A Review of Users' Search Contexts for Lifelogging System Design

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ABSTRACT

The development of mobile and wearable technology has made it possible for people to collect and retrieve large amounts of data about their daily activities. We reviewed selected literature from four related research areas that actively engage in the investigation and modelling of users' search contexts. We discuss their similarities and their potential use for lifelogging. This paper represents a first step toward the conceptualisation of search contexts from an interdisciplinary perspective.

Categories and Subject Descriptors

H.1.2 [**User/Machine Systems**]: Human factors; H.3.3 [**Information Search and Retrieval**]: Search process

General Terms

Search context, User modelling, Lifelogging, Activity tracking, Eye tracking

1. INTRODUCTION

The development of mobile technology and wearable activity monitors, has made it possible for people to collect and retrieve large amounts of data about their daily activities. Consumer products such as Nike$^+$ fuelband, Fitbit trackers, UP by Jawbone and Strava have been developed to track daily activities for achieving personal health management goals. As indicated in [14, 17], these applications are a "new class of lifelogging systems that have been designed to allow people to capture various kinds of personal information about their body's state (usually about performance and consumption) to improve their daily self-monitoring, make informed decisions and gain self knowledge (with specific goals of data gathering)." Most studies in this area have focused on automated data sourcing and data processing, particularly the recognition of everyday activities (see e.g., [13, 24]). More recent research has been concerned with the modelling of user long-term goals [23].

The design issues in lifelogging systems for personal health management not only require knowledge about interactive information systems design but also a good understanding of health information seeking and search behaviours. Various research communities have worked on these areas, such as IR (information retrieval) system design, IIR (interactive information retrieval, including information seeking and human-computer interaction) and eye tracking but there tends to be little or no interaction between these communities.

Drawing on research literature from these research communities and using the design of lifelogging systems as a specific example, the main purposes of this conceptual paper are (1) to characterise different approaches to capturing, analysing and modelling of user characteristics and user contexts; (2) to assess the fitness of such data for understanding the relationships between and within the information search contexts, with particular emphasis on the understanding of user contexts and search behaviours.

The following section reviews selected literature from four related research areas that actively engage in the investigation and modelling of users' search contexts. We discuss their similarities and their potential use for lifelogging in section 3, followed by our future research agenda.

2. SEARCH CONTEXTS IN DIFFERENT RESEARCH FIELDS

We now review four research areas of research, namely IR system design, IIR, lifelogging system design and eye tracking. We believe that data from these areas share common conceptual features that are useful for designing lifelogging systems.

2.1 IR Approach

The capturing of search contexts has been recognised as an important task for IR system design. Researchers have extensively used a technique known as relevance feedback to automatically modify the user's original query based on initial search results to improve search effectiveness [21]. These studies have focused on improving the retrieval performance of automatic search techniques. User queries and associated top search results generated by the system were representative of search contexts.

Some studies have focused on examining large amounts of search logs to represent user search contexts at the levels of search sessions and search tasks. For example, using cluster-

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ing techniques, researchers have attempted to model search tasks from a set of noncontinuous queries based on search logs [18]. To design a query suggestion tool in a digital library, search contexts have been represented as data-spaces from popular queries, semantic term relationships and statistical information in search logs [1]. However, since search logs are quite sparse descriptions of complex information needs in search activities, it is relatively difficult to interpret contextual information.

Researchers have also characterised search contexts from various sources of user interaction data to infer user search interests or personalise search results. For example, by considering queries, search results clicks and web page visits, pre-query search activities have been analysed to infer short-term user search interests [25]. Based on manually annotated search activities and the identification of the search topic domain and the reading level of resources, atypical web search sessions and the divergence from typical searches were analysed to personalise search results [7]. In these studies, a rich set of user interaction data from queries was used to infer user interests (e.g. user interactions with search results, click-through data and web page visits).

The computational models of search behaviours have been useful for revealing the specific relationship between search context and search success. These models do not adequately consider high-level search intentions, search goals or information seeking goals in interactive search environments.

2.2 IIR Approach

Controlled user experiments are conducted to understand user search behaviours by considering various user characteristics and/or manifestations of user information needs, such as search questions and search terms. For example, in evaluating the effectiveness of a technique of eliciting more robust terms from user information need descriptions [12], the results showed that additional information from users significantly improve retrieval performance. In a study of successive searches that considers the evolution of user information problems, it was found that behavioural characteristics of searches (e.g., the number of unique pages visited) can differentiate stages of successive search [15]. In contrast to the IR system design approach, the capturing and analysis of search contexts by the IIR approach have been achieved by direct observations of user search behaviours in controlled user experiment settings. This approach deals with many variables that are less controlled than in classic IR and allows users to behave less restricted. IIR results are harder to compare but findings are more rewarding since it offers a glimpse in a more realistic search environment that captures original search contexts directly and in a more natural form.

In considering search contexts and behaviours, one of the typical examples of the IIR approach is to conceptualise user's information search as interactions with other components of the IR system. This is triggered by the user's information problems and influenced by the current state of knowledge and the information-seeking goals [3]. Similarly, IIR researchers have specified levels of user goals and their representations in which the leading search goal is construed at the level of search task [26]. Search contexts and behaviours on the whole have been conceptualised as part of user information-seeking behaviours that are influenced by the state of knowledge, goals, intentions and tasks.

More recently, user studies have been conducted to collect rich user interaction data to better model user behaviours [8, 10]. For example, in a study of modelling searcher frustration, a controlled user experiment in which a set of prepared search tasks were presented to participants, with particular reference to user perceptions of search results and emotional sensor data [8]. Another rich set of user search data in writing tasks has also been collected for modelling search missions [10]. Although these studies have focused on the modelling of search contexts and search behaviours, it's recognised that fine-grained user interaction data in user experiments are able to provide deeper understanding of user interaction issues.

2.3 Lifelogging Approach

Research on the design of lifelogging system has focused on automatic recognition of everyday activities from lifelog data, such as images, accelerometer reading, location and temperature [24, 27]. For example, to characterise everyday activities various techniques, such as low-level feature extraction, semantic lexicons construction for concept-based retrieval and concept detection have been used to index lifelog images [24]. A recent study of lifelogging system design has attempted to build up a mobile platform for daily activity tagging and recognition from sensor stream data [27]. Similar to the IR system design approach, research in this area has not specifically investigated the higher level of search contexts and how the systems fit into everyday information seeking contexts.

Since self-tracking takes place in highly contextualised personal information environments that are directly related to the daily activities (e.g. sport and walking) or health (e.g., heart rate monitoring and calorie counts), the notion of lifelong user profiles [22] has attracted some attention. This contextualised information environment involves users or groups of users, with long-term information-seeking goals and tasks. For example, researchers have proposed that lifelong user modelling needs to adequately support self monitoring and reflection by using visual abstraction techniques and the concept of meta-cognition [23]. In the design of lifelogging systems for self-tracking, it is challenging to summarise logged data in ways that users can make sense for achieving daily tasks and long-term use.

As reviewed in previous sections, the capturing, analysis and modelling of search contexts have made good progress due to the development of mobile technology and wearable devices, with rich data from various sources. These data could be used to infer user characteristics, search contexts and the higher level conceptualisation of information-seeking strategies (e.g., [4, 8, 25]). The availability of eye tracking devices and data, as reviewed below, enables us to better understand user cognitive states and search contexts.

2.4 Eye Tracking Approach

Eye tracking has a long history [11, 19] and are now technologically matched with a range of desktop eye trackers [2]. Even though eye-tracking is still expensive and optional accessories, they will quickly become part of (mobile) devices and provide valuable implicit user information in high resolution.

Eye tracking has two broad application domains — interactive and predicative. When used interactively, it serves as an input device to enable users to navigate an application or content "hands-free", as a substitute for mouse and key-

Table 1: Comparison of the four fields based on five common features

Data Feature	IR	Interactive IR	Lifelogging	Eye Tracking
Granularity	● ❍ ❍	● ● ❍	● ● ●	● ● ●
Volume	● ● ●	● ❍ ❍	● ● ●	● ● ●
Realism	● ❍ ❍	● ● ●	● ● ●	● ● ❍
Standardization	● ● ●	● ❍ ❍	● ❍ ❍	● ● ❍
Scalability	● ● ●	● ❍ ❍	● ❍ ❍	● ● ❍

Note. The rating scale is low (● ❍ ❍), medium (● ● ❍) or high (● ● ●).

board input. When used predicatively, it records and infers user cognitive states (e.g. the user's level of attention) as a deeper form of user input analysis. Both domains are useful for lifelogging. The interactive mode helps creating more seamless and fine grained user logs and profiles that do not only include how a user navigated applications or the web, but also which parts of the screen and what parts of the content were the focus. The predictive mode enables lifelogging systems to detect and record details about implicit user states and activities on a cognitive level. Eye movements are cognitively controlled and there is a strong tendency of consistent eye movement behaviour during face processing, scene perception and visual search that are independent of cultural background of the person [20]. Eye tracking has demonstrated to detect users' attention [6], the type of information search task based on intrinsic parameters [5, 16] and reading and linguistic behaviours [20].

3. DISCUSSION

We described four areas of research that are all focused on capturing user contexts to model the user and produce quality predictions. Table 1 compares the four research areas based on five selected features. We think that these features show how these fields relate in terms of how user context data is obtained and processed. We used the categorised papers from the earlier sections of this review and qualitatively mapped them on a three-point scale (low (● ❍ ❍), medium (● ● ❍) or high (● ● ●)) for the data features of *granularity*, *volume*, *standardization*, *quality* and *scalability*. It indicates the unique profile of each area and suggests how they can be combined for a conceptual framework.

- *Granularity* refers to the level of detail in the recorded user context data. IR often centers around the submitted user query and their search results, occasionally extended with additional click-through data. IIR more generally centres on the user activity as it focuses on a wide range of activities to complete information tasks (e.g. keyboard, mouse and bookmarking). Life logging applications and eye tracking have both very high level data granularity that records very low-level physiological activities (e.g. heart rates in lifelogging or eye movements in eye tracking [11]).

- With *Volume* we refer to the general amount of data that has been collected in the field across users studies. IR enables almost immediate data collection based on many well-defined test collections and a highly structured experimental procedure. In IIR this feature is limited as experiments are complex and time consuming due to their reliance on human subjects and their individual treatment. The same counts for life logging even though this may be distributed to individual and collected later. Eye tracking research has produced large data sets, although not as accessible as for example in IR. Its accelerating popularity however integrates eye tracking now in all other disciplines and makes data collection easier and more common.

- *Realism* refers to how well user context is captured with respect to a large range of realistic variables that resemble the real conditions of human activity in context. In this respect, IR is low as it over-focuses on the query interaction and tends to restrict other contextual factors. IIR and lifelogging produce both very realistic data as they both capture a large range of additional variables directly from the user's activities when solving a task. Eye tracking also produces very realistic data, although it is noticeable that the data is very focused on a very narrow aspect of the user.

- *Standardisation* describes the level of structuring in the data that allows it to be compared. This is high for IR based on a long research tradition that is well organised in efforts such as TREC, INEX, and CLEF. IIR is working with more variables at a higher variance and for that reason struggles to find structure in the organisation of experiments. Lifelogging is a young discipline with similar problems due to the richness and variance of human-collected data. Eye tracking, although very closely recorded from users, benefits from its focus on a single aspect of physiological human activity.

- *Scalability* is high for IR and generally reduced for the other disciplines due to their reliance on human subjects in an individualised effort to collect data. The only advantage is that eye tracking experiments are very unobtrusive and data can be collected without their constant awareness. This makes it easier to collect data from users.

All four research areas are interconnected and the trend in all of them is to collect detailed user information that best characterises users' behaviour. Some of the research areas have modified their approach over time and refined an initial course-grained to a more fine-grained form of data collection, e.g. IR system design and IIR (e.g. [8, 9]). Others started already from a more fine-grained viewpoint, such as eye tracking and lifelogging based on technological conditions and its rapid advancement. Eye tracking, for example, naturally focuses on fine-grained and low-level cognitive behaviours such as eye fixations during reading [20]. Lifelogging likewise focuses on low level physiological data recording [24, 27] because of their focus on the human body as a natural data source. Regardless of these differences, we found that all four disciplines have increasingly converged and we postulate that they can benefit from sharing their underlying conceptual approach toward modelling search context and user behaviour.

4. FUTURE WORK

We want to integrate the features identified from the four disciplines as part of a unified framework and more clearly map it to the requirements of lifelogging system design.

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