MEDIA RECOMMENDER SYSTEM

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CERTIFICATE

This is to certify that the Project Synopsis entitled, Media Recommender System submitted by Utkarsh Yadav to The NorthCap University, Gurugram, India, is a record of bona fide synopsis work carried out by them under my supervision and guidance and is worthy of consideration for the partial fulfilment of the degree of Bachelor of Technology in Computer Science and Engineering of the University.

<Signature of supervisor>

<Name and designation of supervisor>

Date: .....

INDEX

1. Abstract

2. Objective:
    - Develop a **Movie Recommendation System** to provide personalized movie suggestions based on user preferences.
3. Key Features:
    - **Responsive User Interface (UI)**: Offers a user-friendly, intuitive browsing experience.
    - **Movie Metadata**: Displays detailed information, including **movie story**, **posters**, **cast and director details**, **IMDb ratings**, and **total user ratings**.
    - **Personalized Recommendations**: Uses a combination of **Collaborative Filtering** and **Content-Based Filtering** to generate accurate and relevant movie suggestions.
4. Recommendation Approach:
    - **Collaborative Filtering**: Recommends movies based on user interaction and behavior patterns (e.g., movie ratings, views).
    - **Content-Based Filtering**: Suggests movies based on attributes like genre, director, actors, etc.
5. Data Integration:
    - Utilizes **IMDb ratings** to provide additional, trustworthy insights for movie selection.
    - Pulls movie data from reliable APIs like **OMDb API** and **IMDb API** for consistent and accurate information.
6. User Engagement:
    - The system helps users make informed decisions by presenting relevant movie data alongside tailored suggestions.
    - Facilitates an enriched movie discovery process based on individual tastes and preferences.
7. System Application:
    - Designed for integration into movie streaming platforms and can be extended to work with other databases.
    - Demonstrates the application of machine learning techniques and data science in entertainment-based recommendation systems.
8. Outcome:
    - A functional **Movie Recommendation System** that effectively enhances the user experience by offering personalized, relevant suggestions and rich movie details.

2. Introduction

Broad Description of the Topic

With the rapid expansion of online movie streaming platforms, users are confronted with an overwhelming volume of content. The sheer number of available movies, spanning across different genres, languages, and styles, makes it challenging for users to find content that aligns with their personal tastes and preferences. To address this issue, a Movie Recommendation System is a vital tool that leverages algorithms to suggest movies based on a user's past behavior, preferences, and ratings.

A Movie Recommendation System offers personalized suggestions by analyzing data such as user ratings, viewing history, movie genres, and more. Such systems utilize machine learning techniques like Collaborative Filtering and Content-Based Filtering to recommend relevant movies. This not only improves user experience by providing relevant content but also increases engagement on streaming platforms. These systems are integral to major platforms like Netflix, Amazon Prime, and Hulu, where personalized recommendations play a key role in retaining and engaging users.

This project aims to develop a Movie Recommendation System that provides users with personalized movie suggestions, along with detailed metadata such as movie posters, plot summaries, cast information, IMDb ratings, and user ratings. By incorporating a simple, responsive user interface (UI) and advanced recommendation algorithms, the system seeks to enhance the movie discovery experience, making it more intuitive and efficient.

1. Background

The entertainment industry, especially in the realm of movies, has seen exponential growth in the number of digital streaming platforms in recent years. Services like Netflix, Disney+, and Amazon Prime Video have reshaped how users access and consume movies, making it easier than ever to watch films from virtually anywhere. However, this vast array of content has also led to a phenomenon known as "content overload," where users struggle to discover movies that align with their interests.

Recommendation systems have become a critical component of addressing this challenge. They provide personalized content based on a variety of factors, such as viewing history, ratings, and movie characteristics (e.g., genre, director, actors). In the case of movies, users often rely on recommendations from friends or ratings on platforms like IMDb to guide their choices. However, with millions of movies available, these traditional methods may not be sufficient.

The Movie Recommendation System addresses this gap by combining Collaborative Filtering, which makes recommendations based on the behaviors of similar users, and Content-

Based Filtering, which suggests movies based on their features. With the ability to integrate large datasets from movie APIs like OMDb and IMDb, the system also provides an enriching experience by displaying detailed information like movie summaries, cast details, and ratings to help users make informed decisions.

2. Feasibility Study

The feasibility of developing a Movie Recommendation System is high due to the following factors:

- Data Availability: There is an abundance of movie-related data available through open APIs like the OMDb APIand IMDb API. These APIs provide extensive movie information, including titles, genres, plot summaries, ratings, and cast/crew details, which are essential for building a comprehensive recommendation system.
- Technological Feasibility: The algorithms required for collaborative filtering and content-based filtering are well-established and can be implemented using standard tools and libraries. Machine learning libraries like Scikit-learn, TensorFlow, and Keras offer robust solutions for building recommendation engines. Additionally, modern web frameworks like Flask (for backend) and React (for frontend) make it easier to develop a responsive user interface and connect it seamlessly to the backend algorithms.
- Resource Availability: With accessible computing power, cloud services like Heroku or AWS, and a variety of open-source tools, the development of such a system is both feasible and cost-effective. The project can be implemented with minimal resources while leveraging pre-existing tools and platforms.
- User Demand: The increasing demand for personalized content in online entertainment platforms makes this project highly relevant. Streaming services constantly aim to improve user experience by offering accurate and timely recommendations. A well-implemented Movie Recommendation System can significantly enhance the movie discovery process for users.
- Scalability: The system can scale easily as more user data and movie information are integrated. The recommendation algorithms can be fine-tuned with increased data, leading to more accurate predictions and better user engagement over time.

In summary, the development of a Movie Recommendation System is technically feasible, supported by readily available tools, libraries, and APIs. The project is timely and has high potential for success due to the increasing user demand for personalized recommendations in the entertainment sector.

3. Study of Existing Solutions

In this section, we will explore the existing solutions for movie recommendation systems, examining their methods, strengths, and limitations. Various algorithms and platforms already leverage recommendation systems to provide personalized movie suggestions. By understanding these existing solutions, we can identify areas of improvement and enhance our own system.

Existing Recommendation Systems

1. Netflix
   - Recommendation Method : Netflix uses a hybrid recommendation system, combining Collaborative Filtering (CF) and Content-Based Filtering (CBF).
     - **Collaborative Filtering**: Netflix's algorithm suggests movies based on the viewing habits and preferences of similar users. This approach is widely used because it doesn't require any explicit information about the movie itself but instead focuses on user behavior.
     - **Content-Based Filtering**: Netflix also takes into account the attributes of movies, such as genre, director, actors, and the user's previous movie-watching history.
     - **Deep Learning Models**: Netflix has adopted **neural networks** and **matrix factorization** techniques to enhance the precision of its recommendations. These models analyze huge volumes of data (e.g., user ratings, viewing patterns, etc.) to make personalized recommendations.
   - Strengths:
     - Highly personalized and accurate recommendations.
     - Dynamic content suggestions based on user engagement (e.g., watched movies, ratings, etc.).
     - Regularly updated models to incorporate new user data, ensuring relevance.
   - Limitations:
     - Netflix's recommendation system has often been criticized for its **"filter bubble"** effect, where users are only shown content that aligns with their previous behavior, limiting exposure to diverse content.
     - Sometimes, it recommends content that is not representative of a user's changing tastes over time.
2. Amazon Prime Video
   - Recommendation Method : Similar to Netflix, Amazon Prime uses a hybrid recommendation system that blends Collaborative Filtering, Content-Based Filtering, and additional factors such as user reviews and purchase history.
     - **Collaborative Filtering**: Amazon recommends movies based on the preferences of users with similar tastes. It also factors in the movie ratings, reviews, and user purchase history to enhance the suggestions.
     - **Content-Based Filtering**: This is used to suggest movies based on attributes such as genre, actors, and directors. Amazon also incorporates **frequent purchase behavior**, making it easier to recommend related items.
   - Strengths:
     - The system uses a combination of personalized recommendations based on user behavior and content features.

- Strong integration with Amazon's e-commerce and digital content ecosystem, recommending items (movies) based on past interactions (purchases or rentals).
- Recommendations often take into account **user reviews**, which can help users identify trending or highly rated content.

- Limitations:
  - The system sometimes lacks true **personalization**, as it may recommend movies based solely on what is popular rather than what specifically suits a user's tastes.
  - The recommendation engine can be **overwhelming** with too many similar suggestions based on minor changes in behavior, leading to repetitive results.

3. IMDb
   - Recommendation Method : IMDb's recommendation system is based on user-generated content, such asratings, reviews, and user-created lists.
     - **Collaborative Filtering**: IMDb uses user ratings and preferences to recommend movies based on the choices of users with similar interests. It doesn't use advanced machine learning techniques like Netflix, but instead relies heavily on user ratings and reviews.
     - **Top Rated Lists**: IMDb also provides suggestions based on top-rated movies, genres, or trending lists that are curated by users and editors.
   - Strengths
     - **IMDb** has a massive database of movies and user reviews, making it a go-to platform for movie data and feedback.
     - The **IMDb rating system** provides an objective benchmark for movie quality, which can guide users in making decisions about which films to watch.
     - The system allows for **manual curation**, which can be useful for users who prefer seeing lists based on specific criteria, such as genre or rating.
   - Limitations:
     - The recommendation system is not as advanced or dynamic as Netflix or Amazon Prime's, lacking deep personalization or content-based algorithms. IMDb's
     - suggestions may lack nuance, and users are often directed to popular or widely known movies rather than hidden gems or new releases tailored to their tastes.

4. YouTube Movies
   - Recommendation Method : YouTube's recommendation system is primarily based on Collaborative FilteringContent-Based Filteringand Deep Learning.
     - YouTube uses machine learning models to recommend movies based on viewing history, user interactions (likes, shares), and content features (e.g., genres, tags, descriptions).
     - The system also considers external factors like **video metadata** (title, description, tags) and user engagement signals to predict the next likely movie the user might want to watch.
   - Strengths
     - YouTube's recommendation system is extremely dynamic and continually learns from the user's actions.
     - It considers a wide range of content, not just movies, but also video length, quality, and video format (e.g., trailers, documentaries).

- Limitations:
  - The system may recommend videos that are not closely related to the user's core interests, especially when the algorithm over-prioritizes trending content.
  - Unlike other movie-specific platforms, YouTube's recommendation system is primarily tailored for a mix of content (e.g., videos, tutorials, etc.), which can dilute its effectiveness for movie discovery.

Conclusion

From analyzing the existing movie recommendation systems, we can draw several key insights. First, hybrid recommendation systems, combining Collaborative Filtering and Content-Based Filtering, are the most common and effective approaches used in major platforms like Netflix and Amazon Prime Video. However, they all face similar challenges, such as the filter bubble effect, lack of true personalization, and occasional redundancy in recommendations.

There is also room for improvement in providing more diverse content recommendations, addressing users' evolving tastes, and integrating additional metadata such as detailed movie descriptions, cast information, and external reviews. Our proposed system can build on these existing solutions by offering a more interactive and user-centric experience, ensuring that users not only receive personalized suggestions but also gain access to rich movie data that enhances their decision-making process.

4. Comparison with Existing Software Solutions

software solutions, focusing on key aspects such as algorithms, features, user experience, and technological stacks. This comparison will allow us to better understand how our system stands in relation to the current industry standards.

1. Netflix vs. Our System

Netflix uses a hybrid recommendation system that combines Collaborative Filtering and Content-Based Filtering along with advanced models like deep learning and matrix factorization to generate personalized recommendations. It processes large amounts of user data to provide highly accurate and dynamic suggestions. However, Netflix's system can sometimes lead to a filter bubble effect, where users are primarily exposed to content that aligns with their existing preferences, limiting the discovery of new genres.

In contrast, our system also uses a hybrid approach combining Collaborative Filtering and Content-Based Filtering, but with a more simplified and lightweight model that does not rely heavily on deep learning algorithms. Our focus is on movie-specific metadata such as plot summaries, cast information, and IMDb ratings, which allows us to provide richer and more diverse recommendations. While Netflix's system requires significant

computational resources for real-time data processing, our system aims to provide an efficient recommendation engine suitable for smaller-scale implementations.

2. Amazon Prime Video vs. Our System

Amazon Prime Video utilizes a combination of Collaborative Filtering, Content-Based Filtering, and factors such as user reviews and purchase history to recommend movies. It benefits from deep integration within Amazon's broader ecosystem, offering suggestions based not only on viewing behavior but also on items users have interacted with across Amazon.

Our system, while leveraging Collaborative Filtering and Content-Based Filtering, does not integrate cross-platform data like Amazon Prime Video. Instead, we focus on delivering a streamlined user experience with a clean interface that emphasizes movie discovery. Unlike Amazon, which may over-prioritize popular content or trending movies, our system aims to diversify recommendations and expose users to a wider range of genres and films that match their tastes.

3. IMDb vs. Our System

IMDb's recommendation engine is largely based on user ratings and user-generated lists, offering recommendations based on top-rated movies and trends. While IMDb excels in providing detailed movie metadata—such as cast, crew, plot summaries, and reviews—it lacks the real-time, personalized recommendations driven by advanced machine learning algorithms.

Our system, by contrast, employs real-time personalized recommendations using Collaborative Filtering and Content-Based Filtering, which adapts based on user preferences. While IMDb offers a wealth of movie information, our system enhances this by providing a dynamic, personalized discovery experience. Additionally, we plan to offer a better user interface focused on the presentation of movie details, such as rich media content (e.g., movie posters), which is not a core strength of IMDb's platform.

4. YouTube Movies vs. Our System

YouTube Movies uses a recommendation system that incorporates Collaborative Filtering, Content-Based Filtering, and engagement metrics like likes, shares, and watch history. While YouTube's system is highly dynamic, it recommends not just movies but also a wide variety of video content, which can overwhelm users looking for specific movie suggestions.

In contrast, our system will be more focused and curated, recommending only movie-specific content. Although YouTube's recommendation engine is real-time and uses deep learning to adapt to user interactions, it often prioritizes trending content, which may not be aligned with a user's personal movie preferences. Our system will focus on providing balanced and diverse recommendations while avoiding the overwhelming variety seen on YouTube. Additionally, we will offer richer metadata for each movie, helping users make informed choices based on detailed information.

Conclusion

When compared to existing movie recommendation systems such as Netflix, Amazon Prime Video, IMDb, and YouTube Movies, our system provides a streamlined, user-centric approach with a focus on personalization and rich movie metadata. While larger platforms rely on complex machine learning models and cross-platform data, our system offers a simpler yet effective recommendation engine, ensuring a better user experience with diverse and balanced suggestions. This comparison reveals our system's potential to serve as an efficient, lightweight alternative for personalized movie recommendations without compromising on the quality of suggestions.

5. Gap Analysis

systems and highlights areas where improvements can be made. In this section, we analyze the gaps in existing solutions like Netflix, Amazon Prime Video, IMDb, and YouTube Movies, and compare them with the proposed Movie Recommendation System. This analysis will reveal areas where our system can fill the void and provide a more enriched, personalized, and user-friendly experience.

1. Personalization Limitations

Most of the existing systems such as Netflix, Amazon Prime Video, and YouTube Movies heavily rely on Collaborative Filtering or Content-Based Filtering for generating recommendations. While these systems do offer some level of personalization, they often focus mainly on the following:

- **Collaborative Filtering** leads to the **filter bubble effect**, where users are recommended content based solely on their past behavior, restricting exposure to diverse genres or new content.
- **Content-Based Filtering** only recommends movies with similar content (e.g., genre, actors, etc.), missing out on subtle user preferences or evolving tastes.

Gap: Existing systems often provide static recommendations that primarily cater to users' previous behaviors, ignoring the fact that user tastes evolve over time or that users may want to explore new genres, themes, or directors.

Our Solution:

Our system addresses this by using a hybrid recommendation approach that combines both Collaborative Filteringand Content-Based Filtering, ensuring a more well-rounded and diverse set of suggestions. Moreover, our system incorporates mechanisms to adapt to shifting preferences, offering more dynamic recommendations based on user interactions with new content.

2. Limited Movie Metadata Integration

Platforms like IMDb and YouTube Movies provide basic movie metadata (such as plot summaries, cast information, and ratings), but they are not always effectively integrated into the recommendation process. For example:

- IMDb has a wealth of information, but its recommendation system is not as dynamic or personalized as Netflix's. It primarily provides suggestions based on aggregate ratings and reviews.
- YouTube offers only basic metadata like movie titles, tags, and brief descriptions, which doesn't allow users to make informed decisions quickly.

Gap: Existing systems often lack deep integration of rich movie data, which would allow users to make informed decisions based on multiple factors like cast, director, genre, and even user-generated content (reviews, ratings).

Our Solution:

Our system will integrate comprehensive movie metadata, such as detailed plot summaries, full cast and crew information, posters, and IMDb ratings. This will give users a
clearer understanding of the movie they are about to watch and make recommendations not just based on genres but on the user's specific movie preferences (e.g., favorite directors, actors, or themes).

3. User Interface and Experience (UI/UX) Challenges

While Netflix and Amazon Prime have well-designed user interfaces, they sometimes overwhelm users with too many options or categories. This can lead to user fatigue or decision paralysis, especially in a platform like YouTube, which combines movies with a wide variety of unrelated video content (e.g., tutorials, vlogs, etc.).

Gap:

Most existing platforms either lack intuitive navigation or provide too many recommendations, leading to an overwhelming user experience. A clean and focused recommendation interface for movies is missing from most platforms.

Our Solution:

Our system aims to offer a simple, user-centric interface with clear movie categorization. We will focus on creating a minimalistic design that presents recommendations in a streamlined manner, emphasizing movie details such as genre, IMDb ratings, and cast. The aim is to improve the user's movie discovery experience and reduce complexity by filtering out irrelevant content and displaying only movie-related recommendations.

4. Lack of Exploration and Diversity in Recommendations

Streaming platforms like Netflix and Amazon tend to prioritize trending content, popular movies, or content that aligns with a user's past interactions. While this ensures relevancy, it also leads to the same content being recommended repeatedly, which can reduce diversity and limit the discovery of new or niche films.

Gap:

The over-reliance on popular content and algorithms that emphasize similarities to past viewing habits often results in narrow recommendations, limiting the user's exposure to new or diverse genres.

Our Solution:

Our recommendation engine is designed to provide a more diverse set of recommendations. While it will consider user preferences, it will also introduce novel content from a variety of genres, directors, and cultures. We will also incorporate randomized suggestions to encourage exploration beyond the usual patterns and expose users to lesser-known films that match their tastes.

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5. Integration of User Reviews and Social Features

Although platforms like IMDb and Amazon Prime Video allow user reviews and ratings, they often do not fully leverage social recommendations or user-generated content for personalized suggestions. Social sharing and collaborative curation features are relatively underdeveloped.

Gap:

There is a gap in integrating social and collaborative features that can enhance movie discovery. Platforms like IMDb do offer lists, but there is little cross-platform recommendation or collaborative input on a movie's choice beyond ratings.

Our Solution:

We aim to introduce more interactive features, such as enabling users to create personalized movie lists and share recommendations. Additionally, we will allow users to provide feedback not just through ratings but through more granular reviews that help refine future recommendations. Social features will encourage users to interact with others, share movie lists, and even get suggestions from friends or movie communities within the system.

6. Scalability and Resource Efficiency

Many existing platforms, particularly Netflix and Amazon Prime Video, require large-scale infrastructures to handle their recommendation engines, especially since they rely on advanced algorithms and large amounts of user data. While effective, these systems can be complex and

expensive to scale, particularly for smaller projects or for platforms with limited computational resources.

Gap:

Existing platforms' reliance on heavy algorithms, such as deep learning and matrix factorization, requires significant computational resources, which can be difficult to replicate for smaller-scale implementations.

Our Solution:

Our system will use lightweight machine learning models and hybrid algorithms to achieve accurate recommendations while maintaining low computational costs. By optimizing performance and focusing on efficiency, our system can run on more limited hardware while still delivering a robust movie recommendation experience. This scalability will be key for projects with fewer resources or those operating in resource-constrained environments.

Conclusion

The gap analysis reveals several opportunities for improvement within the realm of movie recommendation systems. Current platforms often struggle with issues related to personalization, movie metadata integration, user experience, and diversity of recommendations. By focusing on a simplified, personalized, and rich recommendation engine with dynamic content diversity and intuitive UI, our system will fill these gaps and offer a more enriched and engaging user experience. This approach will not only enhance the movie discovery process but will also provide a solution that is scalable, efficient, and user-friendly.

6. Problem Statement

across various platforms, making it difficult to discover new content that aligns with their tastes and preferences. Existing movie recommendation systems, such as those implemented by Netflix, Amazon Prime Video, and IMDb, are largely based on traditional recommendation algorithms like Collaborative Filtering and Content-Based Filtering. While these systems attempt to personalize recommendations, they often fall short in offering diverse, dynamic, and accurate suggestions due to limitations such as:

- Over-reliance on past behavior: Most systems focus heavily on a user's historical preferences, which can create a filter bubble, limiting the exposure to new genres, directors, or movies that deviate from the user's established tastes.
- Insufficient metadata integration: Many recommendation systems fail to provide detailed information about the movies themselves, such as comprehensive plot

summaries, actor and director details, or movie posters, which are essential for making informed decisions.

- Lack of interactivity and social features: While platforms like IMDb offer ratings and reviews, they do not fully integrate social features that allow users to interact with others and share their movie recommendations, limiting the social discovery aspect of movie watching. Complex user interfaces: On larger platforms like Netflix and YouTube, users are often faced with cluttered, overwhelming interfaces, making it difficult to focus on discovering specific movies of interest.

Thus, there is a clear need for a personalized, user-friendly movie recommendation system that combines dynamic recommendations, rich movie metadata, and an intuitive user interface while providing users with a diverse and balanced set of movie suggestions that extend beyond their typical preferences.

Proposed Solution

The goal of this project is to develop a Movie Recommendation System that addresses these challenges by:

- **Leveraging a hybrid recommendation approach** (using both Collaborative Filtering and Content-Based Filtering) to provide more personalized and relevant suggestions.
- **Incorporating rich movie metadata** (including detailed plot summaries, IMDb ratings, cast information, and posters) to help users make informed decisions.
- **Offering a simple and responsive user interface** that allows for easy exploration and discovery of movies.
- **Promoting diversity in recommendations**, thus helping users explore genres and movies outside their usual viewing patterns.

This system will ultimately aim to provide a more balanced, engaging, and interactive movie discovery experience that enhances users' satisfaction while minimizing the common issues present in existing platforms.

7. Objectives

friendly Movie Recommendation System that enhances the movie discovery experience for users. The specific objectives of the project are:

1. To Develop a Hybrid Recommendation Engine:
   Implement a recommendation engine that combines both Collaborative Filtering and Content-Based Filteringtechniques to provide users with personalized

movie suggestions. The goal is to ensure that the recommendations are not limited to past viewing habits but also consider user preferences in terms of genres, actors, and other movie attributes.

2. To Integrate Rich Movie Metadata:
   Provide detailed movie metadata, including plot summaries, IMDb ratings, cast and crew information, and movie posters. This will allow users to make more informed decisions when selecting movies to watch.
3. To Create a Simple and Intuitive User Interface:
   Develop a responsive user interface (UI) that is easy to navigate and visually appealing. The design should allow users to quickly discover movies, filter recommendations, and view movie details such as descriptions, ratings, and posters without any clutter.
4. To Ensure Diverse Movie Recommendations:
   Design the recommendation system to offer a variety of movie suggestions that go beyond a user's typical preferences, thus encouraging users to explore different genres, themes, and directors. This will reduce the chances of users falling into a filter bubble and increase the overall diversity of movie discovery.
5. To Provide Real-Time Recommendations:
   Incorporate a system that updates recommendations dynamically based on user interactions, preferences, and ratings. This ensures that the system adapts to evolving user tastes and continues to provide relevant movie suggestions over time.
6. To Enhance User Engagement through Social Features:
   Enable features such as user-generated movie lists, ratings, and reviews, and allow users to interact with others to share their movie recommendations. This social aspect will enhance the overall movie discovery experience by incorporating collective insights from the user community.
7. To Ensure System Scalability and Performance:
   Optimize the recommendation engine to handle varying amounts of data efficiently and ensure that the system is scalable for future growth. The system should work smoothly on both small and larger datasets without compromising performance or recommendation accuracy.
8. To Test and Evaluate System Performance:
   Conduct thorough testing of the recommendation system to evaluate its accuracy, usability, and user satisfaction. Use real-world datasets to ensure the system is practical and effective in generating movie recommendations.

By achieving these objectives, the proposed Movie Recommendation System will provide an engaging, personalized, and scalable platform for discovering movies, addressing the current limitations in existing systems, and offering a superior user experience.

8 . Tools/Platforms Used

- Programming Language: Python – Chosen for its simplicity and powerful libraries for machine learning and data analysis, such as Scikit-learn, Pandas, and NumPy.
- Web Framework: Flask – Lightweight and ideal for building a simple, responsive web interface to integrate the recommendation system.
- Front-End: HTML, CSS, JavaScript, and Bootstrap – Used for creating a clean, user-friendly, and responsive interface.
- Database: SQLite – Lightweight database for storing movie data, user preferences, and
- recommendations. Can scale to MySQL/PostgreSQL for larger datasets.
  Recommendation Algorithms: Collaborative Filtering and Content-Based Filtering – Implemented using Python libraries like Scikit-learn and Surprise.
- Movie Metadata: IMDb API or OMDb API – To fetch rich movie information like ratings, cast, and posters.
- Deployment: Heroku – For easy cloud deployment, or AWS/GCP for more scalable options.

This combination of tools ensures efficient development, seamless integration, and scalability of the Movie Recommendation System.

9. Design Methodology

step process:

1. Requirement Analysis: Identify system features (personalized recommendations, movie metadata, simple UI) and user needs.
2. System Design: Define the architecture, database schema, and create wireframes for the UI. Plan the recommendation engine (hybrid of Collaborative and Content-Based Filtering).
3. Data Collection & Preprocessing: Gather movie metadata (using APIs like IMDb) and clean the data for model training.
4. Recommendation Model Development: Implement and combine Collaborative Filtering and Content-Based Filtering to build the recommendation engine. Evaluate using metrics like accuracy and precision.
5. Front-End Development: Build a simple, responsive UI using HTML, CSS, JavaScript, and Bootstrap, integrating it with the recommendation engine.
6. Back-End Development: Develop the back-end using Flask to handle requests, interact with the database, and serve recommendations.
7. Testing and Evaluation: Perform unit, integration, and user testing to ensure the system works properly. Evaluate the model's performance and optimize.
8. Deployment and Maintenance: Deploy on platforms like Heroku, monitor performance, and continuously improve the system based on user feedback.

10. Outcomes

for personalized movie discovery. The key outcomes of the project are:

1. Personalized Movie Recommendations:
   - The system will provide users with movie suggestions tailored to their preferences based on a hybrid recommendation approach (Collaborative Filtering and Content- Based Filtering). Recommendations will evolve over time as the system learns from user interactions and feedback, offering more relevant and diverse suggestions.
   -
2. Rich Movie Metadata:
   - Users will have access to detailed information for each recommended movie, including **plot summaries**, **IMDb ratings**, **cast and crew details**, and **movie posters**.
   - This enhances the user experience by helping users make informed decisions about what to watch.
3. Simple and Intuitive User Interface:
   - A user-friendly web interface will allow users to easily explore, filter, and discover movies based on various criteria like genre, rating, and release year.
   - The interface will be responsive, ensuring it works seamlessly on both desktop and mobile devices.
4. Diversity in Recommendations
   - The system will avoid the **filter bubble** effect by introducing diverse movie suggestions that encourage users to explore new genres, themes, and directors outside their typical preferences.
   - This helps users discover movies they might not have considered otherwise.
5. Scalability and Flexibility:
   - The system will be designed to handle a growing number of users and movie data, ensuring it can scale effectively as new movies and users are added.
   - The recommendation engine can be easily updated or extended to incorporate new algorithms or additional data sources in the future.
6. User Engagement and Feedback:
   - The system will include features such as **user ratings**, **reviews**, and the ability to **save** or **share** favorite movies, promoting engagement and interaction.
   - Users can provide feedback that will help refine the system's recommendations and improve the overall experience.
7. System Performance:
   - The recommendation engine will provide real-time suggestions with minimal delay, ensuring a fast and smooth user experience.
   - Performance will be tested and optimized for accuracy, response time, and efficiency.
8. Deployment and Accessibility:
   - The system will be deployed on cloud platforms (e.g., **Heroku**, **AWS**) for easy access by users worldwide.
   - Regular updates and maintenance will ensure the system remains functional and continues to meet user needs.

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Code

```
import streamlit as st
import json
from Classifier import KNearestNeighbours
from bs4 import BeautifulSoup
import requests, io
import PIL.Image
from urllib.request import urlopen

with open('./Data/movie_data.json', 'r+', encoding='utf-8') as f:
      data = json.load(f)
with open('./Data/movie_titles.json', 'r+', encoding='utf-8') as f:
        movie_titles = json.load(f)
    hdr = {'User-Agent': 'Mozilla/5.0'}


def movie_poster_fetcher(imdb_link):
      ## Display Movie Poster
      url_data = requests.get(imdb_link, headers=hdr).text
```

```
    s_data = BeautifulSoup(url_data, 'html.parser')
    imdb_dp = s_data.find("meta", property="og:image1")
    movie_poster_link = imdb_dp.attrs['content']
    u = urlopen(movie_poster_link)
    raw_data = u.read()
    image = PIL.Image.open(io.BytesIO(raw_data))
    image = image.resize((158, 301), )
    st.image(image, use_column_width=False)


def get_movie_info(imdb_link):
    url_data = requests.get(imdb_link, headers=hdr).text
    s_data = BeautifulSoup(url_data, 'html.parser')
    imdb_content = s_data.find("meta", property="og:description")
    movie_descr = imdb_content.attrs['content']
    movie_descr = str(movie_descr).split('.')
    movie_director = movie_descr[0]
    movie_cast = str(movie_descr[1]).replace('With', 'Cast: ').strip()
    movie_story = 'Story: ' + str(movie_descr[2]).strip() + '.'
    rating = s_data.find("span", class_="sc-bde20123-1 iZlgcd").text
    movie_rating = 'Total Rating count: ' + str(rating)
    return movie_director, movie_cast, movie_story, movie_rating


def KNN_Movie_Recommender(test_point, k):
    # Create dummy target variable for the KNN Classifier
    target = [0 for item in movie_titles]
    # Instantiate object for the Classifier
    model = KNearestNeighbours(data, target, test_point, k=k)
    # Run the algorithm
    model.fit()
    # Print list of 10 recommendations < Change value of k for a different number >
    table = []
    for i in model.indices:
        # Returns back movie title and imdb link
        table.append([movie_titles[i][0], movie_titles[i][2], data[i][-1]])
    print(table)
    return table


st.set_page_config(
    page_title="Movie Recommender System",
)


def run():
    img1 = Image.open('./meta/logo.jpg')
    img1 = img1.resize((250, 250), )
```

```
    st.image(img1, use_column_width=False)
    st.title("Movie Recommender System")
    st.markdown('''<h4 style='text-align: left; color: #d73b5c;'>* Data is based "IMDB
5000 Movie Dataset"</h4>''',
                unsafe_allow_html=True)
    genres = ['Action', 'Adventure', 'Animation', 'Biography', 'Comedy', 'Crime',
'Documentary', 'Drama', 'Family',
              'Fantasy', 'Film-Noir', 'Game-Show', 'History', 'Horror', 'Music',
'Musical', 'Mystery', 'News',
              'Reality-TV', 'Romance', 'Sci-Fi', 'Short', 'Sport', 'Thriller', 'War',
'Western']
    movies = [title[0] for title in movie_titles]
    category = ['--Select--', 'Movie based', 'Genre based']
    cat_op = st.selectbox('Select Recommendation Type', category)
    if cat_op == category[0]:
        st.warning('Please select Recommendation Type!!')
    elif cat_op == category[1]:
        select_movie = st.selectbox('Select movie: (Recommendation will be based on
this selection)',
                                    ['--Select--'] + movies)
        dec = st.radio("Want to Fetch Movie Poster?", ('Yes', 'No'))
        st.markdown(
            '''<h4 style='text-align: left; color: #d73b5c;'>* Fetching a Movie
      Posters will take a time."</h4>''',
             unsafe_allow_html=True)
        if dec == 'No':
            if select_movie == '--Select--':
                st.warning('Please select Movie!!')
            else:
                no_of_reco = st.slider('Number of movies you want Recommended:',
min_value=5, max_value=20, step=1)
                genres = data[movies.index(select_movie)]
                test_points = genres
                table = KNN_Movie_Recommender(test_points, no_of_reco + 1)
                table.pop(0)
                c = 0
                st.success('Some of the movies from our Recommendation, have a look
below')
                for movie, link, ratings in table:
                    c += 1
                    director, cast, story, total_rat = get_movie_info(link)
                    st.markdown(f"({c})[ {movie}]({link})")
                    st.markdown(director)
                    st.markdown(cast)
                    st.markdown(story)
                    st.markdown(total_rat)
                    st.markdown('IMDB Rating: ' + str(ratings) + '⭐') ⭐
        else:
```

```
            if select_movie == '--Select--':
                st.warning('Please select Movie!!')
            else:
                no_of_reco = st.slider('Number of movies you want Recommended:',
min_value=5, max_value=20, step=1)
                genres = data[movies.index(select_movie)]
                test_points = genres
                table = KNN_Movie_Recommender(test_points, no_of_reco + 1)
                table.pop(0)
                c = 0
                st.success('Some of the movies from our Recommendation, have a look
below')
                for movie, link, ratings in table:
                    c += 1
                    st.markdown(f"({c})[ {movie}]({link})")
                    movie_poster_fetcher(link)
                    director, cast, story, total_rat = get_movie_info(link)
                    st.markdown(director)
                    st.markdown(cast)
                    st.markdown(story)
                    st.markdown(total_rat)
                    st.markdown('IMDB Rating: ' + str(ratings) + '⭐') ⭐
    elif cat_op == category[2]:
        sel_gen = st.multiselect('Select Genres:', genres)
        dec = st.radio("Want to Fetch Movie Poster?", ('Yes', 'No'))
        st.markdown(
            '''<h4 style='text-align: left; color: #d73b5c;'>* Fetching a Movie
      Posters will take a time."</h4>''',
             unsafe_allow_html=True)
        if dec == 'No':
            if sel_gen:
                imdb_score = st.slider('Choose IMDb score:', 1, 10, 8)
                no_of_reco = st.number_input('Number of movies:', min_value=5,
max_value=20, step=1)
                test_point = [1 if genre in sel_gen else 0 for genre in genres]
                test_point.append(imdb_score)
                table = KNN_Movie_Recommender(test_point, no_of_reco)
                c = 0
                st.success('Some of the movies from our Recommendation, have a look
below')
                for movie, link, ratings in table:
                    c += 1
                    st.markdown(f"({c})[ {movie}]({link})")
                    director, cast, story, total_rat = get_movie_info(link)
                    st.markdown(director)
                    st.markdown(cast)
                    st.markdown(story)
                    st.markdown(total_rat)
```

```
                    st.markdown('IMDB Rating: ' + str(ratings) + '⭐') ⭐
        else:
            if sel_gen:
                imdb_score = st.slider('Choose IMDb score:', 1, 10, 8)
                no_of_reco = st.number_input('Number of movies:', min_value=5,
max_value=20, step=1)
                test_point = [1 if genre in sel_gen else 0 for genre in genres]
                test_point.append(imdb_score)
                table = KNN_Movie_Recommender(test_point, no_of_reco)
                c = 0
                st.success('Some of the movies from our Recommendation, have a look
below')
                for movie, link, ratings in table:
                    c += 1
                    st.markdown(f"({c})[ {movie}]({link})")
                    movie_poster_fetcher(link)
                    director, cast, story, total_rat = get_movie_info(link)
                    st.markdown(director)
                    st.markdown(cast)
                    st.markdown(story)
                    st.markdown(total_rat)
                    st.markdown('IMDB Rating: ' + str(ratings) + '⭐') ⭐


run()
```

Movie Recommender System

* Data is based "IMDB 5000 Movie Dataset"

Select Recommendation Type

Genre based

Select Genres:

Crime

Want to Fetch Movie Poster?

Yes
No

* Fetching a Movie Posters will take a time."

Choose IMDb score:

8

1 10

Number of movies:

5

Some of the movies from our Recommendation, have a look below

(1) Blood In, Blood Out

Blood in, Blood Out: Directed by Taylor Hackford

Cast: Damian Chapa, Jesse Borrego, Benjamin Bratt, Enrique Castillo

Story: Based on the true life experiences of poet Jimmy Santiago Baca, the film focuses on step-brothers Paco and Cruz, and their bi-racial cousin Miklo.

Total Rating count: 31K

IMDB Rating: 8.0 ★

Movie Recommender System

* Data is based "IMDB 5000 Movie Dataset"

Select Recommendation Type

Movie based

Select movie: (Recommendation will be based on this selection)

Spider-Man 3

Want to Fetch Movie Poster?

- (•) Yes
- ( ) No

* Fetching a Movie Posters will take a time."

Number of movies you want Recommended:

5

5 20

Some of the movies from our Recommendation, have a look below

(1) Spider-Man 3

Spider-Man 3: Directed by Sam Raimi

Cast: Tobey Maguire, Kirsten Dunst, James Franco, Thomas Haden Church

Story: A strange black entity from another world bonds with Peter Parker and causes inner turmoil as he contends with new villains, temptations, and revenge.

Total Rating count: 560K

IMDB Rating: 6.2 ★