Proceedings of the International Conference on Artificial Intelligence and Smart Systems (ICAIS-2021)
IEEE Xplore Part Number: CFP21OAB-ART; ISBN: 978-1-7281-9537-7

A Comprehensive Survey on Movie Recommendation Systems

R. Lavanya[1*], Utkarsh Singh[2], Vibhor Tyagi[3]
[1]Department of Computer Science and Engineering, SRM Institute of Science and Technology, Kattankulathur, Chennai- 603203, INDIA, Email ID: lavanyar@srmist.edu.in*
[2]Department of Computer Science and Engineering, SRM Institute of Science and Technology, Kattankulathur, Chennai- 603203, INDIA,
Email ID: singh.utkarsh26@gmail.com, vibhort1999@gmail.com

2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS) | 978-1-7281-9537-7/20/$31.00 ©2021 IEEE | DOI: 10.1109/ICAIS50930.2021.9395759

***Abstract* – Internet technology has occupied an important part of human lives. Users often face the problem of the available excessive information. Recommandation system (RS) are deployed to help users cope up with the information explosion. RS is mostly used in digital entertainment, such as Netflix, prime video, and IMDB, and e-commerce portals such as Amazon, Flipkart, and eBay. The two traditional methods namely, collaborative filtering (CF) and content-based approaches consist of few limitations individually. However, any hybrid system, which utilizes the advantage of both the systems to leverage better results. Some fundamental issues faced by movie recommendation systems such as scalability, cold start problem, data sparsity and practical usage feedback and verification based on real implementation are still neglected. Other issues that require significant research attention are accuracy and time complexity problem, which could make RS, a bad candidate for real-world recommendation systems. This literature survey aims to consolidate and structurally categorize all the major drawbacks present in the most common and popular commercial movie recommendation systems.**

Keywords— Movie recommendation system, NLP, sentiment analysis, knowledge discovery, clustering

I. INTRODUCTION

The recent boom of information technology across the globe has alongside brought the rise of online streaming services. These "OTTs" as they are so often called have amassed the massive content libraries over the years and the competition between these streaming services can be cut-throat. They need customers to come to their platforms and when they get there, they want them to stay. This can be achieved by personalizing the content of the show to each user or more precisely, where they analyse the user's watch pattern and recommend movies in accordance to the inferences they make from the observations.

Since, these OTTs cannot possibly employ people to watch over every user based on their utilization are called Recommendation Systems [RS]. Like the name suggests, RS is used to make recommendations (for movies in this case). Strictly speaking, recommender systems employ three types of filtering methods (i) content-based (ii) collaborative and (iii) hybrid (a combination of the previous two). Content-based filtering uses item properties to find out which items are similar and thus recommends items similar to the one in question. Collaborative filtering, which is also the most used of the three, uses similarities between both the users and the items to help make predictions. In the process, a "user-item" matrix is developed to remain essentially as a score of the explicit feedback given to a number of movies by different number of users. This matrix is of the sparse variety. This sparsity is caused due to two main reasons; (a) users cannot possibly watch every movie in the matrix and (b) sometimes even after watching a movie, user will simply refuse to give an explicit feedback (rating). These ratings in the user-item matrix are exploited in simplistic collaborative filtering systems to make recommendations. Since, these ratings are essential, their absence creates a major headache for a simple CF system; and it is this sparsity that has led to researchers using methods other than ratings to extract information about movies. Researchers have proposed various methods to extract information by using implicit feedback (whether a user watched a movie or not, regardless of whether a rating was given or not), to extracting information from visual sources such as movie posters and still to countless others.

II. LITERATURE SURVEY

A lot of research works have been conducted in the area of recommendation systems. This research work has been initialized by considering some of the more recent research advancements made in the field. Tan Nghia Duong et al. published a research paper [3] where he worked on the principle that features such as movie genres or word vectors are considered good representations of item content. These word vectors/genome tags that movies have can describe a movie efficiently. Many of these "genome tags" are semantically similar and can have varying genome scores. The authors attempted to cut down this complexity by creating a new raw genome tag with a composite score using the "word2vec" algorithm. The previous process led to the elimination of several tags however a significant percentage of tags still remained which were linked together, just not semantically. The authors have employed an autoencoder to find such tags. After this process, the space complexity has been brought down significantly and finally matrix factorization methods were applied to the output to ultimately make recommendations. Upon comparison, authors have arrived to the conclusion that their model has exceed other existing ones in terms of RMSE (Root Mean Square Error) and MAE (Mean Absolute Error). These metrics i.e. RMSE and MAE are used to check the accuracy. Less RMSE and MAE value means less error, which signifies more accuracy.

One of the problems mentioned above was that almost every method that involved in clustering has used hard clusters. Remigio Hurtado et al. tried a different approach in this research [5]. To reiterate the previously mentioned point, almost all the previous research papers have used clustering methods that usually dealt with "hard" clusters, meaning that an item strictly belongs to only one cluster and not to any other. However, this paper does not assume this rigidity and instead assigns the probabilities of an item belonging to a cluster, which is called as a "soft" cluster. A user membership matrix is created to include the probabilities of a user belonging to each cluster. Two soft-clustering methods, like BNMF and CFM were used. A third approach was also proposed, wherein the soft-clustering techniques are combined with regular CF methods. Several quality measures were kept in mind during these soft-clustering approaches such as F-partition coefficient which is the amount of overlap between the clusters, Soft compactness which is the measurement of each item to the cluster, Soft separation which is the minimum distance that should exist between the centroids of any two clusters. In addition to this, paper [16] gives a detailed and comprehensive view on soft set theory and how this approach is better at targeting conflict situation than rough set approach as it provides the results in less computational time (in seconds) of about 8.05%. The authors claimed that the use of soft set theory has a great potential in the field of recommendation systems. It can be used to find out the nearest neighbors of movie items or users while clustering based on strength, support, coverage and certainty.

While talking about the computational time of a movie recommendation system, few models have also been prepared which keep the timeliness and scalability of the system in mind. For ex. The authors of paper [18] developed a simple but effective real time movie recommendation system. Firstly, they partitioned users by evaluating their user profile attributes and using a simple but highly efficient algorithm. Secondly, a virtual opinion leader is chosen for every cluster who is set to represent the opinions of that particular cluster on behalf of all other users in that cluster. This helps in the reduction of the original dimensionality of the user-item matrix. Finally, a weighted slope one – VU method is devised and is implemented on the virtual opinion leader-item matrix to obtain the final recommendations. This method helps in reducing the complexity of the system and helps in getting quicker results. However, the use of only one user from a cluster may result in the loss of some valuable information and thus the predicted accuracy here is not the best.

Online streaming services like Netflix, Amazon Prime, Disney+ Hotstar, to name a few, have humungous content libraries to choose from, in computational terms that is a very time taking problem. Muppana Mahesh Reddy et al. took this problem into account and measured accuracy levels of recommendation systems that included low-rated movies and those that didn't. In their research paper [10] he compared the performances of a MRS where movies less than the average value (for example 2.5 for a scale of 0-5) are never recommended versus the MRS where there is no such cap on recommendations. The research paper method in its very first stage, excludes all the movies rated below the average rating, in the second step the similar movies are calculated using the Pearson Correlation Coefficient and then finally recommendations are made. While simultaneously a similar process was run without the cap and the final results of the two are compared. On comparison, it was noted that the number of movie below the average rating turned out be quite low for their particular dataset (<10%) so they recommended that those movies be ignored for future purposes to help reduce the cost making recommendations.

The above mentioned works are the ones that have the utmost relevance to what have tried to achieve in this research work. However, there also some researches who took completely different approaches. An instance of that would be XIAOJIE CHEN in his work [2] where he uses the posters and stills of movies' to describe the movie by extracting their aesthetic features. A tool named "VGG16" is used to extract CNN (Convolutional Neural Network) features from movies. Several modifications were made to the "VGG16" such has removing its Softmax layer (which is used to classify images rather than hel p describe them). Using the VGG16 output and rating features, an Aesthetic-aware "United Visual Contents Matrix Factorization" model (UVMF-AES) was created to make recommendations to the user(s). The process was optimized by techniques such as negative sampling and finally recommendations were made.

Another approach made was to exploit the written reviews that users' give or in other words another approach was made to exploit written user reviews. Sumaia Mohammed Al-Ghuribi in [4] he used recommendation systems that work on platforms that allow written feedback. This feedback can be more insightful and meaningful is utilized properly. These platforms ask the user to write about their experience, as well as asking them for a simple overall rating and these reviews are later exploited using NLP techniques to gather useful information and improve recommendations. Three main methods are used here; (a) using stacked-autoencoders. (b) Clustering users around cluster centres and making recommendations in accordance to similar users clustered around the same cluster centre (c) a utility based method is used. PCC score, Euclidean distance and Cosine similarity is used to calculate a utility score between items. And user expectations are learned using pointwise ranking, pairwise ranking and listwise ranking. These attributes are used in the utility function. When it comes to “hand-written” user reviews, NLP techniques are used to find out key words which can be classified as opinion words (polarizing, inflammatory), sentiment words (friendly, insightful) and comparative words (better, worse).

Getting relevant feedback is essential in the development of an accurate RS. It is also very important to make good use of that feedback information by extracting valuable data from it which will ultimately supplement your recommendations. Keeping the same idea in mind, several sentiment-based systems have been developed over the last few years which focus on the emotional tone of the reviews provided in the dataset. The authors in [12] worked on the consideration of users’ feelings in the tweets found in microblogging sites. They used tweets in order to understand the general feeling and perceptions of users in response to a movie. They first carried out the sentiment analysis of the tweets. After that, they developed a hybrid recommendation system using both, content based filtering method and collaborative filtering method. In the end, the hybrid system was incorporated with the results of sentiment analysis which boosted their results and helped getting better results than most traditional methods. Similarly, the authors of the paper [14] developed a hybrid model in collaboration with sentiment analysis on Spark platform. They first created a hybrid recommendation system in order to get a precursory recommendation list. Later, they used sentiment analysis to enhance and optimise the list. Finally, the sentiment analysis and the hybrid recommendation system are implemented on Spark platform. This system ensured fast recommendation results by still managing to provide decent accuracy.

Another researcher, Zhou Zhao, worked on written reviews in [7]. This research paper is concerned with w using written user feedback and their emotional status to make recommendations. The emotion lexicons were used from WordNet. In the first step, lexicon corresponding to six basic emotions i.e., love, anger, fear, joy, sadness and surprise was built. The corresponding primary, secondary and tertiary emotions keywords and their synonyms from WorldNet were added to their respective lexicons and were assigned different weights. In the second step, the review was tokenized; the keywords describing emotion such as ‘happier’ or ‘happily’ were converted to their root word ‘happy’ and so on. As the review is read/analysed tokens are added to the six basic emotions given above (they were all initialized to zero before) and in the end the sum of all these various basic emotions tells us about the various emotions of the user’s feedback. The items are then assigned cosine similarities to each other as well as KLD emotion based similarity before finally making the recommendation to the user. The author(s) also performed the experiment using fuzzy words using the Gaussian, Trapezoid and Triangle models. They made Top-N recommendations and compared the results and found out that the fuzzy emotion based recommendation system proved to be more accurate.

One of the easiest works to read and comprehend was done by Minjae Kim et al. In [1]. Here, user movie watch patterns (changes) were analysed over time using Recurrent Neural Networks and Collaborative Filter. The user-item matrix generated by CF was sparse and did not account for changes in consumption pattern. Pearson Correlation Coefficient was applied to group similar users together and a small sequence of user data was input into the RNN which was used to account for the changes in consumption patterns. Different set of nodes, learning rates and iterations were applied via trial and error to get the best results.

Phonexay Vilakone et al. in [9] proposed an algorithm to improve movie recommendation accuracy using (improved) k-cliques. This research paper uses the k-clique method of graphs. To be more precise the maximal clique method (a clique that cannot be extended by adding more vertices or edges to it). Most of the steps here are the same; (a) user logs in (b) cosine similarity is used on users to cluster them (c) user assigned to a cluster (d) the best possible recommendation is given using the data from the cluster. The basic difference in process are at the second step; the users are clustered together using the k-clique (maximal) to find out the most optimum networks inside what would be our otherwise normal user clusters. After clustering is done using the maximal k-clique technique, we then use data from these clique users to provide recommendations to our users. The maximal k-clique technique showed more efficient results than normal k-clique and other CF techniques. The other major difference here is at user-login; when the user logs in to the system, three essential bits of information namely age, gender and occupation are taken from him to help us in maximal k-clique clustering of the user.

Indira et al. proposed a movie recommendation model for multi-cloud environments in [8]. The selected dataset from which features were selected using the Principle Component Analysis (PCA) algorithm, which were then clustered together using “k-means” clustering and the “Hierarchical Agglomerative Clustering (HCA)” algorithms. “K” cluster centres were defined and the dataset was divided into clusters using the distance of each dataset from every respective cluster centre. The main purpose of hierarchical agglomerative clustering was to produce an ordering of the objects. In the proposed system, the HAC algorithm separates ratings (like 5 points/stars, 4, up to 1). So the prioritized clusters are the output of the HAC algorithm. The “pagerrank” algorithm was then used to assign rankings. After comparisons with other models, the authors concluded that their model produced better precision than other existing models.

Zhou Zhao et al in [6] proposed a model for streaming services that allow users to follow each other on their platforms. It follows something called the “homophily” hypothesis; that users connect to/follow like-minded/similar users and that the users behave differently in a crowd than they would individually. By assuming the previously stated hypothesis, the author attempts to tackle the sparsity problem in matrices. The research works on a multi-modal network which contains two sub-networks. The first network is where the Convolutional Neural Network (CNN) extracts information about items (movies/TV shows) using their textual data and the latter sub-network where the CNN learns about items by extracting information through their visual representation (posters and movie stills). There is a fusion layer which combines the data from the two sub-networks which helps understand the item through both forms of representation, which is finally integrated with the Social-Aware Movie Recommendation (SMR) network (the users’ follower/following network). Upon completion of all of the above mentioned steps, the author(s) used a random-walk learning method to learn about the system to make inferences and finally make recommendations.

One of the major issues that most movie recommendation systems face is the cold-start problem. Cold- start issue arises when a new user enrolls in the system. Since there is no previous data about their preferences, it becomes a bit difficult for the model to suggest a movie that the user may enjoy. The only information that the system can work upon is the users’ profile information (age, gender, location etc.) and therefore, the RS has to make some heavy assumptions. So, to tackle this issue few models have been prepared that work on the principle of knowledge discovery. The authors in [11] proposed HI2Rec, which utilized multiple information in order to learn the user’s and item’s vector representation to get top-N recommendations and address the issues of data sparsity and cold start problem. Initially, they make used of Linked open data to acquire movie related information. Thereafter, they make us of the knowledge representation learning approach and insert the acquired information and the real dataset’s knowledge to a unified vector space. A precursory recommendation list is created with the help of this vector representation and then finally, a collaborative filter method is used to form a final recommendation list. This method was found to outperform many state of the art recommendation models. Similarly, to address the cold start problem, the authors of [19] provided a brief tutorial on the knowledge discovery with linear mixed model. Specifically, they carried out a series of rigorous data analysis and made the use of LME4 R package to help corroborate their claim that young people are likely to be more censorious than the older people when it comes to reviewing the same item.

Data sparsity and accuracy follow an indirect relationship. If we reduce the issue of data sparsity, the accuracy and precision of our model increases. [17] Introduced a new neural user-item coupling learning model. They called it CoupledCF. This CoupledCF learns both, explicit information and implicit information. They believed that various traditional movie recommendation systems assumed the fact that user information is independent from item information and ignored intricate couple relationships between and within users and items. CoupledCF initially takes the help of a CNN based learning network where the user and movie attributes are attained from review texts with the help of an NLP tool (called Doc2Vec) in order to obtain explicit user-movie coupling information. After that, it creates a deep CF in order to acquire this implicit information and ultimately joins the acquired explicit user-movie information with DeepCF to orderly showcase user, movie and user-movie couplings. This model gives more accurate results in comparison to several mainstream recommendation systems.

In paper [19] developed a system based on the integration of opinion mining and similarity analysis. They first collected data and preprocessed it based on some major preprocessing steps. The preprocessed data is then transferred for implicit and explicit attribute extraction. The aspect of the word are further categorized according to the classes. In the end, top-k suggestions are made for a user.

Finally, paper [15] developed a model keeping in mind, the novelty and diversity of recommendations.
The authors here, suggested a new recommendation method based on covariance that works mainly on correlation coefficients. At first, it expresses the positive and negative correlation from experimental samples in spite of having no previous knowledge about the distribution of items. Then CovH, is proposed, that is formed by limiting the popular items in recommendation list which may improve the novelty and diversity of recommendation as compared to Cov.

III. SUMMARY

Here, we have talked about what movie recommendation is, why and where we need it and what research has been done recently in the field. In the literature survey, we have discussed what problems the authors were trying to overcome and how they went about achieving it.

IV. CONCLUSION

Throughout the research, we have found that most movie recommendation systems follow a collaborative filtering approach rather than content based methods. It was also noted that hybrid recommendation systems, were preferred by most authors as they tend to utilize the best of both former approaches.
However, several major drawbacks remain in recommendation systems despite the use of advanced techniques such as deep learning, neural networks, knowledge discovery over the last

few years. These latest techniques have resulted in improvements in some areas of recommendation systems but not all, hence there exists an enormous potential for further advancements in the area.

REFERENCES

[1] Minjae Kim, SungHwan Jeon, Heeseong Shin, Wonseok Choi, Haejin Chung, Yunmook Nah : "Movie Recommendation based on User Similarity of Consumption Pattern Change". 2019 IEEE Second International Conference on Artificial Intelligence and Knowledge Engineering (AIKE)

[2] Xiaojie Chen, Pengpeng Zhao, Yanchi Liu, Lei Zhao, Junhua Fang, Victor S. Sheng , and Zhiming Cui in "Exploiting Aesthetic Features in Visual Contents for Movie Recommendation". IEEE Access, 11 April 2019.

[3] Tan Nghia Duong , Tuan Anh Voung, Duc Minh Nguyen, and Quang Hieu Dang : "Utilizing an Autoencoder-Generated Item Representation in Hybrid Recommendation System". IEEE Access 21 April 2020

[4] Sumaia Mohammed Al-Ghuribi and Shahrul Azman Mohd Noah in "Multi-Criteria Review-Based Recommender System-The State of the Art". IEEE Access, 21 November 2019

[5] Remigio Hurtado, Jesús Bobadilla , Rodolfo Bojorque , Fernando Ortega, and Xin Li : "A New Recommendation Approach Based on Probabilistic Soft Clustering Methods: A Scientific Documentation Case Study". IEEE Access 2018

[6] Zhou Zhao, Qifan Yang, Hanqing Lu, Tim Weninger, Deng Cai, Xiaofei He and Yueting Zhuang in "Social-Aware Movie Recommendation via Multimodal Network Learning". IEEE Transactions on Multimedia (Volume: 20, Issue: 2, Feb. 2018)

[7] Mala Saraswat, Shampa Chakraverty Atreya Kala: "Analyzing emotion based movie recommender system using fuzzy emotion features". Springer (2020)

[8] K. Indira and M. K. Kavithadevi in "Efficient Machine Learning Model for Movie Recommender Systems Using Multi-Cloud Environment". Springer, (2019).

[9] Phonexay Vilakone, Doo-Soon Park, Khamphaphone Xinchang and Fei Hao : "An Efficient movie recommendation algorithm based on improved *k*□clique". Springer (2018).

[10] Muppana Mahesh Reddy, R. Sujithra Kanmani and Dr. B. Surendiran in "Analysis of Movie Recommendation Systems; with and without considering the low rated movies"

[11] Ming He, Bo Wang, and Xiangkun Du: "HI2Rec: Exploring Knowledge in Heterogeneous Information for Movie Recommendation", *IEEE Access 2019*

[12] Sudhanshu Kumar, Kanjar De, and Partha Pratim Roy: "Movie Recommendation System Using Sentiment Analysis from Microblogging Data", IEEE Transactions on Computational Social Systems (Volume: 7, Issue: 4, Aug. 2020)

[13] Zhiyi Chen, Shengxin Zhu, Qiang Niu, and Tianyu Zuo: "Knowledge Discovery and Recommendation with Linear Mixed Model", *IEEE Access 2020*

[14] Yibo Wang, Mingming Wang, and Wei Xu: "A Sentiment-Enhanced Hybrid Recommender System for Movie Recommendation: A Big Data Analytics Framework", Hindawi Wireless Communications and Mobile Computing Volume 2018, Article ID 8263704.

[15] Biao Cai, Yusheng Huang: "Personalised recommendation algorithm based on covariance". The Journal of Engineering, *The 3rd Asian Conference on Artificial Intelligence Technology (ACAIT 2019).*

[16] Khalid Haruna, Maizatul Akmar Ismail, Mohammad Suyanto, Lubna A. Gabralla, Abdullahi Baffa Bichi, Sani Danjuma, Habeebah Adamu Kakudi, Muhammad Sani Haruna, Saber Zerdoumi, Jemal H. Abawajy, And Tutut Herawan:"A Soft Set Approach for Handling Conflict Situation on Movie Selection", *IEEE Access 2019*

[17] QUANGUI ZHANG, LI WANG, XIANGFU MENG, KEDA XU, AND JIAYAN HU: "A Generic Framework for Learning Explicit and Implicit User-Item Couplings in Recommendation", *IEEE 2019*

[18] Jiang Zhang, Yufeng Wang, Zhiyuan Yuan, and Qun Jin: "Personalized Real-Time Movie Recommendation System: Practical Prototype and Evaluation", TSINGHUA SCIENCE AND TECHNOLOGY ISSN 1007-0214 02/12 pp180–191DOI: 10.26599/TST.2018.9010118 Volume 25, Number 2, April 2020.

[19] Nagamanjula R, A.Pethalakshmi:"A Novel Scheme for Movie Recommendation System using User Similarity and Opinion Mining", International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8 Issue-4S2 March, 2019

[20] Pushpalatha, A., Sanmugam J. Harish, Pradeepa K. Jeya, and S. Madhu Bala. "Gadget Recommendation System using Data Science." In 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS), pp. 1003-1005. IEEE, 2020.

[21] Pasumponpandian, A. "A Hybrid-Algorithm for E-project Selection on Social Media." Journal of Information Technology 2, no. 02 (2020): 116-122.