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Personality Based Recommendation System Using Social Media

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Abstract—Recommendation system is the reason of success for most of the social media companies as well as e-commerce sites. Giving recommendation to the uses is one of the interesting and challenging tasks nowadays, it helps to generate revenue, to increase number of users, to reduce the searching time for particular item. Recommendation system helps for making interest in user and eventually it increases the popularity of any site. Huge number of items (product, users, movies, songs, hotels etc.) and its feature sets makes it hard to predict the accurate items to the user. It is important to keep all historic data of user as well as all information about the items to generate recommendation. In this paper, the personality of the user is used with the combination on the most popular recommendation techniques like collaborative filtering (CF) and content based filtering (CB) proposed on the amazon review data set. In the first model the personality of the user is calculated by using the big five model on the twitter account. In the second module Collaborative filtering is used to generate the recommendation based on the historic information of the user wherries in third module, Content based filtering is uses to generate recommendation based on the feature set of the item. Pearson-correlation algorithm is applied on both modules and ranking are generated. Finally union of the both vector space are taken as the final recommendation.

Keywords-*Recommendation System; Collaborative Filtering (CF); Content Based Filtering (CB); Similarity measure, Social Media*

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I. INTRODUCTION

Recommender Systems have change the way of searching information over the internet. It is a system that recommends items to the user among a huge set of available items by studying the pattern of behavior. It helps in making decision of performing any task in internet which include online buying stuff, watching movie or listening to music, reading the books etc.

The main motive behind this system is to improve the performance of recommendation system which in terms help the user to find the required item in less amount of time.

Personality of the user is very important factor which can help to generate the more accurate recommendation. There are lots of information generated by user in social media like facebook, twitter etc, which is the motivation factor for the recommendation system researchers.

There are traditional approach are available for recommendation system like collaborative filtering and content base filtering, both gives the good performance. The hybrid recommendation system combine both the model for the better result.

There are other methods like ensemble learning can be used for significant improvement in the recommendation system. In ensemble technique number of predictors are combined to obtain more accurate prediction. Because of the massive amount of data the time and memory consumption is increases, hence every time use of ensemble method is note the good practice.

There are many recommender systems, most of them just consider user browsing history and recommend similar products based on that historic data. What actually matters is what the customer wants. This depends on a number of factors.

In the proposed approach both the traditional approaches are used in combination with the personality of the user. Items from amazon is recommended to the user based on the similar users profile, the historic information of the user about the purchase or previously searched item and lastly the personality of the user is used for the recommendation.

II. LITERATURE SURVEY

This literature survey consists of brief information about recommendation system and also brief comparison and introduction of various algorithms which are used in recommendation system.

A. Social Media Recommendation

In 1997 the first social recommender systems was introduce. Social media services such as Facebook and Twitter became very popular now a day. There are 2.4 million tweets in a day. 70 percent of the world is online. For using social media like Facebook, Twitter user only need to have internet connection and user can easily access the social media which leads in tremendous increase in the data [17]. For example, largest micro-blogging site twitter, has 37,974,138 followers and the Facebook produces 35,000,000,000 on-line friendships. Hence this rapid growth in social media required the improvement for better performance.

Users have their own profiles and after authentication, one can analyze the same obtain the user's personality and preferences which would be of great help in providing relevant recommendations to user. Twitter REST API is freely available with a developer's account. One can register with the same and obtain data resulting from the queries in various formats. This can then be used for analysis and providing recommendations on the user's feed.

B. Personality

According to Gordon Allport (1961), personality is the dynamic organization within the individual of those psycho-physical systems that determine his characteristic behavior and thought. Hence, in order to achieve maximum efficiency, the recommender system should be adaptive. There are many theories around personality such as Type Theory, Social Learning (Observational Learning, Intrinsic Reinforcement) and the Big Five Model. The Big Five model consists of five factors which can help in evaluating personality. The five factors are:

1. Openness to experience: Includes characteristics such as imagination, open mindedness and insight. Those who fare high in this are curious, creative and have a broad range of interests.

2. Conscientiousness: High level of thoughtfulness, with good control over impulsive behavior and goal focused attitude. Those who score well in conscientiousness are dependable, hardworking, organized, careful and mindful of details.

3. Extroversion: Characteristics such as excitability, talkativeness and high emotional expressiveness are exhibited by people having this trait.

4. Agreeableness: This traits includes attributes like kindness, trust, aff ection and pro social behaviors. People having this trait are friendly, loving, kind and sympathetic.

5. Neuroticism: Anxiety, sadness, irritability and instability are some of the issues that people high in neurotic ism. These factors are to be considered while evaluating one's personality and providing him recommendations. These factors are to be considered while evaluating one's personality and providing him recommendations.

C. Existing Social Media Recommender Systems

Most popular and widely used technique for social recommendation system is collaborative filtering (CF). Social media gives two inputs rating information and social information. CF is basic model of many recommendation system. Required information is obtained by using social network analysis. The CF framework has mainly two parts

1. Collaborative Filtering model and
2. Social information model.

D. Traditional Recommendation System

It uses the user specific and item specific profile attributes and accordingly they are categories broadly into three categories are as follows [16]

- Content-based Filtering System
- Collaborative Filtering System
- Hybrid Technique

Recommender systems first became an independent research area in the mid-1990s. A traditional collaborative filtering algorithm represents a user as an N-dimensional vector of items, where,

$u = \{u1, u2, \ldots un\}$ be the sets of users
$v = \{v1, v2, \ldots vm\}$ be the set of items
N = number of distinct catalog items

According to the user's ratings to item the user is classified into the positive or negative categories. For getting best-selling of items the inverse frequency 'IFT' multiplied with the vector component by algorithm which makes less well-known items much more relevant. This vector for almost all customers is extremely sparse there are lots of unknown ratings. Density of rating matrix is often < 1%. The task of the recommender system is to predict the rating for the user on non-rated item [1].

E. Content Based Recommender Systems

A content based recommendation system work on the comparison of the features of the item. Depending the users past behavior to the particular item the similar items are search in the dataset and the recommendation get generated. For taking the historic information users explicit and implicit behavior are taken into consideration for example rating of user to item, clicks of the user to item. Based on that data, a user's profile is generated and it is used for making recommendation to the user. And the accuracy of the system is improved further when user spends more time and generate more implicit and explicit data. Comparison with the item previously rated by user with the other users is performed. Content base recommendation system also uses the various classification and clustering algorithms for recommendation of similar items [14]. A similarity measure between the users like a cosine similarity measure is used to score these candidate items.

F. Collaborative Filtering Based Recommendation Systems

The past behavior about product (ratings, likes, tags etc) is used for calculating similar type of user. The basic idea behind collaborative filtering is that if the user agreed to another user in past then user might be agree to same user in future also [11].

Types of Collaborative filtering:

- User-based collaborative filtering
- Item-based collaborative filtering
- Matrix factorization methods

G. Matrix factorization methods

Matrix factorization methods is mostly used decompose the user's X item matrix of preference data into a more compact, denser representation that can be used to extrapolate the expected preference of items the user has not encountered. One of the most common of these techniques is singular value decomposition; gradient descent has proven to be an effective way of factorizing the matrix in a manner that is computationally efficient and useful for recommendation but does not preserve all the mathematical properties of a proper singular value decomposition. Other techniques based on matrix decomposition have included factor analysis and eigenvalue decomposition [15].

H. Computing similarity for user-oriented methods:

Computing user-user similarity is a critical step for user-oriented methods. There are many techniques proposed to tackle this problem such as Pearson Correlation Coefficient, Co-sine similarity, and probability-based similarity, among which Cosine similarity are the most widely used ones. Most popular similarity distance measures are as follows.

- Euclidian distance:

  This is most widely and commonly used for measuring the proximity between the users. Euclidean distance is also known as simply distance. The Euclidean distance between two points is the length of the path connecting them. It is well suited for dense data and the continuous data. By using Pythagorean Theorem distance between two points X and Y is given by the.

$$\sqrt{\sum_{i=1}^{k}(x_i - y_i)} \quad \ldots (1)$$

- Manhattan distance:

In Manhattan distance Cartesian coordinates are calculate by adding the sum of absolute difference between two points. It is simply the absolute sum of difference between the x-coordinates and y-coordinates. To find the Manhattan distance between two point A and B, we just have to sum all the absolute values of x-axis and y – axis.

In a plane with p1 at (x1, y1) and p2 at (x2, y2).

$$\boldsymbol{Manhattan\ distance} = |x1 - x2| + |y1 - y2| \quad \ldots(2)$$

- Minkowski distance:

  The generalize form of Euclidean distance and Manhattan distance is known as Minkowski.

$$d^{MKD}{}_{(I,J)} = \sqrt[\lambda]{\sum_{k=0}^{n-1} |y_{i,k} - y_{j,k}|^{\lambda}} \quad \ldots(3)$$

Where,
i and j are the recorded data,
k is index of a variable,
n is total number of variables,
y and λ are the order of the Minkowski metric.

- Cosine similarity:

  To find the normalize dot product between two attribute Cosine similarity is used. It computes the cosine of the angle using the rating vectors. Formula for calculating the cosine similarity between users is given as, [14].

$$sim(A, B) = \cos(\theta) = \frac{A.B}{|A||B|} \quad \ldots(4)$$

- Jaccard similarity:

  Instead of using metrics to find the similarity between the users the jaccard similarity uses the objects as a set. Similarity between two sets can be measure by the cardinality of intersection between two set divided by cardinality of union between two set. Jaccard similarity between two sets A and B is given as,

$$\boldsymbol{Jaccard\ Similarity}\ J(A, B) = \frac{|Intersection\ (A, B)|}{|Union\ (A, B)|} \quad \ldots(5)$$

- Aggregating ratings for user-oriented methods:

  To predict the missing ratings for user, the similar user's rating is aggregated and the predication for the unrated item is obtain. The most popular strategy for user-oriented method is weighted average rating,

$$R_{ij} = R_i + \frac{\sum_{uk \in N_i} S_{ik}\ (R_{kj} - R_k)}{\sum_{uk \in N_i} S_{ik}} \quad \ldots(6)$$

Where, N_i is the set of users who have rated the j^{th} item v_j.

I. Hybrid Recommender Systems

In Hybrid recommendation system combination of the collaborative filtering and content base filtering are taken for the better result and to avoid certain limitations of content and collaborative filtering systems.

There are three broad categories of hybrid recommendation systems [5].

1. Combining different recommender
2. Adding content based characteristics to CF models
3. Adding CF based characteristics to content based models.

J. Cluster Models

To find similar type of user, the cluster models divide the users into number of segments and treat the task as a classification problem. KNN and K-mean are the mostly use algorithm in clustering method. The goal of algorithm is to group and assign the user to the particular group which is most similar to user. The clustering model then takes another features of customer like the purchases and ratings of the customers to generate recommendations [9].

The grouping or segments are typically performed using a clustering or an unsupervised learning algorithms. Because it is difficult to perform optimal clustering over large data sets, for this reason most applications use various forms of greedy clustering algorithm. There is an initial set of segments for the starting of algorithms, which often contain one randomly selected customer each. Then it match repeatedly for that customers to the existing segments by having some provision for creating new or merging existing segments.

K. Ensemble Learning:

Ensemble learning is very popular technique which helps to improve the performance of the system by combining more than one classifier together rather than working single classifier on single task [17].

There are two task in ensemble learning: developing a population of base learners from the training data, and then combining them to form the composite predictor.

L. Watson API:

Watson is a computer named after the founder of IBM. This computer was trained to answer questions. It is a platform by IBM that has multiple APIs for data analytics tasks namely NLP APIs (Alchemy), Dialog API, Language Translator, Personality Insights, Relationship extraction, Tone analyzer, Text to speech and speech to text translator, etc. IBM has their own hosting on Bluemix. Personality Insights API is used to extract the personality. The input given to this API is the twitter handle of the user. Data of Twitter public feeds is taken, pre-processed and personality is calculated. Personality insights API is free for every new developer's account. But has a limited number of calls. This is the only API that uses Twitter data and provides output in the form of JSON considering the Big Five standard. 3500 words are required for an approximate result. Above 6000 words gives good results. The output is given in the form of JSON. It consists of various factors such as openness, conscientiousness, extroversion, agreeableness and neuroticism. These are the parameters used in the big five model. The API also provides other parameters such as adventurousness, practicality, emotionality, artistic interests, intellect, liberalism, achievement striving, etc.

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M. Twitter API:

Twitter is widely used to express oneself. The Twitter API v1.1 is used to extract a user's public posts [9]. The input given to the same is the user's Twitter handle. The developer's account requires an application to be built and a host. Arguments given to the API consists of consumer key, consumer secret, twitter access token and twitter access secret. The API allows 250 calls per 15 minutes. The API consists of many filters such as geographical location, specific words, logical operations on keywords, etc. Not only this, Twitter also provides live streaming of tweets. Given a twitter handle, one can receive live tweets of the person. This is done through continuous polling. It requires high bandwidth.

N. Amazon Associates:

The Amazon Associates Program is a program for people to enable advertising of Amazon products [10]. Anyone can register for this program and get the required information used to advertise the products. In return for advertising their products, Amazon gives a share of profits for every product sold using the Associates platform since the associates are providing a marketing muscle to Amazon. For the purpose of the recommender system, Amazon Associates ID was created. This would enable efficient searching of products. Not only products, the details associated with each product are also displayed. This enables user to get the details for each product. Moreover, product indexing too has been provided which acts as a primary key for every product. This helps to improve search efficiency for the end user as well as for the person recommending products.

III. Proposed Approach

The figure shows the proposed model of the recommendation system.

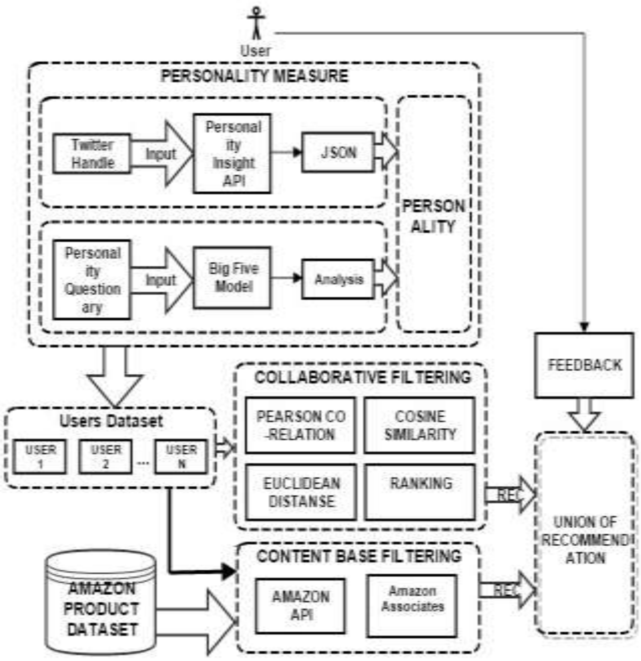

Fig 1. System Architecture

User's social behavior are used to create the personalized profile. By using Twitter API the personality of the user is calculated. If the user don't have the twitter account or don't want to share their twitter information, then by using Big 5 model the personality is calculated.

For calculating the personality, information of the user like tweets, tags, likes, location, family and close friend relation are taken into consideration [12]. So that the profile of each user who is on the social media can be obtained.

This personality information is used to form the clustering of the user. In Collaborative Filtering module Pearson's correlation technique is used to find the similarity between the user and ranking is generated. Using this ranking the recommendation vector obtained.

Depending on the users personalized profile and historical data, user get the list of recommendation. Amazon API is used for performing the content based filtering on this data. Here the all features product like category, price, reviews etc, are used to calculate the similar type of products. Finally, in optimization module, the intersection of recommendation of the both module is taken for getting more precise recommendation for the intended user.

After successful recommendation again user's feedback on the recommendation is taken and accordingly feedback is categories into negative and positive feedback. This feedback is helps to further improvement in the recommendation and to evaluate the performance of the system.

IV. Experiments

A. Dataset:

1) Dataset Informatino:

This Review data is for research purposes only and it get available after making request to Prof. Julian McAuley (julian.mcauley@gmail.com).

This dataset consists of reviews from amazon. The data span a period of 18 years, including ~35 million reviews up to March 2013. Reviews include product and user information, ratings, and a plaintext review.

TABLE I. Dataset Statistics

Table Head	Dataset Statistics	
1	Number of reviews	34,686,770
2	Number of usesrs	6,643,669
3	Number of products	2,441,053
4	Users with > 50 reviews	56,772
5	Median no. of words per review	82
6	Timespan	Jun 1995 - Mar 2013

2) Data Format:

```
reviewerID: A3UTQPQPM4TQO0,
asin: 0000013714,
reviewerName: betty burnett,
helpful: [0, 0],
reviewText: We have many of the old, old
issue. But the number had depleted. There
were not  enough books to allow us to use
them regularly. With the additional supply
the books will be used more often.  They
arre a good old standby for gospel
singing.,
overall: 5.0,
summary: I was disappointed that you would
only allow me to purchase 4 when your
inventory showed that you had 14
```

```
available.,
unixReviewTime: 1374883200,
reviewTime: 07 27, 2013
```

Fig2 . Data Format of amazon review dataset

Where, similarity distance measures are as follows.

- product/productId: asin, e.g. amazon.com/dp/B00006HAXW
- product/title: title of the product
- product/price: price of the product
- review/userId: id of the user, e.g. A1RSDE90N6RSZF
- review/profile Name: name of the user
- review/helpfulness: fraction of users who found the review helpful
- review/score: rating of the product
- review/time: time of the review (unix time)
- review/summary: review summary
- review/text: text of the review

3) Data Cleaning:

Data cleaning is the key to extracting meaningful associations between extracted features from the sources mentioned above. By using Python and Amazon API the required data with category is obtained which further group into number of product reviewed by the same user and same product reviewed by number of reviewer. Watson API helps in cleaning of twitter data by using various pre-processing methods.

4) A Big Five Personality Questionnaires:

Here is the list of questions to predict the personality of the user with no Twitter account. The user can give one response for each question. The five options are

- Agree strongly
- Agree a little
- Neither agree nor disagree
- Disagree a little
- Disagree strongly

By answering the list of the questionnaires the big five module calculate the personality of the user.

The formula to calculate the five factors of personality is:

- Openness = 5R + 10 (add reverse of response of 5th and response of 10th question)
- Conscientiousness = 3R + 8
- Extraversion = 1R + 6
- Agreeableness = 7R + 2
- Neuroticism = 4R + 9 (R = item is reverse scored.)

V. RELATED WORK

Many popular recommendation systems make use of collaborative filtering technique and content based filtering technique. Memory based collaborative filtering technique is easy to implement as well as widely used by many system but it has certain problems like it has limited scalability for large dataset and works poorly in sparse data. The processing time is very high. In the model based approach the machine learning and mathematical concepts are used. It lead to increase the performance of the system.

Recently the users are not considered as a single entity for finding out their interest. Instead it is studied that even though user are multifaceted their choices can be predicted with the help of social network such as twitter, facebook etc. user can have similar taste with other person, and can even depend on the choice of their friend and family in the network. Now various giants in software industry like amazon also started of using trust network for recommending items to the user. This solves the sparsity problems of the dataset.

VI. CONCLUSION

The architecture for PRec is highly modular and enables using various algorithms under the business knowledge layer. We have designed an interface for entering business rules that can be used for explicit user feedback.

For the proof of concept the web system is implemented using Django framework in python.

Recommendations based on personality are an effective way of providing dynamism. Moreover, providing user feedback gives the user a sense of control to what is being shown to him. The advantage of this model is that since general algorithms are used, this recommender system is scalable and can easily be integrated with any system.

Though the system comes with many advantages, there are a few improvements that can be done to the same. Using multiprocessing modules, all the cores of the hardware can be used successfully.

Despite these shortcomings, personality based recommender system is an effective way of giving recommendations to users.

REFERENCES

[1] Eyun Gong, Qi Zhang, Xuyang Sun, Xuanjing Huang,"Who Will You "@"?",Shanghai Key Laboratory of Data Science,School of Computer Science, Fudan University,CIKM'15, October 19–23, 2015, Melbourne, Australia.,2015 ACM. ISBN 978-1-4503-3794-6/15/10 ...$15.00.,DOI: http://dx.doi.org/10.1145/2806416.2806458.

[2] Peng Cui, Zhiyu Wang and Zhou Su,"What Videos Are Similar with You? Learning a Common Attributed Representation for Video Recommendation",Department of Computer Science and Technology, Tsinghua University, Beijing, China,cuip@tsinghua.edu.cn, zy-wang08@mails.tsinghua.edu.cn,suhmily@gmail.com,MM'14, November 3–7, 2014, Orlando, Florida, USA,Copyright 2014 ACM 978-1-4503-3063-3/14/11$15.00.,http://dx.doi.org/10.1145/2647868.265494

[3] Bo-Wen Zhang,Bin Geng ,Xu-Cheng Yin,Xiao-Ping Cui ,Jiao Qu ,Fang Zhou,Li Song ,Hong-Wei ,Hao,"Social Book Search Reranking with Generalized Content-Based Filtering",Department of Computer Science and Technology, School of Computer and Communication Engineering,University of Science and Technology Beijing, Beijing 100083, China,Copyright 2014 ACM 978-1-4503-2598-1/14/11 ...$15.00.

[4] Hernan Badenes, Mateo N. Bengualid, Jilin Chen, Liang Gou , Eben Haber, Jalal Mahmud,Jeffrey W Nichols, Aditya Pal, Jerald Schoudt, Barton A Smith, Ying Xuan, Huahai Yang, Michelle X. Zhouo,"System U: Automatically Deriving Personality Traits from Social Media for People Recommendation",IBM, Buenos Aires, Argentina, RecSys'14, October 6–10, 2014,Foster City, Silicon Valley, CA, USA

[5] Fatemeh Vahedian,"Weighted Hybrid Recommendation for Heterogeneous Networks", Center for Web Intelligence, Depaul University, Chicago, IL 60604,fvahedia @cs.depaul.edu,RecSys'14, October 6–10, 2014, Foster City, Silicon Valley, CA, USA.ACM 978-1-4503-2668-1/14/10 ...$15.00.

[6] "International Journal of Information Technology and Knowledge Management",July-December 2012, Volume 5, No.

2, pp. 443-445,ALGORITHM FOR RESEARCH PAPER RECOMMENDATION SYSTEM,Megha Jain

[7] "Do You Want to Know?Recommending Strangers in the Enterprise", Ido Guy, Sigalit Ur, Inbal Ronen, Adam Perer, Michal Jacovi,CSCW 2011, March 19–23, 2011, Hangzhou, China.,Copyright 2011 ACM 978-1-4503-0556-3/11/03...$10.00..

[8] "Zhejiang Key Laboratory of Service Robot:Combining Social Media Information and Music Content",College of Computer Science, Zhejiang University,MM'10, October 25–29, 2010, Firenze, Italy,Copyright 2010 ACM 978-1-60558-933-6/10/10 ...$10.00

[9] "Research Paper Recommender Systems: A Subspace Clustering Approach",Nitin Agarwal, Ehtesham Haque, Huan Liu, and Lance Parsons Arizona State University, Tempe AZ 85281, USA,Supported by grants from Prop 301 (No. ECR A601) and CEINT 2004.

[10] Greg inden, Brent Smith, and Jeremy York Amazon.com, "Amazon.com Recommendations Item-to-Item Collaborative Filtering,"JANUARY • FEBRUARY 2003 Published by the IEEE Computer Society.

[11] Jun Wang, Arjen P. de Vries, Marcel J.T. Reinders, "Unifying User-based and Item-based Collaborative Filtering Approaches by Similarity Fusion" Information and Communication Theory Group, Faculty of Electrical Engineering, Mathematics and Computer Science, Delft University of Technology, Mekelweg 4, 2628 CD Delft, T@tudelft.nl, arjen@acm.org

[12] Ido Guy, Naama Zwerdling, Inbal Ronen, David Carmel, Erel Uziel "Social Media Recommendation based on People and Tags", IBM Research Lab ,Haifa 31905, Israel,{ido,naamaz,inbal,carmel,erelu}@il.ibm.com

[13] Pasquale Lops, Marco de Gemmis and Giovanni Semeraro,"Content-based Recommender Systems: State of the Art and Trend",Department of Computer Science, University of Bari "Aldo Moro", Via E. Orabona, 4, Bari (Italy),lops@di.uniba.it

[14] MARCO TULIO RIBEIRO and NIVIO ZIVIANI , Computer Science Department,"Multi objective Pareto-Efficient Approaches for Recommender Systems",Universidade Federal de Minas Gerais, and Zunnit Technologies, Brazil, EDLENO SILVA DE MOURA , Computer Science Department.

[15] Zhe Zhao, Zhiyuan Cheng, Lichan Hong, Ed H. Chi, Department of EECS, University of Michigan, "Improving User Topic Interest Profiles by Behavior Factorization", Ann Arbor, MI, USA Google Inc, ountain View,CA,USA,zhezhao@umich.edu, zcheng@google.com,lichan@google.com, edchi@google.com

[16] "A Revisit to Social Network-Based Recommender Systems" Hui Li, Dingming Wu, Nikos Mamoulis, Department of Computer Science ,The University of Hong Kong, Hong Kong,{hli2,dmwu,nikos}@cs.hku.hk

[17] "Recommender Systems",Prem Melville and Vikas Sindhwani,IBM T.J. Watson Research Center, Yorktown Heights, NY 10598,{pmelvil,vsindhw}@us.ibm.com

[18] Acknowledgements: slides are adapted from the lecture notes of the book "Recommender Systems: An Introduction" Dietmar Jannach, Markus Zanker, Alexander Felfernig, and Gerhard Friedrich.Sinno Jialin PAN Data Analytics Department,Institute for Infocomm Research, A*STAR, Singapore

[19] "The Application of Data-Mining to Recommender Systems",J. Ben Schafer, Ph.D. University of Northern Iowa

[20] "Scienstein: A Research Paper Recommender System",Bela Gipp, Jöran Beel, Christian Hentschel, Otto-von-Guericke University, Dept. of Computer Science, Magdeburg, Germany, Fraunhofer Institute for Telecommunications, Berlin, Germany,Bela@Gipp.com, Joeran@Beel.org, christian.hentschel@hhi.fraunhofer.de

[21] "A Social Network Based Approach to Personalized Recommendation of",Participatory Media Content,Aaditeshwar Seth and Jie Zhang,School of Computer Science,University of Waterloo, ON, Canada,WorldBank 2002.

[22] "Personalized Research Paper Recommendation System using Keyword Extraction Based on User Profile",Kwanghee Hong, Hocheol Jeon, Changho JeonDepartment of Computer Science & Engineering, Hanyang University, Korea, khhong@cse.hanyang.ac.kr,Agency for Defense Development, Seoul, Korea, hochuls@chollian.net,Department of Computer Science & Engineering, Hanyang University, Korea,chj5193@hanyang.ac.kr