End-to-End Cross-Domain Text-to-SQL Semantic Parsing with Auxiliary Task

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Abstract

In this work, we focus on two crucial components in the cross-domain text-to-SQL semantic parsing task: schema linking and value filling. To encourage the model to learn better encoding ability, we propose a column selection auxiliary task to empower the encoder with the relevance matching capability by using explicit learning targets. Furthermore, we propose two value filling methods to build the bridge from the existing zero-shot semantic parsers to real-world applications, considering most of the existing parsers ignore the values filling in the synthesized SQL. With experiments on Spider, our proposed framework improves over the baselines on the execution accuracy and exact set match accuracy when database contents are unavailable, and detailed analysis sheds light on future work.

1 Introduction

Text-to-SQL semantic parsing is to translate natural language questions into SQL queries (Warren and Pereira, 1982; Popescu et al., 2003; Li and Jagadish, 2014; Iyer et al., 2017; Yu et al., 2018a; Dong and Lapata, 2018a), which can be further executed against large scale databases to obtain query results. These semantic parsers not only offer the chance of communicating with databases to the users who are unknown of the underlying database query language, but are handy toolkits for experts to synthesize complex SQL queries by providing high-quality samples.

More recently, there has been significant interest in cross-domain text-to-SQL modeling innovation (Yu et al., 2018c; Guo et al., 2019; Bogin et al., 2019a; Wang et al., 2019; Shi et al., 2020; Yu et al., 2020), and different benchmarks are proposed, such as WikiSQL (Zhong et al., 2017) and Spider (Yu et al., 2018d). Especially for the Spider dataset, some of the SQL queries are nested which are more complicated than those in WikiSQL. Furthermore, the attribute that training and test set do not have overlap databases makes the task zero-shot. Therefore, linking entities in the question to the correct schema (columns and tables) from the unseen databases becomes a major problem in the cross-domain text-to-SQL parsing task. Another tricky problem is that some questions contain database-dependent values in different domains, which requires the model to extract them and fill in the corresponding positions for composing an executable SQL query. However, this value filling problem is ignored by a lot of previous work in the cross-domain text-to-SQL parsing, making those parsers impractical.

Considering the importance of the schema linking and value filling for a real-world text-to-SQL parser in the cross-domain setting, we propose a framework with enhanced schema encoding ability and value filling ability. In this framework, based on sequence-to-sequence architecture, we design an auxiliary task column classification for multi-task training. The classifier determines whether a specific column is used in the gold SQL query, as shown in Figure 1. With this auxiliary task, the encoder has better relevance matching capa-
bility (between the question and schema), supervised by explicit learning signals. In this way, the decoder can distinguish relevant and irrelevant schema more easily, leading to better schema linking performance. Furthermore, in our framework, we propose two value filling methods, including a heuristic method and a neural baseline, to make the zero-shot parsers usable in real-world applications. With further analysis based on these two simple baselines, we provide more insights on the value filling subtask, paving ways for future work.

2 Framework

Given a question $X = \{x_1, x_2, ..., x_n\}$ and schema $S$ consists of tables $T = \{t_1, t_2, ..., t_{|T|}\}$ and columns $C = \{c_1, c_2, ..., c_{|C|}\}$, our goal is to map the question-schema pair $(X, S)$ into the correct SQL query $Y$, which can be represented as a sequence of tokens of SQL, or other intermediate representations. In this work, we adopt the intermediate representation as our learning target.

2.1 Input, Encoding and Decoding

For a question, following Yu et al. (2018b) and Guo et al. (2019), we firstly group tokens into a segment if that subsequence matches any column name or table name, and add a special indicator [column] or [table] to it, as shown in Figure 1. For the schema, we combine the column names with the corresponding table names. For example, table country has a column population, we then concatenate them into country population as an enhanced column name. In this way, the model can obtain better representation for distinguishing those columns that share the same column name but belong to different tables. Though Graph Neural Network (Bogin et al., 2019c) or Relational Transformer (Wang et al., 2019) can achieve similar purpose using schema graph structure, we argue that this technique is simple to apply without introducing extra model complexity.

To encode the processed question and schema, we use the pretrained transformer BART (Lewis et al., 2019) as the backbone. The input sequence is the concatenation of processed question tokens and processed columns, as shown in Figure 1. After feeding the input sequence into the encoder, we then obtain the question representation $\{h_{c_1}, h_{c_2}, ..., h_{c_{|C|}}\}$, where $\{h_{c_i}\}$ denotes a sequence of hidden vectors of $i$–th column, because each column contains several tokens. We further apply two aggregation functions $f_{avg}$ and $f_{lstm}$ on the question and column representation, respectively. Concretely, the aggregation function $f_{avg}$ is an averaging function \(\frac{1}{|C|} \sum_{i=1}^{m} h_{c_i}\) applied on each question segment which is determined in the pre-processing step. The obtained question segment representation is denoted with $q_i$, which is further used for the decoding process. The aggregation function $f_{lstm}$ is parameterized with a bidirectional LSTM and the last hidden states from both directions are concatenated to obtain the aggregated representation of each column.

For the decoder, we adopt the coarse-to-fine decoder from Dong and Lapata (2018b) and Guo et al. (2019). The decoder firstly generates the overall structure of the target SQL such as \texttt{SELECT} \_ \_ \texttt{WHERE} \_ \_ \texttt{ORDER BY} \_ \_, and then conducts schema grounding in the fine-grained decoding process, including the \texttt{column linking} and \texttt{table linking}. For more details about the coarse-to-fine decoder, please refer to Dong and Lapata (2018b) and Guo et al. (2019).

2.2 Multitask Learning

To improve the schema encoding quality, an auxiliary column classification task is designed for the model. This auxiliary task exploits the direct supervision signals to enhance the encoder’s relevance matching capability. Specifically, we apply the aggregation function $f_{avg}$ on the representations of token sequence $\{h_{c_i}\}$ for each column, obtaining $s_i$. An dot-product based attention mechanism is further applied on $s_i$ and question segment representations $\{q_j\}$, to obtain question-aware column representation $\hat{s}_i$ with equation $\hat{s}_i = \text{MLP}(\left\{s_i; r_i\right\})$, where $r_i = \sum_{j=1}^{n} \alpha_j q_j$ and $\alpha_j \propto \exp(s_j^\top q_j)$. Finally, a binary classifier is applied on $\hat{s}_i$: If the column is used in the target SQL sequence, then a positive label is assigned; Otherwise, it is classified with a negative label.

2.3 Value Filler

To bridge the gap between existing zero-shot semantic parsers (Guo et al., 2019; Bogin et al., 2019b; Wang et al., 2019) and real-world applications, we propose two value fillers.

Heuristic Method. Our heuristic method is based on the database search and string matching. For

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1We only leverage the encoder part of BART for the encoding, to save computational resources.
each question token $x_i$, we search for its candidate cell values by executing the following SQL query

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SELECT \{column\} FROM \{table\} WHERE
\{column\} LIKE \{token\} OR \{column\} LIKE \{token\}
```

for each column and the corresponding table. If there is a cell value string $v$ from the database is retrieved, and string $v$ has high similarity with a substring of the question (measured by the Levenshtein distance), then we build a projection $P$ from \{table, column\} → \{v\}. We also collect all numbers mentioned in the question as number candidate list $N$, where the rule-based method is applied. With the projection $P$ and number candidates $N$, we fill in the blank with value $P$\{table, column\}, where the value is used in the specific table and column. If multiple candidates are available, we choose the unused one in the queue, whose ordering is based on the collection sequence. If the column type is number, then a number will be assigned from the number candidate list $N$ based on the collection sequence. If all numbers are used, the default value 1 is used. If there is no projection for \{table, column\}, a placeholder is assigned.

**Neural Baseline.** Based on the value candidates including retrieved cell values in $P$ and the numbers in $N$, instead of filling the blanks with heuristic rules, we leverage the neural model for composing the executable SQL. To achieve this, we firstly use a placeholder \mask\, as shown in Figure 1, to denote the value to be filled in the incomplete SQL. The input sequence for the model is the concatenation of the question, the incomplete SQL and value candidates, which is further fed into roberta-base (Liu et al., 2019) encoder, obtaining the \mask\ token hidden states $u_{mask}$. For the value candidates, averaging aggregation function $g_{avg}$ is applied to produce the value candidate representation $u_{v_j}$. By querying the value candidates with $u_{mask}$, best value candidate can be obtained based on $p(u_{v_j}|u_{mask}) \propto \exp(u_{mask}^T u_{v_j})$.

### 3 Experimental Setup

We conduct our experiments on the Spider (Yu et al., 2018d) dataset\(^2\). For the Spider dataset, there are two methods of evaluation: One is exact set match accuracy, requiring an exact set match between the predicted SQL and the oracle SQL, except for the values in the SQL; the other one is execution accuracy, requiring an exact match on the execution outputs. In our work, we provide results on both evaluation metrics to provide a complete baseline system for the benchmark. Considering some privacy issues in real world cases, database contents might be unavailable in the model development phase. So in this work, for exact set match accuracy metric, we further evaluate our models under two different settings: without using cell value and using cell value with one model without retraining. To achieve this, our model is trained without leveraging cell values from the database and can be evaluated directly when database contents are unavailable. When the model can access the database contents, if a question token $x_i$ matches the cell values in column $c$, column name of $c$ is inserted before $x_i$, as a signal for the model. More training details are provided in Appendix.

### 4 Results and Analysis

For the end-to-end evaluation with execution accuracy, Table 1 shows the main results. We report the results based on the heuristic value filler because we find that there is no significant difference between heuristic method and neural baseline model while the heuristic method is more efficient. On the development set, our model achieves 67.6% execution accuracy and 62.6% on the test set.

We further show the results of exact set match

| Model                             | Dev | Test |
|----------------------------------|-----|------|
| GAZP (Zhong et al. (2020))       | -   | 53.5 |
| BRIDGE (Lin et al. (2020))       | -   | 59.9 |
| **Ours** (heuristic method)      | 67.6| 62.6 |

**Table 1:** Results on execution accuracy in test set.

| Model                             | Dev | Test |
|----------------------------------|-----|------|
| **without using cell value**     |     |      |
| EditSQL (Zhang et al., 2019) v1  | 57.6| 53.4 |
| IRNet v2 (Guo et al., 2019)      | 63.9| 55.0 |
| RASQL (anonymous)                | 60.8| 55.7 |
| RYANSQL v2 (Choi et al., 2020)   | 70.6| 60.6 |
| **Ours**                         | 68.0| 61.3 |
| **using cell value**             |     |      |
| BRIDGE (Lin et al. (2020))       | 65.5| 59.2 |
| RATSQL v2 (Wang et al., 2019)    | 65.8| 61.9 |
| RATSQL v3 (Wang et al., 2019)    | 69.7| 65.6 |
| **Ours**                         | 70.0| 61.9 |

**Table 2:** Results on exact set match accuracy in test set (we are comparing with leaderboard results on the submission date – May 31, 2020).
Table 3: Ablation study on dev set.

| Model                                | Dev  |
|--------------------------------------|------|
| exact set match accuracy             |      |
| Full Model                           | 70.0 |
| - w/o Auxiliary Task                 | 68.0 |
| execution accuracy                   |      |
| No Value Filler                      | 41.4 |
| Heuristic Method                     | 67.6 |
| Neural Baseline                      | 67.4 |

Table 4: Accuracy breakdown for different hardness.

| Split          | Easy | Medium | Hard | Extra Hard | All  |
|----------------|------|--------|------|------------|------|
| exact set match accuracy without using cell value | 87.4 | 72.6   | 54.0 | 42.7       | 68.0 |
| Dev            | 81.9 | 67.7   | 52.5 | 30.3       | 61.3 |
| Test           | 83.0 | 68.8   | 51.8 | 30.8       | 61.9 |
| exact set match accuracy with using cell value   | 85.0 | 70.2   | 60.9 | 43.3       | 67.9 |
| Dev            | 83.6 | 64.2   | 55.1 | 40.9       | 62.6 |
| Test           |      |        |      |            |      |

Generalization As we can see from Table 1 and Table 2, there is a large performance gap between the development set and hidden test set. To investigate more on this issue, a breakdown of the accuracy by the query hardness level is provided in Table 4, in all three settings.

5 Conclusions

In this work, we leverage an auxiliary task to enhance the schema encoding ability of encoder. We also propose two value filling baseline models to bridge the gap between the existing models and a usable text-to-SQL parser. With experiments on Spider dataset, we show improved performance over the baselines, with the execution accuracy and exact set match accuracy when database contents are unavailable.
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A Appendices

A.1 Experimental Setup

Within the encoder, the hidden size is 1024 for the pretrained transformer. For the LSTM in the aggregation function $f_{lstms}$, the hidden size is 512. The hidden size of parameters in the decoder LSTM and the binary classifier of auxiliary task is 300. The overall model size is 822M in disk. Adam optimizer with default hyper-parameters is used. Batch size is 32 and accumulating gradient is applied. The learning rate is set to 5e-4 for the non-pretrained parameters and 2.5e-5 for pretrained parameters. The weight between the main parsing task and the auxiliary task is 1:0.5. The experiment is conducted with Tesla V100 16GB and PyTorch version 1.3.0. The Levenshtein distance is calculated by the FuzzyWuzzy library. The exact set match accuracy and execution accuracy is calculated by the official evaluation script.

The model is trained up to 20K steps for 10 hours on single GPU. The best parsing model is selected based on the exact set match accuracy on development set. For the neural value filler, query level accuracy is used for selecting best model.

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4 https://github.com/seatgeek/fuzzywuzzy
5 https://github.com/taoyda/spider/blob/master/evaluation.py