Modeling Mixed-initiative Conversational Search

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Overview

Search is ubiquitous and in increasing demand in this age. Conventionally, search is cast as single-turn retrieval: A search system ranks all the pages on the internet according to their relevance to the query and returns the rank list as "ten blue links" [1]. A study [2] revealed that about 60% of the queries are less than two words, and 98.2% of the queries are less than seven words. Short queries are especially challenging for single-turn search systems due to their ambiguity.

Existing commercial search engines attempted to address query ambiguity through search result page (SERP) diversification. However, it is passive and inefficient as the diversified SERP reduces the portion of relevant contents to each user. Further, this approach may not be practical to search scenarios like mobile or voice searches with limited bandwidth for showing results [3].

With the development of machine learning, natural language processing, and computing power, it has become much easier to process and understand complex user statements. This helped develop highly interactive information-seeking systems that support multi-turn user-system interactions beyond user-initiative single-turn systems. They are known as conversational search systems and are becoming an increasingly popular research topic and important frontier of IR [4, 5].

Although existing work has demonstrated the benefits of introducing system-initiative interactions in conversational search, such as asking clarifying questions, fully mixed-initiative conversational search is still a dynamic and complex process that needs more systematic research.

My research focuses on modeling mixed-initiative conversational search, particularly implementing a fully mixed-initiative conversational search system equipped with a conversational search policy trained and working cooperatively with its core result retrieval and generation models.

To this end, I designed a conversational search policy model that can choose mixed-initiative conversational search actions, simulate and model the risk of each action [6, 7], and can infer the reasoning behind these decisions from historical conversational search logs and improve generalizability [8]. Furthermore, I designed a zero-shot inferencing pipeline to generate high-quality clarifying questions based on query facets [9]. As a new search paradigm, there has yet to be any mature online service for conversational search, which significantly restrain the availability of sizeable conversational search datasets. To facilitate the automatic creation of a large conversational search dataset, I developed a user simulation system [10].

How To Train A Conversational Search Policy?

In conversational search, an alternative approach to directly retrieving results while facing an ambiguous query is to ask clarifying questions (CQ) to the user proactively. This approach has drawn attention from both NLP and IR communities. Most attentions are focused on generating [11, 12, 13] and selecting CQ [14, 6, 15], or incorporating CQ with the query [16, 17, 18, 19]. However, their work assumed that users were dedicated to the search session after submitting the search query and would give an answer to any CQ asked. I argued that asking CQ upon ambiguous query is also a risky decision [7, 6], in that the CQ can be irrelevant, over-specific, etc., making the user uncomfortable (like racial innuendo [20]). Hence asking CQ should not always be taken as an alternative to direct result retrieval. Therefore, a mixed-initiative conversational search system needs a decision-making model for its actions. There is some work addressing this need [21, 14, 22], but they cast the decision-making problem as single-turn classification. My work [6, 7] was the first to cast the problem as conversational search policy learning and explored the sequential decision-making configuration of the problem. I showed that reinforcement learning (Q-learning) could efficiently learn the conversational search policy.

Figure 1 is my risk-aware conversational search system structure with conversational search policy. Unlike previous systems, it first calls the clarifying question and result retrieval models independently to obtain questions and potential results as action candidates. After that, the conversational search policy (risk-decision module) jointly evaluates the query, context, and the candidates to decide between the clarifying question or the answer. Compared to previous systems, its advantage is that it preemptively evaluates the candidates and reduces the chance of asking bad clarifying questions to the users. Training this policy model was challenging since no annotated conversational search logs were available. To solve this problem, I employed Deep Q-Learning [23] and empirically designed rewards for the Q-learning algorithm.

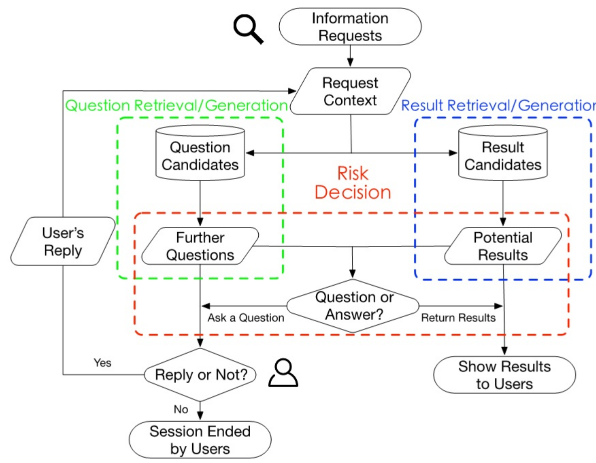

Figure 1: Risk-aware Conversational Search

Through experiments with different types of user simulators, I showed that my approach outperformed several deterministic decision baselines on three datasets, including MSDialog, Ubuntu Dialog Corpus, and OpendialKG [24, 25, 26]. *My proposed risk-aware conversational search system can control the risk in conversational search, boost conversational search result quality, and improve user experience.*

How To Generalize Policy Training Without Making User Assumptions?

Conversational search systems should be adaptive to a wide range of user types. However, existing conversational search systems are mostly developed with explicit user assumptions. Particularly, their policy models are trained with assumptions about users' patience, tolerance, cooperativeness, etc.[7, 6, 27], which are often instantiated as action rewards in the reinforcement learning process. When tested with different types of users, these systems often fail to generalize. Thus, in real-world applications where user behaviors are unpredictable and varying, this could cause user loss.

My work [8] demonstrated a simple imitation learning (IL) method to train conversational policy without making explicit user assumptions and tuning rewards based on user assumptions. It automatically inferred the reward function from historical conversational search logs containing implicit user behavioral information. The reward-free IL algorithm both reduces the tuning cost and improves generalizability.

The IL algorithm I use is the generative adversarial imitation learning (GAIL) algorithm [28], which alternatively trains a discriminator and a policy model. It shares structural similarities with generative adversarial nets (GANs) [29]. The goal of the discriminator is to distinguish model-generated trajectories from expert conversation trajectories. The policy model aims to generate trajectories more like the best historical conversation and less like what it has already generated.

With this iterative training process, the policy model is optimized to approximate the expert, generating the ground truth trajectories in the dataset.

By definition, training GAIL needs to identify the best historical conversation trajectories as positive examples. To get the best trajectory, I designed a session-level conversational search evaluation metric named Expected Conversational Reciprocal Rank (ECRR), which balances the search result quality and search efficiency in its scoring function. I then use this ECRR metric to compute and rank trajectories to find the expert trajectory for each conversation. Through experiments, I showed that *GAIL can efficiently learn the expert policy without making user assumptions and generalize significantly better to unseen users compared to previous baselines.*

How To Generate High-Quality Clarifying Questions When Facing Data Scarcity?

Existing research on generating clarifying questions for conversational search such as [11, 30, 12, 31, 32] exhibit two limitations about the datasets. The first is the lack of sizable conversational search datasets with ambiguous faceted queries. Second, requiring a conversation dataset to cover all possible search topics unbiasedly is unrealistic. Therefore, a more practical solution is to generate clarifying questions in a zero-shot setting, meaning the generation system does not need to be trained on any conversational search data. However, directly applying existing zero-shot language generation methods often yield unsatisfactory results because of two reasons: First, they generate superficially relevant content that does not actually help clarify the search need, such as repeating the original search query. Second, they usually generate narratives instead of asking questions.

In my work [9], I designed a constrained language generation pipeline (Fig. 2) to address these challenges. First, to ensure the generation is useful for clarification, I leverage the idea of constrained language generation, with search facets as the constraints. The constrained language generation algorithm, NeuroLogic Decoding [33], modifies the beam search process and incentivizes the generation model to rank generations beams that contain the facet words higher during beam search. Next, to avoid generating narratives, I give the generation model eight clarifying question prompts to guide the generation process. Then, I use a weighted sequential dependency model [34] to rank the eight prompted generations and return the top question.

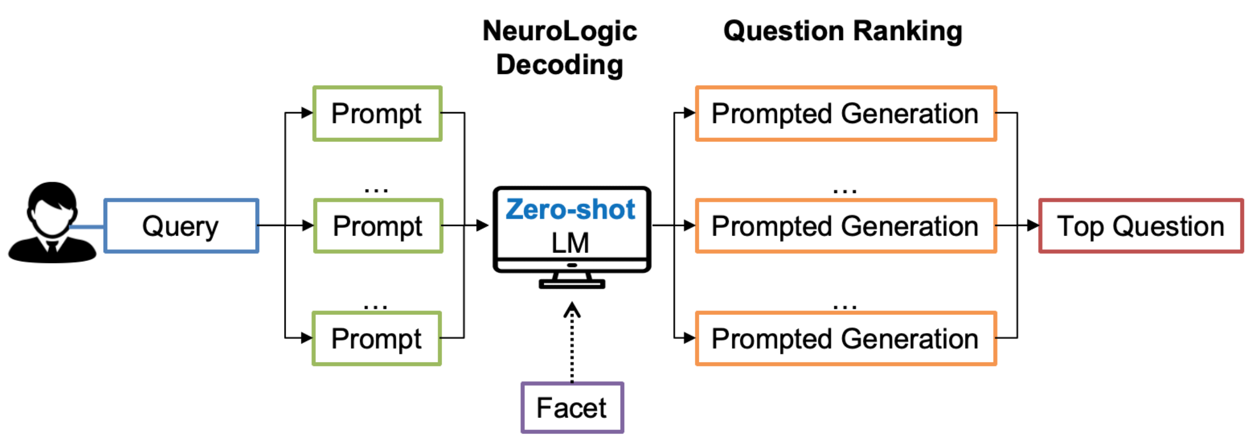

Figure 2: Zero-shot Clarifying Question Generation System

Experiment results evaluated by automatic language generation metrics and human judgment on the Clariq-FKw dataset show that my proposed zero-shot approach significantly outperforms existing models, even if they are finetuned on the training set (unlike my proposed approach).

How To Simulate User Responses For Automatic Multi-Turn Dataset Creation?

Most research about conversational search [13, 14, 7, 35, 15, 12, 11] is limited to training their system on datasets with observed or artificial conversation logs. Such a dataset would lack training signals and evaluation references when a conversation veers away from the dataset, especially when the system generates a question not listed in the dataset and steers the conversation in an unseen direction. Eventually, conversational search systems should be trained, evaluated, and deployed in an open-ended setting. However, training and evaluating them this way is challenging; it requires humans to generate responses to open clarifying questions, which is expensive and unscalable.

Past work [27, 35] has demonstrated that a user response simulator that automatically generates human responses can help evaluate conversational search systems. Such a system aims to generate user-like answers to system-generated clarifying questions based on a query and the user's search intent. I propose that a user response simulation system can also enable studies such as training a multi-turn conversational search system by generating synthetic conversations and rewards and perhaps using Reinforcement Learning from Human Feedback (RLHF) [36].

My work [10] showed that the current state-of-the-art user simulation system could be significantly improved by replacing it with a smaller but advanced T5 [37] natural language generation model. Further, I present an in-depth investigation of the task of simulating user response for conversational search to supplement existing works with an insightful hand-analysis of what challenges are still unsolved by the advanced model and propose our solutions for them. The major challenges I identified include (1) dataset noise, (2) existing models struggle to generate the correct answer type, and (3) the standard evaluation will misevaluate generated responses because of user cooperativeness mismatch. Except for the dataset noise issue, I propose two solutions to generate responses with better type accuracy and avoid misevaluation. My solution to the former is to improve user simulators with knowledge from question-answering tasks, using one of the current state-of-the-art models for QA—UnifiedQA [38]. Further, I propose to train a classifier that predicts answer types to guide the UnifiedQA through constrained generation, using RoBERTa [39] as the classifier, which is representative of state-of-the-art text classifiers. My solution to the misevaluation is to partition the training and evaluating data, then separately train and evaluate data with only matched cooperativeness.

I conduct experiments on two popular datasets for user response simulation—Qulac [13] and ClariQ [14]. My proposed solutions lead to further improvements over the T5 baseline.

Future Work

Today, models like GPT-4 [40] and LLaMA [41] pioneer the arrival of the era of large language models (LLMs). In the future, I propose to design a comprehensive mixed-initiative conversational search system that will bridge the gap between LLMs and a search system that can perform true conversational search. In particular, I wish to explore the following directions:

1. End-To-End Training For Conversational Search System

My past work has covered various parts of a mixed-initiative conversational search system, including conversational search policy, clarifying question generation, and user simulation. However, they are mostly done independently. In reality, these parts are interconnected within the system. For example, the policy model needs to compare the retrieved results and possible clarifying questions to make decisions, while the clarifying question model can benefit from being able to predict users' responses. These potentials make it appealing to train all these models jointly end-to-end.

2. From Large Language Model To Mixed-Initiative Conversational Search System

Since OpenAI released ChatGPT [40], LLMs are no longer mere academic research tools but also real online applications. The multi-turn conversation capability of these LLMs is a clear indicator that a mature online conversational search system is around the corner. However, since these LLMs are not directly designed for conversational search, using them as the backbone of a conversational search system raises many potential concerns. For example, **how to leverage their language generation capability in a retrieval task?** and **how to train them and evaluate their generations given that conversational search is a new search paradigm with no industry standard?** To answer these questions, one needs to iteratively test and evaluate various LLM-based conversational search systems configurations and conduct user studies.

By exploring the above directions, I hope to contribute to developing modern conversational search systems to improve user experiences.

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