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On interactive learning-to-rank for IR: Overview, recent advances, challenges, and directions

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ABSTRACT

With the amount and variety of information available on digital repositories, answering complex user needs and personalizing information access became a hard task. Putting the user in the retrieval loop has emerged as a reasonable alternative to enhance search effectiveness and consequently the user experience. Due to the great advances on machine learning techniques, optimizing search engines according to user preferences has attracted great attention from the research and industry communities. Interactively learning-to-rank has greatly evolved over the last decade but it still faces great theoretical and practical obstacles. This paper describes basic concepts and reviews state-of-the-art methods on the several research fields that complementarily support the creation of interactive information retrieval (IIR) systems. By revisiting ground concepts and gathering recent advances, this article also intends to foster new research activities on IIR by highlighting great challenges and promising directions. The aggregated knowledge provided here is intended to work as a comprehensive introduction to those interested in IIR development, while also providing important insights on the vast opportunities of novel research.

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1. Introduction

In the last decades we have witnessed the production and sharing of huge amounts of data, boosted by a constantly growing data production rate. Human beings and electronic devices have never generated so much data in such a short time [1]. These factors were promoted with important advances on information technologies related to data capturing, storing, and sharing. Moreover, with the popularization of the Internet and mobile devices, a great portion of previously consumer-only users became prolific data generation sources. Therefore, with so much data around, the information technology industry is challenged to deliver more effective and efficient indexing and searching engines.

When dealing with large repositories, finding data, which are relevant to a given user query, context or information need, becomes a hard task. For instance, considering unstructured or multimedia data, traditional search methods relied only on metadata as a source for relevance estimation, implying on important issues related to annotation costs and accuracy. Relying on textual annotations is subject to language problems related to synonym and polysemy. With the advances on data processing capabilities, content-based methods for large-scale scenarios became an important and complementary alternative. However, low-level features, widely used for multimedia data applications, such as image and video retrieval, sometimes are not able to properly represent data concepts and user preferences, causing the well-known *semantic-gap* problem [2].

Consequently, introducing user perception into retrieval methods became an important asset for effectiveness enhancement and result personalization. One common strategy relies on Relevance Feedback (RF) [3], in which the user interacts with the system by implicitly or explicitly providing relevance assessments for the retrieved items. This information is then explored by systems in order to refine and customize new retrieval results. Hence, by interactively exchanging information with the system, the user allows her preferences to be learned and optimized, improving the search experience.

Interactive learning has been explored in the information retrieval field for decades with the purpose of tackling several inherent issues. The possibility of including the user in the retrieval loop has allowed significant effectiveness enhancements

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over time. By taking advantage of all available data and explicitly or implicitly collected user preferences, learning-to-rank models [4] leveraged online adaptiveness and consequently improved user search experience.

The obstacles naturally present in information retrieval tasks range from the cost of large-scale data annotation to the subjectivity of user search intents. Moreover, researchers have faced many theoretical and practical difficulties for conducting experimental studies and performing data analysis. In spite of the great advances from the last decades [5,6], the information retrieval community, specially on multimedia retrieval, still suffers from the absence of well-established standards, e.g., when considering user–system interaction models, evaluation protocols, and benchmarks.

In the effort for jointly exploring several information related sciences (information retrieval, machine learning, human-computer interaction, computer vision, data mining, etc.) and boosted by the large-scale data production and sharing, interactive information retrieval (IIR) became a very active research field in the last decade. Moreover, for boosting the user–system knowledge transfer and personalization, recent work has gone beyond simple relevance feedback towards integrating more diverse information and techniques into the interactive search process (see Section 6).

This work reviews several interactive retrieval related aspects focusing mainly on recent advances, important challenges and promising research directions. We have selected and described several works from important conferences and journals. The main publication venues and periods consulted in this work were the following: (i) Conferences: CBMI (2011–2014), CIKM (2011–2014), CLEF (2011–2013), ECIR (2011–2014), ECML-PKDD (2011–2014), ICIP (2011–2014), ICME (2011–2014), ICMR (2011–2014), SIGIR (2011–2014), and WSDM (2011–2015); (ii) Journals: IEEE-MM (2011–2015), IEEE-TCOMP (2011–2015), IEEE-TIP (2011–2015), IJMIR (2012–2014), JASIST (2011–2015), JVCIR (2011–2015), MTAP (2011–2015), PR (2011–2015), and PRL (2011–2015). Important works from other venues were also considered. Our focus is on recent work that exploits mostly machine learning techniques and multiple modes of information (textual, visual, etc.).

As a broad and comprehensive representation of the IIR field and consequently of the structure of this survey, in Fig. 1, we present a conceptual map covering several foundation areas and aspects that are integrated for the construction of modern interactive retrieval systems. As an overview of the IIR literature covered in this work, Table 1 presents a categorization and representative works on the concepts from Fig. 1.

The remainder of this text is organized as follows. In Section 3, the bibliometric information considering the main recent publications discussed throughout this paper is summarized. Section 2 summarizes the findings of previous overview works on the interactive retrieval field. Section 4 overviews traditional concepts on IIR and recent works. Next, Sections 6 and 7 describe common learning-to-rank strategies for IIR and recent boosting alternatives, respectively. With regard to experimental evaluation and user aspects, Sections 7 and 8 present common and new experimental and modeling theoretical and practical tools. Section 9 illustrates several interactive multimedia retrieval applications. Finally, Sections 10 and 11 describe the main open challenges and promising research directions in IIR and Section 12 presents our final considerations.

2. Previous work

Thomee and Lew [5] presented an overview on interactive image retrieval (IIR) considering all papers in ACM, IEEE, and Springer digital libraries on the subject of interactive content-based image retrieval over the period of 2002–2011 (over 170 papers). The authors provided a detailed review by clustering interactive search topics according to the user's point of view and the system's point of view. On the user's perspective, the authors described trends and advances related to query specification, types

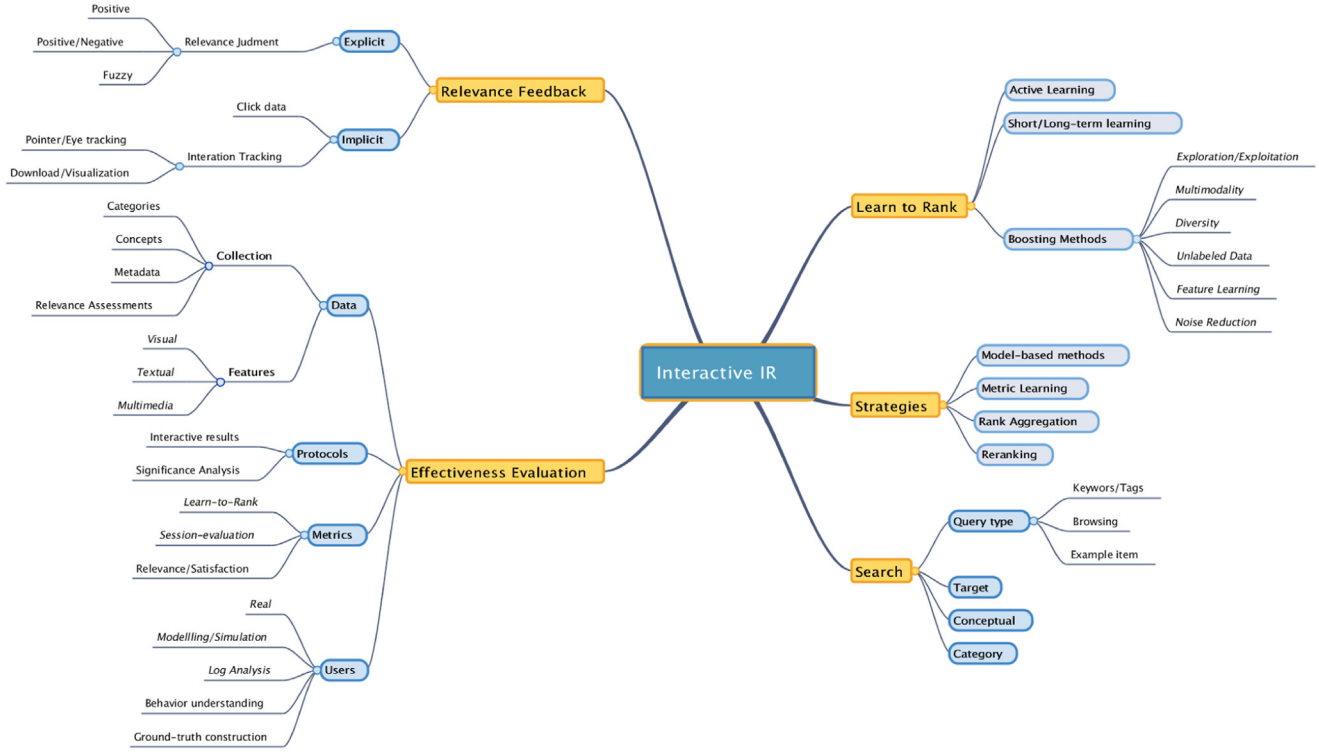

Fig. 1. Conceptual map of the interactive information retrieval field.

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