An Empirical Study on Clarifying Question-Based Systems

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ABSTRACT

Search and recommender systems that take the initiative to ask clarifying questions to better understand users' information needs are receiving increasing attention from the research community. However, to the best of our knowledge, there is no empirical study to quantify whether and to what extent users are willing or able to answer these questions. In this work, we conduct an online experiment by deploying an experimental system, which interacts with users by asking clarifying questions against a product repository. We collect both implicit interaction behavior data and explicit feedback from users showing that: (a) users are willing to answer a good number of clarifying questions (11 on average), but not many more than that; (b) most users answer questions until they reach the target product, but also a fraction of them stops due to fatigue or due to receiving irrelevant questions; (c) part of the users' answers (17%) are actually opposite to the description of the target product; while (d) most of the users (84%) find the question-based system helpful towards completing their tasks. Some of the findings of the study contradict current assumptions on simulated evaluations in the field, while they point towards improvements in the evaluation framework and can inspire future interactive search/recommender system designs.

KEYWORDS

Empirical Study; Question-based Systems; Asking Clarifying Questions; Conversational Search; Conversational Recommendation

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1 INTRODUCTION

One of the key components of conversational search and recommender systems [5, 7] is the construction and selection of good clarifying questions to gather item information from users in a searchable repository. Most current studies either collect and learn from human-to-human conversations [1, 2, 4], or create a pool of questions on the basis of some "anchor" text (e.g. item aspects [5], entities [6–8], grounding text [3]) that characterizes the searchable items themselves. Although the aforementioned works have demonstrated success in helping systems better understand users, most of them evaluate algorithms by the means of simulations which assume users are willing to provide answers to as many questions as the system generates, and that users can always answer the questions correctly, i.e. they always know what the target item should look like in its finest details. On the basis of such assumptions, their evaluations (e.g. Zhang et al. [5], Zou et al. [6], Zou and Kanoulas [7]) focus on whether the system can place the target item at a high ranking position. To the best of our knowledge, there is no empirical validation of whether and to what extent users can respond to these questions, and the usefulness perceived by users while interacting with the system.

In this paper we conduct a user study by deploying an online question-based system to answer the following research questions: (1) To what extent are users willing to engage with a question-based system? (2) To what extent can users provide correct answers to the generated questions? (3) How useful do users perceive while interacting with a question-based system? We believe that answering these research questions can help the community design better evaluation frameworks and more robust question-based systems.

2 STUDY DESIGN

In our study, the users interact with a question-based system in the domain of online retail. The user is answering questions prompted by the system with a "Yes", a "No" or a "Not Sure", in order to find a target product to buy. The architecture of our system is shown in Figure 1, with the user going through 4 steps.

Step 1: Category selection. In this step, the users select an Amazon category [1] that they feel most familiar with to fit their interests, e.g. a category from which they have purchased products before.

Step 2: Target product assignment. We randomly assign a target product to the user from the selected category. The user is requested to read the title and the description of the product carefully. A picture of the product is also provided. This simulates a use case in which the user really knows what she is looking for, as opposed to an exploratory use case. If the user is not familiar with the target product the user can request a new product.

Step 3: Find the target product. After the user indicates that the conversation with the system can start, the target product disappears from the screen and the system selects a question to ask to the user. The user needs to provide an answer on the basis of the target product information she read in the previous step. Once the user answers the question, a 4-by-4 grid of the pictures of the top sixteen ranked products is shown to the user, along with the next clarifying question. The user can stop answering questions at any time when

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[1] Categories and dataset we used: http://jmcauley.ucsd.edu/data/amazon/links.html

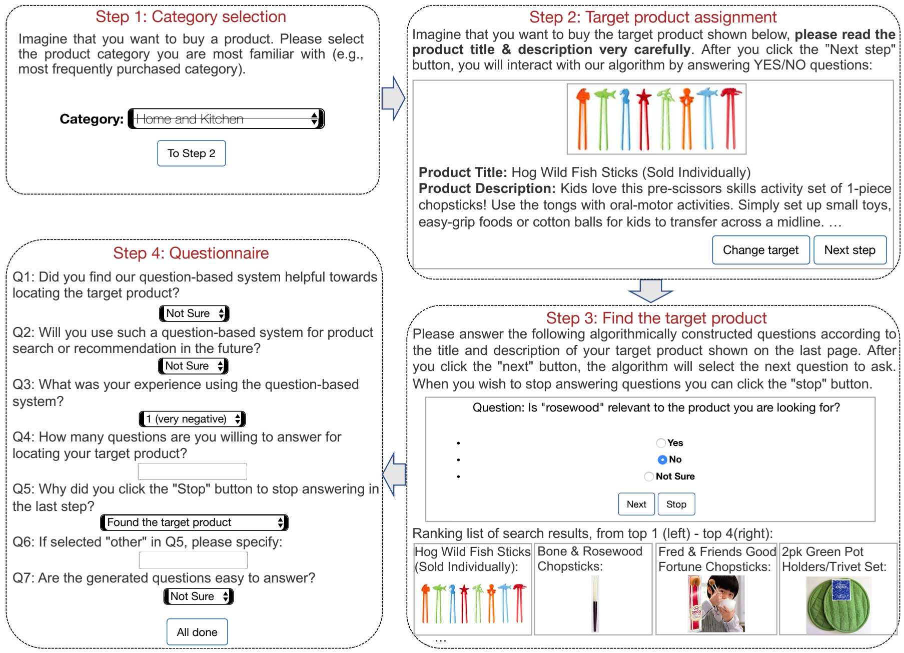


Figure 1: System architecture and main UI pages

she wants to stop during her interaction with the system. To select what clarifying question to ask, a state-of-the-art algorithm [7] is deployed to first extract important entities from each product description (e.g. product aspects) and construct questions in the form of "Is *[entity]* relevant to the product you are looking for?". Then, it selects to ask the information-theoretically optimal question, that is the question that best splits the probability mass of predicted user preferences over items closest to two halves, and updates this predicted preference on the basis of the user's answer [7]. In this work, we update the predicted preference using the correct answer, i.e. the answer which agrees with the description of the product, independent of the user's answer. In other words, we study the user behavior under a perfect system from an information theoretical point of view, leading to a best-case analysis and conclusions.

Step 4: Questionnaire. In this step users are asked a number of questions about their experience with the system for further analysis.

3 EXPERIMENTS AND ANALYSIS

3.1 Research Questions

Our research questions revolve around the user engagement and perceived value of the system: **RQ1** Are users willing to answer the clarifying questions, how many of them, when do they stop and why, and how fast do they provide the answers? **RQ2** To what extent can users provide correct answers given a target product, and what factors affect this? **RQ3** How useful do users find the clarifying questions, what is their overall experience, and how likely is it to use such a system in the future?

3.2 Participants

Prior to the actual study, we ran a pilot study with a small number of users, in a controlled environment, and iterated over the experimental design, and the user interface until no issues or concerns were reported. For the actual study 53 participants located in the USA were recruited through Amazon Mechanical Turk and 1025 conversations were collected. The participants were of varying gender, age, career field, English skills and online shopping experience. In particular, gender: 34 male, 19 female; age: 2 in 18-23, 8 in 23-27, 14 in 27-35, 29 older than 35 years old; career field: 22 in science, computers & technology, 8 in management, business & finance, 7 in hospitality, tourism, & the service industry, 3 in education and social services, 2 in arts and communications, 2 in trades and transportation, 9 did not specify their career field; English skills: all of them were native speakers; online shopping experience: 44 were mostly shopping online, 9 did online shopping once or twice per year. Participants were paid 2.5 dollars to complete the study. Also, we only engaged Master Workers [2], filtered out those users who spent less than 3 seconds on reading the product title and descriptions, and users who gave random answers (~50% correct/wrong), for quality control.

3.3 User Willingness to Answer Questions

In **RQ1**, we first investigate whether users are willing to answer the system's questions and how many of them, both by observing the actual number of questions users answered when interacting with the question-based system and what they declared at the exit questionnaire. The results in Figure 2 show that users answer a minimum of 2 and a maximum of 48 questions. The average number of questions answered per target product is 11.4, the median is 7, and 70.3% of users answered 4-12 questions per product, while at the exit questionnaire about 50% of the users declare that they are willing to answer 6-10 questions. Further, we explore why users stop answering questions. Users could select one out of six answers during the exit questionnaire: "The target product was

[2]High performing workers identified by Mechanical Turk who have demonstrated excellence across a wide range of tasks.

Table 1: The % of correct, "not sure", and incorrect answers.

Correct	73.1%	Not sure	9.6%	Incorrect	17.3%

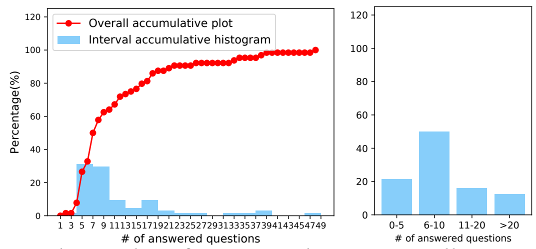
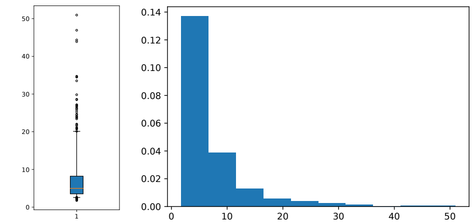


Figure 2: The number of questions the users actually answered in the system (left) and declared in the exit questionnaire (right). In the system, the average number of answered questions per product is 11.4, and 70.3% of users answered 4-12 questions per product. In the questionnaire, 50% users are willing to answer 6-10 questions.

found", "A similar product was found", "I got tired of answering questions", "I could not answer the questions", "The questions asked were irrelevant", and "Other". The results under the oracle condition show that while a small percentage of users stop due to fatigue (14%) or due to irrelevant questions being asked (7%), the big majority of users (77%) stop because they located the target product. We then analyze how quick are the users in answering questions. Figure 3a shows a box-plot of the time spent per answer, while 3b better demonstrated the distribution. From the results, we observe that the minimum time for answering one question is 1.75 seconds, the average time is 7.1 seconds, and the median time is 4.98 seconds. 86.5% of the users spent from 1.75s to 11.59s. Despite a median time of 5 seconds to answer a question, in the exit questionnaire 98% of the users indicate that the system's questions are easy to answer.

3.4 User Answers Noise

In **RQ2**, we first explore to what extent can users provide correct answers. As one can observe in Table 1, users provide correct answers 73.1% of the time, they are not sure 9.6% of the time and they are wrong 17.3% of the time. We then explore what features affect the percentage of incorrect answers. In particular, we first investigate whether the percentage of incorrect answers is different for different users. The results in Figure 4a show the percentages of correct, "not sure", and incorrect answers vary across users. Further, we explore whether the percentage of correct answers differs across target products. The results are shown in Figure 4b from which we conclude that the percentage of incorrect answers varies across target products, but not as much as it varies across users. The percentages of correct, "not sure", and incorrect answers for different questions asked by the system are shown in Figure 4d. Here we observe some dramatic differences across questions, with a smaller subset of questions receiving almost always incorrect answers. This might be because some questions are more ambiguous than others. This finding suggests improvements of question-based systems in multiple directions. For instance, one can try to improve the question pool by considering different question characteristics, or one could develop question selection strategies that also account for the chance of user providing the wrong answer. Further, we explore whether the percentage of incorrect answers is correlated to the question index, or whether it remains stable throughout the conversation. The results are shown in Figure 4c, where the lines show the



(a) Box plot **(b) Histogram of time spent**

Figure 3: Time spent per question by a user in order to provide an answer. The average time for answering one question is 7.1 seconds.

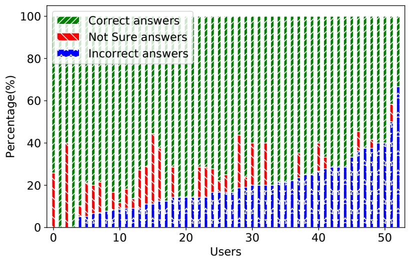
average percentages of correct, "not sure", and incorrect answers as a function of the question index within the conversation, while the histogram shows the average incorrect answer percentages of a sliding window. As it can be observed the percentages fluctuate, but in principle they remain at similar levels throughout the conversation. Last, we explore whether the percentage of incorrect answers is correlated to the time spent to give the answers. The results within different time intervals are shown in Figure 4e. We divide the time spent per question (1.75s - 50.96s) into 5 equal non-overlapping buckets (or frames). We see the percentage of incorrect answers decreases with more time spent. Also, we calculate the time spent when users are giving a correct answer, a "not sure" answer, and an incorrect answer, with the averages being 6.59s, 10.81s, and 7.12s respectively, and the median 4.65s, 8.20s, 5.06s respectively. This suggests users usually spent more time when they are not sure about the answers, but almost the same time when they are right or wrong about a question.

3.5 User Perceived Helpfulness

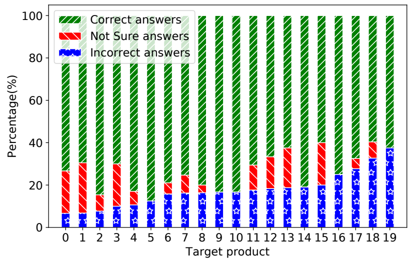
Regarding **RQ3**, we explore how useful do users perceive while interacting with such a question-based system. We ask the user (a) whether they think the question-based system is helpful, (b) whether they will use such a system in the future, and (c) what their rating is for the system, ranging from 1 (very negative) to 5 (very positive). The results using oracle answers are shown in Figure 5, in the three plots respectively. From the results we collected, most users think the question-based system is helpful and they will use it in the future. Specifically, 83.9% of users are positive about the helpfulness, 5.4% are neutral, and 10.7% are negative. Further, 60.7% of users are positive about using such a system in the future, 30.4% of users are neutral, and 8.9% of users are negative. Regarding user ratings, the results show 46.5% of 5-star ratings, 37.5% of 4-star ratings, 7.1% of 3-star ratings, 7.1% of 2-star ratings, and 1.8% of 1-star ratings. 84% of the users gave a rating at least as high as a 4.

4 CONCLUSION AND DISCUSSION

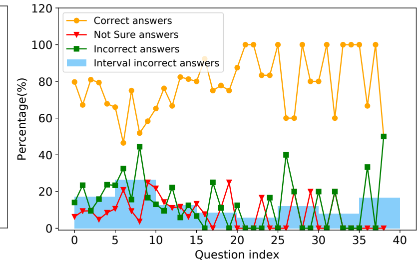
In this paper we conduct an empirical study using a question-based product search system to gain insight into user behavior and interaction with such systems. We deploy a state-of-the-art question-based system online and collect interactive log data and questionnaire data for analysis. We find that users are willing to answer a certain number of the system generated questions and stop answering questions when they find the target product, only if the questions are relevant and well-selected. While users are able to answer these questions effectively, they also provide incorrect answers at a rate



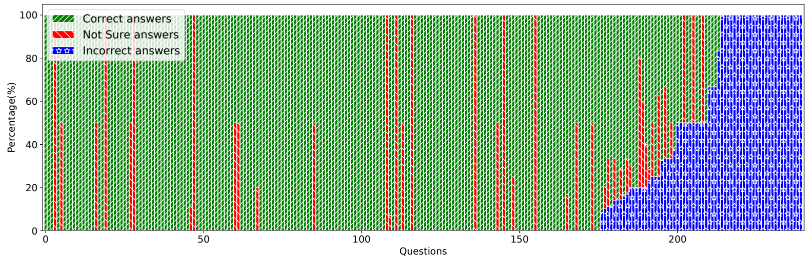
(a) Results under different users



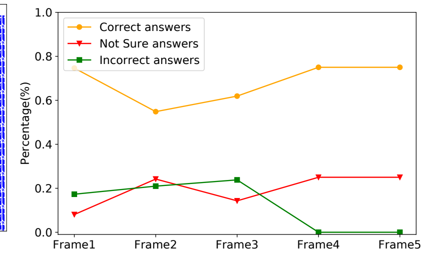
(b) Results under different target products



(c) Results under different question index

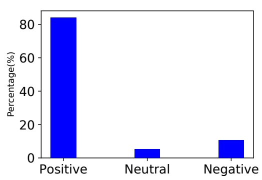


(d) Results under different questions

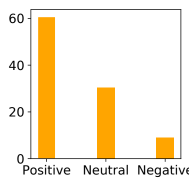


(e) Results under different time windows

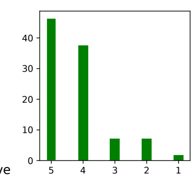
Figure 4: The percentage of correct answers, "not sure" answers, which cannot be classified, and incorrect answers. (a) The % varies per user; (b) The % varies across different target products; (c) The % remains stable through out the conversation; (d) The % varies per question, with only few questions receiving most of the incorrect answers; (e) the % of incorrect answers decreases with more time spent.



(a)



(b)



(c)

Figure 5: User perceived helpfulness. (a) Is the question-based system helpful; (b) will you use the question-based system in the future; (c) ratings. Most users are positive towards question-based systems.

of about 17%, which varies across users, products and question characteristics. Last, most users are positive towards question-based systems, and think that these systems help them towards achieving their goals. The take-home message, if there is one, is that current research should drop the assumption that users are happy to answer as many questions as the system generates and that all questions are answered correctly.

One limitation of this work is the isolated clarifying-based environment of the study. A more realistic experiment would require clarifying questions to be embedded in an existing environment, where the user is enabled to not only answer questions, but also reformulate her query or filter results by selecting pre-defined item attributes, and browse the results to the preferred depth. Also a mixed-initiative approach under which a system switches from asking questions, to understanding user searches, and combining the two is worth studying. A further limitation of this work is the fact that this was not an in-situ experiment but a simulation of a use case of a question-based system by involving crowd workers. Hence, the findings are as good as our simulation of a user looking for a target product. Other factors, such as question quality, question format, and noisy answers, may affect the results, and studying therefore these factors in an A/B testing experiment would be beneficial. We leave all these as future work.

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REFERENCES

[1] Qibin Chen, Junyang Lin, Yichang Zhang, Ming Ding, Yukuo Cen, Hongxia Yang, and Jie Tang. 2019. Towards knowledge-based recommender dialog system. *arXiv preprint arXiv:1908.05391* (2019).

[2] Raymond Li, Samira Ebrahimi Kahou, Hannes Schulz, Vincent Michalski, Laurent Charlin, and Chris Pal. 2018. Towards Deep Conversational Recommendations. In *Advances in Neural Information Processing Systems 31*. Curran Associates, Inc., 9725–9735.

[3] Peng Qi, Yuhao Zhang, and Christopher D Manning. 2020. Stay Hungry, Stay Focused: Generating Informative and Specific Questions in Information-Seeking Conversations. *arXiv preprint arXiv:2004.14530* (2020).

[4] Yueming Sun and Yi Zhang. 2018. Conversational Recommender System. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval (SIGIR '18)*. ACM, New York, NY, USA, 235–244.

[5] Yongfeng Zhang, Xu Chen, Qingyao Ai, Liu Yang, and W. Bruce Croft. 2018. Towards Conversational Search and Recommendation: System Ask, User Respond. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management (CIKM '18)*. ACM, New York, NY, USA, 177–186.

[6] Jie Zou, Yifan Chen, and Evangelos Kanoulas. 2020. Towards Question-Based Recommender Systems. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '20)*. Association for Computing Machinery, New York, NY, USA, 881–890.

[7] Jie Zou and Evangelos Kanoulas. 2019. Learning to Ask: Question-Based Sequential Bayesian Product Search. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management (CIKM '19)*. Association for Computing Machinery, New York, NY, USA, 369–378.

[8] Jie Zou, Dan Li, and Evangelos Kanoulas. 2018. Technology Assisted Reviews: Finding the Last Few Relevant Documents by Asking Yes/No Questions to Reviewers. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval (SIGIR '18)*. ACM, New York, NY, USA, 949–952.