Towards More Realistic Generation of Information-Seeking Conversations

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Abstract

In this paper, we introduce a novel framework SimSeek (simulating information-seeking conversation from unlabeled documents) and compare two variants of it to provide a deeper perspective into the information-seeking behavior. We first introduce a strong simulator for information-symmetric conversation, SimSeek-sym, where questioner and answerer share all knowledge when conversing with one another. Although it simulates reasonable conversations, we take a further step toward more realistic information-seeking conversation. Hence, we propose SimSeek-asym that assumes information asymmetry between two agents, which encourages the questioner to seek new information from an inaccessible document. In our experiments, we demonstrate that SimSeek-asym successfully generates information-seeking conversations for two downstream tasks, CQA and conversational search. In particular, SimSeek-asym improves baseline models by 1.1–1.9 F1 score in QuAC (Choi et al., 2018), and by 1.1 of MRR in OR-QuAC (Qu et al., 2020). Moreover, we thoroughly analyze our synthetic datasets to identify crucial factors for realistic information-seeking conversation.

1 Introduction

Conversational question answering (CQA) involves modeling the information-seeking process of humans’ dialogue. In the task, systems are asked to answer context-dependent questions that need to be understood in conversational flow. It makes CQA complex since even the same word could be interpreted differently depending on the context, and almost infinite cases of conversational context can be given with the question. To build robust system that can handle innumerable cases, large-scale CQA datasets (Choi et al., 2018; Reddy et al., 2019; Saeidi et al., 2018; Penha et al., 2019; Campos et al., 2020; Feng et al., 2020) have recently been developed. Still, it is practically infeasible to cover most of the interactions in real-world scenarios, which motivates automated methods for generating realistic CQA datasets.

Figure 1: Examples of two conversation scenarios. In the former, the questioner can access the evidence document, allowing them to ask less related information to the conversation (q1, q2 in (a)). In the latter, questioners are encouraged to seek new information from the hidden document. Hence, information-seeking behaviors are frequently observed; open-ended, unanswerable, and “Anything else?” questions (q1, q2, q3 in (b)).
However, generating realistic CQA is a more challenging task, which requires synthesizing multiple interdependent ingredients, e.g., conversation history, appropriate follow-up question, and accurate answer from grounding document. Most of the literature has discussed only sub-parts of the overall process. A line of research in conversational question generation (CQG) aims to generate human-like follow-up questions upon conversational history (Gao et al., 2019; Pan et al., 2019; Qi et al., 2020; Gu et al., 2021). Another line of research has greatly improved answer accuracy (Huang et al., 2018; Chen et al., 2019; Qu et al., 2019b; Kim et al., 2021; Zhao et al., 2021). In other words, they are limited in assuming that all other ingredients (i.e., held-out conversations by humans and their gold answer) are provided. Thus, the prior approaches cannot construct whole conversations upon the unlabeled corpus and therefore have never shown a practical use of synthetic conversations.

In this paper, we delve into the problem of generating a realistic CQA dataset from unlabeled documents. We focus on information-asymmetric conversations where reference information is unequally distributed to two agents, encouraging more realistic conversation. As illustrated in Figure 1 (a), when questioners have excessive information, they often assume and ask for external knowledge less relevant to the conversation. On the other hand, information asymmetry drives them to seek new information in conversational style or sometimes fail to do so (q₁, q₂, and q₃ in Figure 1 (b)). We claim that simulating these information-seeking behaviors is an important step towards a more realistic generation of CQA.

To take a further step towards generating realistic CQA, we propose and contrast two novel frameworks, SimSeek (Simulating Information-Seeking conversation) that can generate synthetic conversation upon the unlabeled corpus, replicating each scenario. We first introduce a strong simulator for information-symmetric conversation (1) SimSeek-sym where CQG model generates context-dependent questions based on the answer candidates, which are automatically provided in advance by an extractive model. Although it succeeds in generating reasonable conversations, we propose a more realistic approach that designs information-asymmetry, (2) SimSeek-asym. In SimSeek-asym, the CQG component first asks questions without accessing any answer-containing document and target answer. Then, an answerer model predicts corresponding answers to the questions.

To demonstrate the effectiveness of SimSeek in a semi-supervised setup, we conduct experiments in one of the challenging CQA benchmarks, QuAC (Choi et al., 2018). To the best of our knowledge, it is the first successful adaptation of the synthetic datasets for the semi-supervised CQA. In the experiment, SimSeek-asym consistently improves backbone CQA models by 1.1-1.9 F1 score, outperforming other CQA generation baselines. Besides, our resulting dataset could also enhance dense retrieval models for the conversational search task. Our framework improves the baseline dense retriever, DPR (Karpukhin et al., 2020) on the conversational search benchmark, OR-QuAC (Qu et al., 2020), by 1.1 of MRR and 1.3 of R@5.

To provide a deeper perspective into the information-seeking behavior, we thoroughly analyze how the two frameworks synthesize the results differently. Following Qi et al. (2020), we quantify various properties, specificity, answer relevance, and informativeness of the synthetic datasets. We compare them with a human-annotated dataset on the metrics and find that information asymmetry makes conversations closer to the human’s information-seeking behavior.

Our main contributions are summarized as:

- We propose a novel framework, SimSeek, which can generate synthetic information-seeking conversations from unlabeled documents.
- To the best of our knowledge, we are the first to demonstrate the effectiveness of synthetic datasets in the semi-supervised CQA, achieving competitive performance with humans.
- We provide insight into realistic information-seeking conversations by contrasting two proposed approaches that simulate each CQA scenario.

2 Background

In the information-seeking conversation, there are two roles, questioner and answerer, who converse with the specific topic. To provide appropriate information to the questioner, the answerer can utilize the document that consists of answer-containing passage ε and its background knowledge B which includes the title of the document and its abstractive description. Let q₁ is the current question and
Figure 2: Overview of our frameworks, SimSeek-sym and SimSeek-asym. (a) SimSeek-sym consists of answer-grounded CQG and conversational answer extractor to simulate information-symmetric conversation. Both models can access the same evidence passage. (b) SimSeek-asym consists of prior-grounded CQG and conversational answer finder to simulate information-asymmetric conversation. Each model access background knowledge $B$ and evidence passage $c$ to output question and answer, respectively.

3 SimSeek: Simulating Information-Seeking Conversation

We introduce two novel frameworks, SimSeek-sym and SimSeek-asym, that generate the synthetic conversations in different CQA scenarios, as illustrated in Figure 2. Each framework tackles the following CQA scenarios, respectively: (1) information-symmetric conversation where questioner and answerer share all information about the topic and (2) information-asymmetric conversation where questioners cannot access the evidence document when asking questions.

3.1 SimSeek-sym

We propose SimSeek-sym to simulate the information-symmetric conversation. SimSeek-sym consists of two components, conversational answer extractor (CAE) and answer-grounded conversational question generator (CQGanswer). At every turn $t$, the CAE identifies candidate spans that are likely to be answers to questions from the evidence passage, considering the conversation history. Then, the CQGprior generates conversational question that is likely to be answered by identified spans (Figure 2 (a)).

Conversational Answer Extractor

The component detects spans that are likely to be answered to the subsequent question in the conversation. It aims to select phrases from the passage $c$ which are natural to the conversational flow. Specifically, the CAE model $p_{\text{sym}}(a_t \mid H_t, c)$ calculates the likelihood of answer span $a_t$ and predicts the most probable prediction $\hat{a}_t$ without taking the current question $q_t$. By the likelihood values, we obtain the set of top-k answer candidates $\hat{A}_t = \{\hat{a}_1^t, \hat{a}_2^t, \ldots, \hat{a}_k^t\}$. By jointly encoding the history $H_t$ with the passage $c$, we enable the component to consider conversational flow when extracting answer candidates. We adapt 2D span extraction model proposed by Lewis et al. (2021). 

Answer-grounded CQG

Given the passage and answer spans extracted from it, the CQGanswer generates a follow-up question on the held-out conversation. Thus, it should satisfy multiple objectives at once: generating proper question for the answer and coherent with the history. Formally speaking, the CQGanswer synthesizes the conversational question $q$ based on the history, document,
and extracted answer, i.e., $p_{\text{q}}^{\text{sym}}(q_t \mid c, \mathcal{A}_t, \mathcal{H}_t)$. We employ a T5-based sequence-to-sequence model as backbone of the component (Raffel et al., 2020). In particular, we highlight target answer $a_t$ as rationale span in the passage $c$ using a special token, “<hl>”, following Gu et al. (2021). In addition, we adopt a mask prediction scheme that aligns its objective with that of the pre-training phase, shown to be sample efficient in prior work (Chada and Natarajan, 2021).

3.2 SimSeek-asym

To replicate the information-asymmetric scenario, we introduce a novel framework SimSeek-asym consisting of two components, prior-grounded conversational question generator (CQG$_{\text{prior}}$) and conversational answer finder (CAF). At every turn, the CQG$_{\text{prior}}$ first generates conversational question, only relying on prior knowledge (i.e., background information involving the topic) with the conversational history. Then, the CAF comprehends the generated question and returns the most probable answer to the question (Figure 2 (b)).

Prior-grounded CQG We introduce prior-grounded CQG (CQG$_{\text{prior}}$) that can ask the question from insufficient information. Hence, CQG$_{\text{prior}}$ depends neither on the answer at the current turn nor answer-containing passage. Instead, the generator asks question solely based on the prior knowledge about the topic, $\mathcal{B}$. Specifically, it synthesizes conversational question $q_t$ from given the history $\mathcal{H}_t$ and background $\mathcal{B}$, i.e., $p_{\text{q}}^{\text{asym}}(q_t \mid \mathcal{H}_t, \mathcal{B})$.

For a fair comparison of two CQG components, T5-based sequence generator is adopted to implement the CQG$_{\text{prior}}$, same with the CQG$_{\text{answer}}$. Although they share the same architecture, CQG$_{\text{prior}}$ plays a crucial role for simulating more realistic information-seeking conversation. We emphasize that proper level of information insufficiency encourages the model to learn to ask questions that implicate information needs. We further demonstrate a thorough analysis on it in Section 6.

Conversational Answer Finder The conversational answer finder (CAF) annotates answer to the generated question given the evidence passage. Formally, its objective is modeling $p_{\text{a}}^{\text{asym}}(a_t \mid q_t, c, \mathcal{H}_t)$. CAF plays the answerer’s role in the information-seeking scenario by providing the requested information from the passage $c$. Note that any CQA model can be adopted as the CAF component, enabling SimSeek-asym to generalize toward other advanced CQA approaches effectively.

4 Experimental Setup

In this section, we specify our experimental setup and compare our framework to baseline approaches for generating CQA datasets. More implementation and experimental details are in Appendix A.

4.1 Datasets

**QuAC** QuAC (Choi et al., 2018) consists of 100k QA pairs in information-asymmetric dialogues, where a questioner asks questions based on a topic with background information, and an answerer returns the answers in the form of text spans in Wikipedia document. Restricting the questioners from accessing the answer-containing document, the authors encourage them to seek new information on a topic via conversation. To simulate a semi-supervised setup, we split the original training set of QuAC into three subsets, QuAC$_{\text{seen}}$, QuAC$_{\text{unseen}}$, and the validation set$^1$. Detailed statistic is described in Table 6. Following Choi et al. (2018), we evaluate models with the F1 score for QuAC. Since the test set is only available in the QuAC leaderboard, we evaluate models on the development set$^2$. We further detail the experimental setup in Appendix A.2.

**OR-QuAC** Qu et al. (2020) extend the original QuAC dataset to open-domain setup$^3$. It assumes that a ground-truth document is not given in advance, which means the answerers do not know what to be asked before a conversation begins. Instead, they first need to search relevant passages from web-scale documents (about 11M chunked passages) based on the given conversational history and current question. After reading the retrieved passage, they predict an answer to the question. Following the original setup in Qu et al. (2020), we only regard previous questions $\{q_1, q_2, ..., q_{t-1}\}$ as history without answers. Since OR-QuAC is similar partitioned with our QuAC splits (see details in Table 6), we use same synthetic conversations that are used for CQA task. More experimental details are in Appendix A.3. For evaluation, mean reciprocal rank (MRR), Recall@5 (R@5), and Re-

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$^1$Subsets are partitioned following Elgohary et al. (2019)

$^2$quac.ai

$^3$github.com/prdwb/orconvqa-release
call@20 (R@20) are used to evaluate first stage conversational retrieval.

4.2 Synthetic CQA Generation

To train all modules in our frameworks, SimSeek-sym and SimSeek-asym, we assume source labeled dataset $D = \{(\hat{B}_i, \hat{c}_i, \hat{q}_i, \hat{a}_j)\}_{i=0}^{\left|D\right|}$, where the $q$ and $a$ denote all questions and answers up to turn $T$ in a conversation. Once each module is trained using the $D$, the modules sequentially generates pseudo conversational questions $\hat{q}$ and answers $\hat{a}$ on $M$ number of unlabeled documents $C = \{(\hat{B}_j, \hat{c}_j)\}_{j=0}^{M}$. For semi-supervised CQA setup, we set QuAC\textsubscript{seen} as $D$ and documents in QuAC\textsubscript{unseen} as $C$. The number of turns $T$ is set to 6 in our generations. For OR-QuAC experiment, we follow the semi-supervised setup since OR-QuAC shares the same document split with the semi-supervised setup. All CQG models are based on T5-large (Raffel et al., 2020) model, and we use 5 for beam size of beam search and 0.98 for top-$p$ value of nucleus sampling (Holtzman et al., 2020) with 1.2 temperature. We employ the same backbone for the CAF with corresponding CQA student models, RoBERTa-base (R-base), RoBERTa-Large (R-large), and Longformer-large (L-large) (Liu et al., 2019; Beltagy et al., 2020).

4.3 Baselines for Synthetic CQA Generation

We introduce strong baselines for synthesizing CQA datasets and compare them with our methods. For a fair comparison, we train all components of approaches on the same labeled dataset $D$, and generate the synthetic dataset $\hat{D}$ on the unlabeled corpus $C$.

Back-translation Back-translation is one of the most widely used methods for data augmentation in NLP fields (Sennrich et al., 2016; Fadaee et al., 2017; Xie et al., 2020). We translate an existing question $q$ from the labeled dataset $D$ into another target language and then translate it back into the source language to obtain a paraphrased question. We set the target language as German (de) while the source language is English (en). Specifically, we use translation models for both directions (en -> de) and (de -> en), which are pre-trained on WMT-19 (Ng et al., 2019).

De-contextualization Elgohary et al. (2019) rewrite conversational questions of QuAC into self-contained questions that could be understood without the conversation. Following Kim et al. (2021), we consider the resulting dataset, CANARD, as an additional dataset for training CQA models. Note that CANARAD\textsubscript{train} and QuAC\textsubscript{seen} share the same passages.

PAQ-CANARD For the single-turn QA generation, Lewis et al. (2021) propose PAQ, the pipeline strategy composed of three phases, answer extraction, question generation, and round-trip filtration. Even though it is not designed to generate context-dependent questions, we generate decontextualized conversations like CANARD (Elgohary et al., 2019). Thus, we fine-tune every component of the PAQ on CANARD\textsubscript{train}. Then, we include it as one of the baselines leveraging single-turn QA.

PAQ-QuAC We construct a baseline by using a straightforward way to extend the single-turn QG framework, e.g., PAQ (Lewis et al., 2021), to a conversational setup. We replace the question generator in PAQ with CQG\textsubscript{answer} model that also takes the conversation history as input. Different from our SimSeek-sym, the baseline utilizes the original answer extractor model of Lewis et al. (2021), which extracts answer candidates regardless of conversational history, i.e. $p_a(a | c)$. From a given answer-containing passage $c$, top-$k$ answer candidates are extracted by the model in advance. Then, we randomly take out an answer from the candidates to feed it to the CQG\textsubscript{answer} at every turns.

4.4 CQA Models

After building synthetic CQA datasets upon the unlabeled corpus $C$, the baseline CQA models are trained on the datasets. By comparing the resulting CQA performances, we evaluate the effectiveness of the generated dataset $\hat{D}$. We test three backbone architectures for CQA, base and large size of RoBERTa (Liu et al., 2019), and Longformer-large (Beltagy et al., 2020). By contrasting various sizes of pre-trained models, we show the different effects of data augmentation. In addition, we involve Longformer architecture that has been shown to be effective for encoding much longer history (Zhao et al., 2021), which achieves competitive performance with the state-of-the-art approach.
5 Experimental Results

We demonstrate the effectiveness of our frameworks, comparing them to the aforementioned baseline approaches. In the following experiments, every approach is measured with the end performance in downstream tasks.

5.1 Semi-supervised CQA

We evaluate the effectiveness of our frameworks on a semi-supervised setup which leverages both labeled ($\mathcal{D}$) and synthetic ($\hat{\mathcal{D}}$) datasets. Table 1 shows the results. The “Human Annotation” indicates the student CQA models are trained on the human-annotated dataset, i.e., QuAC\textit{unseen}, and is understood as upper bound of synthetic dataset generation. On the other hand, the “None” is a de-facto baseline that does not use any unlabeled corpus $\mathcal{C}$, but rather trained on the labeled dataset $\mathcal{D}$ and its perturbed dataset, i.e., $|\mathcal{D}| = 0$. Similarly, Back-Translation and De-contextualization do not take the $\mathcal{C}$ but only perturb or transform the questions in the $\mathcal{D}$. The question augmentation methods often degrade the baseline performance (None), showing limited improvement only in the RoBERTa-large backbone.

PAQ-CANARD shows the lowest performance in all CQA backbones when using the synthetic dataset alone ($\hat{\mathcal{D}}$), which shows that it is tricky to use single-turn QA generation to CQA. However, adopting CQG model that can generate the conversational questions (PAQ-QuAC) improves CQA performance with a gap of 6-9 F1 scores in the setting. It indicates that CQA models need to be trained to understand the conversational questions. SimSeek-sym, whose components are history-dependent, achieves higher scores than the baseline approaches. On the other hand, results of the combined training ($\mathcal{D} + \hat{\mathcal{D}}$) show a different tendency. Most of the baselines cause significant performance degradation even though CQA models are trained on larger dataset, which implies the difficulty of generating realistic CQA examples.

On the other hand, our proposed framework SimSeek-asym consistently improves CQA perfor-
Figure 3: Assessment of synthetic CQA datasets upon three evaluation metrics. Specificity and informativeness are proposed by Qi et al. (2020) to automatically evaluate the quality of generated questions. In addition to those metrics, we further analyze answer relevance which checks the relevance of the answer with given conversational context. We find that the synthetic dataset from SimSeek-sym often too generic (low question specificity) and clearly obvious to be answered (high answer relevance) at the same time. However, we observe the human-annotated dataset (Original) shows moderate scores over all the metrics indicating some ambiguity is in the real scenario. On the other hand, the synthetic dataset from SimSeek-asym-L-large shows the most similar patterns with the human-annotated dataset.

5.2 Utility in Conversational Search

We also demonstrate the effectiveness of our synthetic dataset in another information-seeking task, conversational search. It is an open-domain CQA problem that retrieves relevant document from a given conversational context. Table 2 shows the retrieval performances of baseline passage retrieval model, DPR (Karpukhin et al., 2020), and how it is improved by our method on OR-QuAC dataset (Qu et al., 2020). Training the DPR with more steps without additional synthetic dataset significantly degrades the performance, which implies overfitting. SimSeek-sym performs better than further training baseline but still fails to lift the score. SimSeek-asym-L-large, which employs Longformer-large as the backbone for CAF module, only improves the performance of the baseline DPR model. Note that although dense retrievers do not encode any answers to questions on OR-QuAC, retrieval performances vary depending on the capabilities of answerer model. It implies that interacting with a better answerer encourages the questioner to generate more realistic questions that are likely to be asked in information-asymmetric conversation.

6 Analysis and Discussion

6.1 Assessment of Synthetic Dataset

We further explore which factors determine the gain from synthetic conversations. For quantifying the properties of question-answer pair, we adopt three metrics, question specificity, answer relevance, and answer informativeness, proposed by Lowe et al. (2017); Qi et al. (2020). We train two additional classifier models. One is specificity classifier $p_s(q_t = \text{specific} | H_t, q_t)$ to evaluate specificity of the synthetic questions as suggested by Qi et al. (2020). Another is answer relevance classifier $p_r(a_t = \text{relevance} | H_t, q_t, a_t)$ judging relevance between conversational context and corresponding answer. We train the classifiers by contrasting negative examples. Specifically, frequent questions which appear more than once in the training dataset
or random questions are sampled for the negative examples to train \( p_r \) by 50% of the time (Qi et al., 2020). To train \( p_s \), we select random answers in the same conversation for the negatives by 50% of the time. More implementation details are in Appendix A.4. In addition to the two classifiers, we also adopt the informativeness metric proposed by Qi et al. (2020). It computes how much \( a_t \) provides distinct and new information compared to previous answers \( a_{1:t-1}, \text{i.e.,} 1 - \max_{1 \leq i < t} \text{Precision}(a_t, a_i) \).

It is another proxy to judge the usefulness of the corresponding question \( q_t \).

Figure 3 shows results of three metrics among various synthetic datasets and human-annotated dataset (Original). Especially, we plot the scores (y-axis) by conversational turns (x-axis) to get better understanding. First, we observe our SimSeek-asym datasets show similar patterns with the Original until 3rd turn in specificity (Figure 3 (a)). However, the scores increase drastically as conversation progresses while the specificity of human questions increases slowly. In case of SimSeek-sym, it shows lower question specificity across all turns, indicating that the questions are often generic, e.g. “What else?” or “Anything else?”. Even though the general questions can be occurred naturally in information-seeking conversation, they make divergence of the conversation flow as discussed in Qi et al. (2020). The similar tendency is observed in Table 3. Actual percentage of the “Anything else?” questions from SimSeek-sym is significantly higher than those of original QuAC and SimSeek-asym. Thus, keeping moderate specificity like Original is one of improvement points.

On the other hand, both answer relevance and informativeness show similar tendency. First, SimSeek-sym shows the highest answer relevance across all turns as shown in Figure 3 (b). And it keeps its informativeness relatively high while informativeness scores of others continuously decrease (Figure 3 (c)). It implies the answers of SimSeek-sym are clearly answerable and the questions for them are less ambiguous which is far from realistic information-seeking. Actually, the number of unanswerable questions in SimSeek-sym are significantly less than others as shown in Table 3. Second, SimSeek-asym-L-large shows the most similar pattern with the Original in both answer relevance and informativeness. It implies that the synthetic questions and answers generated by SimSeek-asym-L-large mimic the realistic information-seeking conversation of human very well. However, when the RoBERTa-based model is used for the CAF, those two metrics decrease significantly as progress of conversation indicating importance of answerer, again.

### 6.2 Intrinsic Evaluation of CQG models

Table 4 presents intrinsic evaluation results of our two kinds of CQG models. Scores represent the lexical similarity of the generated questions with the ground-truth questions when ground-truth conversational history is given. The sub-component of SimSeek-sym, CQG\textsubscript{answer} significantly outperforms CQG\textsubscript{prior} in BLEU scores of all n-gram levels. The contrasting results to our experiments (Section 5.1) imply that accurate generation grounded on the answer is not enough to generate realistic conversation. Instead, we presume other vital factors, such as question based on information asymmetry, proper answer selection in natural conversational flow, and their chained interactions, contribute to a better synthetic CQA generation.
Upset with tribal government and the failures of the federal government to enforce treaty rights, about 300 Oglala Lakota and AIM activists took control of Wounded Knee on February 27, 1973. Indian activists from around the country joined them at Pine Ridge, and the occupation became a symbol of rising American Indian identity and power. Federal law enforcement officials and the national guard cordoned off the town, and the two sides had a standoff for 71 days.

What happened at Wounded Knee?
Indian activists from around the country joined them at Pine Ridge, and the occupation became a symbol of rising American Indian identity and power.

What happened after they took control of Pine Ridge?
Federal law enforcement officials and the national guard cordoned off the town, and the two sides had a standoff for 71 days.

What happened during the standoff?
During much gunfire, one United States Marshal was wounded and paralyzed.

Table 5: Examples of the resulting datasets simulated by SimSeek-sym and SimSeek-asym. In the first case (above), SimSeek-sym asks unspecific questions repeatedly, which can effortlessly achieve the goals, answer relevance and coherence with the conversation; but it leads to the shallow conversation. On the contrary, SimSeek-asym successfully mimics diverse information-seeking behaviors that are commonly occurred in human dialogue.

6.3 Qualitative Analysis
We explore how SimSeek-sym fails to simulate realistic conversations, but SimSeek-asym successfully mimics information-seeking behaviors.

The first case in Table 5 shows the synthetic conversation simulated by SimSeek-sym. In the example, consecutive and disjoint spans are selected for answers from the evidence document as the conversation progresses. Moreover, all questions contain a common phrase “What happened ···” while mentioning keywords that have appeared in previous answers. Asking these ambiguous questions repeatedly would be the best option for the answer-grounded CQG to achieve answer relevance and coherence with the conversation easily.

On the other hand, we observe various information-seeking behaviors in the second case from our SimSeek-asym. The lack of information impels questioners to ask open-ended questions using uncertain words such as “some of the things” in q4. When they cannot find adequate follow-up questions on the conversation, they ask an additional information as in q5. They sometimes fail to acquire new knowledge when the question cannot be answered by the evidence document (see q6, a6).

7 Related work
Conversational Question Answering With the advent of recent large-scale CQA datasets (Choi et al., 2018; Reddy et al., 2019), numerous studies proposed methods to resolve the challenging task. Most works focused on developing model structures (Zhu et al., 2018; Qu et al., 2019a,b) that are
specialized in the CQA task. Several works demonstrated the effectiveness of the flow mechanism in CQA (Huang et al., 2018; Chen et al., 2019). Most recently, leveraging self-contained questions (Kim et al., 2021) or encoding longer context (Zhao et al., 2021) have been shown to be effective in the task.

**Synthetic QA Generation**  Many question generation (QG) researches have sparked advances in various QA tasks (Dhingra et al., 2018; Dong et al., 2019; Lewis et al., 2019; Alberti et al., 2019; Puri et al., 2020; Lewis et al., 2021). Usually, it is used for data augmentation, unsupervised or semi-supervised QA, and domain adaptation. Most of early studies propose to generate them in a cloze-style (Dhingra et al., 2018; Lewis et al., 2019) or by using pre-defined templates (Fabbri et al., 2020). Recent studies for the synthetic QA generation propose the pipeline strategies composed of three sub-phases, answer extraction, question generation, and various data selection steps such as round-trip filtration (Alberti et al., 2019; Puri et al., 2020; Lewis et al., 2021).

**Conversational Question Generation**  Many works attempt to generate human-like conversational questions. Pan et al. (2019); Gao et al. (2019) introduce the challenge of CQG and successfully extend the single-turn question generation to consider conversational input. Their proposed models show effectiveness compared to single-turn question generators. However, most of the works are based on the information-symmetric assumption that can access the evidence document (Pan et al., 2019; Gao et al., 2019; Nakanishi et al., 2019; Gu et al., 2021). Recently, Qi et al. (2020) study information-asymmetric conversation. They first attempt to generate the conversational questions without evidence document and provide various analyses for the questions. Our work is different from the previous works in that we generate a whole conversation based on both CQA scenarios when only unlabeled document is given. Also, we successfully adapt the synthetic datasets to semi-supervised CQA.

**Assessment of synthetic conversations**  Most CQG works compare their methods on automatic reference-based evaluation such as BLEU and ROUGE scores (Pan et al., 2019; Gao et al., 2019; Nakanishi et al., 2019; Gu et al., 2021). However, the reference-based evaluation is limited in measuring directed generation and inappropriate to measure open-ended generation problem. To mitigate the problem in response generation, Lowe et al. (2017) explore model-based evaluation. Similarly, Mehri and Eskenazi (2020) propose reference-free evaluation protocol for open-domain dialogue based on pre-trained dialogue model. For another open-ended generation, information-asymmetric conversation, Qi et al. (2020) propose model-based evaluation metrics, specificity and informativeness, to evaluate synthetic conversational questions. We also inherit those metrics to compare synthetic conversations from two CQA scenarios.

**8 Conclusion**

In this work, we propose a novel framework, SimSeek, simulating information-seeking conversation from given unlabeled documents. We assume two scenarios according to the existence of information symmetry and compare them in the semi-supervised CQA and conversational search task. Experimental result shows that our SimSeek-asym based on an information-asymmetric scenario achieves competitive performance gain with a human upper bound. Moreover, we provide insightful analyses to help understand the information-seeking conversation better. As a result, we find the clue that asking questions with proper specificity and ambiguity is an important step to simulate more realistic conversations in terms of information-seeking.

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**References**

Chris Alberti, Daniel Andor, Emily Pitler, Jacob Devlin, and Michael Collins. 2019. Synthetic qa corpora generation with roundtrip consistency. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 6168–6173.

Iz Beltagy, Matthew E. Peters, and Arman Cohan. 2020. Longformer: The long-document transformer. arXiv:2004.05150.

Jon Ander Campos, Arantxa Otegi, Aitor Soroa, Jan Milan Deriu, Mark Ciuleiebak, and Eneko Agirre. 2020. Doqa-accessing domain-specific faqs via conversational qa. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7302–7314.
Rakesh Chada and Pradeep Natarajan. 2021. Few-shotqa: A simple framework for few-shot learning of question answering tasks using pre-trained text-to-text models. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 6081–6090.

Yu Chen, Lingfei Wu, and Mohammed J Zaki. 2019. Graphflow: Exploiting conversation flow with graph neural networks for conversational machine comprehension. arXiv preprint arXiv:1908.00059.

Eunsol Choi, He He, Mohit Iyyer, Mark Yatskar, Wentau Yih, Yejin Choi, Percy Liang, and Luke Zettlemoyer. 2018. Quac: Question answering in context. arXiv preprint arXiv:1808.07036.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In NAACL.

Bhuwan Dhingra, Danish Danish, and Dheeraj Rajagopal. 2018. Simple and effective semi-supervised question answering. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 582–587.

Li Dong, Nan Yang, Wenhui Wang, Furu Wei, Xiaodong Liu, Yu Wang, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. 2019. Unified language model pre-training for natural language understanding and generation. Advances in Neural Information Processing Systems, 32.

Ahmed Elgohary, Denis Peskov, and Jordan Boyd-Graber. 2019. Can you unpack that? learning to rewrite questions-in-context. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 5918–5924.

Alexander Richard Fabbri, Patrick Ng, Zhiguo Wang, Ramesh Nallapati, and Bing Xiang. 2020. Template-based question generation from retrieved sentences for improved unsupervised question answering. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4508–4513.

Marzieh Fadaee, Arianna Bisazza, and Christof Monz. 2017. Data augmentation for low-resource neural machine translation. arXiv preprint arXiv:1705.00440.

Song Feng, Hui Wan, Chulaka Gunasekara, Siva Patel, Sachindra Joshi, and Luis Lustras. 2020. doc2dial: A goal-oriented document-grounded dialogue dataset. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 8118–8128, Online. Association for Computational Linguistics.

Yifan Gao, Piji Li, Irwin King, and Michael R Lyu. 2019. Interconnected question generation with coreference alignment and conversation flow modeling. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (ACL), pages 4853–4862.

Jing Gu, Mostafa Mirshekari, Zhou Yu, and Aaron Sistco. 2021. Chainqc: Flow-aware conversational question generation. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 2061–2070.

Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. 2020. The curious case of neural text degeneration.

Hsin-Yuan Huang, Eunsol Choi, and Wen-tau Yih. 2018. Flowqa: Grasping flow in history for conversational machine comprehension. In International Conference on Learning Representations.

Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense passage retrieval for open-domain question answering. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6769–6781.

Gangwoo Kim, Hyunjae Kim, Jungsoo Park, and Jae-woo Kang. 2021. Learn to resolve conversational dependency: A consistency training framework for conversational question answering. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 6130–6141.

Hanjoo Kim, Minkyu Kim, Dongjoo Seo, Jinwoong Kim, Heungsook Park, Soeun Park, Hyunwoo Jo, KyungHyun Kim, Youngil Yang, Youngkwon Kim, et al. 2018. Nsml: Meet the mlaas platform with a real-world case study. arXiv preprint arXiv:1810.09957.

Diederik P. Kingma and Jimmy Ba. 2017. Adam: A method for stochastic optimization.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, et al. 2019. Natural questions: A benchmark for question answering research. Transactions of the Association for Computational Linguistics (TACL), 7:452–466.

Patrick Lewis, Ludovic Denoyer, and Sebastian Riedel. 2019. Unsupervised question answering by cloze translation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4896–4910.
Patrick Lewis, Xuyang Wu, Linqing Liu, Pasquale Minervini, Heinrich Küttler, Aleksandra Piktus, Pontus Stenetorp, and Sebastian Riedel. 2021. Paq: 65 million probably-asked questions and what you can do with them. Transactions of the Association for Computational Linguistics, 9:1098–1115.

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

Ryan Lowe, Michael Noseworthy, Iulian Vlad Serban, Nicolas Angelard-Gontier, Yoshua Bengio, and Joëlle Pineau. 2017. Towards an automatic Turing test: Learning to evaluate dialogue responses. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) (ACL), pages 1116–1126, Vancouver, Canada. Association for Computational Linguistics.

Shikib Mehri and Maxine Eskenazi. 2020. Unsupervised evaluation of interactive dialog with dialogpt. In Proceedings of the 21th Annual Meeting of the Special Interest Group on Discourse and Dialogue, pages 225–235.

Mao Nakanishi, Tetsunori Kobayashi, and Yoshihiko Hayashi. 2019. Towards answer-unaware conversational question generation. In Proceedings of the 2nd Workshop on Machine Reading for Question Answering, pages 63–71, Hong Kong, China. Association for Computational Linguistics.

Nathan Ng, Kyra Yee, Alexei Baevski, Myle Ott, Michael Auli, and Sergey Edunov. 2019. Facebook FAIR’s WMT19 news translation task submission. In Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1), pages 314–319, Florence, Italy. Association for Computational Linguistics.

Boyuan Pan, Hao Li, Ziyu Yao, Deng Cai, and Huan Sun. 2019. Reinforced dynamic reasoning for conversational question generation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2114–2124.

Gustavo Penha, Alexandre Balan, and Claudia Hauff. 2019. Introducing mantis: a novel multi-domain information seeking dialogues dataset. arXiv preprint arXiv:1912.04639.

Raul Puri, Ryan Spring, Mohammad Shoeybi, Mostofa Patwary, and Bryan Catanzaro. 2020. Training question answering models from synthetic data. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 5811–5826.

Peng Qi, Yuhao Zhang, and Christopher D Manning. 2020. Stay hungry, stay focused: Generating informative and specific questions in information-seeking conversations. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 25–40.

Chen Qu, Liu Yang, Cen Chen, Minghui Qiu, W Bruce Croft, and Mohit Iyyer. 2020. Open-retrieval conversational question answering. In Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval, pages 539–548.

Chen Qu, Liu Yang, Minghui Qiu, W Bruce Croft, Yongfeng Zhang, and Mohit Iyyer. 2019a. Bert with history answer embedding for conversational question answering. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 1133–1136.

Chen Qu, Liu Yang, Minghui Qiu, Yongfeng Zhang, Cen Chen, W Bruce Croft, and Mohit Iyyer. 2019b. Attentive history selection for conversational question answering. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, pages 1391–1400.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer.

Siva Reddy, Danqi Chen, and Christopher D Manning. 2019. Coqa: A conversational question answering challenge. Transactions of the Association for Computational Linguistics, 7:249–266.

Marzieh Saeidi, Max Bartolo, Patrick Lewis, Sameer Singh, Tim Rocktäschel, Mike Sheldon, Guillaume Bouchard, and Sebastian Riedel. 2018. Interpretation of natural language rules in conversational machine reading. arXiv preprint arXiv:1809.01494.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Improving neural machine translation models with monolingual data. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 86–96, Berlin, Germany. Association for Computational Linguistics.

Nako Sung, Minkyu Kim, Hyunwoo Jo, Youngil Yang, Jingwoong Kim, Leonard Lausen, Youngkwon Kim, Gayoung Lee, Donghyun Kwak, Jung-Woo Ha, et al. 2017. Nsml: A machine learning platform that enables you to focus on your models. arXiv preprint arXiv:1712.05902.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funktowicz, et al. 2019. Huggingface’s transformers: State-of-the-art natural language processing. arXiv preprint arXiv:1910.03771.
Qizhe Xie, Zihang Dai, Eduard Hovy, Thang Luong, and Quoc Le. 2020. Unsupervised data augmentation for consistency training. *Advances in Neural Information Processing Systems*, 33:6256–6268.

Jing Zhao, Junwei Bao, Yifan Wang, Yongwei Zhou, Youzheng Wu, Xiaodong He, and Bowen Zhou. 2021. Ror: Read-over-read for long document machine reading comprehension. *arXiv preprint arXiv:2109.04780*.

Chenguang Zhu, Michael Zeng, and Xuedong Huang. 2018. Sdnet: Contextualized attention-based deep network for conversational question answering. *arXiv preprint arXiv:1812.03593*. 
A Implementation Details

All our implementations are based on huggingface’s transformers library (Wolf et al., 2019) and NAVER Smart Machine Learning (NSML) platform (Sung et al., 2017; Kim et al., 2018).

A.1 Training models in SimSeek

We train overall four models, CAE, CQA_{answer}, CQA_{prior}, and CAF on QuAC_{seen} split for SimSeek. We optimize all models using AdamW optimizer with linear learning rate (lr) scheduling (Kingma and Ba, 2017). The best performing checkpoint is selected according to validation score.

We employ 2D span extraction model proposed in PAQ with bert-base-uncased backbone for CAE (Devlin et al., 2019; Lewis et al., 2021). We find using previous question and answer pair, $(q_{t−1}, a_{t−1})$, instead of the whole history $H_t$ is enough to get reasonable performance. The qa pair is appended to $c$ with [SEP] token for input representation. We set overall maximum sequence length to 512 and the maximum history length 32. We train it for 3 epochs with 8 for batch size, $3e^{-5}$ for lr, 0.1 for lr warming up, and 0.01 for weight decay on 2 32GB V100 GPUs. We set maximum sequence length for the input representations to 512 and maximum context length to 384. The context means $c$ and $B$ for CQA_{answer} and CQA_{prior}, respectively.

We adopt three CQA backbone architectures, RoBERTa-base, RoBERTa-large (Li et al., 2019), and Longformer-large (Beltagy et al., 2020), which are shown to be effective in CQA task. Please note that any CQA models can be used for CAF model as a teacher. For all CQA models, we concatenate the title, sub-title, and previous history to question text, separating with the special token [SEP]. We train all models for 2 epochs without weight decay on all datasets and set maximum answer length 64. CQA models return “CANNOTANSWER” when all scores of answer logits do not exceed a pre-defined threshold. RoBERTa backbones are trained for batch size 12 per each GPU without weight decay. We set the maximum length for query and sequence as 128 and 512, respectively. Due to their limitation of the input sequence length, a single question-answer pair at previous turn $(t−1)$ is included to the input, shown to be most effective in prior works (Qu et al., 2019a). When Longformer architecture is adopted, we find the optimal setup of the maximum length for query and sequence as 768 and 2048, respectively. It encodes all previous history and titles when providing answers. They are trained with batch size 1 per each GPU. For large size of models, we train them with learning rate 1.5e-5 on 8 32GB V100 GPUs.

A.2 Semi-supervised CQA

We split the original QuAC dataset into two subsets of QuAC_{seen} and QuAC_{unseen}, following CANDAR Elgohary et al. (2019). To control the effect of sample size, we generate maximum 6 question-answer pairs for each passage when using SimSeek and PAQ-based QA generation approaches. When simulating conversations with SimSeek-sym, final answers are randomly selected among top-5 span candidates detected by the answer extractor. In addition, we use technique for considering unanswerable questions at the answer extraction step. Those special answers are included to answer candidates whenever the answer extractor fails to provide top-k candidates. For all components, we use the same hyperparameter setup as they are trained, otherwise specified.
Table 6: Data statistics of QuAC dataset used in our experiments. Note that we use questions and answers in QuAC\textsubscript{unseen} to represent human upper bound. OR-QuAC also contains 11M of chunked passages collection for the retrieval. We split datasets following CA-NARD (Elgohary et al., 2019), which is similar with OR-QuAC (Qu et al., 2020)

A.3 Conversational Search

We employ dual-encoder based dense retriever, DPR, for our baseline (Karpukhin et al., 2020). Especially, we initialize the encoders with pre-trained DPR model on Natural Questions (Kwiatkowski et al., 2019). To represent query input, we concatenate questions \{q_1, q_2, ..., q_t\} with [SEP] token. We truncate the input length when longer than 128 but retain first question q_1 at the same time (Qu et al., 2020). The context input is concatenation c and its title with [SEP]. The maximum length for the context input is 384. We train the model for 10 epochs with 128 for batch size, 3e-5 for lr, 0.1 for lr warming up, and 0.01 for weight decay. All DPR models are trained by using in-batch negative without any usage of hard negatives (Karpukhin et al., 2020).

A.4 Specificity and Answer Relevance Classifier

Following Qi et al. (2020), we train specificity classifier and also answer relevance classifier to evaluate synthetic conversations. Based on a single encoder, binary classification is conducted to discriminate positive and negative examples as next sentence prediction task of Devlin et al. (2019). The negative sampling schemes are described in Section 6.1. All models are initialized with pre-trained BERT-large (Devlin et al., 2019), bert-large-uncased, and trained for 3 epochs with 1e-5 for lr on 1 32GB V100 GPU.

B Data Statistics

Table 6 shows data statistics used in our experiments.