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Movie Recommendation System using RNN and Cognitive thinking

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***Abstract*—Systems such as Netflix, Amazon, Flipkart, etc. have a huge user base spanning the entire globe. The products and services that these giants provide are also commensurately overwhelming in amount. A particular user can't be expected to browse through the entire repertoire on his/her own. This is where a recommendation system comes in handy. Such a system can suggest a user similar as well as completely different products and services without any explicit search being carried out by the user. A recommendation system helps increase user engagement and may ensure a loyal consumer base if deployed correctly. Incase of movies, demographic factors such as age and region play an important role in determining user preferences. Age of a person is a latent factor which influences his or her genre preferences. Hence, we have decided to explore the trends that come into play in determining a person's genre preferences. The main aim is to build a recommendation system for an app in order to increase convenience as well as user interaction using an ensemble Recommendation System model which will utilize 4 different individual learners and combine their results accordingly to provide near perfect recommendations to any user.The movie recommendation system will incorporate cognitive thinking by considering the age of the user and recommending genres based on age group psychology.**

Keywords- Recommendation System, Cognitive Thinking, Collaborative Filtering Method, Popularity Model, RNN, Modified RNN

I. INTRODUCTION

Movies are a great way to relieve stress for many people. However, with so many genres to choose from, it can be overwhelming for movie lovers to decide what to watch. [1] This is exactly wherein a recommendation system kicks in. Recommendation systems are useful in recommending movies because they can analyze user behavior and preferences to provide personalized recommendations, which can help users discover new movies that they are likely to enjoy. Recommendation systems can save a user's time by reducing the need for them to search for new movies manually by providing relevant recommendations automatically. They can be used to generate revenue for movie studios and streaming services by promoting movies that are likely to be popular with users.

With rapid advancements in AI, recommendation systems are becoming more and more personalized and accurate in generating recommendations. These developments have been facilitated by incorporating cognitive thinking. Cognitive thinking in recommendation systems refers to the ability of the system to incorporate human-like cognitive processes into its recommendations. [2] This involves creating recommendation systems that can reason, learn, and adapt to new situations, allowing them to provide more accurate and personalized recommendations for users.

We are aiming to build an ensemble learning recommendation system that will cater to an Indian audience which is eager to explore the famed gallery of Indian masterpieces. [3] Demographic metrics such as age, region, gender play a huge role in determining a user's preferences for a film. A toddler is always eager to enjoy an animated movie, the youth is ready to explore genres such as fantasy, science fiction, thriller,etc. Whereas older people tend to stay away from gore, action. The older class tends to enjoy lighthearted drama, family drama, and comedy movies. Thus, our primary aim is to build a recommendation system which recommends age appropriate movies to a user.

A. Popularity Model

Popularity-based recommendation systems recommend items (in this case, movies) based on their overall popularity, without taking into account the preferences or characteristics of individual users. [4] The advantage of a popularity-based recommendation system is that it is simple to implement and can provide good recommendations for new or infrequent users who have not provided sufficient data to make personalized recommendations.

B. Content based recommendation

Content-based filtering is a type of recommendation system that uses the characteristics or attributes of an item to recommend similar items to the user. [5] Content-based filtering focuses on the items themselves, rather than the user's behavior or preferences. It recommends items that are similar to ones the user has already expressed interest in. In the context of movie recommendation systems, content-based filtering uses the features of movies, such as genre, actors, directors, or plot, to recommend similar movies to the user.Content-based filtering can recommend movies to users based on the genre of movies, cast, plot, etc.

C. Singular Value Decomposition + CF

SVD (Singular Value Decomposition) is a matrix factorization technique frequently used in predicting user-item evaluations in recommendation systems. [6] It decomposes a matrix into three matrices that can be used to lower the matrix's dimensionality and find latent characteristics or variables. In regard to recommendation systems, SVD can be used to identify latent features or factors that are not explicitly defined in the dataset. These factors may be related to the user's preferences or the item's features, but are not directly observable in the data.

D. RNN based Sequential Model

The speciality of Recurrent Neural Networks (RNNs) lies in their ability to effectively process sequential data, where the order of data points matters. [8] Unlike traditional feedforward neural networks that process data in a fixed sequence, RNNs use a hidden state that can retain information about previous inputs, allowing them to capture temporal dependencies in data.

A RNN-based recommendation system is a type of movie recommendation system that uses recurrent neural networks (RNNs) to generate recommendations. RNNs are a type of neural network that are particularly well-suited for processing sequential data, such as movie ratings over time.

The advantage of using an RNN-based recommendation system is that it can capture the temporal dependencies in movie ratings and make personalized recommendations based on a user's past preferences. A. Smirnov, A. Kashevnik [9] suggested that RNN-based models can be trained on different types of data, such as text-based reviews or movie metadata, to enhance the recommendations. However, RNN-based recommendation systems may suffer from issues such as overfitting, lack of interpretability, and difficulty in handling cold-start problems

II. LITERATURE REVIEW

In this section [10], a comprehensive analysis of existing movie recommendation algorithms has been conducted. Subhrajyoti Ranjan Sahu proposed a RNN based approach, RNNs are designed to accept a set of inputs with no preset size restriction. They have the ability to memorize sections of the provided facts and generate predictions. They have applications in processing natural language and speech recognition. RNNs are designed to accept a variety of inputs with no predetermined size restriction. They are able to memorize bits of the information and predict outcomes.

They implement speech recognition and natural language processing.

On the basis of computational information processing, a new sort of technology is evolving. This technology is intelligent because it replaces humans in tasks requiring intelligent information processing. Modern computer-based technologies enable intelligent machine operation. Cognitive mimetics is the study of the cognitive and behavio ral similarities between humans and artificial intelligence. Cognitive mimetics offers one method for analyzing and designing intelligence by focusing on the internal information states and their corresponding processes and contents.Cognitive modeling and the psychology of thinking provide a framework for investigating how individuals process information during specific, practical tasks. This provides a foundation for the advancement of AI in such contexts.[16]

A hybrid system was proposed by [11] M. Kaur and A. Mohta. In addition to employing a content-based technique, the system makes use of a collaborative filtering algorithm. While making recommendations, we take into account other factors as well, like the atmosphere of the films. The connections that exist between users and things, on the other hand, have an effect on the recommendation.

M. B. Hossain and M. S. Arefin [12] concentrated on content-based and collaborative filtering classical recommendation systems.As a result of the research, a novel approach was developed that combines Bayesian networks and collaborative filtering. Both of these approaches have limitations. The system that has been suggested to you contains probability distributions that can be applied to arrive at conclusions, and it has been tailored to meet the requirements of the current endeavor.

As mentioned in the study, M. Jiang, Z. Yang, and C. Zhao [13] developed a collaborative filtering approach based on user characteristics. In traditional collaborative filtering algorithms, the strategy tackles data sparsity and cold start. The time-interest weight function enhances the modified cosine similarity formula, while the user preference degree and trust degree raise the precision of recommendations. Ultimately, using the hetrec2011 dataset, the improved collaborative filtering system outperforms the classic recommendation algorithm \in accuracy. Eliminates data sparsity and cold start.

III. DATASET

We have used 3 datasets in order to train our individual models. The first dataset (IMDb Bollywood) consists of various features describing a movie such as genre, Director, year of Release, average rating, total votes received, duration, and cast. The dataset consists of 15000 rows and 10 columns.The features of the dataset include name, duration, year, genre, rating, votes, actor 1, actor 2, actor 3.

The second dataset (Indian movies) consists of regional movies as well as bollywood movies with features such as Rating, Votes, Genre, Language, etc. This dataset has been primarily used to train the popularity model. It consists of nearly 50000 rows.

The MovieLens 100K dataset contains 100,000 ratings, given by 943 users to 1,682 movies. Each rating is a score between 1 and 5, where 1 is the lowest rating and 5 is the highest rating. It has been mainly used for training the collaborative model.

A. Data Preprocessing

The preliminary step involved in the creation of any machine learning model is data preprocessing where the dataset is made compatible with the code which will be written. [14] A huge dataset is likely to consist of many missing values, values not in the proper format as well as some noise. Most of the time , a huge amount of features leads to multicollinearity which leads to a decrease in performance. Hence, it is necessary to drop features which aren't relevant. In our case, features such as duration of the movie, year of release are irrelevant to the process of recommendation and hence, have been dropped from the dataset entirely

Missing values need to be taken care of before the ml model starts learning.The list of genres are separated using the one hot encoding technique. [15] The Votes and Rating columns consist of a lot of missing values. Since these 2 columns play a crucial role in generating recommendations, the rows containing missing values have been dropped.The genre column of the dataset consists of a list of various genres.

	index	Movie Name	Rating	Votes	Genre	Language
0	2	Apna Sapna Money Money	5.3	1892	Comedy, Musical, Romance	hindi
1	4	Parivar	7.4	21	Comedy, Drama, Family	hindi
2	6	Jacqueline I Am Cog	7.9	16	Drama	hindi
3	7	A Mighty Heart	6.6	26885	Biography, Drama, History	urdu
4	9	Raktalekha	6.3	12	Drama	bengali
...	...	...	...	...	...	...
22027	50586	Akshara	6.5	90	Thriller	telugu
22028	50587	Atal Jaler Ahwan	6.6	14	Drama	bengali
22029	50592	Saaho	5.2	16102	Action, Thriller	telugu
22030	50594	Jai Santoshi Maa	6.3	114	Drama, Fantasy	hindi
22031	50596	Prassthanam	5.8	1201	Action, Drama	hindi

22032 rows × 6 columns

Fig. 1. Dataset 1:Movie Lens

	Name	Year	Duration	Genre	Rating	Votes	Director	Actor 1	Actor 2	Actor 3
0		NaN	NaN	Drama	NaN	NaN	J.S. Randhawa	Manmauji	Birbal	Rajendra Bhatia
1	#Gadhvi (He thought he was Gandhi)	(2019)	109 min	Drama	7.0	8	Gaurav Bakshi	Rasika Dugal	Vivek Ghamande	Arvind Jangid
2	#Homecoming	(2021)	90 min	Drama, Musical	NaN	NaN	Soumyajit Majumdar	Sayani Gupta	Plabita Borthakur	Roy Angana
3	#Yaaram	(2019)	110 min	Comedy, Romance	4.4	35	Ovais Khan	Prateik	Ishita Raj	Siddhant Kapoor
4	...And Once Again	(2010)	105 min	Drama	NaN	NaN	Amol Palekar	Rajat Kapoor	Rituparna Sengupta	Antara Mali
...	...	...	...	...	...	...	...	...	...	...
15504	Zulm Ko Jala Doonga	(1988)	NaN	Action	4.6	11	Mahendra Shah	Naseeruddin Shah	Sumeet Saigal	Suparna Anand
15505	Zulmi	(1999)	129 min	Action, Drama	4.5	655	Kuku Kohli	Akshay Kumar	Twinkle Khanna	Aruna Irani
15506	Zulmi Raj	(2005)	NaN	Action	NaN	NaN	Kiran Thej	Sangeeta Tiwari	NaN	NaN
15507	Zulmi Shikari	(1988)	NaN	Action	NaN	NaN	NaN	NaN	NaN	NaN
15508	Zulm-O-Sitam	(1998)	130 min	Action, Drama	6.2	20	K.C. Bokadia	Dharmendra	Jaya Prada	Arjun Sarja

15509 rows × 10 columns

Fig. 2. Dataset 2: Indian Movies

B. Data Visualization

Data visualization enables deep dives into datasets and helps discover trends, outliers, and other latent patterns that might not be immediately obvious from the raw data alone. Data visualization methods such as scatter plots, heat maps, and histograms help uncover patterns in the data and highlight outliers by highlighting associations between variables.

1) Pie Chart:

Fig. 3 shows a pie chart depicting the distribution of different genres of movies in the IMDb Bollywood movies dataset. A movie can have more than one genre. The Action and Drama genres are the predominant genres as shown by the chart below. Occurrences of genres such as Mystery, Fantasy, Horror are significantly less in numbers.

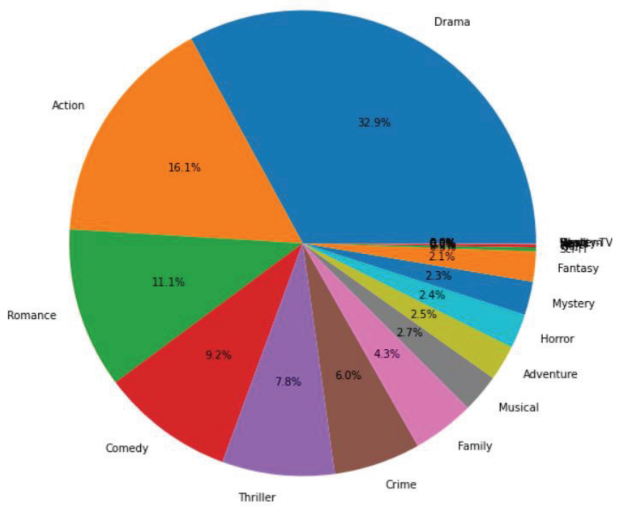

Fig. 3. percentage of films in each genre

2) Word Cloud:

It is a graphical representation of the most frequently occurring words in a text corpus, where the size of each word in the cloud represents its frequency or importance in the corpus. The Following Word Cloud shown in Fig. 4 is a visualization of the Genre feature of the IMDb Bollywood dataset which clearly shows that Drama, Action, and Romance are commonly recurring themes in movies.

Fig. 4. Word Cloud based on Genres

3) Correlation matrix:

Figure 5 shows a correlation matrix that illustrates the correlation coefficients between features expressed in numerical terms in the Indian Movies dataset. The feature score quantifies the popularity measure of a movie by utilizing the features Votes and Rating. As clearly portrayed below, the score feature largely varies directly with Rating and has weak correlation with Votes.

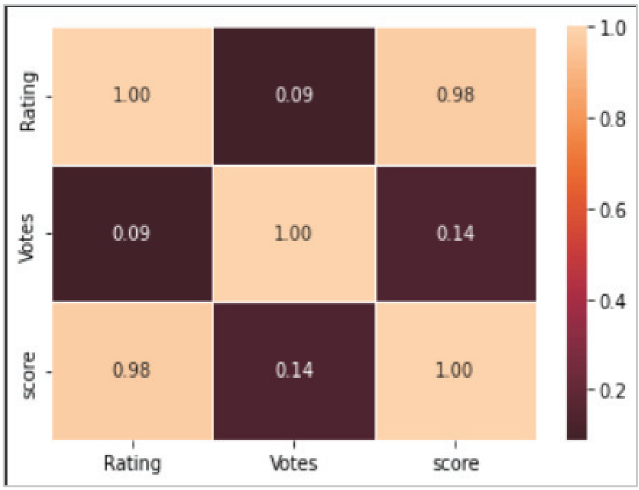

Fig. 5. Correlation matrix

The barchart shown in Fig.6 displays the average popularity scores of movies present in the Indian movies dataset categorized according to language.

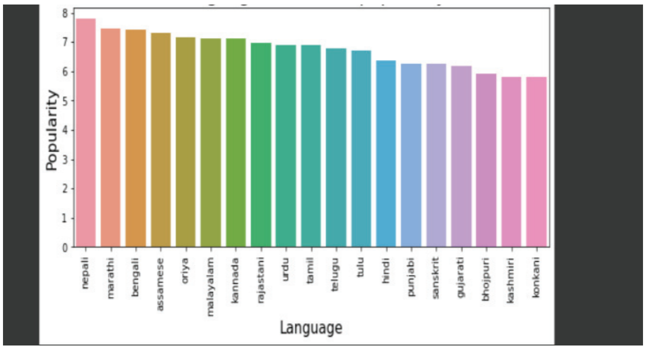

Fig. 6. Graph of Popular movies w.r.t. languages

IV. METHODOLOGY

A. SVD + CF

Data gathering and preparation are essential to constructing a recommendation system. One of the main responsibilities is establishing a user-item interaction matrix that collects user-product interactions like ratings and purchase histories. This matrix can be factored into a user-feature matrix, a feature-feature matrix, and an item-feature matrix using Singular Value Decomposition (SVD). These matrices can be trimmed to a lower rank to reduce their dimensionality, which determines the model's latent characteristics. We can forecast ratings for movies the user hasn't seen using user and item similarities. The highest-rated movies can be ranked and suggested to the user. Recommendation generation is based on the interaction matrix and SVD factorization of user-product correlations. Overall, this method generates individualized recommendations that improve user experience and engagement.

B. Content based:

The first step was to gather data on the movies, including features such as genre, director, actors, and ratings. Once this data was gathered, we preprocessed it to ensure that it is in a format that can be used by our recommendation system.The next step was to define similarity metrics that will be used to calculate the similarity between movies based on their features. Common metrics include Euclidean distance and cosine similarity. After defining the similarity metrics, we created a user profile by using these metrics to calculate the similarity between the user's watched movies and the other movies in the dataset. This allowed us to identify movies that are similar to the user's watched movies and that the user is therefore likely to enjoy. Finally, we recommended movies to the user by using the defined similarity metrics to calculate the similarity between the user's watched movies and the other movies in the dataset. This allowed us to generate a list of recommended movies that are tailored to the user's individual preferences.

C. Popularity based:

The first step in building a recommendation system was to create a user-rating matrix that represents the ratings of users for different movies. Once this was done, we calculated the popularity of each movie by computing the average rating across all users who have rated the movie. Sorting the movies by their popularity in descending order, from most popular to least popular, allowed us to identify the top-rated movies. To recommend movies to users, we simply suggested the top-rated movies based on their popularity. These recommendations can be static, meaning they do not change over time, or they can be periodically updated based on changes in popularity.

D. Rnn based Sequential Model :

To create a user-rating matrix, we first preprocessed the rating data and converted it into a sequential format suitable for an RNN. Once this is done, we trained the RNN on the preprocessed rating data. The goal is for the RNN to learn how to model the relationships between user ratings and movie features over time. Once the RNN has been trained, we use it to generate recommendations for movies that the user has not yet seen by feeding the RNN with the user's past ratings and using the RNN to predict future ratings.In this system, age is used as a factor to model the user's preferences over time. Users' movie preferences are likely to change as they age, and this is accounted for by incorporating age into the RNN model.

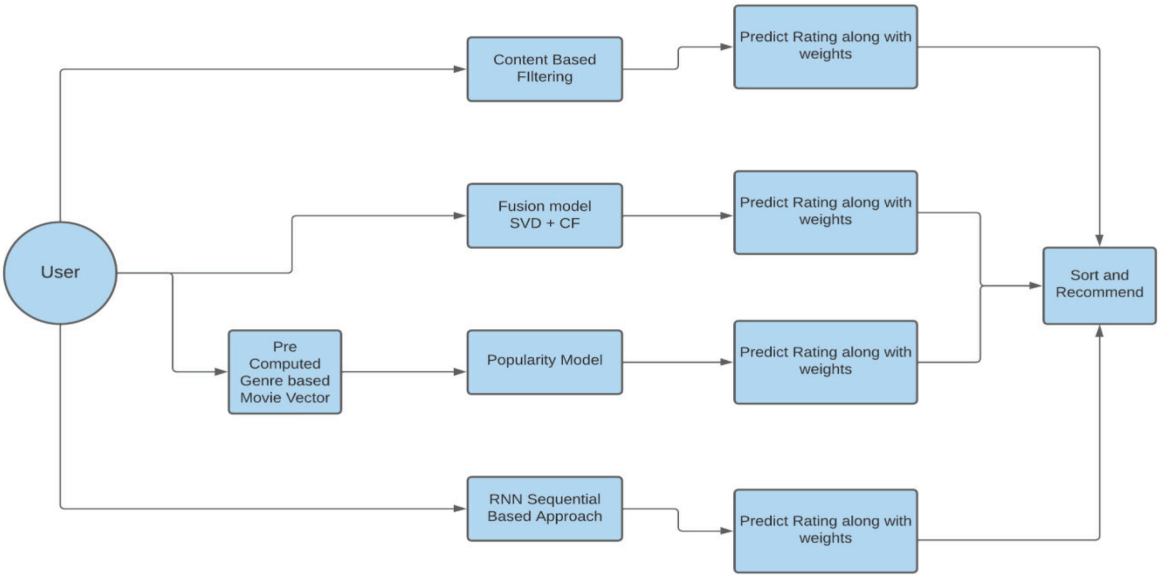

Fig. 7. System Diagram

E. Hybrid Model:

All the models work in parallel and their output will be combined accordingly to provide a much better recommendation as shown in Fig 7. Combining several weak learners into a single strong learning model is known as Ensemble Learning. The result of all the models will be stored in a list along with their weight and rating and later sorted accordingly before recommending them to the users. Top 10 movies will be recommended based on user preferences and likes/dislikes.

V. Result and Analysis

Comparisons of several models' accuracies and MSE were made using this library as a resource. The data from each user was divided into two distinct groups, with the first group being classified as training data and the second group as testing data. In order to conduct an analysis of the model's anticipated ratings, the RMSE and MAE assessment metrics were applied. The user was given recommendations for the top 10 films with the highest average rating.

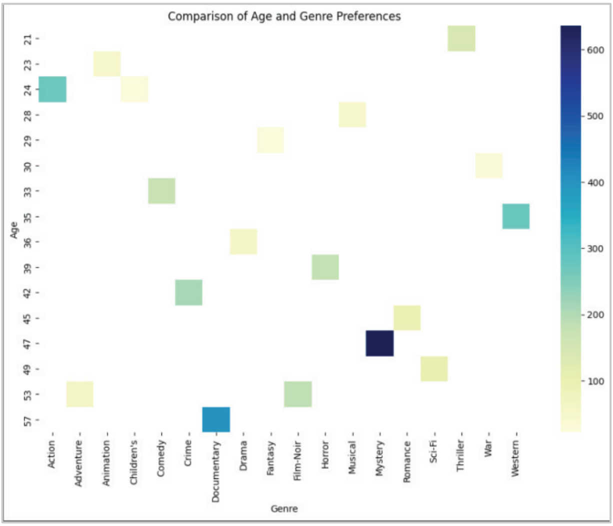

Fig. 8. Age and Genre Preferences(Movielens Dataset)

Figure 8 represents user genre preferences from the movie lens dataset, and age is an important factor that affects the final recommendation of movies to users. This information can help us tailor our recommendation system to the specific preferences of different age groups, improving the system's performance and effectiveness. This data comes from a movie lens dataset, and we have also conducted a survey to get an idea about trends in age wise genre preferences.Users in the age group of 20-30 and 30-40 tend to prefer action movies more than any other genres shown in Fig.9. Comedy as a genre is preferred by almost all age groups as shown in Fig.10. Figures 11 and 12 demonstrate that horror and sci-fi genres get along well with the youth but not with the older age group in general. The results of the survey conducted show that the data we have obtained is reliable and can be used with confidence in building our recommendation system.

Given below are the plots of individual genres with respect to different age groups. The results are well in keeping with the trends observed in the dataset above.

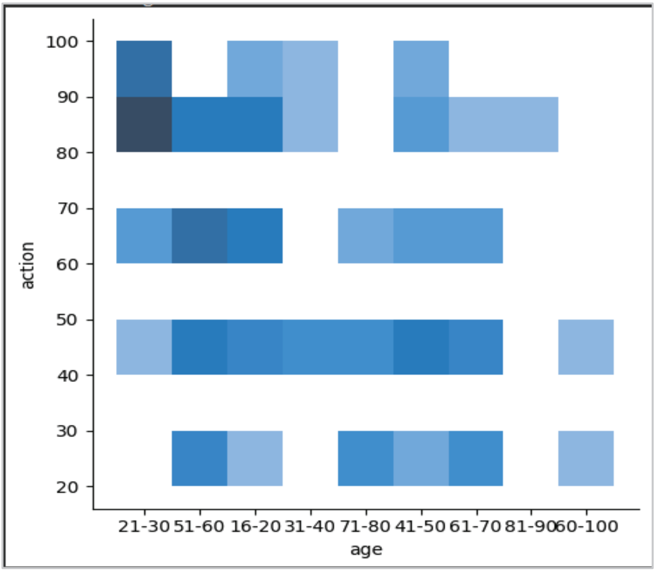

Fig. 9. Age and Genre Preferences.(Action)

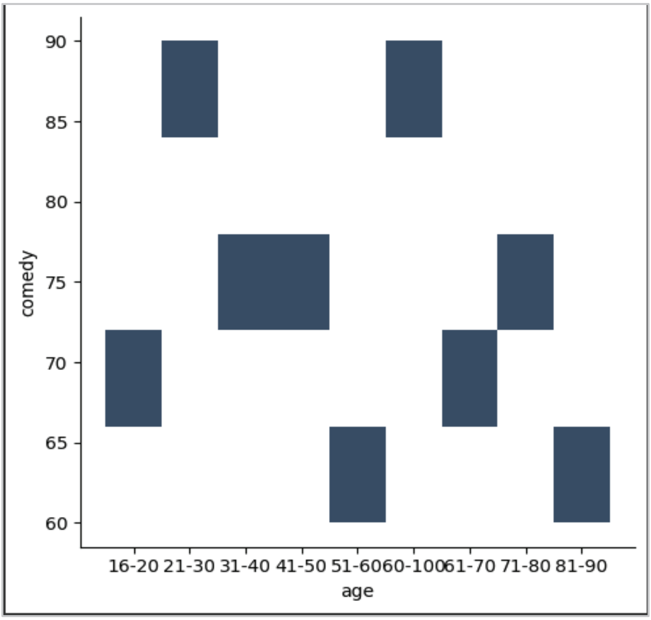

Fig. 10. Age and Genre Preferences(Comedy)

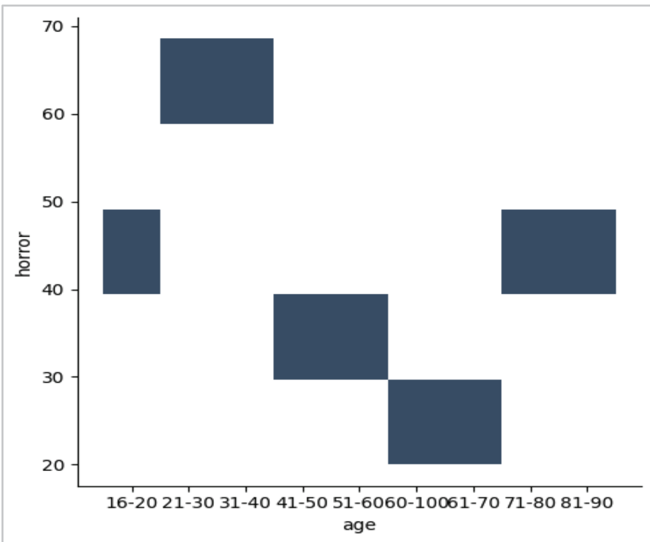

Fig. 11. Age and Genre Preferences.(Horror)

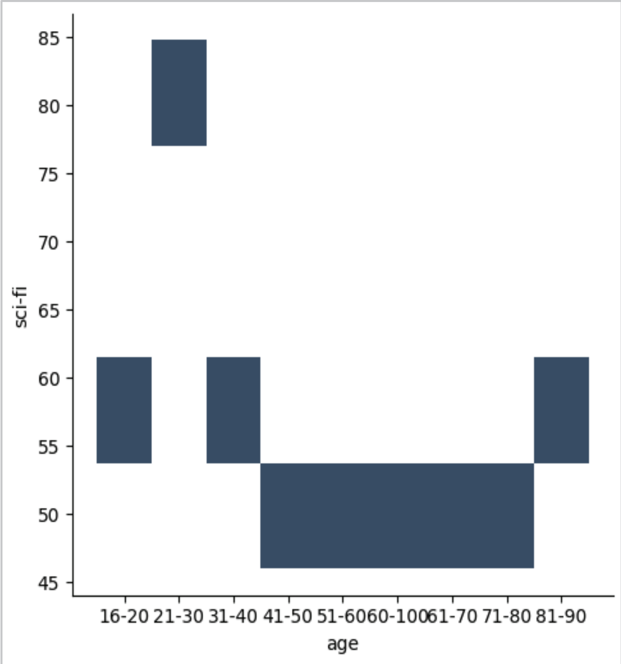

Fig. 12. Age and Genre Preferences(Sci-Fi)

A. Combined Model

The testing precision is improved and the rating precision is much better when the best individual models are combined in a weighted linear fashion, the results can be seen in fig 13.. The aforementioned models were combined into one model to produce suggestions. The combined model (SVD + CF) now recommends movies from the testing set. The top films from the popularity model, combination model (SVD + CF), and content-based model (movie similarity) were combined, and the top films chosen for the final recommendation list were those with the highest estimated ratings. Standard parameters cannot be used to evaluate the model because the initial ratings were not included, despite the fact that the quality and variety of the recommendations have improved. Popularity model solved the issue of Cold start problem by recommending the trending and popular movies of genres based on user preferences.

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	Std
MAE (testset)	0.7388	0.7385	0.7351	0.7367	0.7469	0.7392	0.0041
RMSE (testset)	0.9387	0.9362	0.9316	0.9369	0.9458	0.9378	0.0046
Fit time	5.07	2.68	3.29	1.99	1.94	2.99	1.15
Test time	0.40	0.56	0.36	0.43	0.26	0.40	0.10

Average MAE: 0.7392270902525307
Average RMSE: 0.9378438578420916

Fig. 13. Result of combined models

The evaluation metrics of our RNN model which takes age as a parameter are shown in Fig.14 .

Mean Absolute Error (MAE): 2.5363504815128985
Root Mean Squared Error (RMSE): 2.773208267981314

Fig. 14. Evaluation metrics of RNN Recommendation system considering age.

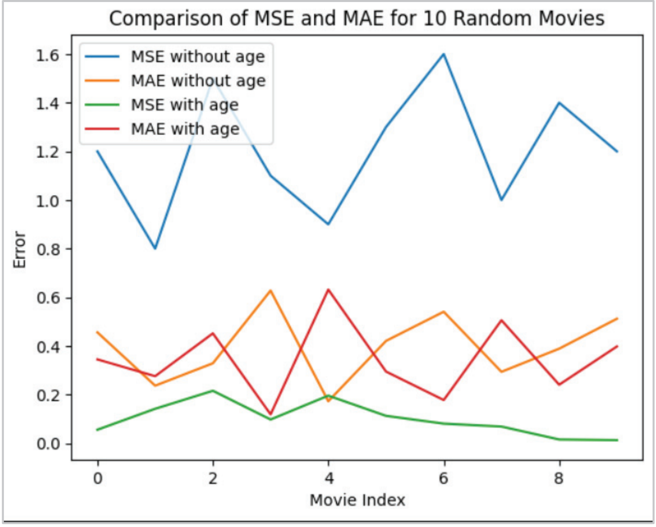

Fig. 15. Comparison of MSE and MAE for 10 random movies

Fig. 15 clearly depicts the effectiveness of considering age while recommending movies as the mae and the mse are both lower for the age based model when compared to the standard RNN model used for recommendation.

VI. Conclusion

After carrying out a comprehensive survey and canvassing people from different backgrounds, we found that demographic parameters like gender and age strongly influence user preferences. Cognitive thinking can play a big part in recommending movies by helping to analyze and understand what users like and how they act. Age of a user plays a significant role in determining his or her movie preferences and hence, recommendations based on a user's age can be more personalized and effective. Furthermore, incorporating user sentiments while generating recommendations is certainly a viable option to pursue in future in order to enhance user engagement.

VII. Future Scope

There are a number of prospective enhancements that could improve the functionality and user experience of the system. These include the incorporation of additional movie databases, user-specific data, sentiment analysis of reviews to implement a feedback mechanism, and the creation of user communities. By implementing these enhancements, the movie recommendation system could become more precise, personalized, and user-friendly. Future research could investigate the feasibility and effectiveness of these enhancements, as well as explore other potential future opportunities to further improve the system's performance.

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