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MONERS: A news recommender for the mobile web

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Abstract

Mobile web news services, which served by mobile service operators collecting news articles from diverse news contents providers, provide articles sorted by category or on the basis of attributes, such as the time at which they were posted. The mobile web should provide easy access to the categories or news contents preferred by users because user interface of wireless devices, particularly cell phones is limited for browsing between contents.

This paper presents a mobile web news recommendation system (MONERS) that incorporates news article attributes and user preferences with regard to categories and news articles. User preference of news articles are estimated by aggregating news article importance and recency, user preference change, and user segment's preference on news categories and articles. Performance of MONERS was tested in an actual mobile web environment; news organized by category had more page hits, while recommended news had a higher overall article read ratio.

Keywords: Recommendation system; Mobile web; News

1. Introduction

The mobile web allows users navigate the Web using wireless devices such as cell phones and personal digital assistants (PDAs). During early days of the mobile web, ring tones and wallpaper were the most commonly accessed content, but in recent years there has been a significant increase in the use of data content such as music, movie information, and news (Kelly, Gray, & Minges, 2003; Kim, Lee, Cho, & Kim, 2004). Because news services on the mobile web are so ubiquitous, there are many users.

Currently, most mobile web news services are sorted by category or by news article attributes, such as recency. An inconvenient user interface may constitute a barrier to browsing between contents; therefore, mobile web news services should provide easy access to the categories or content preferred by users. Researchers have conducted many studies on personalizing news services in order to make recommendations, using the existing web (Billsus & Pazzani, 2000; Goldberg, Nichols, Oki, & Terry, 1992; Konstan et al., 1997; Shepherd, Watters, & Marath, 2002). News can be filtered using collaborative filtering, which is based on similarities among user preferences, or by using information filtering, which uses news article keywords and user profiles (Aas, 1997; Belkin & Croft, 1992; Foltz & Dumais, 1992; Konstan et al., 1997; Mostafa, Mukhopadhyay, & Lam, 1997).

User interface, user behavior, and browsing between content are different on the mobile web than they are in a web-based service (Brunato & Battiti, 2003; Ho & Kwok, 2003; Kim et al., 2004); therefore, the mobile web requires its own recommendation method, adapted to its features.

This paper presents a mobile web news recommendation system, Mobile News Recommendation Systems (MONERS), which incorporates news article attributes, user preferences with regard to category and news articles, and user segments. MONERS incorporates the news article's importance, as well as its recency, calculated by the difference between the time it was posted and the present. It also

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incorporates a user segment that is focused on user profiles, reading patterns of news articles, changes in user interest, and usage patterns. Users of the actual mobile web tested the news recommender's performance, and its performance was measured and analyzed.

Section 2 summarizes studies related to news article recommendation and the mobile web. Section 3 introduces MONERS' flow and recommendation algorithms. Section 4 presents the experiment used to analyze the news recommendation method performance, and an analysis of the results. Section 5 discusses this study's implications and conclusions.

2. Related work

2.1. News recommendation

Personalization and recommendation involving news services on the web use the following approaches:

- Collaborative filtering: This is a method for calculating expected user preference for a product, using evaluation by, or the preferences of, other users who have experienced the product (Billsus & Pazzani, 1998; Goldberg et al., 1992; Konstan et al., 1997). Collaborative filtering is currently widely applied and is used not only for news but also for various products such as music or movies (Billsus & Pazzani, 1998; Goldberg et al., 1992; Konstan et al., 1997). The basic input data consist of the preference matrix between users and products; to collect explicit user preferences for this input data, a purchasing intention or implicit preferences, such as an inquiry or visit, may be used. Similarity among users is calculated by the Pearson correlation coefficient or the cosine measure (Konstan et al., 1997; Mild & Natter, 2002; Sarwar, Karypis, Konstan, & Riedl, 2000). Based on the similarity calculation, we can find neighbors with similar tendencies to a particular user. We can calculate the user's expected preference for a product based on his or her average preference for other products and his or her neighbors' preference for the product (Konstan et al., 1997; Mild & Natter, 2002; Sarwar et al., 2000).
- Information filtering: Unlike collaborative filtering, information filtering is a method for finding similar products by comparing user information—a user profile—with product information. Generally, a user profile can be generated based on documents or information that the user has created or visited. After the user profile has been compared with product information, only products with a high similarity level are recommended (Aas, 1997; Belkin & Croft, 1992; Billsus & Pazzani, 2000; Claypool et al., 1999; Foltz & Dumais, 1992; Kim, Lee, & Park, 2004; Mostafa et al., 1997). Term Frequency-Inverse Document Frequency (TF-IDF) indexing is applied to the vector presentation, and methods for categorizing documents and information are applied to enhance performance of information filtering (Billsus & Pazzani, 2000; Billsus, Pazzani, & Chen, 2000).

In collaborative filtering, the nearest neighbor algorithm requires computation that grows with both the number of customers and the number of products and has a sparsity problem; if there are few user preferences, its recommendation performance is low (Claypool et al., 1999; Sarwar et al., 2000). Information filtering also has some inherent flaws, since it is applicable only to products that include text-based information, and understanding the context of keywords can be difficult. With regard to solving the shortcomings of these two methods, researchers have presented solutions that use both methods simultaneously (Claypool et al., 1999; Kim et al., 2004). Others have presented ways to reduce the dimensions of the keyword vector or the user preference vector (Billsus & Pazzani, 1998), or to calculate similarity among users using a neural network or association rules (Jennings & Higuchi, 1992; Mobasher, Dai, Luo, & Nakagawa, 2001; Shepherd et al., 2002).

2.2. Recommendation on the mobile web

Many studies have been undertaken on providing personalized web service to users or on recommending personalized products to web users (Billsus & Pazzani, 1998; Billsus & Pazzani, 2000; Claypool et al., 1999; Goldberg et al., 1992; Konstan et al., 1997; Mobasher et al., 2001; Shepherd et al., 2002). Since a cellular phone provides a limited user interface and low data storage and business logic for clients, there is little use for keyword-based searches; furthermore, browsing between pages is inconvenient (Brunato & Battiti, 2003; Ho & Kwok, 2003; Varshney, 2003). VISCORS is a wallpaper-recommending system on the mobile web that applied collaborative and information filtering to the choice and purchase of a wallpaper for relieving users' enormous navigation (Kim et al., 2004). Mobile web users can be identified by contexts that include their location and their access time and day of the week (Brunato & Battiti, 2003; Korpipää, Mäntyjärvi, Kela, Keränen, & Malm, 2003; Varshney, 2003; Varshney, Vetter, & Kalakota, 2000). At present, mobile service providers operate various location-based services, such as 'searching friends', to notify users about where their friends are, or to make recommendations about nearby restaurants. Efforts are also being made to use cellular phone equipment to extract information about contexts, such as user environment, user behavior, and mechanical cellular phone action (Korpipää et al., 2003).

The limitations of cellular phones and mobile devices necessitate personalization in order to recommend appropriate and well-timed content to users. A mobile phone can also provide a more interactive service by fulfilling 'push' service through short message services (SMS) or other interactive channels (Ho & Kwok, 2003). With regard to the mobile web, researchers recognize that content recommendation is one of the most important applications for future development, along with mobile auctions, mobile offices, and mobile education (Varshney, 2003).

3. MONERS

3.1. Considerations for mobile web news recommendation

Three points must be considered when designing news content personalization for the mobile web. The first is news content. On the mobile web, news services focus on the distribution of current news rather than on past or related news articles; searching past or related articles and browsing between pages is not easy, so mobile web news services mainly provide current reports or important articles sorted by news category. It is therefore important, when personalizing news, to consider the recency and importance of news articles.

The second is the news service. On the mobile web, the purpose of a news service is not to provide past news articles but to provide current articles. Even though it is possible to learn about preferences for past news articles, it is difficult to apply the collaborative filtering method when there is no user preference for current news articles, or when few users have read the present day's articles. Therefore, learning user preference requires learning preferred news categories. Preferred category information can be used to recommend articles by selecting current news articles belonging to preferred categories. Information about changes in user interest is also helpful when recommending news articles, in that articles from recently preferred categories may be selected.

The third point relates to the social behavior of users. Users can be classified into a user group by article usage pattern and demographic information. User segments with similar content or similar usage patterns can be used to make recommendations by selecting articles preferred by the segment. It is not easy to place new users in a segment, as there is no content usage history; in this case, they can be placed in a segment with a similar demographic.

Based on these three points, an equation to calculate news article preference for an individual user might take this form:

$$p_{ij} = f(\text{priority}_j, \text{recency}_j, \text{user}_j, \text{seg}_j, \text{seg\_weight}_j) \qquad (1)$$

where p_{ij} is i user's preference for j news article, priority_j is the importance of j news article, recency_j is the weight for the recency of j news article, user_j is the weight of preference change with respect to the user for the category to which news article j belongs, seg_j is the preference of the segment of user i for the category to which news article j belongs, and seg_weight_j is the weight of preference calculated by the ratio of users who have read news article j in the segment of user i.

The next section describes MONERS' flow and how each parameter of Eq. (1) can be calculated.

3.2. Calculation of news article preference by user

Fig. 1 shows the flow of MONERS using the attributes referred to in Section 3.1. When a user accesses MONERS news service with a cellular phone, the system determines whether he/she is a new user. If so, he/she is temporarily placed in a similar segment on the basis of demographics. If he or she has used the system before, his or her individual preferences for news categories are retrieved. The news service presents articles to the user after weighting their importance and recency, determined by comparing the time the article was posted on the mobile web with the present time. A user's segment and the news category preferences of the user, as well as his or her preferences, are regularly updated after collecting user data; calculations about news articles can be made only with a user's request in real time.

The following are MONERS' methods of calculation for each parameter of Eq. (1):

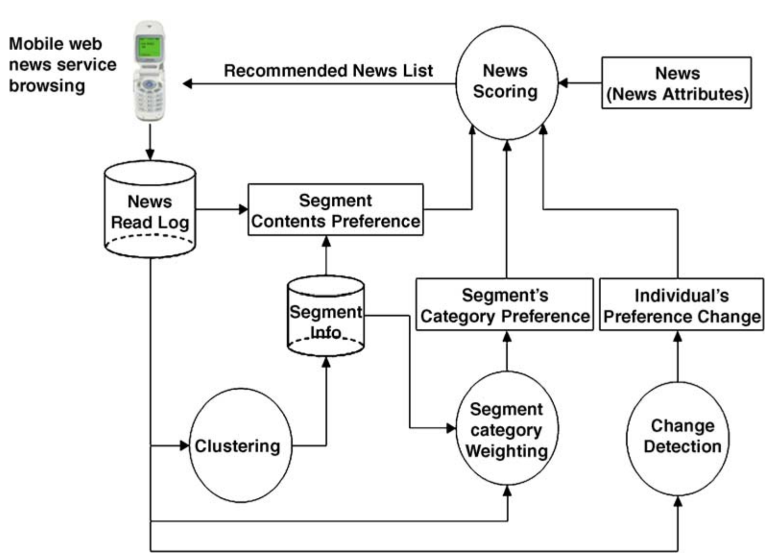

Fig. 1. Mobile news recommendation systems (MONERS) flow.

- News importance
  News articles are rated from level 1–7, according to their importance; the level determines the article's weight. For example, the weight of headline news, at the 'most important' level 1, is 1.5; the weight of 'important' level 2 is 1.45. News content providers such as off-line newspapers supply information on the importance of news articles.
- News article recency
  Recent news has more weight and, as time passes, its weight is lowered. Eq. (2) calculates the weight decrease in news article recency, shown in Fig. 2.

$$\text{recency}_j = -\left(\frac{\text{time}_{\text{present}} - \text{time}_{\text{posted}}}{86,400}\right)^2 + 1 \tag{2}$$

  where $\text{time}_{\text{present}}$ is the present time and $\text{time}_{\text{posted}}$ is the time article j was posted to the mobile news service. The difference between the two times is calculated by the second unit and a denominator 86,400, meaning seconds per 24 hours. If the article-posted time is 2:37:14 PM and the current time is 4:13:5 PM, the recency weight of j news article is $-(\frac{58,385-52,634}{86,400})+1=$ 0.9334375. If the difference between the present and posted time is over 24 hours, the recency weight of the article becomes zero.
- Change in user interest
  When applying users' category preferences, more weight is given to a news category that has drawn recent user interest. The following equation gives more weight to a category that has an increased preference over a designated period of time:

$$\text{user}_j = \left[\log_{10}\left(\left(\frac{\text{user}_{j,\text{s\_days}}}{\text{user}_{j,\text{l\_days}}}\right)(10^{1-\text{DF}}-1)+1\right)+\text{DF}\right] \tag{3}$$

  where user_j is the preference change weight for the category to which j news article belongs, and $\text{user}_{j,\text{s\_days}}$ is the user's category preference for the past s_days; s_days refers to a short-time preference and l_days to a long-time preference. MONERS uses a 1-week preference as a short-time preference and a 3-week preference as a long-time preference. DF is a differential factor with a value of 0.5; when the DF value is 0.5, the weight value can be obtained as shown in Fig. 3 according to the ratio of $\frac{\text{user}_{j,\text{s\_days}}}{\text{user}_{j,\text{l\_days}}}$.

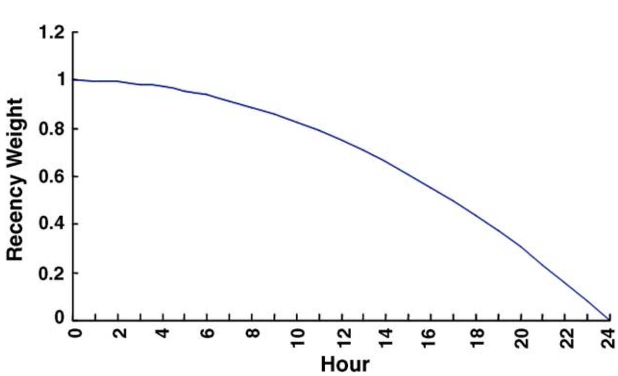

Fig. 2. Weight decrease for news article recency.

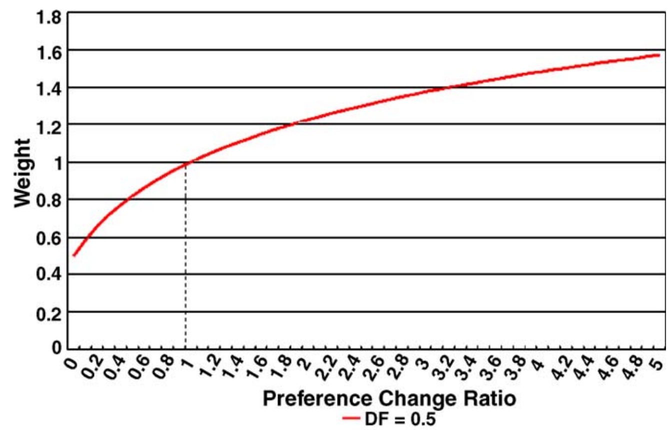

Fig. 3. Weight of category preference change.

As shown in Fig. 3, Eq. (3) is devised so that the value of the category preference change weight becomes 1 when short-term and long-term preferences are the same, and the weight's value of the weight is between 0.5 and 1.6 even if the short-term category preference increases or decreases sharply. If $\text{user}_{j,\text{s\_days}}$ is 0.5 and $\text{user}_{j,\text{l\_days}}$ is 0.25, the preference change weight value is 1.2262; i.e., if recent preference for the category doubles, the change in preference weight value increases 1.2262 times.

- User segment category preference
  This is the news category preference of the segment to which a user belongs. A user segment is formed through k-mean clustering using Euclidean distance measure. Clustering is performed using a user's category preference, age, and sex.
  Supposing that users in the same segment prefer similar kinds of news, the segment's preference for a news category is calculated as follows:

$$\text{seg}_{\text{sc}} = \frac{r_{\text{sc}}}{\sum_{j=1}^{N} r_{sj}} \tag{4}$$

  where r_{sc} is the number of times that users in segment s read news articles in category c, N is the total number of categories, seg_{sc} is segment s's preference for category c, the value of which is obtained by dividing the number of times that users read the articles in category c by the number of times that users read articles in the total number of categories. In Table 1, seg_{11} is $\frac{12}{30} = 0.4$.
  It is difficult to assign new users to a segment via clustering because they have no or little experience using mobile web news services. Therefore, a temporary segment is established for new users; after gaining a certain amount of experience, they can be assigned to a

Table 1
Category preference by segment

	Category 1	Category 2	Category 3	Total
Segment 1	12	8	10	30
Segment 2	5	10	15	30
Segment 3	12	18	10	40
Total	29	36	35	

segment via clustering. The temporary segment for new users is determined by age and sex; the most suitable segment for their age and sex can be found through the following equation:

$$\mathrm{MIN}\left[\left(\frac{U_{\mathrm{age}}-A_{i,\mathrm{age}}}{S_{i,\mathrm{age}}}\right)+\left(\frac{U_{\mathrm{sex}}-A_{i,\mathrm{sex}}}{S_{i,\mathrm{sex}}}\right)\right] \tag{5}$$

where U_{age} and U_{sex} are the user's age and sex; males are indicates with 1, and females with 0. $A_{i,\mathrm{age}}$ is the average age in segment i and $S_{i,\mathrm{age}}$ is the standard age deviation in segment i. Similarly, $A_{i,\mathrm{sex}}$ is the average sex value in segment i and $S_{i,\mathrm{sex}}$ is the standard sex deviation in segment i.

- User segment article preference
  If only the weight of category preference for all users in the same segment is applied, all new articles in the same category are given the same preference weight. Therefore, more weight is given to an article read by more users in the same segment, making it more likely that this article will be recommended. The weight of article preference for users in a segment is calculated as follows:

$$\mathrm{seg\_weight}_j=\left[1+\frac{r_j}{\sum_{s=1}^{m}r_s}\right] \tag{6}$$

where r_j means the number of times users in a segment read article j ($1 \leqslant j \leqslant m$), and m is the total number of articles. When users in a segment read a total of 50 articles 250 times and read article j 20 times, $\mathrm{seg\_weight}_j$ is $(1+\frac{20}{250})=1.08$.

The following equation calculates each user's preference for each news article, when all the above factors are taken into consideration:

$$\begin{aligned}p_{ij} &= \mathrm{priority}_j\times[1+\mathrm{seg}_{\mathrm{sc}}]\\ &\quad\times\left[-\left(\frac{\mathrm{time}_{\mathrm{present}}-\mathrm{time}_{\mathrm{posted}}}{86,400}\right)^2+1\right]\\ &\quad\times\left[\log_{10}\left(\left(\frac{\mathrm{user}_{j,\mathrm{s\_days}}}{\mathrm{user}_{j,\mathrm{l\_days}}}\right)(10^{1-\mathrm{DF}}-1)+1\right)+\mathrm{DF}\right]\\ &\quad\times\left[1+\frac{r_j}{\sum_{s=1}^{m}r_s}\right]\end{aligned} \tag{7}$$

When the news importance weight for article j is 1.5, p_{ij} (user i's expected preference for news article j) can be determined by using the weights that are calculated using the above equations as follows:

$$\begin{aligned}p_{ij} &= 1.5\times(1+0.4)\times 0.9334375\times 1.2262\times 1.08\\ &= 2.5959.\end{aligned}$$

4. Experiments and results

4.1. Experiments

An experiment on the use of this news recommendation service was carried out on service members who were registered with a Korean mobile service provider's intelligent wireless service. The news recommendation service's usage log from October 2003 to the end of April 2004 was analyzed.

When a news service is accessed, screens similar to ones in Fig. 4 appear. The root menu of a news service consists of recommended news, news by category, and current news. Recommended news provides personally recommended news articles from all categories; current news arranges news articles according to recency; news by category organizes news into categories such as politics, business, sports, etc.; if a user selects a category, articles in that category are displayed.

4.2. Comparison of recommendation performance

Fig. 5 shows the number of times users accessed each menu; this information was gathered by analyzing the news service usage log.

Although the number of times users accessed each menu varied, recommended news and news by category were more popular than current news.

Various measures have been used to compare the performance of news service recommendations; these have been based on errors between users' evaluation scores and expected preference (Breese, Heckerman, & Kadie, 1998; Sarwar et al., 2000). It is difficult to show whether an article has been read on the mobile web because it is not easy to obtain a user's explicit rating of an article, and each article

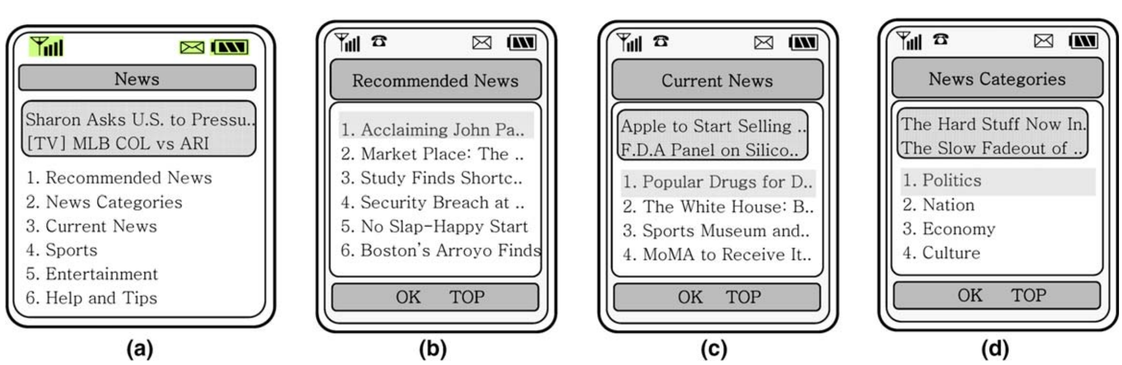

Fig. 4. Examples of news service screens: (a) news service, (b) recommended news, (c) current news, (d) news categories.

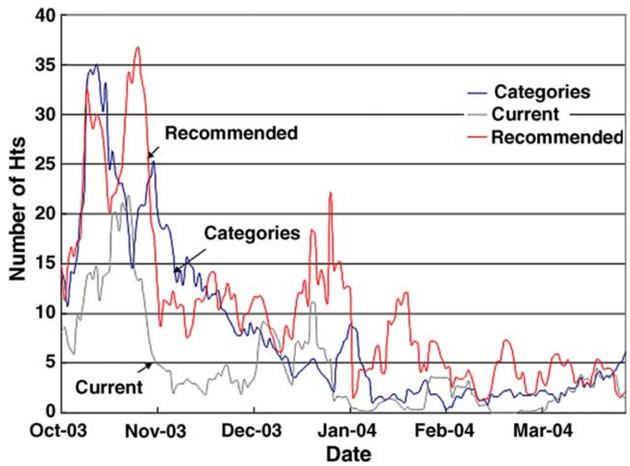

Fig. 5. Number of times users accessed each news menu.

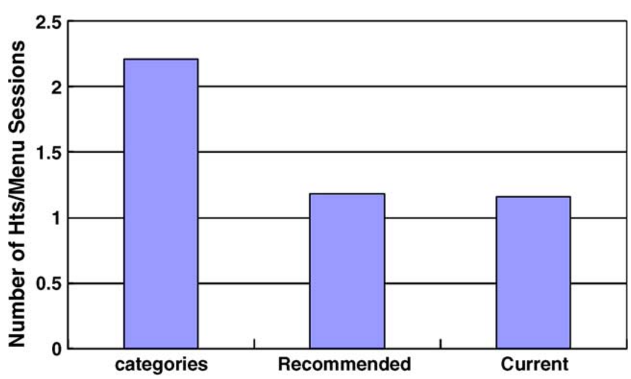

Fig. 6. Number of news accesses by menu.

consists of several pages. This study was able to measure how many articles and how many pages of an article on the mobile web were read.

Fig. 6 shows the number of news articles read when a user accessed one menu. News by category had more hits than did recommended news or current news. News hits are the number of pages accessed; if a user sees two pages of an article consisting of four pages, it results in two news hits. The number of menu sessions shows how many times a user accessed the news selection menu (current, categories, and recommended), rather than news content.

Fig. 7 shows the article read ratio of news articles by menu; this measures how far users read when they access

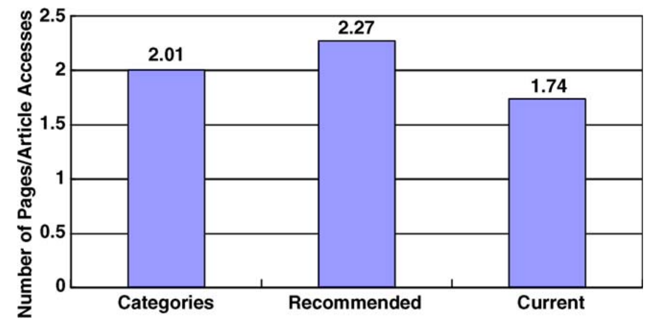

Fig. 7. Article read ratio by menu.

one article consisting of several pages. An article is usually composed of four or five pages; if users read the entire article, it probably indicates that they find it interesting.

An ANOVA test verified the difference between news hits by menu and by article read ratio. The ANOVA test's null hypothesis, that verifies the difference of news hits by menu, is H_0: $\mu_1 = \mu_2 = \mu_3$, where μ_i constitutes average news hits on menu i. As shown in Table 2, results indicated that the null hypothesis must be rejected because the value of F is 180.751 and the p-value is 0.0000. This suggests that there is a difference between news access hits by menu. Duncan's test using Post Hoc analysis indicates that there were more hits for news sorted by category than for recommended news, and that there were a similar number of hits for current news and recommended news.

The ANOVA test's null hypothesis for verifying the difference of the article read ratio by menu is H_0: $\mu_1 = \mu_2 = \mu_3$ and μ_i is the article read ratio for menu i. As shown in Table 2, the null hypothesis is rejected because the value of F is 15.970 and the p-value is 0.000. Rejection of the null hypothesis indicates that there is a difference between article read ratios by menu. Duncan's test using Post Hoc analysis suggests that the article read ratio for recommended news is higher than that for news by category or recency. The article read ratio for news by category is higher than that for news by recency.

5. Discussion

5.1. Performance of MONERS recommendation

As the comparison between performances in Section 4.2 indicates, news by category had the most news hits, and

Table 2
Results of ANOVA test

	News hit		Article read ratio	
	Average	Std.	Average	Std.
Category	2.21	1.899	2.01	1.623
Recommended	1.17	0.593	2.27	1.175
Current	1.11	0.411	1.74	1.377
ANOVA (F-value)	180.751 (sig. = 0.000)		15.970 (sig. = 0.000)	
Duncan's test	Category > Recommended, Current		Recommended > Category > Current	

current and recommended news had a similar number of hits. News by category enables users to read various articles in one category; they can access news categories interesting to them such as MLB news or entertainment. Users often selected several news articles in one category; however, if a news article consisted of several pages, they tended to read more pages of recommended articles than articles sorted by category or recency. Recommended news had the highest article read ratio, followed by news by category; news sorted by recency had the lowest ratio. A high article read ratio indicates that users find an article interesting; it is useful, therefore, to personalize news categories for users, and to present it in the mobile device's upper news menu. It can also be useful to provide personalized recommended news articles within various news categories as recommended news in the upper menu.

5.2. Collaborative filtering and information filtering as methods for recommending news

The application of collaborative filtering to news recommendation on the mobile web requires learning about preferences for news articles or categories. This will allow for detailed measurements of similarities among users, as well as expected preferences. When dealing with a great deal of information, sparse data can lead to low performance (Billsus & Pazzani, 1998; Mild & Natter, 2002; Sarwar et al., 2000). As it is inconvenient to search or browse past articles using the mobile web, only current news is provided. The most current news and news with high importance get the most hits on the mobile web. When users have read the current articles, preferences about news articles can be learned, and collaborative filtering can be applied; however, it is difficult to recommend a news article to users if the article has not been read or only a few users have read it.

In collaborative filtering preferences, learning about news categories reduces the scalability or sparsity problem more effectively than does learning about preferences with regard to news articles. However, the level of recommendation is limited to news categories; since the preference value is calculated on the level of news category, all articles in one news category such as baseball news or entertainment news have the same preference value. In this situation, articles in a news category are arranged according to their recency or importance without considering the preferences of users. MONERS learns preferences about news categories with user segments, and calculates preferences for news articles in categories by utilizing an article's recency and importance, along with the number of hits by users in the same segment.

When information filtering is applied to news, keywords from news articles read by users are extracted to create a user profile, which is then compared with registered news articles to allow for recommendation of news articles with a high similarity to a user profile (Belkin & Croft, 1992; Foltz & Dumais, 1992; Mostafa et al., 1997). When information filtering alone is applied to news recommendation, it can be difficult to recommend important current news, including new keywords or hot news recently accessed by many users. Therefore, news services on the mobile web can recommend or present articles based on keywords that can either be directly input by users or picked up using information filtering. For example, if "U2" is a user's preferred entertainer and "Curt Schilling" is the preferred athlete, articles that include these keywords will be recommended or presented to the user on the mobile web.

6. Conclusion and limitations

This paper presented the MONERS news recommendation system, a system that incorporates the characteristics of users as well as the nature of the mobile web news service and content. MONERS calculates the distance between the present time and the time an article was posted to determine news recency; it also incorporates the importance of news articles. MONERS also considers changes in user preference with regard to news categories. It can identify preference for news category by user segment and preference for particular articles by users in the segment.

For real-time recommendation, regular analysis, which would include learning about various preferences and segment composition, is carried out by batch work. The function of providing personalized news content is performed only when users access a news service. This study measured the performance of recommendations using the article read ratio; this measure is only suitable when a news article consists of several pages. While news by category had more page hits, the article read ratio for recommended news articles was higher than for news articles sorted by recency or news category.

This study focused only on news service; future research should devise a method to expand this personalized recommendation service to general content supplied by the mobile web, as well as to content only the mobile web can supply.

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