A Web Recommendation System based on Individual Preference Estimated from Twitter

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Abstract

This paper proposes a web recommendation system that estimates and dynamically updates individual preference with twitter, in order to reduce web search effort. The proposed system gathers personal comments on twitter, extracts object-predicate pairs by text analysis, and ranks the objects with weighting of the paired predicates in accordance with a prepared predicate-point dictionary such as "like so much (+5 points)" and "hate (-5 points)." We implemented the proposed system on a server in our laboratory using Twitter API for getting comments on Twitter, Yahoo API! for the text analysis and Bing API for the web search. In an experiment, we evaluated recall and precision of the objects ranking obtained by the proposed system. We also evaluated a precision of web page recommendation searched by top-ranked object. From the experimental result, the proposed web recommendation system provided higher relevance ratio compared to that of conventional system.

Keywords: *Individual Preference, Micromedia, Recommendation, Text Analysis, Twitter, Web Search.*

1. Introduction

Purpose of web search becomes diverse, as data increases and becomes diverse on web. Diversification of user's needs and information on web causes a lot of time and labor in web search. In the circumstance of web search, general user thinks and inputs words related to information user wants to find in web search engines, such as "Google" and "Yahoo!." User then struggles to select pages and finally find intended information from enormous amount of searched result. However, the meaning of word sometimes changes according to used situation. Also user often has scarce knowledge and cannot express desired information by words, and user end up finding unintended information. That is the case especially for the user to find something new interesting information without user's clear goal, which might be best search result [1].

In order to reduce the effort in web search, there has been increase in research about system to recommend user information according to the individual preference, that is recommendation technology [2-6]. For example, "products recommendation," serviced by Amazon, analyzes display and purchase histories in web sites and recommends user goods that remain in the purchase histories of other users who have similar display and purchase histories in products web sites [2]. "Interest match" provided by Yahoo! Japan is the system that displays an advertisement on those who are likely to be interested in the advertiser's goods, or service from previous browse history and search keywords [3]. However in these recommendation services and these services, because of using past browse and search history, the novelty of information often loss. To solve this problem, it was proposed that web page is recommended according to accumulated the individual preference [4-6]. Dr. Takasuka et al. proposed the web page recommendation system that extracts individual preference from only URL history of user browsing web pages and recommends web page according to the browse history of other user who has similar individual preference [4]. This system defines web page browsing itself as the user's action having a certain interest. However, the system is inappropriate to recent user who finds out desired information browsing web page regardless of the interest. On the other hand, Dr. Thakur et al. proposed the web page recommendation system using individual preference extracted from meta-data in browsed web page [5]. This method predicts the user's preference from meta-data such as keywords included in web page. However these recommendation systems, because of using only web brows history, cannot reflect user's intention of web search and process. Dr. Youssouf et al. proposed the recommendation system that expands user's individual preference with domain ontology coming from mobile terminals [6].

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In this paper we propose a recommendation system with the individual preference estimating with real-time public comments on micromedia such as Social Network Service (SNS), Blog and Twitter, that has become popular in recent years. Comments posted on micromedia are reports on the current situation in many cases and then the system gives user only preferable information using the estimated preference in real time. For example, user probably wants to know good restaurants in Yokohama when user comments such as "Yokohama now" and "I am hungry…" on Twitter. However there is huge amount of gourmet information in Yokohama. The proposed system gives user only results searched using terms "Yokohama," "gourmet," and the estimated preference such that user can access preferable information in real time without a lot of time and labor.

The remaining part of the paper is organized as follows. In Section 2, algorithm and implementation of the proposed system are presented. In Section 3 and 4, experimental method and result are described. Section 5 gives some discussion and section 6 concludes the paper.

2. Proposed System

In order to user interesting information in real time without a lot of time and labor, we had proposed the recommendation system with the individual preference that was estimated and updated real-timely using public comments on Twitter [7].

2.1 System Architecture

Figure 1 shows the system architecture of the proposed recommendation with individual preference created using micromedia. The system consists of mycromedia, morphological analysis, object ranking (individual preference), pre-selected predicate and score dictionary and web search parts. Every when user posts comment on micromedia, the pair of object and predicate in the comment is extracted by morphological analysis. In object ranking part, score is added to the extracted object with weighed according to the pre-selected predicate and score dictionary. Web search is conducted using top several keywords of the object ranking and the top a few results are shown to user. Method in detail in each functional part is shown in the implemented system configuration in next section.

2.2 Implemented System Configuration

Figure 2 shows the implemented configuration of the proposed system. For simple prototyping of the system, we implemented core part of the proposed system on Google App Engine (GAE) [8]. We also used Twitter API to
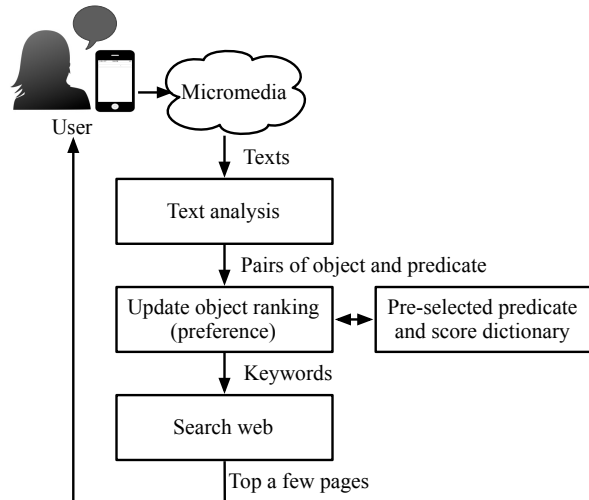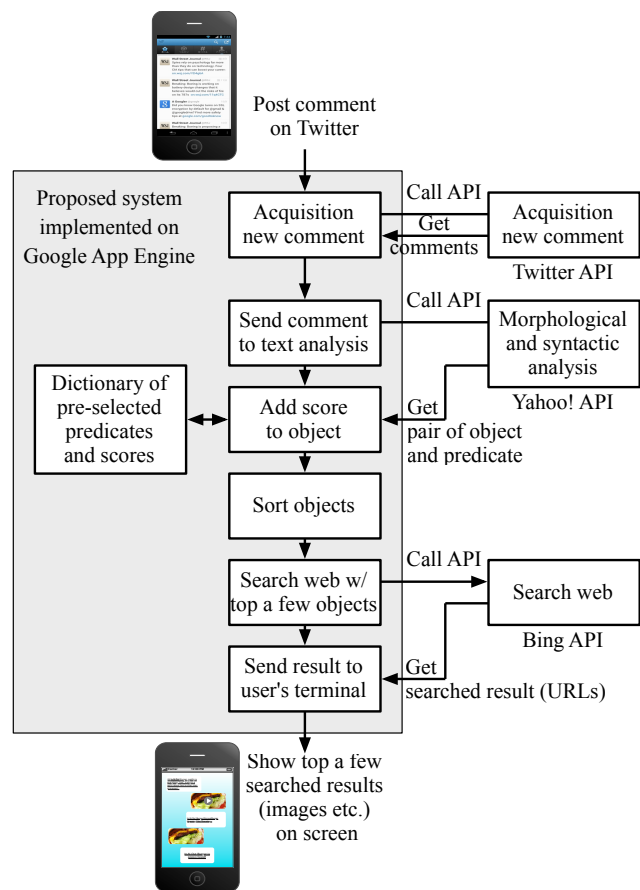

Fig. 1.   Proposed system architecture

Fig.2 Implemented configuration of proposed system

obtaining comment on "Twitter" serviced by Twitter Inc., that is one most popular maicromedia systems [9]. We also used Yahoo! API and Bing API for text analysis and web search respectively [10][11]. Detail operation and data

flow of the proposed system in each comment on Twitter are as follows:

(1) The system calls Twitter API to obtain new comment from Twitter in XML-file and saves the XML as text file, when user posts new comment to Twitter,.

(2) The system calls Yahoo! API to send the text file of comment to Yahoo! text analysis engine for morphological and syntactic analysis, and obtains a pair of object and predicate extracted from the comment.

(3) If the extracted predicate corresponds to the predicate in the pre-selected predicates-score table, the system adds score to the object. The total score of the i-th object (x_i) is expressed as follows:

$$\text{Total\_score}(x_i) = \sum_{j=1}^{J}\left(P_j^i * M_j^i\right) \qquad (1)$$

$$N_i = \sum_{j=1}^{J} M_j^i \qquad (2)$$

Where, i and j are the index of object and pre-selected predicate respectively. P_j^i is the score of j-th predicate in i-th object (x_i). M_j^i is the number of the occurrence of j-th predicate in x_i and equals to the total number of times when x_i is occurred. Table 1 shows example of dictionary of pre-selected predicates and scores.

(4) The objects are sorted according to those total score every times when new comment is posted, that is object ranking and corresponds to user preference.

(5) The system calls Bing API to send a few higher ranked objects to Bing web search engine and get top a few URLs of searched result.

(6) The system finally shows images of those URL's on screen of user's terminal.

Using real example comment, the proposed system works like below. When user posts comment "I like Tokyo so much!" on Twitter, the proposed system obtains the comment in XML file and save the comment in text file. The system then sends the text to Yahoo! text analysis engine and gets the object "Tokyo" and the predicate "like." The system then adds two points to "Tokyo" and sorts objects in the order of total points. The system finally sends "Tokyo" with a few higher ranked objects to Bing web search engine, get URLs of Bing search result and shows images of those URL's on screen of user's terminal. The system shows those searched result on the user terminal every time when user posts new comment on Twitter.

3. Experimental Method

We evaluated two important outputs of the proposed system; accuracy of objects ranking that is user preference,

Table 1 Example of dictionary of pre-selected predicates and scores

Index (j)	j-th predicates	Score (P_j)
1	Like so much	3
2	Like	2
3	So-so	1
4	N/A	0
5	Don't like	-1
6	Hate	-2

and searched result using the user preference, that is recommendation.

3.1 Objects ranking

Here, we evaluated the objects ranking in proposed system by comparing to the preference obtained from pre-evaluation questionnaire survey. Test subjects were eight graduate students who were familiar to use of Twitter.

First, we investigated preference of the test subjects with questionnaire survey in advance [11]. We got each test subject to provide the words of their own favorite, not-favorite, interesting and not-interesting things, and then evaluate the words in six grades; "like so much," "like," "so-so," "N/A," "don't like" and "hate." Next, we got each test subjects to use the proposed system for thirty days of winter and summer seasons (mid-February to mid-March and mid-June to mid-July) in 2013, respectively. The dictionary of the pre-selected predicates and scores were same as shown in table 1. Finally, we evaluated the objects ranking extracted from the proposed system comparing to the preference extracted from pre-evaluation questionnaire survey in each test subject, using recall and precision expressed as follows [12]:

$$\text{Recall} = \frac{\left|T_i^{(A)} \cap \Im L_i^{(A)}\right|}{\left|T_i^{(A)}\right|} \times 100 \quad [\%] \qquad (3)$$

$$\text{Precision} = \frac{\left|T_i^{(A)} \cap \Im L_i^{(A)}\right|}{\left|\Im L_i^{(A)}\right|} \times 100 \quad [\%] \qquad (4)$$

Where i and A are the index of the words (objects) and the experiment identifier, respectively. $T_i^{(A)}$ and $\Im L_i^{(A)}$ are the words list obtained from pre-evaluation questionnaire test and the map of the words list obtained from the proposed system in experiment A, respectively. Recall is expressed as rate of the number of the words by the proposed system ($L_i^{(A)}$) included in the words by the pre-evaluation questionnaire test ($T_i^{(A)}$), to the total number of interesting words in the pre-evaluation questionnaire ($|T_i^{(A)}|$). Precision is also expressed as rate of the number of the words by the proposed system ($L_i^{(A)}$) included in the words by the pre-evaluation questionnaire test ($T_i^{(A)}$), to the total

number of the words by the proposed system ($|\Im L_i^{(A)}|$). Recall and precision thus mean whether objects (words) provided by the proposed system needs to be for the test subject.

3.2 Recommendation

Here, we evaluated the recommendation using the objects ranking in the proposed system. Test subjects were six out of eight graduate students who conducted experiment of object ranking shown in section 3.1. The proposed system showed the test subject top-20 web pages out of web pages searched by the top-ranked word in the object ranking obtained from the use of the proposed system through the 2nd period (summer season). The test subject then selected interesting web pages out of the top-20 web pages recommended by the proposed system. Since the number of browsing pages of the search result with web search engine is generally one to two, we thus set the number of inspections 20 affairs [13]. We finally calculated the accuracy of the recommendation for each test subject, using precision expressed as follows [12]:

$$\text{Precision} = \frac{\left|T_i^{(B)} \cap \Im L_i^{(B)}\right|}{\left|\Im L_i^{(B)}\right|} \times 100 \quad [\%] \qquad (5)$$

Where i and B are the index of the web pages and the experiment identifier, respectively. Precision here is expressed as rate of the number of the web pages needed by the test subject ($T_i^{(B)}$) included by the web pages recommended by the proposed system ($\Im L_i^{(B)}$), to the total number of the web pages recommended by the proposed system ($|\Im L_i^{(B)}|$). Precision here thus means whether the web pages recommended by the proposed system needs to be for the test subject.

4. Result

4.1 Objects ranking

Figure 3 shows the result of the recall of the interesting objects list obtained from the proposed system comparing to that obtained from the pre-evaluation questionnaire, for each test subject, in 1st and 2nd period (winter and summer seasons), respectively. Median of the recall was 50.0 and 71.7% with standard deviation of 21.2% and 12.6% in winter and summer seasons, respectively. Figure 4 also shows the result of the precision of the interesting objects list obtained from the proposed system comparing to that obtained from the pre-evaluation questionnaire, for each test subject, in 1st and 2nd period (winter and summer seasons), respectively. Median of the precision
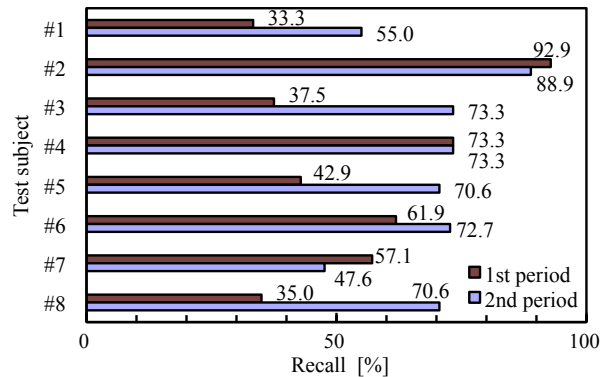

Fig. 3 Recall of objects ranking in 1st and 2nd period (winter and summer seasons) for each test subject
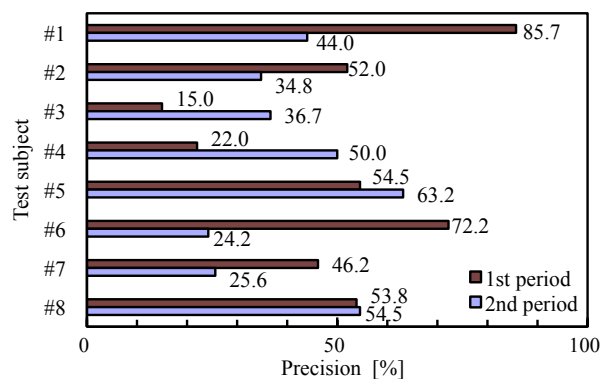

Fig. 4 Precision of objects ranking in 1st and 2nd period (winter and summer seasons) for each test subject

was 52.9 and 40.3% with standard deviation of 23.4% and 13.8% in winter and summer seasons, respectively.

The total numbers of interesting words obtained from the pre-evaluation questionnaire ($|T_i^{(A)}|$) were seventeen and sixteen in average for the eight test subjects, in winter and summer seasons, respectively. The total numbers of interesting words obtained from the proposed system ($|\Im L_i^{(A)}|$) were twenty-four and twenty-seven in average for the eight test subjects, in winter and summer seasons, respectively. The number of the words by the proposed system ($L_i^{(A)}$) included in the words by the pre-evaluation questionnaire test ($T_i^{(A)}$), that is $|T_i^{(A)}| \cap \Im L_i^{(A)}|$, were nine and ten in average for the eight test subjects, in winter and summer seasons, respectively. The numbers of interesting words obtained from the proposed system were about 1.5 times as many as that obtained from the pre-evaluation questionnaire test in both winter and summer season. However, the number of the words by the proposed system included in the words by the pre-evaluation questionnaire test was about half less than that obtained from the proposed system in both winter and summer season.

Table 2 shows comparing top-five ranking results of objects obtained from the pre-evaluation questionnaire test to that obtained from use of the proposed system, for test

Table 2 Questionnaire and proposed system results in winter season

Ranking	Questionnaire results		Proposed system result	
	Preference	Words	Total score	Words
1	5	Sakannaction	18	Sakannaction
2	5	Chigasaki	8	Chigasaki
3	4	Snowboarding	8	Snowboarding
4	4	Beef stew	8	Beef stew
5	4	Ice cream	2	Ice cream

Table 3 Questionnaire and proposed system results in summer season

Ranking	Questionnaire results		Proposed system result	
	Preference	Objects	Total score	Objects
1	5	Dart	18	Dart
2	5	Sakannaction	8	Sakannaction
3	5	Table tennis	8	Table tennis
4	4	Wrist watch	2	Wrist watch
5	4	Beach	2	Beach

subject #2 whose recall was best of all recall of test subjects, in 1st period (winter season). Table 3 also shows example of comparing top-five ranking results of words obtained from the pre-evaluation questionnaire test to that obtained from the proposed system, for test subject #2 whose recall was best of all recall of test subjects, in 2nd period (summer season). Objects ranking result obtained from the proposed system was same as that obtained from the questionnaire in both winter and summer seasons. We can see the difference in between the objects ranking list of winter and that of summer seasons. The proposed system thus was able to extract the preference change of the test subject in seasonal difference.

4.2 Recommendation

Figure 5 shows precision of web pages recommended by the proposed system after 2nd period (summer seasons) for each test subject. The total number of the web pages recommended by the proposed system ($|\Im L_i^{(B)}|$) was twenty as described in section 3.2. The number of web page needs to be for the test subject #1, #2, #3, #4, #5 and #6 were 15, 19, 12, 13, 14 and 15 pages out of the 20 web-pages recommended by the proposed system, respectively. Precisions of the recommendation were all higher than precision of the conventional recommendation system (40-50%) for all test subject [14]. Median of the precision was 73.0% with standard deviation of 21.2%.

4. Discussion

There was much variation in the recall and precision values of the objects ranking of the eight test subjects in both periods (winter and summer seasons). For the reason of the variation in the recall, we consider that the number of tweets was low for short period in all test subjects and the percentage of the difference in the number of the

tweets became much bigger both between test subjects and between 1st and 2nd periods. The numbers of the tweets in 1st period (2nd period) were 6 (19), 17 (13), 26 (24), 36 (20), 15 (22), 8 (16), 8 (12) and 7 (16) for the test subject #1, #2, #3, #4, #5, #6, #7 and #8, respectively. The number of tweets depends largely on individuals and seasons. We thus need to carry out experiment for much longer periods and evaluate the proposed system with much more test subjects and tweets.

Only one word, that was top-ranked object, was used in web search for the recommendation by the proposed system. Since there may not be necessarily connected with each other in high ranked objects, combination of those high ranked objects is not smart for search keywords. We thus consider that when an object in new comment is included in higher ranked objects list (for example top-10 ranking), combination with environmental information such as location and time might be better [15]. The usefulness of the proposed system depends greatly on the design of the dictionary of pre-selected predicates and score, but it may be no big problem for top providers such as Google and Yahoo!. We will enhance our proposed system considering collaborative filtering techniques for users having similar preferences [16][17].

5. Conclusion

This paper proposed a system to support gathering personalized information and dynamical updating individual preference with micromedia such as SNS, blog and twitter, in order to reduce effort of web search. The proposed system gathers personal comments on micromedias and estimates individual preference ranking from text analysis, in which object-predicate pairs are extracted and the objects are ranked weighting in accordance with a prepared predicate

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dictionary. We implemented the system using a server in our laboratory, Twitter API for getting comments on Twitter, Yahoo API! for text analysis and Bing API for web search. From an experiment, recall and precision of the objects ranking obtained by the proposed system showed variation in terms of test subjects and experiment seasons, but precision of recommendation of the web pages searched with the top-ranked object was higher than that of conventional recommendation system. We finally discussed future challenges to improve proposed system, that are to design pre-selected predicate and score for ranking objects, and to collect a large amount of comments on micromedias.

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