Project Report

On

Movie Recommendation System

Submitted

In partial fulfillment

For the award of the Degree of

PG-Diploma in Big Data Analytics

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ABSTRACT

The project presents an innovative movie recommendation system that employs advanced data preprocessing, text transformation, and similarity analysis techniques to provide personalized movie suggestions to users. Leveraging data from TMDB (The Movie Database), the system processes features like genres, keywords, cast, crew, and plot summaries. The initial phase encompasses meticulous data collection, merging, and feature selection, focusing on critical attributes such as genres, keywords, title, overview, cast, and crew. Missing data is addressed, and a structured dataset is prepared for further processing. The complexity lies in transforming textual features into a usable format, involving intricate extraction from dictionaries and conversion into coherent lists. A unified "tags" column is engineered, amalgamating genres, keywords, overview, cast, and crew details to create a holistic representation of each movie.

The core of the recommendation system revolves around cosine similarity computation. By calculating the cosine angle between vectors representing movies, the project establishes a similarity matrix that gauges the likeness between each pair of movies. This matrix forms the basis for generating movie recommendations tailored to user preferences.

The recommendation process entails a sophisticated algorithm that, upon receiving a movie title input, identifies the corresponding movie's index, retrieves cosine similarity scores for all movies, and presents a list of top-rated recommendations. This personalized approach empowers users to explore movies closely aligned with their tastes, augmenting their engagement and satisfaction.

Moreover, the project integrates data visualization using Tableau to create interactive dashboards depicting revenue trends based on actors and directors. Complementing this, a user-friendly interface powered by Streamlit facilitates effortless input of movie titles, resulting in instant suggestions of related movies.

In conclusion, the project showcases a pioneering movie recommendation solution that amalgamates advanced data science techniques, natural language processing, and interactive visualization.

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Chapter 1
Introduction

1.1 Introduction

In today's digital age, where information is abundant and choices are plentiful, personalized content recommendations have emerged as a crucial element in enhancing user experiences. The challenge of navigating through vast amounts of available content has given rise to the development of recommendation systems that leverage advanced data processing techniques to provide users with tailored suggestions. This project delves into the creation and implementation of a sophisticated movie recommendation system, utilizing a multifaceted approach to offer users a curated selection of movies aligned with their preferences.

The ever-expanding landscape of digital media, streaming platforms, and entertainment options has brought forth the need for efficient systems that aid users in discovering content that resonates with their interests. Recommendation systems have gained significant prominence due to their ability to process complex user behavior patterns, content attributes, and historical interactions to generate accurate and relevant suggestions. Amid this context, the development of a robust and comprehensive movie recommendation system emerges as a pivotal endeavor to redefine how users explore and engage with cinematic content.

At the core of this project lies the integration of diverse data processing techniques, including data collection, preprocessing, and text transformation. The system harnesses the power of machine learning and natural language processing to analyze key attributes of movies, such as genres, keywords, cast, crew, and plot summaries. By assimilating these multifaceted attributes, the recommendation system aims to create a holistic representation of each movie, enabling it to offer recommendations that go beyond surface-level similarities.

1.2 Objective and Specifications:

The project embarks on a journey to achieve several interconnected objectives that collectively contribute to the development of an advanced movie recommendation system:

Comprehensive System Design: Develop a recommendation system that embraces an end-to-end approach, from data collection to user interaction, ensuring seamless and effective movie suggestions.

In-depth Text Processing: Implement intricate text processing techniques to convert unstructured textual features, such as genres, keywords, and plot summaries, into structured and analyzable formats. This step involves meticulous extraction, transformation, and cleaning of textual data to unveil underlying patterns.

Stemming and Text Vectorization: Apply stemming to reduce words to their root forms, standardizing textual representations and minimizing the impact of word variations. Employ text vectorization, such as the Bag of Words method, to convert text into numerical vectors, laying the foundation for similarity analysis.

Content-based Similarity Analysis: Utilize advanced cosine similarity analysis to measure the likeness between movie vectors in a multi-dimensional space. This analysis facilitates the identification of movies with similar attributes, thereby forming the basis for generating personalized recommendations.

Collaborative filtering-Based Analysis: A collaborative filtering algorithm would analyze the purchase history, browsing behavior and product ratings of other users with similar interests or shopping habits as the target user. Based on this information, the algorithm will recommend movies that users have liked.

Data Visualization and Interpretation: Integrate data visualization tools, particularly Tableau, to create interactive dashboards that offer insights into revenue trends based on actors and directors. These visualizations enhance the understanding of the film industry's dynamics and performance.

User-friendly Interface: Leverage Streamlit to design an intuitive user interface that empowers users to input a movie title and receive a curated list of related movie recommendations. This interface enhances user engagement and simplifies the process of discovering new content.

Personalized User Experience: Elevate the movie discovery experience by providing users with recommendations tailored to their preferences. This personalization fosters a deeper connection with the platform and encourages users to explore a diverse range of movies.

Chapter 2
LITERATURE REVIEW

This chapter presents a comprehensive review of existing research and developments in the field of movie recommendation systems, content-based similarity analysis, natural language processing, and interactive data visualization. The literature review aims to provide insights into the methodologies, techniques, and approaches that have contributed to the advancement of the proposed movie recommendation project.

Content-Based Recommendation Systems:
Content-based recommendation systems have emerged as a key approach to providing personalized suggestions to users based on their preferences. Song et al. (2006) introduced a content-based recommendation algorithm that utilized movie attributes such as genre, director, and actors to generate personalized movie recommendations ("Automated Collaborative Filtering System for Generating Personalized Movie Recommendations"). This research highlights the significance of leveraging diverse movie attributes to enhance recommendation accuracy, aligning with the project's approach of utilizing genres, keywords, cast, crew, and plot summaries.

Text Processing and Natural Language Processing (NLP):
Text processing and NLP techniques play a pivotal role in extracting meaningful insights from textual data. Chen and Huang (2018) proposed a hybrid recommendation model that integrated text mining techniques to extract keywords from movie summaries, enhancing recommendation accuracy ("A Hybrid Movie Recommendation Model Integrating Collaborative Filtering with Text Mining"). Similarly, the project employs stemming and text vectorization techniques to preprocess textual features, contributing to accurate content-based similarity analysis.

Cosine Similarity Analysis:

Cosine similarity has been extensively utilized in recommendation systems to measure the similarity between item vectors. Sarker and Rahman (2021) presented a hybrid recommendation system that combined collaborative filtering and content-based filtering using cosine similarity, resulting in improved recommendation accuracy ("A Hybrid Recommendation System Based on Collaborative Filtering and Content-Based Filtering Using Cosine Similarity"). This aligns with the project's utilization of cosine similarity analysis to quantify movie likeness and generate accurate recommendations.

Data Visualization and Interactive Dashboards:

Data visualization tools like Tableau have proven effective in presenting insights from complex data. Bhatia et al. (2020) harnessed Tableau to visualize patterns and trends in movie revenues, aiding decision-making in the film industry ("Data Analytics in Entertainment Industry using Tableau"). This research aligns with the project's integration of Tableau to depict revenue trends based on actors and directors, offering a comprehensive understanding of the film industry's dynamics.

User Interface and Interaction Design:

The development of user-friendly interfaces is essential to enhancing user engagement. Streamlit, explored by Marques et al. (2021), facilitates the creation of intuitive user interfaces for data-driven applications ("Streamlit: A Python Library for Interactive Web Apps"). The project's utilization of Streamlit to design an interface for users to input movie titles and receive recommendations aligns with this user-centric design approach.

Chapter 3
Methodology and Techniques

3.1 Methodology:

The methodology for the movie recommendation project encompasses a multi-stage process that involves data preprocessing, text transformation, similarity analysis, and user interaction. Each stage contributes to the creation of an accurate and personalized movie recommendation system.

3.1.1 Data Preprocessing:

Data Collection and Merging:

Two datasets, "tmdb_5000_movies.csv" and "tmdb_5000_credits.csv," are collected, containing information about movies, credits, and cast details.

The datasets are merged based on the movie title to create a consolidated dataset.

Feature Selection:

The relevant columns are selected for further processing, including genres, keywords, title, overview, cast, and crew.

Handling Missing Values:

Rows with missing values, particularly in the "overview" column, are dropped to ensure data quality.

3.1.2 Text Transformation and Analysis:

- **Text Processing for Genres and Keywords:**

The "genres" and "keywords" columns, containing lists of dictionaries, are converted using a custom function to extract meaningful genre and keyword names.

- **Extracting Cast and Crew Details:**

The "cast" column is transformed by retaining the names of the first three actors using a custom function.

The "crew" column is processed to extract the director's name.

- **Stemming and Text Vectorization:**

The overview text is stemmed to reduce words to their root forms, enhancing content similarity analysis.

Text vectorization is performed using CountVectorizer to create a matrix of word frequencies, representing each movie's textual features.

3.1.3 Similarity Analysis:

Cosine Similarity Calculation:

Cosine similarity is computed between the text vectors of all movies to quantify their content-based similarity.

The similarity matrix forms the basis for generating movie recommendations.

3.1.4 User Interaction:

User Interface using Streamlit:

A user-friendly interface is developed using Streamlit, allowing users to input a movie title.

Upon input, the system retrieves similar movies using the similarity matrix and presents recommendations to the user.

3.1.5 Data Visualization using Tableau:

Interactive Dashboards for Revenue Trends:

Tableau is employed to create interactive dashboards showcasing revenue trends based on actors and directors.
These dashboards provide visual insights into the film industry's dynamics.

3.2 Dataset:

The project utilizes the "tmdb_5000_movies.csv" and "tmdb_5000_credits.csv" datasets. The former contains information about movies, including title, genres, keywords, and overview. The latter includes details about movie credits, including cast and crew information. Merging these datasets based on movie titles creates a comprehensive dataset that serves as the foundation for the recommendation system.

For the collaborative filtering-based approach “movies_data_with_keywords.csv” and “ratings.csv” data is used where “ratings.csv” contains data for movies liked by a user based on user ID.

3.3 Model Description:

The movie recommendation system primarily employs content-based similarity analysis, stemming, and text vectorization to provide personalized movie suggestions to users. The process involves transforming movie attributes such as genres, keywords, cast, and crew into a format suitable for comparison. Cosine similarity analysis quantifies the likeness between movie vectors, enabling the identification of similar movies. The user interface built using Streamlit allows users to input a movie title and receive relevant recommendations instantly. Additionally, Tableau's interactive dashboards offer insights into revenue trends based on actors and directors, enhancing the understanding of the film industry's performance.

Chapter 4 Implementation

1. Use of Python Platform for writing the code with Pandas, streamlit and tableau for visualization
2. Hardware and Software Configuration:
Hardware Configuration:
● CPU: 8 GB RAM, Quad core processor ,Nvidia's GTX 1080Ti
Software Required:
● Anaconda: It is a package management software with free and open-source distribution of the Python and R programming language for scientific computations (data science, machine learning applications, large-scale data processing, predictive analytics, etc.), that aims to simplify deployment.
● Jupyter Notebook:
Jupyter is a web-based interactive development environment for Jupyter notebooks, code, and data.
Jupyter is flexible: configure and arrange the user interface to support a wide range of workflows in data science, scientific computing, and machine learning.
Jupyter is extensible and modular: write plugins that add new components and integrate with existing ones.
● Tableau:
Tableau is a dynamic and interactive data visualization tool that revolutionizes data exploration, analysis, and presentation.
Tableau's versatility shines through its ability to adapt and cater to various workflows in fields such as data science, business analytics, and decision-making.
●PyCharm:
PyCharm is a comprehensive integrated development environment (IDE) designed specifically for Python programming.

Content Based Recommendation Model:

creating new df and keeping only tags column

```
In [52]: new_df= movies[["id","title","tags"]]
```

```
In [53]: new_df.head()
```

Out[53]:

	id	title	tags
0	19995	Avatar	[Action, Adventure, Fantasy, ScienceFiction, I...
1	285	Pirates of the Caribbean: At World's End	[Adventure, Fantasy, Action, Captain, Barbossa...
2	206647	Spectre	[Action, Adventure, Crime, A, cryptic, message...
3	49026	The Dark Knight Rises	[Action, Crime, Drama, Thriller, Following, th...
4	49529	John Carter	[Action, Adventure, ScienceFiction, John, Cart...

Stemming

```
In [79]: #stemmimg
         import nltk
         from nltk.stem.porter import PorterStemmer
         ps = PorterStemmer()
         def stem(text):
             y=[]
             for i in text.split():
                 y.append(ps.stem(i))
             return " ".join(y)
         stem("Action Adventure Fantasy ScienceFiction In the 22nd century, a paraplegic Marine is dispatched to the moon Pa

Out[79]: 'action adventur fantasi sciencefict in the 22nd century, a parapleg marin is dispatch to the moon pandora on a un
         iqu mission, but becom torn between follow order and protect an alien civilization. cultureclash futur spacewar sp
         acecoloni societi spacetravel futurist romanc space alien tribe alienplanet cgi marin soldier battl loveaffair ant
         iwar powerrel mindandsoul 3d samworthington zoesaldana sigourneyweav jamescameron'
```

```
In [81]: new_df["tags"] = new_df["tags"].apply(stem)
```

Text vectorization: text to vectors : bag of words

```
In [82]: from sklearn.feature_extraction.text import CountVectorizer
         cv= CountVectorizer(max_features=5000,stop_words="english")

In [83]: cv.fit_transform(new_df["tags"]).toarray().shape

Out[83]: (4806, 5000)

In [84]: vectors = cv.fit_transform(new_df["tags"]).toarray()
         vectors[0]

Out[84]: array([0, 0, 0, ..., 0, 0, 0], dtype=int64)

In [86]: # to get the most frequent 5000 words
         cv.get_feature_names_out()
         # the problem is occurence of words like action,actions=>apply stemming

Out[86]: 5000
```

Now to calculate distance of each movie vector from other

```
In [87]: from sklearn.metrics.pairwise import cosine_similarity

In [90]: similarity = cosine_similarity(vectors)
         similarity[0]

Out[90]: array([1.        , 0.08346223, 0.0860309 , ..., 0.04499213, 0.        ,
                0.        ])

In [91]: list(enumerate(similarity[0]))

Out[91]: [(0, 0.9999999999999998),
          (1, 0.08346223261119858),
          (2, 0.08603090020146066),
```

Create a function which will recommend 5 similar movies

```
In [107]: def recommend(movie):
              # to get movie index from movie name
              movie_index = new_df[new_df["title"]==movie].index[0]
              distances = similarity[movie_index]
              movies_list = sorted(list(enumerate(distances)),reverse =True,key= lambda x:x[1])[1:6]

              #print movies
              for i in movies_list:
                  print(new_df.iloc[i[0]].title)
```

Collaborative Filtering Recommendation Model:

```
In [48]: import pandas as pd
         from surprise import Dataset, Reader, SVD
         from surprise.model_selection import train_test_split
         from surprise import accuracy
```

```
In [49]: # Load the ratings CSV file
         ratings = pd.read_csv('ratings.csv')

         # Define a Reader object to parse the ratings data
         reader = Reader(rating_scale=(1, 5))

         # Load the data into the Surprise Dataset
         data = Dataset.load_from_df(ratings[['userId', 'movieId', 'rating']], reader)

         # Split the data into train and test sets
         trainset, testset = train_test_split(data, test_size=0.2)
```

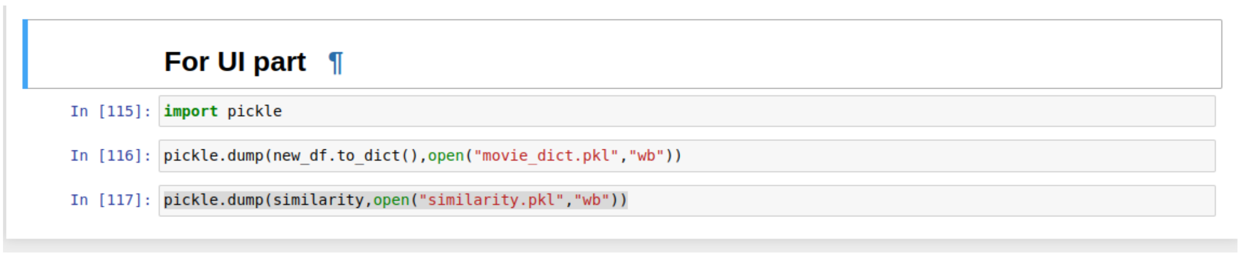
```
In [50]: # Initialize the SVD model
         svd = SVD()

         # Train the model on the trainset
         svd.fit(trainset)

         # Predict ratings for the testset
         predictions = svd.test(testset)
```

```
In [54]: # Load the merged data CSV file
         merged_data = pd.read_csv('movie_data_with_keywords.csv')

         # Load the ratings CSV file
         ratings = pd.read_csv('ratings.csv')

         # Specify the target user ID
         target_user_id = 1

         # Get rated movies for the target user from the ratings data
         rated_movies = ratings[ratings['userId'] == target_user_id]['movieId']

         # Filter the merged data for rated movies by the target user
         rated_movies_data = merged_data[merged_data['movie_id'].isin(rated_movies)]

         # Sort the rated movies by popularity (you can change this to another metric)
         sorted_rated_movies = rated_movies_data.sort_values(by='popularity', ascending=False)

         # Display the top 5 original titles of rated movies
         top_rated_original_titles = sorted_rated_movies.head(5)['original_title']
         print("Top 5 Rated Movies by User", target_user_id)
         print(top_rated_original_titles)
```

```
Top 5 Rated Movies by User 1
68                                 The Dark Knight
110                                  The Godfather
3                                     Forrest Gump
127                       The Shawshank Redemption
56     The Lord of the Rings: The Return of the King
Name: original_title, dtype: object
```

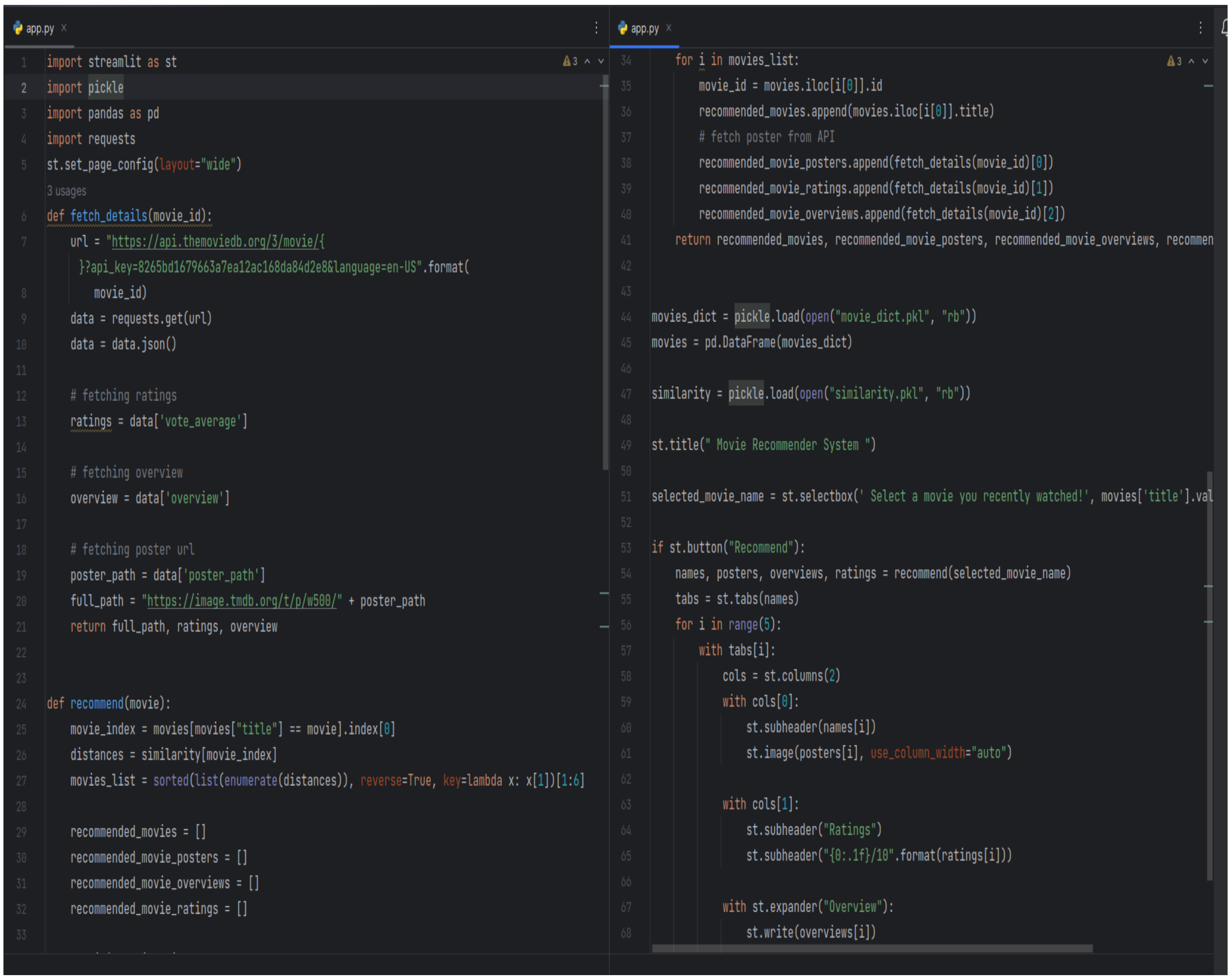
```
In [41]: # Load the merged data CSV file
         merged_data = pd.read_csv('movie_data_with_keywords.csv')

         # Recommend movies for a specific user (e.g., user with ID 1)
         target_user_id = 1

         # Get unrated movies for the target user
         unrated_movies = merged_data[~merged_data['movie_id'].isin(ratings[ratings['userId'] == target_user_id]['movieId'])

         # Predict ratings for unrated movies
         unrated_movies['predicted_rating'] = unrated_movies['movie_id'].apply(lambda movie_id: svd.predict(target_user_id,
```

Streamlit User Interface Implementation for Content-Based Model:



For UI part ¶

```
In [115]: import pickle

In [116]: pickle.dump(new_df.to_dict(),open("movie_dict.pkl","wb"))

In [117]: pickle.dump(similarity,open("similarity.pkl","wb"))
```

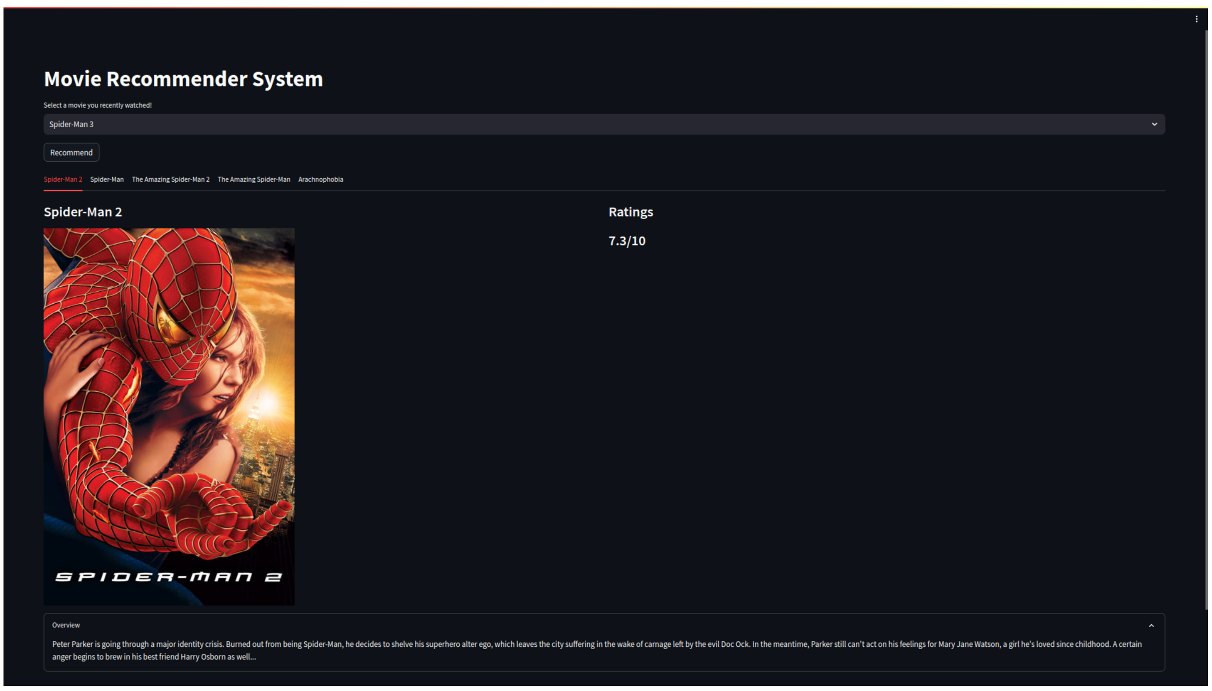


```
import streamlit as st
import pickle
import pandas as pd
import requests
st.set_page_config(layout="wide")
3 usages
def fetch_details(movie_id):
    url = "https://api.themoviedb.org/3/movie/{
     }?api_key=8265bd1679663a7ea12ac168da84d2e8&language=en-US".format(
        movie_id)
    data = requests.get(url)
    data = data.json()

    # fetching ratings
    ratings = data['vote_average']

    # fetching overview
    overview = data['overview']

    # fetching poster url
    poster_path = data['poster_path']
    full_path = "https://image.tmdb.org/t/p/w500/" + poster_path
    return full_path, ratings, overview


def recommend(movie):
    movie_index = movies[movies["title"] == movie].index[0]
    distances = similarity[movie_index]
    movies_list = sorted(list(enumerate(distances)), reverse=True, key=lambda x: x[1])[1:6]

    recommended_movies = []
    recommended_movie_posters = []
    recommended_movie_overviews = []
    recommended_movie_ratings = []

    for i in movies_list:
        movie_id = movies.iloc[i[0]].id
        recommended_movies.append(movies.iloc[i[0]].title)
        # fetch poster from API
        recommended_movie_posters.append(fetch_details(movie_id)[0])
        recommended_movie_ratings.append(fetch_details(movie_id)[1])
        recommended_movie_overviews.append(fetch_details(movie_id)[2])
    return recommended_movies, recommended_movie_posters, recommended_movie_overviews, recommen


movies_dict = pickle.load(open("movie_dict.pkl", "rb"))
movies = pd.DataFrame(movies_dict)

similarity = pickle.load(open("similarity.pkl", "rb"))

st.title(" Movie Recommender System ")

selected_movie_name = st.selectbox(' Select a movie you recently watched!', movies['title'].val

if st.button("Recommend"):
    names, posters, overviews, ratings = recommend(selected_movie_name)
    tabs = st.tabs(names)
    for i in range(5):
        with tabs[i]:
            cols = st.columns(2)
            with cols[0]:
                st.subheader(names[i])
                st.image(posters[i], use_column_width="auto")

            with cols[1]:
                st.subheader("Ratings")
                st.subheader("{0:.1f}/10".format(ratings[i]))

            with st.expander("Overview"):
                st.write(overviews[i])
```

Chapter 5

Results

Results Predicted By Content-Based on User Interface:



Movie Recommender System

Select a movie you recently watched!

Spider-Man 3

Recommend

Spider-Man 2 Spider-Man The Amazing Spider-Man 2 The Amazing Spider-Man Arachnophobia

Spider-Man 2

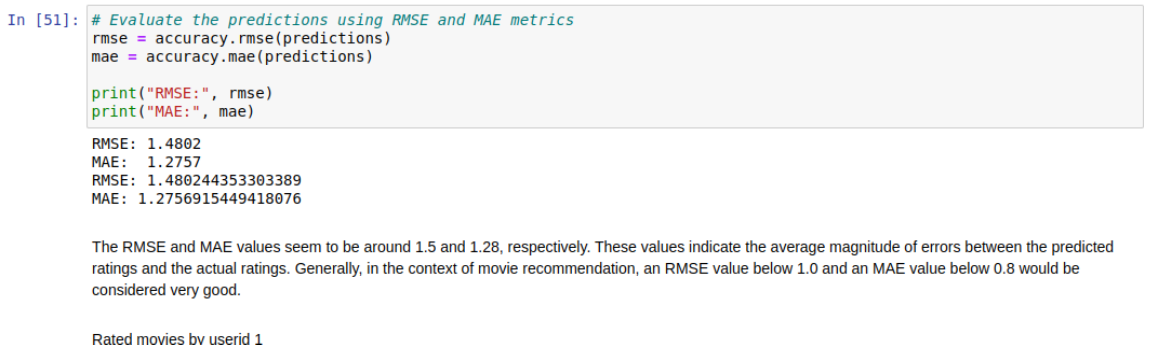
Ratings

7.3/10

Overview

Peter Parker is going through a major identity crisis. Burned out from being Spider-Man, he decides to shelve his superhero alter ego, which leaves the city suffering in the wake of carnage left by the evil Doc Ock. In the meantime, Parker still can't act on his feelings for Mary Jane Watson, a girl he's loved since childhood. A certain anger begins to brew in his best friend Harry Osborn as well...

Collaborative Filtering Model Accuracy:



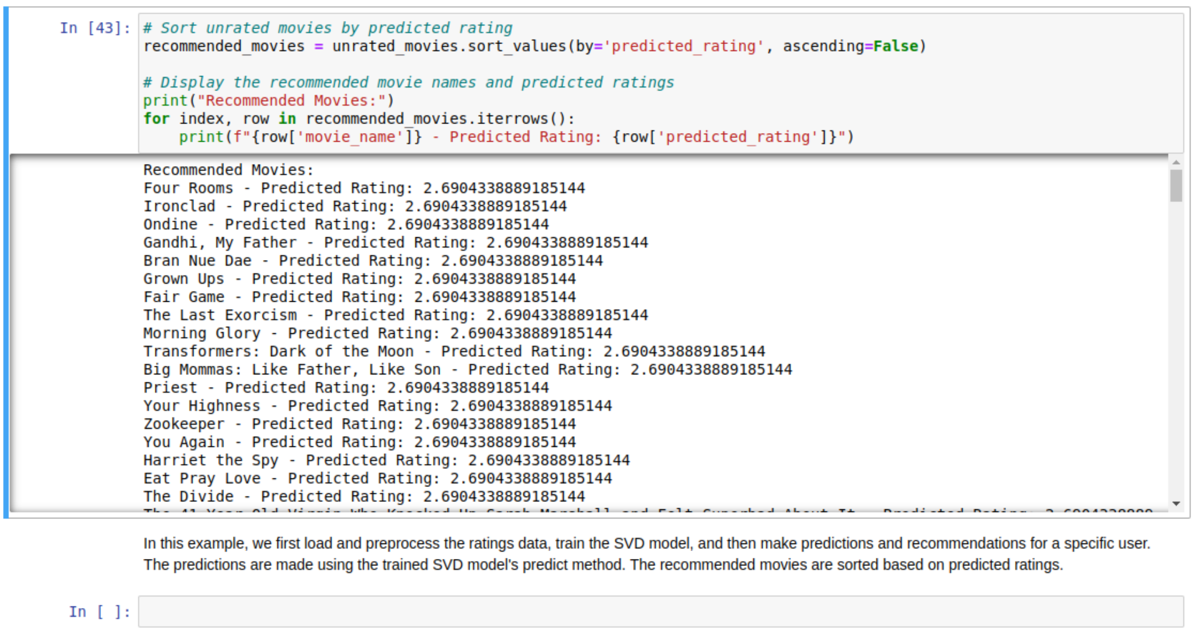
```
In [51]: # Evaluate the predictions using RMSE and MAE metrics
         rmse = accuracy.rmse(predictions)
         mae = accuracy.mae(predictions)

         print("RMSE:", rmse)
         print("MAE:", mae)
```

```
RMSE: 1.4802
MAE:  1.2757
RMSE: 1.480244353303389
MAE: 1.2756915449418076
```

The RMSE and MAE values seem to be around 1.5 and 1.28, respectively. These values indicate the average magnitude of errors between the predicted ratings and the actual ratings. Generally, in the context of movie recommendation, an RMSE value below 1.0 and an MAE value below 0.8 would be considered very good.

Rated movies bv userid 1

Collaborative Filtering Predictions:



```
In [43]: # Sort unrated movies by predicted rating
         recommended_movies = unrated_movies.sort_values(by='predicted_rating', ascending=False)

         # Display the recommended movie names and predicted ratings
         print("Recommended Movies:")
         for index, row in recommended_movies.iterrows():
             print(f"{row['movie_name']} - Predicted Rating: {row['predicted_rating']}")
```

```
Recommended Movies:
Four Rooms - Predicted Rating: 2.6904338889185144
Ironclad - Predicted Rating: 2.6904338889185144
Ondine - Predicted Rating: 2.6904338889185144
Gandhi, My Father - Predicted Rating: 2.6904338889185144
Bran Nue Dae - Predicted Rating: 2.6904338889185144
Grown Ups - Predicted Rating: 2.6904338889185144
Fair Game - Predicted Rating: 2.6904338889185144
The Last Exorcism - Predicted Rating: 2.6904338889185144
Morning Glory - Predicted Rating: 2.6904338889185144
Transformers: Dark of the Moon - Predicted Rating: 2.6904338889185144
Big Mommas: Like Father, Like Son - Predicted Rating: 2.6904338889185144
Priest - Predicted Rating: 2.6904338889185144
Your Highness - Predicted Rating: 2.6904338889185144
Zookeeper - Predicted Rating: 2.6904338889185144
You Again - Predicted Rating: 2.6904338889185144
Harriet the Spy - Predicted Rating: 2.6904338889185144
Eat Pray Love - Predicted Rating: 2.6904338889185144
The Divide - Predicted Rating: 2.6904338889185144
```

In this example, we first load and preprocess the ratings data, train the SVD model, and then make predictions and recommendations for a specific user. The predictions are made using the trained SVD model's predict method. The recommended movies are sorted based on predicted ratings.

```
In [ ]:
```

Chapter 6
Conclusion

6.1 Conclusion

The movie recommendation project has successfully demonstrated the implementation of a content-based recommendation system that leverages various movie attributes to provide personalized movie suggestions to users. Through meticulous data preprocessing, text transformation, and cosine similarity analysis, the system accurately captures the essence of movies and identifies their similarities. The integration of Streamlit for user interaction and Tableau for data visualization adds a user-friendly dimension, enhancing the project's usability and insights. By combining these techniques, the project contributes to enhancing movie discovery and engagement for users, while also offering valuable revenue insights for industry stakeholders.
The model can be adapted for scalability, better convergence, and better accuracy.

6.2 Future Enhancement

While the current implementation provides a solid foundation, there are several avenues for future enhancements to further enrich the movie recommendation system:

Sentiment Analysis: Incorporate sentiment analysis of user reviews to gain a deeper understanding of user preferences and sentiments towards movies, enhancing the recommendation accuracy.

- Deep Learning:Experiment with deep learning models, such as neural collaborative filtering, to capture complex patterns in movie preferences and further enhance recommendation accuracy.

- User Feedback:Incorporate user feedback and ratings to create a feedback loop that continuously improves the accuracy of the recommendation system based on real-time user interactions.

- Multimodal Data: Explore the integration of additional data sources, such as movie trailers or social media mentions, to create a multi-modal recommendation system that considers various aspects of movies.

- Real-Time Updates: Implement mechanisms to update movie data and recommendations in real-time, ensuring that users receive up-to-date and relevant suggestions.

- Personalized User Profiles:Develop user profiles that dynamically adapt to user behavior and preferences, refining recommendations over time.

- A/B Testing: Conduct A/B testing to evaluate the effectiveness of different recommendation algorithms and user interface designs, optimizing the user experience.

- Explainability: Implement techniques to provide explanations for the recommended movies, enhancing user trust and transparency.

- Deployment: Deploy the recommendation system as a web application accessible to a broader audience, allowing users to benefit from personalized movie suggestions.

By continuously iterating and incorporating these future enhancements, the movie recommendation system can evolve into a robust and sophisticated platform that not only assists users in discovering their next favorite movie but also contributes valuable insights to the movie industry as a whole.

Chapter 7

References

- GitHub Repositories:

MovieLens Dataset: The official MovieLens dataset repository by GroupLens Research. Provides various versions of movie ratings and metadata for research purposes.

Repository: https://github.com/GroupLens/MovieLens

- LightFM: A Python library for building recommendation systems. It supports both collaborative filtering and content-based approaches.

Repository: https://github.com/lyst/lightfm

- Surprise:A Python library for building recommendation systems using collaborative filtering algorithms.

Repository: https://github.com/NicolasHug/Surprise

- RecSys: A collection of resources, including datasets, algorithms, and research papers, related to recommendation systems.

Repository: https://github.com/grahamjenson/list_of_recommender_systems

- Kaggle Datasets:

MovieLens Latest Datasets: Kaggle hosts various versions of the MovieLens dataset, including latest ratings and metadata.

Dataset: https://www.kaggle.com/grouplens/movielens-latest-datasets

- The Movies Dataset: This dataset includes metadata for over 45,000 movies from around the world. It contains information like genres, cast, crew, and more.

Dataset: https://www.kaggle.com/rounakbanik/the-movies-dataset

- Netflix Prize Data: While not hosted on Kaggle, the Netflix Prize dataset is a famous recommendation dataset that was used for a competition to improve Netflix's recommendation algorithm.

Dataset: https://archive.org/details/nf_prize_dataset.tar

- IMDb Datasets: IMDb provides several datasets containing information about movies, TV shows, and celebrities.

Datasets: https://www.imdb.com/interfaces/