Data Agnostic RoBERTa-based Natural Language to SQL Query Generation

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Abstract—Relational databases are among the most widely used architectures to store massive amounts of data in the modern world. However, there is a barrier between these databases and the average user. The user often lacks the knowledge of a query language such as SQL required to interact with the database. The NL2SQL task aims at finding deep learning approaches to solve this problem by converting natural language questions into valid SQL queries. Given the sensitive nature of some databases and the growing need for data privacy, we have presented an approach with data privacy at its core. We have passed RoBERTa embeddings and data-agnostic knowledge vectors into LSTM based submodels to predict the final query. Although we have not achieved state of the art results, we have eliminated the need for the table data, right from the training of the model, and have achieved a test set execution accuracy of 76.7%. By eliminating the table data dependency while training we have created a model capable of zero shot learning based on the natural language question and table schema alone.

Index Terms—Artificial neural networks, Human computer interaction, Natural language processing

I. INTRODUCTION

HUMAN beings have been exponentially generating vast amounts of data over the past few decades, be it medical records [7] or even financial market-related information [8]. Relational databases have proven to be a highly reliable database architecture to store this data due to their simplicity and intuitiveness. However, accessing data through these databases necessitates a user to have prerequisite knowledge of a query language such as SQL. This creates a barrier between the typical average user and the benefits of these databases, as the user is often unable to interact with the databases. This paved the way for the NL2SQL task which is aimed at improving human-computer interaction by eliminating the need for the user to know a query language. Solving the task involves coming up with deep learning approaches to convert a natural language question into an SQL query. The state of the art models [6] can achieve up to 86.6% logical form accuracy in these queries but most of the high accuracy models depend on the table data in some manner, either by using them as features while training, or by checking query results to perform execution guided decoding to achieve such high levels of accuracy. Most modern databases store sensitive and private records and hence, data privacy has become of paramount importance. Keeping this in mind, we introduce our approach that utilizes only the table schema and is entirely independent of the table data at each step of its operation. There exists a performance v/s privacy tradeoff and we have tried to maximize the performance of the model whilst not compromising on data privacy. This data-agnostic approach can be applied to several industries, which require data confidentiality, such as hospital medical records, military data, financial market-related data, and several others. This approach serves a dual purpose of making the model highly scalable, as well as guaranteeing data privacy when used with third-party contracts.

Our main contributions to the field are as follows:

1) We eliminate the utilization of the table data, creating a data-agnostic model that gives predictions based on the table schema and the natural language question alone, keeping in mind the performance v/s privacy tradeoff.

2) We create a model capable of zero shot learning. As the model does not explicitly train on one particular table by using its cell data, we can make a highly scalable model that can predict queries on previously unseen databases.

3) We employ a RoBERTa model to create embeddings from the natural language question and the table schema. The final prediction model uses these embeddings along with two knowledge vectors to come up with the final prediction.

II. RELATED WORK

The dataset used was the WikiSQL dataset [1], a corpus of 80654 hand-annotated instances of natural language questions, SQL queries, and SQL tables extracted from 24,241 HTML tables from Wikipedia. It can be broadly classified as a semantic parsing database. The concept of using a transformer such as BERT as an encoder to generate feature embeddings was inspired by the “A Comprehensive Exploration on WikiSQL with Table-Aware Word Contextualization” paper [2]. BERT [3] is a deep bidirectional transformer based model that is first pre-trained on a very large text corpus using masked language model loss and then next sentence prediction loss. This gives the model some “knowledge” or “context” of the language it is being trained on. After the pre-training process, the model can be fine-tuned using transfer learning for the specific task it is meant to perform, which, for our purpose, is the NL2SQL task. We have used a BERT-based model named RoBERTa [4], which uses a more optimized pretraining method and has been proven to perform better than its predecessors. RoBERTa
uses dynamic masking during its pretraining on the masked language model task, replaces the next sentence prediction task, and uses a much bigger text corpus in general to achieve better results. The paper titled “Content Enhanced BERT-based Text-to-SQL Generation” [5] introduces two table content-aware vectors, viz. the question mark and header mark vectors, that can be used as features to improve the performance of the overall model. We have built on top of this knowledge and come up with a different algorithm to extract such vector features, without using the table content.

III. GENERATION OF KNOWLEDGE VECTORS

As described above, we have introduced two knowledge vectors, the Question Mark Vector and the Header Mark Vector. These knowledge vectors are binary vectors which encode the knowledge of which headers or which tokens in the question may be of significant importance to the model. Hence these can be thought of as vectors that “mark” which parts of the header or the question are to be given more attention. These vectors are first concatenated together, and then passed to the model as additional features so as to gain more “confidence” in its predictions. A visual representation of this process may be found in Fig 1.

For this purpose, we have employed two simple iterative algorithms as described below.

A. Generation of Question Mark Vector

\[
\text{vector} = [0] * \text{len(natural_language_question)}
\]

for word in natural_language_question do

if contain(headers, word) then

\[
\text{index} = \text{get_index(word)}
\]

vector[index] = 1

end if

end for

Since the Question Mark Vector is of the same length as the natural language question, we first initialize the vector as a zero vector of this length. Then, a for loop is used to iterate over every word in the natural language question. The function “contain” is described below:

function contain(sentence, phrase)

for word in sentence do

if word == phrase then

return true

end if

end for

return false

end function

The function contain(sentence, phrase) returns a boolean value. If the given phrase matches any of the words in the sentence completely (full match), it returns true. If the phrase does not completely match with any of the words in the sentence, a value of false is returned.

Applying this function to the headers, we check for each word in the natural language question, whether that word is contained within the headers or not. If the contain function returns a value of true, we mark the index (returned by the get_index function, which returns the index at which the word is located in the question) where the word is located with the value “1” to denote that this word may be of importance to the model when it comes to generating the SQL query. Otherwise, the value of the vector remains “0”. In this manner we iterate over all the words in the natural language question and generate the corresponding Question Mark Vector.

Using this vector can help divert the attention of the model to these particular words while making predictions.

B. Algorithm: Generation of Header Mark Vector

\[
\text{vector} = [0] * \text{len(headers)}
\]

for word in headers do

if contain(natural_language_question, word) then

\[
\text{index} = \text{get_index(word)}
\]

vector[index] = 1

end if

end for

This algorithm is very similar structurally to Algorithm 1, but it generates a Header Mark Vector. Since the Header Mark Vector is of the same length as the list of headers in the input table, we first initialize the vector as a zero vector of this length. Then, a for loop is used to iterate over every word in every header in the input table. Note here that we iterate not over the headers themselves, but over every word in the header as well. This allows us to check for partial matches from the natural language question in the list of headers as well.

Applying the contain function to the natural language question this time, we check for each word in the list of headers, whether that word is contained within the natural language question or not. In this manner we iterate over all the words in the list of headers and generate the corresponding Header Mark Vector. It is our observation that often when a word in the table schema and the natural language question match, the header is a part of the query, be it in the Select Aggregate column or in the Where Clause Column. The table cell content has not been utilized in the generation of these vectors, which is in line with our goal of data privacy.

For brevity, we shall henceforth refer to the Question Mark Vector as QMV and the Header Mark Vector as HMV.

IV. THE MODEL

A single SQL query might have multiple equally valid serializations. We cannot train a sequence-to-sequence-style model, as it chooses one correct serialization and penalizes the algorithm for picking other valid serializations. This is a problem documented as the “order matters” problem. Hence we have decided to follow a sketch-based approach as described in the SQLNet paper. The basic structure of every SQL query is the same, which reduces the task of generating complete SQL queries to predicting only certain key characteristics of the SQL query, much like a fill-in-the-blanks task. The relative ordering of the where clauses inside a sketch do not matter and the model is not penalized for choosing an order that is different from the ground truth query as long as all the clauses
have been correctly predicted. The following is the sketch of an SQL query:

```
SELECT {aggregate} {column} FROM {table}
WHERE {column} {operator} {value}
AND*
WHERE {column} {operator} {value}
*(Repeating WHERE blocks)
```

For our model, the initial step is to generate RoBERTa Embeddings from the natural language question and the table schema. We then generate the two knowledge vectors with the algorithms described above. The next step involves passing these features into 3 sub-models to generate the values which will be filled into the SQL sketch for the final SQL query.

Fig. 1. Architecture of the model showing the different layers

A. RoBERTa Embedding Layer

The NL2SQL task is essentially a semantic parsing task and we have observed that the tokens of the natural language utterance might not always match with the tokens in the header, thus sometimes, the two knowledge vectors may fail to provide the downstream submodels with useful information as in these cases, they will be nothing more than a vector of zeroes. This could also adversely affect the model if the model develops a high dependency on these vectors to calculate its predictions. Thus we must try to extract a significant amount of information from the natural language utterance and the table schema. Furthermore, it would be highly beneficial if we can develop a sense of “knowledge” or “context” within the model so that it can identify different words being used to mean the same thing in the particular case of a complete word token mismatch. That is why we have chosen to use RoBERTa, a deep bidirectional transformer based model as the base model in our architecture. These models are pre-trained on masked language modeling tasks and next sentence prediction tasks. This provides the model with the sense of “knowledge” or “context” that we were looking for to solve the above problem. RoBERTa uses Byte-Pair Encodings (BPE) and it requires placing some special “sentinel” tokens, viz. <s>and </s>, to generate a proper input sequence. We have used tokenized input to keep a track of the indices of possible “Where Value” (i.e. the value(s) to be filled in the where clause of the aforementioned sketch) subsequences. Let us name the question tokens $q_1, q_2, q_3, q_4, \ldots q_n$ and, let us name the header tokens as $h_1, h_2, h_3, h_4, \ldots h_n$. A proper RoBERTa input sequence would look like: $<s>, q_1, q_2, q_3, q_4, \ldots q_n, </s>, h_1, </s>, h_2, </s>, h_3, </s>, h_4, </s>, \ldots h_n, </s>$

The $<s>$ token represents RoBERTa’s default beginning-of-sequence (BOS) token and the $</s>$ tokens represent RoBERTa’s default separator (SEP) tokens as well as the end of sequence (EOS) token. RoBERTa’s default tokenizer adds the special tokens into the input sequence and then converts all the tokens into their respective ids from the vocabulary it was trained on. We generate two embeddings from this layer; one to represent the context of the natural language question, and the other to represent the context of the table schema in downstream tasks.

B. Select Aggregate Prediction

Select Aggregate refers to the way the results, desired by the user, are to be displayed. The user might want to view rows directly from the database or he/she might want the program to perform some arithmetic operations on the queried results and then display the results as calculated. The problem has been formulated as:

$$P(sa) = f_{1,sa}(f_{2,sa}(Q, QMV, H, HMV) + b_{sa})$$  \(1\)

Where $f_{1,sa}$ and $f_{2,sa}$ are functions learnt by the model and $b_{sa}$ is the bias.

We have passed the above features into an LSTM based network and formulated the problem as a classification task where the aggregates are the different classes to obtain a list of probabilities. The various kinds of selection aggregates supported by the model are non, min, max, average, count, sum. These aggregates are maintained in a list hardcoded into
the model. The addition of newer aggregates can be done by adding the aggregates into the list maintained in the model without disturbing the indexing of the previous entries. As the model predicts numbers referring to the indices of these aggregates, changing the ordering in the list would lead to severe impairment of performance.

C. Select Column Prediction

The Select Column refers to the column from which the final displayed data is to be taken. We have limited ourselves to single column querying as the WikiSQL dataset does not have the required data to train a multi-column query model. We can observe that the Select Column is dependent on both the natural language utterance as well as the table schema. The natural language utterance guides the probability of a column being the Select Column while the table schema provides us with the different columns, one out of which is the Select Column. Thus in a way, the table schema provides us with the different columns, one out of which is the Select Column. Thus in a way, the table schema provides us with the various classes for this classification problem. The prediction of the Select Column will require the Question embedding, Question Mark Vector, Header embedding, Header Mark Vector as input features and can be formulated as follows:

\[
P(sc) = f_{1,sc}(f_{2,sc}(Q, QMV, H, HMV) + b_{sc})
\]

Where \( f_{1,sc} \) and \( f_{2,sc} \) are functions learnt by the model and \( b_{sc} \) is the bias. We have passed the above features into an LSTM based network to calculate the probability accordingly. Even if the natural language utterance does not contain the name of a header specifically, the RoBERTa embedding of the word used to indicate the header will be close value to the desired value as the two words have been used in the same context. We have made an important assumption here that the column names are descriptive of the column content. If this is not the case, the performance of the model will be severely impaired as the model does not cross-check with table cell data to make more confident predictions since it is data agnostic.

D. Where Number Prediction

This value isn’t directly present in the final predicted SQL query, however, it is responsible for the structure of the query itself. We have divided each where clause into three parts, viz. Where Column, Where Operator, and Where Value. These where clauses appear as repeating blocks in the SQL query and we need to find out exactly how many times it repeats, that is why we need to predict the Where Number first. We can observe that the Where Number is dependent on both the natural language utterance as well as the table schema. The natural language utterance might contain conjunctions that directly point us towards the number of where clauses while the table schema might help the model decide the Where Number in the unlikely event that one token in the natural language utterance has been used in the context of more than one columns in the table schema. We have defined this as a classification problem, making an assumption that the Where Number does not exceed 4, leaving us with 5 classes (0 to 4). The problem has been formulated as:

\[
P(wn) = f_{1,wn}(f_{2,wn}(Q, QMV, H, HMV) + b_{wn})
\]

Where \( f_{1,wn} \) and \( f_{2,wn} \) are functions learnt by the model and \( b_{wn} \) is the bias. Since very rarely queries exceed 4 where clauses, the model works. Since the WikiSQL dataset has stored the where clauses as a list of dictionaries, this method helps us reduce computation, as we do not need to store the ground truth values of the Where Number separately, the length of the list will give us the ground-truth value, thus saving memory and computation time.

E. Where Column Prediction

The Where Column is a part of a where clause, it describes the column with which the Where Value is to be compared with. It is important to note that each where clause can only have one Where Column, as having more than one Where Column is equivalent to having one additional where clause. We can observe that the Where Column is dependent on both the natural language utterance as well as the table schema. While the natural language utterance guides the selection of the Where Column, the table schema provides the list from which the column is to be selected. Essentially providing us with the different classes for this classification task. This is quite similar to the Select Column Prediction task, thus we have provided the Question Embedding, Question Mark Vector, Header Embedding, and Header Mark Vector as input features. Additionally, it is important to note that the prediction of the Where Column also depends on the Where Number as that value serves as the number of predictions the model needs to output. The problem has been formulated as:

\[
P(wc) = f_{1,wc}(f_{2,wc}(Q, QMV, H, HMV, P_{wn}) + b_{wc})
\]

Where \( f_{1,wc} \) and \( f_{2,wc} \) are functions learnt by the model and \( b_{wc} \) is the bias. The above features have been passed into an LSTM based network to obtain a list of probabilities. Since the components of the where clause are interlinked, we have used a beam search algorithm to compute the most probable combination of the Where Column, Operator, and Value, with a beam size of 4. We have achieved an increment of approximately 5% in logical form accuracy after using beam search as compared to the normal method.

F. Where Operator Prediction

The Where Operator is the second part of each where clause. It provides the description of how the Where Value is to be compared with the data in the queried Where Column. We can observe that the Where Operator is dependent on the natural language utterance itself and the type of the Where Column. For eg: If the Where Column is of text type then the \(< \) and \(> \) operators make little sense. Thus, the Where Column heavily influences the selection of the Where Operator. So we have provided all the input features hoping the model can extract out the context of the Where Column and relate it to words in the
natural language utterance. The problem has been formulated as:

\[ P(wo) = f_1,wo(f_2,wo(Q, QMV, H, HMV, P_{wn}, P_{wc}) + b_{wo}) \]  

(5)

Where \( f_1,wo \) and \( f_2,wo \) are functions learnt by the model and \( b_{wo} \) is the bias. The Where Number instructs the number of predictions we require from the model and the Where Column provides information for each prediction. The input features are passed into an LSTM based model which outputs a list of probabilities. These probabilities point to the index of the Where Operators which are stored in a list hardcoded into the model. Currently, the supported operators are: \(<,>,=,\neq\). More operators can be added to the list as long as the indices of the present operators aren’t changed. If the present order is changed, the model will be impaired severely as the model predicts indices of the operators instead of predicting the operators directly.

G. Where Value Prediction

The Where Value is the last prediction before obtaining the predicted final SQL query. It provides the data which is compared with the queried Where Column data. An important observation to be made is that the Where Value is always a subsequence of the natural language utterance. Thus if the model outputs the start and end index of the tokenized natural language utterance, we can easily form the Where Value from that information. This is why we tokenized the natural language utterance while taking inputs for the RoBERTa model. RoBERTa encodings work differently based on whether the word has space before it or not, so tokenizing the words definitely leads to a slight loss of information but it enhances ease of computation in this particular downstream task. So we train the sub model to output two indices marking the start and end indices of the Where Value phrase present in the natural language utterance. We formulate the problem as:

\[ P(wv) = f_1,wv(f_2,wv(Q, QMV, H, HMV, P_{wn}, P_{wc}, P_{wo}) + b_{wv}) \]  

(6)

Where \( f_1,wv \) and \( f_2,wv \) are functions learnt by the model and \( b_{wv} \) is the bias. Since this task is the most complicated, we decided to provide every feature we have generated so as to not miss out on any information. This increases computational complexity but improves performance. A similar LSTM based network has been made along with beam searching to optimize performance. Since we have decided to remove the table cell data, this sub-task has been affected the most. In addition to being a subsequence of the tokenized natural language sequence, the Where Value, especially in cases when the Where Operator is ‘=’, will always be present inside the table. Thus using table data would give the model a huge boost in confidence for predicting a certain set of words as the desired Where Value. This is where the performance v/s privacy tradeoff adversely affects the model.

V. RESULTS

We have evaluated our model on the WikiSQL dataset with the logical form and execution accuracy metrics. The method of calculating the execution accuracy does involve the model querying the database which goes against our core objective of data privacy, but this is not a necessary step and neither does it affect the model’s training in any way. The only purpose of such querying is to obtain an additional evaluation metric to better understand our model’s performance. The final model when deployed would not need to calculate any such metrics, thus keeping the data completely private.

We have compared our model with the state of the art model as well as the baseline SQLNet Model:

Note: Accuracy has been shortened to acc. and execution has been shortened to exec.

| Model                      | Dev acc. | Dev exec. | Test acc. | Test exec. |
|----------------------------|----------|-----------|-----------|------------|
| HydraNet(State of the Art) | 86.6     | 92.4      | 86.5      | 92.2       |
| SQLNet                     | -        | 69.8      | -         | 68.0       |
| Our Model                  | 69.4     | 77.0      | 68.9      | 76.7       |

The following are the accuracies for the individual tasks performed by the sub-models:

| Dataset          | Dev | Test |
|------------------|-----|------|
| Select Aggregate | 90.4| 90.3 |
| Select Column    | 95.1| 94.6 |
| Where Number     | 97.7| 97.7 |
| Where Column     | 88.8| 87.6 |
| Where Operator   | 91.2| 90.7 |
| Where Value      | 85.1| 84.7 |

VI. ZERO SHOT LEARNING

We prepared a previously unseen table set for the model by eliminating the intersection of the tables that were present in both train and test sets from the test table set. Then we took the queries based on these tables to obtain a dataset to test for the zero shot learning capabilities of the model and obtained the following metrics. These schemas were completely unknown to the model before running predictions on them:

| Dataset          | Zero Shot |
|------------------|-----------|
| Logical Form Acc | 66.3      |
| Execution Acc    | 74.7      |

Since our model does not use the cell data present in the tables while training and making predictions, it prevents the model from overfitting on the training tables. Most importantly, it results in a highly scalable generalized model. The similarity in the metrics obtained from the two experimental setups proves that the model is highly generalized and has no high variance problems.
VII. PERFORMANCE v/s PRIVACY TRADEOFF

While data privacy might be desirable, it does have a detrimental impact on the overall performance of the model. The knowledge vectors are being given lesser information as the role of the tabular data in their generation is being completely removed. Hence the model has less information to base its predictions on. It could be the case sometimes that none of the words in the natural language question match with the table headers, but instead, they match with some cell in the table data. In such cases, our model has to predict the SQL queries solely based on the natural language question and the header embeddings. We make another important assumption that the names given to the column headers are relevant to the information they are storing. If this is not the case, our model would not be able to perform well as it uses the header embeddings to generate a context for what the columns represent. We have refrained from using Execution Guided Decoding to boost our performance, as it does not align with our concept of maintaining complete data privacy. The loss of information to the model is evident and that is what impairs its performance. In our study, we have tried to show no compromise on the data privacy aspect of the tradeoff, whilst trying to maintain as high a performance as possible on the NL2SQL task.

VIII. FUTURE PROSPECTS AND APPLICATIONS

The model we have proposed currently predicts only a particular type of query, namely single table queries. In future works the model can be generalized to a great extent to support multi-table queries, multi column queries as well as a combination of the two. This would require the implementation of an SQL join prediction submodel as well as a select number prediction submodule as well as a larger and richer dataset containing various types of such queries to train the model on. Presently the model only contains basic select aggregates and WHERE operators, but it is highly flexible, and newer ones can be added by appending the entries into the lists hardcoded into the model. We had limited data in the WikiSQL dataset and hence could not train the model with newer select aggregates and where operators. Presently the model only works with SELECT statements but many database users might require the UPDATE and DELETE functionality as well, which could be added to the model as well. WHERE isn’t the only SQL clause that is used to filter query results. The model can also be extended to support other clauses like HAVING and GROUP BY. Furthermore the concept of the NL2SQL task can be extended to support Data Definition Languages (DDL) with the purpose of creating databases and tables instead of just Data Manipulation Languages (DML) to query an existing database. The scope for NL2SQL remains vastly unexplored.

In our model we have employed the base model of RoBERTa (RoBERTa-base) to create embeddings of the natural language question and the headers. However, there exists an even larger model of RoBERTa, called RoBERTa-large, which has more parameters and has been proven to have higher accuracy in masked language modeling tasks and next sentence prediction tasks. Hence, by using RoBERTa-large to generate the embeddings which are then passed into the model, it may be possible to attain even higher accuracy on the training and test sets as well as the zero-shot learning task.

This model can be deployed as an Application Programming Interface (API) for use in fields where data privacy is of critical importance. This list includes, but is not limited to, military databases, medical record databases, financial information databases and market information databases. Since our model is data agnostic, it is also highly scalable, as it does not have to process all the cell data contained in the database. This makes it suitable for applications even where the database size is very large.

IX. CONCLUSION

In this paper, we demonstrate the use of a data-agnostic model on a popular semantic parsing task, NL2SQL on the WikiSQL dataset. We observed that existing approaches either use table data as a part of the input features or for execution guided decoding. Since the primary focus of our work was on data privacy, we propose a completely data-blind model that effectively predicts SQL queries using only the table schema and natural language utterances by generating knowledge vectors through word matching techniques.

As described in the Results section, our model achieves 77.0 % execution accuracy on the train set and 76.7 % execution accuracy on the test set, on the WikiSQL dataset. This performance is inferior to the state of the art performance due to the performance v/s privacy tradeoff. Creating a data blind model allows us to train a highly generalized model capable of zero shot learning.

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APPENDIX A

METHODOLOGY

In this Appendix we shall describe our Deep Learning Model for ease of reproducability. The complete code for our work can be found at
Let us first describe our data preprocessing methods:

We have iterated over every line of the WikiSQL dataset and tokenized the natural language question using the nltk tokenizers. Furthermore we have also generated the Knowledge vectors as described in section III We have saved these generated features in a separate file and used that file for training.

Our Model can be broadly divided into two parts:

A. RoBERTa-base model

The RoBERTa model used for generating embeddings was a standard pretrained model that is available for open access. The code is available at: https://github.com/huggingface/transformers. The same has been made available as a Python package named "transformers". The documentation is available at https://huggingface.co/transformers/.

We have used the RoBERTa Base model along with its pretrained weights as provided in the package mentioned above, without changing anything.

B. LSTM based Sub-models

We have used 6 submodels for each of the query sketch sub part prediction tasks. The Architecture of Sub-model is described below, following the PyTorch syntax, which is a Python module:

1) Select Column SubModel: The submodel contains the following layers:

SCP(
(enc_h) : LSTM (input_size = 1536, hidden_size = 50, num_layers = 2, batch_first = True, dropout = 0.3, bidirectional = True)
(enc_n) : LSTM (input_size = 1536, hidden_size = 50, num_layers = 2, batch_first = True, dropout = 0.3, bidirectional = True)
(W_att) : Linear (in_features=105, out_features=103, bias=True)
(W_c) : Linear (in_features=105, out_features=100, bias=True)
(W_hs) : Linear (in_features=103, out_features=100, bias=True)
(sc_out) : Sequential
(0): Tanh()
(1): Linear(in_features=200, out_features=1, bias=True)
)
(softmax_dim1): Softmax(dim=1)
(softmax_dim2): Softmax(dim=2)
)

2) Select Aggregate SubModel: The submodel contains the following layers:

SAP(
(enc_h) : LSTM (input_size = 1536, hidden_size = 50, num_layers = 2, batch_first = True, dropout = 0.3, bidirectional = True)
(enc_n) : LSTM (input_size = 1536, hidden_size = 50, num_layers = 2, batch_first = True, dropout = 0.3, bidirectional = True)
(W_att) : Linear (in_features=105, out_features=103, bias=True)
(W_c) : Linear (in_features=105, out_features=100, bias=True)
(W_hs) : Linear (in_features=103, out_features=100, bias=True)
(W_out) : Sequential
(0): Tanh()
(1): Linear(in_features=200, out_features=1, bias=True)
)
(softmax_dim1): Softmax(dim=1)
(softmax_dim2): Softmax(dim=2)
)

3) Where Number SubModel: The submodel contains the following layers:

WNP(
(enc_h) : LSTM (input_size = 1536, hidden_size = 50, num_layers = 2, batch_first = True, dropout = 0.3, bidirectional = True)
(enc_n) : LSTM (input_size = 1536, hidden_size = 50, num_layers = 2, batch_first = True, dropout = 0.3, bidirectional = True)
(W_att_h) : Linear (in_features=103, out_features=1, bias=True)
(W_hidden) : Linear (in_features=103, out_features=200, bias=True)
(W_cell) : Linear (in_features=103, out_features=200, bias=True)
(W_att_n) : Linear (in_features=105, out_features=1, bias=True)
(wn_out) : Sequential
(0): Linear(in_features=105, out_features=100, bias=True)
(1): Tanh()
(2): Linear(in_features=100, out_features=5, bias=True)
)
(softmax_dim1): Softmax(dim=1)
(softmax_dim2): Softmax(dim=2)
)

4) Where Column SubModel: The submodel contains the following layers:

WCP(
(enc_h) : LSTM (input_size = 1536, hidden_size = 50, num_layers = 2, batch_first = True, dropout = 0.3, bidirectional = True)
(enc_n) : LSTM (input_size = 1536, hidden_size = 50, num_layers = 2, batch_first = True, dropout = 0.3, bidirectional = True)
(W_att) : Linear (in_features=105, out_features=103, bias=True)
(W_c) : Linear (in_features=105, out_features=100, bias=True)
(W_hs) : Linear (in_features=103, out_features=100, bias=True)
(W_out) : Sequential
(0): Tanh()
(1): Linear(in_features=200, out_features=1, bias=True)
)
(softmax_dim1): Softmax(dim=1)
(softmax_dim2): Softmax(dim=2)
)

5) Where Operator SubModel: The submodel contains the following layers:

WOP(
(enc_h) : LSTM (input_size = 1536, hidden_size =
50, num_layers = 2, batch_first = True, dropout = 0.3, bidirectional = True)
(enc_n) : LSTM (input_size = 1536, hidden_size =
50, num_layers = 2, batch_first = True, dropout = 0.3, bidirectional = True)
(W_att): Linear(in_features=105, out_features=103, bias=True)
(W_c): Linear(in_features=105, out_features=100, bias=True)
(W_hs): Linear(in_features=103, out_features=100, bias=True)
(wo_out): Sequential(  
(0): Linear(in_features=405, out_features=100, bias=True)  
(1): Tanh()  
(2): Linear(in_features=100, out_features=2, bias=True)  
)
(softmax_dim1): Softmax(dim=1)
(softmax_dim2): Softmax(dim=2)
)

6) Where Value SubModel: The submodel contains the
following layers:
  WVP(  
(enh) : LSTM (input_size = 1536, hidden_size =
50, num_layers = 2, batch_first = True, dropout = 0.3, bidirectional = True)
(enc_n) : LSTM (input_size = 1536, hidden_size =
50, num_layers = 2, batch_first = True, dropout = 0.3, bidirectional = True)
(W_att): Linear(in_features=105, out_features=103, bias=True)
(W_c): Linear(in_features=105, out_features=100, bias=True)
(W_hs): Linear(in_features=103, out_features=100, bias=True)
(W_op): Linear(in_features=4, out_features=100, bias=True)
(wv_out): Sequential(  
(0): Linear(in_features=405, out_features=100, bias=True)  
(1): Tanh()  
(2): Linear(in_features=100, out_features=2, bias=True)  
)
(softmax_dim1): Softmax(dim=1)
(softmax_dim2): Softmax(dim=2)
)

The RoBERTa Model was initialized with pretrained
weights, from the python package as mentioned above. The
sub models used were based on a similar model described in
the paper titled "Content Enhanced BERT-based Text-to-SQL
Generation." [5]. We used Transfer Learning to fit the model
according to our needs, hence the weights were initialized
using pre-trained weights from this GitHub repository. It can
be noted that these weights were obtained after training on
default PyTorch initialized weights.

The RoBERTa model has been optimized using the Adam
optimizer with learning rate = 0.00001 and weight decay =
0.0 Each of the LSTM based sub models have been optimized
using the Adam optimizer with learning rate = 0.001 and
weight decay = 0.0. The minibatch size was set to 8 and the
maximum sequence length hyperparameter was set to 222.
The WikiSQL dataset has separate train, dev and test sets.
Therefore, we did not split the dataset into these parts.
The code was written with a GPU runtime accelerator in
Google Colab workspace. Hence the exact model of the GPU
cannot be mentioned, however it was most likely an NVIDIA
Tesla K80.