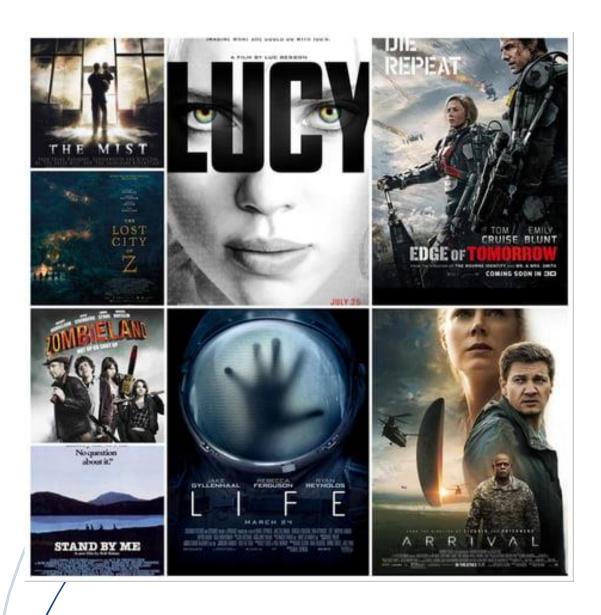
Movie Recommendation System



UEMK, 8TH SEMESTER, FINAL YEAR PROJECT BY GROUP – 47.

MOVIE RECOMMENDATION SYSTEM

Project report in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology

In

COMPUTER SCIENCE AND ENGINEERING

Submitted By

UNIVERSITY ROLL NO. 12018009019006

DEBANJAN BHATTACHARYA

SOUMYADEEP MAJI

SHOURYADEEP MAHATO

UNIVERSITY ROLL NO. 12018009019576

UNIVERSITY ROLL NO. 12018009019188

ARKADYUTI DAM UNIVERSITY ROLL NO. 12018009019654

SOUMYAJIT ROY UNIVERSITY ROLL NO. 12018009019386

Under the guidance of

Prof. Varsha Poddar

&

Prof. Dr. Sukalyan Goswami

Department of Computer Science



UNIVERSITY OF ENGINEERING & MANAGEMENT, KOLKATA

University Area, Plot No. III – B/5, New Town, Action Area – III, Kolkata – 700160.



UNIVERSITY OF ENGINEERING & MANAGEMENT

'University Area', Plot No. III-B/5, Main Arterial Road, New Town, Action Area-III, Kolkata - 700 160, W.B., India City Office: 'ASHRAM', GN-34/2, Salt Lake Electronics Complex, Kolkata - 700 091, W.B., India (Established by Act XXV of 2014 of Govt. of West Bengal & recognised by UGC, Ministry of HRD, Govt. of India)

Ph. (Office): 91 33 2357 7649

: 91 33 2357 2969 : 91 33 6888 8608

Admissions : 91 33 2357 2059
Fax : 91 33 2357 8302
E-mail : vc@uem.edu.in
Website : www.uem.edu.in

CERTIFICATE

This is to certify that the project titled Movie Recommendation System submitted by Debanjan Bhattacharya (University Roll No. 12018009019006), Shouryadeep Mahato (University Roll no. 12018009019576), Soumyadeep Maji (University Roll No. 12018009019307), Aniket Roy (University Roll No. 12018009019188), Arkadyuti Dam (University Roll No. 12018009019654), and Soumyajit Roy (University Roll No. 12018009019386), students of UNIVERSITY OF ENGINEERING & MANAGEMENT, KOLKATA, in partial fulfillment of requirement for the degree of Bachelor of Computer Science Engineering, is a Bonafede work carried out by them under the supervision and guidance of Prof. Varsha Poddar & Prof. Dr. Sukalyan Goswami during 8th Semester of academic session of 2018-2022. The content of this report has not been submitted to any other university or institute. I am glad to inform that the work is entirely original and its performance is found to be quite satisfactory.

Signature of Guide	Signature of Guide
Signature of Head of the Department	•

ACKNOWLEDGEMENT

We would like to take this opportunity to thank everyone whose cooperation and encouragement throughout the ongoing course of this project remains invaluable to us.

We are sincerely grateful to our guide Prof. Varsha Poddar and Prof. Dr. Sukalyan Goswami of the Department of Computer Science, UEM, Kolkata, for his wisdom, guidance and inspiration that helped us to go through with this project and take it to where it stands now.

Last but not the least, we would like to extend our warm regards to our families and peers who have kept supporting us and always had faith in our work.

Debanjan Bhattacharya

Soumyadeep Maji

Shouryadeep Mahato

Aniket Roy

Arkadyuti Dam

Soumyajit Roy

TABLE OF CONTENTS

ABSTRACT01
CHAPTER – 1: INTRODUCTION02-03
CHAPTER – 3: PROBLEM STATEMENT
3.1. Project Title04
3.2. Project Requirements04
CHAPTER – 4: PROPOSED SOLUTION
4.1. Types Of Recommenders05
4.2. About The Dataset05
4.3. Simple Recommender05
4.4. Content Base Recommender06
4.5. Final Result07-08
CHAPTER – 5: CONCLUSION & FUTURE SCOPE
6.1. Conclusion09
6.2. Future Scope09
BIBLIOGRAPHY10

<u>ABSTRACT</u>

The purpose of this project is to build a **Movie Recommendation System** that suggests users various movies and similar contents depending on the type of recommendation system in play.

To define a recommendation system, it is a kind of system that provides suggestions to users for certain resources like books, movies, songs, etc., based on some particular data set. Movie recommendation systems usually predict what movies a user will like based on the attributes present in previously liked movies. Such recommendation systems are beneficial for organizations that collect data from large amounts of customers, and wish to effectively provide the best suggestions possible. A lot of factors can be considered while designing a movie recommendation system like the genre of the movie, actors present in it or even the director of the movie. The systems can recommend movies based on one or a combination of two or more attributes.

In this paper, the recommendation system has been built on two types of recommenders: (i) Simple Recommender and (ii) Content-based Recommender. Two different approaches are used to achieve the results for both types of recommendation system. The dataset used for the system is downloaded from a free-source database in .csv format and is named as "tmdb_5000_movies.csv" in our project.

INTRODUCTION

1. What is a recommendation system?

A recommender system, or a recommendation system, is a subclass of the information filtering system that seeks to predict the "rating" or "preference" a user would give to an item.

Recommender systems are used in a variety of areas, with commonly recognized examples taking the form of playlist generators for video and music services, product recommenders for online stores, or content recommenders for social media platforms and open web content recommenders. These systems can operate using a single input, like music, or multiple inputs within and across platforms like news, books, and search queries. Recommender systems have also been developed to explore research articles and experts, collaborators, and financial services.

2. What is a movie recommendation system?

A movie recommendation system is a domain-specific recommendation program that seeks to predict the "ratings" or "preferences" of a user towards a particular movie or a set of movies. Therefore, the main focus of our recommendation system is to filter and predict only those movies which a user would prefer given some data about the user him or herself.

3. Types of movie recommender systems being used.

a.) Simple Recommender – The Simple Recommender offers generalized recommendations to every user based on movie popularity and (sometimes) genre. The basic idea behind this recommender is that movies that are more popular and more critically acclaimed will have a higher probability of being liked by the average audience. We will sort our movies based on ratings and popularity and display the top movies of our list. As an added step, we can pass in a genre argument to get the top movies of a particular genre.

Methodology for Simple Recommender System: -

We will use the TMDB Ratings to come up with our Top Movies Chart. We will use IMDB's weighted rating formula to construct our chart. Mathematically, it is represented as follows:

Weighted Rating (WR) = (vv + m. R) + (mv + m. C)(vv + m.R) + (mv + m.C),

where,

- **v** is the number of votes for the movie
- **m** is the minimum votes required to be listed in the chart
- **R** is the average rating of the movie
- C is the mean vote across the whole report

The next step is to determine an appropriate value for m, the minimum votes required to be listed in the chart. We will use **95th percentile** as our cutoff. In other words, for a movie to feature in the charts, it must have more votes than at least 95% of the movies in the list.

b.) **Content Based Recommender** – The recommender we built in the previous section suffers some severe limitations. For one, it gives the same recommendation to everyone, regardless of the user's personal taste. If a person who loves romantic movies (and hates action) were to look at our Top 15 Chart, she/he wouldn't probably like most of the movies. If she/he were to go one step further and look at our charts by genre, she/he wouldn't still be getting the best recommendations.

For instance, consider a person who loves Dilwale Dulhania Le Jayenge, My Name is Khan and Kabhi Khushi Kabhi Gham. One inference we can obtain is that the person loves the actor Shahrukh Khan and the director Karan Johar. Even if she/he were to access the romance chart, she/he wouldn't find these as the top recommendations.

To personalize our recommendations more, we are going to build an engine that computes similarity between movies based on certain metrics and suggests movies that are most similar to a particular movie that a user liked. Since we will be using movie metadata (or content) to build this engine, this also known as Content Based Filtering.

We will build two types of Content Based Recommenders based on:

- Movie Overviews and Taglines
- Movie Cast, Crew, Keywords and Genre

Methodology for Content Based Recommender:

Cosine Similarity – We will be using the Cosine Similarity to calculate a numeric quantity that denotes the similarity between two movies. Mathematically, it is defined as follows:

$$cosine(x,y) = x.y | /|x||.||y||$$

Since we have used the TF-IDF Vectorizer, calculating the Dot Product will directly give us the Cosine Similarity Score. Therefore, we will use sklearn's linear kernel instead of cosine similarities since it is much faster.

PROBLEM STATEMENT

<u>Project Title</u> - To build a movie recommendation system that filters movies based on specific types of data taken from the user. In our project, we have priorities specific data fields like ratings, votes, movie descriptions, genre, overviews and taglines, movie cast, crew, and certain keywords to extract accurate information and then display the movies accordingly.

<u>Project Requirements</u> - The main language to be used in this project is Python and the concept of data processing is being used to get the desired result in the form of movie recommendations.

Modules used in the project -

- 1. <u>Backend part</u> Pandas, NumPy, Literal_eval, and Sklearn (TfidfVectorizer, CountVectorizer, linear_kernel, cosine_similarity).
- 2. Front-end part Streamlit, Pickle, and Requests.

PROPOSED SOLUTION

A.) Backend Solution

1. Types of recommenders:

- i. Simple Recommender
- ii. Content-based Recommender

2. About the dataset:

The dataset consists of movies released on or before July 2017. Data points include cast, crew, plot keywords, budget, revenue, posters, release dates, languages, production companies, countries, TMDB vote counts and vote averages.

This dataset also has files containing 26 million ratings from 270,000 users for all 45,000 movies. Ratings are on a scale of 1-5 and have been obtained from the official GroupLens website.

- **The Full Dataset**: Consists of 26,000,000 ratings and 750,000 tag applications applied to 45,000 movies by 270,000 users. Includes tag genome data with 12 million relevance scores across 1,100 tags.
- **The Small Dataset:** Comprises of 100,000 ratings and 1,300 tag applications applied to 9,000 movies by 700 users.

We will build our Simple Recommender using movies from the Full Dataset whereas all personalized recommender systems will make use of the small dataset.

3. Modules used:

The major modules that are used in this part of the solution are as follows:

- I. <u>Pandas</u> a python library used for data processing.
- II. <u>NumPy</u> a python library used for working with arrays. It also has functions that can be used in other domains such as linear algebra, Fourier transform, and matrices.
- III. <u>ast</u> a python module that helps python application process tress of the python abstract syntax grammar.
- IV. <u>Sklearn</u> stands for Scikit-learn is the most useful and robust library for machine learning in Python. It provides a selection of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction via a consistence interface in Python.
- V. <u>Warnings</u> Base category for warnings triggered during the process of importing a module (ignored by default).

4. Simple Recommender:

quali	fied.head(15)						
	title	year	vote_count	vote_average	popularity	genres	wr
96	Inception	2010	13752	8	167.583710	[Action, Thriller, Science Fiction, Mystery, A	7.574986
65	The Dark Knight	2008	12002	8	187.322927	[Drama, Action, Crime, Thriller]	7.525542
95	Interstellar	2014	10867	8	724.247784	[Adventure, Drama, Science Fiction]	7.486823
662	Fight Club	1999	9413	8	146.757391	[Drama]	7.426909
262	The Lord of the Rings: The Fellowship of the Ring	2001	8705	8	138.049577	[Adventure, Fantasy, Action]	7.392365
3232	Pulp Fiction	1994	8428	8	121.463076	[Thriller, Crime]	7.377689
1881	The Shawshank Redemption	1994	8205	8	136.747729	[Drama, Crime]	7.365349
329	The Lord of the Rings: The Return of the King	2003	8064	8	123.630332	[Adventure, Fantasy, Action]	7.357291
809	Forrest Gump	1994	7927	8	138.133331	[Comedy, Drama, Romance]	7.349263
330	The Lord of the Rings: The Two Towers	2002	7487	8	106.914973	[Adventure, Fantasy, Action]	7.322066
2912	Star Wars	1977	6624	8	126.393695	[Adventure, Action, Science Fiction]	7.261532
77	Inside Out	2015	6560	8	128.655964	[Drama, Comedy, Animation, Family]	7.256609
2285	Back to the Future	1985	6079	8	76.603233	[Adventure, Comedy, Science Fiction, Family]	7.217402
3337	The Godfather	1972	5893	8	143.659698	[Drama, Crime]	7.201108
1990	The Empire Strikes Back	1980	5879	8	78.517830	[Adventure, Action, Science Fiction]	7.199854

5. Content-based Recommender:

```
In [30]: Recommendations_based_on_a_movie = 'Toy Story 2'
         print("Below are the Top 10 Recommendations based on the movie -->"+Recommendations_based_on_a_movie)
         get_recommendations(Recommendations_based_on_a_movie).head(10)
         Below are the Top 10 Recommendations based on the movie -->Toy Story 2
Out[30]: 1541
                              Toy Story
         42
                         Toy Story 3
Small Soldiers
         1191
                 The 40 Year Old Virgin
         1779
                 A LEGO Brickumentary
         4387
         891
                        Man on the Moon
         787
                         The Great Raid
         3379
                           Factory Girl
         2569
                             Match Point
                         The Nutcracker
         2303
         Name: title, dtype: object
```

```
In [31]: Recommendations_based_on_a_movie = 'The Dark Knight'
print("Below are the Top 10 Recommendations based on the movie -->"+Recommendations_based_on_a_movie)
          get_recommendations(Recommendations_based_on_a_movie).head(10)
           Below are the Top 10 Recommendations based on the movie -->The Dark Knight
Out[31]: 3
                                         The Dark Knight Rises
                                                 Batman Forever
           428
                                                 Batman Returns
           3854
                   Batman: The Dark Knight Returns, Part 2
          1359
                                                          Batman
                                                      Slow Burn
           2507
           1181
           119
                                                  Batman Begins
                         Law Abiding Citizen
Sherlock Holmes: A Game of Shadows
           879
           205
          Name: title, dtype: object
          We see that for The Dark Knight, our system is able to identify it as a Batman film and subsequently recommend other Batman films as its top
          recommendations.
```

B.) Front-end Solution (Website)

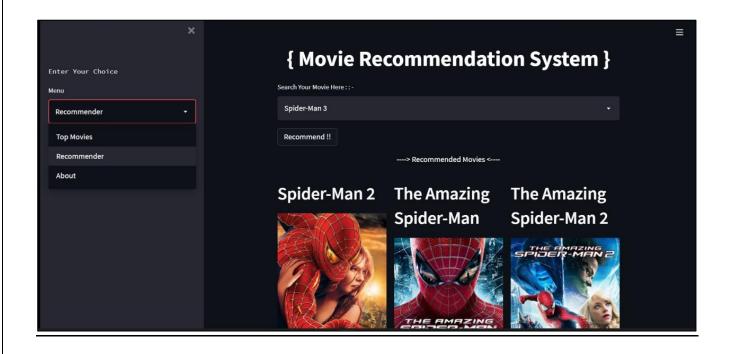
Following are the major modules used to achieved the result:

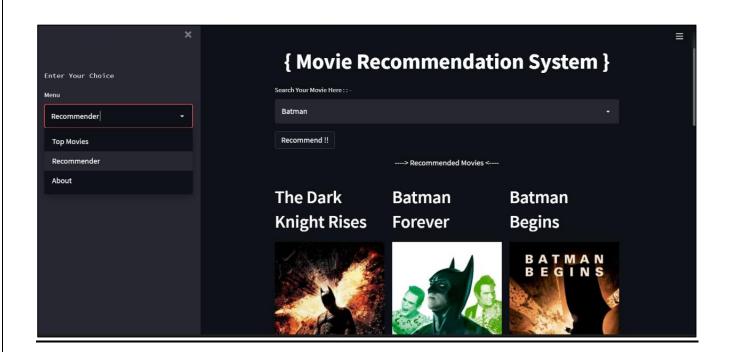
- I. <u>Streamlit</u> Streamlit is an open-source app framework in Python language. It helps us create web apps for data science and machine learning in a short time. It is compatible with major Python libraries such as scikit-learn, Keras, PyTorch, SymPy(latex), NumPy, pandas, Matplotlib etc.
- II. <u>Pickle</u> Python pickle module is used for serializing and de-serializing a Python object structure. Any object in Python can be pickled so that it can be saved on disk.
- III. <u>Requests</u> The requests module allows you to send HTTP requests using Python. The HTTP request returns a Response Object with all the response data (content, encoding, status, etc.).

1. Simple Recommender displaying the top movies based on overall user ratings.



2. <u>Content-based Recommender showing output of the movies similar to the required one based on the similarity score used in the engine.</u>





CONCLUSION & FUTURE SCOPE

Conclusion:

In this project, we have built 2 different types of recommendation engines based on different ideas and algorithms. They can be summarized as follows:

- 1. **Simple Recommender**: This system used overall TMDB Vote Count and Vote Averages to build Top Movies Charts, in general and for a specific genre. The IMDB Weighted Rating System was used to calculate ratings on which the sorting was finally performed.
- 2. Content Based Recommender: We built a content-based engines; one that took movie overview and taglines as input and the other which took metadata such as cast, crew, genre and keywords to come up with predictions. We also devised a simple filter to give greater preference to movies with more votes and higher ratings.

Future Scope:

Cosine similarity calculation do not work well when we don't have enough rating for movie or when user's rating for some movie is exceptionally either high or low. As an improvement on this project some other methods such as adjusted cosine similarity can be used to compute similarity.

Adjusted cosine similarity, which is similar to cosine similarity, is measured by normalizing the user vectors Ux and Uy and computing the cosine of the angle between them. However, unlike cosine similarity, when computing the dot product of the two user vectors, adjusted cosine similarity uses the deviation between each of the user's item ratings, denoted Ru, and their average item rating, denoted Ru, in place of the user's raw item rating.

In equation form, the adjusted cosine similarity computation is expressed as:

$$sim(u_x, u_y) = \frac{\sum\limits_{i \in P_{u_x, u_y}} (r_{u_x, i} - \bar{r}_{u_x}) (r_{u_y, i} - \bar{r}_{u_y})}{\sqrt{\sum\limits_{i \in P_{u_x, u_y}} (r_{u_x, i} - \bar{r}_{u_x})^2} \sqrt{\sum\limits_{i \in P_{u_x, u_y}} (r_{u_y, i} - \bar{r}_{u_y})^2}}$$

where Pux,uy represents the subset of items $i \in I$ for which both users have rated, Rux,i is the rating of user Ux on item i and Ruy,i in the rating of user Uy on item i. The main advantage of this approach is that in item-based collaborative filtering, the item vectors consist of ratings from different users who often have varying rating scales.

BIBLIOGRAPHY

- 1. Kaggle.com Obtained the dataset for your project
- **2. Streamlit.io** Learning and implementation of Streamlit concept in Python and using the syntaxes to get the desired results.
- **3. Stackoverflow.com** Concept on how to use HTML codes in a Python program for easier website modification.
- **4.** Ivyproschool.com Initial idea about the movie recommendation system.
- **5. Themoviedb.com** Obtaining the API key and display images for the content-based recommender.