Phase-2 Submission

Delivering personalized movie recommendations with an AI-driven matchmaking system

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Github Repository Link:

https://github.com/harishinikarthikeyan/Phase-2.git

1. Problem Statement

This project addresses the challenge of efficiently recommending personalized movie content to users by developing an AI-powered matchmaking system. With an explosion of content on streaming platforms, users struggle to discover relevant movies matching their tastes.

Type of Problem: This is primarily a recommendation system, often solved using a mix of clustering, ranking, and regression/classification techniques.

Why It Matters: Improved recommendations enhance user experience, boost

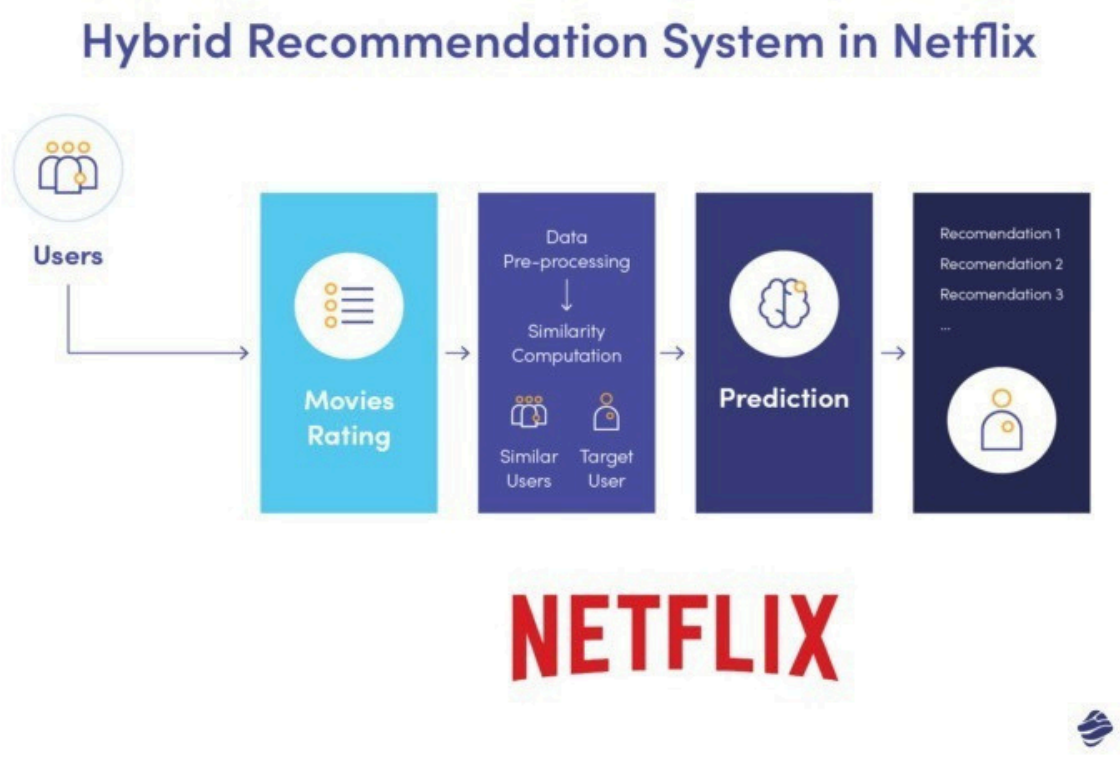
user

arentden tion, and reduce content churn for platforms like Netflix, Amazon Prime, YouTube.

2. Project Objectives

Develop a hybrid recommendation model combining content-based and collaborative filtering.
Personalize user experiences by analyzing user behavior and movie metadata.
Improve the relevance and diversity of recommendations.
Evolve model goals after data analysis to prioritize explainability and performance on sparse data.

3. Flowchart of the Project Workflow



4. Data Description

Source: [e.g., MovieLens dataset from Kaggle or GroupLens]

Type: Structured data

Records: ~100,000 user ratings across ~10,000 movies

Features: Movie metadata (genres, title, year), user ratings, timestamps

Target Variable: User ratings or recommendation score

Nature: Static dataset

5. Data Preprocessing

Removed null values from metadata and user ratings

Dropped duplicate entries based on userId-movieId pairs.
Converted timestamps to readable datetime.
Encoded genres using multi-hot encoding.
Normalized rating values between 0 and 1 for model consistency.

6. Exploratory Data Analysis (EDA)

Univariate:

Distribution of ratings (most ratings are 4 or 5).

Popular genres (Drama, Comedy, Action).

Bivariate/Multivariate:

Correlation of user preferences by genre.
Popularity vs. average rating plots.

Insights:

Older movies tend to have higher ratings.
Users exhibit genre-specific preferences that can be clustered.

7. Feature Engineering

Extracted release year from movie titles.

Created “rating frequency” and “average rating” features.

Constructed user profiles by aggregating rated genres.

Applied TF-IDF vectorization for movie overviews (if text data available).

Optional PCA on user-item matrix to reduce sparsity.

8. Model Building

Models Implemented:

Content-Based Filtering using cosine similarity on TF-IDF features.
Collaborative Filtering via Matrix Factorization (SVD).
Compared with KNN-based recommender for baseline performance.

Evaluation Metrics:

RMSE for rating prediction
Precision@K, Recall@K for top-N recommendations

Data Split:

80-20 train-test split using stratification on userId.

9. Visualization of Results & Model Insights

RMSE Plot: Shows convergence of matrix factorization model.
Top-N Hit Rate bar chart per model.
Feature Importance plot for content-based filtering (genre and overview).
User Clusters visualized using t-SNE for latent embeddings.

10. Tools and Technologies Used

Programming: Python

IDE: Jupyter Notebook / Google Colab
Libraries: pandas, numpy, scikit-learn, seaborn, matplotlib, surprise, TensorFlow (if deep model used)
Visualization: seaborn, matplotlib, Plotly

11. Team Members and Contributions

Name	Contributions
Hameetha	Data cleaning, EDA
HariHaran	Feature engineering, documentation
Harishini	Model tuning, evaluation visualization
Harish kumar	Model development,programming