Framework for Product Recommandation for Review Dataset

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Abstract: In the social networking era, product reviews have a significant influence on the purchase decisions of customers so the market has recognized this problem The problem with this is that the customers do not know how these systems work which results in trust issues. Therefore a different system is needed that helps customers with their need to process the information in product reviews. There are different approaches and algorithms of data filtering and recommendation .Most existing recommender systems were developed for commercial domains with millions of users. In this paper we have discussed the recommendation system and its related research and implemented different techniques of the recommender system .

***Keywords –** Recommendation, product, review, rating matrix, consumer, collaborative filtering, recommenderlab*

*****

I. INTRODUCTION

In this paper, we are going to study about recommendation [1] systems. Recommendation systems are typically used by companies; especially e-commerce companies like Amazon.com, to help users discover items they might not have found by themselves and promote sales to potential customers. A good recommendation system can provide customers with the most relevant products [2]. This is a highly-targeted approach which can generate high conversion rate and make it very effective and smooth to do advertisements. So the problem we are trying to study here is that, how to build effective recommendation systems that can predict products that customers like the most and have the most potential to buy. Based on the research on some existing models and algorithms, we make application-specific improvements on them and then design three new recommendation systems, Item Similarity, Bipartite Projection and Spanning Tree. They can be used to predict the rating for a product that a customer has never reviewed, based on the data of all other users and their ratings in the system. We implement these three algorithms, and then test them on some existing datasets to do comparisons and generate results.

II. FUNCTIONALITY OF THE RECOMMENDER SYSTEM FRAMEWORK

The proposed system supports collaboration between persons in a software environment. Only collaborations performed through synchronous interactions are supported. The main goal of the system is to recommend items to participants of discussions. To do that, the system needs to recognize the context of the discussion or the theme being dealt, analyzing the messages exchange in a software tool like an Internet chats. The system recommends items from a digital base classified in the same subject of the discussion (context or theme). Figure1 presents an overview of the system architecture, detailing its main components and some interfaces. The first module is the Session Analyzer, responsible for identifying the subject of the discussion. This is made using a Text Mining tool that analyzes texts in the messages exchanged in the chat tool. A thesaurus should be defined to represent the subjects possible to be discussed (including an hierarchy of the subjects). The thesaurus also contains the terms used to express those subjects in the written language. This thesaurus is specific to the local environment and needs to be defined by people of the environment using automatic and manual methods, e.g., [Ch96]. The recommender module receives the current subject of the discussion and selects items from a digital base to suggest for the discussion participants. It is possible to exist more than one subject in the same session, as will be explained later. The recommendation [1] intends to accomplish the knowledge reuse, suggesting to the participants information or solutions that were useful to other persons of the software environment. To do that, the system has to store a knowledge base that will be maintained by people of the organization. The environment personnel must add items to the digital base, classified in subjects according to the thesaurus.

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A. Product reviews

Every message sent by a participant in a discussion session will be analyzed to find keywords. Keywords represent subjects as defined in the thesaurus. The text classification method is based on Rocchio's[11] and Bayes' algorithms. The method analyzes the context of the words and not only the presence of keywords, eliminating ambiguities. There is a subject pointer, indicating what subject of those in the thesaurus is the current one being discussed. The pointer navigates over the thesaurus structure as different subjects are being dealt[12]. The list of subjects discussed in a session will be stored in the discussion history for later analyses.

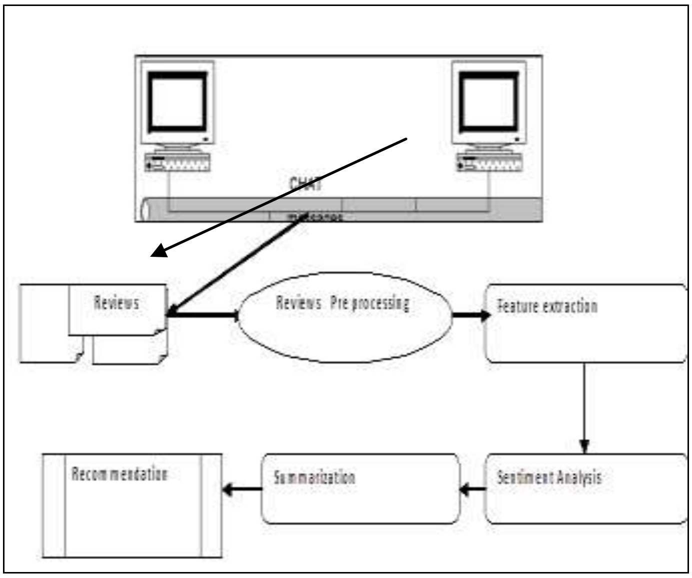

Figure 1. Recommendation Framework

B. Review Preprocessing

Before starting the Feature extraction process, a pre-processing phase is needed, in order to prepare the text for further processing. First of all, the input text is split into sentences, and each sentence is then analyzed by a Part-of-Speech Tagger. The following algorithmic steps best describes preprocessing the reviews.

Step 1: Identify Frequent nouns
Step 2: Identify Relevant nouns
    Step 2.1 - Identify Adjectives
    Step 2.2 - Identify New candidate features i.e nouns
Step 3: Map the Feature indicators
Step 4: Remove Unrelated nouns

C. Feature extraction

A "product feature" or "product aspect" is a component or an attribute of a certain product. For example, features of camera resolution of a smart phone ,battery life and screen size of a mobile etc,. A product may have a lot of features, some being more important for customers when making a buying decision than others. Bafna and Toshiwal (2013) on the other hand use a probabilistic approach to improve the feature extraction with the assumption that nouns and noun phrases corresponding to product features of a given domain have a higher probability of occurrence in a document of the this domain than in a document of another domain.

D. .Sentiment Analysis

Sentiment analysis takes input from feature extraction phase, It will detect whether a review text represents a positive or negative (or neutral) opinion[7]. An "opinion" is a sentiment, view, attitude, emotion or appraisal about an entity such as a product, a person or a topic or an aspect of that entity from a user or a group of users.

E. Summarization

After identifying sentiment polarity in previous phase, it will create a smaller version of a review document that retains the most important information of the source.[8] "Automated text summarization aims at providing a condensed representation of the content according to the information that the user wants to get. But the problem with this is, that "it is still difficult to teach software to analyze semantics and to interpret meaning.
A new way to solve this issue by taking into consideration the distance of each opinion word with respect to product feature and then calculating the overall opinion of the sentence. This turns out to be highly useful. Summarization of the reviews is done by extracting the relevant excerpts with respect to each feature-opinions pair and placing it into their respective feature based cluster.

F. Recommendation

Recommendation technique has been widely discussed in the research communities of information retrieval, data mining, and machine learning. Due to all these values the recommendation system is commercially successful to do product, movie and other recommendations. We proposed a framework where we can get genuine rating from the customer feedback. The existing system also has the same features of proposed system but we tried to implement some concepts to overcome from a number of problems which the existing system has.

III. SOURCE OF PRODUCT REVIEWS

In India we use ecommerce sites like FLIPKART, SNAPDEAL, JUNGLEE, AMAZON, etc. These are the most famous and the most used sites in India for shopping. Every year BBC, TIMES OF INDIA and a few more news media survey these ecommerce sites to know the current status of Indian people and their mindsets. The eBay shopping mart was started in 1995 according to a BBC survey in 2013; it says that 606 million dollars have been invested for this site. There are 33.500 employees in eBay and the revenue is 16.05 billion dollars. Another ecommerce site is FLIPKART in India; it started in 2007, the investment was 210 million dollars till 2013 and the survey says that most of the investors are foreigners (BBC). After the US succeeded in ecommerce sites, many people started investing in India in E-Business. There are 15,000 employees working for FLIPKART and the revenue is 1billion dollars. The business today says that FLIPKART has 5 million products and it sells more than 600 crore products in a day.

From these surveys we can see that most of us wish to get products online rather than direct shopping, because it reduces time and it is not a complex task to purchase compared to the older method. These sites becomes an important factor in our day-to-day life, so it is necessary to take care of things like organizing the products in a correct domain, protecting a customer's details like credit and debit card pin numbers, interactive and attractive web pages, etc. There are many aspects to concentrate on the ecommerce site to give better enrichment in the process of buying a product. In this paper we have concentrated on reviews and ratings of a product which is a vital factor for sales. All the ecommerce sites encourage customers to write feedback about the product to help the customers to know about the product's positives and negatives.

For example, a customer who wants to buy a Sony laptop wants to know the feedback from the laptop users to know which laptop is better in the market. In this case the reviews and ratings given by the customers will be useful for him to get best one from the pool. Hence this example reveals the importance of feedback and rating method in the ecommerce field. Nowadays all ecommerce sites expect comments and ratings from the customer to correct their mistakes in the future version of that product. Some of the websites get only ratings from the customers. Some get the A consumer who mostly gives the genuine and Quality reviews and ratings from persons who own it. But we cannot say that all of us give a very genuine rating in blogs which leads to consumers to get confused or negative about the product. So in order to make accurate ratings to facilitate customers we generate ratings from the customer feedback. We could think a product from many aspects, i.e., "price," "Quality," "Quantity," and much more. So we generate a system to analyze ratings from all the maximum aspects which we could think as much as possible. Most ecommerce sites expect both feedback and rating from the customer [5] without knowing the customer's mentality. Customer feels flexible in giving feedback rather than ranking a product because when he gives feedback he will explain a product in various aspects but in case of raking he cannot apply this method. A customer always gives genuine feedback than rating.

A. .Related Work

There are many works done on this framework to make ratings [4]. They use mainly two methods called the document level sentiment classification and extractive review summarization. The document level sentiment classification help us to conclude a review level documents, which is expressing a document's overall opinion whether it is positive or negative. The extractive review summarization method helps us to generate rating by extracting useful information from the customer feedback. They implement information retrieval concepts to remove some words that are not needed to calculate the rating. The project has been divided into four stages according to the concepts that have to be implemented. The first stage consists of stemming and stop word removal, the second stage has opinion word extraction and extracting common words. The third stage is clustering sentiment analysis with classification of polarity, and finally the product aspect ranking, document level classification, and extractive review summarization is the fourth stage. In a paper [6] the authors had proposed a sentiment-based rating prediction technique within the framework of matrix factoring for product recommendation.

From the title of the paper we understand what the paper is about (toward the next generation of recommendation systems: a survey of the state of the art and possible extensions). This paper speaks elaborately about the present generation of recommendation system and its limitations. It gives an idea to overcome from all the limitations, how we could extend the recommendation systems and make it available even for a broader range of applications. These extension ideas make us understand about the users and their point of view toward the item they buy. They discuss the three-recommendation system which plays a vital role in today's world of ecommerce to do product recommendation. The important note in this discussion is to make us to realize how the rating part varies in each recommendation.

In a paper they have been compared three categories of getting recommendation of a product. They are real world social recommendation , social network, and the user item rating matrix. The real-world social recommendation is all about the direct recommendation, i.e., if a customer wants to buy a laptop, he gets recommendation from laptop users whom he knows. Then the social network recommendation gets recommendation of a product from the social media like Face book and Twitter etc. The last one is the user item rating matrix; it is in the form of matrix by considering the items and user's interest toward an item. Importance is also given to the low rank matrix factorization.

From these three papers we understand the importance of reviews given by the user. Each and every review and rating is an important aspect for the inflation of a product value in the market. We cannot generate a system to calculate a very accurate rating because people's mind varies. But we can try to produce a genuine rating from our system with the help of customer reviews, hence in our proposed system we develop a framework where the customer can post their feedbacks and get the ratings .

IV. TECHNIQUES FOR RECOMMENDATION SYSTEM

There are numerous techniques available for recommendation system They are Content based recommendation system, Collaborative Recommendation, Knowledge-based recommender systems, Demographic recommender systems. Even we can develop a hybrid system with two more techniques.

A. Content based recommendation system

In content-based (CB) system, Ratings expressed by a single consumer have no role in recommendations provided to other consumers. The core of this approach is the processing of the contents describing the items to be recommended. Content Based approach learns a profile of the consumer interests based on some features of the objects the consumer rated. After the system exploits the consumer profile to suggest suitable items by matching the profile representation against that of items to be recommended. Content -based techniques are limited by the features that are associated either automatically or manually with the items. No CB system can provide good suggestions if the content does not contain enough information to distinguish items the consumer likes from items the consumer does not like. Enough ratings have to be collected before a CB system can really understand consumer preferences and provide accurate recommendations. Therefore, when few ratings are available, such as for a new consumer, the system would not be able to provide reliable recommendations.

B. Collaborative Recommendation

The collaborative approach to recommendation is altogether different: Rather than recommend items because they are like things a purchaser has purchased previously, framework prescribe things other comparative shopper have preferred. Rather than find the similarity of the items, system find the similarity between the consumers [5]. Often, for each consumer a group of closest neighbor consumers is found with whose past ratings there is the strongest relation. Scores for unseen items are predicted based on a combination of the scores known from the nearest neighbors. If a new item appears in the database there is no way it can be recommended to a consumer until more information about it is obtained through another consumer either rating it or specifying which other items it is similar to. Thus ,if the small number of consumers rated the product then to recommendation very poor because the system must form the mass comparison to find the target consumer.

If a consumer whose tastes are unusual compared to the rest of the population there will not be any other consumers who are particularly similar, leading to poor recommendations. Therefore, if one consumer liked the Zee News weather page and another liked the NDTV weather page, then it not necessarily both neighbors because the system must form the mass comparison to find the target consumer. The neighborhood is defined in terms of similarity between users, either by taking a given number of most similar users (k nearest neighbors) or all users within a given similarity threshold.

C. Knowledge-based recommender systems

Knowledgebase approaches are prominent in that they have functional knowledge: they have knowledge about how a particular item meets a particular consumer need, and can therefore reason about the relationship between a need and a possible recommendation. A knowledge-based recommendation system avoids some drawbacks. It does not have a ramp-up problem since its recommendations do not depend on a foundation of consumer ratings. It does not have to collect information about a particular consumer because its opinions are independent of individual preferences. These characteristics make knowledgebase recommenders not only valuable systems on their own, but also highly complementary to other types of recommender systems. The system has the former Knowledge about the objects being recommended and their features and it must have the capacity to map between the consumer’s requirements and the object that might satisfy those requirements consumer knowledge: To offer good recommendations , the system must hold some knowledge about the consumer.

D. Demographic recommender systems

Demographic recommender systems intend to categorize the consumer based on personal attributes and make recommendations based on demographic classes. The benefit of this approach is that it may not oblige a history of consumer [5] ratings like collaborative and content-based techniques. Some recommender systems do not like to utilize the demographic information because this form of information is difficult to collect: Till some years ago, indeed, consumers were unwilling to share a large quantity of personal information with a system.

E. Hybrid Approach

Hybrid approach combines two or more techniques described earlier in different ways to improve recommendation performance in order to tackle the shortcoming of underlying approaches including cold-start or data sparsity problem. Cold-start concerns the issue that the system cannot draw any inferences for consumers or items about which it has not yet gathered sufficient information. Sparsity concerns the number of ratings obtained is usually very small compared to the number of ratings to be predicted. For example, a knowledge-based and a collaborative system might be combined together to achieve more robust recommender system than the individuals components. The knowledge-based component can overcomes the cold-start Problem with making recommendations for new consumers whose profiles are compact, and the Collaborative approach can help by finding those consumers who have similar preferences in the Domain space that no knowledge engineer could have predicted. However, current hybrid approaches still suffer from a few drawbacks.

First, there is insufficient contextual information to model consumers and items and therefore weaknesses to predict consumer taste in domains with complex objects such as education. Finally, there is also the shortcoming in closest neighbor based computing, Scalability problem, since the computation time grows fast with the number of consumers and Objects. The most common approaches that generally used in hybrid approach are content based (CB) and collaborative filtering (CF). Besides, hybrid recommenders can also be sorted based on their operations into seven different characters including weighted, switching (or conditional), mixed, feature-based (property-based), feature combination, cascade, and Meta level. Interested readers can refer to and for further discussion of hybridization Approaches.

F. Association mining

The goal of the techniques is to detect relationships or connections between certain values of categorical variables in large information sets. These techniques enable analysis and researchers to uncover hidden patterns in heavy information sets. The extraction of information about the consumers' purchasing behavior, preferences and activities is being implicitly accomplished, without the necessity of explicitly calling for these into the aggregation procedure. Recommender System utilizes a proactive methodology, permitting the extraction of information about consumers' communication with the items. The gathering of use information is as a rule verifiably attained, without the need of

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an express demand from the piece of the consumers' assessment. It allows the incremental discovering and putting away, both of the current associations between oftentimes bought items, as significantly as those less regularly obtained. As a result, the RS is able to offer a list of personalized products to each consumer , depending on the current products he is just purchased, without the need for a history or a minimal number purchased products .

V. IMPLEMENTATION OF RECOMMENDATION SYSTEM ALGORITHMS

We have attempted to work our research in open source software R[10]. In this we have observed different rating matrices available for recommender system. The following list is the rating matrices. This matrix containing ratings (typically 1-5 stars, etc.). A recommender is created using the creator function Recommender(). Available recommendation methods are stored in a registry.

[1] "ALS_realRatingMatrix" "ALS_implicit_realRatingMatrix"
[3] "ALS_implicit_binaryRatingMatrix" "AR_binaryRatingMatrix"
[5] "IBCF_binaryRatingMatrix" "IBCF_realRatingMatrix"
[7] "POPULAR_binaryRatingMatrix" "POPULAR_realRatingMatrix"
[9] "RANDOM_realRatingMatrix" "RANDOM_binaryRatingMatrix"
[11] "RERECOMMEND_realRatingMatrix" "SVD_realRatingMatrix"
[13] "SVDF_realRatingMatrix" "UBCF_binaryRatingMatrix"
[15] "UBCF_realRatingMatrix"

We have used recommenderlab package here for implementation below section.

A. *Create a matrix with ratings*

Step1 : create a matrix with 10x10 size

```
>mat <- matrix(sample(c(NA,0:5),100, replace=TRUE, prob=c(.7,rep(.3/6,6))),
 nrow=10, ncol=10, dimnames = list(
   user=paste('u', 1:10, sep="),
   item=paste('i', 1:10, sep=")
  ))
```

Step 2: Display the matrix

```
>mat
```

```
       item
user    i1 i2 i3 i4 i5 i6 i7 i8 i9 i10
  u1    NA  2 NA NA NA NA NA NA NA  NA
  u2    NA NA  5 NA NA NA NA  4  5   2
  u3    NA NA NA NA NA NA NA NA NA  NA
  u4    NA  4  2 NA  5 NA NA NA  0  NA
  u5    NA NA  0 NA NA NA  4  0 NA  NA
  u6    NA NA NA  2 NA NA  4 NA NA  NA
  u7    NA  2  2  3 NA  0  0 NA  3   1
  u8     1 NA NA NA NA NA NA  3 NA  NA
  u9     3  1 NA NA  0  3 NA  0 NA  NA
  u10    4  4 NA NA  1  0  1  4 NA  NA
```

Figure 2. Matrix with users-items

Step 3: coerce into a realRatingMAtrix
>r <- as(mat, "realRatingMatrix")
>r
10 x 10 rating matrix of class 'realRatingMatrix' with 34 ratings.

Step 4: get information about users and items from realRatingMAtrix
>dimnames(r)
$user
[1] "u1" "u2" "u3" "u4" "u5" "u6" "u7" "u8" "u9" "u10"
$item
[1] "i1" "i2" "i3" "i4" "i5" "i6" "i7" "i8" "i9" "i10"

>rowCounts(r)
u1 u2 u3 u4 u5 u6 u7 u8 u9 u10
1 4 0 4 3 2 7 2 5 6
>colCounts(r)
i1 i2 i3 i4 i5 i6 i7 i8 i9 i10
3 5 4 2 3 3 4 5 3 2
>rowMeans(r)
u1 u2 u3 u4 u5 u6 u7 u8
2.000000 4.000000 NaN 2.750000 1.333333 3.000000 1.571429 2.000000
u9 u10
1.400000 2.333333

Step 5: Find the histogram of ratings
>hist(getRatings(r), breaks="FD")

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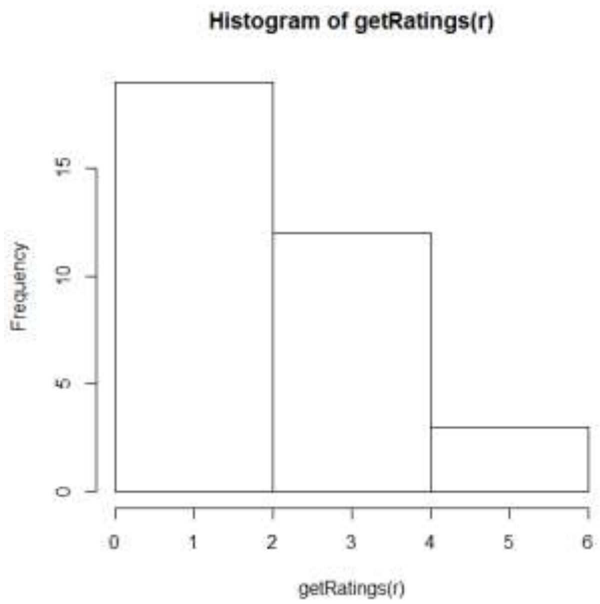

Figure 3. getRating Graph

Taking frequency in y-axis and get ratings in x-axis generated the histogram which is shown in fig-3.

Step 6: inspect a subset

>image(r[1:5,1:5])

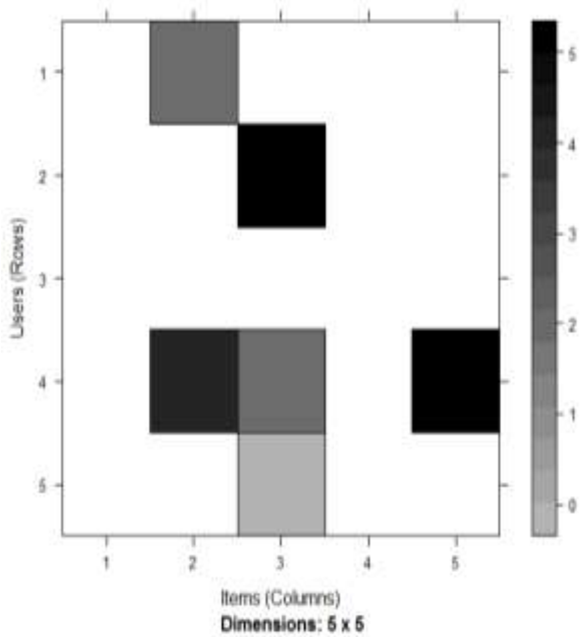

Figure 4. Inspecting users with items

Since the top-N lists are ordered, we can extract sub lists of the best items in the top-N shown in fig-3.

Step 7: coerce it back to see if it worked which resulted as shown in fig-4

user \ item	i1	i2	i3	i4	i5	i6	i7	i8	i9	i10
u1	NA	2	NA	NA	NA	NA	NA	NA	NA	NA
u2	NA	NA	5	NA	NA	NA	NA	4	5	2
u3	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
u4	NA	4	2	NA	5	NA	NA	NA	0	NA
u5	NA	NA	0	NA	NA	NA	4	0	NA	NA
u6	NA	NA	NA	2	NA	NA	4	NA	NA	NA
u7	NA	2	2	3	NA	0	0	NA	3	1
u8	1	NA	NA	NA	NA	NA	NA	3	NA	NA
u9	3	1	NA	NA	0	3	NA	0	NA	NA
u10	4	4	NA	NA	1	0	1	4	NA	NA

Figure 5. coerce the users-items back

Step 8: coerce to data.frame (user/item/rating triplets)

	user	item	rating
4	u1	i2	2
9	u2	i3	5
25	u2	i8	4
30	u2	i9	5
33	u2	i10	2
5	u4	i2	4
10	u4	i3	2
15	u4	i5	5
31	u4	i9	0
11	u5	i3	0
21	u5	i7	4
26	u5	i8	0
13	u6	i4	2
22	u6	i7	4
6	u7	i2	2
12	u7	i3	2
14	u7	i4	3
18	u7	i6	0
23	u7	i7	0
32	u7	i9	3
34	u7	i10	1
1	u8	i1	1
27	u8	i8	3
2	u9	i1	3
7	u9	i2	1
16	u9	i5	0
19	u9	i6	3
28	u9	i8	0
3	u10	i1	4
8	u10	i2	4
17	u10	i5	1
20	u10	i6	0
24	u10	i7	1
29	u10	i8	4

Step 9: binarize into a binaryRatingMatrix with all 4+ rating a 1

>b <- binarize(r, minRating=4)

>b

10 x 10 rating matrix of class 'binaryRatingMatrix' with 10 ratings.

>as(b, "matrix")

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	i1	i2	i3	i4	i5	i6	i7	i8	i9	i10
u1	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
u2	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE
u3	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
u4	FALSE	TRUE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
u5	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
u6	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
u7	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
u8	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
u9	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
u10	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE

Figure 6. Recommendations as 'topNList'

B. .Create a recommender model

To implement the actual recommender algorithm we need to implement a creator function which takes a training data set, trains a model and provides a predict function which uses the model to create recommendations for new data. The model and the predict function are both encapsulated in an object of class Recommender. Let us Discuss the recommendation model with MSWeb dataset.

Step 1: use MSWeb dataset
>data(MSWeb)
Step 2: create a sample of 10
>MSWeb10 <- sample(MSWeb[rowCounts(MSWeb) >10,], 100)
Step 3:create a recommender with popular method for binaryRatingMatrix
> rec <- Recommender(MSWeb10, method = "POPULAR")

Step 4**: Display the method output**
> rec

Recommender of type 'POPULAR' for 'binaryRatingMatrix' learned using 100 users.

Step 5: get the model
The model can be obtained from a recommender using getModel().
>getModel(rec)

$topN
Recommendations as 'topNList' with n = 285 for 1 users.

In this case the model has a top-N list to store the popularity order and further elements .
Many recommender algorithms can also predict ratings. This is also implemented using predict() with the parameter type set to "ratings". We can implement several standard evaluation methods for recommender systems. Evaluation starts with creating an evaluation scheme that determines what and how data is used for training and testing. Create an evaluation scheme which splits the first 1000 users in the dataset into a training set (90%) and a test set (10%). For the test set 15 items will be given to the recommender algorithm and the other items will be held out for computing the error.
Usual metrics for evaluating a recommendation engine is Root Mean Squared Error(RMSE). A/B site testing is used, which focuses on the user interaction with the website and understanding the crucial components in the website with a parameter such as Click Through Rate (CTR).

VI. CONCLUSION

Recommender systems for product reviews open up new opportunities of retrieving personalized information on the social networking sites. It also helps to alleviate the problem of information overload which is a very common phenomenon with information retrieval systems and enables users to have access to products and services which are not readily available to users on the system. Studied underlying technology of recommendation system, implemented the recommender algorithms and performances were discussed. This knowledge will empower infant researchers and serve as a road map to develop new recommendation techniques.

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