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ICTRE: The Informal Community Transformer Into Recommendation Engine

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***Abstract*—Social influence plays an important role in product marketing. However, it has rarely been considered in traditional recommender systems. In this paper we present a new paradigm of recommender engine which can utilize information in social networks, including user preferences, item's general acceptance, and influence from social friends. A probabilistic model is developed to make personalized recommendations from such information. Presently human is encompassed by a colossal measure of data on the web. That highlights the continuous need of recommendation or suggestion systems in the different areas. Tragically cold start problem is still a critical issue in these systems on new clients and new items. So we are using social network site and adding customers profile in it and that added data as interest of someone is using over e-commerce site for recommendation. We are solving cold star problem and short life resources problem in this paper.**

***Keywords—Recommendation Systems, Conceptual recommendation, cold start problem, collaborative filtering*.**

I. INTRODUCTION

In order to overcome information overload, recommender systems have become a key tool for providing users with personalized recommendations on items such as movies, music, books, news, and web pages. Intrigued by many practical applications, researchers have developed algorithms and systems over the last decade. Some of them have been commercialized by online venders such as Amazon.com, Netflix.com, and IMDb.com. These systems predict user preferences (often represented as numeric ratings) for new items based on the user's past ratings on other items. Before we introduce the system, let us first show a typical scenario. Angela wants to watch a movie on a weekend. Her favorite movies are dramas. From the Inter-net, she finds two movies particularly interesting, "Revolutionary Road" and "The Curious Case of Benjamin Button." These two movies are all highly rated in the message board at Yahoo Movies.

Because she cannot decide which movie to watch, she calls her best friend Linda whom she often hangs out with. Linda has not viewed these two movies either, but she knew that one of her officemates had just watched "Revolutionary Road" and highly recommended it. So Linda sug-gests "Why don't we go to watch Revolutionary Road together?" Angela is cer-tainly willing to take Linda's recommendation, and therefore has a fun night at the movies with her friend. If we review this scenario, we can see at least three factors that really contribute to the Angela's final decision. The first factor is Angela's own preference for drama movies. If Angela did not like drama movies, she would be less likely to pick something like "Revolutionary Road" to begin with. The second factor is the public reviews on these two movies. If these movies received horrible reviews, Angela would most likely lose interest and stop any further in-vestigation. Finally, it is the recommendation from Angela's friend, Linda, that makes Angela finally choose "Revolutionary Road." Interestingly, Linda's opinion is also influenced by her officemate. If we recall the decisions that we make in our daily life, such as finding restaurants, buying a house, and looking for jobs, many of them are actually influenced by these three factors.

1.1. Motivation

The main motivation of the project is to reduce cold start problem at the level of users and items. On the other hand, items with a considerable measure of activities will be exceptionally suggested. The problem is even present in systems with Short life Resources (SLiR), where items appear and disappear before having enough actions to be recommended, like news in a news site, or offers on products in commercial sites. The product itself can live for longtime, but the offer disappears after few days. To overcome this problem, designs iCTRE module ,it is a generic model that transforms users' actions in online social network into concepts, then it builds a matrix of concepts. The resulting matrix can be used to offer recommendation benefiting from any collaborative filtering algorithms. iCTRE was evaluated on , live tests were done on real users to recommend them offers over products. iCTRE not only solve the cold start problem..

1.2. Objective

1. The main objective of this project to overcome cold start problem.
2. To improve the Collaborative filtering.
3. To reduce time as well as cost.

II. LITERATURE SURVEY

I.

Number	Paper Name	Author Name	Proposed System	Referred Point
1.	Social Media Recommendation	Zhi Wang, Wenwu Zhu, Peng Cui.	In this paper, present the framework of social media recommendation, with a focus on two important types of recommendations interest-oriented social media recommendation and influence-oriented social mediare commendation. For each case, we present the design of the recommendation that takes both social property and content property into account, such as user relations, content similarities, and propagation patterns. Furthermore, we present theoretical results and observations on the social media recommendation approaches.	In this Paper, we referred the interest-oriented social media recommendation and influence-oriented social mediate commendation.
2.	Social Media Recommendation based on People and Tags	Ido Guy, NaamaZwerdling, Inbal Ronen, David Carmel, ErelUziel IBM Research LabHaifa 31905, Israel {ido,naamaz,inbal,carmel,erelu}@il.ibm.com	In this paper, the system recommends items related to people and tags that are related to the user. Each recommended item is accompanied by an explanation that includes the people and tags that led to its recommendation, as well as their relationships with the user and the item.	In this Paper, we referred the items based filtering.

3.	LIKE and Recommendation in Social Media	Ido Guy, NaamaZwerdling, Inbal Ronen, David Carmel.	In this paper, the author have demonstrated their strength in improving the quality of user experience, and positively impacted the success of social media. New types of data introduced by social media not only provide more information to advance traditional recommender systems but also manifest new research possibilities for recommendation.	In this Paper, we referred the social media.
4.	Social Media, Recommendation Engines and Real-Time Model Execution.	K. Kurosawa and Y. Desmedt.	In this paper, Recommendation engines are not new they take forms from market basket analysis in retail to advanced analytic systems providing next best offer or next best activity suggestions. They are also very popular for making suggestions or recommendations of similar items when a particular product or offering is selected. Amazon is probably the most famous example that uses recommendation engine analytics.	In this Paper, we have referred recommendations of similar items when a particular product or offering is selected.

5.	Social Media Usage and Maintaining Privacy, Confidentiality and Professionalism	R. Cramer and V. Shoup.	Student nurses have a responsibility to understand the benefits and consequences of participating in social media; NSNA recommendations encompass personal and professional social media use. Healthcare organizations and Universities that utilize electronic and social media typically have policies in place to govern employee or student use of such media in the workplace. The policies often do not address the nurses' use of social media outside of the workplace, or outside of the clinical setting. It is in this context that the nurse or student nurse may face potentially serious consequences for inappropriate use of social media.	In this paper, we have referred consequences for inappropriate use of social media.
6.	An Analysis and Recommendations of the Use of Social Media within the Cooperative Extension System	Dr. Lee Humphreys.	Social media has become a huge and integral component of how people spend their time online; people are spending enormous amounts of time on websites used to share information and connect with people. New forms of relationship building and social capital occur through social networking sites. Within Cooperative Extension, it is imperative to keep up with evolving forms of communication to connect with an ever changing audience. Interviews were conducted throughout New York and Wisconsin with educators in both rural and urban counties, with varying amounts of social media.	In this Paper, we referred the Social media.

III. SOFTWARE REQUIREMENT SPECIFICATION

A. User Classes and Characteristics

To design products that satisfy their target users, a deeper understanding is needed of their user characteristics and product properties in development related to unexpected problems that the user's faces every now and then while developing a project. The study will lead to an interaction model that provides an overview of the interaction between user characters and the classes. It discovers both positive and negative patterns in text documents as higher level features and deploys them over low-level features (terms).

In proposed work is designed to implement above software requirement. To implement this design following software requirements are used.

1. Operating system: Windows XP/7.
2. Coding Language : JAVA/J2EE
3. Database : MYSQL
4. Tool : Eclipse Luna

IV. IMPLEMENTATION STATUS

The proposed system designs iCTRE module which overcome this problem, it is a generic model that transforms users' actions in online social networks (like Twitter and Facebook) into concepts, then it builds a matrix of concepts. The resulting matrix can be used to offer recommendation benefiting from any collaborative filtering algorithms. iCTRE was evaluated on Twitter; live tests were done on real users to recommend them offers over products like an example of SLiR resources. Results were so encouraging so far. iCTRE not only solve the cold start problem, but also protects the users from entering their interests in different systems. attempt to incorporate social trust information into their recommendation models, given that model-based CF approaches outperform memory-based approaches . These approaches further regularize the user-specific Both the trust influence of trustees and trusters of active users are involved in our model.

1. iCTRE, that transforms users actions in GPSN into a source of recommendation based on domain concepts.
2. iCTRE not only solve the cold start problem, but also protects the users from entering their interests in different systems.

V. SYSTEM ARCHITECTURE

The iSoNTRE offers a methodology to transform the general purpose social networks into a source of recommendation. In traditional social recommender systems, after having information from the recommendation based social networks (epinions or flickers) different recommendation methods are proposed and evaluated

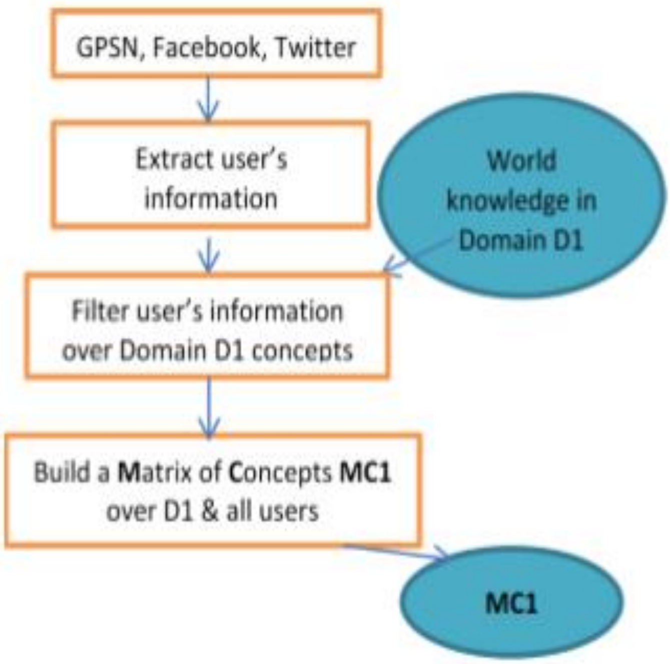


Figure 1. System Architecture part1

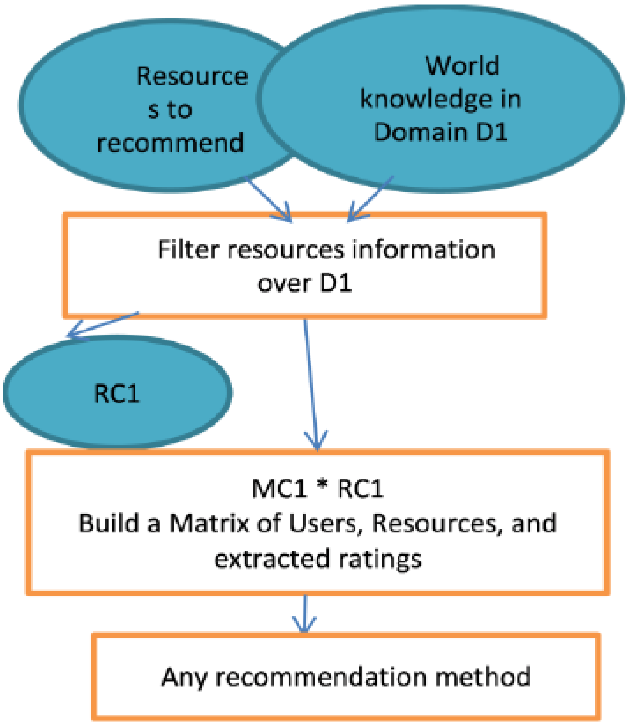


Figure 2. System Architecture part2

Figure 2. further illustrates how these three factors impact customers' final buying decisions. Intuitively, a customer's buying decision or rating is decided by both his/her own preference for similar items and his/her knowledge about the characteristics of the target item. A user's preference, such as Angela's interest in drama movies, is usually reflected from the user's past ratings to other similar items, e.g. the number of drama movies that Angela previously viewed and the average rating that Angela gave to those movies. Knowledge about the target item can be obtained from public media such as magazines, television, and the Internet. Meanwhile, the feedbacks from friends are another source of knowledge regarding 6 the item, and they are often more trustworthy than advertisements. When a user starts considering the feedbacks from his/her friends, he/she is then influenced by his/her friends. Note that this influence is not limited to that from our immediate friends. Distant friends can also cast their influence indirectly to us; e.g., Angela was influenced by Linda's officemate in the previous scenario. Each one of these three factors has an impact on a user's final buying decision. If the impact from all of them is positive, it is very likely that the target user will select the item. On the contrary, if any has a negative influence, e.g., very low ratings in other user re-views, the chance that the target user will select the item will decrease. With such an understanding in mind, we are going to propose a social network-based recommender system (SNRS) in the following subsections. As we mentioned, social influences can come from not only immediate friends but also distant friends. The techniques for handling these types of influences are different. We shall begin with the immediate friend inference, in which we only consider influences from immediate friends. Then, in the distant friend inference, we will describe how we incorporate influences from distant friends via leveraging the immediate friend inference.

VI. ALGORITHM FOR RELEVANT FEATURE DISCOVERY

. Efficient Algorithms play important role in the relevant feature discovery from text document using text mining. The following steps explain the relevance feature of text documents:

1. Start.
2. Search item they have .
3. User decides the item with maximum rating
5. Buy the product using efficient technique.
6. Recommend the item to user friend.
7. Stop.

VII. MATHEMATICAL MODEL

S = {s, e, X, Y, φ}
S = Set of system
s = Start of the program
X = Input of the program
X = {MC, RC}
Where,
MC = all users, concepts, and the extracted ratings in one matrix **MC**, with N users and K concepts.
RC = Resource - Concept Matrix with extracted rating of each resource towards each concept **RC** Matrix with M resources and K concepts.

- Build the matrix of user, resources and extracted rating **MC * RC**.

User-User based recommendation adopting the neighborhood algorithm.

$$\mathbf{_{u,cj}} = \mathbf{a_0} + \sum_{\mathbf{i=1}}^{\mathbf{n}} \left(\mathbf{w(u,i)}.\left(\mathbf{a_{i,j}} - \mathbf{a_i}\right)\right)$$

Where,
u.cj = the predicted value for user **u** for an item **i** related to concept **j**.
$\mathbf{a_0}$ = the actions mean for the user **u** on the facet **c**.
i:1…n = users having actions on the same facet.
$\mathbf{a_i}$ =actions mean for user **i** n the facet.

w(u,i) similarity between users u and i . Calculated using cosine correlation based on common concepts.

$$w(x,y) = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n}(x_i)^2 \sum_{i=1}^{n}(y_i)^2}}$$

Y = Output of the program
Y = {R}
Where,
R = Recommendation of resources.
e = End of the program.

VIII. EXPERIMENTAL SET UP AND RESULT TABLE

1. Result Table

	User 1	User 2	User3
User 1		0,9	
User 2	0,8		0,7
User 3		0,2	
User 4	0,6	0,4	

Table 2.An example of a relation matrix

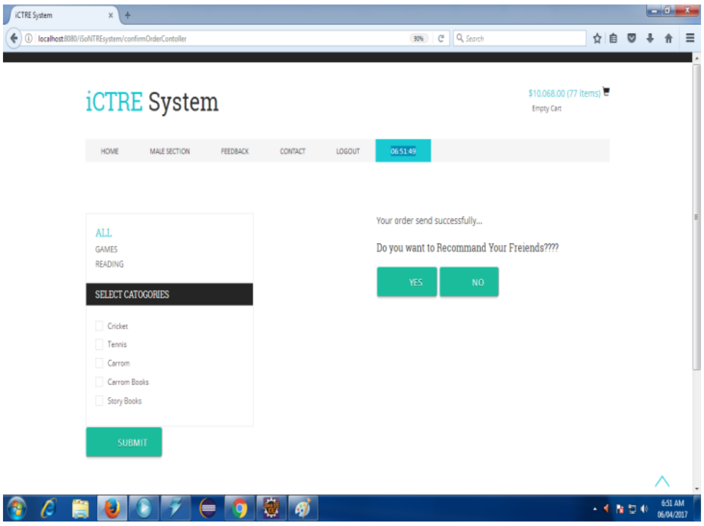
1. Result Evaluation

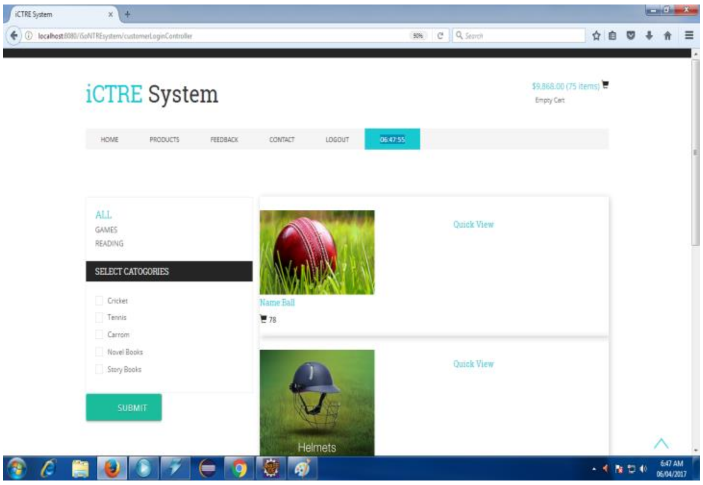
Social networks are a fundamental part of the social media family sites. Online social networks like Facebook and Twitter continue to grow. Figure 1 shows the number of users using some social networks within a month in the United States only.

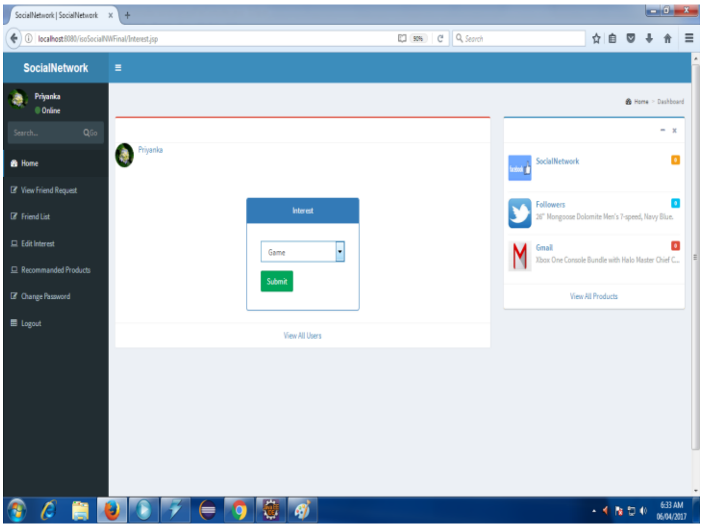
Facebook has 141 million users and Twitter has 93 million users compared to a mere 8 million on Flickr and 1 million on epinions. Amazon is not considered as a social network but instead is a recommender system. However it has been added in order to compare figures.

Fig 1.A comparison between different sites over one moth use in United States

Online social networks are divided into General Purpose Social Networks GPSN like Twitter and Facebook, towards Domain Based Social Networks DSSN like epinions for product recommendation, Flickr for photo, LinkedIn for professional relations and so on. Usually the social network is denoted by the graph G (U,F) where U○ is the set of users, andF is the set of friendship links. This graph is translated into a matrixӧ , where each user , uhas a set of uFwho are the users trusted by user u ,as well as uFwho are the users who trust the user u.When relation in the social network are symmetric, meaning that is user u is friend with user v then user v is also a friend of user u ,like the case in Facebook, then uF= uF. The contrary is the case of non-symmetric social networks like Twitter, where user v can follow a user u ,but the user v doesn't necessarily follow the user u .In this casȇ. The relation between two users (know, trust, follow…) is represented by a positive value in the interval Su,v €[0,1]. Where 0 means there is no relation and 1 means the relation is very strong. The value between reflect the level of the relation. The value of relationship is either obtained explicitly by asking the user to provide the system by how much he trusts other users, or implicitly by observing the actions between the two users.







CONCLUSION

Item	Existing System	Proposed System
Algorithms	1) Only Collaborative filtering techniques.	1) Collaborative filtering techniques. 2) Apriori Algorithm
Accuracy	Low	High
Complexity	Low	High
Explanation	The existing system uses Collaborative filtering techniques for recommendation to users. But collaborative filtering suffers usually from cold start problem at the level of users and items. The problem is even present in systems with Short life Resources (SLiR), where items appear and disappear before having enough actions to be recommended, like news in a news site, or offers on products in commercial sites. The product itself can live for longtime, but the offer disappears after few days. The solution to this problem is content based solution technique. In this technique the item can be recommended based on his similar items. But a new user who has not yet provided actions can still occurs from a cold start problem.	iSoNTRE not only solve the cold start problem, but also protects the users from entering their interests in different systems. It proves also that the spontaneous actions of users can be much useful in different domains.In the proposed iCTRE module introduced, is a generic model that transforms users' actions in online social networks (like Twitter and Facebook) into concepts, then it builds a matrix of concepts. The resulting matrix can be used to offer recommendation benefiting from any collaborative filtering algorithms. iCTRE was evaluated on Twitter; live tests were done on real users to recommend them offers over products like an example of SLiR resources. Results were so encouraging so far. iCTRE not only solve the cold start problem, but also protects the users from entering their interests in different systems. attempt to incorporate social trust information into their recommendation models, given that model-based CF approaches outperform memory-based approaches . These approaches further regularize the user-specific Both the trust influence of trustees and trusters of active users are involved in our model.

Social Network Analysis is the study of social structure. The social network analysts are interested in how the individual is embedded within a structure and how the structure emerges from the micro-relations between individual parts. We Design iCTRE, a framework that transforms users actions in GPSN into a source of recommendation based on domain concepts. In order to achieve this goal we had to deal with the extracted row data and transform this data into user, resource, extracted rating matrix. iCTRE was evaluated on Twitter, live tests were done on real users to recommend them offers over products like an example of SLiR resources. Results were so encouraging so far. iCTRE not only solve the cold start problem, but also protects the users from entering their interests in different systems. It proves also that the spontaneous actions of users can be much useful in different domains. By iCTRE the user will not be only some previous ratings but also the concepts that are interesting for him, which is not the case in most of the existing recommendation systems like Amazon, and Epinions. So that the cold start problem of a new user can be transmitted to a warm start in any recommendation system. We still have a lot to do: we have to elaborate different strategies in the recommendation core, and to define how to link the matrix with existing recommender systems and to test the methodology over. We have to test our system in different datasets and systems, and to use other ways to conduct our experiments, and we're working on to test our work on Facebook. Moreover, the matrix of iCTRE can serve in different domains not only in the recommendation domain.

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