



Streamflix Movie Recommender System

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Business Understanding

Business Understanding



Overview

Streamflix aims to enhance user experience with a movie recommendation system that will leverage collaborative and content-based methods for more personalized top 5 movie suggestions.



Business Problem

User retention and engagement issues are impacting company revenue, customer satisfaction and Streamflix's competitive edge in the streaming industry.



Objective

To develop and deploy a hybrid recommendation system to improve prediction accuracy by capturing user-item interactions and movie attributes for a personalized experience.

Data Understanding

Data Understanding



Data Source

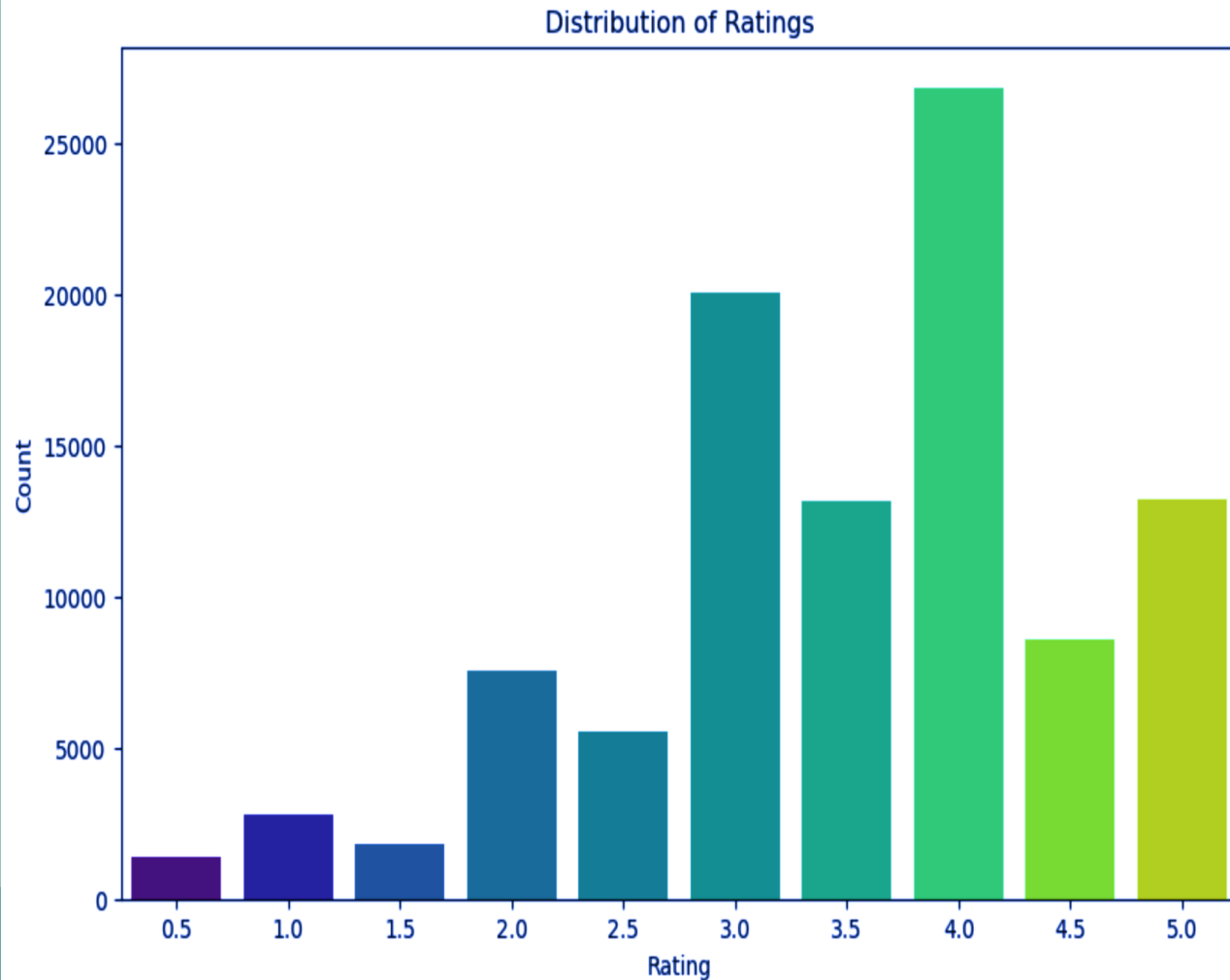
Our data is from the MovieLens dataset by the GroupLens research lab at the University of Minnesota.



Features of Importance

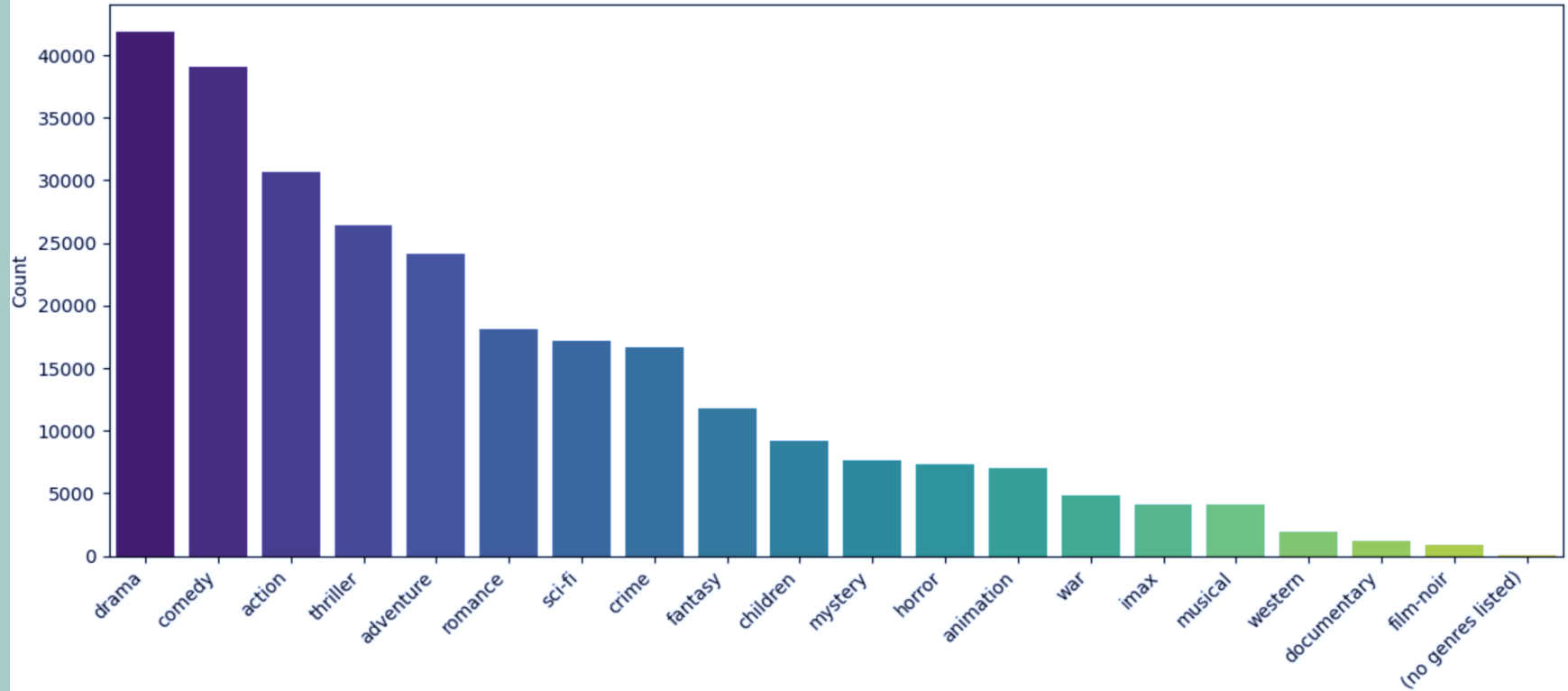
- Movie_id - unique movie identifier.
- Title - movie title.
- Genres - movie genres.
- User_id - unique identifier for users .
- Rating - ratings given by the users.

Observations



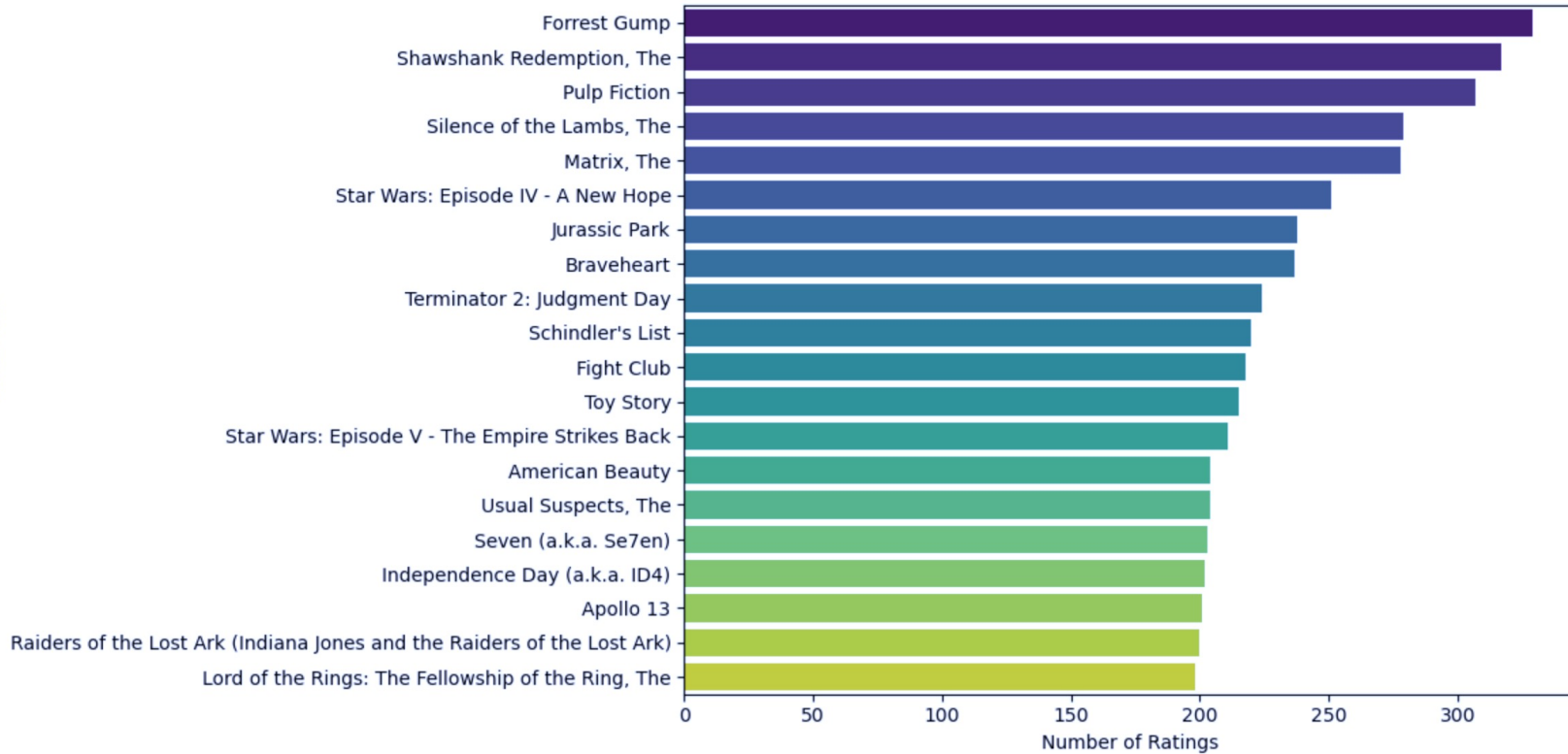
- The most common rating is 4.0.
- The distribution is positively skewed towards higher ratings.

Distribution of Movie Genres



- Drama is the most preferred genre followed closely by comedy.
- Niche genres like animation, war, IMAX, musical and Western appear to have fewer than 10,000 movies each.

Top 20 Rated Titles by Number of Ratings

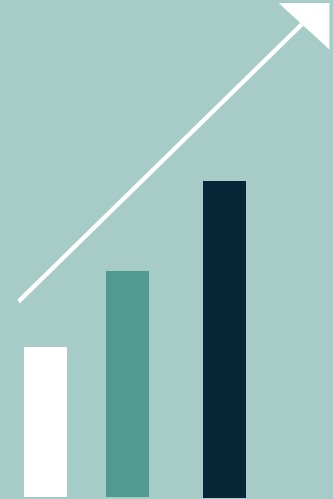


- 'Forrest Gump' has the highest number of ratings followed by 'The Shawshank Redemption' and 'Pulp Fiction'.

Modeling Results



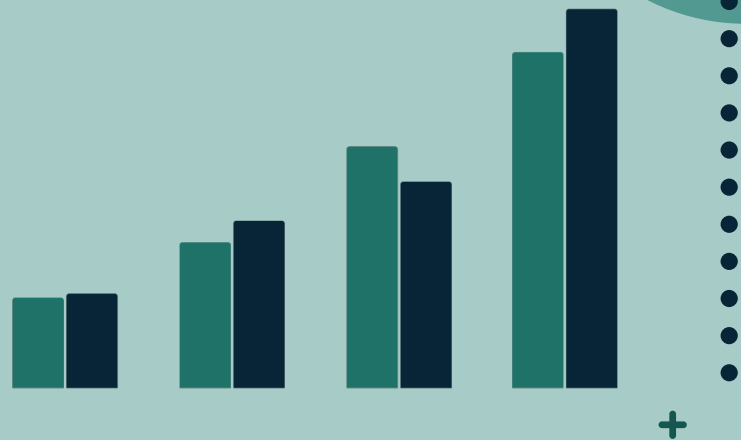
- Baseline dummy model yielded an RMSE of 1.43, SVD model outperformed KNN with an RMSE of 0.862 vs. 0.975.
- Developed a CollabBasedModel for collaborative filtering and a ContentBasedModel for content-based filtering and combined both techniques creating a hybrid model.
- The hybrid model tested various collaborative filtering weights, showing improved RMSE scores with higher weights reaching 1.1221 at a weight of 0.8 indicating better prediction accuracy with higher collaborative filtering emphasis.



Conclusions

Conclusions

- The collaborative filtering model with an RMSE of 0.86 outperforms the hybrid model which shows higher RMSE of 1.24
- This illustrates that collaborative filtering in a hybrid approach yields better accuracy and recommendation quality.



Recommendations

Recommendations



Experiment with smaller increments around the optimal collaborative filtering weight ($0.6 > k < 0.8$)



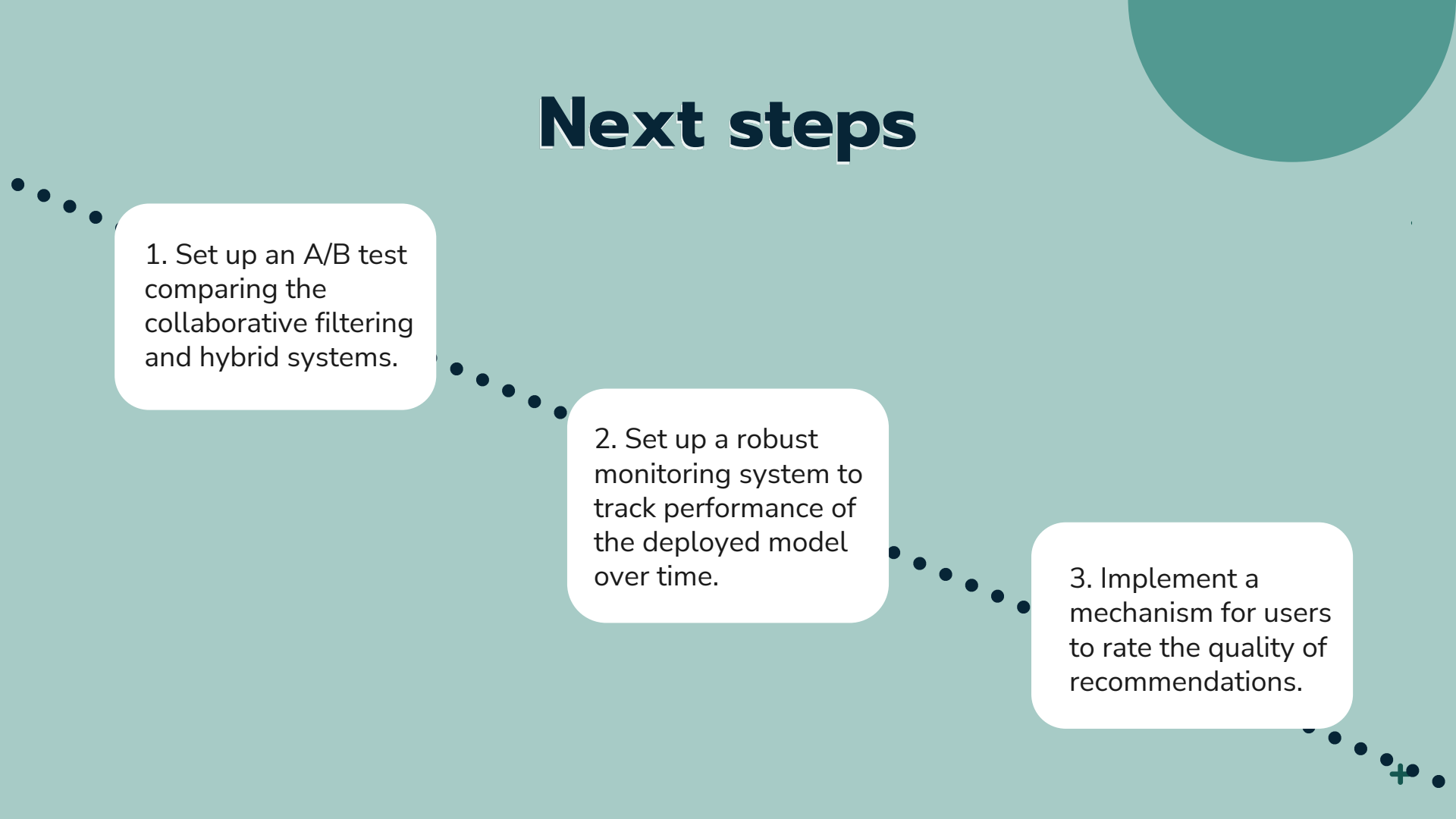
Use cross-validation to confirm that improvements in RMSE are consistent and not due to random variations or overfitting.



Integrate deep learning-based models and other advanced methods to enhance model capabilities..

Next Steps

Next steps



1. Set up an A/B test comparing the collaborative filtering and hybrid systems.

2. Set up a robust monitoring system to track performance of the deployed model over time.

3. Implement a mechanism for users to rate the quality of recommendations.

Thank You!

For follow-up questions

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