T-RAG: End-to-End Table Question Answering via Retrieval-Augmented Generation

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Abstract

Most existing end-to-end Table Question Answering (Table QA) models consist of a two-stage framework with a retriever to select relevant table candidates from a corpus and a reader to locate the correct answers from table candidates. Even though the accuracy of the reader models is significantly improved with the recent transformer-based approaches, the overall performance of such frameworks still suffers from the poor accuracy of using traditional information retrieval techniques as retrievers. To alleviate this problem, we introduce T-RAG, an end-to-end Table QA model, where a non-parametric dense vector index is fine-tuned jointly with BART, a parametric sequence-to-sequence model to generate answer tokens. Given any natural language question, T-RAG utilizes a unified pipeline to automatically search through a table corpus to directly locate the correct answer from table cell. We apply T-RAG on recent open-domain Table QA benchmarks and demonstrate that the fine-tuned T-RAG model is able to achieve state-of-the-art performance in both the end-to-end Table QA and the table retrieval tasks.

1 Introduction

Tabular data is commonly seen in open-domain documents (Cafarella et al., 2009; Zhang and Balog, 2018a), such as the Web and Wikipedia, as well as in domain-specific papers, journals, manuals, and reports. Answering questions over these tables requires table retrieval and understanding of the table structure and content. Table QA task is generally more challenging than executing SQL queries over relational database tables due to the lack of schema information. Most existing studies tackle Table QA as two separate sub-tasks: (1) Table retrieval (Cafarella et al., 2008, 2009; Zhang and Balog, 2018a; Shraga et al., 2020a,b), and (2) QA over tables (Yu et al., 2018; Herzig et al., 2020; Yin et al., 2020; Glass et al., 2020). Recently, the DTR (Herzig et al., 2021) and the CLTR (Pan et al., 2021) models have been proposed as end-to-end solutions for Table QA. Both models consist of a two-step pipeline of a retriever to generate a set of candidate tables and a reader to answer questions over these tables. The two components are trained individually, causing error propagation from retrievers to readers, i.e. with incorrect table candidates, it is impossible for the readers to locate the correct answer despite the design of the models. While dense retrieval and Retrieval Augmented Generation (RAG) (Karpukhin et al., 2020; Lewis et al., 2020b) have achieved great success in open-domain QA over free text, none of the studies in the literature leverage a non-parametric memory model along with a parametric memory model for the open-domain Table QA task.

In this paper, we describe a novel end-to-end Table QA model, T-RAG, replacing the two-step framework with a single training process. To train T-RAG, we utilize Dense Passage Retrieval (DPR) (Karpukhin et al., 2020) and RAG strategies. Specifically, we jointly train a DPR component (Glass et al., 2021) together with the BART-based (Lewis et al., 2020a) sequence-to-sequence (Seq2Seq) model. To the best of our knowledge, T-RAG is the first Table QA model where the query encoder for a non-parametric dense vector index is fine-tuned along with a parametric generation model. We evaluate the performance of T-RAG on NQ-TABLES (Herzig et al., 2021) and E2E_WTQ (Pan et al., 2021), two recent end-to-end Table QA benchmarks. The experimental results indicate that T-RAG outperforms the state-of-the-art models on the end-to-end Table QA task.

The major contribution of this work is that, we propose the first end-to-end Table QA pipeline, leveraging DPR along with the Seq2Seq component of RAG. T-RAG employs a simple but effective one-step training that reduces error accumulations and simplifies model fine-tuning. In the
experiments, T-RAG achieves state-of-the-art performance on two tasks. We find T-RAG improves the results for end-to-end Table QA on two recent benchmarks. The RAG component of the end-to-end model fine-tuned over Table QA benchmarks also yields state-of-the-art results on the table retrieval task.

2 Related Work

Table Retrieval Traditional table retrieval models usually concatenate tables into documents while disregarding the underlying tabular structure (Pyreddy and Croft, 1997; Wang and Hu, 2002; Liu et al., 2007; Cafarella et al., 2008, 2009). New approaches are proposed to retrieve tables with a set of features of the table, query and table-query pair (Zhang and Balog, 2018b; Sun et al., 2019; Bhagavatula et al., 2013; Shraga et al., 2020a). Zhang and Balog (2018b) uses semantic similarities to build an ad-hoc table retrieval model with various features. A neural ranking model is introduced in Shraga et al. (2020b), where tables are defined as multi-modal objects and the Gated Multimodal Units are used to learn the representation of query-table pairs. Pan et al. (2021) later follows this work and improves the table retrieval with a 2-step retriever. Kostić et al. (2021) discusses the use of dense vector embeddings to enhance the performance of bi- and tri-encoder in retrieving both table and text.

Table QA Most early Table QA solutions are fully supervised models, focusing on converting natural language questions into SQL format and using the SQL-format questions to query the given tables, as seen in Yu et al. (2018); Lin et al. (2019); Xu et al. (2018). Open-domain QA over text (Yu et al., 2020) usually utilizes multiple knowledge sources. For instance, Oguz et al. (2021) proposes a model can convert structured, unstructured and semi-structured knowledge into text for open-domain QA. Therefore, more recent efforts have been put into investigating the use of external knowledge in enhancing the performance of Table QA. Jiménez-Ruiz et al. (2020) first proposes the Semantic Web Challenge on Tabular Data to Knowledge Graph Matching (SemTab) to encourage such solutions for both table understanding and Table QA. Recently, the transformer-based, weakly supervised solutions have been proposed for Table QA. These solutions fall into two categories: (1) Logic form-based solution, such as the TAERT (Yin et al., 2020) model, which is trained to capture the representation of natural language sentences as well as tabular data; (2) Answer cell prediction solutions, such as TAPAS (Herzig et al., 2020) and the RCI (Glass et al., 2020) model. The current state-of-the-art RCI model exploits a transformer-based framework. Instead of retrieving the table cells directly for any given question-table pairs, the RCI model identifies the most relevant columns and rows independently and locates the intersection table cells as the final answers.

End-to-End Table QA Sun et al. (2016) publishes the first end-to-end table cell search framework. This work leverages the semantic relations between cells and maps queries to table cells with relational chains. The DTR model (Herzig et al., 2021) addresses the end-to-end Table QA problem with a table retriever and a TAPAS-based reader model. Later, the CLTR model (Pan et al., 2021) introduces a similar two-step solution, using BM25 as the retriever. The model re-ranks the BM25 results and locates the table cells using the RCI scores. Recently, Chen et al. (2021) proposes a new task for QA over both free text and tables and provides a solution including a retriever with early fusion techniques and a cross-block reader. In addition, the open-domain OTT-QA benchmark is released to evaluate models for end-to-end QA over text and table.

3 The End-to-End Table QA with T-RAG

The overall architecture of T-RAG is illustrated in Figure 1. In this example, we encode the questions “who was the editor for Ikar?” using the query encoder and pre-process the tables, e.g., T_1 and T_2, from the table corpus for encoding. The encoded tables are later indexed into the Approximate Nearest Neighbors (ANN) data structure for querying. The encoded question is appended to each table before inputting it to the BART-based generator for answer prediction. The DPR and the RAG components are trained jointly without explicitly considering the table-level ground truth.

Setup We define the one-step, end-to-end Table QA task as follows. Given a massive corpus C of tables t_i and any natural language question q_i, we train a model to directly generate answer a_i from the table cell without any intermediate steps. Labeled datasets are available to us with ground truth samples in the format of \{q_i, t_i, a_i\} where a_i
stands for the answers.

Table pre-processing is implemented before the training. We process the tables $t_i$ into a structure-preserving format, where: (1) column headers are appended before cell values, separated by a special symbol “|”; and (2) the separator “*” is appended to the end of each row; (3) for the tables with additional information such as titles, we append them in front of the tables. The tables are segmented into the length of 512 tokens for training. For each question, we retrieve hard negatives from the corpus $C$ and use them as additional negative samples to enhance the T-RAG training.

**Soft Hard Negatives** We implement a BM25-based hard negative mining for T-RAG. For each question, we first retrieve a pool of the most relevant tables from the corpus using BM25. From the table pool, we discard the ground truth table. The top-ranked, non-positive tables are used as the hard negative candidates. In the training process, instead of using the top 1 negative table, we exploit a soft hard negative mechanism, where we select the hard negative at random from the top $k$ negative tables.

**RAG** For the implementation of RAG, we jointly train a DPR-based retriever and a BART-based generator. We index the tables in $C$ using a keyword-based search engine, Anserini\(^1\), to harvest the hard negative training samples using BM25. Later, T-RAG exploits BERT\(_{BASE}\) to encode questions along with the ground truth table and the hard negative tables. To train RAG, T-RAG employs the answer-level ground truth and use a Seq2Seq generator, the BART\(_{LARGE}\) model, for answer predictions. The previously encoded tables are indexed with the open-source FAISS (Johnson et al., 2017) library into the ANN data structure for querying. The encoded questions are concatenated to each of the top retrieved tables and used as a prompt to generate the answer. More concretely, the generator predicts probability distributions for possible answer candidates as the next token. The probability distributions are later marginalized to produce a single weighted sequence probability for each answer candidate. Finally, a standard beam search decoder (Sutskever et al., 2014) is used to identify the most relevant candidates as the final answers to the questions at test time. Along with the answers, our model can also return the relevant table $t_i$ containing the correct answers from $C$ for evaluation and annotation purposes.

### 4 Experiments

**Data** We validate T-RAG on two open-domain benchmarks, NQ-TABLES and E2E_WTQ. NQ-TABLES is the table subset of the Natural Questions dataset (Kwiatkowski et al., 2019), with a table corpus extracted from the English Wikipedia articles and samples in the $\{q, T, a\}$ format, where $q$, $T$, and $a$ denote question, ground truth table, and answer, respectively. E2E_WTQ contains the look-up subset of WikiTableQuestions (Pasupat and Liang, 2015). While a substantial amount of tables in NQ-TABLES are transposed infobox tables, the E2E_WTQ only contains well-formatted but more complex tables. The data statistics are shown in Table 1.

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\(^1\)https://github.com/castorini/anserini
In the experiments, we set: (1) training batch size = 128; (2) number of epochs = 2; (3) learning rate = 3e-5; and (4) gradient accumulation steps = 64.

**Evaluation metrics:** Following the evaluation script in SQUAD (Rajpurkar et al., 2016), we evaluate end-to-end Table QA using exact match (EM) and token F1 metrics for NQ-TABLES. The accuracy for the top 1 returned answer and mean reciprocal rank (MRR) are used to measure the performance on E2E_WTQ. We also evaluate T-RAG on the table retrieval task for a fair comparison with existing work. We utilize the original metrics in Herzig et al. (2021) and Pan et al. (2021), with recall (R) for NQ-TABLES, and precision (P), normalized discounted gain (N), and mean average precision (MAP) for E2E_WTQ.

**Experimental Results** We compare the end-to-end Table QA performance of T-RAG against the state-of-the-art DTR and CLTR models in Table 2. We find T-RAG yields better results than the previous best models for both datasets with all evaluation metrics.

To further validate T-RAG against the existing models, we also evaluate the model performance on table retrieval. The table retrieval results for NQ-TABLES and E2E_WTQ are shown in Table 3a and 3b, respectively. The results indicate that T-RAG outperforms the simple baselines models such as BM25, as well as the strong state-of-the-art models in the experiments.

**Qualitative Analysis** We further evaluate the table retrieval results on NQ-TABLES. We notice that the DPR-based baseline of our approach achieves 43.89 for R@1 and 81.57 for R@10; both outperform the state-of-the-art DTR results. In addition, the retrieval performance is further improved with the more effective end-to-end RAG training. To validate the effectiveness of our soft hard negative technique, we test the method on the E2E_WTQ dataset. Instead of using the top 1 negative table from the BM25 results, we set $k = 3$ and achieve a 27.17% absolute gain for Hit@1 accuracy in the end-to-end Table QA task.

Besides, we perform thorough error analysis on E2E_WTQ and find that over 21% of the errors come from questions that involve numerical values. The finding indicates that understanding different types of numbers remains a challenge in Table QA.

**5 Conclusion and Future Work**

In this paper, we present a novel Table QA model that achieves state-of-the-art performance on recent benchmarks. Instead of training a retriever and a reader model independently, T-RAG unifies the procedure into a single pipeline of only one training step, which reduces the error accumulations from two separate models. In the experiments, T-RAG outperforms the current best models for end-to-end Table QA. We additionally demonstrate the advantages of T-RAG with the table retrieval task, and T-RAG beats the existing numbers on both benchmarks.

In the future, we plan to validate T-RAG on domain-specific datasets, such as AIT-QA and TAT-QA (Katsis et al., 2021; Zhu et al., 2021) and extend the model to solve multi-modal QA problems, with the corpus containing both tables and passages, as presented in the OTT-QA and Hybrid-QA benchmarks (Chen et al., 2020a,b). To further improve the model performance, we also plan to investigate algorithms to better understand numeric values.
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