Bidirectional Attention for SQL Generation

Tong Guo, Huilin Gao

Abstract

Generating structural query language (SQL) queries from natural language is a long-standing open problem. Answering a natural language question about a database table requires modeling complex interactions between the columns of the table and the question. It has been attracting considerable interest recently and driven by the explosive development of deep learning techniques. In this paper, we apply the sketch-based approach or synthesizing way to solve this problem. Based on the structure of SQL queries, we break down the model to three sub-modules and design specific deep neural networks for each of them. We employ the bidirectional attention mechanisms and character-level embedding with convolutional neural networks (CNNs) to improve the result. Experimental evaluations show that our model achieves the state-of-the-art results in WikiSQL dataset.

1 Introduction

In recent years, with the explosive development of deep learning techniques [Krizhevsky et al. 2012], the problem of generating SQL from natural language has been attracting considerable interest recently. We refer to this problem as the natural-language-to-SQL problem (NL2SQL). Relational databases store the structured data, which is a large amount of entities or numbers. Due to the large number of entities or numbers, which enlarge the word vocabulary for deep learning for natural language processing. And the larger vocabulary will make it harder to find the exact data for a natural language query. For example, in question-answering (QA) problem, we use matching network [Wu et al., 2016] to get the best answer given a question. In the QA problem, the larger amount of entities will lead to the larger class number of answer and will decrease the accuracy of other deep learning models. But generation of SQL from natural language is a good way to handle this application, which could leverage the benefit of relational database itself.

The study of translating natural language into SQL queries has a long history. Recent works consider deep learning as the main technique. [Cai et al., 2017] employs an improved encoder-decoder framework based on neural machine translation [Casacuberta and Machine, 1997; Cho et al. 2014] to solve this problem. [Dong and Lapata, 2016] uses augmented pointer network [Vinyals et al., 2015] to tackle this task, which is a attentional sequence to sequence model as sequence neural semantic parser and achieves state-of-the-art results on a variety of semantic parsing datasets. In [Zhong et al., 2017], Seq2SQL breaks down this task to several sub-modules or sub-SQL to solve and incorporates execution rewards in reinforcement learning. But Seq2SQL has the "order-matter" problem, which means the order of the two conditions in the WHERE clause does not affect the execution results of the query. It is well-known that the order affects the performance of a sequence-to-sequence style model [Vinyals et al., 2016]. SQLNet [Xu et al., 2017] introduces the attention mechanisms [Bahdanau et al., 2015] for the model of [Zhong et al., 2017] and solve the "order-matter" problem by proposing the sequence-to-set technique for the WHERE clause of SQL.

The problem of NL2SQL can be considered as a special instance to the more generic semantic parsing problem. There are many works considering parsing natural language into a logical form [2012; Artzi & Zettlemoyer, 2011; 2013; Cai & Yates, 2013; Reddy et al., 2014; Liang et al., 2011; Quirk et al., 2015; Chen et al., 2016]. Parsing natural language into a logical form has a wide application in question answering and dialog system. And there are some datasets such as GeoQuery [Tang & Mooney, 2001] and ATIS [Price, 1990].

Our main contributions in this work are three-fold. First, we apply bidirectional attention to add the relevant information between two sequences for prediction. Second, we leverage character-level embedding and convolutional neural networks (CNNs) to maps each word to a vector space as the new embedding input. Last, we design the model which bypasses the previous state-of-the-art approach on the WikiSQL dataset, and yield the new state-of-the-art on an NL2SQL task.

2 Task Description

In the NL2SQL task, given a question and a database table, the machine needs to generate a SQL to query the database table, and find the answer to the question. The question is described as a sequence of word tokens: $Q = \{w_1, w_2, \cdots, w_n\}$,
where \( n \) is the number of words in the question, and the table is described as a sequence of columns \( C = \{ c_1, c_2, \ldots, c_n \} \), where \( m \) is the number of columns in the table. The table also has a number of data rows which contains the answer to the question.

We now explain the WikiSQL dataset [Zhong et al., 2017], a dataset of 80654 hand-annotated examples of questions and SQL queries distributed across 24241 tables from Wikipedia. We present an example in Fig. 1. It has several features:

1. Our model synthesizes a SQL query under the condition that the table which the SQL will execute is determined. In other words, our model need not predict the exact table in all tables.
2. The SQL has a fixed structure: SELECT \( S_{COLUMN1} \) FROM TABLE WHERE \( S_{COLUMN2} \) EQUALS \( S_{VALUE1} \) [AND \( S_{COLUMN3} \) EQUALS \( S_{VALUE2} \)], where there are one column or one aggregator in the SELECT clause and there are 0-4 conditions in the WHERE clause. Although there is no JOIN clause in the SQL, the task is still challenging as the baseline achieves.

Before we describe the main SQL generation part of our model, we first describe the bi-directional attention mechanism [Seo et al., 2017] for two sequences. The bi-directional attention mechanism captures the relevant information between question and columns.

### 3.1 Bi-attention

Bi-attention is an extended form of attention mechanism. The attention mechanism is the information of the most relevant words of second sequence to each word of first sequence. The bi-attention also computes the information signifies which words of first sequence have the closest similarity to one of the words of second sequence.

Take the COLUMN-SELECT module as example, the attention compute the question word which is the most relevant to each column of the columns. The bi-attention also computes the column which has the closest similarity to one of the question words.

#### Forward Attention

Suppose we have two sequence of vector representation, \( S_1 \) and \( S_2 \), which dimension is \( R^{k_1 \times d} \) and \( R^{k_2 \times d} \), where \( d \) is the features dimension size.

Then we compute the co-attention matrix \( M \in R^{k_1 \times k_2} \):
Figure 3: Overall architecture of our model

\[ M = S_1 W S_2^T \]  \hspace{1cm} (1)

where \( W \in \mathbb{R}^{h \times h} \) is a trainable matrix. Eq. 1 contains the similarities information of each token between the two sequences. Then we apply softmax operation to the second dimension of the matrix \( M \):

\[ M_1 = \text{softmax}(M) \]  \hspace{1cm} (2)

Then we reshape \( M_1 \) to \( M_2 \in \mathbb{R}^{h \times s \times 1} \) and reshape \( S_1 \) to \( S_{11} \in \mathbb{R}^{h \times s \times d} \) and apply element-wise multiplication to get \( M_3 \in \mathbb{R}^{h \times s \times d} \):

\[ M_3 = M_2 \cdot S_{11} \]  \hspace{1cm} (3)

Note that the \( \cdot \) operation contains the broadcasting mechanism of NumPy [NumPy, 2005]. Then we reduce the sum of the second dimension of \( M_3 \) to get the representation of forward attention information \( A_1 \in \mathbb{R}^{h \times d} \):

\[ A_1 = \text{sum}(M_3) \]  \hspace{1cm} (4)

**Backward Attention**

Suppose we already have the co-attention matrix \( M \in \mathbb{R}^{h \times s} \) in Eq. 1. Then we reduce the max value of the first dimension of \( M \):

\[ M_3 = \text{max}(M) \]  \hspace{1cm} (5)

where \( M_3 \in \mathbb{R}^{1 \times s} \). Then we apply softmax to \( M_4 \):

\[ M_4 = \text{softmax}(M_3) \]  \hspace{1cm} (6)

Then we reshape \( M_4 \) to \( M_5 \in \mathbb{R}^{h \times d} \) and apply element-wise multiplication with broadcasting mechanism:

\[ M_6 = M_5 \cdot S_2 \]  \hspace{1cm} (7)

where \( M_6 \in \mathbb{R}^{h \times d} \). Then we reduce the sum of the first dimension of \( M_6 \) to get \( M_7 \in \mathbb{R}^{1 \times d} \):

\[ M_7 = \text{sum}(M_6) \]  \hspace{1cm} (8)

Then we compute the element-wise multiplication \( A_2 = M_7 \cdot S_1 \) to get the representation of backward attention information \( A_2 \in \mathbb{R}^{h \times d} \). Note that the dimension of backward attention representation and forward attention representation are equal and are the same as the sequence \( S_1 \) dimension. In the next section we use the bi-attention mechanism for several components of our model.

### 3.2 Our Model

In this section, we present our model to tackle the WikiSQL task. As shown in Fig. 3, our model contains four modules:

1. The character-level and word-level embedding layer to map each character and word to vector space. The embedding layer is shared by the next three modules.
2. The COLUMN-SELECT module which predict the column of SELECT clause.
3. The AGGREGATOR-SELECT module which predict the aggregator of SELECT clause.
4. The WHERE module which predict the conditions of WHERE clause.
The detailed description of our model is provided as follows.

**Character-level embedding and word-level embedding**
We use the character-level GloVe [Pennington et al., 2014] pre-trained 300 dimension to initialize the character-level embedding $E_c \in R^{q \times wd}$, where $q$ is the word number and $w$ is the character number of each word and $d$ is 300. We leverage convolutional neural networks to get the next representation of $E_c$. We use three convolution kernels, which sizes are height 1 * width 5, height 1 * width 4, height 1 * width 3. The convolution layer and max-pooling layer are 1 as [Kim, 2014] did. The input channel is 100 and output channel is 100 so the last dimension of 3 convolution results can concatenate to 300. After the max pooling and concatenation, the dimension of the final result is $q \times d$, which dimension is the same as the word embedding dimension.

We use the word-level GloVe pre-trained with 300 size to initialize the word-level embedding $E_w \in R^{q \times wd}$. As for the words which are not in the GloVe, we initialize them to 0. The experiment shows that if we initialize the words which are not in GloVe to a random value and make them trainable, the result decreases. The word-level embedding and character-level embedding are concatenate as a 600 size embedding as the input of the next network module.

As one column contains several words, we encode the words of one column into one vector representation by running after a LSTM [Hochreiter and Schmidhuber, 1997]. We take the last state of the LSTM for the representation of one column and consider it as one item of columns, which is the same as one word in the question.

**COLUMN-SELECT module**
Each token is represented as a one-hot vector and fed into a word embedding vector before feeding them into the bi-directional LSTM. We have the question embedding $E_q \in R^{q \times wd}$ and the column embedding $E_c \in R^{c \times wd}$, where $q$ is the max word number of questions and $c$ is the columns number of a table. The embedding $E_q$ and $E_c$ can be computed as the hidden states of a bi-directional LSTM respectively and get the bi-LSTM encoded representation $H_q \in R^{q \times h}$ and $H_c \in R^{c \times h}$, where $h/2$ is the hidden size of LSTM.

Then we apply bi-directional attention to $H_q$ and $H_c$ according to Eq. 1 to Eq. 8, where $H_{col}$ is the first sequence $S_1$ and $H_q$ is the second sequence $S_2$, to get the bi-attention info $B_f \in R^{q \times ch}$ and $B_b \in R^{c \times ch}$. Then we concatenate the last dimension of forward attention info $B_{f-agg}$ and the backward attention info $B_{b-agg}$ to $[B_{f-agg} : B_{b-agg}] \in R^{q \times ch}$ and apply the operations below to get the final prediction $P_{agg} \in R^c$ for column in the SELECT clause:

$$P_{agg} = \text{softmax}(W_1 \tanh(W_2 [B_{f-agg} : B_{b-agg}] + w_3 H_q))$$

(9)

where $W_1 \in R^{2ch \times ch}$, $W_2 \in R^{ch \times ch}$, $W_3 \in R^{ch \times 1}$ are all trainable weights and $P_{agg}$ is the probability distribution over all columns of one table.

**AGGREGATOR-SELECT module**
There are 5 types of aggregation keywords in SQL: 'MAX', 'MIN', 'COUNT', 'SUM', 'AVG'. So we consider the 5 aggregation as 5 columns and we add the 6th value to the 5 aggregation to represent the situation which has no aggregation operation. Then we have the question embedding $E_q \in R^{q \times d}$ and the column embedding $E_{col} \in R^{c \times d}$ and we also compute the bi-LSTM hidden states $H_q \in R^{q \times h}$ and $H_{agg} \in R^{c \times h}$. The rest computation is the same as the COLUMN-SELECT module: apply the bi-attention to $H_q$ and $H_{agg}$ to get the attention representation $[B_{f-agg} : B_{b-agg}] \in R^{q \times ch}$ according to Eq. 1 to Eq. 8. Then we compute the final prediction for aggregator $P_{agg} \in R^n$:

$$P_{agg} = \text{softmax}(W_2 \tanh(W_1 \sum ([B_{f-agg} : B_{b-agg}])))$$

(10)

where $W_1 \in R^{2ch \times ch}$, $W_2 \in R^{ch \times ch}$ are all trainable weights and sum apply to the first dimension and $P_{agg}$ is the probability distribution over 6 choices of SQL aggregators.

**WHERE module**
The WHERE clause is the most challenging part. The order of conditions does not matter, so we predict the probability of column slots and choose the top columns as a set. We predict the number of conditions and the column slots first. Then we leverage the column predictions to choose from the columns candidates. Then we use the chosen columns as embedding input to predict the operator slots and value slots for each column. We describe them below.

(1) **Condition number**
Suppose the number of conditions of WikiSQL is ranging from 0 to N and we consider it as a $(N+1)$-class classification problem. We compute the bi-LSTM hidden states $H_q$ of the question embedding $E_q$ and compute the number of conditions $K \in R$ as below:

$$K = \arg \max( \text{softmax}(W_2 \tanh(W_1 H_q)))$$

(11)

where $W_1 \in R^{ch \times ch}$ and $W_2 \in R^{ch \times N}$ are all trainable weights.

(2) **Column slots**
We compute bi-attention information $[B_f : B_b] \in R^{q \times ch}$ of the question hidden states $H_q \in R^{q \times h}$ and column hidden
states $H_{col} \in \mathbb{R}^{c \times h}$. Then we compute the bi-attention information according to Eq. 1 to Eq. 8 and compute final column prediction $P_{col} \in \mathbb{R}^{c}$, which is the same computation as COLUMN-SELECT module. We choose the top $K$ scores of $P_{col}$ as the prediction of $K$ columns and pad 0 to N columns. We leverage the chosen and padded LSTM representation $H_{topcol} \in \mathbb{R}^{N \times h}$ for the predictions of operator slots and value slots.

(3) Operator slots

There are 3 type of operator keywords in SQL: 'GT', 'LT', 'EQL'; which indicates 'greater than', 'less than', 'equal' separately. We start from the hidden states $H_{q} \in \mathbb{R}^{q \times c}$ and $H_{col} \in \mathbb{R}^{c \times h}$. And we use the result of column name slots predictions $P_{col}$ to choose the top $K$ column from $H_{col}$ and get $H_{topcol} \in \mathbb{R}^{N \times h}$. Then we apply the bi-attention of Eq. 1 to Eq. 8 to get the final attention representation $[B_{f-op}, B_{b-op}] \in \mathbb{R}^{N \times 2h}$ for $H_{q}$ and $H_{topcol}$, which is the concatenation of the last dimension of the two sequence representation. Then the computation is to get predictions $P_{op} \in \mathbb{R}^{N \times c}$ for each condition:

$$P_{op} = \text{softmax}(W_{i}\tanh(W_{j}[B_{f-op}, B_{b-op}] + W_{o}H_{col}))$$

(12)

where $W_{i} \in \mathbb{R}^{2kh \times c}$, $W_{j} \in \mathbb{R}^{bkh \times h}$, $W_{o} \in \mathbb{R}^{h \times c}$ are all trainable weights and $P_{op} \in \mathbb{R}^{N \times c}$ is the probability distribution over 4 choices of condition operator for each column.

(4) Value slots

As the order of value slots must corresponding to the column slots, so we cannot use the mechanisms like 4.1 to predict a set of values. So we employ the sequence-to-sequence structure to generate the values. The structure is well-developed: suppose we have an input sequence, and we employ an encoder to encode the input sequence into a vector. Then we employ a decoder to decode the output sequence from the vector.

We employ bi-LSTM to be the encoder which take the question embedding $E_{q} \in \mathbb{R}^{q \times d}$ as input and the encoder’s output is $H_{q} \in \mathbb{R}^{q \times h}$. At decoder phase we need to predict the value which is a sub-string of the question, so we use pointer network [Vinyals et al., 2015] to point to the sub-string of question. The LSTM decoder of pointer network is unidirectional and 2 layers. In training, the LSTM decoder takes the ground truth $G_{v} \in \mathbb{R}^{N \times q \times m}$ as input and outputs the $G_{v} \in \mathbb{R}^{N \times q \times h}$, where $m$ is the max word number and is one-hot encoding. Then $H_{q} \in \mathbb{R}^{q \times h}$ and $H_{topcol} \in \mathbb{R}^{N \times h}$ participate the next computation:

$$P_{val} = \text{softmax}(W_{4}\tanh(W_{3}G_{v} + W_{2}H_{q} + W_{o}H_{topcol}))$$

(13)

Where the inputs $G_{v}, H_{q}$ and $H_{topcol}$ are expanded to the same dimension and $W_{i} \in \mathbb{R}^{bkh \times c}$, $W_{j} \in \mathbb{R}^{bkh \times h}$, $W_{o} \in \mathbb{R}^{h \times c}$ are all separated trainable weights. The output of the pointer network is $P_{val} \in \mathbb{R}^{N \times q}$, where $q$ is the question length. In engineering we flat the specific dimension for the computation. For example, suppose we have batch size dimension $B$ and $N$ conditions as the second dimension, then we flat the dimension to $B \times N$ as the first dimension. Note that we generate the condition values for each of the $K$ conditions. The END token also appears in the question and the model stops generating for this slot when the END token is predicted. We prepare the exact ground truth for each sub-module of WHERE module and give each sub-module of WHERE module a separated loss.

Loss function

The loss function of our model is the same as SQLNet [Xu et al., 2017]. We use the cross-entropy loss for the prediction of COLUMN-SELECT module and AGGREGATOR-SELECT module. For the WHERE module, we also use cross-entropy loss for the value slots and operator slots, but we need to penalize the predicted columns that are not in the ground truth so we define the loss function as below for all the $K$ predicted columns:

$$L_{wherecol} = -\sum_{j=1}^{K}(\gamma C_{j}\log(P_{val,j}) + (1-C_{j})\log(1-P_{val,j}))$$

(14)

where we choose $\gamma = 3$ and $C_{j} = 1$ if the ground truth contains the j-column. $C_{j} = 0$ if the ground truth does not contain the j-column. The final objective function is:

$$L = L_{agg} + L_{val} + L_{where}$$

(15)

where $L_{agg}, L_{val}, L_{where}$ are the loss of AGGREGATOR-SELECT, COLUMN-SELECT and WHERE module separately.

4 Experiments

In this section, we present more details of the model and the evaluation on the dataset. We also analyze the evaluation result.

4.1 Experimental Setting

We tokenize the sentences using Stanford CoreNLP [D. Manning et al. 2014]. The LSTM contains 2 layers and the size of LSTM hidden states h is 50 and the output size of bi-LSTM is 100. The dropout [Hinton et al. 2012] for LSTM cell is 0.3. We use different LSTM weights for predicting different slots. Each LSTM which encodes the embedding is an independent weight. Although we do not share the bi-LSTM weight, we find that sharing the same word embedding vector is better. Therefore, different components in
Table 1: Our baselines are Seq2SQL [Zhong et al., 2017] and SQLNet [Xu et al., 2017]. The third row is our model with bi-attention and +char_emb means our model with CNN-based character-level embedding. Acc_{agg} and Acc_{sel} indicate the accuracy on the aggregator and column prediction accuracy on the SELECT clause, and Acc_{where} indicates the accuracy to generate the WHERE clause.

|       | dev          | test          |
|-------|--------------|--------------|
|       | Acc_{agg} | Acc_{sel} | Acc_{where} | Acc_{agg} | Acc_{sel} | Acc_{where} |
| Seq2SQL | 90.0% 90.1% | 90.3% 90.1% | 69.0% 71.1% | 90.3% 90.1% | 71.9% 71.9% |
| SQLNet | 90.1% 91.5% | 90.3% 90.9% | 74.1% 74.6% | 90.3% 90.8% | 72.8% 72.8% |
| Our Model | 90.1% 91.1% | 90.3% 91.9% | 74.7% 74.7% | 90.3% 91.9% | 72.8% 72.8% |
| +char_emb | 90.1% 92.5% | 90.3% 92.5% | 74.7% 74.7% | 90.3% 92.5% | 72.8% 72.8% |

Table 2: Overall result on the WikiSQL task. The "result match" indicates the execution of database accuracy and the "query string match" is to compare whether predicted SQL and ground truth SQL match exactly.

|       | dev          | test          |
|-------|--------------|--------------|
|       | Result match | Query string match | Result match | Query string match |
| Seq2SQL | 62.1% 69.8% | 53.5% 63.2% | 60.4% 68.0% | 51.6% 61.3% |
| SQLNet | 70.3% 70.3% | 63.5% 64.1% | 68.2% 68.2% | 61.5% 61.5% |
| Our Model | 72.5% 71.1% | 64.1% 64.1% | 69.0% 69.0% | 62.5% 62.5% |
| +char_emb | 79.5% 73.0% | 66.2% 66.2% | 72.8% 72.8% | 64.5% 64.5% |

our model only share the word embedding. We use the Adam optimizer [Kingma and Adam, 2015] with learning rate 0.001 and 0 weight decay to minimize the loss of Eq. 15. We train the model for 100 epochs with fixed word embedding and trainable character embedding. Then we use the pre-trained 100 epoch model to train the next 100 epoch with all trainable embeddings. The character-level embedding are all trainable in 0 to 200 epoch. The batch size is 64. We randomly re-shuffle the training data in each epoch. In addition, our final model is chosen as the models that perform the best on development set in each part in the process of training. We implement all models using PyTorch [Facebook, 2017].

4.2 Evaluation

We evaluate our model on the WikiSQL dataset. The decomposition results are presented in Tab. 1 and the overall results are presented in Tab. 2. We display the separated results of each module and the query-match accuracy which compare whether two SQL queries match exactly. From the evaluation result we find that bi-attention mechanisms mainly improve the WHERE clause result and character-level embedding mainly improve the COLUMN-SELECT clause. The execution result is higher because different SQL may obtains the same result. For example, the two SQL queries SELECT COUNT (player) WHERE No. = 23 and SELECT COUNT (No.) WHERE No. = 23 produce the same result in the table of Fig. 1.

4.3 Analysis

The improvement of COLUMN-SELECT clause which is attributed by CNN-based character-level embedding is around 2%, as the baseline result is already 90%. We think it is because with the help of the character-level embedding, the model can be more robust to the minor difference of a word between training data and test data. The improvement of attention is 2.5% and the improvement of the bi-attention mechanisms is 3% to 3.5%. The improvement from attention to bi-attention is 0.5% to 1%. We also observe that if we initialize the words which are not in the GloVe the random initialization and train the embedding, the result does not improve. The reason is that we do not add the mask technique which set the rare words to a minimal value in the model in order that the rare words do not participate in the activation function such as sigmoid. We consider the mask technique as a future work.

5 Conclusion

In this paper, based on the structure of SQL and the observation that a sequence-to-sequence model suffer from the "order-matters" problem, we design specific deep neural network for each sub-string of SQL. In the WHERE prediction module, we choose the top probabilities of the column candidates as the chosen set for the prediction of conditions. We apply the bi-directional attention mechanism and the CNN-based character-level embedding to improve the result. The experimental evaluations show that our model achieves the state-of-the-art results in the WikiSQL dataset.

We observe that the accuracy is around 90% on the COLUMN-SELECT clause prediction and AGGREGATOR-SELECT clause prediction because the number of candidate column in the SELECT clause is limited to one. The task will be more challenging if the SQL extends to more than one column candidates and more complex cases like ORDER-BY, GROUP-BY or even JOIN. And the technique of NL2SQL can be applied to Knowledge Graph query or other semantic parsing tasks. There will be a lot of work to research.
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