

ChatQA: Building GPT-4 Level Conversational QA Models

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Abstract

In this work, we introduce ChatQA, a family of conversational question answering (QA) models that obtain GPT-4 level accuracies. Specifically, we propose a two-stage instruction tuning method that can significantly improve the zero-shot conversational QA results from large language models (LLMs). To handle retrieval-augmented generation in conversational QA, we fine-tune a dense retriever on a multi-turn QA dataset, which provides comparable results to using the state-of-the-art query rewriting model while largely reducing deployment cost. Notably, our ChatQA-70B can outperform GPT-4 in terms of average score on 10 conversational QA datasets (54.14 vs. 53.90), without relying on any synthetic data from OpenAI GPT models.

1. Introduction

Most recently, ChatGPT (OpenAI, 2022) and its follow ups (OpenAI, 2023; Anthropic, 2023b; Google, 2023) have led to the paradigm shift of building question answering (QA) models in production and research community. In particular, the following aspects of the QA models are preferred in real-world applications: *i)* The users can interact with the QA models in a conversational way, thus one can easily raise follow-up questions; *ii)* The generalist models can generate answers in zero-shot manner without dataset-specific fine-tuning, while matching the accuracies of fine-tuned expert models; *iii)* The QA models are capable of integrating retrieved chunks of evidence in both open-domain or long document settings, where the provided context is much longer than the context window of LLM (e.g., Anthropic, 2023a; Xu et al., 2023b). To this end, we focus on the conversational QA covering these three aspects.

However, building a conversational QA model that can match the accuracy of the state-of-the-art black-box model, i.e., GPT-4 (OpenAI, 2023), is still a grand challenge for the

research community. In this work, we introduce ChatQA-70B, a white-box conversational QA model with a detailed specification and GPT-4 level accuracy, through the proposed two-stage instruction tuning recipe, an enhanced retriever for retrieval-augmented generation (RAG) in conversational QA, and a detailed data curation process.

Specifically, we make the following contributions:

1. We propose a two-stage instruction tuning method and a dataset curation recipe that can largely enhance LLM’s capability of integrating user provided or retrieved context for zero-shot conversational QA tasks. We demonstrate that our method significantly outperforms regular instruction tuning or RLHF-based recipes (e.g., Llama2-Chat).
2. For RAG in conversational QA, we show that fine-tuning the state-of-the-art single-turn query retriever on both human-annotated or synthetic multi-turn QA dataset works as well as utilizing the state-of-the-art LLM-based query rewriting model, i.e., GPT-3.5-turbo (OpenAI, 2022).
3. We build a family of ChatQA models based on Llama2-7B, Llama2-13B, Llama2-70B (Touvron et al., 2023), and in-house GPT-8B, GPT-22B models. We conduct comprehensive study on 10 conversational QA datasets, including 5 datasets with long documents that need retrieval and 3 datasets with tables. In terms of average score, our ChatQA-70B model (54.14) can outperform GPT-3.5-turbo (50.37) and GPT-4 (53.90) without utilizing any synthetic data from ChatGPT models.
4. We study the “unanswerable” scenario, where the desired answer is not included in the provided or retrieved context, thus the LLM needs to generate “cannot answer” to avoid hallucination. Our ChatQA-70B outperforms GPT-3.5-turbo in this regard, while still has a slight gap compared to GPT-4 (around 3.5%).

We organize the rest of the paper as follows. We discuss related work in § 2. We introduce the two-stage instruction tuning method and data curation for ChatQA in § 3, and study retrieval in conversational QA in § 4. We present the

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experimental setup in § 5, results in § 6, and conclude the paper in § 7.

2. Related Work

2.1. Conversational QA

Question answering in a conversational way naturally improves user experiences by addressing follow-up questions. The model can also raise clarification questions for users if necessary, which can reduce hallucination. Thus, it becomes the default format of deploying QA models in production (e.g. OpenAI, 2022; Google, 2023; Anthropic, 2023b).

In recent years, many conversational QA datasets have been introduced, where the models are asked to answer questions based on provided context or documents. The provided context or documents can be: *i*) text-only documents from various domains (Feng et al., 2020; Anantha et al., 2021; Saeidi et al., 2018; Adlakha et al., 2022; Aliannejadi et al., 2021; Reddy et al., 2019; Qu et al., 2020; Wu et al., 2023; Deng et al., 2022; Guo et al., 2021; Choi et al., 2018; Campos et al., 2020), or *ii*) documents comprising plain text along with tables (Pasupat & Liang, 2015; Nakamura et al., 2022; Chen et al., 2022a).

In contrast to the latest LLM-based generalist solution (e.g., OpenAI, 2022), most of the previous studies focus on fine-tuned expert models on specific domains or datasets (Feng et al., 2020; Izacard & Grave, 2021; Chen et al., 2022a; Gao et al., 2022; Nakamura et al., 2022; Adlakha et al., 2022; Wu et al., 2023).

2.2. Retrieval for Multi-Turn QA

Conversational QA involves retrieval-augmented generation (RAG) in open-domain setting, or when the provided documents are longer than the context window of LLM. The dense retrievers are usually trained to retrieve the top- k relevant chunks given a single question (e.g., Lin et al., 2023a; Wang et al., 2022a; Izacard et al., 2022). In conversational QA, the follow-up questions (e.g., with pronouns referring to entities mentioned in the previous conversation) may have insufficient information for retrieval, while feeding them along with all of the dialogue history can be redundant, thus leading to sub-optimal results.

2.2.1. CONVERSATIONAL QUERY REWRITING

Most of the previous solutions are query rewriting methods. The latest turn of question is rewritten to be a standalone query without additional information from previous dialogue history (Vakulenko et al., 2021a; Ye et al., 2023; Mo et al., 2023), so it can be directly used by retrieval model to retrieve relevant context (Vakulenko et al., 2021b; Mele et al., 2021; Raposo et al., 2022; Mo et al., 2023). Many

datasets have been collected to facilitate this line of research (Elgohary et al., 2019; Chu et al., 2020; Qu et al., 2020; Anantha et al., 2021; Brabant et al., 2022), alongside multiple proposed query rewriting methods (Ishii et al., 2022; Yu et al., 2020; Wu et al., 2022; Del Tredici et al., 2021; Chen et al., 2022b; Galimzhanova et al., 2023). For example, Wu et al. (2022) and Chen et al. (2022b) proposed to use reinforcement learning methods for the query rewriting. Yu et al. (2020) investigated few-shot generative models like GPT-2 for query rewriting. Galimzhanova et al. (2023) studied instruction tuned GPT-3.5-turbo and showed that it achieved state-of-the-art results for conversational query rewriting.

2.2.2. FINE-TUNING RETRIEVER FOR MULTI-TURN QA

Some previous work fine-tune a single-turn query retriever on in-domain conversational query and context pairs (Feng et al., 2020; Gao et al., 2022; Adlakha et al., 2022; Wu et al., 2023), so it can directly take a concatenation of dialog history and current query as input. In this work, we focus on the zero-shot evaluation. We fine-tune a single-turn query retriever on a high-quality multi-turn dataset. Then, we evaluate zero-shot capability of the fine-tuned retriever on five benchmark datasets. Surprisingly, we find this simple approach can obtain comparable zero-shot results as the state-of-the-art query rewriting model, i.e., GPT-3.5-turbo.

2.3. Instruction Tuning

The goal of instruction tuning is to equip LLMs with the capability to follow natural language instructions (Wei et al., 2022a; Sanh et al., 2022; Mishra et al., 2022; Iyer et al., 2022; Du et al., 2022; Ouyang et al., 2022; Wang et al., 2023b; Zhang et al., 2023b; Gao et al., 2023; Chung et al., 2022; Muennighoff et al., 2022; Xu et al., 2023a; Wang et al., 2022c; Zhou et al., 2023). There has been a surge in the development of high-quality instruction tuning datasets, including FLAN (Chung et al., 2022), Self-Instruct (Wang et al., 2022b), unnatural Instructions (Honovich et al., 2022), Dolly (Conover et al., 2023b), and OpenAssistant (Köpf et al., 2023).

Although numerous research on instruction tuning has been conducted, a few works focused on improving RAG or context awareness generation for QA. Lin et al. (2023b) introduced a retrieval-augmented instruction tuning method, which appends top- k retrieved chunks for LLM fine-tuning. Wang et al. (2023a) applied instruction tuning after retrieval-augmented pretraining. In contrast, we propose a two-stage instruction tuning method to improve generation with retrieval or provided context. We find that appending top- k retrieved chunks for LLM fine-tuning does not help for a wide range of conversation QA tasks (see §6.3 for details).

Similar to the latest work (Zhang et al., 2023a), we demon-

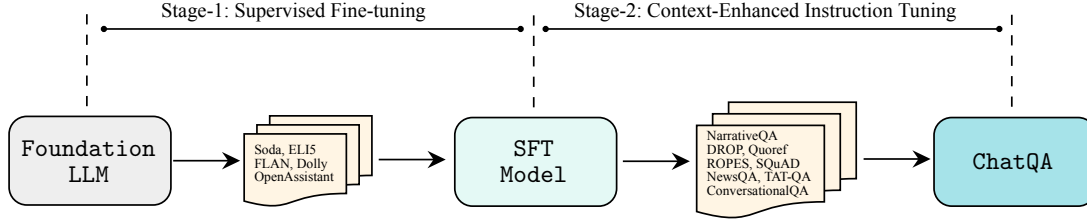


Figure 1. Two-stage instruction tuning framework for ChatQA.

strate that adding a small amount of “unanswerable” samples in instruction tuning can steer the model to generate “cannot answer” output when it is necessary, thus significantly reduce hallucination.

After the release of ChatGPT (OpenAI, 2022), instruction tuning became an indispensable ingredient to build the state-of-the-art dialogue agent which has astonishing zero-shot capability to a wide range of tasks. The conversational QA capability plays a crucial role in a dialogue agent, yet there has been limited research dedicated to this vital aspect.

3. ChatQA

In this section, we propose a two-stage instruction tuning method for ChatQA. See Figure 1 for an illustration. Our method starts with a pretrained LLM foundation model. At stage-1, we apply supervised fine-tuning (SFT) as in Ouyang et al. (2022) on a blend of instruction-following and dialog datasets. After that, our model exhibits good capability to follow instructions as a conversational agent. However, its capability for contextualized or RAG-based QA remains limited. Hence, we introduce a subsequent stage, called context-enhanced instruction tuning, which is designed specifically for enhancing our model’s capability for context-aware or retrieval-augmented generation in conversational QA.

3.1. Stage-1: Supervised Fine-tuning

To construct a large and comprehensive supervised fine-tuning (SFT) dataset, we follow Xu et al. (2023b), Wang et al. (2023a) and gather a combined set of 128K SFT samples from high-quality instruction tuning datasets. It consists of 1) a social dialogue dataset Soda (Kim et al., 2022), 2) a long-form QA dataset ELI5 containing elaborate answers (Fan et al., 2019), 3) FLAN and chain-of-thought datasets (Wei et al., 2022b; Chung et al., 2022; Longpre et al., 2023), 4) LLM synthetic instruction tuning datasets, including Self-Instruct (Wang et al., 2022b) and Unnatural Instructions (Honovich et al., 2022), and 5) a private crowd-sourced conversational dataset, as well as two public human-written conversation datasets: OpenAssistant (Köpf et al., 2023), and Dolly (Conover et al., 2023a).

We unify the structure of all the SFT data in a conversational format. We first add a “System” role at the beginning to set up a general instruction guiding LLM to provide polite and helpful answers. We also add “User” and “Assistant” roles to incorporate instruction and response pairs from the instruction tuning datasets. We apply fine-tuning using this unified format on an LLM foundation model.

3.2. Stage-2: Context-Enhanced Instruction Tuning

To further enhance the model’s conversational QA capability over a given context, we conduct a second stage instruction tuning, which integrates contextualized QA datasets into the instruction tuning blend. Specifically, the stage-2 instruction tuning datasets consist of a blend of contextualized single-turn QA and conversational QA datasets. We present further details for the stage-2 instruction tuning datasets below.

3.2.1. HUMAN ANNOTATED DATA

In addition to the public available datasets, one of the key elements for stage-2 is to obtain a high-quality document-grounded conversational QA dataset. We create a human-annotated conversational QA (called HumanAnnotatedConvQA) dataset only consisting of 7k dialogues. To build this dataset, we first collected 7k documents covering diverse topics from the Internet. Then, we instruct the annotator to act both as a curious user asking questions (and follow-up questions) about the document and as an agent to give the answers. We create a multi-turn conversation for each document, resulting in a total of 7k conversational QA dialogues with an average of 5 user-agent turns per dialogue. Details of data collection guideline can be found in Appendix G.2.

To reduce hallucinated answers in unanswerable cases, we aim to empower our model to explicitly indicate it when the answer cannot be found within the given context. To obtain these unanswerable data samples, we requested annotators to identify all parts of the context locations that are relevant to the user’s question. Hence, it enabled us to construct unanswerable scenarios by deleting the text from the corresponding locations in the context. After deleting the relevant text to the question, we use a sentence, “Sorry. I cannot find the answer based on the context”, as

the response for the unanswerable questions. Finally, we construct another 1.5k user-agent turns with unanswerable annotations, which provides a good trade-off of answerable and unanswerable cases (see §6.5 for details).

3.2.2. SYNTHETIC DATA GENERATION

To validate the quality of the HumanAnnotatedConvQA, we leverage GPT-3.5-turbo to generate a synthetic conversational QA dataset given its powerful instruction-following and text generation capability. Note that large-scale synthetic data for conversational QA has also been explored in Dai et al. (2022). In this work, we focus on midsize high-quality synthetic data for LLM fine-tuning.

The instruction for GPT-3.5-turbo comprises three parts: 1) system role guiding the model to provide helpful answers, 2) examples of conversational QA indicating the required data types, and 3) a document that directs the model to generate conversational QA based on its content. We collect 7k documents (average ~ 1 k words per document) from common crawl, which cover a wide range of domains. Each document is used for generation of a single conversational QA sample, which leads to a total of 7k multi-turn QA dialogues with an average of 4.4 user-agent turns per dialogue (called SyntheticConvQA).

Similar to the HumanAnnotatedConvQA, we construct another 1.5k user-agent turns with unanswerable annotations in this synthetic dataset. Since there are no annotations of the context location for the agent’s answer, we construct synthetic unanswerable samples from SyntheticConvQA. Specifically, we first cut the document (for each dialogue) into different chunks. Then, we consider it as a valid unanswerable sample only when there are chunks that have “high overlaps” with the agent’s answer to be removed and the rest of the chunks show “low overlaps” with the agent’s answer. We use the 4-gram recall score between each chunk and the agent’s answer (which measures the ratios of the answer’s 4-gram phrases are within each chunk) as the metric to measure their overlaps, and consider it higher than 0.5 as “high overlaps” and lower than 0.1 as “low overlaps”.

3.2.3. TRAINING BLENDS

In this part, we introduce the details of training blends for stage-2 instruction tuning. To boost the QA capability in handling tabular documents and arithmetic calculation, we add the TAT-QA dataset (Zhu et al., 2021) which contains both elements. In addition, we integrate contextualized single-turn QA datasets to further strengthen the QA capability of our model. We also retain the stage-1 SFT dataset in the training blend to maintain the model’s instruction-following capability.

Finally, the training blend for stage-2 consists of: 1) A

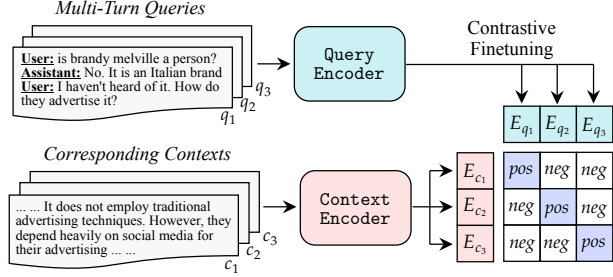


Figure 2. Illustration of fine-tuning retriever for multi-turn QA.

conversational QA dataset: HumanAnnotatedConvQA or SyntheticConvQA,¹ 2) single-turn QA datasets: DROP (Dua et al., 2019), NarrativeQA (Kočiský et al., 2018), Quoref (Dasigi et al., 2019), ROPES (Lin et al., 2019), SQuAD1.1 (Rajpurkar et al., 2016), SQuAD2.0 (Rajpurkar et al., 2018), NewsQA (Trischler et al., 2017), TAT-QA (Zhu et al., 2021), and 3) all of SFT datasets from stage-1.

We follow the similar template as in stage-1 to unify all single-turn QA and conversational QA datasets. The differences are in two parts: 1) Following the system role, we append relevant context for the single-turn question or the multi-turn conversation, and 2) Just before the single-turn question or multi-turn conversation, we integrate further instruction based on the answer types of different QA datasets (e.g., short answer, long answer, arithmetic calculation). We use the format for SFT dataset from stage-1.²

4. Retrieval for Multi-Turn QA

In conversational QA tasks, when a document becomes too lengthy to feed directly into LLMs, a retriever that can handle conversational queries becomes essential. This conversational retriever encodes the concatenation of the dialogue history and the current query, and then retrieve relevant context from documents. After that, only the relevant context will be used as inputs for LLMs. The state-of-the-art retrievers, e.g., Dragon (Lin et al., 2023a), are optimized for single-turn queries, resulting in a limited generalization capability for multi-turn conversational queries. In Figure 2, we depict our retriever fine-tuning method to alleviate this issue. We propose to use conversational query and context pairs for further fine-tuning a single-turn retriever to better cope with conversational inputs.

An alternative solution is conversational query rewriting

¹Unless specified otherwise, the experiments use HumanAnnotatedConvQA as the default setting.

²Details of the templates for both stage-1 and stage-2 instruction tuning as well as the synthetic data generation can be found in the Appendix A.

Models	Average		Doc2Dial		QuAC		QReCC		TopiOCQA		INSCIT	
	top-1	top-5	top-1	top-5	top-1	top-5	top-1	top-5	top-5*	top-20*	top-5*	top-20*
Adlakha et al. (2022)	-	-	-	-	-	-	-	-	-	70.40 [△]	-	-
Wu et al. (2023)	-	-	-	-	-	-	-	-	-	-	-	71.10 [△]
E5-unsupervised [†] (Wang et al., 2022a)	31.56	59.22	23.02	55.33	43.49	77.68	44.71	84.99	26.25	37.67	20.32	40.44
E5-unsupervised + Rewrite [‡]	33.23	61.02	25.56	58.00	46.00	80.01	45.50	85.89	27.58	39.15	21.53	42.04
E5-unsupervised + Fine-tune [†]	47.79	75.00	45.28	80.96	46.52	80.74	53.37	89.91	41.01	51.07	52.79	72.31
Dragon [†] (Lin et al., 2023a)	46.29	73.09	43.33	75.61	56.80	82.86	46.17	81.96	57.68	78.80	27.49	46.22
Dragon + Rewrite [‡]	54.46	80.13	47.60	80.60	47.10	77.15	51.73	85.78	73.07	88.19	52.79	68.92
Dragon + Fine-tune [†]	52.72	80.67	48.94	83.01	52.64	81.95	50.73	87.17	67.86	86.28	43.43	64.94
- SyntheticConvQA [◇]	52.98	81.15	48.64	83.47	54.75	83.23	49.63	86.70	64.48	85.24	47.41	67.13

Table 1. Retrieval results across five multi-turn QA datasets with the average top-1 and top-5 recall scores. Compared to rewriting, fine-tuning performs much better on E5-unsupervised and is comparable on Dragon. *Since the average context length in TopiOCQA and INSCIT is smaller than in other datasets, we report top-5 and top-20 to roughly match the context lengths of top-1 and top-5, respectively, in those datasets. [†]The inputs for these two models are a concatenation of the dialogue history and the current query. [‡]The input for this model is the rewritten query. [◇]denotes that the HumanAnnotatedConvQA dataset is replaced with the SyntheticConvQA for fine-tuning. [△]The numbers are not apple-to-apple comparison (e.g., they use the training set for fine-tuning).

method which uses a query rewriter to rewrite the current question based on the conversational history. The rewritten query is then directly used as the input to a single-turn query retriever for retrieving relevant context. In addition to the embedding and search cost, the query rewriting model introduces a large amount of extra computational expense to generate the rewritten query.

4.1. Fine-tuning Retriever for Multi-turn QA

To build a high-quality fine-tuning dataset, we leverage the conversational QA dataset from either the HumanAnnotatedConvQA or the SyntheticConvQA to construct conversational query and context pairs.

For the HumanAnnotatedConvQA, we directly take the annotations of the conversational query and context pairs, and use them to further fine-tune a single-turn query retriever. For the SyntheticConvQA, we first cut each document in the conversational QA dataset into different chunks. Then, we calculate the 4-gram recall score between agent’s answer and each chunk. After that, we consider the chunk that has the highest recall score as the gold chunk for the current user’s question. Finally, the constructed conversational query and context pairs are used to fine-tune a single-turn query retriever.

4.2. Conversational Query Rewriting

To build powerful conversational query rewriting model, we take GPT-3.5-turbo as the rewriter given that Galimzhanova et al. (2023) demonstrated the state-of-the-art query rewriting results using GPT-3.5-turbo. Similar to Galimzhanova et al. (2023), we not only provide GPT-3.5-turbo with the rewriting task instruction, but also give it few-shot rewriting examples to enhance the quality of rewriting results. More

details can be found in Appendix B.1.

4.3. Comparisons

In Table 1, we compare the query rewriting and fine-tuning methods across five datasets in the zero-shot setting. More details about these datasets can be found in §5.2.1. We conduct experiments on a state-of-the-art retriever, Dragon (Lin et al., 2023a), and a strong unsupervised retriever, E5-unsupervised (Wang et al., 2022a), which is not finetuned on MS MACRO (Nguyen et al., 2016). In terms of the experiments on Dragon, we find that fine-tuning performs marginally worse than query rewriting in average top-1 recall by 1.74%, while it achieves better results on average top-5 recall by 0.54%. It demonstrates the effectiveness of the fine-tuning approach for the conversational retrieval. In addition, we observe that the results are comparable between using HumanAnnotatedConvQA and SyntheticConvQA for fine-tuning. This highlights that our human-annotated dataset is in high-quality, and we *do not rely on* ChatGPT models for building the state-of-the-art multi-turn query retriever.

Surprisingly, fine-tuning performs significantly better than rewriting on E5-unsupervised. We conjecture that since E5-unsupervised does not use human-annotated query and context pairs in the pre-training stage, it leads to weak generalization for the high-quality rewritten query. In contrast, using a high-quality dataset to fine-tune E5-unsupervised brings a giant boost, with more than a 15% improvement on both average top-1 and top-5 recall scores.

Therefore, fine-tuning a good single-turn retriever on high-quality conversational query context pairs performs on par with leveraging the state-of-the-art rewriter. However, rewriting method requires extra computational time for autoregressive generation process and probably also API cost

for using powerful models like GPT-3.5-turbo. In contrast, our proposed multi-turn fine-tuning bypasses these issues. For the QA evaluations across these five datasets, we consistently use the retrieved top-5 results from the fine-tuning approach for all the QA models. We put more results on comparisons between rewriting and fine-tuning methods in the Appendix B.2.

5. Experimental Setup

In this section, we present the details of our experimental setup for the conversational question answering task.

5.1. Baselines

We conduct experiments on different model sizes. First, to show the effectiveness of stage-2 context-enhanced instruction tuning, we compare against the **Llama2-SFT-{7B, 13B, 70B}**, which is the Llama2-7B/13B/70B foundation model after the stage-1 supervised fine-tuning (SFT). Second, we compare against **Llama2-Chat-{7B, 13B, 70B}** since Llama2-Chat models are shown to possess strong instruction following and conversational QA capabilities (Touvron et al., 2023). Aside from Llama2 models, we also conduct experiments on our in-house GPT-{8B, 22B} foundation models, which are pretrained with 3.5 trillion tokens, and we compare against their stage-1 SFT baselines **GPT-SFT-{8B, 22B}**. Finally, we compare against two very strong OpenAI models: **GPT-3.5-turbo-0613 (4k)** and **GPT-4-0613 (8k)**. For fair comparison, when retrieval is needed, we use the same top- k retrieved chunks from our best retriever as the context for all baselines and our ChatQA models. Note that we have carefully tuned the instructions for all the baselines to ensure they achieve as good as possible results.³

5.2. Evaluation Benchmarks

5.2.1. LONG DOCUMENT DATASETS

We collect five conversational QA datasets with long documents which cannot be directly fitted into LLMs with a sequence length of 4K tokens. Hence, we run our best multi-turn query retriever to get top-5 relevant chunks as the inputs (experiments can be found in §4.3).

- Doc2Dial (Feng et al., 2020) is a document-grounded conversational QA dataset covering four domains: DMV, SSA, VA, and Student Aid. Each sample comprises a dialogue where a user poses queries regarding the document, and an agent responds those questions. The average document length is around 101K words.
- QuAC (Choi et al., 2018) is based on Wikipedia docu-

ments. Originally, the document is short. Since each dialogue is linked to multiple Wikipedia URLs, we extract text from these links to increase the document size to approximately an average of 15K words. It contains unanswerable cases where answers cannot be found within the given context.

- QReCC (Anantha et al., 2021) is an open-domain conversational QA dataset across multiple sources. Similar to QuAC, each dialogue also has corresponding URLs. We extract text from those URLs to construct the documents. In the end, the average document size is around 5K words, with a maximum document size of 20K words.
- TopiOCQA (Adlakha et al., 2022) is grounded on the whole Wikipedia. It incorporates topic switching and requires the agent to search the entire Wikipedia for answers to user questions.
- INSCIT (Wu et al., 2023) is also grounded on the whole Wikipedia. It studies the case where user questions are under-specified and require clarification.

For Doc2Dial, QuAC, and QReCC, we segment documents into around 300-word chunks, and we retrieve top-5 relevant chunks as context for each user question. For TopiOCQA and INSCIT, we follow their original segmentation, resulting in smaller chunks. Hence, we retrieved top-20 chunks to obtain similar context length to the first three datasets.

5.2.2. SHORT DOCUMENT DATASETS

To increase the diversity of document lengths, we collect five conversational QA datasets with short documents (less than 1.5K words). On average, 1 word will be tokenized into 1.5 tokens. Hence, the document can be directly fitted into LLMs with a sequence length of 4K tokens.

- CoQA (Reddy et al., 2019) is a conversational QA dataset with each dialogue grounded on a short passage. The answers are generally short, and the passages cover a wide range of domains like children’s stories, literature, mid/high school exams, news, Wikipedia.
- DoQA (Campos et al., 2020) covers three domains: cooking, travel, and movies collected from active Stack Exchange⁴ forums. The dataset contains unanswerable cases where answers cannot be found within the given document.
- ConvFinQA (Chen et al., 2022a) is based on the Financial domain. Each document contains a single financial report table along with relevant text surrounding the

³The prompts for these baselines can be found in Appendix C.

⁴<https://stackoverflow.com/>

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Models	Average	Doc2Dial	QuAC	QReCC	CoQA	DoQA	ConvFinQA	SQA	TopiOCQA	HybridDial	INSCIT
Llama2-7B-SFT	34.81	30.26	19.21	37.55	62.75	21.76	34.43	32.18	32.88	48.96	28.16
Llama2-7B-Chat	38.86	33.27	25.83	46.02	72.28	33.15	36.58	26.14	36.68	47.02	31.67
ChatQA-7B	47.71	37.88	29.69	46.97	76.61	41.57	51.61	61.87	45.45	54.51	30.96
GPT-8B-SFT	34.46	31.03	20.07	37.69	59.24	21.72	15.44	40.06	38.17	52.29	28.86
ChatQA-8B	49.36	36.76	33.95	45.54	77.90	44.65	61.68	60.74	47.03	53.81	31.50
Llama2-13B-SFT	37.69	30.68	21.59	38.25	69.52	21.70	41.14	37.85	35.26	52.22	28.73
Llama2-13B-Chat	40.34	34.74	27.89	47.19	72.50	32.60	41.54	25.39	39.25	49.82	32.52
ChatQA-13B	50.86	38.05	34.28	48.06	77.23	43.31	65.44	66.41	48.88	56.19	30.79
GPT-22B-SFT	38.83	32.98	22.83	39.92	68.19	22.83	30.54	47.01	38.07	54.22	31.66
ChatQA-22B	53.53	39.71	36.89	50.47	80.32	44.88	72.08	69.08	48.83	58.20	34.11
Llama2-70B-SFT	43.22	34.42	25.65	41.88	73.04	28.21	46.64	58.90	37.20	55.52	30.71
Llama2-70B-Chat	45.21	36.87	32.47	49.40	80.41	38.97	46.85	37.62	44.31	50.35	34.88
ChatQA-70B	54.14	38.90	41.82	48.05	78.57	51.94	73.69	69.14	50.98	56.44	31.90
- SyntheticConvQA [◇]	54.08	39.19	38.33	48.73	79.83	48.65	76.44	68.63	51.30	55.68	33.98
- w/o stage-1 [†]	52.18	38.43	37.52	46.08	73.51	49.42	72.15	72.08	51.28	50.74	30.56
- w/o single-turn [*]	52.25	38.30	37.89	47.08	76.74	46.43	72.42	67.41	49.85	53.16	33.18
- w/o ConvQADat [△]	48.97	35.47	28.19	41.68	75.80	31.68	73.83	68.05	45.90	58.40	30.70
GPT-3.5-turbo (4k)	50.37	34.83	37.17	50.46	79.33	41.11	73.15	60.63	44.30	47.42	35.27
GPT-4 (8k)	53.90	34.16	40.29	52.01	77.42	43.39	81.28	79.21	45.09	49.81	36.34

Table 2. Zero-shot conversational QA results across 10 datasets. [◇] denotes that the HumanAnnotatedConvQA is replaced with the SyntheticConvQA. [†] denotes that the stage-1 (SFT) is removed and only ChatQA stage-2 tuning is applied. ^{*}denotes that the single-turn QA datasets are removed from the ChatQA stage-2 training blends. In both “w/o stage-1” and “w/o single-turn” settings, the SyntheticConvQA data is used. In terms of average scores, our ChatQA models greatly surpass SFT and Chat counterparts. Our best model, ChatQA-70B, slightly outperforms GPT-4. [△] denotes that the HumanAnnotatedConvQA is removed from the ChatQA stage-2 training blends.

table. This dataset involves arithmetic calculation and complex numerical reasoning.

- SQA (Pasupat & Liang, 2015) is grounded on documents which contain only a single Table without any surrounding text. The documents are collected from Wikipedia, and the questions are highly compositional, which requires the model with robust table comprehension ability to give correct answers.
- HybridDial (Nakamura et al., 2022) is a conversational QA dataset grounded on documents containing both Wikipedia tabular and textual data. The questions are complex which requires reasoning over the documents.

Over all the 10 datasets, ConvFinQA, SQA, and HybridDial datasets contain tabular data in the documents, while documents of the remaining datasets are text-only.⁵

5.3. Evaluation Metrics

Given that F1 score is the most commonly used automatic metric to assess QA models, we use it for all datasets except for ConvFinQA. In ConvFinQA, we follow Chen et al. (2022a) to use exact match metric since the answers in ConvFinQA are about extracting numbers from documents as

well as arithmetic calculations. Hence, the answer only makes sense when it is exactly the same as the answer. When models generate the arithmetic formula, we will calculate its final result based on a calculator and compare it with the gold answer.

In addition, we also conduct human evaluations to assess the correctness of generated answers between our best model and GPT-4.

6. Results

6.1. Main Results

6.1.1. OVERVIEW

In Table 2, we compare different model variants and OpenAI models across 10 conversational QA datasets.

We find that our ChatQA method greatly improves the model’s conversational QA capability. In terms of averaged scores, Llama2-Chat models surpass SFT model counterparts by a small margin, while our ChatQA models achieve around or over 10 point of absolute improvement over SFT and Chat counterparts. For example, ChatQA-13B improves on Llama2-13B-SFT and Llama2-13B-Chat by 13.17 (from 37.69 to 50.86) and 10.52 (from 40.34 to 50.86), respectively. This is because context-enhanced instruction fine-

⁵Details of these benchmark datasets are in the Appendix C.

tuning enables the model to learn how to effectively extract useful information from retrieved or relevant context.

Compared to OpenAI models, our best model ChatQA-70B surpasses GPT-3.5-turbo by 3.77 average score and can outperform GPT-4 by 0.24 average score. In addition, a much smaller size of ChatQA-13B is able to marginally outperform GPT-3.5-turbo by an average score of 0.49.

Notably, our proposed stage-2 instruction tuning brings a significant boost to GPT-22B-SFT by 14.70 average score. As a result, ChatQA-22B is only behind GPT-4 by a small gap (53.53 vs. 53.90), despite having a considerably smaller model size than Llama2-70B. This highlights the efficiency of the proposed instruction tuning method.

6.1.2. IMPORTANCE OF STAGE-1 SFT

In Table 2, we conduct an ablation study on the importance of stage-1 SFT, which enhances the instruction-following capability of ChatQA. We remove the stage-1 SFT from the fine-tuning stages and only apply stage-2 context-enhanced instruction tuning on top of foundation LLM. We find that the average score drops 1.9 (from 54.08 to 52.18). Aside from the SQA, removing stage-1 makes the model consistently perform worse on other datasets. Results indicate that stage-1 still plays an important role, even through all of SFT datasets of stage-1 are blended in stage-2 instruction tuning as well. We conclude that building instruction-following capability first is beneficial for stage-2 tuning.

6.1.3. EFFECTIVENESS OF SINGLE-TURN DATA

To investigate how single-turn QA datasets affect model’s multi-turn QA capability, we conduct an ablation study by removing them from the ChatQA-70B training blends in stage-2. As shown in Table 2, incorporating single-turn QA datasets in the stage-2 training blends (ChatQA-70B) generally make the scores increase across all benchmark datasets, leading to an average improvement of 1.83 score. Interestingly, we observe improvement in ConvFinQA, SQA, and HybridDial (table-based datasets), despite the added single-turn QA datasets not having tabular data in the documents. These results align with our intuitions. Adding single-turn datasets improves the model’s capability to extract answers from context, resulting in better scores in conversational QA datasets.

6.1.4. EFFECTIVENESS OF CONVERSATIONAL QA DATA

We further explore the how conversational QA data affect the model’s multi-turn QA capability by removing HumanAnnotatedConvQA data from the ChatQA stage-2 training blends. As illustrated in Table 2, “w/o ConvQAData” makes the results significantly worse than ChatQA-70B (average scores degrading from 54.08 to 48.97). We observe

	Ours Win	Tie	GPT-4 Win
Average	13.81%	69.09%	17.10%
Doc2Dial	14.29%	68.00%	17.71%
QuAC	11.67%	73.33%	15.00%
QReCC	11.11%	77.22%	11.67%
CoQA	7.78%	80.00%	12.22%
DoQA	22.78%	57.78%	19.44%
ConvFinQA	16.67%	67.78%	15.55%
SQA	11.11%	61.67%	27.22%
TopiOCQA	19.31%	60.69%	20.00%
HybridDial	7.78%	78.33%	13.89%
INSCIT	15.56%	66.11%	18.33%

Table 3. Human evaluation (A/B testing) comparing our ChatQA-70B to GPT-4 over 10 datasets. In terms of average scores, our model and GPT-4 are tie most of the time (69.09%), and GPT-4 achieves slightly higher win rate ($\sim 3.3\%$) than ours.

large degradation in datasets with text-based documents, such as QuAC, QReCC, and DoQA. However, the degradation in datasets with table-based documents (e.g., ConvFinQA, SQA) are small, thanks to having TAT-QA (Zhu et al., 2021) in the training blends.

Interestingly, “w/o ConvQAData” can still outperform Llama2-70B-SFT (48.97 vs. 43.22) and Llama2-70B-Chat (48.97 vs. 45.21). This further demonstrates the effectiveness of our proposed stage-2 tuning, which enhances the model’s capability to handle the contextualized QA task.

6.1.5. HUMAN ANNOTATED DATA VS. GPT-3.5-TURBO SYNTHETIC DATA

In Table 2, we also compare our ChatQA models using the 7k GPT-3.5-Turbo synthetic dataset (SyntheticConvQA) and our collected 7k human-annotated dataset (HumanAnnotatedConvQA). First, we find that both achieve comparable results in terms of average scores, which suggests that we do not need to rely on synthetic data from OpenAI models to build the state-of-the-art conversational QA models. Second, we find that using human-annotated data achieved significant improvements on QuAC and DoQA datasets. This can be attributed to the fact that the human-annotated data have higher quality on unanswerable cases which exists in QuAC and DoQA datasets. Eventually, it leads to the overall improvements on these two datasets. Detail results and analyses on unanswerable cases can be found in §6.5.

6.1.6. HUMAN EVALUATION

Despite F1 scores being the most commonly used metrics for evaluating the quality of QA models, there are often multiple ways to answer questions, which makes the automatic metrics less than perfect. Therefore, we use human evaluations to further compare our ChatQA-70B with GPT-4. In this human evaluation, we ask annotators to verify the facts

Models	Avg-text	Avg-table	Avg-ret	Avg-nonret
ChatQA-13B	45.80	62.68	40.01	61.72
ChatQA-70B	48.88	66.42	42.33	65.96
GPT-3.5-turbo (4k)	46.07	60.40	40.41	60.33
GPT-4 (8k)	46.96	70.10	41.58	66.22

Table 4. Fine-grained studies on average scores of different dataset types. Avg-text covers datasets where the documents only have text, including Doc2Dial, QuAC, QReCC, CoQA, DoQA, TopiOCQA, and INSCIT. Avg-table covers datasets with table in the documents, including ConvFinQA, SQA, and HybridDial. Avg-ret covers datasets with long documents requiring retrieval, including Doc2Dial, QuAC, QReCC, TopiOCQA, and INSCIT. Avg-nonret covers datasets with short documents which do not require retrieval, including CoQA, DoQA, ConvFinQA, SQA, and HybridDial.

in ChatQA-70B and GPT-4’s outputs and determine which model provides a more accurate response to the question ⁶. The human evaluation results over the 10 datasets are shown in Table 3. We first find that our ChatQA-70B and GPT-4 are tie most of the time (69.09%), and GPT-4 achieves slightly higher win rate ($\sim 3.3\%$) than ours. This further confirms our model has powerful capability to produce correct answers. Second, we find that our model achieves slightly better win rate than GPT-4 in ConvFinQA, which indicates the strong arithmetic calculation ability of our model. Third, we find that GPT-4 achieves significantly better win rate in SQA task, which suggests that there is still a gap between our model and GPT-4 on tabular reasoning task.

6.2. Fine-grained Analyses

In Table 4, we further compared our models and OpenAI models across different dataset types in our conversational QA benchmarks. In the comparison between ChatQA-70B and GPT-4, ChatQA-70B achieves better results in text-only documents (avg-text), demonstrating its superior text understanding ability. Meanwhile, GPT-4 shows better QA capability in tabular data given the comparisons in avg-table. Regarding the datasets that require or do not require retrieval, ChatQA-70B and GPT-4 are comparable (gaps are within an average score of 1).

In the comparison between ChatQA-13B and GPT-3.5-turbo, ChatQA-13B demonstrates better tabular QA capability, given the scores in Avg-table. ChatQA-13B also shows better scores in datasets where documents do not need retrieval, while being on par with GPT-3.5-turbo in text-only documents and documents that need retrieval.

6.3. Top- k Chunks for Stage-2 Instruction Tuning

For all the datasets used in stage-2 tuning, the context is provided as continuous paragraphs or documents containing

⁶More human evaluation setup can be found in the Appendix D.

Models	Avg-CQA	Avg-ret	Avg-nonret
ChatQA-70B	54.14	42.33	65.96
- w/ “top-5” chunks	54.04	42.91	65.16

Table 5. Ablation study on using “top-5” retrieved chunk as the context for the stage-2 instruction tuning. We report average scores on all 10 conversational QA datasets (Avg-CQA), five retrieval datasets (Avg-ret) and five non-retrieval datasets (Avg-nonret).

the answer. In contrast, the model needs to handle the top- k retrieved chunks during inference for long documents. To address this train/test mismatch, we investigate whether replacing some continuous paragraphs with retrieved top- k chunks will enhance the model’s robustness.

We use NarrativeQA for this study, since each question has a corresponding long document. Initially, we use a summary of the long document as the context, which contains the answer. To incorporate discontinuous contexts, we first cut the long document into 300-word chunks. Then, we use the Dragon retriever to retrieve the top-4 chunks related to the question as additional context. Finally, we consider the retrieved four chunks along with the summary of the long document as the “top-5” chunks. ⁷ We use this reconstructed NarrativeQA to replace the original one for the stage-2 instruction tuning.

In Table 5, we observe that using “top-5” chunks as the context for training leads to improvements on the datasets that require retrieval. But it degrades the performance on non-retrieval datasets. Overall, these two models perform comparable. It is because incorporating “top-5” retrieved chunks in stage-2 tuning aligns with the inference stage where retrieval is needed, which improves the Avg-ret score. However, mixing continuous and discontinuous documents could make the stage-2 tuning less stable, leading to sub-optimal results on non-retrieval datasets. We believe more future work can be conducted regarding the balance of incorporating continuous context and top- k retrieved chunks in stage-2 tuning.

6.4. Ablation Studies for Inference Stage

In Table 7, we show ablation studies on how the number of retrieved context/chunks, context ordering, and different retrievers affect the conversational QA results.

First, we find that using more contexts as inputs do not always improve the results. Utilizing top-5 contexts as input yields better results compared to using either top-3 or top-10 contexts. Intuitively, more contexts have higher prob-

⁷Note that, we do not directly use top-5 retrieved chunks for training, because they may not contain the answer. In such cases, fine-tuning the model to generate answer could encourage hallucination.

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Models	Avg-Both	Avg-QuAC	QuAC (no*)	QuAC (yes*)	Avg-DoQA	DoQA (no*)	DoQA (yes*)	Avg-CQA
ChatQA-70B								
- 1k unanswerable [†]	76.88	80.89	75.10	86.67	72.88	64.49	81.26	54.16
- 1.5k unanswerable[†]	77.25	80.76	77.66	83.85	73.74	68.81	78.67	54.14
- 2k unanswerable [†]	77.10	80.82	77.59	84.05	73.38	67.95	78.80	53.86
- 2.5k unanswerable [†]	75.87	78.81	73.76	83.85	72.93	66.54	79.31	53.78
- SyntheticConvQA [◇]	69.84	72.92	55.38	90.42	66.77	45.09	88.45	54.08
GPT-3.5-turbo (4k)	73.27	78.34	61.91	94.76	68.21	51.99	84.43	50.37
GPT-4 (8k)	80.73	87.42	83.45	91.38	74.05	74.28	73.82	53.90

Table 6. Accuracies on answerable and unanswerable samples across QuAC and DoQA datasets. Avg-Both is the averaged score between QuAC and DoQA, and Avg-CQA is the average score across the 10 conversational QA datasets. [◇] denotes that the HumanAnnotatedConvQA is replaced with the SyntheticConvQA. *“no” denotes the unanswerable samples, while “yes” denotes the answerable samples. [†]We conduct ablation studies in terms of the number of unanswerable samples in HumanAnnotatedConvQA. We use 1.5k unanswerable samples for our final ChatQA-70B, as it produces both high-quality generation and less hallucination.

Models	Avg.	D2D	QuAC	QReCC	TopiO	INSCIT
ChatQA-70B	42.31	39.19	38.33	48.73	51.30	33.98
- # of ctx: top-3	41.91	37.20	38.35	48.94	52.78	32.27
- # of ctx: top-10	40.71	37.06	36.95	47.61	49.40	32.53
- ctx reverse ordering	42.48	39.08	38.85	49.63	51.16	33.69
- ctx swing ordering	42.30	39.35	38.09	49.09	50.98	33.99
- ctx random ordering	42.01	39.32	38.28	48.79	50.13	33.51
- Dragon Retrieval	40.50	37.92	38.44	47.88	50.39	27.87

Table 7. Ablation studies on input context across datasets that require retrieval. All models use SyntheticConvQA. D2D denotes Doc2Dial, and TopiO denotes TopiOCQA. We study the number of contexts used in inputs (# of ctx), context ordering (reverse, swing, random), and the use of retrieved context from the original Dragon. In comparison, ChatQA-70B (default setting) uses “Dragon + Fine-tune” to retrieve the top-5 contexts, and arranges them sequentially from the first to the fifth context in top-5.

ability to contain correct answers (better recall scores). As a result, using top-5 contexts achieves better results than using top-3. However, as the number of contexts further increases, the model may suffer from “lost in the middle” phenomenon (Liu et al., 2023) and the difficulty of extracting answers from the provided context could also increase, which leads to inferior results by using top-10 contexts.

Second, we study how using different orderings of top-5 contexts affects the results. We compare sequential ordering (from 1st context to 5th context) to reverse ordering (from 5th to 1st context), swing ordering (given the “lost in the middle” phenomenon, we arrange the most relevant context to appear at the beginning and the end of the input context. Hence, the ordering becomes {1st, 3rd, 5th, 4th, 2nd}), and random ordering (random shuffle the top-5 contexts). We find using sequential ordering is comparable to using reverse and swing orderings, and random shuffling is slightly worse. Results indicate that our model excels in extracting the correct answer from lengthy contexts, regardless of the answer’s location. This is because, during the ChatQA fine-tuning, the answer’s location is randomly distributed within

the context.

Third, we observe that when we replace “Dragon + Fine-tune” with the original non-finetuned Dragon retriever, the average score drops by 1.81 (from 42.31 to 40.50). In addition, the score drops significantly in INSCIT dataset (from 33.98 to 27.87) due to the large performance gap between the two retrievers (as shown in Table 1). Basically, when the quality of retrieval improves, it directly enhances the performance of question answering.

6.5. Evaluation of Unanswerable Case

6.5.1. EVALUATION SETUP

In this section, we study another aspect of the model’s capability, which is to discern if a question can be answered within the provided context. Generating an answer in unanswerable case will lead to hallucination. To allow this evaluation, we require the model to indicate it when no answer can be found in the given context.

We use QuAC and DoQA datasets which have such unanswerable cases to evaluate such capability. Specifically, for unanswerable case, we consider the model indicating that the question cannot be answered as correct⁸, and as for answerable cases, we consider the model not indicating the question is unanswerable as correct (i.e., the model giving an answer). Note that for answerable cases, we only select the samples where correct context is retrieved. Our model checkpoints (ChatQA-70B w/ 1.5k unanswerable and ChatQA-70B w/ SyntheticConvQA) are same ones reported in Table 2.

In the end, we calculate the average accuracy score of unanswerable and answerable cases as the final metric. We consider this average accuracy as a reliable metric since it is

⁸We collect a set of heuristic matching patterns from all generated samples to determine if the model suggests that the question is unanswerable. More details can be found in the Appendix E.

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Context	Conversation	Assistant Responses
The process for Board hearings has changed. If you're appealing a VA decision under the new process, keep reading below to learn how to request and prepare for a hearing. You'll follow the new process if you're : Appealing a VA decision you received on or after February 19, 2019. Participating in the Rapid Appeals Modernization Program Opting into the new process using VA Form 10182 If you're using VA Form 9 to appeal a VA decision you received before February 19, 2019, go to the Board of Veterans' Appeals BVA Hearing page ... The Board of Veterans Appeals schedules hearings in docket order the order in which they receive requests ...	User: What can I learn at my Board hearing? Assistant: Do you want to learn exactly what to expect? ... User: Is it necessary for me to consider requesting a Board hearing? Assistant: You can request a video conference hearing if you want to provide testimony to a judge about your appeal. User: when will I follow the new process for a Board hearing? Assistant:	ChatQA-70B: If you're appealing a VA decision you received on or after February 19, 2019, you'll follow the new process. GPT-4: You'll follow the new process for a Board hearing if you're appealing a VA decision you received on or after February 19, 2019, participating in the Rapid Appeals Modernization Program, or opting into the new process using VA Form 10182. Ground Truth: You will follow the new process if appealing a VA decision if you received it on or after February 19, 2019.
title: How did Arya survive this confrontation unscathed? There was no time or intention to turn her into White Walker. Let us look at the scene from S04E04. A white walker brings a baby holding in his lap and puts it on an ice table (or whatever it is) for the arrival of the Night King. ... When Arya drops the dagger, Night King looks surprised. This shows he doesn't know what would happen next. There was no time to think and turn her into a white walker by touch. There was no planning in this scene like S04E04. ...	User: How did Arya survive this confrontation unscathed? Assistant: Arya was quick enough to react, drop the dagger and do the rest. User: How old is the child that they lay on the altar of ice? Assistant:	ChatQA-70B: The child appeared to be a baby. GPT-4: The text does not provide information on the exact age of the child that was laid on the ice altar. Ground Truth: a baby
Massif Chornohora Uholka / Wide Meadow Svydovets Maramoros Rozok Jasmund ...	Type of nature reserve Carpathian Biosphere Carpathian Biosphere Carpathian Biosphere Carpathian Biosphere Presov Preserved Jasmund National Park Preserved area 2476.8 ha 11860 ha 3030.5 ha 2243.6 ha 67.1 ha 492.5 ha User: which of the forests is a carpathian biosphere reserve? Assistant: Chornohora, Uholka / Wide Meadow, Svydovets, Maramoros, Kuziy / Trybushany User: which of those covers more than 3100 ha? Assistant:	ChatQA-70B: Uholka / Wide Meadow GPT-4: Chornohora, Uholka / Wide Meadow, Svydovets, Maramoros Ground Truth: Uholka / Wide Meadow
title: Summary of enemy aircraft damaged/destroyed (John B. England)	Date 24 April 1944 27 May 1944 18 August 1944 13 September 1944 6 October 1944 6 October 1944 27 November 1944 14 January 1945 ...	Location Munich, Germany Strasbourg, France Paris, France Nordhausen, Germany Berlin, Germany Berlin, Germany Magdeburg, Germany Berlin, Germany Number 3 1 0.5 2.5 1 2 4 1 Type Me-110 Me-109 Me-109 Me-109 Me-109 Me-109 FW-190 Me-109 Status Destroyed Damaged Destroyed Destroyed Damaged Destroyed Destroyed Destroyed
	User: what were all of the dates in which john b. england destroyed or damaged enemy planes? Assistant: 24 April 1944, 27 May 1944, 18 August 1944, 13 September 1944, 6 October 1944, 27 November 1944, 14 January 1945 ... User: on which of those dates did john b. england destroy or damage more than one enemy plane? Assistant:	ChatQA-70B: 6 October 1944, 13 September 1944, 27 November 1944 (missing 24 April 1944) GPT-4: 24 April 1944, 13 September 1944, 6 October 1944, 27 November 1944 Ground Truth: 24 April 1944, 13 September 1944, 6 October 1944, 27 November 1944

Table 8. Case studies on ChatQA-70B and GPT-4. We use blue color to highlight the relevant context for the last user question. And we use green and red color to highlight the correct and incorrect parts in the assistant responses.

in the same spirit of F1 metric which measures the harmonic mean of precision and recall scores.

6.5.2. RESULTS

In Table 6, we compare our models with OpenAI models across QuAC and DoQA datasets. First, we find that compared to using SyntheticConvQA, using HumanAnnotatedConvQA significantly increase the average accuracies on both QuAC and DoQA. It is because the unanswerable annotations are in higher quality for human-annotated data, which significantly improve the accuracy for unanswerable cases. Second, OpenAI models show powerful capability in this task, especially for GPT-4. Compared to them, our best model achieved a significantly better average accuracy than GPT-3.5-turbo, while we still has a slight gap compared to GPT-4 (around 3.5%). Third, we find that models achieving higher accuracy on unanswerable samples tends to get lower accuracy on answerable samples, and vice versa. We speculate that when a model tends to be “aggressive” and offer somewhat relevant answers to those unanswerable questions, it will boost the accuracy for answerable cases, but reduces accuracy for unanswerable ones. Conversely, when a model is more “conservative” and strictly checks if the question can be answered, it will result in the opposite effects.

We conduct ablation studies in terms of the number of unanswerable samples in HumanAnnotatedConvQA. We find

that using a small amount of unanswerable samples (e.g., 1.5k) is able to achieve remarkable results on the unanswerable evaluation, as well as the overall conversational QA score (i.e., Avg-CQA). Interestingly, incorporating more unanswerable samples does not necessarily lead to higher accuracy scores in the unanswerable evaluation.

6.6. Case Study

In Table 8, we show four examples of ChatQA-70B and GPT-4 outputs. More examples can be found in Appendix F. The first example (about *Board hearing*) is a simple information seeking problem, and both ChatQA-70B and GPT-4 answer correctly. In the second example (about *Arya*), the model needs to find implicit information (highlighted in blue) for giving the answer. GPT-4 tends to be safe on providing an answer, and it replies that the context does not provide exact information about the age which is also correct.

Both the third and fourth examples require the model to have good tabular understanding and reasoning ability. In the third example (about *Massif*), ChatQA-70B gives correct answer by comparing the size of preserved area against 3100 ha, while GPT-4 fails to do so. In the fourth example (about *John B. England*), ChatQA-70B correctly lists three dates but misses one date, while GPT-4 correctly answers the question.

7. Conclusion

In this paper, we build a family of ChatQA models, varying in model sizes from 7B to 70B. Comprehensive evaluations on 10 conversational QA datasets show that our best ChatQA-70B model can remarkably outperform GPT-3.5-turbo and perform on par with GPT-4 without using any synthetic data from ChatGPT models. In addition, we demonstrate that fine-tuning a single-turn query retriever using our curated conversational QA data performs comparably to the state-of-the-art LLM-based query rewriting model, without incurring extra computational time and potential API costs associated with rewriting. Furthermore, we show that incorporating a small amount of “unanswerable” samples can significantly enhance our model’s capability to handle scenarios where answers are unavailable. The unanswerable case evaluation highlights that our best model ChatQA-70B only has a slight gap compared to GPT-4.

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A. ChatQA Instruction Tuning

A.1. Stage-1: Supervised Fine-tuning

The format template of LLM inputs in stage-1 is as follows:

System: This is a chat between a user and an artificial intelligence assistant. The assistant gives helpful, detailed, and polite answers to the user's questions based on the context. The assistant should also indicate when the answer cannot be found in the context.

User: {Question 1}

Assistant: {Answer 1}

...

User: {Latest Question}

Assistant:

We use the {Latest Answer} from Assistant as the supervision for model outputs.

A.2. Stage-2: Context-Enhanced Instruction Tuning

Based on the stage-1 format template, the LLM inputs in stage-2 adds {Context for Latest Question} and {Instruction} from User, as depicted below:

System: This is a chat between a user and an artificial intelligence assistant. The assistant gives helpful, detailed, and polite answers to the user's questions based on the context. The assistant should also indicate when the answer cannot be found in the context.

{Context for Latest Question}

User: {Instruction} + {Question 1}

Assistant: {Answer 1}

...

User: {Latest Question}

Assistant:

Same as Stage-1, we use the {Latest Answer} from Assistant as the supervision for model outputs.

As for the {Instruction}, we use different instructions for different datasets based on the answer types. Details can be found below:

"Please give a full and complete answer for the question." This is for datasets with long answers. We use it for the HumanAnnotatedConvQA or SyntheticConvQA.

"Answer the following question with a short span. The answer needs to be just in a few words." This is for datasets with short answers. We use it for SQuAD1.1, SQuAD2.0, NarrativeQA, DROP, ROPES, NewsQA, and Quoref.

"Answer the following question with a number from context or the math arithmetic

using +, -, *, or /.” This is for datasets using arithmetic calculation or extracting numbers from the context. We use it for the TAT-QA dataset where questions need the arithmetic calculation or extracting numbers from the context.

“Answer the following question with a short span, or a full and complete answer.” This is for datasets with both short and long answers. The model needs to tell whether to generate short or long answers based on the questions. We use it for the TAT-QA dataset where questions do not need the arithmetic calculation, since we observe the lengths of the corresponding answers can be both short and long.

For the stage-1 SFT data used in stage-2 instruction tuning, we keep the same format template as in stage-1. In other words, the {Context for Latest Question} and {Instruction} are empty.

A.3. Prompts for Synthetic Data Generation

We use a two-step prompting on GPT-3.5-turbo for obtaining a high-quality multi-turn QA conversation. In step-1, we prompt GPT-3.5-turbo to generate a multi-turn QA conversation based on a given document. However, we find that the generated conversation lacks pronouns or common nouns to refer back to words or phrases in dialogue history. Hence, in step-2, we prompt GPT-3.5-turbo to revise the generated conversation by adding pronouns or common nouns. For both stages, we give GPT-3.5-turbo few-shot examples to ensure a high-quality generation.

The in-context few-shot prompt in step-1 is as follows (aims to generate multi-turn QA conversation):

You are a helpful, pattern-following assistant.

role-user:

PersonA has access to information in the following passage:

###There are certain important aspects of college preparation. The student preparing for college should define their goals and interests. The student should also plan financially and academically. We have a checklist that helps students get ready financially and academically.###

Generate a conversation of around four turns between PersonA and PersonU where PersonU needs information from PersonA that is in the passage. Use only information found in the passage.

PersonU starts the conversation and only asks questions. Most of PersonU’s questions are follow-up or continuations of previous questions.

Conversation:

role-assistant:

PersonU: I need to know how to prepare for college.

PersonA: You should first define your goals and interest and be sure to know the costs and how to plan financially and academically for college.

PersonU: Is there something I can use as a guide to get ready for it?

PersonA: you can use our checklist to get ready financially and academically.

PersonU: Any other tip?

PersonA: Be sure to check out the reasons to attend a College or Career schools.

PersonU: Ok, that sounds good. Can you give me more tips?

PersonA: Another thing to take into consideration is to explore your career options.

role-user:

PersonA has access to information in the following passage:

###There are several disability compensation benefits. One of the benefits is the annual clothing allowance. This allowance covers the cost of purchasing new clothes up to a limit of 200 dollars annually.###

Generate a conversation of around two turns between PersonA and PersonU where PersonU needs information from PersonA that is in the passage. Use only information found in the passage.

PersonU starts the conversation and only asks questions. Most of PersonU’s questions

are follow-up or continuations of previous questions.

Conversation:

role-assistant:

PersonU: I heard about a disability benefit for clothing. What is it about?

PersonA: This is a disability compensation benefit known as an annual clothing allowance.

PersonU: I am quite interested about such benefits.

PersonA: Would you like to find out if you are eligible?

role-user:

PersonA has access to information in the following passage:

###Vascepa (icosapent ethyl) is a prescription fish oil medication approved for treating adults with extremely high triglycerides, defined as a triglyceride level of 500 mg/dL or higher. While using this medicine, you may need frequent blood tests at your doctor's office. Vascepa is only part of a treatment program that may also include diet, exercise, and weight control. Follow your doctor's instructions very closely. You should not use Vascepa if you are allergic to icosapent. To make sure Vascepa is safe for you, tell your doctor if you have: 1 liver disease; 2 diabetes; 3 a thyroid disorder; 4 problems with your pancreas; 5 a bleeding or blood-clotting disorder; 6 if you are allergic to fish or shellfish; or. 7 if you drink large amounts of alcohol, Vascepa (icosapent) works in the liver and bloodstream to reduce very low-density triglycerides.###

Generate a conversation of around three turns between PersonA and PersonU where PersonU needs information from PersonA that is in the passage. Use only information found in the passage.

PersonU starts the conversation and only asks questions. Most of PersonU's questions are follow-up or continuations of previous questions.

Conversation:

role-assistant:

PersonU: I heard about a medication called Vascepa. What is it used for?

PersonA: Vascepa is a prescription fish oil medication used for treating adults with extremely high triglyceride levels.

PersonU: Are there any side effects or precautions I should be aware of?

PersonA: While using Vascepa, you may need frequent blood tests, and it's important to follow your doctor's instructions closely. It's important to talk to your doctor about any allergies or existing conditions you have.

PersonU: Is it effective in lowering cholesterol levels?

PersonA: Vascepa is used together with a low-fat diet and other treatments to lower total cholesterol in people with severe high cholesterol.

role-user:

PersonA has access to information in the following passage:

{Document}

Generate a conversation of around three turns between PersonA and PersonU where PersonU needs information from PersonA that is in the passage. Use only information found in the passage.

PersonU starts the conversation and only asks questions. Most of PersonU's questions are follow-up or continuations of previous questions.

Conversation:

role-assistant:

The in-context few-shot prompt in step-2 is as follows (aims to revise the multi-turn QA conversation by adding pronouns and common nouns):

You are a helpful, pattern-following assistant.

role-user:

Given the following conversation between PersonU and PersonA:

###PersonU: I've heard about adobo sauce in Mexican cuisine. Can you tell me more about it?

PersonA: Adobo sauce is a dark red sauce made from ground chiles, herbs, and vinegar. It's used as a marinade and cooking sauce in Mexican and Southwestern cuisines.

PersonU: What are the main ingredients in adobo sauce?

PersonA: The main ingredients are typically chile peppers, garlic, and vinegar. However, there can be variations in the recipe.

PersonU: How can I make adobo sauce at home?

PersonA: One way to make adobo sauce at home is by using smoked jalapeno peppers called chipotles. You can stew the chipotles in a sauce with tomatoes, garlic, vinegar, salt, and spices. It's also possible to find canned adobo sauce in the Hispanic foods section of many grocery stores.

PersonU: Are there any other uses for adobo sauce?

PersonA: Adobo sauce can be used as a condiment or as a marinade for various dishes. It enhances the flavor of meats and can be used as a cooking and serving sauce. Additionally, adobo is also used in a stew-like presentation of meat prepared in this sauce.

PersonU: Is adobo sauce easy to preserve?

PersonA: Yes, you can preserve adobo sauce by freezing or canning it when you're done making it. This allows you to store it for up to a year and enjoy its flavors whenever you want.###

Modify PersonU's questions to use pronouns or common nouns to refer back to words or phrases in PersonU's previous questions or PersonA's previous responses.

role-assistant:

PersonU: I've heard about adobo sauce in Mexican cuisine. Can you provide more information about it?

PersonA: Adobo sauce is a dark red sauce made from ground chiles, herbs, and vinegar. It's used as a marinade and cooking sauce in Mexican and Southwestern cuisines.

PersonU: What are the main ingredients in the sauce?

PersonA: The main ingredients are typically chile peppers, garlic, and vinegar. However, there can be variations in the recipe.

PersonU: How can I make the sauce at home?

PersonA: One way to make it at home is by using smoked jalapeno peppers called chipotles. You can stew them in a sauce with tomatoes, garlic, vinegar, salt, and spices. It's also possible to find canned adobo sauce in the Hispanic foods section of many grocery stores.

PersonU: Are there any other uses for it?

PersonA: It can be used as a condiment or as a marinade for various dishes. It enhances the flavor of meats and can be used as a cooking and serving sauce. Additionally, it is also used in a stew-like presentation of meat prepared in this sauce.

PersonU: Is it easy to preserve?

PersonA: Yes, you can preserve it by freezing or canning it when you're done

making it. This allows you to store it for up to a year and enjoy its flavors whenever you want.

role-user:

Given the following conversation between PersonU and PersonA:

###PersonU: I've heard about a test called urinalysis. What is it used for?

PersonA: Urinalysis is a test that evaluates a sample of your urine. It is used to detect and assess a wide range of disorders, such as urinary tract infection, kidney disease, and diabetes. It examines the appearance, concentration, and content of urine.

PersonU: Can it help diagnose bladder cancer?

PersonA: Yes, urinalysis can be used as a screening and diagnostic tool for bladder cancer. One way to test for bladder cancer is to check for blood in the urine, which is called hematuria. This can be done during a urinalysis by examining the urine cells under a special microscope.

PersonU: What other conditions or diseases can be detected through urinalysis?

PersonA: Urinalysis is commonly used to diagnose urinary tract or kidney infections, evaluate causes of kidney failure, screen for the progression of chronic conditions like diabetes mellitus and high blood pressure, and it can be used in combination with other tests to diagnose certain diseases. It is a versatile test that helps detect abnormalities in the urinary tract.

PersonU: Where can I get a urinalysis done?

PersonA: Urinalysis can be performed in various healthcare settings, including doctors' offices, urgent care facilities, laboratories, and hospitals. You can provide a urine sample in a specimen cup, and the sample can be analyzed on-site or sent to a laboratory for testing.

PersonU: How much urine is typically needed for a urinalysis?

PersonA: Usually, only small amounts of urine, ranging from 30 to 60 ml, are required for urinalysis testing. It's a non-invasive and relatively simple test that provides valuable information about your health.###

Modify PersonU's questions to use pronouns or common nouns to refer back to words or phrases in PersonU's previous questions or PersonA's previous responses.

role-assistant:

PersonU: I've heard about a test called urinalysis. What is it used for?

PersonA: Urinalysis is a test that evaluates a sample of your urine. It's used to detect and assess a wide range of disorders, such as urinary tract infection, kidney disease, and diabetes. It examines the appearance, concentration, and content of urine.

PersonU: Can it help diagnose bladder cancer?

PersonA: Yes, urinalysis can be used as a screening and diagnostic tool for bladder cancer. One way to test for bladder cancer is to check for blood in the urine, which is called hematuria. This can be done during a urinalysis by examining the urine cells under a special microscope.

PersonU: What other conditions or diseases can be detected through this test?

PersonA: Urinalysis is commonly used to diagnose urinary tract or kidney infections, evaluate causes of kidney failure, screen for the progression of chronic conditions like diabetes mellitus and high blood pressure, and it can be used in combination with other tests to diagnose certain diseases. It is a versatile test that helps detect abnormalities in the urinary tract.

PersonU: Where can I go to get this test done?

PersonA: Urinalysis can be performed in various healthcare settings, including doctors' offices, urgent care facilities, laboratories, and hospitals. You can provide a urine sample in a specimen cup, and the sample can be analyzed on-site

or sent to a laboratory for testing.

PersonU: How much urine is typically needed for the test?

PersonA: Usually, only small amounts of urine, ranging from 30 to 60 ml, are required for urinalysis testing. It's a non-invasive and relatively simple test that provides valuable information about your health.

role-user:

Given the following conversation between PersonU and PersonA:

{multi-turn QA conversation}

Modify PersonU's questions to use pronouns or common nouns to refer back to words or phrases in PersonU's previous questions or PersonA's previous responses.

role-assistant:

B. More Details and Results for Retrieval in Conversational QA

B.1. Query Rewriting Prompts for GPT-3.5-turbo

The in-context few-shot query rewriting prompt we use for GPT-3.5-turbo is as follows:

You are a helpful, pattern-following assistant.

role-user:

Given the following conversation between PersonU and PersonA:

PersonU: Hello, I would like to know what to do if I do not agree with any decision.

PersonA: disagree with our decision about your monthly income adjustment amounts?

PersonU: no. Where can I find my SHIP contact information?

PersonA: You can find your local SHIP contact information in the back of your Medicare & You 2020 Handbook online.

PersonU: and how do they calculate the adjustments?

Instead of having this entire conversation, how can PersonU get what he or she is looking for using a single question? Respond with that question.

role-assistant:

How is the calculation for adjustments made by SHIP determined?

role-user:

Given the following conversation between PersonU and PersonA:

PersonU: I need to know how to prepare for college.

PersonA: You should first define your goals and interest and be sure to know the costs and how to plan financially and academically for college.

PersonU: Is there something I can use as a guide to get ready for it?

Instead of having this entire conversation, how can PersonU get what he or she is looking for using a single question? Respond with that question.

role-assistant:

What resources or guides can I use to help me prepare for college?

role-user:

Given the following conversation between PersonU and PersonA:

{Dialogue History + Latest Question}

Instead of having this entire conversation, how can PersonU get what he or she is looking for using a single question? Respond with that question.

role-assistant:

B.2. More Results for Retrieval in Conversational QA

Models	Average		Doc2Dial		QuAC		QReCC		TopiOCQA		INSCIT	
	top-1	top-5	top-1	top-5	top-1	top-5	top-1	top-5	top-5*	top-20*	top-5*	top-20*
Dragon (w/ dialog history)	46.29	73.09	43.33	75.61	56.8	82.86	46.17	81.96	57.68	78.80	27.49	46.22
Dragon + Rewrite (w/ dialog history)	47.57	74.12	44.54	76.98	57.23	83.04	46.45	82.60	60.94	81.74	28.69	46.22
Dragon + Rewrite (w/ single query only)	54.46	80.13	47.60	80.60	47.10	77.15	51.73	85.78	73.07	88.19	52.79	68.92
Dragon + Fine-tune (w/ dialog history)	52.72	80.67	48.94	83.01	52.64	81.95	50.73	87.17	67.86	86.28	43.43	64.94
Dragon + Fine-tune + Rewrite (w/ dialog history)	53.17	80.84	49.30	84.64	55.04	83.23	51.23	87.99	60.50	81.03	49.80	67.33

Table 9. Comprehensive multi-turn retrieval results across five datasets.

In Table 9, we show comprehensive comparisons between fine-tuning and rewriting methods.

Interestingly, we find that compared to only using the rewritten query as input (Dragon + Rewrite (w/ single query only)), giving additional dialog history (Dragon + Rewrite (w/ dialog history)) makes the average scores significantly drop. This is because Dragon is originally pretrained on single-turn queries, it will naturally have better generalization ability when a single-turn rewritten query instead of a multi-turn conversation is provided. And the rewritten query already contains sufficient information from the dialog history.

In addition, we observe that “Dragon + Fine-tune” performs on par with “Dragon + Fine-tune + Rewrite”. In other words, for the multi-turn fine-tuning method, replacing original query with rewritten query as inputs yields comparable results. This is because rewritten query will not provide much additional information for the model since the dialog history has already been provided, and it might even cause negative effects (e.g., results on the TopiOCQA dataset) since it makes the whole conversation input not natural. This once again demonstrates how effective the fine-tuning method is in equipping the model with the capability to comprehend the multi-turn context.

C. Conversational QA Benchmarks

C.1. Data Statistics

Doc2Dial We use the test set of Doc2Dial for the evaluation. It consists of 719 dialogs with 3939 user-agent turns.

QuAC We use the validation set of QuAC for the evaluation since its test set cannot be directly obtained. Its validation set consists of 1000 dialogs with 7354 user-agent turns. Among these 7354 user-agent turns, there are 1486 (around 20.2%) unanswerable questions. For the combined evaluation of answerable and unanswerable questions, we set the ground truth response for the unanswerable question as “Sorry. I cannot find the answer based on the context.”, same as the one we set in our stage-2 tuning. For the fair comparison, we replace the unanswerable responses in the baseline models (i.e., Llama2-SFT/Chat, GPT-3.5-turbo, GPT-4) with the same sentence (Details can be found in Appendix E).

QReCC We use the test set of QReCC for the evaluation. Its test set includes some dialogue samples source from the QuAC dataset. To avoid overlap with other benchmark datasets, we remove those QuAC-sourced samples, resulting in 2805 user-agent turns.

TopiOCQA We use the validation set of TopiOCQA since its test set is not available yet. Its validation set consists of 205 dialogs with 2514 user-agent turns. Each question has a total of four human-written answers. It has unanswerable cases. However, we do not include this dataset in unanswerable case evaluation because we only find 46 questions with no

answer being found, which is not sufficient enough for the unanswerable case evaluation. Given that this dataset use the whole Wikipedia as the retrieval corpus, we leverage its topic information for multi-turn retrieval since we focused more on conversational QA over documents which typically narrow down to a specific topic or domain.

INSCIT We use the validation set of TopiOCQA since its test set is not available yet. Its validation set consists of 86 dialogues with 502 user-agent turns. Each question has an average of 1.9 human-written answers. It has unanswerable response for a few questions. However, we do not include this dataset in unanswerable case evaluation because every question always has at least one answerable response, which means every question is answerable. INSCIT also use the whole Wikipedia as the retrieval corpus. Hence, we also leverage its topic information for multi-turn retrieval for the same reason mentioned in TopiOCQA.

CoQA We use the validation set of CoQA since its test set cannot be directly obtained. Its validation set consists of 500 dialogues with 7983 user-agent turns. Each question has a total of four human-written answers. It has unanswerable cases. However, we do not include this dataset in unanswerable case evaluation for the same reason as in the TopiOCQA dataset. We only find 13 questions with no answer being found, which is not sufficient enough for the unanswerable case evaluation.

DoQA We use the test set of DoQA for the evaluation. Its test set consists of 1200 dialogues with 5394 user-agent turns across Cooking, Travel and Movie domains. Among 5394 user-agent turns, there are 1479 (around 27.4%) unanswerable questions. We use the same strategy as the one mentioned in QuAC dataset to incorporate unanswerable samples into the evaluation.

ConvFinQA We use the validation set of ConvFinQA since its test set cannot be directly obtained. Its validation set consists of 421 dialogues with 1490 user-agent turns.

SQA We use the test set of SQA for the evaluation. Its test set consists of 1025 dialogues with 3100 user-agent turns.

HybridDial We use the test set of HybridDial for the evaluation. Its test set consists of 243 dialogues with 1111 user-agent turns.

C.2. Details of Incorporating Table as Context

We use the markdown format to process the table in the document (i.e., using “|” to separate each cell in the table). However, as the number of rows in a table increases, it is harder for the model to link the values of cells in the last few rows to their corresponding headers in the table. To address this issue, we append the headers to the corresponding cell values in each row, so as to make it easier for the model to capture the connections between the cells and their respective headers. For example, a original markdown table

```
| Boat | Crew | Nation | Date | Meet | Location |
| M1x | Mahe | FR | 2009 | | Poznan |
| M2- | Hamish | US | 2012 | Olympics | Lucerne |
| M2+ | Igor | DE | 1994 | | Indianapolis |
```

will be converted to

```
| M1x (Boat) | Crew: Mahe | Nation: FR | Date: 2009 | Meet: | Location: Poznan |
| M2- (Boat) | Crew: Hamish | Nation: US | Date: 2012 | Meet: Olympics | Location: Paris |
| M2+ (Boat) | Crew: Igor | Nation: DE | Date: 1994 | Meet: | Location: Indianapolis |
```

We apply this table processing strategy to all tabular datasets.

C.3. Prompts for the Benchmarks

We use the prompt format mentioned in §A.2 for benchmarks in ChatQA, Llama2-Chat, GPT-3.5-turbo and GPT-4. We keep the {Context for Latest Question} the same for all models, while we adjust the {Instruction} for the baselines (i.e., Llama2-Chat, GPT-3.5-turbo and GPT-4) to ensure they do not get sub-optimal results. We use different

instructions for test benchmarks with different answer types (e.g., long answer, short answer, arithmetic calculation). The {Instruction} for all models on the benchmarks are as follows:

C.3.1. CHATQA

We keep the {Instruction} consistent between the data blends in stage-2 and test benchmarks based on different answer types.

We use “Please give a full and complete answer for the question.” for DoQA, INSCIT, HybridDial, Doc2Dial, QuAC, and QReCC, since these datasets generally have long answers for the questions.

We use “Answer the following question with a short span, or a full and complete answer.” for SQA and TopiOCQA, since these datasets have both short and long answers based on the questions.

We use “Answer the following question with a short span. The answer needs to be just in a few words.” for CoQA, since it generally has short answers for the questions.

We use “Answer the following question with a number from context or the math arithmetic using +, -, *, or /.” for ConvFinQA, since this dataset requires the model to either extract numbers from the context or do arithmetic calculation. We will calculate the number based on the arithmetic formula the model generates and compare it with the gold answer.

C.3.2. LLAMA2-CHAT

Note that we tried original Llama2-Chat prompt template⁹, which gives slightly worse results compared to using the one in §A.2. We have tried several {Instruction} for Llama2-Chat. We find the ones below works the best.

We use “Please give an answer in just one sentence.” for DoQA, INSCIT, HybridDial, Doc2Dial, QuAC, and QReCC, since these datasets generally have long answers but within one sentence. We notice that it is important to give Llama2-Chat specific instruction like “one sentence” instead of “full and complete answer” to prevent the model from generating very long answers.

We use “Answer the following question with a short span, or one sentence.” for TopiOCQA, since this dataset has both short and long answers based on the questions, and the long answers are generally within one sentence.

We use “Answer the following questions with one or a list of entities.” for SQA, since the answer for this dataset always consists of one or a list of entities from the context.

We use “Answer the following question with a short span. The answer needs to be just in a few words.” for CoQA, since it generally has short answers for the questions.

We use “Answer the following question with just a number from context or just the math arithmetic using +, -, *, or /.” for ConvFinQA, since this dataset requires the model to either extract numbers from the context or do arithmetic calculation. We extract the arithmetic formula generated by the model and use a calculator to get its final result.

C.3.3. GPT-3.5-TURBO & GPT-4

We have tried several {Instruction} for GPT-3.5-turbo and GPT-4, we find the ones below works the best (applied for both GPT-3.5-turbo and GPT-4).

We use “Please give an answer in just one sentence.” for DoQA, INSCIT, HybridDial, Doc2Dial, QuAC, and QReCC, since these datasets generally have long answers but within one sentence. Similar to Llama2-Chat, we also find OpenAI models tend to generate quite long answers given the instruction of “full and complete answer”. Hence, we make the instruction more specific (i.e., “one sentence”) to prevent the model from generating very long answers.

We use “Answer the following questions in JUST a few words or one sentence.” for TopiOCQA, since this dataset has both short and long answers based on the questions, and the long answers are generally within

⁹<https://gpustools.org/llama-2-prompt-template/>

You will be provided some text paragraphs (**context**), a **dialogue history** (between User and Assistant), a **final question** from User that could be answered based on the given text paragraphs, and two **responses** to the final question.

You will be given a human rewritten **reference answer** for the final question. **Note that the reference answer would indicate it when the answer cannot be found.**

Note that the dialogue history could be empty.

What you need to do:

1. After reading the text paragraphs (context), the dialog history, the question, and the reference answer, you have to select the response that is more factually correct.
2. If both are equally factually correct, select both. If neither is factually correct, select neither.

===== **Attention** =====

--> Consider both responses are **Equally Good**, as long as both of them answer the question, and do **NOT** have unverifiable or factually incorrect content.

--> Please penalize **verbosity** if the response has some content that are **NOT directly relevant to the question**

--> Please penalize it if some content in the response can **NOT be verifiable**..

Context:
\${context}

Dialogue History:
\${dialogue_history}

Final Question:
\${question}

Reference Answer:
\${reference}

Response1: \${response1}

Response2: \${response2}

Select an option

Response1	1
Response2	2
Both	3
Neither	4

Submit

Figure 3. Human evaluation instructions and the interface for annotators.

one sentence.

We use “Answer the following questions with one or a list of entities. Do not give a detailed explanation. Answer needs to be as short as possible.” for SQA. We find that OpenAI models often give detailed explanation for SQA dataset unless specifically instructed not to.

We use “Answer the following question with a short span. The answer needs to be just in a few words.” for CoQA, since it generally has short answers for the questions.

We use “Answer the following questions with just a number from context or just the math arithmetic using +, -, *, or /.” for ConvFinQA, since this dataset requires the model to either extract numbers from the context or do arithmetic calculation. We extract the arithmetic formula generated by the model and use a calculator to get its final result.

D. Human Evaluation

We conduct human evaluation across the ten test benchmark datasets. We randomly select 60 samples for each dataset, and each sample is labelled by three annotators, which results in a total of 1800 annotations.

We ask the annotators to verify the facts in models’ outputs and determine which model provides a more accurate response to the question. We use Amazon Mechanical Turk platform to conduct the human evaluation. The details of our human evaluation instructions and the interface shown to annotators are illustrated in Figure 3.

E. Unanswerable Case Evaluation

For unanswerable case, we consider the model indicating that the question cannot be answered as correct. For answerable cases, we consider the model not indicating the question is unanswerable as correct (i.e., the model giving an answer). We find that ChatQA always generates “Sorry. I cannot find the answer based on the context” when it finds the question is unanswerable, since we use this sentence as a response for unanswerable questions in the stage-2 tuning. As for Llama2-Chat, GPT-3.5-turbo, and GPT-4, their outputs for unanswerable questions usually follow some specific patterns. Below, we list the heuristic matching patterns derived from all generated samples in DoQA and QuAC datasets to determine if the model suggests that the question is unanswerable. When we find the generated output contains the pattern listed below, we interpret it as an indication that the question is unanswerable, and we will replace its answer with “Sorry. I cannot find the answer based on the context.” for the F1 evaluation.

i’m not sure, cannot find, does not provide, cannot provide, cannot answer, cannot be found, cannot be determined, don’t have information, do not have information, couldn’t find, no information in the context, does not mention, not explicitly mentioned, i don’t have any, i do not have any, does not specify, doesn’t provide, not able to, unable to, doesn’t specify, there is no information, there is no mention, not mentioned, i don’t have enough information, there is no specific information, there is no specific mention, no information found, I don’t have that information

F. Case Study

More examples on ChatQA-13B, ChatQA-70B, GPT-3.5-turbo, and GPT-4 can be found in Table 10. We use blue color to highlight the relevant context for the last user question. And we use green and red color to highlight the correct and incorrect parts in the assistant responses.

ChatQA: Building GPT-4 Level Conversational QA Models

Context			Conversation	Assistant Responses																																				
Pos	Rider	Time/Retired	User: what racers are shown?																																					
1	Loris Capirossi	38:04.730	Assistant: Loris Capirossi, Valentino Rossi, Jeremy McWilliams, Tohru Ukawa, ... , Henk Van De Lagemaat, Maurice Bolwerk, Roberto Rolfo, Marcellino Lucchi.	ChatQA-13B: Loris Capirossi																																				
2	Valentino Rossi	+0.180																																						
3	Jeremy McWilliams	+0.534																																						
4	Tohru Ukawa	+0.537																																						
5	Shinya Nakano	+0.742																																						
6	Ralf Waldmann	+7.019	User: of those, what times were recorded?	ChatQA-70B: +1 Lap																																				
7	Franco Bertaini	+20.889	Assistant: 38:04.730, +0.180, +0.534, +0.537, ... , +1:40.635, +1 Lap, Retirement.	GPT-3.5-turbo: 38:04.730																																				
8	Stefano Perugini	+20.891																																						
9	Jason Vincent	+21.310																																						
10	Anthony West	+26.816																																						
11	Alex Hofmann	+26.933																																						
...			User: of those times, which were not actual times?	GPT-4: 38:04.730																																				
23	Arno Visscher	+1:40.635	Assistant: +1 Lap, Retirement	Ground Truth: +1 Lap																																				
24	Henk Van De Lagemaat	+1 Lap																																						
Ret	Maurice Bolwerk	Retirement																																						
Ret	Andre Romein	Retirement																																						
Ret	Roberto Rolfo	Retirement																																						
Ret	Marcellino Lucchi	Retirement	User: which of was an actual finish?																																					
			Assistant:																																					
<div>2014 compared to 2013 mst 2019s net sales decreased \$ 305 million, or 3% in 2014 as compared to 2013 ... space systems 2019 operating results included the following (in millions):</div> <table><thead><tr><th></th><th>net sales</th><th>backlog at year-end</th></tr></thead><tbody><tr><td>2015</td><td>\$ 9105</td><td>\$ 17400</td></tr><tr><td>2014</td><td>\$ 9202</td><td>\$ 20300</td></tr><tr><td>2013</td><td>\$ 9288</td><td>\$ 21400</td></tr></tbody></table> <div>2015 compared to 2014 space systems 2019 net sales in 2015 decreased \$ 97 million, or 1%, compared to 2014. these decreases were partially offset by higher net sales of approximately \$ 235 million for businesses acquired in 2014; and approximately \$ 75 million for the orion program due to increased volume.</div>				net sales	backlog at year-end	2015	\$ 9105	\$ 17400	2014	\$ 9202	\$ 20300	2013	\$ 9288	\$ 21400	User: what was the average backlog in 2015?																									
				net sales	backlog at year-end																																			
			2015	\$ 9105	\$ 17400																																			
			2014	\$ 9202	\$ 20300																																			
			2013	\$ 9288	\$ 21400																																			
			Assistant: 17400																																					
			User: what was it in 2014?																																					
			Assistant: 20300	ChatQA-13B: 17400 + 20300 + 21400																																				
			User: what is the sum of those years?	ChatQA-70B: 17400 + 20300 + 21400																																				
			Assistant: 17400 + 20300	GPT-3.5-turbo: 9288 + 9202 + 9105																																				
User: what was the average backlog in 2013?	GPT-4: 17400 + 20300 + 21400																																							
Assistant: 21400	Ground Truth: 17400 + 20300 + 21400																																							
User: what is the total sum for all 3 years?																																								
Assistant:																																								
				ChatQA-13B: There are 8 Gymnastics participated in the championship.																																				
<div>The XVI World Rhythmic Gymnastics Championships were held in Brussels, Belgium, on November 20-22, 1992.</div> <table><thead><tr><th>Rank</th><th>Gymnast</th><th>Country</th><th>Point</th></tr></thead><tbody><tr><td>1</td><td>Oxana Kostina</td><td>Russia</td><td>9.775</td></tr><tr><td>2</td><td>Maria Petrova</td><td>Bulgaria</td><td>9.700</td></tr><tr><td>3</td><td>Diana Popova</td><td>Bulgaria</td><td>9.625</td></tr><tr><td>4</td><td>Carmen Acedo</td><td>Spain</td><td>9.625</td></tr><tr><td>5</td><td>Irina Deleanu</td><td>Romania</td><td>9.550</td></tr><tr><td>6</td><td>Ekaterina S.</td><td>Ukraine</td><td>9.525</td></tr><tr><td>7</td><td>Viktoriya Yani</td><td>Ukraine</td><td>9.475</td></tr><tr><td>8</td><td>Maria Sansaridou</td><td>Greece</td><td>9.425</td></tr></tbody></table>			Rank	Gymnast	Country	Point	1	Oxana Kostina	Russia	9.775	2	Maria Petrova	Bulgaria	9.700	3	Diana Popova	Bulgaria	9.625	4	Carmen Acedo	Spain	9.625	5	Irina Deleanu	Romania	9.550	6	Ekaterina S.	Ukraine	9.525	7	Viktoriya Yani	Ukraine	9.475	8	Maria Sansaridou	Greece	9.425	User: What is the XVI World Rhythmic Gymnastics Championships?	ChatQA-70B: There are 8 gymnasts* participated in the championship.
			Rank	Gymnast	Country	Point																																		
			1	Oxana Kostina	Russia	9.775																																		
			2	Maria Petrova	Bulgaria	9.700																																		
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Assistant: The XVI World Rhythmic Gymnastics Championships were held in Brussels, Belgium, on November 20-22, 1992	GPT-3.5-turbo: There were a total of 8 gymnasts* who participated in this championship.																																							
User: How many Gymnastics participated this championship?	GPT-4: The context does not provide the total number of gymnasts who participated in the XVI World Rhythmic Gymnastics Championships.																																							
Assistant:	Ground Truth: There are 8 gymnasts participated this championship.																																							
				*Both models correct the User's typo of "Gymnastics" to "gymnasts"																																				

*Both models correct the User's typo of "Gymnastics" to "gymnasts"

Context	Conversation	Assistant Responses																																				
<p>The 3000 metres steeplechase or 3000-meter steeplechase is the most common distance for the steeplechase in track and field. It is an obstacle race over the distance of the 3000 metres, which derives its name from the horse racing steeplechase.</p> <table> <tr> <th>Year</th><th>Athlete</th><th>Location</th></tr> <tr> <td>1968</td><td>Jouko Kuha (FIN)</td><td>Stockholm</td></tr> <tr> <td>1969</td><td>Vladimiras Dudinas (URS)</td><td>Kiev</td></tr> <tr> <td>1970</td><td>Kerry O'Brien (AUS)</td><td>Berlin</td></tr> <tr> <td>1971</td><td>Kerry O'Brien (AUS)</td><td>Adelaide</td></tr> <tr> <td>1972</td><td>Anders Gärderud (SWE)</td><td>Helsinki</td></tr> <tr> <td>1973</td><td>Ben Jipcho (KEN)</td><td>Helsinki</td></tr> <tr> <td>1974</td><td>Anders Gärderud (SWE)</td><td>Helsinki</td></tr> <tr> <td>1975</td><td>Anders Gärderud (SWE)</td><td>Stockholm</td></tr> <tr> <td>1976</td><td>Anders Gärderud (SWE)</td><td>Montréal</td></tr> <tr> <td>1977</td><td>Michael Karst (FRG)</td><td>Stockholm</td></tr> <tr> <td>...</td><td></td><td></td></tr> </table>	Year	Athlete	Location	1968	Jouko Kuha (FIN)	Stockholm	1969	Vladimiras Dudinas (URS)	Kiev	1970	Kerry O'Brien (AUS)	Berlin	1971	Kerry O'Brien (AUS)	Adelaide	1972	Anders Gärderud (SWE)	Helsinki	1973	Ben Jipcho (KEN)	Helsinki	1974	Anders Gärderud (SWE)	Helsinki	1975	Anders Gärderud (SWE)	Stockholm	1976	Anders Gärderud (SWE)	Montréal	1977	Michael Karst (FRG)	Stockholm	...			<p>User: Hello, can you tell me about the 3000 metres steeplechase?</p> <p>Assistant: The 3000 metres steeplechase is the most common distance for the steeplechase in track and field that goes over the distance of the 3000 metres, which derives its name from the horse racing steeplechase.</p> <p>User: Can you tell me the men that are part of it?</p> <p>Assistant: Some of the men are Henry Rono and Michael Karst.</p> <p>User: Which locations did Kerry O'Brien ran for?</p> <p>Assistant:</p>	<p>ChatQA-13B: He ran in Berlin, Adelaide, and Stockholm.</p> <p>ChatQA-70B: Kerry O'Brien ran in Adelaide and Berlin.</p> <p>GPT-3.5-turbo: Kerry O'Brien ran in Berlin, Adelaide, and Champaign.</p> <p>GPT-4: Kerry O'Brien ran in Berlin and Adelaide.</p> <p>Ground Truth: He ran for both Berlin and Adelaide.</p>
Year	Athlete	Location																																				
1968	Jouko Kuha (FIN)	Stockholm																																				
1969	Vladimiras Dudinas (URS)	Kiev																																				
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1977	Michael Karst (FRG)	Stockholm																																				
...																																						
<p>title: Non-EU family member traveling to Schengen countries. source: You can travel visa-free only if you have a "residence" card of a family member of a union citizen" issued under article 10 of the free movement directive (or if you are a citizen of a country whose nationals don't require visas in the Schengen area). A residence card issued by Romania to the spouse of a Romanian citizen is not necessarily an article 10 card. If you do not have an article 10 card, EU countries other than Romania must issue you a visa free of charge and on the basis of an expedited procedure. The grounds for refusal of that visa are strictly limited. These provisions are also dependent on your traveling with or joining your spouse. In case you are not, you'll need a regular Schengen visa. As Relaxed pointed out in a comment, it appears that your concern stems in part from the fact that Romania is not yet a full participant in the Schengen agreement. These rules apply to all EU countries, not just Schengen countries, because they are based on the EU right of freedom of movement.</p>	<p>User: Can I travel from Romania to the Schengen area visa-free?</p> <p>Assistant: You can travel visa-free only if you have a "residence card of a family member of a union citizen" issued under article 10 of the free movement directive</p> <p>User: I have a temporary residence card also, can we travel together visa-free?</p> <p>Assistant: If you do not have an article 10 card, EU countries other than Romania must issue you a visa free of charge and on the basis of an expedited procedure.</p> <p>User: How do I get a article 10 card?</p> <p>Assistant:</p>	<p>ChatQA-13B: The grounds for refusal of that visa are strictly limited. These provisions are also dependent on your traveling with or joining your spouse. In case you are not, you'll need a regular Schengen visa.</p> <p>ChatQA-70B: Sorry. I cannot find the answer based on the context.</p> <p>GPT-3.5-turbo: To obtain an article 10 card, you would need to meet the requirements set out in the free movement directive and apply for it through the appropriate channels in Romania.</p> <p>GPT-4: The text does not provide information on how to obtain an article 10 card.*</p> <p>Ground Truth: Sorry. I cannot find the answer based on the context.</p> <p>*In the evaluation, we will detect this unanswerable pattern and replace it with "Sorry. I cannot find the answer based on the context" to match with the ground truth.</p>																																				
<p>title: Bengal fox. "Vulpes bengalensis" is a relatively small fox with an elongated muzzle, long, pointed ears, and a bushy tail about 50 to 60% of the length of the head and body. Its dorsal pelage is very variable, but mostly grayish and paler ventrally; its legs tend to be brownish or rufous. It is more daintily built than "Vulpes vulpes". The tail is bushy with a prominent black tip which distinguishes it from "V. vulpes". Back of ears are dark brown with black margin. Its rhinarium is naked and the lips are black, with small black hair patches on upper part of muzzle (shaft) in front of eyes.</p> <p>title: Red fox. The red fox is considered a more specialised form of "Vulpes" than the Afghan, corsac and Bengal foxes in the direction of size and adaptation to carnivory; the skull displays far fewer neotenus traits than in other species ...</p> <p>title: Bengal fox. The ears have the same colour as the nape or maybe darker, but not having a dark patch as in "V. vulpes". Extensive variation in coat colour exists across populations and seasonally within populations, but generally varies from grey to pale brown ...</p>	<p>User: what is red fox?</p> <p>Assistant: It is the largest of the true foxes and one of the most widely distributed members of the order Carnivora.</p> <p>User: where did it originate?</p> <p>Assistant: The species is Eurasian in origin.</p> <p>User: how did it evolve?</p> <p>Assistant: It is considered a more specialised form of "Vulpes" than the Afghan, corsac and Bengal foxes in the direction of size and adaptation to carnivory.</p> <p>User: what is the appearance of this third type of fox?</p> <p>Assistant:</p>	<p>ChatQA-13B: The ears have the same colour as the nape or maybe darker, but not having a dark patch as in "V. vulpes". Extensive variation in coat colour exists across populations and seasonally within populations, but generally varies from grey to pale brown.</p> <p>ChatQA-70B: "Vulpes bengalensis" is a relatively small fox with an elongated muzzle, long, pointed ears, and a bushy tail about 50 to 60% of the length of the head and body.</p> <p>GPT-3.5-turbo: I'm sorry, but I couldn't find any information about a third type of fox in the given context.</p> <p>GPT-4: The context does not provide information on a third type of fox.</p> <p>Ground Truth: It is a relatively small fox with an elongated muzzle, long, pointed ears, and a bushy tail about 50 to 60% of the length of the head and body.</p>																																				

Table 10. Case study for ChatQA-13B, ChatQA-70B, GPT-3.5-turbo, and GPT-4. We use blue color to highlight the relevant context for the last user question. And we use green and red color to highlight the correct and incorrect parts in the assistant responses.

G. Human Annotated Conversational QA Data

G.1. Statistics of User-Agent Turns

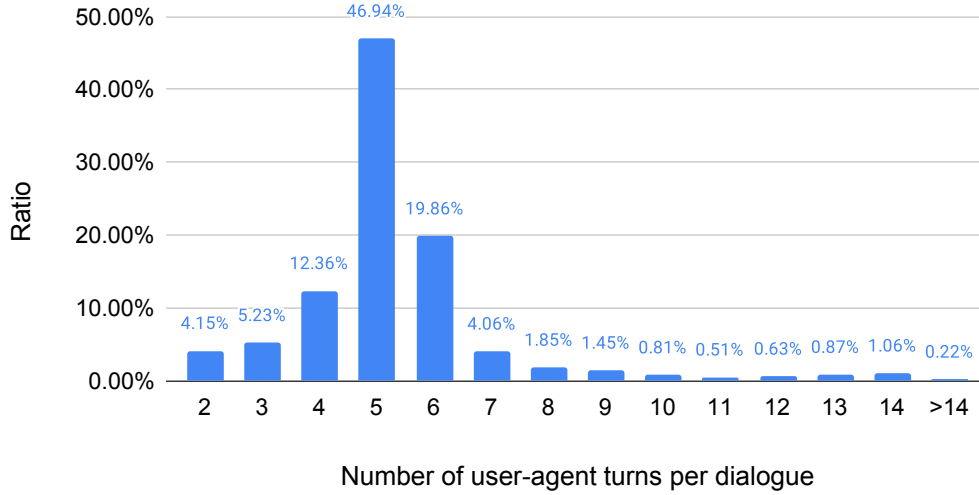


Figure 4. Statistics regarding the number of user-agent turns for each dialogue

Figure 4 illustrates the statistics regarding the number of user-agent turns per dialogue over the 7k human annotated conversational QA data.

G.2. Guidelines for Conversational QA Data Collection

In this section, we demonstrate the guidelines we provide for the conversational QA data collection. We request the annotators to act as both user and agent to construct the conversational QA sample based on the given document, which makes the annotation more efficient. The guidelines consists of three parts: 1) What does conversational QA samples look like; 2) What kinds of conversational QA samples we need; and 3) What we need to annotate.

G.2.1. WHAT DOES CONVERSATIONAL QA SAMPLES LOOK LIKE

One conversational QA sample is based on a document that we provide. The user and agent behaviors are as follows:

- User behavior: 1) Ask questions to agent based on the given document; 2) Answer questions from agent when agent wants to clarify something.
- Agent behavior: 1) Answer questions from user based on the document; 2) Ask questions to the user when the user’s question is not clear, or too general/broad.

G.2.2. WHAT KINDS OF MULTI-TURN QA SAMPLES WE NEED

We list the requirements for user’s questions and agent’s responses below.

User’s Questions

- User’s questions can refer to his/her previous (or multiple turns before) question.
- User’s questions can also refer to the previous (or multiple turns before) answer from the agent.
- Try to use pronouns or common nouns to replace the entities mentioned before.

- Try to make the user's questions diverse. For the same type of questions, try to use different ways to express it in different dialogue annotations.
- Other user question types we need
 - Given the answer from agent, ask for extra information (e.g., What else ...; any other ...; is there more ...).
 - Switch the topic and starting a new thread in conversation.
 - Ask two questions at the same time.

Agent's Response

- Try to make the agent's answer within 1-2 sentences. If the answer has to be long, try to make it concise.
- Try not to directly copy the whole relevant context from the document as the answer. Instead, try to construct the answer by paraphrasing the chosen context.
- Try to come up with a small proportion of cases where agent asks questions to user to clarify something. Specifically, when the user's question is too broad or not clear, the agent needs to narrow down the scope by asking clarification questions to see which specific aspects that the user cares more about.

G.2.3. WHAT WE NEED TO ANNOTATE

We list what we need to annotate for each conversation below.

- For each document, we need to annotate the user's questions and corresponding agent's responses. The average number of user-agent turns per conversation needs to be around five.
- For each user's question, we need to annotate all the relevant context within the document.