RECOMMENDATION SYSTEMS

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Introduction

- Our hybrid recommendation system offers personalized movie suggestions, enhancing user experience on streaming platforms.
- It combines collaborative filtering and content-based filtering to deliver accurate recommendations.
- The system improves user engagement and satisfaction.
- It provides valuable insights into audience preferences.
- Benefits include enhanced experiences for end users, improved engagement for streaming platforms, and valuable data for studios.

BUSINESS UNDERSTANDING

Business Problem

- Users struggle with selecting movies due to overwhelming options on streaming platforms.

Solution

- **Personalized Recommendations**: System suggests movies based on user ratings to enhance decision-making.

Stakeholders

Primary Users: End Users, Streaming Platforms **Secondary Users**: Movie Studios, Market Researchers

Value Brought

User Satisfaction: Faster movie selection **Engagement**: Higher retention rates **Insights**: Better content strategies

DATA UNDERSTANDING

Movies Dataset:

- **Entries:** 9,742
- **Columns:** movieId, title, genres

Ratings Dataset:

- **Entries:** 100,836
- **Columns:** userId, movieId, rating

Tags Dataset:

- **Entries:** 3,683
- **Columns:** userId, movieId, tag

Links Dataset:

- **Entries:** 9,742
- **Columns:** movieId, imdbId, tmdbId

DATA CLEANING

- The datasets had no missing values and duplicated rows

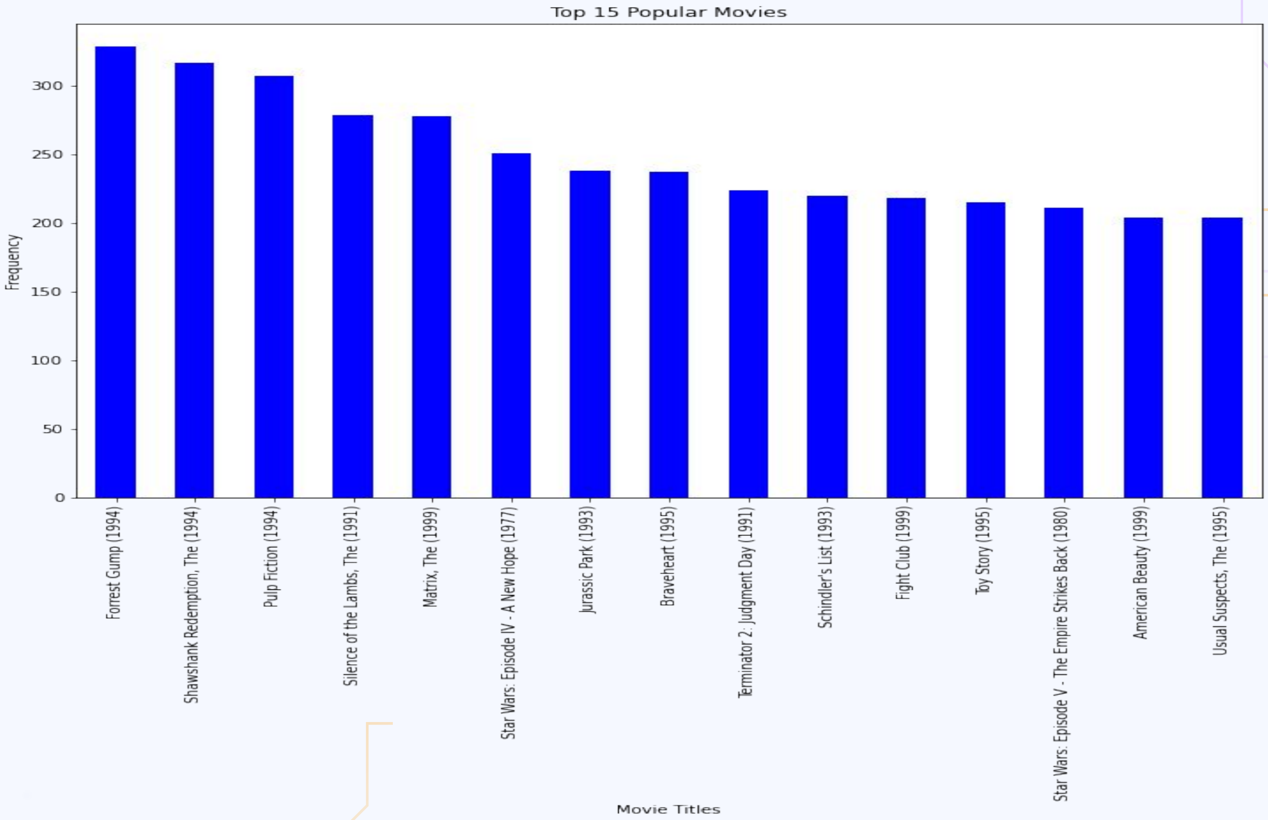
Merging Movies and Ratings Datasets

- The movies_df and ratings_df Data Frames are merged using the movieId column as the key.

Exploratory Data Analysis

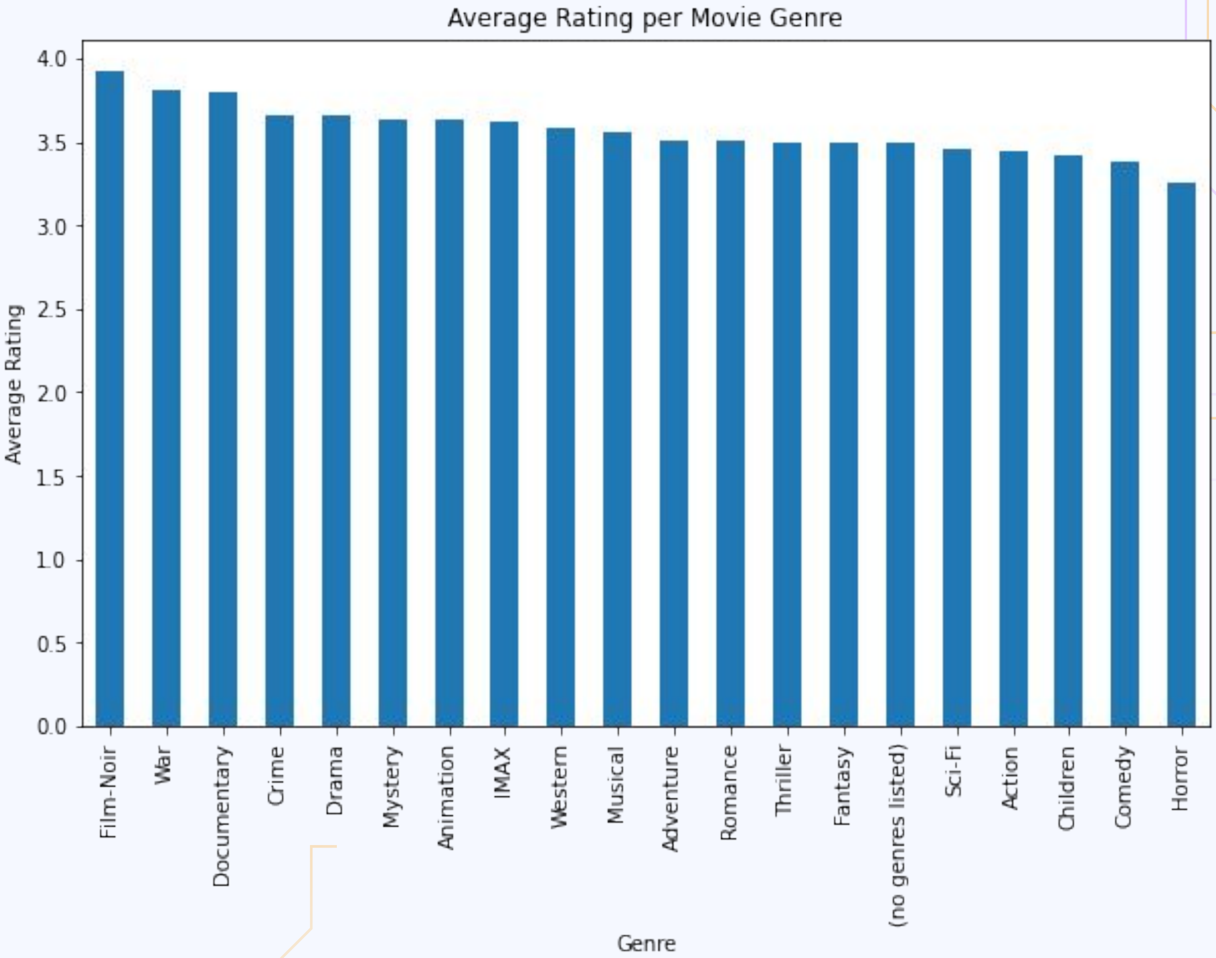
- The bar chart shows that **Forrest Gump (1994)** has the highest frequency of mentions, while **The Usual Suspects (1995)** has the lowest among the top 15.

- This highlights the most popular movies based on frequency, providing insights into audience preferences.

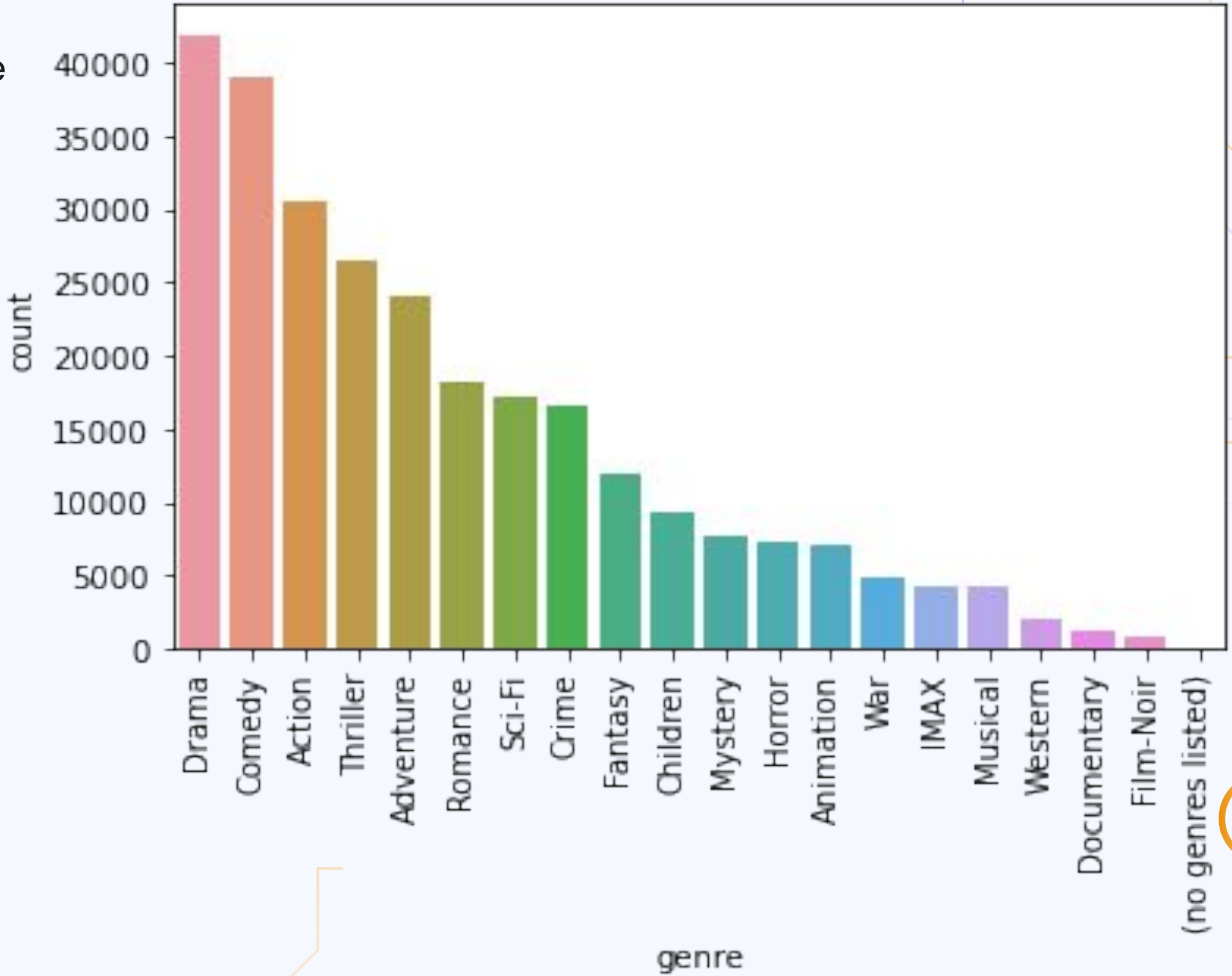


- The bar chart shows that **Film-Noir** has the highest average rating, while **Horror** has the lowest.

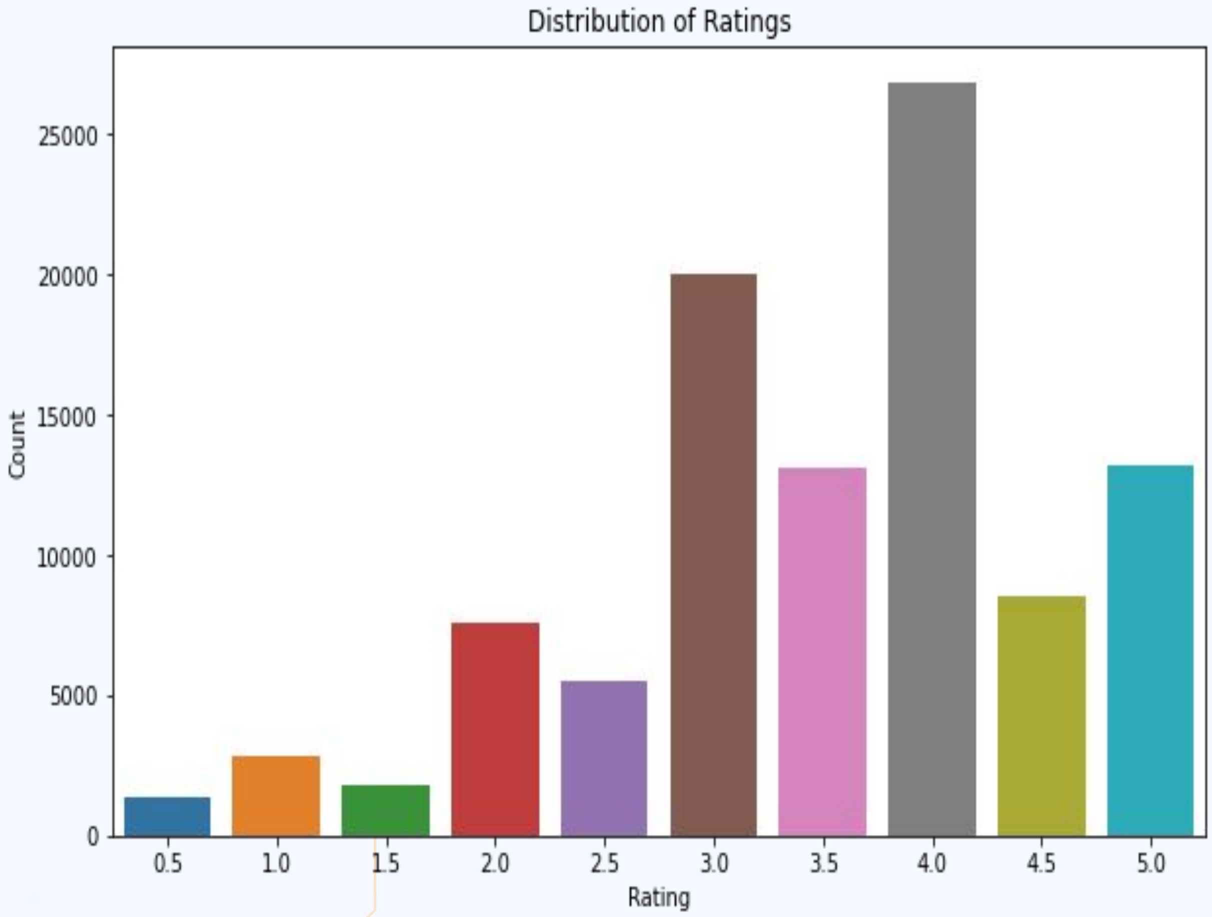
- It highlights the varying average ratings across different movie genres, providing insights into audience preferences.



- Dominant genres like Drama and Comedy should be prioritized in recommendations, as they are most popular.
- Recognizing lesser-represented genres can enhance diversity and personalization in recommendations.



- The bar chart above shows the distribution of ratings in the dataset.
- This distribution suggests a positive skew, with higher ratings being more common.



PREPARING DATA

Filter Relevant Columns

Define Rating Scale

Load Data into Surprise – we used `Dataset.load_from_df` to format the data for collaborative filtering.

Divide data into training (80%) and testing (20%) sets using `train_test_split`.

MODELLING

COLLABORATIVE FILTERING USING SVD

- Employs Singular Value Decomposition (SVD) to predict user ratings based on historical data.
- Technique that relies on user-item interactions to predict user preferences.

SVD Model:

- Matrix factorization technique that decomposes the user-item interaction matrix into latent factors.

Performance Metrics:

- Evaluated using RMSE and MAE:
  - **RMSE:** 0.8688
  - **MAE:** 0.6681

CONTENT-BASED FILTERING USING COSINE SIMILARITY

- Recommends movies based on similarities in content
- Computing the cosine similarity matrix based on the TF-IDF vectors.

HYBRID RECOMMENDATION SYSTEM

- Combines collaborative filtering (SVD) and content-based filtering (cosine similarity) to provide more accurate and diverse recommendations.
- Generates recommendations by leveraging both user interaction data and content similarity.

RESULTS AND PERFORMANCE

Collaborative Filtering (SVD):

- RMSE: 0.8688, MAE: 0.6681

KNN Model:

- RMSE: 0.9414, MAE: 0.7193

Hyperparameter Tuning:

- Best RMSE score for SVD: 0.866918163661489
- Best RMSE score for KNNBasic: 0.9311428065101948

CONCLUSIONS

- The hybrid system demonstrates exceptional accuracy (RMSE: 0.8688) in predicting user ratings, ensuring personalized recommendations.
- The hybrid approach addresses the cold-start issue by using content-based filtering for new users, ensuring everyone receives valuable recommendations.
- By offering personalized and timely recommendations, the system boosts user engagement and satisfaction, leading to higher retention.
- The system is designed for continuous improvement with additional features, real-time updates, and user feedback integration

RECOMMENDATIONS

- Update recommendations dynamically based on user interactions.
- Utilize autoencoders or neural collaborative filtering for better accuracy.
- Incorporate trailers, reviews, and images to enrich and diversify recommendations
- Incorporate a wider range of movies, genres, and user interactions to improve accuracy and cater to diverse preferences.
- Regularly re-tune SVD and KNN model hyperparameters with GridSearchCV to ensure optimal performance.
- Allow users to rate and provide feedback on recommendations to continuously refine the algorithms.

Thank You!

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