 columns. This dataset comprises real-world questions from the Stack Exchange website,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

Software Engineering in Open Source Systems (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 2: 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.

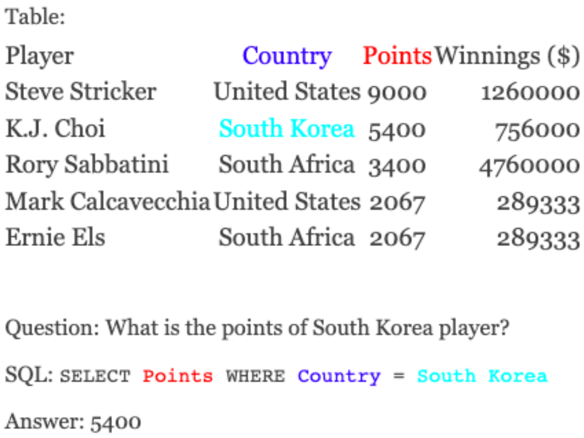


Table:

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?

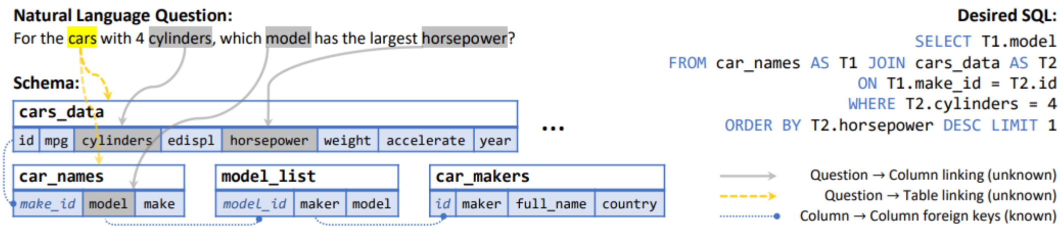
SQL: `SELECT Points WHERE Country = South Korea`

Answer: 5400

Figure 3: 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


Natural Language Question:
For the cars with 4 cylinders, which model has the largest horsepower?
Schema:
cars_data
id
mpg
cylinders
edispl
horsepower
weight
accelerate
year
...
car_names
make_id
model
make
model_list
model_id
maker
model
car_makers
id
maker
full_name
country
Desired SQL:
Question → Column linking (unknown)
Question → Table linking (unknown)
Column → Column foreign keys (known)

```
                                   SELECT T1.model
FROM car_names AS T1 JOIN cars_data AS T2
                         ON T1.make_id = T2.id
                        WHERE T2.cylinders = 4
         ORDER BY T2.horsepower DESC LIMIT 1
```

Figure 4: 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.

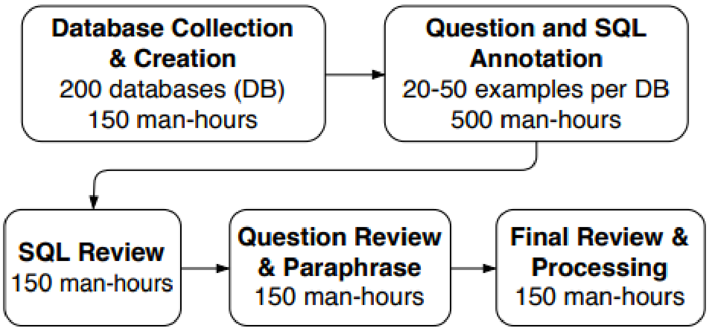


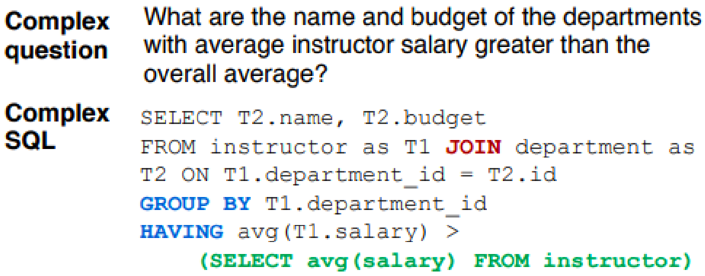
Figure 5: Process of creating SPIDER dataset[YZY+18]

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 6: Example of Question-Query set from SPIDER[YZY+18]

SPIDER's exact matching accuracy[5] was 12.4% compared to existing state-of-the-art models. As a result of its low accuracy, SPIDER presents a strong research challenge. Current SPIDER accuracy is above 75.5% with an exact set match without values (refers to values in the WHERE clause) and above 72.6% with values using PICARD4.2.8.

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

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

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

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

3.2.3 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.

This chapter has 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

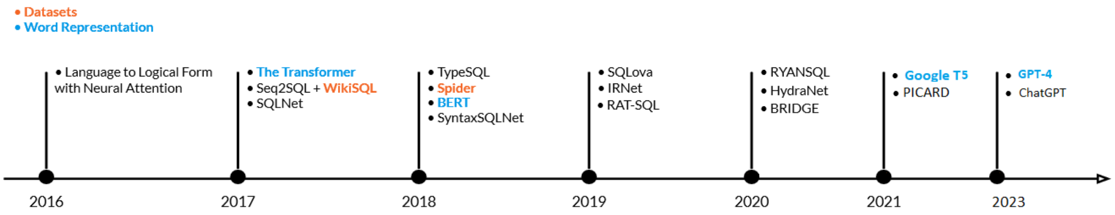


Figure 7: Timeline of the deep learning process for Text-to-SQL.

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

An efficient text-to-SQL solution requires state-of-the-art natural language processing techniques. As a result of the neural network's capacity to take only numerical inputs and not plain text, word embedding has been used to represent numerical words. Aside from that, in the past few years, language models have evolved to become increasingly popular as a solution for increasing performance in natural language processing tasks. Believing that words have numerical representations that differ from others, word embeddings aim to map each word to a multidimensional vector, incorporating valuable details 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 essential to note that language models are not a substitute for word embeddings since they are neural networks and need a way to transform words into vectors. Relying on the specific problem they want to solve, researchers can adapt the pre-trained model's inputs and outputs and train it for an additional number of epochs on their dataset. Thus, we can achieve state-of-the-art performance without complex architectures [DCLT18]. Recent neural network architectures, like the Transformer[VSP+17], have been used to achieve such performance by these models, which excel at handling NL and sequences of NL that are characterized by connections between words. Several language models have been used to handle the text-to-SQL task, including BERT [DCLT18]. BERT is a pre-trained language model that has been shown to achieve state-of-the-art performance in various NLP tasks. BERT is a Transformer-based model that utilizes a bidirectional encoder to understand 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+].

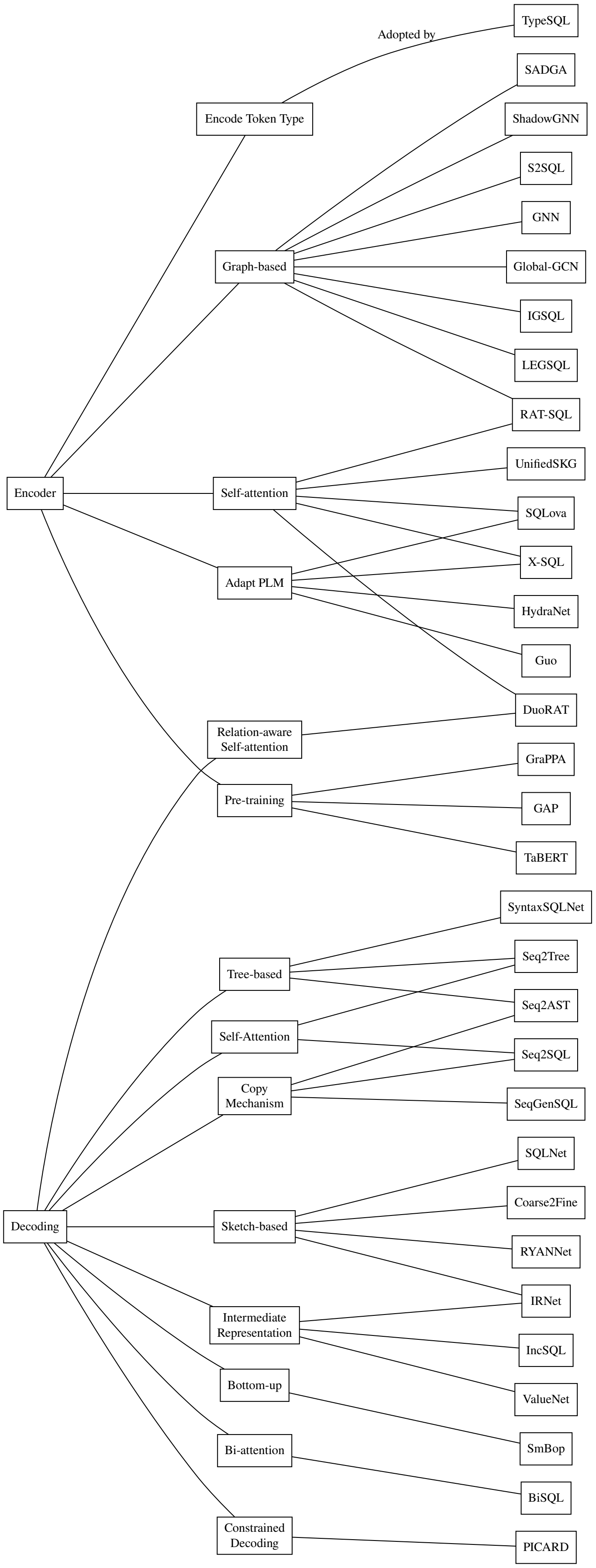


Figure 8: Text-to-SQL state-of-the-art Topology

4.1 Encoding

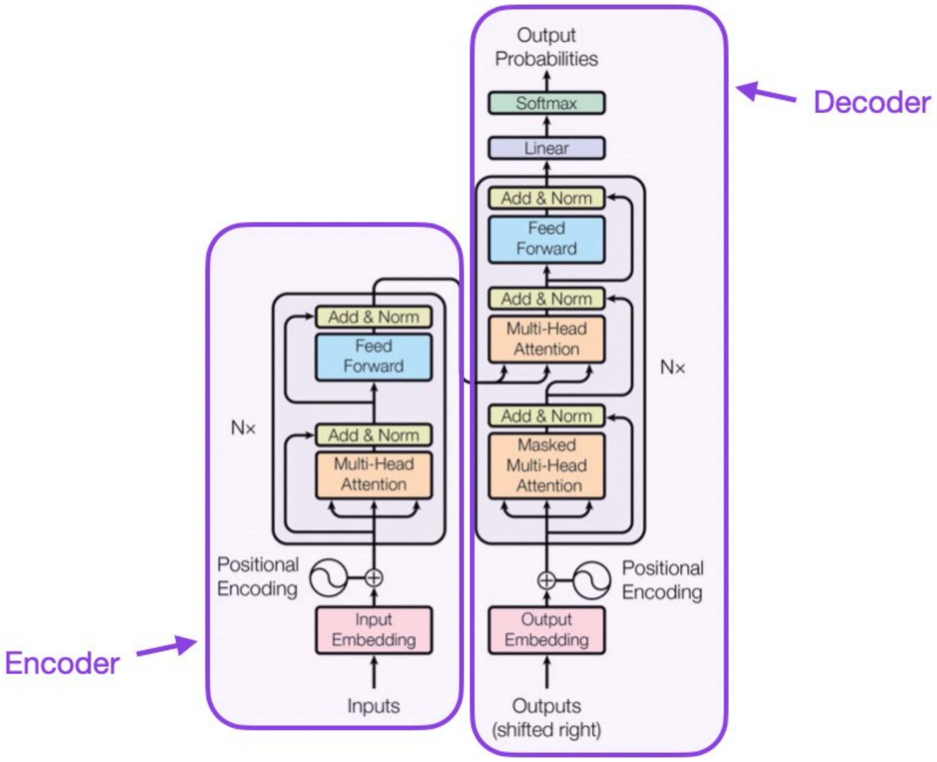


Figure 9: Transformer architecture featured in “Attention is all you need” [VSP+17]

Encoders[KNNV22] are a crucial component in natural language processing tasks and consist of a multi-layered assembly of recurrent elements, such as Long Short-Term Memory (LSTM) units, Gated Recurrent Units (GRUs), or other similar structures. These recurrent elements work in tandem to process an input sequence, with each unit being responsible for handling a single element within the sequence, capturing the pertinent information for that specific element, and subsequently propagating this information forward to the next recurrent unit in the stack.

The primary function of an encoder is to systematically transform textual data into a suitable numerical or vector representation that retains the inherent relationships and dependencies among words, phrases, and sentences[CvMG+14]. This is achieved through a combination of techniques, such as tokenization, embedding, and the use of attention mechanisms, which together facilitate the encoding process.

Tokenization serves to break down the input text into smaller, manageable units, such as words or subwords, while embeddings assign a dense vector representation to each token, thus allowing machines to efficiently process and compare these tokens. Attention mechanisms, on the other hand, enable encoders to weigh the importance of different input elements and selectively focus on the most relevant parts of the input sequence when generating the final encoded representation.

By effectively converting the textual data into a machine-understandable format, encoders play a pivotal role in empowering machines to recognize intricate patterns, relationships, and contextual cues within the text. Consequently, this ability to accurately discern the context of sentences and phrases forms the foundation for a wide array of natural language processing tasks, ranging from machine translation and sentiment analysis to text summarization and question-answering systems.

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[DCZ22]. 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[DCZ22]. 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[DCZ22].

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

Table 2: Methods used for encoding in text-to-SQL [DCZ22]

4.1.1 Encode Token Types

Token Type Encoding is an innovative technique introduced in TypeSQL[YLZ+18], which focuses on transforming natural language queries into SQL-like structures by annotating each token with its corresponding SQL token type. This method has demonstrated impressive performance in accurately encoding intricate queries that involve multiple subqueries and join operations, thereby providing a more effective means of bridging the gap between natural language and SQL.

TypeSQL

In TypeSQL, the core methodology involves a knowledge-based type system and a type-aware neural network model[YLZ+18]. The knowledge-based type system is responsible for identifying and disambiguating the types of entities and values mentioned in the input text. This system uses a combination of pre-defined types, a type dictionary, and a type hierarchy. The type dictionary maps entities and values to their corresponding types, while the type hierarchy defines the relationships between different types, allowing the model to infer implicit relationships between entities in the input text. TypeSQL, similar to SQLNet, adopts a sketch-based approach and treats the task as a slot-filling problem. As shown in Figure 10, the model is tasked with predicting the slots starting with '$'.

The results of TypeSQL demonstrate its effectiveness in generating SQL queries from natural language inputs. When tested on the WikiSQL dataset without considering the content of databases, TypeSQL surpasses the previous best model by 5.5% in execution accuracy. TypeSQL's simpler yet effective approach of encoding column names and logically grouping model components leads to significant improvements in the challenging WHERE clause sub-task. Moreover, the incorporation of word types enables TypeSQL to better encode rare entities and numbers. When given complete access to the database, TypeSQL achieves an execution accuracy of 82.6%, outperforming the previous content-aware system, SQLNet by a remarkable 17.5%.

Despite its success, the Token Type Encoding approach in TypeSQL does have certain limitations, particularly when it comes to handling queries with ambiguous or uncommon syntax patterns. Additionally, this methodology encounters challenges when faced with queries containing nested subqueries or intricate aggregation operations, as it may struggle to accurately capture the relationships and dependencies among the various tokens.

Another drawback of TypeSQL's Token Type Encoding technique is its susceptibility to issues when dealing with out-of-vocabulary words. In these cases, the method may generate incorrect or incomplete SQL encodings, which can adversely impact the overall effectiveness of the system. Nonetheless, the introduction of Token Type Encoding in TypeSQL has laid the foundation for further research and development in the field of neural text-to-SQL generation, providing valuable insights and paving the way for more advanced techniques to address these limitations and improve the overall performance of natural language to SQL conversion systems.

SELECT `$AGG $SELECT_COL` **WHERE** `$COND_COL $OP $COND_VAL`
(**AND** `$COND_COL $OP  $COND_VAL`)*

Figure 10: SQL Sketch. The tokens starting with “$” are slots to fill. “*” indicates zero or more **AND** clauses.[YLZ+18]

Model	EMA
TypeSQL[YLZ+18]	8.0
EditSQL [TNDN20]	36.4
GNN [BBG19]	40.7
Global-GNN [BBG19]	52.7
RATSQL [WSL+]	69.7
ShadowGNN[CCZ+21]	72.3
LGESQL[CCC+21]	75.1
S^2SQL[HGW+22]	76.4

Table 3: The exact match accuracy on the Spider dev set.

4.1.2 Graph-based Methods

Graph-based methods are an effective approach for encoding the structural information found in database schemas. They have become particularly important as DBs have grown more complex, such as those found in the Spider dataset. These methods involve using graphs to represent the DB schema structure, with nodes representing tables and columns, and edges representing relationships between them, such as primary and foreign key constraints.

Bogin et al.[BBG19] were among the first to propose using graphs in this manner, utilizing Graph Neural Networks (GNN) [LTBZ17] to encode the graph structure. Also, They employed Graph Convolutional Networks (GCNs) and gated GCNs for capturing DB structures and selecting relevant information for SQL generation. RAT-SQL[WSL+] added more relationships to the DB schema graphs, such as ”both columns are from the same table.”

In addition to encoding DB schema information, graph-based methods have been used to represent natural language (NL) questions alongside the schema. Various types of graphs have been used to capture semantics in NL and facilitate linking between NL and table schema. For example, LGESQL[CCC+21] utilized line graphs to capture multi-hop semantics using meta-paths, while SADGA[CYXH] adopted a graph structure to provide a unified encoding for both natural language utterances and DB schemas, assisting in question-schema linking.

In order to improve the generalization of graph-based methods for unseen domains, ShadowGNN [CCZ+21] takes a unique approach. It disregards the names of tables or columns in the database and instead employs abstract schemas within the graph projection neural network. This results in delexicalized representations of questions and DB schemas, allowing the model to better handle new or previously unseen domains. S2SQL[HGW+22] integrated syntax dependency among question tokens into the graph to enhance model performance even more.

In summary, graph-based methods have proven to be valuable for encoding structural information in DB schemas, bridging the gap between natural language questions and schema elements, and enhancing the performance of models in context-dependent text-to-SQL tasks. Upon examining the results from the Spider benchmark $Table$3, it is evident that there has been a significant overall performance improvement when comparing graph-based methods.

4.1.3 Self-attention

Self-attention is a fundamental component in natural language processing (NLP) models, particularly those based on the Transformer architecture. It serves as the primary building block of the transformer structure, as mentioned in the works of X-SQL[HMCC19], SQLova[HYPS19], and UnifiedSKG[XWS$^+$22]. These models employ the original self-attention mechanism by default.

The self-attention mechanism allows the model to weigh and aggregate different words or tokens in a sequence based on their relative importance[VSP$^+$17]. In essence, it helps the model to focus on the most relevant parts of a given input while processing it. This is accomplished by computing attention scores between each pair of tokens in the input, which are then used to produce a weighted sum of the input tokens. The mechanism is particularly effective in handling long-range dependencies within the text.

However, the original self-attention mechanism can be modified to cater to specific tasks or address particular challenges. One such modification is relation-aware self-attention, employed by RAT-SQL[WSL$^+$] and DuoRAT[SLB$^+$21]. This variation of self-attention is designed to take advantage of the relationships between tables and columns when working with structured data.

Relation-aware self-attention extends the original self-attention by incorporating information about the structure and relations in the input data. This additional information is used to adjust the attention scores, allowing the model to focus on the most relevant relationships between different elements in the input. As a result, models equipped with relation-aware self-attention can better handle tasks involving structured data, such as SQL query generation or table-based reasoning.

4.1.4 Adapt PLM

Adapt Pre-trained Language Models (PLM) methods aim to utilize the knowledge encapsulated in pre-trained language models, such as BERT[DCLT18], to improve their performance on text-to-SQL tasks. These methods modify or extend the original PLMs to better align with the specific requirements of the task.

One common approach is to encode both the natural language questions and the database schemas using PLMs. For instance, SQLova[HYPS19] and RYANSQL[CSKS21] concatenate the question words and schema words as input to the BERT encoder. This approach allows the model to learn representations that capture the relationships between questions and the underlying schema. In figure 11, the authors of RYANSQL[CSKS21] propose a novel encoder that combines the BERT encoder with a self-attention mechanism to capture the interactions between the question and schema words. As you can see it passes the question words and database tables schemas through embedding layers, then concatenates them and passes them through the BERT encoder. The output of the BERT encoder is then passed through a self-attention layer to capture the interactions between the question and schema words. The self-attention layer is then concatenated with the BERT encoder output and passed through a feed-forward network to produce the final representation of the question and schema.

Some methods go a step further by adjusting the embeddings produced by the PLMs. X-

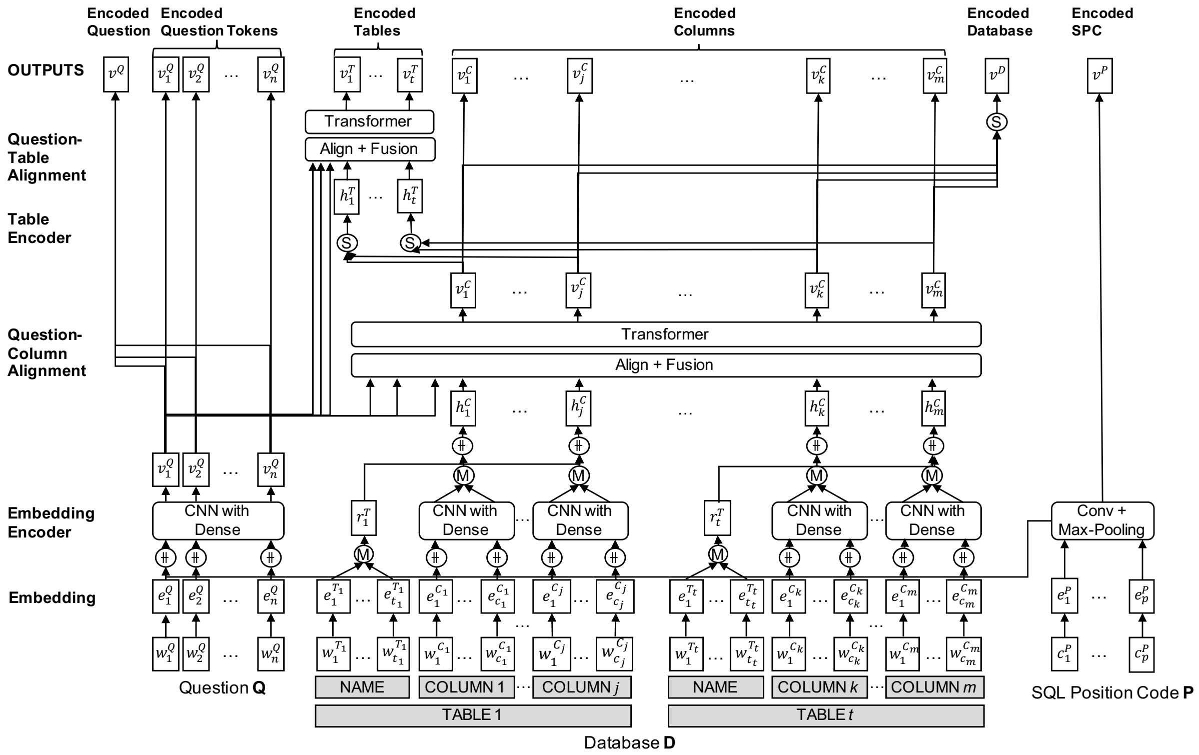


Figure 11: Network architecture of the proposed input encoder. ⊕ represents vector concatenation, Ⓜ represents max-pooling and Ⓢ represents self-attention.[CSKS]

Model	Execution Accuracy
Seq2SQL[ZXS]	60.8
TypeSQL[YLZ+18]	74.5
SQLova[HYPS19]	90.2
Guo[GG20]	91.1
HydraNet[LCH+20]	92.4

Table 4: The execution accuracy on the WikiSQL dev set.

SQL[HMCC19] proposes the replacement of the segment embeddings from the pre-trained encoder with column-type embeddings for the WikiSQL dataset. Guo and Gao [GG20] introduce an approach that encodes additional feature vectors for matching between question tokens and table cells, as well as column names. These feature vectors are then concatenated with the BERT embeddings of questions and DB schemas.

HydraNet[LCH+20] uses BERT to encode the question and individual columns, an approach that is more aligned with the tasks BERT is pre-trained on. After obtaining BERT representations for all columns, the model selects the top-ranked columns for SQL prediction

Examining the WikiSQL benchmark results in Table 4, we can observe a significant overall performance improvement when employing pre-trained language models (PLMs) compared to previous methods. This enhancement can be attributed to the ability of PLMs, such as BERT, to capture complex linguistic patterns and relationships within the input data. By leveraging the knowledge encapsulated in these models and adapting them to the text-to-SQL task, researchers have been able to achieve better alignment with the specific requirements of the problem domain. As a result, PLM-based approaches have demonstrated superior performance in generating accurate SQL queries from natural language questions, surpassing traditional methods and showcasing the potential of PLMs in addressing complex language understanding tasks.

4.1.5 Pre-training

Pre-training methods are a crucial part of training transformer-based models for text-to-SQL tasks. These methods aim to align the models with the required tasks by using various objectives and pre-training data. Some popular pre-training methods include TaBERT[YNYR], Grappa[YWL+20], and GAP[SNW+20], which utilize different strategies to achieve their goals.

TaBERT [YNYR] focuses on tabular data for pre-training. It employs two main objectives: masked column prediction and cell value recovery. These objectives help the model better understand the structure and semantics of tables, allowing it to generate SQL queries more effectively.

Grappa [YWL+20] generates synthetic question-SQL pairs over tables for pre-training. It uses BERT and relies on two primary objectives: masked language modeling and predicting column presence and SQL operations. Masked Language Modeling (MLM) helps the model understand the language structure in the context of SQL queries while predicting column presence and SQL operations allowing it to learn how columns and operations are related to the questions.

GAP [SNW+20] pre-trains BART [LLG+20] on both synthesized text-to-SQL and tabular data. It utilizes four objectives: MLM, column prediction, column recovery, and SQL generation. The combination of these objectives enables the model to understand language patterns and table structures while also learning to generate SQL queries that match the given text.

In summary, various pre-training methods have been proposed to better align transformer-based models with text-to-SQL tasks. A glance at the SPIDER Benchmark results $Table5$ highlights the performance improvement when incorporating advanced pre-training methods with RATSQL. The integration of GAP, which leverages multiple objectives, leads to a more effective understanding of text-to-SQL tasks. A further enhancement is observed when combining RATSQL with GraPPa, a method that uses synthesized question-SQL pairs. These findings emphasize the value of using cutting-edge pre-training techniques to boost transformer-based models like RATSQL in text-to-SQL tasks.

Model	**EMA Dev.**
RATSQL	62.7
RATSQL + GAP	71.8
RATSQL + GraPPa	73.4

Table 5: The exact match accuracy on the Spider dev set.

4.2 Decoding

Decoders [CvMG$^+$14] form an integral part of sequence-to-sequence models in natural language processing tasks, and they are constructed as a multi-layered architecture of recurrent elements, such as Long Short-Term Memory (LSTM) units, Gated Recurrent Units (GRUs), or other analogous structures. The primary responsibility of a decoder is to generate an output sequence by predicting an output, denoted as y, for each time step. This output sequence can be a series of words, phrases, or even entire sentences, depending on the specific problem being addressed.

At each time step, the current recurrent unit within the decoder receives a hidden state from the preceding recurrent unit. This hidden state encapsulates the information gathered up to that point and serves as a vital input for the current recurrent unit to make an informed prediction. Moreover, decoders can also incorporate attention mechanisms to help focus on the most relevant parts of the input sequence when generating the output. This is particularly useful in tasks that require the decoder to selectively attend to different input elements during the decoding process.

Decoders are commonly employed in a wide range of natural language processing applications [KNNV22], including but not limited to, machine translation, text summarization, question-answering systems, and dialogue generation. In question-answering tasks, for instance, the output sequence generated by the decoder is often a collection of words.

Numerous approaches have been suggested to enhance the decoding process for more precise and efficient SQL generation, ultimately bridging the divide between natural language and SQL query formulation. As illustrated in the table below, we have classified these techniques into five primary categories, along with additional methodologies[DCZ22].

Methods	Adopted by	Applied datasets	Addressed challenges
Tree-based	Seq2Tree Seq2AST SyntaxSQLNet	- - Spider	Hierarchical decoding
Sketch-based	SQLNet Coarse2Fine IRNet RYANSQL	WikiSQL WikiSQL Spider Spider	Hierarchical decoding
Bottom-up	SmBop	Spider	Hierarchical decoding
Self-Attention	Seq2Tree Seq2SQL	- WikiSQL	Synthesizing information
Bi-attention	BiSQL	Spider	Synthesizing information
Relation-aware Self-attention	DuoRAT	Spider	Synthesizing information
Copy Mechanism	Seq2AST Seq2SQL SeqGenSQL	- WikiSQL WikiSQL	Synthesizing information
Intermediate Representation	IncSQL IRNet ValueNet	WikiSQL WikiSQL Spider	Bridging the gap between natural language and SQL query
Constrained decoding	PICARD	Spider	Fine-grained decoding

Table 6: Methods used for decoding in text-to-SQL [DCZ22]

4.2.1 Tree-based

In the realm of text-to-SQL research, tree-based decoders have emerged as a popular approach for generating logical forms or Abstract Syntax Trees (AST) from input text. Two key papers in this area are Dong and Lapata [DL16] with their Seq2Tree model and Yin and Neubig [YN17] with their Seq2AST model. While these works do not specifically focus on text-to-SQL datasets, they inspire the development of tree-based decoding methods within the text-to-SQL context, such as SyntaxSQLNet by Yu et al. [YYY+18].

The Seq2Tree model by Dong and Lapata [DL16] creates logical forms through a top-down approach, where components of the sub-tree are generated based on their parent nodes, independently from the input question. This model learns the syntax of the logical forms implicitly, without any explicit guidance. On the other hand, the Seq2AST model by Yin and Neubig [YN17] explicitly integrates syntax into the generation process through the use of an AST. This approach decodes the target programming language by constructing an AST that adheres to the language's syntax rules.

Taking inspiration from these approaches, SyntaxSQLNet by Yu et al. [YYY+18] adapts the tree-based decoding method to SQL syntax. This model employs a recursive structure that calls various modules to predict different SQL components, ultimately generating a valid SQL query. The model's tree-based decoding technique is tailored to the SQL language and facilitates a more structured prediction process.

In summary, tree-based decoders in text-to-SQL research offer a structured way to generate logical forms or AST, making use of either implicit or explicit syntax learning. By adapting these methods to the specific requirements of SQL syntax, researchers can develop more effective models for translating natural language questions into SQL queries.

4.2.2 Sketch-based

Sketch-based decoders have gained attention in text-to-SQL research as an approach that simplifies the generation of SQL queries by leveraging predefined query structures, or ”sketches.” These sketches follow SQL grammar and allow the model to focus on filling in the slots rather than predicting the output grammar and content simultaneously.

SQLNet by Xu et al. [XLS] is an example of a sketch-based model that aligns with SQL grammar. The sketch captures dependencies between predictions, which means that the prediction for each slot is conditioned only on the slots it depends on. This approach effectively avoids issues arising from equivalent serializations of the same SQL query.

Dong and Lapata [DL18] further refine the sketch-based approach by decomposing the decoding process into two stages. The first decoder predicts a rough sketch, while the second decoder fills in the low-level details based on the input question and the sketch. This coarse-to-fine decoding has been adopted in other works, such as IRNet by Guo et al. [GZG+19].

To handle complex SQL queries with nested structures, RYANSQL by Choi et al. [CSKS21] introduces a recursive method for generating SELECT statements. This model employs sketch-based slot filling for each of the SELECT statements, enabling the generation of more intricate queries.

In summary, sketch-based decoders simplify the text-to-SQL generation process by providing predefined query structures that follow SQL grammar. This approach enables models to focus on filling in content slots, captures dependencies between predictions, and allows for the handling of complex queries with nested structures. By decomposing the decoding process into multiple stages, sketch-based decoders can efficiently translate natural language questions into accurate SQL queries.

4.2.3 Bottom-up

Bottom-up decoders offer an alternative approach to tree-based and sketch-based decoding mechanisms, which are typically top-down in nature. One example of a bottom-up decoder is the method employed by Rubin and Berant [RB21].

In a bottom-up decoding mechanism, the model starts with a set of K trees, each of height t. The decoder then scores trees of height t+1, which are constructed based on SQL grammar from the current set of trees in the beam. The K highest-scoring trees are retained, and a new representation of these trees is generated and placed in the new beam. This process iteratively builds the trees from the bottom up until a complete SQL query is formed.

This bottom-up approach contrasts with top-down methods, where trees or sketches are generated from the root node or a coarse representation, and then progressively filled in or expanded by adding more details or subtrees. The bottom-up method focuses on constructing trees by iteratively expanding them based on the current best candidates, effectively narrowing down the search space and improving the efficiency of the decoding process.

In summary, bottom-up decoders present an alternative to top-down methods for generating SQL queries from natural language input. By iteratively expanding and scoring trees based on the current beam, these decoders can efficiently generate accurate SQL queries while maintaining a manageable search space.

4.2.4 Attention Mechanism

Attention mechanism decoders play a critical role in integrating encoder-side information during the decoding process. By computing attention scores and multiplying them with hidden vectors from the encoder, a context vector is generated, which is then used to produce an output token.

Various attention structures have been employed to enhance the decoder's performance and effectively propagate the information encoded from questions and database schemas. One such example is SQLNet (by Xu et al.) [XLS], which introduces the concept of column attention. This technique involves using hidden states from columns and multiplying them by embeddings for the question to calculate attention scores for a given column. The attention scores are then used to help the model focus on relevant columns when generating the SQL query.

Another approach, proposed by Guo and Gao [GG20], incorporates bi-attention over a question and column names for SQL component selection. This method enables the model to simultaneously attend to both the question and column names, which can improve the model's ability to identify and select relevant SQL components.

Wang et al. [WTL19] adopt a structured attention mechanism [KDHR17] that computes marginal probabilities to fill in the slots of their generated abstract SQL queries. This approach allows the model to better capture the structure of SQL queries and enhances the overall generation process.

DuoRAT [SLB+21] implements a relation-aware self-attention mechanism in both its encoder and decoder components. This attention mechanism accounts for relationships between different elements within the input data, thus improving the model's ability to comprehend and generate accurate SQL queries.

Other works, such as those by Scholak et al. PICARD [SSB21] and UnifiedSKG by Xie et al. [XWS+22], use sequence-to-sequence transformer-based models or decoder-only transformer-based models that incorporate the self-attention mechanism by default. The self-attention mechanism allows the model to weigh the significance of each input token concerning other tokens in the sequence, which can enhance the quality and coherence of the generated output.

In summary, attention mechanism decoders have been an essential aspect of Text-to-SQL research, with various structures designed to improve the propagation of information and the generation of accurate SQL queries. By continuously refining and adapting these attention mechanisms, researchers aim to further enhance the performance of Text-to-SQL models.

4.2.5 Copy Mechanism

The Copy mechanism is a vital component in various Text-to-SQL models, as it facilitates the direct copying of specific words or tokens from the input sequence to the generated output. Several research papers have implemented this mechanism to improve the performance of their models.

Seq2AST by Yin and Neubig [YN17] and Seq2SQL by Zhong et al. [ZXS] both employ the pointer network, introduced by Vinyals et al. [VFJ17], to calculate the probability of copying words from the input sequence. The pointer network is a type of neural network that can learn to point to specific positions in the input data, allowing the model to copy tokens directly from the input when generating output sequences.

Wang et al. [WBS17] take a different approach to the copy mechanism by using types, such as columns, SQL operators, and constants from questions, to explicitly restrict the locations in the query that can be copied from. This method helps the model focus on copying only relevant tokens to generate coherent and accurate SQL queries. Additionally, they develop a new training objective that encourages the model to only copy from the first occurrence of a token in the input sequence, which can prevent potential redundancies in the generated output.

Furthermore, the copy mechanism has been adopted in the context-dependent text-to-SQL task, as demonstrated by Wang et al. [WLC20]. In this scenario, the copy mechanism is particularly beneficial for models that need to handle complex input data, such as multiple questions or queries, and generate output sequences that accurately reflect the context.

In summary, the copy mechanism plays a crucial role in various Text-to-SQL models by allowing them to copy specific tokens from the input sequence directly, enhancing the accuracy and coherence of the generated SQL queries. By adopting different techniques and refining the copy mechanism, researchers continue to improve the performance of their models in the Text-to-SQL domain.

4.2.6 Intermediate Representations

Intermediate representations (IRs) are employed in Text-to-SQL research to bridge the gap between natural language and SQL queries. By using IRs, researchers can simplify and abstract SQL queries, making it easier for models to learn and generate an accurate output.

IncSQL by Shi et al. [STC$^+$18] is one such approach that defines actions for different SQL components, allowing the decoder to decode these actions instead of raw SQL queries. This method reduces the complexity of the decoding process and can improve the overall performance of the model.

IRNet by Guo et al. [GZG$^+$19] introduces SemQL, an intermediate representation for SQL queries designed to cover most of the challenging Spider benchmark. SemQL simplifies SQL queries by removing the JOIN ON, FROM, and GROUP BY clauses and merging the HAVING and WHERE clauses. ValueNet by Brunner and Stockinger [BS21] builds upon SemQL by introducing SemQL 2.0, which extends the original representation to include value representation. Additionally, NatSQL by Gan et al. [GCX$^+$21] modifies SemQL by removing set operators, such as INTERSECT, which combine the results of two or more SELECT statements.

Suhr et al. [LB99] implement SemQL as a mapping from SQL to a representation with an under-specified FROM clause, which they call SQLUF. Rubin and Berant employ a relational algebra augmented with SQL operators as intermediate representations, offering another approach to simplifying SQL queries.

However, one of the main challenges with intermediate representations is that they are typically designed for specific datasets and cannot be easily adapted to others. To address this issue, Herzig et al. [HSC$^+$21] propose a more generalized intermediate representation by omitting tokens in the SQL query that do not align with any phrase in the natural language utterance.

The success of intermediate representations in Text-to-SQL tasks has inspired researchers to explore their use in other executable language domains, such as SPARQL for database systems. Works by Saparina and Osokin [SO21] investigate the potential of intermediate representations for SPARQL queries.

In conclusion, intermediate representations play an essential role in Text-to-SQL research by simplifying and abstracting SQL queries, making it easier for models to learn and generate an accurate output. The exploration of various intermediate representation techniques continues to improve the performance of Text-to-SQL models and inspire advancements in other related domains.

4.2.7 Constrained decoding

Constrained decoding methods are employed in natural language processing tasks, such as text-to-SQL, to improve the quality of generated outputs by imposing certain constraints or utilizing auxiliary models during the decoding process. These methods aim to prevent the generation of invalid tokens, exclude non-executable partial SQL queries, or facilitate the generation of complete SQL queries.

PICARD by Scholak et al., [SSB21] is an example of a method that sets constraints on the decoder to avoid generating invalid tokens. Other methods, such as those proposed by Wang et al. [WTB$^+$18] and Hwang et al. [HYPS19], adopt an execution-guided decoding mechanism that eliminates non-executable partial SQL queries from the output candidates.

Some approaches, like Global-GNN, Bogin et al. [BGB19], use separately trained discriminative models to rerank the top-K SQL queries in the decoder's output beam. This technique allows the model to reason about complete SQL queries rather than considering each word and database schema in isolation.

Chen et al. [CSLJ20] employ a gating mechanism to select between the output sequence encoded for the question and the output sequence from the previous decoding steps at each step for SQL generation. This approach helps in generating more accurate and coherent SQL queries.

Müller and Vlachos [MV19] draw inspiration from machine translation and apply Byte Pair Encoding (BPE) (Sennrich et al.[SHB16]) to compress SQL queries into shorter sequences, guided by AST. This technique reduces the difficulties in SQL generation, leading to improved performance in text-to-SQL tasks.

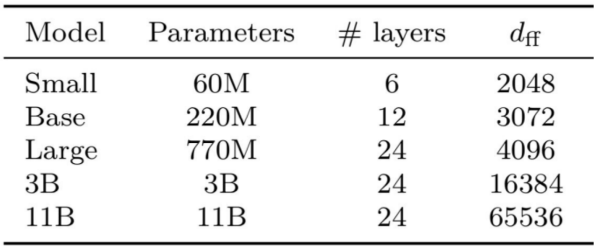
4.2.8 T5 + PICARD

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

T5

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

Text-To-Text Transfer Transformer (T5) Model implemented by Raffel et al. [RSR+19] uses the BERT encoder-decoder architecture proposed by Vaswani et al. (2017)devlin-etal-2019-bert and they showed in their studies that it will outperform decoder-only language models. Originally T5 was introduced with five pre-trained models — Small (60 million parameters), Base(220 million parameters), Large(770 million parameters), 3B(3 billion parameters), and 11B(11 billion parameters)[RSR+19].



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

Figure 12: T5 models with their Nr. of parameters, layer and feed-forward parameters[RSR+19]

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

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

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

So fundamentally, it is in a sequence-to-sequence framework; hence, T5 is perfectly suitable for transfer learning machine translation. T5 can handle various tasks, and it can be fine-tuned

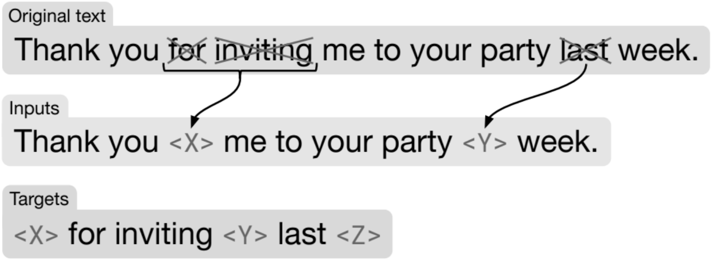

Original text
Thank you ~~for inviting~~ me to your party ~~last~~ week.
Inputs
Thank you <X> me to your party <Y> week.
Targets
<X> for inviting <Y> last <Z>

Figure 13: Pre-training by Replace Corrupted Spans [RSR+19]

for different NLP tasks, such as summarization, Corpus on Linguistic Acceptability (COLA), classification, multiple text translation, also regression problems like STSB that predict how similar two sentences are. And in our case Text-to-SQL.

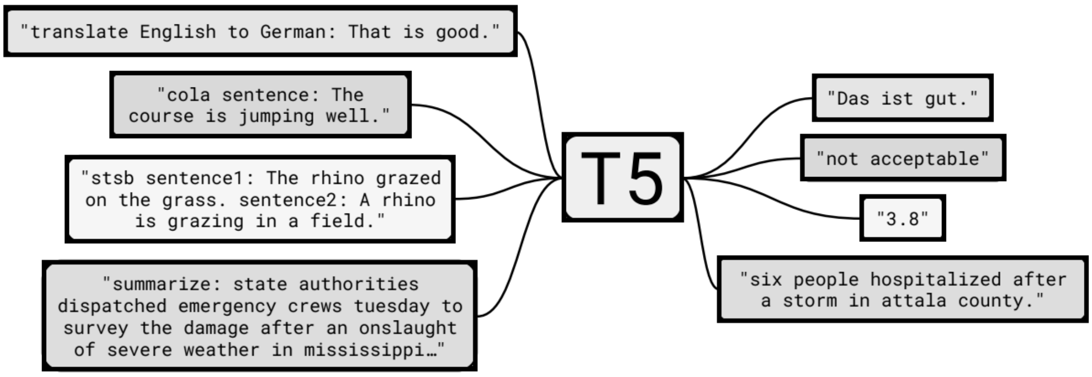

"translate English to German: That is good."
"cola sentence: The course is jumping well."
"stsb sentence1: The rhino grazed on the grass. sentence2: A rhino is grazing in a field."
"summarize: state authorities dispatched emergency crews tuesday to survey the damage after an onslaught of severe weather in mississippi…"
T5
"Das ist gut."
"not acceptable"
"3.8"
"six people hospitalized after a storm in attala county."

Figure 14: Each task uses text as input in the model and generates target text. In this way, the same model, loss function, and hyper-parameters are used across various diverse tasks, including translation. [RSR+19]

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

Colossal Clean Crawled Corpus (C4)

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

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

Beam Search

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

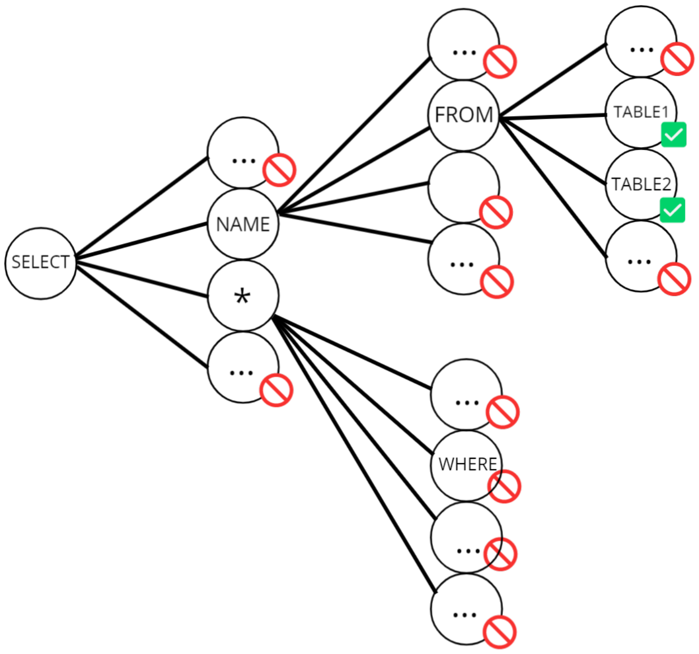


Figure 15: 4-Beam Search

Beam search is a widely used search algorithm in natural language processing and machine learning. It is beneficial in sequence-to-sequence (seq2seq) models, which generate output sequences based on input sequences. Beam search is used to find the most likely sequence of output words given an input sequence.

The basic idea behind beam search is to maintain a set of the most likely sequences at each step of the decoding process. This set of sequences, called the ”beam,” is initially set to the starting point of the decoding process, and at each step, new sequences are generated by considering all the following possible words. The new sequences are then ranked based on their likelihood, and the highest-ranking sequences are added to the beam. The process is repeated until a stopping criterion is met [MLGftADNI19]. Beam search is handy in seq2seq models because it allows the model to generate multiple output sequences rather than just a single sequence. This is important because, in many cases, there may be multiple valid outputs for a given input sequence. By generating multiple outputs, beam search allows the model to explore the space of possible outputs and find the most likely sequences.

One of the critical advantages of beam search is that it is computationally efficient. Because it only considers a small number of sequences at each step, it can quickly find the most likely sequences without exploring the entire space of possible outputs. This makes it well-suited for use in applications with limited computational resources, such as on mobile devices or in real-time systems. Another advantage of beam search is that it can be used with other techniques, such as attention mechanisms, to improve the performance of seq2seq models. Attention mechanisms allow the model to focus on specific parts of the input sequence when generating the output, which can help to improve the quality of the generated sequences.

In conclusion, Beam Search is a robust algorithm widely used in natural language processing and machine learning, particularly in the context of sequence-to-sequence (seq2seq) models. It allows the model to generate multiple output sequences rather than just a single sequence and is computationally efficient, making it well-suited for use in applications where computational resources are limited. Additionally, it can be combined with other techniques, such as attention mechanisms, to improve the performance of seq2seq models.

PICARD

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

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

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

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

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

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

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

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

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

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

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

4.3 Data Augmentation

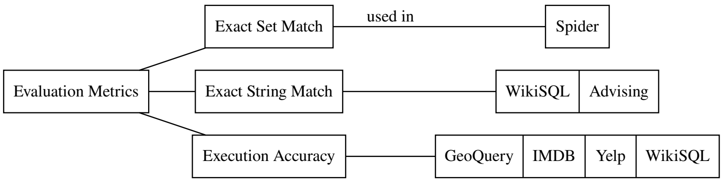
Data augmentation has proven to be an effective technique for improving the performance of text-to-SQL models, allowing them to address more complex or novel questions (Zhong et al. [ZYK] and Wang et al. [WSL$^+$]), achieve cutting-edge results with less supervised data, and enhance their adaptability to various question types (Radhakrishnan et al. [RSL20]).

Typical data augmentation approaches involve rephrasing questions and employing pre-established templates to boost data variety. Iyer et al. [IKC$^+$17] made use of the Paraphrase Database (PPDB) (Ganitkevitch et al. [GVDCB13]) to create rephrased training questions. Moreover, researchers have utilized neural models to generate natural-sounding expressions for sampled SQL queries, thus broadening the available data pool. For example, Li et al. [RSR$^+$19] fine-tuned the pre-trained Raffel T5 model [RSR$^+$19] on WikiSQL, using the SQL query to predict natural expressions and subsequently synthesizing SQL queries from WikiSQL tables to produce corresponding natural expressions with the refined model.

The quality of the augmented data is essential, as poor-quality data can adversely affect the performance of the model[YWL$^+$20]. Numerous methods have been applied to enhance the quality of augmented data. Zhong et al. [ZYK] employed an utterance generator to create natural expressions and a semantic parser to convert these expressions into SQL queries. They filtered out insufficient data by retaining only instances where generated SQL queries matched the sampled ones. Wu et al. [YWL$^+$20] implemented a hierarchical SQL-to-question generation process to obtain high-quality data, breaking down SQL queries into clauses, translating each clause into a sub-question, and merging the sub-questions to form a comprehensive question.

To further diversify augmented data and encourage question variety, Guo et al. [GZG$^+$19] incorporated a latent variable into their SQL-to-text model. Wang et al. utilized a Probabilistic Context-Free Grammar (PCFG) to explicitly model the composition of SQL queries [YZT21], which facilitated the sampling of compound SQL queries. These data augmentation methods collectively contribute to the enhancement of text-to-SQL models, allowing them to more effectively handle a broader range of questions and adapt to previously unencountered data.

5 Evaluation Metrics



The F1 score is a metric used to evaluate the performance of many machine learning jobs. 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 percentage of true-positive predictions to the total actual positive values. The F1 score is between 0 and 1, with more elevated values representing better performance. Precision indicates the accuracy of the classifier's prediction of the positive class. It is computed 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. [IKC+17], 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. [FDKZ+18] 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. [YZY+18] 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. [SCPT21] has 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.

5.1 Naïve 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.

5.2 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 [ZYK].

5.3 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 [YZY+18]. If every element from the set of predicted queries is included in the reference query, it returns a score of 1.0; otherwise, it returns a score of 0.0.

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

5.4 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.

5.5 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.

6 Experiments

Since the SEOSS Dataset[RM19] has only been evaluated and trained with SQLNet and RatSQL, in this section, we aim to further explore its potential by conducting experiments using state-of-the-art methods currently proposed for the SPIDER challenge. To assess the effectiveness of these approaches, we compare the outcomes with those of SQLNet and RatSQL, as reported in the SEOSS-Queries research paper[THM22]. The findings from these experiments are detailed in the subsequent section, showcasing the capabilities of contemporary solutions in tackling the SPIDER task.

Additionally, taking advantage of the publicly available ChatGPT APIs, we decided to experiment with the ChatGPT model. Employing both the SPIDER and SEOSS datasets, we compared the results with those obtained from earlier experiments. The insights derived from these experiments are presented in the following section, further illustrating the potential of modern solutions in addressing the SPIDER task.

6.1 Limitations

Our experiment faced several limitations, primarily due to the extensive computational resources required when leveraging the T5 model. For our experiment, we used a single Nvidia RTX 3070 16GB GPU with 20GB Memory, which constrained us to smaller models with tighter restrictions. Despite these limitations, we managed to achieve admirable results. Utilizing a larger T5 model could have led to even higher scores. As a result, investing in a more powerful GPU for our experiment should be considered to capitalize on our model's potential fully. In addition, during the ChatGPT experiment, cost constraints limited our ability to experiment with GPT-4.0, as its usage cost is approximately 30 times higher than that of GPT-3.5-turbo. We had to experiment with different methods to find the best prompt for ChatGPT to force him to act as a text-to-SQL agent, but this led to wasting money.

Model	**Usage**
GPT-4	$0.06 / 1K tokens
GPT-3.5-turbo	$0.002 / 1K tokens

Table 7: Cost comparison between GPT-4 and GPT-3.5-turbo

6.2 SEOSS evaluation with T5 PICARD

After studying the SEOSS dataset, we decided to experiment with the PICARD model4.2.8 to evaluate its performance against that of SQLNet and RatSQL. We decided to use the T5-Base and T5-Large models for our experiment, as they are 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	lex	4	0.3071	0.3039
T5-base	parse with guards	2	0.3297	0.3576
T5-base	parse with guards	4	0.3286	0.3512
T5-large	lex	2	0.3672	0.3629
T5-large	parse with guards	4	0.4274	0.4822

Table 8: 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:

The T5-large model generally performs better than the T5-base model in both exact matching accuracy and execution accuracy. As we could have a predicate, the parse with guards Picard mode performs better than the lex Picard mode in both models. So we decided to continue only with parse with guards. 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 from base to large.

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 Appendix of this thesis, where you can also find them in the project repository.

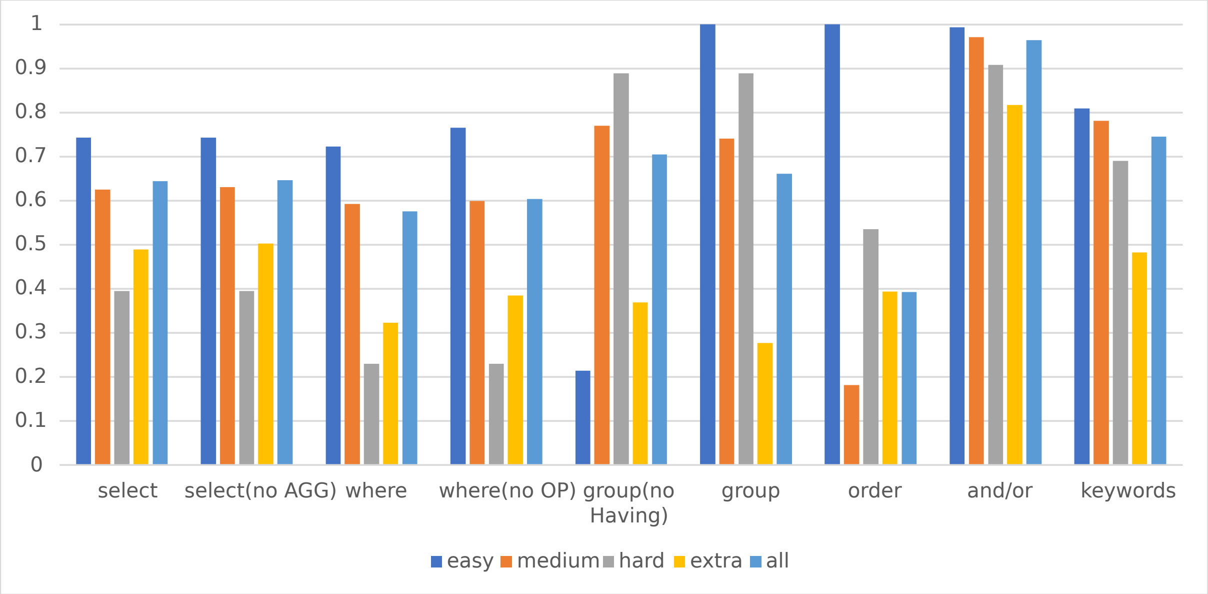


Figure 16: F1 Scores of Component Matching - PICARD T5-Large 4-Beam

6.2.1 EZ-PICARD - Microservices Practices

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.

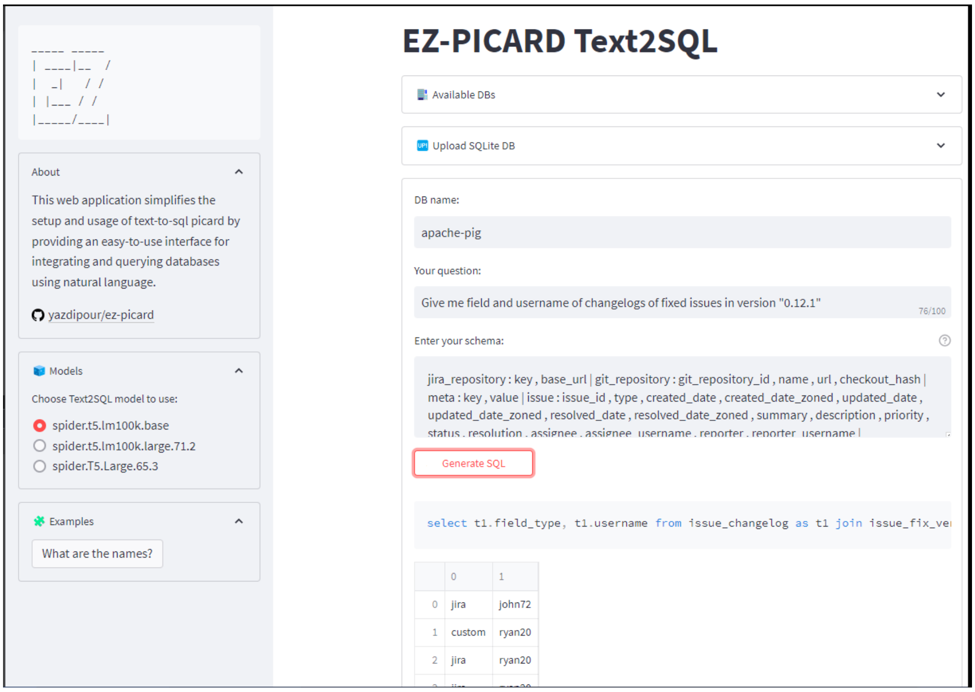
PICARD is a method for constrained inference on top of an existing model, but it is not a model itself. Currently, the PICARD parser and the supporting software are not supported for PostgreSQL, MySQL and others, which would require changes to the PICARD parser, translation of Spider databases and text-to-SQL 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 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

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

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



```
----- -----
| ----|--  /
|  _|   / /
| |___ / /
|_____/____|
```

EZ-PICARD Text2SQL

This web application simplifies the setup and usage of text-to-sql picard by providing an easy-to-use interface for integrating and querying databases using natural language.

yazdipour/ez-picard

Choose Text2SQL model to use:

- ● spider.t5.lm100k.base
- ○ spider.t5.lm100k.large.71.2
- ○ spider.T5.Large.65.3

What are the names?

DB name:

apache-pig

Your question:

Give me field and username of changelogs of fixed issues in version "0.12.1" 76/100

Enter your schema:

jira_repository : key , base_url | git_repository : git_repository_id , name , url , checkout_hash | meta : key , value | issue : issue_id , type , created_date , created_date_zoned , updated_date , updated_date_zoned , resolved_date , resolved_date_zoned , summary , description , priority , status , resolution , assignee , assignee_username , reporter , reporter_username |

```
select t1.field_type, t1.username from issue_changelog as t1 join issue_fix_ve
```

	0	1
0	jira	john72
1	custom	ryan20
2	jira	ryan20

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.

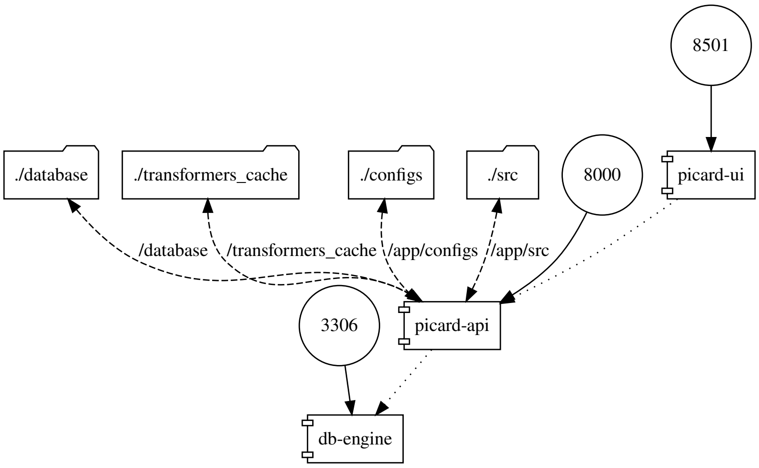


Figure 17: EZ-PICARD Architecture

6.3 SEOSS evaluation with GPT 3.5 and GPT 4

Here we discuss our experience using the ChatGPT API for the Text-to-SQL task on the SEOSS dataset. We will provide a brief overview of the Generative Pre-trained Transformers (GPT) architecture and delve into the specifics of ChatGPT, emphasizing its capabilities and potential for addressing this particular challenge.

6.3.1 GPT Architecture

Generative Pre-trained Transformers (GPT) [RNSS18] represent the state-of-the-art in language modeling, being built upon the revolutionary Transformer architecture. This architecture has profoundly influenced the field of natural language processing due to its utilization of self-attention mechanisms. These mechanisms enable the parallel processing of sequences, leading to more efficient training and enhanced performance across a wide range of NLP tasks.

Inherently generative, GPT models are designed to create text based on the context they are given. They are pre-trained on vast quantities of textual data, which enables them to learn the underlying structure and patterns present in natural language. The pre-training phase consists of unsupervised learning using a masked language modeling objective. Following pre-training, GPT models can be fine-tuned for specific tasks, such as translation, summarization, or, as in our example, Text-to-SQL.

Prior to the introduction of GPT-4, OpenAI had developed three earlier GPT versions and had been refining GPT language models over an extended period. The first GPT model, launched in 2018, incorporated 117 million parameters. The next version, GPT-2, was released in 2019 and demonstrated a substantial increase, incorporating 1.5 billion parameters. GPT-3, which currently powers ChatGPT, made its debut in 2020 and operates with 175 billion parameters. OpenAI, however, has chosen not to reveal the number of parameters used in GPT-4 [Ope23].

Considering the consistent growth in parameter counts with each successive model, it is logical to assume that the most recent multimodal iteration features a higher number of parameters than its predecessor, GPT-3, which consists of 175 billion parameters. Also, some researchers have speculated that GPT-4 may have as many as 1 trillion parameters or more[BCE+23].

6.3.2 ChatGPT

ChatGPT and Large Language Model (LLM) models represent an evolution in language models tailored explicitly for conversational interfaces. These models exhibit a distinct behavior compared to older language models. While previous models operated on a text-in and text-out basis (accepting a prompt string and returning a completion to append to the prompt), GPT-3 and GPT-4 models follow a conversation-in and message-out approach [BCE+23]. They expect input formatted in a chat-like transcript format and return a completion representing a model-generated message within the chat. This format is designed for multi-turn conversations but can also be effective in non-chat scenarios. For our experiment with the SEOSS dataset, we utilized the ChatGPT API to submit natural language questions and retrieve generated SQL queries. The API allowed for the seamless integration of ChatGPT into our workflow and provided an efficient and effective means to process the dataset. Throughout the evaluation, we observed that ChatGPT successfully generated accurate and syntactically correct SQL queries for a wide range of questions. The model excelled at handling complex queries and demonstrated a deep understanding of the underlying database schema. However, there were instances where ChatGPT generated SQL queries that deviated from the desired output, particularly in edge cases and questions with ambiguous semantics. To mitigate this issue, we employed a combination of custom LLM prompts to ensure the generated queries met the required quality standards.

6.3.3 ChatGPT Prompting

6.3.3.1 Rules

ChatGPT employs prompts to direct its response generation process [WFH+23]. To maximize the effectiveness of ChatGPT in various applications, it is essential to understand the art of crafting effective prompts. The following guidelines have been established to optimize the performance of ChatGPT in generating accurate, relevant, and context-aware responses:

1. **Give ChatGPT an identity and intended audience**: By assigning a role or identity to ChatGPT (e.g., ”You are a text-to-sql assistant, do... or As an assistant, explain...”) and specifying the target audience, the model can adopt a specific perspective or tone, providing tailored responses to the context.

2. **Offer and give specific context**: Including relevant background information or context in the prompt helps the model generate more accurate and meaningful answers, particularly when dealing with complex or domain-specific queries.

3. **Highlight information to include or exclude**: Clearly specifying what information should be incorporated or omitted in the response enables ChatGPT to generate responses that better align with user expectations (e.g. ”Do not use any aliases”).

4. **Choose a relevant tone of voice and writing style**: Indicating the desired tone (e.g., formal, informal) or writing style (e.g., persuasive, explanatory) in the prompt can guide ChatGPT in producing responses that are more suitable for the specific application.

5. **Give examples to base the response on**: Providing example responses can help ChatGPT understand the desired output format and style, allowing it to generate similar responses.

6. **Specify response length**: Mentioning the required response length (e.g., ”In 256 characters or less, do...”) helps in obtaining outputs that conform to the desired word count or character limit. When we know the desired response length, with this rule we can also control the number of tokens generated by the model that will have a cost effect.

7. **Clarity and specificity**: Crafting clear and concise prompts, along with avoiding ambiguous or vague questions, can significantly improve the quality of the generated responses. Easily by providing exact information and clear instructions to the model, we can get significantly better results.

These guidelines, when employed systematically, can enhance the performance of ChatGPT in a wide range of natural language processing tasks. By iterative refining and experimenting with different prompt styles, we can achieve improved outcomes in our specific applications.

6.3.3.2 Roles

Prompts are input messages with an associated role, which can fall into one of three categories: system, user, or assistant. The role of the message's author supplies context for the conversation and influences the model's response. [Ope23]

- **System**: A high-level directive for the conversation, typically used to offer guidance or establish the context for the assistant.
- **User**: A message submitted by the user, usually in the form of a question or a request for the assistant to process.
- **Assistant**: The response produced by the assistant is based on the context provided by the system and user messages. The assistant processes the messages according to their order in the list and generates a response accordingly. Employing system instructions can effectively guide the assistant's behavior throughout the conversation. The assistant prompt is usually used to provide historical context for the conversation.

Now we outline our approach to discovering the optimal prompt for text-to-SQL ChatGPT agents and present some preliminary results. The initial step in identifying the best prompt involves defining a set of criteria to evaluate the quality and accuracy of the generated SQL commands.

Potential criteria include the syntactic correctness of the SQL commands (i.e., adherence to the rules and patterns of SQL syntax) and the semantic correctness of the SQL commands (i.e., alignment with the meaning and intent of the natural language queries).

Given that ChatGPT is a conversational agent, we must also consider the quality of the output in terms of the context and format of SQL. Consider an example from the SEOSS dataset: ”Generate syntactically correct read-only SQL to answer the following question: What was changed in version 0.12.1.” ChatGPT's output, in this case, would be a conversion with a query, which is not the desired outcome.

ChatGPT3.5-Turbo Prompt Attempt#1

Prompt:

```
Generate syntactically correct read-only SQL to answer the following question: What was
changed in version 0.12.1
```

ChatGPT:

```
Certainly! Here's the SQL statement to return what was changed in version 0.12.1:
SELECT changes FROM version_history WHERE version_number = '0.12.1'.
Note that the syntax may vary slightly depending on the specific database management system
being used and the structure of your tables,
but this should work in most cases assuming there is a table named version_history with
columns version_number and changes.
```

Now we must find a way to guide ChatGPT toward generating the correct SQL query. We can filter the result and obtain output in our desired style by specifying precisely what we want. The following is the prompt we used to enhance the quality of the output.

ChatGPT3.5-Turbo Prompt Attempt#2

Prompt:

```
Write one valid SQL query in markdown format without talking and giving a description.
Generate syntactically correct read-only SQL to answer the following question: What was
changed in version 0.12.1
```

ChatGPT:

```
SELECT changes FROM version_history WHERE version_number = '0.12.1'
```

We can utilize the system role to provide context and the user role to pose the question. In the system role, we can limit the system to acting as an agent or assistant for a specific task. We can also supply the system with a database schema. We can present the question in the user role, and the assistant will generate the SQL query. We used the following prompt to improve the output quality as a text-to-SQL agent using the SEOSS dataset.

Final Prompt

role(System):

```
You are a helpful assistant for generating syntactically correct read-only
SQL to answer a given question.
Database: $dbname
The following are tables you can query:
---------------------
$schemas
---------------------
Do not use IN keyword.
If it is necessary to use AS then use it like T1 T2 ..., but if the alias
name is not going to be used in query again, then do not use.
Do not filter WHERE for being NOT NULL if it is not necessary.
If in using COUNT(*) and COUNT(COLUMN) there is no difference then use COUNT(*).
Write one valid SQL in markdown format.
```

role(User):

```
Generate syntactically correct read-only SQL to answer the following question: $question
```

By incorporating system and user roles, we effectively guide ChatGPT to generate the desired SQL query in response to a natural language question [WFH+23]. This approach demonstrates the importance of carefully crafting prompts and roles to achieve the most accurate and contextually appropriate results from ChatGPT in text-to-SQL tasks.

In this prompt, we first provided a system message that set the context for the system, including information about the database, tables, and specific syntax requirements for the generated SQL query. The user message then contained the natural language question for which the assistant was expected to generate the corresponding SQL query. Using this prompt structure allowed us to effectively communicate the task requirements and constraints to ChatGPT, resulting in more accurate and syntactically correct SQL query generation.

Initially after generating queries and analyzing the results, we found that the generated SQL queries were syntactically correct but semantically incorrect or needed refinements. For instance, ChatGPT tent to use AS keyword to name tables even when It was not necessary or use IN keyword even for simple conditions. This sort of behavior tent to reduce the accuracy of the generated SQL queries and

Prompt	**accuracy**
Simple asking prompt	11%
Prompt + Format constraints	28%
Prompt + Format Constraints + DB Schema	44%

After running the GPT-3.5 model on the SEOSS dataset, we found that the accuracy of the generated SQL queries was 44.7%. This is a significant improvement over the 11.6% accuracy of the simple asking prompt. We also found that the accuracy of the generated SQL queries was 28.9% when we added the format constraints to the prompt. This is a significant improvement over the 11% accuracy of the simple asking prompt. We also found that the accuracy of the generated SQL queries was 44% when we added the database schema to the prompt. This is a significant improvement over the 11% accuracy of the simple asking prompt. After that, we did the same with GPT 4 and we saw a significant jump in accuracy, especially for easy and medium questions.

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
GPT 3.5-turbo	0.551	0.460	0.130	0.190	0.447
GPT 4	0.709	0.505	0.104	0.131	0.524

Table 9: Comparison between Exact Match Accuracy

The table presents a comparison of the exact match accuracy for various models that have not been fine-tuned for our dataset. These models are assessed across five difficulty levels: easy, medium, hard, extra hard, and all. The large GPT models demonstrated the highest accuracy across all levels. Upon investigating the reasoning behind the lower accuracy on the hard level, we discovered that the model occasionally generated correct but complex queries, which led to confusion in our evaluation method.

Model	**Execution Accuracy**	**Time**	**Parameters**	**Cost**
PICARD + T5Base	0.307	400min	220M	Local Hardware
PICARD + T5Large	0.427	720min	770M	Local Hardware
GPT 3.5-turbo	0.447	37min	175B	$2
GPT 4	0.524	78min	1T	$14

Table 10: Expermiment Accuracy vs Resources used

6.4 Spider evaluation with GPT 3.5 and GPT 4

Throughout this thesis, we have explored the advancements in Text-to-SQL models and their performance on the SPIDER benchmark. Our analysis revealed the significant progress made in the field, with more recent models demonstrating remarkable improvements in generating accurate SQL queries from natural language text.

The integration of powerful pre-trained language models, such as BERT, and cutting-edge architectures like T5 has played a vital role in the observed advancements. The models' ability to learn from limited labeled data, quickly adapt to new tasks or domains, and handle complex SQL queries has been substantially enhanced by employing techniques such as active learning, meta-learning, and multi-task learning.

Our experiments with ChatGPT-3.5 and ChatGPT-4.0 have showcased their superior performance, achieving scores of 81.30% and 85.20% on the SPIDER benchmark, respectively. These results highlight the potential of utilizing the latest huge language models for Text-to-SQL tasks, further pushing the boundaries of what is possible in this domain.

As the field of natural language processing continues to evolve, we can expect even more sophisticated models and techniques to emerge, enabling more accurate and efficient understanding and generation of SQL queries from natural language input. Future research in this area may focus on enhancing the models' ability to handle ambiguous or imprecise input, as well as exploring novel methods to improve their adaptability and generalization capabilities across diverse tasks and domains.

Accuracy	easy 248	medium 446	hard 174	extra hard 166	all 1034
GPT 3.5 execution	0.964	0.883	0.644	0.596	0.816
GPT 3.5 exact match	0.972	0.881	0.621	0.596	0.813
GPT 4 execution	0.980	0.930	0.678	0.651	**0.855**
GPT 4 exact match	0.980	0.933	0.667	0.639	**0.852**

Table 11: Comparison between Accuracies

In conclusion, our experience using the ChatGPT API for the Text-to-SQL task on the SEOSS dataset was positive. The model's powerful natural language understanding capabilities, combined with the ease of integration through the API, make it a valuable tool for addressing such tasks. Additionally, by incorporating a few values from the database into the system input prompt, ChatGPT can better comprehend the database structure and generate more accurate queries. Also, by including the history of queries in prompts, we can improve the model's accuracy, but it will increase the overall time and money required to generate the queries. Future work could involve further fine-tuning ChatGPT specifically for Text-to-SQL tasks or exploring more advanced techniques for error correction and query validation.

6.4.1 Cost Reduction

We also compared the cost of running the queries generated by the different models. We found that the GPT 4 model was the most expensive to run, followed by the GPT 3.5-turbo. This is because GPT 4 is a larger model requiring more resources. However, the GPT 4 model was also

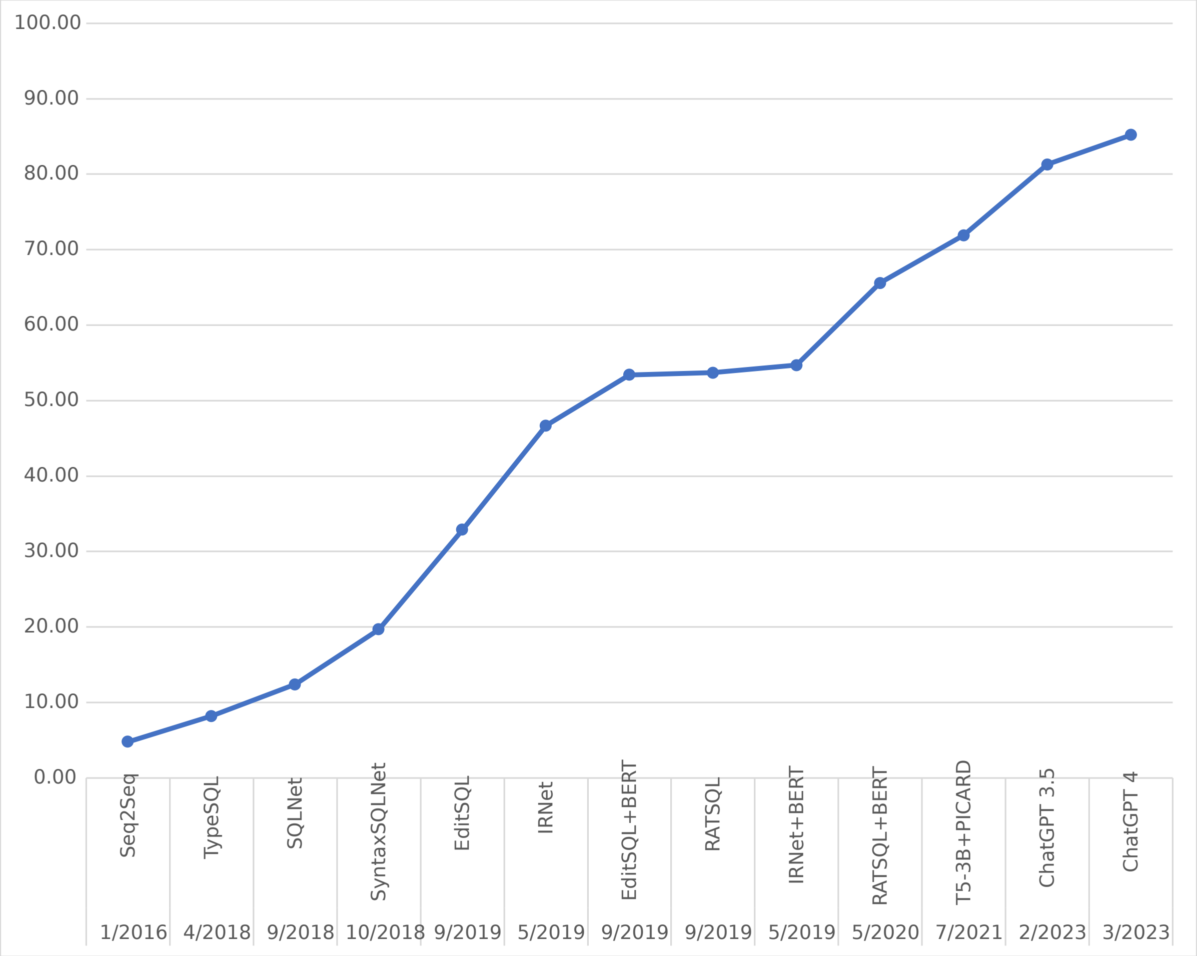


Figure 18: SPIDER benchmark Exact Match Results including our experiments

the most accurate, which means that it could generate more efficient queries requiring fewer resources to run. This is an important consideration when choosing a model for a production environment.

We can reduce the cost by minimizing the number of tokens we send to OpenAI API. We can do this by only giving the necessary information for the model to understand the task. Also, the number of tokens we receive from the model can be reduced by prompting the model to generate only the SQL query.

The other technique we used to reduce the cost was to use the GPT 3.5 turbo model to generate the SQL query, and for failed queries, we used the GPT 4 model to generate the SQL query. This technique reduced the cost significantly but nearly 45%.

6.4.2 Further Refinement

In order to optimize the performance and precision of the model, various strategies can be implemented. These approaches focus on providing the model with more context and relevant information, which in turn enhances its ability to generate accurate SQL queries. The following sections outline two such methods that have proven to be effective in refining the model's output.

6.4.2.1 Database Sample Integration

A selection of brief examples was utilized within the prompt to enhance the precision of the produced SQL queries.

Employing an identical prompt configuration as the preceding one, several records from database tables, in conjunction with the database schema, may be incorporated to facilitate GPT's comprehension of the database's intricacies. This enabled the model to assimilate the information and generate increasingly precise SQL queries.

6.4.2.2 Incorporating History and few shot examples

The model's capacity to learn from prior queries or some examples was augmented, thus improving the generated SQL queries' accuracy.

By examining previous query outcomes and employing them within the prompt in the assistant capacity, the model's generation of increasingly precise SQL queries can be supported by presenting a historical record of actions. While implementing these refinement strategies, a potential increase in API costs is an important consideration. As the number of tokens per request increases due to the inclusion of additional context and information, the cost associated with each API call will rise significantly. It is crucial to weigh the benefits of improved accuracy and precision against the increased expenditure and strike a balance that ensures optimal model performance and cost efficiency.

Example of a Prompt with History and Database Sample

role(System):

```
You are a helpful text-to-sql assistant for generating syntactically correct read-only
SQL to answer a given question.
Database: concert_singer
The following are tables you can query:
---------------------
table name: stadium table columns: Stadium_ID [number (13)], Location [text (LA)], Name
[text (SLA)], Capacity [number (30000)], Highest [number (20000)], Lowest [number (100)],
Average [number (1000)] table name: singer table columns: Singer_ID [number (1)], NName
[text (John Doe)],Country [text (USA)],Song_Name [text (Beautiful Day)],Song_release_year
[text (2020)],Age [number (30)],Is_male [others (Yes)] table name: concert table
columns: concert_ID [number (101)],concert_Name [text (Rock Night)],Theme [text (Rock
Music)],Stadium_ID [text (13)],Year [text (2023)] table name: singer_in_concert table
columns: concert_ID [number (101)], Singer_ID [text (1)]
---------------------
Do not use IN keyword.
If it is necessary to use AS then use it like T1 T2 ..., but if the alias
name is not going to be used in query again, then do not use.
Do not filter WHERE for being NOT NULL if it is not necessary.
If in using COUNT(*) and COUNT(COLUMN) there is no difference then use COUNT(*).
Write one valid SQL in markdown format.
```

role(User):

```
Generate syntactically correct read-only SQL to answer the following question: How many
singers do we have?
```

role(Assistant):

```
SELECT count(*) FROM singer
```

role(User):

```
Generate syntactically correct read-only SQL to answer the following question: What are the
names, countries, and ages for every singer in descending order of age?
```

role(Assistant):

```
SELECT name, country, age FROM singer ORDER BY age DESC
```

role(User):

```
Generate syntactically correct read-only SQL to answer the following question: $question
```

6.4.2.3 Retries and Feedback

In certain situations, ChatGPT may generate incorrect or unsatisfactory outputs. To improve the model's performance, we have investigated several techniques involving retries and feedback. Our experiments have led to the following observations:

Retry without modifications: Asking ChatGPT to retry without providing any specific guidance or feedback rarely led to improved results. Even when repeating the process multiple times, there was no significant improvement in the quality of the outputs and ChatGPT will insist on the correctness of the output.

Rephrasing the user's question: Requesting the model to rephrase the user's question before attempting to generate an answer yielded better outcomes in some cases. This method proved helpful in easy and medium tasks, resulting in the generation of new and improved queries. However, this approach's effectiveness diminished after the first retry, with no further improvements observed.

Human-guided feedback: Incorporating a human agent's feedback to point out issues in the generated output and instructing ChatGPT to address the problem led to noticeable improvements. In our experiments, we provided feedback in the form of ”This is wrong. $reason,” and ChatGPT made appropriate adjustments based on the given reason.

Example a Feedback Prompt

role(User):

```
Show the stadium name and the number of concerts in each stadium.
```

role(Assistant):

```
SELECT stadium.Name, COUNT(concert.concert_ID) AS Num_Concerts FROM stadium LEFT JOIN concert
ON stadium.Stadium_ID = concert.Stadium_ID GROUP BY stadium.Name;
```

role(User):

```
This is wrong: Name is not a good column for grouping.
```

ChatGPT:

```
SELECT stadium.Name, COUNT(concert.concert_ID) AS Num_Concerts FROM stadium LEFT JOIN concert
ON stadium.Stadium_ID = concert.Stadium_ID GROUP BY stadium.Stadium_ID;
```

Our experience with this approach indicates that it is particularly effective for easy and medium-difficulty utterances. We were able to fix 93% of such utterances output using human-guided feedback. However, for extra hard utterances, the success rate was lower, with only 8% of them being fixed in the first retry. Despite this limitation, the overall effectiveness of a single retry in generating outputs that match the gold standard was promising.

Since evaluation metrics often struggle with accurately assessing queries containing ”INTERSECTION,” ”UNION,” or ”EXCEPT” keywords, there is a high rate of false positives. ChatGPT may generate correct alternative queries using JOINs that convey the same meaning, but the evaluation metrics fail to recognize them as correct. Providing an additional prompt can guide ChatGPT to generate alternative queries using JOINs, leading to improved accuracy. Utilizing this technique, we could fix 10% of extra-hard tasks. As a result, the queries in the SPIDER dataset serve as a valuable resource for enhancing evaluation methods rather than solely focusing on improving the model itself.

Example a Feedback Prompt

role(User):

```
Find the first name of students who have both cat and dog pets.
```

role(Assistant):

```
SELECT DISTINCT S.Fname FROM Student S JOIN Has_Pet AS HP1 ON S.StuID = HP1.StuID JOIN
Pets AS P1 ON HP1.PetID = P1.PetID AND P1.PetType = ’Cat’ JOIN Has_Pet AS HP2 ON S.StuID =
HP2.StuID JOIN Pets AS P2 ON HP2.PetID = P2.PetID AND P2.PetType = ’Dog’;
```

role(User):

```
This is wrong: rewrite it with intersect.
```

ChatGPT:

```
SELECT T1.Fname FROM student AS T1 JOIN has_pet AS T2 ON T1.stuid = T2.stuid JOIN pets AS T3
ON T3.petid = T2.petid WHERE T3.pettype = ’cat’ INTERSECT SELECT T1.Fname FROM student AS
T1 JOIN has_pet AS T2 ON T1.stuid = T2.stuid JOIN pets AS T3 ON T3.petid = T2.petid WHERE
T3.pettype = ’dog’;
```

Although this human-guided approach can yield better results, it is not effective since it requires expert user guidance, which deviates from the zero-shot learning paradigm. However, exploring these methods can inform future work on prompt engineering techniques and facilitate the development of more effective strategies for refining model outputs.

7 Conclusion

In this thesis, we provided an in-depth analysis of state-of-the-art text-to-SQL solutions from a cross-domain perspective, delivering a comprehensive overview of the latest advancements in the field. We demonstrated the efficacy of pre-trained embeddings in enhancing schema linking and SQL structure accuracy through empirical results. This study aimed to elucidate the fundamental similarities and differences between older models and contemporary approaches.

We also examined datasets' influence on text-to-SQL models' performance, highlighting the Spider dataset as a challenging benchmark for text-to-SQL tasks and investigating the demanding SEOSS dataset. We conducted experiments with state-of-the-art models, including ChatGPT, and compared various models for text-to-SQL tasks. Our findings revealed that the PICARD + T5 model is a promising option, but further improvement could be achieved through fine-tuning, which might necessitate access to high-performance computing resources. These findings underscore the importance of considering both model architecture and computational resources when assessing the performance of NLP models.

Our exploration of evaluation metrics emphasized the need for more robust measures to assess text-to-SQL systems. Additionally, as research in the transformer and language models field expands, emerging challenges such as the Conversation-to-SQL task have surfaced, indicating the need for further investigation.

In conclusion, the text-to-SQL domain has experienced significant progress in recent years due to the creation of innovative datasets, models, and evaluation metrics. This area presents a wealth of opportunities for continued research and technological growth, paving the way for more advanced, efficient, and versatile solutions to complex natural language processing tasks.

8 Discussion and Future Directions

The field of text-to-SQL is a rapidly growing area of research, encompassing numerous systems and approaches designed to generate SQL queries from natural language text. Despite considerable advancements, several areas still warrant further exploration and improvement.

One promising direction for future research is cross-domain text-to-SQL. By incorporating domain-specific knowledge into models trained on existing datasets, these models can become more adaptable and applicable across different domains. This adaptability also enhances their capacity to handle scenarios where tables are corrupted or unavailable. Furthermore, addressing real-world applications, such as advanced handling of user inputs not present in existing datasets and providing database administrators with tools to manage database schemas and update content, is essential for the practical implementation of text-to-SQL systems. Multilingual text-to-SQL and developing database interfaces for individuals with disabilities are essential areas for future research.

The growth of LLM has significantly impacted various research fields, including text-to-SQL. Integrating text-to-SQL tasks into LLMs can lead to the development of more versatile question-answering systems for databases and dialogue systems with database-driven knowledge. Additionally, exploring the interconnection between SQL and other logical forms, as well as generalized semantic parsing, will contribute to a more comprehensive understanding of the subject, facilitating the creation of more adaptable and generalizable systems. Prompt learning, an emerging strategy within the LLM landscape, can be employed to enhance the robustness of text-to-SQL systems. This approach involves training models to respond to specific prompts or questions, thereby improving their performance in generating accurate SQL queries from natural language text.

In conclusion, the domain of text-to-SQL holds immense potential for growth and progress, with numerous significant practical applications and opportunities for integration with related fields, particularly in light of the ongoing advancements in large language models.

9 List of Acronyms

LSTM	Long Short-Term Memory	2
BERT	Bidirectional Encoder Representations from Transformers	2
ATIS	Air Travel Information System	3
NLQ	Natural Language Query	8
RDB	Relational Database	8
NL2SQL	Natural Language to SQL	8
NLG	Natural Language Generation	15
SEDE	Stack Exchange Data Explorer	19
SEOSS	Software Engineering in Open Source Systems	20
GNN	Graph Neural Networks	31
PLM	Pre-trained Language Models	32
MLM	Masked Language Modeling	34
AST	Abstract Syntax Trees	38
BPE	Byte Pair Encoding	42
T5	Text-To-Text Transfer Transformer	43
COLA	Corpus on Linguistic Acceptability	44
C4	Colossal Clean Crawled Corpus	44

PCFG Probabilistic Context-Free Grammar 48

GPT Generative Pre-trained Transformers 57

LLM Large Language Model 57

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