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Abstract

Mobile advertising has become one of the most exciting new technological frontiers in advertising area in recent years. The ubiquitous nature of mobile phones makes it possible for advertisers to target users effectively. This paper proposes a targeted mobile advertising system (TMAS) that works as a platform to provide consumers personalized ads based on the consumers' contextual and preference. The platform allows shops to provide contextual and time-sensitive ads and consumers to locate ads and promotion information using their smart phone. A demonstration is conducted to show the validity of the key process in the TMAS.

Keywords: Mobile advertising, Pull strategy, Targeted advertising, Intelligent searching

1. Introduction

Mobile phone is by far the most popular personal communications device for people. As new multi-function mobile phones, like smart phones, are used more and more widely, it is emerging as a coveted media platform for marketers (Yuan and Steinberg 2006). The nature of mobile phone makes itself an ideal marketing channel, especially for the local advertising. For example, it is personal, accessible anytime and anywhere, location aware and so on (Sultan and Rohm 2008). People only need to use a small app on their smart phones to type in their needs like "food" or "yard sale", and personalized local ads can be listed on their smart phone.

The growth of mobile advertising offers companies exciting advertising opportunities. According to recent forecasting report, global mobile marketing spending is expected to be worth about $19 billion by 2011 (BusinessWeek). However, mobile users are a huge group. How to reach the valuable targeting audience is a vital problem to every advertiser. Mobile phone's unique personal attributes offer new opportunities for advertisers to achieve targeted advertising by using personalization technology. Effective and efficient ads can be delivered to the right mobile user in the right context, according to the mobile user's demographics, contextual and preference information (Yuan and Tsao 2003; Xu et al. 2007).

Right now the most common mobile ads formations are Short Message Service (SMS) and Multimedia Message Service (MMS) (Okazaki and Taylor 2008). They are push type that messages are proactively sent out to mobile users (Carat Interactive 2002). Typically, push marketing should be reserved for companies who have an established relationship and permission to push communications to mobile users. So it is also called permission-based marketing (Barwise and Strong 2002). However, since mobile phone is a very important communication channel, mobile advertising can also be user-driven (Tripathi and Nair 2006), and the dynamics of business-to-consumer relationships can be greatly enhanced (Peters et al. 2007). Pull strategies involve sending information that is requested by the consumer (Barwise and Strong 2002). It is quite suitable for the advertisers whose ads are small, time limited and local ads with quota, such as ads of local companies, coupons and promotions in local mall, yard sale information, and so on. Future customers with smart phone will be more active when they demand advertisement information. Comparing with push-based advertising, pull-based methods, which let customers be in charge, are gaining support.

In this paper we will propose a targeted mobile advertising system framework based on pull marketing strategies. It combines targeted advertising technique and pull marketing strategy. An experiment is conducted to try to demonstrate the proposed system from two perspectives: it can provide targeted ads for mobile users; it can works as a platform to match the ads and mobile users efficiently and fairly.

This paper is organized as follows: Section 2 reviews the related works on targeted mobile advertising and pull advertising. Section 3 proposes a system framework of pull targeted mobile advertising and presents the operation process of the system. Section 4 presents the experiment design. Section 5 focuses on the experiment results and their implications. The final section highlights the contributions of this research and concludes the paper.

2. Related Works

Targeted mobile advertising

Targeted advertising means that the right person should receive the right message at the right time in order to increase the effectiveness of advertisements (Adam 2002). So, targeted mobile advertising refers to providing consumers with personalized information based on their time of day, location and interests (Scharl et al. 2005). Two significant research domains may be distinguished within targeted mobile advertising: scheduling and personalization. Scheduling refers to which ads to send out to which customers at what particular time, given a limited capacity of broadcast time slots, in order to maximize customer response and revenues from retailers paying for each ad broadcast. De Reyck and Degraeve (2003) first solved the problem by using integer programming. Then a decision support system was developed for automatically scheduling and optimizing broadcasts of advertisements to mobile phones (De Reyck and Degraeve 2006). Tripathi and Nair (2007) made the integer programming more effective by utilizing additional contact history information to better scheduling of ads.

Personalization seems to be a more important and difficult challenge for current advertisers. It is more individualized than the primary targeted advertising, which simply divides customers in a market into specific segments (Kazienko and Adamski 2007). It aims to assign a suitable advertisement to a single web user rather than to a group of individuals. In targeted advertising, the most important issue is starting with the right data. Generally, marketers can personalize ads based on the users' profile and contextual information (Balasubramanian et al., 2002). Contextual information covers aspects such as location, time, user activities and weather (Xu et al., 2008). User profiles are built by users' preference information, demographics and so on (Germanakos et al., 2008). Contextual information is related to users' short-term interests, while long-term interests can be derived from user profiles (Langheinrich et al., 1999). Data mining techniques are widely used in targeted advertising especially in the Internet environment (Li et al., 2007). In some studies, detailed segmentation and clustering models are used to discover web access patterns for identifying web users (Srivastava et al. 2000) and other advertising problems (Chickering and Heckerman 2003). For example, the demographic analysis revealed that the unmarried working youth segment has a higher propensity to access pull mobile advertisements (Okazaki 2004). The classification model is also used to match Web sessions with optimal advertisements (Li et al. 2007). Besides data mining method, the fuzzy approach was also used in target advertising based on user profiles (Yager, 2000). The assignment of appropriate advertisements to each active user can be accomplished according to the fuzzy rules stored in the system.

Mobile users who need some ads information would like the mobile service which is customized to their interests and relevant for them (Xu, 2006). However, many mobile users are cautious to the privacy issue and they also worry about the spam problem in push type mobile advertising like SMS advertising service (Bamba and Barnes, 2007).

Push and Pull advertising

When we implement targeted mobile advertising, there are two delivery categories – push and pull, which severally root in push and pull marketing strategies (Carat Interactive 2002). Both push and pull advertising should be carefully targeted and be of relevance to mobile users to improve their response and acceptance. Push advertising is categorized as messages that are proactively sent out to mobile users (Carat Interactive 2002). SMS mobile advertising has typically been considered an application of a push strategy in the mobile environment (Barwise and Strong, 2002), meaning that information and marketing activities flow from the producer to the consumer (Spiller and Baier, 2005). The problem is that sending messages to mobile users needs permissions from them. Though former research has already proved that obtaining consumers' permission can increase their acceptance of mobile advertising (Barwise and Strong 2002), this kind of push mobile advertising can only reach a limited range of mobile users.

Rather than push mobile advertising which is initiated by advertisers, pull mobile advertising is triggered by mobile users. Pull strategies involve sending information that is requested by the consumer (Barwise and Strong 2002). A few mobile advertising systems that involve pull marketing strategies are proposed in former literature. Okazaki (2004) proposed a mobile advertising platform "Tokusuru Menu" to examine the factors influencing consumers' motives to mobile ads. It enables subscribers to freely access the promotional information delivered by various companies. Mahmoud and Yu (2006) discussed a novel mobile agent platform that can be used for comparison shopping in a mobile wireless environment, through which businesses can better understand and communicate with the mobile consumer. Another mobile advertising system called MALCR is provided and described in (Yuan and Tsao, 2003), which is based on both pull type advertising and push type advertising. Advertising through MALCR proceeds in two ways—the pull mode and the push mode.

The typical and prime method in pull advertising is search engine. Search engine is not only a useful way to pull users to ads information from advertisers but also a targeting process that provides users what they are actively seeking. Choi (2007) proposed a new, ubiquitous, GPS/Web-enabled mobile search mechanism based on the user's physical location and search intentions. Using fuzzy query, together with user's physical location and distance from user's physical location, the GPS/Web enabled mobile devices can receive more personalized and locally targeted search results.

A few scholars still argue that the push model will dominate mobile advertising since it saves consumers' time and money (Quah and Lim, 2002). Pull advertising blurs the line between advertising and service (Katz-stone, 2001). However, as mobile advertising market grows, more and more various ads will be involved in mobile channel especially in local, pull mobile advertising will be the dominate direction of future mobile advertising just like in online channel. Since the smart phone is used more and more widely, a targeted advertising service based on pull marketing strategies on smart phone will be quite helpful in people's life in future.

3. Targeted mobile advertising system based on pull strategy

We develop a targeted mobile advertising system (TMAS) for mobile advertising based on pull strategy. TMAS works as a platform between two different users: advertisers and consumers (mobile users). It uses personalization and pull techniques to deliver targeted ads that can better match consumers' needs. Specifically, it allows consumers to actively specify their needs, and a list of personalized advertisements will be provided to them based on their contextual information including demographics, preference, and others. Also, advertisers can get the valuable information from the platform, which is derived from consumer's feedback and clicks to adjust their advertising.

The framework of TMAS is presented in Fig.1. It includes three modules: Ads Management, User Profile Management, and Ads Intelligent Searching. A Mobile Advertising Service Provider (MASP) interfaces between advertisers and consumers, similar to the role of a retailer in a mobile ads market. In a conventional push mode, mobile ads that are provided by advertisers are pushed to relevant consumers based on the pre-specified customer profile (Carat Interactive, 2002; Scharl et al. 2005). In contrast, in a pull mode, a mobile user actively drags ads to himself/herself to meet his/her needs (De Reyck and Degraeve 2003; Okazaki 2004). Moreover, his/her demands are transmitted back to the advertisers in terms of mobile ads effectiveness and feedback reports which is a kind of common report usually provided by Ads service providers to report the ads effectiveness. It can help to improve advertisers' marketing strategy and ads design.

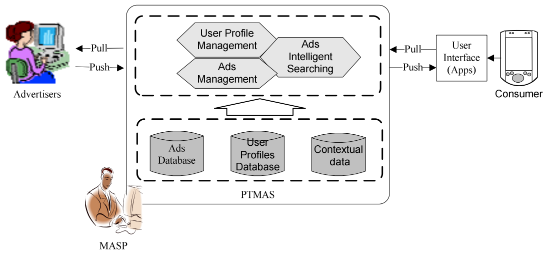

Fig.1 Framework of pull and targeted mobile advertising system

The function of Ads Management Module is to manage the ads data. The data can be used by advertisers to revise their ads. It is commonly used in the current advertising market. Some sophisticated and integrated software are available in the market, such as x10ads and csBanner1. The User Profile Management Module is responsible for creating profiles for new consumers and updating existing user profiles based on their behavior. Ads Intelligent Searching Module provides personalized search results according to the contextual information of the consumers including location, demographic and preference. It is the key to TMAS. It is the typical characteristic of the pull type advertising. The detail process will be described in the following section.

Figure 2 is used to illustrate the detailed process of TMAS, where IDEF0 is adopted because it can model the input, output, control, and mechanism of each process while decomposing a complicated process into sub-processes at the next level. Four kinds of information collected from consumers are used in providing the pull targeted advertising service. First, the keywords input by the consumers. Note that the keyword searching is one of the most direct and efficient way in information retrieval (Aho and Corasick 1975). It helps the system quickly to identify the needs and to reduce the range of relevant ads. The second major source of information is the contextual data that is gathered from consumers' real-time context. It covers a wide range of data (Abowd and Mynatt 2000), including location (Varshney 2003; Leppaniemi and Karjaluoto 2005), time (Venkatesh et al. 2003), weather (Kwon and Kim 2009) and so on. Context-awareness on a mobile device has been an important advantage to provide useful and relevant contents and information to the mobile subscribers ubiquitously (Tarasewich 2003; Jung 2009). The third type of information is demographic data of consumers. Finally, the consumers' behavior and

[1] http://www.cgiscript.net/cgi-script/csNews/csNews.cgi?database=cgi.db&command=viewone&id=23

feedback data are also useful to TMAS. It can be used not only update user profiles but also to generate ads effect and feedback report that can help advertisers to know more about the needs of their customers and to improve advertisement strategies.

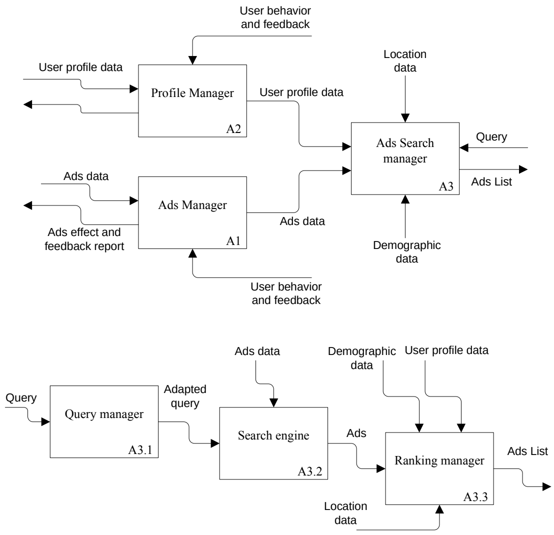

Fig.2 the Detailed Process of TMAS in IDEF Representation

The process begins when a consumer types-in keywords and to solicit mobile ads. All mobile ads are provided by advertisers through the Ads Manager (A1) and stored in the Ads Database. When the system receives the input keywords, it uses them to search in the Ads Database and fetches a batch of ads that are relevant to the consumer's need. Then, the Ads Search Manager (A3) is activated and contextual data is collected (mainly location data). The user profile is called up from Profile Manager (A2) that maintains and updates the User Profile Database. In the Ads Search Manager, Query Manager (A3.1) analyzes the query based on keywords specified by the consumer to prepare the search. Then, Search Engine (A3.2) provides the initial filter to advertisements according to the keywords. Finally, the Rank Manager (A3.3) is the kernel process that matches the ads with the consumers' needs. The higher-interested ads to the consumer should be ranked on the top. When the searching result is presented to the consumer, the system will monitor his/her behavior and feedback and then use them to update the consumer's profile. In addition, the information will also be stored in the Ads Database to form the ads effect and feedback report that will be used to pull customers' needs to advertisers in the future.

The matching between consumers and ads involves many criteria. Also, each consumer has his/her own preference on selecting these criteria. Therefore, it is a multi-criteria decision making (MCDM) process. The attributes that can be taken into account for ads ranking can be distance, discount, service level, quota, expiration date, etc.. Some attributes can be represented into fuzzy functions such as service level and price level. They do not have clear quantitative boundary. We can use some fuzzy comments to describe attributes, such as economic, mediocre, or deluxe for price range and bad, medium, or good for service level. Membership functions can be used to represent the degree of truth as an extension of valuation. Therefore, a fuzzy MCDM method can be adopted for the matching. As mentioned, the Ads Search Manager is an intelligent searching process that provides personalized mobile ads for consumers based on their demographic, preference and contextual information. Demographics and preference data are considered as two categories of user profiles data (Amato and Straccia 1999). They are often used to model user profiles in electronic commerce (Dastani et al. 2005). A user profile indicates explicit representation of a person's identity. It is also considered as the computer representation of a user model (Schreiber et al. 1989). In the TMAS, the Profiles Manager (A2) manages and updates user profiles. Consumers' preference information is very important in this MCDM problem. A user preference can be modeled as a vector of weights to represent the interests of the consumer to different criteria as below:

Let ui denote the preference of attribute i (fi) in the user profile. The preference vector can be defined as $U = (u_1, u_2, ..., u_i, ..., u_m)$, $0 \le u_i \le 1$ and $1 \le i \le m$. TMAS can learn the change of consumers' preference to provide personalized mobile ads. Thus, maintaining an updated user profiles is very important. Here, we use historical behavioral data of consumers' to update their preference. Specifically, when a posted ad ADx is chosen by a consumer y, the consumer preference Uy will be updated as $U_y \xrightarrow{AD_x} U_y'$. The self-learning process allows preference vectors to evolve themselves based on empirical data (Yang 2010).

With the preference information, the MCDM problem can be described as:

$$\max_{a_j \in A} \{ f(a_j) \} \qquad (1)$$

Suppose a decision space A contains n ads that are the result of initial searching $A = \{a_1, a_2, ..., a_n\}$. Let $f_{ij} = f_i(a_j)$ denotes the value of attribute $f_i(a)$ of ad a_j. $f(a_j) = (f_1(a_j), f_2(a_j), ..., f_m(a_j))^T$ represents all the attributes values of ad a_j. If the membership function of $f_i(a)$ is represented as $\mu_{\tilde{f}_i}(a)$, the MCDM problem can be described as:

$$\max_{a_j \in A}\{\mu_{\tilde{f}}(a_j)\} \tag{2}$$

where $\mu_{\tilde{f}}(a_j) = (\mu_{\tilde{f}1}(a_j), \mu_{\tilde{f}2}(a_j), ..., \mu_{\tilde{f}m}(a_j))^T \in [0,1]^m \subseteq R^m$.

We use the Deviation Method of Minimum Subordinative Degree to rank the alternative ads A. The membership of cost attributes and benefit attributes can be calculated by formula (3) and (4).

$$\mu_{\tilde{A}_j}(f_i(a)) = \frac{\sup\{f_i(a)\} - f_i(a)}{\sup\{f_i(a)\} - \inf\{f_i(a)\}} \tag{3}$$

$$\mu_{\tilde{A}_j}(f_i(a)) = \frac{f_i(a) - \inf\{f_i(a)\}}{\sup\{f_i(a)\} - \inf\{f_i(a)\}} \tag{4}$$

$\inf\{f_i(a)\}$ is the lower bound of $f_i(a)$ in A, and $\sup\{f_i(a)\}$ is the upper bound of $f_i(a)$ in A. Let $(\mu_{\tilde{f}1}(a^+), \mu_{\tilde{f}2}(a^+), ..., \mu_{\tilde{f}m}(a^+))^T$ denote the membership vector of the positive ideal solution and $(\mu_{\tilde{f}1}(a^-), \mu_{\tilde{f}2}(a^-), ..., \mu_{\tilde{f}m}(a^-))^T$ denote the membership vector of the negative ideal solution. The distance between a and a^+ should be

$$D(a, a^+) = \sum_{i=1}^{m} u_i(\mu_{\tilde{f}i}(a^+) - \mu_{\tilde{f}i}(a)) \tag{5}$$

The distance a and a^- should be

$$D(a, a^-) = \sum_{i=1}^{m} p_i(\mu_{\tilde{f}i}(a) - \mu_{\tilde{f}i}(a^-)) \tag{6}$$

Let
$$\begin{cases} D(a^-) = \max\limits_{1\le j\le n}\{D(a_j, a^-)\} \\ D(a^+) = \max\limits_{1\le j\le n}\{D(a_j, a^+)\} \end{cases} \tag{7}$$

We can use $\xi(a_j)$ to denote the relative ratio of membership, where

$$\xi(a_j) = D(a_j, a^-)/D(a^-) - D(a_j, a^+)/D(a^+) \tag{8}$$

It represents the degree that how ad a_j approaches positive ideal ad a^+ and how a_j is far away from negative ideal ad a^-. By comparing $\xi(a_j)$, the initial searching results are ranked before they are posted to the consumer. The Ads Search Manger guarantees that the most personalized ads appear in the top positions.

In addition, the user profile can be updated after an ad a_j is clicked by the consumer. The updating procedure can be shown as the follow:

Input:

Consumer C_k's profile: $U^{C_k} = (u_1^{C_k}, u_2^{C_k}, ..., u_i^{C_k}, ..., u_m^{C_k})$, $1 \le i \le m$.

The attributes of clicked ad j: $f(a_j) = (f_1(a_j), f_2(a_j), ..., f_m(a_j))^T$, $1 \le i \le m$

Output:

Updated user profile: $\tilde{u}^{C_k}$.

Updating profiles:

Let ε be the update parameter, which indicates the sensitivity of user profile updating.

Compute $\tilde{u}_i^{C_k} = u_i^{C_k} + \varepsilon[\mu_{\tilde{A}_j}(f_i(a_j)) - u_i^{C_k}]$ (for i=1 to m)

The updated profile: $\tilde{u}^{C_k} = (\tilde{u}_1^{C_k}, \tilde{u}_2^{C_k}, ..., \tilde{u}_i^{C_k}, ..., \tilde{u}_m^{C_k})$, $1 \le i \le m$.

4. Demonstration of TMAS

This section demonstrates the validity and reliability of TMAS system the aspect of consumers and advertisers. In the consumer side, two functions are provided: (1) a consumer could get targeted ads that match his/her preference from the platform; and (2) a consumer's preference is updated based on his/her past behavior. Similarly, to an advertiser, two functions are provided: (1) an advertiser could deliver ads to the potential customers via the platform providing fair impression and chances of clicks to ads; and (2) an advertiser could improve the ads by using the feedback from the TMAS.

As shown in Figure 1, TMAS works as a platform to match mobile users and ads. In the section, we demonstrate a pizza restaurant (advertiser) located in a shopping mall distributes lunch promotion coupon to customers. There are five stages involved. A demon system is built to simulate the key process of Ads Search Manager:

(1) *Post ads on TMAS by the advertiser*. For demonstration, we generated 20 promotion ads of pizza randomly with their attribute of distance (f1), discount (f2), price level (f3), and service level (f4), as shown in Tab.1.

Tab.1 20 ads and their attributes.

AdsID	f_1	f_2	f_3	f_4	AdsID	f_1	f_2	f_3	f_4
AD01	19.57	0.96	4.00	4.00	**AD11**	40.79	0.57	3.00	2.00
AD02	15.96	0.95	4.00	4.00	**AD12**	16.99	0.52	3.00	1.00

AD03	18.41	0.82	1.00	5.00	**AD13**	32.09	0.51	1.00	3.00
AD04	47.52	0.74	3.00	4.00	**AD14**	5.38	0.74	5.00	1.00
AD05	22.07	0.83	4.00	4.00	**AD15**	30.02	0.92	5.00	3.00
AD06	23.12	0.79	4.00	2.00	**AD16**	48.53	0.82	2.00	3.00
AD07	32.29	0.59	2.00	3.00	**AD17**	5.89	0.62	3.00	3.00
AD08	45.37	0.97	5.00	3.00	**AD18**	44.95	0.96	3.00	5.00
AD09	37.10	0.61	4.00	1.00	**AD19**	49.83	0.69	5.00	1.00
AD10	37.77	0.71	4.00	4.00	**AD20**	16.64	0.98	3.00	5.00

(2) *Consumer requests ads from TMAS*: In this stage, the system receives a query (pizza) from consumers. We generated 100 mobile user profiles randomly. Tab.2 shows 10 of the sample.

Tab.2 Sample of 10 user preference

UserID	u_1	u_2	u_3	u_4
User 01	0.455	0.251	0.250	0.042
User 02	0.214	0.438	0.230	0.116
User 03	0.345	0.339	0.311	0.003
User 04	0.098	0.568	0.172	0.160
User 05	0.080	0.457	0.082	0.379
User 06	0.284	0.263	0.182	0.270
User 07	0.066	0.639	0.144	0.150
User 08	0.261	0.221	0.243	0.273
User 09	0.334	0.451	0.151	0.062
User 10	0.292	0.165	0.129	0.412

(3) *TMAS lists targeted ads for consumer.* After receiving the request, ads sorted by Eq. (8) are listed for the consumer. To measure the relevancy of searched results of the consumer, we use three metrics "Precision"(Pj), "Average Cumulative Precision"(ACP) and "Precision at position n"(P@n) (Jarvelin and Kekalainen, 2000; Zareh Bidoki et al., 2010). $\xi(a_j)$ is the relative ratio of affiliation membership which denotes the precision of each ad respected to a given query.

$$P_j = \frac{\xi(a_j)+1}{2}, P_j \in [0,1] \qquad (9)$$

Pj represents the degree of how an ad j matches the user's preference. Pj=0 means ad j is irrelevant to the user while Pj=1 means ad j is perfectly matched to the user's need. The ACP is computed for a single query and is defined as the average of the P values for all searched results.

$$ACP = \frac{\sum_{i=1}^{N} P_i}{N} \qquad (10)$$

The results obtained over 10 consumers are listed in Table 3. Where Pmax indicates the match between the users with the most matched ads (AD14 for User01) and ACP means the precise of the match between the users with the first five ads (AD14, AD10, AD13, AD11, and AD19 for User01). As shown in the table, the maximum precision values of all consumers are between 0.736 and 0.895, and the ACP values are between 0.674 and 0.812. These numbers mean that every ad in top position provided by the platform is relevant and personalized to the consumer.

Tab.3 the results over 10 consumers

UserID	P_{max}	ACP	Ranking（Top 5）
User01	0.895	0.739	$AD_{14} \succ AD_{10} \succ AD_{13} \succ AD_{11} \succ AD_{19}$
User02	0.829	0.689	$AD_{12} \succ AD_{19} \succ AD_{11} \succ AD_{13} \succ AD_{6}$
User03	0.891	0.812	$AD_{14} \succ AD_{19} \succ AD_{12} \succ AD_{17} \succ AD_{15}$
User04	0.905	0.758	$AD_{19} \succ AD_{14} \succ AD_{17} \succ AD_{9} \succ AD_{5}$
User05	0.798	0.690	$AD_{13} \succ AD_{10} \succ AD_{17} \succ AD_{3} \succ AD_{7}$
User06	0.736	0.674	$AD_{18} \succ AD_{3} \succ AD_{4} \succ AD_{2} \succ AD_{12}$
User07	0.832	0.785	$AD_{13} \succ AD_{11} \succ AD_{12} \succ AD_{7} \succ AD_{17}$
User08	0.753	0.722	$AD_{4} \succ AD_{5} \succ AD_{17} \succ AD_{15} \succ AD_{10}$
User09	0.794	0.682	$AD_{17} \succ AD_{12} \succ AD_{11} \succ AD_{9} \succ AD_{7}$
User10	0.838	0.763	$AD_{18} \succ AD_{4} \succ AD_{10} \succ AD_{1} \succ AD_{3}$

Precision at n measures the relevancy of the top n results with respect to a given query can be obtained by

$$P@n = \frac{\sum_{i=1}^{n} P_i}{n}, P@n \in [0,1] \qquad (11)$$

(Noted that Pj is the precise of each ad in ranking result while both ACP and P@n is the degree of relevant of the whole ranking result for each query). Figure 3 presents the average P@n values at top n rank over 100 consumers. The average P@n value ranges from 0.82 to 0.65. P@n value represents the relevancy of the whole top n ads in the searched results. Relatively high P@n value of top 10 positions demonstrates that the intelligent searching process can help consumers to find the ads that are relevant to their needs in top 10 ranking results.

Figure 4 shows the ACP value of top 10 ads over 100 consumers. In the experiment, every consumer gets a relatively high value of ACP ranged from 0.64 to 0.87. This also means that every consumer can get precise ads in top 10 results from the intelligent searching on the platform. The above three indexes (P, P@n, and ACP) show that ads posted by the platform are precise to the consumers. Therefore, the consumers with different preference in the experiment get their satisfied ads from the platform.

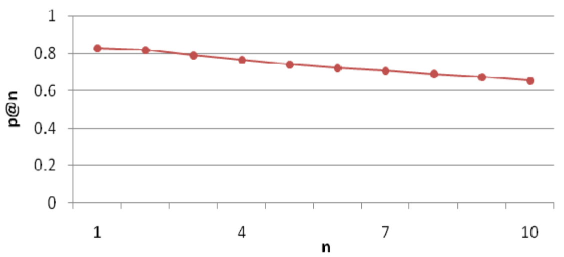

Fig.3 The average P@n of top n rank

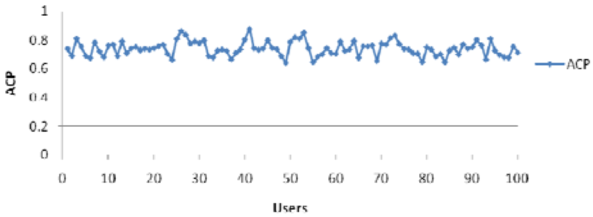

Fig.4 the Average Cumulative Precision of each user over 100 consumers.

On the other hand, since TMAS is a platform, matching the demand from both sides of users, it not only ensure a consumer can located highly relevant ads, but also needs to make sure each ad has the equal opportunity to be viewed by the suitable consumers. Thus, we use "number of times that an ad is ranked in top 10 (N)" and "expected click-through (EC) " to measure the chance that an ad can be retrieved from the platform. In order to compute the expected number of click-through for an ad j at position k, an exponentially decaying attention model with factor δ > 1 is employed in our experiment. Based on (Breese et al., 1998), the average click-through can be computed as p/δk-1. Exponential decay of attention is a standard assumption which is adopted in (Feng et al., 2007) that used the actual click-through data obtained from Overture in 2003 for the top affiliated websites (such as Yahoo!, MSN and AltaVista) to fit in an exponential decay model with δ = 1.428 (R2 = 0.997).

Figure 5 shows the number of times that each ad is ranked in top 10 results and the expected click-through in the experiment over 100 consumers. We can see that the variation of EC value is quite similar to N value. When an ad has higher chance to be ranked in top, it could get more clicks from consumers. We also computed the variance and variance/mean ratio (VMR) to see the variation in N and EC values. The variance and VMR of N value are 192.74 and 4.28, while the variance and VMR of EC value are 44.99 and 3.65. These show that the degree of dispersion in N and EC is relatively small. Every piece of ads can get a relatively fair opportunity to be seen and clicked by the consumers.

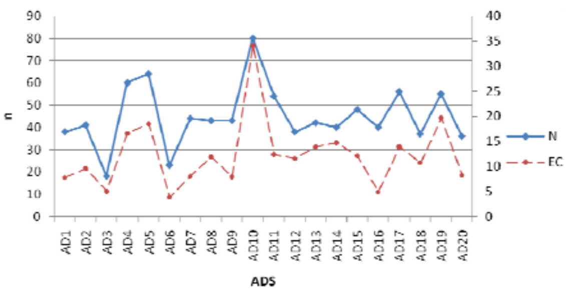

Fig.5 the N and EC value of all ads in the experiment

(4) *TMAS updates consumer preference.* In the stage, we will use the consumer's click feedback to update the user preference. We assume that each consumer only click on one ad from the searched result. Therefore, the 100 user profiles generated above are updated by the procedure mentioned in Section 3. For example:

Input:

Consumer C_1's profile: $U^{C_1} = (0.455, 0.251, 0.250, 0.042)$.

The attributes of clicked AD14: $f(a_{14}) = (5.38, 0.74, 5, 1)$

Output:

Updated user profile: $\tilde{u}^{C_1}$.

Updating profiles:

Let ε = 0.1 be the update parameter, which indicates the sensitivity of user profile updating.

Compute $\tilde{u}_i^{C_1} = u_i^{C_1} + 0.1*[\mu_{\tilde{A}_{14}} f_i(a_{14}) - u_i^{C_1}]$ (for i=1 to m)

The updated profile: $\tilde{u}^{C_1} = (0.456, 0.250, 0.230, 0.061)$.

The 10 sample user preference and updated user preference are shown in Tab.4.

Tab.4 10 Sample updated user preference

User	U	$\tilde{U}$
U01	(0.455, 0.251, 0.250, 0.042)	(0.456, 0.250, 0.230, 0.061)
U02	(0.214, 0.438, 0.230, 0.116)	(0.222, 0.431, 0.226, 0.119)
U03	(0.345, 0.339, 0.311, 0.003)	(0.338, 0.323, 0.320, 0.017)
U04	(0.098, 0.568, 0.172, 0.160)	(0.087, 0.578, 0.184, 0.149)
U05	(0.080, 0.457, 0.082, 0.379)	(0.074, 0.454, 0.092, 0.377)
U06	(0.284, 0.263, 0.182, 0.270)	(0.294, 0.268, 0.176, 0.261)
U07	(0.066, 0.639, 0.144, 0.150)	(0.074, 0.619, 0.155, 0.151)
U08	(0.261, 0.221, 0.243, 0.273)	(0.274, 0.235, 0.232, 0.256)
U09	(0.334, 0.451, 0.151, 0.062)	(0.318, 0.466, 0.143, 0.070)
U10	(0.292, 0.165, 0.129, 0.412)	(0.304, 0.149, 0.139, 0.406)

(5) *TMAS feedbacks to advertisers for improving ads effectiveness.* Finally, the system uses the updated user profiles to revise data and compute the indexes. For each ad, the information of all consumers that clicked the ad is very valuable to the advertiser. In the demonstration, if the average user profile of all consumers that clicked ad j is $\bar{U} = (\bar{u}_1, \bar{u}_2, ..., \bar{u}_i, ..., \bar{u}_m)$, we use $f_i'(a_j) = \frac{n\bar{u}_i f_i(a_j)}{\sum_{i=1}^{m} \bar{u}_i}$ to change the ad's attributes to simulate the improvement of advertisers' advertising strategies. For example, if most of consumers that clicked an ad are discount fancier, the advertiser will give more discount in his ads.

We use the updated 100 user profiles to simulate the same consumers in the stage 1 of the experiment. All ads are also improved based on the feedback. Figure 6 shows the ACP values of each consumer in the two stages. Most of consumers'

ACP value in stage 2 is higher than stage 1. The average ACP of all consumers in stage 2 is 0.775 with an increase of 4.7% to stage 1. Thus, if consumers' user profiles can be updated based on their past click behavior, the platform can provide more precise targeted ads. Consumers can also get more satisfied ads from the platform.

Figure7 shows the EC values of each ad in the two stages. The number of clicks is what the advertisers want. In the figure, EC value of all 20 ads increases more or less in stage 2 (with an average increase of 4.3%). The expected clicks of ads increases after they are improved based on ads effectiveness and feedback information from the platform. If advertisers can acquire valuable information from the platform to improve their advertising strategies, their ads will get more clicks form consumers on the platform.

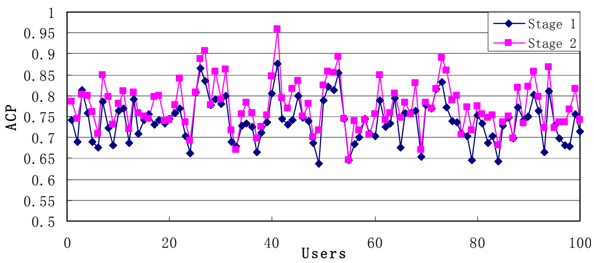

Fig.6 the ACP value of all consumers in the two stages.

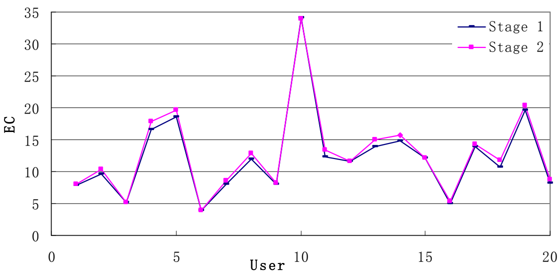

Fig.7 the EC value of all ads in the two stages.

5. Conclusion

In years, the mobile advertising market is maturing. As we can see for many service providers, such as Apple, it is an emerging service to provide an independent advertising service whose primary business is serving mobile ads. We proposed a personalized mobile advertisement platform, called TMAS, to provide the consumers the right ads on their mobile devices and an effective channel for advertisers to access customers. Specially, the TMAS allows consumers to located ads via their mobile phones referring to their needs by and contextual data. To help advertisers, ads effectiveness and feedback information in TMAS can also be used to improve their advertising decision and ads design. The demonstration shows that mobile users can get precise ads from the platform and advertisers can get fair impressions for their ads.

However, there is a trade-off for consumers between privacy protection and mobile ads service effectiveness. That is, when the more detailed information is used the better-personalized ads will be served. Future research can look into the balancing between providing the highly and effectively personalized mobile advertisement without scarifying privacy protection.

References

[1] R. Unni, R. Harmon, Perceived effectiveness of push vs. pull mobile location-based advertising. Journal of Interactive Advertising 7 (2) (Spring 2007) Published online at http://www.jiad.org/article91.

[2] Y. Li, B. Steinberg, Sales call: more ads hit cell phone screens, Wall Street Journal, Eastern Edition 247 (27) (2006) B3.

[3] C. Peters, C.H. Amato, C.R. Hollenbeck, An exploratory investigation of consumers' perceptions of wireless advertising, Journal of Advertising 36 (4) (Winter 2007) 129-146.

[4] B. De Reyck, Z. Degraeve, Broadcast scheduling for mobile advertising, Operations Research 51 (4) (Jul/Aug2003) 509-517.

[5] A.K. Tripathi, S.K. Nair, Narrowcasting of wireless advertising in malls, European Journal of Operational Research 182 (3) (November 2007) 1023-1038.

[6] B. De Reyck, Z. Degraeve, MABS: Spreadsheet-based decision support for precision marketing, European Journal of Operational Research 171 (3) (June 2006) 935-950.

[7] P. Kazienko, M. Adamski, AdROSA—Adaptive personalization of web advertising, Information Sciences 177 (11) (June 2007) 2269-2295.

[8] F. Sultan, A.J. Rohm, How to market to generation m(obile). MIT Sloan Management Review, 49 (4) (Summer 2008) 35-45.

[9] P. Barwise and C. Strong, Permission-based mobile advertising, Journal of Interactive Marketing 16 (winter 2002) 14-24.

[10] Businessweek, Mobile ad biz comes of age, May 14, 2007, Available at: http://www.businessweek.com.

[11] S. Okazaki, How do japanese consumers perceive wireless ads? a multivariate analysis, International journal of Advertising 23 (4) (2004) 429-54.

[12] M. Ferris, Insights on mobile advertising, promotion, and research, Journal of Advertising Research 47 (1) (March 2007) 28-37.

[13] A.K. Tripathi, S.K. Nair, mobile advertising in capacitated wireless networks, IEEE

Transactions on Knowledge & Data Engineering 18 (9) (September 2006) 1284-1296.
[14] S. Okazaki, C.R. Taylor, What is SMS advertising and why do multinationals adopt it? Answers from an empirical study in European markets, Journal of Business Research 61 (1) (January 2008) 4-12.
[15] S. Yuan, C. Cheng, Ontology-based personalized couple clustering for heterogeneous product recommendation in mobile marketing, Expert Systems with Applications 26 (4) (May 2004) 461-476.
[16] Scharl, A. Dickinger, J. Murphy, Diffusion and success factors of mobile marketing, Electronic Commerce Research and Applications 4 (2) (Summer 2005) 159-173.
[17] S. Okazaki, The tactical use of mobile marketing: how adolescents' social networking can best shape brand extensions, Journal of Advertising Research 49 (1) (March 2009) 12-26.
[18] F, Roman, G. Florian, H. Klaus, P. Michael, The march of mobile marketing: new chances for consumer companies, new opportunities for mobile operators, Journal of Advertising Research 49 (1) (March 2009) 54-61.
[19] L. Chiagouris, B. Wansley, Branding on the Internet, Marketing Management 9 (2) (2000) 34-8.
[20] P. Barwise, C. Strong, Permission-based mobile advertising, Journal of Interactive Marketing 16 (1) (2002) 14-24.
[21] L. Spiller, M. Baier, Contemporary direct marketing, Upper Saddle River, NJ: Prentice-Hall, 2005.
[22] S. Yuan, Y. W. Tsao, A recommendation mechanism for contextualized mobile advertising, Expert Systems with Applications 24 (4) (May 2003) 399-414.
[23] Carat Interactive. The future of wireless marketing, White Paper, Boston, MA, 2002, available at: http://www.bjoconsulting.com/download/Wireless_WhitePaper.pdf.
[24] G. P. Cachon, The allocation of inventory risk in a supply chain: push, pull, and advance-purchase discount contracts, Management Science 50 (2) (February 2004) 222-238.
[25] J.T.-S. Quah, G.L. Lim, Push selling–multicast messages to wireless devices based on the publish/subscribe model, Electronic Commerce Research and Applications 1 (3-4) (2002) 235-246.
[26] Katz-Stone, Wireless revenue: ads can work, Australia. internet.com, 2001, Available from: http://www.wirelessauthority.com.au/r/article/jsp/sid/445080.
[27] S.A Adam, model of web use in direct and online marketing strategy, Electronic Markets 12 (4) (2002) 262-269.
[28] D.W. Oard, G. Marchionini, A conceptual framework for text filtering. Technical report CS-TR3643, University of Maryland, College Park, MD, 1996. Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.30.7951&rep=rep1&type=pdf.
[29] C. Mitidieri and J. Kaiser, Attribute-based filtering for embedded systems, Second International Workshop on Distributed Event-Based Systems (DEBS'03), in conjunction with The ACM SIGMOD/PODS Conference, San Diego, US, 2003.
[30] B. L.D. Bezerra, F. A.T. Carvalho, A symbolic approach for content-based information filtering, Information Processing Letters 92 (2004) 45–52
[31] M. Klusch, S. Ossowski, and O. Shehory, Opinion-based filtering through trust, CIA 2002, Lecture Notes in Artificial Intelligence 2446 (2002) 164-178.
[32] M.J. Pazzani, A framework for collaborative, content-based and demographic filtering, Artificial Intelligence Review 13 (1999) 393–408.
[33] R. van Meteren, M. van Someren, Using content-based filtering for recommendation, Machine Learning in the New Information Age (MLnet/ECML2000) Workshop, Barcelona, Spain, 2000.
[34] P. Shoval, V. Maidel, B. Shapira, An ontology- content-based filtering method, International Journal Information Theories & Applications 15 (2008) 303-314.
[35] J.J. Jung, Contextualized mobile recommendation service based on interactive social network discovered from mobile users, Expert Systems with Applications 36 (2009) 11950-11956.
[36] G. D. Abowd, E. D. Mynatt, Charting past, present, and future research in ubiquitous computing. ACM Transactions on Computer-Human Interaction, 7 (1) (2000) 29-58.
[37] M. Leppaniemi, H. Karjaluoto, Factors influencing consumers' willingness to accept mobile advertising: a conceptual model, International Journal of Mobile Communications 3 (3) (2005) 197-213.
[38] U. Varshney, Location management for mobile commerce applications in wireless internet environment, ACM Transactions on Internet Technology 3 (3) (2003) 236-255.
[39] V. Venkatesh, V. Ramesh, A.P. Massey, Understanding usability in mobile commerce, Communications of the ACM 46 (12) (2003) 53-56.
[40] P. Tarasewich, Designing mobile commerce applications, Communications of the ACM

46 (12) (2003) 57-60.
[41] L.K. Brackett, B.N. Carr, Cyberspace advertising vs. other media: consumer vs. mature student attitudes, Journal of Advertising Research 41 (5) (2001) 23-32.
[42] O. Kwon, J. Kim. Concept lattices for visualizing and generating user profiles for context-aware service recommendations, Expert Systems with Applications 36 (2009) 1893-1902.
[43] S. Myaeng, R.R. Korfhage, Integration of user profiles: models and experiments in information retrieval, Information Processing and Management 26 (6) (1990) 719-738.
[44] G. Amato, U. Straccia, User profile modeling and applications to digital libraries, ECDL'99, Lecture Notes in Computer Science 1696 (1999) 184-197.
[45] M. Dastani, N. Jacobs, C. M. Jonkerc, J. Treur, Modelling user preferences and mediating agents in electronic commerce, Knowledge-Based Systems 18 (2005) 335–352.
[46] F. A. Schreiber, F. Barbic, S. Madeddu, Dynamic user profiles and flexible queries in office document retrieval systems, Decision Support Systems 5 (1) (March 1989) 13-28.
[47] A.V. Aho, M.J. Corasick, Efficient string matching: an aid to bibliographic search, Communications of the ACM 18 (6) (June 1975) 333-340.
[48] E. Aimeur, G. Brassard, J. M. Fernandez, and F. S. Mani Onana, Privacy-preserving demographic filtering. ACM Symposium on Applied Computing (SAC2006), Dijon, France, April 23-27, 2006.
[49] R. Briggs, N. Hollis, Advertising on the web: is there response before click-through? Journal of Advertising Research 37 (2) (1997) 33-45.
[50] C. J. Keng, H. Y. Lin, Impact of telepresence levels on internet advertising effects, CyberPsychology & Behavior 9 (1) (2006) 82-94.
[51] D. L. Hoffman, P. N. Thomas, Marketing in hypermedia computer-mediated environments: Conceptual foundations, Journal of Marketing 60 (3) (1996) 50-68.
[52] C. H. Cho, J. G. Lee, T. Marye, Different forced-exposure levels to banner advertisements, Journal of Advertising Research 41 (4) (2001) 45-56.
[53] Y. Wang, and Y. Luo, Area ranking of fuzzy numbers based on positive and negative ideal points, Computers and Mathematics with Applications 58 (2009) 1769-1779.
[54] G. You, S. Hwang, and H. Yu, Supporting personalized ranking over categorical attributes, Information Sciences 178 (2008) 3510-3524.
[55] A. M. Zareh Bidoki, P. Ghodsnia, N. Yazdani, and F. Oroumchian, A3CRank: An adaptive ranking method based on connectivity, content and click-through data, Information Processing and Management (2010), doi:10.1016/j.ipm.2009.12.005.
[56] K. Jarvelin, and J. Kekalainen, IR evaluation methods for retrieving highly relevant documents. In Proceedings of the ACM conference on research and development on information retrieval (SIGIR) (2000).
[57] J. S. Breese, D. Heckerman, C. Kadie, Empirical analysis of predictive algorithms for collaborative filtering. Proceedings of the Fourteenth Conference on Uncertainty in Artificial Intelligence. University of Wisconsin Business School, Madison, Wisconsin (1998) 43–52.
[58] M. Langheinrich, A. Nakamura, N. Abe, T. Kamba, Y. Koseki, Unintrusive customization techniques for web advertising, Computer Networks 31 (11-16) (1999) 1259-1272.
[59] S. Balasubramanian, R.A. Peterson, S.L. jarvenpaa, Exploring the implications of M-Commerce for markets and marketing, Journal of the Academy of Marketing Science 30 (4) (2002) 348-361.
[60] D.J. Xu, S.S. Liao, Q, Li, Combining empirical experimentation and modeling techniques: A design research approach for personalized mobile advertising applications, Decision Support Systems 44 (2008) 710－724.
[61] P. Germanakos, N. Tsianos, Z. Lekkas, C. Mourlas, G. Samaras, Improving M-Commerce Services Effectiveness with the Use of User-Centric Content Delivery, Journal of Electronic Commerce in Organizations 6 (1) (2008) 1-19.
[62] R.R. Yager, Targeted E-commerce marketing using fuzzy intelligent agents, IEEE Intelligent Systems 15 (6) (2000) 42-45.
[63] D.J. Xu, The Influence of Personalization in Affecting Consumer Attitudes toward Mobile Advertising in China. Journal of Computer Information Systems 47 (2) (2006) 9-19.
[64] F. Bamba, S.J. Barnes, SMS advertising, permission and the consumer: a study, Business Process Management Journal 13 (6) (2007) 815-831.
[65] D.Y. Choi, Personalized local Internet in the location-based mobile web search, Decision Support Systems 43 (1) (2007) 31-45.
[66] Y. Yang, Web user behavioral profiling for user identification, Decision Support Systems 49 (3) (2010) 261-271.