



## Review Of Literature Related To The Study On The Parameters Related To The Context-Aware Iterative Intent Estimation For Exploratory Search

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**Abstract:** The prior research efforts that relates to proposed work falls into: (i) Theoretical Frameworks of Exploratory Search (ii) Proximity-based Relevance Manifestation, (iii) Context-aware Information Search, (iv) Interactive Search Intent Modeling, (v) User Search-Interactions, and (vi) Search Intent Visualization. The definition of exploratory search is complex and multifaceted. Almost all searches are in some way exploratory. Although there may be circumstances where exploratory strategies are used continually to allow people to discover new associations, kinds of knowledge, and decision making, they are often motivated by a complex information problem, a poor understanding of terminology and information space structure (White et al., 2006a). As illustrated in this example, exploration is an important aspect of many search processes. However, it is not only the act of exploring that makes a search exploratory; it also must include complex cognitive activities associated with knowledge acquisition and the development of intellectual skills. Learning is an important mental function reliant on the acquisition of knowledge and supported by perceived information. It leads to the development of new capacities, skills, values, understanding, and preferences. Once a person has acquired information and internalized it, such that they understand its meaning, translation, interpolation, and interpretation, they may then apply that knowledge in new domains and pursue higher-order learning activities such as analysis, synthesis, and evaluation (Anderson and Krathwohl, 2001; Bloom, 1956).

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### Introduction:

Modern information retrieval interfaces typically involve multiple pages of search results, and users who are recall minded or engaging in exploratory search using ad hoc queries are likely to access more than one page. Document rankings for such queries can be improved by allowing additional context to the query to be provided by the user herself using explicit ratings or implicit actions such as clickthroughs. Existing methods using this information usually involved detrimental UI changes that can lower user satisfaction. Instead, we propose a new feedback scheme that makes use of existing UIs and does not alter user's browsing behaviour; to maximise retrieval performance over multiple result pages, we propose a novel retrieval optimisation framework and show that the optimal ranking policy should choose a diverse, exploratory ranking to display on the first page. Then, a personalised re-ranking of the next pages can be generated based on the user's feedback from the first page. We show that document correlations used in result diversification have a significant impact on

relevance feedback and its effectiveness over a search session. TREC evaluations demonstrate that our optimal rank strategy (including approximative Monte Carlo Sampling) can naturally optimise the trade-off between exploration and exploitation and maximise the overall user's satisfaction over time against a number of similar baselines.

A fundament search activity begins with the formulation of search intension and mines meaningful information from available information space. This helps the user in gaining intellectual skills and cognitive understanding. Traditional search systems usually support lookup searching in that user has a proper wisdom of their information goal. This type of search relies on traditional 'Query-Result' paradigm in that user pose a query for the relevant document retrieval, browse through results and analyze them to fulfill his information need. This approach performs well in the case of short navigational information requests and fulfills an information location need, but

fails in information discovery need [39]. For discovery oriented applications such as uncovering the information pattern from genomics, health care data, scientific data etc., additional assistance is required to formulate queries and navigation in data space to gain the desired information.

In such scenarios, the user usually uncertain about his information goals and/or less familiar with data semantics and context that makes the phrasing of information request challenging. Also, initial search aims and intentions evolve as new information is encountered. Hence, the burden of analyzing, reorganizing and keeping track of the information gathered falls on the user alone. Exploratory search is one such emerging research area that realizes the importance of user's efforts in multiple phases of discovering, analyzing, and learning. Exploratory search systems can deliver pleasing quality information due to their recall-oriented reformulation from short typed ill-phrased query to precise query. User's search tasks can be categorized into three behaviors: Lookup, Learn and Investigate that is shown in Figure 1. The user may perform multiple types of search task in parallel, therefore searches are denoted by overlapping clouds. Generally, there is interplay between search tasks, for example lookup task interplay with investigate or learn. If we analyze the search behaviors, we can relate traditional search tasks with the lookup tasks in that carefully formulated queries yield precise result with the minimal relevance comparison. For exploratory search tasks, the system seeks more involvement beyond just a query specification and result presentation. A group of tasks allied with exploratory search is of type learn and investigate. Learning behaviour are aiming to knowledge acquisition in that user tries to develop addition, knowledge about the domain and better understand the problem context. It is an iterative process that simulates analogical thinking and relate users' experiences to return a set of data objects. Reformulating queries and comparing results take much time in learning.

### Review of literature

As suggested earlier, exploratory search can describe either the problem context that motivates the search or the process by which the search is conducted (Marchionini, 2006a). These two elements are tightly coupled; the resolution of vague or complex information problems requires exploratory search behaviors. Exploratory search covers a broader class of search activities than traditional IR and IIR, which targets query-document matching under the assumption that relevant information exists and that a well-formed query statement will retrieve it from the collection. Information visualization focuses on the visual representation of large collections to help people

understand and analyze data. Information visualization is an important tool to support exploratory searches; however, it does not target information seeking or information use. People engaged in exploratory searches are generally: (1) unfamiliar with the domain of their goal (i.e., need to learn about the topic in order to understand how to achieve their goal); (2) unsure about the ways to achieve their goals (either the technology or the process); and/or even (3) unsure about their goals. Exploratory search is a specialization of information seeking, which describes the activity of attempting to obtain information through a combination of querying and collection browsing. Affective and cognitive uncertainties are persistent characteristics in information seeking and, in particular, exploratory search. Indeed, Wilson (1999) refers to uncertainty during information seeking as an ever-present, unpleasant factor. Uncertainty is a natural user experience within the process of information seeking and acquiring meaning. It can give rise to feelings of doubt, confusion, frustration, and anxiety (Kuhlthau, 2004). Kuhlthau's model of the information search process portrays information seeking as a process of construction, with uncertainty decreasing as understanding increases (1991, 2004).

Increased uncertainty indicates a zone of intervention for human intermediaries such as reference librarians and system designers. Growing uncertainty is also an important part of exploratory search. The creativity, innovation, and knowledge discovery that is often necessary as part of exploratory searches requires traveling beyond what is known by the user. In a similar way to research practice, exploratory search involves original thought, lateral thinking, and serendipity (Bawden, 1986; Foster and Ford, 2003). The complexity of research practice leads to a nonlinear, dynamic process involving a tacking back and forth between deduction and induction (Budd, 2004). It involves balancing divergent thinking with the convergence of ideas (Ford, 1999). The processes of exploring and working with information are critical for building connections, discovery, and creativity. These processes rely on the effective provision, processing, and manipulation of information at all stages of an exploratory search.

Searches are often motivated by an incompleteness (Ingwersen, 1992; Mackay, 1960; Taylor, 1968) or a "problematic situation" (Belkin, 1982a,b) in the mind of the searcher that develops into a desire for information. When a search begins, a searcher's state of knowledge is in an "anomalous state," and they have a gap between what they know and want to know. The gap is a situation-driven phenomenon, known as their information need. Exploratory searches may also be driven by curiosity or a desire for personal development; a user may only

wish to learn more about a particular subject area to increase their knowledge rather than solve an information problem. Exploratory searches often involve complex situations. Engelbart (1962) suggested that these situations include “the professional problems of diplomats, executives, social scientists, life scientists, physical scientists, attorneys, designers—whether the problem situation exists for 20 minutes or 20 years.” He advocated for human-machine symbiosis during the resolution of complex situations and emphasized that this should not involve “isolated clever tricks that help in particular situations,” but instead, “a way of life in an integrated domain where hunches, cut-and-try, intangibles, and the human ‘feel for a situation’ usefully coexist with powerful concepts, streamlined terminology and notation, sophisticated methods, and high-powered electronic aids.”

The problem context in exploratory search is ill-structured, and users require additional information from external sources to clarify their goals and actions (Simon, 1973). Exploratory searchers are engaged in weak problem solving (Newell and Simon, 1972) with a lack of prior domain knowledge and/or unclear or unsystematic steps through the information space.<sup>1</sup> In information seeking, complex situations or tasks are often framed as wider information tasks involving problem solving (Attfield et al., 2003; Byström and Järvelin, 1995; Kuhlthau, 1993; Vakkari, 1999; Wilson, 1999). Ingwersen and Järvelin (2005) defined models of the tasks at varying levels of abstraction. The work task, viewed as the catalyst behind search activity, provides a problem context within which the searcher operates. Within the context of a single work task, users generally perform a number of smaller search tasks, designed to reach their goal incrementally. As part of this process, users must divide the larger work tasks into smaller tasks and tackle each in sequence or, if possible, in parallel. However, for work tasks that are complex or poorly defined, it can be difficult for users to divide the task into manageable chunks, since the information required to accomplish that task cannot be determined in advance (Byström and Järvelin, 1995; Vakkari 1999). These are areas where exploratory search systems can help users develop an improved knowledge of the task environment and, hence, facilitate more effective search task selection.

During exploratory searches, it is likely that the problem context will become better understood by the searcher, allowing them to make more informed decisions about interaction or information use. The recognition and acceptance of an information problem typically resides at the beginning of the information-seeking process (e.g., Ellis, 1989; Marchionini, 1995; Wilson, 1997). The problem can be

internally motivated (e.g., curiosity) or externally motivated (e.g., an assignment). It may be characterized by a gap (Dervin, 1977), a visceral need (Taylor, 1968), an anomaly in a searcher’s knowledge state (Belkin, 1982a,b), as a defect in a mental model, or as an unstable collection of noumena (Marchionini, 1995). Once the problem has been accepted, it must then be understood and defined. To do so, it must be limited, labeled, and a framework for the answer constructed. Taylor (1968) referred to this as the “conscious need.” During this process, attributes of candidate solutions emerge that will ultimately guide user interaction behavior. This process leads to the development of Taylor’s “formalized need” and the possible articulation of an information seeking task. The user defines the problem internally as a task with properties that allow progress to be judged and a search strategy to be selected. The problem definition phases are an important part of exploratory search (perhaps even more so than in other problem contexts). The answer framework may still be poorly defined or highly variable in exploratory searches, but it is expected that a structure exists upon which an answer can be constructed.

The problem solution can be constructed from information within relevant documents and knowledge accumulated during the search, including the examination of partially relevant and irrelevant documents. The information need derived from the problem is prone to develop during the search and evolve from an initial, vague state into one known and understood by the searcher (Ingwersen, 1994). As the information need evolves, the searcher’s ability to articulate query statements and identify relevant information increases based on their improved level of problem comprehension (Belkin, 2000). Evidence from a number of studies on information-seeking behavior (Harter, 1992; Spink et al., 1998; Tang and Solomon, 1998) has shown that information needs are transient and developing. In exploratory searches, the problem context may remain undefined or in significant flux for much of the search session. There may also be periods of heightened uncertainty and confusion as people discover new information and assimilate knowledge. Tools to support exploratory search should help users define the problem, make sense of encountered information throughout the current session and across multiple sessions, and handle uncertainty and confusion by providing progress updates, explanations for system actions, and summaries of major themes present in encountered information.

Marchionini’s model describes exploratory search at an intellectual level, derived from many of the educational objectives of Bloom’s taxonomy (1956). However, the model does not examine the interaction

behaviors that are likely associated with exploratory search activities. For example, exploratory searchers may exhibit a behavior akin to “way finding” (a concept borrowed from urban planning; Lynch, 1960), where they naïvely traverse the information landscape with no prior knowledge of the whereabouts of the information target, if a target exists. Way finding tasks generally require the navigator be able to conceptualize the space as a whole. This is analogous to what Thorndyke and Goldin (1983) refer to as survey knowledge. For example, a scientist visualizing data sets computed off-line may have no preconception of the shape or organization of the data. Therefore, wayfinding assistance requires support for both exhaustive and directed searches and must facilitate topological knowledge acquisition (i.e., help users learn about the location of information objects and paths through the information space). Exploratory searchers navigating an unfamiliar document collection may need similar assistance. Wayfinding is an area where trails followed by previous “trailblazing” users can help the current user (Bush, 1945; Wexelblat and Maes, 1999; White et al., 2007). Serendipitous browsing stimulates analogical thinking, and users can relate their experiences to other comparable situations. Exploratory searches may be more concerned with recall (maximizing the number of possibly relevant objects that are retrieved) than precision (minimizing the number of possibly irrelevant objects that are retrieved). Thus, they are not well supported by today’s Web search engines that are highly tuned toward precision in the first page of results. The principle of least effort (Zipf, 1949), applied in the information-seeking context, suggests that a searcher will tend to use the most convenient search method, in the least exacting mode available, and will stop searching when minimally acceptable results are found (Mann, 1987). Although this is often regarded as a guiding principle in information-seeking research, it is less applicable for exploratory searches. As stated earlier, exploratory searches are as much about the journey (and the learning that occurs) as the destination, if a destination exists. Systems that accelerate learning and promote topic coverage will help users assimilate knowledge more efficiently, but it is unlikely that users will simply terminate an exploratory search once relevant information fragments have been encountered. For example, if multiple sources of evidence are required, it is likely that users will need to validate these sources to determine their reliability before concluding. Distinctions among different types of search activities suggest that lookup searches lend themselves to formal turn-taking, where the searcher poses a query, and the system performs the retrieval and returns results. The human and system take turns in retrieving the best

result. However, exploratory search requires human participation in a continuous and exploratory process. This may involve the application of dynamic query filters to adjust the result presentation in real time (Ahlberg et al., 1992), dramatic evolution of information needs over the course of the search, and fundamental shifts in understanding. Information seeking as berrypicking (Bates, 1989) is an influential metaphor and conceptual framework when considering information need evolution. Users often start with some vague information need and iteratively seek and select fragments of information that cause the information need and behavior to evolve over time; there is no one path of behavior to a single best query and retrieval set. Bates observed that during berrypicking, library users employed a wide variety of information navigation strategies, such as footnote chasing, citation chaining, reviewing a journal series, browsing entire areas at different levels of generality, and browsing and summarizing works by author. These existing information-seeking strategies need to be supported by system features and user interface designs, bringing humans more actively into the search process.

The problem context is an important motivating factor, but is also highly dynamic in exploratory search scenarios. Over the course of an exploratory search, this dynamism may decrease as topic familiarity grows and user knowledge increases. This makes subtask identification more straightforward and the identification of pertinent information easier. Supporting the gathering and re-representation of information—as is common practice in sense-making (Dervin, 1977)—helps reduce the uncertainty inherent in the problem context. Search strategies that are exploratory in nature (e.g., berrypicking, information foraging) can be used for this task, but this need not always be the case. It is possible for a user to better define the problem context through systematic learning mechanisms such as hypothesis formulation and testing, as in exploratory data analysis (EDA; Tukey, 1977). In many respects, exploratory search is similar to EDA, especially during the early stages where the interaction between the perceived problem context and the information encountered occurs most rapidly. In EDA, the role of the researcher is to explore the data in as many ways as possible until a plausible “story” of the data emerges. In some respects, the researcher is a detective, collecting evidence and clues related to the central question of the case. This is also true of exploratory searchers, who are motivated to search by the problem context, although the relevance of encountered information to this context may not be immediately apparent. Relevance depends on the stage in the search and the searcher’s level of domain knowledge, among other factors.



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