

# ONLINE MOVIE RECOMMENDATION SYSTEM

**Chapter 1** 

## **INTRODUCTION**

Movie Recommendation systems are information filtering tools that aspire to predict the rating for users and items, predominantly from big data to recommend their likes. Movie recommendation systems provide a mechanism to assist users in classifying users with similar interests. This makes movie recommender systems essentially a central part of websites and e-commerce applications. The primary objective of movie recommendation systems is to suggest a recommender system through data clustering and computational intelligence. We need a system to consolidate all these data into a representable, user friendly interface where the user can be recommended the best movie of his choice by quick filtering of the information on the web.



## **Different types of recommendation engines**

The most common types of recommendation systems are **content-based** and **collaborative filtering** recommender systems. In collaborative filtering, the behavior of a group of users is used to make recommendations to other users. The recommendation is based on the preference of other users. A simple example would be recommending a movie to a user based on the fact that their friend liked the movie. There are two types of collaborative models **Memory-based** methods and **Model-based** methods. The advantage of memory-based techniques is that they are simple to implement and the resulting recommendations are often easy to explain. They are divided into two:

- User-based collaborative filtering: In this model, products are
  recommended to a user based on the fact that the products have been liked by
  users similar to the user. For example, if Derrick and Dennis like the same
  movies and a new movie come out that Derick like, then we can recommend
  that movie to Dennis because Derrick and Dennis seem to like the same
  movies.
- **Item-based collaborative filtering**: These systems identify similar items based on users' previous ratings. For example, if users A, B, and C gave a 5-star rating to books X and Y then when a user D buys book Y they also get a recommendation to purchase book X because the system identifies book X and Y as similar based on the ratings of users A, B, and C.

Model-based methods are based on Matrix Factorization and are better at dealing with sparsity. They are developed using data mining, machine learning algorithms to predict users' rating of unrated items. In this approach techniques such as dimensionality reduction are used to improve accuracy. Examples of such model-based methods include Decision trees, Rule-based Model, Bayesian Model, and latent factor models.



# <u>Datasets to use for building recommender</u> <u>systems</u>

### **Dataset**

 I choose the TMDb movie data set for data analysis. This data set contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and revenue. I would like to find other intresting patterns in the dataset.

### Contain:

- Total Rows = 10866
- Total Columns = 21
- After Seeing the dataset we can say that some columns is contain null values

### **Conclusions**

- Drama is the most popular genre, following by action, comedy and thriller.
- Drame, Comedy, Thriller and Action are four most-made genres.
- Maximum Number Of Movies Release In year 2014.
- 'Avatar', 'Star Wars' and 'Titanic' are the most profitable movies.
- Short or Long duration movies are more popular than long duration movies.
- Average runtime of the movies are decreasing year by year.
- May,june,november and december are most popular month for releasing movies, if you want to earn more profit.



## **Technology used and Its Characteristics**

## **Software Requirements:**

- Backend Language: PYTHON.
- Editor: Pycharm, Jupyter notebook.



## **Hardware Requirements:**

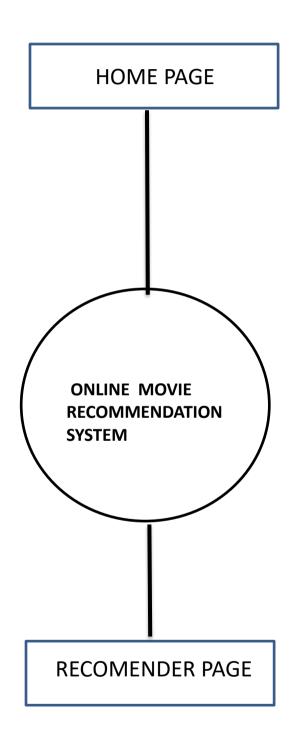
- Operating system: Windows 7 & above
- Ram: 2Gb and more
- Storage: min 50GB or more







## **PROPOSED SYSTEM**



# Walkthrough of building a recommender system

We are going to use the movie lens to build a simple item similaritybased recommender system. The first thing we need to do is to import pandas and numpy.

```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
```

Next, we load in the data set using pandas <code>read\_csv()</code> utility. The dataset is tab separated so we pass in <code>\t</code> to the <code>sep</code> parameter. We then pass in the column names using the <code>names</code> parameter

#### Observation From The Dataset

- The columns 'budget', 'revenue', 'budget\_adj', 'revenue\_adj'
  has not given.But for this dataset i will assume the currency is
  in US dollor.
- The dataset contain lots of movies where the budget or revenue have a value of '0'.

In [5]:

# Data Cleaning (Removing The Unused Information From The Dataset)

Information That We Need To Delete Or Modify

- 1. We need to remove duplicate rows from the dataset
- 2. Changing format of release date into datetime format



- 3. Remove the unused colums that are not needes in the analysis process.
- 4. Remove the movies which are having zero value of budget and revenue

# Remove the unused colums that are not needes in the analysis process

- 5. We can see that 21 columns in the dataset, We can drop the the colums which are not usable in the data analysis process. columns like: imdb\_id,overview etc.

  The columns like imdb\_id, homepage,tagline, overview, budget\_adj and revenue\_adj are not required for my analysis and I will drop these columns.
- Drop theses rows which contain incorrect or inappropriate values.
  - 6. As you can see in this database of movies there are lots of movies where the budget or revenue have a value of '0' which means that the values of those variables of those movies has not been recorded. Calculating the profits of these movies would lead to inappropriate results. I think this may be due to varying factors like the lack of information, or the movies that were never released. I have chosen to eradicate these values during the data cleaning phase.

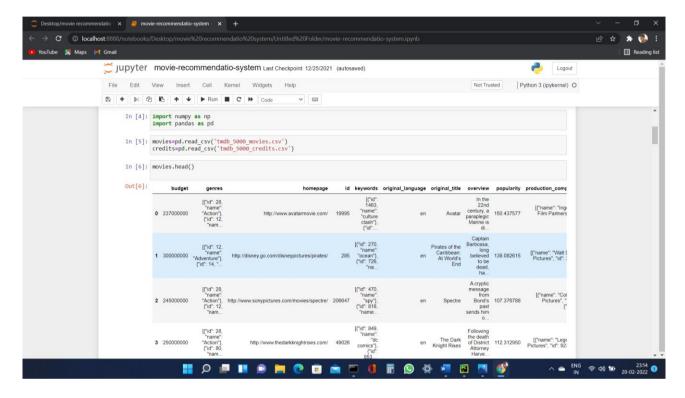
The first column shows the highest profit made by a movie and second column shows the highest in loss movie in this dataset.

As we can see that 'Avatar' movie Directed by James Cameron earn the highest profit in all, making over 2.5B in profit in this dataset. And the most in loss movie in this dataset is **The Warrior's Way**. Going in loss by more than 400M was directed by Singmoo Lee.

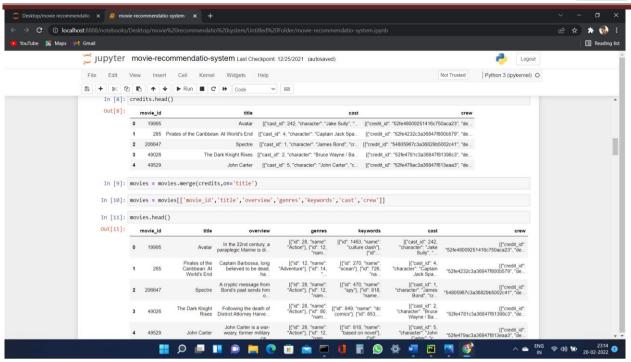


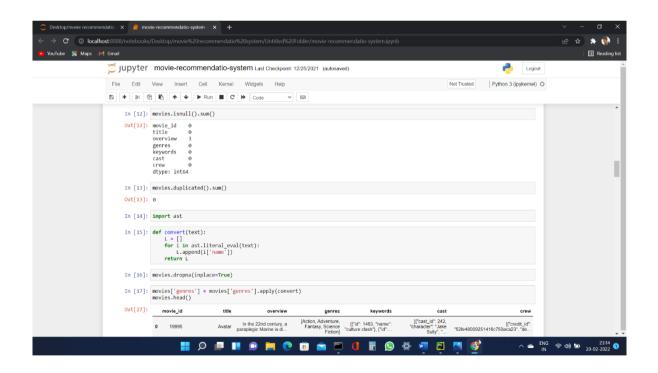
## **DATA PREPROCESSING IN JUPYTER**

## **NOTEBOOK**

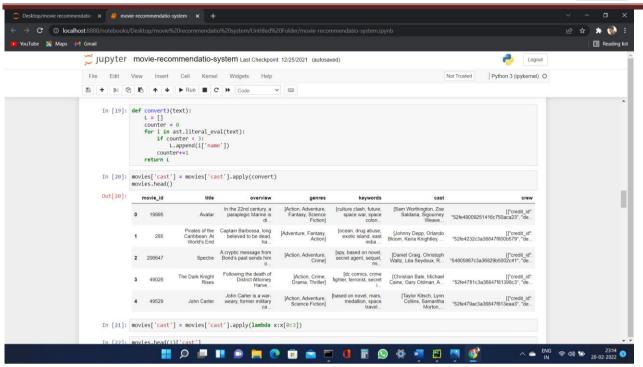


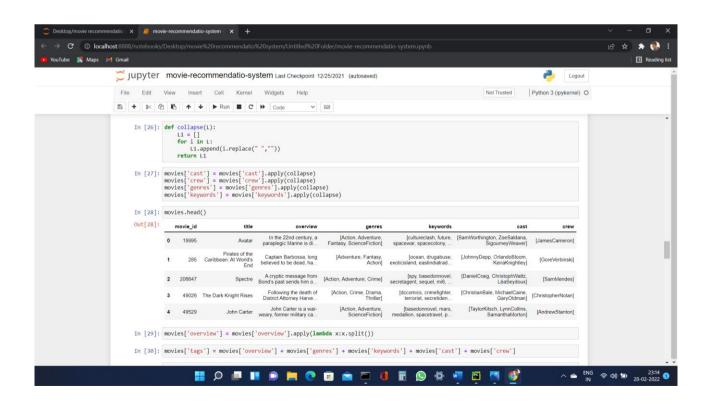




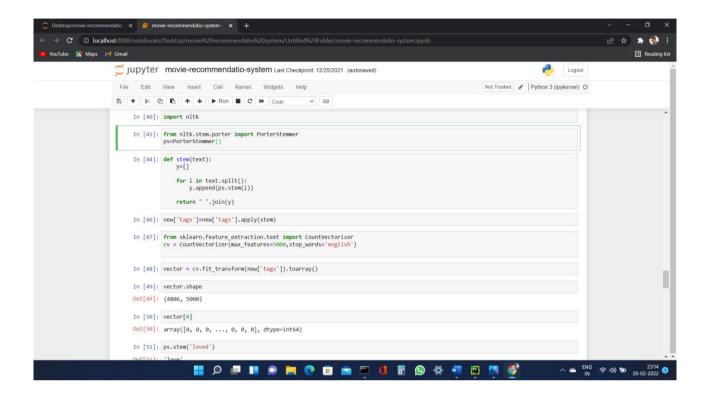


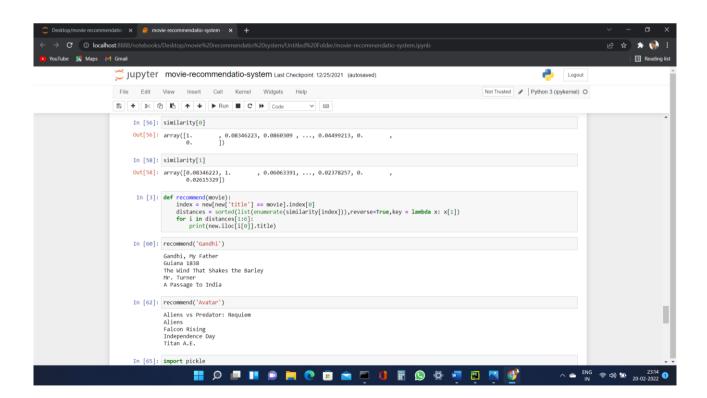




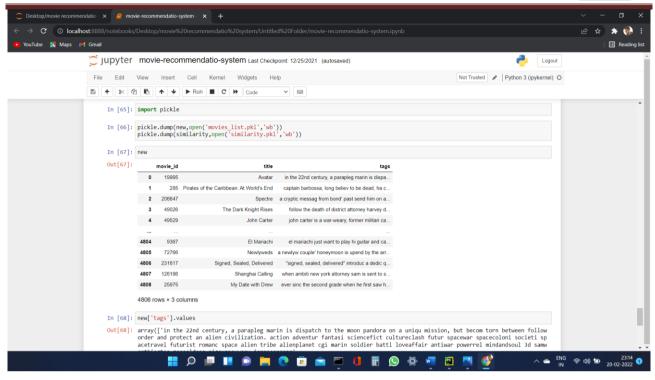


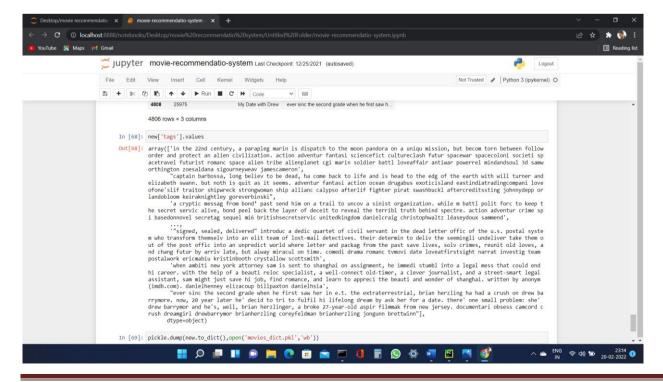










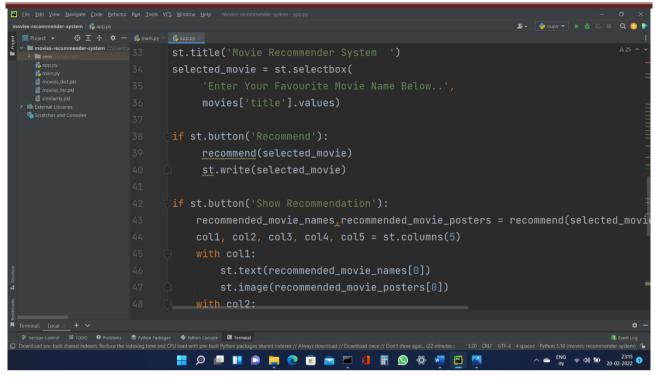


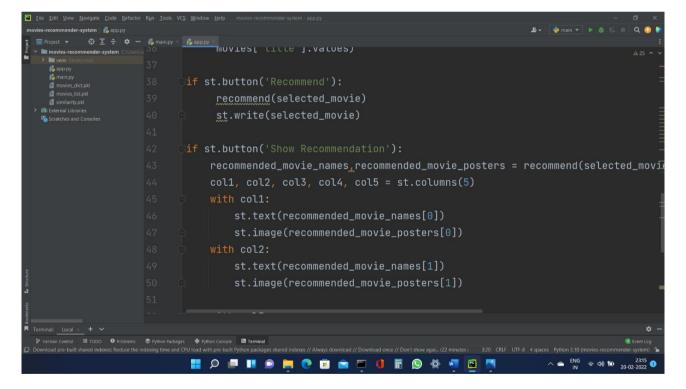


## **PYTHON**

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| Province | Standard | Standard
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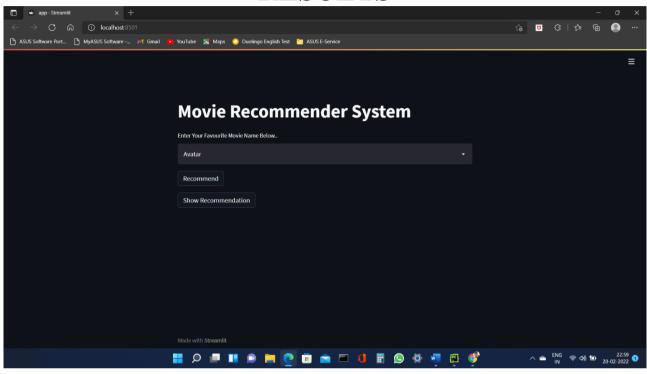


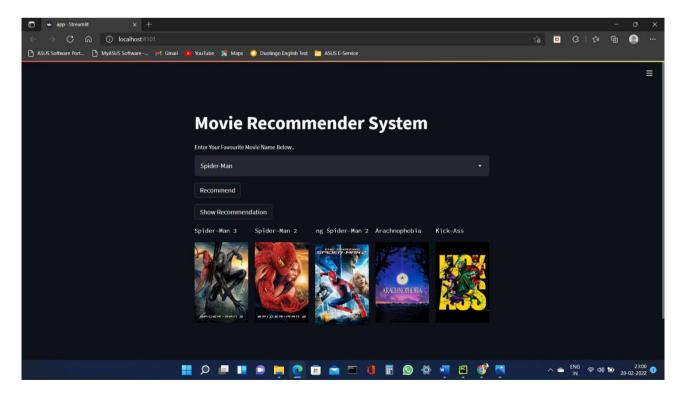




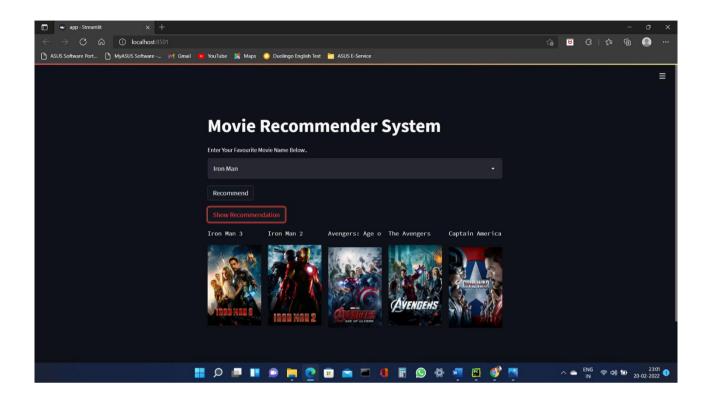


## **RESULTS**









### **CONCLUSION**

The amount of data available on the internet for different kinds of movies, genre, actor, director is very huge. Therefore, this system is used to consolidate all these data into a representable, user friendly interface where the user can be recommended the best movie of his choice by quick filtering of the information on the web

### REFERENCES

YOUTUBE: <a href="https://youtu.be/bbObhCQ-c2g">https://youtu.be/bbObhCQ-c2g</a>

W3SCHOOLS: <a href="https://www.w3schools.com/">https://www.w3schools.com/</a>

