N-BEST HYPOTHESES RERANKING FOR TEXT-TO-SQL SYSTEMS

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ABSTRACT
Text-to-SQL task maps natural language utterances to structured queries that can be issued to a database. State-of-the-art (SOTA) systems rely on finetuning large, pre-trained language models in conjunction with constrained decoding applying a SQL parser. On the well established Spider dataset, we begin with Oracle studies: specifically, choosing an Oracle hypothesis from a SOTA model’s 10-best list, yields a 7.7% absolute improvement in both exact match (EM) and execution (EX) accuracy, showing significant potential improvements with reranking. Identifying coherence and correctness as reranking approaches, we design a model generating a query plan and propose a heuristic schema linking algorithm. Combining both approaches, with T5-Large, we obtain a consistent 1% improvement in EM accuracy, and a 2.5% improvement in EX, establishing a new SOTA for this task. Our comprehensive error studies on DEV data show the underlying difficulty in making progress on this task.

Index Terms— Text-To-SQL, Semantic parsing

1. INTRODUCTION

Large language models (LM) are widely used for natural language generation [1, 2, 3]. Recently, the use of large LMs has extended to semantic parsing tasks such as code generation. For general-purpose code generation, large LMs such as Codex [4] are trained on massive, paired codebases (code, NL). For domain-specific code generation tasks, such as Text-to-SQL that aims to convert natural language instructions to SQL queries, multiple public domain datasets are available (with associated leaderboards), including Spider [5], CoSQL [6] and SParC [7]. However, the amount of training data in these datasets is much smaller than the natural language and code pairs mined from the internet. In such cases, instead of training a new model from scratch, the pretrain/finetune strategy with publicly available LMs has been shown to be more accurate. For example, in UnifiedSKG [8], the T5 model [1] is finetuned for various semantic parsing tasks (including Text-to-SQL), achieving SOTA performance. Besides the amount of the training data, another challenge with SQL generation is that the generated code is underspecified without the corresponding schema ¹. To handle this challenge, implicit or explicit schema linking becomes an important sub-task for SQL code generation [9, 10, 11].

In this paper, we focus on complex, cross-domain, SQL generation using Spider [5] a large-scale, Text-to-SQL dataset consisting of 200 complex databases covering 138 domains. Spider is a well established dataset with nearly 70 entries on the leaderboard, demonstrating the difficulty of the task. The data is split into training, development (DEV), and test sets without overlaps in databases across these sets, as the aim of this task is to learn models that can issue queries from natural language text to previously unseen databases in the training set. Furthermore, SQL queries in this dataset contain nested sub-queries, requiring the model to understand compositional structures. The model performance is based on two metrics, exact-set-match accuracy (EM) and execution accuracy (EX); the former compares individual query components between the predicted and groundtruth SQL queries, while the latter compares their execution output.

Similar to general-purpose code generation, the output of Text-to-SQL models is constrained to follow SQL grammar. Previous solutions have employed encoder/decoder models, with the decoder being constrained to produce well-formed outputs [12, 13]. An approach that is more compatible with large pretrained LMs is to remove the constraints on decoder: [14, 15] prune the finalized hypotheses from beam search to those that are syntactically correct. Meanwhile, PICARD [16], a top entry on the Spider leaderboard ², in addition to finetuning the pretrained T5 model, also imposes SQL syntax constraints during beam search (via constrained decoding). It achieves an EM of 74.8% and an EX of 79.2% on the Spider DEV set. Natural ways to potentially improve these metrics include increasing the model size or collecting and/or synthesizing additional training data [17].

In this paper, we take a different approach: we first perform an Oracle analysis on n-best lists obtained from PICARD and observe significant improvements (7.7% absolute improvement in EM and EX) even at small beam sizes (such as 10). The gap in performance between 1-best and Oracle motivates reranking approaches. We propose 2 reranking

¹For Text-to-SQL, in addition to SQL grammar constraints, there are schema constraints.
²https://yale-lily.github.io/spider
approaches that are motivated by the issues with the current, large pretrained LMs: coherence [18] and correctness. To improve coherence, we explore n-best reranking using a query plan produced by an independent model. Next, to improve correctness, we propose a heuristic algorithm performing schema linking on n-best lists – imposing constraints that are missing in PICARD. The combined reranking approaches consistently yield improvements across all T5 model sizes, obtaining a 1.0% absolute improvement in EM and a 2.5% absolute improvement on EX. Lastly, to analyze persistent gap with Oracle results, we performed a detailed analysis of errors and metrics. Our studies show that annotation and metrics issues can be significant factors to improving models and evaluation on Spider.

Contributions. The contributions of this paper are: a) Using Oracle analysis and rerankers on n-best lists, we outperform SOTA performance on a competitive Spider task; b) Analysis of errors on Spider DEV data, showing much work remains to be done on metrics and annotation.

2. RELATED WORK

We review related work in 4 categories: a) reranking approaches; b) coherence in LMs; c) schema linking for text-to-SQL; d) noise in Spider.

Rerankers. N-best list reranking has a long history in speech recognition, machine translation, and semantic parsing communities [19, 20, 21, 22, 23, 24, 25]. These are performed with a much larger 2nd-stage model [26, 27] or using additional knowledge sources not available during the first pass [28, 29]. On Spider, a larger 2nd-stage reranker was successfully used in [30]. Some reranking methods combine outputs from multiple systems [31] or use improved output confidence [32]. Imposing task specific constraints [14, 15] to remove invalid options can be a helpful strategy to improve reranking. In our work, in addition to the output target being structured queries (instead of natural language), the 1st-stage model is large (T5 family), and the baseline model imposes additional knowledge during beam search in the form of SQL parsing. Our proposed methods are designed for this setting.

Coherence with query plan. Coherence issues with LMs [33] are associated with hallucination phenomenon [34, 35]. While these are well-known problems in unstructured text generation with LMs [36, 37, 38, 39], coherence issues with structured text generation is somewhat less unexplored: [40] uses semantic coherence for data augmentation, while [41] uses a reconstruction model for reranking semantic parses, and [14, 15, 16] use parsers to improve coherence with SQL grammar. Our reranker is designed to improve semantic coherence, and it is distinct from [41] in that, our query plan model predicts the structure of a query (from natural language), and orders the n-best list for consistency.

Correctness with schema linking. Historically, schema linking (SL) has been explored for Text-to-SQL. Schema has been encoded in model input for small encoder/decoder mod-
table name vocal does not exist in the database).

4. RERANKING APPROACHES

In this section, we discuss our two reranking approaches over n-best hypotheses.

4.1. Improving Coherence with Query Plan

Text generation is a challenging topic, and large LMs tend to lose coherence [18, 39]. This is compounded in text-to-SQL with such models: apart from conforming to syntactic structures, models have to perform semantic mapping from natural language to SQL over long spans in complex questions involving compositionality, grouping/ordering/counting. Furthermore, nested queries are likely to appear with WHERE, EXCEPT, UNION, and INTERSECT clauses, while grouping/ordering/counting tend to occur with GROUP BY, HAVING, ORDER BY, LIMIT.

We build a model that focuses specifically on this aspect: a multi-label classification model that generates a query plan predicting whether a SQL query contains the aforementioned 8 clauses. The output of this model is then used as a coherence check reranker against the n-best hypotheses from the baseline model. We finetune a RoBERTa-Large using the classification head with binary cross entropy (BCE) loss. The model is trained using the training partition of Spider dataset. Input of the model consists of a natural language query and a database schema, while the labels are obtained from groundtruth SQL queries.

4.2. Improving Correctness with Schema Linking

The motivation for this approach comes from the fact that certain aspects of schema linking (values, columns, and tables) from natural language query (on the input side of the model) to a SQL query (on the output side of the model) can be hard for the model to learn to map: this is because these mappings tend to be irregular, and a relatively small training dataset may not cover a large fraction of the irregularities. For example, a primary key field on "student identification" could be named in several ways as a column such as "stud_id", "sid", "s_id" etc. Similarly, values that are strings can be arbitrarily represented, such as "True" vs "T" vs "Yes".

We implement an algorithm to perform value linking in WHERE clauses. For each predicted SQL query in the n-best list, we follow three steps:

1. Extract slot names and their respective values from the conditions in the WHERE clause; then check if the slot value exists in any of the referenced tables in the FROM clause of the query;
2. Obtain a list of candidate slot names and values, which are exact or partial occurrences of the column/table names and string values in the question with name-based and value-based linking described in RAT-SQL [12];
3. Perform prefix and abbreviation matches on slot values with categorical types in a table schema definition (such as matching “left” to “L”).

5. EXPERIMENTS

This section presents the experimental setup, baselines, Oracle analysis, and the main results.

5.1. Dataset and Metrics

We briefly describe the dataset and metrics used in this paper. More details can be found in [5].

5.1.1. Dataset

Spider is a large-scale, cross-domain paired text-to-SQL dataset: it contains 10,181 questions and 5,693 unique complex SQL queries on 200 databases (covering 138 domains), each with multiple tables. The standard protocol splits this into 8,659 examples on 146 databases for training, and 1034 examples on 20 databases are used for development (DEV); the test set that includes 2,147 examples from 34 databases are held back. The split is done without overlaps of databases across these sets.

Task difficulty levels. Spider categorizes the SQL query complexity into 4 difficulty levels: easy, medium, hard, and extra hard. Queries that contain more SQL keywords (GROUP BY, ORDER BY, INTERSECT), nested subqueries, column selections and aggregators are considered harder.

5.1.2. Metrics

On Spider, Text-to-SQL model performance is evaluated based on two metrics: exact-set-match accuracy (EM) and execution accuracy (EX). Note that all our results are on the Spider DEV set.

Exact-set-match accuracy (EM). EM compares each clause between a prediction and its corresponding groundtruth SQL query. The predicted SQL query is correct only if all of the components match. This metric does not take values into account. EM can lead to false positives and false negatives.

Execution Accuracy (EX). EX compares the execution output of the predicted SQL query and its corresponding groundtruth SQL queries. However, it is important to note that EX can also lead to false positives and false negatives.

5.2. Models

We use PICARD [16] as our baseline model in this paper. We finetune on three T5 model sizes, T5-Base$, T5-Large$, and T5-3B on p3dn.24xlarge instances (8 NVIDIA Tesla V100 GPUs) and employ DeepSpeed to save memory. The input to the models contain several segments separated by |.

3Note that EM implemented by Spider ignores table join conditions.
4Note that the models are LM adapted, initialized from T5 model and trained for additional 100K steps on the LM objective discussed in [1]
5https://github.com/microsoft/DeepSpeed
including natural language query, database name, serialized database schema. We take the serialization scheme mentioned in [45] and enable database content by appending database values to the column names [15]. All the T5 models are fine-tuned with teacher forcing and cross-entropy (CE) loss for up to 3000 epochs using a batch size of 2000 and a learning rate of $1 \times 10^{-4}$. During inference, an incremental SQL parser is integrated into beam search, with a beam size of 4.

To improve coherence, we fine-tune a RoBERTa-Large model with a sequence classification head on p3.2xlarge instances (1 NVIDIA Tesla V100 GPU) for query plan prediction. We reuse the input from the baseline model. The output is one-hot encoding label extracted from groundtruth queries based on existence of WHERE, GROUP BY, HAVING, ORDER BY, LIMIT, EXCEPT, UNION, and INTERSECT clauses. The RoBERTa model is finetuned with binary cross entropy (BCE) loss for up to 100 epochs using a batch size of 5 and a learning rate of $1 \times 10^{-5}$.

### 5.3. Oracle Analysis

We open the beam up and perform Oracle analysis on n-best hypotheses. Specifically, we conducted these experiments over a set of beam sizes (and correspondingly n-best hypotheses), 10, 15, 20, and 25; also a few selected T5 model sizes, T5-Base$^4$, T5-Large$^4$, and T5-3B.

Table 1. 1-best accuracies as beam size is changed.

| Beam size | T5-Base | T5-Large | T5-3B |
|-----------|---------|----------|-------|
|           | EM% | EX% | EM% | EX% | EM% | EX% |
| 4         | 66.6 | 68.3 | 74.8 | 79.2 | 75.5 | 79.3 |
| 10        | 67.1 | 68.4 | 75.1 | 79.4 | 75.6 | 79.3 |
| 15        | 67.1 | 68.5 | 74.7 | 79.2 | 75.5 | 79.2 |
| 20        | 67.3 | 68.7 | 74.8 | 79.2 | 75.5 | 79.2 |
| 25        | 67.3 | 68.7 | 74.7 | 79.1 | 75.6 | 79.2 |

Search errors. Table 1 presents the analysis by increasing the beam size (and choosing the 1-best hypothesis): opening up the beam, improves the accuracy by a small amount initially (going from 4 to 10) for all models. However, the performance on EM and EX saturate after that, suggesting that search errors contribute a small proportion of overall errors.

Table 2. Oracle accuracies as beam size is changed.

| Beam size | T5-Base | T5-Large | T5-3B |
|-----------|---------|----------|-------|
|           | EM% | EX% | EM% | EX% | EM% | EX% |
| 10        | 67.1 | 68.3 | 75.1 | 79.4 | 75.6 | 79.3 |
| 15        | 74.7 | 75.5 | 82.8 | 87.1 | 85.2 | 87.3 |
| 20        | 75.4 | 76.6 | 82.9 | 87.6 | 86.2 | 87.9 |
| 25        | 76.1 | 77.6 | 83.5 | 88.0 | 86.3 | 88.0 |

Model errors. In Table 2, the first row is the 1-best obtained from baseline, while the other rows show Oracle accuracies for the three models sizes over different beams. As can be observed, both EM and EX improve significantly: for example, the T5-Large model achieves 7.7%, 7.8%, 8.4% and 8.7% absolute improvements for EM; similarly 7.7%, 8.2%, 8.6% and 8.6% absolute improvements for EX.

Table 3. T5-large: 1-best and Oracle over difficulty levels.

| Difficulty | Count | 1-best | Oracle |
|------------|-------|--------|--------|
|            | EM%  | EX%   | EM%  | EX%  |
| Easy       | 248  | 89.1  | 93.1 | 96.0 |
| Medium     | 446  | 80.9  | 88.6 | 92.6 |
| Hard       | 174  | 65.5  | 74.7 | 79.3 |
| Extra      | 166  | 48.8  | 60.2 | 67.5 |
| Total      | 1034 | 75.1  | 82.8 | 87.1 |

### 5.4. Results

5.4.1. Improving Coherence with Query Plan Modeling

Table 4 lists reranking results using query plan (QP) coherence on the 10-best hypotheses obtained from the baseline using a T5-Large model. It can be seen that using structural consistency with QP can help both EM and EX, obtaining 0.7% and 0.5% absolute improvements respectively. We present an example improved by QP. A query plan that combines GROUPBY and HAVING clauses is presented below.

Question: Find the average life expectancy and total population for each continent where the average life expectancy is shorter than 72?

```sql
Pred SQL: SELECT avg(lifeexpectancy), sum(population) FROM country
WHERE lifeexpectancy < 72 GROUP BY continent
```

With QP: `SELECT continent, avg(lifeexpectancy), sum(population) FROM country GROUP BY continent HAVING avg(lifeexpectancy) < 72`

Table 4. Reranking with query plan (QP) coherence checks on 10-best hypotheses from baseline using T5-Large.

| Method | T5-Large |
|--------|----------|
|        | EM% | EX% |
| Baseline | 75.1 | 79.4 |
| QP      | 75.8 | 79.9 |

To understand the QP model better, we present its performance on each of the clauses in Table 5 in terms of F-1 score, precision and recall. While the model performs well on WHERE, GROUP BY, HAVING, ORDER BY, LIMIT, INTERSECT, it does not perform as well on
EXCEPT and UNION. We conjecture low training data counts for these clauses as a potential reason. The macro F-1 score for this model is 0.89.

Table 5. QP model performance per clause.

| Clause     | F1  | R   | P   |
|------------|-----|-----|-----|
| where      | 0.97| 0.97| 0.98|
| groupBy    | 0.96| 0.96| 0.96|
| having     | 0.97| 0.95| 0.99|
| orderBy    | 0.96| 0.97| 0.95|
| limit      | 0.95| 0.96| 0.94|
| except     | 0.73| 0.76| 0.71|
| union      | 0.62| 0.44| 0.99|
| intersect  | 0.96| 0.97| 0.95|

5.4.2. Improving Correctness with Schema Linking

Table 6 shows the reranking performance with schema linking over 10-best hypotheses obtained from a baseline model with T5-Large. With this approach, we see an absolute improvement in EX of 1.9%.

Table 6. Reranking with schema linking (SL) on 10-best hypotheses obtained from baseline using T5-Large.

| Method | T5-Large |
|--------|----------|
|        | EM%  | EX%  | EM%  | EX%  |
| Baseline | 75.1 | 79.4 | 75.6 | 79.3 |
| SL      | 75.4 | 81.3 | 76.1 | 80.4 |

Below, we present 2 examples of schema linking errors (one of column name; and another of cell value) which are fixed by the proposed method.

**Example 1**
- **Question:** What is the abbreviation of Airline “JetBlue Airways”?
- **Pred SQL:** `SELECT abbreviation FROM airlines`<br>WHERE `abbreviation` = “JetBlue Airways”
- **Fixed SQL:** `SELECT abbreviation FROM airlines`<br>WHERE `airline` = “JetBlue Airways”

**Example 2**
- **Question:** What is the total population of Gelderland district?
- **Pred SQL:** `SELECT sum(population) FROM city`<br>WHERE `district` = “Gelderland”
- **Fixed SQL:** `SELECT sum(population) FROM city`<br>WHERE `district` = “Gelderland”

In Ex 1, the question asks for the abbreviation of Airline “JetBlue Airways”, where “JetBlue Airways” is a slot value for a slot name “airline”. The model gets misled by an available column name that matches the query word “abbreviation”. In Ex 2, we need a SQL query for the total population of “Gelderland” district. The expected slot value is “Gelderland”, the predicted SQL obtained a cell value of “Geeland”.

Syntax Checks with a Full Parser. Since incremental parsing can still allow syntactically incorrect full hypotheses, we investigated the errors from the baseline model. Around 2% of the hypotheses are indeed syntactically incorrect. For example, intermediate SQL queries from Fig. 1 such as `SELECT count(*) FROM`, which are invalid queries but valid prefixes, are allowed by the incremental parser as outputs. We run a full SQL parser, filtering invalid hypotheses, and selecting the hypothesis with the highest remaining score. Analysis. Results from our experiments showed that the full parser does not improve performance. We investigated the errors for the 23 examples with syntactically incorrect 1-best predictions: for 16 of them all other hypotheses are incomplete SQL queries, while the other 7 do not have any hypotheses that improves either EM or EX. These are errors that cannot be improved even with an Oracle selection, meaning that these are residual search errors.

5.4.3. Combined Results

We examine if the gains from SL and QP are additive, and if they carryover to different model sizes. We then combine SL and QP in order, presenting the results in Table 7.

Table 7. Performance of rerankers (QP, SL, SL + QP) on 10-best lists obtained from different T5 model sizes.

| Method | T5-Base | T5-Large | T5-3B |
|--------|---------|----------|-------|
|        | EM%    | EX%     | EM%   | EX%   |
| Baseline | 67.1   | 68.3    | 75.6  | 79.3  |
| QP      | 67.8   | 68.9    | 75.8  | 79.4  |
| SL      | 67.2   | 70.0    | 75.4  | 81.3  |
| SL + QP | 67.9   | 70.4    | 76.1  | 81.9  |

From the table, it can be seen that the performance of the different rerankers are consistent across model sizes: the SL approach yields a consistent gain of between 1.1% to 1.9% in EX. Similarly, QP yields a consistent gain as well. Overall the gains combining the approaches are additive on both EM and EX across model sizes. Based on the one-sided t-tests, improvements on T5-base and T5-large are significant at $\alpha = 0.1$, while the gain on T5-3B is significant at $\alpha = 0.15$.

5.4.4. Analysis of gains across difficulty levels

Table 8 shows that the gains from the proposed approach (combining SL and QP) consistently carry over all the pre-defined difficulty levels. Furthermore, the gains are bigger on harder examples, considering both EM and EX.

6. DISCUSSION ON ERRORS

Given that proposed reranker still has a gap with Oracle, we analyze errors with metrics computation and annotation.

6.1. Metrics Errors

PK/FK Swaps. EM implementation by Spider is done by replacing foreign keys with primary keys. This is problematic
Table 8. T5-large model: Performance of rerankers (combining SL and QP) on 10-best lists

| Diff | count | Baseline | SL + QP |
|------|-------|----------|---------|
| Easy | 248   | 89.1     | 89.5    |
| Med  | 446   | 80.9     | 81.6    |
| Hard | 174   | 65.5     | 68.4    |
| Extra| 166   | 48.8     | 49.4    |
| Total| 1034  | 75.1     | 76.1    |

and may lead to false positives. The following example contains a prediction that is marked as exact match incorrectly.

Question: How many flights depart from 'APG'?

Gold SQL: `SELECT count(*) FROM flights WHERE sourceairport = 'APG'`
Pred SQL: `SELECT count(*) FROM flights WHERE destairport = 'APG'`

*Note that airportcode from airports table is PK for sourceairport and destairport from flights table*

We fixed the EM implementation and obtained the revised $EM^*$ in Table 9. Generally there is a 3-4% absolute gap between the original and revised EM implementation.

Table 9. Revised EM implementation.

| Method   | T5-large LM | T5-3b |
|----------|-------------|-------|
|          | EM% | EM*% | EM% | EM*% |
| PICARD   | 75.1| 72.1 | 76.4| 72.5 |
| SL + QP  | 76.1| 72.9 | 76.4| 72.5 |

Query rewrite errors. Since SQL queries can sometimes be rewritten in multiple ways, EM can yield false negatives. We conducted error analysis over hypotheses selected after our combined reranking system (SL + QP) using finetuned T5-large model with PICARD. We found that 7.9% of predictions are correct using EX, but incorrect with EM; also, 4.8% of hypotheses are correct SQL but different to the corresponding groundtruth SQL. In such examples with SQL rewrites, EX serves as a complementary metric to EM.

Content-only match errors. As described in [5], it is possible to obtain a predicted SQL that returns the same result as the groundtruth SQL but semantically different. We found that 4.4% of the hypotheses on DEV data generated from T5-Large model using PICARD are false positives of this type.

Redundant column errors. We found that some predicted or groundtruth SQL queries contain redundant columns. The columns repeat information or do not need to be included, however retaining such column won’t affect the semantics of the query, but can result in EX errors.

6.2. Annotation Errors

We found 5 unique groundtruth SQL queries with annotation errors in DEV set. In Spider, some natural language queries are presented multiple times; consequently, the 5 unique groundtruth SQL queries are assigned to 7 DEV examples. We show an example with annotation error whose natural language query has been written in two different ways below. The annotation error is at least 0.7%.

Question: What is first, middle, and last name, along with id and number of enrollments, for student who enrolled the most in any program?

Gold SQL: `SELECT t1.student_id, t1.first_name, t1.middle_name, t1.last_name, count(*) t1.student_id`
FROM ...
Pred SQL: `SELECT t1.student_id, t1.first_name, t1.middle_name, t1.last_name, count(*)`
FROM ...

6.3. Summary and Outlook on Errors

As we have seen, 0.7% of the DEV examples have incorrect groundtruth SQL queries. We also identified issues with EM implementation in Spider – foreign keys are automatically replaced with the corresponding primary keys, resulting in 3-4% of the predictions on DEV examples being incorrectly marked as exact matches (false positives). Also, each example in Spider is annotated with only one groundtruth SQL – leading to about 4.8% of the predictions on DEV examples being false negatives. Using EX, results in 4.4% of the predictions on DEV being false positive, while another 0.8% of the predictions are false negative. Our studies show that metrics and annotation need further research attention on Spider.

7. CONCLUSIONS

We began with Oracle studies, showing large gains can be obtained with n-best hypotheses reranking for a SOTA Text-to-SQL system. Motivated by correctness and coherence issues in text generation using large PLMs, we proposed two reranking approaches: a) schema linking; b) query plan modeling. On a competitive Spider dataset, applying our proposed reranking methods to 10-best hypotheses obtained from a SOTA system (PICARD), we achieve improvements of 1% in EM and 2.5% in EX. We analyzed errors in metrics computation and annotation – showing these can be significant factors to improving models and evaluation on Spider.
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