A State Of The Art Survey On Cold Start Problem In A Collaborative Filtering System

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Abstract: Internet is being flooded with information. Finding the necessary information is a difficult task. Recommender System is a panacea to this problem. Recommender System can help us finding a needle in a haystack. Recommender System takes a user- profile as an input and tries to find out products that shall be of interest to the user. Recommender System faces several challenges. One issue is the Cold- Start problem where a new product is not recommended to the user due to the unavailability of the necessary information about the product. In this paper, we survey the various solutions available to address the cold- start product when the recommender System uses a Collaborative Filtering based recommender systems. This study investigates how the cold-start problem is handled in the existing Recommender Systems and their application domains and also provides an analysis of various performance metrics.

Index Terms: Cold-Start Problem, Collaborative- Filtering, Machine Learning, Matrix Factorization, Recommender Systems..

1. INTRODUCTION

Recommender Systems are tools that can recommend items that are of interest to the user. There is a user profile and the user profile can be constructed using implicit and explicit information from the user. The implicit way includes the history of browsing, demography information etc. The explicit information includes asking the users to rate items and filling up questionnaires [1], [2], [25], [48]. Recommender Systems are classified as Collaborative Filtering (CF) and Content Based Filtering. Collaborative- Filtering is a technique where the items are recommended to the user based the similarity of the user with a group of users. Collaborative Filtering can be classified as Neighborhood approach and Latent Factor Model[3], [8], [34]. In Neighborhood- Based approach the interest of the user is determined using a group of users he is associated with. In the Latent Factor Model, the users interests are identified as factors that can be of interest to the user [6], [40], [2], [55]. The items in the repository keep on updating. When a new item comes to the repository, it cannot be recommended as there are no implicit or explicit information about that item. This is addressed as Cold- Start problem in literature. The Cold-Start problem can be new- user cold- start problem where is a new user and there is no information about the user or new- item cold- start problem where there is a new item and there is no information about the items [11], [42], [56], [51]

This paper investigates the cold- start problems in recommender systems. This survey is expected to aid researchers to have a better understanding about the cold-start problem and thereby make better implementation and proceed further in their research directions [20], [55], [4]. The main objective of this study is to identify the techniques that can handle the cold 'items' and cold 'users'. This study also aids in domain identification in a better way. The results of this study sums up in identification of the ways of cold- start problems identification, techniques that can handle this issue and also proper domain- identification. This paper is organized as follows: Section 2 discusses on the existing works on cold start problem..Section 3 explains the role of machine learning techniques in recommender systems. Section 4 describes various techniques adopted to handle cold start problem. Section 5 deals with the various performance metrics applied in handling cold start recommender systems. Section 6 evaluates some possible future directions based on the survey done. Section 7 concludes the survey work.

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2 COLD- START PROBLEM

The Cold- Start problem in recommender system is gaining much importance these days. The widely used algorithms in the Collaborative- Filtering and Content- Based Filtering are being affected much by this issue [14]. The Cold- Start problem can be item- based or User- Based (i.e) the new item issue are usually referred as cold- items and a new user is usually referred as cold- users in literature [15], [19], [34], [26]. If the cold- users and the cold- items can be handled effectively much better, then personalized recommendations can be achieved. Most literature handles cold- users by relating them to the most popular items [22]. Some literature works even investigates on item labeling [34]. Labels can specify the user- preference and also product details. But these labelling alone will not handle the cold- start issue. Many other solutions include mining the data from social networks [6], [29] and also the transfer learning algorithm [26].

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3 MACHINE LEARNING

Recommender Systems started to bloom in the early 90's. Researchers started to give a lot of attention in combining machine learning (ML) algorithms with Recommender Systems. Machine Learning algorithms started in the late 1950's and now a huge cliché of Machine Learning Algorithms such as K- Nearest Neighbor, clustering [32] , Bayes Network [9] are a few to be mentioned. Personalized Recommendations can be well handled by using ML algorithms. Finding the best suited ML is always a challenging task. 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 1) 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 1
COLD START HANDLING ON MACHINE LEARNING IN RECOMMENDER SYSTEMS

S. No	References	Machine Learning Technique used to handle Cold-Start Problem	Datasets
1.	Viktoratos, Tsadiras, and Bassiliades 2018	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	Learns the relevance of features using probabilities. It is based on graph theory.	MovieLens
3.	Creusefond and Latapy n.,2018	Relevant Features are extracted for the new item. The new item is then inserted into a relevant group based on discovered features.A linear regression model with stochastic gradient is used.	Private dataset
4.	Kumar and Thakur ,2018	Markov Model, Fuzzy Clustering and K-Means Model	MovieLens
5.	Gupta and Goel , 2018	Fuzzy clustering	MovieLens
6.	D'Addio et al. , 2018	Sentiment- Based representation, Feature extraction and matrix factorization	MovieLens, Amazon
7.	Ye, 2018	Sequential rule mining	Private dataset from Zhejiang university of China
8.	Osadchiy et al., 2019	Pairwise association rules	Dietary dataset
9.	Gouvert et al.,2018	Pairwise association rules	Transactional dataset from real word dietary intake recall system
10.	Deng et al., 2019	K- Medoids Clustering	MovieLens

The above table can aid the researchers and practitioners to identify the trends or how Machine Learning can be used in recommender systems to make better personalized recommendations.

4 HANDLING COLD- START PROBLEMS

4.1 Contextual Information

A recommender system can use contextual information to make better recommendations. A context can be time- aware, place- aware or a companion- aware information. The contextual factors are sometimes fully observable and sometimes partially observable. Time- aware recommenders usually use a decay function or a time- sliding window protocol [4]. Place-aware Recommenders use wireless technology to get the location of the user and make recommendations [2]. Community-aware systems takes the user-preferences or any other social information as input and thereby can detect similar user clusters. It is based on the concept of homophily [4]. When handling cols start problem, relevant contextual information does matter in recommender systems and that it is important to take this contextual information into account when providing recommendations (Table 2).

TABLE 2
COLD START HANDLING USING CONTEXTUAL INFORMATION

S.No	References	Contextual Information used	Datasets
1.	S. Yu et al., 2019	Textual features from the users and collaborative features from user ratings are combined along with contextual data.	MovieLens NetFlix, Yelp
2.	Hawashin et al., 2018	User Interest Extractor which uses the hidden interests of the group to handle new users.	MovieLens
3.	A. Patel et al., 2018	Deep learning and demographic information are combined to address the cold start problem.	MovieLens

4.2 Cross- Domain Recommenders.

Recommender Systems are usually based on single domain. To handle the cold- start problems, integration of several domain into one recommender system is done. Cross Domain Tensor Factorization [52], where the source domain and the target domain are mingled to get recommendations. Cross-Domain Recommenders also uses SVM's classification [62], Ordered Weighted Averaging (OWA) operators and uninorm aggregation function [41] where better recommendation accuracy can be reached (Table 3)..

TABLE 3
COLD START HANDLING ON CROSS DOMAIN RECOMMENDER SYSTEMS

S.No	References	Methodology	Datasets
1.	Revathy and Anitha et al., 2019	Cross-domain Recommenders using K-NN can handle Cold Start problems.Demographic similarity and Pearson-Correlation coefficient can be used to address the cold-start problem.Active-Learning Based model where users can be asked to rate a new item.	MovieLens
2.	Fernández-Tobías et al., 2019	Cross domain recommender with item metadata	MovieLens
3.	X. Wang et al., 2018	Cross-Domain Latent Feature Mapping and neighborhood based gradient boosting trees	Amazon transaction data

4.3 Matrix Factorization

Matrix Factorization is widely used in recommenders because of their accuracy and scalability. Matrix Factorization characterizes items and users that are obtained from the item rating patterns. Another advantage of the Matrix Factorization is that it is a memory- efficient model. Matrix Factorization can integrate different types of feedback from the users. Matrix Factorization based on SVD, PCA, Contextual- Factors based matrix Factorization algorithms are explored in literature. A context Aware Matrix Factorization [59], Non- Negative Matrix Factorization [58], attribute- mapping using SVD++ [64], Temporal dynamics based on Matrix- Factorization [18] are some of the algorithms that are most prevalent (Table 4).

TABLE 4.
COLD START HANDLING USING MATRIX FACTORIZATION

S.No	References	Matrix Factorization	Datasets
1.	M. Patel et al., 2018	Singular Value decomposition, Principal Component Analysis	MovieLens
2.	Bayomi et al. ,2019	The profile of the user is enriched using 3 user models namely the user model, segment model and contextual model. The models are combined to form a hybrid model which can address the cold- start issue	CoRE
3.	Zhu et al., 2019	Active Learning and using the attributes of items(Latent Factorization Model)	MovieLens
4.	Abhishek ,2018	ELO rating system, Matrix Factorization	Private dataset
5.	H. Wang et al., 2019	The neural matrix factorization model (NeuMF) model that ensembles linear generalized matrix factor-ization (GMF) and non-linear multi-layer perceptron (MLP) is used.	Online shopping dataset
6.	Y. Yu et al., 2018	novel matrix factorization recommendation algorithm based on integrating social network information such as trust relationships, rating information of users and users' own knowledge.Social regularization term is used.	"Movies", "Wellness & Beauty", and "Home & Garden"
7.	Gouvert et al., 2018	Poisson matrix factorization (PMF)is a multi-modal extension of PMF applied to listening counts	Million Song Dataset.
S.No	References	Matrix Factorization	Datasets
8.	Vlachos et al., 2019	Matrix factorization	MovieLens
9.	Ryu et al., 2018	a Location-based Matrix Factorization using a Preference Propagation method (LMF-PP) to address the cold start problem.	LMF-PP, a large-scale real world web service QoS dataset1
10.	S. Liu et al., 2019	a time-semantic-aware Poisson tensor factorization captures periodic effects of user activity with a time-aware factorization model.	Trip Advisor datasets

4.4 Socially- Influential Models.

Recommender Systems works on a group of users or sometimes on a single user. The influence of the social factors on a user must be considered to model the interests of the user. Community- Based Collaborative Filtering where a user is influenced by the social factors has gained great interest in the recent years.In [27], the descriptive tags and the twitter trending is analyzed. Further, in [46] A Diversified Integrated Social Network Analysis (DISCOVER) which is a similarity based Venue Recommender is proposed. [30] uses Bloom Filter Based Clustering, [20] is an ontology- based advertisement Recommender System that combines data the user uses from Social Networking sites (Table 5)

TABLE 5
COLD START HANDLING USING

S. No	References	Cognitive Processing	Datasets
1.	Angadi and Gorripati , 2018	Community- Based Collaborative- Filtering algorithm which uses temporal dynamics to address the Cold- Start problem.	MovieLens
2.	Shi et al. ,2018	Cold- Sampling strategy where known items are identified randomly and the historical information are shadowed. Thus cold items are predicted	MovieLens, WeiboDouban
3.	Bellogín et al. ,2018	Argues that selecting a proper set of neighbor's will have a great effect in the prediction of cold start users and thereby making recommendations.	Facebook, HetRec 2011
4.	J. Liu et al., 2018	Top 250 Algorithm	Epinions and Ciao
5.	Tran and Lee ,2018	Regularized Multi-Embedding (RME) that uses the following (1) which items a user likes, (2) which two users co-like the same items, (3) which two items users often co-liked, and (4) which two items users often co-disliked.	MovieLens
7.	J. Liu et al., 2018	A hybrid collaborative filtering recommendation model, calledTrustCF, based on user- item ratings and trust among users.Person Correlation Coefficient is used.	Epinion ciao
8.	Parvin et al., 2018	A social regularization method called TrustANLF is used which combines the social network information of users in a nonnegative matrix factorization framework.	Epinions1 , FilmTrust
9.	Zhou et al., 2019	Cold-Start problem is addressed by identifying the indirect friends of the user by using the social balance theory.	WS-DREAM

4.5 Similarity Measures

Central to most item-item approaches is a similarity measure between items. Frequently, it is based on the Pearson correlation coefficient, similarity between ij measures the tendency of users to rate items i and j similarly. Several other measures have been proposed to compute similarities between users or items. Mean Squared Difference (MSD), Spearman Rank Correlation (SRC), Significance Weighting (Table 6).

TABLE 6
COLD START HANDLING USING SIMILARITY MEASURES

S.No	References	Similarity Measure	Datasets
1.	Duricic et al. 2018	Katz Similarity	Epinions dataset
2.	Barman et al., 2019	calculate the similarity based on item genre or category	MovieLens
3.	Meng et al. 2019	Wasserstein distance	MovieLens

4.6 Other Methods

Sometimes methods that widely deviate from the basic ideas are also proposed in literature. These methods exploit the different ways of representing the information both the user-side and the item- side. In [21], tree- structures based on Java is used to structure items and users. Also, text are represented as word embeddings [31], tag- based representation [65], Boolean kernel methods [45] are available in literature which can handle the data sparsity problems (Table 7)

TABLE 7
OTHER METHODS IN HANDLING COLD- START PROBLEM

S.No	References		Datasets
1.	Zhang et la.,2019	Taxonomic Side of information and user Latent vectors.	MovieLens
2.	Charan et al., 2018	Integrating tools like Hive, Spark etcin a Hadoop ecosystem.	MovieLens

5. PERFORMANCE MEASURES

The survey has been carried out to handle the cold- start issues in Recommender Systems and also aid the researchers and practitioners in their study [57], [14], [34], [26]. On studying the algorithms in- depth, it was identified that the following performance metrices were used in estimating the goodness of any cold- start algorithm. Metrics such as Precision, Recall, F- Score were used. Error Prediction was carried out by using RMSE(Round Mean Square Error) and MAE (Mean Absolute Error). The calculation was also carried out using AUC, ROC, Jaccard Coefficient and many more (Table 8).

6. POSSIBLE RESEARCH CHALLENGES

The possible research directions would be using pair-wise and point-wise learning combined with the extracted features of the 'cold' items to rate the new items. Hidden interest of the user such as item- plot similarity can be used to rate new items [59][65][66]..Another approach is to combine sentiment analysis and user similarities to address the cold items. Jaccard coefficients can identify optimal neighbors. One way is to identify better coefficient than Jaccard. The neighbors that are closer and thereby fitting the new item into a closer pair. Collective probability matrices with domain adaptations (Cross Recommenders) can address cold-items. Tri-factorization ,Preference propagation is one way to address the cold- start problem [31], [40], [62] . Collaborative- filtering works by trying to identify the similarities among users. One can try in identifying the differences between users. And thereby try to predict how to users totally opposite to each other can predict a new item rating and thereby fix an optimal rating to start in the beginning6. Possible Research Challenges

TABLE 7
OTHER METHODS IN HANDLING COLD- START PROBLEM

S.No	References	Metrics Used
1.	De Carvalho et al., (2018)	Precision, Recall F-Measure
2.	Barman, S. D et al., (2019), Katarya, R. (2018)	Precision, Recall F-Measure
3.	He, J., et al.,(2018), Ma, T et al.,(2015), Aslanian, E., et al.,(2016)	Precision, Recall F-Measure, Accuracy
4.	Lv, G., et al.,(2016)(Gogna, A etal.,(2015)	Accuracy
5.	Anwaar, F., et al.,(2018)	RMSE, MAE
6.	Sang, A et al.,(2017)	Normalized MAE
7	Naz, S et al.,(2019)	ROC
8	Huang, K.,et al(2019)	AUC
9	Cheng, J. et al.,(2019)	Jaccard Coefficient
10	Lestari, S et al.,(2018)	Rank Score

7.CONCLUSION

In this paper, we have discussed the various methods in handling cold- start problems when a recommender system uses Collaborative- Filtering. There are various techniques like Machine Learning, Contextual Information, Matrix Factorization. This study has several contributions to research based on expert and Intelligent Systems. A brief introduction to the cold- start problem 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. The trends in Machine Learning algorithms are analyzed. The future has more possibilities on the use of machine learning to handle cold- start problems.

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