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A Research Paper on Machine Learning based Movie Recommendation System

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Abstract: In this busy life people like to do things to make their mind calm and watching movie is one of the thing but due to large data set of movie exist in the world it is very difficult for the user to select movie. They have to spend a lot of time in searching and selecting movie. This procedure is time consuming and difficult. So recommendation system make the things easy. In this paper we are building a movie recommendation system with combination of two algorithms KNN algorithm and Collaborative filtering algorithm. Generally recommendation system are made from hybrid-based approach, content-based approach, collaborative filtering approach. This system made using collaborative filtering with different approach like Matrix factorization, user-based recommendation.

Keywords: recommendation systems, matrix factorization, collaborative filtering, content based filtering, memory based, model based, architecture design.

1. Introduction

The recommendation plays a crucial role in practical life, advice in form of recommendation is being taken, generally from an experienced person, because experience makes the efficient outcomes, moreover using a product can have a personal experience, Similarly in modern world as technology surrounds us, there is a need of recommendation from machine. Machine learning works on the same way as a human do learning from data and results. So it's the play of knowledge which deals the aura of recommendation system. There are plenty of recommendation systems that work around us. There are plenty of models that came in light after many years of research, in collaborative filtering model, it considers the last activities[1]. There are numerous algorithms which use data to forecast the specific user required results. Well, we came across this recommendation systems many time, in OTT platforms, music recommendation from various websites or applications, even recommendation from Ecommerce site like similar items, based on the purchase of the user, or by the use of artificial intelligence of image recognition. Certain recommendations like from collaborative approach are broadly divided into model based and memory based methods. In memory-based methods the input is from the user rating matrix and dynamically the result is updated as per that. Whereas in model based methods like neural network generation happens and it learns the acquired facts and suggests the desired recommendation[1].

Recommendation system are useful as now the data complete world has is huge, therefore getting the appropriate result need computation, it helps in facilitating the customers to select their choice (restaurants, books, music album, movies etc.) from huge pile of data available on cloud, servers, webs or in any digital form[2]. Movie recommendation system is worldly in demand these days and much more in future, as there are various film making industry from last more than a century in almost every country on earth and therefore there is a vast collection to choose from. In this giant collection user only wish to watch a certain constraints language, theme, genre and various other. It's the situation when movie recommendation system works. Further it recommends the movies based on the search of the user. It uses the concept of machine learning and work by learning the data sets. The later recommendations could be based on the actor in lead, same genre, similar reviews, search history, language, region, etc. The similar example in daily life are the OTT platforms, the moment a user watches or searches a specific movie further the user gets to see the popup of the recommended movies as per his/her interest on the top list. The technique is used to meet the customer needs and at the same time getting benefitted by the delivering the contents as per the user.

2. Related Work

There are millions of movies exist in the world right now and even if someone use filter like selecting genres their will be thousands movie. OTT platforms like Netflix, Amazon Prime gained huge popularity in past years. Earlier User has to read the other user's reviews then based on the review he/she has to select the movie which is very difficult process. Some people have very unique preference of movie. So, there is a need of very structure recommendation system. Some approaches for recommendation system are collaborative approach, hybrid approach and content-based approach. In collaborative approach data of similar user gets processed.

In content based approach data of single user used to produce output.

$$\begin{bmatrix} 5 & 1 & 4 & 5 & 1 \\ & 5 & 2 & 1 & 4 \\ 1 & 4 & 1 & 1 & 2 \\ 4 & 1 & 5 & 5 & 4 \\ 5 & 3 & 3 & & 4 \\ 1 & 5 & 1 & 1 & 1 \\ 5 & 1 & 5 & 5 & 4 \end{bmatrix} \approx \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1K} \\ u_{21} & u_{22} & \cdots & u_{2K} \\ u_{31} & u_{32} & \cdots & u_{3K} \\ u_{41} & u_{42} & \cdots & u_{4K} \\ u_{51} & u_{52} & \cdots & u_{5K} \\ u_{61} & u_{62} & \cdots & u_{6K} \\ u_{71} & u_{72} & \cdots & u_{7K} \end{bmatrix} \times \begin{bmatrix} v_{11} & v_{21} & v_{31} & v_{41} & v_{61} \\ v_{12} & v_{22} & v_{32} & v_{42} & v_{62} \\ \vdots & & & & \\ v_{1K} & v_{2K} & v_{3K} & v_{4K} & v_{6K} \end{bmatrix} \approx \begin{bmatrix} 0.2 & 3.4 \\ 3.6 & 1.0 \\ 2.6 & 0.6 \\ 0.9 & 3.7 \\ 2.0 & 3.4 \\ 2.9 & 0.5 \\ 0.8 & 3.9 \end{bmatrix} \times \begin{bmatrix} 0.0 & 1.5 & 0.1 & 0.0 & 0.7 \\ 1.3 & 0.0 & 1.2 & 1.4 & 0.7 \end{bmatrix}$$

2.1 Existing Modal

2.1.1 Matrix decomposition

It is an effective approach for small scale project. This algorithm use matrix decomposition for recommending movie. We will make vectors with the given rating of the user and use this for produce result.

2.1.2 Clustering

Matrix decomposition is not good for large system. Clustering is unsupervised technique. If we want to construct large system then we should use clustering because their no need for someone to supervised it continuously as data set increases it will be difficult to monitor. Form user groups/cluster and each user in group suggest same thing. Before clustering the users are scatter and after cluster the users are divided into three groups and users in the same group will get recommend same type of data.

2.1.3 Deep learning approach

Neural network have become very popular. They are applied in different Machine learning strategies they are used in one of the most popular platform Youtube. It is very difficult to recommend videos in youtube because of its scale and external factors.

3. Available dataset:

The data set included in the movie recommendation system is from IMDB official website and from the rest is taken from the Kaggle repository, as huge data comes with corruptness like repetitive values and the as usual irritating thing the NULL values, Python being the topmost preferred language for machine learning provides various inbuilt libraries for dealing the problems of machine learning. Numpy, Pandas helps in interacting with the data via letting to import the dataset and analyze them and deleting or extracting the necessary details. Thus improving the strength of the model in depicting the information.

Name	Domain	Users	Columns	Ratings	Null Values
IMDB 5000 Movie Dataset	Movies	5028	14	5 Star	15
The Movies Dataset	Movies	45548	26	5 Star	64
List of movies in 2018	Movies	259	5	5 Star	0
List of movies in 2019	Movies	224	5	5 Star	0
List of movies in 2020	Movies	241	5	5 Star	0

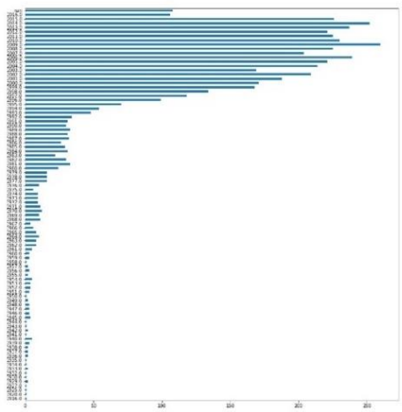
4. Data Cleaning and Exploratory Data Analysis

Data cleaning is the method of deleting or altering data that is inaccurate, incomplete, obsolete, duplicated, or incorrectly formatted in order to prepare it for review. When it comes to data analysis, this data is normally not required or beneficial because it can slow down the process or produce incorrect results. Cleaning data can be done in a variety of ways, depending on how it's stored and what answers you're looking for. Data cleaning isn't only about erasing details to make room for fresh data; it's also about maximizing the precision of a data collection without having to delete something.

Exploratory data analysis is a method of evaluating data sets in order to summarize their key characteristics, and often involves the use of statistical graphics and other data visualization techniques. EDA can be used with or without a statistical model, but it is mainly used to see what the data can teach us outside of formal modelling or hypothesis testing. John Tukey advocated for exploratory data analysis to allow statisticians to look at the data and come up with theories that could lead to new data collection and experiments.

In the project we have used various datasets like movie_metadata.csv, credits.csv etc. Firstly we have loaded the movie_metadata.csv and used the head function on it to print the top 10 values of the dataset and also used shape and columns functions to get the shape of the dataset and the columns of the dataset. We have plotted a graph between Year vs Number of movies released in that year which you can see in Fig 1. Here the graph is from Year 1916 to Year 2016. As the dataset is quite large and it also contains some unnecessary information so we have created a new dataframe and stored only the important columns from movie_metadata.csv in it and all the NaN values are replaced by unknown string. Similarly we have extracted useful information from the dataset movies_metadata.csv and credits.csv. We have done it for all the hollywood movies till the year 2020.

Fig 1: Plot between Year vs Number of movies released



5. Collaborating filtering

In collaborating filtering based systems, items based on similarity between the item and users are published or recommended[3]. It is operated by gathering the data from the users as ratings in a particular field and then the similarity is determined among them to recommend the final result. It is based on opinions of the users[2].

It figure outs the users with the same opinion and then after catching the similarity in reviews it recommends the particular movie.

Advantages:

1. Dependent on the ratings, thus making it content independent.

2. It can suggests fortuitous recommendations based on the similarity of users.
3. It also considers the experience to create real life assessment.

Disadvantages:

1. If the initial ratings are contradictory to the later ones then ambiguity arises.
2. Variations in review cases are difficult to group in agree or disagree nature.
3. Difficult in tackling sparcity situations.

Divided into two major categories:

Memory based method
Model based method

3.1 Memory based method

In an uninterrupted way it analyzes the data item in order to recommend and classify it in certain main groups, works on similarity, as per the movie recommendation of this part cosine similarity is been used. The cosine coefficient or the vector similarity considers the ratings of the two users as points in the vector model and then calculate the cos(theta) between the points[2].

3.2 Model Based method

A pro-posed theoretical model of the behavior of user rating. For recommendation it used the raw data, being in use for last many years.

6. Content-based filtering program

A content-based review program tries to guess the features or character of a user who has been given the features of an item, and responds positively to it.

Movies	User 1	User 2	User 3	User 4	Action	Comedy
Item 1	1		4	5	Yes	No
Item 2	5	4	1	2	No	Yes
Item 3	4	4		3	Yes	Yes
Item 4	2	2	4	4	No	Yes

The last two columns of Action and Comedy Describe the Types of Movies. Now, if we were given these genres, we would not know which users prefer which genre, and as a result, we may find features that are relevant to that user, depending on how you react to movies of that genre.

Once, we are aware of the user's preferences that we can embed in the embedded platform using a feature-generated vector and recommend it according to his or her preference. At the time of recommendation, the matching metrics were calculated from the item's material vectors and the user's preference vectors from his previous records. After that, the top few are recommended.

Content-based filtering does not require other users' data during one user's recommendations.

6.1 **Naïve Bayes: The** Naive Bayes separator is an example of the equipment used to do the separating function. The crux of separation is based on the concept of the Bayes theorem

Using the Bayes' theorem, we can find the chances of A happening, because B happened. Here, B is evidence and A is hypothesis. The assumption made here is that the predictions / features are independent. That the presence of one element does not affect the other. Therefore it is called naive.

Naive Bayes algorithms are widely used in sentiment analysis, spam filtering, recommendation systems etc. They are quick and easy to use but their biggest disadvantage is that the need for forecasts is independent. In many real-life situations, forecasts rely, this precludes the operation of the distinction.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

$$P(y|x_1, ..., x_n) = \frac{P(x_1|y)P(x_2|y)...P(x_n|y)P(y)}{P(x_1)P(x_2)...P(x_n)}$$

7. Matrix Factorization

In this project we have used Similarity score and cosine similarity to recommend items or movies to the users based on what he or she has searched for. We can also use the concept of Matrix Factorization. In recommender systems, matrix factorization is a type of collaborative filtering algorithm. The user-item interaction matrix is decomposed into the product of two lower dimensionality rectangular matrices by matrix factorization algorithms. According to Simon Funk, this method family became well-known during the Netflix prize challenge due to its effectiveness. Matrix factorization is a technique for representing users and objects in a lower-dimensional latent space, Refer Fig 3. Matrix factorization is used in collaborative filtering to determine the relationship between item and user entities. We'd like to predict how users will rate items based on the feedback of customer reviews so that users can get recommendations based on the forecast.

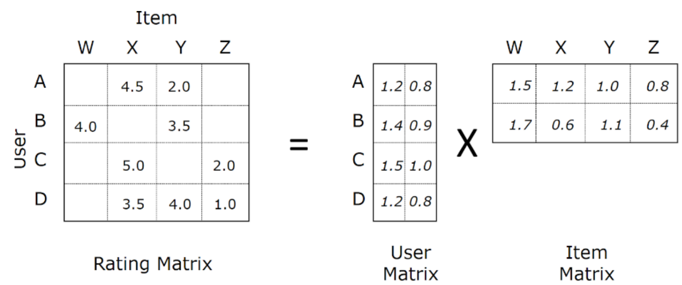


Fig 3: Example of How Matrix Factorization works

7.1 Mathematical Concept of Matrix Factorization

Create a list of users (U), items (I), and S size of |U| and |I|. The matrix |U|*|I| contains all of the user ratings. The objective is to find K latent features. It would produce the product result S given the input of two matrices, P (|U|*k) and Q (|I|*k).

S PQT=S

The association between a user and the features is represented by matrix P, while the association between an item and the features is represented by matrix Q. Calculating the dot product of the two vectors corresponding to U_i and I_j yields the prediction of an item's rating

sij=piT*qj=k=1kpikqkj

To get two P and Q entities, we must first initialize the two matrices and then calculate the difference of the product, which is known as matrix M. Following that, we use iterations to reduce the difference. Gradient descent is a technique that aims to find a local minimum of the difference.

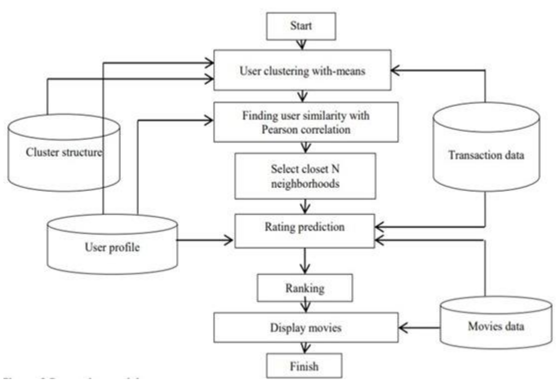
lij2=(sij-sij)2=(sij-k=1Kpikqkj)2

Since the gradient is capable of minimizing the loss, we distinguish the above equation with respect to these two variables separately. The mathematical formula for both p_ik and q_kj can be modified using the gradient. Iterations can be used to update p_ik and q_kj till the total loss converges to a minimum .

8. Architecture Design

The system is on python and Django architecture and heroku server used for deployment HTML, CSS and JAVASCRIPT are used for front-end. Html gives the basic structure and CSS is used for styling like colour, design, font etc.

oriented language it is used to make website interactive with, user. Python is used for backend to manage backend Django is used. For database MYSQL storage is used. Working First layer is UI layer developed with HTML, CSS, JS) with this layer the user will interact with backend. User action in Front end will send request to the backend with the help of REST APL and HTTP request. If user click on any data then data will be, transferred to the backend in request body to processed. HTTPS requests used in the website are GET, POST, PATCH, DELETE. GET method is used to fetch data from the server without any request body. POST method is used to when server accepts data enclosed in request body. DELETE method is used to delete the data from the database. PATCH method is used to update some attribute (update) existing data . PUT method is also for update but it will replace the data. The backend will act according the endpoints(HTTP method) and backend will do operations on the database and send response in return to the frontend and frontend will display the response accordingly.



8.1 Database Design

Database is the foundation of any website. The database should follow ACID properties to work properly. The database used in the Project is MYSQL. Tables names are User Table, Movie Table, User Similarity Table, Movie Type Table.

9. Implementation, Results and Deployment

We have taken the dataset from kaggle i.e why we only have data till 2016, for the year 2018, 2019 and 2020 we have extracted the movies data from Wikipedia. In wikipedia data there is no genre column for the movies so to get that we have used TMDB API and using GET request we are extracting the genre, the result that we got, we have converted it into JSON format and used the key "genre" to get the genre of the desired movie. We have used the lambda function also. After done with the preprocessing of the data we have stored the final data in a CSV file.

After that we have used the reviews.txt file to train a sentimental model so that whenever we get a review we can tell whether it is good or bad. In the sentimental model we have used various libraries like TFidfVectorizer, nltk etc so that we can convert the review text into vector format and on top of this we have trained Multinomial Naive Bayes model and stored that as a pkl file so that we can use it later.

In the final website whenever we write the movie name we also get some auto-suggestions, this we have implemented using javascript and with the final data that we have. Whenever we press enter after writing the movie name we will get the information like title, overview, genre, rating, release data etc about the movie that we have searched. We also get the information about the cast, top user reviews and its sentiments whether good or bad and at the end Top recommended movies based on the movie that we have searched for. All these things are implemented with the help of python, javascript and ajax. What criteria does it use to determine which item is the most similar to the one the user prefers? The similarity scores are used in this case. It is a numerical value that varies from zero to one and is used to calculate how similar two items are on a scale of zero to one. This similarity score is calculated by comparing the text information of both items to each other. As a result, the similarity score is a measure of how close two items' text information are. This can be accomplished using cosine-similarity, Refer Fig 2. The cosine similarity metric is used to determine how similar documents are regardless of their size. It calculates the cosine of the angle formed by two vectors projected in a multi-dimensional space mathematically. Because of the cosine similarity, even if two identical documents are separated by the Euclidean distance (due to the size of the documents), they are likely to be oriented closer together. The higher the cosine similarity, the smaller the angle.

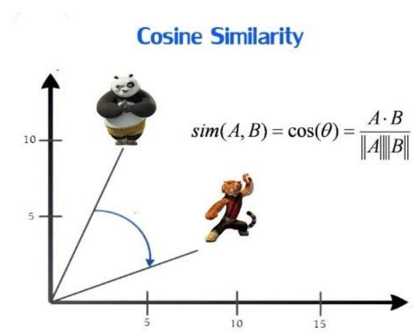


Fig 2: Cosine Similarity

For deployment of the final model we have used Heroku. Heroku is a cloud-based platform-as-a-service (PaaS) that supports a variety of programming languages. Heroku, one of the first cloud platforms, has been in existence since June 2007, when it only supported Ruby. It now supports Java, Node.js, Scala, Clojure, Python, PHP, and Go.

10. Working of recommend systems

There are basically four types in which we can work on recommender system. A. Context Recommender System Context has many meanings and is a multifaceted concept that has been studied in various fields of research including Computer Science, Cognitive Science, Language, Philosophy, Psychology, and Organizational Context. As the context is studied in many fields, each one looks at the context in its own way and is different from the other. We will try to understand the context of the term, especially in the Recommender System domain. In the case of Recommender System, the context parameters depend largely on whether it is RS movie or Tourist Recommender System, etc. In the movie RS, the conditions are the same: Date of view, location (Theatre) viewing, Watch time, season details (during the festival, etc.), a friend (friends, family, etc.), important pre-post events, and postings. In RS Tourism, content is the same: Holiday details, last date, and venue, friend, important pre-shipping events[4]. Traditional recommendation programs often calculate similarities using a three-user matrix. They did not consider contextual information that affects and influences decisions. Contextual information about time, place, friends, weather, and more. Considering content details as one of the building blocks of a program is necessary to produce the most accurate recommendations. Adomavicius and Tuzhilin have proposed a multidisciplinary approach to incorporating contextual information into the development of Adomavicius et al. (2005). They also proposed a multi-dimensional rating system based on a reduction-based approach and explored their approaches to the movie recommendation app that took time, location, and context-related information. Here, recommendations are made using only estimates made in the same context as the target forecast. However, in reality, rarely the same context occurs in the future but rather in the same context. What's worse is the increase in data sparsity. Yap et al. (2007) exploit a different way of capturing contextual information and attempts to improve predictive accuracy using the content method (CB). The authors mimic the context as additional descriptive features of the user and build a Bass Network to make predictions. They increase accuracy even with sound and imperfect information. Umberto and Michele reviewed post-filters, pre-filters, and content moderation content programs. There is research done on selecting the appropriate contextual features, the appropriate themes increase the accuracy of the recommendation system while the less important ones reduce performance both depending on the accuracy of the output and the computer load. Ante Odic et al,[5] describes various approaches to the selection of appropriate content for a movie promotion program. Rahul Gupta et al.[6] demonstrates the ingenuity of the naïve Bayes and the SVD of the context commendation program. B. Network based Recommender System In order to overcome the limitations of the Collaborative Filtering Program, in recent years there has been a lot of research focused on a network-based recommendation system. With a trust-based recommendation strategy, neighbourhood building is done based on a relationship of trust between users.

In the real world, lumbering elephants are exposed by the aggression of speeding midgets. A friend may not be trustworthy in any way. Here, recommend partners should have the same taste and preferences and also need honesty. Social trust is very complex and depends on many factors that make it difficult to model the same in the calculation system. There are many factors that influence trust, e.g. human relationships, psychological factors, the influence of the opinions of others etc. There are many definitions of trust that fall into many categories.[7] Marsh in has an official definition of trust in the sense of calculation, considering both social and technical aspects. Krishten Mori, clarified the concept of trust in the recommendation system and identified various aspects of the network of trust in the recommendation system, including metrics of trust and reputation[8]. There are three key elements of trust that are relevant to developing models of a trust-based recommendation system: transitivity, asymmetry, and personalization. The idea of change is that social trust can be transferred between people. For example, A relies on B, and B relies heavily on C, or A does not know C, A can still get the sense of loyalty to C. However, trust is not entirely compatible with the mathematical sense, for it would not be so if A was more dependent on C, person A had no previous contact with him. There has been a lot of research into modelling the occurrence of trust, also called the distribution of hope. Guha et al. developed a formal framework for trust promoting schemes. Their framework assumes that users clearly state the reliability values of other users. They also introduced the concept of mistrust and spread mistrust. The assets of an asymmetric trust are very important. When two people are involved in a relationship, the trust they have for each other is not the same. Because people are so different in their experiences, backgrounds and history, it is easy to understand the limited level of trust. In the use of shared filtering, trust is different from similarities, in which similarities are equal[9]. This is an important difference because trust allows users to build more connections that would not be possible with the same values. The final asset is to build trust. Trust is an independent, personal opinion. Two people tend to have very different opinions about the integrity of one person. Customization plays an important role in making recommendations for the user. Customizing honesty has a profound effect the accuracy of the recommendation system.

II. LITERATURE SURVEY Recommendation systems capture the problem of the vast amount of information users experience by providing personalized, specialized recommendations and services. Recently, a variety of building recommendation systems have been developed, which can use shared filters, content-based filters, or hybrid filters[9]. The collaborative filtering process is the most mature and widely used. Collaborative filtering recommends items by identifying other users with similar interests; uses their idea to recommend things to the active user. Collaborative commendation programs have been conducted in various application areas.

Group Lens is a news-based platform that has used collaborative methods to help users retrieve articles from a large news database. Ringo is an online social media filtering system that uses shared filters to create user profiles based on their ratings on music albums. Amazon uses news distribution technology to improve its recommendations[10]. The system uses a collaborative filtering method to overcome downside issues by generating a table of similar items offline using an object-to-object matrix. Content-based strategies are associated with content resources and user features. Content-based filtering strategies ignore donations from other users as well as collaborative strategies. Interactive content based and filtration-based filters are widely used today by using them separately and over time combining their results or adding content elements in a collaborative and vice versa. In another recommendation system, the system will generate recommendations based on other users' user preferences whose preferences are similar to the current user. These methods only work when we want to predict the objects or objects of a single user. This approach can be extended to a group recommendation process. An indication of the lack of a relationship between user-targeted metrics and objective metrics was made. The metaphor is used to estimate the weight of each user-focused metric (relationship, youth, land satisfaction, homosexuality) that combines them into a single value so that they have a more reliable way of judging. It is easier for a user to express an opinion about a recommendation instead of answering 60 questions (a list of questions is shorter than the longer version proposed in the ResQue model). This function can be easily extended to other parameters. The user is not aware that the algorithm is not personal and the result is different because the recommendations that the user sees as inconsistent with his decisions. Datasets are used as benchmarks for developing new recommendation techniques and comparing them to other algorithms in the given settings. Here, in this project we used different types of datasets collected from the Kaggle.com. And we used 5 different types of dataset. The following are the dataset ♣ IMDB 5000 movie dataset In this file we will be having all the Hollywood movies till 2017. Even all OTT platform movies are present in this dataset. ♣ The Movies dataset In this data file we have to download credits.csv and movies_metadata.csv files separately as these two csv files are large in size. ♣ List of movies in 2018 This file contains all the movies which are released in 2018 along with the movie ratings. ♣ List of movies in 2019 This file contains all the movies that had been released in the 2019. ♣ List of movies in 2020 Movies which are released in 2020, all the details are present in this file.

10. Conclusions

We cleaned the data that we have obtained from kaggle and IMBD. We have done exploratory data analysis on the data like taking valuable insights from the data, removed the missing values and also done data preprocessing so that we can train our model on it. Now whenever a user visits our website and writes the movie name in the search bar he will see some auto-suggestions related to the movie he or she has searched for.

when he or she will press enter, the page will be redirected to the new page where all the information related to the searched movie like genre, rating, star cast, user reviews and sentiments of the reviews, recommended movies, will be visible to him or her. Our project works only for Hollywood movies but we can extend it so that it can work for any movie, we just need the required data.

A detailed report has been done about how the movie recommender system works and the types of recommender system are being explained. Also, we had done a survey on recommender system for developing its types. And also types of recommender system available and difference between the movie recommender system and tourist recommender system. Filtering types which are being used in the recommender system. And also the datasets used in this project

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