Unsupervised Question Clarity Prediction Through Retrieved Item Coherency

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ABSTRACT

Despite recent progress on conversational systems, they still do not perform smoothly when faced with ambiguous requests. When questions are unclear, conversational systems should have the ability to ask clarifying questions, rather than assuming a particular interpretation or simply responding that they do not understand. While the research community has paid substantial attention to the problem of predicting query ambiguity in traditional search contexts, researchers have paid relatively little attention to predicting when this ambiguity is sufficient to warrant clarification in the context of conversational systems. In this paper, we propose an unsupervised method for predicting the need for clarification. This method is based on the measured coherency of results from an initial answer retrieval step, under the assumption that a less ambiguous query is more likely to retrieve more coherent results when compared to an ambiguous query. We build a graph from retrieved items based on their context similarity, treating measures of graph connectivity as indicators of ambiguity. We evaluate our approach on two open-domain conversational question answering datasets, ClariQ and AmbigNQ, comparing it with neural and non-neural baselines. Our unsupervised approach performs as well as supervised approaches while providing better generalization.

CCS CONCEPTS
• Information systems → Information retrieval; Query intent.

KEYWORDS

Ambiguous Queries, Clarifying Questions, Retrieval Coherency

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1 INTRODUCTION

Recently, the Information Retrieval (IR) and Natural Language Processing (NLP) communities have been enjoying major performance enhancements in many core tasks including ad hoc retrieval, question answering, and conversational search [14, 21, 25, 28, 33]. Despite this recent progress, even the best-performing systems are not able to perform smoothly and coherently on all requests [5, 29, 31]. For example, broad queries can have multiple interpretations and aspects [15, 16, 38, 43], and satisfying such ambiguous requests has long been considered as a challenging task. Consequently, the research community has paid substantial attention to the problem of predicting query ambiguity in traditional search contexts [13, 24, 39, 50]. In some contexts, such as web search, the impact of query ambiguity can be alleviated with approaches such as diversification or session-based data [20, 48]. However, in contexts such as smart assistants, a single response is required, and it is not possible to adapt solutions such as diversification. An alternative approach asks a clarifying question before responding [2, 37, 44]. Studies have shown that when a user has a broad or ambiguous request, they will be more satisfied if they are asked a clarifying question [26, 52]. Zamani et al. [52] conducted a user study on clarifying questions, showing that users appreciate clarifying questions because they are functional and give the user a sense of confidence. People anticipate having conversations with intelligent systems that are similar to the conversations they might have with humans [34]. Thus, asking clarifying questions is essential for developing human-like dialogue systems. A key challenge is determining when query ambiguity is sufficient to warrant clarification. Consider the two conversations in Figure 1. In the first example, the user issues an ambiguous query (“Tell me about defender”). The system identifies the request as ambiguous, and initiates a clarifying question to narrow down the user’s intent. After the user clarifies their intent, the system is able to provide appropriate information. In the second example, the query (“Folk remedies for a sore throat”) is sufficiently
clear that no clarification is required. In this paper, our overall goal is to differentiate between the two cases exemplified in Figure 1, i.e., to determine when the system should ask a clarifying question.

Researchers in the IR and NLP communities have extensively studied “What to ask?” when clarifying a user’s intent [1, 2, 10, 18, 37, 40, 41, 44, 52]. However, before we determine what clarifying question to ask, we must decide when a clarifying question is required. This problem of determining “When to ask?” has received relatively little attention. Addressing this problem requires significant user understanding, which makes test collection development for this task expensive and labor-intensive. As a result, there are few datasets suitable for studying this problem. Aliannejadi et al. [1] were among the pioneers attempting to formulate and curate data for when clarifying questions should be asked. They collected and released a comprehensive dataset, ClariQ, with a focus on asking clarifying questions in open domain conversational systems. ClariQ includes both ambiguous and unambiguous queries. In creating this dataset, they asked human annotators to assign a score for each request based on the level of clarification each query required. Current state-of-the-art query clarity prediction methods on the ClariQ dataset employ fine-tuned large pre-trained language models, such as BERT, to predict this clarification level [1]. However, due to limited available training data, this approach could be potentially biased toward that training set and lack generalizability.

To avoid possible problems related to bias and lack of available training data, we propose an unsupervised method to address query clarity prediction based on the coherency of the retrieved items from the initial user request. Similar to previous query performance prediction methods [3, 6, 11, 23, 53], we base our work on the intuition that a more clear query is more likely to retrieve coherent results when compared to an ambiguous one. The more ambiguous the query is, the more varied the returned items will be. Thus, inspired by coherency metrics [7, 35, 46], we build a graph from retrieved items based on their coherency, treating measures of graph connectivity as indicators of ambiguity. We distinguish our work from other coherency measures in several ways: 1) We deploy coherency metrics in the new context of clarifying questions. 2) We focus on the coherency of retrieved items at the passage level, using contextualized-based embeddings rather than sentence-level similarity 3) We measure coherency by treating passages as potential successors, i.e., we consider a pair of documents to be coherent if a language model predicts that they could be successive passages.

We evaluate our proposed approach on the ClariQ open-domain dialogue corpora, comparing it with current SOTA baselines [1]. In addition, we evaluate the performance of post-retrieval query performance predictors on predicting query clarity level [11, 42, 45, 54]. Further, we investigate the generalizability of supervised SOTA methods and compare them with our proposed method by applying the query clarity measures in a zero-shot setting to the AmbigNQ dataset [32]. AmbigNQ is a recently released dataset with annotations on NQ-OPEN questions containing diverse types of ambiguity [27]. We show that while our unsupervised approach outperforms supervised methods and exhibits greater generalizability.

2 RELATED WORK

Clarifying questions have proven their value in a number of search settings. Zamani et al. [52] explored users’ clarifying questions when searching on the web. These users described clarifying questions in search platforms as convenient, as they save time and steps. Kiesel et al. [26] studied the effect of voice query clarification and concluded that users like to be prompted for clarification.

“What to ask?” has seen substantial recent attention in the IR and NLP communities. For example, Aliannejadi et al. [2] formulated the task of asking clarifying questions in open-domain information-seeking conversational systems and compiled the Qulac dataset, which comprises more than 10K question-answer pairs for multi-faceted topics. They hired human annotators to create clarifying questions. While one way of asking clarifying questions is to select them form a pool of generated questions, Zamani et al. [52] took another approach by training a sequence-to-sequence model and recurrent neural networks on query reformulations as weakly supervised training data. Datasets such as MIMICS and QULAC are considered as functional outcomes of such work. They include multi-faceted queries accompanied with user behavioural signals. Such datasets provide a suitable vehicle for other researchers to train clarifying questions models [40]. Further, Sekulić et al. [41] addressed limitations of previous works by extracting useful facets and proposing a facet-based clarifying question generation approach.

We determine when the system should ask clarifying questions with a graph-based approach. Graphs have long demonstrated their potential for hosting textual similarity measures. Tsekouras et al. [47] present a graph-based text similarity that takes advantage of named entities, boosting the performance of text clustering tasks. Similarly, Putra and Tokunaga [36] propose graph construction methods based on the semantic similarity of vertices for document discrimination tasks based on text coherency. Since graph-based coherency metrics have shown to be effective in other tasks, we adapt graph-based coherency metrics to determine query clarity.

3 PROPOSED APPROACH

We base our approach on the intuition that an ambiguous query will retrieve items that refer to different aspects of the query. For example, consider the query “Tell me about defender” (Figure 1). Here, “Defender” could refer to the Land Rover Defender, the 1981 Defender arcade game, Microsoft Defender, or other things. Thus, retrieved items are likely to show lower coherency, as they may relate to completely different aspects of the query. For a less ambiguous query, such as “Tell me about folk remedies for a sore throat”, we expect the retrieved items to show higher coherency, better reflecting a single intent. To measure coherency, we consider retrieved items as fragments of a larger whole, e.g., passages of a document that are contextually related. We build a coherency network based on the coherency of retrieved items. The graph connectivity measures in the coherency network are considered as indicators of query ambiguity. The nodes of our coherency graph are the retrieved items (passages), with vertex A connected to vertex B if passage B is predicted to be likely successor to passage A according to a given language model and a set of retrieved items $d_i \in D$, a coherency-network $G(D)$ is denoted as $G(D) = (\mathbb{V}, \mathbb{E})$, a directed graph, where $\mathbb{V} = \{d_i \in D\}$, and $\mathbb{E} = \{d_i \rightarrow d_j : \forall d_i, d_j \in \mathbb{V} \mid P_s(d_i, d_j) = 1\}$.

The function $P_s(d_i, d_j) = 1$ when $d_j$ is predicted to be a likely successor to $d_i$; $P_s(d_i, d_j) = 0$, otherwise. Figure 2 plots the coherency network for the top-10 retrieved items for four example
queries from the ClariQ dataset. The two examples on the left represent more ambiguous queries, and the two examples on the right represent less ambiguous queries. As shown in this figure, the structure of the coherency network is related to query ambiguity level. The coherency networks for more ambiguous queries are sparser and more scattered, whereas for less ambiguous queries they are more condensed and connected. We measure the Node Connectivity (NC) of the coherency network as the minimum number of nodes that must be removed to disconnect G or render it trivial[51]. Further, we measure Average Node Connectivity (ANC) which is the average of local node connectivity over all pairs of nodes of G on the coherency network, as an indicator of coherency-network density and subsequently the clarity level of the query [8]. The Local Node Connectivity for two non-adjacent nodes is defined as the minimum number of nodes that must be removed to disconnect the graph [9]. As shown in Figure 2, the nodes in the coherency-network of an ambiguous query are more susceptible to becoming disconnected as nodes are removed.

4 EXPERIMENTS

We ran our experiments on the ClariQ and AmbigNQ datasets. In the following, we briefly explain the details of each dataset. For further details, please refer to the original papers.

ClariQ: ClariQ is a dataset dedicated to the problem of asking clarifying questions in open-domain dialogue systems. It is based on TREC WEB track 2009-2014 data and contains almost 300 search topics. It aims to support research into both "when" to ask clarifying question and "what" clarifying questions to ask. To develop the dataset, human experts were asked to convert the short keyword-based queries into conversational requests. Then two annotators were assigned to rate each query based on the level of clarification required from 1 (the most clear queries) to 4 (the most ambiguous queries). In case of disagreement, a third annotator made the final assessment. Since in this work, we want to predict whether we should ask a clarifying question or not, we interpret the top two levels of query clarity (level 1 and 2) as questions that do not need clarification and the lower two levels (level 3 and 4) as those that require clarification. We train supervised baselines on ClariQ train set, tune them on its development set, and report the performance of our methods, as well as the baselines, on the ClariQ test set.

AmbigNQ: Min et al. [32] introduced AmbigQA, a new task which necessities identifying all possible answers to an open-domain question, along with disambiguated questions to distinguish them. In addition, they construct AmbigNQ, a dataset with over 14K high-quality human annotated questions from the NQ-OPEN dataset [27] containing diverse types of ambiguity. We use this dataset to examine the generalizability of different query clarity methods. Questions in AmbigNQ differ from questions in ClariQ by requiring short precise answers, often named entities. For example, the question "Who plays the white queen in alice through the looking glass?" is considered to be ambiguous since it has been annotated with two answers 'Amelia Crouch (young White Queen)' and 'Anne Hathaway (adult White Queen). If this question appeared in ClariQ, the two answers could be concatenated with each other and the question might not be considered ambiguous. Requests in ClariQ are more general and cannot be necessarily answered by a short phrase or an entity. Moreover, the ClariQ dataset was specifically collected for the purpose of research into clarifying questions. The questions in AmbigNQ are accompanied by different numbers of question-answer pairs. We take the number of possible question-answer pairs as an indicator of the level of question ambiguity. The greater the number of question-answer pairs, the more ambiguous we take the question to be.

4.1 Experimental Setup

In order to build a coherency-network as described in section 3 to determine whether we need to ask clarifying questions, we ought to retrieve passages for a given query. The retrieved items are considered as nodes of the coherency network. We use the MS MARCO V2 corpus which is a comprehensive corpus including more than 138 million passages as the corpus of our retrieval. Further, we employ the well-established BM25 retrieval approach to retrieve passages from the corpus. We selected MS MARCO V2 as the corpus since it has high number of passages and more likely to include relevant answers to each query and BM25 as retrieval methodology since it is well-known approach. Thus, we note that our proposed methodology is not dependent on the corpus nor retrieval methodology. Further, we implement our proposed methods using the NetworkX package to build the coherency network. To build the coherency network, we set \( P_s(d_i, d_j) = 1 \) if and only if a pre-trained language model predicts that \( d_j \) is next sentence of \( d_i \). As pre-trained models, we used BERT base [19] and also the distilled model MiniLM [49], which is lighter than BERT while keeping the same level of performance. Both of these pre-trained models were initially trained on the Masked Language Modeling (MLM) task as well as the Next Sentence Prediction (NSP) task. While MLM teaches the pre-trained language model to understand the relationship between terms, the NSP task goal is to help the model to understand longer-term dependencies and interpret beyond the words to jointly pre-train text-pair representations[19]. Thus, we defined \( P_s(d_i, d_j) \) on NSP task. Every pair of passages are fed into the model followed by a [SEP] token. Then, we encode the passages and obtain
We note that both MiniLM-ANC and BERT-NC outperform all the well-known benchmarks. Some of these methods are based on the intuition that if a query is ambiguous, it is more likely to have lower performance compared to a more specific one. Thus, we considered the SOTA unsupervised QPP methods such as WIG\cite{45}, NQC\cite{42}, SMV\cite{45} and $n(\sigma_j)$\cite{17} that have shown relatively consistent performance on different well-known benchmarks. Some of these methods are based on the intuition that if a query is ambiguous, it is more likely to have lower performance compared to a more specific one. Thus, we considered the SOTA unsupervised QPP methods such as WIG\cite{45}, NQC\cite{42}, SMV\cite{45} and $n(\sigma_j)$\cite{17} that have shown relatively consistent performance on different well-known benchmarks such as Robust04, TREC Web Collections, and MS MARCO \cite{4, 11, 22}. We tuned the hyper-parameters of these QPP methods on ClariQ dev set, and report the best-performing models on the test set.

### 4.2 Baselines

We compare the performance of our methods with the SOTA baselines from the original ClariQ paper \cite{1}. These baselines fine-tune pre-trained language models based on the (limited) training data in ClariQ to predict the level of query clarity. We fine-tuned RoBERTa \cite{30}, BART \cite{12} and BERT \cite{19} as suggested by \cite{1} and tuned the hyper-parameters on the ClariQ dev set by selecting number epochs from \{1,3,5\} and learning rate from \{5/6/7\$e^{-5/7}\} on ClariQ dev set. By carefully tuning learning rates and number of epochs, we were able to outperform the results reported in the original paper (Table 1). Query Performance prediction methods have shown to be highly correlated with retrieval performance on different well-known benchmarks. Some of these methods are based on the intuition that if a query is ambiguous, it is more likely to have lower performance compared to a more specific one. Thus, we considered the SOTA unsupervised QPP methods such as WIG\cite{45}, NQC\cite{42}, SMV\cite{45} and $n(\sigma_j)$\cite{17} that have shown relatively consistent performance on different well-known benchmarks such as Robust04, TREC Web Collections, and MS MARCO \cite{4, 11, 22}. We tuned the hyper-parameters of these QPP methods on ClariQ dev set, and report the best-performing models on the test set.

### 4.3 Results

Since determining “when” to ask clarifying question is a binary classification task, we evaluate our proposed approaches and compared it to baselines in Table 1 in terms of the area under the ROC curve (AOC). As shown in this table, our proposed methods outperform all the QPP methods. We also compared the best of each category, i.e., best of fine-tuned PLM (BART), best of QPP methods (NQC) and best of our proposed methods from each category, i.e., MiniLM-ANC and BERT-NC. We plot the ROC curves in Figure 3. We note that both MiniLM-ANC and BERT-NC outperform all the other baselines with statistical significance ($p < 0.05$). Our methods outperformed the best when using the top-20 retrieved items. Thus, we report all the other performance measures with the top-20 items.

### 4.4 Generalizability Analysis

To determine our query clarity prediction methods generalizability, we evaluate the best performing methods from the ClariQ dataset on the AmbigNQ dataset, we adopt the number of question-answer pairs in AmbigNQ dataset as an indicator of the clarification need level. As reported in \cite{32}, we split the queries in the AmbigNQ dev set into 4 groups, with 1, 2, 3, and 4+ question-answer-pairs. We expect to see that query clarity measures tend to ask question on level 1 less than level 2, and consequently on level 2 less than level 3, and so on. We ran experiments on the best of the baselines i.e., fine-tuned BART vs. our NQC from QPP methods and MiniLM-ANC and BERT-NC from our proposed methods and plotted the predicted percentage on ambigNQ dev set. As shown in Figure 4, we expected to see gradually increasing ambiguity across the four classes. Our method fully satisfies this expectation. The other unsupervised baseline, i.e., best of QPP methods also matches this expectation. However, ambiguity does not increase for the supervised PLM-based approaches, which are trained on the ClariQ training set. This observation, indicates that while supervised baselines showed promising performance, they suffer from lack of generalizability and are biased toward their training data set.

### 5 CONCLUSION

We demonstrated an unsupervised method to determine when clarifying questions should be asked, based on the coherency of the items retrieved by an initial query. We validated our methods through experiments on the ClariQ clarifying question dataset and the AmbigNQ question ambiguity dataset, showing that our unsupervised method performed as well or better than supervised methods, as well as well-established query performance prediction baselines. Due to limited amount of training data available for this task, the generalizability of the approach is important and any bias toward training set should be avoided. Our unsupervised approach demonstrates great generalizability when applied to the AmbigNQ dataset, compared to SOTA supervised baselines.
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