Behavioral Cost-Based Recommendation Model for Wanderers in Town

Kenro Aihara, Hitoshi Koshiba, and Hideaki Takeda

National Institute of Informatics, 2-1-2 Hitotsubashi, Chiyoda-ku, Tokyo 101-8430, Japan
{kenro.aihara,hkoshiba,takeda}@nii.ac.jp

Abstract. This paper proposes a new model for recommendation based on the behavioral cost of recommendees in town. The model is based on cost-benefit analysis of the information provided to the user, referring to the model of temporal discounting and preference reversal. Here we assume that behavioral cost may be regarded as time in temporal discounting. A recommender system based on this model can select information, which is located in the surrounding area (not so far away) and may be preferred by the user, if the system can estimate where the reversal phenomenon may occur. The experiments were made using an experimental social service, called "pin@clip", which is an iPhone-based social bookmarking service in Shibuya, Tokyo, Japan that has been operating since December 2009. The experimental results show that the phenomenon of preference reversals might occur, even though the authors could not obtain statistically significant data.

Keywords: context-aware computing, location-based service, recommender system, behavioral cost, user modeling.

1 Introduction

In recent years, the amount of geotagged information, which contains geographical data, has been rapidly growing. GPS-equipped smartphones facilitate users to embed location data in their content, such as tweets and photos, and to post them to social services like Facebook[1] and Twitter[2]. Meanwhile, map-based online services like Google Maps[3] are getting more and more popular, and one can use them for navigation while one is roving in town.

A lot of recommender systems have been proposed for wanderers [1][2]. Almost all of them seem to be location-aware and assume that the nearer the provided information is located, the more useful it is for users. This assumption implies that the information that may be preferable for the user but located a little further away vanishes from the user because of a massive amount of information, such as micro blogs like Twitter tweets. On the other hand, although a recommender system can filter out the information that is probably uninteresting to the user based on the collaborative

1 http://www.facebook.com/
2 http://twitter.com/
3 http://maps.google.com/

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filtering model that is broadly used in existing recommender systems on the Internet, the authors suppose that the information that may be preferable to the user must depend on the user's situation and the collaborative filtering model is not enough, especially when the user is wandering around in town.

First, this paper shows the proposed model with related models in psychology and behavioral economics. Next, the experimental mobile service for social bookmarking, pin@clip, is introduced briefly. Then, an experiment and its results are described. Finally, the validity of the model and future issues are discussed.

2 Background

2.1 Location-Based Information Services

A lot of network services with location data are proposed, and some of them, such as foursquare[4], are getting popular. Usually location information is given as geographical coordinates, that is, latitude and longitude, a location identifier such as ID for facilities in geographical information services (GIS), or a postal address. Google has launched Google Places[5], which gathers place information from active participating networkers and delivers such information through Google's web site and API (application programmable interface). Google may try to grasp facts and information on activities in the real world where it has not enough information yet even though it seems to have become the omniscient giant in the cyber world. Google already captures some real world phenomena in its own materials. For example, it gathers landscape images with its own fleet of specially adapted cars for the Google Street View service. However, the cost of capturing and digitizing facts and activities in the real world is generally very expensive if you try to obtain more than capturing photo images with geographical information. Although Google Places may be one of the reasonable solutions to gathering information in the real world, it's not guaranteed that it can grow into an effective and reliable source reflecting the real world.

Existing social information services, such as Facebook and Twitter, are expanding to attach location data to users' content.

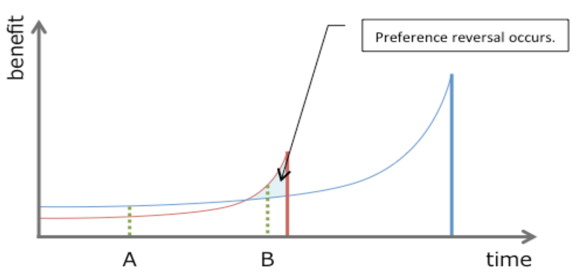


Fig. 1. Preference Reversal Phenomenon

[4] http://foursquare.com/
[5] http://www.google.com/places/

2.2 Filtering Information for Wanderers in Town

In the field of recommender systems, collaborative filtering is one of the popular methods to judge whether information fits the user or not [3][4][5]. The collaborative filtering model is basically based on the assumption that similar users prefer the same information. However, when we consider recommending information to mobile users who are wandering in town, the authors believe that the information must be selected from a set of already filtered candidates in accordance with their situation because the input method and output devices of mobile terminals are highly restricted and also the number of candidates still has to be large even though they are already filtered.

2.3 Phenomena of Human's Preference

In the field of behavioral economics, the phenomena of time preference and temporal discounting are known, which refer to a decrease in the subjective value of a reward as the delay of its receipt increases [6]. People and other animals discount future reward as a function of time. In addition, there is another remarkable phenomenon of preference reversal, which occurs when a subject places a lower selling price on the gamble that he/she chooses than on the other gamble in a pair [7]. For instance, one gamble (the *H* bet) offers a high probability of winning a modest sum of money; the other gamble (the *L* bet) offers a low probability of winning a relatively large amount of money. These bets were also called the *P* bet and the $ bet, respectively, for example,

H bet: 28/36 chance to win $10
L bet: 3/36 chance to win $100

When offered the choice between the two options, most subjects choose the *H* bet over the *L* bet. However, when asked to state their lowest selling price, the majority states a higher price for the *L* bet than for the *H* bet [8]. Therefore, animal and human temporal discounting has been described better as hyperbolic functions than exponential ones in recent psychology.

His notion implies that humans prefer not always rational choices but sometimes irrational and impulsive ones, especially in stressful situations. This paper, therefore, attempts to apply this notion to our model of recommendation for wanderers in town.

3 A Recommendation Model Based on Behavioral Cost

This paper proposes a recommender model, which is based on cost-benefit analysis of the information provided to the user, referring to the model of temporal discounting and preference reversal. Here the authors assume that behavioral cost may be regarded as time in the temporal discounting. Although cost is basically given as distance to reach the location of the information, the authors believe that it depends not only on the geometrical distance but also on his/her cognition. Benefit may be a value that the user can obtain through action influenced by information. The authors would like to emphasize that there can be more preferable information in the middle range than with "low cost–low benefit" or "high cost–high benefit" information if preference reversal phenomena occur. Therefore, a recommender system based on this model can select information, which is located in the surrounding area (not far away) and may be preferred by the user if the system can estimate where the reversal phenomenon occurs.

If a preference reversal phenomenon occurs in the middle range, the system needs to detect its range to determine the preferable information for the user. The authors suppose that the range has to depend on the users' situation, that is, cognitive aspects, such as emotion, objective or destination at that point, accompanying people, physical conditions, such as tiredness, plan of the day, financial status, and so on. To capture such aspects of the users' situation, the system may have to comprehend not only the users' daily activities but also physiological conditions with wearable sensing devices. Of course, it is not easy to perform such daily, lifelong, and extensive logging for humans, even though such technologies are growing rapidly. To begin with, the authors, therefore, try to discover such a range where the reversal phenomenon occurs and to assess the possibility of using such a range for recommender systems.

Fig. 2. pin@clip application. (List mode (left), Map mode (middle), and Information page for Pin (right)).

4 An Experimental System

4.1 pin@clip

The experiments were made on the phenomenon of preference reversals in an experimental social service, called pin@clip, which is an iPhone-based social bookmarking service in Shibuya, Tokyo, Japan that has been operating since December 2009, developed and operated under one of the Japanese governmental projects. Because the pin@clip application[6] for the iPhone is downloadable from Apple's App Store and the service is open and free, the subjects are self-directed.

Using the pin@clip application, users can get "pins", micro blog content of the service. They also can post their own pins, for example, recommendations of their own favorites. When a user posts his/her pin, he or she can choose the location where the pin should be stuck or the store that it should be related to. And also they have to declare their emotion when he/she posts the pin by selecting one of nine emoticons.

[6] pin@clip App. http://itunes.apple.com/jp/app/pin-clip/id338543864?mt=8

Fig. 3. AR mode of pin@clip application

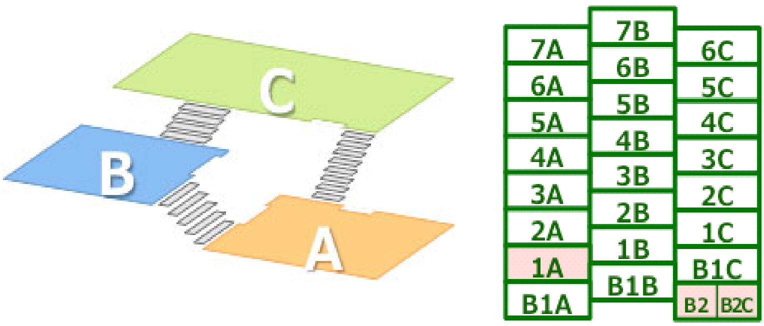


Fig. 4. "Skip floor" architecture of the department store that cooperates in the experiment. Basically each story has three floors. Red shaded floor has entrances.

The pin@clip application provides three display modes: list, map, and augmented reality (AR). The list mode shows pins in a scrollable list. The map mode locates pins in Google Maps. AR mode overlays pins onto the captured image of the iPhone camera in real time.

It also facilitates users to sort pins by five indices in any modes: distance, time line, of similar users, time zones, and recommendation. Time line provides the latest pins in descending order. When the user selects "of similar users", only pins posted by similar users to him/her are selected and sorted by distance. "Time zones" shows pins posted in the same time zone of the current time and sorted by distance. 14 time zones are provided: 12am-6am, 6am-9am, 9am-12pm, 12pm-3pm, 3pm-6pm, 6pm-9pm, and 9pm-12am of weekdays and weekends, respectively. Our recommendation model selects pins for the user when "recommendation" is pushed.

In addition to the basic functions mentioned above, the pin@clip application gives some additional functions for each pin: clip, "give thanks", and "go now". Users can clip their favorite pins for recalling them anytime later. For ratings purposes, they give thanks to preferable pins. If the user decides to go to the location of a pin, he/she sets "go now" to his/her destination.

pin@clip has one special mode for a department store in Shibuya that cooperates in our experiment. When a user enters the store, the pin@clip application shows a dialog box that asks "Do you want to enter the in-store mode?" When he/she enters the in-store mode, the pin@clip application gives not only ordinary pins, such as visitors' pins, but also special pins supplied by store staff. The system could realize his/her location while he/she used the service inside the store, even though GPS signals are unavailable because a significant number of Wi-Fi routers were deployed throughout the building for positioning of the user.

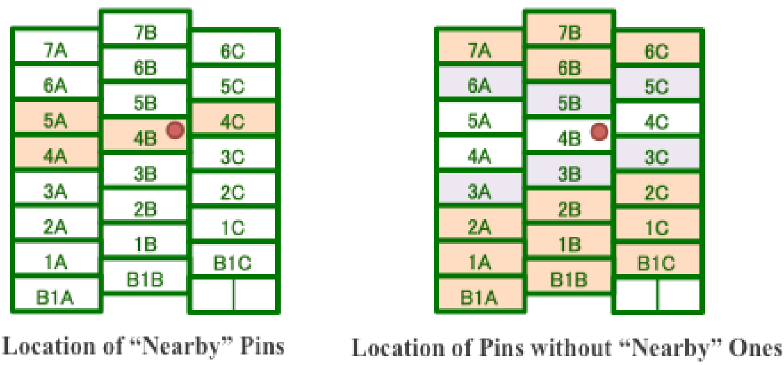


Fig. 5. Locations of Pins to be Provided to the User. (Red dot denotes the location of the user).

4.2 User Data

The pin@clip application collects not only access logs for selected pins, clips, and settings of "go now", but also users' location sensed with GPS and Wi-Fi signals at a specified interval while they use the application. In addition, users are requested to input their gender and age at the first use. Users of the pin@clip service are completely anonymous, and the service doesn't need any personal information, such as name, user account, and email address.

Fig. 6. In-store Mode. (List mode (left) and AR mode (right)).

Similarities and filtering are calculated based on these users' behavior logs. The authors assume that user similarities may depend not only on their demographic attributes and accessed pins that are often used in a lot of existing systems but also on their actual frequency of the accessed area. Because the objective of this paper is not to propose a similarity measure but to apply a behavioral cost model to a recommender system, the authors will explain the similarity measure in detail in another paper.

5 Preliminary Results

5.1 Settings of the Experiment

Place. The experiment was carried out in a department store where users can use the special in-store mode.

Definition of Behavioral Cost. Due to the unique architecture of the building that has seven stories above ground and two basements and each story consists of three "skip" floors (shown in Fig. 4), the authors defined floors between the next upper and lower story as "nearby". Here the authors define the cost to be directly proportional to the number of staircases between two floors.

Group Setting of Users. During the specific period, each user was randomly assigned to one of two groups for comparison when he/she visited a department store for selected products. One was confronted with a list of nearby information; the other was confronted with a list of information without nearby information. 45 subjects were used during the period.

Pins (Provided Content). Prior to the experiment, pins from visitors were prepared, which described a product of the writer's favorite in the floor, and its price was about 1,000 Japanese Yen. The authors assume that benefits of pins can be regarded as equal.

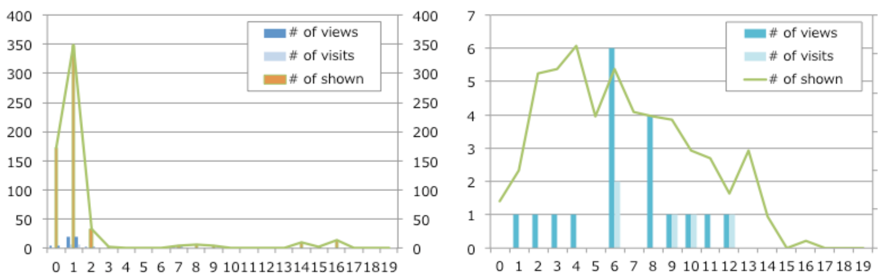
To group A, a list of nearby pins was provided; to group B, a list of pins without nearby ones was provided.

5.2 Results

Fig. 7 shows the experimental results. The graphs include the number of pins shown to the user (right hand y-axis), the number of views by selecting pins in a shown list, and the number of visits to the location of the pin after viewing. The x-axes denote the cost of the shown pin, that is, the number of staircases between the floor where the user is and the floor of the pin. The left graph shows group A results; the right graph shows group B results.

The peak of the number of pins shown to the user is on cost 1 because nearby pins were provided to group A. At cost 14 and 16, provided pins can be observed. The authors consider two possible reasons: one is sensing error and the other is the user accessed the system once and then moved rapidly by using elevators. With group B, it is remarkable that peaks are observed at cost 6 and 8. The authors would like to emphasize that some specific pins that were frequently accessed and preferred were not observed. That suggests that information in this range of cost may be more preferable than nearby and further ones. Although statistically significant data couldn't be obtained in this experiment unfortunately, the observation supports our assumption of the proposed model.

Cost 6 corresponds to 3 stories. Such distance usually brings change of categories of products in the store. Users may be triggered to think of going in another direction when they are confronted with such pins on floors from three or four stories away.



a) Group A b) Group B

Fig. 7. Experimental Results – Comparison between Groups on Selection of Pins and Actions after Pin Views

6 Conclusion

This paper proposed a new model for recommendation based on behavioral cost of recommendees in town. The model is based on cost-benefit analysis of the information provided to the user, referring to the model of temporal discounting and preference reversal. The experimental results support that a phenomenon of preference reversals might occur, even though the authors could not obtain statistically significant data.

The authors continue to develop and provide the pin@clip service. User logs throughout the area of Shibuya have been taken. Analysis of such logs and the development of methods to capture users' situation including cognitive aspects are future issues.

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