Building a Movie Recommender System

Phase 4 Machine Learning Project

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Overview

- In the digital age, users face too many choices.
- Recommender systems provide personalized suggestions.
- **Goal:** Recommend the Top 5 movies for each user based on past ratings.
- Dataset: MovieLens – 100,000 ratings, 610 users, 9,724 movies.

Business and Data Understanding

Business Problem:

- Improve engagement with personalized movies.
- Boost user satisfaction and retention.

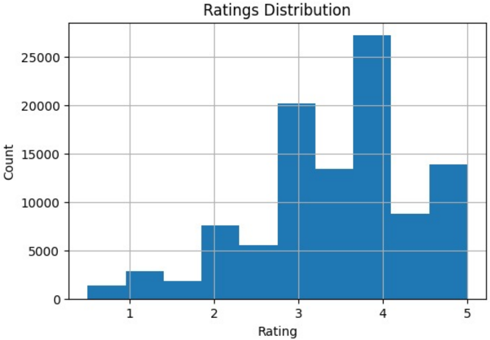
Data:

- Ratings, movie details, tags.
- Cleaned, merged, scaled for stability.

Exploratory Data Analysis (EDA)

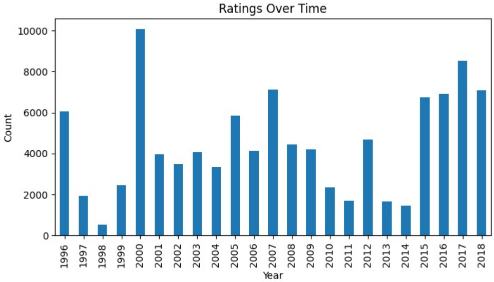
- EDA helps us **understand the dataset** before applying recommendation algorithms.
- Focus areas:
  - **Ratings Distribution** – how users rate movies overall.
  - **Ratings Over Time** – how rating activity changes across years.
- Provides insights into **user behavior and trends**.

Ratings Distribution



- Most ratings fall between **3 and 5 stars**.
- Few movies receive very low ratings (1 or 2).
- Users tend to give **positive reviews** more often.

Ratings Over Time



- Ratings increase steadily after **2000**.
- Peaks suggest years with **popular movie releases**.
- More recent activity ensures **relevant recommendations**.

Modeling Approach

We compared different approaches:

1. Popularity-based – shows trending movies to all.
2. Collaborative Filtering – learns from similar users.
3. Matrix Factorization (SVD) – finds hidden patterns in ratings.

userId	0	1	2	3	4	5	6	7	8	9
userId										
0	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
1	0.0	1.000000	0.034755	0.039183	0.165461	0.137692	0.124770	0.143811	0.135497	0.059023
2	0.0	0.034755	1.000000	0.000000	0.000000	0.041284	0.064996	0.068174	0.000000	0.000000
3	0.0	0.039183	0.000000	1.000000	0.002961	0.006385	0.003619	0.000000	0.006890	0.000000
4	0.0	0.165461	0.000000	0.002961	1.000000	0.130157	0.085226	0.125647	0.048075	0.013898

Evaluation in Plain Language

- **Cross-validation:** Tested model on different groups of users.
- **RMSE (Root Mean Square Error):**
  - Imagine predicting a movie rating out of 5 stars.
  - RMSE tells us how close we were to the actual rating.
  - Lower = better.

Results Summary

- Popularity model: Simple, not personalized.
- Collaborative filtering: Personalized, but less accurate.
- **SVD + Ridge Regression: Best Performer!**
  - RMSE = **3.29**
  - Balanced accuracy + personalization
  - Generated strong Top-5 recommendations

Recommendations

- Adopt SVD-based model for recommendations.
- Use popularity-based fallback for new users (**cold start problem**).
- Retrain regularly as more ratings are collected.

Next Steps

- Test recommender with real users (A/B testing).
- Collect more feedback to fine-tune results.
- Explore hybrid methods combining multiple approaches.

Thank You

Questions?