# TAPEX: Table Pre-training via Learning a Neural SQL Executor

Qian Liu<sup>†\*</sup>, Bei Chen<sup>§</sup>, Jiaqi Guo<sup>©\*</sup>, Zeqi Lin<sup>§</sup>, Jian-Guang Lou<sup>§</sup>
<sup>†</sup>Beihang University, Beijing, China; <sup>§</sup>Microsoft Research, Beijing, China
<sup>©</sup>Xi'an Jiaotong University, Xi'an, China

<sup>†</sup>qian.liu@buaa.edu.cn; <sup>©</sup>jasperguo2013@stu.xjtu.edu.cn

<sup>§</sup>{bei.chen, zeqi.lin, jlou}@microsoft.com

#### **Abstract**

Recent years pre-trained language models hit a success on modeling natural language sentences and (semi-)structured tables. ever, existing table pre-training techniques always suffer from low data quality and low pre-training efficiency. In this paper, we show that table pre-training can be realized by learning a neural SQL executor over a synthetic corpus, which is obtained by automatically synthesizing executable SOL queries. By pre-training on the synthetic corpus, our approach TAPEX dramatically improves the performance on downstream tasks, boosting existing language models by at most 19.5%. Meanwhile, TAPEX has remarkably high pretraining efficiency and yields strong results when using a small pre-trained corpus. Experimental results demonstrate that TAPEX outperforms previous table pre-training approaches by a large margin, and our model achieves new state-of-the-art results on four well-known datasets, including improving the WIKISQL denotation accuracy to 89.6% (+4.9%), the WIKITABLEQUESTIONS denotation accuracy to 57.5% (+4.8%), the SQA denotation accuracy to 74.5% (+3.5%), and the TAB-FACT accuracy to 84.6% (+3.6%). Our work opens the way to reason over structured data by pre-training on synthetic executable programs. The project homepage is at https: //table-pretraining.github.io/.

#### 1 Introduction

Recent years pre-trained language models (LMs) such as BERT (Devlin et al., 2019) and BART (Lewis et al., 2020) hit a success on a range of free-form natural language (NL) tasks. By self-supervised learning on a huge number of NL sentences with extremely large model parameters,

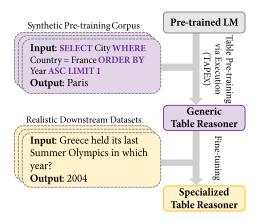


Figure 1: The schematic illustration of the procedure of our proposed TAPEX. Tables not shown for brevity.

these models have demonstrated surprising capabilities on understanding NL sentences. Inspired by the huge success of pre-trained LMs in understanding NL sentences, researchers have attempted to model structured data using pre-training techniques (Herzig et al., 2020; Yin et al., 2020; Yu et al., 2020; Wang et al., 2021b; Deng et al., 2020, 2021; Shi et al., 2021). Different from free-form NL sentences, information stored in structured data exhibit strong underlying structures, for which existing LMs for NL sentences are not well suited. Meanwhile, as one of the most widespread structured data, research on (semi-)structured tables can benefit a wide range of applications (e.g., table question answering). Therefore, an increasing number of studies focus on table pre-training.

In table pre-training, there are generally two key issues to be addressed: (i) where to obtain a large-scale pre-training corpus, and (ii) how to design an effective pre-training task. Existing work generally collects parallel data including NL sentences and tables as the pre-training corpus, because down-stream tasks always involve joint reasoning over free-form NL sentences and tables. They either

<sup>\*</sup> Work in progress. Work done during an internship at Microsoft Research.

crawled tables and their surrounding NL sentences from the Web (Herzig et al., 2020; Yin et al., 2020; Deng et al., 2021; Shi et al., 2021), or synthesized NL sentences on available tables (Yu et al., 2020; Shi et al., 2021). However, according to our preliminary study, the parallel data mined from the Web suffers from low quality, i.e., a considerable amount of NL sentences are not relevant to the tables in the corpus. Conversely, the synthesis method can control the relevance well, but it usually requires experts to write hundreds of NL templates to guarantee the diversity, which is costly. Regarding to the pre-training task, existing work almost employ variants of Masked Language Modeling to strength the linking between NL sentences and tables. For example, TABERT (Yin et al., 2020) proposed the object of Masked Column Prediction to encourage the model to recover the names and data types of masked columns. While these variants perform well, they tend to be less efficient since they usually require a extremely large corpus. The absence of both high quality paired data and efficient pre-training task call for development of new table pre-training approaches.

In this paper, we present TAPEX (for **Table Pre**training via Execution), a novel pre-training approach to empower pre-trained LMs with table reasoning skills. The central point of TAPEX is to train pre-trained LMs to mimic the SQL query execution process on tables. As shown in Figure 1, TAPEX firstly synthesizes a large-scale pre-training corpus by sampling executable SQL queries over available tables, and then continues training on a pre-trained LM to output the execution results of these SOL queries. Since the diversity of SOL queries can be guaranteed systemically, and thus a diverse and high-quality pre-training corpus can be automatically synthesized for TAPEX. Our key insight is that if a model can be trained to faithfully "execute" SQL queries, then it must have a deep understanding of table structures.

In addition to TAPEX, we introduce GETAR, a **Generative Table Reasoning** approach that allows various downstream tasks to be performed on top of the same architecture. Moreover, GETAR is compatible with TAPEX. When augmented by TAPEX, GETAR achieves new state-of-the-art results on four well-known datasets. In summary, our contributions are below:

1. We propose a conceptually simple and empirically powerful table pre-training approach

TAPEX, which automatically synthesizes a pre-training corpus via sampling SQL queries and their execution results over tables. In this way, a high-quality pre-training corpus can be systematically generated, and the pre-training procedure becomes more efficient.

- 2. We present a novel generative table reasoning approach, which formulates downstream tasks as sequence generation and thus enjoys the flexibility to learn any kind of downstream task on top of the same architecture.
- 3. We implement our approach based on a widely used pre-trained LM. Experimental results on four well-known datasets demonstrate that GETAR compares favorably with previous approaches, and TAPEx can boost GETAR by at most 19.5%. Finally, our model achieves new state-of-the-art results on all experimental benchmarks, outperforming previous approaches by a large margin, including advanced table pre-training approaches.

### 2 Reasoning Over Tables

Before diving into the details of our proposed table pre-training, we start by describing how GETAR works. In this section, we first present some preliminary materials on table related downstream tasks. Then we summarize common practices among related work. Finally, we illustrate GETAR in detail and discuss its key advantages.

#### 2.1 Task Formulation

As mentioned in § 1, downstream tasks always involve joint reasoning over free-form NL sentences and tables. Generally, an example from downstream tasks contains a NL sentence x and a (semi-)structured table T as input for models. Each NL sentence consists of K tokens as  $\mathbf{x} =$  $x_1, x_2, \dots, x_K$ , while each table T consists of M rows  $\{r_i\}_{i=1}^M$ , in which each row  $r_i$  contains N cell values  $\{s_{\langle i,j\rangle}\}_{j=1}^N$ . Each cell  $s_{\langle i,j\rangle}$  includes a list of tokens and corresponds to a table header  $c_i$ . As for the output, there are variations among different tasks. In this paper, we focus on two typical tasks which require table reasoning: table question answering (TableQA) and table fact verification (TableFT). TableQA aims to retrieve table content to answer the NL sentence, and thus its output is either a list of cell values, or number(s) calculated over selected cell values by aggregation

functions (e.g., SUM). It is worth noting that for semi-structured tables, the answer may not be exactly table cell values, but their normalized forms (e.g. from 2k to 2,000), which makes downstream tasks more challenging (Oguz et al., 2020). As for TableFT, the output is a binary decision *yes* or *no*, indicating whether the NL sentence describes the same fact as the table content.

#### 2.2 Related Work

Although different downstream tasks share similar task formulations, previous work almost tackle them with distinct architectures.

For TableQA, previous work almost formulate it as a weakly semantic parsing task (Liang et al., 2018; Wang et al., 2019), which employs reinforcement learning to optimize semantic parsers over tables. Although these parsers can retrieve answers by generating executable logic forms (e.g., SQL), they have difficulties in training due to the large search space and the presence of spurious programs (Goldman et al., 2018). In addition, another promising line of work has emerged in recent advances (Mueller et al., 2019; Herzig et al., 2020), which aims at answering NL sentences without logical forms. This line of work predicts answer(s) by selecting table cell values and optionally applying an aggregation operator to the selected region. Thanks to end-to-end training, it can be easily trained, but its modeling capability is limited. For example, it is hard to support compound aggregation operators such as max(Year) - min(Year).

For TableFT, previous work usually employ specialized architectures with limited flexibility (Shi et al., 2020a; Yang et al., 2020). For example, Zhong et al. (2020b) leveraged a graph construction mechanism, a semantic parser and a semantic composition model to capture the connections among the NL sentence and the table. While the approach works well for fact verification, it is difficult to combine with table pre-training techniques.

### 2.3 Generative Table Reasoning

As mentioned above, previous work tackle with different tasks through different architectures, so it is difficult to transfer knowledge across downstream datasets during fine-tuning. Meanwhile, there is rare method which can enjoy the end-to-end training and the modeling power at the same. Therefore, we present a universal approach GETAR (for **Ge**nerative **Table Reasoning**). Unlike previous work, GETAR formulates downstream tasks

as sequence generation, and leverages pre-trained generative LMs to output autoregressively. Taking TableQA as an example, given a NL sentence and its corresponding table, GETAR generates answer(s) by decoding word by word.

**Architecture** GETAR theoretically applies for any LM as long as it can generate sequence, such as GPT3 (Brown et al., 2020) and UniLM (Bao et al., 2020). In our experiments, we implement GETAR on top of BART (Lewis et al., 2020), a widely used pre-trained encoder-decoder model. BART follows a standard sequence-to-sequence Transformer architecture (Vaswani et al., 2017), with modifying ReLU activation functions to GeLU. It is pre-trained via corrupting sentences (e.g., randomly sampling length-variable spans and masking each one with a single [MASK] token) and then optimizing a reconstruction loss. As for the number of layers, we employ the BART<sub>Large</sub> configuration in our experiments, i.e., 12 layers are used in the encoder and decoder.

**Model Input** The input for GETAR contains a NL sentence and its corresponding table. Encoding the NL sentence is relatively straightforward, while encoding the table is non-trivial since it exhibits underlying structures. In practise, we linearize the table into a flatten sequence so that it can be fed directly into the model. By inserting several special tokens to indicate the table boundaries, a linearized table can be represented as  $T^*$ [HEAD],  $c_1, \dots, c_N$ , [ROW],  $r_1$ , [ROW],  $r_2, \dots, r_M$ . Here [HEAD] and [ROW] are special tokens indicating the region of table headers and rows respectively. Notably, we also separate headers or cells in different columns using a vertical bar. Finally, we prefix the linearized table  $T^*$  with the NL sentence x and feed them to the encoder.

Model Output With attending on the encoder, GETAR's decoder is responsible for modeling the outputs of both TableQA and TableFT. For TableQA, the output is the concatenation of answer(s) separated by commas, and the decoder generates it autoregressively. In this way, GETAR can readily support (almost) all operators and their compositions over tables. For TableFT, as BART does for sequence classification tasks (Lewis et al., 2020), the encoder input is also fed into the decoder as input, and a binary classifier upon the representation of the last token is used to give decisions. Notably, GETAR can be easily extended to other

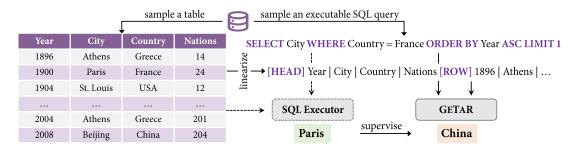


Figure 2: The schematic overview of TAPEX. Having fed the concatenation of the SQL query and the linearized table to GETAR, TAPEX trains it to output the corresponding execution result "Pairs".

table related sequence generation tasks or sequence classification tasks in a similar way.

Fine-tuning Strategy Since our model GETAR accepts various downstream tasks on the same architecture, it is easy to perform multi-task learning. Therefore, we explore two ways of fine-tuning, one for vanilla fine-tuning and the other for multi-task fine-tuning. The former is to fine-tune GETAR on each individual downstream dataset. The latter is inspired by TAPAS (Herzig et al., 2020) and T5 (Raffel et al., 2020), which first fine-tunes GETAR on other downstream datasets, and then continues to fine-tune GETAR on the target downstream dataset. The multi-task fine-tuning is expected to be better than the vanilla fine-tuning because the learning objectives of downstream tasks are similar to each other.

**Discussion** Formulating downstream tasks as sequence generation comes with several advantages: (i) *Flexible*: due to the powerful expressiveness of sequence generation, it can readily adapt to (almost) any kind of output. (ii) *Convenient*: it does not require any modification (e.g., table-specific masking) on pretrained LMs, and can be trained in an end-to-end manner. (iii) *Transferable*: since the formulation enables different tasks to share the same training protocol, it is easy to perform multitask fine-tuning. Empirically, it can benefit each task by transferring the experience of other tasks.

### 3 Table Pre-training via Execution

As introduced in § 2.3, GETAR uses a non-intrusive way to represent tables, i.e., without any modifications on LMs. Although the approach is very flexible, it does not introduce any inductive bias regarding the table structure. This makes GETAR less effective, especially when the training data is relatively small, because the model has to learn to understand the table structure except for down-

stream tasks. Considering the above, it becomes particularly important to inject basic table comprehension and reasoning capabilities into existing models. To fulfill this goal, we propose a novel table pre-training approach TAPEX. It augments GETAR's table understanding with a refreshing pre-training task, *SQL execution*.

#### 3.1 Pre-training Task

Most of the existing table pre-training tasks are reconstruction tasks, similar to the Masked Language Modeling task proposed in BERT (Devlin et al., 2019). They generally take corrupted tables and NL sentences as input and try to recover their corrupted parts, in order to strengthen the linking between NL sentences and tables. While these pre-training tasks perform well, they tend to be less efficient since they usually require a extremely large pre-training corpus. We argue the inefficiency is due to the fact that they do not take full advantage of the table structure, which is the key factor in distinguishing tables from NL sentences.

The regular structure of tables allows us to perform complex queries on them via programming languages such as SQL, while NL sentences do not. Taking it into account, TAPEX adopts SQL execution as its only pre-training task. As illustrated in Figure 2, given a table and an executable SQL query, TAPEx firstly obtains the query's execution result through an off-the-shelf SQL executor (e.g., MySQL). Then it employs the execution result as the supervision to train GETAR. Intuitively, the pretraining procedure is to engage GETAR to learn to be a neural SQL executor. We believe that if a model can be trained to faithfully "execute" SQL queries, then it must have a deep understanding of table structures and possess an inductive bias towards table structures.

Dataset	Type	# Sentences	# Tables	
WikiSQL	Simple QA	80,654	24,241	
WikiTQ	Complex QA	22,033	2,108	
SQA	Conversation QA	17,553	982	
TABFACT	Fact Verification	118,275	16,573	

Table 1: Dataset statistics.

Model	Dev	Test					
Previ	Previous Systems						
Liang et al. (2018)	71.8	72.4					
Agarwal et al. (2019)	74.9	74.8					
Wang et al. (2019)	79.4	79.3					
Min et al. (2019)	84.4	83.9					
Pre-trained	Language Mod	lels					
Herzig et al. (2020)	85.1	83.6					
Yu et al. (2020)	85.9	84.7					
GETAR	87.3	85.8					
GETAR + TAPEX	<b>89.1</b> (+1.8)	<b>89.6</b> (+3.8)					

Table 2: Denotation accuracies on WIKISQL<sup>1</sup>.

#### 3.2 Pre-training Corpus

Figure 2 does not illustrate the synthesis procedure of the pre-training corpus, which is also very important for pre-training. Generally, there are two key factors: the table source and the SQL query sampling strategy.

**Table Source** Following previous work (Yin et al., 2020), we select semi-structured tables that exist on the Web as the table source. However, unlike them requiring millions of raw tables, TAPEX works well even with only a few thousand tables. Therefore, instead of fetching noisy tables from the Web and and then heuristically filtering them, we pick high-quality tables right from existing public datasets. Concretely, we randomly select nearly 1,500 tables from the training set of WIKITABLE-QUESTIONS (WIKITQ) (Pasupat and Liang, 2015) as the table source of our pre-training corpus.

Query Sampling Regarding the sampling of diverse SQL queries, there are various choices in the literature. We can either sample SQL queries according to a probabilistic context-free grammar (Wang et al., 2021a), or instantiate SQL templates over different tables (Zhong et al., 2020a). In our experiments, we follow the latter, where SQL templates are automatically extracted from the SQUALL dataset (Shi et al., 2020b). An exam-

Model	Dev	Test
Previo	ous Systems	
Pasupat and Liang (2015)	37.0	37.1
Neelakantan et al. (2016)	34.1	34.2
Ensemble 15 Models	37.5	37.7
Zhang et al. (2017)	40.6	43.7
Liang et al. (2018)	42.7	43.8
Dasigi et al. (2019)	43.1	44.3
Agarwal et al. (2019)	43.2	44.1
Ensemble 10 Models	_	46.9
Wang et al. (2019)	43.7	44.5
Pre-trained I	Language Model	S
Herzig et al. (2020)	_	48.8
Yin et al. (2020)	53.0	52.3
Yu et al. (2020)	51.9	52.7
GETAR	37.2	38.0
GETAR + TAPEX	<b>57.0</b> (+19.8)	<b>57.5</b> (+19.5)

Table 3: Denotation accuracies on WIKITQ.

ple SQL template is like SELECT num1 WHERE text1 = val1, where num1 and text1 correspond to a numeric column and a text column respectively, and val1 refers to one of the cell values with respect to the column text1. Given a SQL template, at each instantiation, we uniformly sample headers and cell values from a sampled table to fill the template, forming a concrete SQL query. By instantiating each SQL template hundreds of times, we obtain a large-scale pre-training corpus. Notably, SQL queries that execute with empty results are discarded.

#### 4 Experiments

In this section, we evaluate our approach on downstream datasets to verify its effectiveness.

Dataset and Evaluation We evaluate performance of our approach on the WIKISQL (Zhong et al., 2017), WIKITQ (Pasupat and Liang, 2015), SQA (Iyyer et al., 2017) and TABFACT (Chen et al., 2019). The dataset statistics are shown in Table 1. Compared to WIKISQL, which only requires filtering and optionally aggregating on table cell values, WIKITQ requires more complicated reasoning capabilities, such as sorting the given table. For TableQA datasets, the evaluation metric is denotation accuracy, which checks whether the predicted answer(s) is equal to the ground-truth answer(s). As for TABFACT, the evaluation metric is accuracy, which is calculated by the percentage of correctly verified facts. For space considerations, we cannot elaborate on baseline models, and we refer readers to their papers for more details.

<sup>&</sup>lt;sup>1</sup>We evaluate our approach with answer labels from TAPAS, since nearly 2% answers obtained from the official evaluation script of WIKISQL are incorrect.

Model	ALL	SEQ	$\mathbf{Q}_1$	$\mathbf{Q}_2$	$\mathbf{Q}_3$			
Previous Systems								
Pasupat and Liang (2015)	33.2	7.7	51.4	22.2	22.3			
Neelakantan et al. (2017)	40.2	11.8	60.0	35.9	25.5			
Iyyer et al. (2017)	44.7	12.8	70.4	41.1	23.6			
Liu et al. (2019)	_	_	70.9	39.5	_			
Sun et al. (2019)	45.6	13.2	70.3	42.6	24.8			
Mueller et al. (2019)	55.1	28.1	67.2	52.7	46.8			
	Pre-	trained Languag	e Models					
Herzig et al. (2020)	67.2	40.4	78.2	66.0	59.7			
Yu et al. (2020)	65.4	38.5	_	_	_			
Eisenschlos et al. (2020)	71.0	44.8	_	_	_			
GETAR GETAR + TAPEX	58.6 <b>74.5</b> (+15.9)	27.8 <b>48.4</b> (+20.6)	65.3 76.2 (+10.9)	54.1 <b>71.9</b> (+17.8)	57.0 <b>76.9</b> (+19.9)			

Table 4: Denotation accuracies on SQA test set. ALL is the denotation accuracy over all sentences, SEQ the denotation accuracy over all conversations, and  $\mathbf{Q}_i$  the denotation accuracy of the i-th sentence in a conversation.

Model	Dev	Test	Test <sub>simple</sub>	Test <sub>complex</sub>	Test <sub>small</sub>			
Pre-trained Language Models								
Chen et al. (2019)	66.1	65.1	79.1	58.2	68.1			
Zhong et al. (2020b)	71.8	71.7	85.4	65.1	74.3			
Shi et al. (2020a)	72.5	72.3	85.9	65.7	74.2			
Zhang et al. (2020)	73.3	73.2	85.5	67.2	_			
Yang et al. (2020)	74.9	74.4	88.3	67.6	76.2			
Eisenschlos et al. (2020)	81.0	81.0	92.3	75.6	83.9			
GETAR GETAR + TAPEX	81.2 <b>84.6</b> (+3.4)	80.8 <b>84.2</b> (+3.4)	90.7 <b>93.9</b> (+3.2)	76.0 <b>79.6</b> (+3.6)	82.5 <b>85.9</b> (+3.4)			
Human Performance	-	-	-	-	92.1			

Table 5: Model and Human accuracies on TABFACT.

**Implementation Details** We implement our approach in fairseq (Ott et al., 2019). During pretraining, we synthesize up to 5 million pairs of SQL queries and their execution results for TAPEX. In the following, unless specified explicitly, the experimental results are by default evaluated under the 5 million setting. The pre-training lasts for at most 100,000 steps with a batch size of 256. It takes about 3 days on 8 Tesla V100 to finish the pre-training. The best pre-training checkpoint is selected based on the loss of the validation set. For all downstream datasets, the fine-tuning procedure lasts for at most 20,000 steps with a batch size of 128. For both pre-training and fine-tuning, the learning rate is  $3 \times 10^{-5}$ . Note that SQA is a conversational benchmark, which requires our model to model the conversational context. Here we simply prefix each NL sentence with the conversation history, as suggested in Liu et al. (2020).

#### 4.1 Main Results

Table 2 and Table 3 summarize experimental results of various models on the dev set and test set of WIKISQL and WIKITQ respectively. The test

performance is obtained using the best run of our model on the dev set. As shown, with TAPEX, GETAR consistently outperforms all baselines by a large margin. On the test set of WIKISQL, GETAR alone exceeds the best reported performance by 1.1%. When augmented by TAPEX, GETAR + TAPEX registers a denotation accuracy of 89.6%, 3.8% higher than GETAR. Finally, our approach achieves new state-of-the-art results on the well-known dataset WIKISQL, matching the performance of strong supervised baselines.

On the more challenging WIKITQ, our approach GETAR + TAPEX also achieves the state-of-the-art denotation accuracy 57.5%, surpassing the previous best system by 4.8%. More interestingly, we find that GETAR alone only gets the denotation accuracy 38.0%, far from the performance of previous pre-training models. We hypothesize that the performance degradation would be attributed by the relatively small amount of data in WIK-ITQ, which makes learning table structures more difficult. However, TAPEX delivers a dramatic improvement of 19.5% for GETAR, indicating that TAPEX performs effectively in low data regime.

${\tt Source} \mapsto {\tt Target}$	w/o TAPEX	w/ TAPEX
	37.2 42.5 47.4	57.0 58.5 57.2
$\begin{array}{c} SQA \\ TABFACT \mapsto SQA \\ WikisQL \mapsto SQA \end{array}$	57.5 62.1 64.1	70.3 71.0 70.8

Table 6: Experimental results (denotation accuracy) of multi-task fine-tuning on the **Target** dev set. **Source** → **Target** means firstly fine-tuning on **Source** and then fine-tuning on **Target**.

Table 4 presents the performance of various models on the test set of SQA, where GETAR + TAPEX again obtains the state-of-the-art denotation accuracies, both at the conversation level (48.4%) and at the sentence level (74.5%). It is highly non-trivial since SQA is a conversational dataset while our pre-training task is context-free. Meanwhile, the substantial improvement of TAPEX over GETAR on SQA verifies the same conclusion that TAPEX alleviates the low resource issue significantly.

Beyond question answering, our approach also excels at table fact verification. As shown in Table 5, GETAR + TAPEX achieves new state-of-the-art results on all subsets of TABFACT. For example, it surpasses the previous best system by 4.0% on Test<sub>complex</sub>. The remarkable result shows that TAPEX endows GETAR with generic table reasoning capabilities that can be applied to different downstream tasks, regardless of whether it is close in form to our pre-training task or not.

Overall, experimental results on four datasets show that our proposed generative table reasoning approach is flexible to adapt to different tasks, and our proposed table pre-training via execution broadly improves the model ability on understanding tables and reasoning over tables.

### 4.2 Multi-task Results

As discussed in § 2.3, GETAR enables multi-task fine-tuning across datasets, even tasks. Therefore, we choose WIKISQL and TABFACT, whose training data are relatively rich, as the transfer source and the rest as the transfer target. Table 6 presents the experimental results on multi-task fine-tuning. As shown, with or without TAPEX, multi-task fine-tuning boosts the performance of the target dataset consistently, revealing the advantage of GETAR. However, the performance gain of multi-task fine-tuning tends to be marginal when GETAR is augmented with TAPEX, suggesting that our synthetic

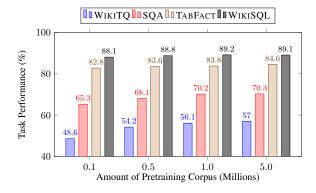


Figure 3: The illustration of downstream datasets performance with different scales of pre-training corpus.

data may be as powerful as the supervised data.

## 5 Pre-training Analysis

In this section, we carefully analyze the pretraining procedure in terms of pre-training accuracy, pre-training scale and pre-training efficiency.

Pre-training Accuracy In order to understand how well our model performs SQL execution after pre-training, we analyze its performance on 23, 294 held-out SQL queries over unseen tables. Overall, the SQL execution accuracy is relatively high, as our model correctly "executes" 88.7% of the SQL queries. For an in-depth understanding, Figure 4 provides a fine-grained analysis of the execution accuracies for each SQL type. As shown, our model performs best on type Count and Filter, indicating that it is highly accurate in table cell selection and counting. Regarding scenarios that require Calculate, Order and Compare, our model also does a good job, demonstrating its strong reasoning capabilities over tables. More surprisingly, our model also excels at nested queries, which necessitate multi-hop reasoning skills. To summarize, TAPEX does motivate a model to be a good neural SQL executor with selection, computation and multi-hop reasoning capabilities.

**Pre-training Scale** Figure 3 illustrates the downstream datasets performance with different scales of pre-training corpus. It can be seen that even if our pre-training corpus is synthetic, scaling up the pre-training corpus generally bring positive effects. The observation is analogous to the one found in language modeling (Brown et al., 2020): the larger the pre-training corpus, the better the downstream performance. By comparison across different datasets, we can find that for simple datasets such as WIKISQL, the gains by scaling up pre-

I able					Execution Performance		
Year	City	Country	Nations	Type	Example SQL	Quantity	Accuracy
1896	Athens	Greece	14	Filter	SELECT City WHERE Country = Greece OR Country = UK OR Country = France	12681	91.5
1900	Paris	France	24	Calculate	SELECT AVG (Nations) WHERE Year < 2000	6997	81.8
1904	St. Louis	USA	12		OFF POT COLUMN (*) VIII VIII CO.	6051	02.6
				Count	SELECT COUNT (*) WHERE Country = USA	6951	93.6
1908	London	UK	22	Order	SELECT City ORDER BY Year DESC LIMIT 1	6815	89.3
				Compare	SELECT Country WHERE Year <= 2000	4339	85.1
2004	Athens	Greece	201	Nested	SELECT City, Country WHERE Year !=	3979	86.2
2008	Beijing	China	204	nestea	(SELECT MIN (Year))	5777	00.2
	, 0			Harring	SELECT Country GROUP BY Country	102	65.7
2012	London	UK	204	naving	HAVING COUNT (*) > 2	102	03.7
	1896 1900 1904 1908  2004	Year         City           1896         Athens           1900         Paris           1904         St. Louis           1908         London               2004         Athens           2008         Beijing	Year         City         Country           1896         Athens         Greece           1900         Paris         France           1904         St. Louis         USA           1908         London         UK                2004         Athens         Greece           2008         Beijing         China	Year         City         Country         Nations           1896         Athens         Greece         14           1900         Paris         France         24           1904         St. Louis         USA         12           1908         London         UK         22                 2004         Athens         Greece         201           2008         Beijing         China         204	Year         City         Country         Nations         Type           1896         Athens         Greece         14         Filter           1900         Paris         France         24         Calculate           1904         St. Louis         USA         12         Count           1908         London         UK         22         Order               Compare           2004         Athens         Greece         201         Nested           2008         Beijing         China         204	1896         Athens         Greece         14         Filter         SELECT City WHERE Country = Greece OR Country = UK OR Country = Trance           1900         Paris         France         24         Calculate         SELECT AVG (Nations) WHERE Year < 2000	Year         City         Country         Nations         Type         Example SQL         Quantity           1896         Athens         Greece         14         Filter         SELECT City WHERE Country = Greece OR Country = UK OR Country = UK OR Country = France         12681           1900         Paris         France         24         Calculate         SELECT AVG (Nations) WHERE Year < 2000

Figure 4: The typical SQL types, examples, quantities and their execution accuracies on the held-out SQL queries.

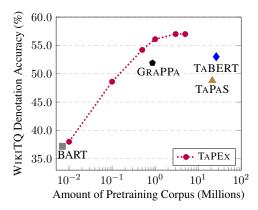


Figure 5: The amount of pre-training corpus vs. WIK-ITQ dev set denotation accuracy. TAPEX surpasses existing table pre-training approaches with a much smaller corpus, demonstrating its high efficiency.

training become marginal, while they remain nontrivial for complex datasets such as TABFACT. Meanwhile, both downstream datasets with smaller amounts show a positive trend by increasing pretraining corpus. Conclusively, the scale matters when the downstream task is difficult or the downstream dataset is relatively small.

Pre-training Efficiency As mentioned in § 1, the pre-training efficiency of existing table pre-training approaches are relatively low, as they usually require a extremely large corpus. Therefore, taking WIKITQ as an example, we compare the pre-training efficiency of TAPEX with TAPAS (Herzig et al., 2020), TABERT (Yin et al., 2020) and GRAPPA (Yu et al., 2020). It is worth noting that part of pre-training corpus for GRAPPA comes from human-annotated, high-quality parallel data. As shown in Figure 5, TAPEX can yield very promising performance when using a much smaller pre-trained corpus, indicating that our proposed SQL execution is a more efficient pre-training task compared to existing table pre-training tasks.

**Limitations** The first limitation of our approach is that it cannot ideally handle large tables. As mentioned above, we employ the table linearization technique to represent a table. It works well when the table is relatively small, but it becomes infeasible when the table is too large to fit in memory. In practice, we usually compress tables by randomly deleting rows, which undoubtedly decreases downstream performance. The second limitation is that our approach may not benefit the performance of text-to-SQL. We have tried to apply TAPEx on a text-to-SQL dataset, where the input remains the same and the output turns to be SQL. However, TAPEX does not show a significant advantage over BART. We attribute it to two factors: First, our synthetic pre-training corpus does not contribute to grounding, one of the most important factors for semantic parsing (Liu et al., 2021). Second, table reasoning capabilities (e.g., calculation) learned by TAPEX may not be necessary for SQL generation. For example, a model could still understand a NL phrase "total" as the aggregation function "sum", even though it is unaware of the mathematical meaning of "sum".

### 6 Conclusion

In this paper, we propose TAPEX, a conceptually simple and empirically powerful table pre-training approach, whose pre-training corpus is automatically synthesized via sampling SQL queries and their execution results. By learning a neural SQL executor on the synthetic corpus, TAPEX dramatically improves downstream performance. Besides, we present a novel generative table reasoning approach GETAR, which is flexible enough to adapt to various downstream tasks. When TAPEX and GETAR are combined, they achieve new state-of-the-art results on four well-known datasets, demonstrating the superiority of our approach.

#### References

- Rishabh Agarwal, Chen Liang, Dale Schuurmans, and Mohammad Norouzi. 2019. Learning to generalize from sparse and underspecified rewards. In *ICML*.
- Hangbo Bao, Li Dong, Furu Wei, Wenhui Wang, Nan Yang, Xiaodong Liu, Yu Wang, Songhao Piao, Jianfeng Gao, M. Zhou, and H. Hon. 2020. Unilmv2: Pseudo-masked language models for unified language model pre-training. In *ICML*.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In Advances in Neural Information Processing Systems, volume 33, pages 1877–1901. Curran Associates, Inc.
- Wenhu Chen, Hongmin Wang, Jianshu Chen, Yunkai Zhang, Hong Wang, Shiyang Li, Xiyou Zhou, and William Yang Wang. 2019. Tabfact: A large-scale dataset for table-based fact verification. In *International Conference on Learning Representations*.
- Pradeep Dasigi, Matt Gardner, Shikhar Murty, Luke S. Zettlemoyer, and Eduard H. Hovy. 2019. Iterative search for weakly supervised semantic parsing. In *Proceedings of NAACL-HLT*.
- Xiang Deng, Ahmed Hassan Awadallah, Christopher Meek, Oleksandr Polozov, Huan Sun, and Matthew Richardson. 2021. Structure-grounded pretraining for text-to-SQL. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1337–1350, Online. Association for Computational Linguistics.
- Xiang Deng, Huan Sun, Alyssa Lees, You Wu, and Cong Yu. 2020. TURL: table understanding through representation learning. *Proc. VLDB Endow.*, 14(3):307–319.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.
- Julian Eisenschlos, Syrine Krichene, and Thomas Müller. 2020. Understanding tables with intermediate pre-training. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages

- 281–296, Online. Association for Computational Linguistics.
- Omer Goldman, Veronica Latcinnik, Ehud Nave, Amir Globerson, and Jonathan Berant. 2018. Weakly supervised semantic parsing with abstract examples. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1809–1819, Melbourne, Australia. Association for Computational Linguistics.
- Jonathan Herzig, Pawel Krzysztof Nowak, Thomas Müller, Francesco Piccinno, and Julian Eisenschlos. 2020. TaPas: Weakly supervised table parsing via pre-training. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4320–4333, Online. Association for Computational Linguistics.
- Mohit Iyyer, Wen-tau Yih, and Ming-Wei Chang. 2017. Search-based neural structured learning for sequential question answering. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1821–1831.
- Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pretraining for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online. Association for Computational Linguistics.
- Chen Liang, Mohammad Norouzi, Jonathan Berant, Quoc V Le, and Ni Lao. 2018. Memory augmented policy optimization for program synthesis and semantic parsing. In *Proceedings of NIPS*.
- Qian Liu, Bei Chen, Jiaqi Guo, Jian-Guang Lou, Bin Zhou, and Dongmei Zhang. 2020. How far are we from effective context modeling? an exploratory study on semantic parsing in context twitter. In *IJ-CAI*.
- Qian Liu, Bei Chen, Haoyan Liu, Jian-Guang Lou, Lei Fang, Bin Zhou, and Dongmei Zhang. 2019. A split-and-recombine approach for follow-up query analysis. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 5316–5326, Hong Kong, China. Association for Computational Linguistics.
- Qian Liu, Dejian Yang, Jiahui Zhang, Jiaqi Guo, Bin Zhou, and Jian-Guang Lou. 2021. Awakening latent grounding from pretrained language models for semantic parsing. In *Findings of the Association for Computational Linguistics: ACL 2021*.
- Sewon Min, Danqi Chen, Hannaneh Hajishirzi, and Luke Zettlemoyer. 2019. A discrete hard EM approach for weakly supervised question answering.

- In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 2851–2864, Hong Kong, China. Association for Computational Linguistics.
- Thomas Mueller, Francesco Piccinno, Peter Shaw, Massimo Nicosia, and Yasemin Altun. 2019. Answering conversational questions on structured data without logical forms. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 5902–5910, Hong Kong, China. Association for Computational Linguistics.
- Arvind Neelakantan, Quoc V. Le, Martín Abadi, Andrew McCallum, and Dario Amodei. 2017. Learning a natural language interface with neural programmer. In 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings. Open-Review.net.
- Arvind Neelakantan, Quoc V. Le, and Ilya Sutskever. 2016. Neural programmer: Inducing latent programs with gradient descent. In *Proceedings of ICLR*.
- Barlas Oguz, Xilun Chen, Vladimir Karpukhin, Stan Peshterliev, Dmytro Okhonko, Michael Schlichtkrull, Sonal Gupta, Yashar Mehdad, and Scott Yih. 2020. Unified open-domain question answering with structured and unstructured knowledge. arXiv preprint arXiv:2012.14610.
- Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. fairseq: A fast, extensible toolkit for sequence modeling. In *Proceedings of NAACL-HLT 2019: Demonstrations*.
- Panupong Pasupat and Percy Liang. 2015. Compositional semantic parsing on semi-structured tables. In *Proceedings of ACL*.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21:1–67.
- Peng Shi, Patrick Ng, Zhiguo Wang, Henghui Zhu, Alexander Hanbo Li, Jun Wang, Cícero Nogueira dos Santos, and Bing Xiang. 2021. Learning contextual representations for semantic parsing with generation-augmented pre-training. In Thirty-Fifth AAAI Conference on Artificial Intelligence, AAAI 2021, Thirty-Third Conference on Innovative Applications of Artificial Intelligence, IAAI 2021, The Eleventh Symposium on Educational Advances in Artificial Intelligence, EAAI 2021, Virtual Event, February 2-9, 2021, pages 13806–13814. AAAI Press.

- Qi Shi, Yu Zhang, Qingyu Yin, and Ting Liu. 2020a. Learn to combine linguistic and symbolic information for table-based fact verification. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 5335–5346, Barcelona, Spain (Online). International Committee on Computational Linguistics.
- Tianze Shi, Chen Zhao, Jordan Boyd-Graber, Hal Daumé III, and Lillian Lee. 2020b. On the potential of lexico-logical alignments for semantic parsing to SQL queries. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 1849–1864, Online. Association for Computational Linguistics.
- Yibo Sun, Duyu Tang, Nan Duan, Jingjing Xu, X. Feng, and Bing Qin. 2019. Knowledge-aware conversational semantic parsing over web tables. In *NLPCC*.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Proceedings of NIPS*.
- Bailin Wang, Ivan Titov, and Mirella Lapata. 2019. Learning semantic parsers from denotations with latent structured alignments and abstract programs. In *EMNLP/IJCNLP*.
- Bailin Wang, Wenpeng Yin, Xi Victoria Lin, and Caiming Xiong. 2021a. Learning to synthesize data for semantic parsing. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2760–2766, Online. Association for Computational Linguistics.
- Zhiruo Wang, Haoyu Dong, Ran Jia, Jia Li, Zhiyi Fu, Shi Han, and Dongmei Zhang. 2021b. Tuta: Tree-based transformers for generally structured table pre-training. In *KDD*.
- Xiaoyu Yang, Feng Nie, Yufei Feng, Quan Liu, Zhigang Chen, and Xiaodan Zhu. 2020. Program enhanced fact verification with verbalization and graph attention network. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 7810–7825, Online. Association for Computational Linguistics.
- Pengcheng Yin, Graham Neubig, Wen-tau Yih, and Sebastian Riedel. 2020. TaBERT: Pretraining for joint understanding of textual and tabular data. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8413–8426, Online. Association for Computational Linguistics.
- Tao Yu, Chien-Sheng Wu, Xi Victoria Lin, Bailin Wang, Y. Tan, Xinyi Yang, Dragomir Radev, R. Socher, and Caiming Xiong. 2020. Grappa: Grammar-augmented pre-training for table semantic parsing. *ArXiv*, abs/2009.13845.

- Hongzhi Zhang, Yingyao Wang, Sirui Wang, Xuezhi Cao, Fuzheng Zhang, and Zhongyuan Wang. 2020.
   Table fact verification with structure-aware transformer. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1624–1629, Online. Association for Computational Linguistics.
- Yuchen Zhang, Panupong Pasupat, and Percy Liang. 2017. Macro grammars and holistic triggering for efficient semantic parsing. In *Proceedings of EMNLP*.
- Victor Zhong, Mike Lewis, Sida I. Wang, and Luke Zettlemoyer. 2020a. Grounded adaptation for zero-shot executable semantic parsing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 6869–6882, Online. Association for Computational Linguistics.
- Victor Zhong, Caiming Xiong, and Richard Socher. 2017. Seq2sql: Generating structured queries from natural language using reinforcement learning. *CoRR*, abs/1709.00103.
- Wanjun Zhong, Duyu Tang, Zhangyin Feng, Nan Duan, Ming Zhou, Ming Gong, Linjun Shou, Daxin Jiang, Jiahai Wang, and Jian Yin. 2020b. LogicalFactChecker: Leveraging logical operations for fact checking with graph module network. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 6053–6065, Online. Association for Computational Linguistics.