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INTEGRATED MOBILE CONTENT RECOMMENDATION: A COMPARISON STUDY

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ABSTRACT

A recommendation system can be used to help mobile device users for content filtering. However, there are problems related to sparsity of information from a first-time user. The problem is also regarding to initial rating of the content in an early stage of the system. Therefore, mobile content filtering is necessary for user to obtain personalised content delivery. This paper proposes the integrated mobile content recommendation method by combining classification and association rule techniques to establish model for new users and first rater on mobile content. The model also enhances the recommendation system in an early stage by recommending relevant items. The experiment has shown that the integrated method can perform better than the other compared methods. This can address the problem of sparsity for mobile content recommendation systems.

Keyword: mobile recommendation, association rule, integrated model

1. INTRODUCTION

Although a recommendation system can help information overloading problem. But most of recommendation systems confront the problem of in early stage such as sparsity for users and items information. So, it is difficult to provide the good recommendation without establishing recommendation model. An establishment of the model has problem that most techniques ignore non-rated items or new items. If a new item appears in the record and it is not rated yet, or the rating is quite low compared to top-rated item, it has less chance to appear at the top even though it might be relevant to the user indirectly based on the user's profile [1, 2]. Therefore, there should be some mechanisms to allow such content to be retrieved by associating the items to the interests of the user.

In this paper, we address the problem of first raters for non-interactive mobile content recommendation systems by proposing an integrated Classification and Association Rules-based technique for extracting knowledge from a mobile content user's profile. The proposed approach can gain knowledge to establish a model for new users based on mobile content from the user's profile, as well as providing association of the non-rated or new items to the relevant items. After that, the research also demonstrates the comparison of proposed method, Multi-level Targeting Classification Association Rule (MTCAR), with the mobile content recommendation techniques. It will be shown how the proposed method performed and compared the results to other methods in mobile content recommendation system.

2. LITERATURE REVIEWS

2.1 Mobile Content Recommendation

The recommendation system plays a vital role in mobile website browsing in order to overcome mobile device limitations due to user interface, screen, connectivity and information overload. Many researchers have proposed personalised applications or content for mobile user using recommendation systems. VISCORS [3], which recommends wallpapers for mobile devices to users through content filtering, is an example of such a system. Another example is MovieLens Unplugged [4], a movie recommendation system for mobile devices. This also focuses on user rating and collaborative filtering to select recommended movies. Some recommendation systems focus on location-based services (LBS) [5, 6]. These systems adjust their recommendations by using the user's short-term and long-term preferences. News recommendations [7] are another example of applications that utilise rating-based recommendations.

Although the recommendation system is implemented on mobile devices, the main tasks of prediction and recommendation should be maintained. Those studies have focused on predictions but did not seek to create relevant items based on user's preferences or demographic factors. Further, tourism and pedestrian applications use the user's location to find useful information. The study of Zipf and Jost [8] was based on a user model related to dynamic personalised service and used adaptive GI (Geographic Information). However, the study focused on pedestrian navigation and POI (Point-of-interest) and was not concerned with user-related information or direction recommendations. It did not include product or result ratings for the recommenders and other users' opinions to construct or establish recommendation systems for the early stages.

Another problem relating to establishing the model is non-rated items or new items. New items appear on a website that have not been rated, or may have ratings that are low relative to older items. They will have less chance of appearing at the top of the list despite their relevance to the user. An associated problem that is faced by the recommendation system is providing content for first-time and revisiting users. As a result, it is a challenge to provide personalised content for a first-time user via recommendation system.

2.2 Collaborative Filtering

The most widely used technique in recommendation system is collaborative filtering. The item-based collaborative filtering is chosen because the research of Papagelis and Plexousakis [9] has shown that the item-based algorithm performed better than the user-based algorithm. Moreover, the study of Yu et al.[10] presented that using Pearson Correlation Coefficient performed better than Kendall Correlation and positive correlated neighbors gains higher accuracy.

2.3 Association Rules

This technique is a model-based approach for recommendation system. It is an appropriate technique used to find associated items or relevant items for the system. This technique constructs the rules and produces the consequences, that is, the results of the relevant items according to antecedent or condition of the mobile content. The example of implementation Association Rules on mobile device for recommendation can be seen from research by Sohn and Kim [11]. They implements AR to find the additional mobile service. They extract the knowledge from the customers to understand what additional services each cluster will be adopted. This research focused on forming the group of user with additional services but not finding the relevant services to present to user. Association rule has been used in mobile applications to find the top N items as well. For example, Liu and Liou [12] find recommendations for mobile users by multiple channels weighting. Another work focused on the segmentation of users with the k-nearest neighbor method for CF. It implemented association rules to find the top N items based on customers' content usage behavior (Recency, Frequency and Monetary) [13]. However, when association rules alone are used in the recommendation systems for mobile content recommendation, it may require a significant amount of computation to find all the possible rules. Alternative approaches are therefore required to speed up this process.

3. METHODOLOGY

3.1 The proposed integrated mobile content recommendation model

The work flow of the integrated mobile content recommendation model is shown in figure 1. The first function begins with user group identifying. It processes the user's information in order to identify the mobile content group that user belongs to. Next, the mobile content filtering will be performed. The top ranking content will be predicted based on user's group information. After that, the Association Rules that related to the predicted items from the previous stage and user's group will be generated. Then, the recommendation generator will collect predicted items from mobile content filtering component including relevant items based on the generated rules. The final recommendation is generated and sent to the user.

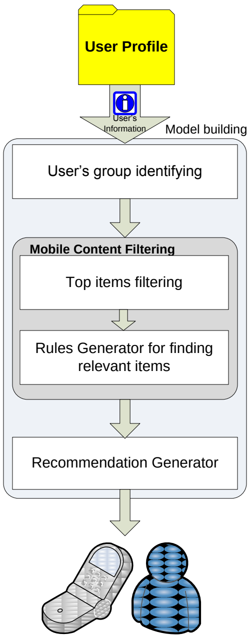

Figure 1. Diagram of building integrated mobile content recommendation model

Figure 2 shows an overview of rules generator module on integrated mobile content filtering model. The AR generator obtains input from the previous components which are user's group identification and top content items filtering. These input are cluster information, user's rating of content items and predicted top content items. Then, the Association Rules are extracted and consolidated to find the set of rules for mobile content filtering. After that, these rules will be used to find the relevant content items for mobile content recommendation generator.

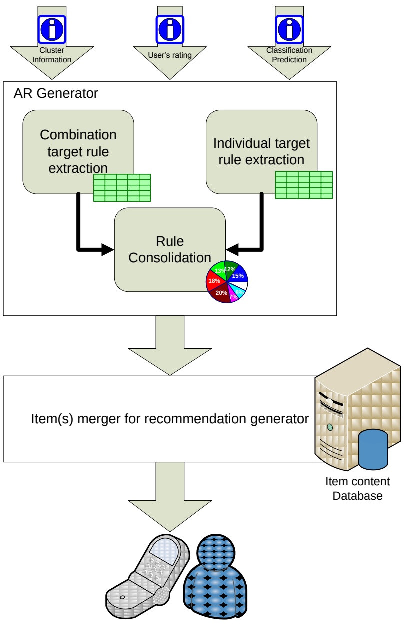

Figure 2. Represent extracting of relevant items module based on Association Rules process

3.2 The Proposed Multi-level Targeting Classification Association Rule Technique (MTCAR)

The proposed methodology is to find the Association Rules on the relevant content items for the mobile content filtering in the recommendation system by combining the classification association rule and multi-level association rules. The purpose is to reduce number of redundant rules and classify relevant content items based on classification and clustering techniques. With all these, is the proposed system will address the current limitation of mobile content recommendation in the early stage. It also enhances the system by finding the relevant items for the user based on user profile.

According to experiment dataset, there is no information related to cluster and class. However in the previous phase as described earlier, mobile content user analysis using clustering, has been done to find the group based on similar demographic factors. In addition, classification technique has been incorporated to predict the top most wanted items based on cluster information. Then, from the classification results, these can be used as targets and antecedent to find the Association Rules from datasets.

In the proposed multi-level approach, the first level will deal with the top ranking items. This stage implements the concept of classification association rules to find the relevant items that are related to the top ranking items. With the top ranking items derived from the classification phase, they are defined as the targets in the rule extraction process. In the first level, only the top three ranked item are used as the target. In the second and subsequent levels of Association Rules, the rules for the level are extracted by setting target from the top level which is the precedent top ranking items.

After the rule for the different levels have been extracted, the next step is rule consolidation. The first step is using rules from the first level to find the target items based on top N. If the system can find relevant items up to top N, it is stopped. In contrast, if the first level rule cannot complete the requirement. The system goes to the next level and finds the target according to ranking of content item in each cluster specifically first, second and third. In addition, if the rule and target are duplicated from the first level, it would be cut off. Finally, the recommended items are derived and prepared to push to mobile recommendation system.

3.3 Experiment Design

The data source used for the experiment was obtained from published research work on the mobile internet content users in Bangkok [14]. This set of data consists of the user's content preference such as multimedia, news or information services on mobile internet. 300 randomly selected records were used as training data. There are 3 datasets which are dataset A, dataset B and dataset C. The pre-processing phase is required to format the data to ensure suitability for each comparing technique. The clustering process has been processed using cluster analysis from [15] in order to find groups of users with similar demographic factors. Before establishing the classification model, all the data and variables are normalised. Then, the experiment is carried out item by item, that is, starting from the first item, then the second item, and the third item consecutively. The classification model has been processed using results from [15] in order to find the appropriate classification technique. After that, the generated rules will be used for finding relevant items for mobile content recommendation. The next phase compares the integrated method with other techniques by using the same dataset for both training and testing in each method. The techniques to be compared with are Collaborative filtering and Association Rules.

4. EXPERIMENTAL RESULTS

4.1 Recommendation System Performance

The comparison results are shown in graphs in Figure 3 – 5. They represent the accuracy rate of recommendation system for top 10 items in each dataset.

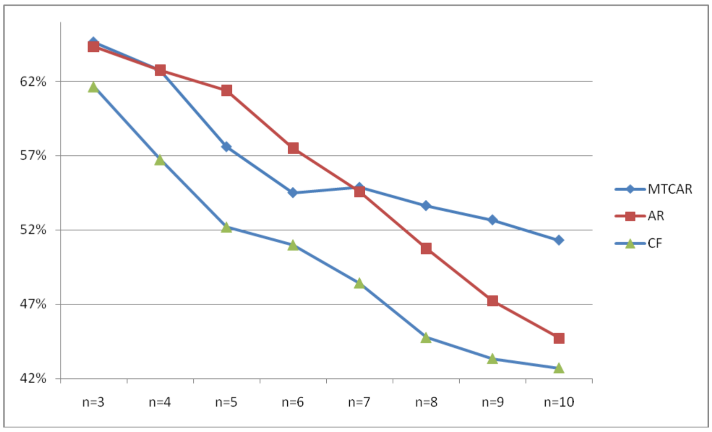

Figure 3. A comparison of accuracy rate between MTCAR and other techniques in dataset A

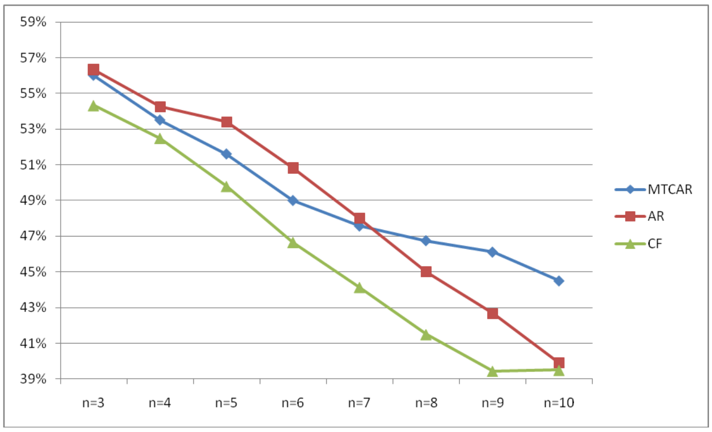

Figure 4. A comparison of accuracy rate between MTCAR and other techniques in dataset B

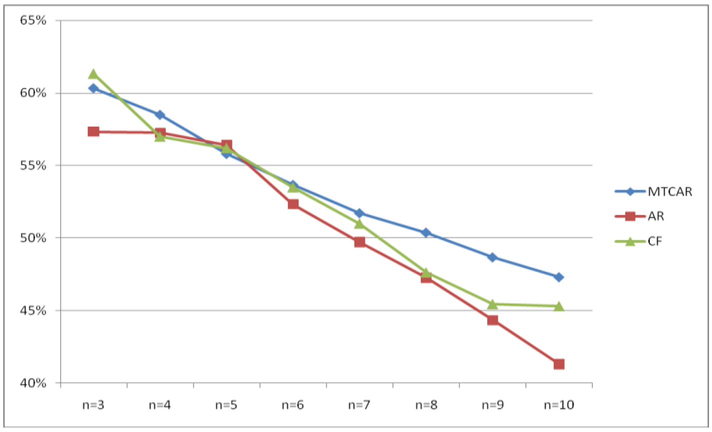

Figure 5. A comparison of accuracy rate between MTCAR and other techniques in dataset C

The comparison results show that MTCAR outperformed the Collaborative Filetering technique. When comparing with the Association Rules, the first 3 or 4 items seem to be similar to Association Rules in dataset A and B, with better performance in dataset C. From top 3 to top 6 items, the 3 methods are comparable results but after top 6 MTCAR can perform better in finding relevent items. It shows significant results in accuracy rate.

4.2 MTCAR Performance Comparison with Association Rules Generation

The other performance of MTCAR compared with Association Rules can be seen from Table 1. It seems that MTCAR generates fewer rules than Association Rules; and MTCAR technique provided better performance in a recommendation for mobile content. They are shown on previous results in terms of accuracy rate. The percentage of rules reduced is calculated from the difference between the number of rules generated by each technique and divided by the number of maximum rules for each dataset.

Table 1. Percentage of number of reduced rules generation

Technique	Dataset A	Dataset B	Dataset C
MTCAR	194	170	190
AR	218	247	211
% of Rules Reduced	11.01%	31.17%	9.95%

Furthermore, Table 2 was shown that the number of recommended items generated from MTCAR was significantly more compared to the association Rules technique. In all datasets, MTCAR gained number of average recommended items generation at 9.7, 9.38 and 9.5 out of 10 items respectively. Whereas, Association Rules obtained average number of recommendation generation at 7.66, 8 and 7.43 consecutively. Moreover, MTCAR can generate number of recommended items on a system of around 27% in dataset A and dataset C. Although dataset B showed lower percentage at around 17% but it was still better in terms of number of items recommendation.

Table 2. Number of generated recommendation for mobile content

Technique	Dataset A	Dataset B	Dataset C
MTCAR	9.7	9.38	9.5
AR	7.66	8	7.43
% of Item Generation	26.63%	17.25%	27.86%

The level of emptiness is shown in Table 3. It was the measure to indicate that a recommendation system was unable to generate recommendation items according to available information. It means the system shows ‘empty’ for these items. The measurement was calculated by sum of empty recommendation items in each user for each dataset. MTCAR can perform better in terms of items generation for mobile content recommendation system. All datasets shown the percentage of emptiness was at 3%, 6% and 5% respectively, while the Association Rules showed a much higher percentage compared to MTCAR techniques, the percentage of the difference was shown at 87%, 69% and 81% for each dataset consecutively.

$$\text{Percentage of ‘empty’ recommendation} = \frac{\sum_{i=1}^{n} \begin{cases} 1 : Item_{i\,j} = \varnothing \\ 0 \end{cases}}{TotalItem_{n\,j}} \qquad (1)$$

Where i is item number of dataset j

Table 3. Level of emptiness generation for a recommendation system

Technique	Dataset A	Dataset B	Dataset C
MTCAR	3%	6%	5%
AR	23%	20%	26%
% of Difference emptiness	87%	69%	81%

4.3 Qualitative Comparison

To verify that MTCAR can be used on mobile content recommendation system, the qualitative comparison is carried on. The data to compare with the proposed method is collated from a large mobile portal site in Thailand and the statistic has been recorded in www.mobilethai.net. The primary data is 552,898 page views for mobile portal site and there are various categories, including news, fortune teller and game downloading. The actual ratio of page views is unable to be disclosed; therefore, it can show roughly the proportion. Furthermore, to compare with the data that has been used in this experiment by MTCAR, the page view category will be filtered to find the content that is a match with experiment data.

As a result, the data on page view was filtered out to news, entertainment, mobile download, and sports. Likewise, the results of recommendation would be reduced to categories that were similar to mobilethai.net mobile portal page view for fair comparison. The results are presented in Table 4.

Table 4. Proportion of mobile content compared to actual mobile portal page view

Content	Mobile Portal Page View	Dataset A	Dataset B	Dataset C
News	40.00%	45.75%	45.92%	42.45%
Entertainment	33.33%	25.20%	26.12%	29.89%
Mobile Download	16.00%	19.74%	19.63%	23.21%
Sports	10.67%	9.31%	8.32%	4.45%
Total	100.00%	100.00%	100.00%	100.00%

It seems that the mobile content recommendation from MTCAR reflects the real world for mobile content usage. This can be seen from figure’s 6 – 9. The proportions of the pie charts are quite similar, which dataset showing the sports content was less compared to actual proportion of mobile portal page view and the mobile download being higher.

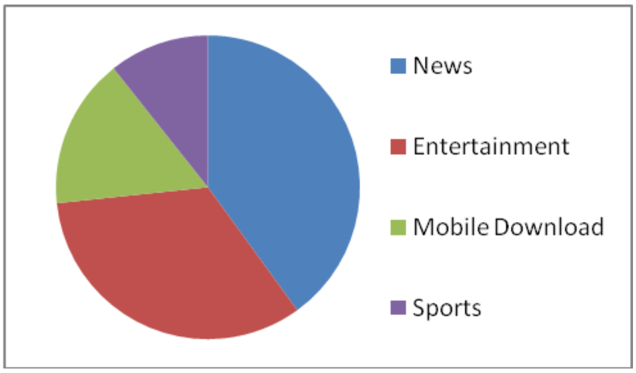

Figure 6. A proportion of mobile content page view

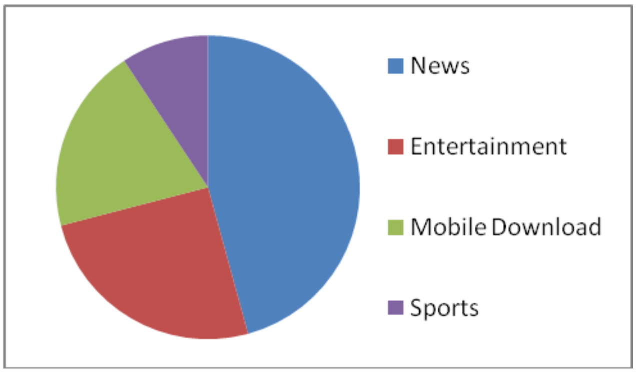

Figure 7. A proportion of mobile content recommendation from dataset A

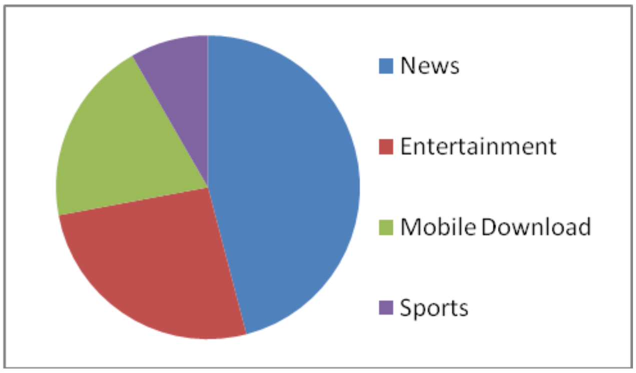

Figure 8. A proportion of mobile content recommendation from dataset B

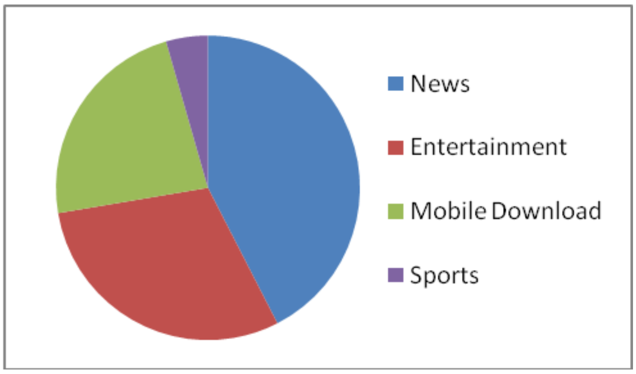

Figure 9. A proportion of mobile content recommendation from dataset C

5. DISCUSSION AND CONCLUSION

After establishing the integrated model for a mobile content recommendation system, the proposed method, MTCAR, a through comparison study was performed with other techniques to recommend appropriate mobile content that matches the needs of the user. In this research, the experiments have shown that MTCAR can perform well compared to other methods. Firstly, the standard measurements, accuracy rate, showed that MTCAR can perform better in terms of finding relevant items after top 6 or top 7, and it can also provide similar accuracy rate for the first 3 items.

The reason why MTCAR provides a better recommendation is due to the MTCAR mechanism. It assembles clustering processes to identify user group and predicts most wanted items from the cluster. Then, the relevant items are derived by association rules, which are generated from user cluster and target items in each cluster. So, relevant items would be created differently according to user demographic factors and their different target items. Whereas, in Collaborative Filtering (CF), it is concerned with user rating and focuses on finding relevant items or recommendations based on those ratings only. The rating is used to find the similarity of item. The same can be observed for Association Rules, this technique is helpful in terms of finding relevant items but the rules are constructed from user profiles only, which is not enough to consider item-based aspects. Therefore, it helps for the first top 3 or 4 items, but in the later stages its performance on finding relevant items decreases.

Secondly, comparisons between MTCAR and Association Rules in terms of rules and recommendation generation, reported that MTCAR returns highly acceptable results with the same support and confidence level. The number of Association Rules that is generated from MTCAR is less than the traditional Association Rules. That means MTCAR implements fewer rules to create a recommendation and gains better results. In addition, the number of items that can be recommended for the top 10 items is almost 10 items, while Association Rules has a limitation of 8 items on this measurement, therefore Association Rules is unable to recommend more items compared to MTCAR. Likewise, the level of emptiness, which means the recommendation system is unable to generate or recommend items to user, also showed that MTCAR provides significant results. MTCAR gains much less emptiness level of a recommendation system compared to Association Rules.

Thirdly, when MTCAR is used with real world data, actual mobile content page view, the top mobile content categories derived from MTCAR in all datasets are similar to mobile content page view with exception of a slight deviation from the page view in a couple of the items in dataset C.

As stated above, it can be seen that MTCAR can be used in a mobile content recommendation system and it will provide better results compared to other techniques. This can address the limitation of recommendation system for first time user by recommending appropriate content that matches the user's needs. It also addresses first content rating in terms of finding relevant items. The proposed method, MTCAR, can enhance the mobile content recommendation system by its performance.

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