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Movie Recommendation Systems using Sentiment Analysis and Cosine Similarity

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ABSTRACT

As Artificial Intelligence and Machine Learning is growing at a rapid rate over the past few years, so is the amount of data increasing exponentially on the internet. Due to this people find it difficult to choose the exact information they are looking for , learners find it difficult to suggest users exactly what they require. Here comes Recommendation Systems into picture to guide users towards the information according to their preferences. In context of Recommendation of Movies and TV shows on Online Streaming platforms ,this paper is aimed to explain making and implementation of Movie Recommendation Systems Using Machine Learning Algorithms, Sentiment Analysis and Cosine Similarity

KEYWORDS: *Recommendation Systems, Collaborative Filtering, Content Based Filtering, Sentiment Analysis*

I. Introduction

The main use of Recommendation Systems is to help users to have personalised results according to their preferences. Recommendation Systems can also be used as a filtering technique to take out the best result from a set of predicted results by use of some Machine Learning Algorithm target according to the viewer search. Movie suggestions for users are dependent on web-based models. As Movies can be segregated on basis of genres like thriller, animation, comedy, action, drama etc. Another way to categorize movies are on the basis of some metadata such as cast ,year of release, language or director. Nowadays, Most of online video-streaming platforms provide a number of similar types of tv shows and movies to the user by the help of utilising users previous search keywords and previous watch history of the user.

These Movie Recommendation Systems [23]-[25]-[48]-[3]-[53] helps the user to search the movies or shows of their choice and hence reduce their time to think about choosing what to watch. The main goal while building a Movie Recommendation System is to make it reliable and efficient in order to provide the suggestions to users accurately what they are looking for. Basically Recommendation Systems are divided into two different types Collaborative Filtering (CF) and Content Based Filtering (CBF).

As humans , it is our tendency to take the decisions to take decision on basis of the facts and data we already have stored in our brain , by looking some information over the web and this behaviour of ours gives rise to the concept of Collaborative Filtering. Resnick et al. [37] introduced the concept of Collaborative Filtering in netnews, to help people find articles they liked in a huge stream of available articles. It helps people to make the choices according to the perspective of other people. If the ratings of two users are similar they are considered as like-minded. While in the case of Content Based Filtering results are suggested on the basis of contextual similarity of two items. As of today with the rise of multiple social media platforms like Facebook, Instagram, Reddit, Twitter etc . people tend to share their ideas easily with other people. Twitter [1]-[2]-[13] is one of the most popular social media platforms founded in 2006 where users can express their thoughts in limited characters with other users. There is a data pool of tweets about the reviews on various movies known as "MovieTweetings" which can be used to get movie reviews from distinct twitter users. In this paper, we propose a movie recommendation system by fusing the movie reviews from Kaggle dataset of 5000 different movies from year 2008 to 2017,taking data from wikipedia of movies from year 2018 to 2020 and their reviews for sentiment analysis from TmdB website using TmdB API.

The main contributions of the paper are as follows:

1. Proposing a Content Based Movie Recommendation System using Cosine Similarity score.
2. A NLP Sentiment analysis model to boost up recommendation system.

II. Related Work

Recommendation Systems are considered as one of effective knowledge management engines that helps us filter out unwanted data and provide targeted data based on the feedbacks from old data and similar data from user's search. Many Recommendation Systems have been introduced till date following different approaches for the computation like CBF, CF and hybrid models for recommendation. Sentiment Analysis is also used to improve the recommendation efficiency.

A. Content Based (CB) , Collaborative Filtering (CF) and Hybrid Filtering

Many Recommendation approaches have been proposed in literature for recommending the results. At first, Collaborative Filtering technique was introduced to use in recommending items based on collection of inputs from users and based on available metadata. One recommendation system was introduced by combination of pre and post purchase ratings proposed by Guo et al. [18]. Soleymani et al. [43] worked on a ranking of movie scenes, based on arbitrary user's emotion and video content based features. Their observations were that the scenes of movies are correlated with users self assessed arousal and valence. Peripheral physiological signals were utilized to categorise and rank video contents. Implicit ratings from the number of pages the users read was inferred by Yang et al. [51]. The more pages users read , the more they tend to like it. This concept is helpful in the cold start process of Collaborative Filtering technique. Optimisation of a Recommendation System is a difficult problem. There are some methods for optimising a recommender system by researchers like particle swarm optimiza-tion [45], gray wolf optimization [22], artificial bee colony [19] and genetic algorithms [6], etc. By using bio-inspired gray wolf optimizer and fuzzy c-mean (FCM) clustering techniques , a recommendation engine was made by Katarya et al. Gray optimizer was only applied to the initial part of the cluster. The movie ratings were then predicted on the basis of similarity scores. The problem of cold start and reducing scalability was solved by the improvement in the existing framework in [21] proposing ABC-KM (artificial bee colony and k-mean cluster) framework for collaborative movie recommendation . With comparison to existing frameworks the combination of hybrid cluster and optimization technique showed better results .

The most widely used and researched recommendation technique is Content-based Filtering. Description of the item and a profile of the users preferences are used in Content-based filtering. Cantador et al. [9] proposed the use of user and item profiles by describing them in terms of weighted lists of social tags to provide music recommendations. Meteran et al. [46] introduced a Personalized Recommender System (PRES) to give suggestions of articles for home improvement by the use of similarity between the user profile vector and a document was formed by using the combination of TF-IDF and the cosine similarity, where as Goossen et al. [17] introduced a new method for news recommendation based on TF-IDF and a domain characteristics which was called CF-IDF. Results of CF-IDF as compared to TF-IDF approaches were better on several measures such as accuracy, recall, and the F1-Score when tested and implemented on the Athena framework. The latest studies have shown that the hybrid methods are better than traditional CF and CBF methods. The major advantage where hybrid methods edge over the traditional methods is they use the combination of multiple individual classic recommendation techniques by improving their drawbacks. In [30], a content-boosted Collaborative Filtering recommender is designed by the authors which used complete content-based features in a collaborative framework. It has shown many improvements in prediction, first-rater and the sparsity problem. Zhang et al. [52] introduced a technique which was based on user recommender interaction that takes input from the user, recommends N number of items to the user, and put the user choice in record until none of the recommended items is being used again as feedback. In [32], a mobile recommender system by combination of a hybrid recommendation engine and a mobile 3D GIS architecture is introduced. For its testing , some users were selected from an age group of 24-48 years. For the evaluation of its performance,users were instructed to search for restaurants, bars and hotel accommodation while walking or driving on highways. The feedback of users displayed a competent performance because of the 3D map-based interface which also helps to overcome the limited display size of the majority of mobile phones.

B. *Sentiment Analysis*

Sentiment analysis [35]-[8]-[29]-[36]-[15]-[50] is commonly used to retrieve user reviews and reactions over a particular item or topic. In [14], rating of products for online software services is depicted by use of sentiment analysis. Its research enhances both CBF and CF algorithms by the use of review techniques such as sentiment analysis and subjective logic. This technique can also be used [28] to calculate the polarity and confidence of review sentences.In [20] , the Valence Aware Dictionary and Sentiment Reasoner (VADER) model for sentiment analysis was proposed by authors. The combination of some lexical features is used for five general rules that embody grammatical and syntactical conventions for expressing and emphasizing the user's sentiment intensity, F_1 score of 0.96 was also recorded to classify the tweets into positive, neutral, and negative classes. In [4], an automatic feedback technique is proposed on the basis of data collection from Twitter database. Some classifiers like Support Vector Machine Naive Bayes, and Maximum Entropy are used over twitter comments. In [39] , authors have proposed a music recommendation engine for mobile phones where songs are recommended to a user based on the mood of the user. A study was performed on 100 participants (50 men and 50 women) to fill out their preferred type of music as choice in their profiles. Afterwards, it was observed that the user's profile has shown 91% user satisfaction rating. The author has proposed the K-Bridge technique to solve the cold start problem of CF systems in [26]. The results showed an enhanced recommendation system can be used by bridging the gap between the communication knowledge , social networking sites and programs being watched over television. Also a rating inference approach to transform text reviews in form of ratings for easy integration in sentiment analysis and CF technique was proposed in [24] .

III. PROPOSED SYSTEM

A hybrid recommender system model is proposed in this paper whose results are improved using sentiment analysis and cosine similarity score. Experimental evaluations, both quantitative and qual-itative demonstrate the validity and effectiveness of our method. In Fig.1, our sentiment based recommendation system is shown. In this part, we are describing the different parts and components of the proposed recommendation system

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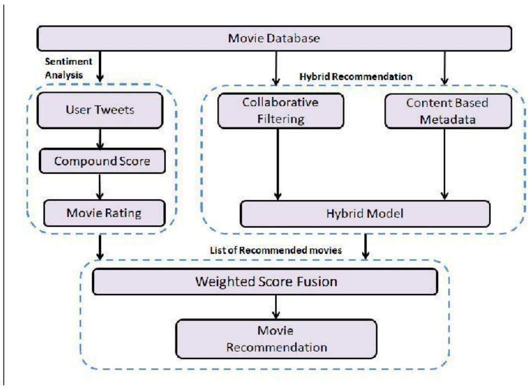

Fig. 1: Proposed Movie Recommendation System.

A. *Datasets used*

There are two different databases to be used to build the recommender system , the first one is movie ratings of Top 5000 movies from year 2008 to 2017 which is available on Kaggle and other is user tweets from MovieTweetings database. MovieTweetings database has collection of reviews of multiple movies that can be easily used in building sentiment analysis model without filtering data out in the pre-processing stage. It provides up to date movie ratings. It is diverse but has a low sparsity. Table I displays details gathered from MovieTweetings database.

Metric	Value
Ratings	646410
Unique Users	51081
Unique Movies	29228
Start Year	1894
End Year	2017

Table I : Details from database of MovieTweetings

Movies are shown distributed according to years in Fig.2. This database has three major components, first is mapping of twitter users with their user IDs, second ratings gathered from users tweets and last component and last component is the information about a movie which includes cast and genre of the movie.

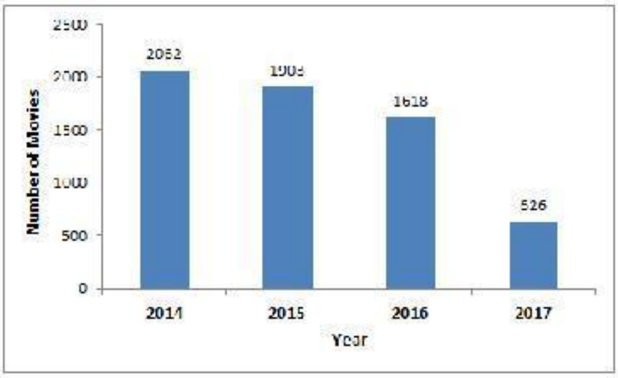

Fig. 2: Distribution of movies according to years.

The data we have extracted from Movie Tweetings database contains mainly the movie release year and users ratings for that particular movie. This data can only be used for social filtering of users so that their ratings won't overlap with each other . It can be further used for collaborative filtering techniques where recommendation is made using the similarity of ratings of different users. In our proposed model the cosine similarity score of similar ratings from different users as well as the socially filtered items are used. To extract the attributes of multiple movies The Movie Database (TMDB) API was used . TMDB is the major source of getting the various attributes of multiple movies in more than 30 different languages. For that we have to set up an official TMDB account and generate one independent API key which will be used everytime we need to extract the information of attributes of a movie . The movie attributes extracted from MovieTweetings database are shown in Table II :

Attribute	Value
MovieID	0451279
Title	Wonder Woman
Runtime	141 min
Genre	Action,Adventure,Fantasy
Director	Patty Jenkins
Writer	Allan Heinberg
Actors	Gal Gadot,Chris Pine
Rating	7.6 Massachusetts Institute of Technology in 1996.
Production Companies	DC Films,Tencent Pictures
Popularity	524.772
Language	en
Production Countries	United States of America
Budget	816303142

Table II: Attributes gathered from MovieTweetings database

B. Preprocessing and Sentiment Analysis of Users Tweets

Tweets extracted from MovieTweetings database contain some unwanted features like emoticons , symbols , web links and repetitive stop words which are removed by preprocessing techniques such as Natural Language processing , tokenization and POS tagging as shown in Fig.3 .

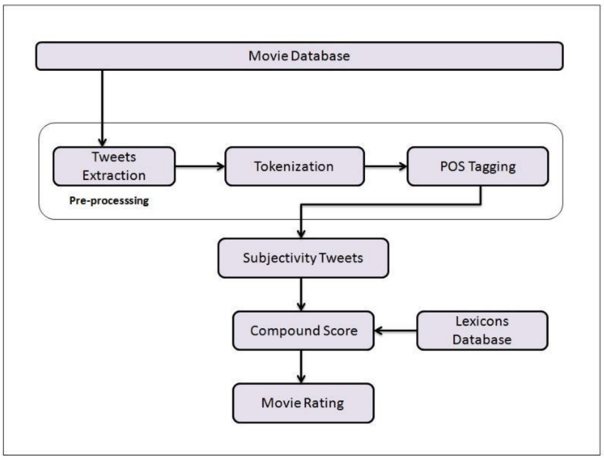

Fig.3: Preprocessing and Sentiment Analysis of extracted tweets

After preprocessing is done, the extracted features are used for sentiment analysis to be used in our proposed model. The use of VADER method is done in the process of Sentiment Analysis and it is computationally very efficient . VADER creates the lexicons of sentiments and maps the sentiment words from the users reviews.

C. Hybrid Recommender System

Content Based recommendation and Collaborative Filtering is combined to build a Hybrid Recommendation System. Let $f = ff\ 1, f2,, fg$ and $q = fq\ 1, q2,, q\,n\,g$ are Content Based Feature vectors and weighted vectors respectively. The Closeness C of two items i and j can be represented as :

$$PN\ n = 1\ f\,n(An\,i\ ;\ An\,j\ );\ \ for \quad C(i\ ,j\ ) \qquad (1)$$

where $f\,n(Ani\ ;\ Anj\ )$ represents the similarity between Ani and Anj values from two different items to be compared. By combining closeness vector C of every item and multiplying it by weighted vectors q, Fij is generated. Fij is called the Feature matrix with dimension $(M\,M)/2$ .Let $U = fu\ 1;\ u2;\ ;\ u\,n\ g$, here u being the user from database, for M items a User-Matrix is made.This User-Matrix is used to predict ratings of users for an arbitrary item i by use of the K-nearest neighbours algorithm. This is commonly used in Collaborative Filtering technique [42]. Analysing K nearest neighbours rating is defined in (2).

$$rating \quad (u;\ i\ ) = 1X/\ K\ k2K\ similarity \qquad (user \quad u;\ user \quad v\,k\ ) \qquad (2)$$

Optimal feature weights q can be found using (3) and (4) as :

$$S(i\ j\ ) = qf\,ij \qquad (3)$$

$$S(i\ ;\ j\ ) = q1\ f1(A1i\ ;\ A1j\ ) + q2\ f2(A2i\ ;\ A2j\ )\ q\,n\ \ f\,n(Ani\ \ ;\ Anj\ ) \qquad (4)$$

IV. Experimental Results

In this section recommendation results drawn from our proposed model are displayed and analysed .

A. Correlation Coefficient

From correlation coefficient accuracy and efficiency of sentiment analysis hybrid model can be determined easily. The statistical analysis between X Sentiment ratings and Y Movie ratings is taken to find the Correlation coefficient. The various types of statistical correlation coefficients are Spearman Rank Order, Correlation Coefficient (SROCC), Kendall Rank Correlation Coefficient (KRCC) and Pearson Linear Correlation Coefficient (PLCC). The calculated value of PLCC was 0.76

B. Evaluation Metric

In general the relevant recommendations are suggested to users using the recommender system, not by predicting values of items directly.
The specific suggestions to likeable users are called Top N recommendation in [10]-[11]-[40]. The very common evaluation metrics RMSE (Root Mean Squared Error) and MSE (Mean Squared Error) can be used , but these two are insignificant for our proposed model . So an alternative evaluation metric known as Precision Score is used by us which is defined as movies that are relevant for users to movies that are recommended by our model. In equation (5) Precision is defined as :

$$Precision \qquad = L\,rel \quad \backslash\ L\,rec \quad /L\,rec \qquad (5)$$

where $L\,rel$ shows the relevant movies and $L\,rec$ shows the recommended movies.

C. Comparative and Qualitative Analysis

Our proposed model is compared with basic recommender models in this section, Sentiment Analysis model and Hybrid models were used by us as base model incorporating our proposed model . Hybrid model is created by use of Collaborative Filtering and Content Based Filtering. Movies are recommended on the basis of similarity of awesome features like the genre, director, actor of the particular movie whereas Sentiment Analysis model takes only the similarity of users tweets and ratings into consideration.
Considering the qualitative results of some of the recommended movies by our proposed model is shown in Table III which also shows that some of the movies are common which were taken from IMDB and TMDB . In Table III , Qualitative analysis of Wonder Woman movie is shown and some movies are intersecting with either IMDB or TMDB.

IMDb	TMDb	Recommendations from the proposed system
Justice League	Guardians of the Galaxy Vol. 2	Batman v Superman: Dawn of Justice
Batman v Superman : Dawn of Justice	Spider-Man: Homecoming	Suicide Squad
Suicide Squad	Logan	Thor: Ragnarok
Thor: Ragnarok	Thor: Ragnarok	Justice League
Spider-Man: Homecoming	Justice League	Warcraft
Deadpool	Pirates of the Caribbean: Dead Men Tell No Tales	Doctor Strange
Logan	Doctor Strange	Guardians of the Galaxy Vol. 2
Captain America: Civil War	Baby Driver	Kong: Skull Island
Doctor Strange	Kong: Skull Island	The LEGO Batman Movie
Guardians of the Galaxy Vol. 2	Life	Batman and Harley Quinn

Table III : Qualitative analysis of movies.

V. Conclusion

Recommendation Systems are a great tool to filter out information and provide only the relevant information to the user. The Recommendation System proposed in this paper uses Sentiment Analysis and Hybrid model of Collaborative Filtering and Content Based Filtering techniques. The main use of Sentiment Analysis in the proposed model was to observe reviews of users for a particular movie. Weighted cosine similarity score was also used to increase accuracy of model. It is found that this proposed model produced much better results than the other basic models. As variety of movie attributes were taken into consideration while training the model, users can be satisfied with the recommended results.

References

[1] Fabian Abel, Qi Gao, Geert-Jan Houben, and Ke Tao. Analyzing user modeling on twitter for personalized news recommendations. In International Conference on User Modeling, Adaptation, and Personalization, pages 1–12. Springer, 2011.

[2] Fabian Abel, Qi Gao, Geert-Jan Houben, and Ke Tao. Twitter-based user mod-eling for news recommendations. In International Joint Conference on Artificial Intelligence, volume 13, pages 2962–2966, 2013.

[3] Gediminas Adomavicius and Alexander Tuzhilin. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE Transactions on Knowledge and Data Engineering, 17(6):734–749, 2005.

[4] Minara P Anto, Mejo Antony, KM Muhsina, Nivya Johny, Vinay James, and Aswathy Wilson. Product rating using sentiment analysis. In International Con-ference on Electrical, Electronics, and Optimization Techniques, pages 3458– 3462. IEEE, 2016.

[5] Ehsan Aslanian, Mohammadreza Radmanesh, and Mahdi Jalili. Hybrid recom-mender systems based on content feature relationship. IEEE Transactions on Industrial Informatics, 2016.

[6] Jesus Bobadilla, Fernando Ortega, Antonio Hernando, and Javier Alcala´. Im-proving collaborative filtering recommender system results and performance us-ing genetic algorithms. Knowledge-based systems, 24(8):1310–1316, 2011.

[7] Robin Burke. Hybrid recommender systems: Survey and experiments. User modeling and user-adapted interaction, 12(4):331–370, 2002.

[8] Erik Cambria. Affective computing and sentiment analysis. IEEE Intelligent Systems, 31(2):102–107, 2016.

.Ivan´ Cantador, Alejandro Bellog´ın, and David Vallet. Content-based recommen-dation in social tagging systems. In Proceedings of the Fourth Conference on Recommender systems, pages 237–240. ACM, 2010.

[9] Paolo Cremonesi, Yehuda Koren, and Roberto Turrin. Performance of recom-mender algorithms on top-n recommendation tasks. In Proceedings of the Fourth Conference on Recommender Systems, pages 39–46. ACM, 2010. ISBN 978-1-60558-906-0.

[10] Mukund Deshpande and George Karypis. Item-based top-n recommendation algorithms. ACM Transactions on Information Systems, 22(1):143–177, 2004. ISSN 1046-8188.

[11] Simon Dooms, Toon De Pessemier, and Luc Martens. Movietweetings: a movie rating dataset collected from twitter. In Workshop on Crowdsourcing and Human Computation for Recommender Systems, 2013.

[12] Xin Fu and Yun Shen. Study of collective user behaviour in twitter: a fuzzy approach. Neural Computing and Applications, 25(7-8):1603–1614, 2014.
[13] Lahiru S Gallege and Rajeev R Raje. Towards selecting and recommending online software services by evaluating external attributes. In Eleventh Annual Cyber and Information Security Research Conference, page 23, 2016.
[14] Himaanshu Gauba, Pradeep Kumar, Partha Pratim Roy, Priyanka Singh, Debi Prosad Dogra, and Balasubramanian Raman. Prediction of advertisement preference by fusing eeg response and sentiment analysis. Neural Networks, 92: 77–88, 2017.
[15] David Goldberg, David Nichols, Brian M Oki, and Douglas Terry. Using collab-orative filtering to weave an information tapestry. Communications of the ACM, 35(12):61–70, 1992
[16] Frank Goossen, Wouter IJntema, Flavius Frasincar, Frederik Hogenboom, and Uzay Kaymak. News personalization using the cf-idf semantic recommender. In Proceedings of the International Conference on Web Intelligence, Mining and Semantics, page 10. ACM, 2011.
[17] Guibing Guo and Mohamed Elgendi. A new recommender system for 3d e-commerce: An EEG based approach. Journal of Advanced Management Science, 1(1):61–65, 2013
[18] Chia-Cheng Hsu, Hsin-Chin Chen, Kuo-Kuang Huang, and Yueh-Min Huang. A personalized auxiliary material recommendation system based on learning style on facebook applying an artificial bee colony algorithm. Computers & Mathe-matics with Applications, 64(5):1506–1513, 2012.
[19] Clayton J Hutto and Eric Gilbert. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In Eighth International Conference on Weblogs and Social Media, 2014.
[20] Rahul Katarya. Movie recommender system with metaheuristic artificial bee. Neural Computing and Applications, pages 1–8, 2018.
[21] Rahul Katarya and Om Prakash Verma. Recommender system with grey wolf optimizer and fcm. Neural Computing and Applications, pages 1–9, 2016.K. Chen, *Linear Networks and Systems* (Book style). Belmont, CA: Wadsworth, 1993, pp. 123–135.
[22] Rahul Katarya and Om Prakash Verma. An effective collaborative movie rec-ommender system with cuckoo search. Egyptian Informatics Journal, 18(2): 105–112, 2017.
[23] Cane WK Leung, Stephen CF Chan, and Fu-lai Chung. Integrating collaborative filtering and sentiment analysis: A rating inference approach. In Proceedings of the ECAI workshop on recommender systems, pages 62–66, 2006.
[24] Fangfang Li, Guandong Xu, and Longbing Cao. Two-level matrix factorization for recommender systems. Neural Computing and Applications, 27(8):2267– 2278, 2016
[25] Hui Li, Jiangtao Cui, Bingqing Shen, and Jianfeng Ma. An intelligent movie recommendation system through group-level sentiment analysis in microblogs. Neurocomputing, 210:164–173, 2016.H. Poor, *An Introduction to Signal Detection and Estimation*. New York: Springer-Verlag, 1985, ch. 4.
[26] Pasquale Lops, Marco De Gemmis, and Giovanni Semeraro. Content-based rec-ommender systems: State of the art and trends. In Recommender Systems Hand-book, pages 73–105. Springer, 2011.
[27] Steven Loria. Textblob: simplified text processing. Secondary TextBlob: Simpli-fied Text Processing, 2014.
[28] Walaa Medhat, Ahmed Hassan, and Hoda Korashy. Sentiment analysis algo-rithms and applications: A survey. Ain Shams Engineering Journal, 5(4):1093– 1113, 2014.
[29] Prem Melville, Raymond J Mooney, and Ramadass Nagarajan. Content-boosted collaborative filtering for improved recommendations. Aaai/iaai, 23:187–192, 2002
[30] Cristiano Nascimento, Alberto HF Laender, Altigran S da Silva, and Mar-cos Andre´ Gonc¸alves. A source independent framework for research paper rec-ommendation. In Proceedings of the Eleventh Annual International Joint Con-ference on Digital libraries, pages 297–306. ACM, 2011.
[31] Jose´ M Noguera, Manuel J Barranco, Rafael J Segura, and Luis Mart´ıNez. A mobile 3d-gis hybrid recommender system for tourism. Information Sciences, 215:37–52, 2012.
[32] Simon Philip, P Shola, and A Ovye. Application of content-based approach in research paper recommendation system for a digital library. International Journal of Advanced Computer Science and Applications, 5(10), 2014.
[33] Carlos Porcel, A Tejeda-Lorente, MA Mart´ınez, and Enrique Herrera-Viedma. A hybrid recommender system for the selective dissemination of research resources in a technology transfer office. Information Sciences, 184(1):1–19, 2012.
[34] Rudy Prabowo and Mike Thelwall. Sentiment analysis: A combined approach. Journal of Informetrics, 3(2):143–157, 2009.
[35] Kumar Ravi and Vadlamani Ravi. A survey on opinion mining and sentiment analysis: tasks, approaches and applications. Knowledge-Based Systems, 89:14– 46, 2015.
[36] Paul Resnick, Neophytos Iacovou, Mitesh Suchak, Peter Bergstrom, and John Riedl. Grouplens: an open architecture for collaborative filtering of netnews. In Proceedings of the Conference on Computer Supported Cooperative Work, pages 175–186. ACM, 1994.
[37] Ade Romadhony, Said Al Faraby, and Bambang Pudjoatmodjo. Online shop-ping recommender system using hybrid method. In International Conference of Information and Communication Technology, pages 166–169. IEEE, 2013.B. Smith, “An approach to graphs of linear forms (Unpublished work style),” unpublished.
[38] Renata L Rosa, Demsteneso Z Rodriguez, and Grac¸a Bressan. Music recommen-dation system based on user’s sentiments extracted from social networks. IEEE Transactions on Consumer Electronics, 61(3):359–367, 2015.
[39] Alan Said, Alejandro Bellog´ın, and Arjen De Vries. A top-n recommender sys-tem evaluation protocol inspired by deployed systems. In LSRS Workshop at ACM RecSys. Citeseer, 2013.
[40] Vivek Sembium, Rajeev Rastogi, Atul Saroop, and Srujana Merugu. Recom-mending product sizes to customers. In Proceedings of the Eleventh Conference on Recommender Systems, pages 243–250. ACM, 2017.
[41] Yue Shi, Martha Larson, and Alan Hanjalic. Collaborative filtering beyond the user-item matrix: A survey of the state of the art and future challenges. ACM Computing Surveys, 47(1), 2014.
[42] Mohammad Soleymani, Guillaume Chanel, Joep JM Kierkels, and Thierry Pun. Affective ranking of movie scenes using physiological signals and content anal-ysis. In Second Workshop on Multimedia Semantics, pages 32–39, 2008.