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Effective recommendation model using social network for linking user pursuit to product content

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The ongoing advancement of data innovation and the rapid development of the internet has encouraged a blast of data which has highlighted the issue of data overload. In reaction to this issue, recommender programs have evolved and helped users find their fascinating content. With the progressively entangled social setting, how to satisfy customized demands effectively has become another development in customized proposal administration contemplates. To mitigate the sparse issue of recommendation systems, we suggest a new recommendation approach based on fuzzy theory to improve their consistency and flexibility in diverse contexts. The proposed method also employs social network to reflect multifaceted factors of users. In this strategy, we group clients and consider about assortment of complex variables. The results on amazon dataset indicate that the proposed method achieves better efficiency over current methods.

Keywords: Recommender system, E-commerce, Diversification, Fuzzy logic, Amazon dataset

1 Introduction

Throughout recent years, e-commerce, a modern way of retail, has seen tremendous growth and many different sorts of shopping sites have seemed loaded up with a great many various items. In addition to data resources, overloading information is a problem[1], in which case recommendation systems may be successful in resolving this issue[2]. Different recommender systems[3] have been introduced which aim to produce individual recommendations to satisfy the desires and needs of the corresponding users. Depending on how suggestions are made, existing recommendation frameworks can be grouped into three major categories: content-based, collaborative and hybrid filtering[4]. Collaborative filtering is the commonly used method for filtering knowledge that typically operates by looking through a wide number of users and selecting a smaller collection of identical preferences to target users. Content-based approach aims to suggest products close to those scored favorably in the past to the active customer. It depends on the association between the features of products and the preferences of the users. Such approaches depend heavily on product ratings and the ratings are considered as a metric reflecting the preferences of the consumers. In any case, individuals don't generally rate items purchased already, and these prior bought items represent just a small part of the item set. This prompts the problem of data sparsity which seriously affects the accuracy of the recommendations[5]. Nonetheless, substantial additional information may be utilized to mitigate this problem as well as to improve the accuracy of predictions[6]. The proposed model aims to improve the accuracy of the recommendation by contemplating additional information like the attribute of the group, the time factor and the price of the product[7].

The current recommender frameworks underline the precise conjectures of a client's inclination for various products[8], but rarely take into account the associations between the different products[9]. In the e-commerce domain, people often buy various types of products, however different products of the same group are seldom bought in a row[10]. Therefore, given the goods which a consumer has previously purchased, recommendation systems should suggest certain items in similar categories, called cross-category recommendations[11]. The homogenous items are recommended to the consumers, according to the theory and ideology behind the current recommender systems. To solve this difficult problem, we first

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consider the classification characteristics of items and propose a novel strategy for modelling the drift of a consumer's pursuit in various categories using the sequential pattern mining procedure[12]. Second, after a certain time interval, a user often buys items of different categories[13]. Various users can be subject to different purchasing cycles for several category pairs, indicating changes in user expectations with time running out. We propose to utilize the multi-class purchase spans[14] to look for the classifications a client is generally intrigued by at a particular time. Lastly, extensive consumer behaviour research suggests that cost is one of the most prevalent factors influencing the marketing practises of consumers and that users generally have various price preferences[15]. An approach for modelling a user's price preference for various categories, suggesting items where the prices are compatible with each user's price preference is combined with our proposed method[16].

We propose a novel recommender framework suggesting diverse items at various time based on the above mentioned points. The main contributions of this paper are: In order to diversify the suggestions, we propose a method for modelling shifts in a user's pursuit in different categories. The method is controlled based on the technique of hybrid filtering and sequential pattern mining by considering attributes of the group. With the additionally integrated temporal component, we are proposing a new method for modelling each user's tendency of customised multi-class purchase cycle. An approach for modelling each user's price preferences is considered. The methodology utilizes fuzzy logic to portray the value of every item and afterward builds the cost inclination based on the items in the purchasing sequence of a customer. We propose a novel recommender framework fusing the previously mentioned techniques. We also perform multiple tests to test the efficacy of the variables that are considered when recommending items with various features.

2 Materials and Methods

2.1 Related work

The problems posed by big data like resource-overload and data mislead, have become more and more serious. For individual users, one prior issue has been how to quickly and reliably acquire valuable content from vast knowledge. Whereas for an enterprise consumer, how to effectively mine the potential needs of consumers, boost the intelligence level of knowledge seeking and moving, enhance the individualised quality of service in this intensely competitive environment, its E-commerce activities have been placed top in the modifying list. The emergence of personalised recommendation technology has to some degree resolved the dilemma between knowledge diversity and specialisation of customer needs. Nearly all the e-commerce sites, like Amazon have more or less implemented different types of recommendation framework. However, with the growth of e-commerce and the increasing complicated consumer setting, a new trend in the study of customized recommendation service has been how to meet custom needs.

Different recommender systems were implemented based on various recommendation techniques. The content based recommender framework fabricates the client profile depending on the attributes of the products previously purchased by a user and then recommends items with the highest user profile similarities. The similarity can be calculated using weighted sum of the various characteristics that items possess. While the idea behind this technique is clear, some drawbacks do exist. In any case, different products have different attributes, and it is difficult and sensible to bind together the regular highlights for all items. Moreover, the things suggested to clients are consistently like those recently purchased, to be specific, homogeneous proposals. The collaborative filtering system relies heavily on the user-product ratings and can be perceived as the agents of the clients' inclinations. This methodology is performed in a way that a client's missing rating for a product is predicted by summing the scores of clients similar to the target consumer or the rankings of products similar to the target product. Pearson correlation coefficient and cosine similarity are the widely used similarity functions which are executed with two matrices representing the profiles of the users. As this method relies heavily on the ratings of the users for the objects, it also experiences the problem of data sparsity and cold start.

A lot of socialised methods of suggestion have arisen in the last years introduced a novel system for probabilistic factor analysis that inevitably fused the preferences of the consumers and the interests of their trusted groups. The proposed structure was very broad, and it could also be extended to user product ranking vector even if the users did not have specific details on mutual trust between them. In this structure, the term social trust is devised to describe the formulations of the constraints on social trust in the recommender systems explored the problem of social recommendations based on psychological and sociological studies, which showed two significant variables, user's pursuit and relational impact. In this study, they first presented the special importance of these two factors in the prediction of online behaviour. They proposed a novel method of probabilistic factorization of matrixes to fuse them in latent space proposed an approach to social regularisation that incorporated information on the social networks to enhance the recommendation systems.

Several research has indicated that cost is one of the most powerful factors when individuals are shopping. Few recommender systems took price factor into consideration. The most well-known way is that cost is considered as a credit to get the utility of an item for a client in utility based recommender frameworks. Different investigations apply the cost factor in an alternate manner, based on the diminishing minimal utility hypothesis in financial matters. For example, Wang and Zhang proposed a peripheral net utility capacity dependent on the Cobb-Douglas utility capacity and made a joint likelihood model. But, the loads of assorted item properties are different for various buyers and it is hard to acquire with no association. Also, in a web based shopping condition, the inspiration of making bargains among capacity and cost debilitates. Cost of similar items, even items with all the similar attributes and eminence, are dispersed in conventional shopping, subject to area and restricted data. Hence users have to create a trade off between item cost and quality, highlights and other perspectives. However, the prices converge with the development of the virtual environment, and the perception of prices by consumers is even affected. Despite the fact that an user is content with the highlights of an item, a redirection to other comparable items can happen if the buyer is not happy with the cost. In addition, according to the theory of mental accounting, people keep a mental account for any form of spending indicating the level of the budget, and when people make a purchasing decision, mental accounting works. Thus, when a customer is searching for goods in a particular category, the price in expectation is consistent with budget price. We represent the expectation cost as value inclination, demonstrating the most probable value a client prefers for a specific sort of items, and propose a novel method to deal with every client's cost inclination for each classification using fuzzy logic.

Various products purchased by a consumer at different times form a sequence of purchase. The classification characteristics and the order of purchase of the products in the sequence represent the relationships between different categories and variations in the demand and interest of an user. Certain recommender frameworks employed characteristics of categories to improve accuracy of recommendations. As for the recommender systems using purchase sequences, the sequential pattern mining technology is applied to evoke consumer preferential adjustments. The experimental results of the authors indicated that the accuracy of the recommendation had been increased. We also use the sequential pattern mining technology in our research to extract the patterns, but the difference from their studies is that the mining task operates on product category sequences instead of individual products. This shift can indicate the changes of interest of an user; on the other hand, the issue can be lessened by the fact that the number of sequence obtained is too limited, which sometimes occurs in mining work based on sequence of product purchase.

Taking into account the lifecycles and usage attributes of various sorts of items, the inter purchase time among different classes of items are different. Much research focuses on modelling the pattern in purchase intervals based on an interpretation of the purchase series to extract the change in consumer behavior. Some recommendation systems studies use the purchasing interval as an adjustment factor within a recommendation model to increase temporal recommendation diversity. More precisely proposed a shared purchasing probability approach by incorporating a specific purchase period and the preferential value of a consumer for a product is determined by estimating the model parameters. In our research, by examining the purchase sequence of all users with purchase period, we model the inter-purchase interval of a consumer for all different pairs of categories by comparing those of related users. Because product cost, category features and purchase cycle are closely linked to the purchasing decision of a buyer, we combine them collectively to determine the preferred values of a user for various products at a given time. We discuss the techniques of using various types of data and how they can be combined to make suggestions for a consumer in the next section.

2.2 Proposed recommender system

Our suggested recommendation framework produces recommendations by integrating the purchasing interval and product price with the social behaviour of users, and this process is executed in two phases. In this segment, we present the features of the proposed recommendation system and explain how the recommendations are produced step by step. As represented in Fig. 1, the general structure of our methodology is comprised of two sections which are class search stage and hence, an item search stage using online behaviour of an user. In the period of classification search, successive patterns of item classifications are first got from the purchase sequences of all users. Then, we retrieve the categories that a user is most interested in by matching a consumer's purchase series with the sequential patterns. The price choice of every category and the inter-purchase period for the consumer is modelled based on the sequences of purchase and the maximum price of every category. In the item search stage, given a particular suggestion time, we initially register the coordinating level of the time factor for a key item, PT. Likewise, we get the coordinating level of the cost factor for a key item, PC. PT and PC are integrated to acquire the absolute inclination estimation of a client for a key item. Lastly, the user is presented with a recommendation list.

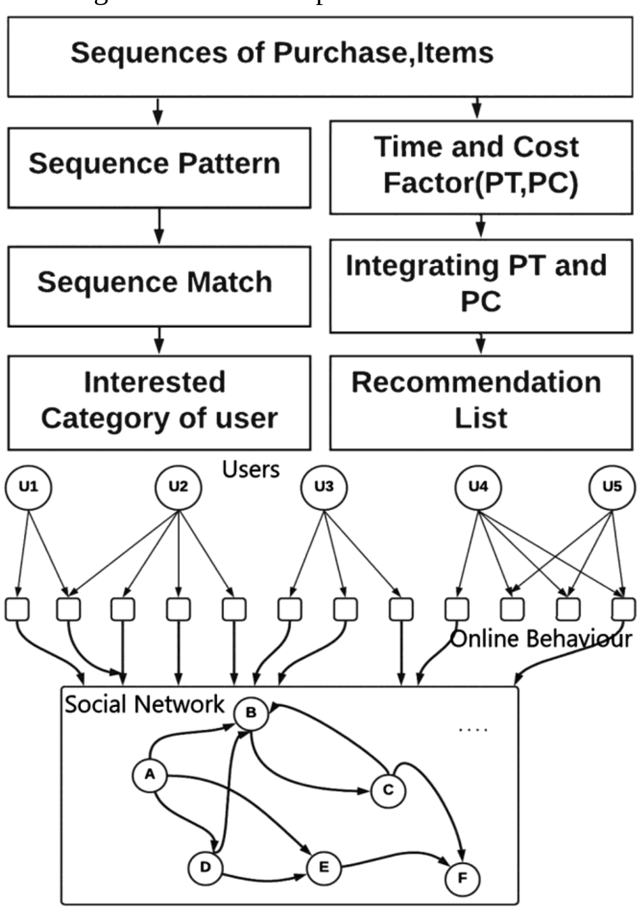

Fig. 1 — Proposed recommendation model.

To generate the sequential patterns for various group of categories, we use the sequential pattern mining technique. For instance, assume that a user buys items I_1, I_2 and I_3 at the time T; I_1 belongs to group of category G_1, I_2 and I_3 belongs to category G_2, and then this shopping activity forms an element (G_1, G_2) in the purchase sequence of the user. A sequential pattern is derived and represented as $< P_1, P_2, ..., P_n >$, where P_j denotes the specific category. The relevant category group for the consumer is recovered by associating the models with the user's purchasing cycle. The proposed model of recommendation assumes that there are n users and m items. Some items were selected by each user, and each item was selected by certain users. Then a bipartite framework can define the relationships between users and objects. Users set is represented as C = {c1,c1,...cn} and products set as I = {i1,i2,…,im}.The adjacency matrix of the recommendation model is represented as M = {m_{jk}} and $m_{jk} = 1$ when a product k is selected by user j, otherwise $m_{jk} = 0$. Cosine similarity is calculated by using equation 1.

$$CS(j,l)=\frac{1}{\sqrt{d(c_j)d(c_l)}}.\sum_{k=1}^{m} m_{jk}\ m_{lk} \qquad \dots (1)$$

where, CS (j,l) represents the similarity between users j and l, d(c_j) represents the number of items selected by user j. We integrate the social relationships of the users to the similarity model. The sequence of purchase of various category is illustrated in Table 1. The derived sequential pattern and the target user's purchase sequence are depicted in Table 2 and table 3 respectively.

Depending on the new arrival of products, arrival time AT is calculated and the overall user preference for a product(UP) is calculated by

$$UP = AT * DP *PT *PC \qquad \dots (2)$$

Table 1 — Illustration of sequence of purchase

User	Sequence of purchase of various category
c_1	$<G_3,G_4,G_5>$
c_2	$<G_1,G_3,G_4,G_5>$
c_3	$<G_1,G_5,G_6>$
c_4	$<G_6,G_2,G_3,G_5>$
c_5	$<G_2,G_4,G_6,G_1>$

Table 2 — Derived sequential pattern

Pattern Length	Sequence of purchase of various category
l_1	$<G_1,G_4>$:0.5,$<G_1,G_5>$:0.75,$<G_3,G_5>$:0.5,$<G_4,G_5>$:0.75
l_2	$<G_2,G_4,G_5>$:0.5

Table 3 — Illustration of target user's purchase sequence

User	Sequence of purchase of various category
u_1	$<G_1,G_4>$
u_2	$<G_2,(G_4,G_5)>$
u_3	$<G_1,G_5>$

where, DP represents the probability of the derived pattern.

We rank the other candidate products in decreasing order of the overall user's inclination value and the topmost N products are suggested to the consumer.

3 Results and Discussion

The proposed model performance is tested on the Amazon dataset. Our data collection consists of approximately 4.5 million image items and a total of 53 categories. The attributes of the product image includes:

Amazon standard identification number (asin): Product's Unique ID

Title: Product's name

Formatted price: Cost of the product

medium image url :url of the product image

Brand: brand name of the product

product type name : Category to which the product fits to.

Rating: Score given by the users

Our model is executed on the test data and are evaluated . The output of the model are compared with the basic mode. The metrics adopted to measure the diversity and accuracy of the proposed model are precision, recall and RMSE. Table 4 depicts the performance of the proposed model with state of art methods for the recommendation list of length 10, 20 and 30. The metrics used to evaluate the proposed model are RMSE, Precision and Recall which are estimated using the Eqs 3, 4 and 5.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(R_{Ax} - R_{Px})^2}{n(Total\ \ Items)}} \quad \dots (3)$$

Table 4 — Performance of proposed model

Length(L)/Methods	Precision	Recall	RMSE
L=10			
CF	0.078	0.305	0.843
MF	0.089	0.327	0.728
SVD	0.088	0.325	0.732
MB	0.105	0.350	0.692
Proposed Model	0.120	0.379	0.612
L=20			
CF	0.075	0.321	0.833
MF	0.084	0.352	0.721
SVD	0.082	0.350	0.723
MB	0.098	0.377	0.688
Proposed Model	0.114	0.399	0.605
L=30			
CF	0.072	0.332	0.825
MF	0.080	0.367	0.711
SVD	0.081	0.365	0.714
MB	0.092	0.395	0.677
Proposed Model	0.105	0.418	0.601

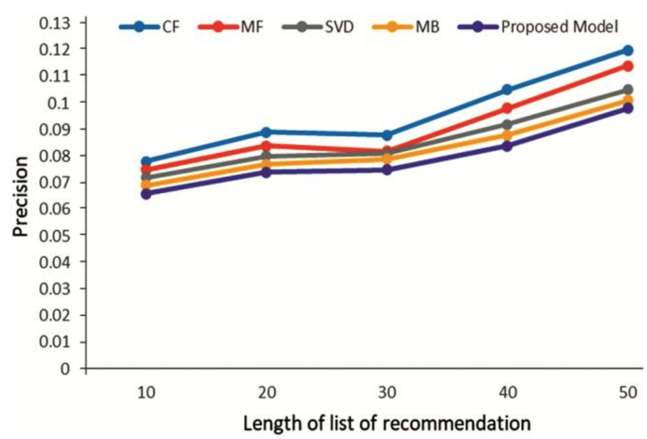

Fig. 2 — Performance of proposed model based on precision.

where, n denotes the total number of items used for testing the model performance. R_{Ax} and R_{Px} represents the actual rating and predicted rating given by user 'x' to any particular item 'i'. Less RMSE value reflects high model accuracy effectiveness.

$$\text{Precision} = \frac{|R \cap P|}{R} \quad \dots (4)$$

$$\text{Recall} = \frac{|R \cap P|}{P} \quad \dots (5)$$

where, R represents the list of recommendation and P represents the products bought by the consumer.

Figures 2 and 3 illustrates the performance of the proposed model against the state of art methods based on the metrics, precision and recall.

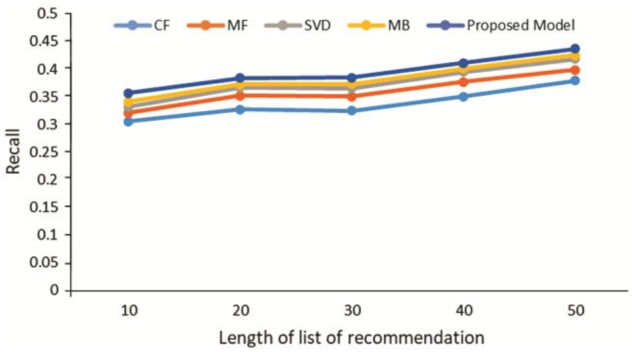

Fig. 3 — Performance of proposed model based on recall.

4 Conclusion

Recommender systems turned out to be exceedingly common in recent years, and are used in a diversity of applications. They gather information about users' preferences for a set of products and predict users potential future tastes or interests. To increase the precision and diversity of recommendations and to mitigate cold start and low intensity problems, we have proposed a new recommendation method based on the social relationships of user. This method takes into account the preferences of the users and the social relations between them. The detailed analysis on amazon dataset indicates that the model presented is more precise and diversified than state of art algorithms. This study shows that merging the social media context can enhance the accuracy of the outcome of recommendations and increase the diversity. This customized recommendation method can be utilised for different situations and areas, like recommending friends with the social network and recommending products within the e-commerce platform. The model shows an especially significant result in integration with multidimensional user information. This extensive analysis of personalized referral strategy, improves its strategy framework.

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