Group 19 Topic: MovieLens Recommender System

Collaborative Filtering and SVD in KDD Pipeline

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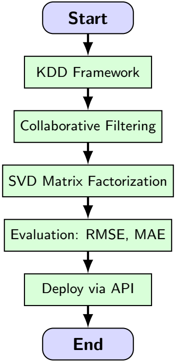
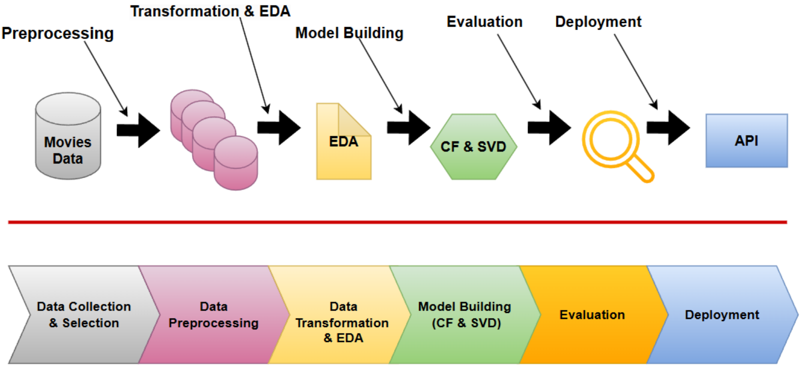
Objectives & Introduction

- Build a scalable movie recommender using Collaborative Filtering + SVD
- Follow KDD process: from data preprocessing to deployment
- Evaluate using RMSE and MAE
- Tackle challenges: data sparsity, cold-start problem



System Architecture



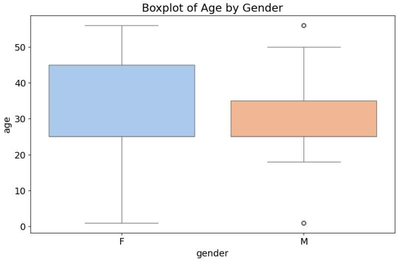
KDD Pipeline integrating MovieLens, CF, SVD, and API

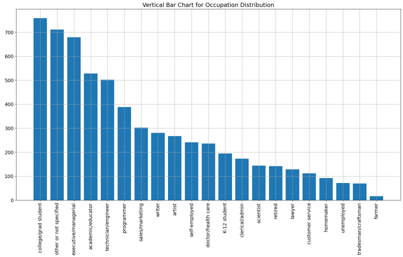
Data Preprocessing

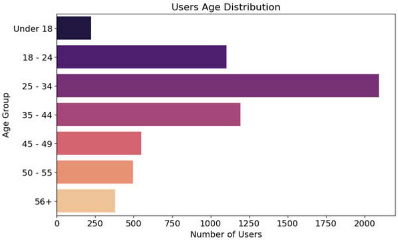
The MovieLens 1M dataset consists of three main files:

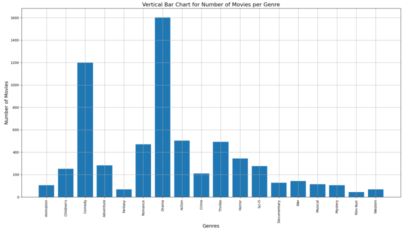
- **users.dat**
  - **Records:** About 6,040 users.
  - **Features:** UserID, Gender, Age, Occupation, and Zip-code.
  - **Purpose:** Provides demographic information.
- **movies.dat**
  - **Records:** Approximately 3,883 movies.
  - **Features:** MovieID, Title, and Genres.
  - **Purpose:** Contains basic movie details for categorization.
- **ratings.dat**
  - **Records:** Nearly 1,000,209 ratings.
  - **Features:** UserID, MovieID, Rating, and Timestamp.
  - **Purpose:** Records user–movie interactions.

Data Visualization









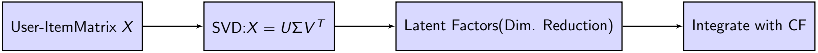
Collaborative Filtering (CF)

User-Item Matrix → Compute Similarities(e.g., Cosine) → Select Top-kSimilar Movies → Predict / Recommend

Explanation:

1. **User-Item Matrix:** Rows are users, columns are movies, and cells represent ratings.
2. **Compute Similarities:** Calculate how closely movies resemble each other based on user ratings.
3. **Select Top-k Similar Movies:** Pick the most similar movies to the target title.
4. **Predict / Recommend:** Generate personalized predictions or directly recommend the Top-N similar titles.

Singular Value Decomposition (SVD)



- **Key Purpose:** Reveal latent patterns in the user-item matrix.
- **Process:**
  - *Center Data* (subtract mean ratings).
  - *Dimensionality Reduction* (keep top-p factors).
- **Outcome:** SVD + CF did not improve RMSE/MAE in our tests.
- **Note:** Direct CF outperformed SVD, likely due to sparse data or insufficient tuning.

Results and Evaluation

Why RMSE and MAE?

- **RMSE (Root Mean Squared Error):** Penalizes larger errors more heavily; highlights big deviations.
- **MAE (Mean Absolute Error):** Reflects the average magnitude of prediction errors; straightforward to interpret.

Method	RMSE	MAE
CF Only	0.9184	0.7344
SVD + CF	2.7405	2.4679

Table: Comparison of CF vs. SVD + CF

Key Observations:

- CF alone achieves lower RMSE and MAE, indicating better accuracy.
- SVD + CF may require more parameter tuning or denser data to outperform CF.

Sample SVD Recommendations:

- **Film ID 45:** Similar titles: 322, 1120, 537, 52, 1885
- **Film ID 60:** Similar titles: 2, 1848, 3489, 1702, 362

System Strengths & Limitations

Strengths:

- CF provides more accurate predictions (low RMSE/MAE).
- SVD helps reduce dimensionality and noise, although CF alone performed better on our dataset.
- Scalable approach for handling large user-item matrices.

Challenges:

- Cold-start problem for new users/items.
- Data sparsity can reduce model effectiveness.
- Parameter tuning (e.g., number of latent factors) can be non-trivial.
- No deep learning methods yet; could explore advanced techniques.
- Deployment: Requires an API or real-time pipeline for practical use.

Conclusion & Future Work

- CF improves movie recommendation accuracy
- CF + SVD show a lack of accuracy in movie recommendations.
- Preprocessing and KDD steps ensure reproducibility
- **Next Steps:**
  - Hybrid recommender with content-based methods
  - Use GNNs, DL for advanced personalization
  - Real-time feedback and retraining
  - Deploy a real-time RESTful API

Thank You!

Questions and Answers?