MovieLens Recommendation System

Personalized Movie Recommendations for Streaming Platforms

Team: Winnie Njoroge • Michelle Mwende • Laban Leploote • Alice Mathenge • Dean Mutie

February 2026

Business Understanding

The Problem: Choice Paralysis

• Users spend 15+ minutes scrolling without clicking "Play"
• 30%+ increase in subscription cancellation likelihood
• Cost of acquiring new customer is 5x retaining existing one

Our Solution

- • Collaborative filtering system
- • Top-5 personalized recommendations
- • Reduce time-to-play
- • Surface hidden gems
- • Increase engagement & retention

Success Criteria

- ✓ RMSE < 1.0 on 5-point scale
- ✓ Diverse genre recommendations
- ✓ Address cold start problem
- ✓ Scale to thousands of users

Data Understanding

MovieLens 100K Dataset: https://grouplens.org/datasets/movielens/latest/

100,836
Ratings

610
Users

9,742
Movies

~98%
Sparsity

File	Records	Description
ratings.csv	100,836	User ratings of movies
movies.csv	9,742	Movie metadata (title, genres)
tags.csv	3,683	User-generated tags
links.csv	9,742	External database IDs

✓ *Real user behavior data from GroupLens Research (University of Minnesota)*

Data Preparation

1

Cleaning

Removed duplicates
Validated rating range
Checked missing values

2

Filtering

Min 20 ratings/user
Min 10 ratings/movie
94.9% data retained

3

Splitting

70% Training
15% Validation
15% Test

Final Dataset Statistics

📊 Total Ratings: 95,668

👥 Active Users: 609

🎬 Movies: 3,535

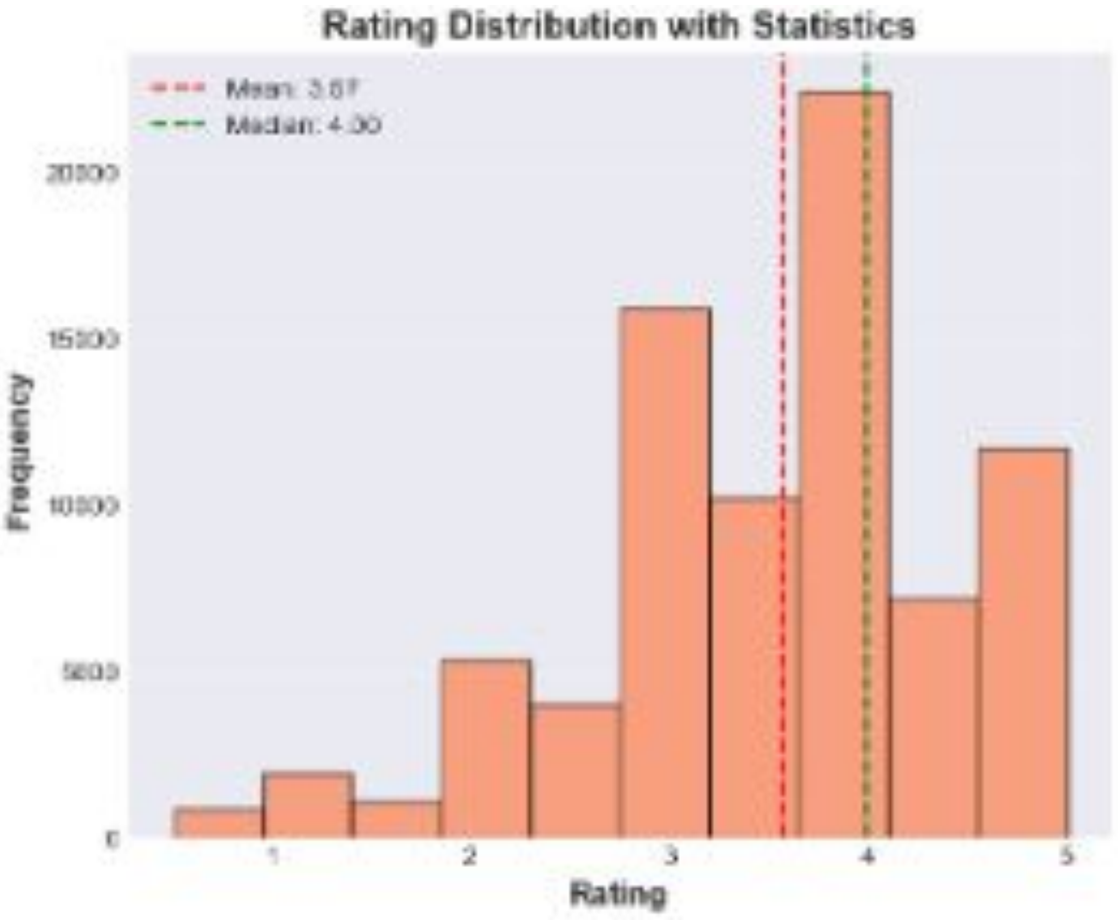
📈 Avg Ratings/User: 165

⭐ Mean Rating: 3.50 / 5.0

🎯 Matrix Sparsity: 98%

Exploratory Data Analysis

Rating Distribution Analysis



Key Insights

⭐ Mean Rating: 3.50/5.0

🎯 Mode: 4.0 stars (26.6%)

📊 Left-skewed distribution

💡 Positive rating bias

👤 Self-selection effect

Users tend to rate movies they expect to like → Positive bias

User & Movie Behavior Patterns

👥 User Activity

Mean ratings/user: **165**

Median ratings/user: **96**

Most active user: **2,698 ratings**

Least active user: **20 ratings**

Standard deviation: **197**

🎬 Movie Popularity

Mean ratings/movie: **10**

Median ratings/movie: **3**

Most rated movie: **329 ratings**

Movies with ≥50 ratings: **377 (4%)**

Long-tail effect: **Extreme**

🔍 Key Findings

- Power users exist with vastly different activity levels (20 to 2,698 ratings)
- Extreme long-tail in movie popularity - few blockbusters dominate
- Need diversity mechanisms to avoid recommending only popular movies
- User activity doesn't predict rating generosity - all users matter equally

Modeling Strategy

Iterative Approach: From Simple to Complex

Baseline: Global Average
Establish minimum performance
1.0204

SVD: Matrix Factorization
Capture latent factors (50 factors)
0.8566

KNNWithMeans: Collaborative Filtering
Find similar users (k=40)
0.8601

KNNBasic: Collaborative Filtering
Find similar movies (k=40)
0.9414

NMF: Non-Negative Matrix Factorization
Interpretable components (15 factors)
0.8872

🏆 **Best Model**

SVD

✓ Best accuracy
✓ Scalable
✓ Fast inference
✓ Handles sparsity
✓ Auto-learns patterns

Model Evaluation Results

Model	RMSE	MAE	vs Baseline	Status
BaselineOnly	0.8536	0.6561	-	Benchmark
SVD ⭐	**0.8566**	**0.6575**	**16%**	**SELECTED**
KNNWithMeans	0.8601	0.6597	15.7%	Good
NMF	0.8872	0.6807	13.1%	Good
KNNBasic	0.9414	0.7300	7.7%	Better

📊 Final Model Performance

Test RMSE: 0.86 (16% better than baseline)

Test MAE: 0.66 stars

✓ Meets target: RMSE < 1.0

68% of predictions within ±1 star

Coverage: 98.3% of user-movie pairs

📈 Error Analysis

Best on middle ratings (3.0-4.5 ⭐)

Slightly higher error on extremes

No severe misclassifications (>2 stars: 5%)

Nearly unbiased (mean error: 0.02)

Good generalization: Training RMSE = 0.82

Personalized Recommendations

Example: User who highly rated Action, Drama & Thriller movies

Rank	Movie Title	Predicted Rating	Genres
1	Shawnshank Redemption (1994)	⭐ 5.0	Crime | Drama
2	Dark Knight (2008)	⭐ 5.0	Action | Crime | Drama
3	Philadelphia Story (1940)	⭐ 5.0	Comedy | Drama | Romance
4	Rear Window (1954)	⭐ 5.0	Mystery | Thriller
5	North by Northwest (1959)	⭐ 5.0	Action | Adventure | Mystery | Romance | Thriller

✨ Recommendation Quality Indicators

🎯 Strong genre alignment with user preferences

🌟 High predicted ratings (5.0) indicate strong matches

🎬 Mix of classic and modern films for variety

📊 Diverse themes within preferred genres

Hyperparameter Tuning: SVD Optimization

GridSearchCV with 3-Fold Cross-Validation

Parameter Grid Tested

n_factors: [50, 100, 150]
n_epochs: [20, 30]
lr_all: [0.002, 0.005, 0.01]
reg_all: [0.01, 0.02, 0.05]

54 combinations tested
162 total trainings (3-fold CV)
Training time: 2.7 minutes

Best Parameters Found

n_factors: **150**
n_epochs: **30**
lr_all: **0.01**
reg_all: **0.05**

Performance Results

Model	RMSE	MAE
Original SVD	0.8566	0.6575
Tuned SVD	**0.8399**	**0.6445**
Improvement	**1.95%**	**1.98%**

Key Finding:

Hyperparameter optimization improved RMSE from 0.8566 to 0.8399
Absolute improvement: 0.0167 stars (1.95% reduction in error)
This demonstrates the value of systematic optimization using GridSearchCV

Ensemble Methods

Combining multiple models for improved predictions

SVD
(Weight: 0.3377)

KNN Item
(Weight: 0.3363)

NMF
(Weight: 0.3260)

Weighted Ensemble Prediction

📊 Results

SVD alone: 0.8566
Ensemble: 0.8496

✓ Marginal improvement
✗ Added complexity

Decision: Use SVD

💡 Ensemble Insights

- Ensemble provides minimal improvement over single best model (SVD)
- Added complexity not justified for production deployment
- SVD captures most collaborative filtering signal independently

Recommendations & Next Steps

🚀 Deployment Roadmap

Phase 1: MVP

Weeks 1-4

- Deploy SVD to staging
- Set up API endpoints
- A/B test with 20% users
- Monitor dashboards

Phase 2: Enhancement

Months 2-6

- Implicit feedback integration
- Hybrid cold-start approach
- Diversity controls
- Expand to 50% users

Phase 3: Advanced

Months 6-12

- Context-aware recommendations
- Explainability features
- Multi-objective optimization
- Full production (100%)

✨ Best Practices

- Retrain model monthly with new ratings data
- Monitor performance metrics weekly
- Ensure diversity: top-5 span ≥3 genres
- Maintain fallback to content-based recommendations

Thank You

Questions & Discussion

Team:
Winnie Njoroge • Michelle Mwende • Laban Leploote
Alice Mathenge • Dean Mutie

📧 Contact: movielens-team@example.com