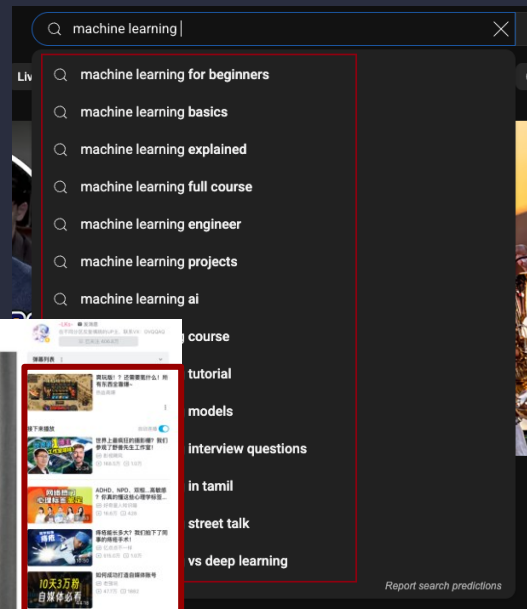




Building a Time-Aware Movie Recommendation System

CS 182 Final Project
陈睦尧 夏鸣飞 张颢

Introduction



Not only for movies!

Google search results for "movie recommendation system".

Kaggle
https://www.kaggle.com/datasets/parasharmanas/m...
Movie Recommendation System
The Movie Recommendation System is a machine learning-based application that provides personalized movie recommendations to users.

Analytics Vidhya
https://www.analyticsvidhya.com/blog/2020/11/cr...
Building a Movie Recommendation System with Machine ...
May 1, 2023 — Build a movie recommendation system using various filtering techniques. [Learn to implement code](#), visualize data, & recommend top movies.
Types of Recommendation... **Movie Recommendation...**

MovieLens
https://movielens.org/
MovieLens
MovieLens helps you find movies you will like. Rate movies to build a custom taste profile, then MovieLens recommends other movies for you to watch.
[Login page](#) [About | MovieLens](#) [Contact Us](#) [Terms of Use](#)

GitHub
https://github.com/rcz7795/Movie-Recommendation-...
rcz7795/Movie-Recommendation-System
A movie recommendation system that considers user-user similarity, movie-movie similarity, global averages and matrix factorization.

Kaggle
https://www.kaggle.com/code/raunakbanik/movie...
Movie Recommender Systems
The Simple Recommender offers generalized recommendations to every user based on movie popularity and (sometimes) genre. The basic idea behind this recommender ...

People also ask

- What is the AI tool for movie recommendations?
- What is the R rating system for movies?
- What algorithm is used for movie recommendation system?
- What is content based recommendation system for movies?

Feedback

Amazon search results for "movie recommendation".

Showing results for movie recommendation
Search instead for movie recommendation

Results
Check out product page for other buying options.

The New York Times Book of Movies: The Essential 1,000 Films to See
4.4 out of 5 stars
\$25.00
You Save: 23.00%
Prime members get FREE delivery Tomorrow, Jan 8
Or non-members get FREE delivery Sat, Jan 7 on \$35 of items shipped by Amazon
Arrives before Father's Day

101 Movies to See Before You Grow Up: Be your own movie critic—the most Things!
4.4 out of 5 stars
\$14.99 (10% off & more off)
See options
Library Binding
You Save: 22.00%
Prime members get FREE delivery Thu, Jan 5
Or non-members get FREE delivery Sat, Jan 7 on \$35 of items shipped by Amazon
Only 4 left in stock—order soon
Movie Buying Choices
\$11.48 (30% off & more off)

What to watch: Keep track of series/movie recommendations in this handy
4.4 out of 5 stars
\$8.99
You Save: 9.00%
Prime members get FREE delivery Thu, Jan 5
Or non-members get FREE delivery Sat, Jan 7 on \$35 of items shipped by Amazon
Arrives before Father's Day

Video Format
Prime Video
DVD
Blu-ray

Department
Books & TV
Movies & Films
Prime Video
Books
Home & Entertainment
Performing Arts

Video Genre
Comedy
Drama
Romance
Action & Adventure
Animation
Arts, Culture & Entertainment
Documentary
Faith & Spirituality
Fantasy
Horror
International
See more

Customer Reviews
4.4 out of 5 stars
Movie & TV Show Release Date
2010 & newer
2010-2019
2000-2009
1980-1999
1960-1979
See more

Video Length
21 to 30 Minutes
31 to 60 Minutes
61 to 90 Minutes
More Than 90 Minutes

MPAA Rating
Unrated
PG
PG-13
R
See more

Uber app interface showing a map and ride options.

Go anywhere with Uber

Ride **Rent** **Courier**

Berkeley Amtrak Train Station, 700 Univ...
Berkeley City Club, 235 Durant Ave, Berk...

Today Now

See prices Log in to see your recent activity

Map showing the route from Berkeley Amtrak Train Station to Berkeley City Club.

Not only for movies!

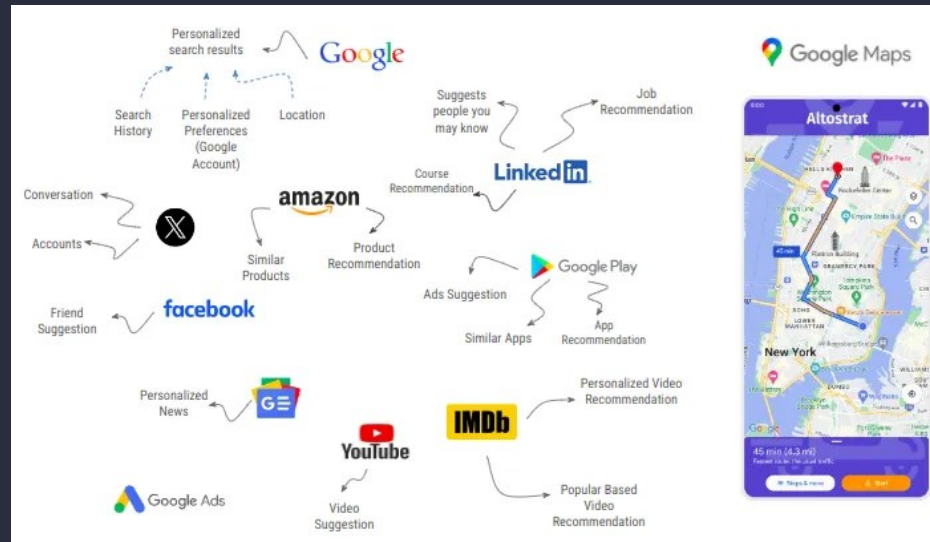


Figure from [medium](#)

Dataset

Movies: 3883 x 3

```
data > movies.csv > data
1 | movie_id title genres
2 0 1 Toy Story (1995) Animation|Children's|Comedy
3 1 2 Jumanji (1995) Adventure|Children's|Fantasy
4 2 3 Grumpier Old Men (1995) Comedy|Romance
5 3 4 Waiting to Exhale (1995) Comedy|Drama
6 4 5 Father of the Bride Part II (1995) Comedy
7 5 6 Heat (1995) Action|Crime|Thriller
8 6 7 Sabrina (1995) Comedy|Romance
9 7 8 Tom and Huck (1995) Adventure|Children's
10 8 9 Sudden Death (1995) Action
11 9 10 GoldenEye (1995) Action|Adventure|Thriller
12 10 11 American President, The (1995) Comedy|Drama
13 11 12 Dracula: Dead and Loving It (1995) Comedy|Horror
14 12 13 Balto (1995) Animation|Children's|Comedy
15 13 14 Nixon (1995) Drama
16 14 15 Cutthroat Island (1995) Action|Adventure|Thriller
17 15 16 Casino (1995) Drama|Thriller
18 16 17 Sense and Sensibility (1995) Drama
19 17 18 Four Rooms (1995) Thriller
20 18 19 Ace Ventura: When Nature Calls (1995) Comedy|Drama
```

Users: 6040 x 5

```
data > users.csv > data
1 | user_id gender age occupation zipcode age_desc occ_desc
2 0 1 F 1 10 48067 Under 18 K-12 student
3 1 2 M 56 16 70072 56+ self-employed
4 2 3 M 25 15 55117 25-34 scientist
5 3 4 M 45 7 02460 45-49 executive/managerial
6 4 5 M 25 20 55455 25-34 writer
7 5 6 F 50 9 55117 50-55 homemaker
8 6 7 M 35 1 06810 35-44 academic/educator
9 7 8 M 25 12 11413 25-34 programmer
10 8 9 M 25 17 61614 25-34 technician/engineer
11 9 10 F 35 1 95370 35-44 academic/educator
12 10 11 F 25 1 04093 25-34 academic/educator
13 11 12 M 25 12 32793 25-34 programmer
14 12 13 M 45 1 93304 45-49 academic/educator
15 13 14 M 35 0 60126 35-44 other or not specified
16 14 15 M 25 7 22903 25-34 executive/managerial
17 15 16 F 35 0 20670 35-44 other or not specified
18 16 17 M 50 1 95350 50-55 academic/educator
19 17 18 F 18 3 95825 18-24 clerical/administrative
20 18 19 M 1 10 48073 Under 18 K-12 student
```

Ratings: 1000209 x 3

```
data > ratings.csv > data
1 | user_id movie_id rating timestamp user_embedding
2 0 1 1193 5 978300760 0 1192
3 1 1 661 3 978302109 0 660
4 2 1 914 3 978301968 0 913
5 3 1 3408 4 978300275 0 3407
6 4 1 2355 5 978824291 0 2354
7 5 1 1197 3 978302268 0 1196
8 6 1 1287 5 978302039 0 1286
9 7 1 2804 5 978300719 0 2803
10 8 1 594 4 978302268 0 593
11 9 1 919 4 978301368 0 918
12 10 1 595 5 978824268 0 594
13 11 1 938 4 978301752 0 937
14 12 1 2398 4 978302281 0 2397
15 13 1 2918 4 978302124 0 2917
16 14 1 1035 5 978301753 0 1034
17 15 1 2791 4 978302188 0 2790
18 16 1 2687 3 978824268 0 2686
19 17 1 2018 4 978301777 0 2017
20 18 1 3105 5 978301713 0 3104
```



Our approach I: SVD

Assumption: there exists a low dimensional latent space of features in which we can represent both users and items and such that the interaction between a user and an item can be obtained by computing the dot product of corresponding dense vectors in that space.

SVD decomposes this matrix into three components:

$$M = U \cdot \Sigma \cdot V^*$$

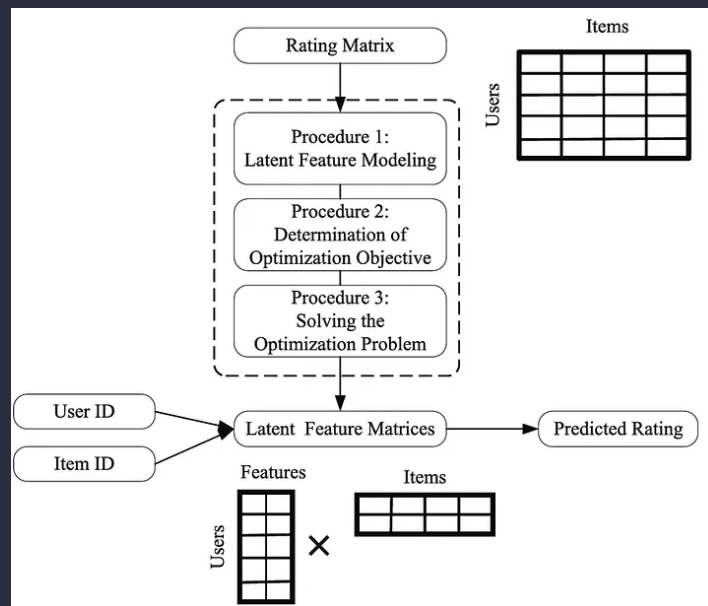
U: A left singular vectors matrix representing user latent factors.

Σ: A diagonal matrix containing the singular values, which capture the importance of each latent factor.

V^AT: A right singular vectors matrix representing item latent factors.

We **keep only the top 30 latent factors**, which capture the most important patterns in the data.

We then **reconstruct** the matrix using these factors → this gives us **predicted ratings** for movies the user hasn't rated yet.



Result

Test RMSE: 0.8736



Our approach II: Deep Learning (baseline)

Core Approach: Discover feature matrices for users and movies

Network Architecture: Embedding Layer → Dot Product Layer

- Each user and movie is assigned an embedding layer, representing their feature vectors
- Parameters are updated through training

By learning low-dimensional vector representations:

1. Similar users have close vectors; similar items have close vectors
2. High dot product between user and item vectors indicates preference

SVD Comparison:

- Finds global optimum but is static
- May not yield optimal predictions

Neural Network Advantage:

Better captures inherent characteristics of users and movies for prediction

Result

Test RMSE: 0.8616

Our approach III: Time-aware Model

Timestamp Utilization:

We explicitly leverage timestamp data recording when users rate movies

Objective:

Capture temporal distribution patterns in users' movie preferences

Model Architectures:

1. Time-Feature Additive Model:
 - Processes time features separately
 - Adds result to user-movie dot product
1. User Temporal Preference Model
 - Adds time-attention layer on user embeddings
 - Learns temporal biases (e.g., higher ratings on weekends/evenings)
1. User & Movie Temporal Preference Model
 - Adds movie-specific time layer
 - Captures preference shifts across eras
1. LSTM Temporal Evolution Model
 - Incorporates LSTM to track preference trajectories
 - Models sequential effects (e.g., action movie after action movie)
 - Challenge: High complexity and computational cost (20 min for a training epoch)

Timestamp Processing:

Implemented three-tier hierarchical categorization:

1. Year level
2. Week level (weekday/weekend)
3. Day period (daytime/evening/early morning)

Result

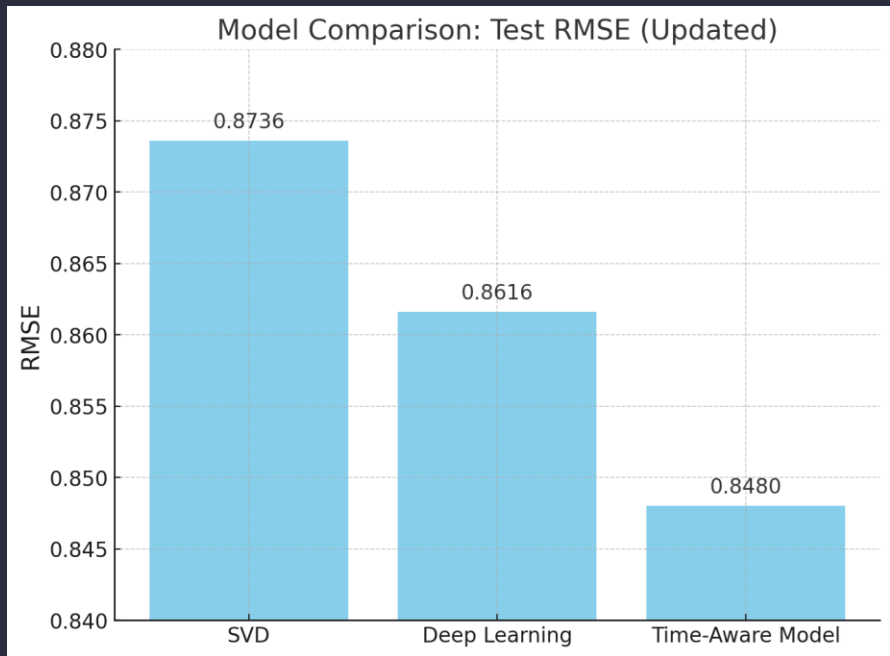
Model 1 Test RMSE: 0.8530

Model 2 Test RMSE: 0.8532

Model 3 Test RMSE: 0.8480



Methods Comparison





Methods Comparison

Model	Accuracy (RMSE)	Pros	Cons
SVD	Worst 0.8736	Simple, efficient	Ignores nonlinear interactions
Deep Learning CF	Good 0.8616	Models nonlinear interactions, more expressive	Still lacks explicit time-awareness
Time-Aware CF	Best 0.8480	Captures evolving user preferences, best accuracy	More complex, needs user history data

Thank you