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SURVEY ON RECOMMENDER SYSTEMS FOR SOLVING COLD START PROBLEM

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Abstract—Recommender system is an information filtering system which is used to extract the exact content from massive amount of data set based on user preference or behavior. It will become popular in various areas include news, research article, artificial intelligence, data mining, big data analytics, products, etc. The task of recommender system is to predict the user's ratings for each item and ranking the items. In research area RS plays a major role. There are different approaches in recommender system such as time-aware, event-aware, content-aware and location-aware. This paper mainly focuses on the aspects of RS, issues and challenges of RS. It also includes the survey on cold start problem.

Keywords— Cold Start, Recommender Systems, User Behavior, Big Data, Information Filtering.

I. INTRODUCTION

Recommender systems (RSs) are software tools mainly used for recommending the items which are based on the user's preferences. The preference of the user will be determined either implicit or explicit by the systems. The implicit collection of information includes identifying the histories of users, browsing demographics, etc. the explicit way of collecting information includes the users to fill up questionnaires or rate items. Some of the application domains related RSs are e-commerce, travel websites, online entertainment, etc.

Most recommendation problems comes under the factor called rating structure. In its most common formulations, the recommendation problem is reduced to the problem of estimating items rating which are not viewed by a user. This estimation is formally based on this user to rate the other item.

- Book recommendation [Amazon]
- Movie recommendation [Netflix]
- News recommendation [Yahoo]
- Music recommendations [Pendura].

RSs are classified into 3 categories:

- Content Based Recommendations: It means the user will prefer the past recommended items to be identified.

• Collaborative Recommendations: The people who like the various items will be preferred by the user.

• Hybrid Approaches: This method comes under the combination of both collaborative and content based recommendations.

1.1. Challenges

1.1.1. Content-based recommendation

a) *Overspecialization*- the user does not get the information which is different from anything that the user has seen before. This will become the major problem when the user needs to search the new items but the system won't accept to make it happen.

b) *Limited content analysis problem*- In this scenario the user may provide 2 different items with same set of attributes and hence they cannot differentiate.

c) *New user problem*- Here, the user does not have any search history as well as sufficient ratings before so the user does not get the accurate recommended information.

1.1.2. Collaboration Based Recommendations

• New user problem
• New Item Problem
• Sparsity in ratings - Some of the filtering methodologies will be used namely demographic filtering.
• Power user attack will be happened because of the power impact.

1.1.3. Hybrid Approaches

It is a combination of both content based and collaborative filtering so the limitations of these approaches will suffer the advantages.

1.2. Issues in Recommender System

• Cold start problem.
• Scalability of the approach
• Recommending the items in the Long tail
• Accuracy of the prediction
• Novelty and diversity of recommendation
• Sparse, Missing, Erroneous and Malicious data
• Conflict resolution while using ensemble/ hybrid approaches
• Ranking of the recommendations
• Impact of context-awareness
• Impact of mobility and pervasiveness
• Big-data
• Privacy concerns

II. SOLUTIONS OF THE COLD START PROBLEM

The major concern of the cold start problem is non-accessibility of data needed to achieve recommendations. Thus non-accessible data is gathered using the various proposed methods. The gathering of information is done by asking the user explicitly or making use of existing data implicitly. Hence the solutions are divided into two groups depending on the method of gathering this data. There are various methods for gathering the missing data based on the type of information gathering. A survey on the existing solutions of how to gather the missing information is described as follows:

2.1. Accuracy of Related Recommendation

A user is attracted if the recommendation is related to them. Accuracy of related recommendation is defined as the ratio of the amount of related recommendations to the amount of total recommendations. The various metrics for evaluating the accuracy is described in [1]. The efficiency and helpfulness of the scheme is measured using this metric. If small related recommendations are done as gathering the user's profile, the scheme's rate of accuracy might drop. Hence, the solutions proposed must protect the total accuracy. This can be done by choosing the fewer amounts of query pieces which have great information.

2.2. Decreasing Bias

The communication among the users and items are assumed to be obtained by ratings. The communication among them is independent for some ratings. For example, the ratings are very high for the most popular items and some items are rated without considering the knowledge in utilizing it. These unfair ratings hindrances cause special recommendations. The solution includes the usage of baseline predictors to decrease the bias, although it needs the history of ratings to achieve maximum accuracy.

2.3. Adaptability

According to the principle of the RS, the solutions are flexible enough to use. RS can utilize several filtering mechanisms and rating designs. The effort needed to make it fit with the system is decreased on using solutions that are adaptable.

2.4. Diversity

Generally there are various items in e-Market such as electrical items, household items, clothing, furniture, etc. An expert RS must suggest the items that cover up all these types of items. This can be done only when the interests of users are known. Hence, the solutions must have conditions for designations.

III. EXPLICIT COLLECTION OF INFORMATION

When we want to know about someone's interests, the more suitable way is to ask them directly. The user is directly asked for missing data in case of explicit solutions. In this method, a opinion poll is conducted for the users to rate the items given to them. This explicit form of information collection gathers more related information, since it has the control on what it asks. But the limitation in this method is that the users are mostly hesitant to contribute in the opinion polls as it takes more time and effort. Choosing a small set of best useful items is one of the solutions. The other solution is to provide incentives or use visualization.

The explicit ways aim to gather the relevant information needed without pressurizing the users. The two widely used methods are:

- Active Learning
- Approaches on Interview

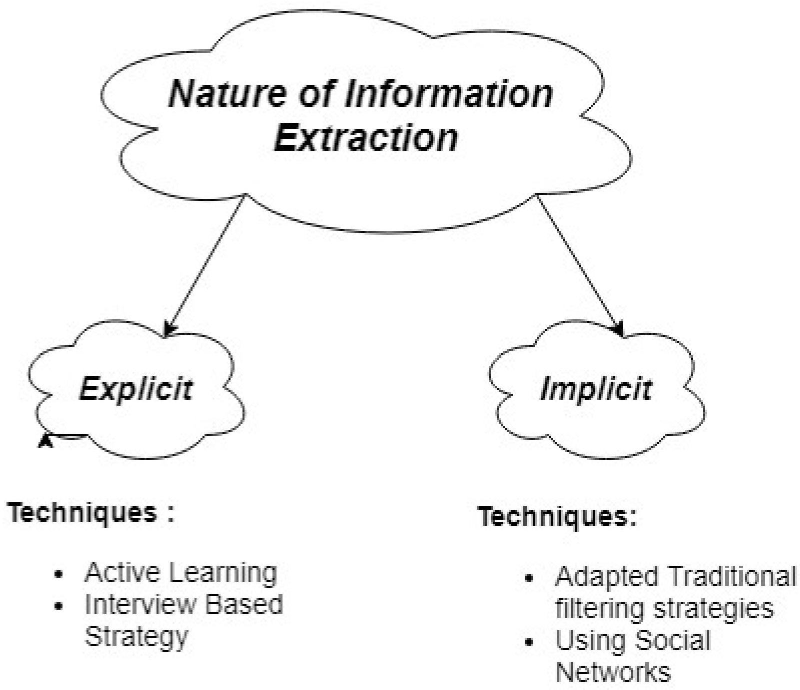


Figure 1.Taxonomy of Solutions for the cold start problem

3.1. Accuracy of Related Recommendation

The explicit method of gathering the data is to tell the users to give ratings for the items. It is best to choose the items that are more relevant in order to enhance the knowledge of user's profile. And it is also important to see to that the amount of items chosen is small so that it does not cause the user to overwhelm. The method used for choosing a set of small and relevant items is named as Active Learning (AL). If the training data is decided first, then it acts as a 'passive' entity. But in case of AL, there is 'active' participation of the system in both the learning process and adaptation of the same in system. There are various heuristics utilized to choose the items, which in turn improves different aspects of the system.

The AL strategies can either be personalized or non-personalized. Personalized AL strategy offers different lists of items to different users to improve personalization. This list is prepared based on the user opinions and feedbacks. Non-personalized AL strategy offers only one list of items and gives this same list to all the users.

As the non-personalized strategy give common preferences for all their users, it is simple and generic to implement. This strategy optimizes the system performance by increasing the accuracy of prediction and decreasing the error rate. Hence, this is helpful when quantitative calculations are considered more than qualitative calculations. The selection of items with varied user ratings of various users is known as uncertainly reduction strategy. Requesting the new users to rate these items reduces the uncertainty and also categorizes the users. An uncertainty based AL is implemented with a 'Bayesian framework' in [2].

Requesting the users to rate the similar set of chosen items aids in understanding an average user's interests only. The feedbacks are used to adjust the items in personalized strategies. This guarantees personalization and increases the confidence of user. A personalized AL strategy which uses the user's personality data was proposed in [3]. The user's personality is evaluated by making the users fill a questionnaire. The selection of relevant items for rating is done using matrix factorization based AL. The recommendations are offered by the interaction of conversational RS with the user in a parallel manner. This interaction is performed by both user and system. An 'exploration-exploitation' based solution in conversational RS was proposed in [4]. This method achieves both the user profile learning and offering related recommendations at the same time.

3.2. Approaches on Interview

In interview approach the, users will be given with an item from a group of items and they will be asked for some suggestions. usually there will be three responses which includes keywords namely dislike, unknown or like [20]. A rough user profile and a basic index list for these items are created, that will be enlightened in the entire process of the interview. Previous approaches used static form of interview as solutions which fix the list of items, but these approaches lead to a drawback of overture and personalization problems. Therefore there is a need for an adaptive interview for adapting user's feedback on the enlighten item list. Most recent researches show that they use decision tree rather than adaptive interviews. [14], [20]. An interview is considered as best when the process is short but the solution should be a compact solution [14], [20], to carry out this process it is mandatory to choose a minimal number of items that conveys most effective information. There are numerous ways for the selection of items, that has various tradeoffs among two aspects namely user effort and information accuracy [2]. Popular, Pure and random energy policies are some of these tradeoffs. Aggregation of two or more approaches can also be used as an example for popularity of entropy and log popularity. The work described in [14] introduce a decision tree based on adaptive interview which uses LFM that focuses CF. At every node of the tree an item is placed using users feedback and CF and there is a need to choose a branch. Many researchers recommend to show multiple items instead of providing one item at a given instance.

This suggested approach has a high probability for the user to get familiarized with the given items, hence it makes a greater scope for the user to create more rating. The Work in [15] indicates that collective lists of items are given to user for getting feedback using bootstrapping method. This algorithm initially creates more number of random trees and then picks out the best among them through an examination of linear combinations. According to this solution, the questions that are on board tend to boost up in linear along with an increase in the number of trees. The writer of [20] provides a different scenario where the questions asked are limited. Each branch represents a sparse weight vector that learns from a framework of "L1 constrained optimization". In accordance with the product of weight vector and response, the users are en-routed to their child nodes. Approaches on interview are considers as best strategy for an informal RS, where the system and the user need to interact in the entire process. On behalf of querying users suggestion on items, [29] recommends to query general questions, as processed by means of survey, for understanding the preference of user. At every instance the queries that are to be asked are chosen by a bandit based explore strategy together with the trained user profile. However it may look that every strategy are tailor made in an interview for choosing the items, they are not sufficient [14]. This arises since in the predestined conventional method it is insufficient to choose a query in an on stream interview which tries to optimize the AL heuristics [20].

IV. IMPLICIT COLLECTION OF INFORMATION

The role of implicit solution is to learn custom user choices through minimal amount interaction. To carry out this approach we could use existing facts that includes substitute sources or demographics that are similar to social media. These days social media like twitter and facebook serves as a primary source of information to a person. After determining the user profile, learned priorities are used for filtering the strategies including the rating matrix for providing recommendations. Since there is only a limited interaction, the users of the system feel comfortable and they are very rare to leave. Yet recommending an useful fact is a major demand in these types of systems. There is a need for the system to gather more information and screen them to get an advantageous knowledge. Some common approach for gathering information that are implicit is described briefly in the following.

4.1. Adaptation Traditional Screening Approach

Traditional screening approaches namely CF and CBF are very limited in the when considered in the scope of cold start examples, as a result of deprivation of information. Consider a scenario where CF based on neighborhood analyze the history ratings of user to find a neighbor for them. One of the ways to take them for a cold start scenario is to customize them so that they could work on sparse data. In [17] a similarity indicator for neighbors on CF, makes the RS to consider a neighbor for an unique user. This proposed method for similarity indicator is weighted linear aggregation of simple similarity measures that uses neural network for optimization. In [26] the algorithm of CF is joined with the classification algorithms, like naïve Bayes and C4.5 algorithm, for choosing a neighborhood for a unique user. At first the classification model are trained for the system using users demographic, which further classifies the unique users to demographics based group.

As it is complicated to find better information from the individual source, the work given in [27] has multiple models for collecting various distinct information. By letting on the model to train one another by a semi-supervised learning, the integration is performed by the use of co-training algorithm.

4.2. Working with Social Network

Social media namely twitter and facebook has acquired a great fame among the world wide web, which captures a large user scale. In accordance with the International Telecommunication union (ITU), there is an rough estimate of about 3 billion users of internet world wide and research shows that facebook users constitute about 61% of them. Hence it has become a worthy repository of personal data. A social profile of an user consists of different information such as opinions, likes, friend circles, dislikes and demographic. Therefore the usage of social media for a cold start problem is valuable. As there are different types of informative facts that are available in social media, there comes various ways to make use of them. Some of these strategies includes the following.

4.2.1. Extract User Preference

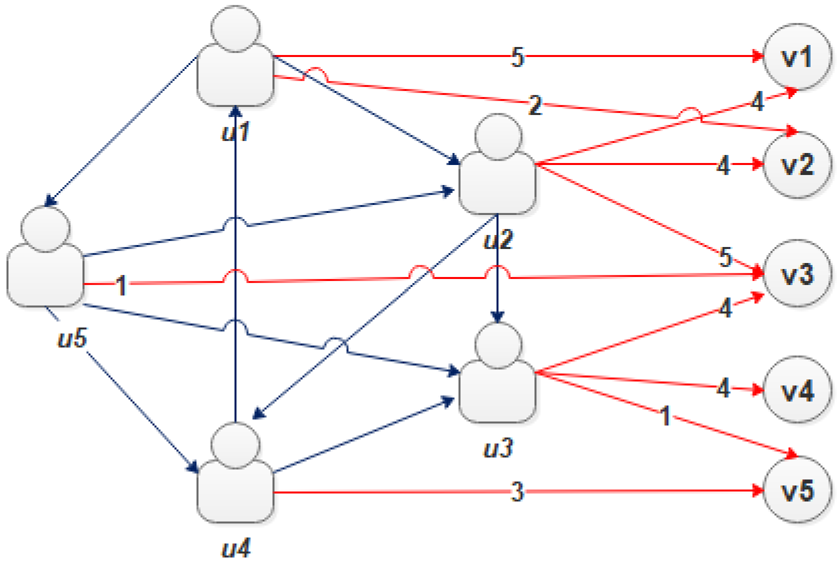
Most of the information that are shared by users in social network may help them understand the situation. Information like friends, favourite items, etc. could be meaningful for making out user's preference in both indirect and direct methods. This helps the system to read the minds of the user to understand exactly which items would be preferred by the user and suggest items that suits them the best. In an implied way, these data could help the system to draw a sufficient conclusion in user preference. The latter has more advantage when considered in a long run. In many works [21] [31] the social profile information of the user are being used for understanding the information of their personality. They might vary from the way of accessing the information and the content of the accessing the information. In [22], a crawler will be introduced that can be used for crawling into a facebook user account and can be used for the retrieval of information like the user liked pages, links, shared content status updates etc. User's choices are evoked in various areas such as movies, TV and music, with this information.

The author of [31] approached the repository of an open project called "personality Project" that has access to a information in the multiple profile of a facebook users. For developing experimental profiles of user we need to choose the information like shared links, updated status and friend list from the repository. After creating the data and gathering user profiles [21] there is an application of matrix factorization and neighborhood based on CF. whereas [31] has the application of active learning and matrix factorization. Some benefits of this method include creation of generic profile for a learned user and to suggest items along multiple areas [21] [31]. The drawback of this method is that the data that is being used is unary, which means dislike or like information only. Based on these the ratings can be more accurate. There is also a chance of failure due to strict privacy settings.

4.2.2. Connecting Social Circle of Users

Users of social network these days are often determined through their friends as they might turn to share same views with them. Some correlation theories of social network like social influence and homophile can conclude this [22]. A neighbor for a particular user can be introduced through the usage of social relations like group membership, following relations, friendship and trust relations. The intelligence of social relation of a user together with the information of ratings is used by the social recommender system for providing recommendations [22].

Figure 2 depicts the contrast among social RS and traditional RS. However the ratings matrix is utilized by Traditional RS only which is projected in Fig 2(b), social RS also use a social relations matrix in order to confine the associations connecting diverse user [22]. Procedure used by conventional RS such as zone based CF are insufficient in favor of establish neighborhoods intended for a original user as nearby one has no past ratings. Separately the proposal finished by conventional RS is inadequate to persons which are opening adjacent to the neighbors. In public RS, transitive associations can be fashioned among users crosswise diverse neighborhoods, allow to defeat the over restriction [16].



(a) Users Connected

	v1	v2	v3	v4	v5
u1	5	?	2	?	?
u2	4	4	5	?	?
u3	?	?	4	4	1
u4	?	?	?	?	3
u5	?	?	1	?	?

(b) Traditional RS

	v1	v2	v3	v4	v5
u1	5	?	2	?	?
u2	4	4	5	?	?
u3	?	?	4	4	1
u4	?	?	?	?	3
u5	?	?	1	?	?

	v1	v2	v3	v4	v5
u1	0	1	0	0	1
u2	0	0	1	1	0
u3	0	0	0	0	0
u4	1	0	1	0	0
u5	0	1	1	1	0

(c) Social RS

Figure 2.Traditional RS Vs Social RS

In favor of a known user, "linked consumer" be everyone those people through whom the client share a common relative in addition to "parallel users" be those citizens who split regular first choice with the user. Every associated user may not be comparable users. In fact, explore demonstrate that the junction among associated and similar users is less than 10% [22]. Also, some similar users might not be connected [16]. Trust values help measure the similarity between users [16]. A users trust value for another user indicates how much the former trusts the latter. A web-of-trust (WOT) [16] is a weighted di-graph where nodes represent users and edges represent connections, weighted with trust values. Trust values can be obtained by asking the user to specify them or automatically by examining their relation parameters like mutual friends count, frequency of interactions, etc. [16]. The initial WOT can be expanded by applying trust metrics like ”propagation” and ”aggregation” upon the initially obtained trust values [16].Common RS can be view as modified filter approach which make use of common relative sequence all along with ratings. After computing trust values, sociable RS applies filtering strategies. CF is most commonly used and both variance of CF can be applied [22]. Neighborhood based social RS mine social relations to find most similar user , and form a locality.

In Social Based Free weight Mean [6],[16] it is assumed that all connected exploiter are similar exploiter . The root [4] establish a WOT and use it to breakthrough most similar drug user . In [4] a new cartel metric function called “TidalTrust” is used. The key idea behind TidalTrust is that shortest track in WOT have more accurate faith estimates and the paths with higher trust economic value yield accurate results. Two argument : path depth and doorstep are Set initially and trust 6 senses of value are computed between all users. If two users ‘x’ and ‘y’ are disconnected, transitivity property is used with a mutually connected third party ‘z’. After computation trust values, all users within a distance of path depth and having trust value greater than threshold, are selected as most similar users. In [5], another new trust metric called “MoleTrust” is introduced. MoleTrust work is in two degree. In the first stage, all cycles are removed from the WOT to reduce the work done during computation of trust values. In the second stage, trust values are computed by performing random passes on the directed acyclic WOT graph obtained after the first stage. After all trust values are computed, users who are within a distance of a predefined argument, Maximum Depth and have rated the same object item are declared as similar users.

For LFM based CF, there are different way of life to utilize mixer data. Some resolution factorize both the ratings intercellular substance and social matrix to obtain drug substance abuser ’s feature film while some of them build a rough user profile by analyzing the profiles of similar users [22]. In some methods, users missing ratings are obtained by aggregating ratings given by their similar users [22]. Although social RSs are well suited for the new user cold head start job, there exists few problems. A user may have a large no. of social relations and excavation for most similar users, in that eccentric, is tedious. Also, casual and contextual relationships introduce noise as such relations are misleading. Conversely, too few social relations can also cause unsuccessful person of the process.

V. IMPLICIT VS EXPLICIT SOLUTION

Implicit and Explicit suggestion can be used for comparison in the following parameters :

- Interaction of User

It refers to how much important it is for the organization of rules to interact with the exploiter to learn about them.

- Efforts of User

It indicates how much body of oeuvre the exploiter has to do to help the system understand his/her druthers. Work is usually to rate some given items or answer questions. If the user feels overwhelmed by the work, he or she may leave the system.

- Self Assurance

It implies, how much the system can improve itself by learning from user's feedbacks during the testimonial process [18].

- Relations

It shows how much data that are more informative could be recovered.

- Geographic expedition -Exploitation dilemma

It indicates how the organization has to choose between recommending an item that allows it to learn more (explore) about the drug exploiter or an item that keeps the substance abuser interested [19].

- Secrecy

Privacy context, which allow users to control the entropy they percentage , may restrict the information accessed by the system of rules . It refers to how much the system is restricted by privateers' context.

In Table 1, compare are made between the two course of solution based on the above described parametric quantity. These parameters affect the caliber of the passport in the long run and contrast the functional aspects of the two exercise set of resolution. From the equivalence, the following conclusions can be drawn. Since assurance and user sweat are related to level of user interaction, explicit root have better compass for improvement as the recommendation process progresses, but require considerable user effort and can thus overwhelm the user. On the other bridge player, implicit solutions may require lesser user effort, but have express growth of confidence. They however do not face the exploration-exploitation dilemma, which explicit solutions can face. An implication of this dilemma is that the system may need to restrict its learning process after a certain point of time, since recommending excessive psychometric test items reduce overall quality of the recommendations and tryout the user's forbearance, which is unacceptable. When it comes to privateers, implicit solutions could face restrictions. Thus, a investigator has to brand a trade wind -off between the benefit and shortcoming while choosing between one of these approaches.

	Parameters	Explicit Solutions	Implicit Solutions
1.	User Interaction	Largely dependant on user interactions.	Very little or no interaction.
2.	User Effort	Considerable user effort is required which runs the risk of losing the user.	No user effort required. User is more comfortable.
3.	Confidence	More scope for improving as user's feedback can be observed.	Lack of interaction limits scope of learning from feedbacks.
4.	Relevance	Queries can be designed easily to acquire relevant information.	Available data may not be relevant. Filtering is required to find them.
5.	Exploration-Exploitation dilemma	Faces the Exploration-Exploitation dilemma. After a certain point, RS has to stop learning and start recommending.	Knowledge is already gained. Hence no such dilemma during recommendation.
6.	Privacy	Not an issue.	Strict privacy settings can cause failure.

Table 1.Implicit Vs Explicit Solution

VI. CONCLUSION

The cold start crisis in recommender system arise in two scheme as new user cold start problem and new exploiter cold start problem. All solution for the new user cold start problem collects missing information about users. According to the literature study, the existing answer are separated into two category based on how they gather the misplaced information unambiguously or absolutely. The methods are compared in addition to their power and restrictions have been acknowledged. The idea of this paper is to disseminate public through the cold start problem in recommender system and its existing explanations.

VII. FUTURE WORK

Our Future works includes the problems that are still open for improved result and interested investigator can initiate this inquiry work in this track. Crossbreeding of the two explicit and implicit proficiency for enhanced solution of the cold start problem may be an interesting problem for investigators.

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