MATRIX FACTORIZATION TECHNIQUES FOR RECOMMENDER SYSTEMS

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Recommender System: Introduction

HOME > TECH

Netflix's Recommendation Engine Drives 75% Of Viewership

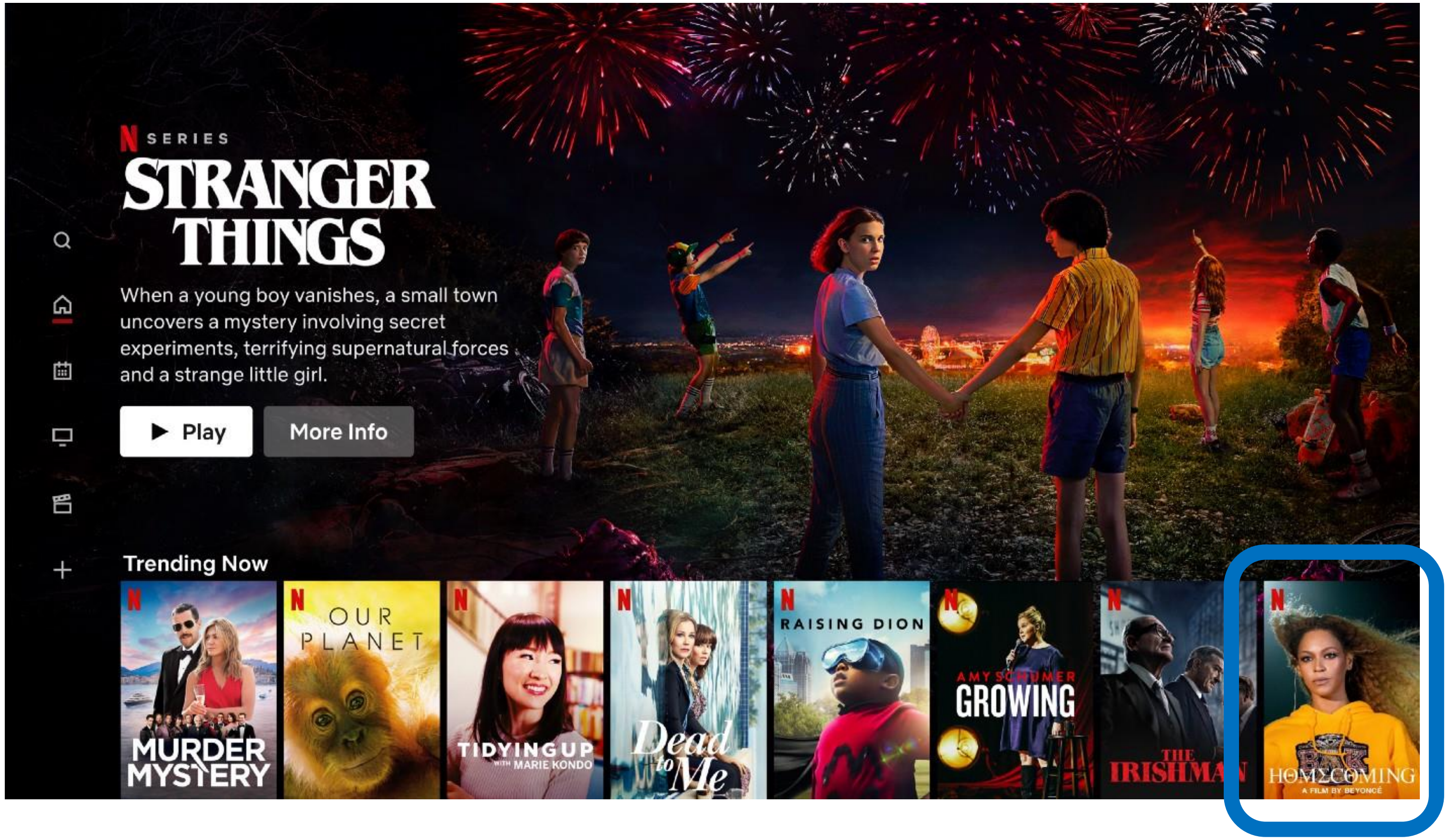
Dylan Love Apr 9, 2012, 7:06 PM

Netflix is pulling back the curtain in a two-part blog post to reveal some behind-the-scenes workings, such as the fact that 75% of the content watched on the service comes from its recommendation engine.

Flickr/Jdlasica

https://www.businessinsider.com/
netflixs-recommendation-engine-drives-75-of-viewership-2012-4

Recommender System: Introduction



https://uxplanet.org/what-can-we-learn-about-design-from-netflix-502f6a384aa8

Item

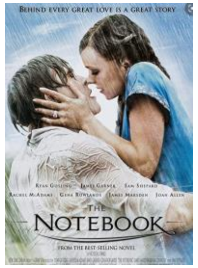
Recommender System (RS) Recommends..

1.
{Items}
to
{Users},

2.
(mostly)
Fixed number of items
(UI constraints)

RS Basics: Collaborative Filtering

User 1  

User 2  

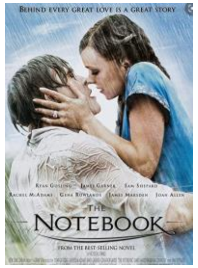
User 3  

User 4  

RS Basics: Collaborative Filtering

User 1

User 2



User 3

What movie would you recommend for user 3?

User 4

RS Basics: Collaborative Filtering

User 1

User 1 and 3 have similar movie taste!

User 3

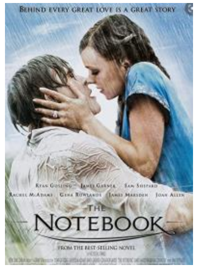
Recommends
<Betman>

This is **user-based collaborative filtering** (CF)

RS Basics: Collaborative Filtering

User 1

User 2



User 3

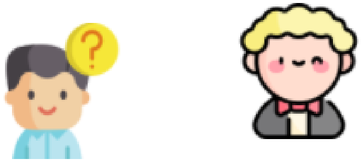
What movie would you recommend for user 4?

User 4

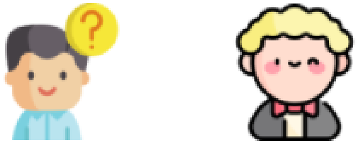
RS Basics: Collaborative Filtering

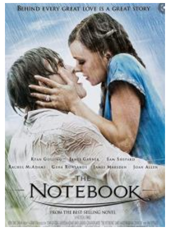
Item 1 

Item 2 



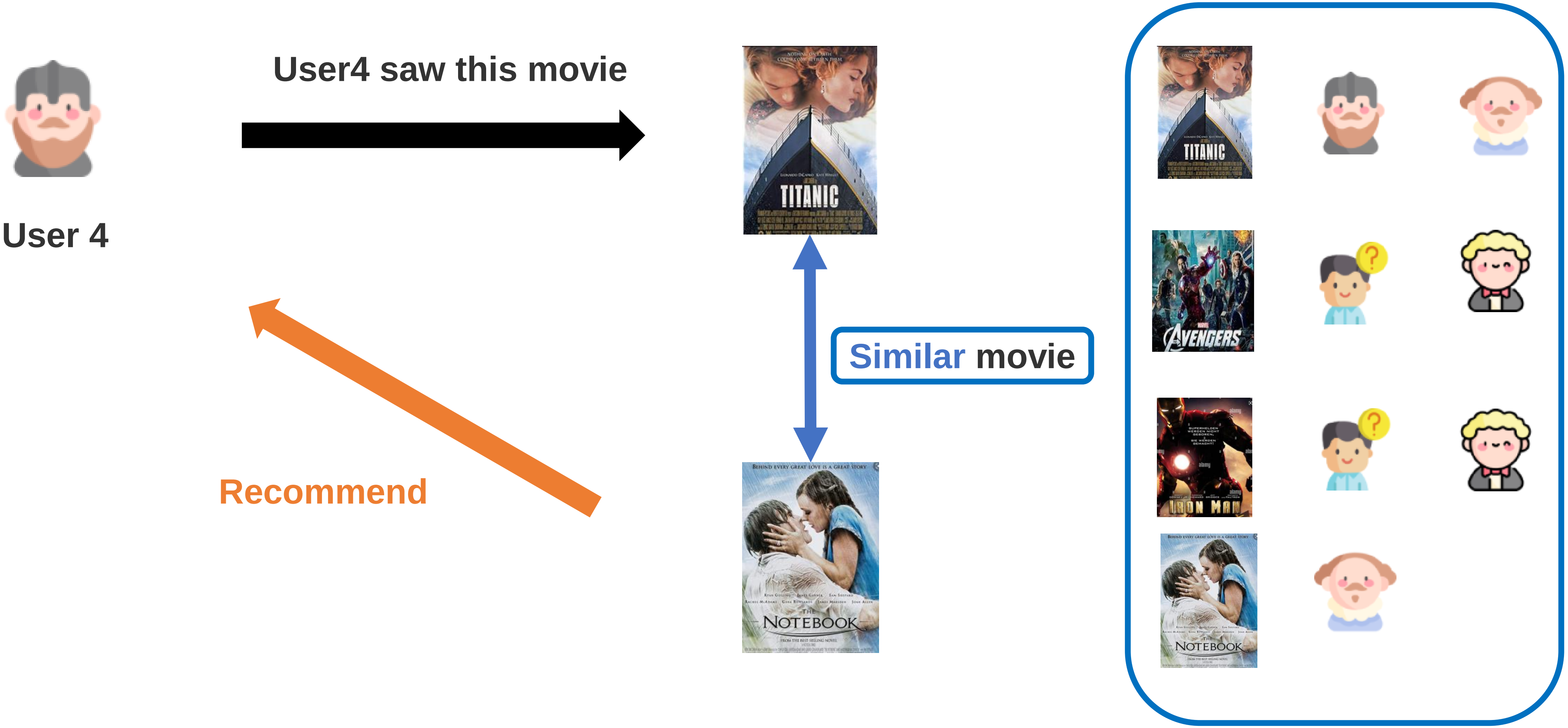
Item 3 



Item 4 

Now, flip row & columns ! (user & item)

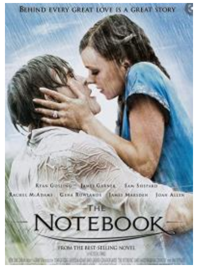
RS Basics: Collaborative Filtering



This is **item-based collaborative filtering**

RS Basics: Cold Start Problem

User 1  

User 2  

User 3  

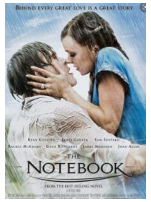
User 4  

What if new item / user comes?
(cold-start problem)

New movie release

RS Basics: Cold Start Problem

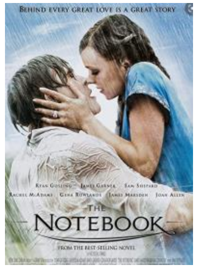
Utilize **meta-info of each item** as features, and find similar item!

	Action	Romance	Comedy	Real story-based
	1	0	0	0
	0	1	1	0
	1	0	0	0
	0	1	1	0

RS Basics: Cold Start Problem

User 1

User 2



This is ***content based filtering*** and
It can be a solution for cold-start problem.

User 3

Recommend

User 4

New movie release

RS Basics: Types of Feedback

***Explicit* feedback:**

- Explicit input by users regarding their interest in products.

e.g.) user ratings (1~5 scores), preference (thumbs-up/down button)

★★★★★

***Implicit* feedback**

- Indirectly reflect opinion through observing user behavior

e.g.) purchase history, browsing history, search patterns, or even mouse movement.

- Relatively abundant

The Netflix Prize

Netflix prize

Oct. 2006, Netflix released
a dataset containing **100 million movie ratings**

BellKor's Pragmatic Chaos team's
SVD++ won US$1,000,000 (the best) !

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- Matrix Factorization (MF)-based RS

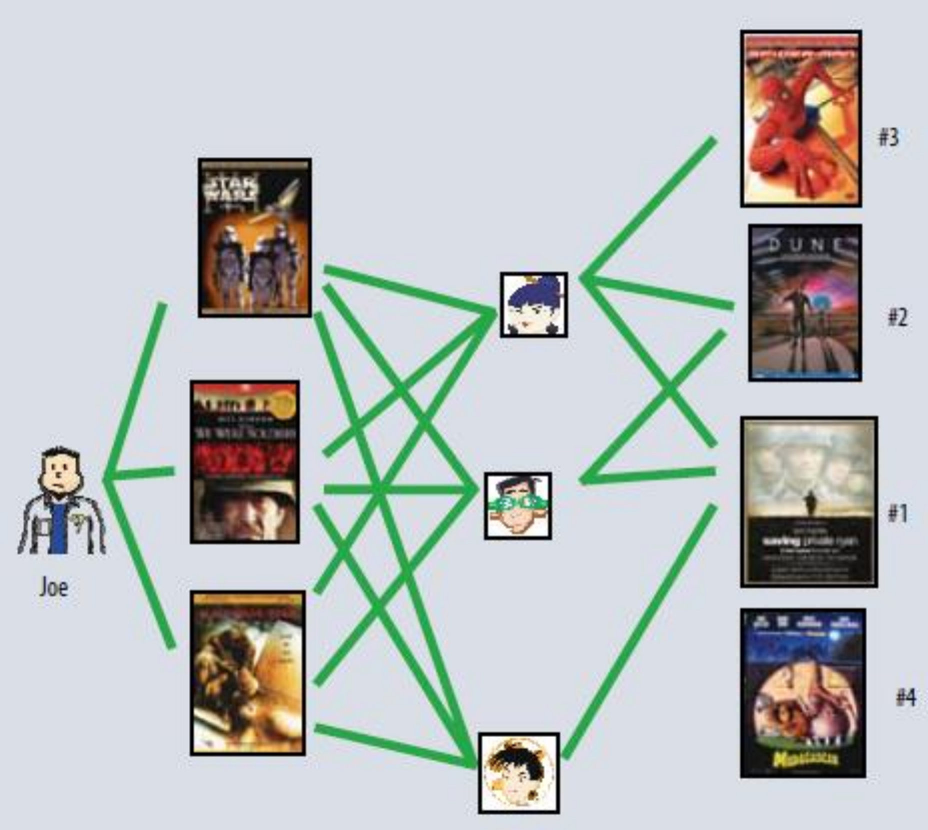
- Thus, MF is proven to be powerful & efficient !

Collaborative Filtering

Analyzes *relationships* between user-items

Neighborhood method

Latent factor model



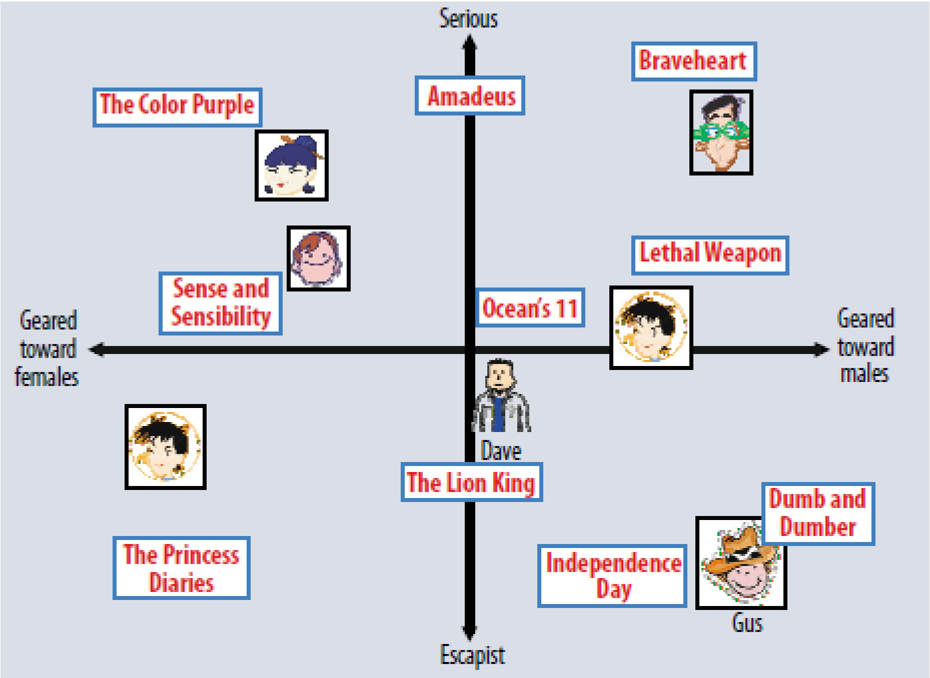
- Centered on computing relationships between items (users), based on *neighbors*

- Recommend items with the order of: #1, #2, #3, and #4.

Collaborative Filtering

Analyzes *relationships* between user-items

Neighborhood method



e.g.)
Two hypothetical dimension

Latent factor model

- characterizing both items and users on *factors* inferred from the ratings patterns
- Such as genre, children-oriented, ..., or completely uninterpretable dimensions.

Collaborative Filtering

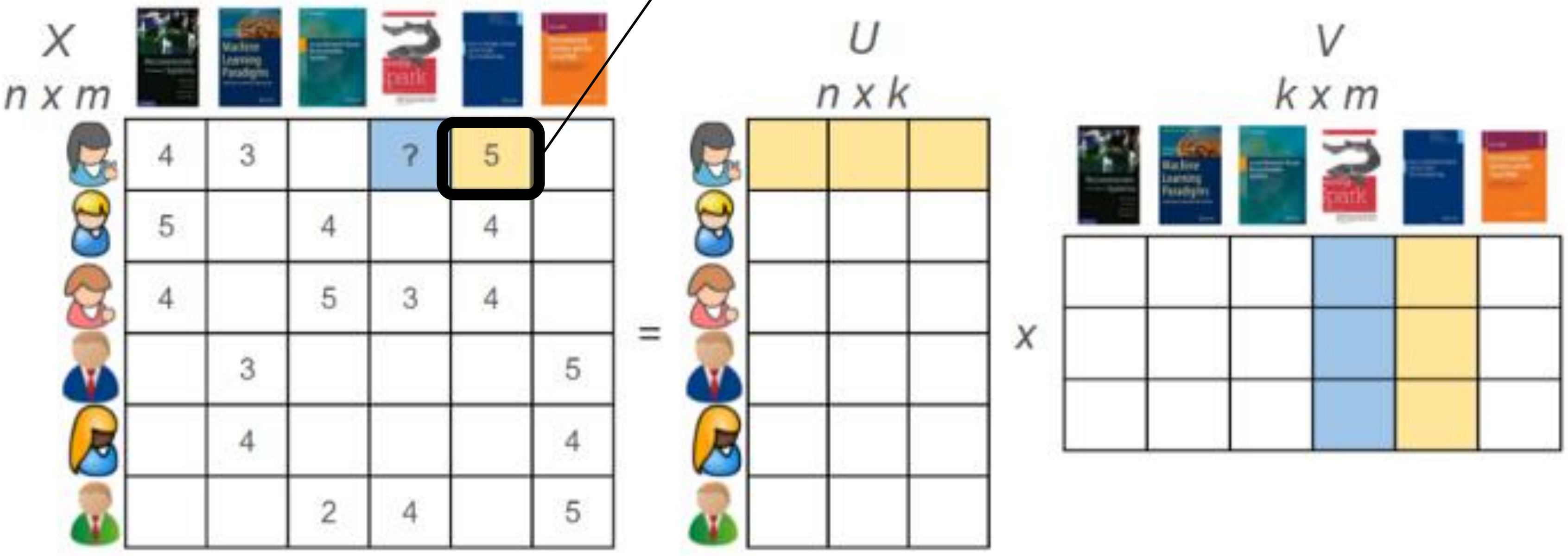
Collaborative Filtering

Analyzes *relationships* between user-items

Matrix factorization

Neighborhood method

Latent factor model



https://heartbeat.comet.ml/recommender-systems-with-python-part-iii-collaborative-filtering-singular-value-decomposition-5b5dcb3f242b

Basic Matrix Factorization for RS

Will show you various versions of MF in RS.

Basic Matrix Factorization for RS

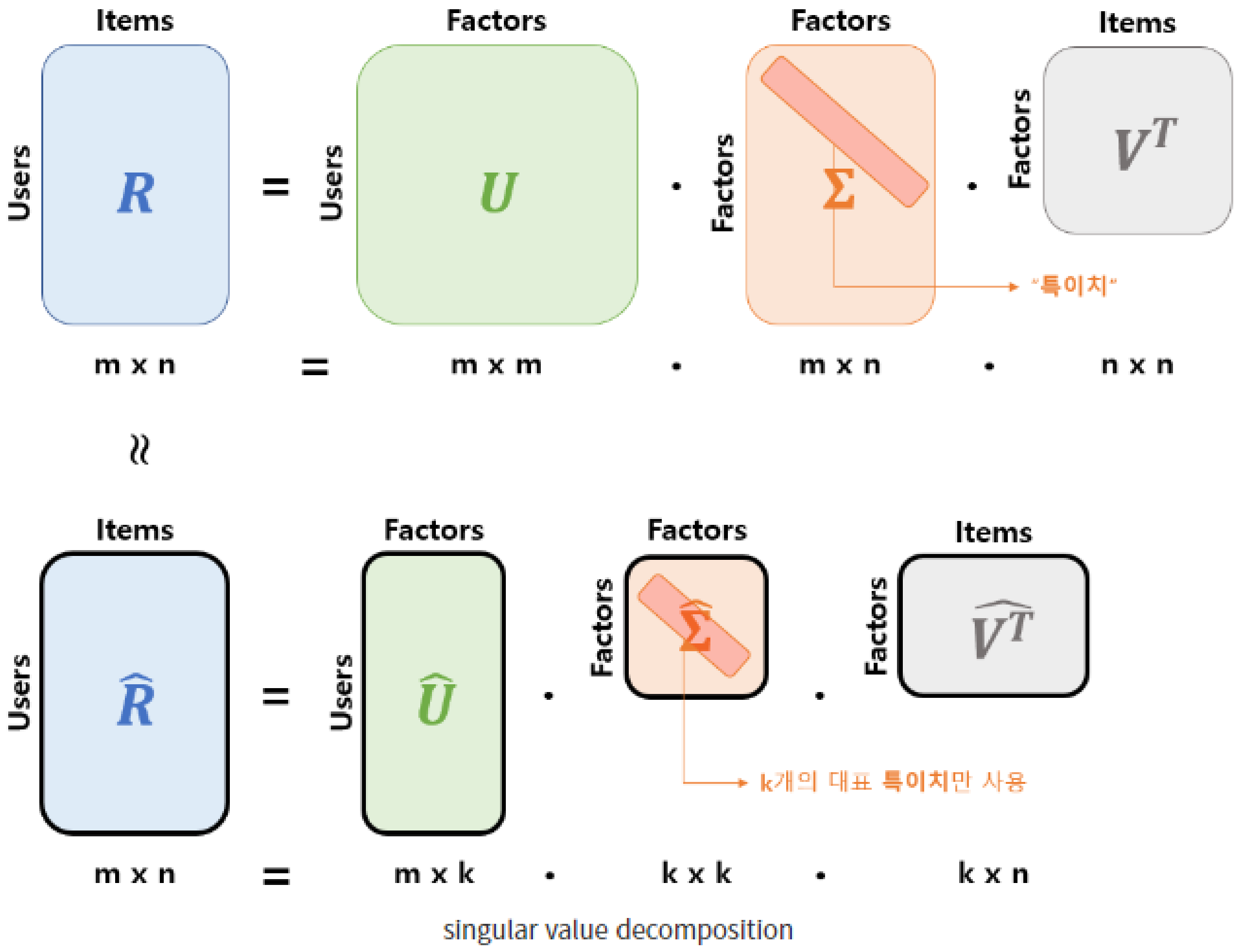
Item factor vector

$$\hat{r}_{ui} = q_i^T p_u$$

Inferred
Interaction (rating)

User factor vector

Basic Matrix Factorization for RS



https://seing.tistory.com/67

$$\hat{r}_{ui} = q_i^T p_u$$

This equation is highly related with **SVD**

However,

The rating matrix is **incomplete**

Basic Matrix Factorization for RS

Modeling derectly the
observed ratings only.

Learning the factor vectors
: squared error on the set of known ratings

$$\min_{q^*, p^*} \sum_{(u,i)\in\kappa} (r_{ui} - q_i^T p_u)^2 + \lambda(\|q_i\|^2 + \|p_u\|^2)$$

(regularizer to avoid overfitting)

-> Performing optimization with
Stochastic gradient descent

Adding Biases

“Systematic Tendency”

some users to give higher ratings than others,
and for some items to receive higher ratings than others

$$b_{ui} = \mu + b_u + b_i$$

overall
average rating
(known)

observed
deviations of
user
(to be found)

observed
deviations of
item
(to be found)

Adding Biases

Prediction

$$\hat{r}_{ui} = \mu + b_i + b_u + q_i^T p_u$$

Optimization

$$\min_{p*,q*,b*} \sum_{(u,i)\in\kappa} (r_{ui} - \mu - b_u - b_i - p_u^T q_i)^2 + \lambda$$

$$(\| p_u \|^2 + \| q_i \|^2 + b_u^2 + b_i^2)$$

Temporal Dynamics

Until now, the models are static.

In reality, the perception *changes* as time goes on.

$$\hat{r}_{ui}(t) = \mu + b_i(t) + b_u(t) + q_i^T p_u(t)$$

Assuming product itself is static.

MF with implicit feedback

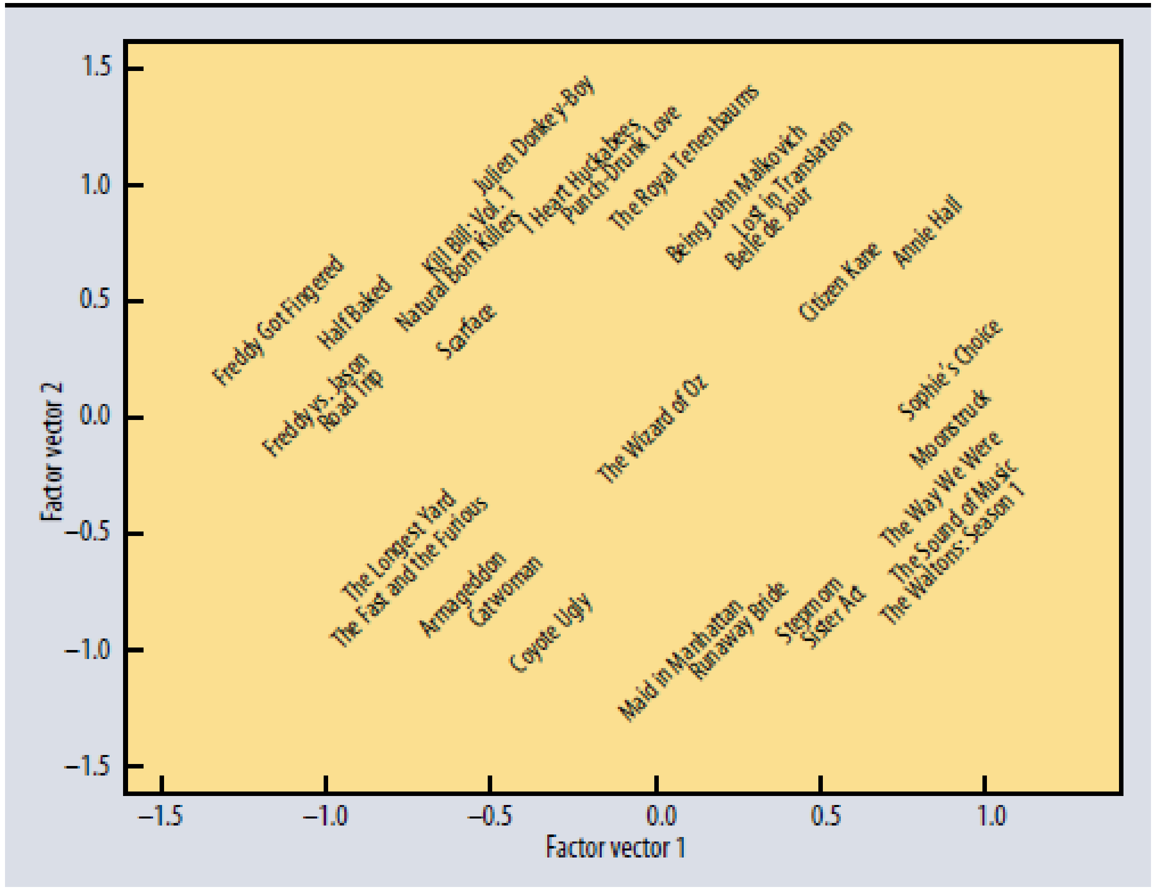
Without knowing
exact preference (rating),

Relies on implicit feedback
(behaviors e.g. search patterns, or clicks)

The model states
“probably likes the product” or
“probably not interested in the product”
Using confidence score c_{ui} (design choice e.g., how many times watched)

$$\min_{p*,q*,b*} \sum_{(u,i)\in K} c_{ui}(r_{ui} - \mu - b_u - b_i - p_u^T q_i)^2 + \lambda(\| p_u \|^2 + \| q_i \|^2 + b_u^2 + b_i^2)$$

Evaluations



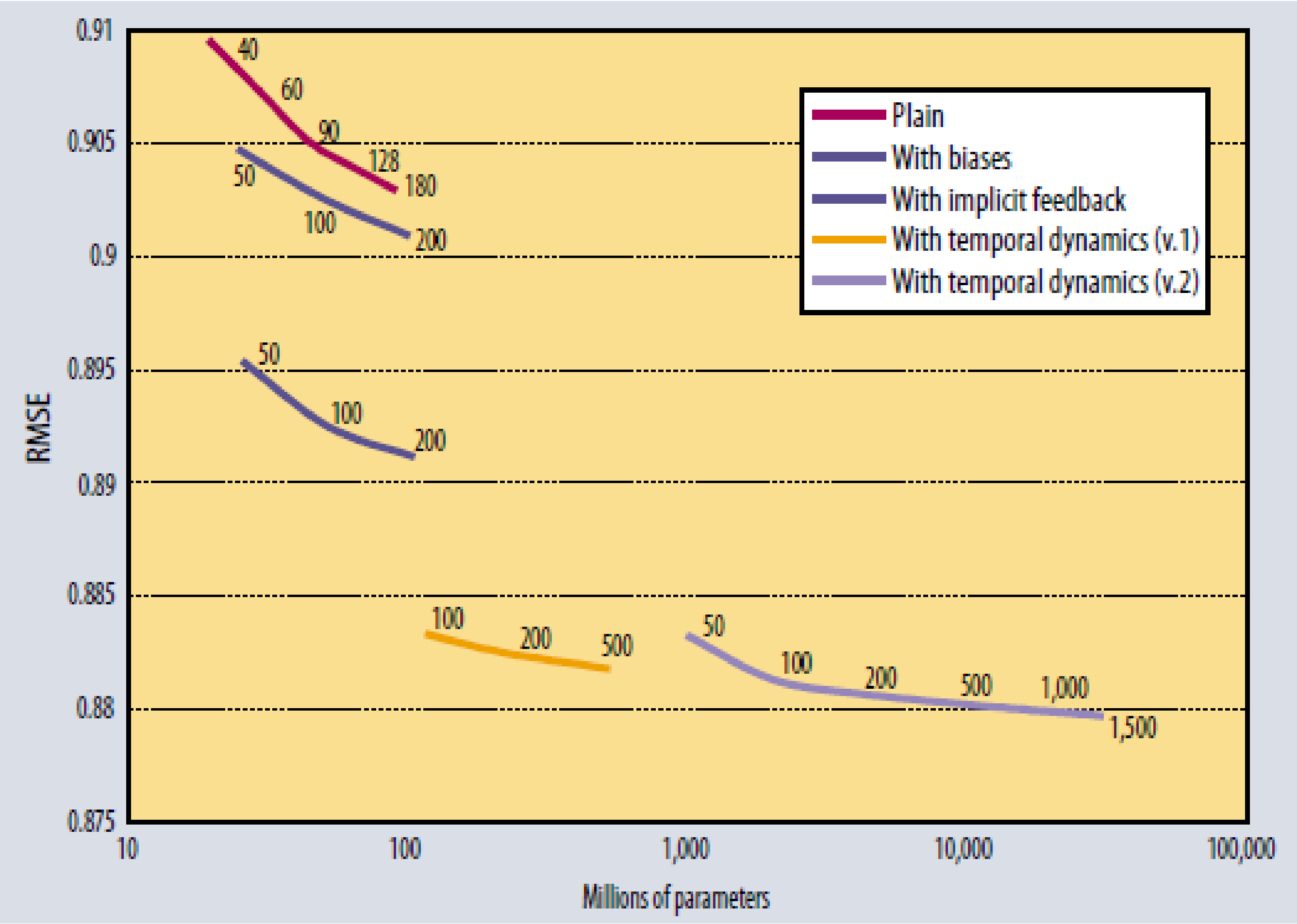
Showing 2-d plot:

Well-clustered based on genres

(Strong female leads, fraternity humor, ...)

I don't know much about the movies ☺..

Evaluations



Each variant have contribution,
while temporal info. is shown to be most important.

**unfortunately, I couldn't find what v.1 & v.2 are exactly meaning in the paper ☺...*

Summary

Why MF is good?

Fast and simple

Parallely computable

Generally applicable

Weakness?

Less expressive factors
compared to recent models

Thank you!

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