Stream to Success

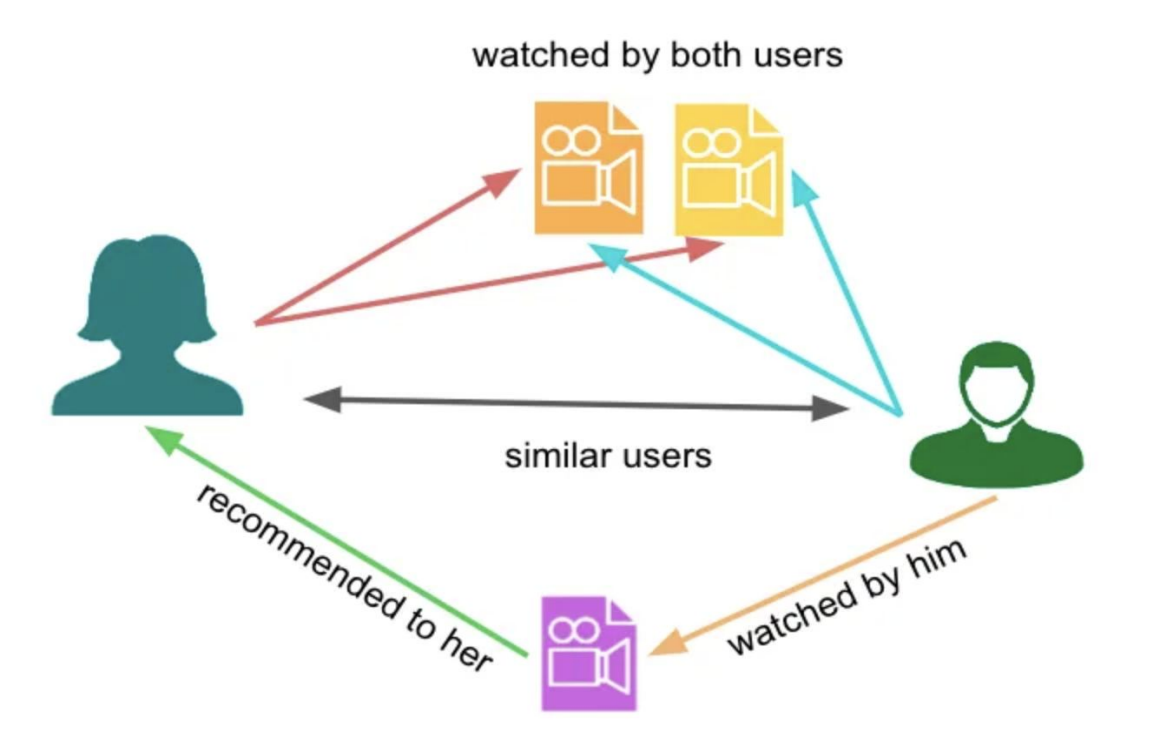
An Exploratory Approach to Personalized Recommendation Systems

The Dataset

- ratings.csv
- movies.csv
- tags.csv
- links.csv

Filtered (21k) version of the 100k MovieLens Dataset | GroupLens Research Lab | University of Minnesota

Collaborative Filtering



How we're evaluating our algorithms:

RMSE: Root Mean Squared Error

- Illustrates the difference between *predicted* ratings and *actual* ratings.

- The more each score approaches 0 (aka, *no* difference between predicted and actual ratings), the better.

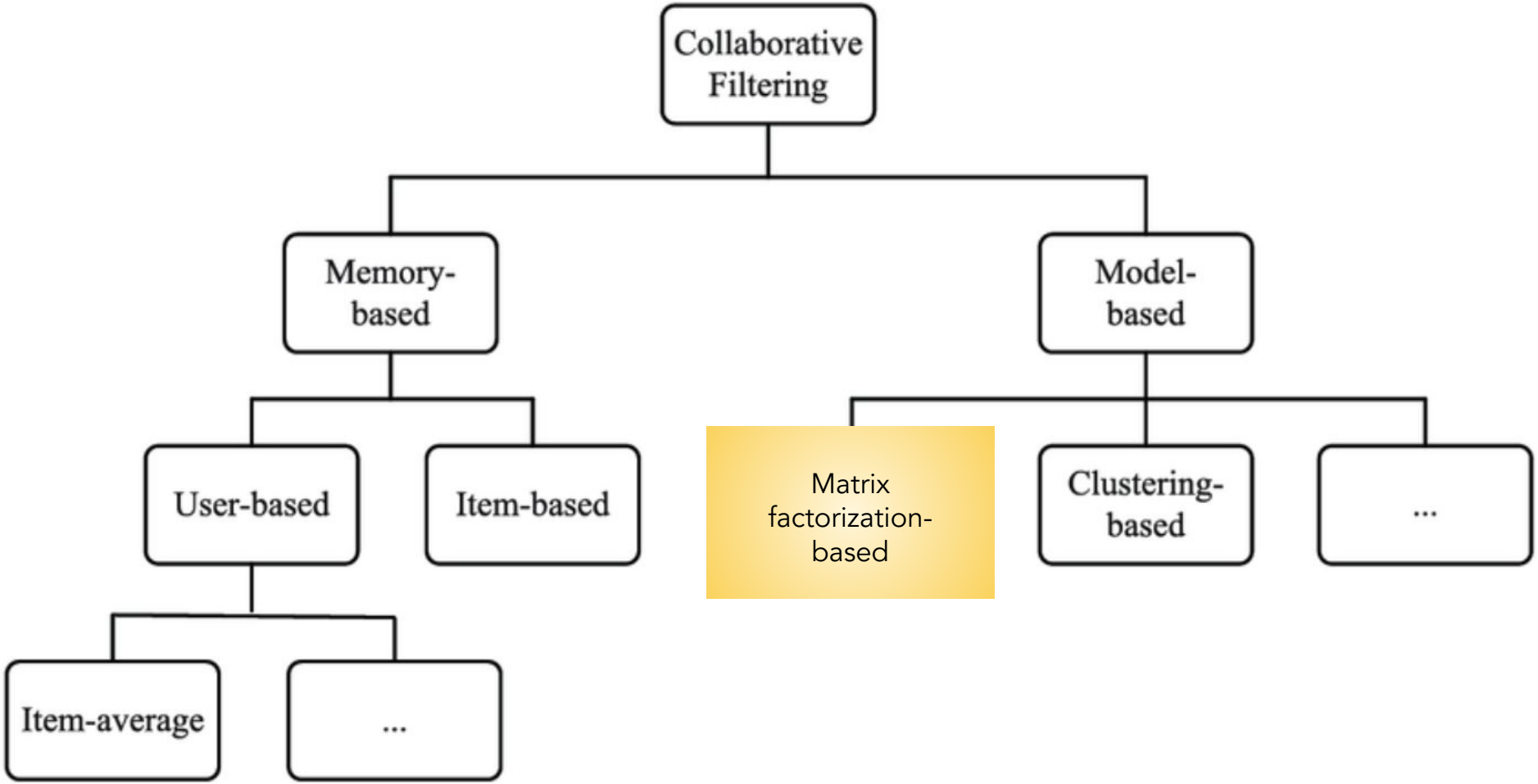
- We are looking for a *low* RMSE score.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

$\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ are predicted values

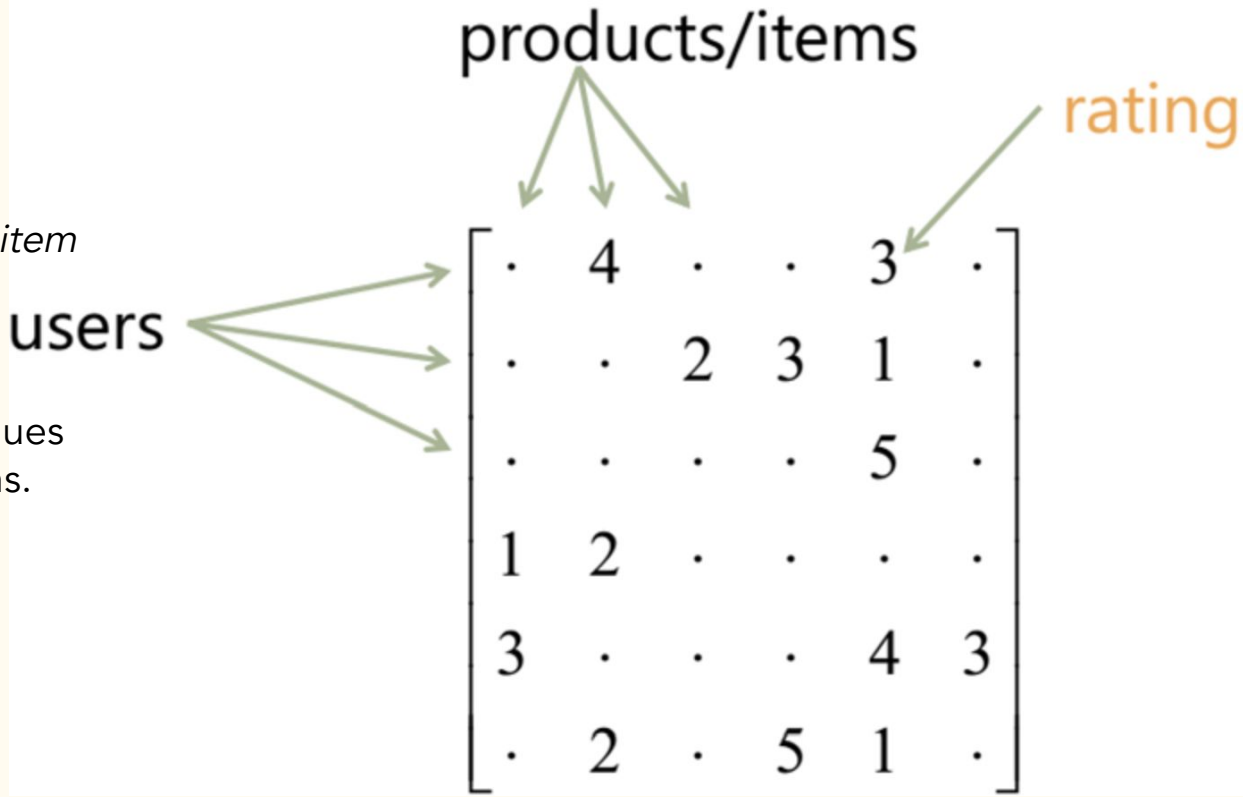
$y_1, y_2, \ldots, y_n$ are observed values

n is the number of observations

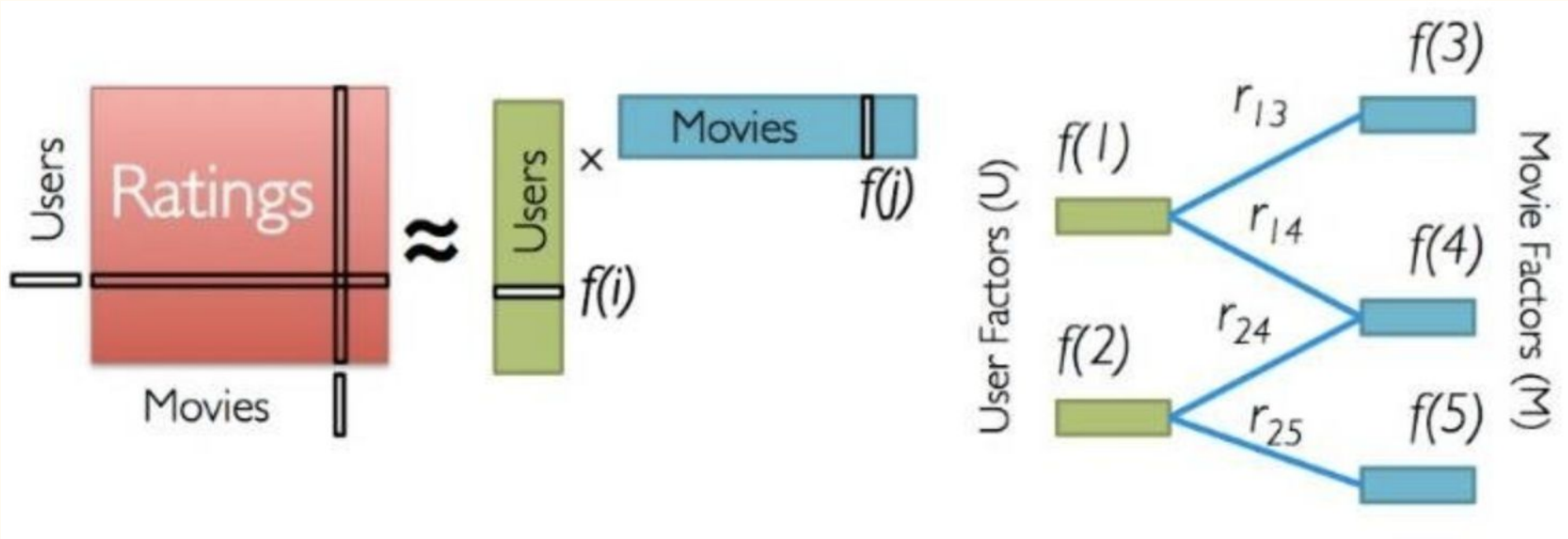

Collaborative Filtering
Memory-based
Model-based
User-based
Item-based
Matrix factorization-based
Clustering-based
...
Item-average
...

Matrix Factorization Algorithms

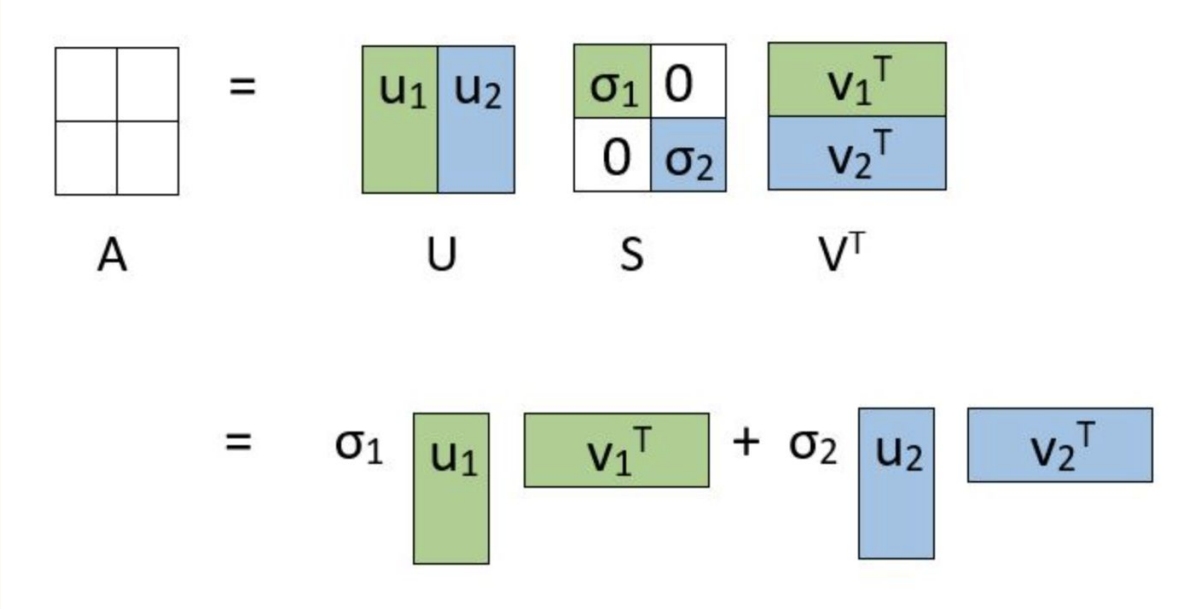
A process of decomposing a *user-item matrix*
into latent (underlying) factors, capturing hidden patterns and enabling prediction of missing values for personalized recommendations.

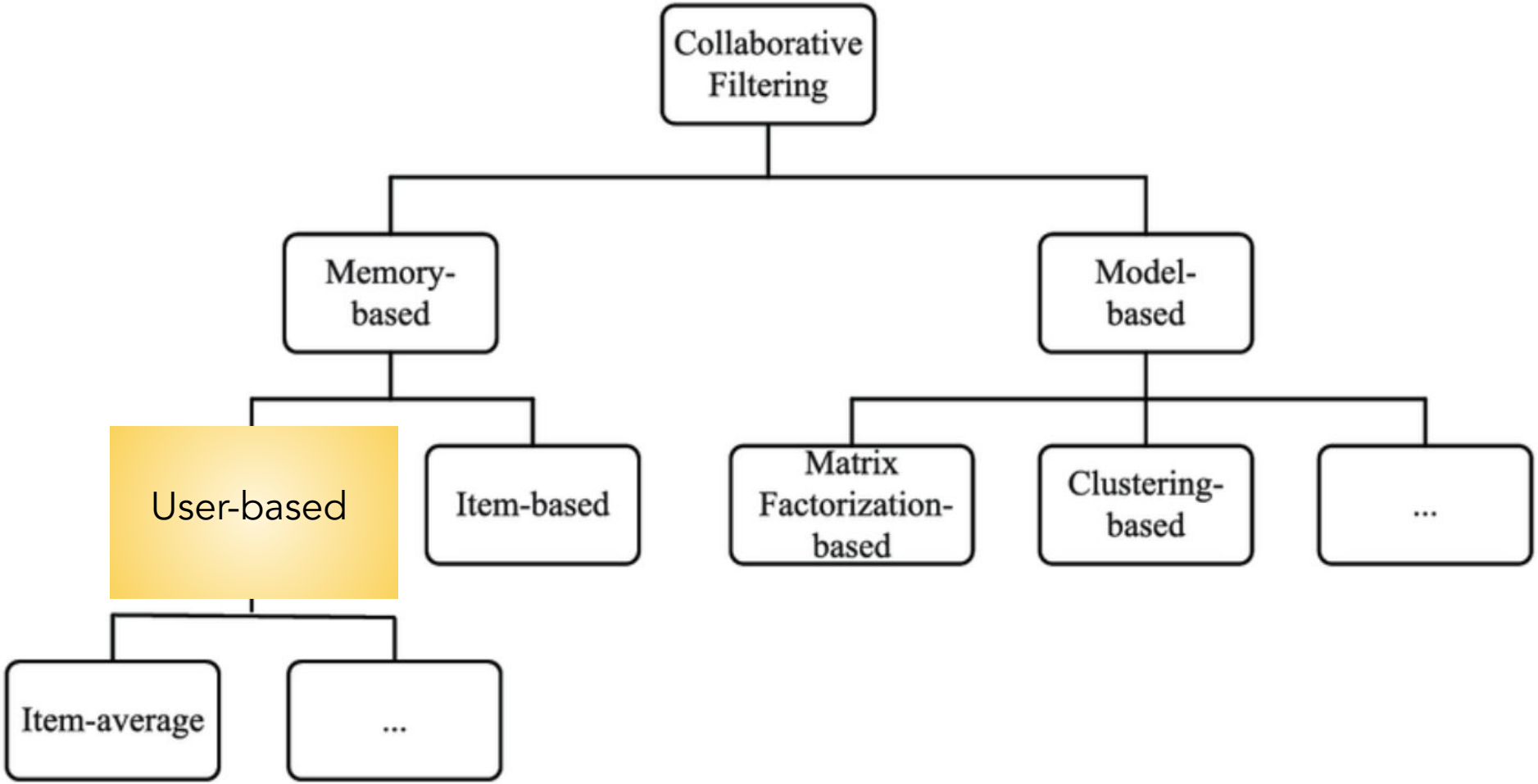


Alternating Least Squares (ALS) Algorithm



Singular Value Decomposition (SVD) Algorithm




Collaborative Filtering
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Matrix Factorization-based
Clustering-based
...
Item-average
...

Memory-based
(e.g., *k*-nearest neighbors)

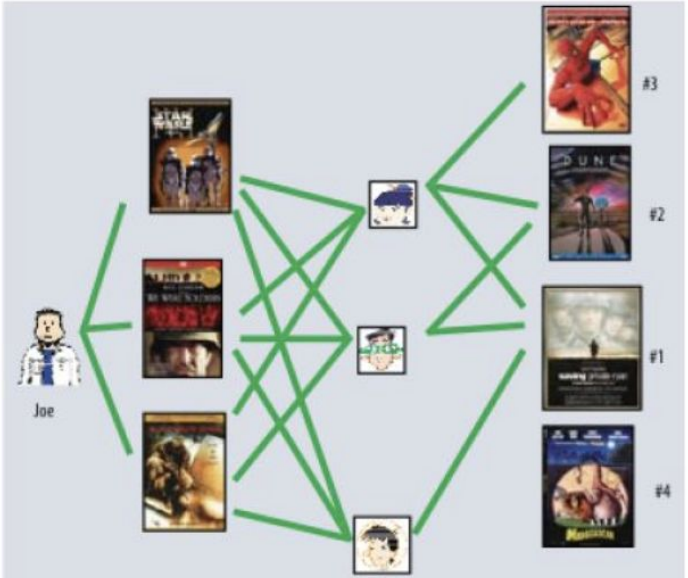


Figure 1. The user-oriented neighborhood method. Joe likes the three movies on the left. To make a prediction for him, the system finds similar users who also liked those movies, and then determines which other movies they liked. In this case, all three liked *Saving Private Ryan*, so that is the first recommendation. Two of them liked *Dune*, so that is next, and so on.

Model-based
(e.g., matrix factorization)

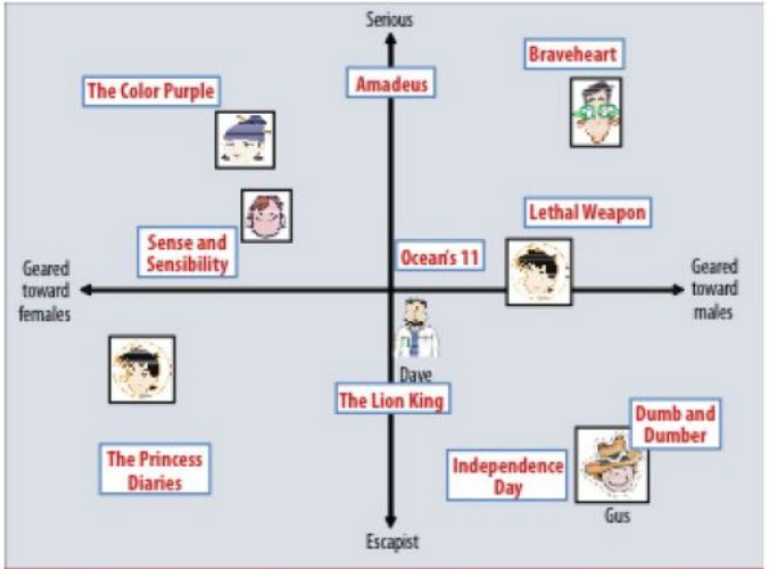
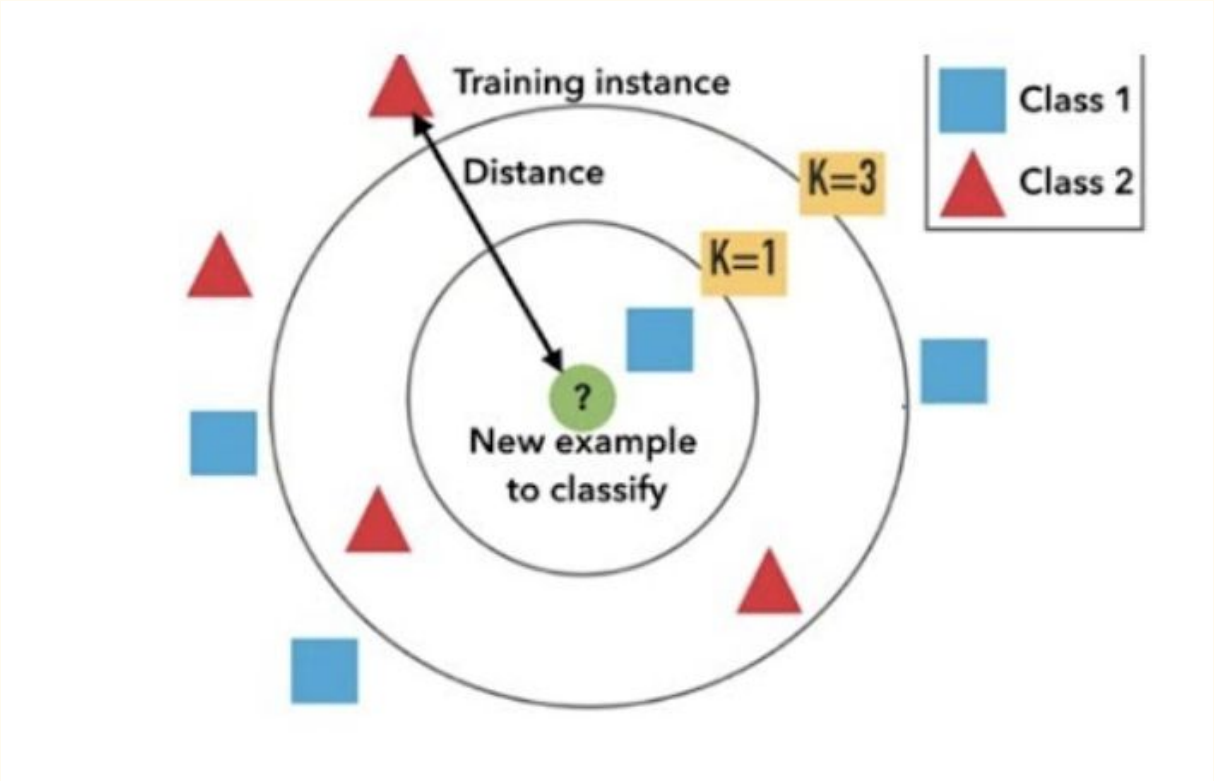


Figure 2. A simplified illustration of the latent factor approach, which characterizes both users and movies using two axes—male versus female and serious versus escapist.

KNNWithMeans Algorithm

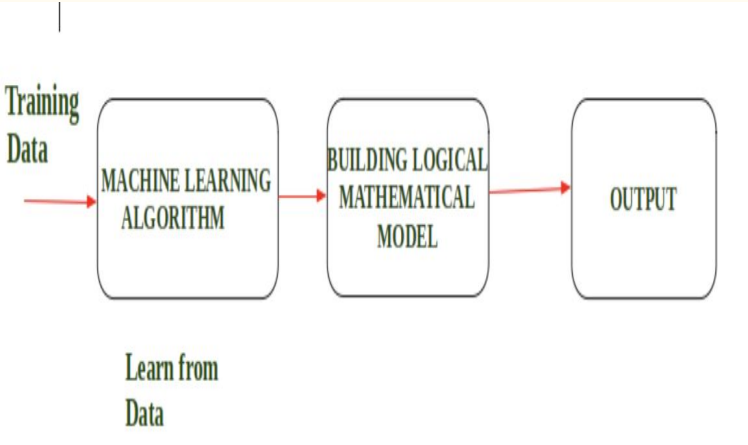


Our Findings

On average, the tuned KNN model's predictions deviate from *actual* ratings by around 0.38 stars. This is an improvement upon the ALS, SVD and first KNN model scores.

Model	RMSE Score
ALS	0.57
SVD	0.48
KNN	0.38
KNN2	0.32

KNN Output: User 59



Movie Title	Predicted Rating
Brazil	4.87
The Big Lebowski	4.86
The Shawshank Redemption	4.86
Life is Beautiful	4.86
12 Angry Men	4.84
Shaun of the Dead	4.84
The Usual Suspects	4.83
Eternal Sunshine of the Spotless Mind	4.82
Spirited Away	4.82
Requiem for a Dream	4.79

Recommendations

- Use and refine the tuned KNN2 model
- To address the cold start problem, we suggest a content-based or hybrid approach

Next Steps:

1. Scale up dataset.
2. Explore additional metrics, like NDCG or MAP.
3. Track user feedback.

Image Sources

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Thank you. Let's Connect!

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Questions?