Relevance Models Based on the Knowledge Gap

Yasin Ghafourian\textsuperscript{1,2}\textsuperscript{[0000–0001–9683–9748]}

\textsuperscript{1} Research Studios Austria FG, Vienna 1090, Austria
\textsuperscript{2} Vienna University of Technology (TU Wien), Vienna 1040, Austria
\texttt{yasin.ghafourian@researchstudio.at}

Abstract. Search systems are increasingly used for gaining knowledge through accessing relevant resources from a vast volume of content. However, search systems provide only limited support to users in knowledge acquisition contexts. Specifically, they do not fully consider the knowledge gap which we define as the gap existing between what the user knows and what the user intends to learn. The effects of considering the knowledge gap for knowledge acquisition tasks remain largely unexplored in search systems. We propose to model and incorporate the knowledge gap into search algorithms. We plan to explore to what extent the incorporation of the knowledge gap leads to an improvement in the performance of search systems in knowledge acquisition tasks. Furthermore, we aim to investigate and design a metric for the evaluation of the search systems’ performance in the context of knowledge acquisition tasks.

Keywords: Information Retrieval · Knowledge Delta · Knowledge Acquisition.

1 Motivation and Problem Statement

Web search is nowadays considered more to be a source for accessing information resources and exploration, and educational resources are also not an exception to this. Web search has become the most popular medium for education in schools, universities and for professional training \cite{1, 2}. In addition, web search is being used more often for the aim of gaining new knowledge \cite{3}. There have been numerous studies done on the information-seeking behaviors of students and academic staff in different parts of the world (some examples are \cite{4, 5, 6, 7}) which also verify that the majority of individuals and students consider the internet to be the most useful information source for learning.

Marchionini \cite{2} categorises the search activities into two broad categories of look-up and exploratory search activities. Look up search is the activity in which users know in particular what information they want and have a concrete expectation of what the desired search results be, while in exploratory search users go through multiple iterations of searching the online resources. With regard to using search systems for learning purposes, look-up search is viewed as a type of search that users initiate based on their current knowledge of the subject of interest that leads them to the relevant neighborhood of information.
From this neighborhood, users will then start their exploration into the learning resources and might reformulate their query multiple times according to their findings with the aim of reaching more satisfying resources.

Users typically have different levels of background knowledge on the topic in question. We define a user’s background knowledge as the current level of the user’s familiarity with the topic. Due to different levels of background knowledge, users might perceive the relevance of the documents on a topic differently.

Search engines currently do not take this diversity in the background knowledge levels of the users into account and assume that users’ information needs are well represented in their queries. This is a clear limitation. The optimal sequence of documents leading to satisfying a user’s learning goal depends on the user’s specific background knowledge. What if search engines could exploit information about the user’s background knowledge to provide the suitable (sequence of) documents helping the user to satisfy their learning goal as fast as possible.

As search engines are being used by students and researchers, it is crucial for search engines to pursue more developments in this direction so as to be a better fit for learning tasks, especially knowledge acquisition tasks. We define knowledge acquisition tasks as tasks in which users aim to acquire knowledge with a learning goal as part of a sequence of interactions with an information retrieval (IR) system. Supposing that we have a search system specialized for knowledge acquisition tasks that takes the users’ knowledge level into account, it will provide the users with resources that best fit their learning needs according to their knowledge level. This, in turn, saves effort from users in terms of spending longer search times and consuming documents that are returned as relevant but cannot be utilised by the users according to their knowledge level.

To incorporate the users’ knowledge level into the search, one needs to enable the search system to have a model representing the users’ knowledge within the topic of interest (“what the user knows”). Furthermore, one needs to define and represent the knowledge to be acquired (“what the user wants to know”). The goal is then to overcome the gap between these two representations. We call this gap the knowledge gap. Having defined the knowledge gap, the objective is to develop a retrieval method that provides users with an order list (a path) of resources, that helps them to overcome the knowledge gap. A suitable order will be one where more complex resources requiring more background knowledge will be preceded by resources that are more easily approachable based on the user’s background knowledge. In this research, we will investigate the means to measure the knowledge gap and understand how one applies it within a search system designed for acquiring knowledge so that the users can effectively overcome the knowledge gap. In the rest of this paper, we will first discuss the research questions that we seek to answer throughout this research. Later and in the section that follows, we will provide a brief overview of the research surrounding the concepts of the knowledge gap and the knowledge delta. Finally, we will explain our planned methodology to approach the research questions.
2 Research questions

Our motivation is to investigate on how to improve the retrieval effectiveness of the search systems for knowledge acquisition by incorporating the knowledge gap into the ranking mechanisms. We propose our main research question as follows:

**High level research question:** How can the search system help users to effectively overcome their knowledge gap in a knowledge acquisition task?

This high-level research question is comprised of three fine-grained research questions to be investigated:

- RQ1: How can we model users’ background knowledge, target knowledge and the knowledge gap in knowledge acquisition tasks?
- RQ2: To what extent can the incorporation of the knowledge gap into a search system facilitate a more efficient journey for users in knowledge acquisition tasks?
- RQ3: How should search systems be evaluated in the context of knowledge acquisition tasks?

3 Background and related work

In this section we provide the result of our literature review done in an attempt to capture the viewpoint of the papers that discuss the concepts of knowledge gap and knowledge delta and how they approach and incorporate these concepts.

3.1 Knowledge Gap

What we defined earlier, i.e the gap between the users’ knowledge level and the level of knowledge in the field of interest for learning has been discussed in the literature under the title of knowledge gap. Knowledge gap is one of the causing factors of information need [9]. Another factor that causes information need is referred to as Anomaly in the state of knowledge by Belkin et al. [10] which is the phenomenon in the state of knowledge that causes the information need. In one of the early studies on information use, Dervin and Nilan [11] used the phrase **knowledge gap** to refer to a situation where a person’s cognitive state has recognized an incompleteness in its currently possessed information. This incompleteness happens as a result of interaction with information sources or through thinking processes, and thereby later that incompleteness will turn into an information need. Additionally, Thellefsen et al. [12] use knowledge gap and information need interchangeably in a discussion where some of the definitions of knowledge gap are covered to argue the intricacy of the concept of information need and the importance of incorporating users’ information need while developing a knowledge organization system. In a research done by Yu et al. [13] the knowledge gap also has a similar explanation, however, the research is more focused on knowledge predictive models for the knowledge state of users.
which are being calibrated through questionnaires. Considering the definition of knowledge gap, there are studies that use the same definition and provide search solutions that are adaptive to the knowledge gap \cite{14,15,16}. In addition, there are similar studies that seek to model the knowledge gap by modeling the knowledge of the user and compare it against an existing knowledge level for the topic of interest \cite{1,17,18,19,20,21}. Among these works, the work done by Zhao et al. \cite{21} explores the knowledge paths between users’ already acquired knowledge and the target knowledge that the user aims to obtain. Considering this knowledge path and in the context of recommender systems, the authors’ method recommends a number of papers to the users so that their learning goals are achieved in the best satisfying way. Similarly, as our goal will be to assist users in knowledge acquisition tasks, we will take into consideration the target knowledge that users aim to obtain. Having modeled the knowledge from users’ background knowledge and the target knowledge level, our goal is to estimate the knowledge gap between these levels. Thereafter, we will use the modeled knowledge gap to improve the retrieval effectiveness of the search systems for knowledge acquisition.

3.2 Knowledge Delta

Knowledge delta is another concept that is semantically closely related to knowledge gap. One definition of knowledge delta in the literature is the amount of knowledge change in a user’s knowledge level which can be measured through questionnaires. As a case in point, we can refer to the work of Grunewald et al. \cite{22}, where the expertise gain is calculated through asking users of a ”Massive Open Online Courses” system about their knowledge level in a field before and after taking an online course and denoting it as knowledge delta. Similar studies have also been done to measure the knowledge change of the users \cite{22,23,24,25,26}.

In all the aforementioned works, knowledge delta is used as a concept that demonstrates the change in users knowledge level. This concept is also associated with the name of knowledge gain in other works such as \cite{27}.

4 Research Methodology

The methodology begins with the investigation to find an answer to the first research question all the way to the third research question. The steps of the methodology are three-fold. Firstly, we will build a model for a user’s knowledge and use it to build a model for the user’s knowledge gap. Secondly, we will ask users to participate in knowledge acquisition tasks to gain knowledge on learning goals that will be defined for them. During this experiment, we will utilize the modeled knowledge gap for each user during the user’s search session in order to provide the user with better results for learning. during this step, we will investigate the extent of improvement that incorporating the knowledge gap will bring about in a learning session. Thirdly, we will design a function whose output is a measure that will score the user’s learning progress throughout the session.
RQ1: How can we model users’ background knowledge, target knowledge and the knowledge gap in knowledge acquisition tasks?

To answer this research question, we need to design learning tasks for the users and we need to estimate the users’ domain knowledge. Each learning task will set gaining knowledge on a sub-topic within a topic as a goal for the users. This goal will establish a desired level of knowledge as the target knowledge that a user wants to acquire. We will choose a fixed number of sub-topics and assign each user to a sub-topic for the learning task.

As it was mentioned under section 3, several studies have modeled a user’s knowledge in a variety of tasks and in different ways [1, 16, 21, 28, 29]. Extending the work done by Zhang et al [29], we aim to represent the user’s knowledge of a topic with a set of concepts within that topic.

We will assess the user’s knowledge before and after the learning session using knowledge tests. We will design the knowledge tests in such a way that the user’s knowledge of each concept can be attributed to a level of learning according to Bloom’s taxonomy of educational objectives [30, 31].

Having completed the knowledge test, each user’s knowledge will be represented with its set of constituent concepts. There are a variety of options to represent the user’s knowledge. One such way is a one-dimensional vector of concepts and the user’s understanding of the concepts as weights. The same model will also be used to represent the target knowledge. The knowledge gap will then be computed between these two models.

Having modeled the knowledge gap, the methodology continues the investigation by moving to the second research question.

RQ2: To what extent can the incorporation of the knowledge gap into a search system facilitate a more efficient journey for users in knowledge acquisition tasks?

After the pre-task knowledge assessment, users will have access to a search interface connected to a search engine (hereafter collectively referred to as the search system) to carry out their learning tasks. The interface will allow for the recording of the users’ interactions which will later be used as features to evaluate the quality of the learning sessions.

Each user will participate in at least two learning sessions during this experiment. In one learning session, the search system will not take the knowledge gap into account and original retrieved results by the system will be presented to the user. In the other learning session, the search system will take the knowledge gap into account and adapt the results before presenting them to the user. There are several ways to adapt the search results to the knowledge gap. One such way will be to re-rank the results of the user’s each query submission based on a personalized understandability score of those results. For each of the learning sessions, we will design a different learning task. So as to ensure that learning about one topic doesn’t affect the user’s knowledge about other topics. After the learning session, the users will be asked to take a knowledge test again (Post-task
knowledge tests). Comparing the result of the pre-task knowledge test with the post-task test for each user, we will have a score for the progress of the user’s knowledge. On the other hand, for each user, we will compare the knowledge gained in the learning sessions to observe the effect of incorporating the knowledge gap on the quality of the learning session. We will evaluate this quality based on the interaction features recorded during the session.

**RQ3: How should search systems be evaluated in the context of knowledge acquisition tasks?**

In this research question, we will investigate how to define evaluation performance metrics for search systems in knowledge acquisition tasks. Previously in [32], we have explained why current retrieval metrics are insufficient in this context as they treat each query during the session independently and don’t consider the users’ knowledge factor in the evaluations. Correspondingly, we proposed three directions forward as well as their advantages and shortcomings: 1) online evaluation approach, 2) prerequisite-labeled relevance judgements approach, and 3) session-based evaluation approach. It’s essential to mention at this point that what has been defined in this research proposal as knowledge gap was defined as knowledge delta in [32]. However, in order to maintain a greater consistency with the literature in this area considering the subtle distinction between the knowledge delta and the knowledge gap, we have adopted the term knowledge gap in this research proposal.

Our objective will be to extend this previous work and formalise the session-based evaluation approach. The goal is to design a session-based evaluation function that gauges the quality of learning sessions in knowledge acquisition tasks. Up until this point in the methodology, we will have collected data on knowledge that the users have gained and information about learning sessions. In addition we will have recorded the users’ interactions with the search system. As a result, a function that will serve as a new performance metric will be designed. This performance metric will use interaction features, such as time, number of queries used, etc., as cost indicators. It will combine these cost indicators such that the function’s value aligns well with the experiences from the qualitative data (Knowledge tests). As a result, for the evaluation of future learning sessions, it will suffice to only have access to cost indicators and to use the designed function to evaluate the learning session.

There two main research challenges for the implementation of the discussed methodology:

1. The challenge that exists for the implementation for research question two is maintaining a balance between guiding a user to resources that are better suited for them and are adapted to their level of knowledge by the system, and just responding to the queries the user submitted.
2. In defining the learning goal for the experiments, the level of understanding of the user in the topic is a variable and the desired change in the level of understanding for the sake of experiments should be fixed. (e.g. Does it suffice if users are just familiarized with a concept, or should they be able to use it or should they be able to implement it?)
Acknowledgements

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 860721.

References

[1] Lora Aroyo et al. “Interactive ontology-based user knowledge acquisition: A case study”. In: European Semantic Web Conference. Springer. 2006, pp. 560–574.
[2] Gary Marchionini. “Exploratory search: from finding to understanding”. In: Communications of the ACM 49.4 (2006), pp. 41–46.
[3] Ujwal Gadiraju et al. “Analyzing knowledge gain of users in informational search sessions on the web”. In: Proceedings of the 2018 Conference on Human Information Interaction & Retrieval. 2018, pp. 2–11.
[4] al-Haddabi Huda Sulaiman. “Information needs and information seeking behaviour at the College of Medicine, The Sultan Qaboos University, Oman/Huda Sulaiman al-Haddabi”. PhD thesis. University of Malaya, 2005.
[5] Ntando Nkomo. “A comparative analysis of the web information seeking behaviour of students and staff at the University of Zululand and the Durban University of Technology”. PhD thesis. 2009.
[6] MAGNUS O IGBINOVA and IGUEH IJ CLN IKENWE. “Information Seeking Behavior of Academic Librarians for Effective Performance: A study of UNIBEN, AAU and AUCHI Poltechnic, EDO State, Nigeria.” In: (2014).
[7] Kwesi Gyesi. “Information Seeking Behaviour of Graduate Students of the University of Professional Studies, Accra (UPSA)”. In: Library Philosophy and Practice (e-journal) 4155 (2020).
[8] Diane Kelly and Nicholas J Belkin. “A user modeling system for personalized interaction and tailored retrieval in interactive IR”. In: Proceedings of the American Society for Information Science and Technology 39.1 (2002), pp. 316–325.
[9] Erica Cosijn and Peter Ingwersen. “Dimensions of relevance”. In: Information Processing & Management 36.4 (2000), pp. 533–550.
[10] Nicholas J Belkin, Robert N Oddy, and Helen M Brooks. “ASK for information retrieval: Part I. Background and theory”. In: Journal of documentation (1982).
[11] Brenda Dervin and Michael Nilan. “Information needs and uses”. In: M. Williams (Ed.), Annual Review of Information Science and Technology 21 (1986), pp. 3–33.
[12] Martin Thellefsen, Torkild Thellefsen, and Brent Sørenson. “A pragmatic semiotic perspective on the concept of information need and its relevance for knowledge organization”. In: KO KNOWLEDGE ORGANIZATION 40.4 (2014), pp. 213–224.
Ran Yu et al. “Topic-independent modeling of user knowledge in informational search sessions”. In: Information Retrieval Journal 24.3 (2021), pp. 240–268.

Nenad Stojanovic. “On the role of a user’s knowledge gap in an information retrieval process”. In: Proceedings of the 3rd international conference on Knowledge capture. 2005, pp. 83–90.

Luca Soldaini. “The knowledge and language gap in medical information seeking”. In: ACM SIGIR Forum. Vol. 52. 2. ACM New York, NY, USA. 2019, pp. 178–179.

Yao Zhang and Chang Liu. “Users’ Knowledge Use and Change during Information Searching Process: A Perspective of Vocabulary Usage”. In: Proceedings of the ACM/IEEE Joint Conference on Digital Libraries in 2020. 2020, pp. 47–56.

Ye Xiong. “An Automated Feedback System to Support Student Learning of Conceptual Knowledge in Writing-To-Learn Activities”. PhD thesis. New Jersey Institute of Technology, 2020.

Khushboo Thaker et al. “Recommending Remedial Readings Using Student Knowledge State.” In: International Educational Data Mining Society (2020).

Stefanie N Lindstaedt et al. “Getting to know your user–unobtrusive user model maintenance within work-integrated learning environments”. In: European Conference on Technology Enhanced Learning. Springer. 2009, pp. 73–87.

Rohail Syed. “Models and Algorithms for Understanding and Supporting Learning Goals in Information Retrieval”. PhD thesis. 2020.

Weidong Zhao, Ran Wu, and Haitao Liu. “Paper recommendation based on the knowledge gap between a researcher’s background knowledge and research target”. In: Information processing & management 52.5 (2016), pp. 976–988.

Franka Grünewald et al. “Designing MOOCs for the support of multiple learning styles”. In: European conference on technology enhanced learning. Springer. 2013, pp. 371–382.

M Monica Daglio, Giuseppe Fattori, and Anna V Ciardullo. “Assessment of readability and learning of easy-to-read educational health materials designed and written with the help of citizens by means of two non-alternative methods”. In: Advances in health sciences education 11.2 (2006), pp. 123–132.

M Monica Daglio, Giuseppe Fattori, and Anna V Ciardullo. “Evaluation of easy-to-read information material on healthy life-styles written with the help of citizens’ collaboration through networking”. In: Promotion & education 13.3 (2006), pp. 191–196.

A Schaumberg. “Variation in closeness to reality of standardized resuscitation scenarios: Effects on the success of cognitive learning of medical students”. In: Der Anaesthesist 64.4 (2015), pp. 286–291.
[26] Henrique Carvalho de Resende et al. “Introducing Engineering Undergraduate Students to Network Management Techniques: a Hands-on approach using the Citylab Smart City”. In: 2020 IEEE Global Engineering Education Conference (EDUCON). IEEE. 2020, pp. 1316–1324.

[27] Pertti Vakkari et al. “Modeling the usefulness of search results as measured by information use”. In: Information Processing & Management 56.3 (2019), pp. 879–894.

[28] Ran Yu et al. “Predicting user knowledge gain in informational search sessions”. In: The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval. 2018, pp. 75–84.

[29] Xiangmin Zhang et al. “Predicting users’ domain knowledge in information retrieval using multiple regression analysis of search behaviors”. In: Journal of the Association for Information Science and Technology 66.5 (2015), pp. 980–1000.

[30] BS Bloom. “Taxonomy of Educational Objectives, Handbook I: The Cognitive Domain. New York: David McKay Co Inc. as cited in file”. In: D:/bloom.html (1956).

[31] Lorin W Anderson, Benjamin Samuel Bloom, et al. A taxonomy for learning, teaching, and assessing: A revision of Bloom’s taxonomy of educational objectives. Longman, 2001.

[32] Yasin Ghafourian, Petr Knoth, and Allan Hanbury. “Information retrieval evaluation in knowledge acquisition tasks”. In: Proceedings of the Third Workshop on Evaluation of Personalisation in Information Retrieval (WEPIR) (2021), pp. 88–95.