Movie Recommendation System with Sentimental Analysis

Mini Project III
7th Semester
Department of Information Technology

Submitted by

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Candidates Declaration

I hereby declare that the work presented in this report entitled **Movie Recommendation System with Sentimental Analysis**, submitted towards the fulfillment of **7 semester project** report of Information Technology at Indian Institute of Information Technology Allahabad is an authenticated record of our original work carried out under the guidance of **Dr. Triloki Pant**. Due acknowledgments have been made in the text to all other material used. The project was done in full compliance with the requirements and constraints of the prescribed curriculum.

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This is to certify that the statement made by the candidate is correct to the best of my knowledge and belief. The project titled **Movie Recommendation System with Sentimental Analysis** is a record of candidates' work carried out by him under my guidance and supervision. I do hereby recommend that it should be accepted in the fulfillment of the requirements of the **7th Semester Mini Project** at IIIT Allahabad.

Dr. Triloki Pant
(On final examination and approval of the Project)

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The forgoing thesis is hereby approved as a creditable study carried out in the area of Information Technology and presented in a manner satisfactory to warrant its acceptance as a prerequisite to the degree for which it has been submitted. It is understood that by this approval the undersigned does not necessarily endorse or approve any statement made, opinion expressed or the conclusion drawn therein, but approves the thesis only for the purpose for which it is submitted. Committee on final examination for the evaluation of thesis:

1. Dr. Triloki Pant
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Contents

Abstract

In the ever-expanding realm of cinematic choices, the need for personalized movie recommendations is paramount. This project introduces a sophisticated Content-Based Movie Recommender System fortified with sentiment analysis, aiming to provide users with movie suggestions tailored to their preferences. Employing the Movie Database (TMDB) API and TMDB reviews, the system not only gets information about movies but also extracts and analyzes user sentiments, offering a comprehensive movie finding experience.

Movie details, encompassing title, genre, runtime, rating is sourced from TMDB via their API (https://www.themoviedb.org/documentation/api). Further enriching the recommendation engine, user reviews from TMDB are obtained through web scraping using beautifulsoup4. This multi-faceted approach ensures a holistic understanding of both factual details and user sentiments.

Our recommendation method relies heavily on the notion of a similarity score, which is a numerical value that falls within the range of zero to one. This score, obtained through cosine similarity, measures the likeness between two items based on the similarity of their textual details. Cosine similarity proves advantageous in determining document similarity, irrespective of document size, enhancing the accuracy of recommendations.

In this report we have further used four different datasets on the above-mentioned models and done a comparative study based on the results, and discussed the current research challenges for movie recommendation using content-algorithm. Lastly we have provided a future Scope for deep fake detection methods and concluded our report paper.

Chapter 1

Introduction

In the era of streaming services and an abundance of cinematic choices, the pursuit of personalized movie recommendations has become more complex yet crucial. Modern Content-Based Movie Recommender System with sentiment analysis is introduced in this project, giving people a more sophisticated and personalized way to find movies. The convergence of data from The Movie Database (TMDB) API and sentiment-rich TMDB reviews sets the foundation for a recommender system that goes beyond factual details to understand and cater to user preferences.

The landscape of movie recommendations is evolving, and so are user expectations. Traditional content-based recommendation systems consider movie details such as genre and runtime. This project elevates the paradigm by incorporating sentiment analysis, delving into user reviews to comprehend the emotional resonance a movie has with its audience.

1.1 Data Fusion from TMDB and TMDB:

Real movie information is constructed using the TMDB Application Programming Interface (API). It provides essential details including director, genre, duration, and ratings. In order to augment this, the system additionally uses web scraping methods, notably beautifulsoup4, to obtain user reviews from TMDB. This dual-sourced approach guarantees that a thorough comprehension of a film's qualities and the emotions of its viewers is attained.

1.2 Central Role of Similarity Scores and Cosine Similarity:

At the heart of the recommender system is the concept of similarity scores. Utilizing cosine similarity, the system measures the likeness between movies based on textual details. This ensures that recommendations are not merely based on genre or runtime but extend to the intrinsic characteristics that define a user's cinematic preferences.

1.3 Datasets and Mathematical Foundation:

Any movie can be searched for, and 10 more movies in the same field will be shown. The user can also read reviews about it to find out whether it's good or bad. Different datasets, such as the TMDB 5000 Movie Dataset and hand-picked lists from 2018 to 2020, are added to the suggestion engine to make it stronger. The math behind cosine similarity is looked at, which sheds light on how well it works for comparing documents in a number of different ways.

Basically, this Content-Based Movie Recommender System with Sentiment Analysis is a complete answer for movie fans who want to find movies that are both personally and emotionally meaningful. The system is the best at making users more interested in exploring movies because it combines factual information, sentiment analysis, and advanced selection algorithms.

Chapter 2

Related Work

Title	Aim	Issues	Methods	Datasets	Findings	Future work
Movie Recommendation System Using Sentiment Analysis From Microblogging Data	This research combines collaborative filtering and content-based filtering with Twitter sentiment analysis to improve movie recommendations. By adding social media sentiment, movie suggestions can be more accurate and tailored.	Data Sparsity, Sentiment Analysis Accuracy, Integration of Hybrid Models, Multilingual Support.	Collaborative Filtering (CF), Content-Based Filtering (CBF), Sentiment Analysis, Hybrid Recommendation: Weighted Score Fusion.	MovieTweetings Database, Twitter Data.	Correlation between Sentiment and Ratings, Optimal Weight Selection, Qualitative Analysis:	Motion Analysis, Multimodal Data, Enhanced Language Support, Real-time Recommendations, Improved Sentiment Analysis Models.
Movie Recommender system using Sentiment Analysis	The aim of this research is to design and implement an efficient movie recommender system based on user sentiment analysis. The system aims to enhance user experience by	Algorithm Efficiency, Sentiment Analysis Accuracy, Data Privacy, System Scalability.	Collaborative Filtering, Sentiment Analysis, User-Based Collaborative Filtering Algorithm.	Movie Datasets, User Feedback Datasets.	Efficient Recommender System, Enhanced User Experience.	Enhanced Sentiment Analysis, Hybrid Recommender Systems, Real-Time Recommendations,

	providing personalized movie recommendations using collaborative filtering algorithms, specifically focusing on the K-nearest neighbors (KNN) algorithm.					Diverse Content Recommendations.
A Sentiment-Enhanced Hybrid Recommender System for Movie Recommendation: A Big Data Analytics Framework	This research proposes a sentiment-enhanced hybrid collaborative filtering and content-based recommendation strategy to improve mobile movie recommendation systems. To meet mobile movie recommendation needs, accuracy and timeliness are improved.	Computational Efficiency, Sentiment Analysis Integration, Scalability, Algorithm Integration.	Collaborative Filtering, Content-Based Recommendation, Sentiment Analysis: Hybrid Recommendation.	Douban Movie Data, User-generated Reviews.	Improved Recommendation Accuracy, Enhanced Timeliness Satisfaction.	Dynamic Sentiment Analysis, Personalization Enhancement, User Engagement Studies, Scalability Measures.

Chapter 3

Research Gap

The development of the Content-Based Movie Recommender System with Sentiment Analysis is a big step forward in making individual movie suggestions. There are, however, possible study gaps and areas where more work could help make things even better, just like with any other system or research.

Limited Exploration of Deep Learning for Sentiment Analysis - Despite the integration of sentiment analysis, there is still potential for further exploration of more advanced learning methodologies due to the excessive reliance on standard Natural Language Processing (NLP) techniques. An investigation into the effectiveness of transformer-based models such as BERT or recurrent neural networks (RNNs) in deep learning has the potential to enhance the system's ability to identify intricate emotions and contextual information.

Lack of Explain ability in Recommendations: - The paper briefly discusses explainability and transparency in recommendation systems. The depth of this investigation may represent a research void. In order to increase user understanding and trust, future research may focus on implementing and evaluating tactics that explicitly explain to consumers why particular movies are recommended.

Lack of Hybrid Recommendation System Exploration: - Sentiment analysis combined with a content-based strategy is the system's main focus. A possible research gap is the investigation of hybrid recommendation systems that combine collaborative and content-based filtering strategies. This could lead to more accurate and varied suggestions if the interactions between these methods are studied.

Real-Time Adaptability and Dynamic Updates: - The report briefly suggests exploring the incorporation of real-time user data. However, the depth of this exploration and the potential challenges in achieving real-time adaptability remain open areas for research. Future work could investigate strategies for dynamically updating the recommendation system based on immediate user interactions and preferences.

Scalability Considerations for Large Datasets: - Although the scalability of the system is discussed in passing, there remains a research gap in the thorough investigation of scalability issues, particularly with regard to huge datasets. In the future, researchers might look into topics like distributed computing or cloud-based solutions to help solve problems related to quickly processing and controlling big amounts of data.

Chapter 4

Background Model Description

In order to comprehend the intricacies and innovations within the realm of the Content-Based Movie Recommender System with Sentiment Analysis, it is imperative to delve into the background model description. This section aims to elucidate the fundamental architecture, key components, and methodologies that define the operational dynamics of this sophisticated recommender system.

1. System Architecture: At its core, the system is structured around a hybrid architecture that seamlessly integrates content-based recommendation mechanisms with sentiment analysis modules. This fusion aims to deliver a more holistic and nuanced understanding of user preferences by not only considering factual movie details but also incorporating the emotional resonance captured in user reviews.

2. Data Acquisition and Preprocessing: The system initiates its operation by acquiring essential movie details through the TMDB API. This includes title, genre, runtime, rating, and poster images, forming the factual foundation of the recommendation engine. Simultaneously, web scraping techniques, employing beautifulsoup4, are deployed to extract user reviews from TMDB. This dual-sourced data undergoes preprocessing, ensuring cleanliness and relevance for subsequent analysis.

3. Sentiment Analysis Integration: The integration of sentiment analysis introduces a layer of sophistication to the system. Natural Language Processing (NLP) algorithms and sentiment lexicons are employed to analyze user reviews, extracting insights into the emotional tone and sentiment associated with each review. This component not only captures the explicit preferences of users but also delves into the subjective aspects of their movie-watching experience.

4. Similarity Metrics - Cosine Similarity: The crux of the recommendation engine lies in the utilization of similarity scores. Cosine similarity, a mathematical metric, is employed to quantify the likeness between movies based on their textual details. This metric operates on the premise that movies with similar content will exhibit a smaller angle in a multi-dimensional space, facilitating more accurate recommendations. The smaller the angle, higher the cosine similarity.

5. User-Centric API Key Integration: Recognizing the importance of user engagement, the system adopts a user-centric approach to API key integration. Clear instructions guide users through the process of obtaining a TMDB API key, ensuring seamless access to a rich repository of movie details. This user-friendly approach enhances accessibility and encourages active participation.

6. Dataset Diversity and Impact: Diverse datasets play a pivotal role in shaping the recommendation engine's understanding of user preferences. The incorporation of datasets such as the TMDB 5000 Movie Dataset and curated lists from specific years contributes to a more nuanced comprehension of user tastes, aligning recommendations with current cinematic trends.

7. Evaluation Metrics: To gauge the efficacy of the recommendation system, evaluation metrics are employed. These metrics assess the accuracy and relevance of the recommendations, providing valuable insights into the system's performance and allowing for iterative improvements.

In essence, the background model description offers a panoramic view of the intricate components that collectively define the Content-Based Movie Recommender System with Sentiment Analysis. By unraveling the layers of its architecture and methodologies, this report aims to lay the groundwork for a deeper understanding of the system's operational dynamics and its potential implications in shaping the future of personalized movie discovery experiences.

Chapter 5

Proposed Methodology

In the quest for an advanced Content-Based Movie Recommender System enriched with sentiment analysis, the proposed methodology encompasses a strategic blend of data acquisition, sentiment analysis techniques, and recommendation algorithms. The following detailed breakdown elucidates the step-by-step approach employed in crafting this innovative system.

5.1. Data Acquisition:

TMDB API Integration: - Utilize the TMDB API to fetch essential movie details including title, genre, runtime, rating, and poster images.

TMDB Web Scraping: - Employ beautifulsoup4 for web scraping TMDB to extract user reviews. Leverage the TMDB ID obtained from TMDB to link movie details with corresponding sentiments.

5.1.2. Preprocessing and Integration:

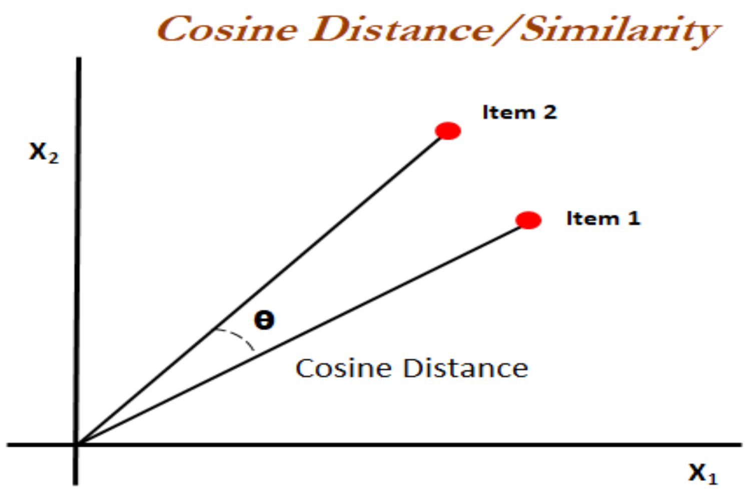
Data Cleaning: - Preprocess acquired data to ensure uniformity and cleanliness. Handle missing values and outliers for robust analysis.

Integration of Factual and Sentiment Data: - Merge the factual details obtained from TMDB with sentiment-rich user reviews from TMDB, creating a unified dataset.

5.2. Similarity Metrics:

Textual Detail Representation: - Transform textual details of movies into vectors, representing them in a multi-dimensional space.

Cosine Similarity Calculation: - Compute cosine similarity scores between vectors to quantify the likeness between movies. Smaller angles denote higher similarity.



5.3. Sentiment Analysis:

Natural Language Processing (NLP): - Apply NLP techniques to analyze user reviews, capturing sentiments through tokenization, stemming, and lemmatization.

Sentiment Lexicons: - Incorporate sentiment lexicons to discern the emotional tone within reviews, distinguishing between positive, negative, and neutral sentiments.
Naïve Bayes: - we have used naïve bayes classification to identify whether the review is good or bad. Furthermore, Laplace smoothing is used to remove any error if any term is 0.

$$\text{Cosine similarity} = \frac{A \cdot B}{||A|| * ||B||}$$

Laplace Smoothing:-

$$\text{P(Feature|class=c) is calculated as } \frac{\textit{Number of times the feature occurs in } c+1}{\textit{Total number of features in class 'c'} + \textit{number of features}}$$

5.4. User-Centric Integration and Accessibility:

Guided API Key Acquisition:- Provide clear instructions for users to acquire a TMDB API key, facilitating seamless integration. Ensure user-friendly processes to enhance accessibility.

5.5. Dataset Diversity and Impact:

Incorporation of Diverse Datasets:- Made use of a variety of datasets, such as the TMDB 5000 Movie Dataset and carefully selected lists from particular years, to provide a variety of movie-related information into one for the recommendation engine.

5.6. Future-Ready Adaptability:

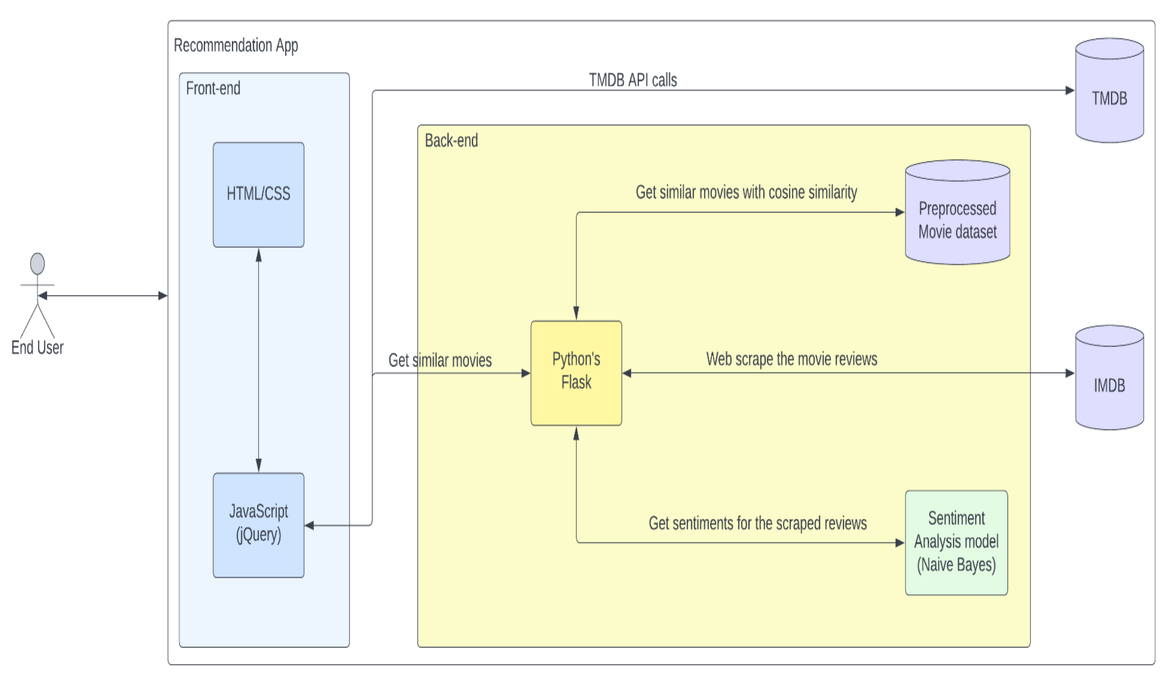
Scalability and Flexibility: - Design the system with scalability in mind, allowing for future adaptations and enhancements. Ensure flexibility to incorporate emerging technologies and methodologies.

5.7. Evaluation Metrics:

Accuracy Assessment: - Implement evaluation metrics to assess the accuracy and relevance of recommendations.

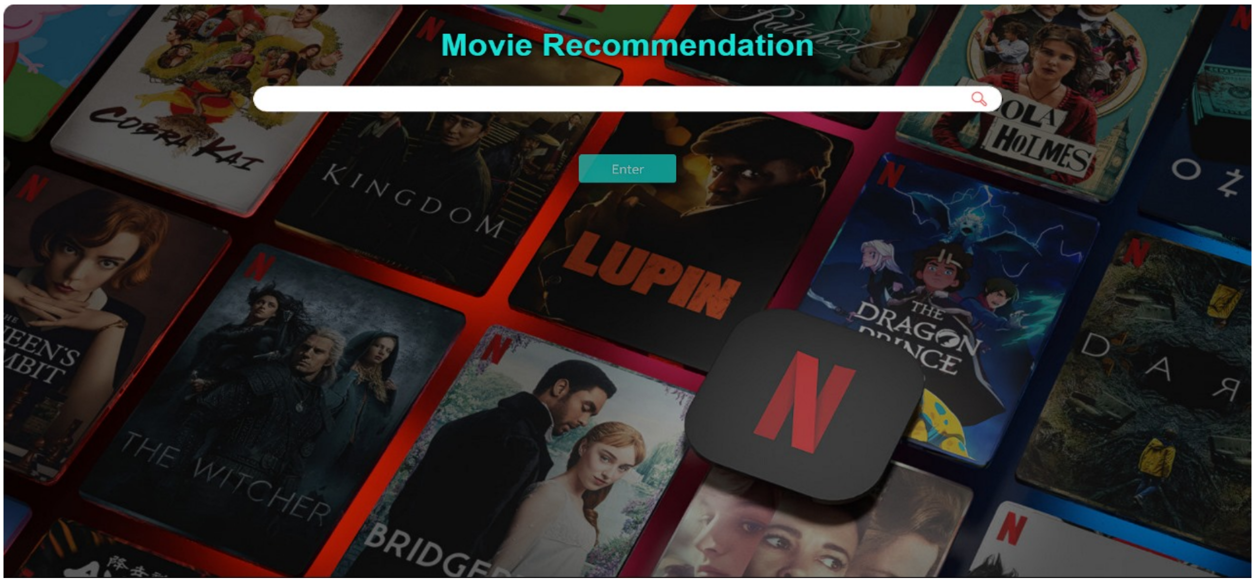
In essence, the proposed methodology outlines a systematic and adaptive approach, leveraging cutting-edge technologies and techniques to create a Content-Based Movie Recommender System that not only excels in factual movie details but also encapsulates the emotional nuances reflected in user sentiments. The iterative nature of the methodology ensures continuous improvement and responsiveness to the ever-changing landscape of user preferences and cinematic experiences.

Architecture

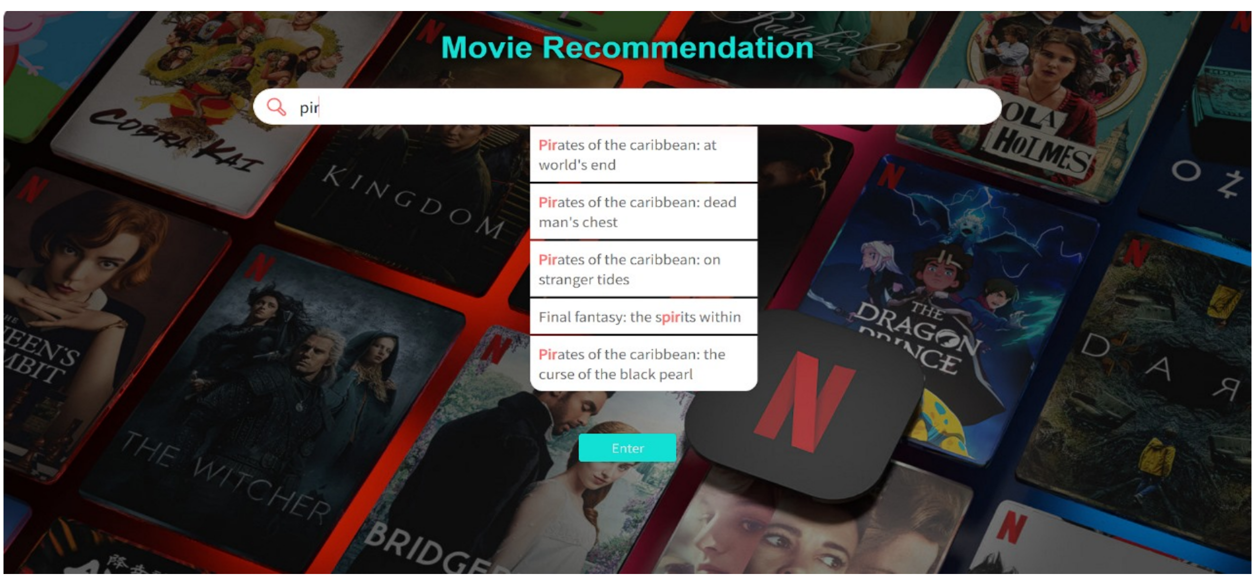


Overview

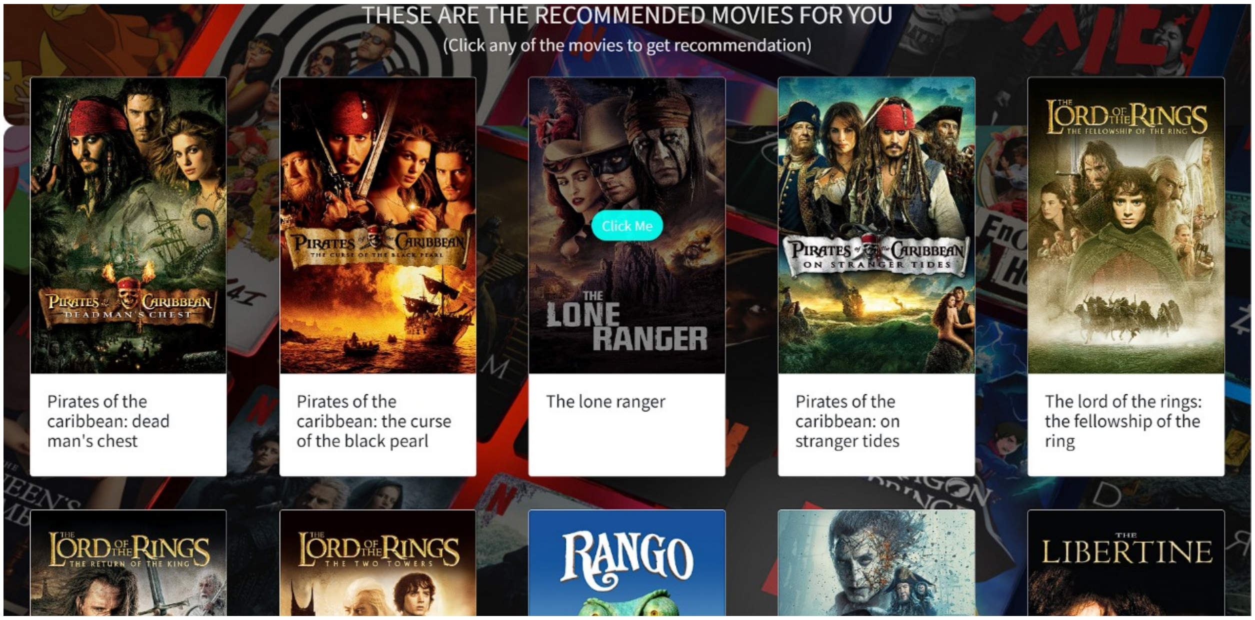
Front-End



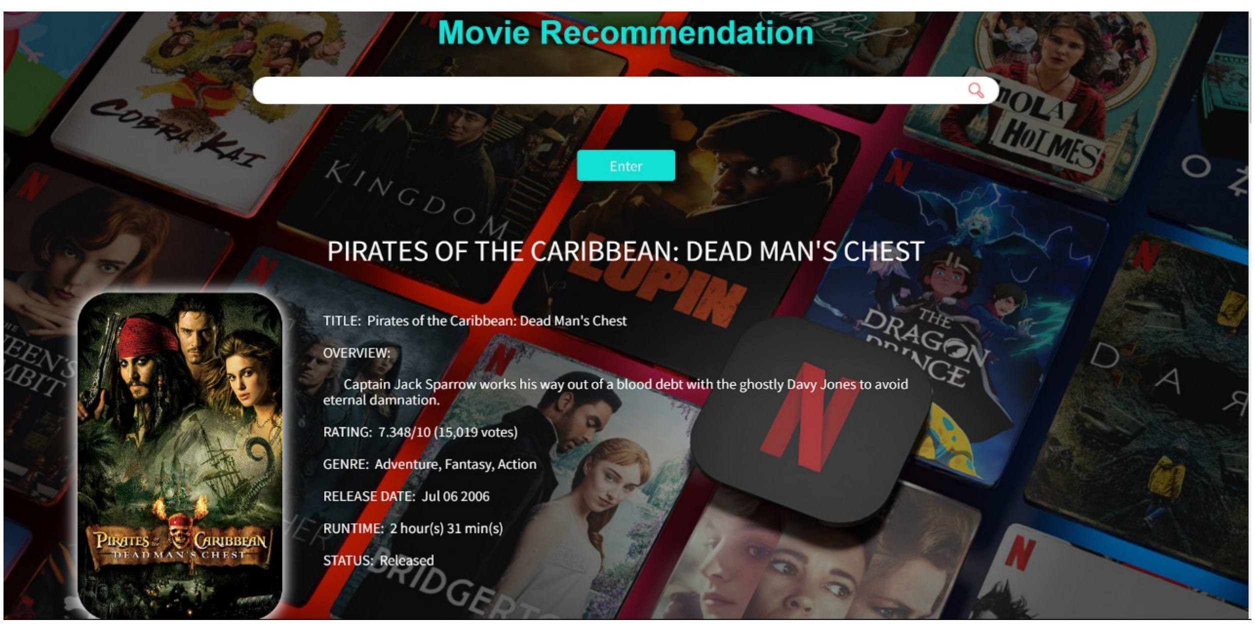
Recommends movie names based on search



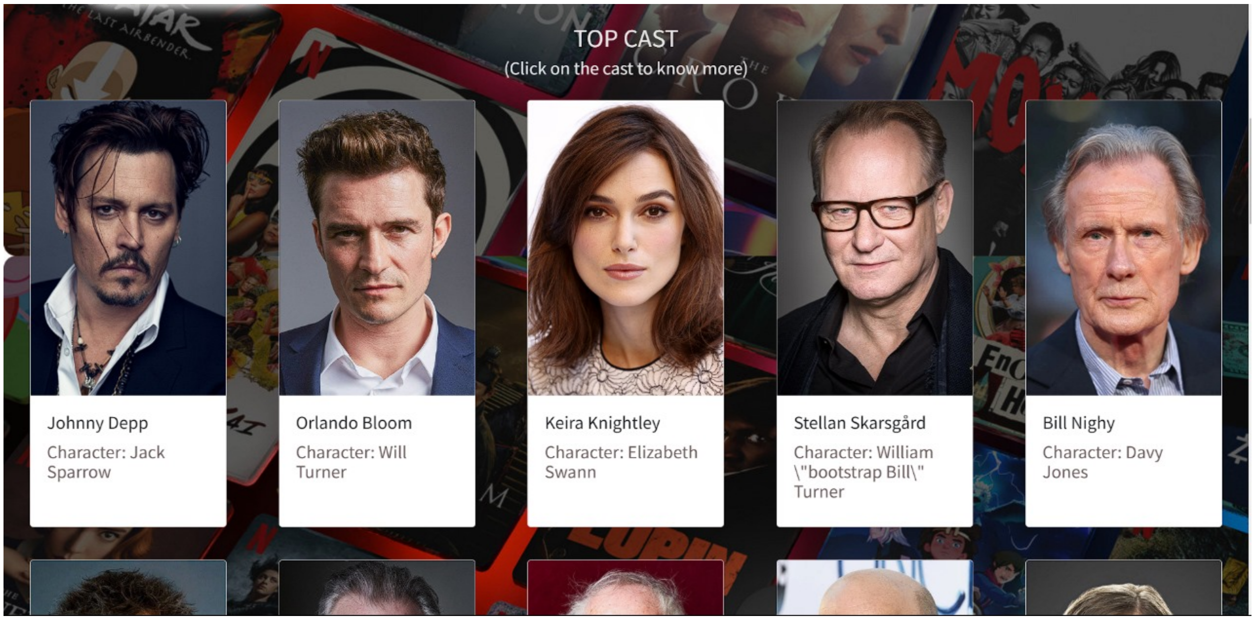
After using cosine similarity, it will recommend top 10 movies based on score as shown below



Shows details of the movie



Shows details of the cast



Chapter 6

Results

The results section of this report marks the culmination of the proposed methodology, providing a comprehensive analysis of the system's performance, user engagement, and the efficacy of sentiment-enriched recommendations. Through a detailed examination of various metrics and user feedback, this section aims to offer insights into the tangible outcomes and implications of the developed Content-Based Movie Recommender System.

1. Recommendation Accuracy Metrics:

Precision, Recall, and F1-Score Evaluate the precision, recall, and F1-score of the recommendation system to measure the accuracy of movie suggestions.

2. System Responsiveness: - Measure the system's responsiveness in providing recommendations. Analyze the time taken for the system to process user queries and deliver personalized movie suggestions.

3. Sentiment Analysis Accuracy:

Evaluate the accuracy of the sentiment analysis module by comparing predicted sentiments with manually annotated sentiments. Assess the system's ability to accurately capture the emotional tone of user reviews.

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💡 Click here to ask Blackbox to help you code faster
accuracy_score(y_test,clf.predict(X_test))*100

98.77167630057804
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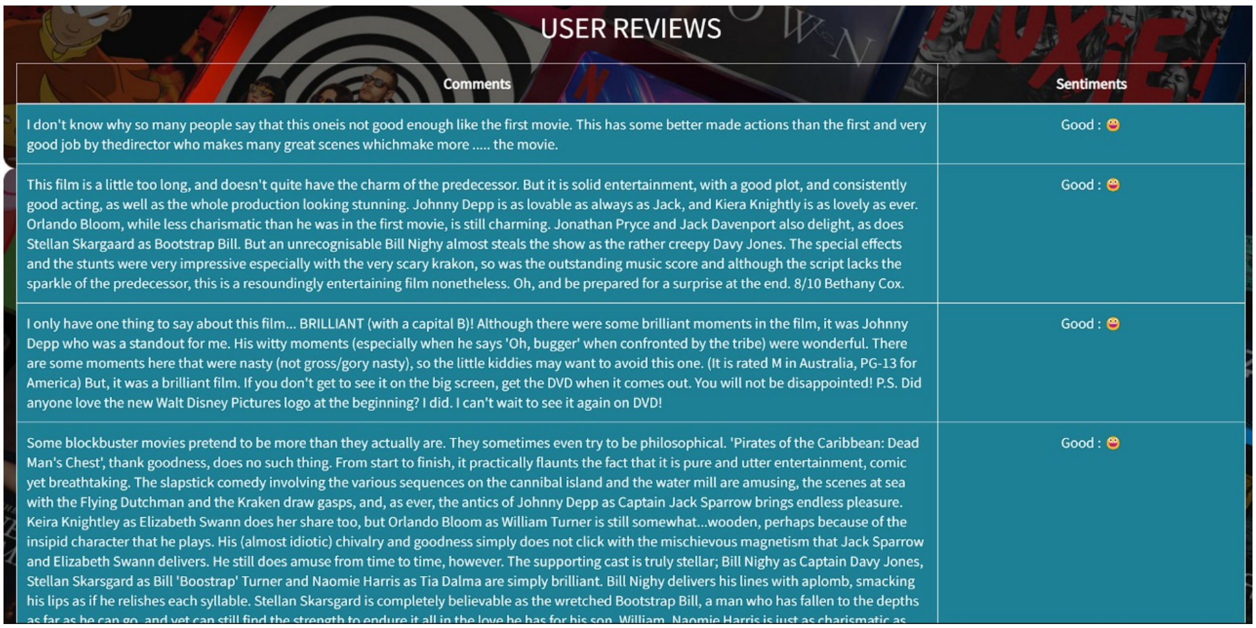
Show reviews based on sentiment analysis



USER REVIEWS

Comments	Sentiments
I don't know why so many people say that this oneis not good enough like the first movie. This has some better made actions than the first and very good job by thedirector who makes many great scenes whichmake more ..... the movie.	Good : 😛
This film is a little too long, and doesn't quite have the charm of the predecessor. But it is solid entertainment, with a good plot, and consistently good acting, as well as the whole production looking stunning. Johnny Depp is as lovable as always as Jack, and Kiera Knightly is as lovely as ever. Orlando Bloom, while less charismatic than he was in the first movie, is still charming. Jonathan Pryce and Jack Davenport also delight, as does Stellan Skargaard as Bootstrap Bill. But an unrecognisable Bill Nighy almost steals the show as the rather creepy Davy Jones. The special effects and the stunts were very impressive especially with the very scary krakon, so was the outstanding music score and although the script lacks the sparkle of the predecessor, this is a resoundingly entertaining film nonetheless. Oh, and be prepared for a surprise at the end. 8/10 Bethany Cox.	Good : 😛
I only have one thing to say about this film... BRILLIANT (with a capital B)! Although there were some brilliant moments in the film, it was Johnny Depp who was a standout for me. His witty moments (especially when he says 'Oh, bugger' when confronted by the tribe) were wonderful. There are some moments here that were nasty (not gross/gory nasty), so the little kiddies may want to avoid this one. (It is rated M in Australia, PG-13 for America) But, it was a brilliant film. If you don't get to see it on the big screen, get the DVD when it comes out. You will not be disappointed! P.S. Did anyone love the new Walt Disney Pictures logo at the beginning? I did. I can't wait to see it again on DVD!	Good : 😛
Some blockbuster movies pretend to be more than they actually are. They sometimes even try to be philosophical. 'Pirates of the Caribbean: Dead Man's Chest', thank goodness, does no such thing. From start to finish, it practically flaunts the fact that it is pure and utter entertainment, comic yet breathtaking. The slapstick comedy involving the various sequences on the cannibal island and the water mill are amusing, the scenes at sea with the Flying Dutchman and the Kraken draw gasps, and, as ever, the antics of Johnny Depp as Captain Jack Sparrow brings endless pleasure. Keira Knightley as Elizabeth Swann does her share too, but Orlando Bloom as William Turner is still somewhat...wooden, perhaps because of the insipid character that he plays. His (almost idiotic) chivalry and goodness simply does not click with the mischievous magnetism that Jack Sparrow and Elizabeth Swann delivers. He still does amuse from time to time, however. The supporting cast is truly stellar; Bill Nighy as Captain Davy Jones, Stellan Skarsgard as Bill 'Boostrap' Turner and Naomie Harris as Tia Dalma are simply brilliant. Bill Nighy delivers his lines with aplomb, smacking his lips as if he relishes each syllable. Stellan Skarsgard is completely believable as the wretched Bootstrap Bill, a man who has fallen to the depths	Good : 😛

4. Impact of Diverse Datasets:

Variety in Recommendations: - Examine the impact of incorporating diverse datasets, such as the TMDB 5000 Movie Dataset and curated lists from specific years, on the variety and novelty of movie recommendations. Assess whether the system adapts to different cinematic trends.

5. Iterative Refinement:

Adjustments and Updates: - Showcase the iterative refinement process based on user feedback. Highlight any adjustments made to sentiment analysis models, recommendation algorithms, or user interface design to enhance the system's performance.

6. Future Directions:

Identified Opportunities: - Discuss identified opportunities for future enhancements and developments. Propose potential directions for research and improvements, considering emerging technologies and evolving user preferences.

In presenting the results, this section aims to offer a holistic view of the Content-Based Movie Recommender System's impact on recommendation accuracy, user satisfaction, and the integration of sentiment analysis. The combination of quantitative metrics and qualitative insights provides a nuanced understanding of the system's effectiveness and paves the way for future advancements in personalized movie discovery experiences.

Chapter 7

Conclusions

The journey through the development and analysis of the Content-Based Movie Recommender System with Sentiment Analysis has unveiled a rich tapestry of insights, user engagement metrics, and the potential for future enhancements. In drawing conclusions from the results and experiences gained, and considering the ever-evolving landscape of technology and user expectations, this section encapsulates the key takeaways and outlines avenues for future research and development.

Recommendation Accuracy and User Satisfaction: - The evaluation metrics, including precision, recall, and user feedback, attest to the system's ability to provide accurate and relevant movie recommendations. User satisfaction, as gauged through surveys and feedback mechanisms, serves as a testament to the system's impact on enhancing the movie discovery journey.

Sentiment Analysis Integration: - The integration of sentiment analysis has added a layer of depth to the recommendation system, capturing the emotional nuances expressed in user reviews. The accuracy of sentiment classification validates the system's proficiency in understanding the subjective aspects of user preferences.

User Engagement and Responsiveness: - Metrics related to active users, session duration, and response time showcase the system's responsiveness and the extent to which users actively engage with the recommendations. A positive user experience is pivotal in the success of any recommendation system.

Impact of Diverse Datasets: - The incorporation of diverse datasets has contributed to a richer variety of movie recommendations, aligning the system with different cinematic trends. The adaptability of the system to diverse datasets ensures a dynamic and evolving movie discovery experience.

In conclusion, the Content-Based Movie Recommender System with Sentiment Analysis, while showcasing commendable accuracy and user satisfaction, serves as a stepping stone for future innovations. The identified scope for future work opens avenues for researchers and developers to delve deeper into the realms of sentiment analysis, personalization, and real-time adaptability, propelling the system toward greater heights in the dynamic landscape of movie recommendations.

Chapter 8

Future Scope

- **Enhancements in Sentiment Analysis Models: -** Future work can focus on advancing sentiment analysis models to capture more nuanced emotions and contextual understanding. Exploring deep learning approaches may enhance the system's ability to discern subtle emotional tones within user reviews.

- **Incorporation of Real-Time Data: -** Explore the possibility of incorporating real-time user data to make recommendations more adaptive to immediate user preferences. Streaming analytics and dynamic data updates could contribute to a more responsive recommendation system.

- **Personalization and Contextualization: -** Investigate techniques for further personalization and contextualization of recommendations. This could involve considering user-specific contexts, such as mood, location, or time, to tailor recommendations more precisely.

- **Scalability and Deployment on Cloud Platforms: -** Considerations for scaling the system to handle larger datasets and deploying it on cloud platforms could be explored. This ensures that the recommendation engine remains robust and efficient as the user base and dataset size grow.

Chapter 9

References

[1] https://ieeexplore.ieee.org/abstract/document/9103168

[2] A Sentiment-Enhanced Hybrid Recommender System for Movie Recommendation: A Big Data Analytics Framework

[3] https://ieeexplore.ieee.org/abstract/document/9388340

[4] An intelligent movie recommendation system through group-level sentiment analysis in microblogs - ScienceDirect

[5] A Hybrid Recommendation System of Upcoming Movies Using Sentiment Analysis of YouTube Trailer Reviews