

# **RECOMMENDATION SYSTEM FOR TOP MOVIES**

## **GROUP 4**

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## PROJECT GOAL

The goal of this project is to build a personalized recommendation system for the users of a movie streaming company.

**Outcome:** To improve user engagement and retention through tailored movie suggestions

# BUSINESS PROBLEM AND OBJECTIVE

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Users are overwhelmed with choices in a competitive streaming market hence the need for a recommendation system to guide them in content discovery.

## Objectives:

- ❖ Boost engagement by offering tailored movie suggestions.
- ❖ Increase user retention through consistent, relevant recommendations.
- ❖ Solve the cold start problem for new users with no ratings.

# DATA OVERVIEW

Source of dataset: MovieLens website

4 datasets of which 2 were used - movies dataset and rating dataset

## Key variables:

- ❖ User ID
- ❖ Movie ID
- ❖ Ratings
- ❖ Genres

# METHODOLOGY

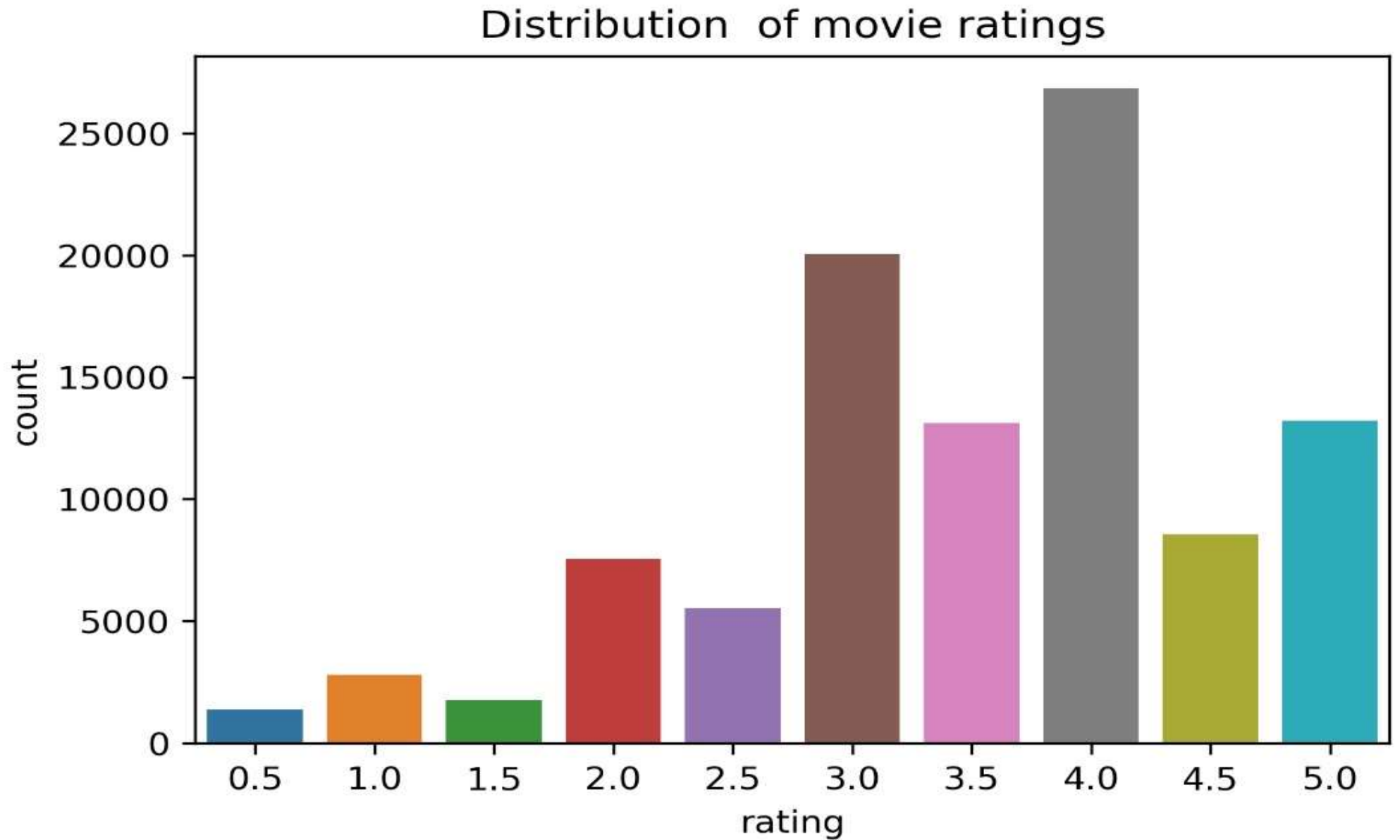
- Exploratory data analysis
- Data cleaning and preprocessing
- Model Development
  - ❖ Collaborative Filtering(SVD)
  - ❖ Content based Recommendation
- Evaluation Metrics(RMSE, Precision)

# EXPLORATORY INSIGHTS

- Entries in the dataset- 100836
- Users in the dataset- 610
- Number of movies- 9724
- Average number of ratings per user: 165.3
- Average number of ratings per movie: 10.37
- Average rating- 3.5

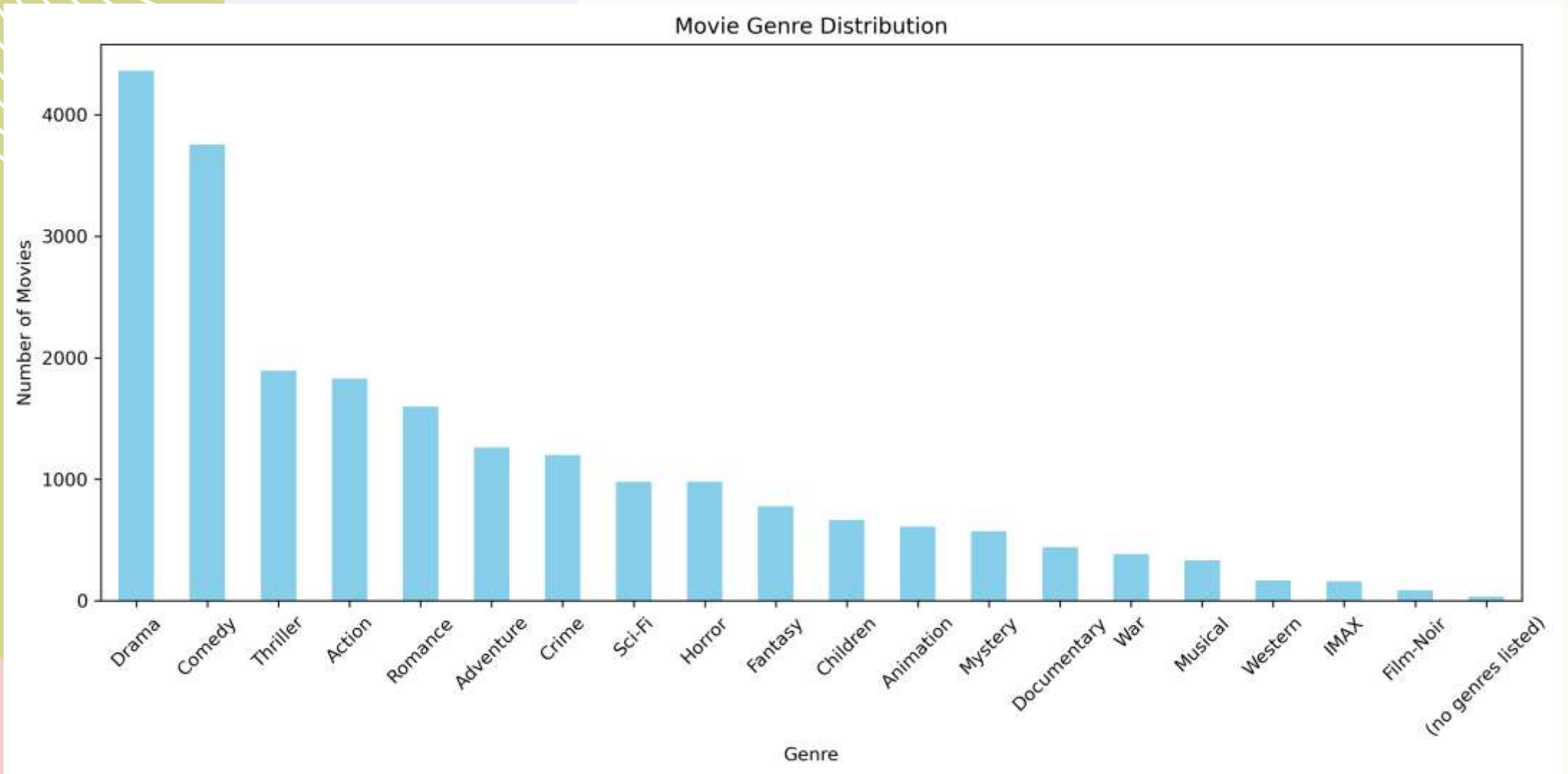


# DISTRIBUTION OF MOVIE RATINGS



# MOVIE GENRE DISTRIBUTION

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# RECOMMENDATION MODELS

- **Collaborative Filtering(SVD)**
  - Learns user preferences based on similar users
  - Personalized top 5 movie list per user
- **Content-based recommendation**
  - Recommends top-rated movies overall
  - Recommends similar movies for a new user –based on genres
  - This model addresses cold start (when user has not rated movies yet)
  - Used TF-IDF vectorization

# RECOMMENDATION MODELS

- **Hybrid CF-CBF Recommendation Model**
- Normalizes CF and CBF scores for a common scale
- Blend the two models using a weighting factor  $\alpha$ (e.g., 0.5)
- Sorts and returns top 5 movie recommendations

# MODEL PERFORMANCE

- We implemented Collaborative Filtering(CF) using SVD from the Surprise library. It performs better for active users.
- Evaluation matrix RMSE = 0.87 for Collaborative Filtering is achieved. This is acceptable for rating prediction.
- Collaborative Filtering is ideal for personalized recommendations once the user has rated many items/movies.
- We used TF-IDF vectorization of genre for Content-Based Filtering(CBF) to recommend top N unseen movies for all users, addresses cold-start users

# **BUSINESS IMPACT**

- Improved user experience
- Higher Retention and engagement
- Competitive edge in the market
- Foundation for advanced features e.g. hybrid systems

# RECOMMENDATIONS

- Hyper-parameter tuning for CF to improve RMSE
- To include more features such as movie description for TF-IDF to improve the model.
- Optimize the SVD model by using different similarity measures
- Optimize alpha to balance the right weight of CF and CBF



**THANK YOU!**