Current Challenges for Studying Search as Learning Processes

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ABSTRACT

Search of resources and information is among the most frequent activities on the Web. While established information retrieval approaches address the relevance of search results to an information need, the actual learning scope of a user is normally disregarded. Recent research in the *search as learning* (SAL) area has recognized the importance of learning scopes and focused on observing and detecting learning needs.

The article at hand takes a critical look at existing works in SAL and related research disciplines. It aims to give a concise, interdisplinary overview which allows for the deduction of possible directions and necessary actions for prospective research works. It becomes apparent that past research employs a strong emphasis on *textual* resources, neglecting the diversity of online multimedia contents for learning and the impact of multimodal features on the learning process. We argue that exploring multimodal learning resources should be one focus of future SAL projects.

CCS CONCEPTS

• **Information systems** → **Multimedia and multimodal retrieval**; *Web searching and information discovery*; • **Applied computing** → Interactive learning environments;

KEYWORDS

search as learning, learning analytics, multimodal data, multimedia retrieval, educational psychology

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1 INTRODUCTION

Information Retrieval research has, for a long time, centered around the concept of an "information need" – a desire to amend a certain identifed lack of information. While fact search is certainly one facet of Web search, recent research points to a multitude of other usage behaviours which are to-date insufficiently supported by technology.

The *Search as Learning* domain examines one of these alternative search facets, that is, search sessions that are related to a learning intent. It relies on the assumption that current search systems are regularly used to access and internalise new knowledge, related to a defined (conscious or unconscious) learning objective. This is reflected in the prevalence of *informational* search intents, which, contrary to transactional or navigational search intents, imply a dedicated learning intent [9]. Technologies developed under the SAL paradigm will have to roughly fulfil the following goals: (a) supporting the users in their learning tasks through an enhanced retrieval and ranking process; (b) enable the accurate detection and prediction of learning needs and scopes, e.g. whether a user intends to acquire declarative or procedural knowledge, as well as respective knowledge gains during search relying on available data (e.g. queries, resource features, behavioural and navigational data); (c) addressing and evaluating both general Web search scenarios as well as semi-informal learning settings that involve search for scholarly information, specifically literature and videos in digital library portals (e.g. the TIB's web portals[1]). In this paper, we give a brief overview of research results regarding SAL processes from the fields of information retrieval and educational psychology. Based on the current state of the art, we identify current challenges for SAL research (Section 3). In particular, we identify a lack of consideration of multimodal resources in SAL, even though their usefulness is supported by multimedia learning research. This article limits its scope to research on individual learning, for the sake of conciseness. Anyhow, the integration of the insights provided by research on collaborative and social learning into SAL systems is, indeed, another interesting research topic.

The remainder of the paper is organised as follows. Related work is briefly reviewed in Section 2. In Section 3, we describe the main challenges of future work in the SAL field from our perspective, while some conclusions are drawn in Section 4.

[1] https://av.tib.eu/

2 RELATED WORK

As stated by Ghosh et al. [17], information science research contains a number of studies which seek to connect search processes and knowledge building (e.g. [13, 19]). Anyhow, it is only recently that research efforts from information science, educational psychology, learning analytics and information retrieval are united with the objective of improving learning support in information retrieval systems. The following paragraphs give a short summary of the main contributions which constitute today's understanding of SAL processes. Subsequently, Section 3 deduces some of the main research gaps.

2.1 SAL in Educational Psychology

Learning can be defined as the act of gaining new or modifying or reinforcing existing knowledge [31]. So far, research has mostly focused on the use of the Internet to gain factual knowledge or to learn about complex, conflicting issues of fragile evidence, that is, conceptual knowledge. Procedural knowledge, i.e., how to perform a certain task, has been hardly examined in the SAL context.

Process model: Commonly, the information seeking process is described as a sequence of processing steps (e.g., [8, 16]): (1) Identifying and defining the information need and generating respective search terms; (2) locating information sources, e.g., web pages, by evaluating and selecting links from search engine result pages (SERPs); (3) evaluating the information presented in web pages; (4) processing and extracting content from web pages identified as useful; and (5) comparing, integrating, and synthesizing information from several resources to prepare the final task outcome (in the user's mind or externally). In particular, step 5 involves a learning component when referring to an internal integration of the retrieved information.

Measuring learning outcomes: The achieved learning is measured as the outcome of the above process. Evaluation methods include counting correctly restored concepts in problem-specific essay tasks or knowledge tests with multiple-choice or true-false items (cf. [38]). However, previous research mostly has focused on learning from textual resources and does not specifically address learning from multimedia data, such as graphical representations or videos. Research from the field of multimedia learning indicates, however, that visual material in addition to text might be beneficial to learning outcomes: [32] find that additional visualisations support, in particular, the learning of procedural knowledge. [5] state that using multimedia, animations and hypertext elements can lead to "deep comprehension of the material", but also lead to problems due to split attention. In their study, adapted animations contribute in particular to the learning of dynamic information. The study presented in [10] suggests that the integration of video material improves learning performance, even in learner types who preferred verbal material over visuals.

Learning success factors: Several studies have examined factors that influence learning success in the processing steps mentioned above. Identified factors include prior domain knowledge (e.g., [37]), personal beliefs with respect to knowledge and how it develops (e.g., [26]; [21, 30]), prior training on evaluating Internet information (e.g., [20, 34, 36]), and usage of alternative search interfaces (e.g., [28]). While research on learning with hypertext and hypermedia systems, i.e., closed learning environments, has shown that an optimal navigational path results in better learning outcomes (e.g., [27]), this remains an open question for Web search scenarios.

2.2 SAL in Information Retrieval

Supporting informal learning has been subject to a plethora of research, whereas learning as an implicit part of search and information retrieval has only recently been recognized [1]. Recent efforts include the automatic identification of users' learning needs and intents from query logs, e.g., declarative or procedural knowledge ([14]). Vakkari [31] provides a well-structured survey of features indicating learning needs as well as user's knowledge and knowledge gain throughout the search process. Other works seek to predict the users' prior domain knowledge as one of the factors correlated to positive learning outcomes: Zhang et al. [39] identify distinctive features in the users' search behavior as predictors of domain knowledge; Cole et al. [11] observe behavioral patterns as reliable indicators; Collins-Thompson et al. [12] find that the usage of intrinsically diverse search queries is positively correlated to increased knowledge gain. A recent study [15] investigates the correlation of search behaviour and users knowledge gain and knowledge state in search sessions across a range of topics, finding only weak correlations with session features but medium correlation with the respective search topics.

Initial efforts aim at integrating the insights of the SAL community into information retrieval systems. Building on the features proposed by Eickhoff et al. [14], Weingart and Eickhoff [35] investigate adapted query expansion and re-ranking techniques in order to improve retrieval results with respect to the users' learning needs. Similarly, Syed and Collins-Thompson [29] examine the effect of keyword density on knowledge gain in language learning tasks.

While several studies underline the positive impact of visual elements on learning processes, e.g., in Web navigation [33] or e-Learning [24], the aforementioned works disregard multimodal aspects and features. In the context of Web search, Karanam et al. [22] show that the assignment of highly relevant pictures to text and hyperlinks significantly reduces the users' efforts to accomplish their search goals. It thus seems likely that the quality and efficiency of SAL processes can be notably increased by considering resource modality aspects and, in particular, retrieving non-textual resources based on the users' learning needs. However, visual elements need to be chosen dynamically based on the learning objective. So far, there are only approaches outside the SAL context that aim at accomplishing this enrichment in an automated way, e.g., Agrawal et al. [3, 4] suggest two different methods based on image metadata and aggregated Web search results, respectively, to enrich textbooks for schools with images. Other proposals address the assignment of relevant videos [2, 23].

3 CHALLENGES

Search as learning is an inherently interdisciplinary research area – current research works unite findings from educational psychology, learning analytics and information retrieval to provide enhanced support for learning tasks during Web search. Given the recentness

of SAL research, it is unsurprising that the review of published works reveals a number of open research questions.

Theoretical frameworks for SAL: . Current SAL research employs a diverse set of theoretical frameworks from different research domains – publications refer, for instance, to Bloom's taxonomy of learning objectives and its derivatives [6, 7] and/or Marchionini's exploratory search paradigm [25]. Anyhow, an integrated view on Search as Learning as an independent concept is still missing. While the currently used frameworks cover important facets of SAL processes, the importance of learning on the Web justfies the development of a unified, theoretical model of Search as Learning itself.

Detection and prediction of learning: A crucial challenge is the detection and understanding of learning and knowledge acquisition in heterogeneous and unstructured online interactions. This includes, for instance, the detection of learning-related search missions, the prediction and classification of learning intents, as well as the prediction of user knowledge and knowledge gain [15] troughout a search mission. However, given that such information is not explicitly provided throughout the search session, SAL research and tools have to consider a wide variety of implicit features observable throughout search sessions, for instance, considering the user interactions, behavioural features, session-related information and multimodal characteristics of the resources used as part of the search process.

Data acquisition: Current works in *Search as Learning* reference the usage of navigational logs, click-through data and eye-tracking experiments as their data sources. Only few of the datasets are openly available for other researchers. The availability of standardised, structured datasets about SAL processes (from lab experiments and collected in the wild) will largely enhance the research landscape – by providing a common base for research and evaluation. Furthermore, data acquisition could use not only controlled laboratory experiments, but also semi-formal settings in crowdsourcing platforms (which would also lead to an important extension of the possible range of participants reached by a study). Structured data acquistion will moreover allow the identification of potential new criteria and features, the discovery of formerly unknown correlations and inter-relationships, and the development of formal, standardised methods for comparative evaluation.

Retrieval and ranking beyond textual resources: Whereas the aforementioned challenges address the understanding and classification of learning throughout search missions, detected learning needs and behaviour have to be supported through dedicated retrieval and ranking processes. For instance, ranking of resources should consider the actual knowledge state of a user and his/her learning intent. In particular, research shows that the inclusion of non-textual resources in educational materials can contribute to the learners' comprehension, internalisation and entertainment. However, SAL research so far has not reached a state where the direct reflection of learning-specific features is reflected through the actual retrieval method. In addition, multimodal resource features are so far under-investigated, despite their relevance for particular learning needs. To provide comprehensive support for different types of learners and learning tasks, interactively (and individually) composed learning materials should include text as well as images and video material of different types. This stream of research – covered on the information retrieval side, for instance, in the domain of multimedia retrieval – has not been tackled in an SAL context, yet.

4 CONCLUSIONS

Aforementioned challenges can only be fully tackled throu collaboration of experts from the related research domains: aquisition of reliable ground truth data involves experiments and quasi-experiments best organised by researchers with psychological background and deep insight in study design, using the full toolkit offered by psychological research. On the other hand, development of predictive models requires knowledge in data analysis and artificial intelligence while expertise in scalable data processing is required to obtain, organise, process and publish collected data to make sure it is reusable across disciplines.

Analysis must be an iterative process – experts from learning analytics can analyse the datasets, discover formerly unknown features of the observed learning processes, discover novel correlations and evaluation measures. Results should be directly fed back in the study design process and validated (or revoked) by further experiments.

Finally, multimodal retrieval should be introduced to SAL research as a novel facet, given that learning research strongly suggests that the inclusion of image and video resources may enhance students' learning outcome. For this purpose, media types and multimodal features have to be included as a feature in the retrieval process (depending on enhanced retrieval of multimodal features and adapted ranking procedures). Some of these challenges will be tackled by the research project "SALIENT: Search as Learning: Investigating, ENhancing and PredicTing Learning during Multimodal Web Search", funded by the Leibniz Assocation in Germany from 2018 to 2021. It is a collaborative research project involving partners from information retrieval (L3S), educational psychology (IWM), and multimedia retrieval (TIB).

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