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A Survey on Product Recommendation System in E-Commerce

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Abstract:- Due to the uncontrolled growth of communication networks, Increase the information and overhead of communication in this communication networks has become a major challenge that online access to information has become a problem for most users. E-Commerce users and online stores customer's problem also is to find their products from among very much similar products in the store. So get advice about products and services that correspond to the needs and preferences of customers, to save time in finding the desired product and reduce information overhead, it would be desirable for customers Ecommerce. In order to, Product Recommendations System (PRS) by providing recommended to buy the product to customers in e-commerce, is trying to solve this problem and reduce the overhead of network communication. In this paper, several PRSs in e-commerce are investigated.

Keywords: Product Recommendation System, Recommended Buying, Online Stores, E-Commerce.

1. Introduction

With the development of communication networks, especially the Internet, information overload has become a major challenge. Communication networks are pervasive and affect almost every aspect of daily life of the users. Users to use the features and applications of communication networks need to search and find information and services. At this time that is achieved to the required information through massive amounts of information similar, a lot of time of users would be a waste and finally, users may fail to reach their desired information.

Therefore, A tips and in fact a useful suggestion according to user's interests and criteria, keeps them out of confusion and wasted time.

E-commerce like Internet has grown immensely, and today there is more of this type of business.

Ease of purchase and availability of boarding and lack of transportation problems and other benefit causes this type of business has gained great popularity among users. In other hand, the rapid development in this field has made electronic store users and customers are faced with the problem of information overload. Find the desired item online that match the user's criteria requires a lot of time and searching. In many cases, the user may not be able to find the products they need according to their interests.

PRS in e-commerce is the service that takes a set of the user's criteria as input and among the items in the database, searches products in accordance with the user's criteria and finally suggests the list of products that match with user criteria as the output to the user. Users by this recommendation can find needed products without wasting time and confusion and make more accurate decisions about product purchases. In addition, PRS can monitor the history of customer purchase behavior, preferences and predict customer needs and products with customer's needs as closely related to the recommendations proposed purchase of the customers. Users can also rely on the recommendations of products that are associated with their priorities, recognize and decide to buy. Hence, the system can recommend products to users in identifying items suitable for their needs and preferences in an effective way to help and solving the problem of too much information overload in e-commerce and help to sales growth [1].

The overall structure of the PRS is shown in Figure 1. As noted, PRS is a service which takes a series of desired product of the users as input and the processing of these criteria and search among items in a database, List of products that are closely related with user metrics output to the user as suggestions.

The difference between the PRSs might be caused by differences in the methods of collecting and processing customer metrics that take place on these criteria, as well as ways to search among products. However, the goal of PRSs personalized recommended guiding the customer to buy.

For example, for providing personalized recommendations, there are two ways to receive users' preferences: implicit and explicit. First, the implicit method collects users' behavior to infer their preferences. When detecting changes, these user preference data change simultaneously. For example derive implicit rating information from transaction history to identify preference of users and investigate the behavior of electronic book readers to capture measure, and classify implicit information for discovering user interests and construct matrix factorization models that use implicit feedback. Second, the explicit method filters and analyzes interactions and feedback to infer users' specifications. For example collect feedback from customers about books they have read to construct recommendations. Based on the user defined reading preferences, and build a personalized news recommender system on the Web [1].

Various publications are also several ways to search for products and make purchasing recommendations to electronics store customers is offering that the several of these methods in terms of the PRSs will be reviewed.

This investigation is organized in four sections. Second section briefly describes PRS and various proposed models for that. Section 3rd compares the proposed models for PRS and finally section 4th concluded the paper and includes some of the future works.

2. PRS

In this section we have described investigated PRSs.

2.1. A Social Recommender Mechanism for E-Commerce

In the source [1], a social recommendations system with Detection priority of the members through close friends and social network developed. The basic idea of trust and reputation systems is to obtain a score for users. According to these results, other users can decide whether they are traded by a trusted user or not. IN fact this mark establishes the reliance on the recommendations of any person that is obtained by close friends in social network.

Social networking sites have become an important service to a wide range of applications such as collaborative work, shared services, rating, sharing resources, and search for new friends and to be included. Social network is a network formed by a set of specific relationships between members is connected together. Social theory suggests that the position of Member Relations web based access to resources, friends, and affect [1].

2.1.1. The Proposed Model for the Recommended Social System

In product purchasing, people tend to ask for advice or suggestions from people with similar interests or professional expertise, or from close friends. However, close friends may not have the expertise or interest in certain products. Furthermore, we may not always believe the suggestions of product experts with whom we have no acquaintance. Consulted sources also differ when product types vary. Therefore, an effective product recommendation should appropriately incorporate these factors. In this study, we propose a social recommender system that comprehensively employs preference analysis, recommendation trust analysis, and social relation analysis modules, as well as a personalized decision module, in order to construct a more comprehensive and personalized framework for product recommendation in e-commerce[1].

Four analysis modules have been developed to analyze the information from the constructed form network. The objectives of the analysis modules included in the system are described as follows:

- The preference similarity analysis module measures the preference similarity between two customers based on the product rating records of each customer. A group of users with the same similarity level can be identified. The preference of a targeted customer towards a specific product can be predicted by a group of other customers with the same preference similarity. The preference similarity degree of two customers can be estimated according to their product purchases or rating records.
- The recommendation trust analysis module computes the reputation quality (success rate) of the product recommendations of a customer according to his/her product rating records. The recommendation predication accuracy is positively associated with the recommendation trust (expertise reputation) of recommenders. In the social recommendations system, the recommendation trust of a recommender is evaluated by his/her success rate of product recommendations.
- The social relation analysis module analyzes the relation closeness degree between two customers according to implicit interaction records or explicit closeness ratings between them in a social network. The closeness value of a relation path between two users is measured by the weakest tie strength (closeness) at the edge of the path. When there are multiple relation paths between two users, the path with the strongest closeness value is used to represent the social relation strength between the two users.
- The personalized product recommendation module computes the personalized factor weights for product evaluation and recommendation based on individual factor ratings with respect to different product categories. These criteria are significantly affected by the impact of personality traits, such as gender, age, and economic status. In order to achieve the personalized recommendation criteria, users are invited to evaluate the relative importance of preference similarity, recommendation trust, and relationship closeness.

2.1.1.1. Advantages & Disadvantages of Proposed Model

In This recommendation system the customer confidence is more considered and Lead to a rating of Recommended Indicators Due to the success of the previous recommendations by any other recommendations. The important thing is that the accuracy of the recommendations is the greater its impact on the customer's personal decision to be higher. The strength of this system is that emphasizes the theoretical perspectives of the confidence to recommend. In fact, the customer can select recommender with high confidence and accuracy of recommendations to help.

The weaknesses of the social recommendation system based on the comments of customer's friends and associates on social networking to anticipate customer needs. If does not available accurate knowledge of customers on social networks, identifying his or her needs will not be accurate.

Another weak point is the lack of attention to product specification. Product characteristics (including price, quality, brands on the market, year of manufacture, etc.) recommended should be made clear to the customer to choose the product to be accurate.

The new customer is one of the weaknesses of this recommendation system. Because gathering information about a new customer social networks can be time consuming and difficult.

2.2. An Associative Classification-Based Recommendation System For Personalized Recommendation

In source [2] the recommendation system based on Association classification for personalization in B2C e-commerce applications is presented. Based on associative classification method, for the product recommendation Issue can build an evolving system. This system consists of four stages which are:

- Requires the processing module
- Production Association classification Module
- Pruning classification module
- Validation System Performance Module

First, historical requirement data are selected and transformed into proper phrase datasets. Then Data mining procedure then starts to search for a set of associated, frequently occurring phrase patterns (classifiers). In this regard, stemming algorithm and a common stop word list in English are adopted to reduce the dimensions of the text documents and improve the efficiency of the classifier extraction.

In this research, four thesaurus collections are used to match the requirements. For every collection, there exist several sub collections, each containing a set of synonyms. The four thesaurus collections are represented as N={N1,N2,...}, V={V1,V2,...}, ADJ={ADJ1,ADJ2,...}, ADV={ADV1,ADV2,...}, for noun, verb, adjective, and adverb, respectively. A lot of semantic rules are represented as IF–THEN rule formats and stored in the semantic rule database to indicate the inference relationship between requirements and a set of predefined phrases, P≡{p1,p2,...,pI}. Suppose after stop words removal and stemming, one customer requirement is transformed into a word set, Y≡{y1,y2,y3}, and the semantic meaning of such a requirement is represented as IF–THEN rule formats as the following:

IF $y_1 \in V_2$, $y_2 \in ADJ_1$, and $y_3 \in N_3$

THEN the semantic meaning of Y is associated whit p_2.

By preprocessing, customer requirements are represented as a set of phrases which are used in the following procedure to generate the classifiers.

The next step is to classify the mining association rules. Explore Traditional association rules assumes all of the items included in the transactions are a set of items. Also to solve the Recommendations problem needed to association rules by considering the class label data. So in this paper, two sets of items defined which one includes customer requirements and other includes items classes' label.

After generating Classifiers using association rule learning, one important problem originates from the need for determining appropriate thresholds for the support and confidence levels. If the support and confidence thresholds are planned with low values, the number of the classifiers could be very huge. Excessive classifiers extend the time to identify the class labels for given requirement information. To the contrary, useful classifiers may be ignored if the support and confidence criteria are specified very strict. Besides, noisy and redundant information impair the classification quality. The generated classifiers are pruned by which only those classifiers with good quality are kept for recommendations.

Finally, to evaluate how accurately the proposed recommendation system assigns class labels based on future customer requirements, this research applies the accuracy measurement to validate the system performance. Accordingly, assumed that can apply a test set T, the S record of classified classes $C^{\bar{t}_s}$, according to the following equation [2]:

$$a = \sum_{s=1}^{S} \frac{v_s}{S},$$

$$s.t. \quad v_s = \begin{cases} 1 \ if \ \ C(\bar{t}_s) \in C^{\bar{t}_s} \mid \forall \bar{t}_s \in \bar{T} \\ 0 \ \ otherwise \end{cases}$$

$$\forall s = 1,2,3, \dots, S \qquad (1)$$

Where a means the recommendation accuracy, namely the percentage of the transactions in the test set that are correctly classified.

2.2.1. Advantages and Disadvantages of Associative Classification-Based Recommendation System

In this recommendation system, customer's criteria is collected to words and then Using data mining association rules, the relationship between these words have been found and classified in The class with the specified label. The product related with this class is provided as a recommended product to the customer. The strength of this system is accurate to collect the customer's measures and eliminate "new customer's" problem by collecting the customer's buying criteria through explicit way.

The weakness of this system is that there is noisy and insufficient information in the information presented by the customer can reduce the accuracy of system and performance of PRS is threaten.

2.3. The Recommendation System Based on Clustering Analysis Based on Priority

In The source [3] a PRS proposed based on clustering comments of user and reviews. In this work, product Reviewers also considered as the part of users and affects their preferences in the clustering. This paper classified the product review methods into two branches: analyzing in the review level and analysis in the features level. First branch of analyze has been primarily based on the review's document-level analysis results (such as Manufacturer, year of manufacture and etc,.). However, analysis in the review not leads to assess the real value of product characteristics. On the other hand, analysis in the features level reviewed products in the actual value. This system consists of the following steps.

2.3.1. Preprocessing Step

Ordered pairs <attribute, comment> are extracted from raw textual studies using statistical methods to identification the features of product and similar features are extracted from the study. Then all the comments are Placement that is associated with each of the features found in a review.

Near the end of this step, need to assess every opinion word's sentiment strength (also called polarity value). It can provide with a triple of polarity scores for each opinion word: positivity, negativity and words. Each ranges from 0.0 to 1.0, and Pos(s) +Neg(s) +Obj(s) =1. The triple scores can then be merged into a single sentiment value:

$$O_s = Neg(s) * R_{min} + Pos(s) * R_{max} + Obj(s) *((R_{min}+ R_{max})/2)$$

Where R_{min} and R_{max} represent the minimal and maximal scales respectively. Comments amount feeling that related whit a feature is obtained by the above equation and calculated the average of these feelings. Product that comments about it are more positive and obtained Values for this are in the desired number field is more suitable options for recommendation.

2.3.2. Generating Recommendation Step

Three methods for generating recommendations and actually comments clustering in this system are proposed:

- The probability regression Recommendation model based on KNN: in This method, the personal opinions of the buyers are collected directly and through which a group member k of those who their preference's features are similar to the current buyer is introduced

And then the Recommendations system advises products with high similarity to the personal opinions of the members of the group.

- The probability regression Recommendation model based on K-Means: Another method is clustering comments that have the same priority and then according to the priority characteristics of each cluster, the products are very similar to the characteristics of each cluster, are recommended to the cluster. New buyers due to their priority features is given, based on kNN algorithms, are implemented to the cluster that have the same priority features. Indeed, clustering is an effective method to increase the accuracy of PRS.
- Recommendation of the latent class regression model (LCRM): In this method, after clustering customers based on their priority features in the clusters with the same priority, again the buyer's comments in a cluster are investigated based on the priority level of review, and are gained k similar comments. Then from product's tank, products that are very similar to this k comments are chose as the estimated products to recommend to the desired cluster.

This paper demonstrates the outperforming accuracy of LCRM from several aspects: (1) deriving more stable reviewer-level preferences; (2) performing more effective clustering of reviewers; and (3) generating more accurate recommendation even when the buyer's stated preferences were less complete. Experimental evaluation shows that the recommendation system performance by clustering features in the comments and priorities on developing e-commerce sites, improved [3].

2.3.3. Advantages & Disadvantages of This System

This system focus on customer and reviewer comments that priorities and criteria are similar to each other. The customers who are shopping for the first time can use reviews and other customer comments cluster as guidance in choosing the product. Products that have already been offer to this cluster present to new customers.

Disadvantage of this system is not used of communication between products. In fact, product Features the new client will not be notified. Apparently the only other customer and reviews comments present to new customer and new customer is classification in group with similar opinions. Additionally another disadvantage of this system is not recommended associated products with customer's desired products that can increase customers' freedom of choice.

2.4. Dynamic Template Based PRS

In source [4], a PRS with the dynamic templates is introduced. Since users have different needs at different times and customer's purchase due to variety of requirements at different times are vary considerably, hence the constant PRS cannot Responder the needs of customers. In this paper, the behavior of the users during the life cycle is considered and the needs of customers in each period manually classified. This classification facilitates recommendation process and helps to personalization product recommendation.

Each user may have several life cycle stages. Formally in this system, customer purchase history is taken which can be divided into several categories according to the specified time. Then using machine learning techniques trains products for specific customer for each specified time period.

After the system was able to detect period that user is located, products needed for each stage in both graph based and cluster based methods recommended to customer.

2.4.1. Advantages and Disadvantages of this Template

This system for customers who constantly go to the store to buy is very good. Another advantage of this system is investigating customer needs at the time of his life cycle.

The problem with this system appears lack purchase history of customers who buy from the store for first time that cause of failure to provide accurate advice to customers.

Considering that each customer must to be continuously identified for time period to specify needs, this system with increase the volume of customers will faced to the problem of computational overhead.

2.5. Mining User-Contributed Photos for Personalized PRS

In source [5], a system proposed solutions on personalized products recommendation based on user-contributed photos from social media sites. The input of this approach is user shared photos of the same webpage and their corresponding textual descriptions. In this paper, a new hierarchical user interests mining (Huim) approach for personalized PRS is proposed, which includes four stages. (1) Use of visual data and UGC for user interest mining (2) hierarchical user interest representation. User's information (UGC and enriched tags of the photos) to a hierarchical public topic space is mapped. And represented user interest by a high dimensional topic vector. And apply proposed to Huim promote discussions of interest (3) Products representation. Products are mapped to the same public topic space to get their topic distribution vectors. Each product also corresponds to a point. The public topic space acts as a bridge between user and products. (4) Product ranking. In the public topic space, both user's interest and a product are represented by a high dimensional topic vector. Thus the relevance of user and product can be measured by the correlation of their topic vectors. In this paper used the cosine of them to measure their relevance and then determined the ranks of the products.

2.5.1. Advantages and Disadvantages of This Recommended System

The advantages of this PRS use the customer's picture at User's Profile. Another advantage of this system is to more identification customer gives more accurate personalized recommendations to users.

The disadvantages of this PRS is that if sufficient knowledge of user is unavailable or if the user's first visit to the System, This system may not be provide accurate and effective advice to users. In fact, the history of customer buying behavior is the system requirements.

2.6. A PRS Based on Combining Collaborative Filtering and Sequential Pattern Analysis

In resource [6], developed a PRS, called HOPE, which integrates CF-based recommendation using implicit rating and SPA-based recommendation. This section presents the overview of the system, followed by the detailed description of each step of the framework.

Overall framework of this recommendation system, HOPE system consists of two main processes: CF process and SPA process. The CF process is the way in which the customer experience and preferences are adapted with entire customer and an arbitrary subjective ID is assigned to each customer and purchase products based on specified criteria of that ID suggested to customer. The CF process is the same as the traditional CF process, except that an implicit rating derived from transaction data of users is used instead of explicit rating. Therefore, in this study implicit rating for each user about an item (The ratio of desired item purchase to the total number of items purchase by the user) using purchase information is obtained. Thus, it calculates the similarity between a target user and other users using the implicit rating and selects the top k users based on the similarity score as neighbors of a target user. Finally, the predicted preferences of a target user on items purchased by the top k neighbors (CFPP) are calculated based on the ratings of the neighbors. The SPA process derives sequential patterns from transaction data of other users, and predicted preferences on items (SPAPP) are calculated by matching all subsequences of a target user's purchase sequence data with each derived sequential pattern. In this method, transaction data sorted for each person by the date of purchase and then purchase sequential data is generated. Sequential data is series of items that which are arranged according to the time of purchasing; then the sequential patterns of users sequence data except the goal user can be achieved by using SPA. Actually, repeated items that appear in other users' purchase transactions causes sequential patterns are predictable. Finally, the weighted sum of normalized CFPP and SPAPP is calculated as a final predicted preference (FPP) on each candidate item to recommend, and then the top n items with the highest FPP are recommended.

2.6.1. Advantages and Disadvantages on this System

The advantages of this PRS are combination of cooperation filter and sequential patterns. Also another advantages are, choose customers who have a lot of near shopping behavior and investigation products Sequential patterns.

The problem of noise in the data that predicts explicit rating collaborative filtering using the user's mental ID and determine customer needs from this ID can be noted as Disadvantage.

2.7. A Highly Adaptive Recommender System Based on Fuzzy Logic for B2C E-Commerce Portals

In source[7], introduced a prototype of e-commerce portal, called e-Zoco, of which main features are: (i) a catalogue service intended to arrange product categories hierarchically and describe them through sets of attributes, (ii) a product selection service able to deal with imprecise and vague search preferences which returns a set of results clustered in accordance with their potential relevance to the user, and (iii) a rule-based knowledge learning service to provide the users with knowledge about the existing relationships among the attributes that describe a given product category.

Portal embedded in this study compared the following components:

Products catalogues systems, customer management systems, messaging systems, products evaluation systems, management issues system, lexicographic based search engine, sales management system, bid management system, secret data management system and reporting system.

Today, features that available in the e-commerce portals in following:

- Catalogue browsing
- Lexicographic search
- Advanced Search
- Mixed search
- Results arrangement

Product selection systems are distinguished from traditional search engines in that they provide more advanced capabilities, such as the interpretation of vague or imprecise search criteria or the results clustering and classification according to their relevance. Product selection systems can be broadly classified according to the kind of products for which recommendation is offered as:

(i) Product selection systems for low involvement products (LIP), such as books, music albums, or films.

(ii) Product selection systems for high involvement products (HIP), such as appliances, video or photo cameras, musical instruments or vehicles.

In the case of LIP, the click-to-buy rates are usually higher compared to those of HIP. Consequently, recommendations for LIP are usually offered with the help of the customer's past purchases or past searches, demographic details, or explicitly specified interests. Collaborative Filtering (CF) is one of the most widely used techniques to offer recommendations for LIP products. CF techniques try to match the customer's tastes and preferences with that of all other customers to identify those like-minded and then offer the products bought by them as recommendations.

In the case of HIP, product selection systems are usually developed to take as input a set of product features or attributes to match against the set of products available in the database. As result, the system generates a ranking of products most likely to be of interest to the customer. Product selection in the case of high involvement products results more complex compared to low involvement products.

2.7.1. Portal Architecture

This system first is a hierarchical catalog contains general and specific classes. Each class is a combination of products that are hierarchically organized. Members of a specific class, inherit general class to properties. All classes in the catalog associated with the transaction. Any product that has sold at least is one member of classes of catalogue [7].

As mentioned, e-commerce customers want to have accurate and useful metrics that they just have not made aware of certain models and brands, but also they will explore models available on the market [7].

Then, this system performs product recommendation in three phases:

- Identify the needs of users (search criteria).
- Search among the items in the catalogue and find the product that is the closest match.

- Organize and present the results to the customer.

2.7.2. Advantages and Disadvantages of this Recommended Systems

The advantages of this system can be noted to differentiate products with high involvement (high risk selection) and low involvement products (choose low risk). The accuracy of the products can aware customers of product features and helps to customer careful and assists with requirements selection.

The disadvantages of this system assign it to the C2C stores (auction stores and auction sites) that customers are in contrast with each other and reliability and security of customers in these sites is challenging.

The other disadvantage of this system is the high computational complexity for products with high involvement and probability of confuse customers during the long process of determines criteria research.

3. Comparison between All Recommended Systems

Generally, each PRS try to improve part of the buy recommendations process. This improved to increases the accuracy of personalization product recommendations and helps to customers to choose the desired product. Also PRSs want to solve challenges will be faced (which was discussed earlier). Hence, for comparison about Efficiency of PRSs, we must evaluate these systems in terms of overcoming challenges.

In this paper, several recommendation systems investigated and the advantages and disadvantages of each mentioned. In this section, we get an aggregation of advantages and disadvantages of these PRSs in Table 1 and 2.

As can be seen Table 1, shows the positives and negatives of each PRS and Table 2 shows the performance of PRSs have been investigated to overcome some of the challenges.

Table 1: Positives and Negatives of Each PRS

PRS	Advantages	disadvantages
Social Recommender Mechanism	- More attention to the recommendation trust. - Ranking recommender Based on the success of previous recommendations. - Ability of customer to choose the recommender with high level of trust. - Increase the effectiveness of the customer's personal decision with increase the accuracy of recommendation.	- rely on the opinions of Customer's family members and friends in social networks to anticipate customer's needs. - If does not correct understand of customers in the social networks, identifying needs will not be accurate. - Lack of attention to the characteristics of the products. - New customer problem

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Associative Classification-Based Recommendation System	- Carefully collect the customer's criteria - Remove the new customer problem whit collecting purchasing criteria through explicit	- Exist noise and insufficient data in presented information by the customer can reduce the accuracy of the system.
Preference-Based Clustering Reviews	- Focus on customer and reviewer comments that priorities and criteria are similar to each other. -Use cluster of reviewer and other comments customer comments for new customers as guidance in product selection	- Do not use the features of the products - Do not advise the associated products with customer's desired product.
Product Recommendation With Temporal Dynamics	-It's very good For customers who constantly go to the store to buy. - Assess customer needs at different stages of his life cycle.	- Lack of purchase history for customer's that first purchase from a store - To increase the volume of customers will be faced with the problem of computational overhead.
Mining User-Contributed Photos For Personalized Product Recommendation (Huim)	- Use the Customer's Picture Profile for identification. - Better understanding of the customer gives accurate users personalized recommendations.	- If sufficient knowledge of user is unavailable or if the user's first visit to the System, This system may not be provide accurate and effective advice to users.
Combining Implicit Rating-Based Collaborative Filtering And Sequential Pattern Analysis (HOPE)	- Combination of cooperation filter and sequential patterns. - Choose customers who have a lot of near shopping behavior - Investigation products Sequential patterns	- The problem of noise in the data that predicts explicit rating collaborative filtering using the user's mental ID and determine customer needs from this ID
Highly Adaptive Recommender System	- Differentiate products with high involvement (high risk selection) and low involvement products (choose low risk). - Care on the product features - Overcome to new customer problem	- assign it to the C2C stores - Lack of system development -High computational complexity for products with high involvement and probability of confuse customers during the long process of determines criteria research.

Table 2: Solve the Challenges by PRSs

PRSs	Noisy Data	Attention on the Product Features	System Development	Customer Needs Change with Changing Times		Recommender Ranking	New Customer	Customer Criteria Collection
Social Recommender Mechanism	×	×	√	×		√	×	×
Associative Classification-Based Recommendation System	×	√	√	√		×	√	√

Preference-Based Clustering Reviews	×	×	√	×		√	√	×
Product Recommendation With Temporal Dynamics	×	√	√	√		×	×	×
Mining User-Contributed Photos For Personalized Product Recommendation (Huim)	×	√	√	×		×	×	×
Combining Implicit Rating-Based Collaborative Filtering And Sequential Pattern Analysis (HOPE)	×	√	√	×		√	×	×
Highly Adaptive Recommender System For C2C	×	√	×	√		×	√	√

4. Conclusions and Suggestions for Future

PRSs are one of a method that adoption to deal with the problem of information overload in e-commerce. The purpose of PRS is providing buy recommendations to help electronic stores customers to avoid wasting time and confusion among many products available in store. Provide accurate recommendations will cause to Careful selection of the product by the customer.

In this paper, several recommendation systems investigated and the advantages and disadvantages of each mentioned. Can be said that each PRS try to address the aspect of current challenges in this area and any of this have been not overcome to the existing problems completely.

As future work, we will design the two-level PRS in E-commerce Using data mining applications that will overcome to most of this challenging and due to the results it will provide accurate buy recommendation to customers.

References

[1]Yung-Ming Li, Chun-Te Wu, Cheng-Yang Lai, "A social recommender mechanism for e-commerce: Combining similarity, trust, and relationship", (2013), Elsevier Decision Support Systems, vol 5, pp. 740–752.

[2] Yiyang Zhang, Jianxin (Roger) Jiao, "An associative classification-based recommendation

system for personalization in B2C e-commerce applications", (2007), Elsevier Expert Systems with Applications, vol 33, pp. 357–367.

[3] Li Chen, Feng Wan, "Preference-based clustering reviews for augmenting e-commerce recommendation", (2013), Elsevier Knowledge-Based Systems, Vol. 50, pp. 44–59.

[4] Wenxing Honga, Lei Li, Tao Li, "Product recommendation with temporal dynamics", Elsevier Expert Systems with Applications, (2012), Vol. 39, pp. 12398–12406.

[5] He Feng, Xueming Qian, "Mining user-contributed photos for personalized product recommendation", (2014), Elsevier Neurocomputing, Vol. 129, pp. 409-420

[6] Keunho Choi, Donghee Yoo, Gunwoo Kim, Yongmoo Suh, "A hybrid online-product recommendation system: Combining implicit rating-based collaborative filtering and sequential pattern analysis", (2010), Elsevier Electronic Commerce Research and Applications, Vol. 11, pp. 309–317

[7] Jose Jesus Castro- Schez, Raul Miguel, David Vallejo, Lorenzo Manuel López – López, "A highly adaptive recommender system based on fuzzy logic for B2C e-commerce portals", (2011), Elsevier Expert Systems with Applications, vol 38, pp. 2441–2454.