MOVIE RECOMMENDER SYSTEM USING SENTIMENT ANALYSIS

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Abstract - Today, recommendation systems are among the most crucial AI tools for reaching people with relevant data. Content-based filtering and collaborative filtering are examples of methods formerly used in RS. As a result, there are constraints associated with these methods, such as the dependence on users' browsing histories. This study offers a hybrid RS that combines Collaborative Filtering, Content-based Filtering, and Movie Sentiment Analysis to compensate for the impact of such dependencies. In this study, we created a user-emotion-based recommender system to provide movie recommendations based on a user's viewing habits.

Keywords: Recommendation Systems, KNN algorithm, Collaborative filtering, Item-based collaborative filtering, Content based filtering.

I. INTRODUCTION

The proliferation of online resources has brought forth the paradox of information overload in the modern day. The primary goal of recommendation systems [1.] is to help users make decisions based on their past selections. These are often found in knowledge management and e-commerce applications, particularly those dealing with media and consumer goods, as well as travel and hospitality.

The time spent searching for and finding the movies we like is cut significantly by movie recommendation systems. The first step is for RS to look at the movies we've already seen and the locations we've already visited and provide some recommendations. With the proliferation of digital information [2.], RSs are more useful for guiding decision-making across a wide range of contemporary pursuits. Content-based filtering (CBF) and collaborative filtering (CF) are the two basic types of recommendation systems.

Users' opinions and responses to the film are taken into account throughout the movie recommender system's development and operation [3]. Based on the user's viewing history and ratings, our algorithm will recommend the best film to the user. User feedback, both positive and negative, is recorded. Users may rate their moviegoing experiences by clicking the "Good" or "Sad" emoticon, with the latter indicating that the user enjoyed the film while the former indicated that they did not.

II. RELATED WORK

Numerous methods for improving recommender systems have previously been investigated. Some are determined by how heavily the data is weighted, while others are based on what the users want. There are currently several algorithms available that may help the user save both time and effort.

Having a solid foundational understanding of how users rate movies is essential. For the most part, it use film datasets for testing and assessment [4]. However, research is now underway to fix the inefficient functioning of the planned algorithm and system.

- Collaborative Filtering System
- Content based System
- Hybrid System

A. Collaborative Filtering System

Most recommender system predictions are made through collaborative filtering, which is based on a narrow and broad formula, respectively. Narrow now refers to those predictions that must be created or assessed in light of automated predictions [5.] that guide users toward making decisions based on the preferences of others. Let's say Mohan and Ram both enjoy product X and provide favorable comments on it; as a result, Mohan will have more information about other products based on Ram's and Ram's friends' reviews. Financial data, mineral exploration data, etc. are some of the most common applications of CF. There are two other groups into which they might be placed:

- Memory Based approaches
- Model Based approaches

B. Content-based Filtering

Content-based filtering, or CBF for short, is a method that takes into account the user's prior actions and ratings on individual things in order to provide recommendations for similar or related items.

Content-based filtering might also recommend past-era values or films to be seen or rewatched. Using the data we provided, it detects the items we have reviewed and then suggests others like them.

Our technology will recommend a film to the user based on their preferences and previous viewing history. Users may rate movies in the massive collection and have those with similar tastes recommended to them.

C. KNN Algorithm

One of the most crucial algorithms for the recommendation engine. K-nearest-neighbor is the full name of this method. The closest neighbor principle operates on the assumption that similar objects are grouped together into a single, smaller cluster based on their proximity to one another. Since the distance between T and the B cluster is small and the two groups are otherwise indistinguishable, we may infer that T is a member of the B cluster.

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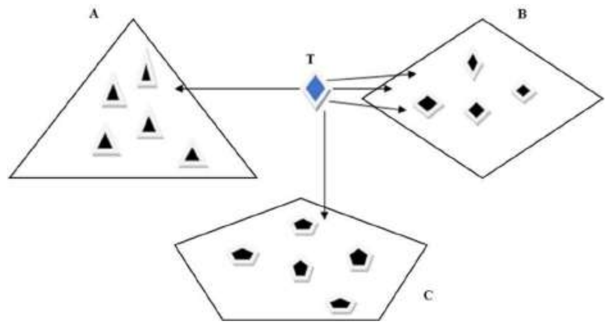


Fig.1 ..KNN algorithm Example

D. Collaborating Filtering Algorithm

This algorithm's primary goal is described only in terms of two distinct types of labor: project-based work and user-based work. However, user-based algorithms are widely employed because of their efficiency for making recommendations to users.

The primary function of this algorithm is to provide recommendations to the user based on their predicted interests and the interests of other users. We employ this algorithm [8.] extensively in our recommender system to assist users find films that suit their tastes.

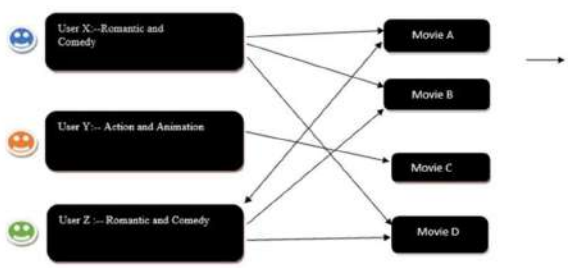


Fig 2. User CF Algorithm Example

We need to provide an example of this algorithm in action in order for it to be fully understood. Let's say user X often watches movies (A,B,D) because he like the romantic comedies.Second, User Z also like both romantic and comedic films, but he is only interested in seeing Movie(B,D).Since the interests of Users X and Z are so similar, we can confidently recommend Movie A to User Z on the grounds that X has already seen it. Similarly, User Y exclusively watches Movie C, which is Action and Animation, yet neither User X nor User Z enjoy it [9].

III. RESEARCH METHEDOLOGY

A. KNN Collaborative Filtering Algorithm

We have utilized the KNN filtering method, commonly known as the Collaborative filtering[9.] technique, to determine which items are closest to the ones we're looking for. The most typical use of this technique is in generating neighbor recommendations or score predictions.

a) ***Calculating Similarity between Users***

Calculating the value of an item rated anticipated by the two users on their suggestion it predicts similarity [10] is one way to assess the proximity between the agent.

In order to anticipate a movie, each viewer will utilize an N-dimensional vector to rate each object. For clarity, we've included an example: to define the proximity between X1 and X3, we must first choose our set of movies, which we'll refer to as "M1, M2, M4, and M5", and only then calculate their similarity scores. The discovered X1 score vector is 1,3,4,2, while the X3 score vector is 2,4,1,5. The cosine parallel formula measures how similar X1 and X3 are to one another.

X/M	M1	M2	M3	M4	M5
X1	1	3	3	4	2
X2	3	1	4		
X3	2	4		1	5
X4	2		2		

Fig. 3. users' similarity evaluation

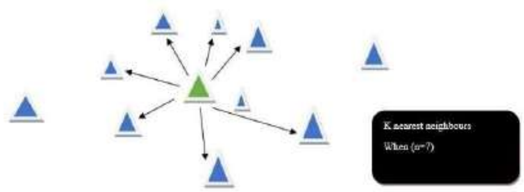
Cosine similarity is the sole formula that is likely to be used to determine a connection between two numbers m and m'.

The angle of cosine [13.] between a pair of users may be used to determine how similar they are to one another as a vector.

$$sim(x, y') = \cos(\vec{X}, \vec{Y}) = \frac{\vec{X} \cdot \vec{Y}}{|\vec{X}| \cdot |\vec{Y}|} = \frac{\sum_{s \in s_{xy}} r_{x,s} r_{y,s}}{\sqrt{\sum_{s \in s_{xy}} (r_{x,s})^2} \sqrt{\sum_{s \in s_{xy}} (r_{y,s})}^2}$$

a) ***KNN Selection of Nearest Neighbour***

The supplied KNN method counts the number of users who are neighbors of U and returns that number as the sim(u,u') value for the users' similarity. As a user, you must now make a choice that will serve as the initialization for the K value used to determine which neighbors are most like you.



*b) **Predict Score Calculation***

Now that we know who our K closest neighbors are, we can figure out how they stack up against one another in terms of score. Here is the key formula used in making such a prediction:-

Step 2: If you want to make a matrix that closely matches the user's perspective during movie viewing, you may use the Cosine Similarity method to find out how similar the users are.

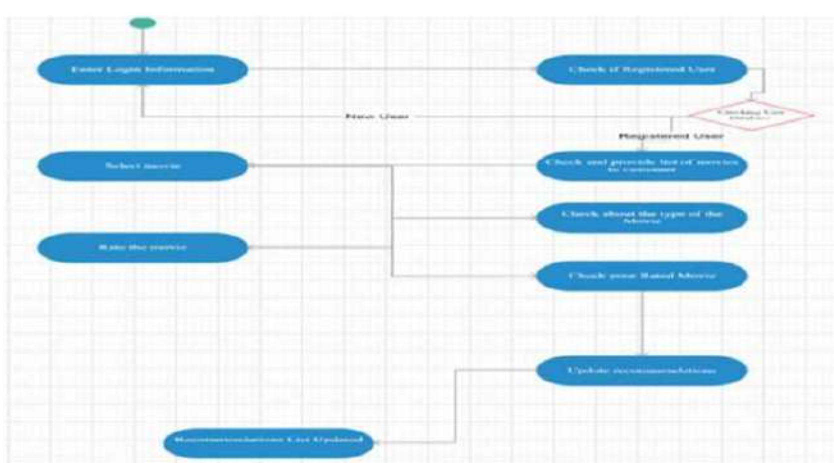
Step 3: The second stage involves taking the resulting K with neighbors that is u and finding the N-th score that displays the largest amount.

Step 4: Use the formula for the predict score to determine the worth of i given the desired u. That's why the KNN collaborative filtering [11.] method is so useful for making movie recommendations. This initiative will also use user feedback to provide movie recommendations. Similarly to how Netflix and Amazon Prime Video promote movies to you based on what you've seen before, our prototype can make suggestions about your viewing interests when you log in.

IV. SYSTEM DESIGNING OF THE SYSTEM

*A. **Architecture Diagram***

B. The server-side workings of our project are shown below in an architectural diagram.Based on the user's historical viewing habits, it will suggest a film for them to watch.



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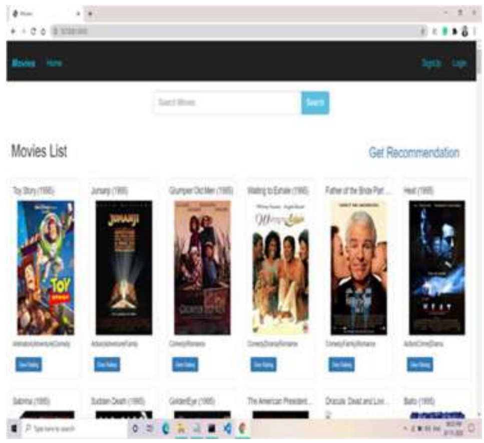
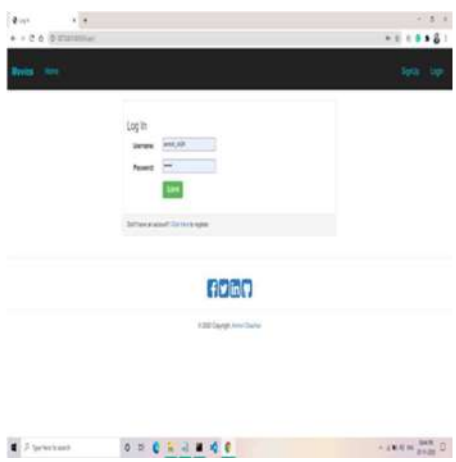
I. EFFECTS OF THE OPERATION ON OUR SYSTEM

In order for our system to function properly, we will advise the user login system to gather all the types of behavioral characteristics of the user, which will then be saved in the user's database [14.] through the user's login module. After a user logs in, the system suggests a movie based on the user's previous viewing history and preferences.





V. CONCLUSION

Movie recommendation systems are helpful because they shorten the time and effort required to find the exact film a user is looking for, given the information provided. In this study, we utilize numerous ML algorithms, such as the Collaborative Filtering [15.] Algorithm with the KNN Algorithm, to provide movie recommendations based on the sentiment analysis of the user. I've tested and analyzed our algorithm using a large dataset that will be put to use in making a user-specific movie recommendation, and it performs well. In this study, we propose and outline a user-emotion-based framework for a movie recommendation system.

REFERENCES

[1] Connor, M., Herlocker, J.: Clustering Items for Collaborative Filtering. In: Proceedings of SIGIR 2001 Workshop on Recommender Systems (2001)

[2] Golbeck, J.: Generating Predictive Movie Recommendations from Trust in Social Networks. In: Stølen, K., Winsborough, W.H., Martinelli, F., Massacci, F. (eds.) iTrust 2006. LNCS, vol. 3986, pp. 93–104. Springer, Heidelberg (2006).

[3] Mohapatra, H., Panda, S., Rath, A., Edalatpanah, S., & Kumar, R. (2020). A tutorial on PowerShell pipeline and its loopholes. International journal of emerging trends in engineering research, 8(4), 975-982.

[4] Xu, X. (2012). From cloud computing to cloud manufacturing. Robotics and computer-integrated manufacturing, 28(1), 75-86.

[5] Mohapatra, H. (2009). HCR using neural network (Doctoral dissertation, Biju Patnaik University of Technology). Retrieved from https://www.academia.edu/39142624/HCR_USING_NEURAL_NE TWORK

[6] Yan, Bo, and Guanling Chen. "AppJoy: personalized mobile application discovery", Proceedings of the 9th international conference on Mobile systems applications and services - MobiSys 11 MobiSys 11, 2011.

[7] Manikrao, U. S., & Prabhakar, T. V. (2005, August). Dynamic selection of web services with recommendation system. International conference on next generation web services practices (NWESP'05). DOI: 10.1109/NWESP.2005.32

[8] Von Reischach, F., Guinard, D., Michahelles, F., & Fleisch, E. (2009, March). A mobile product recommendation system interacting with tagged products. 2009 IEEE international conference on pervasive computing and communications (pp. 1-6). IEEE.

[9] Choi, K., Yoo, D., Kim, G., &Suh, Y. (2012). A hybrid online- product recommendation system: combining implicit rating-based collaborative filtering and sequential pattern analysis. Electronic commerce research and applications, 11(4), 309-317.

[10] Goldberg, D., Nichols, D., Oki, B. M., & Terry, D. (1992). Using collaborative filtering to weave an information tapestry. Communications of the ACM, 35(12), 61-70.

[11] Bell, R. M., & Koren, Y. (2007, October). Scalable collaborative filtering with jointly derived neighborhood interpolation weights. Seventh IEEE international conference on data mining (ICDM 2007) (pp. 43-52). IEEE.

[12] Arora, G., Kumar, A., Devre, G. S., & Ghumare, A. (2014). Movie recommendation system based on users' similarity. International journal of computer science and mobile computing, 3(4), 765-770.

[13] Bhatt, B., Patel, P. P. J., Gaudani, P. H. (2014). A review paper on machine learning based recommendation system. International journal of engineering development and research, 2(4), 3955-3961

[14] Campadelli, P., Casiraghi, E., & Ceruti, C. (2015, September). Neighborhood selection for dimensionality reduction. International conference on image analysis and processing (pp. 183-191). Cham: Springer.

[15] Bhatt, B., Patel, P. P. J., Gaudani, P. H. (2014). A review paper on machine learning based recommendation system. International journal of engineering development and research, 2(4), 3955-3961