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Reliable Natural Language Interfaces using LLMs, Self-Correction and Incremental Schema Analysis

Bachelor Thesis

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Abstract

This thesis explores the integration of large language models (LLMs) into PostgreSQL database systems in order to make the database accessible via natural language instead of the postgres SQL dialect. The research focuses on implementation strategies, performance optimization, and practical applications of this concept.

Contents

List of Figures

List of Abbreviations

GPT	Generative Pretrained Transformer
SQL	Structured Query Language
API	Application Programming Interface
LLM	Large Language Model
DBMS	Database Management System
NL2SQL	Natural Language to SQL

1 Introduction

1.1 Problem Statement and Motivation

Database systems represent a backbone of modern computer science, allowing for rapid advancements whilst shielding us from the problem categories that come along with managing and querying large amounts of, usually structured, data efficiently. However, most Database Management Systems (DBMS) have traditionally required specialized knowledge, usually of the Structured Query Language (SQL), in order to become useable. Whilst this barrier may be percieved differently across diverse usergroups it represents a fundamental misalignment between end-user goals (e.g. analysts, researchers, domain experts etc.) and the underlying DBMS, thus often requiring software engineering efforts in order to reduce this friction.

This barrier is the reason entire classes of software projects exists (for example, admin / support panels), data analytics tools etc. which therefore introduce significant churn and delay between the implementation of a database system and reaching the desired end user impact. Often these projects span multiple years, require costly staffing and yield little to no novel technical value.

Emerging technologies such as Large Language Models (LLMs) have proven themselves as a sensible tool for bridging fuzzy user provided input into discrete, machine readable formats. Prominent models in this field have demostrated outstanding capabilities that enable computer scientists to tackle new problem classes, that used to be challenging / yielded unsatisfying results with logical programming approaches.

This thesis is exploring ways to overcome the above outlined barrier using natural language queries, so that domain experts, business owners, support staff etc. are able to seamlessly interact with their data, essentially eliminating the requirement of learning SQL (and its pitfalls). By translating natural language to SQL using Large Language Models this translation becomes very robust (e.g. against different kinds of phrasing) and enables novel applications in how businesses, researchers and professionals interact with their data — it represents a fundamental shift (ie. moving away from SQL) towards a more inclusive and data driven world.

1.2 Objectives of the Thesis

This thesis aims to address the aforementioned challanges when it comes to database accessibility. The following objectives are the core research area of this thesis:

1. Develop a database extension that can translate natural language queries into semantically accurate SQL queries using Large Language Models.

2. To evaluate the effectiveness and feasibility of different Models aswell as prompt engineering techniques in order to improve the performance of the system.

3. Identify and address issues when it comes to handling amibguous, complex and domain specific user input.

4. Benchmark the performance of the implementation against common natural language to SQL (NL2SQL) benchmarks.

5. Idenitfy potential use cases for real world scenarios that could deliver a noticable upsides to users.

6. Analyze the short commings and limitations of this approach and propose potential solutions to overcome them.

1.3 Research Questions

RQ1 — Are natural language database interfaces feasible for real world application?

The primary research questions when it comes to natural language database interfaces evolve around their semantic accuracy and reliability, therefore questioning their feasibility for real world usage. LLMs have notoriously been known for their ability to hallucinate / produce false, but promising outputs. This behaviour can be especially dangerous when opting for data driven decisions that rely on false data due to a mistranslation from natural language to SQL. LLMs could cause hard to understand and debug behaviour, like false computation of distributions when the intermediate format is not being shown to the user. This thesis tries to determine whether such hallucinations could be reasonably prevented and whether the associated performance and hardware requirements are suitable for a real world deployment, outside of research situations.

Specifically the two big underlying questions are:

1. Is the semantic accuracy of natural language database interfaces high enough to yield a noticable benefit to users?

2. Is it possible to run such an interface on reasonable, mass available hardware (e.g. excluding high end research GPUs).

RQ2 — What approaches are most effective in resolving ambiguity when translating natural language queries into SQL?

To provide semantically correct results ambiguity in the user-provided natural language queries must be adequately addressed. This thesis investigates various approaches to ambiguity management and resolution. Natural language queries can demonstrate ambiguity even at low levels of complexity — e.g. there are two different types of "sales" in a database schema, and the user asks to retireve "all sales".

Such situations present the second major challenge associated with the practical implementation of natural language database interfaces. The success of this concept will significantly depend on whether suitable designs and mitigation techniques can be implemented without creating problems with regards to the aforementioned performance and hardware requirements. The research focus lies on both preventative measures through optimized pre-processing stages and prompt engineering techniques as well as reactive strategies that post process LLM output, either on the basis of further user input or context inference.

RQ3 — Which strategies are increasing semantic accuracy of queries?

In order to enhance the semantic accuracy a series of improvements may be applied to the pipeline. Potential optimizations include supplying (parts of) the schema during LLM prompting, implementation of interactive contextual reasoning through a conversational interface which would allow for user refinement, the implementation of a robust SQL parsing and validation mechanism and a hybrid approach partly relying on traditional NLP preprocessing techniques. This research will quantify semantic accuracy using popular NL2SQL benchmarks and empirically evaluate the impact each approach has on the benchmark performance. Furthermore this research will take a look at the optimal combination of the aforementioned solutions in order to develop a system that strikes the right balance between accuracy and performance.

1.4 Structure of the Thesis

This thesis is following a research and development methodology in order to implement a natural language interface for databases, in particular postgres is used.

1. **Literature Review** — An analysis of the existing research in the fields of natural language interfaces (NLI) for databases, GPU integration for acceleration of database operations, and LLM/AI Model integration within database systems. This phase establishes the theoretical foundation for this research and identifies current state-of-the-art approaches, their benefits and shortcomings.

2. **Decomposition & Requirements** — Decomposing the problem statement into its fundamentals and deriving system requirements for the design phase from it. The goal of this section is to arrive at a list of functional and non-functional requirements that must be taken into account and fulfilled by the design and implementation phases respectively.

3. **System Design** — Design of a system architecture that can utilize GPU acceleration for LLM integration from within postgres. The primary goals of the system design phase are to arrive at an architecture that yields low latency natural language processing, schema-aware SQL query generation, ambiguity detection and resolution whilst maintaining a high semantic accuracy.

4. **Implementation** — The implementation of a PostgreSQL extension according to the above system design that relies on `rust` and `pgrx`. This extension will provide a GPU accelerated framework for executing LLMs, implement a natural language to query generation pipeline that relies on the SQL schema and create database functions and operators for both query generation and execution.

5. **Evaluation and Benchmarking** — An assesment framework and benchmark that introspects the implementations performance in multiple dimensions. Namely the most relevant dimensions for this thesis are:

   (a) Semantic Accuracy — Measuring the overall accuracy of results delivered for a given natural language input.

   (b) Ambiguity Resolution Capabilities — How well the system performs when confronted with ambiguous natural language input and database schemas.

   (c) Performance Metrics — Measuring the latency, throughput and resource utilization of the implementation.

6. **Discussion** — Analysis and interpretation of the evaluation phase results against the research goals of this thesis. Evaluating the performance and accuracy results recorded during the benchmarks against the question whether real world deployments of NILs are feasible. Furthermore the effectiveness of ambiguity resolution capabilities and semantic accuracy enhancement strategies are showing a statistically significant effect.

7. **Summary and Outlook** — Summarizes the contributions, addresses limitations of this thesis and the implementation, and proposes directions for future research alongside possible applications. Primary future research topics include advanced GPU optimization techniques (e.g. further quantization), accuracy and performance impact of model fine tuning, techniques, scalability of such a system in enterprise scenarios and the evaluation of security and privacy considerations (e.g. managing access control).

2 Literature Review

In this section a comprehensive literature review is performed to asses the research landscape on NL2SQL (sometimes also referred to as Text-to-SQL or T2SQL) and NLIDBs. From the time their development accelerated in the late 1990s and early 2000s (Androutsopoulos, Ritchie, & Thanisch, 1995; Popescu, Etzioni, & Kautz, 2003; Tang & Mooney, 2001; Zelle & Mooney, 1996) until now, observing multiple larger paradigm shifts happening over time (Deng et al., 2020; F. Li & Jagadish, 2014; Yaghmazadeh, Wang, Dillig, & Dillig, 2017; Yu et al., 2020; Zhong, Xiong, & Socher, 2017). In particular this research focuses on the recent advancements when it comes to language models and how they can be harnessed for effective NL2SQL systems (D. Gao et al., 2023; Lei et al., 2025; J. Li et al., 2023; Rahaman, Zheng, Milani, Chiang, & Pottinger, 2024; Rajkumar, Li, & Bahdanau, 2022; B. Zhang et al., 2024).

This literature review is covering the foundational concepts, challenges, key advancements and research gaps associated with using natural language instead of SQL. It lays the foundation for this thesis and helps to set the research questions introduced in the previous chapter in context.

2.1 Foundations of Natural Language Interfaces to Databases

Earlier papers in the research landscape on Natural Language Database Interfaces (NLIDBs) date over half a century back, into the early 1970s. Two decades after the first major research systems where developed in this domain, Androutsopoulos, Ritchie, and Thanisch have published an introduction and an overview over NLIDBs where an overview of state-of-the-art approaches were provided. (Androutsopoulos et al., 1995) Their work outlined multiple key issues and challenges associated with NLIDBs, and compared them against existing / competing solutions like formal query languages, form-based interfaces and graphical interfaces. These challenges (like unobvious limits, linguistic ambiguities, semantic inaccuracy, tedious configuration etc.) have shaped this field of research and are still considered relevant metrics today.

Early NLIDBs primarily relied on traditional natural language processing (NLP) techniques in order to achieve natural language understanding capabilities. With Chill an inductive logic programming (ILP) approach was first introduced for NL2SQL systems, marking one of the key events when it comes to machine learning usage. (Zelle & Mooney, 1996) In 2001 Tang and Mooney have extended the approach of ILP parsing for natural language database queries with multi clause construction, yielding promising results in the field of NLIDBs. (Tang & Mooney, 2001)

Building on the systematic overview of Androutsopoulos, Ritchie, and Thanisch and the first machine learning approaches from Zelle and Mooney aswell as Tang and Mooney, Popescu et al. have proposed a novel approach for implementing NLIDBs and outperformed at the time state-of-the-art solutions from Zelle and Mooney (1996) Tang and Mooney (2001) — achieving 80% semantic accuracy. (Popescu et al., 2003) The novelty of the Percise system lies in its natural language processing approach, specifically its lexical mapping strategy, allowing Percise to identify questions it can, and can't answer (introducing the concept of *semantically tractable questions*) which therefore results in a better and interactive end user experience. Their experiements also showed that this approach is *transferrable* and *unbiased* — it is possible to feed in new, unknown questions into the system and maintain performance characteristics, whereas it was shown that Zelle and Mooney (1996) were suffering from a distribution drift of the questions asked. (Popescu et al., 2003)

The theoretical foundations and research questions highlighted by the aforementioned works, shaped the research field and highlighted the following, ongoing research:

1. The trade-off characteristics derived from choosing a machine learning vs. traditional NLP approach (e.g. CHILL versus PERCISE). E.g. coverage versus correctness. (Popescu et al., 2003; Zelle & Mooney, 1996)

2. The linguistic challenges associated with bringing NLIDBs into use (e.g. semantic inaccuracy, linguistic ambiguity, unclear language coverage etc.) (Androutsopoulos et al., 1995)

3. The value of systems and approaches which double down on reliability and semantic accuracy rather than giving promising but incorrect answers. (Androutsopoulos et al., 1995; Popescu et al., 2003)

Fundamentally this highlights the tension and mismatch between the characteristics of natural language, which is able to be ambiguous, *semantically untractable* or able to be incomplete in meaning and formal languages like SQL which always have on deterministic and *semantically tractable* meaning they convey in each statement. As Schneiderman and Norman have pointed out according to Popescu, Etzioni, and Kautz, users are "unwilling to trade reliable and predictable user interfaces for intelligent but unreliable ones" which induces performance expectations on NLIDB implementations to be highly certain about the questions it can, and can't answer, whilst maintaing as high as possible natural language coverage. (Popescu et al., 2003)

2.2 Traditional NL2SQL Approaches

Prior to the wide-spread dominance of machine learning approaches for natural language processing a variety of traditional, rather discrtete approaches have been explored in the field of NL2SQL / NLIDBs. These logical programming approaches have laid the foundations for transitioning towards the application of machine learning techniques for NL2SQL.

2.2.1 Rule-based and Grammar-based Systems

Foundational research of NL2SQL system mostly focused around applying rule engines that were tedious to set up and expensive to maintain / transfer across database systems. These rule engines mostly relied on the systematic identification of linguistic patterns / were trying to template SQL from information that was derived from processing the natural language query. (Codd, 1974; Hendrix, Sacerdoti, Sagalowicz, & Slocum, 1978; Woods, Kaplan, & Nash-Webber, 1972) These approaches mostly tried to formalize natural language queries into formal grammers which could then be deterministically mapped into a valid SQL query. (Woods et al., 1972) These approaches have strong downsides when it comes to the variety of natural language constructs they can process, aswell as runtime adoption of new / unknown databases, query constructs etc. A potential upside of this class of NL2SQL systems is that they can confidently and reproducably identify questions they can, and can't answer — thus leading to very reliable and predictable user interfaces.

2.2.2 Semantic Parsing using String-Kernels

A significiant milestone in parsing techniques of natural language queries was reached by Kate and Mooney in 2006. The introduction of string kernels for semantic parsing represented a novel achievement, when it comes to fusing logical programming approaches using a formal grammer like LSNLIS developed by Woods et al. (1972) and learning / training approaches to understand unseen language patterns / unknown natural language query structures. This allowed for more flexible pattern recognition when compared to traditional rule-based systems.

The core innovative characteristic of this approach lies in its capability to understand similarities between natural language expressions based on subsequence patterns rather than relying on exact matches. This made KRISP, the research NLIDB system developed by Kate and Mooney (2006) much more robust to language variations in phrasing and noise (e.g. spelling mistakes) in the input. As the Kate and Mooney demonstrated through experiments on real-world datasets, this approach compared favorably to existing systems of the time like CHILL, especially in handling noisy inputs — a frequent challenge rigid rule-based systems faced in real world scenarios (Kate & Mooney, 2006; Zelle & Mooney, 1996).

2.2.3 Graph Matching Methods

Reddy, Lapata, and Steedman (2014) brought together several research threads and reapplied emerging graph matching research models to natural language processing, specifically to natural language queries. Graph matching was applied once the natural language query was parsed using a Combinatory Categorial Grammar (CCG) approach into a semantic graph which denotes the relationship between semantic entities in it. This graph could then be matched against the actual graph derived from the database, since they share topological traits that can be used for matching (Reddy et al., 2014). This approach allowed to apply querying systems without having any question-answer pairs or manual annotations for training the system, which implies easier scalability / transferability across domains, since the system does not require any additional tweaks.

Even though this approach was novel and showed improved the performance over existing state-of-the-art approaches, it was showing that graph matching quickly reaches its limitations. This approach relied heavily on the CCG parser's accuracy, with parsing errors accounting for 10-25% (depending on the dataset) of system failures (Reddy et al., 2014). Furthermore it struggled with both ambiguous language constructs and potential mismatches between natural language representation of relationships and database layouts — more complicated database designs, which may not match the users intuitive understanding resulted in a different topology and hence could not be matched (Reddy et al., 2014, p. 387).

2.2.4 Interactive Systems

In 2014 F. Li and Jagadish identified that perfect translation of natural language into SQL was challenging due to natural language not being made for query expressions as it heavily relies on contextual information and clarifying questions in order to disambiguate conversations (F. Li & Jagadish, 2014). These learnings relate to early prior art from Montgomery and Codd which also made this observation — "natural language is not a natural query language." (Montgomery, 1972). The solution introduced by NaLIR further emphasized how important an interactive, conversational usage model is, when offering a natural language interface (F. Li & Jagadish, 2014).

NaLIR could accept logically complex English language sentences as input and translate them into SQL queries with various complexities, including aggregation, nesting, and different types of joins etc. The key innovative characteristic of NaLIR lies in its interactive communication mechanism (much like RENDEZVOUS) that could detect potential misinterpretations and engage users to resolve ambiguities present in their natural language query without forcing them to entirely rephrase their query F. Li and Jagadish (2014). This approach, while showing awareness for its limitations (with regards to entirely automating / deriving SQL generation from potentially ambiguous or faulty user input) showed that it was possible to overcome these limtations through choosing the right interaction model — "In our system, we generate multiple possible interpretations for a natural language query and translate all of them in natural language for

the user to choose from" —, rather than optimizing the generation part of the system F. Li and Jagadish (2014).

2.2.5 Query Synthesis

Yaghmazadeh et al. (2017) introduced SQLizer, which synthesizes SQL queries from natural language (Yaghmazadeh et al., 2017). This paper presents a novel approach when it comes to NL2SQL as it is merging prevalent semantic parsing techniques (outlined above) with an program synthesis (or query synthesis) approach. SQLizer makes use of a three stage processing model for natural language models: first generating a sketch of the query using semantic parsing, then using type-directed synthesis to complete the sketch and finally using automated repair, if required.

Yaghmazadeh, Wang, Dillig, and Dillig show that alternating between repairing and synthesis yields results that beat state-of-the-art NL2SQL approaches like NaLIR. SQLizer is fully automated and database-agnostic, requiring no knowledge of the underlying schema. The authors evaluated SQLizer on 455 queries across three databases, where it ranked the correct query in the top 5 results for roughly 90% of the queries. This represents a significant improvement over NaLIR (F. Li & Jagadish, 2014), the previous state-of-the-art system (Yaghmazadeh et al., 2017).

Potential short commings of this approch include queries which yield empty results, dealing with language variations as SQLizer is still using semantic parsing, and domain-specific terminology, all while still requiring users to select from multiple query options which reduces the overall usability of the system (Yaghmazadeh et al., 2017, p.22-23).

2.2.6 Limitations of Traditional Approaches to NL2SQL

Despite being innovative and achieving state-of-the-art results, many of the above outlined approaches face severe challenges when moving outside of an research environment. Many of these systems performed comparatively good on research benchmarks that were often composed of controlled question types and limited data variety. Ultimatively no standard benchmark existed for NL2SQL in this era, hence comparing different NL2SQL systems against each other is a problem on its own. Despite not having a standard benchmark that all approaches could be unifiably evaluated against, several fundamental challenges emerged / remained with these approaches:

1. **Limited linguistic coverage** — Prevalent rule-based and semantic-parsing based systems were only able to process the a small subset of the natural language they were programmed for. This severely limited their ability to handle different phrasings of the same end-user goal (Hendrix et al., 1978; Kate & Mooney, 2006; Montgomery, 1972; Woods et al., 1972).

2. **Transferability** — Traditional approaches typically required extensive manual configuration or at least a training phase / adaption for each database they were deployed for, hindering cross domain usage through being expensive and time-consuming to adapt (Androutsopoulos et al., 1995; Woods et al., 1972).

3. **Brittleness** — Many of the systems introduced in this subchapter did not handle synonyms, paraphrasing, or spelling errors well. Manual adaption / handling was needed in order to becomes resilient against each class of problems (Kate & Mooney, 2006; Yaghmazadeh et al., 2017).

4. **Poor scalability** — With potentially more complex underlying databases, traditional solutions often showed to perform worse. Reddy, Lapata, and Steedman found, that with increasing schema complexity more compute was required to resolve the natural language query to a suitable query candidate making them less transferable and scalable than initially

anticipated (Reddy et al., 2014) — "Evaluating on all domains in Freebase would generate a very large number of queries for which denotations would have to be computed ... Our system loads Freebase using Virtuoso and queries it with SPARQL. Virtuoso is slow in dealing with millions of queries indexed on the entire Freebase, and is the only reason we did not work with the complete Freebase." which indicates underlying system design issues with runtime complexity.

These flaws of traditional NL2SQL approaches made it apparent, that a different class of approaches is needed, which increase transferability and reduce the brittleness since users are "unwilling to trade reliable and predictable user interfaces for intelligent but unreliable ones" according to Popescu et al. (2003). Whilst many approaches outlined tractable ways to increase user satisfaction and accuracy (like Codd did in 1974 with a conversational approach), NLIDBs were and are not considered to be a solved problem.

2.3 Neural NL2SQL Approaches

The previously outlined limitations of traditional approaches to solving NL2SQL / implementing NLIDBs pushed the research branch around neural network application forward to step in and propose new solutions which address the brittleness, transferability and scalability concerns addressed with logical programming approaches. Neural approaches showed to yield significant improvements in terms of transferability and overall accuracy which led to a paradigm shift in this research field.

2.3.1 Early Neural Approaches

In 2017 Zhong, Xiong, and Socher released Seq2SQL which represents a significant breakthrough and leap in NLIDB research. Seq2SQL was an early research system that in the field of neural network application and as one of the first papers to frame the implementation of NLIDBs / NL2SQL Systems as a reinforement learning problem. The system utilized iterative query execution in the reward function to improve its accuracy (Zhong et al., 2017). In the same paper Zhong, Xiong, and Socher introduced WikiSQL, a training dataset, which enables large scale (in 2017) model training.

SQLNet (Xu, Liu, & Song, 2017) addressed primarily the order-sensitivitiy trait of Seq2SQL (Zhong et al., 2017) that was prevalent due to being a derivative approach from sequence-to-sequence approaches. SQLNet diverges from sequence-to-sequence and joins multiple research threads, employing a sketch-based query generation. SQLNet breaks down complex queries into smaller (hence more manageable) sub-queries which can then be individually sketched and refined, yielding a system that outperformed state-of-the-art by 9% to 13% (Xu et al., 2017).

Yu, Li, Zhang, Zhang, and Radev have introduced TypeSQL, a variation of the SQLNet-approach, in 2018. TypeSQL's primary difference to SQLNet is the encoding of type information for SQL generation. The approach scanned for entity references and values in natural language and was able to improve performance by 5.5% over SOTA-Models like SQLNet whilst requiring significantly less training time, indicating that type information was a useful information for deriving accurate SQL queries from user input (Yu, Li, et al., 2018).

2.3.2 Intermediate Neural Developments

Later in 2018 Yu, Yasunaga, et al. released SyntaxSQLNet, a followup research to TypeSQL, which represented a slight change in approach and research focus. In direct comparison SyntaxSQLNet focused primarily around complex query generation using a syntax tree decoder,

allowing for longer and more cohesive query generation (Yu, Yasunaga, et al., 2018). This advancement over TypeSQL allowed more complex queries to be reliably generated, enabling multiple clauses aswell as nested queries. SyntaxSQLNet was one of the earlier research efforts which utilized Spider instead of WikiSQL (introduced by Zhong et al. (2017)), a large-scale NL2SQL dataset, incorperating 10.181 hand annotated natural language question and alongside 5.693 unique SQL examples that spread across 138 different domains (Yu, Zhang, et al., 2018). This research led the transition of comparatively simple, research-grade, neural systems for NLIDBs towards systems which are feasible in the real world.

Building on the above approaches, Guo et al. have introduced IRNet, a neural network approach using intermediate representation as a bridge between natural language and SQL in which semantic queries could be expressed. The intermediate format SemQL (or semantic query language) was utilized to transform and synthesize queries on the actual database schema more accurately than Seq2SQL. IRNet followed a three phase approach: schema linking between the natural language query and database layout, synthesis of SemQL as intermediate representation and deterministic conversion of SemQL to SQL. This approach allowed IRNet to outperform state-of-the-art approaches on the Spider benchmark by 19.5%, placing IRNet at an overall accuracy of 46.7% (Guo et al., 2019).

Following IRNet, graph neural networks (GNN) have been explored as alternative architecture by Bogin, Berant, and Gardner (2019), representing the database schema as a graph and using message passing to model relationships between tables, columns and natural language input. This approach demonstrated the capability to improve reasoning and query generation capability. Bogin et al. showed that when evaluating against the Spider benchmark GNN outperforms both SyntaxSQLNet (and therefore SQLNet & TypeSQL). Although presenting a signficiant advancement over previous state-of-the-art approaches, GNN falls behind in performance against IRNet by 6% (Bogin et al., 2019; Guo et al., 2019).

2.3.3 Relation-Aware Transformer Approaches

The release of RAT-SQL (Relation-Aware Transformer for SQL) Wang, Shin, Liu, Polozov, and Richardson (2020) represents the most significant leap in research of neural NL2SQL approaches. RAT-SQL diverged from earlier research through emphasizing the relationship between natural language and the database schema elements using relation-aware self-attention representing a novel approach for solving *schema linking* (Wang et al., 2020).

RAT-SQL's primary innovations was the ability to infer, understand and utilize the relationship between individual tokens in the natural language query and link it to the database schema. Thus allowing for reasoning capabilities on the actual database schema while generating the query.

This architecture yielded a 57.2% in exact match accuracy when being evaluated on the Spider benchmark, substantially outperforming comparative approaches like GNN, IRNet and IRNet V2 by 10.5%, 9.8% and 8.7% respectively. Although overall accuracy improved across all approaches when being paired with BERT (Bidirectional Encoder Representations from Transformers, a popular pre-trained lanugage model from Google) the δ between the indivudual approaches remained relatively steady, leaving RAT-SQL outperforming state-of-the-art approaches by 5% to 12.2% further demonstrating the capability advancement yielded by this system (Wang et al., 2020).

2.3.4 Comparative Analysis of Neural Approaches

The evolution from early neural approaches to RAT-SQL emphasized the rapid advancements that happened in the research field of neural NL2SQL approaches:

3 Decomposition & Requirements

3.1 Problem Decomposition

3.2 Requirements

4 System Design

4.1 Architecture Design

4.1.1 Interface Design

4.1.2 Data Model

4.1.3 Integration into SQL

4.2 Technical Implementation Strategies

5 Implementation

5.1 Development Environment and Tools

5.2 Integration of the Model

5.3 Development of the PostgreSQL Extension

5.4 Optimization

6 Evaluation

6.1 Test Environment and Methodology

6.2 Performance Tests

6.2.1 Latency

6.2.2 Throughput

6.2.3 Scalability

6.3 Use Cases

6.3.1 Natural Language Queries

6.3.2 Text Generation Within the Database

6.3.3 Semantic Search and Text Classification

6.4 Comparison with Alternative Approaches

7 Discussion

7.1 Interpretation of Results

7.2 Limitations of the Implementation

7.3 Ethical and Data Privacy Considerations

7.4 Potential Future Developments

8 Summary and Outlook

8.1 Summary of Results

8.2 Addressing the Research Questions

8.3 Outlook for Future Research and Development

Appendix

Installation Guide

API Documentation

Code Examples

Test Data and Results

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