Conversational Question Reformulation via Sequence-to-Sequence Architectures and Pretrained Language Models

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Abstract

This paper presents an empirical study of conversational question reformulation (CQR) with sequence-to-sequence architectures and pretrained language models (PLMs). We leverage PLMs to address the strong token-to-token independence assumption made in the common objective, maximum likelihood estimation, for the CQR task. In CQR benchmarks of task-oriented dialogue systems, we evaluate fine-tuned PLMs on the recently-introduced CANARD dataset as an in-domain task and validate the models using data from the TREC 2019 CAS T Track as an out-domain task. Examining a variety of architectures with different numbers of parameters, we demonstrate that the recent text-to-text transfer transformer (T5) achieves the best results both on CANARD and CAS T with fewer parameters, compared to similar transformer architectures.

1 Introduction

Natural-language dialogue capabilities play an essential role as an enabling technology in intelligent personal assistants to understand and connect people (Gao et al., 2018). Effective dialogue systems require many components, including natural language understanding, dialogue state tracking, and natural language generation (Zhao and Eskenazi, 2016). Of late, practitioners in industry (Ren et al., 2018) and researchers in academia (Elgohary et al., 2019) have made substantial progress in a variety of methods to improve end-to-end task-oriented dialogue systems.

Due to the complex and nuanced nature of human communication, conversations often contain utterances that include coreference, ellipsis, and other phenomena; thus, a good dialogue system should be able to resolve these ambiguities to accurately reconstruct the user’s original intent. We present an example from Elgohary et al. (2019) in Figure 1 to illustrate the task of conversational question reformulation (CQR).

However, as we can observe from Figure 1(a), applying maximum likelihood estimation (MLE) purely based on human-rewritten sentences introduces a strong independence assumption that does not consider conversation dependencies or linguistic structure. Thanks to great progress made by language models pretrained on large corpora using self-supervised learning objectives (Devlin et al., 2018; Radford et al., 2018; Dong et al., 2019; Raffel et al., 2019), there are now many models equipped with knowledge of various language structures extracted from human-generated texts. We can leverage these models to relax the independence assumption in a pure MLE objective, shown in Figure 1(b).

We list the contributions of this work as follows:

• We conduct, to our knowledge, the first empirical study leveraging pretrained language models to relax the independence assumption made in using an MLE objective in a CQR task.

• We achieve the state of the art in terms of BLEU on two CQR benchmarks of task-oriented dialogue systems: (a) conversational open-domain

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question answering with CANARD and (b) conversational search with TREC CAsT.

In summary, this work demonstrates a simple yet effective way to resolve coreference and ellipsis in a CQR task by leveraging pretrained language models. Furthermore, among representative models, we find that a well-tuned text-to-text transfer transformer (T5) reaches performance that is on par with humans on the in-domain CANARD dataset and achieves the best performance on the out-of-domain CAsT dataset.

2 Related Work

Conversational search (Radlinski and Craswell, 2017) covers a broad range of techniques that facilitate an IR task in a conversational context: natural language interactions, cumulative clarification (Ahmamejadi et al., 2019), feedback collection, and information needs profiling during conversations. CQR is an important component of conversational search systems. In order to resolve users’ information needs to retrieve relevant answers, a CQR module that leverages pretrained models is a promising approach, compared to alternatives that track dialogue states based on “cheap” but noisy implicit feedback from users (Ahmad et al., 2018, 2019) or “expensive” but sparse judgments (Jeffrey et al., 2019).

Open-domain question answering (QA) systems return answers in response to user questions, both in natural language, from a broad range of domains (Sun et al., 2018). With great progress coming from contributions by the NLP and IR communities, high quality datasets for single-turn (Rajpurkar et al., 2018; Kočiský et al., 2018; Dhingra et al., 2017) and multi-turn (conversational) (Reddy et al., 2019; Choi et al., 2018) open-domain QA are available today. These datasets have led to many successful supervised techniques for various tasks (Chen et al., 2017; Seo et al., 2017; Huang et al., 2019).

Recently, to improve dialogue understanding, researchers have proposed collecting annotations on resolving multi-turn dialogues in the context of question answering tasks (Ren et al., 2018; Elgohary et al., 2019). Building on this line of thought, our work addresses the problem of modeling question rewrites in multi-turn dialogues, especially in the context of open-domain conversational QA.

3 Conversational Question Reformulation

3.1 Problem Formulation

We first formally define the conversational question reformulation (CQR) task, which is also called question de-contextualization (Elgohary et al., 2019) or conversational question (query) understanding in the context of task-oriented dialogue systems (Ren et al., 2018). Consider a topic $t$ from a set of topics $T$, given a topic-oriented utterance sequence (i.e., the conversation history): $H^t = \{u_1, \cdots, u_i, u_{i+1}, \cdots, u_N\}$ of $N$ utterances, each of which could be a question $q_i$ or an answer $a_i$ at the $i$-th turn. The task is to reformulate the question $q_i$ into $\bar{q}_i$ that incorporates the context $H^t_{<i} = \{u_j\}_{j=1}^{i-1}$. In other words, we wish to automatically reformulate the input question $q_i$ by infusing information that exists in the context $H^t$ but is missing from the question itself.

Following the definitions of Ren et al. (2018) and Elgohary et al. (2019), we further refine the task scope of reformulating $q_i$. Given a question $q_i$ with its historical context $H^t_{<i}$ and a human-rewritten ground truth $\bar{q}_i$, our objective is to induce a function $F(\{q_i, H^t_{<i}\}) = \bar{q}_i$, where $\bar{q}_i$ is comprised of tokens $\{y_k\}_{k=1}^m$ of length $m$ from the context comprising the dialogue sequence $\{q_i, H^t_{<i}\}$ (current and historical utterances), modeled as a sequence of tokens $\{x_k\}_{k=1}^n$ of length $n$. The tokens $y_k$’s can either be drawn from the context $H^t_{<i}$ or the current input $q_i$. In the reconstruction of the ground truth, human annotators are asked to maintain the sentence structure of $q_i$ by copying phrases from the original utterances and performing as few edits as possible.

Finally, given probability $P$ conditioned on a parameterized function $\hat{F}$ and the context (current and historical utterances), the overall objective of the task is then defined in terms of finding the parameters $\theta$ by maximum likelihood estimation:

$$\theta = \arg \max_\theta \prod_{t=1}^T \prod_{i=1}^N P_{\theta}(\bar{q}_i|\hat{F}(\{q_i, H^t_{<i}\}, \theta)).$$

3.2 Sequence-to-Sequence Architectures and Pretrained Language Models

As both the input $q_i$ and the output $\bar{q}_i$ are posed in natural language, a reasonable choice for the parameteric function is a sequence-to-sequence (S2S) model (Sutskever et al., 2014; Vaswani et al., 2017). With this design, we can incorporate context-
dependent sentence-level structures when generating output tokens, since the model can consider both the previously-generated sequences as well as the context.

To extract information from the conversation flow, a simple approach, proposed by Xiong et al. (2018) and Elgohary et al. (2019), is to concatenate the historical utterances \( H_{t<i} \) with the current input \( q_i \), and then use a S2S model to infer the output sequence \( \hat{q}_i \) based on it. To optimize parameters in the S2S model, we can adopt a supervised learning approach to train the S2S model to generate the \( \hat{q}_i \) tokens, given the \( q_i \) tokens as ground truth output.

However, Eq (1) makes an important assumption: here, we consider each conversation topic \( t \) and each \( i \)-th turn independently. Since a topic-oriented conversation is often coherent and smoothly spans several utterances, an approximation of the parameterized function \( \hat{F}(\cdot, \theta) \) purely based on Eq (1) could be sub-optimal. To relax this assumption, we introduce pretrained language models (Devlin et al., 2018; Radford et al., 2018; Raffel et al., 2019) to leverage language structures extracted from large corpora. Specifically, we adopt these models and fine-tune their pretrained weights, as in previous work (Radford et al., 2018; Raffel et al., 2019).

### 4 Experiments

#### 4.1 Dataset

To evaluate the capability of various models in reformulating conversational questions, we conduct experiments on the CANARD dataset (Elgohary et al., 2019), an existing large open-domain dataset for CQR (containing over 30k training samples). Each sample in the CANARD dataset includes an original query from the QuAC dataset (Choi et al., 2018), its context (historical utterances and their answers), and the corresponding rewritten question by human annotators. In addition, we also evaluate model performance on the dataset provided by the TREC 2019 Conversational Assistant Track (CaST).

Statistics of the CANARD and CaST datasets are presented in Table 1.

#### 4.2 Setup

To train and evaluate our sequence-to-sequence (S2S) models, we construct model input largely following Elgohary et al. (2019). Specifically, we concatenate each original question and its context by adding special separator tokens between them. Separator tokens are also added to contextual information to separate historical utterances. The human-rewritten questions serve as the ground truth target sequences. For encoder- or decoder-only models (e.g., GPT-2, BERT, and UniLM), each training input sequence (as described above) is concatenated with its target sequence, and the models are trained to recover the target sequence using standard masking tricks.

We train each model on the CANARD training set and select the checkpoint with the best performance on development set. In addition to comparing model performance on the CANARD test set, we directly use the model trained on CANARD to perform CQR on the CaST dataset.\(^2\) Model performance is computed by the BLEU score between model output and the human-rewritten ground truth. Table 2 shows the settings of the neural models.

Table 1: Statistics of the datasets used in this work.

| Dataset | CANARD | CaST |
|---------|--------|------|
| Train   | 31,538 | 31,538 |
| Dev     | 3,418  | 3,418 |
| Test    | 5,571  | 5,571 |

Additional model-specific training details are as follows. (a) LSTM: Following the script provided by Elgohary et al. (2019), we train a bidirectional LSTM S2S model with attention; the word embeddings are initialized with GloVE.\(^3\) (b) GPT-2 (Radford et al., 2018), which can be characterized as a pretrained decoder-only transformer: To focus on rewriting questions, we fine-tune the model (GPT-2 medium) by masking the cross entropy loss at the positions of the contextual tokens. (c) BERT (Devlin et al., 2018), which can be characterized as a pretrained encoder-only transformer: Following the S2S fine-tuning procedure proposed in Dong et al. (2019), we fine-tune BERT-large (cased) by randomly masking the tokens with 70% probability in targeted sequences.\(^4\) (d) UniLM (Dong et al., 2019), where the model architecture is the same as BERT large and pretrained using three types.

\(^2\)Note that for CaST, only historical questions are included as contextual information.

\(^3\)https://github.com/aagohary/canard

\(^4\)https://github.com/microsoft/unilm
of language-modeling tasks: The method for fine-tuning is the same as BERT. (e) **T5** (Raffel et al., 2019), an encoder–decoder transformer that maps natural language understanding tasks to text-to-text transformation tasks: We fine-tune the T5-base model with the same settings used in Nogueira and Lin (2019).

In addition, we list human performance of CQR (denoted as **Human**), as measured by Elgohary et al. (2019), and the baseline performance using questions without any reformulation (denoted as **Raw**) for comparison.

### 4.3 Results

Our main results in terms of BLEU on CANARD and CAsT are shown in Table 3, using greedy search decoding for inference. In general, all neural S2S models perform better than the original questions (Raw), except for LSTM on CAsT. This indicates that the PLMs (GPT2, BERT, UniLM, and T5) have obtained at least some generalization capability on the CQR task.

Among all neural S2S models, T5 demonstrates a better ability to learn CQR from human-rewritten questions with fewer model parameters. Specifically, in the CANARD test set, T5 beats the other neural S2S models with 58.08 BLEU, which is close to human performance, 59.92. Furthermore, on CAsT, T5 achieves the highest BLEU score (75.07), four points better than the second-best model (71.21). These results demonstrate T5’s superior generalization ability.

In addition, we also perform S2S model inference using beam search and top-\(k\) random sampling decoding.

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5. **https://github.com/castorini/docTTTTTquery**

6. Note that beam search (top-\(k\) random sampling) is equal to greedy search when the beam width (top-\(k\)) is set to 1.

7. We did not perform GPT-2 inference with beam search.

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Figure 2 (left side) illustrates that random sampling with larger top-\(k\) leads to poor BLEU scores. Under this decoding strategy, T5 still maintains better BLEU scores compared to the other S2S models.

### 5 Conclusion

In this paper, we conduct experiments on conversational question reformulation (CQR) via neural sequence-to-sequence (S2S) models and demonstrate that our fine-tuned T5-base model achieves the state of the art, in one case achieving performance on par with humans (at least measured by BLEU). In addition, experiments on the CAsT dataset show that our fine-tuned T5-base model can be directly used in a transfer setting and beats other neural S2S models by quite a large margin.

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Since the original implementation does not support beam search.

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For random sampling, we perform model inference with 10 repetitions and average over them.
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