cTBLS: Augmenting Large Language Models with Conversational Tables

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Abstract

Optimizing accuracy and performance while eliminating hallucinations of open-domain conversational large language models (LLMs) is an open research challenge. A particularly promising direction is to augment and ground LLMs with information from structured sources. This paper introduces Conversational Tables (cTBLS), a three-step architecture to retrieve and generate dialogue responses grounded on retrieved tabular information. cTBLS uses Transformer encoder embeddings for Dense Table Retrieval and obtains up to 125% relative improvement over the retriever in the previous state-of-the-art system on the HYRBIDIALOGUE dataset. cTBLS then uses a shared process between encoder and decoder models to perform a coarse+fine tabular knowledge (e.g., cell) ranking combined with a GPT-3.5 LLM response generator to yield a 2x relative improvement in ROUGE scores. Finally, human evaluators prefer cTBLs +80% of the time (coherency, fluency) and judge informativeness to be 4x better than the previous state-of-the-art.

1 Introduction

Equipping conversational AI with multimodal capabilities broadens the range of dialogues that humans have with such systems. A persisting challenge in multimodal conversational AI is the development of systems that produce conversationally coherent responses grounded in textual and non-textual modalities (Sundar and Heck, 2022).

It is well-established that large language models (LLMs) possess real-world knowledge stored within their parameters, as demonstrated by recent research (Roberts et al., 2020; Heinzerling and Inui, 2021). Nevertheless, the incorporation of conversation-specific extrinsic knowledge into these models to yield precise responses remains an active area of investigation. While humans can easily retrieve contextual information from tables by examining rows and columns, LLMs often struggle to identify relevant information amidst conversational distractions.

HYBRIDIALOGUE (Nakamura et al., 2022), a dataset of conversations grounded on structured and unstructured knowledge from tables and text, introduces the task of responding to messages by utilizing information from external knowledge and prior dialogue turns. The authors also present an approach and experimental results on HYBRIDIALOGUE that represents the current state-of-the-art (SoTA).

This paper proposes an extension to the SoTA approach of HYBRIDIALOGUE in the form of Conversational Tables (cTBLS) [1], a novel three-step encoder-decoder architecture designed to augment LLMs with tabular data in conversational settings. In the first step, cTBLS uses a dual-encoder Transformer-based (Vaswani et al., 2017) Dense Table Retriever (DTR) to retrieve the correct table from the entire corpus based on the user's query. The second step employs a fine-tuned dual-encoder Transformer to track system state and rank cells in the retrieved table according to their relevance to the conversation. Finally, cTBLS utilizes GPT-3.5 to generate a natural language response by prompting it with the ranked cells.

While previous research separated knowledge retrieval and response generation between encoder and decoder models, this paper demonstrates that LLM decoders can perform these tasks jointly when prompted with knowledge sources ranked by language model encoders. Furthermore, by pre-training the Dense Table Retriever to perform retrieval over a corpus of tables, cTBLS can be extended to new knowledge sources without re-training, by appending additional knowledge to the corpus.

Compared to the previous SoTA, experiments

[1] Our code will be available at https://github.com/avalab-gt/cTBLS

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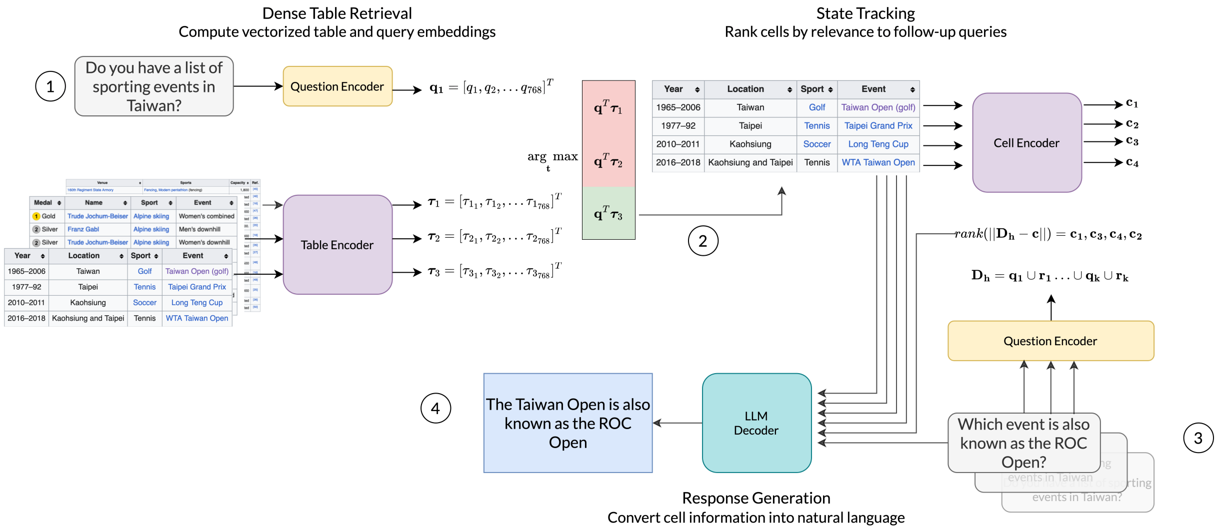


Figure 1: cTBLS for conversations on HYBRIDIALOGUE. Dense Table Retrieval identifies the table most relevant to the initial query. The retrieved table is provided to the state tracker for follow-up queries. State Tracking ranks cells in the table based on their ability to answer a follow-up query. Response Generation utilizes a LLM Decoder provided with the ranked cell information and the follow-up query to convert tabular data into a natural language response and continue the conversation. Details on individual components are provided in Section 3.

on cTBLS show up to 125% relative improvement in table retrieval and a 2x relative improvement in ROUGE scores. In addition, human evaluators prefer cTBLs +80% of the time (coherency, fluency) and judge informativeness to be 4x better than the previous SoTA.

Our contributions are as follows:

1. The introduction of Conversational Tables (cTBLS), a novel three-step encoder-decoder architecture designed to augment LLMs with tabular data in conversational settings.

2. Experimental results demonstrating that Dense Table Retrieval, which utilizes neural models fine-tuned with a summary of tabular information, outperforms sparse techniques based on keyword matching for table retrieval.

3. The presentation of evidence that augmenting state-of-the-art LLM decoders using knowledge sources ranked by encoder language models leads to better results on automatic (ROUGE-Precision) and human (Coherence, Fluency, and Informativeness) evaluation for knowledge-grounded response generation while limiting the number of API calls to these models.

This paper presents the cTBLS system and demonstrates its application to the HYBRIDIALOGUE dataset. In Section 2, we review the existing literature in the fields of Table Question Answering and Knowledge Grounded Response Generation. Section 3 describes the various components of cTBLS as presented in Figure 1. In Section 4, we evaluate the performance of cTBLS against previous methods for conversations over tables and report experimental results from automatic and human evaluations. Finally, Section 5 concludes the paper and outlines potential directions for future research.

2 Related Work

2.1 Table Question Answering

Table Question Answering is a well-researched precursor to conversations over tables. In WIKITABLEQUESTIONS, Pasupat and Liang (2015) transform HTML tables into a knowledge graph and retrieve the correct answer by converting natural language questions into graph queries. FRETS (Jauhar et al., 2016) uses a log-linear model conditioned on alignment scores between cells in tables and individual QA pairs in the training set. Cho et al. (2018) introduce NEOP, a multi-layer sequential network with attention supervision to answer queries conditioned on tables. Hannan et al. (2020) propose MANYMODALQA, which uses a modality selection network and pre-trained text-based QA, Table-based QA, and Image-based QA models to jointly answer questions over text, tables, and images. Chen et al. (2020c) present HYBRIDER, which performs multi-hop QA over tables using keyword-matching for cell linking followed by BERT (Devlin et al., 2019) for reasoning. Chen et al. (2020a) propose OTT-QA, which uses a fusion retriever to identify relevant tables and text and a cross-block reader based on a long-range Sparse Attention Transformer (Ainslie et al., 2020) to choose the correct answer. Heck and Heck (2020) perform multi-task fine-tuning of Transformer encoders by modeling slot filling as question answering over tabular and visual information in Visual Slot. Herzig et al. (2020) and Yin et al. (2020) extend BERT for Table Question Answering by pre-training a masked language model over text-table pairs in TAPAS and TaBERT, respectively. Recent work building off the Transformer architecture for Table Question Answering includes (Eisenschlos et al., 2021; Li et al., 2021; Herzig et al., 2021; Zayats et al., 2021; Zhao et al., 2022; Huang et al., 2022; Yang et al., 2022; Chen, 2022). Jin et al. (2022) provide a comprehensive survey of advancements in Table Question Answering.

2.2 Knowledge Grounded Response Generation

Early work related to grounding responses generated by language models in real-world knowledge was motivated by the need to improve prior information for open-domain dialogue (Heck et al., 2013; Hakkani-Tür et al., 2014; Hakkani-Tür et al., 2014; Huang et al., 2015; Jia et al., 2017). More recently, knowledge grounded response generation has been applied to mitigate the hallucination problem (Maynez et al., 2020; Shuster et al., 2021) in LLMs. RAG (Lewis et al., 2020) fine-tunes LLMs using Dense Passage Retrieval (Karpukhin et al., 2020) over a Wikipedia dump to ground responses for Open Domain Question Answering. KGPT (Chen et al., 2020b) and SKILL (Moiseev et al., 2022) pre-train a Transformer encoder (Vaswani et al., 2017) with English Wikidump for Natural Language Generation. Fusion-in-Decoder (Izacard and Grave, 2021) fine-tunes decoder models using evidence acquired through Dense Passage Retrieval.

Recent research also includes a dual-stage approach where LLMs generate knowledge sources based on prompts (Yu et al., 2022; Bonifacio et al., 2022; Jeronymo et al., 2023). Closest to our work, Wizard of Wikipedia (Dinan et al., 2018) jointly optimizes an encoder-decoder Transformer to produce dialogue responses conditioned on retrieved knowledge and dialogue context but does not extend their approach to the multiple modalities. REPLUG (Shi et al., 2023) ensembles output responses generated by prompting large language models with inputs from a dense retriever in a zero-shot setting. However, this requires multiple API calls to state-of-the-art LLMs. LLM-AUGMENTER (Peng et al., 2023) incorporates external knowledge in LLM responses by matching keywords in dialogue state to candidate knowledge sources obtained through web-search. A survey of knowledge fusion in LLMs is available in Colon-Hernandez et al. (2021) and Richardson and Heck (2023).

In contrast to prior research that focuses on either Table Question Answering or Knowledge Grounded Response Generation, our work, cTBLS, addresses the challenge of generating responses grounded on tabular knowledge. Moreover, while cTBLS is fine-tuned to retrieve tables and filter out incorrect references, it leverages the power of SoTA pre-trained LLMs for response generation. Furthermore, by fine-tuning open-source table and knowledge retrievers to remove inaccurate references, cTBLS reduces the number of API calls to the SoTA LLMs.

3 Method

The challenge of developing conversational systems grounded in tabular information consists of three tasks, namely table retrieval, system state tracking, and response generation. Table retrieval requires identifying the most relevant table in the dataset based on a given natural language query. System state tracking is responsible for ranking the cells in the table, enabling the system to provide responses to follow-up queries about the table. Finally, response generation involves converting the ranked cells into a natural language response.

3.1 Table Retrieval

Table retrieval is a prerequisite to answering queries when the exact table to converse over is unspecified. The objective is to identify the correct table from a vast corpus. cTBLS proposes formulating table retrieval as document retrieval by assigning a relevance score to each table based on its relevance to the natural language query. Inspired by Karpukhin et al. (2020) and Huang et al. (2013), cTBLS uses a dual-encoder-based Dense Table Retrieval (DTR) model. The DTR model pre-computes a vectorized embedding of all tables in the corpus. Given a

Figure 2: An example of table-associated text in the context of Wikipedia, where the input to the DTR text-encoder includes the page title, the introduction to the article, the section title, and the introduction paragraph.

query at inference, the retrieved table is closest to the query in the embedded space, indicated by the upper-left portion of Figure 1.

The DTR model consists of a table encoder and a question encoder, initialized from RoBERTa-base (Liu et al., 2019). The input to the table encoder comprises the table's title and, if available, textual information associated with the table. Figure 2 presents an example of table-associated text in the context of Wikipedia, where introductions from the page and section provide additional grounding. The input to the question encoder is the current query to be answered. Taking the average over the sequence of the last hidden state at the table and question encoder results in 768-dimensional embeddings of the table information and the query.

The DTR model is optimized through a contrastive prediction task, which aims to maximize the similarity between embeddings of a given query q and the table to be retrieved τ while minimizing the similarity to other incorrect tables τ_{n_i} for $i = 1, \ldots, N$. As per (Karpukhin et al., 2020), normalized embedding vectors are utilized to optimize the objective in Equation 1:

$$\arg\min_{\tau} \left(-\log \frac{e^{q \cdot \tau}}{e^{q \cdot \tau} + \sum_{i=1}^{N} e^{q \cdot \tau_{n_i}}} \right) \quad (1)$$

Given a batch B of d-dimensional query embeddings $\mathbf{Q}$ and table embeddings $\mathbf{T}$, the DTR model computes the similarity $\mathbf{Q}\mathbf{T}^T (\in \mathbb{R}^{B \times B})$ between every query and table in the batch. This similarity computation enables the sampling of negatives from other query-table pairs, resulting in B^2 training samples in each batch, consisting of B positive pairs along the diagonal and $B^2 - B$ negatives.

3.2 Coarse System State Tracking

Given a table, system state tracking involves ranking cells in the table by their relevance to conversational queries. In contrast to quesiton-answering, conversational queries require leveraging information from external modalities in conjunction with prior dialogue turns to generate coherent responses (Sundar and Heck, 2022). cTBLS addresses system state tracking through two sub-tasks - coarse and fine system state tracking. Coarse system state tracking ranks cells in the table, while fine system state tracking identifies fine-grained information in the most relevant cell to answer the query.

cTBLS uses a RoBERTa-base dual-encoder architecture for coarse system state tracking. The cell encoder embeds all cells and associated hyperlinked information, and the question encoder generates embeddings for the dialogue history ($\mathbf{D_h}$) that includes the current turn's query as well as previous queries and responses.

To rank cells based on their relevance to the follow-up query, as illustrated in the upper-right section of Figure 1, the question and cell encoders are optimized using a triplet loss configuration. This optimization aims to minimize the distance between the anchor $\mathbf{D_h}$ and the positive cell c, while pushing the negative cell $\bar{c}$ further away from $\mathbf{D_h}$ by a margin m (Equation 2).

$$\arg\min_{c_i} \left(\max\{d(\mathbf{D_h}, c) - d(\mathbf{D_h}, \bar{c}) + m, 0\} \right) \quad (2)$$

$$d(x, y) = ||x - y||_2 \quad (3)$$

For our approach, we utilize an anchor-positive-negative triplet consisting of the complete dialogue history (including queries and responses from previous turns) concatenated with the current query as the anchor, the correct cell as the positive, and other cells from the same table that are not relevant to the query as negatives. We measure the distance between the anchor and the positive and between the anchor and the negatives using the 2-norm distance function $d(\cdot)$.

3.3 Fine System State Tracking and Response Generation

In contrast to coarse system state tracking, fine system state tracking involves identifying the exact phrase that answers the query from a ranked subset. The extracted phrase is converted into a natural language response that is coherent within the context of the conversation.

cTBLS employs GPT-3.5 (Brown et al., 2020) to perform fine system state tracking and response generation jointly. GPT-3.5 is prompted to generate a natural language response to a follow-up query conditioned on cells of the table ranked by their relevance to the query as obtained from the coarse state tracker. The prompt includes the dialogue history, ranked knowledge sources, and the query to be answered. The bottom-right section of Figure 1 outlines this process.

4 Experiments

4.1 HybriDialogue

The HybriDialogue dataset (Nakamura et al., 2022) comprises 4800 natural language conversations grounded in text and tabular information from Wikipedia. Crowdsourced workers break down multi-hop questions from the OTT-QA dataset (Chen et al., 2020a) into natural questions and conversational responses related to tabular data. On average, dialogues in the dataset consist of 4-5 conversation turns, with a total of 21,070 turns available in the dataset. Examples of conversations can be found in Figures 3 and 4.

4.2 Table Retrieval

The first conversation turn of HybriDialogue requires selecting the correct table based on the input query for which we use the Dense Table Retriever outlined in Section 3.1. The Dense Table Retriever is fine-tuned for 20 epochs using Adam (Kingma and Ba, 2014) with a learning rate of 1e-6 and a linear learning schedule with five warmup steps. The loss function is a modification of the contrastive loss implementation from ConVIRT (Zhang et al., 2022), with image embeddings replaced by table embeddings. The table retriever used in the HybriDialogue paper (Nakamura et al., 2022) was the BM25Okapi Retriever (Trotman et al., 2014) from rank-bm25. According to the results presented in Table 1, cTBLS-DTR outperforms BM25 in terms of Mean Reciprocal Rank (MRR), Top-1 Accuracy, and Top-3 Accuracy on HybriDialogue.

	MRR @10	Top 1 Acc	Top 3 Acc
BM25	0.491	0.345	0.460
cTBLS-DTR	**0.846**	**0.777**	**0.901**

Table 1: BM25 vs cTBLS-DTR for retrieval on first turn of conversation, results on HybriDialogue testing dataset. cTBLS-DTR obtains up to 125% relative improvement over sparse table retrieval

4.3 Coarse State Tracking

Coarse state tracking ranks cells from a table based on their relevance to a query. As before, the dual-encoder coarse state tracker of cTBLS consists of RoBERTa-base fine-tuned using Adam with a learning rate of 1e-6 and a linear learning schedule with five warmup steps. In contrast to table retrieval, the state tracker uses triplet margin loss with a margin of 1.0 (Equation 2) instead of contrastive loss (Equation 1). The results, as demonstrated in Table 2, show that fine-tuning RoBERTa-base solely on HybriDialogue surpasses the performance of SentenceBERT (Reimers and Gurevych, 2019). Furthermore, it nearly attains the same MRR @10 as TaPas (Herzig et al., 2020), even without additional table pre-training on the SQA dataset (Iyyer et al., 2017).

	MRR@10
SentenceBERT (Reimers and Gurevych, 2019)	0.603
TaPas (Herzig et al., 2020)	**0.689**
cTBLS - RoBERTa-base	0.683

Table 2: System state tracking results on HybriDialogue. cTBLS achieves nearly the same Mean Reciprocal Rank (MRR) @ 10 as TaPaS, without additional table pre-training on SQA (Iyyer et al., 2017)

4.4 Fine State Tracking and Response Generation

cTBLS uses GPT-3.5 (text-davinci-003) with the existing dialogue context, the current query, and the retrieved references from coarse state tracking to obtain a natural language response. Since fine-tuning the best available version of the model is cost prohibitive, we opt to prompt GPT-3.5 to generate responses instead.

	Top-1	Top-3	Top-10
cTBLS - RoBERTa-base	0.559	0.778	0.925

Table 3: Top-k accuracy for cTBLS on coarse system state tracking. cTBLS ranks the correct cell as the top reference in 56% of follow-up queries on HybriDialogue. The correct cell is ranked in the Top-3 and Top-10 retrievals in approximately 78% and 93% of conversations, respectively.

Model	TR	KR	RG	ROUGE-1	ROUGE-2	ROUGE-L
-	BM25	Top-1	DialoGPT	0.207	0.042	0.181
-	BM25	Top-3	DialoGPT	0.212	0.045	0.186
-	BM25	Top-1	GPT3.5	0.428	0.207	0.369
-	BM25	Top-3	GPT3.5	0.475	0.242	0.413
-	DTR	Top-1	DialoGPT	0.222	0.051	0.195
-	DTR	Top-3	DialoGPT	0.226	0.059	0.199
-	DTR	Top-1	GPT3.5	0.494	0.255	0.424
-	DTR	Top-3	GPT3.5	0.560	0.295	0.479
HYBRIDIALOGUE	Gold	Top-1	DialoGPT	0.438	0.212	0.375
cTBLS NoK	Gold	-	GPT3.5	0.487	0.229	0.422
cTBLS Top-1	Gold	Top-1	GPT3.5	0.603	0.304	0.517
cTBLS Top-3	Gold	Top-3	GPT3.5	**0.642**	**0.322**	**0.548**

Table 4: Ablation study on automatic evaluation metrics ROUGE-1, ROUGE-2, and ROUGE-L Precision. Using Dense Table Retrieval (DTR) improves results over BM25 across Top-1 and Top-3 knowledge for DialoGPT and GPT3.5. Furthermore, using Top-3 knowledge sources results in better results than using only Top-1 knowledge sources for DialoGPT and GPT3.5 using both table retrieval methods. cTBLS No Knowledge (NoK), Top-1 Knowledge, Top-3 Knowledge, and HYBRIDIALOGUE use ground truth table retrieval. cTBLS exhibits a 2x relative improvement in ROUGE Precision over HYBRIDIALOGUE. TR: Table Retrieval, KR: Knowledge Retrieval, RG: Response Generation

The results presented in Table 3 demonstrate that the coarse state tracker successfully retrieves the correct cell in approximately 56% of conversations during inference. Furthermore, it achieves Top-3 and Top-10 retrievals in approximately 78% and 93% of conversations, respectively. Motivated by these results, the fine state tracker of cTBLS is evaluated in two different configurations by prompting GPT-3.5 augmented with the Top-1 and Top-3 knowledge references (cTBLS Top-1 and cTBLS Top-3). Due to limits on token length associated with the OpenAI API, we remove stopwords from the knowledge provided in the prompt and do not experiment with Top-10 knowledge augmentation.

Since LLMs store factual information in their weights (Roberts et al., 2020; Heinzerling and Inui, 2021), we compare to few-shot prompting (using two examples) with no knowledge sources (cTBLS-NoK). Furthermore, to enable a meaningful comparison with existing research (Nakamura et al., 2022), we measure cTBLS against the system proposed by HYBRIDIALOGUE that utilizes a fine-tuned DialoGPT-medium (Zhang et al., 2019) model augmented with Top-1 knowledge.

Table 4 presents ROUGE-1, ROUGE-2, and ROUGE-L precision (Lin, 2004) for all models assessed. The results demonstrate that superior downstream performance can be achieved through improvements in table retrieval. Specifically, when keeping the number of knowledge sources constant, we observe an improvement in ROUGE precision scores when transitioning from BM25 to DTR, and from DTR to gold table retrieval. The inclusion of additional knowledge sources leads to an improved n-gram overlap with the ground truth reference, as evidenced by the Top-3 knowledge augmented models outperforming their Top-1 counterparts utilizing the same table retriever, and cTBLS Top-1 outperforming the baseline model cTBLS NoK. Moreover, cTBLS Top-3 achieves the best performance across all automatic metrics, suggesting the benefits of splitting knowledge retrieval into coarse and fine state tracking, and utilizing additional knowledge sources. Finally, all three configurations of cTBLS demonstrate superior performance to HYBRIDIALOGUE.

4.5 Human Evaluation

To gain a deeper understanding of cTBLS, we conducted human evaluation using the metrics outlined by Nakamura et al. (2022), namely Coherence, Fluency, and Informativeness. For the evaluation of these metrics, we enlisted crowd workers from Amazon Mechanical Turk (AMT) to assess 50% of the test data. The evaluation process involved a comparison between the responses generated by HYBRIDIALOGUE and cTBLS Top-3.

	cTBLS Top-3 vs HYBRIDIALOGUE
Coherence	0.842
Fluency	0.827

Table 5: Coherence and Fluency - cTBLS Top-3 is more conversationally coherent than the best performing HYBRIDIALOGUE system 84.2% of the time and is more fluent 82.7% of the time.

	Informativeness
HYBRIDIALOGUE	0.124
cTBLS - NoK	0.306
cTBLS Top-1	0.456
cTBLS Top-3	**0.500**

Table 6: Human Evaluation Metrics - Fraction of cases where model response is semantically equivalent to ground truth response. Using more knowledge sources results in responses that are more informative, helping reduce hallucination.

In accordance with the methodology delineated in Nakamura et al. (2022), Coherence was defined as the degree to which a response continued the conversation in a logically coherent manner based on prior context. Fluency, conversely, was determined by evaluating absence of grammatical and spelling errors, and appropriate use of parts of speech.

To ensure the quality of the evaluated responses, we engaged crowd workers possessing a Masters qualification on AMT and originating from English-speaking countries (USA, Canada, Australia, New Zealand, or Great Britain). Each task required approximately 30 seconds to complete, and workers were remunerated at a rate of $0.05 per task. Moreover, to minimize bias and guarantee the dependability of the evaluations, we assigned two crowd workers to assess each response, with a response deemed more coherent or fluent only if both evaluations concurred.

The results presented in Table 5 reveal that the responses generated by cTBLS Top-3 were more coherent than those produced by HYBRIDIALOGUE in 84.2% of cases and exhibited greater fluency 82.7% of the time, suggesting that improvements in table retrieval, knowledge retrieval, and response generation lead to better downstream performance.

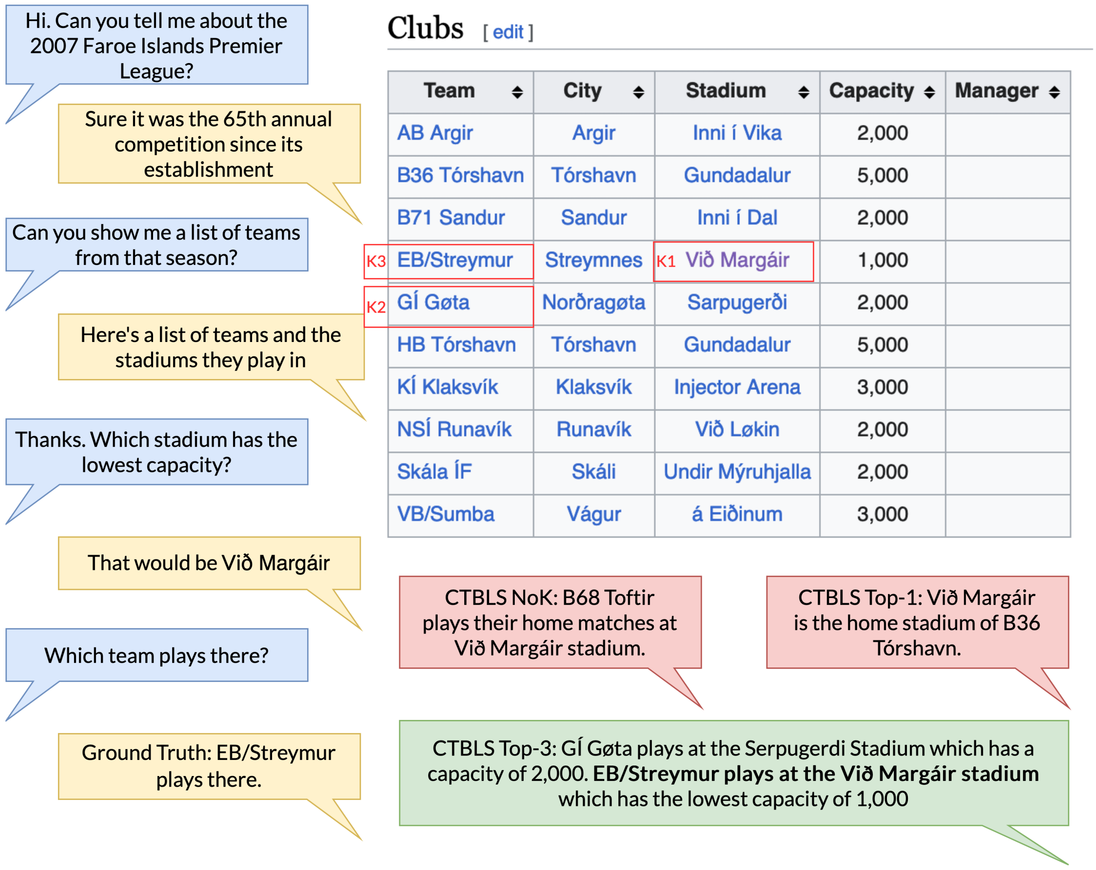
Informativeness represents the accuracy of machine-generated responses when compared to the ground-truth (Nakamura et al., 2022) and serves as a measure of hallucination in LLMs. Hallucinated responses tend to be less informative, deviating significantly from the ground-truth.

To evaluate informativeness, crowd workers determined whether generated responses were semantically equivalent to the ground truth response. Each response was assessed by two Turkers, and a response was deemed more informative only if there was inter-annotator agreement. The absence of illustrative examples in the prompting process resulted in responses generated by cTBLS Top-1 and cTBLS Top-3 being longer than the ground truth response. Consequently, the knowledge-augmented cTBLS responses were considered informative if all the information provided in the ground truth was encapsulated in the model response, even if cTBLS included supplementary information.

The data in Table 6 indicate that cTBLS Top-3 encompasses the same information as the ground truth response 50% of the time, a higher rate than cTBLS Top-1 at 45.6%, exemplifying the benefits of partitioning retrieval into coarse and fine state tracking and augmenting with additional knowledge. Based on these findings, we hypothesize that the attention mechanism in decoder models facilitates additional knowledge retrieval. cTBLS NoK generates the correct response 30.6% of the time, suggesting that HYBRIDIALOGUE comprises questions and answers predicated on general world knowledge embedded in the weights of LLMs. Responses produced by HYBRIDIALOGUE are informative in merely 12.4% of instances.

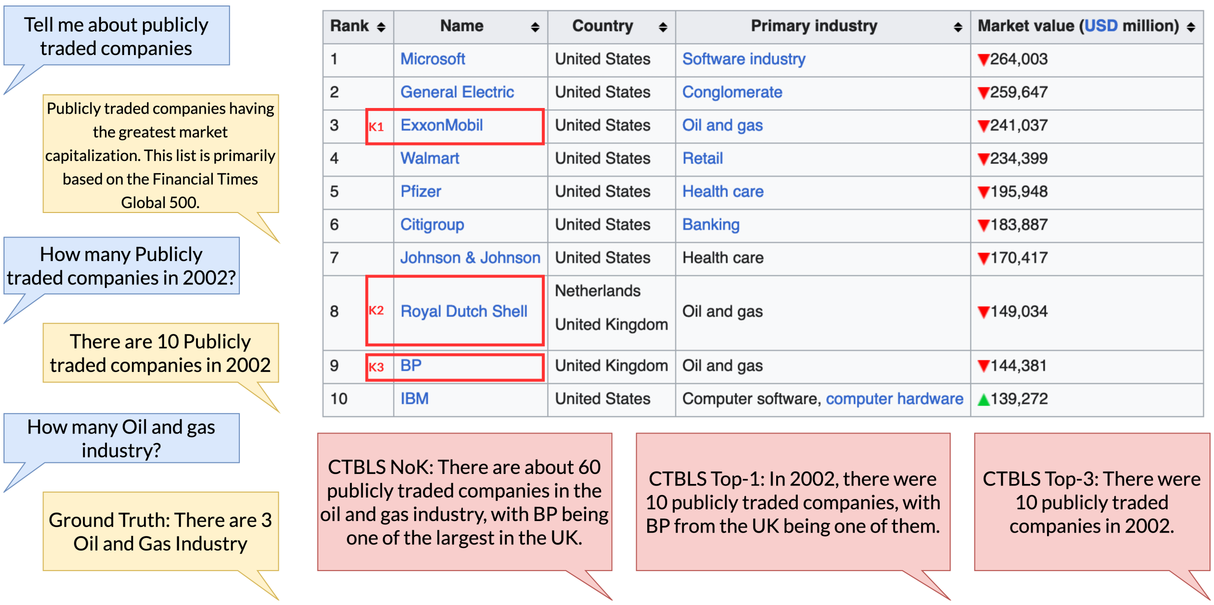
Figure 3 presents a comparison of responses generated by various configurations of cTBLS on the HYBRIDIALOGUE dataset. The entire dialogue history constitutes the context and is depicted as an exchange between the user (in blue) and the system (in yellow). The final question box represents the follow-up query to be addressed, while the last answer chat box indicates the ground truth response. Knowledge K1, K2, and K3 correspond to cells of the table retrieved during state tracking, based on which responses are produced. cTBLS NoK generates a response solely relying on the context, cTBLS Top-1 formulates a response conditioned on K1, and cTBLS Top-3 devises a response based on K1, K2, and K3.

cTBLS NoK creates a hallucinated response, answering with the random Faroese club B68 Toftir. Similarly, cTBLS Top-1 hallucinates a response, opting for B36 Tórshavn, as K1 refers to the stadium Viò Margáir rather than the correct club's



Team	City	Stadium	Capacity	Manager
AB Argir	Argir	Inni í Vika	2,000	
B36 Tórshavn	Tórshavn	Gundadalur	5,000	
B71 Sandur	Sandur	Inni í Dal	2,000	
EB/Streymur	Streymnes	Við Margáir	1,000	
GÍ Gøta	Norðragøta	Sarpugerði	2,000	
HB Tórshavn	Tórshavn	Gundadalur	5,000	
KÍ Klaksvík	Klaksvík	Injector Arena	3,000	
NSÍ Runavík	Runavík	Við Løkin	2,000	
Skála ÍF	Skáli	Undir Mýruhjalla	2,000	
VB/Sumba	Vágur	á Eiðinum	3,000	

Figure 3: Generated responses vs Ground Truth on HybriDialogue test set. Questions are in blue and responses in yellow. K1, K2, and K3 represent the Top 3 knowledge sources ranked by relevance to the query "Which team plays there?". cTBLS Top-3 is able to leverage K3 to generate the correct response while cTBLS NoK hallucinates a response and cTBLS Top-1 generates an incorrect response based on K1. Table obtained from Wikipedia available here



Rank	Name	Country	Primary industry	Market value (USD million)
1	Microsoft	United States	Software industry	▼264,003
2	General Electric	United States	Conglomerate	▼259,647
3	ExxonMobil	United States	Oil and gas	▼241,037
4	Walmart	United States	Retail	▼234,399
5	Pfizer	United States	Health care	▼195,948
6	Citigroup	United States	Banking	▼183,887
7	Johnson & Johnson	United States	Health care	▼170,417
8	Royal Dutch Shell	Netherlands United Kingdom	Oil and gas	▼149,034
9	BP	United Kingdom	Oil and gas	▼144,381
10	IBM	United States	Computer software, computer hardware	▲139,272

Figure 4: Generated responses vs Ground Truth on HybriDialogue test set. Despite selecting the rows of the table corresponding to Oil and gas industries, cTBLS NoK, Top-1, and Top-3 struggle with counting and hallucinate a response. Table obtained from Wikipedia available here

name. In contrast, cTBLS Top-3 produces the accurate response, EB/Streymur, since K3 contains the necessary information. This example demonstrates the benefits of augmenting response generation with additional pertinent knowledge, which aids in mitigating the hallucination problem (Maynez et al., 2020).

5 Conclusion

In this paper, we introduce Conversational Tables (cTBLS), a system designed to address multi-turn dialogues that are grounded in tabular data. cTBLS separates tabular dialogue into three distinct tasks, specifically table retrieval, system state tracking, and response generation. The dense table retrieval system of cTBLS yields an enhancement of up to 125% relative to keyword-matching based techniques on the HYBRIDIALOGUE dataset, with regard to Top-1 Accuracy and Mean Reciprocal Rank @ 10. Furthermore, cTBLS conducts system state tracking utilizing a two-step process shared between encoder and decoder models. This methodology results in natural language responses exhibiting a 2x relative improvement in ROUGE scores. Human evaluators favor cTBLS +80% of the time (coherency and fluency) and judge informativeness to be 4x better than the previous state-of-the-art.

6 Limitations

Although cTBLS enhances LLMs with tabular knowledge to generate grounded responses, certain limitations remain to be addressed.

Firstly, the efficacy of cTBLS is constrained by the total number of knowledge sources employed during the augmentation process. Token length restrictions in the OpenAI API limit the knowledge augmentation to the top three cells of the table. Another limitation is the incapacity of cTBLS to handle queries pertaining to the entire table. Figure 4 demonstrates one such instance in which the state tracker module accurately retrieves three rows of the table corresponding to oil and gas industries, yet the response generation module fails to utilize this information when transforming the retrieved state into a response. Generally, cTBLS encounters difficulties with counting, comparing the values of cells, and other mathematical operations, an issue we aim to address in future research.

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