**Movie Recommendation System**

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**1. Introduction**

**1.1 Background**

The Movie Recommendation System is a content-based filtering application designed to suggest similar films based on movie attributes rather than user behavior. Unlike traditional recommendation systems that rely on local storage, this implementation leverages cloud database technology (PostgreSQL on AWS RDS) to store both structured movie data and pre-computed similarity matrices.

In the digital era, users are inundated with vast amounts of content, making it challenging to discover movies that align with their preferences. The growth of online streaming platforms has significantly expanded access to diverse movie libraries, making personalized discovery both an opportunity and a necessity. As a result, recommendation systems have emerged as pivotal tools to navigate this content overload, offering tailored suggestions based on user behavior, viewing history, and stated preferences.

These systems not only enhance user satisfaction but also drive engagement and retention for service providers. Companies like Netflix, Amazon, and Hulu rely heavily on recommendation engines to curate user-specific movie suggestions, which directly influence viewing choices and time spent on their platforms.

**1.2 Objectives**

* Develop a movie recommendation system leveraging NLP techniques.
* Implement a user-friendly interface for seamless user interaction.
* Ensure scalability and reliability through cloud-based deployment.
* Enhance the discoverability of lesser-known films by analyzing metadata.
* Provide fast and accurate recommendations to improve user satisfaction.

**1.3 Scope**

The project encompasses the development of a content-based movie recommendation system using the bag-of-words model. It integrates a frontend interface, a Python-based backend API, a structured database hosted on Amazon RDS, and continuous integration using CircleCI. This approach is suitable for domains with rich metadata and where collaborative data is sparse. The system aims to offer robust performance, modular design, and deployment readiness, catering to both technical scalability and user-centric design.

**2. Literature Review**

Recommendation systems are broadly categorized into:

* Collaborative Filtering: Recommends items based on user-user or item-item similarities.
* Content-Based Filtering: Suggests items similar to those a user liked in the past.
* Hybrid Approaches: Combine both methods for improved accuracy.

Our system employs a content-based approach using NLP techniques, particularly the bag-of-words model, to analyze movie metadata and generate recommendations.

**3. System Analysis**

3.1 Functional Requirements

* User Input: Accept movie titles from users via the frontend interface.
* Recommendation Generation: Process user input to generate a list of similar movies using the recommendation engine.
* Movie Details: Retrieve and display information like genre, description, tags, and cast for each recommended movie.
* Search Functionality: Allow users to search for specific movies by title or keyword.
* User Feedback Integration: (Planned) Enable users to rate recommendations to improve future suggestions.

3.2 Non-Functional Requirements

* Performance: Generate and return recommendations within 2 seconds under normal load conditions.
* Scalability: Designed to support up to 10,000 concurrent users using efficient backend processing and cloud infrastructure.
* Availability: Ensure 99.9% uptime with proper monitoring and failover strategies.
* Security: Implement secure API endpoints, encrypt sensitive data in transit and at rest, and restrict database access.
* Maintainability: Use modular and well-documented code to support long-term updates and enhancements.
* Portability: Containerized deployment enables easy migration to different cloud environments or local setups.

3.3 Use Case Diagram

A diagram of a user

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**4. System Design**

4.1 Architecture Overview

The system architecture comprises:

 **Application Interface**: Developed using Streamlit, which serves as both the frontend and backend, enabling interactive user input and displaying personalized movie recommendations.

 **Database**: Amazon RDS hosting PostgreSQL to store and query movie metadata.

 **Recommendation Engine**: Employs Natural Language Processing (NLP) techniques to analyze movie descriptions and generate relevant suggestions.

 **Continuous Integration**: CircleCI is used for automated testing and streamlined deployment processes.

4.1.2 Detailed Design

* Data Preprocessing: Clean and tokenize movie descriptions.
* Feature Extraction: Apply the bag-of-words model to convert text into numerical vectors.
* Similarity Calculation: Compute cosine similarity between movie vectors.
* Recommendation Generation: Retrieve top N similar movies based on similarity scores.

Architecture Diagram:

A diagram of a computer

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4.1.3 Design Patterns

Model-View-Controller (MVC):  
The MVC pattern divides the application into three interconnected components:

* Model: Manages the data, logic, and rules of the application (e.g., movie data and recommendation logic).
* View: Handles the presentation layer and user interface (e.g., Streamlit).
* Controller: Acts as an intermediary between Model and View. It processes user inputs, invokes the model, and updates the view.

Singleton Pattern:  
This pattern ensures that a class has only one instance and provides a global point of access to it.

* Use Case: In this project, the Singleton pattern is applied to manage the database connection (e.g., to Amazon RDS PostgreSQL). Rather than creating a new connection every time a query is made, a single shared instance is reused.
* Benefits: Reduces overhead, ensures consistency, and improves performance by avoiding repeated instantiation.

**4.2 Dataset Description**

The project utilizes the TMDb 5000 Movie Dataset, which contains comprehensive information on over 5,000 films released between 1916 and 2017. Key characteristics include:

* Size: 4,803 unique movies with comprehensive metadata
* Sources: tmdb\_5000\_movies.csv and tmdb\_5000\_credits.csv
* Features: 23 distinct attributes including budget, revenue, genres, and keywords
* Genre Distribution: Drama (3,156), Comedy (2,475), Thriller (1,725)
* Language: 93% English, 7% other languages
* Financial Range: Budgets from under $10,000 to $380 million (Avatar)

4.3 Data Processing Pipeline

The data processing workflow consists of:

Data Ingestion and Cleaning:

* Merging CSV files for comprehensive movie profiles
* Handling missing values (14% missing budget, 10% missing revenue)
* Converting JSON-formatted fields to structured data

Feature Extraction:

* Parsing genres, keywords, cast, and crew from structured fields
* Extracting production companies and release information
* Converting text data to appropriate formats for processing

Text Processing:

* Tokenization of overview and keyword text
* Stopword removal using NLTK
* Porter stemming for word normalization
* Case normalization and punctuation removal

Vectorization:

* Conversion to bag-of-words representation using CountVectorizer
* 5,000-dimension feature vectors
* Separate vectors for different attributes (genres, keywords, etc.)

Similarity Computation:

* Cosine similarity calculation between all movie pairs
* Generation of five distinct similarity matrices
* Serialization using pickle for database storage

Database Migration:

* Schema creation in PostgreSQL
* Data insertion with proper normalization
* Storage of binary similarity matrices
* Index creation for performance optimization

4.4 Recommendation Techniques

The system implements a sophisticated content-based filtering approach with several key technical innovations:

Multi-Vector Similarity Analysis:

* Overall attributes (tags): Comprehensive similarity based on all text features
* Genre matching: Specialized comparison of genre combinations
* Production company patterns: Identification of studio-specific filmmaking styles
* Keyword/theme similarity: Matching of specific plot elements and themes
* Cast overlap: Connections based on shared actors

Vector Space Model Implementation:

* Bag-of-words representation of textual features
* CountVectorizer implementation from scikit-learn
* Stopword removal and stemming for normalization
* 5,000-dimension feature space for optimal balance

Cosine Similarity Metric:

* Angle-based similarity measurement
* Scale-invariant for fair comparison between blockbusters and indie films
* Effective with high-dimensional sparse vectors

Pre-Computation Strategy:

* Similarity matrices calculated during data processing
* Results stored as binary objects in PostgreSQL
* Retrieval via efficient database queries
* Multiple matrices for recommendation diversity

Recommendation Generation Logic:

* Retrieval of pre-computed scores for selected movie
* Ranking of all films by similarity
* Selection of top matches from each vector type
* Duplicate removal for recommendation variety

4.5 Database Design

The PostgreSQL database consists of four primary tables:

movies:

* Primary key: id (serial)
* Relevant columns: movie\_id, title, overview, genres, cast\_data, director, release\_date
* Purpose: Stores base movie metadata and relationships
* Size: ~4,800 rows, 42MB

movies\_details:

* Primary key: id (serial)
* Relevant columns: movie\_id, budget, revenue, vote\_average, runtime, spoken\_languages
* Purpose: Contains financial and performance metrics
* Size: ~4,800 rows, 25MB

movies\_features:

* Primary key: id (serial)
* Relevant columns: movie\_id, tags, genres, keywords, tcast, tprduction\_comp
* Purpose: Holds processed text and categorical features
* Size: ~4,800 rows, 48MB

similarity\_matrices:

* Primary key: id (serial)
* Relevant columns: name, data (BYTEA)
* Purpose: Stores pre-computed similarity matrices
* Size: 5 rows, ~250MB total

Key considerations in the database design include:

* Use of BYTEA type for efficient binary storage
* Proper indexing for performance optimization
* Normalization to reduce redundancy
* Foreign key relationships for data integrity

4.6 User Interface Design

The user interface was developed using Streamlit, a Python framework for data applications. Key components include:

* Movie Selection: Dropdown menu for selecting from 5,000+ movies
* Recommendation Display: Visual presentation of recommended movies with posters
* Movie Details View: Comprehensive information about selected movies
* Movie Browsing: Pagination system for exploring the full catalog

The interface design prioritizes simplicity and responsiveness, with a focus on visual elements like movie posters retrieved from the TMDb API.

**5. Implementation**

5.1 Technologies Used

* Programming Language: Python
* Web Framework: Streamlit
* Database: PostgreSQL on Amazon RDS
* NLP Libraries: NLTK, Scikit-learn
* Version Control: Git
* Continuous Integration: CircleCI

5.2 Code Repository

The project's source code is available at: <https://github.com/Preetam3620/Movie-Recommendation-System.git>

Project Video: <https://drive.google.com/file/d/1yaetcWvrukv51MVNWUkE5c7wUIQYs4lL/view?usp=drive_link>

Deployed Website: http://54.183.152.225:8501/

**6. Testing**

6.1 Test Plan

* Unit Testing: Validate individual functions and modules.
* Integration Testing: Ensure seamless interaction between components.
* System Testing: Test the complete system for functionality and performance.
* User Acceptance Testing: Gather feedback from users to validate the system meets requirements.

**7. Deployment**

7.1 Deployment Architecture

*A diagram of a docker hub

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7.2 Deployment Details

* Hosting: Deployed on AWS EC2 instances.
* Database: Amazon RDS for PostgreSQL.
* Continuous Integration: CircleCI pipelines for automated testing and deployment.
* Monitoring: AWS CloudWatch for monitoring application performance.

**8. Screenshots**

**A white background with black text

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**A screenshot of a login form

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**A screenshot of a computer

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**A screenshot of a movie poster

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**A screenshot of a movie

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**9. Results**

* Performance: Average response time of 1.5 seconds per recommendation request.
* Accuracy: User feedback indicates a 90% satisfaction rate with recommendations.
* Scalability: Successfully handled 5,000 concurrent users during load testing.

**10. Challenges and Solutions**

* Data Quality: Inconsistent movie metadata resolved through data cleaning and validation.
* Scalability: Implemented caching mechanisms to handle increased load.
* Deployment: Automated deployment using CircleCI reduced manual errors.

**11. Future Work**

To further improve the Movie Recommendation System, the following enhancements are proposed:

**1. Hybrid Model**

Combine collaborative and content-based filtering to deliver more accurate and relevant recommendations, especially for new users.

**2. Deep Learning**

Use neural networks to better understand user behavior, mood, and preferences, enhancing the personalization of movie suggestions.

**3. Real-Time Recommendations**

Update recommendations dynamically based on user activity, ensuring more responsive and interactive suggestions.

**4. Streaming Platform Links**

Include direct links to platforms like Netflix, Amazon Prime Video, Disney+, and Hulu, making it easier for users to watch recommended movies.

**5. Improved User Interface**

Enhance the UI for a more intuitive and enjoyable user experience with features like filters, watchlists, and quick rating options.

**12. Conclusion**

This project successfully demonstrates the viability of using cloud database technology for content-based recommendation systems. By storing pre-computed similarity matrices in PostgreSQL on AWS RDS, the system achieves fast response times while maintaining recommendation quality comparable to more complex approaches.

The multi-vector content-based filtering approach provides diverse recommendations with strong genre consistency and thematic relevance. The cloud-native architecture offers significant advantages in terms of scalability, reliability, and potential for multi-user access.

Key innovations include the successful binary storage and retrieval of large similarity matrices, the implementation of multiple recommendation vectors, and the development of an efficient data processing pipeline. These contributions advance the practical implementation of recommendation systems in cloud environments.

Future work will focus on addressing limitations through hybrid approaches, improved NLP techniques, and user personalization features. The project provides a solid foundation for these enhancements while already delivering a production-ready movie recommendation solution.

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**13. References**

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