Context-Aware User's Interests for Personalizing Mobile Search

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***Abstract*—In the past, most personalized retrieval models have been solely based on the computational behavior of the user to model the user profile. Personalized mobile search should however take the changing environment of the mobile user into account in order to better improve the search results quality. In this paper we propose an approach to personalize search results for mobile users by exploiting both cognitive and spatio-temporal context of the user. We propose to model the user on three semantic dimensions: time, location and interests. A case based reasoning approach is adopted to select the appropriate user profile for re-ranking the search results. In the absence of a standard evaluation framework for mobile search, we propose an evaluation scenario based on diary study entries. Our experiments undertaken in front of Yahoo boss search service[1] shows that our retrieval approach is effective.**

I. Introduction

Within the emerging mobile information retrieval (IR) environment, it is widely believed that users information needs are strongly related to their contextual factors such as user interests, location and time [1], [2]. Unfortunately, most traditional search engines do not consider the search context in the retrieval process and are not tuned to mobile environment. Recent works in IR community [2], [3] attempt to improve search accuracy in this environment by providing appropriate results according to the user context. Such systems are faced to two main challenging questions: how to model the user context and how to consider this model in the document relevance computation step? Another important issue is how to evaluate the strategies and techniques involved in these new systems.

Current research and development works within the IR community attempt to answer the above challenges. While some works have addressed issues related to the inherent physical limitations of the mobile devices [4], [5], other works exploit the user location to offer proximity search services [6], [7]. Another important search effort attempts to build the user profile to personalize search results. Earlier personalization techniques [8], [9] were based solely on the computational behavior of the user (visited URL, viewed documents) to model his interests regardless of his surrounding environment. The main limitation of such approaches is that they do not take into account the dynamicity of the user interests regarding his environment context. 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?.

There have been several attempts to answer these questions. Regarding situation-aware user profile modeling, the authors in [10] 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 [11] the user situations are represented by temporal zones and the user interests are learnt from his past search activities and weighted according to the identified temporal zones. In [12] the user situations are represented by the frequently visited locations by the user and the user interests are learnt based on a user questionnaire approach. In [13] the user situations are represented by leisure activities (eating, seeing, doing, reading, and shopping) and the user interests are learnt from the past search activities occurred within these activities. Concerning the representation schema proposed to model the relation between the user situations and interests, [10] propose a relation-entity representation, [11] exploit metadata mechanism, [12] use a tree-based representation and [13] exploit activity patterns. Regarding the strategy adopted for search personalization, it is performed by means of query refinement in [10], profile-document matching in [11] and filtering techniques in [12], [13].

In order to endow a personalized IR system with the capability to provide specifically a mobile user with information that matches his interests coupled with his environment, we extend in this paper our previous work [14] on building and learning the user profile for desktop search. Our contribution consists to enhance the search context by spatio-temporal annotations, namely the location of the user and the time to characterize his search situation. The user profile is learnt for each identified situation, on the basis of past search activities occurred in this situation. Unlike previously related works, our approach for a context-aware personalized mobile search has several new features: (1) first, we propose to build a four

[1]http://developer.yahoo.com/search/boss/

level semantic representation of the user search situations as concepts from location and time ontologies, (2) second, our approach is implicit and automatic; no efforts are needed from the user, (3) 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. Furthermore, in the absence of a standard evaluation framework, we propose an evaluation protocol in context devoted for our proposed approach.

The paper is organized as follows. Section 3 presents our motivations and our general approach for inferring spatio-temporal user interests. In section 4, we present our situation-based ranking model. In section 5, we present our experimental evaluation and discuss the obtained results. The last section presents our conclusion and points out possible directions for future work.

II. Motivations and Background

A. Motivations

In mobile IR, users' interests may change anytime due to change in their environment (location, time, near persons, . . .). Static approaches for building the user profile are therefore poorly useful, so we rather focus on more flexible techniques, any time capable of adjusting the user interests to the current search situation. Our general approach for search personalization relies on building a user profile in a specific search situation. Our work is thus driven by two main assumptions: (1) mobility implies that each user will have several profiles and several situations, (2) user's interests are coupled with his environment; in other words, users's interests are likely to be similar within similar situations. 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: (1) 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. (2) the second reason is typically technical, it considers the fact that these contextual elements can easily be acquired in an automatic way. Our approach to model user's interests relies on a graph-based ontological representation developed in our previous work [14]. This type of representation allows us to entirely benefit from all the semantic relations within the general ontology to better model the user's interests. We summarize below the terminology and notations used in our contribution, then we detail our approach.

B. Terminology and Notations

- **search activity**: a search activity expresses the following events: the user submits a query, to a search engine; the latter returns a ranked list of documents, then the user expresses his preferences on the returned documents.
- **search situation**: encapsulates the spatio-temporal context of a search activity. Search situation, denoted S, is represented as a vector of four conceptual dimensions issued from temporal and space ontologies.
- **user profile**: refers to the user's concepts of interest related to a search situation. The user profile, denoted G, is represented as a graph of semantically related concepts issued from the ODP[2] ontology.
- **user model**: a user model is composed of a set of situations with their corresponding user profiles, denoted $U = \{(S^i, G^i)\}$, where S^i is a situation and G^i its corresponding user profile.
- **case** : a case models the relation between a situation and its associated user profile and represents an element from U, it is denoted $Case = (S, G)$.

C. Research Overview

Our general approach for search personalization relies on building and selecting the most appropriate user profile in a particular search 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) [15]. A case is composed of a *Premise* part wich is a description of the case and contains its characteristics, and of a *value* part wich is the result of the reasoning based on the *premise*. The *premise* part of a case referred in our situation similarity computing seatings, is a specific search situation S, while the *value* part of a case is its corresponding user profile G. Each case from our case base represents then a specific element from U. The overall process supporting our approach for search personalization is detailed in Algorithm 1. The algorithm considers in turn each new submitted query q^* and its situation S^*. A situation based similarity measure is set up and allows to select the most similar situation from the past ones. We choose to set a threshold value β and believe that queries are from the same situation if the situation similarity is above the threshold. When the computed similarity is above the threshold, we re-rank the search results of the query q^* using the user profile G^{opt}. After the user clicks or views interesting documents, the query profile G^* is built. If the computed similarity value is equal to 1, the user profile G^{opt} is updated by merging it with the new constructed one G^*, otherwise, we insert into the case base a new case with the situation S^* and its user profile initialized by the graph-based profile G^* of the new submitted query.

With respect to this general view, we address in the remainder of this paper the following research questions: 1) How to model the user search situations?, 2) How to build and maintain the graph-based user profile in a specific search situation?, 3) How to select the most similar search situation among the past ones? and 4) How to personalize the search results using the user profile?

[2]http://www.dmoz.org

Algorithm 1 General approach for personalizing mobile search using spatio-temporal user profile

for each new query q^* and its associated situation S^* **do**
- Retrieve the most similar case that verifies :
$S^{opt} = \arg\max_{S^i \in PS} \left(\sum_j \alpha_j \cdot sim_j \left(X_j^*, X_j^i \right) \right)$
if $sim(S^*, S^{opt}) \geq \beta$ **then**
- Re-rank the search results of the query q^* using the user profile G^{opt}
- Build the graph-based ontological profile G^* of q^*
if $sim(S^*, S^{opt}) = 1$ **then**
- Update the case containing the user profile: G^{opt} using G^*
else
// A new situation is detected
-Insert the new situation S^* with its G^* into the case base
end if
else
// No personalization is done
- Build the ontological profile G^* of the query q^*
- Insert the new situation S^* with its G^* into the case base
end if
end for

III. A SITUATION BASED RANKING MODEL

A. Situation Modeling

To model the user environment, we propose to rely on a semantic representation of time and location rather then on a physical one. Our assumption in fact is that users interests are related to the semantic behind the physical environment (it is not matter if you are in "*Heathrow*" or "*Roissy Charles de Gaulle*" but that you are in an "airport". We propose then 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 "48.78, 2.21" 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 a class name extracted from a classification category of location types (like ADL feature type thesaurus[3]), and represents the place's demographic (school), environmental (beach), historic (monument), personal (residence) or commercial (shop), etc.
- *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: morning, midday, afternoon, evening and night.

More specifically, a situation S can be represented as a vector whose features X are the values assigned to each dimension:

$$S = (X_l, X_u, X_v, X_w) \ . \tag{1}$$

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.

[3]http://www.alexandria.ucsb.edu/gazetteer/FeatureTypes /ver100301/

B. Learning the User Profile

Below, we give an overview of the graph-based ontological representation of the user profile detailed in our previous work [14]. User profiles are built over each identified situation by combining graph-based query profiles. A query profile G_q^s is built by exploiting clicked documents D_r^s by the user and returned with respect to the query q^s submitted at time s. First a keyword query context K^s is calculated as the centroid of documents in D_r^s:

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

Then, K^s is matched with each concept c_j of the ODP ontology represented by single term vector $\vec{c_j}$ using the cosine similarity measure as follows:

$$sw(c_j) = \cos\left(\vec{c_j}, \vec{K^s} \right) \tag{3}$$

Based on the obtained weighted concept set, we activate for each concept its semantically related concepts using score propagation as explained in [14]. The user profile G^i, within each identified situation S^i, is initialized by the profile of the first query submitted by the user at the situation S^i.

C. Retrieve the Most Similar Situation

To determine the expected user profile for a new summited query q^* its associated 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 verifies:

$$S^{opt} = \underset{S^i \in PS}{\arg\max} \left(\sum_j \alpha_j \cdot sim_j \left(X_j^*, X_j^i \right) \right) \tag{4}$$

Where X_j^* (resp. X_j^i) 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 discussed below:

- *location type dimension* : For any situation S the feature X_l is given by a classification scheme of geographic places. The similarity between two location types X_l^* and X_l^i depends on how closely they are related in the taxonomy. We use a similarity measure like in [16] which is defined by:

$$sim_{location}\left(X_l^*, X_l^i \right) = \frac{2 * depth\,(lcs)}{(depth\,(X_l^*) + depth\,(X_l^i))} \tag{5}$$

where lcs is the Least Common Subsumer of X_l^* and X_l^i, and $depth$ is the number of nodes on the path from a node to the root in the taxonomy.

- *season dimension* : For any situation S the feature X_u is an element of the predefined list {*autumn, winter, spring and summer*}. We assume that situations within successive seasons are more similar than situations within non successive ones. The similarity between two seasons X_u^* and X_u^i is computed as:

$$sim_{season}\left(X_u^*, X_u^i\right) = \begin{cases} 1 & if\ X_u^* = X_u^i \\ 1/2 & if\ X_u^*\ and\ X_u^i\ are \\ & successive\ seasons \\ 0 & otherwise \end{cases} \quad (6)$$

The same similarity measure applies for the *day of the week* and the *time of the day* dimensions as detailed in our previous work [17].

D. Re-Ranking the Search Results

In order to insure a better precision of the search results, the personalization phase takes place only if the following condition is verified:

$$sim\left(S^*, S^{opt}\right) \geq \beta \quad \text{where } \beta \text{ is a threshold value.}$$

The corresponding user's profile G^{opt} is used to re-rank the search results returned 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 $score_c(d_k, C^{opt})$ leading to a final $score_f\left(d_k\right)$ as follows:

$$score_f\left(d_k\right) = (1-\gamma)*score_o\left(q^*, d_k\right) + \gamma*score_c\left(d_k, G^{opt}\right) \quad (7)$$

Where γ ranges from 0 to 1. The personalized score $score_c(d_k, G^{opt})$ 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:

$$score_c\left(d_k, G^{opt}\right) = \sum_{c_j \in G^{opt}} sw\left(c_j\right) * \cos\left(\vec{d_k}, \vec{c_j}\right) \quad (8)$$

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

E. Maintaining the User Profile

Depending on the similarity value between the current situation S^* and the most similar one S^{opt}, two scenarios are plausible:

1) $sim\left(S^*, S^{opt}\right) \neq 1$: a new case is added to the case base which is composed of the current situation S^* with its corresponding learned profile G^*.
2) $sim\left(S^*, S^{opt}\right) = 1$: 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 two principles: (1) enhance the weight of possible common concepts that can appear in two profiles related to the same situation 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:

$$sw_{c^{opt}}\left(c_j\right) = \begin{cases} \eta * sw_{c^{opt}}\left(c_j\right) + (1-\eta) * sw_{c^*}\left(c_j\right) \\ \quad if\ c_j \in G^{opt} \\ \eta * sw_{c^*}\left(c_j\right)\ \ otherwise \end{cases} \quad (9)$$

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

IV. Experimental Evaluation

In order to empirically evaluate the performance of our context-based personalized mobile search approach, and in the absence of a standard evaluation framework, we propose an evaluation framework that is undertaken through a user study and based on a diary study entries. The main objectives of the experimental evaluation are the following: 1) to evaluate the accuracy of our proposed CBR technique to select an appropriate situation and 2) to evaluate the personalized search effectiveness. In the following, we describe our experimental datasets, and then present and discuss the obtained results.

A. Experimental Datasets

As stated above, the main problem we faced to evaluate our approach, is the absence of an evaluation benchmark and dataset for evaluating context-aware approaches for mobile search. 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 I illustrates an example of such diary entries, each diary entry represents a userid, date, time, place and the user query. 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. 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. We build our document collection by collecting the top 100 results retrieved from the publicly available Yahoo boss search API 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. 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.

B. Experimental Results and Discussion

1) ***Evaluating the Accuracy of the CBR Technique to Select the Most Similar Situation:*** In order to evaluate the

TABLE I
AN EXAMPLE OF SOME DIARY ENTRIES.

User_ID	Date	Time	Place	Query
1	20-fvr	14h30	place de la concorde	”histoire obélisque”
2	27-fvr	11h10	périphérique	”Parking relais Bordeaux”
6	16-fvr	16h30	salle des fêtes d’escalquens	”lyndi hop”

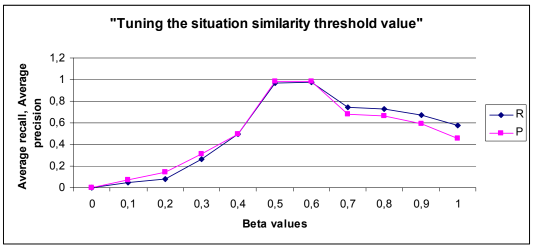
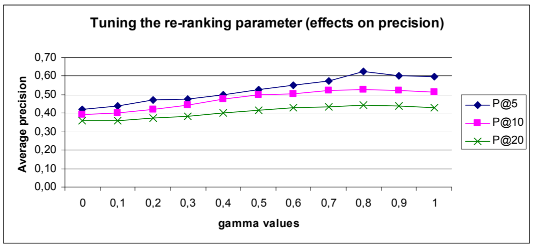


Fig. 1. Effect of the parameter Beta on the situations similarity accuracy.

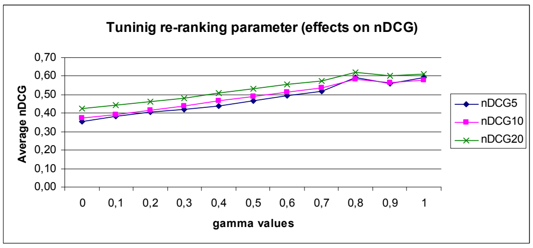
accuracy of our CBR technique to identify similar situations and particularly to set out the threshold similarity value, we propose to use a manual classification as a baseline and compare it with the results obtained by the CBR technique. So, we manually classify the initial user contexts into groups of similar situations, and we compare the manual constructed groups to the results obtained by our similarity algorithm, with different β threshold values. The α_i values in formula 4 are fixed according to the users’ feedback from the diary study. Our measure of accuracy is based on the precision and recall measures defined as follows: $P = \frac{CAG}{AG}$; $R = \frac{CAG}{MG}$, 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 1 shows the effect of varying the threshold situation similarity parameter β in the interval [0 1] on the overall precision (P) and recall (R). Results show that the best performance is obtained when the threshold value $\beta = 0.6$ achieving a very high accuracy of 0.97 recall and 0.98 precision, this shows the effectiveness of our situation similarity algorithm. Consequently, we use the identified optimal threshold value ($\beta = 0.6$) of the situation similarity measure for testing our search personalization effectiveness presented below.

*2) **Personalized Retrieval Effectiveness Results**:* 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 ($\beta = 0.6$). We divided the query set into k equally sized subsets, and using $k-1$ training subsets for learning the user interests and the remaining subsets as a test set. The testing step consists of evaluating the personalized retrieval effectiveness for each testing query using the user profile compared to a baseline search, here performed by Yahoo boss search using only the testing query. In the absence of an initial score of the document results list of Yahoo boss, the re-ranking procedure is done based on a combination for each document of its original rank and its personalized rank. We use the standard precision metric (P) [18] and the normalized Discounted Cumulative Gain (nDCG) [19] computed at different cut-off points (5, 10 and 20) as the evaluation metric as they better estimate the quality of the search results at the top of the ranked list. We 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.
In this experiment, we study in a first time, the effect of combining the original document’s rank of Yahoo boss (corresponding to the original document score in formula 9) and the personalized document rank obtained according to our approach, on the retrieval effectiveness. Figure 2(a) (resp. Figure 2(b)) shows the improvement of our personalized search in terms of P5, P10 and P20 (resp. 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.

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. 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 are 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, 19,58% at P20, and in terms of accumulated gain achiving an improvment 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 2). As shown in table 2, our proposed approach has shown significant p-value according to the t-test at P5, P10, P20, nDCG5, nDCG10 and nDCG20. Besides, we notice that we have observed a slight decline of performance on a few (2-3) queries (eg. ”entrée pitiè-salpêtière hôpital”) that we estimate to be very precise, this is consistent with the results mentioned in [20] concerning the limits of the



(a)



(b)

Fig. 2. Effect of the parameter gamma in the combined rank. (a) on precision, (b) on nDCG.

TABLE II
AVERAGE TOP-N PRECISION AND NDCG COMPARISON BETWEEN OUR PERSONALIZED SEARCH AND YAHOO BOSS OVER ALL 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%*

effectiveness of personalization techniques on queries that are very precise (not ambiguous).

V. CONCLUSION

This paper describes our approach for a context-aware personalized mobile search. It 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 by exploiting a CBR technique. We have presented an evaluation protocol based on real mobile search contexts obtained from a diary study for mobile search. We evaluated our approach according to the proposed evaluation protocol and show that it is effective. In future work, several aspects in our proposed user modeling approach can be enhanced. Regarding the situation modeling, we plan to extend it by adding a dimension representing the query as it is a part from the context. Concerning, the location dimension, we plan to evaluate the accuracy of the identified location semantics when directly acquired from the spatial ontology in real mobile scenarios.

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