Mobile Advertising: Triple-win for Consumers, Advertisers and Telecom Carriers

(position paper)

Chia-Hui Chang
National Central University
No. 300, Jung-Da Rd., Chung-Li
Tao-Yuan, Taiwan 320, R.O.C.
886-3-4227151 x 35327
chia@csie.ncu.edu.tw

Kuan-Hua Huo
National Central University
No. 300, Jung-Da Rd., Chung-Li
Tao-Yuan, Taiwan 320, R.O.C.
886-3-4227151 x 35327
985202044@cc.ncu.edu.tw

ABSTRACT
Mobile devices (e.g. smart phone, PDAs, vehicle phone, and e-books) are becoming more popular. However, mobile broadband subscriptions are only 20 percent of the mobile subscriptions. Part of the reasons is due to the high payments requirement for broadband subscriptions. On the other hand, US mobile ad spend will exceed US$1 billion in 2011 according to emarketer.com. Therefore, the idea of this paper is to increase broadband subscribers by providing free or discounted fees through the deployment of mobile advertising framework by the telecommunication system. Telecom operators can run the ads agent platform to attract investments from advertisers. Subscribers read promotional advertisements that are sent to subscribers' mobile phones to get discounted payment. While the advertisers pay a reasonable price for advertising, the possible commercial activities will bring revenues to advertisers. As a result, this framework is a triple-win for telecom carriers, advertisers and subscribers. We describe a framework for delivering appropriate ads of the ideal time at the ideal place to the ideal subscriber is the three key issues on how to show the ads, when to show the ads, and what potential ads to be clicked by the subscribers. We take user velocity and user location into consideration.

Categories and Subject Descriptors
D.3.3 [**Programming Languages**]: Language Constructs and Features – *abstract data types, polymorphism, control structures*. This is just an example, please use the correct category and subject descriptors for your submission. The ACM Computing Classification Scheme: http://www.acm.org/class/1998/

General Terms
Your general terms

Keywords
Mobile advertising, Ad classification, Ad taxonomy construction

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INTRODUCTION
In recent years, we have seen the trends in the growing popularity of mobile device (e.g. mobile phone, PDAs, vehicle phone, and e-books) and mobile commerce application (e.g. mobile financial application, mobile inventory management, and mobile entertainment, etc.). According to the report of International Telecommunication Union (ITU), mobile cellular subscriptions have reached an estimated 5.3 billion (over 70 percent of the world population) at the end of 2010. In addition, the number of mobile devices in some countries is larger than their population, e.g. Taiwan, England, Netherlands, and Italy. Intuitionally, mobile device is now playing an increasingly important role in human life. Moreover, it is becoming a special market potential. According to IAB[1] (Interactive Advertising Bureau), mobile advertising is accepted by a lot of consumers, comparing to online advertising on World Wide Web due to its highly interactive with users, which is hard to achieve for other media. Mobile advertising is an alternative way of web monetization strategies, especially for telecommunication corporations to expand revenue. Furthermore, it is predicted that the average annual growth will rose by 72% in the next five year.

There are many ways of mobile communication, such as WAP, GPRS, 3G modem, and PHS. However, due to high charge of internet access, not all users have mobile internet access. Mobile broadband subscriptions are 1 billion (about 20 percent of the mobile subscriptions)[2]. In Taiwan, for example, the ratio of the mobile web users to the mobile users is less than 50%. Meanwhile, VAS (Value-Added Services) is deeply influenced by prices. There are about 75% customers, who will consider prices rather than interest when choose VAS [14][15]. Therefore, the lower VAS prices and internet accessing charges the customers get, the more customers we find. Thus, a way to reduce the internet accessing fee mobile devices is important.

In this paper, we propose a framework for mobile advertising, which involves the telecomm operators, the advertiser, and the subscriber. It is dubbed "triple-win" that all of them get benefits from each other. Figure 1 shows the layout of this framework. The telecom operator provides the Ads Agent Platform to attract campaign for advertisers. The advertiser registers commercial ads with the telecom operators, and pays a reasonable price. The users

1 http://www.iab.net/media/file/StateofMobileMarketing.pdf

2 http://www.mobiletechnews.com/info/2011/02/02/131112.html

subscribe for promotional ads, which are sent to their mobile devices by the Ads Agent Platform in order to get discounted internet accessing from the telecom carrier. Within this framework, the advertiser gets repay when the ads bring potential customers; the telecommunication gets benefit by increasing the number of internet subscribers; and the subscriber also gets coupons and discounted internet accessing. As a result, this framework is triple-win for the telecom carrier, the advertisers and the subscribers.

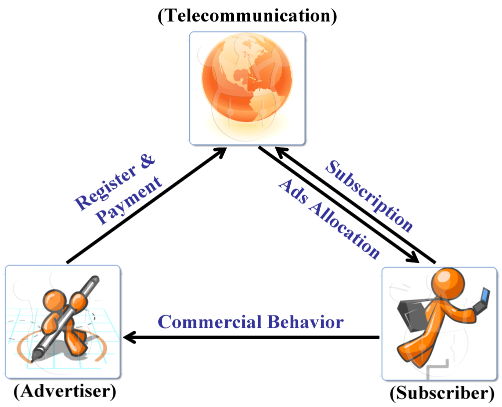

Figure 1. The framework contains 3 key players.

However, delivering appropriate ads of the ideal time at the ideal place to the ideal subscriber are key issues. We consider HWW (How, When and What), the three key issues that we really care about: (1) How do we show the ads in subscribers' mobile phone? (2) When should we show the ads to ensure subscribers will read ads without redundancy? (3) What potential ads will be clicked by the subscribers?

Since the subscribers get discounted internet access, we have to ensure the subscribers will read mobile ads. One possible way to this problem is to employ a particular application, say a browser, to show mobile ads. In such a scenario, the users read the ads while using the application. This mechanism is fair if the internet access is charged by number of data packets. However, the disadvantage is that the users only read ads when this particular application is running which does not fully utilize the bandwidth if the users subscribe an unlimited wireless internet access. Thus, we also suggest using the terminate but stay resident mechanism (TSR) such as the BroadcastReceiver service application in android to ensure that the textual ads will remain loaded and wake up for presenting mobile ads. By recording the time users spent on ads, we can give discount price for mobile internet services.

As for what ads to be shown on the subscribers' mobile devices, we propose the utilization of location information and users' accessibility for ad allocation. The idea is that while assessing users' interest based on their profiles, the system could also consider ads that are near the location of the users. More specifically, the system decides whether to push ads to users according to users' accessibility, e.g. whether the users are able to reach the product promoted in an ad. The mechanism we will use is the speed which controls the accessibility of users.

In this paper, we describe our design for mobile advertising platform based on three aspects: context, content and user preference. The system makes utilization of velocity-detection and content-match to allocate personalized ads. In order to decrease redundant ads and to increase business value, mobile ad matching system should consider subscriber's current status and activities before delivering personalized mobile ads.

1. RELATED WORK

1.1 Consumer Behavior and Personalized Advertising

Marketing researchers have studied consumer behaviors [4] for decades from analyzing the factors of consumer behaviors and to model building. Turban et al. analyzed the main factors on consumer's decision, including consumer's individual characteristics, the environment and the merchant's marketing strategy (such as price and promotion). Varshney and Vetter [16] also proposed the use of demographics, location information, user preference, and store sales and specials for mobile advertising and shopping application. Rao and Minakakis [15] also suggest that customer profiles, history, and needs are important for marketing. Chen et al. [2] collect 13 factors of mobile advertising such as weather, user's activity, location, time, device type, promotion, price, brand, background of user, preference, interest, searching history, and virtual community. Xu et al. proposed a user model based on experimental circumstances studies of the restaurants, and used Baysian Network to analyze which variables would affect the attitude of consumers toward mobile advertising.

In summary, the most effective factors can be divided into three parts: Content, Context and User Preference. Content factor includes brand, price, marketing strategy, etc. Context factor includes user location, weather, time, etc. At last, User Preference includes brand, interest, user activity, etc.. Online (Web) advertising is shown to be more effective than traditional media since it predicts user's intent by the pages that the user visits. However, for mobile advertising, more contextual information and user preference can be obtained based on the location, speed of users' mobile device.

1.2 Web Contextual Advertising

In contextual advertising, an ad generally features a title, a text-based abstract, and a hyperlink. The title is usually depicted in bold or a colorful font. The latter of the abstract is generally clear and concise due to space limitations. The hyperlink links to an ad web page, known as the landing page.

Several studies pertaining to advertising research have stressed the importance of relevant associations for consumers [11] and how irrelevant ads can turn off users and relevant ads are more likely to be clicked [1][6][9][10]. They show that advertisements that are presented to users who are not interested in can result in customer annoyance. Thus, in order to be effective, researchers conclude that advertisements should be relevant to a consumer's interest at the time of exposure. Novak et al. [1][12] reinforce this conclusion by pointing out that the more targeted the advertising, the more effective it is. As a result, certain studies have tried to determine how to take advantage of the available evidence to enhance the relevance of the selected ads. For example, studies on keyword matching show that the nature and number of keywords impact the likelihood of an ad being clicked [1].

Ribeiro-Neto et al. [15] proposed a number of strategies for matching pages to ads based on extracted keywords. To identify the important parts of the ad, the authors explored the use of different ad sections (e.g., bid phrase, title and body) as a basis for the ad vector. The winning strategy required the bid phrase to appear on the page, and then ranked all such ads using the cosine of the union of all the ad sections and the page vectors [10][11][13]. While both pages and ads are mapped to the same space, there exists a discrepancy (called "impedance mismatch") between the vocabulary used in the ads and on the pages. Hence, the authors improved matching precision by expanding the page vocabulary with terms from similar pages.

Besides, in contextual advertising, Fan et al. proposed the utilization of sentiment detection for blogger-centric contextual advertising. The results clearly indicated that their proposed method can effectively identify those ads that are positively correlated with the given blog pages [5][6].

1.3 Mobile Advertising

Mobile advertising is predicted to will become an important telecommunication's revenue and monetization strategies. Comparing to web-based advertising, there are several advantages of mobile advertising, including high penetration rate, personal communication device, individually addressable, multimedia capability, and interactive. Thus, advertisers can associate each user with fully personalized ads to increase large value of mobile ads.

The existing mobile advertising methods can be divided into 3 categories including SMS, Applets, and Browser. SMS typically contain one or more commercial offers or ads that invite users to subscribe or purchase products and services. Mobile ads embedded in applets are contextual ads that are set pop-up when users are using the applets. The browser is a particular applet for retrieving, presenting, and traversing information resource on the World Wide Web. Mobile ads showed in browser are more similar contextual advertising on the web. Note, both applets and browsers require data transmission through the internet. This leads to additional payment of internet charges to users, while receiving SMS is free for users.

SMS, one of the world's most popular message services, is so far the most common mobile advertising for enterprises. However, due to infrastructure limitations, it does not support customized mobile ads per individual. Thus, many users treat these SMS as spam. As indicated by Giuffrida et al. in [7], even though the mobile advertising makes a substantial improvement in overall business performance by targeting users with most relevant offers based on user purchase histories, the hard limit imposed by the carrier forces them to target clusters of consumers and send to all users in a cluster.

In addition, AdMob is a mobile advertising company acquired by Google in November 2009. It is one of the world's largest mobile advertising platforms and claim to serve more than 40 billion mobile banner and text ads per month across mobile Web sites and handset applications. Furthermore, on April 8, 2010, Apple Inc. announced iAd as a mobile advertising platform for its mobile devices including iPhone, iPod, iPad. iAd, prat of Apple's iOS 4, allows third-party developers to embed ads into their applications directly. When users tap on an iAd banner, a full-screen ad appears within the application. In conclusion, the mobile advertising is significant for the mobile phone industry, thus, the two largest smart phone OS providers (Android and iOS) have created the platform for programmers to benefit users by free applications.

As mentioned earlier, mobile broadband adoption using 3G are about 20 percents of all mobile subscriptions worldwide due to high price. Thus, it seems promising to explore the mobile advertising market for telecom industry. In fact, the telecom industry has used SMS for mobile advertising since a long time ago. However, such advertising mechanism does not work well since users do not gain any benefit. On the other hand, web-based advertising provided by Google and Apple is more acceptable by users for the reason of free applications. By providing discounted broadband subscriptions, users are more willing to read advertisements. After all, the idea of paying broadband subscription fee to receive ads will not make users feel good, even for free applications. For example, VIBO Telecom Inc. in Taiwan, provides MobiBon service for users to obtain bonus by reading online ads. However, the data transmission of MobiBon is paid by users. We believe that the proposed framework in this paper could solve the dilemma and increase the revenue for telecom industry.

2. DESIGN METHODOLOGY

2.1 Address the 3 key issues for mobile advertising

Sending the most potential ads at the ideal time to the right subscribers is the core value of effective mobile advertising. Here, we consider the transmission media, the transmission time and selection mechanisms for mobile advertisement and discuss them respectively.

- *SMS or Broadband Ads?*

There are 2 mechanisms for existing mobile advertising: SMS and broadband advertisement. SMS is one of most common way of mobile advertising. It often contains textual ads to promote products and services. However, the infrastructure limitation of SMS makes full customization infeasible [7]. On the other hand, broadband ads are not restricted by this limitation and can be supported by cloud computing technique.

For broadband advertising, the access prices/fees of mobile broadband services will also affect the advertising mechanism. If the access fees are charged by packages, the style of the ads and the number of ads to be delivered can be limited. If, however, the subscribers have unlimited internet access, various style of ads can also be considered. Here, we consider a design of ad allocator which can be applied for both situations via mobile broadband service. While delivering ads to subscribers, the potential ad allocator also records the time that user spent on ads, the number of mobile ads that are clicked/closed by the user in exchange for discounted mobile broadband access. This kind of design can work for either kinds of charging methods.

In addition, due to the limited size of smartphone screen and data transmission charge, we use the textual ads as the mobile ads to save the screen space. We show the mobile ads on the top of screen to get subscribers attention. If the subscribers are interested in the ads, he/she can read the detail by clicking on the ads. The subscribers can also submit query to the mobile ad allocator for promotions and select products by themselves. In the meantime, the mobile ad allocator provides maps and the location information of the products. He/she can visit the nearby stores. We consider such activities to be more effective, since the subscriber is more likely to buy their favorite products.

- *When to show the ads?*

Two timing often used in mobile advertising are trigger-based and fixed-schedule. The trigger-based timing refers to activities which happen after certain user events. For example, the mobile ads are sent to the user when the user sends or receives SMS in [14]. In our framework, the mobile ad allocator is designed with both fixed schedule as well as trigger-based advertising. To avoid redundant ads and to reduce the system loads, the mobile ad allocator does not match or show ads when the phone is on standby mode. When a smart phone is running on standard power mode, mobile ads are shown in an interval of 30 minutes. However, ads will also be triggered when the smart phones wake up from standby mode for five minutes or by submitted queries.

- *Ads Allocation Factors*

As mentioned earlier, mobile advertising has a wide variety of factors to be considered, including: context, content and user preference. In our framework, we consider one context factor (locality) and three dimensions of content factor including product category and promotion activity as well as short-term interest represented by user query.

- Locality: We consider the reachibility of ads based on user location and velocity. That is, the system calculates the available range of a user and then selects mobile ads from the available range for recommendation. The motivation is to attract customers who are near the store.
- Product category: the system categorizes ads can be classified into 9 categories: clothing, healthy & beauty, baby & kids, computers, electronics, furniture, grocery & gourmet, outdoor living and book & office supplies. The ad category is paired with the long-term interest of the user.
- Promotion: price and discount are the most significant factor for customers' decision. For users who make decisions based on price and discount, such information is a key factor.
- Finally, user query reflects the factor for short-term requirement that is trigger-based advertising. Such information can be used to locate ads that are of short-term interest to users.

These four factors and the mapping between the user and the content are used for personalized ads allocation.

2.2 System Architecture

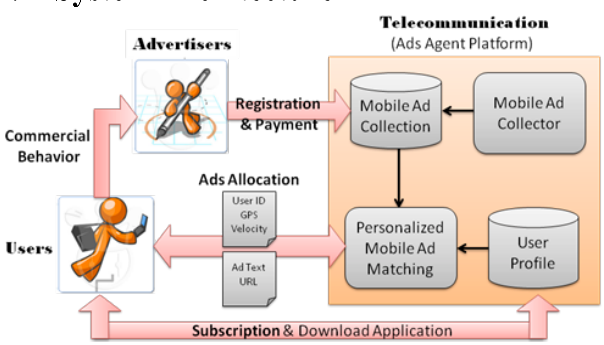

Figure 2. Ad Agent Platform

As shown in figure 3, the Ad Agent Platform consists of three components: the mobile ad database, the user profile and the personalized ad matching. When the advertiser registers commercial mobile ads, we obtain the data for the mobile ad database. Similarly, we can attain subscriber's information as user profile when they subscribe for the mobile advertising service and download the mobile ad allocator which is developed by carrier to get discounted broadband access. The ad allocator matches mobile ads with user profiles based on subscriber's location information and current velocity.

2.3 Personalized Ad Matching

Personalized ad matching can be regarded as an information retrieval problem. In other words, we can calculate similarity between the user information and the ad information with combination of various IR models.

Ad Allocation Algorithm
1. Ads filtering based on GPS and velocity v. Radius = v * m 2. Content similarity scoring based on long-term and short-term: $Sim_{score}(\vec{u},\vec{a}) = \alpha \times Jaccard(u,a) + Cos(q(u),t(a)) + Cos(q(u),p(a))$ − Jarccard similarity for 5 product categories and promotion − Cosine similarity for user query and ad titles / landing pages 3. If the highest score of filtered ads in step 1 is less than α, then add top ranked 50 ads by discounted score.

Figure 3. Personalized ad matching algorithm

Our ad matching algorithm is given in figure 4, which contains 3 steps: ad filtering, content similarity computation and adjustment. In our opinion, we try to find the ad which is satisfying the user needs from context information. That is, we suppose probably the user needs, and then we select the most related ad though the scoring function of the candidate ads.

First, we calculate the radius, the available distance, **Radius**, which a user **u** can arrive in **m** minutes. Assuming the velocity of the user **u** is **v**, then we get **Radius=v*m**. The mobile ads in this range is denoted by **R(u)={a|d(a,u)<Radius}** where **d(a,u)** represents the distance between the user **u** and the store of the ad **a**.

Next, for each candidate ad, we calculate the content similarity score between ad **a** and user **u**. The long-term factors include the promotion activity and five product category, which are binary attributes, so we calculate them by Jaccard similarity $Jaccard(u,a)$. Furthermore, the short-term factor, represented by user query, $q(u)$ is compared with ad titles $t(a)$ and landing pages $p(a)$ to get the cosine similarity, denoted by $Cos(v_1,v_2) = v_1 \bullet v_2$. Note that Jaccard similarity scores can sometimes dominate the content similarity score. So, the Jaccard similarity score is multiplied by a weighted value α, α ∊ [0.1, 0.2].

Finally, after the calculation of content similarity, if the highest score of the filtered ads in R(u) is less than α, then the top *k* ads with discounted content similarity score are added based on distance average. For ads with distance less than average distance, the discounted score is calculated by $Sim_{discounted}(u,a) = 0.5 \times Sim_{score}(u,a)$; while, for ads with distance larger than average distance, the discounted score is calculated by $Sim_{discounted}(u,a) = 0.3 \times Sim_{score}(u,a)$. On completion of ordering the scores, we can get the ads that are most appropriate for the user **u**.

Different from other locality design method, availability area, which shown in ad filtering, is calculated for recommending nearby ads.

3. MOBILE AD COLLECTOR

In general, the information of mobile ads is acquired from the advertiser when the advertiser registers the advertisement with the telecom carrier. However, we didn't have a massive amount of mobile ads in live data because this framework does not run in a real business environment. Thus, we build a mobile ad collector, which collect ads from online advertisements.

3.1 Ad-crawler Platform

Due to the lack of considerable amount of mobile ads, we proposed a mobile ad collector, which collect online advertisements automatically from Google AdSense[3] as shown in

[3] http://www.labnol.org/google-adsense-sandbox/

[5]. First, we choose some general topic words as the query term to request web pages from search engines such as Google and Yahoo! About 200,000 web pages are retrieved as our web page set. Next, we place these web pages on the ad-clawer platform to obtain the corresponding online ads assigned by Google AdSense. The information of these online advertisements consisted of hyperlink, title and abstract. For matching with user, we extract promotion information and conduct ads classification into five categories for each online ad from its landing page

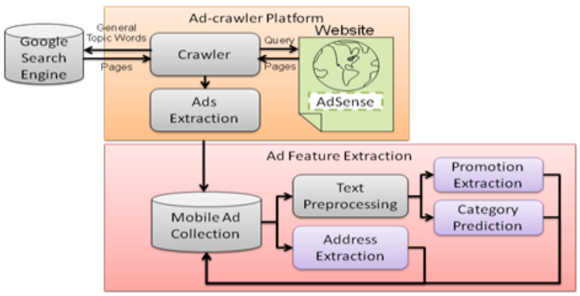

Figure 4. The mobile ad collector

In order to calculate the similarity between the user and the ad, we extract features including postal address, promotion activity, product category and user query (or the brand name) as the mobile ads factors in our system. We extracted these features for each online ad from its landing page as follows.

3.2 Ad Feature Extraction

- *Postal Address Extraction*

First, we describe the process of the postal address extraction. The landing page of each online advertisement may contain the location information for consumers. A landing page could even contain more than one postal address. For example, the location search page for KFC[4] lists ten postal addresses in one web page. Thus, an ad could be associated with more than one postal address. Unfortunately, only 4,003 online advertisements contain postal addresses (a total of 9,327 postal addresses are extracted). Hence, we randomly assign a geographic coordinates around a user to each online advertisement for the rest 54,709 online advertisements. Using Google Map API[5], we convert each geographic coordinates into a post address.

- *Text Preprocessing*

Before introducing the promotion activity identification and the product category classification, the landing page of each online advertisement is processed for term representation. The preprocessing steps include HTML tag removal, tokenization, stemming, etc. Finally, we count term frequency in each landing page. To be brief, the text preprocessing is a process to translate the raw landing pages into term features and term frequency.

- *Promotion Activity Identification*

Next, we introduce the promotion activity identification, which is regarded as a classification task. The promotion classifier is implemented with the tool WEKA[6] using bag of words representation. We train a model to classify whether an ad contains promotional information with supervised learning. We manually label 550 online ads with postal addresses in Illinois for 10-fold cross validation. The (weighted) average precision, recall and F-Measure are about 88.9%.

Table 1. The average F-Measure is 0.889.

Class	Precision	Recall	F-Measure
no promotion	0.907	0.94	0.923
promotion	0.846	0.773	0.808
Weighted Average	0.889	0.891	0.889

- *Category Prediction*

The last task is the product category prediction. Five classes including delicacies, clothing, residence, transportation and life service are used for product categories. To prepare training data, we define some query keywords for each category (except for the last category: life service), and use an IR system to retrieval top relevant ads for manual labeling. Relevant ads are used ad positive examples, while negative examples are chosen randomly. For each categorization task, around 300 training examples including equal number of positive and negative examples are collected for training data. Then, a binary classifier is trained by state-of-the-art learning algorithm using 10-fold cross-validations. Note that if an ad is not classified to any category, we attributed with the life service category. In brief, we make use of an IR system to prepare the training data for each product. Such a mechanism may also assist advertisers to predict product categories and shopping web sites to classify an immense amount of products into categories automatically in commercial activity. Table 2 shows the performance (weighted average) of the categorization tasks are acceptable (above 90%) except for the category "residence" (81.4%).

Table 2 Ad Categorization Performance

Class	#Examples	Precision	Precision	F-measure
Delicacies	313	0.911	0.911	0.911
Clothing	302	0.984	0.983	0.983
Residence	302	0.815	0.815	0.814
Transportation	302	0.931	0.930	0.930

4. PRELIMINARY RESULTS

We built a simulated platform to evaluate the effectiveness of our approach. The location of the experiment is set at Illinois, USA. Two situations are copied in the simulated platform: surrounding situation is when the user goes around without particular destination, while route situation is when the user travels from a start location to some end location. The simulated platform is a web site written in HTML, Java Script and PHP.

The evaluation is measured by precision, recall and F-measure per user base and then averaged over all subjects. Thus, the precision of a user is defined as the number of ads recommended and clicked over the number of ads recommended. Here, the precision is equal to click through rate (CTR). The recall of a user is defined as the number of ads recommended and clicked over the number of ads clicked. F-measure is computed as normal.

Table 3 shows preliminary result of the proposed approaches with 10 subjects, each with 20 runs of tests. At each run, the user is presented with four ads selected by four approaches. The proposed

4 http://www.kfcclub.com.tw/Story/Store/

5 http://code.google.com/intl/zh-TW/apis/maps/documentation/services.html#Geocoding_Structured

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

approach includes all four factors, while user information excludes locality factor. We also show the performance of the locality factor and random selection as a comparison. As shown in Table 1, the proposed approach in this paper (with four factors) achieves the best performance.

Table 3. Performance with various approaches

Approach	Precision	Recall	F-measure
Our approach	0.555	0.367	0.442
User information	0.349	0.231	0.278
Locality	0.45	0.297	0.358
Random	0.16	0.106	0.128

5. CONCLUSION AND FUTURE WORK

Mobile devices are more and more popular and vital for people's life. So, mobile advertising will be an important market for web monetization. Google and Apple have launched their mobile advertising strategies through AdMob and iAd, which will bring revenue for the OS providers by sharing profits with programmers. While telecom operator still have a hard time increasing the number of broadband subscriptions since many student users still consider the cost to be the main issue. In this paper, we propose the framework that is a triple-win for the telecom operator, the mobile advertisers and the subscribers. We address the three key issues: (1) how to show the mobile ads, (2) when to show the mobile ads and (3) what potential mobile ads will be click by the subscribers. Our system recommends mobile ads to the users based on the factors of velocity-detection and content-match. In order to conduct experiments, we also design a mobile ad collector, which crawls online advertisements automatically. The preliminary result shows that ad allocation based on all factors (locality, product category, promotion and user query) can achieve the best performance.

In the future, personalized advertising base on the individual history can be explored to increase mobile advertising effectiveness. In addition, click fraud is also an important issue that needs to be prevented just like online advertising. Thus, the storing and updating of users' information to telecom carriers has to be secured.

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