A Comprehensive Study on Recommender Systems For E-Commerce Applications

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ABSTRACT: Recommender Systems help consumers navigating through large product miscellany, making decisions in e-commerce environments and overcome information overload. These systems take the behavior, opinions and tastes of a large group of consumers into account and thus constitutes a social or collaborative recommendation approach. In contrast, content-based technique depends on product features and textual item descriptions. Knowledge-based technique, finally, produce item recommendations based on explicit knowledge models from the domain. Demographic technique purpose to categorize the consumer based on personal aspect and make recommendations based on demographic classes. Hybrid approach combines two or more techniques. Marginal utility is economic idea because economists and marketing research use it to discover how much of an item a consumer will purchase. Association rule mining technique concentrates on the mining of associations over sales data and help shop managers to analyze past transaction data and to improve their future business decisions and recommend products to a consumer on the basis of other consumers' ratings for these products as well as the similarities between this consumer's and other consumers' tastes. This paper encapsulates subjective and objective parameter to design effective recommendation technique and also present model on cold start problem in e-commerce recommendation system

The main idea behind the Recommender System for E-Commerce is to build relationship between the products (items), users (visitors/customers) and make decision to select the most appropriate product to a specific user. This system is used by the E-commerce websites to suggest products to their customers. Recommender Systems use Machine Learning algorithms such as Collaborative Filtering and Content Based Filtering. Collaborative Filtering also referred as social filtering, filters information by using the recommendations of other people. Content Based Filtering also referred as cognitive filtering recommend items based on the comparison between the content of the items and a user profile. In user point of view, Recommender Systems helps the user to take correct decision in their online transaction. It recommends the items to users such as books, electronic products and many other products in general. In manufacturer or retailer point of view, Recommender System increases the sales and users browsing experiences.

KEYWORDS: Recommendation Systems, content-based, collaborative-based, hybrid-recommendations,
E-commerce, evaluation metrics.

I. INTRODUCTION

Electronic commerce has had an explosive expansion in the past decades. On-line shopping has become part of human daily lives. Companies need to be able to, at a minimum, develop multiple products that meet the multiple needs of multiple customers. The movement towards E-commerce has allowed companies to provide customers with more options. While expanding the businesses, it increases the amount of information that customers must process before buying the products from online websites. One solution to this information overload problem is the use of Recommender System. It is a program which attempt to predict items that a user may be interested in, given some information about the product or user. Recommender system**s** are used by E-commerce sites to suggest products to their customers. The products can be recommended based on the top overall sellers on a site, based on the demographics of the customer, or based on an analysis of the past buying behavior of the customer as a prediction for future buying behavior. It allows rapid and automated customization and personalization of e-commerce sites. Most existing recommender systems use collaborative filtering methods, content based methods. Many consumers prefer to use free form of text to express their opinions. Produce review forums and discussion groups are popular ways for consumers to exchange their experiences with a product. Some examples of Recommender System are: Amazon.com, CDNOW, eBay, Levis, Moviefinder.com, and Reel.com etc. Using World Wide Web, more than 1.9 billion people around the world have access to the global information resource via the internet. Internet consumers are constantly presented with situations in which they have many options to choose from, they need assistance in exploring or winnowing down the possibilities. When a consumer enters some keywords into a search engine, it provides a listing of best-matching web pages according to consumer criteria. These search engines are not good enough for winnowing down the possibilities, because there still may be thousands of relevant results to select from. The consumer's don't generally know ahead of time where he or she is searching for and may not have the capacity to define the question he/she needs.

A system is required that supports the consumer in finding and picking products and information. When there are too many products to consider or the consumer has a lack of knowledge about the topic or domain then a system required, which uses knowledge of consumer provides the suitable recommendations. This type system is called the recommendation system. The recommender system is different from a search engine in a way that, no keyword input is required every time to look for items. The recommender system is capable to present matching products without the obligation to type any keywords. The system is based the presented products on a profile of the consumer and therefore can enhance the product discovery.

These days, due to the expansion of e-commerce, development of a recommender system is a key to a good business as it helps to navigate through complex information spaces from a large variety of consumer products. In these scenarios, recommender systems have largely been used to suggest items (electronics product, movies, books so on) to consumers based on their learned interests, which are often derived from their past purchasing behavior. Lately, as the online services embrace the world of the social web, consumer-generated content is playing an increasingly important role when it comes to supporting consumer buying decisions. For instance, many online stores now include comprehensive consumer reviews to complement product descriptions, and it is no uncommon for popular merchandise to pull hundreds of reviews from consumers who are only too glad to partake in their ideas and feelings. Indeed, many of us use a website like Amazon, Yelp and Trip Advisor primarily for their review information. In the world of recommender systems, these reviews can serve as a form of recommendation explanation and can play a key role to evaluate the goodness of the product suggestion. We purposed such a system which depends on consumer generated content or reviews and product profile

II. RECOMMENDER SYSTEMS

In technical aspects, complete Recommender Systems will work with one method or with more than one method(s) are Content-Based Filtering (CBF), Collaborative Filtering (CF), Demographic Filtering (DF), Knowledge-Based Filtering (KBF), and so on.

Figure 1: Different categories of RSs

Collaborative Filtering

The general thought of Collaborative Filtering (CF) is that the users who are having common preferences before will have the same in the future also. The new definition of CF is "Having collaborations among the users to assist each other through filtering and recording their reviews about the viewed information". This strategy considers ratings or reviews to match the similarities among the user"s communities and recommends on the basis of those similarities. Recommenders from CF get influenced by the issues such as cold-start (new user or new item)," gray sheep" (users that do not fit in any taste cluster), etc. [8] and the recommendations of similar users using collaboration filtering is shown in Figure 2.

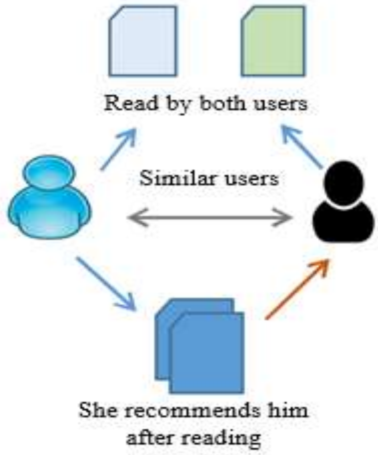
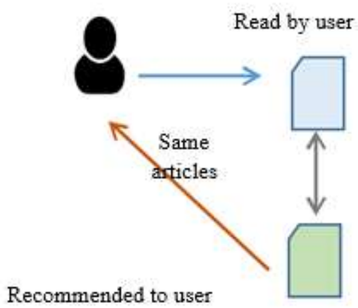


Figure 2: Collaboration Filtering

Content-Based Filtering

This depends on the assumption that users who liked products with specific attributes before will prefer the same in the future also. It uses the items and their attributes by taking the profile of users into sight and give recommendations. It also depends on the product"s description. Also, it identifies the similarity that exists between the products by taking the product"s details into sight. IT is sometimes also called cosine similarity and is denoted in Eq. (1) whereas the recommendation that uses this filtering is represented in Figure 3. Here the item read by one user and the similar articles is recommended to another user. The past data of the user is considered for identifying the same products which the other user might prefer.



Demographic Filtering

This filtering uses demographic information like age, place, educational details and so on for finding the users types. So to clear the issue of the new user and it doesn't require ratings to give recommendations. Nevertheless, it is not that easy to gather sufficient demographic data that is required for online security aspects, restricting the usage of demographic filtering. Till now it is integrated with the rest of recommenders as enforcing approach for best quality [10].

Knowledge-Based Filtering

This filtering depends on the knowledge to guess which product satisfies the user"s demand and provide recommendations accordingly. It is impossible to use CF or CBF perfectly here, as some data related to the user system is available [11]. Many scientists initiated to integrate the strategies of recommendation systems in distinct ways developing Hybrid recommender systems that are considered in this paper. Hybrid Recommender systems combine 2 or more than 2 approaches with the motto of increasing the merits and decreasing the demerits. Fab was the first, which is a meta-level recommender that helps in suggesting websites [12]. It incorporated the integration of CF for finding the users who are having the same website preferences with CBF for finding the websites with the same data. Other works such as [13] followed shortly and hybrid RSs became a popular recommendation approach.

Table 1: Recommendation Techniques [14].

Technique/method	Background	Input	How does it work?
Collaborative	Ratings from U of items in I.	Ratings from u of items in I.	Identify users in U similar to u, and extrapolate from their ratings of i.
Content-based	Features of items in I	u"s ratings of items in I	Generate a classifier that fits u"s rating behavior and uses it on i.
Demographic	Demographic information about U and their ratings of items in I.	Demographic information about u.	Identify users that are demographically similar to u, and extrapolate from their ratings of i.
Knowledge-based	Features of items in I. Knowledge of how these items meet a user"s needs.	A description of u"s needs or interests	Infer a match between i and u"s need.

Table 2: List of features of RS

Number	Merit/Demerit
1	Ability to recognize cross-genre niches
2	It is not required to have Domain awareness
3	Adaptive: improves the quality over time
4	Implicit feedback sufficient
5	New user ramp-up issue
6	New item ramp-up issue
7	"Gray sheep" problem
8	Quality dependent on huge previous data set.
9	Stability vs. plasticity issue
10	Must collect Demographic data
11	Requires no ramp-up
12	Sensitive to preferential updating.
13	Ability to add non-product features
14	Can map from user requirements to products
15	Requires knowledge engineering
16	Suggestion ability static (does not learn)
17	The user gets recommended the kinds of commodities they prefer

Hybrid Recommendation Model

Hybrid RSs integrates the two or more than two recommendation methods with the intention to attain high-performance levels with fewer issues individually from any of those integrated methods. In common cases, collaborative filtering is integrated with the other methods to neglect the ramp-up issue. Table 4 presents some of the integrated methods that are worked with so far. A weighted hybrid recommender is one where the rating of the recommended item can be evaluated from the outcomes of all the valid recommendation approaches available in the system. A switching hybrid is modeled from item-level sensitivity to hybridization approach: the system uses few considerations to shift between the recommendations strategies. The Daily Learner system uses the content/collaborative hybrid where a content-based recommendation model is deployed initially. If the content-based system doesn"t work well then the collaborative recommendation is performed. The hybrid whichever shifted will partially ignore the issue of ramp-up as those collaborative and the content-based systems are raised by the "new user" problem. Nevertheless, Daily Learner"s content-based technique is nearest-neighbor that need not any huge instances for precise classification. Mixed hybrid ignores the problem of "new item" start-up: the content-based component depends on the newly recommended by meeting the user"s demands even though they are not provided any feedback or rating. It does not get influenced by the "new user" start-up problem. Similar to the fallback hybrid, this strategy includes the essential property of "niche-finding" and in that, it brings out the new items that ignore the unwanted content. One of the other ways to attain content is to consider collaborative data as simple extra feature data related to every instance and uses the content-based strategies on this data set. Feature combination hybrid allows the system to consider the collaborative information without depending over it exclusively so that it minimizes the system"s sensitivity to some users whoever rated the product. In contrast, it also allows the system to include data related to item similarities. Cascade hybrid involves with stage by stage procedure. In this strategy, initially, a recommended approach is applied so that to generate coarse feedback of users and other approach filters the recommendations from the candidates set. The cascading enables the system for ignoring the employing secondly, degrading priority, and approach over the well-classified products. This is due to the second step in the cascading concentrates only on those products to which there required further classification. Besides, the cascade has the criteria to tolerate the disturbances generated during the application of the low-priority technique because the rating provided by the high-priority recommender can only be refined, not overturned.

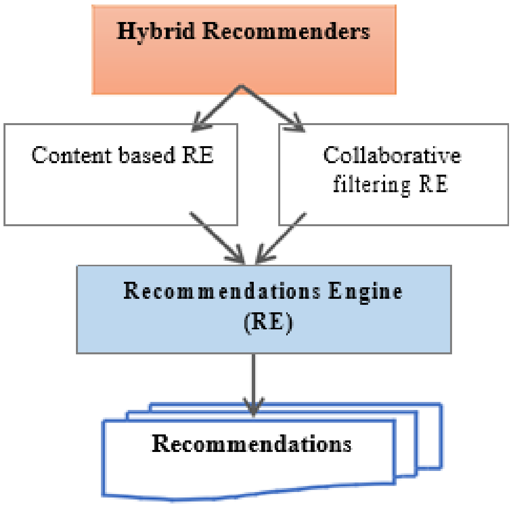


Figure 4: Hybrid Recommendation System

III. Related Works

Users can communicate with the RS through a user interface on the basis of the web site or through a mobile application where a profile holder retrieves the user's properties considering the review generated with the help of explicit method and implicit method. Users‟ preference over distinct items can be forecasted by some of the ranking paradigms that give a list of recommended products by taking personal evaluation into sight. The RS architecture mainly depends on the database which stores and serially updates the description of products and ratings given by the user. Figure 5 represents the architecture of the Recommender system. Because of the services especially clustering and filtering, RS are widely used in e-commerce [15] as they assist the consumers to find recent and official items [16]. Under this section, we stated many approaches related to the recommendation along with the collaborative filtering, content-based filtering, and hybrid recommendation.

In *Collaborative Filtering*, the products are recommended based on the same metrics existing between users and items. There are two kinds of collaborative filtering. One is Neighborhood-based collaborative filtering and model-based collaborative filtering. Usually, it examined the instances of neighborhood-based collaborative filtering that includes the approaches that are user-based and item-based as well [17]. The aim of user-based recommendation is to recommend the items which are liked by the users whoever having similar preferences whereas the objective of item-based recommendation is to recommend the items on the basis of the same properties. In recent times, many of the matrix factorization approaches are used for collaborative filtering. Those approaches help in integrating the user-item rating matrix by using low-rank approximation paradigms and use it to perform forecasting well.

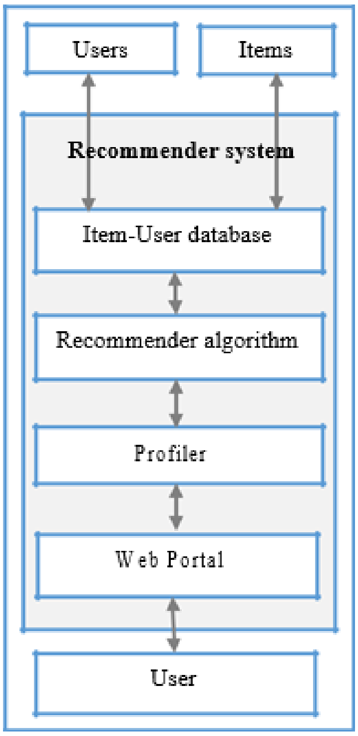


Figure 5: Recommender system architecture

In *Content-based filtering*, the item can be recommended based on the product specifications or the services used while recommending. The product's specifications or the services are together analyzed and must match with the rest of the product's properties existing in the database [11]. Those same properties of a product are then recommended as recommended products. This content-based filtering holds a major application in the websites specifically in e-commerce like Amazon, Flipkart, eBay, and Snap deal effectively use for recommending the products to users. It is impossible to recommend a product only on the basis of content-based or collaborative RS but we must also consider the data gathered in recent days like preferences of users, product specifications as they vary every time [18,19]. So many of the users like to search for e-commerce portals where the combination of both the methods will be there. E-commerce is mainly adapted to the hybrid recommendation system. These RSs might include collaborative, content-based, click through analyses, query suggestions and so on. The implementation procedure of hybrid recommendation systems is represented in Figure 6. The process begins with a new user. If the new user is similar to any other user group then, with the help of hybrid RS the products will be recommended to the new user, those are similar to the user group. If the user is not related to any similar group, then also hybrid RS system will recommend the items based on the combination of the two internal filtering techniques such as content and collaborative filtering In basic level CF approaches, the aim is to focus on the users who receive recommended items that are preferred by the same users or items that match with the same items preferred by the other user. The former is known as user-based CF (UCF), while the latter is known as item-based CF (ICF). Memory-based CF [32] is a basic method that can be applied widely in e-commerce environments like Amazon. Memory-based methods find the similarities between the users by contrasting their ratings on products. The problem of data sparsity [33] in the user-item matrix has highly restricted in applying this type of CF as it is complex to perform predictions by considering the sparsing training information. Few of the methods are proposed to solve this issue like default rating methods, imputation-boosted approaches, and clustering-based methods. Model-based CF detects the association between many items by exploring the user-item matrix and later retrieves a set of recommendations considering the relations. a prediction method is introduced in model-based CF primarily through machine learning approaches for forecasting the data that is not known. Basically used model-building approaches involve neural networks, matrix factorization, and latent semantic models. The correlations between user-to-user are described with their preferred ratings without considering particular characteristics and item‟s attributes. Additionally, these methods consume high time in building and update to some extent. Rafailidis et al. [34] introduced a new measure of user-preference dynamics and a model of user-item interactions on time by applying a tensor that considers time as a dimension. In addition to these works, we presented the recent works on hybrid recommendation systems to recommend various items on a different application such as e-learning, e-commerce, movies, etc. are shown in Table 4

Author	Application	Methodology
Verbert et al. (2012) [20]	E-learning	Addressed the complete report on CA recommender systems which employed with settings of TEL(Technology Enhanced Learning). The survey states that there is a high enhancement in CA recommender systems for TE.
Ruiz-Iniesta et al. (2014) [21]	E-Learning	Suggested a strategy for a recommendation based on the contextual knowledge to

		recommend resources for a study like lecture notes and so on. It uses the user‟s contextual data like awareness on a specific domain.
Do et.al.(20 15) [22]	E-Learning	Recommended a structure for CA recommendation for assisting related study materials for learners. Outcomes revealed that the recommender‟s performance increased by the incorporation of contextual data.
Salazar et al. (2015) [23]	E-Learning	Suggested a strategy for incorporating the contextual knowledge services under the U-MAS platform to recommend study resources. Here outputs depict the strategy‟s effectiveness in virtual learning platforms and enhance the ways of learning.
Jiang et al. (2015) [25]	E-commerce	Integrates the reviews of single and multi-users rated products. Many users don‟t ignore reviewing or rating a product.
Wei et al. (2016) [32]	Movies	Integrating a single user‟s tagged movies and many users‟ rated movies. Some do not tag or give ratings.
Luo et al. (2018)[18]	News	Address a hybrid recommendation paradigm integrating LDA and SVD algorithms to analyze the metrics of new implicit features, time and recommendation‟s accuracy.
John K. Tarus (2018) [24]	E-Learning	CF, CA and SPM are integrated since recommender uses both ratings and contextual data to evaluate similarities between learners and generate predictions of learning products, so making recommendations more personalized to the learner hybrid recommendation approach.
Tessy Badriyah (2017) [26]	E-commerce	Suggested 2-phase system to recommend. First Text Mining TF-IDF (term frequency-inverse document frequency) approach for instant generation of tags relying on product specifications. It combines the outcomes of instantly generated tags with a profiler to obtain related recommendations.
Fan Yang (2018) [27]	E-commerce	Implemented a hybrid recommendation algorithm along with the content-based recommendation algorithm, item-based collaborative filtering recommendation algorithm, and demography based recommendation algorithm.
Langcai Cao (2018) [28]	Education	Introduced a genuine recommendation system designed to provide relative study to users via websites TOEFL and IELTS writing ignoring cold start issues. They applied hybrid recommendation paradigms and online ways might attain writing choices when a user gets registered. Besides, they analyzed distinct algorithms for user‟s contribution towards TOEFL and IELTS platforms.
Milind Guptha et.al (2019) [29]	E-Commerce	Suggested a strategy where data is recommended to the user considering the ratings of other "same" users along with the user‟s purchasing history of the same. Two methods are then integrated and relate to

IV EVALUATION METRICS

One of the biggest obstacles during modeling a recommendation system is what metrics to be selected for optimization. This is somewhat tricky since in many cases, the intention is not to recommend the same items which have already bought by a user before. Thus, how can we predict whether our design is working well in recommending the items?

Statistical accuracy metrics

These metrics help in evaluating the accuracy of filtering methods by contrasting with the expected rating directly with the actual rating by the user. The highly used statistical accuracy metrics in common are Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Correlation. MAE is extensively used and is a measure of the deviation of recommendation from user"s actual value. MAE and RMSE can be evaluated as shown in Eq. (2) and Eq.(3)

$$MAE=\frac{1}{N}\sum |\text{predicted} - \text{actual}| \qquad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum(\text{predicted} - \text{actual})^2} \qquad (3)$$

The recommendation system can predict the ratings by the user more precisely only when the MAE and RMSE are lower. Those metrics are better to use only when the recommendations are relied on estimating the ratings or transactions. They provide us a thought of how precise our estimated ratings are and also how exact our recommendations are:

Decision support accuracy metrics

Precision and Recall are the two key among the rest of the metrics and commonly used metrics. These enable the users to prefer products that are almost the same among the prevailing items collection. The metrics present the process for predicting through a binary operation that classifies the usable products and damaged products. Recall@k and Precision@k: These are said as the go-to metrics used for the recommendation systems. Let us start with, what do precision and recall mean for recommendation systems:

$$Precision = \frac{\#\text{our relevant recommendations}}{\#\text{of our recommended products}} \qquad (4)$$

$$Recall = \frac{\#\text{our relevant recommendations}}{\#\text{of all the possible relevant products}} \qquad (5)$$

PASTE OUR SCREENS HERE

CONCLUSION

Recommender systems assist in recommending items to the users based on user information, behavior, product description, etc. These systems are turned out to be an integral part of the majority of web-based applications in recent years for automatic recommendations. Several techniques have been introduced from content-based, collaborative based to novel hybrid recommendation systems for accurate and meaningful recommendations. In this paper, we have presented a brief review of RS along with the merits and demerits of each kind of system. We have presented major RS, like content-based, collaborative, hybrid and knowledge-based and demographic RS. Then we presented the merits and demerits of each recommendation system. In addition to this, we presented the recent works on hybrid recommendation systems along with evaluation metrics to evaluate the performance of the RS model In this project, Recommendation system are an efficient technology that help people to find their interests with less effort, less work and less spending time with more accuracy .This paper explained about the three recommendation system. Thus these recommendation systems have offered many methods for searching and filtering information. Recommender system are rapidly becoming a important tool in E-commerce on the Web and Movie Websites. The improved modelling of users and items, incorporation of the contextual information into the recommendation process, support for multi criteria ratings, and facility of a more flexible and less interfering recommendation process. In future, enhanced clustering algorithms as well as better prediction generation schemes which is used to improve prediction quality for e-commerce have to develop. Recommender systems allow e-commerce sites to be highly customizable for the user and buyer. They allow companies to 5 better understand their users, provide personalized stores, and in turn increase customer satisfaction and loyalty. They are implemented by utilizing various existing data mining tools and adapting them to current needs. Popular approaches include using association rules, collaborative filtering and content-based filtering and hybrid filtering. Recommendations using association rules are generated based on previous transactions the user has already displayed interest in. Collaborative filtering allows the active user to get recommendation based on products that users with similar interest have purchased and rated positively, and by using the active user's previous ratings and transaction history to build a model that provides a new set of similar products. Content based filtering compares the user's personal profile and preferences with the database to find products that are of interest and align with the active user and present them. Recommendations can range from being personalized to community driven and allow for a wide range of possibilities. The recommendations are also being refreshed due to the nature of changing search history, ratings, and arrival of new products. This also poses many challenges which include cold start, handling anonymous users, creating a social recommender system that can accommodate more than one active user, handling various different data sources and scalability with increased data.

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FUTURE SCOPE

Over the years, recommender systems have been extensively used in e-commerce sites but they still pose research and practical challenges including scalability, rich data, and consumer entered recommendations, anonymous users, and connecting recommenders to markets. They are used in large sites such as Amazon, where millions of products are sold, actively making recommendations to thousands of users simultaneously in real-time. The performances monitored include latency in generating recommendations, number of simultaneous requests being handled, number of consumers, number of products and vast amount of rating and review data. In order to alleviate this problem, different techniques from data mining such as dimensionality reduction and parallelism are employed. A problem faced when scaling using data mining techniques is the sparsity of ratings. The recommender system is valuable when users have not rated most of the products. If different groups of users rate different categories of products, it becomes less likely the rated products will overlap and can be used to generate recommendations. Although dimensionality reduction algorithms are employed to fix this, they are ill-suited for extremely sparse data and have to be modified for recommender systems. While large amount of data will slow down the system, lack of data will also hurt the ability to generate recommendations. As more information becomes available, algorithms and techniques must also evolve. Until recently, recommendations are generally based on single value rather than combination of different data. New machine learning algorithms are emerging that solve this issue by building models based on various product attributes, and user features However, a big challenge is posed with seasonal and temporary data. While a snow blower might be a useful recommendation in winter based on a user's search history and behaviour, it is irrelevant in the swimmer. Temporal associations are an emerging problem that requires much more research. Also, several recommenders are designed with a single user as the end consenter, and there is a lack of social recommenders, an example being recommending movies at theatre. Innovative algorithms that take into consideration varying perspectives and preferences of different users are needed. A possible approach is explaining the recommendations to the user in terms how the user’s preference or behaviour led to the recommendation and gather feedback. It is an extremely difficult task to provide recommendations when the user has been browsing and purchasing anonymously. A methodology was proposed that attempts to solve this by studying purchase patterns of users, and predicting purchase probability of new products. In order to study purchase patterns, the user’s web log can be utilized with using information such as IP address, cookies, and other session data. This information can be used to extract products the user has viewed previously. The purchase probability is calculated using associative mining rules to determine products the user might be interested. However, the shortcoming of the approach is that it is temporary. A user visiting from different browser might not be able to get same recommendations as they would get from same browser. Recommender systems are currently treated as virtual salesmen since they only give suggestions to new products, and do not actively market that product. The system should also take into account price-value for the user, and profits for the company. When suggesting new prices based on studying user behaviour, ethical issues are raised because of price discrimination for different users. It is challenging to maintain user loyalty and trust when making recommendations based on generating higher company profits.

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