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New dimensions of temporal serendipity and temporal novelty in recommender system

Chhavi Rana

Department of Computer Science Engineering, University Institute of Engineering and Technology, M D University, Rohtak, Haryana, India.

ABSTRACT

Recommender system focuses on techniques that could predict user interest and give assistance while the user interacts with the Web in finding relevant information. It attempt to make sense of the data generated by his past interaction and predict in future choices. The focus of research in the area of recommender system has been on accuracy in the past decade, but the trend is changing with an increasing interest in this area of research. This paper is an attempt to provide an overview of the state of the art in new dimension of recommender system research. Novelty and serendipity refers to the search of finding something new by a user while browsing world wide web. Traditional recommender system algorithm focuses on accuracy that tries to compare accuracy with past data which limits the scope of novelty and serendipity to a great extent. Novelty pertains to giving something new which the user have not accesses before but similar in taste while serendipity is a chance discovery that could be really beneficial for a user at certain times. This paper will present an outlook on the existing research carried out in this area, their specialized focus with respect to an applicative objectives and the need for a more comprehensive new entrant in this sphere in the light of the current scenario. The paper will also present a novel methodology based on temporal parameters to include the novelty and serendipity in recommender system. In the end, the paper will be concluded by listing some challenges and future trends in this research area.

Keywords: Data Mining, Web Mining, Recommender system, Novelty, serendipity, Temporal dimension, .

INTRODUCTION

Web personalization is the process of customizing a Web site to the needs of each specific user or set of users, taking advantage of the knowledge acquired through the analysis of the user's navigational behavior [8]. Integrating usage data with content, structure or user profile data enhances the results of the personalization process [8]. The personalization of Web services is a leap in the direction of alleviating the information overload problem and making the Web a friendlier environment for its users. Daniel E. O'Leary from the University of Southern California coined the phrase 'AI renaissance 'in 1997, to describe how artificial Intelligence (AI) can make the Internet more usable. Personalization technology is part of that renaissance [18]. As stated in Mobasher and Dai [19] :

"…the Web is ultimately a personal medium in which every user's experience is different than any others".
Principal elements of Web personalization include modeling of Web objects (pages, etc.) and subjects (users), categorization of objects and subjects, matching between and across objects and/or subjects, and determination of the set of actions to be recommended for personalization [20].

Recommender System are part of the personalization technologies and are presented as new generation internet tool that help user in navigating through information on the internet and receive information related to their preferences. Although most of the time recommender systems are applied in the area of online shopping and entertainment domains like movie and music, yet their applicability is being researched upon in other area as well. Internet and

World Wide Web is changing the way people live and communicate with each other. Together with this, there is lot of information bombardment on the user who wants to access some information on the internet. In the midst of this complex environment of web, Recommender System serves as an agent that helps user in getting the relevant information. With the growth of economy and advent of new technology, many people are using internet as a source of information for making comparative analysis of products that they would like to buy online. In this competitive market, many venders are employing different strategies to attract customers. The customers are bombarded with information on the internet, finding relevant among which is a dotting task. Recommendation systems provide one such way to solve this problem by providing user with relevant information based on his user profile. A user profile is generated on the basis of user navigation history and his similarity with other users. Recommender System gives a list of recommendations to the user that is an attempt of predicting user's preferences. A website using a recommendation system can more effectively provide a user with useful and relevant suggestion that could fulfill his current information requirement. As such, these websites have an edge over others in gaining customer loyalty as well as long-term partnership.

The term recommendation system was first introduced by Resnick and Varion [23] to generalize the concept of collaborative filtering [10]. They implemented the first recommender system using collaborative filtering technique. Since then the term is being used by different researchers and is explained in various ways. The most common technique used for building recommendation system is collaborative filtering, so much so that many researchers use both these terms interchangeably. There are few other techniques also which are for making recommendations such as content based filtering, demographic and knowledge based technique but they are not so widely applied. Collaborative filtering is the most successful applied technique, prominent example of which is amazon.com. In all these technique, the user is given recommendation on the basis of similar user profiles, which are calculated through various measures. The commonly used similarity measures are Pearson correlation coefficient, Cosine similarity measure, Manhattan, Jaccard and Eucledian distance calculators.

A number of recommender systems are applied in various domains on the internet and each one of them tries to accurately predict user preference. Although Recommender Systems (RS) are chiefly applied in the area of e-commerce, their domain areas are constantly enlarging. One of the latest examples is their use in the social networking sites which are deploying the strategies of recommendations.

Kohavi and Provost [13] suggest five desiderata for success in data mining applications:
– data rich with descriptions to enable search for patterns beyond simple correlations;
– large volume of data to allow for building reliable models;
– controlled and reliable (automated) data collection;
– the ability to evaluate results; and
– ease of integration with existing processes (to build systems that can effectively take advantage of the mined knowledge).

Rarely are all these criteria satisfied in a typical data mining application. Personalization on the Web, and more specifically in e-commerce, has been considered the "killer application" for data mining, in part because many of these elements are indeed present [17]. There are several commercial recommender system deployed in a variety of application domain (see Table 2) that could provide personalized web experience to a naïve user. These systems could be useful particularly for new user that is finding it difficult to discover relevant data. However, giving personalized recommendation to a new user is a daunting task as little information is available regarding his interest and requirements. These limitations have been actively researched upon in the area of recommender system.

There has been a notion that personalization of websites is simple a poor excuse for bad design [4]. Also it is been said that personalization only works when information is simple to describe in machine-understandable terms, and is relatively unchanging. More complex needs means that the computer has to know a lot about the user, which raises issues of privacy. One of the biggest problems with personalization services is obtaining the information about the users, as it is difficult to get people to take the time to fill in forms and answer questions about themselves. But with the advancement of the area of web mining and a range of researchers working in this field , lot of techniques and approaches has been developed that provides automatic solution for user convenience. The best personalization services, such as that used by Amazon to recommend books, do not require the user to enter any information about themselves.

Table 2: Major Applications Domains of Recommender system websites

Sr. No.	Application	Product
1	E-commerce	Amazon.com, ChoiceStream.com, CleverSet.com, ebay.com
2	Movies	MovieLens.umn.edu, Whattorent.com, Netflix.com, moviefinder.com, reel.com
3	Music	Last.fm, MyStrands.com, Pandora.com, cdnow.com
4	Books	WhatShouldIReadNext.com, Whichbook.net, Lazylibrary.com, Librarything.com, Bookhints.com, Booklamp.com, Goodsreads.com, Bookexplorer.com
5	Travel	Wanderfly.com, Trazzler.com, expedia.com, makemytrip.com
6	Social networking sites	Facebook.com, Myspace.com, linkedin.com
7	Research papers	StumbleUpon.com, MappyFriends.com, StuVu.com, Springo.com, YourVersion.com, Xmarks.com, DailyPerfect.com

State of the Art

Novelty

Another new dimension which is being investigated lately is the idea of novelty. After a time similar items which are popular with everybody are been recommended repeatedly. This becomes very frustrating for the user at times when he looking for something new. Abbassi et al. [1] examines the case of over-specialization in recommender systems, which results from returning items that are too similar to those previously rated by the user. They develops an algorithm Outside The Box (OTB), that attempts to identify regions that are underexposed to users, by taking some risk to help users make fresh discoveries, while maintaining high relevance. On the other hand, Celma and Herrera [5] presents two methods named, item and user centric to evaluate the quality of novel recommendation. They observe that though CF recommend less novel item than CBF, user's perceived quality is higher. This is because CF is biased towards popularity, effecting novelty and network topology while CBF is not affected at all. Park and Tuzhilin [22] deals with the concept of novelty in a whole new way. They attempt to study the long tail problem of recommender systems where many items in the long Tail have only few ratings, thus making it hard to use them in recommender systems. They are rarely recommended but have got potential to interest user at times, finding which is not a trivial task. On the other hand, Vargas and Castells [28] noted that there is lack of well defined evaluation metrics in this area that take into account their ranking. Therefore, they proposed a framework built upon three ground concept namely choice, discovery and relevance and generalizes several state of the art metrics using them. Vargas [28] also presented the application of intent oriented Information Retrieval diversity techniques to the RS field, which is still in progress together with the formalization of novelty and diversity metrics for their evaluation.

Serendipity

Serendipity is a tendency for making fortunate discoveries while looking for something unrelated (http://dictionary.cambridge.org/dictionary/british/serendipity). As explained by Herlocker et al., [11] there is a surprise element attached to it that differs it from the novelty feature. Due to the explosive growth of web and henceforth the choices emerging from it, users are looking for adventurous encounters, in addition to the normal requirement. Although the effect of serendipity in RS is being studied by very few researchers, it is gaining popularity lately. One of prominent work in this direction is carried by Iquinta et al. [12]. He stated that there are some context in which user requires unsearched but still useful items or pieces of information. He proposes a hybrid RS that joins a CBF and serendipity heuristics in order to mitigate the overspecialization problem with surprise suggestion. In addition, Ge et al., [9] emphasis on the need to evaluate the quality of RS beyond accuracy. They analyze the role of coverage and serendipity as indicators of recommendation quality, and presents novel ways to measure them as well. The Table 1 illustrates in brief the work mentioned above according to each parameter**.**

Table 1 Novely and serendipity in Recommender Systems

Sr. No.	Parameter	Description	References
1.	Novelty	Quality of being striking, new and original that discover new items for the user.	Abbassi et. al.,2009
			Celma and Herrera, 2008
			Park and Tuzhilin, 2008
2.	Serendipity	It is propensity for making fortunate discoveries while looking for something unrelated. Differs from novelty in the sense that a surprise element is attached.	Ge, Battenfeld and Jannach, 2010
			Iaquinta et. al., 2007

Temporal serendipity and novelty in recommender system

Temporal serendipity refers to serendipity that is calculated using a time variable and it also reflects the changes in user preference over a period of time. The use of time as a dimension in the area of recommender system research has come into focus recently when Koren [14] won the famous Netflix prize. Netflix is online movie portal that uses recommender system to help user is finding movies of their choices and they announced a prize to find the best algorithm that surpasses the accuracy of their current system. Koren [14] and his team devised a matrix factorization algorithm that uses time as an integral parameter to increase the accuracy of the recommender system algorithm. He further stated that after a period of time only temporal dimension could help in increasing the accuracy of the system. As the goal of novelty and serendipity are contrary to the traditional parameters that calculated accuracy of a recommender system, researchers are often caught in faux to optimize novelty and accuracy. The usage of temporal dimension could facilitate in the optimization of maintaining accuracy as well as novelty and serendipity. We propose a simple measure to add temporal dimension in the prediction module of a recommender system to generate novel as well as serendipitous recommendations. Traditional recommender system consist of two phases. The first phase generates similar users based on calculating distance between them using tradional measures such as cosine similarity. The second phase is the prediction phase that predicts the choice of the target user using similar users.

We now formulate the recommendation modeling problem in terms of predicting the unknown ratings using a matrix representation by transforming it into a weighted matrix approximation problem and using the evolutionary clustering based approach for solving it. Let U = $\{u\}_{u=i}^{n}$ be the set of n users and I= $\{i\}_{i=1}^{m}$_ be the set of m items. Let A = n*m be the ,) ratings matrix such that a_{ij} is the rating of the user u_i _for the item i_j.

There are the two phases of our recommendation model for generating novel as well as serendipitous recommendations using temporal dimension:
(i) Neighborhood computation, which involves the ratings matrix and computing the neighbor of a particular user or item which could be later used for prediction,
(ii) Prediction, which consists of estimating an unknown rating from the neighborhood calculated above, and

The main objective of this component is to compute all the parameters that are required for fast prediction of the unknown rating. We perform similarity computations in order to choose neighborhood for a particular user through Pearson correlation coefficient [23]. In order to compute the rating prediction $R_{ut,at}$ for the target (user, item) pair (ut, at), the following steps are taken.

Firstly, we take the similarity computation values of the target user with each of the surrogate model users who have rated at using the Pearson correlation coefficient given below and we find up to l surrogate users most similar to the target user:

$$S_{u_t,c_i} = \frac{\sum_{a\in i}(R_{u_t,a}-RA_{u_t})(R_{c_i,a}-RA_{c_i})}{\sqrt{\sum_{a\in i}(R_{u_t,a}-RA_{u_t})^2 \sum_{a\in i}(R_{c_i,a}-RA_{c}}} \qquad (1)$$

where I is the set of items rated by both the target user and i-th surrogate user.
$R_{ut,\,a}$ is the rating prediction of user item pair (u_t,a_t)
RA_{ut} the average rating of user time pair ut
$R_{ci,a}$ is the rating prediction of user item pair (c_i,a_t)
RA_{ci} is the average rating of user item pair C_i

Secondly. we compute prediction using the adjusted weighted average:

$$R_{ut,at} = RA_{u_t} + \frac{\sum_{i=1}^{k}(R_{c_i,at}-RA_{ci})S_{ut,ci}\cdot f_{ui}^{\alpha}}{\sum_{i=1}^{l} S_{ut,ci}\cdot f_{ui}^{\alpha}(t)} \qquad (2)$$

where $R_{ci,at}$ is the rating prediction of user item pair (c_i,a_t)
RA_{ci} is the average rating of user item pair C_i
$S_{ut,\,ci}$ is the value calculated in the first step
K is the number of neighbors (clusters)

$$f_{ui}^{\alpha}(t) = \sum e^{-\alpha(t-t_{ui}} \sum \frac{RA_{u_t}}{S_{u_t,c_i}} \qquad (3)$$

MATERIALS AND METHODS

This paper tries to understand the process of changes in user preference and detecting those changes to present generate novel as well as serendipitous recommendations in a recommendation model using a Matlab. In particular, we look at the performance of our approach with benchmark system on predicting user ratings on MovieLens dataset [25]. By doing so, pros and cons of the proposed mechanism is investigated to give a full understanding of the advantage of this approach in the area of recommender system. To compare the performance of our proposed algorithm, we also entered the training ratings set into four other benchmark recommendation engine. Thus, we have done empirical comparison of our approach with classic correlation-based approach, the Pearson Incremental collaborative filtering [21] as a baseline for rating prediction and TimeSVD [16] as well. The tests were run on a Pentium 4 2.80 GHz computer with 512M RAM. Tests were run on Matlab Version 7.01 on Microsoft Windows XP Professional.

The dataset is divided into ten 80%-20% random train-test splits for evaluating the prediction accuracy and then the results are averaged over the various splits. This is done for performing Ten-fold cross validation in which the final results are averaged on these ten sets. For the purpose of comparison, we perform the same experiments using other benchmark recommender models. We use the same train/test ratio *x*, and number of neighbors. We obtained rating predictions for each sample according to the specific recommendation model. We evaluated the results using the MAE metric and also noted the run time elapsed in milliseconds.

RESULTS

In this section, the results of experiments performed to evaluate the effectiveness of our proposed clustering approach is presented. As discussed earlier, we have used the Movielens dataset1 consisting of 100,000 ratings (1-5) by 943 users on 1682 movies. We used mean absolute error (MAE, RMSE and runtime) to evaluate and compare different methods. Four methods were used for comparison:

1. BENC: Benchmark method based on the Pearson correlation coefficient
2. IKNN: Incremental KNN method
3. TimeSVD: Singular value decomposition.
4. TNOVA: Proposed approach

Table 1 Results obtained

Algorithm	Modeling Time(milliseconds per rating)	MAE (t=1)	MAE (t=10)
BENC	1.532	0.7463	0.7435
IKNN	3.23	0.7425	0.7534
TimeSVD	.09	0.7336	0.7336
TNOVA	.09	0.7359	0.7381

The performance comparisons for rating prediction for all the algorithms are summarized in Table 1. The proposed approach have a break the barrier of optimizing accuracy and proved to be as accurate as the traditional algorithm. Clearly, from the Table 1, it can be inferred that the prosed methods performs better than traditional benchmark Pearson similarity based approach IKNN. Furthermore, we can see that the models TimeSVD can indeed outperform our TNOVA method given that they were updated at every time step(i.e. *td*=1) although the difference is not very significant. The two incremental algorithm TimeSVD and IKNN uses a simple strategy to incrementally maintain their model at each time step given new ratings. They use the parameters in the most recent model to initialize the training of the next model. There is very little change in parameters in frequent updates, so we use a parameter td that controls how frequently the model is updated or retrained. Thus our model is less computationally expensive that the other models and yet give promising results.

Challenges and Future Trends

The study of recommendation systems over the last decade have brought to light a number of issues that must be addressed if these systems are to find acceptance within the wider context of personalized information access.

The wealth of research projects described in the previous section means that the demand for better Web Mining solutions for personalization is high. However, many challenging research problems must be addressed if this demand is to be fully met. Issues that cut across all of the applications are henceforth described, where progress will consequently have the broadest impact. The goal of personalization and recommender system is to provide users with what they want or need without requiring them to ask for it explicitly. This does not in any way imply a fully automated process, instead it encompasses scenarios where the user is not able to fully express exactly what they are looking for but in interacting with an intelligent system can lead them to items of interest [2]. Following are listed some of the major issues that needs to be catered to provide a better recommender system with some new dimensions of research. In particular, we discuss the issues that are related to upcoming area of research goals such as serendipity and novelty in area of recommender system research:

a) Privacy

There are some technical limitations with the collection of the needed data, and maybe even more important, there are a large amount of ethical issues involved. There is a thin line between collecting data for the user's benefit and an

Orwellian way of spying. Currently U.S. laws impose little restrictions on private parties communicating information about people, leaving it up to the parties involved to define the extent of any such communication through a contract [29].

b)Recommendation List Diversity

While most research into recommending items has concentrated on the accuracy of predicted ratings, other factors have been identified as being important to users. One such factor is the diversity of items in the recommendation list. In a user survey aimed at evaluating the effect of diversification on user satisfaction, it is found that it had a positive effect on overall satisfaction even though accuracy of the recommendations was affected adversely [30]. There is a great need for a shift in focus that is related to the functionality offered by recommender systems that can exploit directly the usage data, and add more value to the browsing experience of the user.

c) Adapting to User Context

Personalization aims to "hide" the rigidity of the Internet by providing useful, contextually relevant information and services to the user. However, context as a concept has rarely been incorporated into personalization research. One of the reasons for this is that it is hard to arrive at a consensus of what defines context let alone modeling the concept.

d)Using Domain Knowledge

Dai and Mobasher [6] provide a framework for integrating domain knowledge with Web usage mining for user based collaborative filtering. They highlighted that semantics can be integrated at different stages of the knowledge discovery process. Thus, a related practical issue is the requirement for a common representation of the extracted knowledge, i.e., the user models generated by Web mining tools.

e) Managing the Dynamics in User Interests

Most personalization systems tend to use a static profile of the user. However user interests are not static, changing with time and context. Few systems have attempted to handle the dynamics within the user profile. The behavior of users varies over time and it should affect the construction of models. For instance, the interest of a user in insurance scheme advertisements is only expected to last until the user buys a scheme and then it should decrease suddenly. A Recommender system should be able to adapt to the user's behavior, when this changes.

f) Evaluation of personalization models

Finally, an important problem of recommender systems is the lack of studies comparing their performance. This is partly due to the difficulty in producing objective evaluation criteria. Clearly, carrying out a comparative evaluation of various systems at different levels is a difficult task. However, the results of such an evaluation would be of great value to the design of effective recommender systems.

CONCLUSION

Designing and maintaining web based information systems, such as Web sites, is a real challenge. On the Web, it is much easier to find inconsistent pieces of information than a well structured site. The study of recommender system and its research could help a lot in building tools that can support the design, development and maintenance of complex but coherent sites. The approach is multi-disciplinary, involving Software Engineering and Artificial Intelligence techniques. There is a strong relation between structured documents (such as Web sites) and a program; the Web is a good candidate to experiment with some of the technologies that have been developed in software engineering. Novelty and serendipity has been investigated by a lot of researchers recently in the context of recommender systems. It has been an important topic in recommender system research in recent years from the standpoint of supporting human-centered discovery of knowledge. The present day model of web mining suffers from a number of shortcomings as listed earlier. As services over the web continue to grow, there will be a continuing need to make them robust, scalable and efficient. The paper proposes a new approach that tries to optimize the opposite goals of serendipity and novelty using temporal dimension. Te empirical evidence suggests a positive output. Thus, these novel features can be applied to better understand the behavior of these services, and the knowledge extracted can therefore be useful for various indices of optimizations. There is need to study the loopholes in the analysis of user behavior in the traditional form that focuses just on accuracy The development of these new dimension will make recommender system widely acceptable in various other domains that just e-commerce.

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