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A Model for Mobile Content Filtering on Non-Interactive Recommendation Systems

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Abstract— **To overcome the problem of information overloading in mobile communication, a recommendation system can be used to help mobile device users. However, there are problems relating to sparsity of information from a first-time user in regard to initial rating of the content and the retrieval of relevant items. In order for the user to experience personalized content delivery via the mobile recommendation system, content filtering is necessary. This paper proposes an integrated method by using classification and association rule techniques for extracting knowledge from mobile content in a user's profile. The knowledge can be used to establish a model for new users and first rater on mobile content. The model recommends relevant content in the early stage during the connection based on the user's profile. The proposed method also facilitates association to be generated to link the first rater items to the top items identified from the outcomes of the classification and clustering processes. This can address the problem of sparsity in initial rating and new user's connection for non-interactive recommendation systems.**

Keywords-mobile recommendation; content-based filtering; association rule; classification

I. INTRODUCTION

In recent years, users can access information ubiquitously with devices such as mobile or smart phones. The main limitation on mobile phones is the overloading of information. This has led to the focus of development on mobile content recommendation systems. Mobile content is normally available through various kinds of websites. It is a challenge for the recommendation systems to provide first-time users with appropriate personalized content.

Most recommendation systems have problem in the early stage to make a reasonable recommendation due to the lack of user profile information. This problem is known as sparsity for items with initial rating or first rater, and first-time users. It is difficult to establish the recommendation model for users in the early stage of a recommendation system, as there are insufficient amount of rated content to determine the recommended or relevant items. It is also difficult to find similar groups of users because of the sparsity problem especially when using collaborative filtering method. Collaborative filtering (CF) is a commonly used technique in recommendation systems. To focus on this problem, it is a challenge to incorporate a user profile in terms of demographic factors to identify the group of users that a new user belongs to [1]. Some researchers have focused only on item rating for recommendation systems [2, 3] despite the fact that the system needs both user-based information and item rating-based information to recommend the items even for a first-time user on a non-interactive system. A non-interactive system is a system without any feedback from the user [4]. Research by Chen and Yu [5] presented a hybrid technique based on item and user collaborative filtering. However, this technique is not completed in a user's characteristic analysis. They focused only on a user's statistical rating data.

The next problem related to the establishment of the model is 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. Strictly speaking, there should be some mechanisms to allow such content to be retrieved by associating the item 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 top items.

II. RELATED WORKS

A. *Recommendation System*

Personalization has been incorporated in applications such as recommending product items from a menu, as in the case of an infotainment TV show [6]. One of the techniques used to implement a recommendation system is collaborative filtering. This technique has focused on an item-based approach such as that reported in [7]. Some other approaches concentrated on the users. For example, Shani et al. [8] proposed to establish user profiles in recommendation systems. However, a hybrid CF has also been proposed by [5, 9] by combining information from both users and items.

Using only collaborative filtering may not be sufficient to fulfill all the requirements of a recommendation system, especially in addressing the non-interactive and first rater problem. The other approach for recommendation systems is content-based filtering (CBF), which aims to find the correlation among items and user's preferences [10]. Pazzini also proposed a framework for recommendation systems using CF, CBF and demographic factors [1].

Recently, recommendation systems for mobile platforms have been established in the mobile channel media. This was derived from multiple channels including TV, catalogs and the Web [11]. The approach mitigates the problem in the early stage due to the lack of information from new users and new items on the recommendation system. However, this research has not included the demographic factors and it could not identify the consumers' behavior among the different user groups. In addition, an association rule technique has been used for product category or item-based approach. The technique did not find the relationships between the users and the items.

B. *Data Mining and Classification Techniques on Mobile Content and Services*

Data Mining can be used to interpret the problem context and to provide solutions. Techniques such as classification, prediction, association and detection can be used. Wu et al. [12] have shown that some commonly used algorithms in data mining are k-means, SVM, Apriori, and PageRank including Naïve Bayes.

Classification techniques have also been incorporated into the available mobile services. Research has suggested that selecting the best available service is not a simple task. For example, Artificial Neural Networks (ANN) with feed-forward back-propagation neural network were incorporated to assist the selection of different types of particular mobile services [13]. Other research by Cufoglu et al. [14] had proposed which classifier is the most appropriate for classifying user profiles in the same way as Nurmi and Hessinen [15]. Their work also presented the analysis of personalization techniques for contextual data.

However, these research proposals again have not taken care of the problem in the early stage of the mobile content recommendation system for first-time users and non-rated or new items. It mainly focused on the prediction and the accuracy for the identified or known classes. Furthermore, they were not used to handle the relevant items for content recommendation. Some classification techniques are suitable for specific kinds of user data and when they are combined with other techniques, some missing information may not be used to continue with the next phase of the recommendation system in finding the recommended or relevant items. Hence, a more appropriate classification method needs to be established.

C. *Association Rules*

Association Rule (AR) is a rule-based technique that was proposed by Agrawal et al. [16] This technique is an important tool for data mining from databases that can be used to solve knowledge discovery problems and is also suitable for handling categorical data. Association Rule is also capable of finding relevant relationships between the data, and constructs the rules for the association. It was initially used for market basket analysis to determine the relationship among shopping items and to understand the decisions made by the customers in the purchases.

This technique works with large transactions in a database to find the relationship among the items and construct the rules for decision. The model starts with a set of items I which contains $\{i_1, i_2, i_3,\ldots, i_m\}$ and there is a transaction t in the database where t is a set of items, $t \subseteq I$. The transaction database is a set of transactions, $T = \{t_1, t_2, t_3,\ldots, t_n\}$. The Association Rules can measure the quality of the rules by 2 metrics, *support* and *confidence*.

Association rule has been used in mobile applications to find the top N items, as well. For example, Liu et al. [11] used association rules to find multiple channel recommendations for mobile users using channel weighting. 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 (Recency, Frequency and Monetary) [17].

However, when association rules alone are used in the recommendation system 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.

III. METHODOLOGY AND EXPERIMENT

A. *Pre-processing data for Classification and Association Rules*

The data source used for the experiment was obtained from published research work on the mobile internet content users in Bangkok [18]. 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. The clustering process has been processed using cluster analysis from [19] in order to find groups of users with similar demographic factors.

From the clustering stage, the data have been separated into 6 groups, which are the un-clustered group and clustered groups (cluster number 1 to cluster number 5). After that, the top 3 mobile content items in each group are calculated based on the average scores. The top 3 highest scores have been chosen to work on the classification experiments.

The target variable is the item that users may need for their connection session. Before establishing the classification model, all the data and variables are normalized. In addition, the target variables which recorded the user's preference rating (1 to 5) are converted to binary (0 and 1) for the prediction, where 0 is derived from user's preference range from 1 to 3 while 1 is derived from rating 4 or 5. So, '0' means the user is not interested in this item, while, '1' represents the user's preference for this item. This methodology is derived based on binary operation from [20]. Then, the experiment is carried out item by item, that is, starting from the first item, then the second item, and the third item etc. consecutively.

The classification techniques that are used in this experiment are Artificial Neural Networks (ANN), Support Vector Machine (SVM), Bayesian Networks (BS) and Decision Tree with C5.0 algorithm.

After that, the adaptive association rule is applied for rule extraction. The solution to this problem can be used for partitioning and targeting. Partitioning can help to reduce the number of itemsets to be counted, rather than dealing with all the items in the entire database [21]. The Classification Association Rule (CAR) is an alternative method for this approach. However, this technique can be used for solving classification problems in the known-class database. So, the classification phase is needed. The multi-level Association Rules [21] technique is another adaptive association rule technique which divides the problem into levels for extracting the rules. It is a hierarchical concept in which the higher levels of frequent itemsets have more support than the lower levels. The minimum support in the same level is identical. The advantage of this method is that no complete rule processing is required, as the frequent itemsets in the higher level help filter the itemsets in the lower level with less minimum support. This means the lower level needs less support to run the algorithm for rule extraction and it will be run within the frequent itemsets of higher level. This saved significant computational time in extracting the association rules.

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

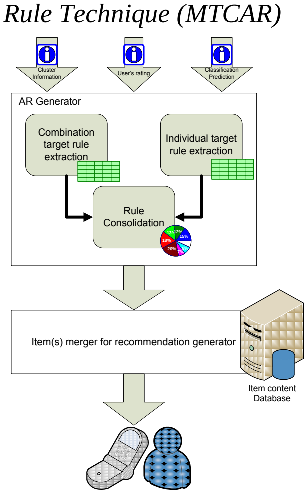

Figure 1. Represent extraction of relevant items module based on Association Rules process

The proposed methodology to find the Association Rules of mobile content filtering for the recommendation system on the relevant content items is a combination of the classification association rule and multi-level association rules. The purpose is to reduce the number of redundant rules and to classify relevant content items based on classification and clustering techniques.

In this stage of constructing the Association Rules for recommending relevant items on the system for the first-time user in establishing the model, the Apriori algorithm has been implemented in this phase. For the first step of Multi-level Targeting Classification Association Rule Technique (MTCAR), the minimum support and confidence are both set at 50%. After that, the rules for the first level are obtained with 3 antecedents. Then, the second level is run separately for each target item based on its ranking specifically first, second and third. With the lower minimum support and confidence, the results of the second level are the rules from each item.

So, from the first level and second level, all rules will be consolidated to rank the outcome sorting by level (first or second level) and order of the ranking items (for the second level). The duplicate rules are eliminated and the rules that show the same result are also cut off using support, confidence, level and sequence.

From the experiment dataset, the data are not clustered, but in the previous phase, clustering has been performed to find the groups based on similar demographic factors. In addition, a classification technique has been incorporated to predict the most wanted items based on cluster information. Then, from the classification results, these can be used as targets and antecedents to find the Association Rules from datasets.

The following description refers to Figure 2. The first level concerns the top-ranked items which are grouped to increase support and confidence of rules for ensuring people's preference towards content items. This stage implements the concept of classification association rules to find the relevant items. The top-ranked items derived from the classification phase are defined as targets for rule extraction. The second level of Association Rules implements the concept of multi-level association rules. The rules for this level are extracted by setting the target from the first level which is top ranking items. The second level also uses support and confidence to measure the rules.

After the rules for 2 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 the top N. If the system can find relevant items up to the top N, it is stopped. In contrast, if the first-level rule cannot complete the requirement, the system goes to the next model and finds the target according to the ranking of content items in each cluster, specifically first, second and third. In addition, if the rules and targets are duplicated from the first level, it will be cut off. Finally, the recommended items are derived and prepared to be delivered to the mobile recommendation system.

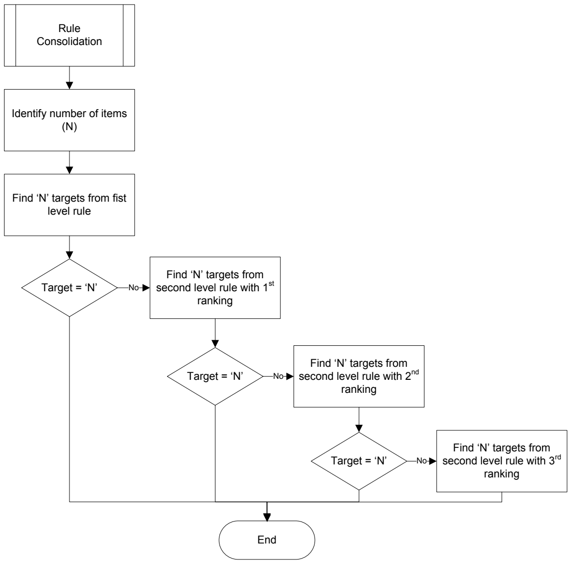

Figure 2. Rule consolidation process

IV. Experimental Results

A. *Classification Results*

The results of classification are shown in Fig. 3-8

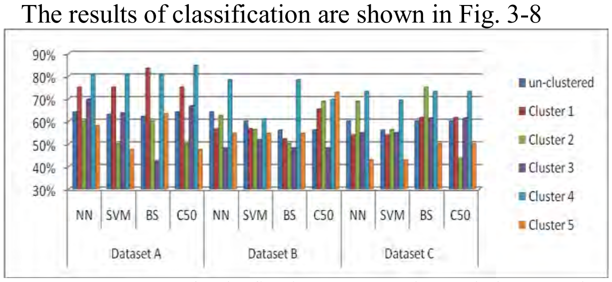

Figure 3. Accuracy rate for the first item compared to each dataset and each classification technique

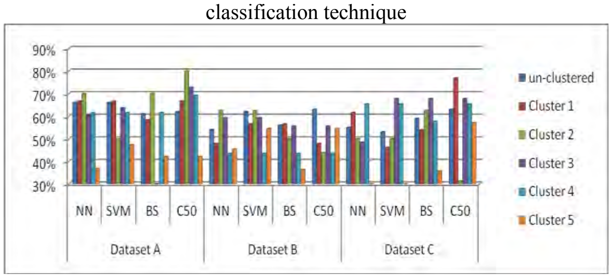

Figure 4. Accuracy rate for the second item compared to each dataset and each classification technique

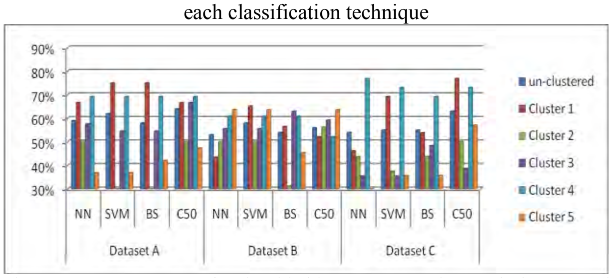

Figure 5. Accuracy rate for the third item compared to each dataset and each classification technique

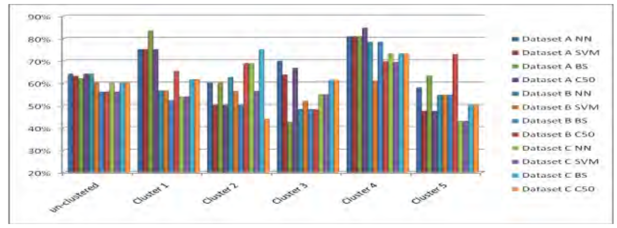

Figure 6. Accuracy rate for the first item compared to each cluster for all datasets

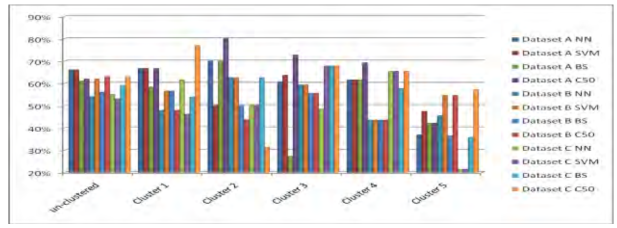

Figure 7. Accuracy rate for the second item compared to each cluster for all datasets

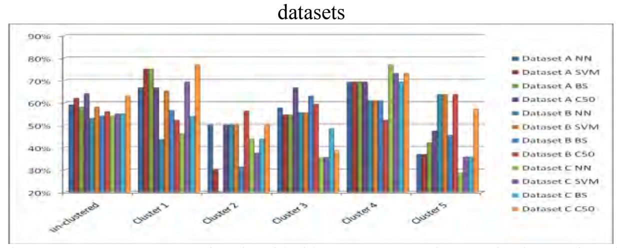

Figure 8. Accuracy rate for the third item compared to each cluster for all datasets

B. *Classification Model Selection*

From the classification results, it can be seen that the datasets and clusters show different results inconsistently. As a result, it cannot be concluded which model is the most suitable for mobile content recommendation for the top items. The classification models are varied due to the data, variables and conditions.

Therefore, the measurement of each cluster and each classification model for each dataset is needed for justifying the model selection. The CM-Score, Classification Model Score, is built in order to generalize the results and to choose the appropriate model. The purpose of this measurement is to find which classifier is the most suitable for cluster-based mobile content recommendation.

The scores for each classifier are calculated based on accuracy rate and the ranking of the items which are first, second and third in each dataset. In this metric, the weight for ranking of items is denoted as 3 points for the first item, then 2 points for the second item and 1 point for the third item. The number of cases in each cluster is also weighted in the metric for generalization of the score based on clustering. The CMScore is shown as follows:

$$CMScore = \sum_{i=1}^{c} \frac{CS_c \bullet AC_c}{n} \tag{1}$$

where

CS = number of cases in cluster c,

AC = accuracy rate of cluster c,

c = cluster number,

n = number of items.

Next, the CMScore for each classification technique is derived, and then the model selection can use these scores to justify what is the appropriate technique to use for predicting the top items for mobile content recommendation.

CMScore, it is concerned with the cluster-based mobile content user groups. Although there is a variable number of cases in each cluster, CMScore tries to generalize the score for a cluster-based group because after clustering analysis, the results found that each cluster is grouped and represent cluster's characteristics such as teenager or mature people with high income. This reflects the real-world situation that different people in the same group have similar preferences. In contrast, people in different groups may like different content items. The principal concept of clustering is to find the similar characteristics of the group that can predict which group incoming or new members belong to.

The CMScore results are shown below

TABLE I. CMSCORE AND WEIGHT RANKING ITEMS

	NN	SVM	BS	C5.0
CMScore	56.4540	56.5894	54.7105	60.8865
Weight ranking	116.6259	114.3763	112.801	123.4508

The CMScore shows that the highest score for classification techniques is Decision Tree with C5.0. Then, when the CMScore is influenced by ranking, the ranking factor is used in CMScore calculation by adding weight 3 for the first item, 2 for the second item and 1 for the third item. The score suggested that Decision Tree is significantly higher than any other techniques based on the CMScore weight ranking.

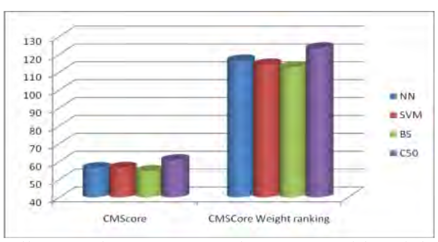

Figure 9. Illustrate the CMScore and CMScore with weight ranking

C. Experiment Results of Association Rules

This section presents the results of extracting the Association Rules to find the relevant items for the recommendation system. Table II shows an example of the extracted rules from the first-level MTCAR. The Consequent represents the relevant items which are derived from target items.

TABLE II. EXAMPLE OF ASSOCIATION RULE EXTRACTION FOR THE CLUSTER 5 BY FIRST-LEVEL RULES WITH 3 CONTENT ITEMS

Consequent	Antecedent	Support %	Confidence %
IM312 = 1.0	IM31 = 1.0 and IM311 = 1.0	50.6849	97.2973
IM312 = 1.0	IM14 = 1.0 and IM31 = 1.0	34.2466	96.0000
IM312 = 1.0	IM14 = 1.0 and IM31 = 1.0 and IM311 = 1.0	34.2466	96.0000
IM312 = 1.0	IM311 = 1.0	54.7945	95.0000
IM312 = 1.0	IM31 = 1.0	53.4247	94.8718
IM312 = 1.0	IM14 = 1.0 and IM311 = 1.0	36.9863	92.5926
IM313 = 1.0	IM14 = 1.0 and IM31 = 1.0	34.2466	84.0000
IM313 = 1.0	IM14 = 1.0 and IM31 = 1.0 and IM311 = 1.0	34.2466	84.0000
IM313 = 1.0	IM31 = 1.0 and IM311 = 1.0	50.6849	83.7838
IM313 = 1.0	IM311 = 1.0	54.7945	80.0000
IM313 = 1.0	IM31 = 1.0	53.4247	79.4872
IM313 = 1.0	IM14 = 1.0 and IM311 = 1.0	36.9863	77.7778

(Please note that IM stands for Item number)

Then, the second-level of rule extraction are shown in Tables III to V with ranking item from first-level targets. They are first, second and third ranking, respectively.

TABLE III. EXAMPLE OF ASSOCIATION RULE EXTRACTION FOR THE CLUSTER 5 BY SECOND-LEVEL RULES WITH FIRST RANKING ITEM

Consequent	Antecedent	Support %	Confidence %
IM311 = 1.0	IM14 = 1.0	52.0548	71.0526
IM31 = 1.0	IM14 = 1.0	52.0548	65.7895
IM312 = 1.0	IM14 = 1.0	52.0548	65.7895
IM313 = 1.0	IM14 = 1.0	52.0548	55.2632
IM23 = 1.0	IM14 = 1.0	52.0548	52.6316
IM32 = 1.0	IM14 = 1.0	52.0548	52.6316
IM326 = 1.0	IM14 = 1.0	52.0548	52.6316
IM11 = 1.0	IM14 = 1.0	52.0548	50.0000

TABLE IV. EXAMPLE OF ASSOCIATION RULE EXTRACTION FOR THE CLUSTER 5 BY SECOND-LEVEL RULES WITH SECOND RANKING ITEM

Consequent	Antecedent	Support %	Confidence %
IM312 = 1.0	IM311 = 1.0	54.7945	95.0000
IM31 = 1.0	IM311 = 1.0	54.7945	92.5000
IM313 = 1.0	IM311 = 1.0	54.7945	80.0000
IM14 = 1.0	IM311 = 1.0	54.7945	67.5000
IM326 = 1.0	IM311 = 1.0	54.7945	60.0000
IM315 = 1.0	IM311 = 1.0	54.7945	55.0000
IM32 = 1.0	IM311 = 1.0	54.7945	55.0000
IM316 = 1.0	IM311 = 1.0	54.7945	50.0000
IM327 = 1.0	IM311 = 1.0	54.7945	50.0000

TABLE V. EXAMPLE OF ASSOCIATION RULE EXTRACTION FOR THE CLUSTER 5 BY SECOND-LEVEL RULES WITH THIRD RANKING ITEM

Consequent	Antecedent	Support %	Confidence %
IM312 = 1.0	IM31 = 1.0	53.4247	94.8718
IM311 = 1.0	IM31 = 1.0	53.4247	94.8718
IM313 = 1.0	IM31 = 1.0	53.4247	79.4872
IM326 = 1.0	IM31 = 1.0	53.4247	64.1026
IM14 = 1.0	IM31 = 1.0	53.4247	64.1026
IM315 = 1.0	IM31 = 1.0	53.4247	53.8462
IM32 = 1.0	IM31 = 1.0	53.4247	53.8462
IM327 = 1.0	IM31 = 1.0	53.4247	51.2821

Finally, the results of the rule consolidation between first-level and second-level of rules are shown in Table VI. The results are the content items with top 10 ranking. The top 3 are done in the classification phase and the rest are done by the MTCAR for the relevant items. These results will be shown in the recommendation system.

TABLE VI. EXAMPLE OF RESULT OF RULE CONSOLIDATION FOR THE CLUSTER 5 BY MTCAR

Rank	Results
1	ITEM#14
2	ITEM#311
3	ITEM#31
4	ITEM#312
5	ITEM#313
6	ITEM#23
7	ITEM#32
8	ITEM#326
9	ITEM#11
10	ITEM#315

V. DISCUSSION ON ESTABLISHING MODEL OF MOBILE CONTENT FILTERING

Access through the mobile Internet with content filtering is a feature that mobile device users would like to have.

Exchanging some allow-to-provide data such as fundamental information like demographic factors can help recommendation systems to provide personalized content by filtering some content. It is also important to provide filtered content to new users and help them experience mobile personalized content using a recommendation system.

In this paper, the knowledge of mobile content filtering for a recommendation system has been extracted to address the problem of sparsity to initial rating or first rater and first-time connection user. The method proposed in this paper can establish the model to handle first-time users and non-rated or new items for a non-interactive recommendation system.

The methodology uses classification that can help mobile content recommendation to classify the users and content to determine the prediction module used. In this stage, different classification techniques have been compared. It can be seen from CMScore that for this type of data on experimental datasets, Decision tree is an appropriate algorithm to predict the top items for users. Normally until this stage, most classification can only comfortably identify the top 3 items.

To predict the relevant top N items for mobile content recommendation, Association Rules help to find the relevant items by extracting rules based on support and confidence. The proposed MTCAR facilitates rule generation with level separation and target determination by top items from the classification phase. Higher the level of confidence, the more confidence will be correlated between content items. As a result, MTCAR can extract rules by reducing the rule complexity and cutting redundant rules by the rule consolidation process.

Finally, the established recommendation systems in this paper can address the problems of first rater or new user for non-interactive recommendation system and finding relevant items. In addition, it gives a process for first-time user connection and not only predicts top content items but also retrieves relevant items.

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