2011 12th IEEE International Conference on Mobile Data Management

Personalizing Mobile Web Search for Location Sensitive Queries

Ourdia Bouidghaghen
IRIT, Paul Sabatier University
118, Route de Narbonne
Toulouse, France
Email: bouidgha@irit.fr

Lynda Tamine
IRIT, Paul Sabatier University
118, Route de Narbonne
Toulouse, France
Email: lechani@irit.fr

Mohand Boughanem
IRIT, Paul Sabatier University
118, Route de Narbonne
Toulouse, France
Email: bougha@irit.fr

***Abstract*—General Web search engines characterized by "one size fits all" provide the same results for the same keyword queries even though these latter are submitted by different users with different intentions. In mobile Web search, the expected results for some queries could vary depending upon the user's location. We believe that identifying user's geographic intent in Web search can help to personalize search results by ranking local search results higher in the search results lists. Therefore, the objective of this paper is twofold: first to identify whether a mobile user query is location sensitive and second to personalize Web search results for these queries. In order to achieve these objectives, we propose to build a location language model for queries as a location query profile. Based on this latter, we compute two features issued from the domains of probability theory and Information theory, namely the Kurtosis and Kullback-Leibler Divergence measures in order to automatically classify location sensitive queries. The classification scheme is then integrated into a personalization process according to two approaches: refinement and re-ranking. Experimental evaluation using a sample of queries from AOL log and top documents returned by Google search, shows that the proposed model achieves high accuracy in identifying local sensitive queries and shows significant improvement on search relevance when integrated to a search engine.**

I. Introduction

General Web search engines characterized by "one size fits all" provide the same results for the same keyword queries even though these latter are submitted by different users with different intentions. Understanding the user intent behind his query may help personalizing the search results and therefore increasing the search results relevance.

In this paper, we focus on Web search queries that have a location intent. While some queries have explicit location information in the query like "pizza hut Kansas City", many others do not, like "airport shuttle", but still expect search engines to return localized search results. According to recent research [1] only about 50% of Web search queries with local intent, have explicit location names. We expect that in the new field of mobile search, the percentage of queries with implicit local intent will be much higher, because queries are often ambiguous or underspecify the information they are looking for [2].

Given the importance of the geographic needs of mobile users ($> 31\%$ according to a recent study [3]) combined with their reduced ability to interact with a device while on the move, makes a strong need to automatically recognize user's intention (local or global) behind the query transparently and to return relevant results accordingly. Effective answering of such queries involves two important challenges: (1) accurately identifying the query sensitivity to location in order to determine whether to provide global or local search results, and (2) personalize the search results for local search queries with user's location.
A first attempt to overcome this problem is proposed by the majority of popular search engines, such as Google map[1], Yahoo Local[2]. It consists in offering users options to explicitly limit the search results to a specific location through advanced search options. Although, it partially solves the localization problem, this solution has two main drawbacks: 1) more input is required from the user, 2) and not all local sensitive queries can be answered by such local search engines, for example the queries "find jaz events", "jobs", "train tickets" cannot be accurately answered by the current local search engines, even if the user explicitly specifies a location name, since only a small part of the Web, mainly yellow pages data and business Web sites are indexed for local search.

We present in this paper a novel method for effective and automatic identification of location sensitive queries and propose to incorporate it in a personalization process in order to return local search results ordered higher in the search results lists. Figure 1 shows the general architecture of our approach, which consists in two major components: the classification component designed to classify queries according to their location sensitivity and the personalization component that customizes the search results given the user's location. The classification process is based on the following intuition: a query which returns results that contain few references to geographical locations is likely to be global, while a query that returns results spread uniformly over many locations without including a significant percentage of results with no locations is likely to be location sensitive. Formally, the classification scheme exploits two different features namely Kurtosis and Kullback-Leibler Divergence measures computed on a location language model of queries, to automatically classify location

[1] http://maps.google.com/
[2] http://local.yahoo.com/

978-0-7695-4436-6/11 $26.00 © 2011 IEEE
DOI 10.1109/MDM.2011.52

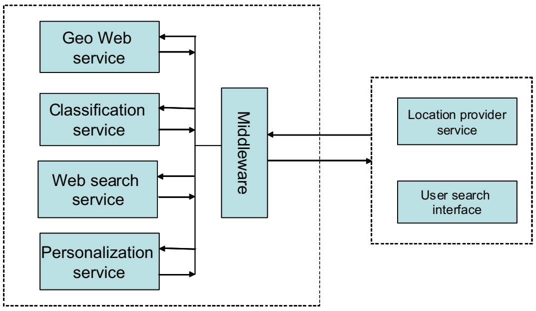

Fig. 1. General architecture of our approach.

sensitive queries. The classification scheme is then integrated into a personalization process according to two approaches: refinement and re-ranking, in order to customize the search results. The Experimental results using a sample of queries from AOL log and the top documents returned by Google search, show that the proposed method achieves high accuracy in identifying location sensitive queries and shows significant improvement on search relevance when integrated to a search engine.

The paper is organized as follows: section 2 reviews some related work, section 3 presents our general approach for automatically identifying local sensitive queries, section 4 describes two possible approaches to personalize the search results given the query sensitivity to location, section 5 presents our experimental evaluation and discusses the obtained results, the last section presents our conclusion and points out possible directions for future work.

II. Problem Statement and Related Work

A. Problem Statement

With respect to the context of mobile search, a "location sensitive query" is defined as a query with an underlying intention to prefer to see local results returned over generic search results (eg. "airport shuttle", "pizza london"), while anything else falls into "global query" category (eg. "free ringtones", "spider-man 3"). Location sensitive queries can further been characterized by considering two subcategories depending on the presence of a location name in the query. We distinguish thus "local explicit query" which contains at least a location name (eg. "pizza london") and "local implicit query" that do not include a location name (eg. "airport shuttle"). Deciding whether a query expressed by a mobile search engine user should produce mostly local or global results is an important and challenging problem. Given a user query, we can distinguish three main challenging questions:

1) how to distinguish global queries from local sensitive ones? Indeed, recognizing location sensitive queries is critical for determining whether to provide generic search results or local ones.
2) how to distinguish between local explicit queries and local implicit ones? This further specification is important since it allows to decide whether to extend the query with the user location in the case of a local implicit query or not in the case of a local explicit one.
3) In case of a local implicit query, how to personalize the search results given the user's location?

B. Related Work

Two lines of works are relevant to our research work here: recognizing user's intention behind the search and personalized Web search.

- **Recognizing user's intention behind the search**: There is a recent interest in identifying user's goals behind his query. Different classification schemes are proposed in the literature to categorize user's intention behind his search. Authors in [4], [5] attempt to categorize mobile queries into a taxonomy with a total of 23 top-level predefined categories covering most of the areas in the Internet information space. Other works [6], [7], [1] exploit classification techniques to categorize queries according to their geographic intent. In [6] authors rely on query term co-occurence in query logs and user click patterns to build three individual classifiers allowing to identify regional sensitive queries. They also describe a meta-classifier as a linear combination of the individual ones. Experiments show that the combined classifier achieved higher accuracy than the individual ones achieving 88% accuracy. In [7] authors defined a categorization scheme for queries based on their geographical locality, and showed how queries can be represented for purposes of determining locality by features based on location names found in the top results they produce. Using these features, several automatic classifiers for determining locality were tested and showed their effectiveness to determine query locality, with the Log-linear Regression classifier achieving best accuracy of 89.45%. In [1] authors combine a tagging technique and different features extracted from a query log to classify queries. Several well-known supervised classifiers were tested. A meta-classifier using a simple majority voting scheme achieves the best performance with 90% classification accuracy.
In the same spirit of work to automatically detect possible local information needs behind mobile search queries, we propose a novel approach to automatically identify query sensitivity to locations. Different from the previous works, our work aims at detecting user's implicit local intent from global one and classifying local sensitive queries on the basis of the presence or not of a location name in the query. We propose to estimate location language models as location profiles for mobile search queries, by exploiting the top N results returned by a general Web search engine. We propose then to exploit two measures namely the Kurtosis and Kullback-Leibler Divergence measures, as features of this location profile to identify the location sensitivity of a query.
- **Personalized Web search**: A strong motivation of personalized Web search is that queries are inherently ambiguous. Personalized Web search assumes that different

information needs can be distinguished when considering the user context in the retrieval process. Therefore, most personalization technologies attempt to model the user context and to exploit it as a factor in ranking. Depending on the contextual factor exploited to personalize mobile Web search, we can distinguish between three different approaches: user's preferences based personalization approaches [8], [9], [10], [11], location-based personalization approaches [12], [13] and social-based personalization approaches [14]. In personalized search systems, the personalization component can affect the search in three distinct phases: (1) as a part of the retrieval process such as topic-sensitive PageRank [15], (2) in a distinct re-ranking activity by combining initial document score and a personalized score expressing user's thematic interests [10] or a combination of interests and location preferences in [11] or by query refinement by adding terms to the query from the user context [16].
However, most of these approaches are generally used for all queries, and few studies have tried to answer how many queries can benefit from personalization [17], [18]. Our proposed query location sensitivity identification technique is relevant to this question. We could imagine that personalization may be helpful in searching ambiguous queries (in our case implicit local queries) but not necessary for clear queries (location explicit queries or global queried in our case). Our proposed automatic method of identifying location implicit queries provides thus an opportunity to use personalization more efficiently.

III. Identifying Location Sensitivity of Mobile Web Search Queries

In order to identify location sensitivity of mobile Web search queries we propose to build a query location language model as a query location profile. Based on this latter, we compute two features namely location Kullback-Leibler Divergence and kurtosis measures in order to classify queries on three types: global, local implicit and local explicit. Here after, we give a formal definition of the location query profile build using a language model and then present our classification features.

A. Building a Location Query Profile

A good way to analyze a query is to take an insight into the type of documents it retrieves. This can be accomplished by examining the top K documents of an initial retrieval and calculating the statistical properties of terms occurring in this set of documents [19], [20]. In a language modeling context, documents are usually ranked in the document collection according to their likelihood of having generated the query. Thus, given a query Q and a document D we compute:

$$P(Q|D) = \prod_{w \in Q} P(w|D)^{q_w} \tag{1}$$

where q_w is the number of times the word w occurs in query Q. Document language models, $P(w|D)$, are estimated using the words in document D [21]. Using this ranking, [19] build a query language model, $P(w|Q)$, out of the top K documents:

$$P(w|Q) = \sum_{D \in R} P(w|D) \frac{P(Q|D)}{\sum_{D' \in R} P(Q|D')} \tag{2}$$

where R is the set of top K documents. We note this query language model, computed over all the query terms, "the content-profile of the query Q".

We are interested in describing the local sensitivity nature of a query. Thus we wish to examine some "location profile" of a query Q, by analogy with the content-based profile described above. Our location query model is initially defined as:

$$\hat{P}(l|Q) = \sum_{D \in R} \hat{P}(l|D) \frac{P(Q|D)}{\sum_{D' \in R} P(Q|D')} \tag{3}$$

where l is a location name from a geographic data base and

$$\hat{P}(l|D) = \begin{cases} 1 & if\ l \in L_D \\ 0 & otherwise \end{cases} \tag{4}$$

where L_D is the set of location names contained in document D.

It is often helpful to smooth maximum likelihood models such as $\hat{P}(l|Q)$. We propose to smooth $\hat{P}(l|Q)$ with a background model. We use the distribution of the collection C over locations as a background model. This collection location model is defined by:

$$\hat{P}(l|C) = \frac{1}{|C|} \sum_{D \in C} \hat{P}(l|D) \tag{5}$$

Our estimate can then be linearly interpolated with this reference model such that:

$$P(l|Q) = \lambda \hat{P}(l|Q) + (1 - \lambda) \hat{P}(l|C) \tag{6}$$

where λ is a smoothing parameter, it is set to 0.9 throughout this study.

B. Classification Features Based on the Location Query Profile

As described above, the location query profile shows the distribution of the top K ranked documents in the result set along the location dimension. At this level we propose to analyze these location query profiles. The underlying assumption of the profile analysis is that global queries result in a profile that show little variance given that the location dimension is not important for these queries. In contrast, we expect location implicit queries to have query profiles with more than one distinctive peak and local explicit queries to have almost one distinctive peak. Figure 2 shows an example from different query types (the query profiles are computed using data described in section V-A) which clearly support our assumption here. Indeed, the global query "zigzone" presents somewhat a flat profile, the local implicit query "jobs" has a profile which presents several distinctive peaks spread over many locations, while the local explicit query "nj lottery" has a profile which presents almost one distinctive peak near the location "jefferson city". In order to conduct this analysis, we

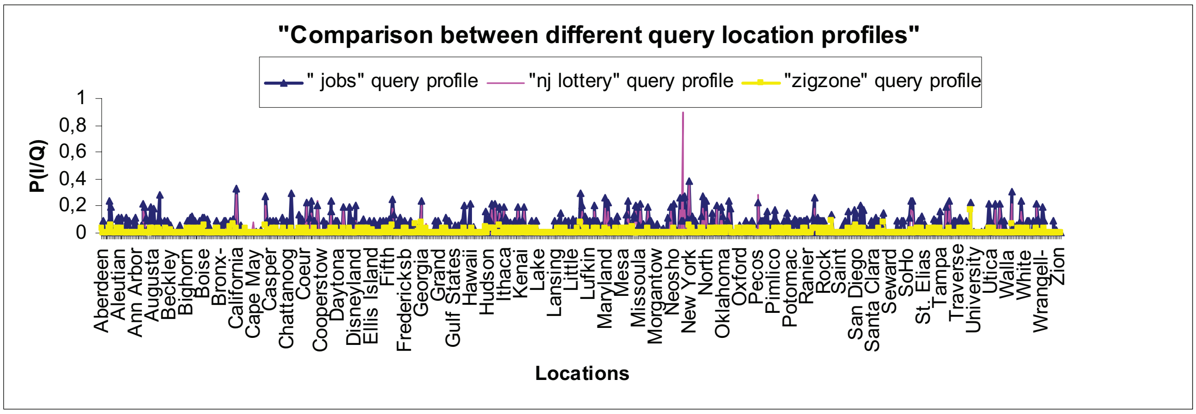

Fig. 2. Comparison between the location profile of a global query "zigzone", an implicit local query "jobs" and an explicit local query "nj lottery".

will compute two appropriate measures for discriminating between location profiles, namely Kullback-Leibler Divergence and Kurtosis. The core data needed to produce these two features could be efficiently computed at page-indexing time (off-line). Then, the final feature computation could be quickly performed at query time using this core data. These measures will then be used in a classification setting, presented in section V, to predict query sensitivity to location.

1) Location Kullback-Leibler Divergence Measure: We propose to measure the difference between the distribution over the locations of documents retrieved in response to a query, and the distribution over the locations of documents in the collection as a whole. This can be quantified by taking the KL divergence [22] between the collection location model and the query location model. That is:

$$D_{KL}(P(l|Q), P(l|C)) = \sum_{l \in L} P(l|Q) \log \frac{P(l|Q)}{P(l|C)} \quad (7)$$

We will refer to this feature as "location KL divergence", noted: locationKL. In our settings, a larger locationKL indicates a location sensitive query.

Note that although locationKL shows the deviation of documents retrieved for a query from the general distribution of documents over locations, it may not allow us to distinguish between queries depending on a single place, named location explicit queries, and location implicit ones.

2) Kurtosis Measure: Another way to capture the form of the locations distribution in the query profile, is to look at its kurtosis. The kurtosis is a measure of the "peakedness" of a distribution, it is a good indicator of whether the data are peaked or flat relative to a normal distribution. We reorder the locations in decreasing $P(l|Q)$, then the features are the statistical properties of the decay of $P(l|Q)$. Specifically, we look at the kurtosis of the rank order. Formally speaking, the kurtosis is defined, according to [23], as a normalized form of the fourth central moment μ_4 of a distribution, computed by:

$$Kurtosis = \frac{\mu_4}{\mu_2^2} \quad (8)$$

where μ_i is the i^{th} central moment, in particular, μ_2 is the variance. Higher kurtosis means more of the variance is the result of infrequent extreme deviations, which we expect to correspond in our case to local explicit queries, as opposed to frequent modestly sized deviations, which we expect to correspond in our case to local implicit queries.

IV. Personalizing Mobile Web Search Using User's Location

Our proposed automatic method for identifying location implicit queries is exploited as an evidence to personalize mobile Web search. Personalization consists in customizing the search results for queries classified as local implicit by considering the determined user's location. Location determination can be done using one of the GSM localization techniques either network-based or handset-based technologies or a combination of these latter. We proposed to test two different ways to integrate the user location namely by query-refinement and document re-ranking.

A. Personalizing by Refinement

To personalize mobile Web search results given the query implicit sensitivity to location, one intuitive way is to expand the original query q by the user's location l_q. Let $q = \{t_1, t_2, \ldots, t_n\}$ be the initial query term set, a new search query q' may then be formulated as $q' = \{t_1, t_2, ..., t_n, l_q\}$. For example, if the original query is "jobs" and the user's location has been determined to be "Jefferson City", the new search query will be "jobs Jefferson City" by adding the determined location to the original search query. The new search query is then submitted to the Web search engine to obtain the search results to return to the user. Because the location "Jefferson City" is now included in the new search query, the search engine is more likely to find jobs offers within "Jefferson City". However, this approach, may induce some errors due to limited precision of the implicit local intent classifier, indeed, the local intent might not be the only intent of the query or even may not exists.

B. Personalizing by Re-Ranking

Another personalization approach is to use the document re-ranking technique to adjust the user's location effects in search results ranking. This consists of retrieving the top K documents with the original query q and then leveraging the search results by increasing the ranks of the documents that match the user's location l_q. Consequently, the Web documents that match the user's location l_q are ranked higher than those that do not match it. The search results are re-ranked by combining for each retrieved document d_k, the original rank score returned by the Web search system $score_o(d_k, q)$ and a location score $score_l(d_k, l_q)$ leading to a personalized final $score_p\,(d_k)$ as follows:

$$score_p\,(d_k) = (1-\alpha) * score_o\,(d_k, q) + \alpha * score_l\,(d_k, l_q) \quad (9)$$

Where α ranges from 0 to 1. Both location and original rank scores could be bounded by varying the values of α. The location score $score_l(d_k, l_q)$ is given by a text matching feature that tells if user's location l_q and/or its variation exists in the document d_k. It is computed as follows:

$$score_l\,(d_k, l_q) = \frac{tf\,(l_q)}{\sum\limits_{l \in L_{d_k}} tf(l)} \quad (10)$$

Where L_{d_k} is the set of location names contained in document d_k, $tf(l)$ is the frequency of the location l and/or of its variants in the document d_k.

V. Experimental Evaluation

Our experimental methodology is designed to achieve two main objectives: 1) evaluate the effectiveness of our location language model approach for classifying search queries into local explicit, local implicit or global categories, and 2) to evaluate its efficiency when really integrated to a search engine in a personalization process. In the following, we describe our experimental data, our evaluation protocol and then present and discuss the obtained results.

A. Data

In order to undergo this experimental evaluation, we build our set of testing queries by randomly selecting an initial set of 1000 queries, from the query log of an America Online search query log [3] [24]. After a filtering step to eliminate porn, duplicate and navigational queries, we obtained a hand labeled set of 200 queries, where each query is assigned a label to indicate whether it is local implicit, local explicit or global. The criterion to asses whether a given query is location sensitive is based on whether the mobile user expects to see local search results ordered high on the results list of a search engine. In our sample test queries, 20,5% were local explicit, 25,5% were local implicit and 54% were global. To obtain the top 50 Web pages that match each query, we use a state-of-the-art Web search engine namely Google via the Google AJAX Search API[4]. This version of Google is a general search

[3]http://www.gregsadetsky.com/aol-data/
[4]http://code.google.com/apis/ajaxsearch/web.html

Fig. 3. A snapshot of the google API search results returned for the query "airport shuttle": it illustrates the presence and the diversity of location names (highlighted in red.

interface (by opposite to Google local API) that do not exploit any IP adress or query categories when returninig the search results. To illustrate this, figure 3 shows an example of top search results for the query "airport shuttle", which is a priori localtion sensitive. We can see that the results obtained by this search API are not biased by the Googles local search features.

In order to compute the location query profiles we need a geo database to recognize and extract the geographical keywords referred in the search results. Given that the AOL query log contains queries in English language, we have focused our location identification on states, counties, and cities in the United States using a list available from the U.S. Census Bureau[5]. The process of geo extraction is conducted by comparing the words in each document with location names in this geo database, and retaining any matching entries and their count per document. We note that at this level we have encountered a problem due to location name ambiguity, which is a well known problem in the field of geographical IR [25], [26]. Indeed, a same location name in a document is associated to different entries in our geo database, this is known as geo-geo ambiguities (eg. "Virginia" is a city in Illinois and in Minnesota). To overcome this problem, we decided to associate the same location occurrence in a document to a unique entry within the database. Another type of ambiguity is geo-non-geo ambiguity (eg. "Denzel Washington", "Orange"). To overcome this problem, we used a list of stop words and a state-of-the-art entity tagger [27] to distinguish person names

[5]http://www.census.gov/

from location names.

B. Evaluation Protocols

Our experimental design consists of evaluating the effectiveness of our proposed technique to identify location sensitive queries and its efficiency when integrated into a search engine over a personalizing process. In order to achieve this objective, we propose appropriate evaluation protocols described as follows.

1) How to evaluate the classification performance?: Our evaluation methodology consists in evaluating the results obtained by our approach using manually labeled queries. This means that, a computational outcome for a query, here its class, is said to be correct only if it matches the labeled results. Using the two features locationKL and Kurtosis of our query location profile, we build a local intent classifier. A 10-fold cross validation is performed, and the results reported are averaged over 10 trials. We use standard F-measure, precision, recall and accuracy measures to rate the performance of the classifiers in predicting the query types. Our experiments were conducted using classifiers and boosting techniques implemented as part of the Weka machine learning software[6] [28]. We tested the effectiveness of several well-known supervised individual classifiers: Decision trees, Naive Bayes, SVM, rule-based classifier but also of meta classifiers using boosting algorithms and aggregate learners based on voting schemes.

2) How to evaluate the effectiveness of the personalized approach?: After a query has been classified as having implicit local intent, and in the absence of user's location information in the query log, we associate for each query a simulated location extracted from the query location profile; more precisely, we take the location representing the pick in the query profile. We evaluate our personalization process by both normalized Discounted Cumulative Gain (nDCG) [29] and the Precision at n metric [30], two commonly used metrics to evaluate search engine relevance, computed at different cut-off ranks (Top1, Top3, Top5, Top7 and Top10) since a characteristic of mobile search is the need of high precision as the user has no time/screen space to scroll down along the result list. We then apply both query expansion and document re-ranking to the queries that are classified as local implicit queries. In both approaches we used Google (again via its AJAX API) as the backend search engine and we exploited the initial search results used to classify the query as the baseline. We submit the Top 10 retrieved Web search results for each approach together with test queries and the user simulated location for each query to a unique judge for relevance judgment. If a test query does not have implicit local intent, the user simulated location will be ignored in the judgment; otherwise, the user location will be considered in the relevance judgment. Relevance judgments have been made using a three level relevance scale: relevant, partially relevant, or not relevant.

[6]http://www.cs.waikato.ac.nz/ml/weka/

TABLE I
LOCATIONKL AND KURTOSIS FEATURE VALUES OF THE FIFTH LOWEST AND/OR HIGHEST VALUES FOR EACH QUERY CLASS IN OUR SAMPLE TEST QUERIES

Query	LocationKL	Kurtosis	Query class
"area codes"	268.07	0.62	local implicit
"yellow pages"	134.65	2.05	
"national parks"	95.25	9.17	
"restaurants"	62.21	7.61	
"looking to hire DJ"	62.05	1.78	
"las vegas special events contacts"	8.81	418.73	local explicit
"chicago magazine"	16.28	281.51	
"campgrounds in the mountains of n.c"	27.53	158.07	
"road conditions brevard county florida"	31.05	135.54	
"park tudor indianapolis"	29.16	133.80	
"outer space decor"	0.35	80.48	global
"funny pictures"	0.40	69.33	
"dictionary"	0.59	77.81	
"ringtones"	0.75	84.23	
"southpark cartman"	1.74	55.07	

C. Results and discussion

1) Effectiveness of Query Location Sensitivity Identification: In this first experiment, we evaluate in a first time, the classification performance based on our two features locationKL and Kurtosis. Table I presents the fifth lowest and/or highest Kurtosis and locationKL values for each query class, obtained from our sample test queries. The contrast between the locationKL and Kurtosis values between the different query intent classes is clear and leads us to confirm a possible correlation between query intent class and locationKL and Kurtosis features. We tested different types of classifiers: Decision trees (J48 an implementation of the C4.5 classifier [31]), Naive Bayes [32], Support Vector Machines (SVM) [33], rule-based classifier (Ripper [34]) and a meta classifier (Classification Via Regression [35]). Table II reports the values of the evaluation metrics obtained by each classifier. Results show that all the classifiers were capable to distinguish between the three query classes achieving comparable F-measures, ranging from 85% to 88%. The meta classifier "Classification Via Regression" achieves the highest accuracy with an F-measure of 88%.

This first experiment demonstrates the effectiveness of the query profile to correctly identify local sensitive queries using a classifier based on the two features locationKL and Kurtosis and to accurately distinguish the three types of queries: global, local implicit and local explicit, achieving over 88% classification accuracy.

In a second time, we evaluated the classification effectiveness of our approach comparatively to the approach described in [7] that also exploits the K top search engine results as a source of evidence to build the query features. In [7], queries are only classified as local or global, so we compared our approaches only on this basis. We implemented their approach using the classifier obtained from Ripper that achieves one of the best classification performance using one

TABLE III
CLASSIFICATION PERFORMANCE ON LOCAL AND GLOBAL QUERIES: COMPARISON BETWEEN OUR APPROACH AND THE APPROACH OF [7] BASED ON THE SAMPLE QUERIES.

Approach	[7] approach			Our approach					
Class	**local**	**global**	**Average**	**local**	**Impro**	**global**	**Impro**	**Average**	**Impro**
Precision	0.76	0.88	**0.82**	0.87	**14%**	0.92	**5%**	**0.90**	**10%**
Rappel	0.62	0.93	**0.77**	0.91	**47%**	0.89	**-4%**	**0.89**	**16%**
F-measure	0.68	0.90	**0.79**	0.89	**31%**	0.90	**0%**	**0.89**	**13%**
Accuracy	86%			90%					**5%**

TABLE II
CLASSIFICATION PERFORMANCE OBTAINED USING A CLASSIFIER COMBINING LOCATIONKL AND KURTOSIS FEATURES.

Classifier	**Class**	**Precision**	**Recall**	**F-measure**	**Accuracy**
Meta	local-implicit	0.81	0.74	0.78	88%
	local-explicit	0.91	0.95	0.93	
	global	0.90	0.92	0.91	
	average	**0.88**	**0.88**	**0.88**	
SVM	local-implicit	0.78	0.74	0.76	87%
	local-explicit	0.95	0.85	0.90	
	global	0.89	0.93	0.91	
	average	**0.87**	**0.87**	**0.87**	
J48	local-implicit	0.78	0.82	0.8	87.5%
	local-explicit	0.92	0.88	0.90	
	global	0.91	0.90	0.90	
	average	**0.88**	**0.87**	**0.88**	
Ripper	local-implicit	0.73	0.80	0.77	86.5%
	local-explicit	0.92	0.90	0.91	
	global	0.91	0.88	0.90	
	average	**0.87**	**0.86**	**0.87**	
Bayes	local-implicit	0.75	0.71	0.73	85%
	local-explicit	0.94	0.80	0.87	
	global	0.86	0.93	0.90	
	average	**0.85**	**0.85**	**0.85**	

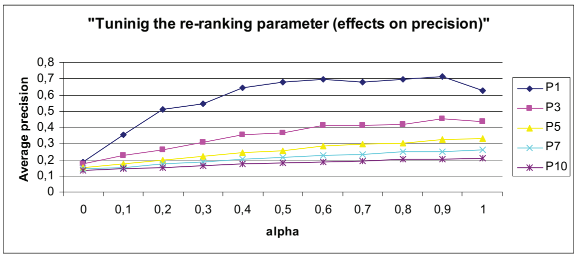

Fig. 4. Tuninig the re-ranking parameter: effects on precision.

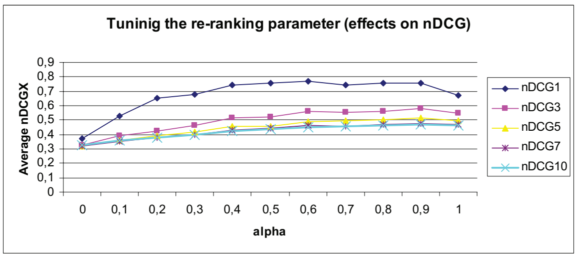

Fig. 5. Tuninig the re-ranking parameter: effects on nDCG.

simple rule, based only on the average number of city locations per returned Web page: if this number exceeds a threshold, the query is classified as local, otherwise as global. We list in Table III the precision, recall, F-measure and accuracy achieved by the Ripper classifier according to both approaches. Performance improvement is computed as follows: $Impro = (P_{our-approach} - P_{[7]approach})/P_{[7]approach} * 100$, where P represents the performance measure (precision, recall, F-measure or accuracy) value for each approach. Results show that, in general, our approach gives higher classification performance than [7] approach with an improvement of 13% at F-measure and 5% at accuracy. Improvements achieved by our approach are mainly over local queries 31% at F-measure, classification performance over global queries are similar between the two approaches.

2) Effectiveness of the Personalization Technique: In this second experiment we evaluate the efficiency of our method of classification of queries based on their local intent when integrated into a search engine over the two personalization processes. This experiment is based on the set of queries that was identified by our classifier to be local implicit. In a first time, we report the study of the effect of combining the original document's score (computed as a ranking function from the baseline) and the location score of the document obtained when considering a user's location, on the retrieval effectiveness. Figure 4 (respect. Figure 5) shows the effect of varying the combination parameter α in the interval $[0..1]$ on the retrieval effectiveness in terms of average P1, P2, P3, P5, P7 and P10 (resp. in terms of nDCG1, nDCG3, nDCG5, nDCG7 and nDCG10) over all the queries classified as local implicit by our classification algorithm. Results show that the best performance is obtained when α is 0.9. This is likely due to the fact that all the results on the top 10 match the query well and thus the distinguishing feature is how well they match the user's location.

In a second time, we present results of comparison of performance between the baseline, the re-ranking personalization approach using the optimal combination parameter $alpha = 0.9$ and the refinement personalization approach. Figure 6 (resp. Figure 7) shows the average P1, P2, P3, P5, P7 and P10 (resp. nDCG1, nDCG3, nDCG5, nDCG7 and nDCG10) obtained by each approach.
Results shows that in general the personalized Web search improved search relevance over the baseline. Using a paired, two-tailed t-test, this improvement of 51.51% at P1, 36.14% at P3, 25.59% at P5, 18.18% at P7, 12.96% at P10, 102.27% at nDCG1, 77.21% at nDCG3, 62.59% at nDCG5, 50.75% at

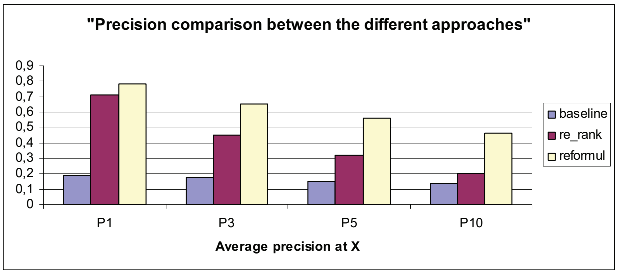

Fig. 6. Average Precision comparison between the different approaches over all queries.

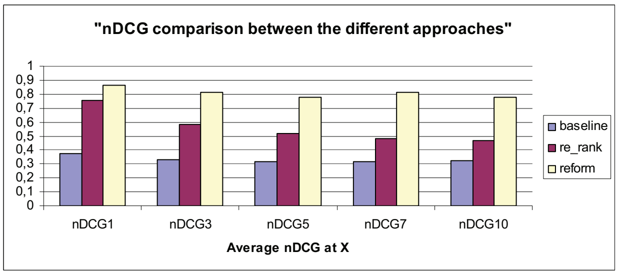

Fig. 7. Average nDCG comparison between the different approaches over all queries.

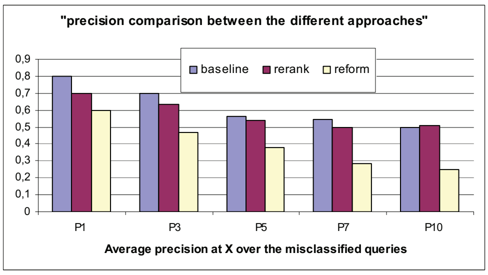

Fig. 8. Average Precision comparison between the different approaches over misclassified queries.

nDCG7 and 47.40% at nDCG10 of the re-ranking personalization approach comparatively to the baseline was found to be statistically significant with $p - values < 0.05$.

Moreover, the query refinement approach improves the search results comparatively to the baseline and the re-ranking approach. Especially it outperforms the re-ranking approach from the Top3 rank. Indeed, the query refinement approach was able to retrieve valid documents that the default query is not able to find. Using a paired, two-tailed t-test, this improvement of 40.70% at P3, 58.60% at P5, 67.17% at P7, 79.91% at P10, 39.31% at nDCG3, 51.22% at nDCG5, 69.07% at nDCG7 and 62.19% at nDCG10 of the reformulation approach comparatively to the re-ranking approach, was also significant with $p - values < 0.05$.

Besides, we take a look to the effect of the personalization approaches on the search results performance of the misclassified queries (global queries). Figure 8 (resp. Figure9) shows the precision and nDCG values at different cut-off

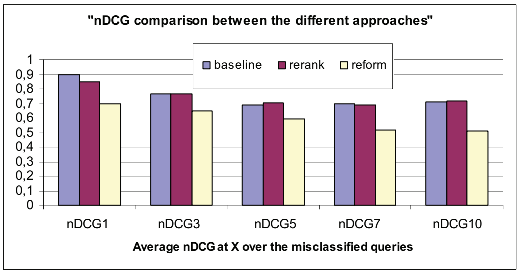

Fig. 9. Average nDCG comparison between the different approaches over misclassified queries.

ranks (Top1, Top2, Top3, Top5, Top7 and Top10) obtained by each approach averaged only on the misclassified queries. This fallout analysis allowed us to observe that both approaches slightly decrease the precision and nDCG at the different cut-off ranks (Top1, Top2, Top3, Top5, Top7 and Top10). Again, using a paired, two-tailed t-test, we find that this decline was significant only for the reformulation approach at Top7 and Top10 with $p - value > 0.05$.

VI. Conclusion and Future Work

In this paper, we presented our approach for personalizing mobile Web search based on evidences obtained from our proposed query local sensitivity identification method. The location identification approach is based on building a location query profile using language models built from the top N search results returned by a general Web search engine. Two measures namely location Kullback-Leibler Divergence and Kurtosis defined on this profile, allow us to effectively classify the three types of queries: global, local explicit and local implicit ones. We have evaluated two personalization techniques for integrating the classification of queries based on their geographical locality on behalf of a general search engine to improve the quality of the search results.

In future we plan to enhance our work in several ways. First, we plan to estimate the computational costs induced by our technique when integrated in the IR process. Second, concerning the location score, the current function is rather simple it is based on a text matching feature, it can be improved by exploiting distance measures from geographical ontologies. Third, in this work, we have focused on the user's location as a sole factor to personalize the search results. Besides this, mobile user's queries seems to be also sensitive to others factors such as user's interests, time, etc [36]. In future, we plan to extend the personalization through the combination of location matching features and other ranking features such as user's interests and time together with the initial score of the search engine. The challenge is to formulate a functional relationship between the different criteria that accurately represent the satisfaction of the several criteria.

ACKNOWLEDGMENT

The authors would like to thank the support of the project QUAERO, directed by OSEO agency, France.

REFERENCES

[1] M. Welch and J. Cho,*Automatically identifying localizable queries*, In 31^{st} annual International ACM SIGIR conference on Research and development in information retrieval, pp. 1185-1186, ACM, 2008.

[2] M. Kamvar and S. Baluja : Deciphering trends in mobile search. Computer, 40(8), 58-62, 2007.

[3] K. Church and B. Smyth, *Understanding the intent behind mobile information needs,* 13^{th} *International conference on Intelligent user interfaces*, pp. 247-256, ACM, 2009.

[4] J. Yi and F. Maghoul and J. Pedersen, *Deciphering Mobile Search Patterns: A Study of Yahoo! Mobile Search Queries*, Proceeding of the 17^{th} international conference on World Wide Web-WWW 2008/ Refereed Track: Mobility, pp. 257-266, ACM, 2008.

[5] M. Kamvar and S. Baluja, *A Large Scale Study of Wireless Search Behavior: Google Mobile Search*, CHI'06: Proceedings of the SIGCHI conference on Human Factors in computing systems- Track: Search&Navigation: Mobiles&Audio, pp. 701-709, ACM, 2009.

[6] S. Vadrevu and Y. Zhang and B. Tseng and G. Sun and X. Li, *Identifying regional sensitive queries in web search*, WWW'08: In proceeding of the 17^{th} International conference on World Wide Web, pp. 507-514, ACM, 2008.

[7] L. Gravano and V. Hatzivassiloglou and R. Lichtenstein, *Categorizing web queries according to geographical locality*, in 12^{th} Int'l. conference on Information and knowledge management, pp. 325-333, ACM, 2003.

[8] M. Daoud and L. Tamine and M. Boughanem and B. Chebaro, *Learning Implicit User Interests Using Ontology and Search History for Personalization*, in International Web Information Systems Engineering-International Workshop on Personalized Access to Web Information (WISE-PAWI), pp. 325-336, Springer, 2007.

[9] L. Tamine and M. Boughanem and N. Zemirli, *Exploiting Multi-Evidence from Multiple User's Interests to Personalizing Information Retrieval*, in IEEE Int'l Conference on Digital Information Management, Youakim Badr, Richard Chbeir, Pit Pichappan (Eds.), IEEE Engineering Management Society, pp. 7-12, 2007.

[10] V. Varma and N. Sriharsha and P. Pingali, *Personalized web search engine for mobile devices*, In International Workshop on Intelligent Information Access (IIIA'06), 2006.

[11] K.W.T. Leung and D.L Lee and W.C. Lee, *Personalized Web Search with Location Preferences*, in proceedings of the 26^{th} International Conference on Data Engineering (ICDE), pp. 701-712, IEEE, 2010.

[12] D. Mountain and A. MacFarlane, *Geographic information retrieval in a mobile environment: evaluating the needs of mobile individual*, Journal of Information Science, 33(5):515530, 2007.

[13] G. Cong and C.S. Jensen and D. Wu, *Efficient Retrieval of the Top-k Most Relevant Spatial Web Objects*, in proceedings of the VLDB Endowment, 2(1): 337-348, ACM, 2009.

[14] P. A. Salz, *Making search social Unleashing search for the mobile generation*, Taptu White Paper, Publisher and Chief Analyst MsearchGroove, 2008.

[15] T. Haveliwala, *Topic-sensitive pagerank*, In Proceedings of the 11^{th} International world wide web conference, 2002.

[16] S. Hattori and T. Tezuka and K. Tanaka, *Context-aware query refinement for mobile web search*, In 2007 International Symposium on Applications and the Internet Workshops, 2007.

[17] J. Teevan and S. T. Dumais and D. J. Liebling, *To Personalize or Not to Personalize: Modeling Queries with Variation in User Intent*, Proceedings of the 31^{st} annual International ACM SIGIR conference on Research and development in information retrieval, pp. 163-170, ACM, 2008.

[18] Z. Dou and R. Song and J. R. Wen, *A Large scale Evaluation and Analysis of Personalized Search Strategies*, WWW'07: Proceedings of the 16^{th} International conference on World Wide Web, pp. 581-590, ACM, 2007.

[19] S. Cronen-Townsend and Y. Zhou and W. B. Croft, *Predicting query performance*, In Proceedings of the 25^{th} Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 299-306, ACM Press, 2002.

[20] V. Lavrenko and W. B. Croft, *Relevance-based language models*, In Proceedings of the 24^{th} Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 120-127, ACM Press, 2001.

[21] W. B. Croft and J. Lafferty (Eds.), Language Modeling for Information Retrieval, 2003.

[22] S. Kullback and R. A. Leibler, *On Information and Sufficiency*, Annals of Mathematical Statistics, 22(1): 79-86, 1951.

[23] M. Abramowitz and I. A. Stegun, *Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables*, NBS Applied Mathematics Series 55, National Bureau of Standards, Washington, DC, 1964.

[24] G. Pass and A. Chowdhury and C. Torgeson, *A picture of search*, In 1^{st} International Conference on Scalable Information Systems, Article 1, ACM, 2006.

[25] C. B. Jones and R. S. Purves, *Geographical information retrieval*, International Journal of Geographical Information Science, 22(3):219-228, 2008.

[26] E. Amitay and N. Harel and R. Sivan and A. Soffer, *Web-a-where: Geotagging web content*, In 27^{st} annual International ACM SIGIR conference on Research and development in information retrieval, pp. 273-280, ACM, 2004.

[27] L. Ratinov and V. Roth, *Design challenges and misconceptions in named entity recognition*, In 13^{st} Conference on Computational Natural Language Learning, pp. 147-155, Association for Computational Linguistics, 2009.

[28] M. Hall and E. Frank and G. Holmes and B. Pfahringer and P. Reutemann and I. H. Witten, *The weka data mining software: An update*, SIGKDD Explorations, 11:10-18, 2009.

[29] K. Jarvelin and J. Kekalainen, *Cumulated gain-based evaluation of IR techniques*, ACM Transactions on Information Systems 20(4), 422-446, 2002.

[30] R. Baeza-Yates and B. Ribeiro-Neto, *Modern Information Retrieval*, New York: ACM Press, Addison-Wesley. Seiten 75 ff, 2009.

[31] R. Quinlan, *C4.5: Programs for Machine Learning*, Morgan Kaufmann Publishers, San Mateo, CA, 1993.

[32] N. Friedman and D. Geiger and M. Goldszmidt, *Bayesian network classifiers*, Machine Learning, 29:131-163, 1997.

[33] J. Platt, *Fast Training of Support Vector Machines using Sequential Minimal Optimization*, Advances in Kernel Methods - Support Vector Learning, B. Schoelkopf, C. Burges, and A. Smola, eds., MIT Press, 1998.

[34] W. W. Cohen, *Learning trees and rules with set-valued functions*, In Proceedings of the Thirteenth International Joint Conference on Artificial Intelligence, pp. 709-716, 1996.

[35] E. Frank and Y. Wang and S. Inglis and G. Holmes and I. Witten, *Using model trees for classification*, Machine Learning, 32(1):63-76, 1998.

[36] T. Sohn and K. A. Li and W. G. Griswold and J. D. Hollan, *A diary study of mobile information needs*, In 26^{th} annual SIGCHI conference on Human factors in computing systems, pp. 433-442, ACM, 2008.