

# MOVIE RECOMMENDATION SYSTEM



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# Business Problem

- Users struggle to discover relevant movies
- Large catalogs cause choice overload
- Sparse feedback limits personalization
- Need accurate, scalable recommendation.

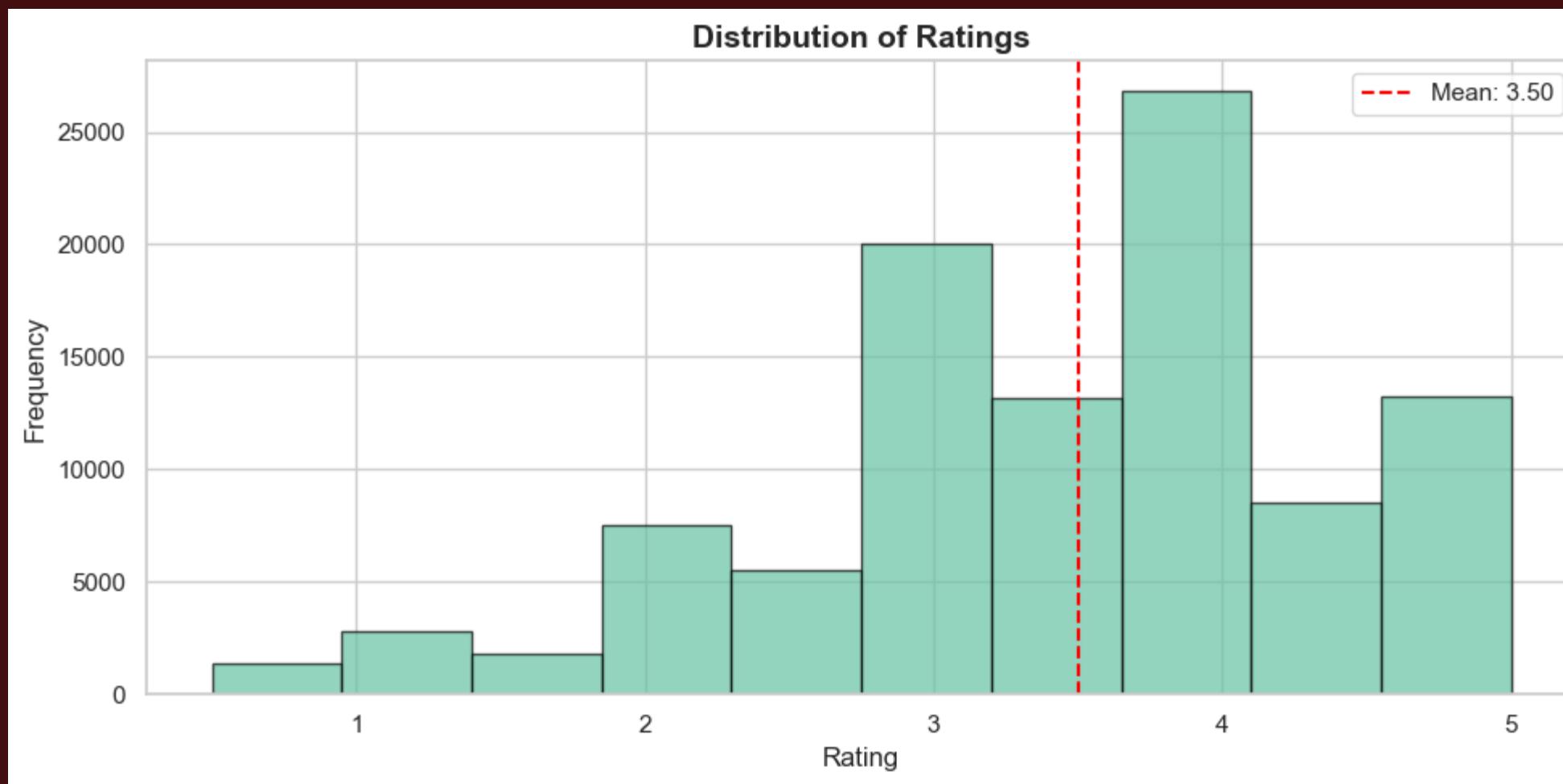


# Dataset Overview



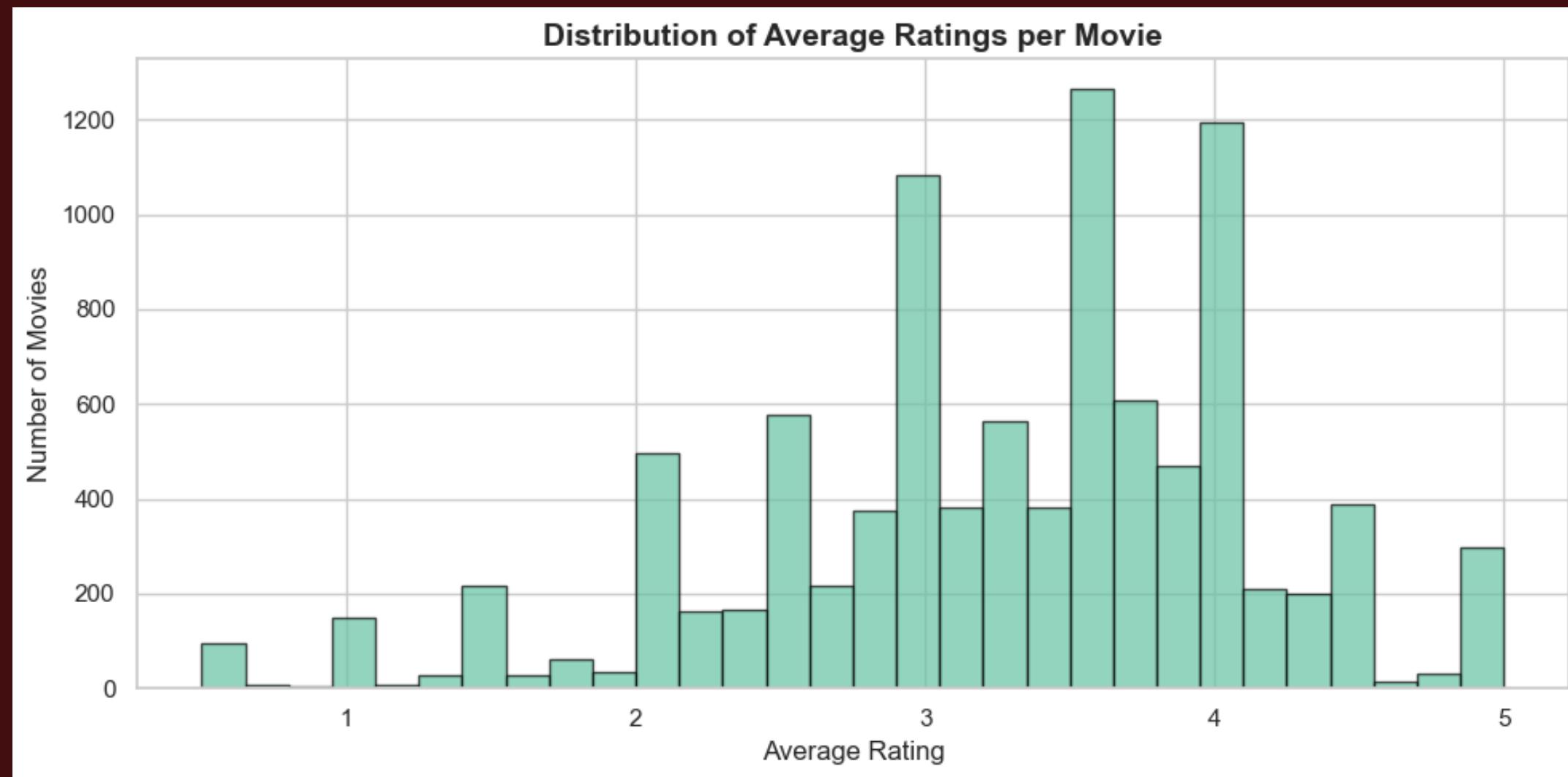
- 100,836 ratings
- 610 users
- 9,742 movies
- 98.3% sparse interaction matrix

# Exploratory Insights (Movie Popularity)



- Ratings range from 0.5 to 5.0
- Mean rating = 3.50
- Majority of ratings fall between 3.0–4.0
- Very few ratings below 2.0

# Movie Popularity



- 7,000+ movies have fewer than 10 ratings
- Only a small number exceed 50 ratings
- Average ratings per movie = 10.4
- Strong long-tail distribution

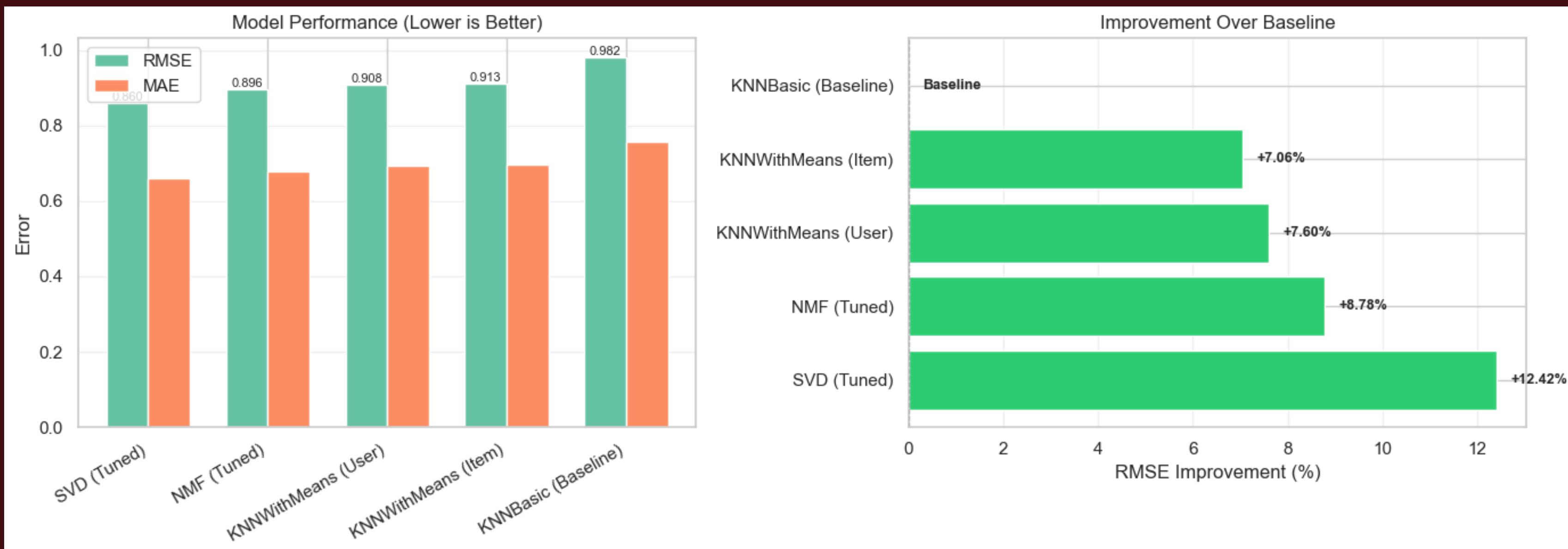


# Modeling Approach

- Baseline: KNNBasic
- Improved KNNWithMeans (user & item)
- Matrix factorization: NMF and SVD
- GridSearch used for tuning

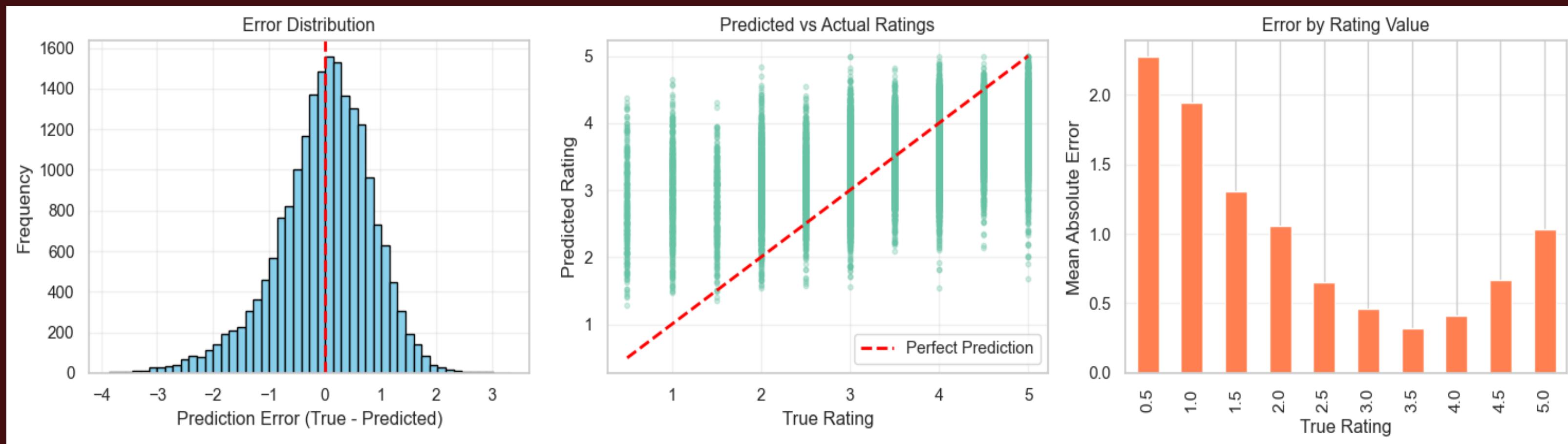
# Model Performance

- Baseline RMSE: 0.982
- Best RMSE (SVD): 0.860
- 12.4% improvement over baseline
- SVD selected as final model



# Error Analysis (SVD)

- Mean error  $\approx -0.016$  (unbiased)
- Errors mostly within  $\pm 1$  rating
- Strong at mid-range ratings
- Weak at extreme ratings





# Recommendation Output

- Estimates user preferences for all unseen movies
- Prioritizes titles with the highest predicted ratings
- Delivers a personalized Top-5 movie list
- Avoids recommending previously rated content



A dark theater with rows of red seats, viewed from the back. The seats are arranged in a semi-circular pattern, receding into the distance. The lighting is low, with some light reflecting off the seats and the floor.

THANK  
YOU