SeaD: End-to-end Text-to-SQL Generation with Schema-aware Denoising

Anonymous ACL submission

Abstract

On the WikiSQL[1] benchmark, most methods tackle the challenge of text-to-SQL with pre-defined sketch slots and build sophisticated sub-tasks to fill these slots. Though achieving promising results, these methods suffer from over-complex model structure. In this paper, we present a simple yet effective approach that enables auto-regressive sequence-to-sequence model to robust text-to-SQL generation. Instead of formulating the task of text-to-SQL as slot-filling, we propose to train sequence-to-sequence model with Schema-aware Denoising (SeaD), which consists of two denoising objectives that train model to either recover input or predict output from two novel *erosion* and *shuffle* noises. These model-agnostic denoising objectives act as the auxiliary tasks for structural data modeling during sequence-to-sequence generation. In addition, we propose a clause-sensitive execution guided (EG) decoding strategy to overcome the limitation of EG decoding for generative model. The experiments show that the proposed method improves the performance of sequence-to-sequence model in both schema linking and grammar correctness and establishes new state-of-the-art on WikiSQL benchmark. Our work indicates that the capacity of sequence-to-sequence model for text-to-SQL may have been under-estimated and could be enhanced by specialized denoising task.

1 Introduction

Text-to-SQL aims at translating natural language into valid SQL query. It enables layman to explore structural database information with semantic question instead of dealing with the complex grammar required by logical -form query. On the WikiSQL benchmark, most models adopt a sketch-based slot filling approach. It decomposes the task of convert query to SQL into several sub-tasks that are relatively easy to handle, e.g., the ‘SELECT‘ column

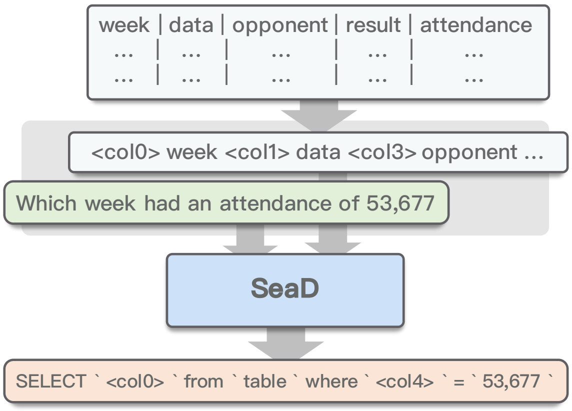


Figure 1: SeaD regards text-to-SQL as seq2seq generation task. During inference, given natural language question and related database schema, SeaD directly generates corresponding SQL sequence in an auto-aggressive manner.

mentioned or the query span corresponding to a condition value. The entire SQL can be recovered from the results of the sub-tasks deterministically.

Though being a typical sequence-to-sequence (seq2seq) task, auto-regressive models (LSTM, Transformer, etc.), however, fail to achieve state-of-the-art results for text-to-SQL task. Previous works attribute the sub-optimal results of seq2seq models to three major limitations. First, SQL queries with different clause order may have exact same semantic meaning and return same results by execution. The token interchangeability may confusion model that based on seq2seq generation. Second, the grammar constraint induced by structural logical form is ignored during auto-regressive decoding, therefore the model may predict SQL with invalid logical form. Third, schema linking, which has been suggested to be the crux of text-to-SQL task, is not specially addressed by vanilla seq2seq model.

In this paper, we present a simple yet effective method to boost the performance of seq2seq model for text-to-SQL task. Instead of building extra sub-

[1] https://github.com/salesforce/WikiSQL

module or putting constraint on model output, we propose two novel schema-awared denoising objectives trained along with the original seq2seq generation task. These denoising objectives deal with the intrinsic attribute of logical form and could facilitate schema linking required for text-to-SQL task. The inductive schema-awared noises can be categorized into two types: *erosion* and *shuffle*. Erosion acts on schema input by randomly permute, drop and add columns into the current schema set. The related schema entity in target SQL query will be jointly modified according to the erosion result. Shuffle is applied via randomly re-ordering the mentioned entity and values in NL or SQL with respect to the schema columns. During training procedure, shuffle is performed during monolingual self-supervision that trains model to recover original text given the noised one. Erosion is applied to seq2seq task that trains model to generate corrupted SQL sequence, given NL and eroded schema as input. These proposed denoising objectives are combined along with the origin seq2seq task to train a SeaD model. In addition, to deal with the limitation of execution-guided (EG) decoding, we propose a clause-sensitive EG strategy that decide beam size with respect to the clause token that is predicted. The proposed method establish new state-of-the-art on the WikiSQL benchmark.

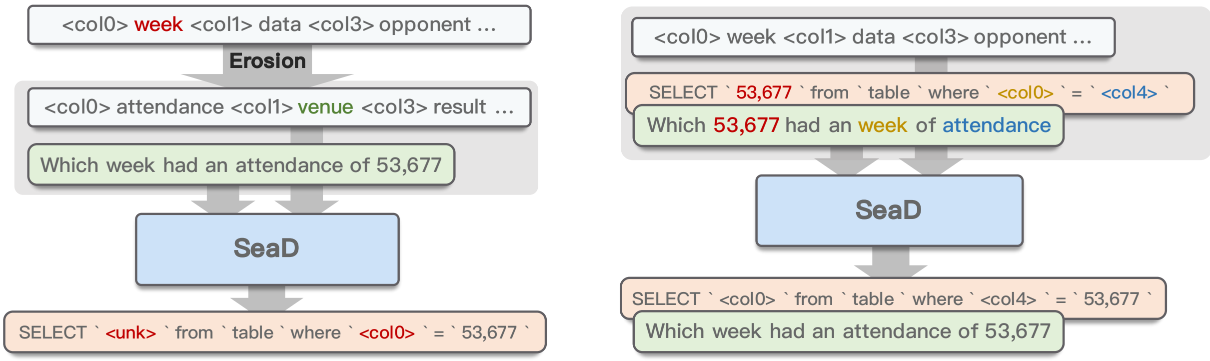
The main contribution of this work is the schema-aware denoising objectives that are designed for text-to-SQL task. The denoising objectives are model-agnostic and could apply to any seq2seq model that are trained in auto-regressive manner. In addition, we also propose a clause-sensitive EG decoding strategy, which can improve the searching efficiency of EG during seq2seq generation. The results of the work demonstrate the effectiveness of the schema-aware denoising approach and shad lights on the importance of task-oriented denoising objective.

2 Related Work

Semantic Parsing The problem of mapping natural language to meaningful executable programs has been widely studied in natural language processing research. Logic forms (Zettlemoyer and Collins, 2012; Artzi and Zettlemoyer, 2011, 2013; Cai and Yates, 2013; Reddy et al., 2014; Liang et al., 2013; Quirk et al., 2015; Chen et al., 2016) can be considered as a special instance to the more generic semantic parsing problem. As a sub-task of semantic parsing, the text-to-SQL problem has been studied for decades. (Warren and Pereira, 1982; Popescu et al., 2003; Li et al., 2006; Giordani and Moschitti, 2012; Bodik). Slot-filling model (Hwang et al., 2019; He et al., 2019a; Lyu et al., 2020) translates the clauses of SQL into subtasks, (Ma et al., 2020) treat this task as a two-stage sequence labeling model. However, the convergence rate between subtasks is inconsistent or the interaction between multiple subtasks may lead to the model may not converge well. Like lots of previous work (Dong and Lapata, 2016; Lin et al., 2018; Zhong et al., 2017; Suhr et al., 2020; Raffel et al., 2019), we treat text-to-SQL as a translation problem, and taking both the natural language question and the DB as input.

Hybrid Pointer Networks Proposed by (Vinyals et al., 2015), copying mechanism (CM) uses attention as a pointer to copy several discrete tokens from input sequence as the output and have been successfully used in machine reading comprehension (Wang and Jiang, 2016; Trischler et al., 2016; Kadlec et al., 2016; Xiong et al., 2016), interactive conversation (Gu et al., 2016; Yu and Joty, 2020; He et al., 2019b), geometric problems (Vinyals et al., 2015) and program generation (Zhong et al., 2017; Xu et al., 2017; Dong and Lapata, 2016; Yu et al., 2018; McCann et al., 2018; Hwang et al., 2019). In text-to-SQL, CM can not only facilitate the condition value extraction from source input, but also help to protect the privacy of the database. In this paper, We use a Hybrid Pointer Generator Network which is similar to (Jia and Liang, 2016; Rongali et al., 2020) to generate next step token.

Denoising Self-training Language model pretraining (Devlin et al., 2018; Yang et al., 2019; Liu et al., 2019; Lan et al., 2019) has been shown to improve the downstream performance on many NLP tasks and brought significant gains. (Radford et al., 2018; Peters et al., 2018; Song et al., 2019) are beneficial to seq2seq task, while they are problematic for some tasks. While (Lewis et al., 2019) is a denoising seq2seq pre-training model, which is effective for both generative and discriminative tasks, reduces the mismatch between pre-training and generation tasks. Inspired by this, we propose a denosing self-training architecture in training to learn mapping corrupted documents to the original.



(a) Erosion

(b) Shuffle

Figure 2: The proposed schema-aware denoising procedure. (a) Erosion denoising randomly drops, adds and re-permutes schema columns. The related column entities in ground-truth SQL sequence will be jointly modified or masked out with respect to the erosion results of the current schema set. Erosion objective trains model to predict the modified SQL sequence under noised input. (b) Shuffle denoising objective re-permutes the mentioned entities in SQL or NL sequence, and trains model to reconstruct the sequence with the correct entity order.

3 Methodology

Given natural language question Q and a schema S, our goal is to obtain the corresponding SQL query Y. Here the natural question $Q = \{q_1, ..., q_{|Q|}\}$ denotes a word sequence, the schema $S = \{\mathbf{c}_1, ..., \mathbf{c}_{|S|}\}$ is composed of a set of columns, where each column $\mathbf{c}_i = \{c_1, ..., c_{|\mathbf{c}_i|}\}$ is a sequence of words. $Y = y_1, ..., y_{|Y|}$ denotes the token-wise raw SQL sequence. We approach this task with directly auto-regressive generation, i.e., predicting the SQL sequence token by token. We choose Transformer as our base architecture, which is a widely adopted in seq2seq translation and generation tasks. In this section, we first present the sample formulation that transform text-to-SQL into typical seq2seq task, followed by a brief introduce of the Transformer architecture with pointer generator. Then we describe the proposed schema-aware denoising method and clause-sensitive EG decoding strategy.

3.1 Sample Formulation

Given training samples $\{X_i, Y_i\}, i = 1, ..., N$, $X = \{Q, S\}$, where Q denotes the NL sequence and S denotes the schema set, Y is the SQL sequence. Sample formulation is a function

$$\widetilde{X}, \widetilde{Y} = format(X, Y)S$$

that transforms heterogeneous data into pairwise token sequence. It is performed by filling template that acts as a prompt to guide seq2seq model to generate different types of token with respected to various contexts. For schema formulation, each column name is prefixed with a separate special token `<coli>`, where `i` denotes the i-th column in the schema set. The column type of each column is also append to the name sequence to form the template for a schema column `<coli> col name : col type`. All columns in schema is formulated and concatenated together to compose the input sequence for schema. The schema sequence is further concatenated with the NL sequence for model input. We explicitly introduce schema-mention alignment to NL sequence by surrounding schema names that are mentioned in NL sequence with bracket tokens `[ ]`, in order to improve the learning of schema linking,

For SQL sequence, we initialize it with raw SQL query and perform several modifications on it: 1) surrounding entities and values in SQL query with a " ` " token, and dropping other surroundings if exist; 2) replacing col entities with their corresponding separate token in schema; 3) inserting spaces between punctuation and words. The formulated SQL sequence is illustrated in Figure 1. The formatting procedure improves consistency between tokenized sequences of source and target, and contributes to the identification and linking of schema entities.

3.2 Transformer with Pointer

Following the previous works on seq2seq semantic parsing, we use Transformer (Vaswani et al., 2017) as the backbone of our model. The vanilla Transformer generate tokens with a feed-forward layer that computes the unnormalized score over the target vocabulary. In text-to-SQL task, however, most schema and value mentions can be extracted from the input sequence. Therefore, we adopt a Hybrid Pointer Generator Network (Jia and Liang, 2016) in our architecture to generate tokens from the target vocabulary V or copy from the input context.

During inference, input sequence X is first encoded into a sequence of hidden states H_{enc}. Then, the decoder produces the hidden states h_{dec} for step t based on previously generated sequence and encoded output. The unnormalized scores $scores_v = \{s_1, ..., s_{|V|}\}$ over V can be obtained from h_{dec} through a feed-forward layer. $V = \{\mathbf{V}_q, \mathbf{V}_c, \mathbf{V}_s\}$ is the target vocabulary, where $\mathbf{V}_q$ denotes corpora token vocabulary, $\mathbf{V}_c$ denotes column token set and $\mathbf{V}_s$ denotes avaliable SQL keywords, e.g. `SELECT, MAX, MIN`, etc. The decoder output h_{dec} is also used to compute the unnormalized attention scores $score_s = \{i_1, ..., i_{|X|}\}$ over the input sequence tokens, where $|X|$ is the sequence length.

We concatenate $scores_v$ and $score_s$ to get the hybrid score $score_{hybrid} = \{s_1, ..., s_{|V|}, i_1, ..., i_{|X|}\}$, where the first $|V|$ elements represent the output distribution of the target vocabulary V and the remained $|X|$ are pointers tokens referred to corresponding input tokens. The final probability distribution is computed by $P = \mathbf{softmax}(score_{hybrid})$, to determine the next token during generation.

3.3 Schema-aware Denoising

Similar to masked language modeling and other denoising task, we propose two schema-aware objectives, erosion and shuffle, that train model to either reconstruct the origin sequence from noising input or predict corrupted output otherwise. The denoising procedure is illustrated in Figure 2.

3.3.1 Erosion

Given input sample $\{Q, S, Y\}$, erosion corrupts the schema sequence S with a serial compositions of three noising operations:

Permutation Re-order the concatenation sequence of schema columns during schema formulation.

Removal For each column, remove it with a dropping probability p_{drop}.

Addition With a addition probability p_{add}, extract a column from another schema that exists in the training database and insert it into current schema set.

During all operations above, the order of separating special tokens remains unchanged, therefore the corresponding anonymous entities in SQL query should be updated along with the erosion operations in schema sequence. In particular, if a column entity mentioned in SQL query is removed during erosion, we substitute the corresponding column token in SQL with a masking token `<unk>` to cope with the absence of the schema information. With such joint modification for schema and SQL sequence, the model is required to identify the schema entities that are truly related to the NL question and learns to raise an unknown exception whenever the schema information is insufficient to compose the target SQL.

Algorithm 1: Training procedure for schema-aware denoising

Input : training corpus $\mathcal{X} = \{(Q_i, S_i, Y_i)\}, i \in 1, ...|\mathcal{X}|$, S2S Transformer Θ

foreach $(Q_i, S_i, Y_i) \in \mathcal{X}$ **do**
  $T_{src}, T_{tgt} \leftarrow Q_i, Y_i$;
  $T_{tgt}, S_i \leftarrow$ `Erosion` (T_{tgt}, S_i)
  with $P_{shuffle}$ **do**
    with P_{swap} **do**
      $T_{src}, T_{tgt} \leftarrow T_{tgt}, T_{src}$;
    end
    $T_{src} \leftarrow$ `Shuffle` (T_{tgt})
  end
  $T_{type} \leftarrow$ `SeqType` (T_{tgt})
  if $T_{type} = SQL$ **then**
    $T_{prefix} \leftarrow$ `<2sql>`;
  else
    $T_{prefix} \leftarrow$ `<2nl>`;
  end
  $T_{src} \leftarrow T_{prefix} + T_{src} + S_i$;
  `TrainOneSample` $(T_{src}, T_{tgt}, \Theta)$
end

3.3.2 Shuffle

Given input sequence $X' = \{\mathcal{Q}, S\}$, where $\mathcal{Q} = \{Q, Y\}$, the shuffle noise reorders the mentioning sequence of entities in the source query while the schema sequence S is fixed. The denoising objective trains model to reconstruct the query sequence $\mathcal{Q}$ with entities in correct order. The objective of recovering shuffled entity orders trains model to capture the inner relation between different entities and therefore contributes to the schema linking performance. It is also notable that, as a self-supervision objective, both Q and Y are engaged in this denoising task and get trained separately. Though we dependent on the SQL query to identify the value entities in NL query, order shuffling with only column entities is sufficient to obtain promising performance. Since no parallel data is required, additional corpus with monolingual data for both SQL and NL could help with the re-order task and will be one of the further direction of this work.

3.3.3 Training Procedure

Inspired by previous works on denoising self-training (Song et al.; Lewis et al.), we propose to train the schema-aware denoising objectives along with the primary seq2seq task. During training, for each training sample, we apply a nosing pipeline to it before feeding it into the model. The noises with different type are applied to the sample individually. Through the control of activate probability, they could share the same weights in the overall objective. Such continual noising pipeline generates random-wise corrupted samples during training. It prevents the model from fast over-fitting and could yield results with better generalization (Siddhant et al.). The whole procedure is summarized in Algorithm 1.

3.4 Clause-sensitive EG Decoding

During the inference of text-to-SQL task, the predicted SQL may contain errors related to inappropriate schema linking or grammar. EG decoding (Wang et al., 2018) is proposed to amend these errors through an executor-in-loop iteration. It is performed by feeding SQL queries in the candidate list into the executor in sequence and discarding those queries that fail to execute or return empty result. Such decoding strategy, while effective, suggests that the major disagreement in the candidate list focuses on schema linking or grammar. Directly perform EG to the candidates generated with beam search leads to trivial improvement, as the candidates consist of redundant variations focuses on selection or schema naming, etc. This problem can be addressed by setting the beam length of most of the predicted tokens to 1 and releasing those tokens related to schema linking (e.g., `WHERE`). We also notice that there are cases that combine incorrect schema linking with some aggregation in `SELECT` clause, which return some trivial results such as 0, thus suppress the EG filter. To mitigate the issue, we suggest to drop aggregate operator in `SELECT` during EG to maximize the effectiveness of it. Note that with such strategy, the condition with inequation in `WHERE` clause should be dropped together to ensure the validity of the ground-truth SQL results.

Model	Dev		Test	
	Acc_{lf}	Acc_{ex}	Acc_{lf}	Acc_{ex}
SQLNet	63.2	69.8	61.3	68.0
SQLova	81.6	87.2	80.7	86.2
X-SQL	83.8	89.5	83.3	88.7
HydraNet	83.6	89.1	83.8	89.2
SeaD	84.9	90.2	84.7	90.1
IESQL ♣	84.6	89.7	84.6	88.8
BRIDGE ♢	86.2	91.7	85.7	91.1
SDSQL ♣	**86.0**	**91.8**	**85.6**	**91.4**
HydraNet+EG	86.6	92.4	86.5	92.2
IESQL+EG ♣	85.8	91.6	85.6	91.2
BRIDGE+EG ♢	86.8	92.6	86.3	91.9
SDSQL+EG ♣	86.7	92.5	86.6	92.4
SeaD+EG$_{CS}$	**87.3**	**92.8**	**87.1**	**92.7**

Table 1: Accuracy (%) of logic form (Acc_{lf}) and execution (Acc_{ex}) of our model SeaD and other competitors. Best results in bold. EG: execution-guided decoding. EG$_{CS}$: the proposed clause-sensitive EG strategy for S2S generation. ♣ denotes methods that leverage additional annotation of dataset. ♢ denotes methods that utilize database content during training.

4 Experiment

To demonstrate the effectiveness of the proposed method, we evaluate the proposed model on WikiSQL benchmark and compare it to other state-of-the-art methods.

4.1 Dataset

As the largest human-annotated dataset of text-to-SQL, WikiSQL consists of $56,355$, $8,421$ and $15,878$ NL-SQL pairs for training, validation and inference respectively. All ground-truth SQL queries are guaranteed with at least one query result. Each SQL contains `SELECT` clause with at most one aggregation operator and `WHERE` clause with at most 4 conditions that connected by `AND`. Each SQL is associated with a schema in database.

4.2 Implementation details

We implement our method using AllenNLP (Gardner et al.) and Pytorch (Paszke et al.). For the model architecture, we use Transformer with 12 layers in each of the encoder and decoder with a hidden size of 1024. We initialize the model weight with `bart-large` pretrained model provided by

Huggingface community (Wolf et al.) and fine-tune it on training dataset for 20 epochs. The batch size during training is set to 8 with a gradient accumulation step of 2. We choose Adam (Kingma and Ba) as the optimizer and set the learning rate to $7e-5$ with a warm-up step ratio of 1%. The weight decay for regulation is set to 0.01. We set the activation probability $P_{swap} = 0.5$ and $P_{shuffle} = 0.3$ to balance the weight between self-supervision and seq2seq objective. P_{drop} for column removal in erosion is set to 0.1. The early stop patience is set to 5 with respect to the BLUE metric (Papineni et al.) on validation set. The overall training procedure spend around 3 hours on an Ubuntu server with 8 NVIDIA V100 GPUs.

4.3 Competitors

We compare the proposed method to the following models: (1) SQLNet (Xu et al., 2017) is a sketch-based method; (2) SQLova (Hwang et al., 2019) is a sketch-based method which leverage the pre-trained language model for representation; (3) X-SQL (He et al., 2019a) enhances the structural schema representation with contextual embedding; (4) HydraNet (Lyu et al., 2020) transforms schema linking into column-wise matching and ranking; (5) IESQL (Ma et al., 2020) treats text-to-SQL as a sequence labeling task; (6) BRIDGE (Lin et al., 2020) is a sequential architecture for modeling dependencies between natural language question and related schema; (7) SDSQL (Hui et al., 2021) is a multi-task model with explicitly schema dependency guided module.

4.4 Comparison with State-of-the-art Models

The comparison results are summarized in Table 1. Models suffixed with ♣ leverage additional annotation of the dataset. Models suffixed with ♢ utilize database content during training procedure. Without using EG, SeaD significantly outperforms all models without the auxiliary of table content or schema linking annotation. When combined with EG decoding, SeaD achieve best performance even compared to those models that utilize additional training information. It indicates the effectiveness of the proposed denoising objectives on modeling text-to-SQL through vanilla seq2seq. Notably, the annotation noise makes aggregation prediction a major challenge for WikiSQL. Previous works suggested to improve AGG prediction via rule-based annotation amendment. As shown in Table 2, we argue that the proposed aggregation dropping strategy for EG achieves comparable enhancement, while less human effort is involved. Combined with the AGG dropped clause-sensitive EG, the SeaD model establishes new state-of-the-art on WikiSQL benchmark.

Model	Dev		Test	
	Acc_{lf}	Acc_{ex}	Acc_{lf}	Acc_{ex}
IESQL+EG+AE	**87.9**	92.6	**87.8**	92.5
SDSQL+EG+AE	86.7	92.5	87.0	92.7
SeaD+EG$_{ACS}$	87.6	**92.9**	87.5	**93.0**

Table 2: Accuracy (%) of logic form (Acc_{lf}) and execution (Acc_{ex}) of our model SeaD and other competitors with EG decoding. Best results in bold. EG: execution-guided decoding. AE: rule-based aggregation enhancement. EG$_{ACS}$: the clause-sensitive EG strategy for S2S generation, with aggregation ignored during decoding.

Model	S_{col}	S_{agg}	W_{col}	W_{op}	W_{val}
SQLova	96.8	90.6	94.3	97.3	95.4
X-SQL	97.2	91.1	95.4	97.6	96.6
HydraNet	97.6	91.4	95.3	97.4	96.1
IESQL	97.6	90.7	96.4	**98.7**	96.8
SeaD	**97.7**	**91.7**	96.5	97.7	96.7
SDSQL	97.3	90.9	**98.1**	97.7	**98.3**
SQLova+EG	96.5	90.4	95.5	95.8	95.9
X-SQL+EG	97.2	91.1	97.2	97.5	97.9
HydraNet+EG	97.6	91.4	97.2	97.5	97.6
IESQL+EG	97.6	90.7	97.9	**98.5**	98.3
SeaD+EG$_{CS}$	**97.9**	**91.8**	**98.3**	97.9	**98.4**

Table 3: Test accuracy (%) on WikiSQL test set for various clause components of SQL. The best results in bold. EG: execution-guided decoding. EG$_{CS}$: clause-sensitive EG decoding for S2S generation.

To analysis the detailed improvement for SeaD on text-to-SQL task, in Table 3 we report the accuracy on WikiSQL test set with respect to several SQL components with and without EG decoding. SeaD shows promising results on column selection, aggregation, where column and where value prediction. It outperforms all method except SDSQL, which leverages rule-based annotation of schema linking. After applying EG decoding, SeaD achieves best performance on four out of five components among all competitors.

4.5 Ablation Study

To evaluate the contribution of each proposed objective, we perform ablation study to SeaD (4) with

Model	Dev		Test	
	Acc_{lf}	Acc_{ex}	Acc_{lf}	Acc_{ex}
Bart	81.4	87.1	81.2	86.8
Bart$_{ptr}$	82.8	88.6	82.4	88.3
Bart$_{ptr}$ + infilling	82.8	88.7	82.7	88.6
SeaD (Shuffle-only)	83.5	89.0	83.2	88.8
SeaD (Erosion-only)	84.2	89.6	84.1	89.4
SeaD	84.6	90.2	84.7	90.1

Table 4: Ablation study for SeaD model on WikiSQL benchmark.

WikiSQL dataset. We start from the Bart model and add components to it in sequence. The pointer net contributes to 1.2% absolute improvement of Acc_{lf} on test set. Combine text infilling, an effective denoising objective utilized by Bart, into training procedure brings 0.3 absolute Acc_{lf} improvement. On the other hand, erosion and shuffle objectives contribute to 1.5% and 0.6% absolute Acc_{lf} improvement for SeaD on test set respectively. It demonstrates the effectiveness of the schema-aware denoising objective for improving seq2seq generation in text-to-SQL task.

5 Conclusions

In this paper, we proposed to train model with novel schema-aware denoising objectives, which could improve performance of seq2seq generation for text-to-SQL task. Combined with the proposed clause-sensitive EG decoding strategy, our model achieves state-of-the-art on the WikiSQL benchmark. The success of the SeaD highlights the potential of utilizing task-oriented denoising objective for seq2seq model enhancement.

References

Yoav Artzi and Luke Zettlemoyer. 2011. Bootstrapping semantic parsers from conversations. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*, pages 421–432.

Yoav Artzi and Luke Zettlemoyer. 2013. Weakly supervised learning of semantic parsers for mapping instructions to actions. *Transactions of the Association for Computational Linguistics*, 1:49–62.

Chenglong Wang Alvin Cheung Rastislav Bodik. Synthesizing highly expressive sql queries from input-output examples.

Qingqing Cai and Alexander Yates. 2013. Large-scale semantic parsing via schema matching and lexicon extension. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 423–433.

Xinyun Chen, Chang Liu, Richard Shin, Dawn Song, and Mingcheng Chen. 2016. Latent attention for if-then program synthesis. *arXiv preprint arXiv:1611.01867*.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Li Dong and Mirella Lapata. 2016. Language to logical form with neural attention. *arXiv preprint arXiv:1601.01280*.

Matt Gardner, Joel Grus, Mark Neumann, Oyvind Tafjord, Pradeep Dasigi, Nelson Liu, Matthew Peters, Michael Schmitz, and Luke Zettlemoyer. AllenNLP: A deep semantic natural language processing platform.

Alessandra Giordani and Alessandro Moschitti. 2012. Translating questions to sql queries with generative parsers discriminatively reranked. In *Proceedings of COLING 2012: Posters*, pages 401–410.

Jiatao Gu, Zhengdong Lu, Hang Li, and Victor OK Li. 2016. Incorporating copying mechanism in sequence-to-sequence learning. *arXiv preprint arXiv:1603.06393*.

Pengcheng He, Yi Mao, Kaushik Chakrabarti, and Weizhu Chen. 2019a. X-sql: reinforce schema representation with context. *arXiv preprint arXiv:1908.08113*.

Shizhu He, Kang Liu, and Weiting An. 2019b. Learning to align question and answer utterances in customer service conversation with recurrent pointer networks. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 134–141.

Binyuan Hui, Xiang Shi, Ruiying Geng, Binhua Li, Yongbin Li, Jian Sun, and Xiaodan Zhu. 2021. Improving text-to-sql with schema dependency learning. *arXiv preprint arXiv:2103.04399*.

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

Robin Jia and Percy Liang. 2016. Data recombination for neural semantic parsing. *arXiv preprint arXiv:1606.03622*.

Rudolf Kadlec, Martin Schmid, Ondrej Bajgar, and Jan Kleindienst. 2016. Text understanding with the attention sum reader network. *arXiv preprint arXiv:1603.01547*.

Diederik Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In *International Conference on Learning Representations*.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2019. Albert: A lite bert for self-supervised learning of language representations. *arXiv preprint arXiv:1909.11942*.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. *arXiv preprint arXiv:1910.13461*.

Yunyao Li, Huahai Yang, and HV Jagadish. 2006. Constructing a generic natural language interface for an xml database. In *International Conference on Extending Database Technology*, pages 737–754. Springer.

Percy Liang, Michael I Jordan, and Dan Klein. 2013. Learning dependency-based compositional semantics. *Computational Linguistics*, 39(2):389–446.

Xi Victoria Lin, Richard Socher, and Caiming Xiong. 2020. Bridging textual and tabular data for cross-domain text-to-sql semantic parsing. *arXiv preprint arXiv:2012.12627*.

Xi Victoria Lin, Chenglong Wang, Luke Zettlemoyer, and Michael D Ernst. 2018. Nl2bash: A corpus and semantic parser for natural language interface to the linux operating system. *arXiv preprint arXiv:1802.08979*.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

Qin Lyu, Kaushik Chakrabarti, Shobhit Hathi, Souvik Kundu, Jianwen Zhang, and Zheng Chen. 2020. Hybrid ranking network for text-to-sql. *arXiv preprint arXiv:2008.04759*.

Jianqiang Ma, Zeyu Yan, Shuai Pang, Yang Zhang, and Jianping Shen. 2020. Mention extraction and linking for sql query generation. *arXiv preprint arXiv:2012.10074*.

Bryan McCann, Nitish Shirish Keskar, Caiming Xiong, and Richard Socher. 2018. The natural language decathlon: Multitask learning as question answering. *arXiv preprint arXiv:1806.08730*.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. BLEU: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics - ACL '02*, page 311. Association for Computational Linguistics.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Köpf, Edward Yang, Zach DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. PyTorch: An imperative style, high-performance deep learning library.

Matthew E Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. *arXiv preprint arXiv:1802.05365*.

Ana-Maria Popescu, Oren Etzioni, and Henry Kautz. 2003. Towards a theory of natural language interfaces to databases. In *Proceedings of the 8th international conference on Intelligent user interfaces*, pages 149–157.

Chris Quirk, Raymond Mooney, and Michel Galley. 2015. Language to code: Learning semantic parsers for if-this-then-that recipes. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 878–888.

Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding with unsupervised learning.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. *arXiv preprint arXiv:1910.10683*.

Siva Reddy, Mirella Lapata, and Mark Steedman. 2014. Large-scale semantic parsing without question-answer pairs. *Transactions of the Association for Computational Linguistics*, 2:377–392.

Subendhu Rongali, Luca Soldaini, Emilio Monti, and Wael Hamza. 2020. Don't parse, generate! a sequence to sequence architecture for task-oriented semantic parsing. In *Proceedings of The Web Conference 2020*, pages 2962–2968.

Aditya Siddhant, Ankur Bapna, Yuan Cao, Orhan Firat, Mia Chen, Sneha Kudugunta, Naveen Arivazhagan, and Yonghui Wu. Leveraging monolingual data with self-supervision for multilingual neural machine translation.

Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. MASS: Masked sequence to sequence pre-training for language generation.

Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. 2019. Mass: Masked sequence to sequence pre-training for language generation. *arXiv preprint arXiv:1905.02450*.

Alane Suhr, Ming-Wei Chang, Peter Shaw, and Kenton Lee. 2020. Exploring unexplored generalization challenges for cross-database semantic parsing. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8372–8388.

Adam Trischler, Zheng Ye, Xingdi Yuan, and Kaheer Suleman. 2016. Natural language comprehension with the epireader. *arXiv preprint arXiv:1606.02270*.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *arXiv preprint arXiv:1706.03762*.

Oriol Vinyals, Meire Fortunato, and Navdeep Jaitly. 2015. Pointer networks. *arXiv preprint arXiv:1506.03134*.

Chenglong Wang, Kedar Tatwawadi, Marc Brockschmidt, Po-Sen Huang, Yi Mao, Oleksandr Polozov, and Rishabh Singh. 2018. Robust text-to-sql generation with execution-guided decoding. *arXiv preprint arXiv:1807.03100*.

Shuohang Wang and Jing Jiang. 2016. Machine comprehension using match-lstm and answer pointer. *arXiv preprint arXiv:1608.07905*.

David HD Warren and Fernando CN Pereira. 1982. An efficient easily adaptable system for interpreting natural language queries. *American journal of computational linguistics*, 8(3-4):110–122.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. HuggingFace's transformers: State-of-the-art natural language processing.

Caiming Xiong, Victor Zhong, and Richard Socher. 2016. Dynamic coattention networks for question answering. *arXiv preprint arXiv:1611.01604*.

Xiaojun Xu, Chang Liu, and Dawn Song. 2017. Sqlnet: Generating structured queries from natural language without reinforcement learning. *arXiv preprint arXiv:1711.04436*.

Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Ruslan Salakhutdinov, and Quoc V Le. 2019. Xlnet: Generalized autoregressive pretraining for language understanding. *arXiv preprint arXiv:1906.08237*.

Tao Yu and Shafiq Joty. 2020. Online conversation disentanglement with pointer networks. *arXiv preprint arXiv:2010.11080*.

Tao Yu, Zifan Li, Zilin Zhang, Rui Zhang, and Dragomir Radev. 2018. Typesql: Knowledge-based type-aware neural text-to-sql generation. *arXiv preprint arXiv:1804.09769*.

Luke S Zettlemoyer and Michael Collins. 2012. Learning to map sentences to logical form: Structured classification with probabilistic categorial grammars. *arXiv preprint arXiv:1207.1420*.

Victor Zhong, Caiming Xiong, and Richard Socher. 2017. Seq2sql: Generating structured queries from natural language using reinforcement learning. *arXiv preprint arXiv:1709.00103*.