FINE-TUNING LANGUAGE MODELS FOR CONTEXT-SPECIFIC SQL QUERY GENERATION

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ABSTRACT

The ability to generate SQL queries from natural language has significant implications for making data accessible to non-specialists. This paper presents a novel approach to fine-tuning open-source large language models (LLMs) for the task of transforming natural language into SQL queries within the retail domain. We introduce models specialized in generating SQL queries, trained on synthetic datasets tailored to the Snowflake SQL and GoogleSQL dialects. Our methodology involves generating a context-specific dataset using GPT-4, then fine-tuning three open-source LLMs—Starcoder Plus, Code-Llama, and Mistral—employing the LoRa technique to optimize for resource constraints. The fine-tuned models demonstrate superior performance in zero-shot settings compared to the baseline GPT-4, with Code-Llama achieving the highest accuracy rates, at 81.58% for Snowflake SQL and 82.66% for GoogleSQL. These results underscore the effectiveness of fine-tuning LLMs on domain-specific tasks and suggest a promising direction for enhancing the accessibility of relational databases through natural language interfaces.

Keywords Text-to-SQL, finetuning, large language models

1 Introduction

The transformation of natural language into SQL queries has been of great interest to both academia and industry due to its potential to enable non-specialists to access data from relational databases using natural language[1][2][3][4][5]. Recent advances in neural models, such as those based on large language models (LLMs), have led to impressive results on benchmarks like Spider[6] and WikiSQL[7]. For instance, the accuracy of the best-performing model on the Spider leaderboard has increased from 53.5%[8] to 86.6%[9] in the last three years. The most recent state of the art (SOTA) parsers in Spider leverage the powerful comprehension and coding capabilities of an LLM.

Until recently, sequence-to-sequence approaches that use language models have been the state of the art. Medium-sized models, such as T5[10], have achieved good results by incorporating SQL-specific designs and domain knowledge through fine-tuning. Notable models, such as PICARD[11], have employed methods like incremental parsing, relation-aware self-attention and skeleton-aware decoding frameworks.

Large language models, like GPT-4[12], and PaLM-2[13], have also shown remarkable success with zero-shot and few-shot prompting, or in-context learning[14]. The advantage of few-shot prompting is that it requires no training, has lower computation requirements, is less likely to over-fit to train data, and is easy to adapt to new data. However, the performance may be sub-optimal compared to fine-tuned alternatives. For example, CodeX[15] and ChatGPT[16] have demonstrated successful results with in-context learning for Text-to-SQL, but still have a clear gap with fine-tuned models that can also benefit from few-shot prompting.[17]

There is a great potential in open-source language models, with recent advances in programming, mathematical reasoning, and text generation tasks. However, previous research on Text-to-SQL has mainly focused on OpenAI models, overlooking the capabilities of open-source models. While open-source models may lack the functionality of their commercial counterparts in understanding context and generating coherent responses, they can be fine-tuned to improve their Text-to-SQL performance through supervised learning.[9]

The first attempts to finetune open-source LLMs for Text-to-SQL have yielded promising results [18][19], surpassing

the OpenAI models on this task with a fraction of the size.

This paper introduces a technique for constructing Text-to-SQL models tailored to a particular context. We specialize the models to a retail context with Snowflake SQL and GoogleSQL, and demonstrate that they outperform GPT-4 in zero-shot tests. This demonstrates the ability of these models to adjust to different SQL dialects and to modify the syntax of the queries.

We explain the process of generating a synthetic dataset of Text-to-SQL data in a retail setting, as well as the base pre-trained models used and the techniques used to finetune them. The results are then presented and discussed.

2 Methods

The input for Text-to-SQL is a prompt that includes a natural language query, the details of the database, and the corresponding SQL dialect. The output is the SQL query that answers the question. The database information typically includes multiple tables, each of which has a name, columns, and data types for the columns.

2.1 Dataset description

The initial segment of the dataset is comprised of a compilation of publicly accessible datasets, namely Spider [6] and Bird-SQL [20]. The Spider dataset is a comprehensive and diverse semantic parsing and text-to-SQL collection, annotated by 11 Yale students, which aims to facilitate large-scale, complex, and cross-domain research. The BIRD (BIg Bench for LaRge-scale Database Grounded Text-to-SQL Evaluation) dataset is specifically developed to address the gap between academic studies and practical applications in text-to-SQL parsing. It highlights emerging challenges, such as incorporating external knowledge, handling inconsistent data, and optimizing SQL efficiency.

Utilizing SQLGlot [21], these datasets were transformed into Google SQL and Snowflake SQL formats. Both versions, Google SQL and Snowflake SQL, were incorporated into the training process, enabling the model to discern the distinct syntax of each. Furthermore, we employ the GPT-4 model(the 0314 version)[12] to create a specialized Text-to-SQL retail dataset.

2.2 Dataset generation

Initially, we establish two representative retail datasets encompassing tables for customers, products, orders, and order lines. One dataset includes additional tables for sellers and payments. After their creation, these datasets are uploaded to the Snowflake and BigQuery data warehouses.

Subsequently, we delineate five business themes to serve as the foundation for question generation and instruct the GPT-4 model to generate additional themes. We also generate supplementary topics for the dataset that contains payment and seller information. This process results in 90 shared topics between datasets, and an extra 10 topics. These themes span a diverse range from customer demographics to seller performance, order seasonality, and product profitability, among others.

Following that, we prompt the GPT-4 model to generate up to 10 questions per topic that can be addressed using the provided data model, with instructions to cease generation if the questions become overly repetitive. Given that the information available for each dataset varies, this process is conducted independently for each dataset.

From the preliminary set of questions, we task GPT-4 with generating SQL queries that correspond to these questions. The GPT-4 model is instructed to construct modular SQL queries that are easy to read and utilize common table expressions (CTEs).

Subsequently, the generated SQL queries are executed on both data warehouses. In case of any errors or absence of results, a self-healing loop is employed to rectify the issue, with a maximum of five retry attempts. If the issue remains unresolved after these attempts, the corresponding question is removed from the dataset.

Next, GPT-4 is instructed to filter the resolved questions, retaining only those for which the dimensions of the dataframe, the column names, and the initial five rows of the results logically align with the corresponding question.

Additionally, GPT-4 is requested to reformulate each retained question up to four times, resulting in five distinct questions that can each be answered using the same SQL query. This approach ensures a broader diversity in the syntax and semantics of the questions, thereby approximating real-world usage.

The resultant dataset comprises 822 unique pairs of question-SQL query. After applying data augmentation through question rewrites, the total dataset encompasses 3732 such pairs (Figure 1). The dataset is subsequently partitioned into training (80%) and testing sets.

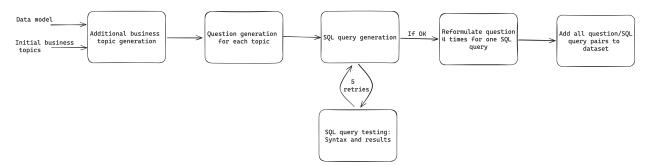


Figure 1: Text-to-SQL Data generation flow

2.3 Models and finetuning

Our base model selection comprises three models of varying parameter sizes, namely Starcoder Plus [22], Code-Llama (the 13 billion parameters version) [23], and Mistral-7b [24].

Starcoder Plus is a 15.5 billion parameter model. It boasts an extensive 8K context length and is proficient in infilling tasks. It efficiently executes large-batch inferences, thanks to its multi-query attention mechanism. This model is a product of the BigCode community – a collaborative, open-science initiative dedicated to the ethical advancement of Large Language Models specifically designed for code generation and manipulation. It is based on StarCoderBase, which was trained on 1 trillion tokens sourced from The Stack [25], a large collection of permissively licensed GitHub repositories with inspection tools and an opt-out process. The model then underwent further fine-tuning specifically for the English language.

Code LLama is a series of large language models specifically designed for code, based on Llama 2[26]. These models exhibit competitive performance in comparison to other open models, offering features such as infilling, handling extensive input contexts, and demonstrating zero-shot instruction following capabilities for various programming tasks. Mistral is a language model consisting of 7 billion parameters, utilizing grouped-query attention (GQA) for efficient inference and sliding window attention (SWA) to manage sequences of varying lengths while minimizing inference costs. In comparison to the 13-billion-parameter Llama 2 model, Mistral demonstrates superior performance across all assessed benchmarks.

The finetuning set-up is the same for each models, with only small changes in parameters.

Due to resource constraints, we opted to employ the LoRa (Low Rank Adaptors) technique for all three models[27]. This approach enabled us to conduct each fine-tuning on a single A100 Nvidia GPU with a memory capacity of 40GB. Moreover, during the training process, we disregarded the prompt loss and focused solely on the completion tokens. By doing so, the model was able to concentrate its efforts on generating the correct SQL query completion rather than the provided prompt text, which served merely as a context.

Furthermore, we refrained from packing the prompt-completion pairs into fixed token length sequences. Instead, we kept them separate, preventing any potential loss of information and ensuring that the prompt contained the full context.

3 Results

Assessing the validity of SQL queries can be a challenging task. Employing a model such as GPT-4 as a judge presents several issues related to accuracy. Moreover, a single question may be answered correctly in multiple ways, and the number and aliases of columns in the results can vary. To address these concerns, we have devised a deterministic evaluation method that takes these factors into account.

3.1 Evaluation methodology

In order to assess the results, we elected to concentrate on the data produced by the SQL query rather than the query itself. To this end, we executed the ground truth query and saved the output. Subsequently, we compared the results to those returned by the generated query. Our initial step involved verifying that both queries yielded the same number of rows. Subsequently, we confirmed that the ground truth columns were present in the generated query's dataframe, without considering column names. This comparison was conducted in a greedy manner. Lastly, we accounted for the possibility that the rows might be returned in a different order with sorting.

Models	Query Duration (Avg.)	Success Rate (%)	Accuracy Rate (%)
GPT-4 (Snowflake)	47.44s	87.36%	45.64%
GPT-4 (Google SQL)	47.40s	90.97%	48.89%
Starcoder (Snowflake)	16.6s	92.93%	62.43%
Starcoder (Google SQL)	19.32s	87.94%	51.05%
Code-LLama (Snowflake)	5.47s	98.73%	81.58%
Code-LLama (Google SQL)	6.46s	97.76%	82.66%
Mistral (Snowflake)	5.67s	96.45%	79.60%
Code-LLama (Google SQL)	6.50s	96.08%	79.44%

Table 1: Benchmark results on the generated dataset, all models except GPT-4 are finetuned

```
SELECT

AVG(products.avg_price)
FROM
products
WHERE
products.most_recent_order_timestamp >= DATEADD (month, -12, CURRENT_TIMESTAMP)

GROUP BY
products.avg_price

WHORER
products.avg_price

GROUP BY
products.avg_price

WIGHT

AVG(avg_price)
FROM
recent_product
AS (
SELECT
AVG(avg_price)
FROM
PRODUCTS
AVG(a
```

Figure 2: Comparison of SQL syntax before and after finetuning on a simple example

(b) Generated SQL query after finetuning

3.2 Results

(a) Generated SQL query before finetuning

Table 1 presents a comparison of the fine-tuned models' results in a zero-shot setting for each SQL dialect, relative to the zero-shot performance of GPT-4, as applied to the generated retail data. Furthermore, the models are executed using quantization with int8 precision. We provide the average duration of result generation, the success rate which is the percentage of SQL queries that return any results and the accuracy, meaning the percentage of SQL queries that return correct results out of the whole test dataset. We also noticed that the finetuned models are much better at writing modular SQL queries that are easy to read and utilize common table expressions (CTEs) (Figure 2)

3.3 Discussion

The development of models specialized for tasks like SQL query generation clearly benefits response latency and computational efficiency. Our investigation revealed that while the Starcoder model exhibited slower response times compared to Mistral and Code-LLama, this was largely due to the absence of certain inference optimization techniques like EETQ quantization[28] at the time of testing. Nevertheless, the fine-tuned models demonstrated a significant performance edge over the zero-shot GPT-4 model, with Code-LLama achieving the highest accuracy rates for both the Snowflake and Google SQL dialects.

The ability of these models to produce syntactically correct SQL queries that are executable by the database system is a testament to the effectiveness of the fine-tuning process. However, the specialized nature of these models does raise questions about their generalizability. Although the models' high accuracy rates are promising, their performance may decline when faced with SQL queries outside the training dataset's scope. This potential overfitting to the training data is a critical consideration for real-world applications, where the diversity of queries can be vast.

Furthermore, the similarity between the training and test datasets may inflate the measured performance of the models. While the test data was deliberately chosen to represent realistic retail SQL tasks, the possibility that the models have learned to excel on a narrow set of problems cannot be ignored. This underscores the need for comprehensive testing on a variety of datasets to fully understand the models' capabilities and limitations.

Despite these concerns, the results of this study are encouraging, particularly for domain-specific applications where the ability to quickly and accurately generate SQL queries can significantly impact the accessibility and usability of database systems. The fine-tuned models' proficiency in understanding and applying complex SQL syntax and

structures suggests that with further refinement and broader testing, we can enhance their applicability and reliability for a wider array of SQL-related tasks.

4 Conclusion

This paper contributes to the field of natural language processing and database querying by detailing the process of fine-tuning open-source large language models (LLMs) to accurately convert natural language questions into SQL queries in a retail context. Our approach, which leverages a synthetic dataset and the LoRa technique, has been shown to significantly enhance the performance of models like Starcoder Plus, Code-Llama, and Mistral, particularly when compared to the zero-shot performance of GPT-4. Code-Llama, in particular, demonstrated exceptional accuracy, surpassing 80% in both Snowflake SQL and GoogleSQL dialects.

Through the course of our discussion, we have acknowledged the potential limitations of our study, including the possibility of overfitting and the lack of generalization beyond the specific dataset and SQL dialects used. These issues highlight the importance of careful dataset curation and rigorous model evaluation in future research.

Moving forward, there is a clear opportunity to expand this research to encompass a wider range of domains and SQL dialects, and to explore the integration of these models into end-user applications. Striking a balance between accuracy through specialization and broader applicability through generalization remains a key challenge in deploying these models.

By focusing on the intersection of machine learning, AI, and user accessibility, this study not only progresses the technical capabilities of Text-to-SQL models but also emphasizes the practical benefits of making complex data systems more accessible to non-experts. Continued refinement of these models brings us closer to a future with lower barriers to data insights, enabling a wider audience to harness the power of data analytics.

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