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A REVIEW PAPER ON MOVIE RECOMMENDATION SYSTEM USING HYBRID METHOD

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***Abstract*: The recommendation of the movie is essential in our social life as it has the potential to provide more pleasure than other forms of entertainment. Depending on the interests of the users or the popularity of the movies, this type of system can provide a selection of movies for them to watch. The recommendation system is used for the purpose of suggesting to buy or view products. Meanwhile, customers may not be able to enjoy all accessible new releases or invisible movies due to their restricted time. They still need to choose which movies to watch when they have extra time. This situation is not conducive even for the film sector. Choosing which movies to watch requires a system that can recommend relevant movies that have not been seen in the past or in recent releases, to satisfy consumers and improve movie sales. This study focuses on a review on hybrid technology, a combination of content-based and collaborative filtering, using a new perspective.**

***Keywords* -.** Movie recommendation, Filtering method, Hybrid Method

I Introduction

The recommendation system is a component of everyday life where individuals rely on knowledge to make decisions about what they want to do [14]. Collaboration filtering models take into account the user's previous purchases, as well as decisions made by other users who have made comparable purchases or given numerical ratings to the items they have purchased. After that, many models are used to guess what the user might be interested in (or how they rate certain goods). However, despite the fact that many approaches have been established in the past. Although search is still used in many applications that customize recommendations and face a lack of accuracy, it is still being used due to its widespread use.

These demands pose little difficulties. Alternating list squares, dissociation of singular value, K-near neighborhood method and general predictive algorithm have been used by various educators to solve this problem. There are two main types of memory-based and model-based collaborative filtering approaches. Memory-dependent methods can be easily adapted to use all ratings before the filtering phase, ensuring that their findings are always up-to-date. On the other hand, a model-based system, such as a neural network, develops a model that learns from the knowledge of user-object evaluation and recommends new goods. In order to produce a stronger and more accurate recommendation system, the recommending system still needs to be improved.

As a result of the system's recommendations, consumers can learn more about the products that interest them. In this study, various approaches have been discussed. The necessities of life are never enough to satisfy a person's self-satisfaction, and therefore there is a constant need for pleasure in everyday life. Watching movies is one of the fun things to do in your spare time. Movies are universally popular, regardless of genre or movie age. This is why the film industry is so profitable [11].

Many films or films are released at the same time to get satisfaction. Audience and earn money. However, some people, due to time or money constraints, may not see all new releases. Some people prefer to watch a movie later and because of this they forget what they were going to see. To jog their memory of what they want to see, most consumers turn to the Internet, such as online retailers selling or renting movies [10].

Video-on-demand services are now readily available on the web and smart phones, due to the use of certain video-streaming applications. Smart televisions and set-top boxes with video-streaming capabilities are becoming more common nowadays. Classification methods that use different data organizations and classification methods are common in the field of machine learning. Data for training classification is possible [8].

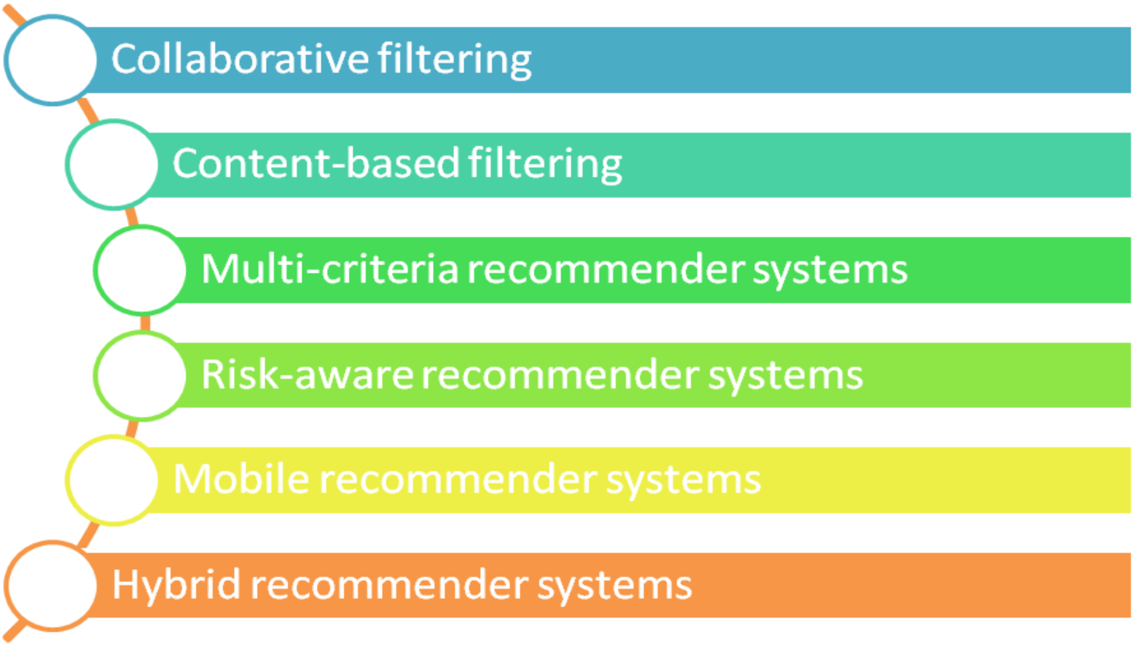

Fig 1: Method for recommendations

II Review Literature

In a work by Ahuja et al. (2021), a recommendation strategy that utilises both KNN algorithms and the K-means technique is envisioned. The client is approached in order to obtain information about the finer points. The user's userid, gender, and age are all provided by the user. The pandas module divides the data generally according to the customer and movies into separate dfs in the processing module. For the K-means module, the movie genre can be shown on an edge of data. WCSS determines the appropriate number of clusters. Pearson's correlation similarity and regularization model uses a matrix to calculate the connection. When determining film ratings, the algorithm employs KNN predictions and the UC grid to compare results.

A pre-processing step eliminates outliers in both Indira and Kavithadevi (2020) and the present study (NPCA-HAC). This is followed by the use of feature selection and principalcomponent analysis. K-means and HAC are used to group the selected characteristics. A trust rating algorithm is used to rate the clustered groupings. The clustering approach utilised in this study resulted in a loss of data owing to dimensionality reduction. Prediction performance and scalability are mutually exclusive. As a result of collaborative filtering, data sparsity, excessive computing complexity, and over-specification can be reduced. Combination models are suggested to provide a real-time item that is tailored to the needs of the consumers. Final recommendation list categorization is based on the MP neuron model. Scalability is an issue that has not been addressed in the suggested paradigm. The new item-centered strategy employs CF and CBF techniques and proposes items based on feelings. Reviews and comments on a certain product are used to extract feelings. Emotions can be used to produce item-to- item similarities. It's a good paradigm, however it doesn't take into consideration scalability and computing time. The method of discovering and crafting a film by taking into account the cinema formats of potential audiences. Users are grouped together based on their shared tastes and the ratings they have given to films they have seen. RNN may be used to evaluate and create movies, as well as to discover patterns in the viewing habits of similar groups of users.

Three methods are employed in [3] and in this paper: a basic RS, a content-based approach, and a CF approach. Machine learning is employed in this project. The chart for the basic recommender system is made using IMDB's method for weighted rating. Two further techniques are followed. Sparsity, new user problems, and decreasing computing efficiency all contribute to decreased performance. It has been shown that item-based collaborative filtering (ICF) is superior to user-based CF in terms of analysis and data processing complexity, as demonstrated in this work. Working performance may be improved by utilising item content and feature vectors. A sign-up system collects the user's personalized information. The experiment's results are used to determine the degree of intimacy between participants. The adjacency matrix of user proximity is formulated at the end of the trial.

This paper (Xu X, 2018) presents a methodology that may take into account feedback from both the item and the user community. It employs Ml tools to increase the quality of suggestion in order to strengthen the model's deep learning. Mapped users and things create a representation of the person and the item. Items may be retrieved and ranked using this visual depiction. As a result, the issue is seen as a way to sort things out. To hone the framework, back propagation is employed.

Two collaborative models are described by Wu et al. (2019) for the usage of a recommender system. User and item collaborative model strategies are used in this work to design a system that takes use of commonalities across entities Explicit rating refers to how customers rate an item on a certain scale. We can ca lculate the total number of NN for each user. PCS [2] is used to discover the correlation between user ratings. Rather of focusing on what the item's users enjoy, items focus on what the thing likes. Recommendation is made based on the item's similarity to the target [6].

Product recommendation system based on content-based filtering proposed in [1] makes use of machine learning algorithm XGBoost to recommend items to the users on the basis of their previous activities and click information collected from the user profile.

Content-based filtering approach has been used by Reddy et al. in [2] for building the movie recommendation system that recommends items to users based on the past behaviour. It also makes recommendations based on similarity of genres. If a movie is highly rated by the user, then movies based on similar genres can also be recommended.

A smart library recommender system has been proposed in [3] which recommends books and other resources to the users and enhances the educational system. The pa-per presents a model that collects data from various sources, after collecting the data, the processing and analysis of the data is conducted. After analysing, the model will then perform collaborative filtering and at the completion of the process, the user receives a recommendation list with items of greater interest and precision. Based on the TrustSVD model and matrix factorization techniques,

Anh Nguyen Thi Dieu et al. provided a new methodology to analyse the rating item and input the implicit effect of item rating to the recommendation system in [4]. The experimental results indicated that this model outperformed the standard Matrix Factorization approach by 18% and the Multi-Relational Matrix Factorization method by 15%..

[5] proposes a survey article on collaborative filtering-based social recommender systems. The authors gave a quick explanation of the task of recommender systems and standard ways that do not employ social network information in this study, and then showed how social network information can be used as an additional input by recommender systems to increase accuracy.

Tae-Yeun Kim et al. in [7] proposed a model of recommendation system which actually recognizes six human emotions. This model is developed by merging collaborative filtering with static speech emotional information recognition that was received in real time from users. It mainly consists of an emotion classification module, emotion collaborative filtering module, and mobile application. In this model the Thayer's extended 2-dimensional emotion model is selected as the emotional model. The SVM classifier was also used to recognize the patterns in the emotion information contained in the optimized featured vectors. This model gives more accurate recommendation to users because of the addition of emotion information.

Haruna et al. [8] proposed a collaborative strategy for the research article recommender system that uses publicly accessible contextual data to identify hidden connections between research papers in order to personalize recommendations. Regard-less of the research field or the user's expertise, this system gives individual recommendations.

3.Hybrid Approach

Collaborative Filtering (CF), content-based filtering, and knowledge-based filtering all have their advantages and disadvantages. If CF has sparsity and cold start issues, then content-based techniques have narrowness and need descriptions of what they look like. It's possible to create a more reliable recommender system by combining two different approaches.

3.1 Types of Hybrid

Weighted Hybrid: The weighted total of the recommendation ratings for each source is used to calculate a score for each suggested item. The user may adjust the weights for each context source by dragging and dropping on sliders. It is desired, but not straightforward, to automatically optimise the weights for each context source. In order to derive an ideal weighting system, empirical bootstrapping can be utilised, but historical data is required.

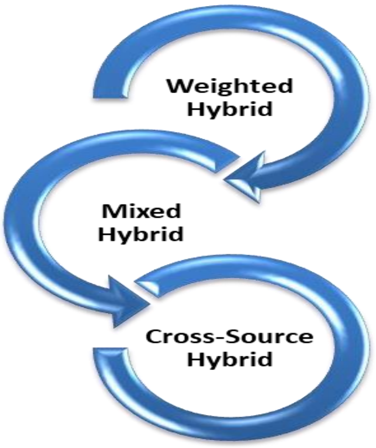

Fig 2: Types of Hybrid

Hybrid Approach

Mixed Hybrid: These recommendations are then sorted by each source and the top-n are selected one at a time by rotating the sources. Individual recommendation ratings are omitted from this technique, which solely evaluates a person's position in a ranked list. Algorithm simply picks the next recommendation from the ranked list if a recommendation is generated from several context sources (i.e. was previously taken from another source).

Cross-Source Hybrid: This method places a high value on recommendations that come from several sources. A suggestion provided by more than one context source / algorithm, such as Facebook's collaborative Filtering and Wikipedia's content-based recommendation, should be regarded as more important [17], according to this study.

Issue with Hybrid Approach

Reliable Integration: The first issue is to make suggestions based on collaborative and content-based data. Collaboration and content-based techniques, either together or separately, may be used in a straightforward manner. This technique, on the other hand, has certain drawbacks. It has been proposed to select a recommended system among traditional ones on the basis of specified quality indicators, however the inadequacies of the selected system are handed down from generation to generation. There is no fundamental rationale for the heuristics-based integration in previous studies [15].

Efficient Calculation: As the number of ratings and users grows, it becomes increasingly difficult for recommender systems to keep up. Memory-based approaches provide a quick and simple solution to this issue because the entire dataset is always used to generate suggestions. Late answers, on the other hand, used a probabilistic technique in an entirely collaborative filtering setting [16] to try to address this shortcoming. On the other hand, an approach for model-based collaborative filtering that gradually trains an aspect model was developed. We are not aware of any studies on incremental adaptation of hybrid recommender systems, thus we cannot comment on them." It's important to think about whether or not past approaches can be used while designing a hybrid architecture.

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III Conclusion

Due to the vast amount of unstructured data on the internet, recommender systems are still a fascinating area for research. Such systems enable the users to get access to their preferred content without having to go through all the available services. So, a good quality recommendation system can remove information barriers for the user's along with increasing the business outcomes. The sorts of recommender systems, such as content-based, collaborative, knowledge-based, and hybrid systems, are classified in this paper, along with their workings, applications, and limits. Currently, hybrid methods are more popular which combine two or more methods to provide accurate recommendations to the users. A survey has also been done to list out the methods that are proposed to overcome these existing limitations. It is expected that in the near future more innovations could be done to come up with much better systems than the existing ones.

REFERENCES

1. Ahuja R, Solanki A, Nayyar A (2021) Movie recommender system using k-means clustering and k-nearest neighbor. Proc 9th IntConf Cloud Comput Data SciEngConflu 2021 263–268.
2. Indira K, Kavithadevi MK (2020) Efficient machine learning model for movie recommender.pdf
3. Yang D, Zhou Z (2019) Personalized mining of preferred paths based on web log. Proc 2013 IEEE 11th IntConf Electron Meas Instruments, ICEMI 2019 2:993–997.
4. Wu CSM, Garg D, Bhandary U (2019) Movie recommendation system using collaborative filtering. Proc IEEE IntConfSoftwEngServSci ICSESS 2018-November 11–15. https://doi.org/10.1109/ICSESS.2018.8663822
5. Xu X, Zhang Y (2018) Collaborative filtering recommendation algorithm based on hybrid similarity. 2017 IntConfComputSyst Electron Control ICCSEC 2017 2018:1372–1375. https://doi.org/10.1109/ICCSEC.2017.8447000
6. Yang D, Zhou Z (2013) Personalized mining of preferred paths based on web log. Proc 2013 IEEE 11th IntConf Electron Meas Instruments, ICEMI 2013 2:993–997.
7. M. Shah, D. Parikh and B. Deshpande, "Movie Recommendation System Employing Latent Graph Features in Extremely Randomized Trees," in Proceedings of the Second International Conference on Information and Communication Technology for Competitive Strategies (ICTCS '16), New York, 2016.
8. Y. Deldjoo, M. Elahi, M. Quadrana and P. Cremonesi, "Using visual features based on MPEG-7 and deep learning for movie recommendation," Int J Multimed Info Retr, vol. 7, p. 207–219, 2018.
9. J. K. Leung, I. Griva and W. G. Kennedy, "Making Use of Affective Features from Media Content Metadata for

Better Movie Recommendation Making," arXiv, 2020.

10. S. Reddy, S. Nalluri, S. Kunisetti, S. Ashok and B. Venkatesh, "Content-Based Movie Recommendation System Using Genre Correlation," in Smart Intelligent Computing and Applications, Singapore, 2019.
11. H. Li, J. Cui, B. Shen and J. Ma, "An intelligent movie recommendation system through group-level sentiment analysis in microblogs," Neurocomputing, vol. 210, pp. 164-173, 2016.
12. P. P. Adikara et al. ISSN 2502-3357 (online) | ISSN 2503-0477 (print) regist. j. ilm. teknol. sist. inf. 7 (1) January 2021 31-42 Movie recommender systems using hybrid model based on graphs with co-rated … http://doi.org/10.26594/register.v7i1.2081 \
13. O.-J. Lee and J. J. Jung, "Explainable Movie Recommendation Systems by using Story-based Similarity," in Explainable Smart Systems 2018 (ExSS ’18), Tokyo, 2018.
14. J. Li, W. Xu, W. Wan and J. Sun, "Movie recommendation based on bridging movie feature and user interest," Journal of Computational Science, vol. 26, pp. 128-134, 2019.

15. W. E. Winkler, "String Comparator Metrics and Enhanced Decision Rules in the Fellegi-Sunter Model of Record Linkage," The Educational Resources Information Center (ERIC), Washington, DC, 2020.
16. C. D. Manning, P. Raghavan and H. Schütze, An Introduction to Information Retrieval, Cambridge:Cambridge University Press, 2019.
17. A. Vukotic, N. Watt, T. Abedrabbo, D. Fox and J. Partner, Neo4j in Action, Greenwich, CT, United States: Manning Publications Co, 2021.