Spatio-Temporal Based Personalization for Mobile Search

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ABSTRACT

The explosion of the information available on the Internet has made traditional information retrieval systems; characterized by ″one size fits all″ approaches, less effective. Indeed, users are overwhelmed by the information delivered by such systems in response to their queries, particularly when the latter are ambiguous. In order to tackle this problem, the state-of-the-art reveals that there is a growing interest towards contextual information retrieval (CIR) which relies on various sources of evidence issued from the user's search background and environment, in order to improve the retrieval accuracy. In this chapter, we focus on mobile context, we highlight challenges they present for IR, and give an overview of CIR approaches applied in this environment. Then, we present our approach to personalize search results for mobile users by exploiting both cognitive and spatio-temporal contexts. Our experimental evaluation undertaken in front of Yahoo search shows that our approach improves the quality of top search results list and enhances search results precision.

INTRODUCTION

Information retrieval (IR) deals with the representation, storage, and access to information according to the user's information need. The main goal of an information retrieval system (IRS) is to bring relevant documents to users in response to their queries. However, the explosion of the information available on the Internet and its heterogeneity has made traditional IRS less effective (Dervin & Nilan, 1986; Shamber, 1994). In (Budzik & Hammond, 2000) the authors show that the main reason is that traditional IRS do not take into account the user context in the retrieval process. Indeed, traditional retrieval models and system design are based solely on the query and the document collection which leads to providing the same set of results for different users when the same query is submitted. In order to tackle this problem, a key challenge in IR is: how to capture and how to integrate contextual information in the retrieval process in order to increase the search performance? In (Allan, 2002) contextual retrieval is defined as "combine search technologies and knowledge about query and user context into a single framework in order to provide the most appropriate answer for users information needs". Thus, contextual IR aims at optimizing the retrieval accuracy by involving two related steps: appropriately defining the context of user information needs, commonly called "search context", and then adapting the search by taking it into account in the information selection process.

One of the fundamental research questions in contextual IR is: which context dimensions should be considered in the retrieval process? Several studies proposed a specification of context within and across application domains (Göker & Myrhaug, 2002; Vieira, et al., 2007). Figure1, presents a context taxonomy presented in (Tamine, Boughanem & Daoud, 2009), it synthesizes five context specific dimensions listed below, that have been explored in contextual IR literature.

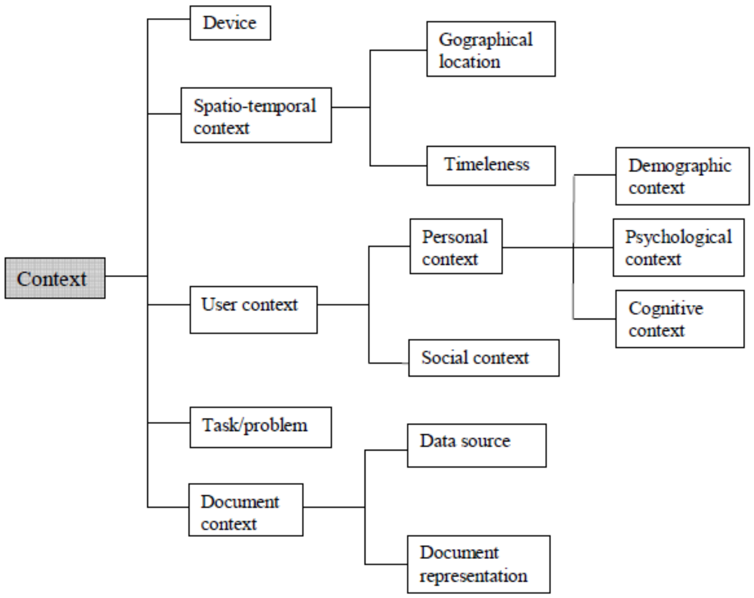


Figure 1: The multi-dimensional concept of context in IR.

1. **Device**: device refers to a physical tool that gives to the user direct access to the information such as computer, mobile phone, PDA etc. Regarding this dimension, adapting retrieval consists mainly in considering the device characteristics. For instance, working with small devices implies that high level of interaction is difficult, memory resources are limited (Göker & Myrhaug, 2002); therefore, the retrieval process should avoid using sophisticated outputs and managing huge resources.
2. **Spatio-temporal contex**: this dimension contains two sub-dimensions related respectively to geographical location and time. According to this dimension, contextual retrieval aims at delivering the information that better addresses the user's situation in spatio-temporal applications where the data and/or query objects change their locations and they are not valid over time like in tourist guide and network routing applications (Tao, Mamoulis & Papadias, 2003; Göker & Myrhaug, 2008).
3. **User context**: user context is the central dimension in contextual IR and the most widely one addressed in the research area. This dimension contains two sub-dimensions related respectively to the personal context of the user and his social environment.
   a) ***Personal context***: deals with the following sub-dimensions:
      - *Demographic context*: personal preference attributes such as language (Google personalized, Yahoo) and gender are used in order to customize the search (Frias-Martinez, et al., 2007; Hupfer & Detlor, 2006).
      - *Psychological context*: anxiety and frustration are examples of user's affective characteristics that influence information-seeking behavior and user's relevance assessments (Bilal, 2000; Kim, 2008).
      - *Cognitive context*: this sub-dimension is the most addressed one in the area. It refers to the user's levels of expertise (Timothy, M., Sherry, C., Robert, 2005) and user interests either short-term ones (Daoud, et al., 2009; Shen, Tan & Zhai, 2005) or long-term ones (Sieg, Mobasher & Burke, 2004; Tamine, Boughanem & Zemirli, 2008).

   b) ***Social context***: points on the user's community such as friends, neighbours and colleagues for instance. According to the social dimension, adapting retrieval aims at leveraging the search according to implied preferences of the user's community rather than just the individual (Lang, 1995; Smyth & Balfe, 2006).

4. **Task/problem:** this dimension refers to the basic goal or intention behind the search activity such as fact-finding vs. exploration task (Navarro-Prieto, Scaife & Rogers, 2006), transactional, informational or navigational task in web search (Jansen, Booth & Spink, 2007).
5. **Document context**: Two main sub-dimensions could characterize the document context. The first one concerns the document surrogates (relevant text fragments) such as form, colors, structural elements, citations, metadata (Tombros, Ruthven & Jose, 2005). The second dimension concerns the data source characteristics and their perception by the users (Xie, 2008).

Most recent research advances in contextual IR have focused on developing models and strategies according to the user's context and task/problem. These dimensions have been addressed by research studies in personalized IR which could be considered as a sub-field of contextual IR, supporting explicit/implicit representations of the user himself involved in the retrieval framework (Anand & Mobasher, 2007). However, the continuous evolution of wireless technologies and the spread of internet enabled mobile devices, has made access to huge and heterogeneous collection of documents on the web, possible anywhere and anytime. This new and extremely challenging search environment accentuate the need and the necessity of considering more contextual factors in order to offer mobile search systems the capability to adapt their search results to the inherently changing context of the mobile user.

In this chapter, we intend to exploit other sources of evidence beyond the cognitive context to better encompass the specific needs of the mobile user. For that purpose, we aim at enhancing the search context by some spatio-temporal annotations, notably the location of the user and the time during his search activity. Our contribution consists in abstracting from sensor data some semantic information to characterize situations in which a user submits a query to the IR system. The idea is to build for every identified situation, a profile grouping the user interests learnt on the basis of past search activities occurred in this situation. Personalizing search results is achieved via a case based reasoning approach in order to dynamically select the most appropriate profile for a given situation. In the absence of a standard evaluation framework for mobile search, we propose a novel evaluation scenario based on diary study entries.

The chapter is organized as follows. Section 2 outlines motivation and challenges of mobile IR and reviews a state-of-the-art related works. Section 3 presents our spatio-temporal based approach for personalization of mobile search. In Section 4, we present our experimental evaluation, discussion and obtained results. The last section presents our conclusion and points out possible directions for future work.

MOBILE INFORMATION RETIEVAL: BACKGROUND AND MOTIVATIONS

The proliferation of mobile technologies such as (PDAs and mobile phones, etc) has made access to huge and heterogeneous collections of documents on the web, possible anywhere and anytime. Search technologies are starting to play an important role in the mobile space.

However, constraints and technical features of mobile devices, such as difficulties of query input and limited display zone, yield to search practices which are different from that of the traditional desk queries. Indeed, studies on logs of mobile Internet user queries (Kamvar & Baluja, 2007a) show that user queries are shorter (thus more ambiguous), that there are fewer requests by session and fewer users who consult farther than the first page of the results list. This brings big challenges for researches in the information retrieval domain. This includes the need to provide information tailored to the resource constraints of mobile devices and for the specific requesting user on the one hand. And on the other hand, taking into account contextual factors influencing the user perception of what is relevant information. In the rest of this section, we firstly discuss context dependency of information needs in mobile environment, and secondly outline the main research works on contextual search applied to mobile environments.

Mobile Queries: Context Dependency

People often need information while mobile. They are likely to be interested in locating different types of content. Sometimes the information required is essential to the task at hand, such as "*finding a hotel for the night*". Other times, the need is associated with a question prompted by a conversation or a nearby object e.g., "a billboard". In particular, changing contexts such as location, time, activity and social interactions are likely to impact on the types of information needs that arise. Understanding mobile information needs and associated interaction challenges is thus fundamental to improve search results accuracy for mobile users.

There have been a number of recent studies that examine mobile information needs (Sohn et al., 2008; Church & Smyth, 2009; Bierig & Göker, 2006). These studies are important because they provide insights into what mobile users look for and how they search for information online. One important finding that emerged ahead from these studies is the importance of context. In particular, according to (Sohn et al., 2008), 72% of the information needs of mobile users are related to contextual factors such as users' interests, location, time and near persons. Furthermore, the results highlighted the importance of the personal context; in (Bierig & Göker, 2006) users' interests were identified to have a strongest effect on the users' perception of usefulness.

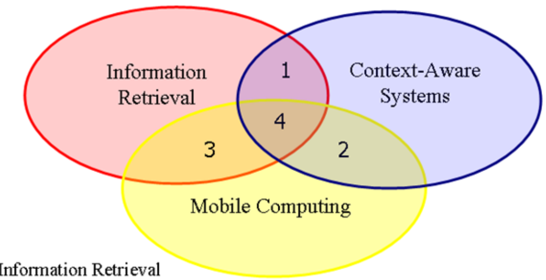
Based on this finding, we have attempted to distinguish different types of query context dependency, noting that some queries may be related to multiple aspects of context:

1. **Interests-based query**: is dependent on the user's current interests. For example, a computer science engineer may be interested on: programming languages, internet security, web technology, while he is at work, and issues queries like: "*java*", "*trojan horse*", etc. When at home, he may be interested on: art, culture, travel and issues queries like: "*da vinci code*", "*trojan war*", etc. In order to better answer such queries the IR system has to personalize the search results by taking into account the user's dynamic interests.
2. **Location-based query**: is dependent on its issuer's current geographic location such as geographic coordinates, address or place-names. For example for queries such as: "*nearby shops*", "*restaurants*", "*route guidance*", "*train connections check*", "*weather reports*", it is clear that the user's location may be taken into account to return accurate search results.
3. **Time-based query**: is dependent on its issuer's current time, for example answering the following search queries: "*find a bar*", "*find a hamburger*", "*movies in theatre*" and so forth, is different when it is morning, afternoon or midnight. The system may enhance the search results accuracy by taking into account the user current time.
4. **Situation-based query**: is dependent on the situation (the activity) the issuer is now. For example if the user issued the query "*first-aid instruction*", search results may be adapted whether the user is in vacation in a mountain or at the beach.
5. **Conversation-based query**: is dependent on any phone or in-person conversation the issuer is involved in. For example: "*apple software*", "*nicotine poisoning*", and so forth. When answering such queries, the system may take into account the user's social context to adapt the search results, which may be different whether the user is with his son or with his friend.

In all this cases, taking the user's context in the retrieval IR seems to be of most importance in order to meet better answer users' information needs. In the following, we give an insight into recent work in IR that attempt to respond to such mobile search information specificities by taking into account different context elements, and situate our work.

Contextual IR in Mobile Environment

Most traditional search engines do not consider the search context in the retrieval process and are not tuned to mobile environments. Recent works in IR community (Göker & Myrhaug, 2008 ; Jones & Brown, 2004) attempt to improve the search accuracy in this environment. This research works can be grouped under the field of "Contextual Mobile Information Retrieval" (CMIR) which can be viewed as an inter-disciplinary research field among IR, context-aware systems and mobile computing, as shown in Figure 2. CMIR aims to tackle the problem of information overload by providing appropriate results according to the resource constraints in one hand and users' location, time and interests on the other hand. Contextual retrieval is achieved by exploiting the mobile context during query reformulation and document re-ranking steps. Below we give an overview of some significant approaches in this domain which we can categorize into three main categories: device-based adaptation approaches, location-based adaptation approaches and user-based adaptation approaches.



1. Contextual Information Retrieval
2. Context-Aware Mobile Systems
3. Mobile Information Retrieval
4. Contexual Mobile Information Retrieval

Figure 2: Research components constituting our research domain.

- **device-based adaptation:** the related works have addressed issues concerning the limited functionality of mobile devices. Their main objectives are: 1) to facilitate query input through automatic query prediction and auto-completion techniques (Kamvar & Baluja, 2007b), and spoken query based search techniques (Schofield & Kubin, 2002), 2) to improve the search results visualization quality: typical approaches applied clustering algorithms (August, Hansen & Shriver, 2002), and summarization techniques (Sweeney & Crestani, 2006) on the search results.
- **location-based adaptation:** this category of works classified under the commonly known location-based IR works (Asadi, et al., 2007), has exploited the ability of mobile devices to be aware of their physical location, in the sense that they are capable of determining and transmitting there current geographical coordinates. While some works propose to filter information based on proximity to user physical locations (Mountain & MacFarlane, 2007; Bouvin et al., 2003), others reformulate the query by including the location context (Hattori, Tezuka & Tanaka, 2007).
- **user-based adaptation:** this category of works aims at personalizing the search results. Personalization aims to return information which matches the user preferences and interests, improving therefore the precision of the search results. Earlier personalization techniques (Samaras & Panayiotou, 2002; Anderson, Domingos & Weld, 2001) were based solely on the computational behavior of the user (visited URL, viewed documents) to model his interests regardless of his surrounding environment (location, time, near people). The main limitation of such approaches is that they do not take into account the dynamicity of the user interests regarding his changing environment. This gives arise to another category of personalization techniques that tackle this limitation by building some situation-aware user profiles. The main problems faced by these approaches are: 1) How to model the user situation and its related interests? 2) How to represent the relation between situation and interests? And 3) How to personalize the search results? In what follows, we review some key points answering these questions.
    - Regarding situation-aware user profile modeling, in (Yau, et al., 2003) the authors propose to model user situations by different physical attributes such as location, time,

light, etc, and/or actions (navigation, reading, etc), and user interests by keywords profiles represented by the most frequent words extracted from documents viewed in the identified situations. In (Panayiotou & Samaras, 2006) the authors propose a temporal-based profile, where the user situation is represented by temporal zones learnt by the study of the daily routine of the user and his activities. The user preferences and interests learnt from his past activities are weighted according to the identified temporal zones. In (Bila, et al., 2008) the authors propose a location-based profile, where the user situations are represented by the frequently visited locations by the user. The user interests are learnt based on a user questionnaire approach with specific queries to the user (e.g., to ask what kinds of activities the user does in a given frequented region). In (Bellotti, et al., 2008) the authors propose to build an activity-based user profile where the user situations are represented by leisure activities (eating, seeing, doing, reading, and shopping) learnt from user time, location and behavior patterns. User preferences and interests are learnt from the past search activities occurred within these activities.

- The second problem deals with the representation schema proposed to model the relation between the user situations and interests. While (Yau, et al., 2003) propose a relation-entity representation, (Panayiotou & Samaras, 2006) exploit metadata mechanism, (Bila, et al., 2008) use a tree-based representation and \cite{Bellotti08} exploit activity patterns.

- The third problem concerns the strategy adopted for search personalization. It is performed by means of query refinement in (Yau, et al., 2003), query-document matching in (Panayiotou & Samaras, 2006), and a combination of query-document matching and filtering techniques in (Bila, et al., 2008; Bellotti, et al., 2008).

Our work presented in this chapter belongs to this last category. We propose a context-aware personalization approach that can be used to adapt search results according to users' information needs expressed by their query in a specific situation. Unlike previously related works, our approach for personalizing mobile search has several new features:

1. Regarding the representation of the context-aware profile: first, we propose to build a four level semantic representation of the user search situations as concepts from location and time ontologies, while in (Yau, et al., 2003) the user situation is represented by low level data. Second, our approach is implicit and automatic; no efforts are needed from the user, while in (Panayiotou & Samaras, 2006); Bila, et al., 2008) the user is solicited in the process of building his profile. Third, our approach does not take any restriction on user's situations or population, while in (Bellotti, et al., 2008) the proposed approach is devoted to some specific situations and specific populations.
2. We propose to use a CBR approach to model the relation between a situation and its related interests. The main advantage of this approach is the flexibility it offers to separately model the user interests, location and time from external ontologies, allowing thus to compute an ontology based similarity between situations.
3. Our strategy adopted for search personalization is based on a re-ranking approach that combines the initial score of a document and its personalized score.

PERSONALIZING MOBILE SEARCH USING A SPATIO-TEMPORAL USER ROFILE

Motivation and General Approach

In mobile IR, the computing environment is continuously changing due to the inherent mobility framework. More specifically, users' interests may change anytime due to change in their environment (location, time, near persons, etc). Just for example, assume that a person being at a "*museum*" submits the query "*Water lilies*", knowing that he is interested both in "*art*" and "*gardens*", we can improve search results by taking into account his interests for "*art*" and not for "*gardens*" given that he is at a "*museum*" and not in a "garden". Static approaches for building the user profile are therefore poorly useful, so we rather focus on more dynamic techniques, any time capable of adjusting the user interests to the current search situation. Our general approach for search personalization relies on building and selecting the most appropriate user profile in a particular search situation. In fact, while a user can have many profiles, one of these profiles is the one primarily corresponding to the current users' query and situation. In order to select the most adequate user profile to be used for personalization, we compare the similarity between a new search situation and the past ones. Comparing past user experiences is referred to in the literature as case-based reasoning (CBR) (Aamodt & Plaza, 1994). In CBR a problem is solved based on solutions of past similar problems. A case is described by a pair tuple <*premise, value*>. *Premise* is the description of the case which contains its characteristics, while the *value* is the result of the reasoning based on the premise. The *premise* part of a case referred in our situation similarity computing seating, is a specific search situation S of a mobile user, while the *value* part of a case is the user profile G to be used for the personalization of the search results. Each case from our case base represents then a specific element from U, denoted: $Case = (S, G)$. Figure 3, gives a general view of our approach. For each new submitted query, we build a new semantic situation, by modeling its associated time and location contexts. A situation based similarity measure is set up and allows selecting the most similar situation, from the past ones from the case base. When the computed similarity is above a threshold value, we re-rank the search results of the query using the user profile associated to the most similar situation. After the user clicks or views interesting documents, the user feedback is used to maintain the case base.

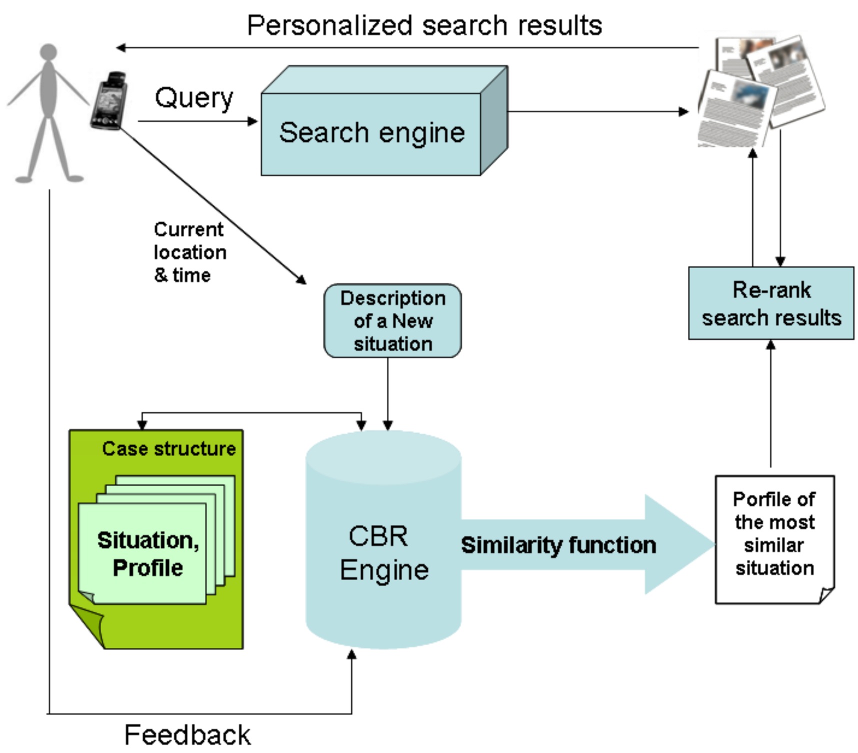


Figure 3: General approach.

With respect to this general view, we address in the remainder of this chapter the following research questions: How to model the user search situations? How to build and maintain a graph-based user profile in a specific search situation? How to select the adequate user profile and how to personalize the search results?

Situation Modeling

In our, approach we propose to model the user situation on the basis of two context elements: location and time. The motivation behind our choice is twofold : first, our intuition is that mobile user's information needs are related to his current activity. Knowing that each human activity is dependent or evolves within time and location space, we assume that these latter are sufficient for our purpose to describe the relation between user's interests and his environment. The second reason is typically technical; it considers the fact that these contextual elements can easily be acquired in an automatic way.
Our challenge when building this situation-aware profile is to use sensory data to identify a user situation. We propose to associate low level information directly acquired from sensors to semantic concepts extracted from temporal and spatial ontologies. Hence, instead of knowing that a user is at location "48.7818034, 2.2183314" and time "Tue Aug 3 12:10:00 CEST 2008" we derive that he is "at beach, summer, holiday, midday". Our situation model is then represented by an aggregation of four dimensions:

- **Location type**: refers to class name (such as beach, school…) extracted from a classification category of location types (like ADL feature type thesaurus[i]).
- **Season**: refers to one of the year's seasons.
- **Day of the week**: refers either to workday, weekend or holiday.
- **Time of the day**: refers to time zone of a day such as morning, night …

More specifically, a situation *S* can be represented as a vector whose features *X* are the values assigned to each dimension: $S = (X_l, X_u, X_v, X_w)$; where X_l (resp. X_u, X_v, X_w) is the value of the location type (resp. season, day of the week and time of the day) dimension. Below, we give an outline of the location and time models on which the situation model relies.

Location Modeling

Location represents the point in space, where the user of the application is located. As discussed in (Dobson, 2005), there are different plausible and correct ways to answer the question: *where is the user located?* and consequently different ways to characterize a location. As returned by location sensor systems (like GPS), location is an absolute position in some geographic coordinates systems. However, user behavior is unlikely to be conditioned by coordinates per se, but rather by what (else) is at these coordinates. Thus, we consider, in our work, a location class label (or named class) as relevant for our purpose of characterizing a situation of search. Such named classes are generally functional (like "yellow pages" naming), more importantly, a label directly represents the place's demographic (*school*), environmental (*beach*), historic (*monument*), personal (*residence*) or commercial (*shop*) significance and is the desired abstraction for our situation identification task. Simple automated place labeling is already commercialized (Google map, Yahoo local, Map-Point), it consists of merging web data such as postal addresses with maps enabling thus Nearest-X services. Also, manual place classification is practiced in most geographic information systems like the Alexandria Digital Library[ii] and GeoNames[iii] servers. To insure the connection between the location coordinates and its semantic classification, a conceptual model is necessary to represent and reason about location. As in the SPIRIT[iv] project, we use a spatial data base (as geo service) and a spatial thesaurus for representing and reasoning on geographic information. Figure 4, shows a simplified model for representing spatial information.

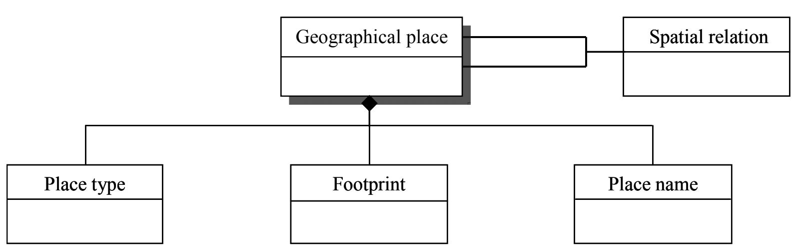


Figure 4: A simple schema of the location model.

Geographic places are related by different spatial relations such as: *contains, part-of, near,* etc. For example the geographical place "*Eiffel Tower*" is near the geographical place "*Champ de Mars*", and the two are part of the geographical place "*Paris*". Moreover, the mapping between the concrete class "Footprint", witch represents the geographic coordinates, and the abstract class "Geographic Place", allows us to relate pure geographic coordinates to semantic places represented by their name and type or class label. For example, if we get from the user GPS device, that he is at coordinate *"48.861073°, 2.335784°",* we can infer from this mapping that the user is at the geographical place "*Le Louvre*" witch is of type "*museum*". In our work, we rely on this mapping to automatically transform the physical locations of the user to more semantical representations, generally expressed as "reverse geo-coding operation". This particularly allows us to group together places of the same type, for example if the user is now in another geographical coordinate given by "40.779447°, -73.96311°", we can infer that the user is in a similar situation "*museum*", although he is not in the same physical place.

Time Modeling

The temporal information is complex; it is continuous and can be represented at different levels of granularity. Many works within geographical IR (Pustejovsky,et al.,2010; Le Parc-Lacayrelle, et al.,2007), has addressed issues on extracting, representing and exploiting temporal aspects of time for computing some temporal relevancy between documents and users' queries. In our work, we exploit time information to decline the users' interests within time context. So, to define the temporal aspects characterizing the situation a user is in while submitting a query, we suggest abstracting the continuum time into some specific and significant periods (abstract time classes), which we expect having an effect on the user behavior (e.g. *morning, weekend, winter*). To allow a good representation of the temporal information and its manipulation, we propose to use OWL-Time ontology (Pan, 2007) and to extend it with some special classes of time: *time of day, day of week and season*. The time ontology abstracts a time point to a set of significant time intervals of our daily life, the mapping between the two is implemented by axioms and predicates. For the *time of day* class we define five periods: *morning, midday, afternoon, evening, night*. For the *day of week* class we distinguish workdays (*Mon, Tue, Thu, Wed, Fry*), and rest-days composed of weekends (*Sat, Sun*) and holidays (*any day on which work is suspended by law or custom*).

User Profile Modeling

Below, we give an overview of the graph-based ontological representation of the user profile detailed in our previous work (Daoud, et al., 2009). This type of representation allows us to entirely benefit from all the semantic relations within the general ontology to better model the users' interests. This representation is based on users' search activity, namely: submitted queries and clicked URLs, viewed document from the retrieved search results list, to model users' interests. A user profile is then built at the end of each search activity, based on three main steps: (1) initializing the query context as a set of keywords extracted from the users' documents of interest in a search activity, (2) mapping the keyword user profile on the reference ontology to build an initial weighted concept set, and (3) inferring the graph-based query profile using a score propagation strategy applied on the initial weighted concept set. These steps are detailed below.

Query Context Initialization

We assume that the user profile could be inferred across similar search situations using the user's documents of interest. Our goal here is to create the query context that holds the user interest as the most relevant terms occurring in the relevant documents judged by the user. Let q^s be the query submitted by a specific user at time s. Let D^s be the set of relevant documents returned with respect to the query q^s, which is represented as a single term vector using the *tf.idf* weighting scheme. The keyword user profile K^s is a single term vector that represents the centroid of the documents in D^s, where the weight of a term t is computed as follows:

$$K^s(t) = \frac{1}{|D^s|} \sum_{d \in D^s} w_{td} \qquad (2)$$

Where w_{td} is the weight of term t in document d. In order to enhance the flat representation of the keyword user profile, a concept-based user profile is built by mapping it on reference ontology.

Mapping the Keyword User Profile on the Ontology

The keyword user profile K^s is mapped on the ODP[v] ontology in order to extract a set of concepts that reflect semantically the user interest. Each concept of the ODP is related to other concepts with different relations (eg. "is-a", "symbolic", "related") and is associated to a set of web pages classified under that concept. Each concept is presented by a single term vector $\vec{c}_j$ extracted from all individual web pages classified under that concept as well as all of its sub concepts. Strategy involved briefly consists of creating a super-document Sd_j for each concept c_j by concatenating the first 60 titles and descriptions associated to the web pages classified under that concept. Then stop words are removed and porter stemming algorithm is applied on the collection of super-documents. Finally, each concept c_j is represented as a single term vector $\vec{c}_j$ where each term's weight w_i is computed using *tf.idf* weighting scheme. Specifically, *tf* is the total term frequency in the superdocument Sd_j as well as in the superdocuments associated to its sub-concepts. Given a concept c_j of the ODP, represented by the term vector $\vec{c}_j$, its similarity weight $sw(c_j)$ with $\vec{K}^s$ is computed as follows:

$$sw(c_j) = \cos(\vec{c}_j, \vec{K}^s) \qquad (3)$$

The result of mapping the keyword query context on the ontology is an initial set containing the top-50 weighted concepts, called $\theta^s = \{(c_1, score(c1)), \ldots, (c_i, score(c_i))\}$. For experimental purpose, we used the top-50 concepts matched with the query context and assume that this number is sufficient to include concepts of interest to the user. Based on this set, we attempt to build a graph of semantically related concepts of ontology using a score propagation detailed in the next section.

Inferring the Graph-Based Query Profile Using Score Propagation

We infer the graph-based representation of the query profile using one-hop score propagation applied on the concept set θ^s. We distinguish the role of different edges in activating linked concepts in the score propagation. Indeed, we re-use the edge weight setting adopted in (Maguitman, et al., 2005) in our score propagation as follows: $w_{ij} = \alpha_S$ for $e_{ij} \in S \cup T$, $w_{ij} = \alpha_R$ for $e_{ij} \in R$, where e_{ij} is the edge linking concept i to concept j. We set $\alpha_S = 1$ because symbolic links seem to be treated as first-class link "is-a" in the ODP web interface, and we set $\alpha_R = 0.5$ because related links are treated differently on the ODP web interface, labeled as "see also" topics. We did not consider "is-a" links in score propagation because we assume that concepts linked by "is-a" relations are activated in the initial concept set, as specific concepts have common terms with their general concepts and they are both matched with the query terms. The process of inferring the graph-based query profile takes θ^s as the initial set of weighted concepts of the ODP ontology. Each concept $c_i \in \theta^s$ propagates its weight to all its linked concepts c_k (made of "is-a", "related" and "symbolic" edges) according to the ontology. When a concept is activated by multiple concepts, its score is recomputed by accumulating its weight with the propagated one. Interrelated concepts are grouped together in order to create a single or disconnected weighted graphs G_i. The weight $w(G_i)$ of the graph G_i is computed by summing the scores of its concept nodes. As the score is propagated at one hop from an initially weighted concept set θ^s, created graphs may have common concepts. So we proceed by combining these graphs together in a single one by merging the node and edge sets as well as their weights. Finally, the ontological query profile G^s_q is represented by the highly weighted graph among the created ones. The user profile is initialized by the query profile G^s_q if the query is the first one submitted in the search situation *S*.

Case-Based Reasoning Approach for Personalization

Our CBR approach is involved across four steps process: (1) identifying the current case, (2) retrieving the most similar case, (3) reusing the case, (4) revising the proposed solution and/or retaining the case.

1. **Identifying the Current Case:** For a current query q^* submitted to the search engine, a current case denoted: $Case^*=(S^*, ?)$ is built. In order to represent the current situation S^*, sensory data related to the query q^* are gathered from GPS sensor and system clock and then abstracted from the time and location ontologies. We obtain then a semantic representation of S^*:

$$S^* = (X^*_l, X^*_u, X^*_v, X^*_w)$$

*Case** is then sent to the case base to complete its value part.

2. **Retrieve the Most Similar Case:** To determine the expected user profile in the current case *Case**, the current situation S^* is compared to the past ones. Let $PS=\{S^1,\ldots, S^n\}$ be the set of past situations, we select the situation S^{opt} that satisfies:

$$S^{opt} = \arg\max_{S^i \in PS}\left(\sum_j \alpha_j \cdot sim_j(X^*_j, X^i_j)\right). \quad (4)$$

Where X^*_j (resp. X^i_j) is the value of the j^{th} feature of the situation vector S* (resp. S^i), sim_j is the similarity metric related to the j^{th} feature of a situation vector and α_j its associated weight.

These metrics are based on concepts proximity in the ontology used to represent the time or location dimensions of the situation model. For any new situation S^* *and any situation* $S^i \in PS$, the similarity between two features X^*_j (of S^*) and X^i_j (of S^i) depends on how closely they are related in the taxonomy. For example, the similarity between the location type *museum* and *theater* is greater than the similarity between *museum* and *hospital*. We use a similarity measure like in (Wu & Palmer, 1994) which is defined by:

$$sim_{location}(X^*_j, X^i_j) = \frac{2 * depth(lcs)}{depth(X^*_j) + depth(X^i_j)}. \quad (5)$$

where *lcs* is the Least Common Subsumer of X^*_j and X^i_j, and *depth* is the number of nodes on the path from a node to the root in the ontology.

3. **Reuse the Case: Re-Rank Search Results:** In order to insure a better precision of the search results, the personalization phase takes place only if the following condition is satisfied:

$sim(S^*, S^{opt}) \geq \beta$; where β is a threshold value.

The corresponding user's profile G^{opt} is used to re-rank the search results returned by the search engine with respect to the current query q^*. The search results are re-ranked by combining for each retrieved document d_k, the original score returned by the system $score_o(q^*,d_k)$ and a personalized score $score_p(d_k, G^{opt})$ leading to a final $score_f(d_k)$ as follows:

$$score_f(dk) = (1-\gamma) * score_o(q^*, d_k) + \gamma * score_p(d_k, G^{opt}). \quad (6)$$

Where γ ranges from 0 to 1. Both personalized and original scores could be bounded by varying the values of γ. The personalized score $score_p(d_k, G^{opt})$ is computed using the cosine similarity measure between the result d_k and the top ranked concepts of the user profile G^{opt} as follows:

$$score_p(d_k, G^{opt}) = \sum_{c_j \in G^{opt}} sw(c_j) * \cos(\vec{d}_k, \vec{c}_j). \quad (7)$$

Where $sw(c_j)$ is the similarity weight of the concept c_j in the user profile G^{opt}.

4. **Revise the Proposed Solution and/or Retain the Case**: The case base is updated based on the user feedback which is used to learn the user profile G^* for the search activity related to the current query q^*. Depending on the similarity value between the current situation S^* and the most similar one S^{opt}, two scenarios are plausible:
   - $sim(S^*,S^{opt}) \neq 1$: a new case is added to the case base which is composed of the current situation S^* with its learned profile G^*.
   - $sim(S^*,S^{opt}) = 1$: the case containing the situation S^{opt} is updated. Let G^{opt} and G^* be the user profiles for the search activities related to the same situation S^{opt}. The updating method is based on the following principles: (1) enhance the weight of possible common concepts that can appear in two profiles related to the same S^{opt}, (2) alter the weight of non-common concepts using a decay factor η . The new weight of a concept c_j in the user profile G^{opt} is computed as follows:

$$sw_{G^{opt}}(c_j) = \begin{cases} \eta * sw_{G^{opt}}(c_j) + (1-\eta) * sw_{G^*}(c_j) & \text{if } c_j \text{ in } G^{opt} \\ \eta * sw_{G^*}(c_j) & \text{otherwise} \end{cases} . \quad (8)$$

   where $sw_{G^{opt}}(c_j)$ is the weight of concept c_j in the profile G^{opt} and $sw_{G^*}(c_j)$ is the weight of concept c_j in the profile G^*.

EXPERIMENTAL EVALUATION

In the development of an IR system for mobile environments, evaluation plays an important role, as it allows to measure the effectiveness of the system and to better understand problems from both the system and the user interaction point of view. It is commonly accepted that the traditional evaluation methodologies used in TREC, CLEF and INEX campaigns are not always suitable for considering the contextual dimensions in the information access process. Indeed, laboratory-based or system oriented evaluation is challenged by the presence of contextual dimensions such as the user profile or the environment which significantly impact on the relevance judgments or usefulness ratings made by the end user (Tamine, Boughanem & Daoud, 2009). Contextual evaluation methodologies have been proposed (Göker & Myrhaug, 2008) to integrate the user context in the evaluation scenario. However, evaluation remains challenging because of the main following reasons (Kjeldskov & Graham, 2003): 1) environmental data should be available and several usage scenarios should be evaluated across them, 2) evaluation, if present, concerns a specific application (eg. tourist guide), generalization to a wide range of information access applications is difficult.

In the absence of a standard evaluation framework for mobile IR, we will give in this section, a brief overview of evaluation methodologies proposed in this domain and then detail our own evaluation framework supported by experimental results analysis.

Overview of Contextual Evaluation Methodologies in mobile IR

We can classify evaluation methodologies within mobile contextual IR, to two main types: evaluation by context simulations and evaluation by user studies.

The first kind of evaluation simulates users and interactions by means of well defined retrieval scenarios (hypothesis). Contextual simulation frameworks allow systems to be evaluated, according to a formative view, with less regard for constraints that arise from using sensor technologies, low-level system functionalities and several social and personal differences of users in interaction with the system. The contextual simulation framework proposed in (Bouidghaghen, Tamine & Boughanem, 2009) is based on hypothetic user search context and queries. User context is represented by a set of possible locations, users' interests are integrated in the evaluation strategy according to a simulation algorithm that generates them using hypothetic user interactions for each query. In (Mizzaro, Nazzi & Vassena, 2008), authors propose a contextual simulation framework based on a set of simulated context descriptors that include location, time and user activities. User's queries are automatically formulated from the context descriptors using different techniques. Context simulation based evaluation method is worthwhile since it is less time consuming and costly than experiments with real users. However, the method has still areas of uncertainty, for example the choice of assumptions underlying the major scenarios is open to criticism for its lack of realism.

The evaluation by user studies is carried out with real users, called participants, to test the system performance through real users' interactions with the system. To evaluate the performance of contextualized search, each participant is required to issue a certain number of test queries and determine whether each result is relevant in its context. There are two types of user studies adopted in the domain. The first one (Göker & Myrhaug, 2008; Panayiotou & Samaras, 2006) is based on the evaluation framework proposed in (Borlund & Ingwersen, 1998) which makes use of "simulated work task situations", where users are assigned a set of predefined tasks to perform in predefined situations. This kind of user studies is criticized because it still rely on artificial information needs and may be confounded by inter-subject and order effects. The second kind of contextual evaluation by user studies (Cheverst, et al., 2000; Mountain & MacFarlane, 2007; Bellotti, et al., 2008) is carried out in realistic use settings, where users are free to use the system as they would wish to use it and for only as long as they want, submitting their own queries arising from their natural information needs within real and natural situations, rather than asking them to perform some predefined series of tasks. The advantage of user studies based evaluation is that they are conducted with real users and thus the relevance can be explicitly specified by them. The main limitation they introduce is that: they may be of little use if the system is not fully developed, they induce extra costs and the experiments are not repeatable.

We propose in this chapter, an evaluation framework based on a diary study as a tool to integrate real user queries and contexts into the Cranfield paradigm. Our evaluation framework integrates the benefits of the state-of-the-art evaluation approaches, by allowing evaluation with real users and real contexts without requiring that the system be fully developed.

Diary Study Based Evaluation Framework

The main problem we faced to evaluate our approach, is the absence of a standard evaluation benchmark and dataset for evaluating context-aware approaches for mobile search. We propose an evaluation framework that is based on a diary study approach. In what follows, we describe our evaluation methodology and the different datasets we build.

Evaluation Methodology: a Diary Study

We conducted a diary study, where mobile users were asked to record the date, the time, their current location, and the query they have while they are mobile. Seven volunteers participated to our study (3 female and 4 male), ages ranged from 21 to 36. All the participants already have experience with using search engines on the web, using a PC or a mobile phone. The diary study lasted for 4 weeks and it generated 79 diary entries, with an average of 11.28 entries per person (min=3, max=35, standard deviation=10.8). Table 1 illustrates an example of such diary entries; each diary entry represents a userid, a user situation (time, date and place) and the user query.

User	Date	houre	place	query
2	27-févr	11h10	périphérique	"Parking relais Bordeaux"
6	16-févr	16h30	musée	"exposition beaubourg artistes"
7	02-mars	19h40	station bus	"Tisseo Horaire bus 2"

Table 1: An example of some diary entries.

Query set

From the diary study entries, we obtained a total of 79 queries expressed principally in the French language. Query length varies between 1 and 5, with an average of 2,99 and a standard deviation of 0.99. The user intent behind these queries is mostly informational "*velo hauteur selle*" or transactional "*paris hotel cardinal*" (query language is French). We represent each query by a three tuple <query, description, narrative>.

Situation set

From the diary study entries, we extract time and location information associated with each query. While the location information is already expressed in semantic concepts, the time entries are not. Thus we transform each date time on a semantic period of the day or the week. We totally obtained 36 groups of similar situations, with an average of 5 groups by user (min=2, max=12) and an average of 3 (min=1, max=8) queries within a same situation group. All the obtained situation groups are used to test the accuracy of the CBR technique to identify similar situations.

Ground Truth

A second problem we face to while building our evaluation framework is to construct a document collection together with relevance judgments according to the collected user queries and their context. To answer this problem, we build our document collection by collecting the top 100 results retrieved from the publicly available Yahoo boss search API[vi] for each query. In our evaluation setting, only the top 50 retrieved documents are used for re-ranking the search results using the user profile. The relevance assessments for the queries were given through an assessment tool available on line. To do, each user who submitted a query (in the diary study), was asked to judge whether a document from the set of top 50 results retrieved from Yahoo as response to his query was relevant or not according to his query and its context. Relevance judgments have been made using a three level relevance scale: relevant, partially relevant, or not relevant.

Experimental Results and Analysis

In this experimental evaluation, we have conducted two set of experiments to evaluate the accuracy of our proposed CBR technique to select an appropriate situation and to evaluate the personalized search effectiveness.

Evaluating the Accuracy of the CBR Technique to Select the Most Similar Situation

In order to evaluate the accuracy of the CBR technique to identify similar situations and particularly to set out the threshold similarity value, we propose to use a manual classification as a baseline and compare it with the results obtained by the CBR technique. So, we manually classify the initial user contexts into groups of similar situations, the weight α_j of the similarity metrics in equation 4, are fixed according to the user's feedback from the diary study. We compare the manual constructed groups to the results obtained by our similarity algorithm in formula 4, with different β threshold values in the interval [0 1]. Our measure of accuracy is based on the precision and recall measures defined as follows:

$$\mathrm{Pr}\,ecision = \frac{CAG}{AG}; \quad \mathrm{Re}\,call = \frac{CAG}{MG}$$

where AG is the total number of automatically constructed groups of similar situations by our algorithm, MG is the total number of the manually constructed groups of similar situations and CAG is the number of correctly automatically constructed groups of similar situations according to the manually ones. Figure 5 shows the effect of varying the threshold situation similarity parameter β in the interval [0 1] on the overall precision and recall. Results show that the best performance is obtained when the threshold value β = 0.6 achieving a high accuracy of 0.97 recall and 0.98 precision.

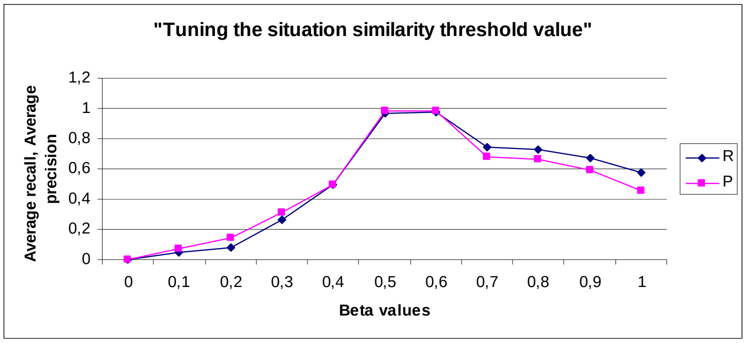


Figure 5: Effect of the parameter Beta on the situations similarity accuracy.

Evaluating the Personalized Search Effectiveness

We evaluated the personalized search effectiveness based on a k-fold cross validation protocol over a set of similar situations of a user using the optimal threshold value identified above ($\beta = 0.6$). The protocol is explained as follows:

- for each group of similar situations of a user, divide the query set into k equally sized subsets, and using $k\text{-}1$ training subsets for learning the user interests and the remaining subset as a test set,
- for each query in the training set, generate the associated profile based on its top n relevant documents listed in the relevance judgments file,
- update user profile concept weights across the queries in the training set, like described in formula 11, and use it for re-ranking the search results of the queries in the test set,
- evaluate the personalized retrieval effectiveness for each testing query using the user profile compared to the baseline search performed by Yahoo boss search using only the testing query,
- pool together the queries and judgments of all the 7 users, so that the evaluation result will be an average over the whole testing queries.

As Evaluation measures we used the *precision* (P) and the *Normalized Discounted Cumulative Gain (nDCG)* measures, computed at different cut-off points (x), they are defined as follows:

- ***Precision at rank x (Px)*:** measures the proportion of relevant document within the Top x ranked list of search results documents list, it is computed as follows: $Px = \frac{RelDoc_x}{x}$; where $RelDoc_x$ is the number of relevant documents that appear within the top x search results,

- ***Normalized Discounted Cumulative Gain (nDCG)***: is the normalized form of the d*iscounted cumulative gain (DCG)* (Jarvelin & Kekalainen, 2002). It is a rank-position oriented measure devoted for the estimation of overall relevance gained by a user when observing the top ranked documents. It is computed as follows:

$$nDCGx = \frac{DCGx}{IDCGx}$$

Where $DCGx$ is d*iscounted cumulative gain* at position x, computed by:

$$DCGx = rel_1 + \sum_{i=2}^{x} \frac{rel_i}{\log_2 i}$$

Where rel_i is the graded relevance of the document at position i in the search results list. And $IDCGx$ is the ideal rank at position x, obtained by sorting documents of a result list by relevance, producing an ideal DCG.

For these two measures we used the cut-off points of 5, 10, and 20. The rationale behind this decision is the fact that the majority of search result click activity (89.8%) happens on the first page of search results (Spink, et al., 2006), that is, users only consider the first 10 (20) documents. The *Px* and *nDCGx* values for all queries and all users are finally averaged to obtain a measure of the average performance.

In this experiment, we study in a first time, the effect of combining the original document's rank of Yahoo (corresponding to the original document score in formula 9) and the personalized document rank obtained according to our approach, on the retrieval effectiveness. Figure 5 (resp. Figure 6) shows the improvement of our personalized search in terms of P5, P10 and P20 (respect. in terms of nDCG5, nDCG10 and nDCG20) with varying the combination parameter γ in the interval [0 1]. Results show that the best performance is obtained when γ is 0.8. This is likely due to the fact that all the results on the top 50 match the query well and thus the distinguishing feature is how well they match the user profile.

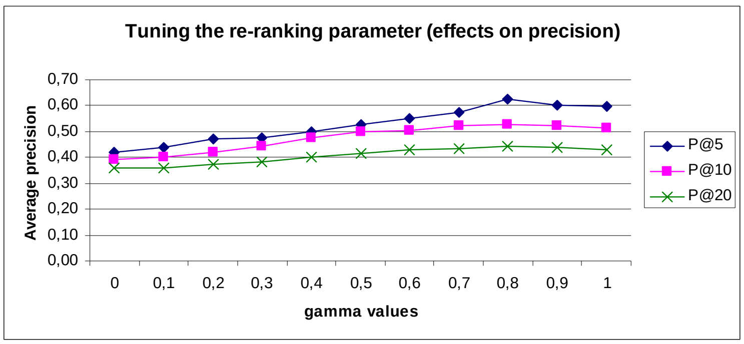


Figure 6: Effect of the parameter gamma on Precision in the combined rank.

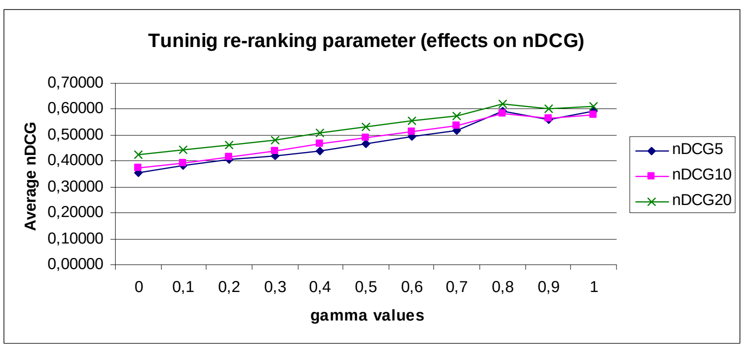


Figure 7: Effect of the parameter gamma on nDCG in the combined rank.

In a second time, we compare our personalized retrieval effectiveness to the baseline search. Table 2 shows the improvement of our personalized search in terms of P5, P10, P20, nDCG5, nDCG10 and nDCG20 over all the tested queries.

	Average precision			**Average nDCG**		
	P5	**P10**	**P20**	**nDCG5**	**nDCG10**	**nDCG20**
Yahoo boss	0.42	0.39	0.36	0.35	0.37	0.42
Our approach	0.60	0.52	0.43	0.59	0.58	0.61
Improvement	**43.03%***	**32.14%***	**19.58%***	**66.65%***	**55.84%***	**44.48%***

Table 2: Average Top-n precision and nDCG comparison between our personalized search and Yahoo boss over all queries.

As we can observe in Table 2, results prove that personalized search achieves higher retrieval precision of almost the queries. We also observe that in general, our approach enhances the initial nDCG5, nDCG10 and nDCG20 obtained by the standard search and improve thus the quality of the top search results lists. Best performance is achieved by the personalized search in terms of average precision at different cut-off points achieving an improvement of 43.03% at P5, 32.14% at P10, and 19.58% at P20, and in terms of accumulated gain achieving an improvement of 66.65% at nDCG5, 55.84% at nDCG10 and 44.48% at nDCG20 comparatively to Yahoo boss. In order to verify if this improvement is statistically significant, we have also conducted a t-test between the means obtained on P5, P10, P20, nDCG5, nDCG10 and nDCG20, by the baseline search performed by Yahoo boss and our personalizing approach. We assume that the difference between ranking is significant if $p < 0.05$ (noted * in table 1). As shown in table 1, our proposed approach has shown significant p-value according to the t-test at P5, P10, P20, nDCG5, nDCG10 and nDCG20.

CONCLUSION AND FUTURE WORK

This chapter gives an overview of a number of representative state-of-the-art contextual IR techniques in the mobile environment and describes our spatio-temporal based personalization approach for mobile search. Our approach for personalizing mobile search consists of three basic steps: (1) inferring semantic situations from low level location and time data, (2) learning and maintaining user interests based on his search history related to the identified situations, (3) selecting a profile to use for personalization given a new situation by exploiting a CBR technique. We have presented a novel evaluation framework based on a diary study approach devoted for a context-aware personalization approach for mobile search. We evaluated our approach according to the proposed evaluation framework and show that it is effective. In future work, we plan to extend this protocol by using real user data provided from a search engine log file. Extending the protocol aims at testing the effectiveness of the personalized search based on real mobile search contexts and click-through data available in the log file.

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KEY TERMS & DEFINITIONS

Mobile IR, Context, time, location, users' interests, personalization, performance evaluation.

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[i] http://www.alexandria.ucsb.edu/gazetteer/FeatureTypes/ver100301/
[ii] http://www.alexandria.ucsb.edu/
[iii] http://www.geonames.org/
[iv] Spatially-Aware Information Retrieval on the Internet: http://www.geo-spirit.org/index.html
[v] http://www.dmoz.org
[vi] http://developer.yahoo.com/search/boss/