A Survey Paper on Alleviating Cold-Start Problem in Recommendation System using Machine Learning Techniques

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***Abstract* - The aim of recommendation systems is to provide users with items that they may be interested in. However, one of the most serious issues for systems to recommend is a problem known as cold start, which happens when new users or items are introduced to the system with no previous knowledge of them. There are many proposals in the literature that aim to deal with this issue. In some cases the user is required to provide some explicit information about them, which demands some effort on their part. In this paper we will introduce how communication information will be used to create a behavioral profile to differentiate users and based on this section will create predictions using machine learning methods. This paper conducts a systematic analysis of the literature to assess the use of machine learning techniques in recommendation systems and to identify areas for further study. The overall survey of this paper will address the research gap and opportunities with the Recommendations system(RS).**

***Index Terms* - recommender system, machine learning, collaborative filtering, systematic review.**

INTRODUCTION

The recommendation system is important in social media and e-commerce. Websites such as Flipkart, Amazon, and YouTube, already use RS to provide customized goods and services to their customers. RSs are used to suggest items to users based on their interests with the rapid growth of the internet, e-commerce companies have been developed very quickly. Particularly with increasing quantity of e-commerce sites, competition has become very fierce. To survive in this highly competitive environment, e-commerce sites have been using a customer relationship management strategy to keep their customers engaged. Widely used techniques in the existing recommender system are collaborative filtering(CF)[1]. Currently, recommendation methods are often divided into the following three main categories: content-based recommendations, CF methods and hybrid recommendations [2].CF recommender systems operate on the basis that similar users have similar tastes and is one of the most popular and successful techniques in RS's[3]. There are many famous RS's provided by top e-commerce application as flip kart, Amazon prime videos and make my trip. The main motive of all RS's is to provide the most appropriate items to the right user at the right time. Vast research studies are going in their field, and many different approaches are proposed which take benefit of different types of data and analyzing techniques. There are various problems when designing an appropriate recommendation system such as scalability, high computation and variations. But in the middle of it all, there is one issue that has received a lot of attention from investigators for the cold problem, which arises during the registration of a new user or adding a new application or item to the system [4]. The quality of RS degrades when there is insufficient or no data at all [5]. Although the problem of starting a cold is a very popular and a future issue in the recommendation process, various research studies are being done to address this problem. The problem of starting Cold is basically divided into two categories namely, the problem of a new user getting started cold means a lack of information about the user's interest or very low ratings provided by this user for any item in the system. The issue of a new user cold start occurs when the user provides no rating at all in the system. Huge numbers of new users signing up every day or less-active users in almost every application create a serious problem for the RS[6] with the growing e-commerce platform. Another major issue is new item cold start problem which refers to the newly added item in any particular system which has very less or no rating provided by the user, so in this scenario analyzing the item and referring it to the user can be a tedious task[7]. Another main issue is shilling attack. It is imperative to handle shilling attacks or profile injection attacks for the sake of the overall achievement of collaborative filtering or privacy-preserving collaborative filtering algorithms. Some researchers have focused on programs to detect shilling attacks in literature [8] [9]. Shilling attacks can be determined by the level of information needed by the attackers to carry out the attack, the attack's purpose, and the scale of the attack[10].According to intent shilling attacks can be grouped as push attacks and random vandalism. The attacks might be classified as low-knowledge attacks and high –knowledge attacks[11].

Recommendation System

RSs use artificial intelligence methods to provide users with item recommendations. For example, an e-commerce may use a machine learning Algorithm to classify product by style and then recommend other product to a user buying a specific product. RS is separated into three parts to drive recommendations: CF, content-based filtering and hybrid filtering [12].This is usually in the context of a ratings matrix which contains the ratings given by different users to various items. In terms of performance and ease, collaborative filtering exhibit better than content based filtering [23].There are few hybrid filtering strategies that combine both content-based and collaborative strategies and try to bring out the best of both strategies[24].

Cold-Start Problem

There are two different forms of cold start problem in RSs: (a) new user cold start problem, (b) new item cold start problem. In new user cold start problem, a new user is introduced to the system, and RS faces problem in giving recommendation as it has no information about the user[25]. In new item cold start problem, the system has no ratings for the new item and it faces difficulty in determining a target user for the item. If cold users and cold items can be managed more effectively, then personalized recommendations can be obtained. Most literature treats cold users by telling them about the most popular things [32]. Out of the two kinds of cold start problems, the new user cold-start problem is more difficult and has been widely studied [26][27].This paper provides a survey of different solutions proposed to address the cold start problem in RSs.

Existing Solutions

Popularity based recommendation system

As the name suggests that the Popularity-based recommendation system works with practice. It basically uses things that are on track right now. For example, if any product is usually purchased by every new user then there is a possibility that it could raise that item to the newly registered user. The problem with the popularity-based complimentary system is that customization is not available in this way.

Content-based recommendation system

In the process of reviewing a collection of documents and descriptions of items previously used by a user, content-based filtering is used, and then generates a profile or model of user preferences based on the features of those rated items. The recommendation system will filter recommendations that are best for the user by using the profile. If the content does not provide sufficient details to correctly discriminate against the products, the issue with the content-based recommendation method is that the recommendation would not be precisely finalized.

Collaborative based recommendation system

The key idea behind the Collaborative-based recommendation system is that the same interest is shared by similar users and a user likes similar items. There are two kind of recommendation systems based on collaboration: user-dependent and object-based. We'll make use of a user-based method of filtering. But they are unable to fix the Cold User problem.

Table 1 Comparisons between the two techniques[30]

Techniques	Idea	Methods Involved	Merit	Demerit

User Based CF	Calculate user similarities using Pearson correlation or cosine values and then take into consideration the weighted average of ratings	Pearson correlation, vector similarity, mean squared difference, etc.	Implementation is easy, more accurate as compared to content based. It is context independent	Non-scalable, user sparsity is low, new items lack ratings for a good ranking cold start problem
Item basedCF	Apply machine learning algorithms to find user ratings of unrated items	KNN, SVD, probabilistic matrix factorization, multi-layered neural nets, etc.	Solves issues of missing or sparse data	Untraceable inference because of hidden or latent factors

Similarity computations in collaborative algorithms

There are many different methods to compute similarity or weight between users or items.

Correlation based similarity

For the calculation of "Wuv" similarity between two users "u" and "v" or between two items "i" and "j", correlation dependent similarity measurements may be used. The degree to which two variables relate linearly to each other[28] is determined by Pearson correlation. The following Pearson correlation measures for users are given. The following Pearson correlation measures for users are given.

$$\boldsymbol{Wuv} = \frac{\sum_{i\epsilon I}(\boldsymbol{Rui} - \overline{\boldsymbol{Ru}})(\boldsymbol{Rvj} - \overline{\boldsymbol{Rv}})}{\sqrt{\sum_{u\epsilon U}(\boldsymbol{Rui} - \overline{\boldsymbol{Ru}})^2}\sqrt{\sum_{i\epsilon I}(\boldsymbol{Rvj} - \overline{\boldsymbol{Rv}})^2}}$$

Pearson correlation measures for items are given in the following.

$$\boldsymbol{Wij} = \frac{\sum_{u\epsilon U}(\boldsymbol{Rui} - \overline{\boldsymbol{Ri}})(\boldsymbol{Ruj} - \overline{\boldsymbol{Rj}})}{\sqrt{\sum_{u\epsilon U}(\boldsymbol{Rui} - \overline{\boldsymbol{Ri}})^2}\sqrt{\sum_{i\epsilon I}(\boldsymbol{Ruj} - \overline{\boldsymbol{Rj}})^2}}$$

Vector cosine similarity

In vector cosine similarity, the term frequency and similarity vectors between two documents are handled by measuring the cosine angle generated by frequency vectors[29]. By treating users or objects such as text and rating instead of frequency of words, similarities based on Vector cosine can be used for collaborative filtering. If "R" is the "m x n" matrix, then the resemblance between two items "i" and item "j" can be calculated as the cosine of the n-dimensional vector corresponding to the matrix R image and the column of the image.

$W_{ij}=\cos(i,j)=\frac{\bar{i}*\bar{j}}{\|\bar{i}\|*\|\bar{j}\|}$

To get the desired similarity computed for n items an nxn similarity matrix is computed. If a vector A={x1,y1}, vector B={x2,y2} then the vector cosine similarity between A and B is given as in following.

$WA,B=\cos(\overline{A},\overline{B})=\frac{\overline{A}*\overline{B}}{\|\overline{A}\|*\|\overline{B}\|} = \frac{x1x2 + y1y2}{\sqrt{x1^2+y1^2}\sqrt{x2^2+y2^2}}$

Table 2. Comparative study of techniques used in recommender systems[31]

Technique	Description	Merits	Demerits
Term Frequency inverse document frequency [36]	This technique finds a score based on the similarity between products	Easy computations	Does not capture the position of text, co-occurrence of text in different documents
Cosine Similarity [31]	A particular score is calculated for every product and cosine is calculated between the respective vectors represented in vector space	It gives a realistic value	The difference in rating scale is not standard throughout
Pearson correlation [30]	A memory-based algorithm which calculates the linear correlation between two variables) and stores it in a variable 'r' (Pearson correlation coefficient)	It helps in determining the degree and direction of correlation and the overall calculation is easy	It gives the wrong results in the case of homogeneous data Not efficient
KNN Classifier [37]	Model-based CF algorithm which finds out the K-nearest neighbors in the proximity and then classifies them accordingly	The training period of KNN classifier is faster as compared to other algorithms	The testing phase of KNN classifier is slower and expensive. It requires a lot of memory for storing the data
Weighted Hybrid [38]	The scores of various techniques are combined to	The averaging effect gives a more	It has a high implementation complexity

	obtain a single score	precise score	
Mixed hybrid	Recommendations from different techniques are obtained simultaneously	Helps in avoiding cold start problem	In case of conflicts prioritization between methods is required

MACHINE LEARNING

In the early 90's, Recommender Systems began blooming. In integrating Machine Learning (ML) algorithms with Recommender Systems, researchers began to pay a lot of attention. Algorithms of ML began in the late 1950s and now a huge cliché of algorithms of ML such as K-Nearest Neighbor, clustering[33], Bayes Network[34] are just a few to be listed. By using ML algorithms, customized suggestions can be well handled. A difficult job is often to find the best fit ML. The key issue is the bridging the ML and Recommender System at the correct level so that better Recommendations can be made. The table (Table 3) below investigates the various ML algorithms that are used in combination with Recommender system and more specifically how ML can handle the cold-start problem. The key issue is the bridging the ML and Recommender System at the correct level so that better Recommendations can be made. The table (Table 3) below investigates the various ML algorithms that are used in combination with Recommender system and more specifically how ML can handle the cold-start problem.

Table 3 Cold start handling on machine learning in recommender systems[35]

S. No	References	Machine Learning Technique used to handle Cold-Start Problem	Datasets
1.	Viktoratos, Tsadiras, and Bassiliades 2018 [39]	Discovers the rules that are not popular. The unpopular rules can handle the lack of data.	Four-Square dataset
2.	Bernardis, Dacrema, and Cremonesi, 2018[40]	Learns the relevance of features using probabilities. It is based on graph theory.	Movie Lens
3.	Kumar and Thakur, 2018	Markov Model, Fuzzy Clustering and K-Means Model	Movie Lens
4.	Gupta and Goel , 2018 [41]	Fuzzy clustering	Movie Lens
5.	D'Addio et al. , 2018[42]	Sentiment-Based representation, Feature extraction and matrix factorization	Movie Lens, Amazon
6.	Osadchiy et al., 2019 [43]	Pairwise association rules	Dietary dataset
7.	Gouvert et.al., 2018 [44]	Pairwise association rules	Transactional dataset from real word dietary intake recall system
8.	Deng et al., 2019 [45]	K-Medoids Clustering	Movie Lens

LITERATURE REVIEW

In previous studies, several methods have been developed to alleviate cold start problem in recommendation system. Collaborative filtering is one of the most widely used techniques in RS. However this approach suffers from some issue such as cold start problem. In recent years , several approaches have been proposed to alleviate the cold start problem. Some of these approaches use additional data sources such as demographics data or trust relations beside the CF method. In order to solve the cold start issue, Safoury et al.[13] used demographic data from users to calculate similarity values between users. Cui C et al.[14] In this paper author proposed a POI recommendation method, which integrates the information of user-uploaded and user-favoured photos and the high order relationship information obtained from user social networks. The main advantage of this method is to alleviate data sparsity problem in POI recommendation by considering different data sources. Nguyen et al.[15] employed the user's demographic data such age, occupation and gender that are easily available in the user's profile. To this end, they made various α-community space models for grouping the users which α is the user similarity factor. Moreover, the missing α-communities are calculated for the new users that used by rule-based induction process to predict unseen items. D. Polrier et al.[16] authors proposed the solution of cold start problem by exploiting blog textual data and labeling them as per the user's opinion and then constructed user item rating matrix for collaborative filtering and improving recommendation. Lam et al. [17] developed a hybrid model based on analysis of two probabilistic aspect models. Their study combined the pure collaborative filtering with users' information to solve the cold-start problem. Kharrat F B et al.[18] according to authors, currently, the most widely used collaborative filtering recommendation algorithm only considers historical score factors, and ignores user characteristics and item characteristics. Because in the historical scoring matrix, the number of users is usually much smaller than the number of items, which leads to sparse scoring data. Robin Burke[7] author explains various hybrid recommendation approaches that can be used to improve the recommendation systems. It combines two or more approaches together to overcome the limitation of the other. It uses various hybrid methods such as cascading, mixed augmented, which can be used in recommendation systems based on the application for better accuracy and results. Luo Zhenghua[19] In this paper, author said hybrid approach plays an important role in collaborative filtering. It combines user-user similarity and item-item similarity. Authors discussed about a new hybrid approach for solving the problem of finding the ratings of unrated items. Two major challenges of recommender systems, accuracy and sparsity of data are addressed in this proposed system. C Preisach et al.[20] argued that many user profiles contain untagged resources that could provide valuable information, especially for the cold-start problem & proposed a purely graph based semi supervised relational approach that uses untagged posts. A. N. Raosli et al.[21] designed a new measure by combining similarity values obtained from a movie "Facebook" page. First the users similarity were computed according to the rating cast on the movie rating system. Then the similarly values obtained from a users genre interest in like information extracted from "Facebook pages" were combined. M. Braunhofer et al.[22] In this paper author proposed a personalized AI strategy that leverages users personality information using a LFM based CF system users fill a questionnaire to help determine their personality based binary prediction, selects relevant items for rating.

PROPOSED METHODOLOGY

This work is based on information theory. In this paper, a new hybrid approach is proposed based on the collaborative filtering , demographic similarity between users in order to alleviate cold start problem of new user type. Also a new approach is proposed based on the click stream data in order to solve the cold start problem of new item type. The proposed work can be divided into some parts. In figure-1 The unstructured data will be converted into the structured form after applying pre-processing and a user-item matrix will be generated. We generate user-product rating Matrix. The main concept of collaborative filtering is to calculate similarity products or users. At present, scholars have proposed many similarity measures, cosine similarity, Adjusted Cosine Similarity, Pearson coefficient, and other methods. Among them, the Adjusted Cosine Similarity is the best among many calculation methods. In this approach, we analyze the Adjusted Cosine Similarity method. That provides top N rating of item.

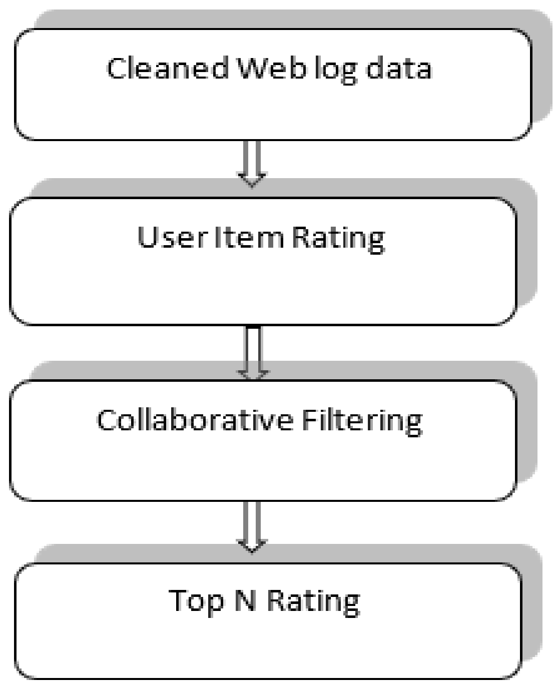


Figure-1

In figure-2, the demographic profile of customers is considered in computing item ratings. This consideration is based on the fact that demographics contribute to differences in people's tastes or preferences. A clustering algorithm such as K-means partitions users based on user demographic Data using Euclidean distance as the distance measure. The prediction for an item using demographics based user clusters will be taken as the average rating of the user cluster for that item.

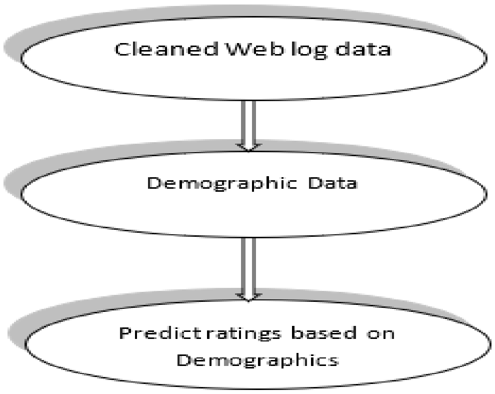
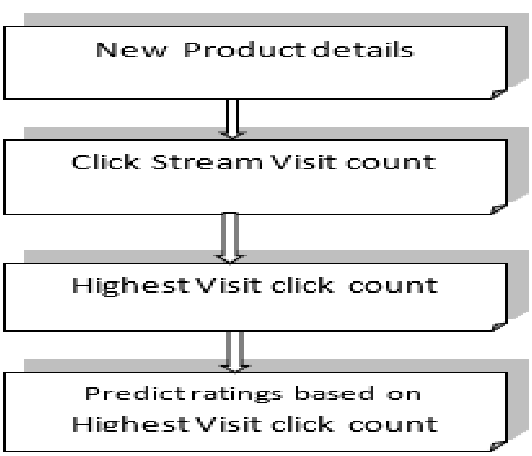


Figure-2

In figure-3, used a click stream scheme for a new item. There is not much information about the new item. So such types of items have not any customer ranking. How to the recommendation of that new item. For that first new item upload with all features and company name of a particular e-commerce website. Whenever registered or unregistered users visit on the website, then count the click on that product of every user. Along with e-commerce websites also count click stream data of that product on social media. Finally find the highest visit click of new item.



In figure-3

Weight computation is one in which the score of a recommended product is computed from the results of all the available recommendation techniques present in these approaches. This integrates the scores from each technique using a linear formula. Therefore, the various techniques must be able to produce their recommendation score, which can be linearly combinable. It is very useful that all of the system's capabilities are brought to bear on the recommendation process.

CONCLUSION

The number of approaches for working with cold-start problems when a recommendation systems uses Collaborative-Filtering have been addressed in this paper. Machine Learning, Contextual Information, and Matrix Factorization are some of the techniques used. This study has several contributions to research based on expert and Intelligent Systems. A brief introduction to the cold-start issue in Recommender Systems is given. A comprehensive study of the various techniques to handle cold-start problems is presented along with the summarization of the evaluation metrics. Trends in ML algorithms are analyzed. This paper mainly introduces the clickstream visit count algorithm along with collaborative filtering and demographic approach.

FUTURE WORK

The future has more possibilities for Machine learning use to handle cold-start problems. The proposed work is currently conceptually based on machine learning. In the future, we will develop in the experimental environment with real-world data and applications.

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