Conversational Search with Mixed-Initiative - Asking Good Clarification Questions backed-up by Passage Retrieval

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Abstract

We deal with a scenario of conversational search with mixed-initiative: namely user-asks system-answers, as well as system-asks (clarification questions) and user-answers. We focus on the task of selecting the next clarification question, given conversation context. Our method leverages passage retrieval that is used both for an initial selection of relevant candidate clarification questions, as well as for fine-tuning two deep-learning models for re-ranking these candidates. We evaluated our method on two different use-cases. The first is an open domain conversational search in a large web collection. The second is a task-oriented customer-support setup. We show that our method performs well on both use-cases.

1 Introduction

A key task in information and knowledge discovery is the retrieval of relevant information given the user’s information need (usually expressed by a query). With the abundance of textual knowledge sources and their diversity, it becomes more and more difficult for users, even expert ones, to query such sources and obtain valuable insights.

Thus, users need to go beyond the traditional ad-hoc (one-shot) retrieval paradigm. This requires to support the new paradigm of conversational search – a sophisticated combination of various mechanisms for exploratory search, interactive IR, and response generation. In particular, the conversational paradigm can support mixed-initiative: namely, the traditional user asks - system answers interaction in addition to system-asks (clarification questions) and user-answers, to better guide the system and reach the information needed (Krasakis et al., 2020).

Existing approaches for asking clarification questions include selection or generation. In the selection approach, the system selects clarification questions from a pool of pre-determined questions (Aliannejadi et al., 2019). In the generation approach, the system generates clarification questions using rules or using neural generative models (Zamani et al., 2020).

In this work we focus on the selection task. While the latter (i.e., generation) may represent a more realistic use-case, still there is an interest in the former (i.e., selection) as evident by the (Aliannejadi et al., 2020) challenge. Moreover, the selection task represents a controlled and less noisy scenario, where the pool of clarifications can be mined from e.g., query logs. A conversation starts with an initial user query, continues with several rounds of conversation utterances (0 or more), and finally ends with one or more documents being returned to the user. Some of the agent utterances are marked as clarification questions.

The task at hand is defined as follows. Given a conversation context up to (and not including) a clarification-question utterance, predict the next clarification question. A more formal definition is given in Section 3 below.

Intuitively, clarification questions should be used to distinguish between several possible intents of the user. We approximate those possible intents through passages that are retrieved from a given corpus of documents. A motivating example from the (Aliannejadi et al., 2020) challenge is given in Figure 1. The user wants to get information about the topic all men are created equal. Through the retrieved passage, the system can ask the mentioned clarification questions.

We use two deep-learning models. The first one learns an association between conversation context and clarification questions. The second learns an association between conversation context, candidate passages and clarification questions.

Evaluation was done on two different use-cases. The first one is an open domain search in a large web corpus (Aliannejadi et al., 2020). The second
is an internal task-oriented customer-support setup, where users ask technical questions. We show that our method performs well on both use-cases.

![Figure 1: A motivating example](http://convai.io)

### 2 Related work

We focus on works that deal with clarification-questions selection. **Aliannejadi et al. (2019)** describes a setup very similar to ours for the aforementioned task. They apply a two-step process. In the first step, they use BERT (Devlin et al., 2019) to retrieve candidate clarification questions and, in the second step, they re-rank the candidates using multiple sources of information. Among them are the scores of retrieved documents using the clarification questions.

The ClariQ⁴ challenge organized a competition for selecting the best clarification questions in an open-domain conversational search. The system by NTES_ALONG (Ou and Lin, 2020) was ranked first. They first retrieve candidate clarification questions and then re-rank them using a ROBERTA (Liu et al., 2019) model which is fine-tuned on the relation between a query and a clarification question.

In **Rao and Daumé III (2018)**, they select clarification questions using the expected value of perfect information, namely a good question is one whose expected answer will be useful. They do not assume a background corpus of documents.

All those works do not exploit passages contents as we do.

### 3 Clarification-questions Selection

A conversation \( C \) is a list of utterances, \( C = \{c_0, \ldots, c_n\} \) where \( c_0 \) is the initial user query. Each utterance has a speaker which is either a user or an agent.² We further assume that agent utterances are tagged with a clarification flag where a value of 1 indicates that the utterance is a clarification question. This flag is either given as part of the conversation or is derived automatically by using a rule-based model or a classifier.

The **Clarification-questions Selection** task is defined as follows. Given a conversation context \( C^j = \{c_0, \ldots, c_{j-1}\} \), predict a clarification question at the next utterance of the conversation.³

The proposed run-time architecture is depicted in Figure 2. It contains two indices and two fine-tuned BERT models. The **Documents index** contains the corpus of documents (recall that we deal with conversations that end with a document(s) being retrieved). This index supports passage retrieval. The **Clarification-questions index** contains the pool of clarification questions. The two BERT models are used for re-ranking of candidate clarification questions as described below.

Given a conversation context \( C^j \), we first retrieve top-k passages from the Document index (See Section 3.1 below). We then use those passages, to retrieve candidate clarification questions from the Clarification-questions index (See Section 3.2 below). We thus have, for each passage, a list of candidate clarification questions.

The next step re-ranks those candidate clarification questions. Re-ranking is done by the fusion of ranking obtain through two BERT models. Each model re-ranks the clarification questions by their relevance to the given conversation context and the retrieved passages (see Section 3.3 below). The components of the architecture are described next in more details.

#### 3.1 Conversation-based passage retrieval

We use Apache Lucene for indexing the documents, configured with English language analyzer and default BM25 similarity (Robertson and Zaragoza, 2009).

Given a conversation context \( C^j \), **Passage retrieval** is performed in two steps. First, top-k documents are retrieved using the conversation context as a verbose query (Ganhotra et al., 2020). Next, candidate passages are extracted from those top-k documents using a sliding window of fixed size with some overlap. Details are given in appendix A.1

#### 3.2 Clarification-questions retrieval

The pool of clarification questions is indexed into a **Clarification index**. We use the passages returned

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¹http://convai.io

²An agent can be either a human agent or a bot.

³We always return clarification questions. We leave it for future work to decide whether a clarification is required.
for a given conversation context $C^j$, to extract an initial set of candidate clarification questions as follows. For each passage $P$, we concatenate the text of all utterances in $C^j$ to the content of $P$, and use it as a query to the Clarification index.

We thus have, for each passage, a list of candidate clarification questions.

### 3.3 Clarification-questions re-ranking

The input to this step is a conversation context $C^j$, a list of candidate passages, and a list of candidate clarification questions for each passage. We use two BERT models to re-rank the candidate clarification questions.

#### Fine-tuning of the models.

The first model, BERT-C-cq is fine-tuned to learn association between a conversation and clarification questions. Fine-tuning is done through a triplet network (Hoffer and Ailon, 2015) used for BERT fine-tuning (Mass et al., 2019). It uses triplets $(C^j, cq^+, cq^-)$, where $cq^+$ is the clarification question of a conversation $C$ at utterance $c_j$ (as given in the conversations of the training set). Negative examples ($cq^-$) are randomly selected from the pool of clarification questions (not associated with $C$).

The second model, BERT-C-P-cq is fine-tuned to learn an association between a conversation, a potential passage and a clarification. We use a weak-supervision assumption that all passages in work (Hoffer and Ailon, 2015) used for BERT fine-tuning (Mass et al., 2019). It uses triplets $(C^j, cq^+, cq^-)$, where $P$ is a passage retrieved for $C^j$, $[SEP]$ is BERT’s separator token, $cq^+$ is a clarification question (with its answer utterance $c_k$) in $C$, and $P$ is a passage retrieved using the conversation context $C^{k+1}$.

Due to the BERT limitation on max number of tokens (512), we represent a conversation context $C^j$ using the first $m$ utterances whose total length is less than 512 characters. We also take the passage window size to be 512 characters.²

#### Re-ranking with the models.

Each candidate clarification question $cq_i$ is fed to the first model with the conversation context as $(C^j, cq_i)$, and to the second model as $(C^j, [SEP] P, cq_i)$, where $P$ is the passage that was used to retrieve $cq_i$. Final scores of the candidates is set by simple CombSUM (Wu, 2012) fusion of their scores from the two BERT models.

### 4 Experiments

#### 4.1 Datasets

We evaluated our method on two datasets. The first, ClariQ (Aliannejadi et al., 2020) represents an information-seeking use-case. The second, Support contains conversations and technical documents of an internal customer support site. Statistics on the two datasets are given in Table 1.

²note that BERT uses tokens while for the passages and representation of conversation we use characters
The ClariQ dataset was built by crowd sourcing for the task of clarification-questions selection, thus it has high quality clarification questions. The Support dataset contains noisy logs of human-to-human conversations, that contain a lot of chit-chat utterances such as *Thanks for your help* or *Are you still there?* We thus used rule-based model to detect agent utterances as ground truth clarification questions in this dataset (details are given in appendix A.2).

Table 1: Datasets statistics

|                      | ClariQ | Support |
|----------------------|--------|---------|
| #docs                | 2.7M   | 520     |
| #conversations (train/dev/test) | 187/51/60 | 500/39/43 |
| #total clarifications| 3940   | 704     |
| #avg/max turns per C | 3/3    | 8.2/80.5|
| #avg/max clarifications per C | 14/18  | 1.2/7/5 |

4.2 Setup of the experiments

Details of the setup are given in appendix A.3. For evaluation metrics, we followed the ClariQ leaderboard\(^5\) and used the Recall@30 as the main metric.

For evaluation, we take the conversation context \(C^j (j \geq 1)\) in the dev/test sets up to the first clarification point, and predict the clarification question at the next utterance \(j\). In ClariQ, since there is no real conversation context (each topic has independent set of clarification questions and their answers), it will be just the basic question (i.e., \(c_0\)), while in Support, \(C^j\) can contain several utterances.

4.3 Results

Table 2 reports the results on the dev sets of the two datasets. On both datasets, each of the BERT re-rankers showed a significant improvement over the initial retrieval from the Clarification-questions index (denoted by IR-Base). For example on Support, BERT-C-cq achieved \(R@30=0.538\) compared to \(R@30=0.294\) of IR-Base (an improvement of 82%).

We can further see that the two BERT models (BERT-C-cq and BERT-C-P-cq), yield quite similar results on both datasets, but, when fusing their scores (BERT-fusion), there is another improvement of about 2.5% over each of the rankers separately. For example on ClariQ, BERT-fusion achieved \(R@30=0.791\), compared to \(R@30=0.77\) of BERT-C-cq.

This improvement can be attributed to complementary matching that each of the two BERT model learns. The second model learns latent features that are revealed only through the retrieved passages, while the first model works better for cases where the retrieved passages are noisy. For example for query 133 in ClariQ, *all men are created equal* (see Figure 1 above), BERT-C-P-cq could find nine correct clarification questions out of 14 in its top-30 (including those two in the Figure), while BERT-C-cq found only three of them.

Table 3 shows the official Clariq leaderboard result on the test set. We can see that our method BERT-fusion\(^6\) was the second best. We note that the top performing system (NTES_ALONG) gave preferences to clarification questions from the test data, capitalizing the specific Clariq properties that topics came from different domains. This is not a valid assumption in general. In contrast, we treat all clarification questions equally in the given pool of clarification questions.

Table 2: Retrieval quality on the dev set of the two datasets

|            | R@5  | R@10 | R@20 | R@30 |
|------------|------|------|------|------|
| ClariQ     | .327 | .575 | .669 | .706 |
| IR-Base    | .352 | .631 | .743 | .770 |
| BERT-C-cq  | .444 | .615 | .750 | .774 |
| BERT-C-P-cq| .538 | .639 | .758 | .791 |
| BERT-fusion| .553 | .639 | .758 | .791 |

Table 3: Retrieval quality on the test set of the ClariQ dataset

| ClariQ | R@5  | R@10 | R@20 | R@30 |
|--------|------|------|------|------|
| NTES_ALONG | .34  | .632 | .8335 | .874 |
| BERT-fusion | .338 | .631 | .807 | .857 |
| TAL-ML  | .339 | .625 | .817 | .856 |
| Karl    | .335 | .623 | .799 | .849 |
| Soda    | .327 | .606 | .801 | .843 |

5 Conclusions

We presented a method for clarification-questions selection in conversational-search scenarios that end with documents as answers.

We showed that using passages, combined with deep-learning models, improves the quality of the selected clarification questions. We evaluated our method on two diversified dataset. On both

\(^5\)https://convai.io

\(^6\)Our run was labeled CogIR in the official leaderboard
datasets, the usage of passages for clarification-questions re-ranking achieved improvement of $12\% - 87\%$ over base IR retrieval.

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A Appendix

A.1 Passage Retrieval details

For document retrieval, we create a disjunctive query from all words in the conversation $C_j$. Following (Ganhotra et al., 2020), we treat the dialog query as a verbose query and apply the Fixed-Point (FP) method (Paik and Oard, 2014) for weighting its words. Yet, compared to “traditional” verbose queries, dialogs are further segmented into distinct utterances. Using this observation, we implement an utterance-biased extension for enhanced word-weighting. To this end, we first score the various utterances based on the initial FP weights of words they contain. We then propagate utterance scores back to their associated words.
Next, each retrieved passage \( p \) is assigned an initial score based on the coverage of terms in \( C \) by \( p \). The coverage is defined as the sum over all terms in each utterance, using terms’ global \( idf \) (inverse document frequency) and their (scaled) \( tf \) (term frequency). Let \( c \) be a conversation with \( n \) utterances \( c = u_1, \ldots, u_n \). Passage score is computed as a linear combination of its initial score \( score_{init}(p, c) \) and the score of its enclosing document. Both scores are normalized.

\[
score(p, c) = \lambda * score(d) + (1 - \lambda) * score_{init}(p, c)
\]

\[
\lambda = 0.5 \quad \text{(we use fixed equal weights)}
\]

The initial passage score \( score_{init}(p, c) \) is computed as a weighted sum over its utterances scores \( score_{ut}(p, u_i) \). Utterance scores are discounted such that later utterances have greater effect on the passage score.

\[
score_{init}(p, c) = \sum_{i=1}^{n} weight_{ut}(i) * score_{ut}(p, u_i)
\]

\[
weight_{ut}(i) = discount\_factor^{(n-i)}
\]

\[
discount\_factor = 0.85
\]

Utterance score \( score_{ut}(p, u) \) reflects utterance’s terms coverage by the passage, considering terms’ global \( idf \) (inverse document frequency) and their (scaled) \( tf \) (term frequency). Multiple coverage scorers are applied, which differ by their term frequency scaling schemes. Finally, the utterance score is a product of these coverage scores \( score_{cov}(p, u) \).

\[
score_{ut}(p, u) = \Pi_{j=1}^{m} score_{cov_j}(p, u)
\]

\[
m = 2 \quad \text{(two scaling schemes are employed)}
\]

\[
score_{cov_j}(p, u) = \sum_{t \in T^{pu}} \text{idf}(t) * \text{scale}_j(t, p)
\]

\[
t^{pu} = t^p \cap t^u \quad \text{(terms appearing in both)}
\]

\[
t^p, t^u = \text{(passage terms, utterance terms)}
\]

Different scaling schemes provide different interpretations of terms’ importance. We combine two \( tf \) scaling methods, one that scales by a BM25 term score, and another that scales by the minimum of \( tf(t) \) in the utterance and passage.

\[
\text{scale}_1 = BM25(t, p) \]

\[
\text{scale}_2 = \min(tf(t, p), tf(t, c))
\]

The final passage score is a linear combinations of its initial score and the score of the document it is extracted from. Candidate passage ranking exploits a cascade of scorers.

### A.2 Rules to detect clarification questions in the Support dataset

We applied the following rules to identify clarification questions in the Support dataset. 1) We consider only sentences in agent utterances that contain a question mark. 2) We look for question words in the text (e.g., what, how, where, did, etc.) and consider only the text between such a word and the question mark. 3) If no question words were found, we run the sentence with the question mark through Allennlp’s constituency parser (Joshi et al., 2018) and keep sentences with a Penn-Treebank clause type of \( SQ \) or \( SBARQ \).

The above rules can detect question-type sentences. However, to filter out chit-chat question types, we apply a 4th rule as follows. We send the detected question and its answer (the next customer’s utterance), as a passage retrieval query (see Section 3.1 in the main paper) to the Documents index and keep only those questions that returned in their top-3 results, a passage from the URL of the dialog.

### A.3 Setup of the experiments

Documents in the document index are represented using two fields. The first field contains the actual document content. The second field augments the document’s representation with the text of all dialogs that link to it in the train-set (Amitay et al., 2005). We used the second field in the customer support dataset (Suppot) only, since it has quite few documents (only 520) and there is a large overlap between documents in the train and dev conversations. In the open-domain dataset (ClariQ) we did not use that field since the corpus contains large number of documents (2.7M) and using this field will prefer a small subset of documents of the train conversations only.

For passage retrieval, we used a sliding window of 512 characters on retrieved documents’ content.

We used common values for the hyper parameters, with \( \lambda = 0.5 \) to combine document and passage scores, and \( \mu = 2000 \) for the dirichlet smoothing of the documents LM used in the FixedPoint.

\[\text{https://gist.github.com/nlothian/9240750}\]
re-ranking.

The full conversations were used to retrieve passages. For feeding to the BERT models, we concatenated the first \( m \) utterances whose total length was less than 512 characters (we take full utterances that fit the above size, do not cut utterances).

We used the pytorch huggingface implementation of BERT\(^8\). For the two BERT models we used bert-base-uncased (12-layers, 768-hidden, 12-heads, 110M parameters). Fine-tuning was done with the following default hyper parameters. max_seq_len of 256 tokens\(^9\) for the BERT-C-cq model and 384 for the BERT-C-P-cq model, learning rate of 2e-5 and 3 training epochs.

We retrieved at most 1000 initial candidate clarifications for each passage. All experiments were run on a 32GB V100 GPUs. The re-ranking times of 1000 clarification questions for each conversation took about 1 – 2 sec.

For evaluation metrics we followed the ClariQ leaderboard\(^10\) and used the Recall@30 as the main metrics.

\(^8\)https://bit.ly/2Me0Gk1
\(^9\) note that here we use tokens while for the passages and representation of conversation we use characters
\(^10\)https://convai.io