Recommending Movies from User Ratings

Sue Lim
September 12, 2023

I. PROJECT BACKGROUND

Goal: Take Advantage of Existing User Ratings

- Our client is a **movie recommendation website**
- It has **millions of user ratings** to take advantage of
- It wants make **personalized recommendations** to its customers

Recommendation

- Use **model-based** collaborative filtering (vs memory-based)
  - It gives the **best performance**
  - It **scales well** once trained
- Use known predictors as much as possible

MovieLens Dataset

- **100,000 ratings** between 1996 and 2018
  - **600 users**
  - **9,000 movies**

- Example

userId	movieId	rating	timestamp
1	1	4	1225734739
1	110	4	1225865086
1	158	4	1225733503
1	260	4.5	1225735204
1	356	5	1225735119

II. MAIN MODEL

Training: Different Models

- **Two Model-Based Models**
  - Singular Value Decomposition (“SVD”)
  - Alternating Least Squares (“ALS”)

- **Three Memory-Based Models**
  - KNNBasic
  - KNNWithMeans
  - KNNBaseline

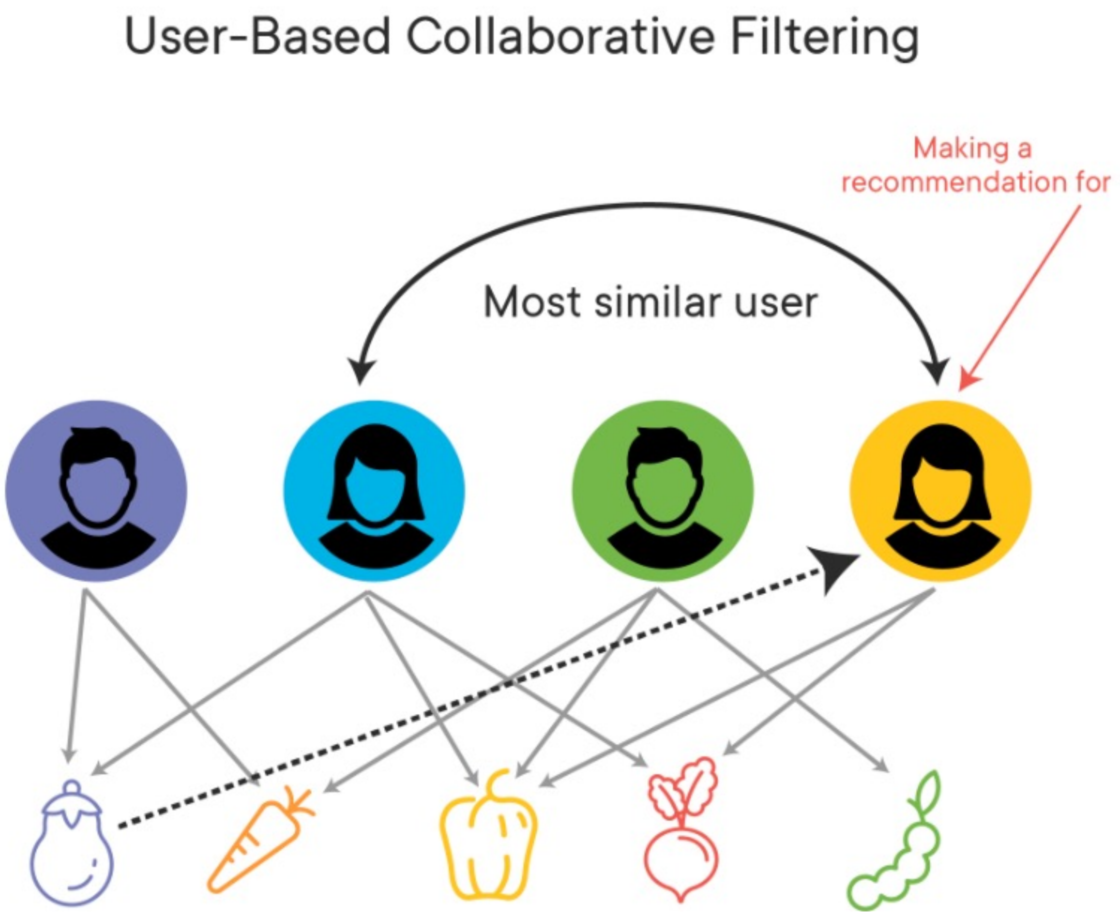
Model-Based Collaborative Filtering

- SVD
- ALS

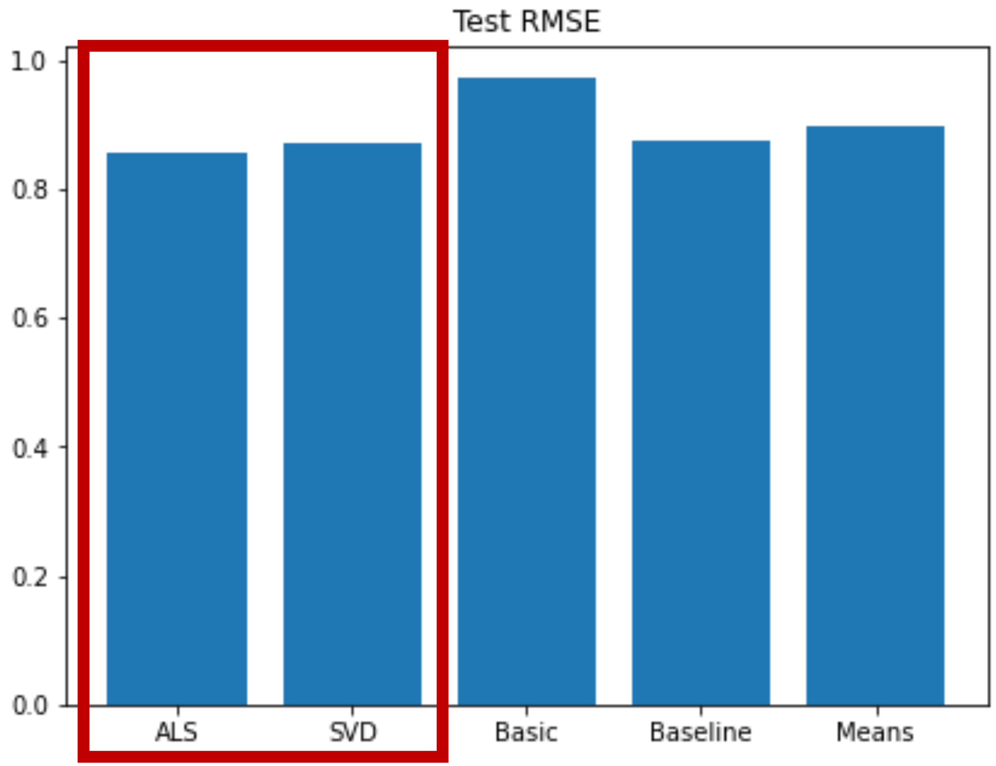
$$
\underbrace{\begin{array}{c|ccccc} \text{Users} \backslash \text{Items} & v & w & x & y & z \\ \hline D & 2 & & & 1 & 4 \\ C & 3 & 1 & 2 & & 2 \\ B & 3 & & & 3 & \\ A & 1 & & 4 & 2 & 1 \end{array}}
\approx
\underbrace{\begin{array}{c|ccc} \text{Users} \backslash \text{Factors} & 1 & 2 & 3 \\ \hline D & -0.63 & 1.34 & -1.55 \\ C & -2.24 & 0.51 & 0.14 \\ B & -1.03 & 1.62 & 0.21 \\ A & -0.06 & 1.63 & 0.33 \end{array}}_{P}
\bullet
\underbrace{\begin{array}{c|ccccc} \text{Factors} \backslash \text{Items} & v & w & x & y & z \\ \hline 3 & -2.10 & -0.45 & -0.34 & -1.09 & -0.78 \\ 2 & 0.52 & -0.07 & 2.46 & 1.05 & 0.89 \\ 1 & 0.02 & 0.19 & -0.19 & 0.07 & -1.47 \end{array}}_{Q^T}
$$

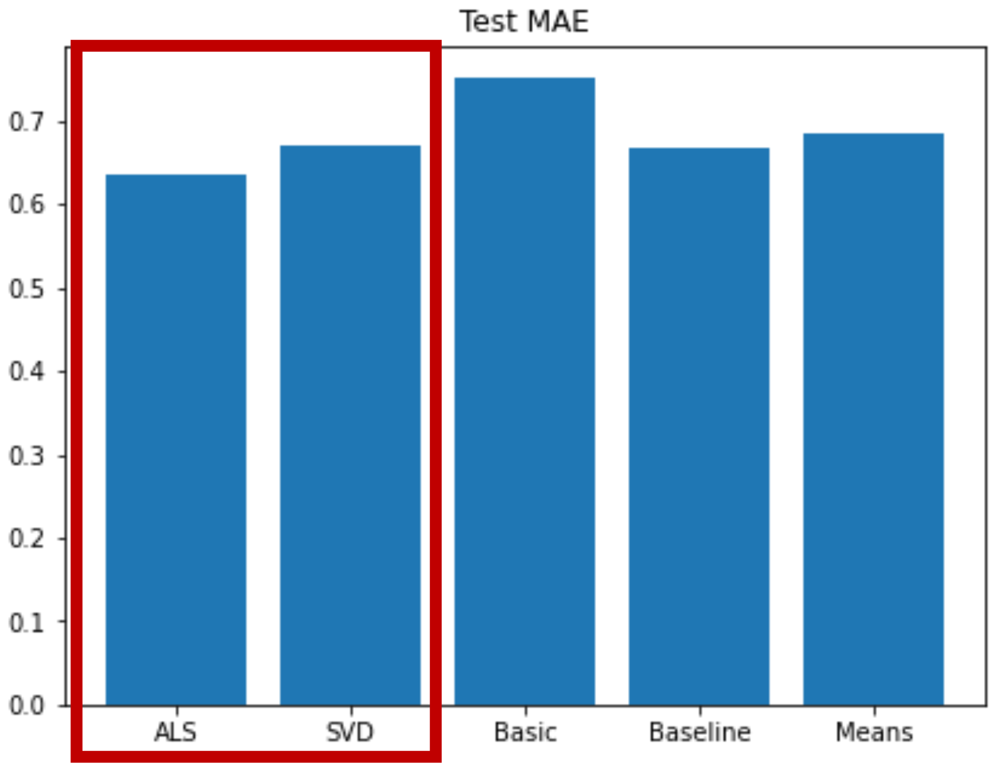
Memory-Based Collaborative Filtering

- KNNBasic
- KNNWithMeans
- KNNBaseline



Result: RMSE and MAE Comparison



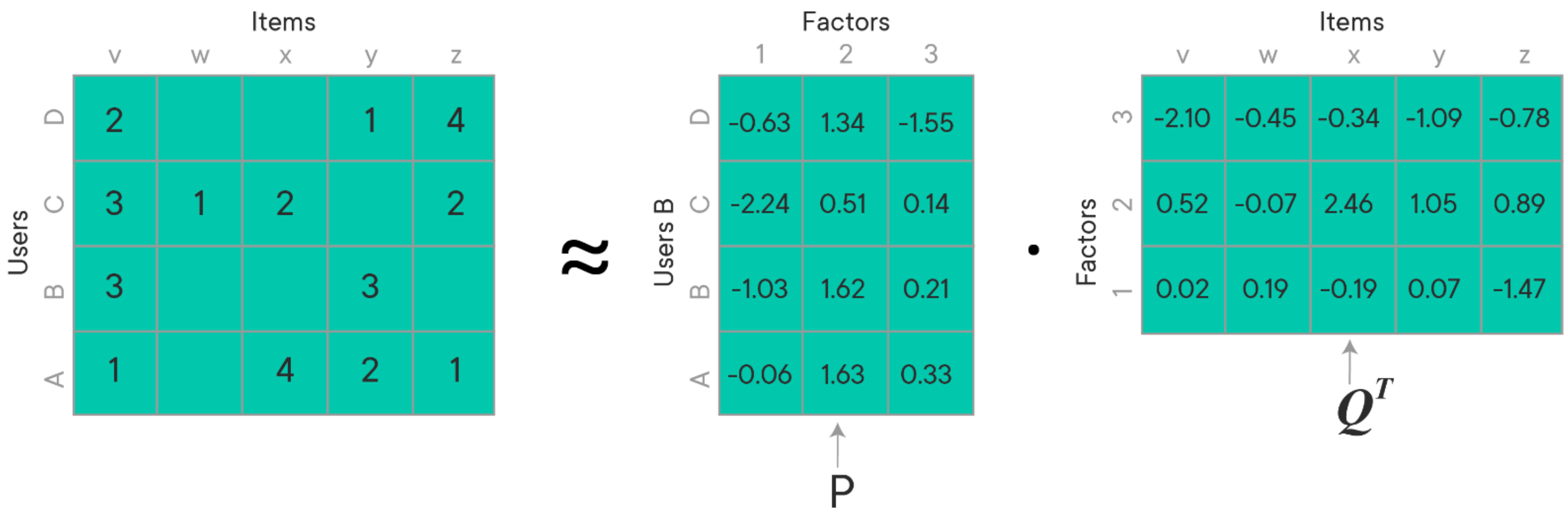


Result: Model-Based vs Memory-Based Methods

Memory-Based	Model-Based
complete input data is required	abstraction (model) that represents input data
does not scale well	scales well
pre-computation not possible	pre-computation possible
relies on similarity metrics between users and items	relies on matrix factorization

ALS: Pre-Defined Predictors

- Movie Genres
- Movie Year
- Rating Year



Result: ALS Example

Title	Genres	Rating
Out of Sight (1998)	Comedy|Crime|Drama|Romance|Thriller	5.0
Like Water for Chocolate (Como agua para choco...	Drama|Fantasy|Romance	5.0
Iron Giant, The (1999)	Adventure|Animation|Children|Drama|Sci-Fi	5.0
Usual Suspects, The (1995)	Crime|Mystery|Thriller	5.0
Young Frankenstein (1974)	Comedy|Fantasy	5.0
Brazil (1985)	Fantasy|Sci-Fi	5.0
Enemy of the State (1998)	Action|Thriller	4.0
Jungle Book, The (1967)	Animation|Children|Comedy|Musical	4.0
Metropolitan (1990)	Comedy	4.0
Elizabeth (1998)	Drama	4.0
Independence Day (a.k.a. ID4) (1996)	Action|Adventure|Sci-Fi|Thriller	4.0
Sex, Lies, and Videotape (1989)	Drama	4.0
Crying Game, The (1992)	Drama|Romance|Thriller	4.0
Star Wars: Episode I - The Phantom Menace (1999)	Action|Adventure|Sci-Fi	4.0
Midnight in the Garden of Good and Evil (1997)	Crime|Drama|Mystery	3.0
My Best Friend's Wedding (1997)	Comedy|Romance	2.0

Result: ALS Example

Factor	Coefficient
user_factor_1	0.020771
user_factor_2	-0.010140
user_factor_3	0.000579
user_factor_4	0.003673
user_factor_5	0.027567
user_factor_6	-0.005106
user_factor_7	0.002362
user_factor_8	0.001284
user_factor_9	-0.001211
user_factor_10	-0.010920
user_factor_11	0.000000
user_factor_12	-0.009925
user_factor_13	0.039773
user_factor_14	-0.051627
user_factor_15	0.024520

Comedy → user_factor_14

user_factor_16	-0.021288
user_factor_17	0.013482
user_factor_18	0.060813
user_factor_19	0.038530
user_factor_20	0.005831
user_factor_21	0.005831
user_factor_22	0.000000
user_factor_23	0.000000
user_factor_24	0.049703
user_factor_25	0.067923
user_factor_26	0.000000
user_factor_27	0.000000
user_factor_28	-0.014799
user_factor_29	-0.008877
user_factor_30	0.000000
user_factor_intercept	0.396125

Thriller → user_factor_18

Fantasy → user_factor_25

Result: ALS Example

Title	Genres	Rating	Prediction
Shakespeare in Love (1998)	Comedy|Drama|Romance	5.0	4.0
Piano, The (1993)	Drama|Romance	5.0	4.0
Naked (1993)	Drama	4.0	3.5
Bowfinger (1999)	Comedy	3.0	3.0

III. CONCLUSION

Recommendation & Key Takeaways

- Use **model-based** collaborative filtering
  - It gives the **best performance**
  - It **scales well** once trained
- Use known predictors

Memory-Based	Model-Based
complete input data is required	abstraction (model) that represents input data
does not scale well	scales well
pre-computation not possible	pre-computation possible
relies on similarity metrics between users and items	relies on matrix factorization

Next Steps

- Look for ways to gather meaningful predictors for users and movies
  - E.g., gender, race, etc. for users and features for movies

Thank You

Sue Lim

- Email: sue.suyeonlim@gmail.com
- GitHub: https://github.com/suesuyeonlim
- LinkedIn: https://www.linkedin.com/in/suelim/