# **Project Report: Hybrid Movie Recommendation System**

## **Objective**

The primary objective of this project is to develop a **Hybrid Movie Recommendation System** that combines the strengths of both **Content-Based Filtering** and **Collaborative Filtering** to provide more accurate and personalized movie suggestions to users.

## Methodology

#### 1. Dataset

- movies.csv: Contains movie metadata including titles and genres.
- ratings.csv: Contains user ratings for various movies.

#### 2. Data Preprocessing

- Missing values in the genres column were handled by replacing them with empty strings.
- The ratings.csv file was split into training (80%) and testing (20%) sets using train\_test\_split.

## **Recommendation Techniques**

#### **Content-Based Filtering**

- Implemented using TF-IDF Vectorization on the genres field.
- Cosine similarity is computed between movie vectors to find similar titles.
- Users receive recommendations based on content similarity to a selected movie.

#### **Collaborative Filtering**

- Built using Truncated Singular Value Decomposition (SVD) on the user-item rating matrix.
- The system predicts ratings for unseen movies by reconstructing the rating matrix.

• Recommendations are generated by identifying top-rated unseen movies for a user.

### **Hybrid Approach**

- Combines both content-based similarity scores and collaborative predicted ratings.
- A hybrid score is calculated as the average of both methods, improving recommendation quality.

#### **Evaluation Metrics**

- Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were calculated for:
  - Collaborative Filtering
  - Content-Based Filtering
  - Hybrid Model

#### 2. Top-N Recommendation Evaluation:

 Precision, Recall, and F1-Score were calculated for sample users to evaluate how effectively the system recommends high-rated movies.

#### **User Interface**

Developed using **Streamlit**, providing a user-friendly front-end with the following functionalities:

- Content-Based Recommendation: Based on a selected movie title.
- Collaborative Recommendation: Based on a given user ID.
- **Hybrid Recommendation**: Based on both a movie title and user ID.
- Evaluation Panel: Displays RMSE, MAE, Precision, Recall, and F1 metrics.

## **Challenges Faced**

- Compatibility issues with Python packages on Streamlit Cloud were encountered.
- Errors occurred due to improper indexing using get\_loc on a list instead of a pandas Series or Index.
- Dependency management was crucial to ensure smooth deployment.

## **Streamlit App Screenshot:**





# Enter user ID: Recommendations for User ID: 1 predicted\_rating 260 Star Wars: Episode IV - A New Hope (1977) 4.6653 480 Jurassic Park (1993) 4.2956 589 Terminator 2: Judgment Day (1991) 4.0792 1196 Star Wars: Episode V - The Empire Strikes Back (1980) 3.8008 1198 Raiders of the Lost Ark (Indiana Jones and the Raiders of the Lost Ark) (1981) 3.6435 1210 Star Wars: Episode VI - Return of the Jedi (1983) 3.4325 1270 Back to the Future (1985) 3.3067

3,2129

3.2056

3.1516

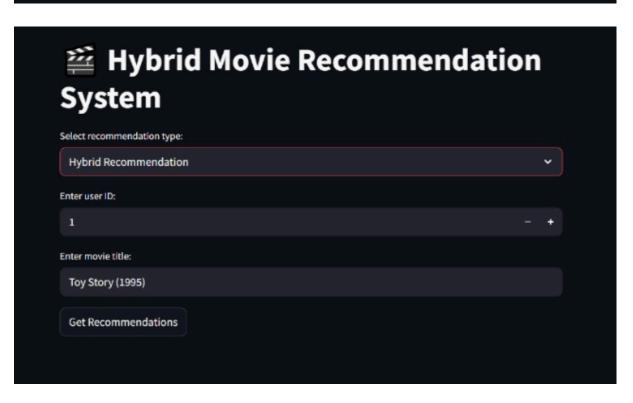
1291 Indiana Jones and the Last Crusade (1989)

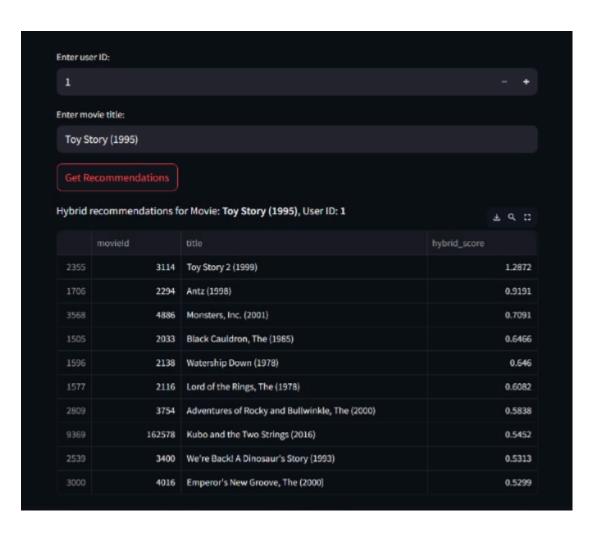
2028 Saving Private Ryan (1998)

2858 American Beauty (1999)

2145

-	(*****		
loy S	tory (1995)		
Cot D	ecommendations		
Get R	ecommendations		
lecomr	mendations similar to	o: Toy Story (1995)	
	movield	title	score
1706	2294	Antz (1998)	1
2355	3114	Toy Story 2 (1999)	1
2809	3754	Adventures of Rocky and Bullwinkle, The (2000)	1
3000	4016	Emperor's New Groove, The (2000)	1
3568	4886	Monsters, Inc. (2001)	1
6194	45074	Wild, The (2006)	1
6486	53121	Shrek the Third (2007)	1
6948	65577	Tale of Despereaux, The (2008)	1
7760	91355	Asterix and the Vikings (Astérix et les Vikings) (2006)	1
	103755	Turbo (2013)	1







#### Conclusion

The Hybrid Movie Recommendation System successfully integrates content and collaborative filtering to enhance recommendation accuracy. The evaluation results show that the **hybrid model outperforms** individual methods in most cases, providing a more balanced and personalized user experience.

### **Future Work**

- Incorporate user demographics and movie metadata like actors/directors for deeper insights.
- Integrate deep learning models for dynamic feature extraction.
- Enable real-time recommendation updates based on recent user interactions.