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A FRAMEWORK FOR INTEGRATED MOBILE CONTENT RECOMMENDATION

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ABSTRACT

Content filtering in a mobile recommendation system plays a vital role in providing solution to help mobile device users obtain their desire content. However, mobile content recommendation systems have problems and limitations related to cold start and sparsity. These problems can be viewed as a user's first time connection to a mobile recommendation system and initial rating of the content in an early stage of the system. Hence, to obtain personalized content for mobile user, mobile content filtering is needed. This paper proposes a framework for integrated mobile content recommendation. The framework makes use of classification and adaptive association rule techniques to build an integrated model. The results demonstrate that the proposed framework outperforms related techniques. This can address the problem of sparsity for mobile content recommendation systems.

Keywords: Mobile Recommendation, Association Rule, Integrated Model, Mobile Content

1. INTRODUCTION

There are many challenges in delivering desired content from the huge amount of mobile content available. Mobile content recommendation is typically needed to deal with the information overload problem. However, most recommendation systems face some problems in the early stage. These problems, which include sparsity and cold start, result from insufficient information being available to generate any recommendation. As a result, the system finds it difficult to provide a good recommendation without first establishing a proper mobile content recommendation model. Most techniques ignore non-rated items or new items. In the early stage of the new content, the amount of downloading or rating information may not be sufficient to determine the item rating. Thus, some new content may not be delivered to the user or appear on the top items list, even though it might be indirectly relevant based on the user's profile[1, 2]. Therefore, some mechanism is needed to allow such content to be retrieved by associating the items to the interests of the user.

Based on the problems and motivations presented, this paper addresses 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 uses the extracted knowledge to establish a mobile content recommendation model for new users, providing an association with non-rated or new items to the relevant items that have been rated. In this paper, in order to demonstrate the performance of the proposed model, the proposed method, Multi-level Targeting Classification Association Rule (MTCAR), is compared with other mobile content recommendation techniques.

The structure of this paper is as follows: Section 2 presents a literature review of mobile content recommendation systems and techniques, while Section 3 shows the research methodology. Section 4 presents the experimental results for the proposed methodology. Finally, Section 5 draws some conclusions.

2. LITERATURE REVIEW

2.1 Mobile Content Recommendation

Due to the challenge of delivering a huge amount of content in a mobile Internet service, the mobile content presented should be appropriate for the user's needs. This will increase the accuracy of information retrieval; mobile content recommendation is necessary to achieve this objective and to help users access the information that they want in a shorter period of time.

Mobile recommendation systems use mobile content filtering techniques to address the information overload problem by reducing the content that is presented to a mobile device user[3]. The mobile recommendation system addresses the problem of finding information from a large collection of information[4].

Many researchers have proposed personalized applications or content for mobile users employing recommendation systems. For product marketing and sale sites such as Amazon.com and Movielens.org, the products or items to be recommended can be books, movies, or TV programs[5]. Most of these recommendations are based on other user ratings or other criteria such as results from symbolic learning, user preferences, or item categories. Such recommendation systems have also been implemented in mobile devices. Examples of the systems include VISCORS[6], MovieLens Unplugged[7], local-based information systems[8] or the news[9].

When recommendation systems are implemented on mobile devices, the main tasks of prediction and recommendation should be maintained. Studies have focused on predictions rather than creating relevant items based on user preferences or demographic factors. Tourism and pedestrian applications employ the user's location to find helpful information[10]. Another problem in 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 recommendation list despite their relevance to the user. As a result, it is a challenge to provide personalized content for a first-time user via a recommendation system.

Melville et al.[11] and Schein et al.[12] addressed the problem of the recommendation system in terms of sparsity and cold start issues, which are due to insufficient information for making any recommendation. However, they focused on the method and metric used for model fitting in creating the recommendation model. Their studies did not address the content and user relationship with respect to other factors, such as user demography. In addition, the technique used was based on other users' ratings instead of the user's behavior. The MONERS system[9] is an application that utilizes rating-based recommendations. It is a hybrid method used to recommend news on mobile devices using a batchwork mechanism and system learning, which are carried out at the server. A user must subscribe to the news service, and the user information (including interests) needs to be submitted and stored at the server.

Content filtering in a mobile content recommendation system can be based on the user profile information. Such profile information can be obtained from a user's input according to his or her interests or from the user's preferences, which are derived from the behavioral usage and inferred from the user's profile. This can be seen from mobile content frameworks such as those proposed by Ninget al.[13], Weißenberg et al.[14], and Jeon et al.[15].

In recent years, data mining using machine learning techniques has provided more relevant information to users in mobile recommendation systems[9, 16, 17]. However, many components and stages are involved in the recommendation process in order to increase the accuracy. There is a need to search for an efficient framework that can provide content to satisfy the user's needs by providing personalized content recommendations. The next section describes the techniques used in mobile recommendation systems.

Most mobile recommendation systems face problems in the early stage (i.e. during the first two interactions) due to a lack of user information. These problems are known as sparsity and cold start. Although data mining techniques can help to solve this problem in the later stage, a model for mobile content recommendation is needed to mitigate sparsity for first time users and first content ratings.

2.2 Techniques Used in Recommendation Systems

The most widely used technique in recommendation systems is collaborative filtering. The present study of Papagel is and Plexousakis[18] showed that the item-based algorithm performed better than the user-based algorithm. Yu et al.[19] found that the Pearson correlation coefficient outperformed the Kendall correlation and that positively correlated neighbors yielded higher accuracy. However, collaborative filtering has a limitation in building a good recommendation for new users with no rated items or new items. This is known as the sparsity and cold start problem. Furthermore, it is unable to recommend items that are dissimilar to items that were already seen in the past.

Another common technique used in recommendation systems is association rules. This model-based approach is used to find associated items or relevant items for the recommendation 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. An example of association rules on mobile devices is provided by Sohn and Kim[20]. They implemented this approach to find additional mobile services. They extracted the knowledge from the customers to understand what additional services each cluster would adopt. This research focused on forming groups of users with additional services but not finding relevant services for the present user. Association rules have been also used in mobile applications to find the best N items for users. This is called top-N analysis. For example, Liu and Liou[17] found recommendations for mobile users by weighting multiple channels. Another work focused on the segmentation of users with the k-nearest neighbor method for collaborative filtering. It implemented association rules to find the top N items based on customers' content usage behavior[21]. However, when association rules alone are used in recommendation systems for mobile content, a significant amount of computation may be required to find all possible rules. Alternative approaches are therefore required to speed up this process.

3. METHODOLOGY

3.1 The Proposed Integrated Mobile Content Recommendation Model

The workflow of the integrated mobile content recommendation model is shown in Figure 1. The first function begins with user group identification. It processes the user's information in order to identify the mobile content group to which the user belongs. Next, mobile content filtering is performed. The top ranking content is predicted based on the user's group information, and the association rules that relate to the predicted items from the previous stage and from the user's group are generated. Then, the recommendation generator collects the predicted items from the mobile content filtering component, including relevant items based on the generated rules. The final recommendation is generated and sent to the user.

Figure 2 shows an overview of the rules generator module. The association rules generator obtains input from the previous components, which are the user's group identification and top content items filtering. This input includes cluster information, users' ratings 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. The details of rule consolidation are shown in the next section. These rules are used to find the relevant content items for the mobile content recommendation generator.

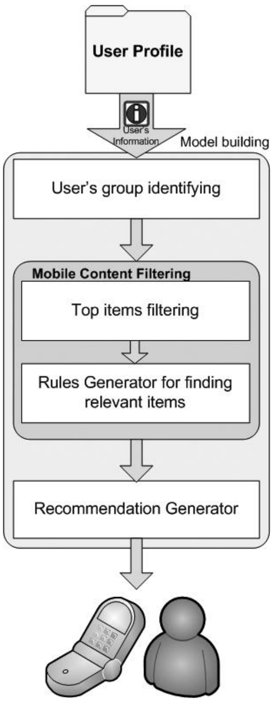

Figure 1. Diagram of the integrated mobile content recommendation model

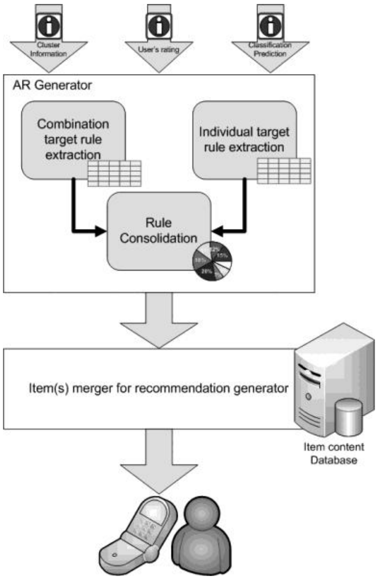

Figure 2. Extraction of relevant items module based on the association rules process

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

The proposed methodology is used to find the association rules for relevant content items. The methodology combines the technique of classification association rule and multi-level association rules. The purpose is to reduce the number of redundant rules and classify the relevant content items based on classification and clustering techniques. The proposed system addresses the current limitation of mobile content recommendations in the early stage. It also enhances the system by finding the relevant items based on the user's profile.

The experimental dataset does not contain any information related to cluster or class. However, in the previous phase, mobile content user analysis with clustering was performed to find a group based on similar demographic factors. In addition, classification is incorporated to predict the top most-wanted items based on cluster information. From the classification results, these can be used as targets and antecedents to find the association rules from datasets.

In the proposed multi-level approach, the first level deals with the top ranking items. This stage implements classification association rules to find 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 items are used as the target. In the second and subsequent levels, the rules are extracted by setting a target from the top level, which the target are the precedent of content items in the top ranking items.

After the rules for the different levels have been extracted, the next step is rule consolidation. The first step uses rules from the first level to find the target items based on the top-N which is specified to predict the best N items. If the system can find relevant items up to the top N, it stops; 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. In addition, if the rule and target are duplicated from the first level, it could be excluded from a list of the recommendation. Finally, the recommended items are derived. Figure 3 shows the rule consolidation process.

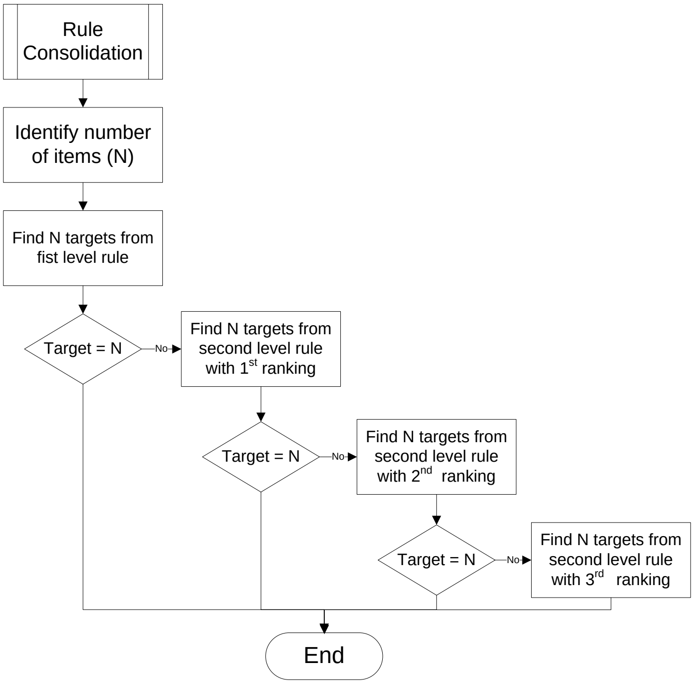

Figure 3. Rule consolidation process

3.3 Experimental Design

The data source used for the experiment was obtained from published research work on mobile internet content users in Bangkok[22]. This set of data consists of user content preferences for multimedia, news or information services on the mobile internet. There are several factors and attributes in the dataset. In this paper, the key demographic factors of gender, age, income, and occupation were selected to find potential groups. These attributes were chosen for acquiring the requisite data from mobile internet users. Three hundredrandomly selected records were used to create a dataset as training data. Three datasets are created (A, B, and C). A pre-processing phase was required to format the data and to ensure suitability for each comparison technique. The clustering process employed the cluster analysis from[23] in order to find groups of users with similar demographic factors. Before establishing the classification model, all data and variables were normalized. The experiment was then carried out item by item, that is, starting from the first item, then the second item, and the third item consecutively. The classification model was processed using results from[23] in order to find the appropriate classification technique. The generated rules are used to find relevant items for mobile content recommendations. 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 used in the comparison study are collaborative filtering[18] and association rules[20].

4. EXPERIMENTAL RESULTS

4.1 Recommendation System Performance

The comparison results are shown in Figures4 through 6. They represent the accuracy rate of the recommendation system for the top 10 items in each dataset.

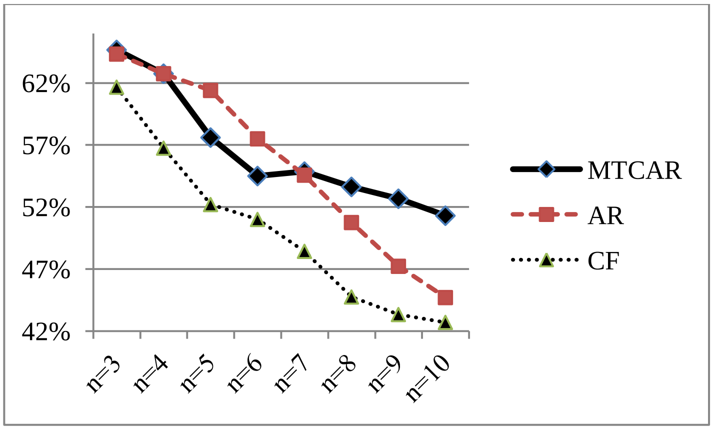

Figure 4. A comparison of accuracy rate between MTCAR and other techniques in Dataset A

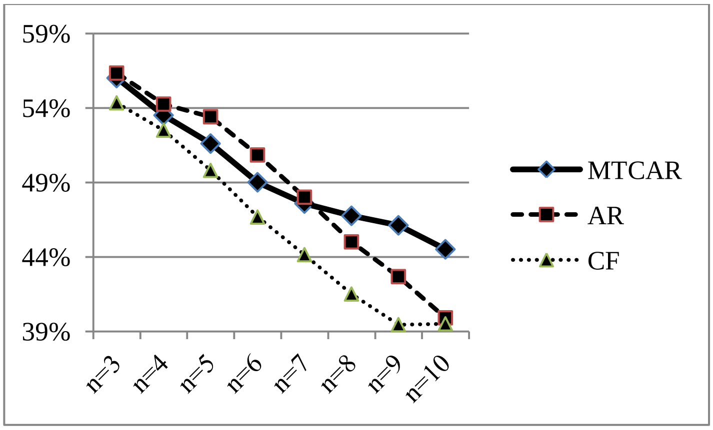

Figure 5. A comparison of accuracy rate between MTCAR and other techniques in Dataset B

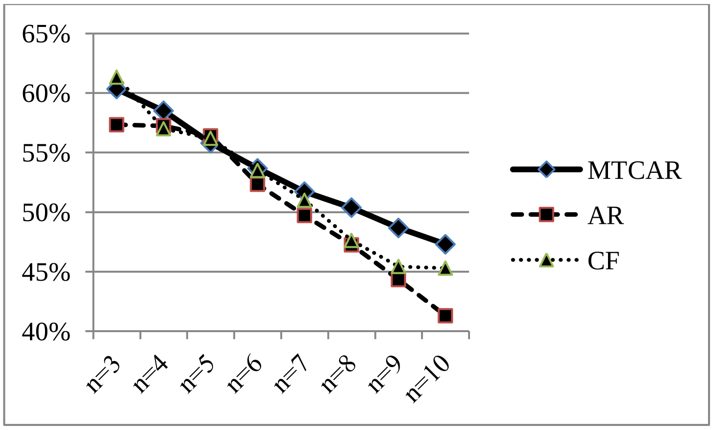

Figure 6. A comparison of accuracy rate between MTCAR and other techniques in Dataset C

The comparison results show that MTCAR outperformed the collaborative filtering technique. Compared with the association rules, the first three or four items seem to be similar to those in Datasets A and B, with better performance in Dataset C. From the top three to the top six items, the three methods have comparable results. After the top six items, however, MTCAR can perform better to find relevent items. It also shows significantly better accuracy.

4.2 MTCAR Performance Comparison with Association Rules Generation

Table 1 compares the performance of MTCAR and association rules. It seems that MTCAR generates fewer rules and provides better performance in the recommendation of mobile content. This can be observed from the 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 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%

Table 2 shows that significantly more recommended items were generated from MTCAR. In all datasets, MTCAR was able to generate an average of 9.7, 9.38, and 9.5 of 10 items, respectively. In contrast, the association rules generated an average of 7.66, 8, and 7.43 items, respectively. Moreover, MTCAR generated the number of recommended items on a system for around 27% more compared to association rules in Datasets A and C. Although Dataset B showed lower percentage at around 17%, it was still better in terms of number of items recommended.

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. This means that the system cannot generate any item from the available items. The measurement was calculated as the sum of empty recommendation items for each user in each dataset Equation 1).Clearly, MTCAR performed better in terms of item generation with 3%, 6%, and 5% emptiness for each respective dataset. The Association Rules showed a much higher percentage compared to MTCAR techniques (87%, 69%, and 81%, respectively).

$$\text{Percentage of empty recommendations} = \frac{\sum_{i=1}^{n} \begin{cases} 1 : Item_{ij} = \emptyset \\ 0 \end{cases}}{TotalItem_{nj}} \quad (1)$$

where i is the item number of dataset j

Table 3. Level of emptiness generated for 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 in mobile content recommendation systems, a qualitative comparison is conducted. The data used in this comparison were collated from a large mobile portal site in Thailand; the statistic has been recorded at www.mobilethai.net as a page view of user's browsing data related to mobile content usage from April 2011 to June 2011. The primary data are 552,898 page views for the mobile portal site, which includes news, fortune telling, and game downloads. The actual ratio of page views is not disclosed; therefore, only the rough proportion is shown. Furthermore, to compare with the data used in this experiment by MTCAR, the page view category is filtered to find content that matches the experimental data.

As a result, the data on page view was filtered to news, entertainment, mobile downloads, and sports. Likewise, the recommendation results were reduced to categories that were similar to mobilethai.net mobile portal page views 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%

The mobile content recommendations from MTCAR reflect to real world mobile content usage, as shown inFigures 7through10. The proportions are quite similar, with less sports content compared to actual proportion of mobile portal page view and more mobile downloads in Dataset C.

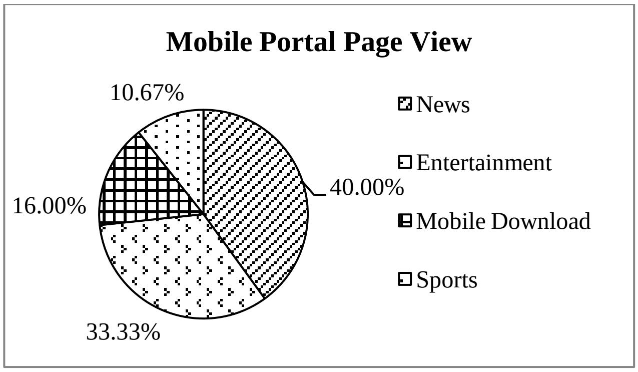

Figure 7. A proportion of mobile content page view

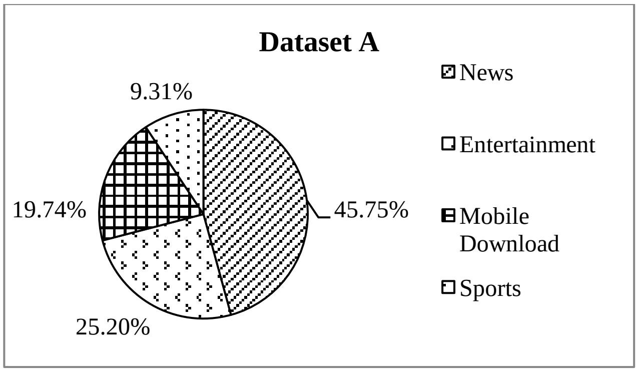

Figure 8. A proportion of mobile content recommendation from Dataset A

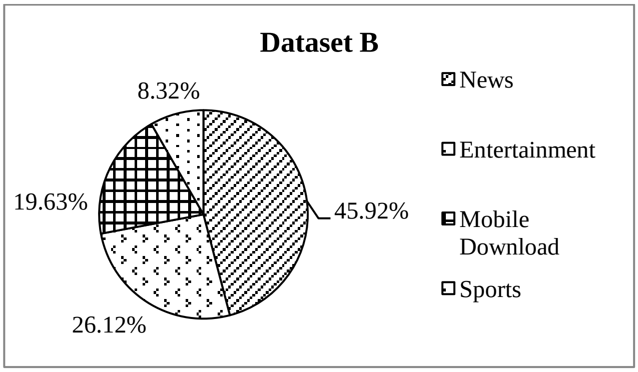

Figure 9. A proportion of mobile content recommendation from Dataset B

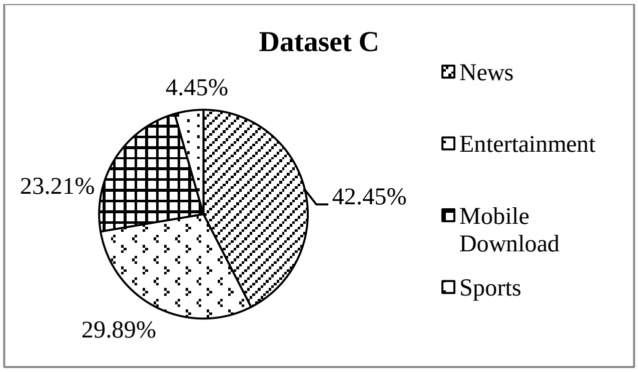

Figure 10. A proportion of mobile content recommendation from Dataset C

5. DISCUSSIONS AND CONCLUSIONS

A framework for an integrated mobile content recommendation system is developed to address the problem of a new user connection or a first time user. After establishing the proposed method, MTCAR, a thorough comparison study was presented to recommend appropriate mobile content that matches the needs of the user. The experimental results show that MTCAR can perform well compared to other methods.The accuracy rate showed that MTCAR performs better in terms of finding relevant items after the top six or top seven items, and it can also provide similar accuracy for the first three items.

The reason why MTCAR provides a better recommendation is due to the MTCAR mechanism. It assembles clustering processes to identify user groups and predicts the most wanted items from the cluster. Then, the relevant items are derived by association rules, which are generated from the user cluster and the target items in each cluster. Thus, relevant items are created according to the user's demographic factors and different target items. In contrast, collaborative filtering focuses on finding relevant items or recommendations based only on user ratings. The rating is used to find similarity item. The same can be observed for, the association rules approach, which generates recommendations from user profiles only.

Comparing MTCAR and association rules in terms of the number of rules and the recommendation generated, MTCAR returned highly acceptable results with the same support and confidence level. Fewer association rules were generated from MTCAR than from the traditional association rules approach. That means MTCAR implements fewer rules to create a recommendation with better results. In addition, the number of items that can be recommended for the top 10 items is nearly 10, while Association Rules has a limitation of 8 items. Moreover, MTCAR also provided better results in terms of emptiness. When MTCAR was used with real world data, the top mobile content categories derived in all datasets were similar to the mobile content page view with the exception of a slight deviation from the page view for a few items in Dataset C.

As illustrated above, MTCAR can be used in a mobile content recommendation system to provide better results compared to other techniques. It can address the limitation of recommendation system for first time users by recommending appropriate content that matches the user's needs. It also addresses first content ratings in terms of finding relevant items. Thus, the proposed method can enhance the performance of a mobile content recommendation system.

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