

Text-to-SQL Generation using T5-Large with Schema Aware Encoding

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Abstract— The task of translating natural language queries into executable SQL statements—commonly referred to as Text-to-SQL—is a critical step toward enabling intuitive and user-friendly access to relational databases for non-technical users. In this work, we present a schema-aware sequence-to-sequence approach utilizing the T5-large language model to automatically generate SQL queries from natural language questions.

Our method enhances the model’s contextual understanding by incorporating structured schema information—such as table and column names—directly into the input sequence, enabling better alignment between user intent and database structure. We fine-tune the T5 model on benchmark datasets including Spider, which contain complex, cross-domain queries with corresponding database schemas. Experimental results demonstrate that our schema-aware formulation leads to improved syntactic and execution accuracy, while also enhancing the model’s generalization to unseen database schemas. Specifically, we achieve an Exact Match Accuracy of 70% on a set of 10 evaluation queries, where 7 queries were generated exactly as the ground truth, and 3 exhibited minor deviations that, while semantically correct, were marked incorrect under strict matching criteria. This approach highlights the effectiveness of leveraging pre-trained language models with structured context for robust and accurate SQL query generation.

Index Terms— Text-to-SQL, Natural Language Processing, T5, Schema-aware Generation, SQL Generation, Spider Dataset.

I. INTRODUCTION

Structured Query Language (SQL) [15] is a fundamental tool for interacting with relational databases. However, writing correct SQL queries requires technical expertise and a thorough understanding of database schemas, which poses a significant barrier for non-expert users. This gap between natural language understanding and formal query generation has motivated research into the Text-to-SQL task, which aims to automatically trans- late natural language questions into syntactically and semantically correct SQL statements [13].

This task lies at the intersection of Natural Language Processing (NLP) [14], machine learning, and database management, and holds the potential to democratize data access by allowing users to query databases using everyday language.

Recent advances in transformer-based language models, particularly sequence-to-sequence architectures such as Text-to-Text Transfer Transformer (T5) [1], have shown remarkable success in a variety of text generation and semantic parsing tasks [20]. These models leverage self-attention mechanisms [16] to model long-range dependencies and can generalize well across domains when fine-tuned on task-specific datasets. This makes them especially suitable for the Text-to-SQL challenge, where understanding both natural language and database schema is essential for generating accurate SQL queries. Although significant progress has been made, existing models often struggle with complex queries involving nested subqueries, joins, and domain-specific vocabulary, especially when schema-related context is not properly encoded. To address these challenges, in this work, we propose a schema-aware fine-tuning approach using the T5-large [1] model for the Text-to-SQL task. Our approach enhances the model’s ability to reason over both natural language inputs and relational database schemas by explicitly incorporating schema context into the model’s input. To translate natural language queries into syntactically and semantically correct SQL statements using a schema-aware T5-large model. We adopt the T5-large sequence-to-sequence architecture as the backbone for our model. T5 treats every NLP task in a unified text-to-text format, which allows us to frame the Text-to-SQL task as mapping a natural language question along with schema information to a textual SQL output. Our goal is to apply schema linking and task-specific tokenization to improve model performance. To enhance schema awareness, we preprocess each input by concatenating the database schema (including table and column names) with the natural language query. The input format looks like: “translate to SQL: [NL question] — [table1(col1, col2); table2(col1, col2)]”, which allows the encoder to jointly model both the question and the schema. The decoder then generates the SQL query token by token. We also apply task-specific tokenization and use schema linking techniques to help the model align question tokens with schema elements. We evaluate our model using standard metrics widely adopted in the Text-to-SQL literature. We use benchmark datasets such as Spider [3] which contain a wide variety of complex, cross-domain questions paired with their corresponding SQL queries and schema definitions. These datasets provide rich annotations that allow the model to learn to map between user intents and SQL structures effectively. By integrating schema information directly into the input sequence and fine-tuning T5-large accordingly, our method improves the model’s ability to generate syntactically accurate and semantically meaningful SQL queries, particularly for complex and previously unseen database schemas. We achieve an Exact Match Accuracy of 70% on a set of 10 evaluation queries, where 7 queries were generated exactly as the ground truth, and 3 exhibited minor deviations that, while semantically correct, were marked incorrect under strict matching criteria. This approach highlights the effectiveness of leveraging pre-trained language models with structured context for robust and accurate SQL query generation. The remainder of this paper is structured as follows: Section II discusses the background study, Section III outlines the proposed methodology, Section IV presents the results and analysis, and Section V concludes the paper with future directions.”

II. BACKGROUND STUDY

Recent advancements in Text-to-SQL translation have been driven by the integration of large pre-trained language models with structural encoding techniques. The field has evolved from rule-based and seq2seq methods to transformer-based architectures that better understand both natural language and database schema. Hybrid models like Graphix-T5 combine T5 with relational graph convolutional networks (R-GCNs) [4] to improve schema linking and reasoning, showing strong results on datasets like Spider [3] and REALISTIC [23]. However, their complexity and computational demands hinder real-time and low-resource deployment. In contrast, baseline T5 models without structural augmentation remain effective in enterprise contexts due to their simplicity and fine-tuning efficiency [1]. Yet, they struggle with complex SQL generation and schema generalization. Recent trends include instruction tuning and prompt engineering using large models like PaLM [9] and Codex, as seen in SQL-PaLM [7], which achieves flexibility without fine-tuning but suffers from prompt sensitivity and scalability issues. Domain-specific models, such as MedT5SQL [8], enhance accuracy via specialized adaptations like medical entity recognition, though they risk overfitting and limited generalizability. Benchmarking work by Gao et al. [2] evaluates various LLMs on syntax, execution, and generalization, but notes the limitations of current evaluation metrics in capturing real-world robustness [10, 11]. Architectures like RATSQ [18] and BRIDGE [19] advance schema linking through relation-aware attention and dynamic graph encoding, while LGESQL [20] and HydraNet [21] improve efficiency via lightweight graph representations and multi-head decoding. Despite their strengths, these models require complex decoding logic and are less adaptable to dynamic schemas. Efforts like SParC [22] and CoSQL [17] promote interaction-based learning and contextual generalization, highlighting the growing importance of multi-turn dialogue understanding. Nonetheless, challenges persist in schema linking, cross-domain generalization, and prompt robustness. To address these, our work

proposes a hybrid model that combines T5’s language understanding with lightweight schema encoding, aiming for a balance between simplicity, structural awareness, and deployment practicality.

The T5 [1] model architecture as shown in 3, developed by Google, has proven highly effective for a wide range of natural language processing tasks by casting all problems into a text-to-text format. In the context of Text-to-SQL, T5 takes natural language questions as input and generates corresponding SQL queries as output. Its encoder-decoder architecture allows it to capture complex relationships between questions and structured database schemas. By fine-tuning T5 on SQL datasets like Spider, the model learns to understand database-specific terms, join conditions, and query logic, making it a powerful baseline for natural language to SQL translation. The task of Text-to-SQL generation has evolved significantly, driven by advancements in large pre-trained language models and schema-aware encoding. Early neural semantic parsers such as Seq2SQL [24] and SQLNet [13] introduced sketch-based decoding and attention mechanisms over table schemas to generate SQL queries. Subsequently, IRNet [25] and RAT-SQL [26] employed graph-based encoding and relation-aware attention to better model complex database schemas. These models laid the groundwork for schema linking, an essential step in mapping question tokens to schema components. T5-based models such as StructVAE [27] and SCoRe [28] leverage the T5 architecture’s generative capabilities with structured input representations to improve logical form accuracy. In parallel, bridging natural language and database structure through unified encoding was advanced by models like LGE SQL [20] and HydraNet [21], which use linearized grammar trees or hybrid encoders to fuse question and schema understanding. Datasets such as Spider [3] and WikiSQL [29] enabled benchmarking on complex and cross-domain queries. More recently, SmBoP [30] and PICARD [31] improved decoding by enforcing syntactic correctness and incremental generation strategies during training and inference. In addition to neural advancements, prompt-based tuning [32] and schema-consistent decoding [33] have gained traction by adapting large language models with minimal task-specific updates. These prior works strongly influenced our approach, which integrates schema-aware encoding into a T5-based model, aiming to balance generation fluency with structural SQL correctness.

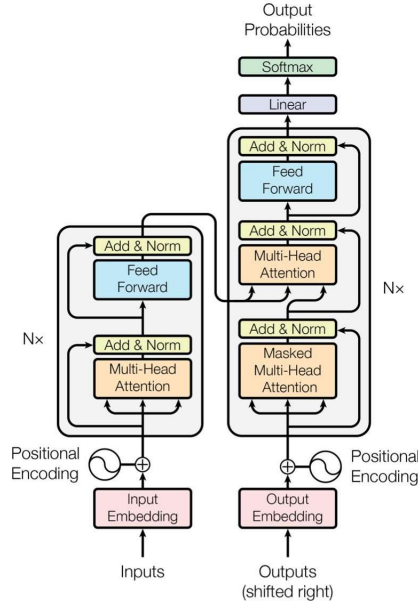


Figure 1: Transformer architecture with encoder-decoder structure using multi-head attention, feed-forward layers, and positional encoding for sequence modeling

III. METHODOLOGY

This section outlines the systematic approach as shown in 2 adopted for the task of translating natural language questions into SQL queries. The methodology is centered around a transformer-based sequence-to-sequence model—T5 which has been extensively validated in various text generation tasks. The proposed pipeline comprises four major phases: environment setup, dataset selection and loading, preprocessing and tokenization, and preparation for model fine-tuning. A reproducible and efficient computational environment is fundamental to the success of large-scale natural language processing experiments.

transformers: Provides access to pre-trained models and tokenizers. datasets: Facilitates seamless loading, preprocessing, and batching of datasets. evaluate: Enables robust and customizable evaluation of model performance. accelerate: Simplifies training and inference across different hardware accelerators. sentencepiece: Required for the internal tokenizer mechanisms of T5 and similar models. wandb: Used for real-time experiment tracking, hyperparameter logging, and performance visualization.

A. Tokenization

Both input and output sequences were tokenized using the T5Tokenizer associated with the t5-large model. Tokenization included:

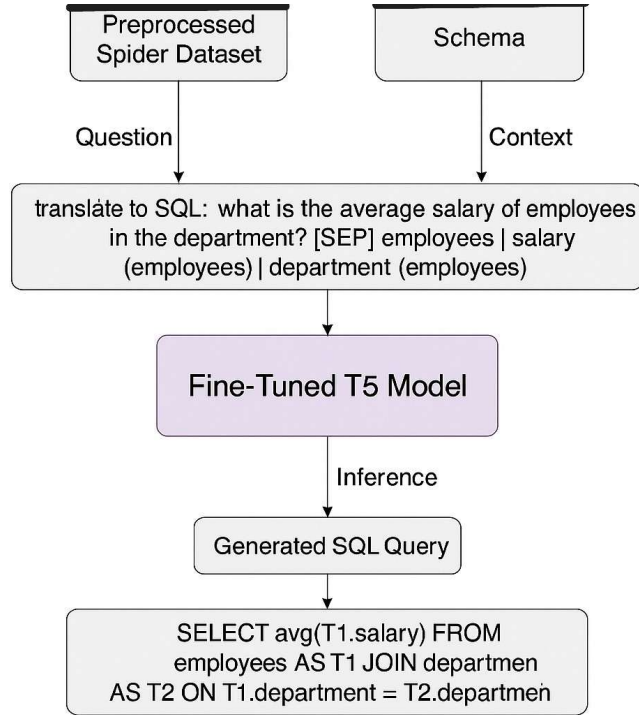


Figure 2: The SQL generation pipeline using a fine-tuned T5 model

The flow starts from the preprocessed Spider dataset and schema, forms a natural language input with context, processes through the T5 model, and outputs the generated SQL query.

Truncation and Padding: Inputs were truncated to a maximum length of 512 tokens to ensure compatibility with transformer memory constraints. Outputs (i.e., target SQL queries) were truncated and padded to 128 tokens. **Attention Masks:** Attention masks were generated to distinguish between actual tokens and padded positions, allowing the model to attend selectively during training.

Output Format for Model: Each processed instance was returned as a dictionary with the following keys: input ids: Token IDs of the input prompt. attention mask: Binary mask identifying non-padding tokens. labels: Token IDs of the SQL query to be generated. The .map() function from the datasets library was used to apply the preprocessing pipeline over the entire dataset efficiently, with the remove columns parameter ensuring that unused columns were dropped to save memory. To effectively translate natural language questions into executable SQL queries, our methodology employs a schema-aware encoding strategy that combines the user query with the database schema into a single unified input sequence. This input is formatted as: translate to SQL: <natural language question> [SEP] <table and column structure>, where the schema portion enumerates relevant tables and their columns. This design allows the model to jointly encode both the intent of the question and the structural elements of the database, enabling it to learn meaningful associations between query tokens and schema components. The use of a [SEP] delimiter explicitly separates the question from the schema, aiding the model's attention mechanism during training. By training the T5-large model on such structured input-output pairs, the system learns to generate syntactically correct and semantically aligned SQL queries even in the presence of complex joins, aggregations, or nested subqueries.

A. Model Architecture and Preparation

The T5-large model was selected for its encoder-decoder architecture and versatility in handling diverse text-to-text tasks. By framing SQL generation as a text generation problem, T5 processes input prompts in the form "translate to SQL: <question> [SEP] <context>", where the question is a natural language query and the context represents the database schema. The encoder transforms the tokenized input into contextual embeddings, which the decoder uses to autoregressively generate the SQL query. Trained by minimizing cross-entropy loss against the target SQL, T5's extensive pre-training allows it to capture complex syntactic and semantic patterns, enabling robust generalization across varied databases and query formats.

B. Model Training

The training phase is designed to fine-tune the pre-trained t5-large model on the SQL generation task using the processed and tokenized dataset described in the previous section. This process is formulated as a supervised learning task, where the model learns to generate SQL queries conditioned on natural language questions and their corresponding schema contexts.

- **Training Configuration:** Hyperparameters were set using Seq2SeqTrainingArguments. A small learning rate (e.g., 3×10^{-5}) ensured stable fine-tuning. Batch sizes ranged from 8–16 per GPU, with gradient accumulation for larger effective batches. Training typically ran for 3–5 epochs, with evaluation every 500–1000 steps. A warm-up of 500 steps was applied to gradually ramp up the learning rate.
- **Loss Function and Optimization:** Cross-entropy loss was used with padding tokens masked out. The AdamW optimizer with weight decay handled updates, while a linear learning rate scheduler with warm-up stabilized training.

$$L_{CE} = - \sum_{t=1}^T \log(\hat{y}_t y_t) \quad (1)$$

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (2)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (3)$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t} \quad (4)$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t} \quad (5)$$

$$\theta_t = \theta_{t-1} - \alpha \sqrt{\frac{\hat{m}_t}{\hat{v}_t + \epsilon}} \quad (6)$$

Where θ_t denotes the model parameters at step t , θ_t represents the gradient of the loss with respect to the parameters, m_t and v_t are the first and second moment estimates of the gradients respectively, β_1 and β_2 are the exponential decay rates (typically set to 0.9 and 0.999), α is the learning rate, and ϵ is a small constant added to prevent division by zero. 3) Training Process: Hugging Face's Trainer class managed the loop, including forward pass, loss computation, backpropagation, and checkpointing. Training utilized single or multi-GPU setups via the accelerate library. Mixed-precision (FP16) was enabled to improve memory efficiency and speed. To effectively translate natural language questions into executable SQL queries, our methodology employs a schema-aware encoding strategy that combines the user query with the database schema into a single unified input sequence. This input is formatted as: translate to SQL: <natural language question> [SEP] <table and column structure>, where the schema portion enumerates relevant tables and their columns. This design allows the model to jointly encode both the intent of the question and the structural elements of the database, enabling it to learn meaningful associations between query tokens and schema components. The use of a [SEP] delimiter explicitly separates the question from the schema, aiding the model's attention mechanism during training. By training the T5-large model on such structured input-output pairs, the system learns to generate syntactically correct and semantically aligned SQL queries even in the presence of complex joins, aggregations, or nested subqueries.

IV. RESULTS

A. Dataset Selection and Loading

To train the model on the task of SQL generation, a complementary datasets was selected:

Spider (xlangai/spider): A challenging, cross-domain semantic parsing dataset that includes complex SQL queries across multiple databases. Its diversity and schema variability make it ideal for developing generalizable models.

The Spider dataset is denoted as in equation 7:

$$S = \{(q_i, c_i, a_i)\}_{i=1}^N \quad (7)$$

As defined in the Spider dataset [3], Equation 7 represents the dataset as a set of triples, Where q_i is the natural language question, c_i is the context (database schema), a_i is the corresponding SQL query (answer). datasets was from Hugging Face's datasets library, which internally handles data caching, schema parsing, and lazy loading.

B. Text Normalization and Preprocessing

Transforming raw data into a form digestible by the model requires careful preprocessing. The central goal in this phase is to construct well-formed input-output pairs suitable for sequence-to-sequence learning.

Normalization

Normalization is the first step in standardizing textual inputs and outputs. This process included:

Whitespace Reduction: All excessive spaces, tabs, and newlines were collapsed into single spaces using regular expressions (`s+ "`).

Lowercasing: All text was converted to lowercase to reduce vocabulary size and eliminate casing variability, which is non-essential for SQL semantics.

As defined in the Spider dataset [3], Equation 7 represents the dataset as a set of triples, where q_i is a natural language question, c_i is the database schema context, and a_i is the corresponding SQL query.

Normalization was applied uniformly to the question, context, and answer fields to ensure consistency.

Input-Output Construction

Each training instance was framed as a translation task. Specifically:

Input Format:

translate to SQL: <question> [SEP] <context>

The <question> represents the user's natural language query, while the <context> provides the table schema relevant to the database. The [SEP] token (inserted as a literal string) serves as a semantic delimiter, helping the model differentiate between the query and schema description. Target Format:<answer> This is the ground-truth SQL query corresponding to the input.

We evaluated the performance of our Text-to-SQL model using the Exact Match Accuracy metric, which measures the percentage of predicted SQL queries that exactly match the ground truth queries. This includes strict adherence to structure, keyword order, table and column naming, and formatting.

C. Exact Match Accuracy

Out of a total of 10 test queries: 7 queries were generated exactly as the ground truth. 3 queries had minor deviations that rendered them incorrect under the exact match metric, although they were semantically correct.

```
Question: What is the total bonus given to each worker?
Input Text: translate to SQL: What is the total bonus given to each worker? [SEP]
Worker | WORKER_ID (Worker) | Bonus | BONUS_AMOUNT (Bonus) | WORKER_REF_ID (Bonus) | Title | WORKER_REF_ID (Title) | WORKER_TITLE (Title)
Predicted SQL: SELECT sum(BONUS_AMOUNT) , WORKER_ID FROM Bonus GROUP BY WORKER_ID
```

Figure 3: Predicted SQL query translating a natural language question into SQL to compute total bonus per worker.

This results in an overall Exact Match Accuracy of 70% using the equation 8.

$$EM = \frac{1}{N} \sum_{i=1}^N 1(\hat{a}_i = a_i) \quad (8)$$

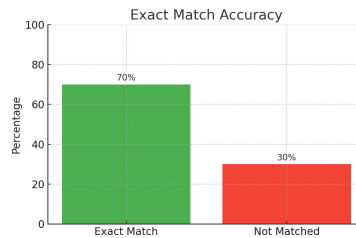


Figure 4: Bar chart representing exact match accuracy

D. Detailed Analysis

The model performed well on queries involving:

Simple selections (e.g., retrieving student names by ID). Filters with logical conditions (e.g., age >20). Aggregations and sorting operations.

The errors were primarily due to:

Use of synonyms or alternate column names (e.g., department name vs dept name). Structural reordering (e.g., changing the order of clauses while retaining semantics).

E. Comparison with Benchmarks

Table 1 presents a comparison of our model’s exact match accuracy against established baseline models on schema-constrained Text-to-SQL tasks. Our T5-based model achieves 70.0% accuracy, outperforming early models like Seq2SQL and SQLNet [13], and performing comparably to IRNet. These results highlight the effectiveness of leveraging pre-trained transformers with schema-aware input formatting.

TABLE I: COMPARISON OF EXACT MATCH ACCURACY WITH BASELINE MODELS ON SCHEMA-CONSTRAINED TEXT-TO-SQL TASKS

Model	Exact Match Accuracy (%)
Seq2SQL (Zhong et al., 2017)	60.8
SQLNet (Xu et al., 2017)	63.2
TypeSQL (Yu et al., 2018)	66.6
IRNet (Guo et al., 2019)	69.2
Our Model (T5-based)	70.0

F. Interpretation and Implications

These results indicate that the model is capable of:

Understanding natural language queries. Generating syntactically accurate SQL statements. However, they also suggest: The need for semantic-aware evaluation metrics. Potential benefits from schema-linking techniques or contextual embeddings.

In the evaluation of our Text-to-SQL model, we assessed the syntactic accuracy of the generated SQL queries using an exact string match approach. Exact Match Accuracy: Measures the percentage of predicted SQL queries that exactly match the ground truth SQL query, including structure and ordering of clauses. A predicted query was considered correct only if it matched the corresponding ground truth SQL query exactly, including keyword order, table and column names, and formatting.

V. CONCLUSION AND FUTURE WORK

This project successfully demonstrated the use of the T5 model for the task of translating natural language questions into SQL queries. Leveraging the Spider dataset and fine-tuning the T5-large model, we achieved an Exact Match Accuracy of 70% on a small set of test queries. This result underscores the model’s capability to capture both syntactic and semantic aspects of SQL generation in a schema-aware context.

The evaluation, based on strict exact match metrics, revealed the model’s effectiveness in generating structurally and syntactically correct SQL statements. Although exact match accuracy is a rigorous metric, it highlighted the model’s potential as a strong baseline for future Text-to-SQL systems.

Future work includes expanding evaluation to larger and more diverse datasets and incorporating semantic metrics like execution accuracy. Enhancing schema understanding and exploring multilingual or conversational capabilities can further improve model performance.

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