Recommender System for Coupon Discount of E-commerce Applications

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***Abstract* — Recommender systems have recently been integrated into many fields to introduce numerous appealing products and help with consumer decisions in item selections. Applying recommender systems to coupon discount applications could improve consumers accessibility to coupons of their interest, leading to increased product sales related to coupons. The research aims to create a recommender system model for coupon suggestions based on customer data interactions. The proposed recommender model is a hybrid model that combines matrix factorization and association rule mining. While matrix factorization utilises customer-item interactions with customer transactions history and information as the implicit feedback, the association rule uses the Apriori algorithm to find frequent itemsets from customer discount transactions to create the weight of each item. As a result, the proposed hybrid recommender model provides overall performance higher than the baseline models and other benchmark models. In addition, the proposed model has a precision rank increase of nearly 20% in the same dataset compared to that of the baseline models.**

Keywords — recommender system, association rule, collaborative filtering, matrix factorization, hybrid recommender

I. INTRODUCTION

Due to the popularity on an e-commerce and online shopping, massive amount of data is generated. This results in the growing attention of the indispensable tool so-called Recommender System (RS). This tool is created to support online shoppers for their decision-making activities since it uncovers relationships or linkages between the shoppers and their preferences; therefore, allowing personalized recommendations. As a result, the RS has been widely implemented in different business areas and applications, including e-commerce that use collaborative filtering techniques to suggest a list of products to users [1, 2]. The discussions on crucial factors for constructing an effective structure to social media recommenders are presented in [3]. The recommender discussions are performed using a mining strategy for specific tweets that analyse various components before obtaining final insight data [4]. In healthcare fields, the utilisation of collaborative filtering on consultation history between doctors and patients is conducted to generate a recommendation list of relevant doctors [5]. Exploration of a learning model on detection of human motion dataset is recommended to predict specific movements to prevent an accident for the elderly [6]. Personalise recommendations on energy saving are reported by observing user regular behaviours and energy usages to suggest actions to save energy [7]. Another energy recommender classifies user lifestyles from residential metering data [8]. Music recommenders based on user preferences apply deep learning and a hybrid model with content-based and collaborative filtering to discover user patterns [9]. Entertainment areas like movie recommendations use algorithms such as K-nearest neighbour, Cosine similarity, and item-based collaborative filtering to improve performance [10, 11].

A. *Problem statements*

Most of online stores compete with one another using various marketing strategies, such as coupons or discounts, to boost their sales. However, they usually implement the RS to their products only, not on their coupon suggestions [12]. It means that these online stores are yet to fully utilised the potential of RS models, as data set related to coupon preferences collected from online customers are neglected. The most common channels for promoting stores' coupons or discount codes include email, messages, and social networks, which are somewhat ineffective [12]. Not all shoppers are interested in constantly monitoring their emails and messages as they find a lot of such information irrelevant to their needs. Some customers might also see it as a spam. They might eventually block the stores. Besides, too much of such general marketing information may impose a burden on the customers to find the right coupons when they look for more discounts on products in their interests.

B. *Main Contributions*

This research proposes a hybrid recommendation model created by combining the Alternating Least Squares (ALS) matrix factorization model [13] and the model of association rule [14]. This can increase the precision of the coupon recommending algorithm to correctly match with the customers' coupon preferences for e-commerce applications. It will accelerate purchasing processes since shoppers can reduce the online searching time. They do not have to scroll through the website to search suitable vouchers or discount codes to be applied with the products that they are purchasing. The process and efforts of searching online coupons for specific products will be reduced as the irrelevant coupons will be filtered out for online shoppers. The lower prices from the stores suggested deals make it easier for shoppers to make buying decisions. It could also result in purchasing more products by these customers and eventually increasing the sales revenues for online stores. Moreover, extracting the data from customer profiles, the developed RS model can suggest the coupons of products from relevant categories that might catch buyers' attention which further increases the sales.

The remaining parts of this paper are organized as follows. Section 2 presents related works in the literature. Section 3 introduces the methodology being used. Section 4 elaborates system design and implementation. Section 5 examines the model performance. Section 6 concludes the paper.

II. RELATED WORKS

The typical RS relates to interactions between customers and items rating. Coupons have similar structures with an additional element, as coupons can be considered items or could link to existing items separately. Coupons themselves do not contain rating but rather use redemption status. Coupons have information details like categories, descriptions, locations, and usage transactions, which may help the suggestion list by specific algorithms to acquire insight relationship for the recommender models.

The Keyword Association Rule reported by Huang [15] can deal with the new coupons that have no rating or connection to existing user, known as cold start problem that commonly happens in the recommender system; while coupons may suffer even more as they are newly generated whenever the deals or promotions occur. The characteristics of data set have been analyzed and found that there is a high probability of the deal names with the same keywords in particular categories, e.g., dining, wellness, and activities. It implies the repetitive buying patterns of customers and finds the meaningful patterns of the wording deals. Therefore, personalized algorithms applying Key association rules are used with an unusual coupon characteristic in coupon RS [15]. Meanwhile, there are still some limitations, as coupon deals contain text details that can be extracted into keywords that favor the association rule algorithm. If the coupons provide short text or do not give deal details at all, it will mainly affect the performance of this model. Besides, some coupon is not in the form of “text”, but a product code or the serial numbers. This will pose some difficulties to the algorithm since the model heavily relies on the keywords to create the association between the previous deals and the new deals.

Satisfying results in recommendation areas can be produced by collaborative filtering using existing transactions between customers and products, although algorithms have a downside from the cold start problem [16]. Many studies deal with these criteria by introducing an additional algorithm for a specific purpose to improve the current model, which results in a hybrid model combining collaborative filtering with various algorithms. The parallel collaborative filtering [17] introduces alternating least squares with weighted regularization (ALS-WR) algorithm that updates the value of matrix factorization in parallel. The hybrid matrix factorization with real-time incremental stochastic gradient descent (SGD) is reported in [18] that integrates SGD into the cost function of implicit feedback for the ALS-WR algorithm to reduce the model retraining time and maintain accuracy.

Prior work from Grivolla and Badia [16] investigates a hybrid recommender model that uses collaborative filtering with user-item interactions. It integrates customer demographic and items under offer for coupon recommendation that involves interaction data from customers and items. The dataset used for testing is from a discount offer distribution website which includes user profiles, description of the product offers, and the coupon redemption data. According to works reported in the literature, both collaborative filter and coupon characteristics are sensitive to the cold start problem, with relevant interaction data being examined that is possibly valuable in model performance improvement. Based on the empirical findings, customers and transactions information can have a significant positive effect on the performance and effectiveness of the recommender system. In contrast, it is observed that the usage of contents based on details of coupon offer data has less performance improvement, which implies that it may not be necessary to choose coupon offer data for further development of coupon recommender systems [16].

In this paper, the hybrid model of Alternate Least Square with Weight Regularization integrated with user-item interaction and customer demographic is explored and chosen as the initial model for the coupon recommender system. It has advantages over individual models, because of the characteristics of the hybrid model that can be combined or switched with different algorithms to cover a specific area. Furthermore, based on matrix factorization derived from the data association, our proposed algorithm is added for the data section in an attempt to improve the model performance and omit insignificant data parts, such as offer details that derive less impact on performance.

III. METHODOLOGY

A. *Collaborative filtering and Matrix Factorization*

The fundamental of collaborative filtering is to utilise past customer behaviors to evaluate associations between customers and items. The interaction happens in form of rating systems which are classified into two categories: one is explicit rating that needs the opinions from customers; the other is implicit rating that collects from customer actions. Both categories have their respective strengths and weaknesses. The explicit rating requires the rating given by customers; while the implicit rating does not need customers' rating but needs to gather from customers' various actions. It could be very uncertain in rating value when their behavior is unintentional and difficult to interpret as the negative feedback [13, 19].

The coupons can be perceived to have a familiar component like products in online shopping. But their characteristics and purposes are very different because coupons may have features of one-time usage or being used for a specific set of product items. It makes the rating system inefficient, as a customer does not need to see the ratings before getting a coupon unlike buying product items. While coupon data is unlikely to contain the explicit feedback such as ratings, the implicit feedback like coupon redemption amount is only optional to use for recommendation models. According to Oard and Kim [20], research on the substitution of the explicit feedback with the implicit feedback shows that the implicit feedback has influence on prediction. Thus, the implicit could be applied in recommender systems.

In the area of collaborative filtering techniques, many algorithms are reported in selections of recommended products, such as usage of memory to perform similarity between items [21], and the Matrix factorization method [22], which further achieves in applying with practical recommender systems named laten factor model for the Netflix prize [23]. The Matrix factorization is one of the selected algorithms as the baseline model in this paper to build coupon RS for predicting customer-item ratings from the existing association by a technique called Singular Value Decomposition (SVD). This latent factor model is based on linear algebra for the matrix factorization which requires the recommender to build matrix between row of customers and column of product items with customer ratings as the matrix values. Then, the SVD decomposes the original matrix into three other matrices U as customer factors, Σ as diagonal factors, and V as item factors, shown in Eq. (1).

$$M = U\Sigma V^T \quad (1)$$

where the columns of U and V are orthonormal matrices; Σ is a diagonal matrix which can be further truncated into smaller matrices by determining the number of columns for the truncations. The truncated SVD is useful to work with sparse matrix for extracting the features matrix of customers and items. As such, the rating can be predicted using the dot product of the features between the matrices U and V. It can apply optimization techniques to reconstruct estimation values of the original matrix. To use the matrix factorization with the implicit feedback that relies on customers and items interactions, the Alternating Least Square with Weight Regularization (ALS-WR) method for factorizing a matrix is introduced by Hu *et al*. [13]. The interactions between customers and items are identified by preferences and confidence values. The preferences tell when customers are interacting with items using binary values that are recorded as '1' if there are customer-item interactions, and '0' if there are no interactions. The confidence values tell how strong values are for the pair of interactions between customers and items which are scaled with the notation α. For example, an item with multiple purchasing transactions will have higher confidence value than that of an item with a single transaction. Therefore, the ALS-WR will be adopted as the base model of the coupon recommender in this paper.

B. Customer-Item Interactions Data

A preference matrix will select the redemption status between customers and coupon pairs from the provided data. This redemption matrix will be treated as the base matrix that tells how many times each customer redeems coupons before combining with other data or algorithms.

	Implicit Feedback from transaction history					Customer Demographics				
	Coupon 1	Coupon 2	Coupon 3	Coupon 4	Coupon 5	Age 18-25	Age 26-35	Age 36-45	Family size	Income
Customer 1	0	0	2	0	1	1	0	0	3	1
Customer 2	1	6	3	0	0	0	1	0	2	3
Customer 3	3	1	1	0	0	1	0	0	4	2
Customer 4	0	2	0	1	3	0	0	1	5	4
Customer 5	0	5	3	1	0	0	1	0	1	1
Customer 6	1	0	2	0	0	0	0	1	3	5
Customer 7	2	4	3	0	2	1	0	0	3	3
Customer 8	0	2	5	1	0	1	0	0	4	1
Customer 9	0	5	2	0	0	0	1	0	3	5

Fig. 1. Preference Matrix combines with transaction history and customer demographics.

The interaction data between customers and coupons for transaction history or customer demographics can be integrated into the preference matrix which transforms into a matrix of associations in Fig. 1. The values in the matrix of Fig. 1 indicate the number of the redeemed coupons for each customer in implicit feedback section and customer details such as age, family size, and income in customer demographic section. It represents the relations of customers and items profile when performing the matrix factorization, thus improving the performance of the RS [16]. To extract these interaction data, the transaction history is required to select every record that claims the discount coupon as the implicit feedback. Whereas the customer demographic information such as age ranges, family size, and customer income, can be acquired directly from customer profiles.

C. Association Rules

Association rule mining is a technique to uncover the relationship among items from transactions. It can be utilised to explain patterns like purchasing and cooccurrence of data by finding the products that are likely to be bought together or most selected [14]. It is divided into two steps. The first step is searching frequent itemsets by calculating support values for all sets of items, then setting thresholds for support values to pick itemsets that frequently appear in the entire transaction. The second step is the creation of association rules by generating all possible rules from one itemset.

The Apriori algorithm is one of the popular association rule algorithms [14, 24]. It is used to generate candidate itemsets by mining all frequent itemsets in transactions where k-itemsets need to be greater than or equal to the minimum support threshold before generating further (k+1)-itemsets. Then, if an itemset is not one of the frequent itemsets or not satisfy the minimum support threshold, the Apriori algorithm executes in pruning all the supersets of the following itemset. It generates frequent itemsets of K by measured minimum support of given itemset from transactions.

IV. System Design And Implementation

When the RS becomes the center of attentions in the research areas, many recommender algorithms are created to solve RS problems in different contexts [19, 21, 22]. A single algorithm can deal with the RS but may not easily improve performance further. Therefore, the RS model needs to rely on more than one main algorithm. It can be achieved by hybrid recommender models that combines different techniques. The hybrid recommender models may improve performance and provide more accurate recommendations than their individual original model counterparts [25]. The hybridization techniques have several approaches: combining the scores from two or more models with weighting technique, switching between recommending results, feature combinations and augmentation, and mixed recommendation model.

A. Hybrid Recommender Model

In this paper, the hybrid recommender model is chosen to apply with coupon recommendation that two recommender models are integrated using feature combinations and weighted technique. The ALS-WR matrix-factorization is being selected to work with implicit feedback data and combining the association rule mining with the Apriori algorithm as show in Fig. 2.

The base matrix rating is built from three main components: customer demographic, customer item interactions, and coupon redemption. The redemption data gathered from coupon redemption stores a list of coupons that are redeemed by each customer. While the customer demographic can separate into age ranges, family size, and customer income. Moreover, the transaction history data can be processed into coupon discount transactions, which are changed into implicit feedback as coupon redeemed amount and used in the association rule. As our proposed model combines ALS-WR matrix factorization with association rule, the association rule mining is another technique that we add to the recommender model by applying an Apriori algorithm to find frequent itemset from customer transactions. In addition, the algorithm will analyse customer applied coupon discount transaction data to find support values and weights based on redemption values. After that, we use these processed data to build a preference matrix of customers and coupons with an additional column of customer demographic. Finally, the value of the matrix is integrated by multiplying the coupon redeemed amount and the association support weight, then examining the model performance of the basic model and our proposed algorithm.

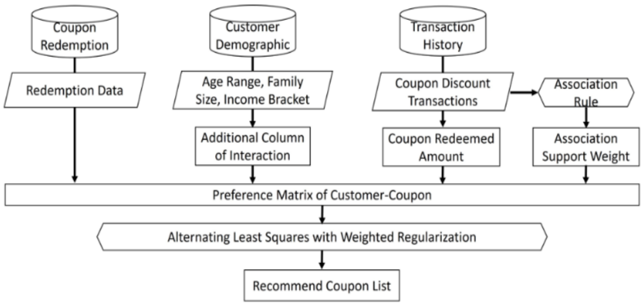

Fig. 2. Proposed hybrid model for coupon recommender

B. Data Preprocessing

In constructing the customer and coupon preference matrix, the data need to be prepared for storing coupon redemption values to display which coupons customers have interacted with before mapping into the preference matrix. The items and coupon data, both have many to many relationships meaning that one coupon can be applied to many items and one item can be applied to many coupons. While the proposed recommender focuses on the coupon information and is not required to acquire insights from item data, the customer's transaction history is an essential factor for providing the customer preferences [16]. Therefore, the item in the history transactions that are applied the coupon discount are selected to match with the coupon ID. The coupon ID is stored as implicit feedback data for each customer ID. Moving on to customer demographics, age ranges, family size, and income bracket can be acquired from the customer table with the data manipulation technique. After that, we take the customer demographic table to apply horizon stack directly with interaction matrix due to both rows referring to the customer ID.

C. ALS-WR Matrix Factorization

The ALS-WR matrix factorization that we choose is implemented by Ben Frederickson in library name implicit as function reported by Hu *et al.* [13]. The parameters that we focus on using this function include the train dataset, alpha value, and factors as a number of latent factors, regularization weight, iterations, and random state. For comparison purposes, we are not using the hyperparameter optimization technique to select the best output for each model. But we rather set the same constant values except for training data of every model to give consistent results.

D. Association Rule Weight

We treat customer transaction history as a basket of items by filtering only transactions being applied coupon discount, which are then matched the relationship between items and coupon. Moreover, we consider date of transaction as one of the baskets of items. For example, some coupons may appear often than other coupons which could imply that customers are taking interest for following coupons. As we assume from the set of coupons being applied in each date, there should be coupons that are frequently selected by customers. We focus on only one itemset and their support value, as it tells how each coupon appears in the entire transaction. After obtaining the coupon for the single itemset and their support values, we need to transform it into weight when combining with the implicit feedback in the matrix factorization. Therefore, the sum of each coupon value from all customers is divided by the total occurred transactions, that are multiplied with the support values to convert into the association weight.

ALGORITHM 1: ASSOCIATION RULE WEIGHT

get transaction history with coupon discount applied stored in *transactio_temp*;
get list of date from *transaction_temp* stored in *date_list*;
for each date in *date_list*, do
    get unique *item_id* in *transaction_temp* filtering by date stored in *item_list*;
    get unique *coupon_id* in *coupon_item_relationship* using *item_list* then stored in *coupon_list*;
    store *coupon_list* in *basket_list* for each date;
end for

encode *basket_list* into dataframe, then applying apriori function;
filtering dataframe that generated by apriori function with one itemsets and minimum support more than 0.1;
for each *coupon_id* in unique *coupon_id* from filtering dataframe, do
    get sum of redemption value of *coupon_id* from *customer_coupon_interaction_dataframe*;
    get number of occur transaction of *coupon_id* from *customer_coupon_interaction_dataframe*;
    take support value for each *coupon_id* in filtering dataframe, then multiply with sum of redemption and divided by number of occur transaction to create weight for each *coupon_id*;
end for

The Algorithm 1 shows the association rule weight algorithm, which will be further utilised in the hybridization technique of the proposed recommender model. It is achieved by multiplying with implicit feedback for every matched coupon ID and applying with the ALS-WR matrix factorization to evaluate the model performance.

V. EXPERIMENTS AND EVALUATIONS

The research aims to explore the potential of the hybrid model and improve the performance of the coupon recommender system over the basic hybrid model reported in the literature. The developed hybrid models select an association rule mining to generate specific weight of each coupon before applying with hybridization technique to the base model. The hybrid recommender from combining the ALS-WR matrix factorization with supplementary data and association rule weight have not been reported previously in the coupon recommender research field. It presents the novelty of this research. We attempt to explore and compare the performances across a range of models from the basic model [15] and several revised models [8, 11, 16] as shown in Table 1. The models are revised by selecting evaluation metrics such as the area under the curve and precision at *k* to compare how each model performs under different components. Shown in Table 1, the first model representing the basic model that utilises the component of redemption data only without using additional data for the recommender. The second model of implicit feedback data uses the components of redemption data and discount transaction. The third model of reproduced baseline [16] uses the components of redemption data, discount transaction, and customer demographic. The fourth model of experiment uses the components of redemption data, all transaction, and customer demographic. The last model is our proposed model that uses the components of redemption data, discount transaction, customer demographic, and association rule.

Table 1: List of models with different components being evaluated

Model No.	Model Name	Components involved
1	Basic [15]	Redemption data
2	Implicit feedback [8]	Redemption data + Discount transaction
3	Reproduced (Baseline) [16]	Redemption data + Discount transaction + Customer Demographic
4	Experiment [8, 11]	Redemption data + All transaction + Customer Demographic
5	Our Proposed Model	Redemption data + Discount transaction + Customer Demographic + Association Rule

A. *AUC Score*

Experiments have been performed to compare these five models. The results of "Area Under the Curve" (AUC) from the set of models are shown in Table 2, where the displayed scores are calculated from the predicted and actual values of customers that get coupons hidden. The sparsity check function is created to check the percentage of sparsity from the input matrix by finding the number of nonzero pairs divided by the total matrix size.

The first model extremely obtains sparsity. As the basic model does not contain many interactions between customers and coupons, it results in the lowest AUC score. After applying the implicit feedback data from coupon discount transaction history in the second model and integrating further one more component of the customer demographic in the third model, both models result in the lower matrix sparsity. But the AUC scores of both the second and third models dramatically improve, compared to that of the first model. In contrast, the fourth model that uses every history transaction gives the lowest matrix sparsity, meaning that there are many interactions between customers and coupons. The fourth model also shows a lower AUC score than the second model that uses only coupon discount transactions. It implies that not every transaction data is worth being utilised. The fifth model as the proposed model in this paper produces a comparable AUC score to the baseline model, with good matrix sparsity.

It is observed from the experiment results in Table 2, both the basic model and our proposed model achieve higher matrix sparsity than the rest of the models, at 99.94% and 99.1%, respectively. It indicates that our proposed model with association weight has less interaction as higher sparsity, while it can perform respectable results of the AUC scores to other models that have low sparsity.

Table 2: Comparisons of matrix sparsity and AUC scores of five models

Model No.	Matrix Sparsity	AUC score
1	99.4%	0.495
2	98.6%	0.880
3	98.3%	0.914
4	85.2%	0.861
5	99.1%	0.912

B. *Results of Precision at K*

From the train and test split for recommender systems, coupons for each customer are randomly masked concerning the size of the dataset, before taking in the training dataset to train with the model. Then, prediction results of the coupon recommend list are taken to verify and calculate with the testing dataset which containing the original record of the dataset. We take precision at *k* to measure overall recommendation performance for each model to tell how each model performs when recommending the top *k* list of coupons to the testing dataset.

The bar chart shown in Figure 3 provides the precisions of each model that can be clearly examined with the top *k* number. The colour codes shown in Fig. 3 represent the results of four types setting: precision at 5 recommendations (P@5), precision at 10 recommendations (P@10), precision at 15 recommendations (P@15), and precision at 20 recommendations (P@20). It is observed that the first basic model has the lowest precision in every *k* across all models. While the fourth model that has an extensive pair of customers and coupons interactions performs poorly than the first model in precision at 5. As the number of *k* increase, it means that the range of predicted coupon for each customer in each model needs to match with the testing set when the calculated precision is expanding, which generally results in decreasing precisions. However, the fourth model appears to have interestingly risen in precision, unlike other models that are starting to drop. It could be an indication in the development of a coupon recommender system for a specific purpose like recommending many coupons or dealing with massive data.

Furthermore, the second and third models which are integrated with discount transaction history and customer demographic respectively, show significant improvement of precisions from the base model in every *k*. It can confirm that there are associations in the data when using additional information in matrix factorization. The results of our proposed model, i.e., the fifth model, reveal that the hybrid algorithm generating weight from association rule mining combined with the third model technique shows a considerable improvement in the precisions. It is observed good improvement of the precision in *k* at 5 and 10; while the precision of *k* at 15 has comparable result, with slightly falling short after precision at 20. The results can be explained with our proposed hybrid algorithm that concentrates on finding relations from coupon discount transactions that customers mainly apply. Therefore, the proposed algorithm adds the weight of popular coupons to increase the prediction of top recommendations when the number of *k* is small. In contrast, when the number of *k* keeps increasing, the unpopular coupons or barely chosen by customers will take a penalty from weighting results in decreasing precision at 15 and 20.

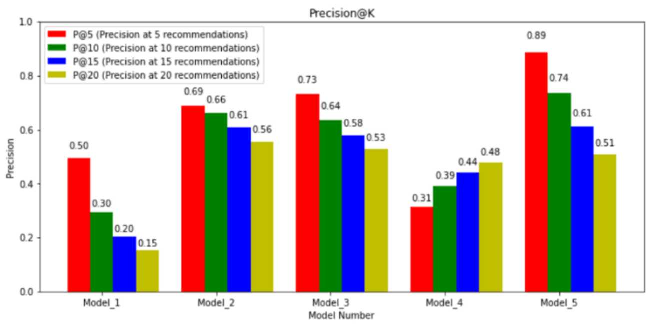

Fig. 3. Results of precision at *K* for each model

VI. Conclusion

This research aims to improve the recommender model for coupon deal applications by integrating the proposed technique into the existing models. This research has developed a hybrid model based on the hybrid recommender system by combining the model with the hybridization weighting technique generated from association rule mining of transaction history. Experiment and evaluations have been conducted. The empirical evidence shows that the proposed model can significantly and successfully increase the coupon recommender system overall performance, compared to the baseline model and other benchmark models. It has been confirmed that the proposed hybrid recommender model with matrix factorization including transaction history and customer demographics information works effectively, leading the performance to be more outstanding than the models without this information. In addition, the experiment results show a data correlation of transaction history led our research direction into selecting and designing the algorithm for a specific purpose in obtaining relation from the provided data. The proposed algorithm could support the implicit feedback field by prioritising the importance of implicit feedback, as it may have a smaller value while frequently getting chosen from the association rule over other high-value implicit feedback with less selection. In normal conditions, the high-value implicit feedback would beat smaller values implicit feedback. However, the proposed algorithm could allow those smaller values with frequent selection success over high value with less selection after completing the weighting of the whole implicit feedback.

A. *Limitations*

As one of the limitations, the evaluations and verifications of the research only utilises a single dataset. The coupons and items have many to many relationships, meaning that the new coupons can be applied with old items. This data relation allows us to investigate the historical data from the connection of customer transactions and leads to less of the cold start problem. However, there are some concerns when some online shops only allow their coupons to be used with new items, which causes a different dataset structure, resulting in no historical data creating the cold start problem.

B. *Future Works*

The RS algorithm may need to generate a specific weight of coupons for each customer because the customers are likely to have various discount coupon consumption histories. Thus, the algorithm can be improved in producing individual weight for a specific customer and coupon. It could help generalize the results of the recommendation list when the number of k recommendations increases. In additional, the matrix factorization with customer demographics reveals an association between customers and coupons data. From this connection, it is possible to expand the experiment in identifying the relation of items demographics with a suitable machine learning approach to map information with the coupon data or classification to analyse which coupon customers prefer based on the item information.

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