Abstract

Current SQL generators based on pre-trained language models struggle to answer complex questions requiring domain context or understanding fine-grained table structure. Humans would deal with these unknowns by reasoning over the documentation of the tables. Based on this hypothesis, we propose DocuT5, which uses off-the-shelf language model architecture and injects knowledge from external “documentation” to improve domain generalization. We perform experiments on the Spider family of datasets that contain complex questions that are cross-domain and multi-table. Specifically, we develop a new text-to-SQL failure taxonomy and find that 19.6% of errors are due to foreign key mistakes, and 49.2% are due to a lack of domain knowledge. We proposed DocuT5, a method that captures knowledge from (1) table structure context of foreign keys and (2) domain knowledge through contextualizing tables and columns. Both types of knowledge improve over state-of-the-art T5 with constrained decoding on Spider, and domain knowledge produces state-of-the-art comparable effectiveness on Spider-DK and Spider-SYN datasets. Our code is available at https://github.com/grill-lab/DocuT5.

1 Introduction

Translating natural language utterances into logical forms (SQL) that are executable against a relational database (text-to-SQL) is an important real-world task, reducing the barriers to entry for data analysis. While leveraging pre-trained language models as SQL generators shows strong performance (Wang et al., 2020; Lin et al., 2020; Scholak et al., 2021), there are still limitations due to a lack of domain or table knowledge. This means that models struggle to adapt to new tables or domains, particularly when the natural language question does not explicitly reference the schema entities and relations.

Cross-domain annotated benchmarks WikiSQL (Zhong et al., 2017) and Spider (Yu et al., 2018) contain a high percentage of natural language questions that directly reference column names contained within the database schema. However, when column mentions are replaced with synonyms (Gan et al., 2021a), or paraphrases (Gan et al., 2021b), prediction accuracy scores drop substantially, even when questions containing domain knowledge are mentioned in the training data.

Researchers leveraged graph neural networks which encoded the input as directed graphs (Bogin et al., 2019; Guo et al., 2019; Wang et al., 2020), augmented with syntactic metadata of the natural language question and database (Hui et al., 2022), or enhanced the schema grounding modules (Liu et al., 2022; Wang et al., 2022). However, these are complicated and often dataset-specific architectures that are non-trivial to adapt to new domains or datasets. On the other hand, Most seq2seq SQL generators (Hwang et al., 2019; Lin et al., 2020; Scholak et al., 2021) only linearize the database schema by enumerating table and column names, and lack the explicit table or domain knowledge for complex operations.

Figure 1: Foreign key failure example by seq2seq model (Scholak et al., 2021) on Spider dev.

In this work, our first contribution is an in-depth behavioural study on a state-of-the-art seq2seq model with constrained decoding (Scholak et al.,...
We find that 19.6% of errors are due to foreign key mismatches, and another 49.2% are due to a lack of domain knowledge. For example, Figure 1 shows a foreign key error where the model fails to identify `countrycode` column in `city` table as a foreign key to `code` column in `country` table. Figure 2 shows the model fails to understand the table context that the `percentage` column is the proportion of language speakers in Aruba.

We argue that existing models suffer from these issues as they fail to incorporate knowledge in a way comparable to a human analyst. Specifically, when translating a request to a SQL query, a person would typically consult the table documentation, especially if it is a new domain or there is uncertainty about terminology. Inspired by this approach, we propose DocuT5 that injects "documentation" into an off-the-shelf seq2seq model without requiring model modification, providing table and domain context during the generation process.

Some recent work by Dou et al. (2022) has shown promising results in adding foreign key context into seq2seq models. We take this a step further by proposing DocuT5, which adds rich domain knowledge via (1) a simplified means for encoding foreign keys (DocuT5-FK) and (2) textual schema descriptions that provide question context of the overall table and specific columns (DocuT5-SD). Because the knowledge encoding is general, it is widely applicable to diverse language model classes and the results show consistent performance improvement across multiple dimensions.

We study the behavior of DocuT5 and previous models on the Spider family of datasets that contain complex questions that are cross-domain and multi-table. This includes the original Spider dev set, as well as Spider-DK (Gan et al., 2021b) that requires domain knowledge, and Spider-SYN (Gan et al., 2021a) that replaces question terms with synonyms. We evaluate against comparable state-of-the-art SQL generators that leverage off-the-shelf pre-trained language models, including the BRIDGE, (Lin et al., 2020), PICARD (Scholak et al., 2021), and UniSAr (Dou et al., 2022).

Our experiments find that encoding foreign keys improves over T5 with constrained decoding by 3.1% and comparable reported results by 2.2% on Spider. Separately, encoding schema description also improves on Spider against T5 with constrained decoding by 2.3% and comparable reported results by 1.4%. Schema description also shows more significant relative improvements on Spider-DK (+2.4%) and Spider-SYN (+2.8%), where schema knowledge is most required. Overall, DocuT5 achieves the best comparable results on Spider, Spider-DK, and Spider-SYN. The contributions of this paper are:

- **Spider behavior analysis**: develop a new text-to-SQL failure taxonomy and categories state-of-the-art seq2seq model failures on Spider, with 19.6% attributed to foreign keys and 49.2% attributed to domain knowledge.
- **Foreign keys**: demonstrate that encoding foreign key knowledge improves model performance by 3.1% on Spider, achieving state-of-the-art against comparable models.
- **Schema descriptions**: Use schema schema descriptions to improve model performance by 2.3% on Spider. Incorporating domain knowledge produces the best reported results on Spider-DK and Spider-Syn datasets.

### 2 Task

We focus on the text-to-SQL generation task in a cross-domain setting. By definition, given a natural language question \(Q\) and a database schema \(S\), we need to infer a correct SQL query, which is executable against a database to retrieve an execution answer \(A\) that satisfies \(Q\). Each database schema consists of a set of tables \(T\) and a set of columns \(C\) belonging to the tables such that \(S = <T,C>\). A foreign key \(FK\) is a column which links two tables based on matching values and schema description \(SD\) are metadata explaining \(S = <T,C>\).

### 2.1 Datasets

**Spider** (Yu et al., 2018) is a cross-domain text-to-SQL dataset which contains 10,181 natural ques-
tion utterances and 5,693 SQL statements for training, with a 535-question dev set. Spider contains 200 databases across a large variety of domains, and most queries contain at least one ORDER BY, JOIN, GROUP BY, or HAVING statements, unlike WikiSQL (Zhong et al., 2017).

Spider-DK (Gan et al., 2021b) is a test set to assess the robustness of text-to-SQL models where questions require rarely observed domain knowledge or paraphrasing.

Spider-SYN (Gan et al., 2021a) is a variant developed by replacing schema-related words with synonyms that reflect real-world question paraphrases, eliminating explicit correspondence between questions and table schemas.

2.2 Metrics

Exact Set Match (EM) (Yu et al., 2018) converts the predicted SQL query into an orderless dictionary, which are compared to the gold SQL queries based on string matching. Each clause has to be exact strings with the corresponding gold SQL clause for EM to be 1, otherwise EM is 0.

Execution Accuracy (EX) is based on the results of executing SQL on the corresponding databases (Zhong et al., 2020). This metric deals with the semantic equivalence of SQL statements, which produce the same execution results despite being syntactically different. Specifically, EX is 1 if the predicted and gold SQL have equivalent execution results, and 0 otherwise.

3 Behavior Analysis

In this section, we conduct an error analysis using a newly developed taxonomy to categorize errors within text-to-SQL models. We reproduce T5 with constrained decoding (Scholak et al., 2021) on Spider dev set. We select the largest available T5 model (3 billion parameters) and activate the constrained decoding framework during inference. Based on the EX accuracy, we save the incorrectly inferred SQL queries from the Spider dev set. In total, there are 214 incorrect natural language questions and SQL pairs to manually categorise.

3.1 Failure Taxonomy

The authors develop the following taxonomy of failure categories to identify text-to-SQL failure patterns. It is important to understand “how” these models are failing to motivate future research directions, and this taxonomy can be used across any text-to-SQL dataset. Experienced computer scientists with experience with SQL (the authors) discuss and agree on the categories of errors during annotation of the 214 failing Spider queries. At least one author performs each annotation, and a majority vote resolves ambiguous instances. The failure taxonomy is:

Incomplete Queries: The predicted SQL queries are only partially decoded because the model predicts the ending tag prematurely.

False Negatives: The natural language question is ambiguous, or generated SQL queries are incorrectly labelled as inaccurate.

Foreign Keys: errors are prevalent in JOIN operations where wrong foreign key columns are used. On a manual inspection, most of these errors are due to inconsistent naming within databases, making it non-trivial to reason over.

Logical Errors: errors miss logical implications within the natural language question. For example, ordering people by age means ordering them in decreasing order of date of birth.

Domain Knowledge: In this scenario, the model cannot capture the meaning of the database schema due to missing table or column knowledge. We further divide this into subcategories:

- Aggregation Errors: Incorrect use of SUM, COUNT, MIN, and MAX functions.
- Incorrect Table: DB entries are retrieved from the incorrect table.
- Incorrect Column: Predicting the wrong columns in SELECT or WHERE clauses. Often attributable to implicitly referenced columns within the question.
- Value Errors: Incorrect values in WHERE clauses. Values mentioned in questions are not exact strings matches to the DB entries.
- Complex Errors: The model fails to understand a mix of paraphrases, complex table structures, and difficult required aggregations.

3.2 Findings

Table 1 shows the breakdown of T5 with constrained decoding errors on the Spider dev set. We find that 22.4% of questions are False Negative, which is not a suitable target category for model improvement. Furthermore, 6.2% of errors are due to Incomplete SQL and 2.8% are due to Logical Errors, both relatively small failure categories.

We specifically focus on Foreign Keys and Domain Knowledge categories based on the dispropor-
tionate amount of errors. For example, 19.6% of errors are due to table joins from incorrect foreign keys. The overall errors caused by Domain Knowledge totalled 49.2% across five subcategories, with Aggregation Errors (17.2%), Incorrect Column (13.4%), and Complex Errors (11.0%).

| Failure Categories       | Percentage |
|--------------------------|------------|
| Incomplete SQL           | 6.2%       |
| False Negatives          | 22.4%      |
| Foreign Keys             | 19.6%      |
| Logical Errors           | 2.8%       |
| DK - Incorrect AGG       | 17.2%      |
| DK - Incorrect Table     | 3.8%       |
| DK - Incorrect Column    | 13.4%      |
| DK - Incorrect Value     | 3.8%       |
| DK - Complex             | 11.0%      |

Table 1: Error Analysis on Spider dev based on T5+3B with constrained decoding.

We investigate whether giving models access to contextual “documentation” helps with Foreign Keys and Domain Knowledge failure categories. Therefore, this categorization is important because it helps us assess what context will help the model for specific failure categories. For example, Value Errors motivate contextualizing column values, especially for hard-to-interpret boolean columns. Incorrect Column errors are due to the model not mapping question intent with the correct column, requiring more context to ground the column for specific use cases. Lastly, Incorrect Aggregation is when the model is having issues discerning the value type of a specific column and explicitly stating whether the column is a date or number would be beneficial.

4 Method

DocuT5 is a new method to include documentation into seq2seq models that is general and widely applicable to diverse models without requiring changes to model structure. Specifically, we focus on improving schema serialization through explicit foreign keys mapping and domain knowledge through additional table and column context. As is standard for seq2seq models, we concatenate the natural language question and serialized database schema and ask the model to generate the SQL.

We employ an off-the-shelf pre-trained language model T5 (Raffel et al., 2020), experimenting with both the T5-Base and T5-Large variants. For all DocuT5 variants, we serialized the database schema by enumerating the table and column names, similar to (Scholak et al., 2021). We also encode database content snippets (anchor texts) by performing fuzzy string matching on the natural language question and the database entries (Scholak et al., 2021; Lin et al., 2020). Lastly, to reduce non-executable hallucinations, we employ constrained decoding to incrementally perform sanity checks at inference (Scholak et al., 2021).

4.1 DocuT5-FK: Foreign Keys

![Figure 3: DocuT5-FK: jointly encoding the natural language question and database schema, including foreign key relations. After every foreign key column, we add a special marker “foreign key”, followed by the referenced table name.](image)

SELECT ... FROM city JOIN country ON city.countryid = country.id WHERE T2.country = 'Australia'

Encoding cross-table relations in textual form is more challenging than, for instance, column-table relations (column belongs to table) because foreign key relations are more intuitively mapped to directed graphs. To reduce complexity and exploit the ability of pre-trained language models to grasp free-form text better than structured data, we add a special “foreign key” marker after every foreign key column in the serialized schema representation, followed by the name of the table it is referenced to. For example, Figure 3 shows the input design for the `city` table, where the foreign key `column` is a reference to the `id` in table `country`. We add only the table reference next to FK column `country`.

Based on initial experimentation, we find that simple patterns for encoding foreign key information are easier for seq2seq models to learn. Therefore, we avoided more complex column-to-column
foreign keys, as used in UniSAr, including only the table name and linking the foreign key table directly in the schema serialization.

We also only selectively add the most beneficial foreign key relation types to keep input less complex. Specifically:

1-to-1 relations associate one record in a table with another record in another table. We add the FK relation marker after both columns if they represent primary keys, otherwise, we add the relation marker only after the non-primary key column.

1-to-Many relations associate one record in a table with multiple records in another table. In this case, we add the foreign key relation only after the foreign key column on the -Many sides.

4.2 DocuT5-SD: Schema Descriptions

As identified in Section 3.1, around 50% of current seq2seq errors result from a lack of domain knowledge. Specifically, the model makes errors due to missing table or column knowledge. For example, when asked Which language is the most popular in Aruba, current models struggle to identify percentage as the target column and what logical operations are required to compute the answer.

To solve for missing domain knowledge, we introduce schema descriptions directly as textual input to leverage pre-trained language models’ ability to reason over text. These descriptions aim to provide paraphrases or database context to create a more specific table definitions. For example, a column named date within table company can mean the date that the company was founded or when the database table was last updated, depending on the contents. Furthermore, we tried to inject cross-table relations into natural language by describing schema entities concerning other entities. Figure 4 shows the model input that explains the table customer, in relation to table store and film.

Computer scientists with working knowledge of SQL and access to a commercial search engine (the authors) develop these high-quality schema descriptions, which will be released as part of the paper. Figure 4 shows how the schema descriptions are included alongside the question and serialized schema, separated by the “description” marker. Annotators follow the subsequent guidelines to keep descriptions short, specific and consistent:

Table definitions describe all tables within a database schema.

Column definitions describe only ambiguous columns, i.e. name is a partial match to its natural language reference (indepyear is explained as independence year) or vague.

Boolean columns make implicit use of domain knowledge and are often ambiguous for pre-trained language models (Gan et al., 2021b). In Figure 4, the definition of column active in the DB sakila_1 contains explanations of the values “0” and “1”.

Structured descriptions: We keep the table description semi-structured by ordering the table and column paraphrases with the same success as the baseline serialized schema, with different separator tokens between table and columns.
5 Experiments and Evaluation

In this section we report the experimental results for including documentation into seq2seq models.

5.1 Experimental Setup

To evaluate our methods, we implement comparable and strong baseline SQL generation systems that use off-the-self pre-trained language models. Specifically, we fine-tune T5-Base and T5-Large models on the Spider train set, with evaluation on the Spider dev set (Scholak et al., 2021). We use the standard Huggingface checkpoints with cross-entropy loss, a constant learning rate of 0.0001 with an Adafactor optimizer, and train for around 400 epochs. We perform an early stop and select the best scoring model by EM on Spider dev set, and evaluate zero-shot on Spider-DK and Spider-SYN testsets. Additionally, we evaluate performance of both T5-BaseCD and T5-LargeCD with constrained decoding (Scholak et al., 2021).

We also compare against the strongest reported results from comparable pre-trained language model SQL generators. PICARD (Scholak et al., 2021) uses constrained decoding and we compare against the comparable T5-Base and T5-Large models. BRIDGE (Lin et al., 2020) uses a BERT-large model for contextualization and a pointer-generator decoder. The recently published UniSAr (Dou et al., 2022) encodes table structures within the textual input to BART-Large and uses constrained decoding.

Similar to how we employ the T5 models, we train DocuT5-FK and DocuT5-SD using T5-Base and T5-Large models under the same training and evaluation methodology. We also evaluate performance of DocuT5-FKCD and DocuT5-SDCD with constrained decoding (Scholak et al., 2021).

5.2 Results

We provide the results and analysis across schema serialization and schema descriptions.

5.2.1 Foreign Keys

Table 2 shows the schema serialization results where foreign keys are explicitly encoded. DocuT5-Base-FKCD improves over the comparable T5-BaseCD model by 0.4% on EM and 1.6% on EX on Spider dev. While results are even more impressive when focusing on T5-Large models. DocuT5-Large-FKCD improves over T5-LargeCD by 3.1% on EM and 3.9% on EX on Spider dev. DocuT5-Large-FKCD is also at least 1.4% better than reported results for similar-sized models, such as UniSar. This is strong evidence that our simple method of injecting foreign key knowledge is highly effective.

Analyzing the individual questions, DocuT5-FKCD does fix not only simple foreign key errors but also grounds natural language mentions to schema entities due to explicit context. By comparison, T5-LargeCD generally attempts to find the “shortest path” across tables. In the first example in Figure 5, DocuT5-FKCD fixes an Incorrect Table error type, because it receives explicit information that tables car_data and car_names are related. While in the second example, DocuT5-FKCD has higher confidence in joining multiple tables together, and can better ground the implicit mention “flights that arrive” to the foreign key “destairport”, which references table “airports”.

Using the failure taxonomy developed in Section 3.1, we investigate how many Foreign Key failure types our model alleviates. For a fair comparison, we inspect the questions predicted correctly by DocuT5-Large-FKCD, which T5-LargeCD fails to infer accurately. Of this subset, our model can correctly predict 14 queries classified previously as Foreign Key failures. This represents 5% of the total failed queries from the baseline T5-LargeCD.

Furthermore, we notice that a number of ques-
| Model                  | Spider dev   | Spider-DK    | Spider-SYN    |
|------------------------|--------------|--------------|--------------|
|                        | EM       | EX       | EM       | EX       | EM       | EX       |
| PICARD-B (Scholak et al., 2021) | 65.8%  | 68.4%  | -       | -       | -       | -       |
| PICARD-L (Scholak et al., 2021)   | 69.1%  | 72.9%  | -       | -       | -       | -       |
| BRIDGE (Lin et al., 2020)         | 70.0%  | -       | -       | -       | -       | -       |
| UniSAr (Dou et al., 2022)         | 70.0%  | -       | -       | -       | -       | -       |
| T5-Large                | 65.3%  | 67.2%  | 39.8%  | 46.5%  | 53.4%  | 57.3%  |
| DocuT5-Large-SD         | 64.4%  | 66.3%  | 41.9%  | 50.5%  | 52.2%  | 55.7%  |
| T5-LargeCD              | 69.1%  | 72.9%  | 45.6%  | 55.0%  | 58.9%  | 64.5%  |
| DocuT5-Large-SDCD       | 71.4%  | 74.7%  | 48.0%  | 59.6%  | 61.7%  | 68.2%  |

Table 3: Spider Results: Schema Description. Our results (bottom) and relevant prior work (top). (CD) highlights when using constrained decoding (Scholak et al., 2021).

5.2.2 Schema Descriptions

Table 3 shows the schema description results where textual context is explicitly encoded for tables and columns. DocuT5-Large-SDCD improves over T5-LargeCD by 2.3% on EM and 1.8% on EX on Spider dev. However, we see a much more significant relative improvement within the Spider-DK and Spider-SYN datasets. DocuT5-Large-SDCD improves over T5-LargeCD by 2.4% EM in Spider-DK and 4.6% EX on Spider-DK, and 2.8% EM in Spider-DK and 3.7% EX on Spider-SYN. Considering a large amount of exact question-schema overlap in the original Spider dev set, Spider-DK and Spider-SYN are good means to assess generalization. Adding schema descriptions is beneficial and should motivate other methods to leverage schema descriptions.

Using the failure taxonomy developed in Section 3.1, we investigate how many Foreign Key and Domain Knowledge failure types our model alleviates. We find that DocuT5-Large-SDCD improves a total of 47 queries: Foreign Key (13) and split across Domain Knowledge by Incorrect Aggregation (8), Incorrect Table (5), Incorrect Column (7), and Incorrect Value (11).

Figure 6 shows specific examples where using schema descriptions helps for each failure category. For example, DocuT5-Large-SDCD can use implicit mentions of schema entities within the question to identify the correct column based on descriptions, i.e. identify both columns date_effective_from and date_effective_to when asked about “effective date period”. Extra column documentation on boolean columns is also beneficial in contextualising correct use cases, i.e. that “left handed players” are players with column hand set to “L” based on description “a player is a right-handed player then hand is R otherwise L”.

Looking at the Spider-DK dataset (Figure 7), we find we can correctly predict queries belonging to the Logical Failures, such as questions asking for the “youngest person”, which means the person with the minimum age or the maximum date of birth. The additional context through schema descriptions allows the model to reason more effectively when there is a question-table word mismatch. Furthermore, it is also clear that stating the column data type in the table documentation is advantageous; for example, “as a DateTime” results in the model getting less confused when identifying the correct logical operation.

On the other hand, Figure 7 shows the results on the Spider-SYN dataset, we find additional context reduces some of the original hallucinations encountered. While we also observe the additional context makes the model more independent during inference. Specifically, our model escapes some of the memorized patterns during training and adapts quickly to new domains, such as knowing that puppies refers to the dogs tables.

6 Related Work

Table Structure: Recently released benchmarks, such as Spider (Yu et al., 2018) and WikiSQL (Zhong et al., 2017) make cross-domain text-to-
SQL prediction more challenging than previous single domain datasets (Dahl et al., 1994; Zelle and Mooney, 1996). The cross-domain setting requires generalization to new database schemas and requires compositional SQL and identifying entity mentions in the natural language question.

Prior works has attempted to encode table structure by converting the schema into a directed graph (Bogin et al., 2019; Guo et al., 2019) and adding global reasoning over the natural utterance through a question-contextualization (Wang et al., 2020). More recently, there have been a number of complex GNN-based approaches that have shown strong performance in the cross-domain SQL setting. Specifically, more advances schema grounded (Wang et al., 2022; Cao et al., 2021), including syntactic metadata (Hui et al., 2022), and iteratively build a semantic enhanced schema-linking graph (Liu et al., 2022). Nevertheless, graph schema representations require complex model architectures with task-specific layers, and none of these methods enhance the schema-specific domain knowledge through the input.

Treating text-to-SQL as a machine translation problem, allows exploiting pre-trained language models that showed semantic knowledge understanding (Hwang et al., 2019; Li et al., 2020). Most seq2seq SQL generators (Hwang et al., 2019; Lin et al., 2020; Scholak et al., 2021) only linearize the database schema by enumerating table and column names. For example, PICARD (Scholak et al., 2021) and BRIDGE (Lin et al., 2020) identified entity mentions within the natural utterance input through database look-ups and fuzzy string matching and appended them to the serialized database input. Yet, as our behavior analysis identifies, complex table operations such as SQL join operations require richer table contextualization. UniSAr (Dou et al., 2022) showed encoding foreign key relationships is beneficial, however, their results are worse on Spider and our method encodes cross-table relations in a much simpler manner.

**Schema Descriptions**: Relying solely on parametric memory learned during pre-training is not ideal, as revising the model’s world knowledge is non-trivial to do in practice. A hybrid model exploiting both parametric memory and a flexible external input allows easier adjustments (Lewis et al., 2020; Shuster et al., 2021; Izacard et al., 2022). It can also reduce hallucinations and factual knowledge incorrectness, which are problems of generative models for knowledge intensive tasks (Roller et al., 2021).

In semantic parsing, input can be augmented by concatenating the top $K$ most similar natural utterance and logical form pairs. Gupta et al., 2022 augmented the inputs of a pre-trained language model with the top nearest neighbor semantic parses and Pasupat et al., 2021 used custom retrieval index.

Another tangential work stream is pre-training seq2seq transformer-based models on aligned tabular and textual data (Herzig et al., 2020; Yin et al., 2020). However, the surrounding text is generally noisy and cannot inject much compositional bias.

We use a similar intuition: large pre-trained language models have been trained on free-form text, therefore high-quality table textual descriptions will provide better schema grounding in domain-specific knowledge.

7 Conclusion

We introduce DocuT5, which allows diverse language model architectures to inject knowledge from external “documentation” to improve domain generalization. Through a newly developed failure taxonomy, we identify that current model errors are 19.6% due to foreign key mistakes and 49.2% due to a lack of domain knowledge. DocuT5 encodes knowledge from the table structure context of foreign keys and domain knowledge through contextualizing cross-table relations. We show that both types of knowledge improve over state-of-the-art T5 with constrained decoding on SPIDER, and domain knowledge greatly helps on Spider-DK and Spider-SYN datasets. Further analysis shows error reduction in foreign keys and domain knowledge failure categories and state-of-the-art performance over comparably pre-trained language SLQ generation models.

8 Acknowledgements

The authors would like to acknowledge Ix Tech Global Ltd, specifically Tom Martin and Brie Read, for supporting this research. Additionally, this work is supported by the 2019 Bloomberg Data Science Research Grant and the Engineering and Physical Sciences Research Council grant EP/V025708/1.
References

Ben Bogin, Jonathan Berant, and Matt Gardner. 2019. Representing schema structure with graph neural networks for text-to-sql parsing. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4560–4565.

Ruisheng Cao, Lu Chen, Zhi Chen, Yanbin Zhao, Su Zhu, and Kai Yu. 2021. Lgesql: Line graph enhanced text-to-sql model with mixed local and non-local relations. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 2541–2555.

Deborah A Dahl, Madeleine Bates, Michael K Brown, William M Fisher, Kate Hunnicke-Smith, David S Pallett, Christine Pao, Alexander Rudnicky, and Elizabeth Shriberg. 1994. Expanding the scope of the atis task: The atis-3 corpus. In Human Language Technology: Proceedings of a Workshop held at Plainsboro, New Jersey, March 8-11, 1994.

Longxu Dou, Yan Gao, Mingyang Pan, Dingzirui Wang, Jian-Guang Lou, Wanxiang Che, and Dechen Zhan. 2022. Unisar: A unified structure-aware autoregressive language model for text-to-sql. arXiv preprint arXiv:2203.07781.

Yujian Gan, Xinyun Chen, Qiuping Huang, Matthew Purver, John R Woodward, Jinxia Xie, and Pengsheng Huang. 2021a. Towards robustness of text-to-sql models against synonym substitution. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 2505–2515.

Yujian Gan, Xinyun Chen, and Matthew Purver. 2021b. Exploring underexplored limitations of cross-domain text-to-sql generalization. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 8926–8931.

Jiaqi Guo, Zecheng Zhan, Yan Gao, Yan Xiao, Jian-Guang Lou, Ting Liu, and Dongmei Zhang. 2019. Towards complex text-to-sql in cross-domain database with intermediate representation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4524–4535.

Vivek Gupta, Akshat Shrivastava, Adithya Sagar, Armen Aghajanyan, and Denis Savenkov. 2022. Retronlu: Retrieval augmented task-oriented semantic parsing. In Proceedings of the 4th Workshop on NLP for Conversational AI, pages 184–196.

Jonathan Herzig, Pawel Krzysztof Nowak, Thomas Mueller, Francesco Piccinno, and Julian Eisenschlos. 2020. Tapas: Weakly supervised table parsing via pre-training. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4320–4333.

Binyuan Hui, Ruiying Geng, Lihan Wang, Bowen Qin, Yanyang Li, Bowen Li, Jian Sun, and Yongbin Li. 2022. S2sql: Injecting syntax to question-schema interaction graph encoder for text-to-sql parsers. In Findings of the Association for Computational Linguistics: ACL 2022, pages 1254–1262.

Wonseok Hwang, Jinyeong Yim, Seunghyun Park, and Minjoon Seo. 2019. A comprehensive exploration on wikisql with table-aware word contextualization. arXiv preprint arXiv:1902.01069.

Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. 2020. Retrieval-enhanced generation for knowledge-intensive nlp tasks. Advances in Neural Information Processing Systems, 33:9459–9474.

Ning Li, Bethany Keller, Mark Butler, and Daniel Cer. 2020. Seqgensql–a robust sequence generation model for structured query language. arXiv preprint arXiv:2011.03836.

Xi Victoria Lin, Richard Socher, and Caiming Xiong. 2020. Bridging textual and tabular data for cross-domain text-to-sql semantic parsing. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 4870–4888.

Aiwei Liu, Xuming Hu, Li Lin, and Lijie Wen. 2022. Semantic enhanced text-to-sql parsing via iteratively learning schema linking graph. In Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pages 1021–1030.

Panupong Pasupat, Yuan Zhang, and Kelvin Guu. 2021. Controllable semantic parsing via retrieval augmentation. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 7683–7698.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. Journal of Machine Learning Research, 21:1–67.

Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Eric Michael Smith, Y-Lan Boureau, et al. 2021. Recipes for building an open-domain chatbot. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 300–325.
Torsten Scholak, Nathan Schucher, and Dzmitry Bahdanau. 2021. Picard: Parsing incrementally for constrained auto-regressive decoding from language models. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 9895–9901.

Kurt Shuster, Spencer Poff, Moya Chen, Douwe Kiela, and Jason Weston. 2021. Retrieval augmentation reduces hallucination in conversation. In Findings of the Association for Computational Linguistics: EMNLP 2021, pages 3784–3803.

Bailin Wang, Richard Shin, Xiaodong Liu, Oleksandr Polozov, and Matthew Richardson. 2020. Rat-sql: Relation-aware schema encoding and linking for text-to-sql parsers. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7567–7578.

Lihan Wang, Bowen Qin, Binyuan Hui, Bowen Li, Min Yang, Bailin Wang, Binhua Li, Jian Sun, Fei Huang, Luo Si, et al. 2022. Proton: Probing schema linking information from pre-trained language models for text-to-sql parsing. In Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pages 1889–1898.

Pengcheng Yin, Graham Neubig, Wen-tau Yih, and Sebastian Riedel. 2020. Tabert: Pretraining for joint understanding of textual and tabular data. arXiv preprint arXiv:2005.08314.

Tao Yu, Rui Zhang, Kai Yang, Michihiro Yasunaga, Dongxu Wang, Zifan Li, James Ma, Irene Li, Qingning Yao, Shanelle Roman, et al. 2018. Spider: A large-scale human-labeled dataset for complex and cross-domain semantic parsing and text-to-sql task. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing.

John M Zelle and Raymond J Mooney. 1996. Learning to parse database queries using inductive logic programming. In Proceedings of the national conference on artificial intelligence, pages 1050–1055.

Ruiqi Zhong, Tao Yu, and Dan Klein. 2020. Semantic evaluation for text-to-sql with distilled test suites. arXiv preprint arXiv:2010.02840.

Victor Zhong, Caiming Xiong, and Richard Socher. 2017. Seq2sql: Generating structured queries from natural language using reinforcement learning. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP).

A Appendix
| Question                                                                 | T5-Large<sup>CD</sup> | DocuT5-Large+FK<sup>CD</sup> |
|-------------------------------------------------------------------------|------------------------|-------------------------------|
| What is the average edispl of the cars of model Volvo?                  |                        |                               |
| SELECT avg(t1.edispl) FROM cars_data AS t1 JOIN model_list AS t2 ON t1.id=t2.modelid WHERE t2.model = "volvo" |                        |                               |
| Count the number of United Airlines flights that arrive in Aberdeen.    |                        |                               |
| SELECT COUNT(*) FROM airlines AS t1 JOIN airports AS t2 ON t1.uid=t2.airport |                        |                               |
| Show names of all high school students who do not have any friends.     |                        |                               |
| SELECT name FROM highschooler WHERE id NOT IN (SELECT student_id FROM likes) |                        |                               |
| How many friends does each student have?                               |                        |                               |
| SELECT COUNT(*) FROM friend AS t1 JOIN likes AS t2 ON t1.student_id = t2.student_id group by student_id |                        |                               |
| Show all effective date period for all templates                        |                        |                               |
| SELECT DISTINCT date_effective FROM templates                           |                        |                               |
| What are the full names of all left handed players, in order of birth date? |                        |                               |
| SELECT first_name, last_name FROM players WHERE hand = "left" ORDER BY birth_date |                        |                               |
| List all American lines abbreviations.                                 |                        |                               |
| SELECT airline, abbreviation FROM airlines WHERE airline = 'American'   |                        |                               |
| What are the full names of all players, sorted from the oldest to youngest? |                        |                               |
| SELECT first_name, last_name FROM players ORDER BY birth_date DESC      |                        |                               |

Figure 5: Spider dev: Text-to-SQL query comparing T5-Large<sup>CD</sup> and DocuT5-Large+FK<sup>CD</sup>, where regular T5 fails to infer that a JOIN was required or which foreign key to use. The orange box is the augmented foreign key information DocuT5-Large+FK<sup>CD</sup> uses for the prediction.

| Question                                                                 | T5-Large<sup>CD</sup> | DocuT5-Large+SD<sup>CD</sup> |
|-------------------------------------------------------------------------|------------------------|-------------------------------|
| How many friends does each student have?                               |                        |                               |
| SELECT COUNT(*) FROM friend AS t1 JOIN likes AS t2 ON t1.student_id = t2.student_id group by student_id |                        |                               |
| Show all effective date period for all templates                        |                        |                               |
| SELECT DISTINCT date_effective FROM templates                           |                        |                               |
| What are the full names of all left handed players, in order of birth date? |                        |                               |
| SELECT first_name, last_name FROM players WHERE hand = "left" ORDER BY birth_date |                        |                               |

Figure 6: Spider dev: Text-to-SQL examples comparing T5-Large<sup>CD</sup> and DocuT5-Large+SD<sup>CD</sup>, where regular T5 fails due to lack of domain knowledge. The orange box is the augmented table and column information DocuT5-Large+SD<sup>CD</sup> uses for the prediction.

| Question                                                                 | T5-Large<sup>CD</sup> | DocuT5-Large+SD<sup>CD</sup> |
|-------------------------------------------------------------------------|------------------------|-------------------------------|
| What is the average edispl of the cars of model Volvo?                  |                        |                               |
| SELECT avg(t1.edispl) FROM cars_data AS t1 JOIN model_list AS t2 ON t1.id=t2.modelid WHERE t2.model = "volvo" |                        |                               |
| Count the number of United Airlines flights that arrive in Aberdeen.    |                        |                               |
| SELECT COUNT(*) FROM airlines AS t1 JOIN airports AS t2 ON t1.uid=t2.airport |                        |                               |
| Show names of all high school students who do not have any friends.     |                        |                               |
| SELECT name FROM highschooler WHERE id NOT IN (SELECT student_id FROM likes) |                        |                               |

Figure 7: Spider-DK: Text-to-SQL examples comparing T5-Large<sup>CD</sup> and DocuT5-Large+SD<sup>CD</sup>, where regular T5 fails due to lack of domain knowledge. The orange box is the augmented table and column information DocuT5-Large+SD<sup>CD</sup> uses for the prediction.
Figure 8: Spider-SYN: Text-to-SQL examples comparing T5-Large$^{CD}$ and DocuT5-Large+SD$^{CD}$, where regular T5 fails due to lack of domain knowledge. The orange box is the augmented table and column information DocuT5-Large+SD$^{CD}$ uses for the prediction.

| Query                                              | SQL Code                                                                 | Correct? |
|----------------------------------------------------|--------------------------------------------------------------------------|----------|
| What are the arriving and leaving date of all puppies? | SELECT date_arrived, date_departed FROM dogs WHERE breed_code = "Puppies" | ✗        |
|                                                    | SELECT date_arrived, date_departed FROM dogs                             | ✓        |
| What is the average and maximum number of seats for all stations? | SELECT average, max(capacity) from stadium                              | ✗        |
|                                                    | SELECT avg(capacity), max(capacity) from stadium                         | ✓        |