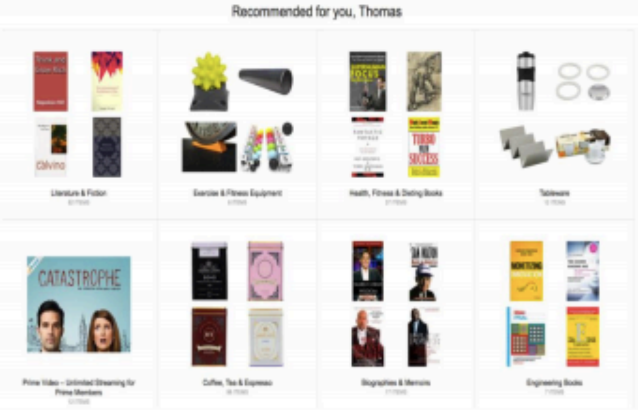
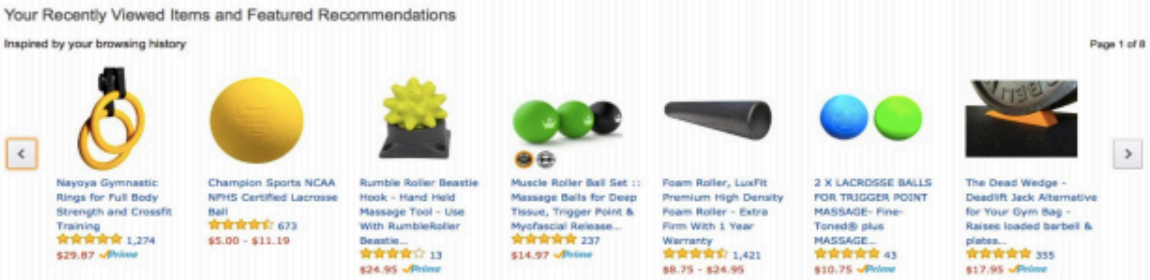
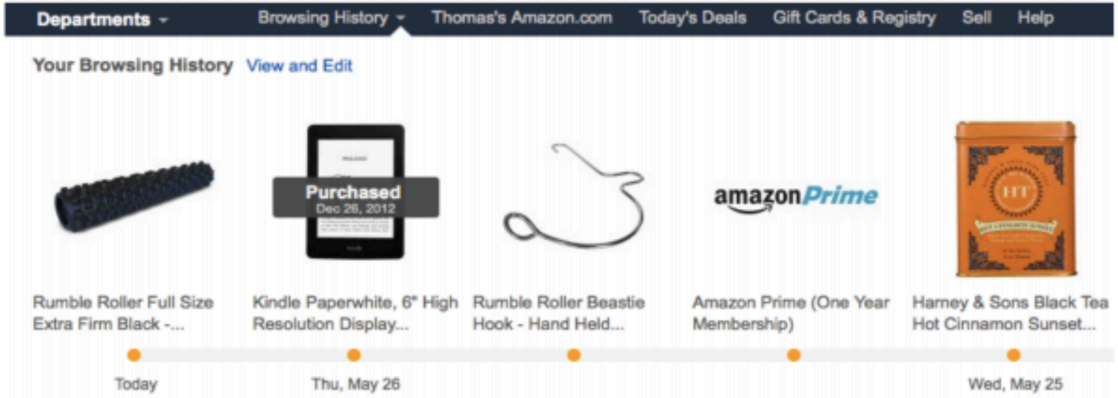
INTRODUCTION TO RECOMMENDER SYSTEM (RS)

ARTIFICIAL INTELLIGENCE

1) "RECOMMENDED FOR YOU, THOMAS"







Clicking on the "Your Recommendations" link on Amazon.com leads users to a page full of products recommended just for you. Amazon **recommends a range of products from different categories you've been browsing**, with the aim of putting products in front of you that you're likely to click, learn more about and buy.

OBJECTIVES

Introduction

Types of Recommender Systems – Collaborative Filtering and Content-based Filtering

Matrix Factorization

INTRODUCTION

Recommender Systems (RSs) are software tools and techniques providing suggestions for items to be of use to a user.

Recommendations are usually personalized, different users or

user groups receive diverse suggestions.

ADVANTAGES

Increase the number of items sold.

Sell more diverse items.

Increase the user satisfaction.

Increase user fidelity.

Better understand what the user wants.

APPLICATIONS

35 % of amazon revenue is from recommendation engine

NETFLIX

amazon

YouTube

movielens

f

twitter

tinder

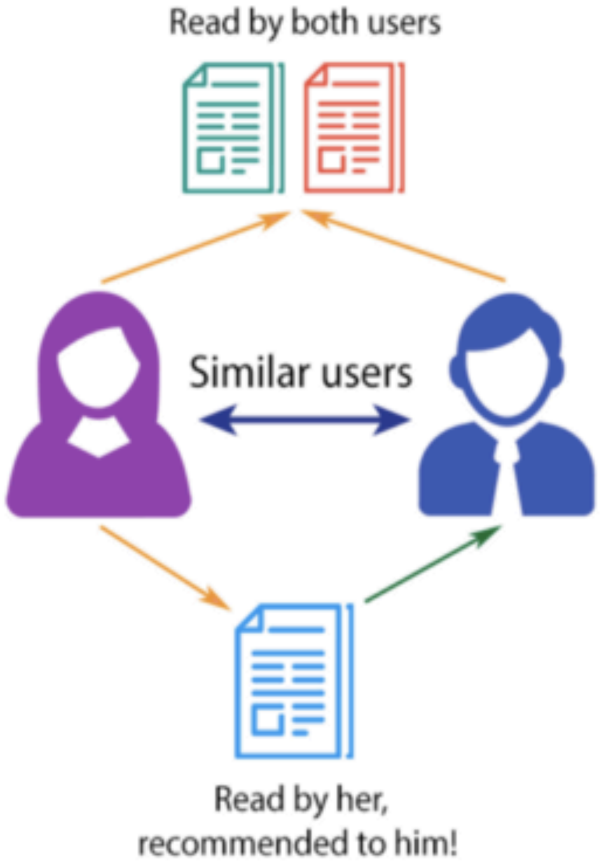
Spotify

COMMON TYPES OF RS

Collaborative filtering

Content-based filtering

COLLABORATIVE FILTERING



CONTENT-BASED FILTERING

SEARCH-BASED FILTERING, AKA

CONTENT-BASED FILTERING

CONTENT-BASED FILTERING

Content-based filtering approaches utilize a series of discrete, pre-tagged characteristics of an item in order to recommend additional items with similar properties.

SEARCH-BASED/CONTENT-BASED FILTERING

Search- or content-based methods treat the recommendations problem as a search for related items.

The algorithm constructs a search query to find other popular items by the same author, artist, or director, or with similar keywords or subjects.

If the user has few purchases or ratings, search based recommendation algorithms scale and perform well.

LIMITATION OF CONTENT-BASED FILTERING

- limited in scope, for example, it can only make recommendations that are similar to the original seed.
- For users with thousands of purchases, however, it's impractical to base a query on all the items.
- The algorithm must use a subset or summary of the data, reducing quality.
- In all cases, recommendation quality is relatively poor.
- Recommendations should help a customer find and discover new, relevant, and interesting items.

COLLABORATIVE FILTERING

COLLABORATIVE FILTERING

Collaborative filtering approaches build a model from a user's past behavior (items previously purchased or selected and/or numerical ratings given to those items) as well as similar decisions made by other users. This model is then used to predict items (or ratings for items) that the user may have an interest in.

The system generates recommendations using only information about rating profiles for different users or items.

STRENGTHS

A key advantage of the collaborative filtering approach is that it does not rely on machine analyzable content and therefore it is capable of accurately recommending complex items such as movies without requiring an "understanding" of the item itself.

LIMITATION OF COLLABORATIVE FILTERING

- requires a large amount of information about a user to make accurate recommendations (cold start problem)

Cold start: For a new user or item, there isn't enough data make accurate recommendations

Scalability – big data (items and users amount)

Sparsity – how many of you actually rated a product?

DATA COLLECTION

Explicit Data Collection

Implicit Data Collection

EXPLICIT DATA COLLECTION

Examples of explicit data collection include the following:

- **Asking a user to rate an item on a sliding scale.**
- **Asking a user to search.**
- **Asking a user to rank a collection of items from favorite to least favorite.**
- **Presenting two items to a user and asking him/her to choose the better one of them.**
- **Asking a user to create a list of items that he/she likes.**

IMPLICIT DATA COLLECTION

Examples of explicit data collection include the following:

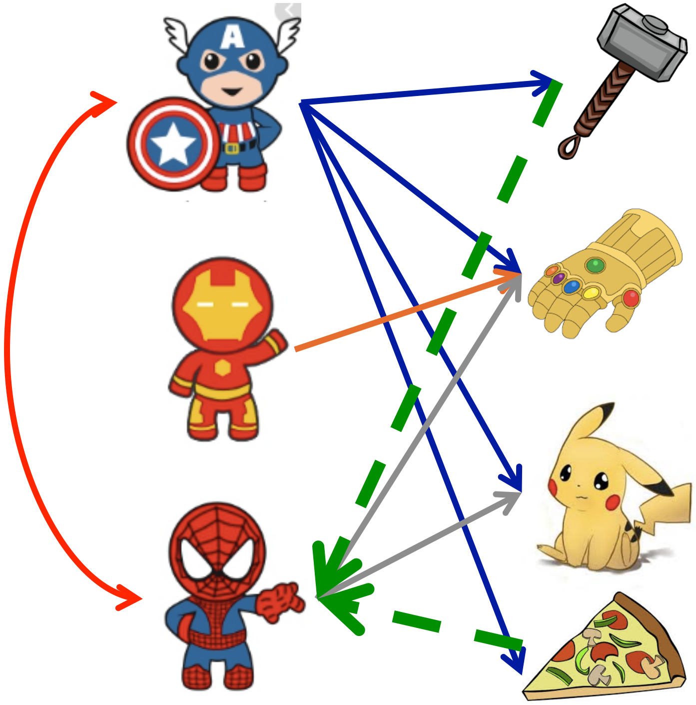
- **Observing the items that a user views in an online store.**
- **Analyzing item/user viewing times.**
- **Keeping a record of the items that a user purchases online.**
- **Obtaining a list of items that a user has listened to or watched on his/her computer.**
- **Analyzing the user's social network and discovering similar likes and dislikes.**

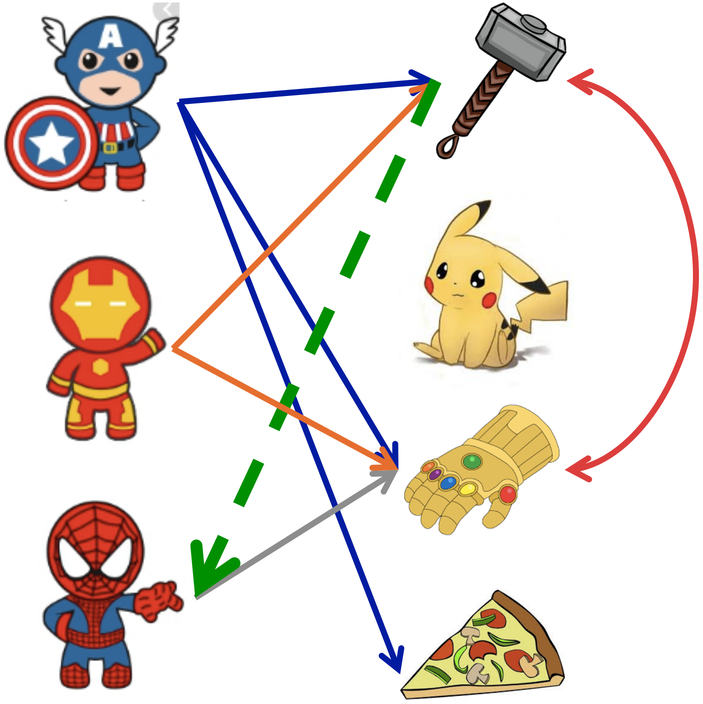
MODELING APPROACH

User-based vs item-based

Collaborative filtering and cluster models focus on finding similar set of customers whose purchased and rated items overlap with the user's purchased and rated items.	**Search-based methods and item-to-item collaborative filtering focus on finding similar items, not similar customers.**

USER-BASED VS. ITEM-BASED





MODELING APPROACH

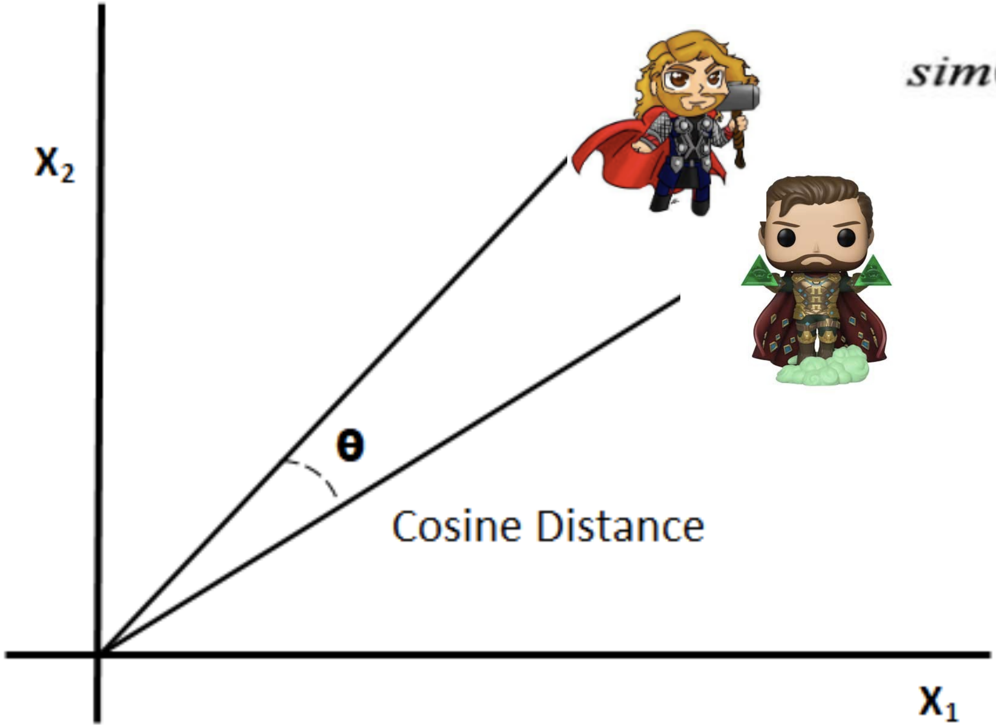
User-based vs. Item-based

Item based approach is usually preferred over user-based approach.

items usually don't change much, and item based approach often can be computed offline and served without constantly re-training	User-based approach is often harder to scale because of the dynamic nature of users (Geo-dependent interests)

USER-BASED COLLABORATIVE FILTERING

Cosine Distance/Similarity



$$sim(A,B) = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|}$$

LIMITATION

Severe performance and scaling issues.

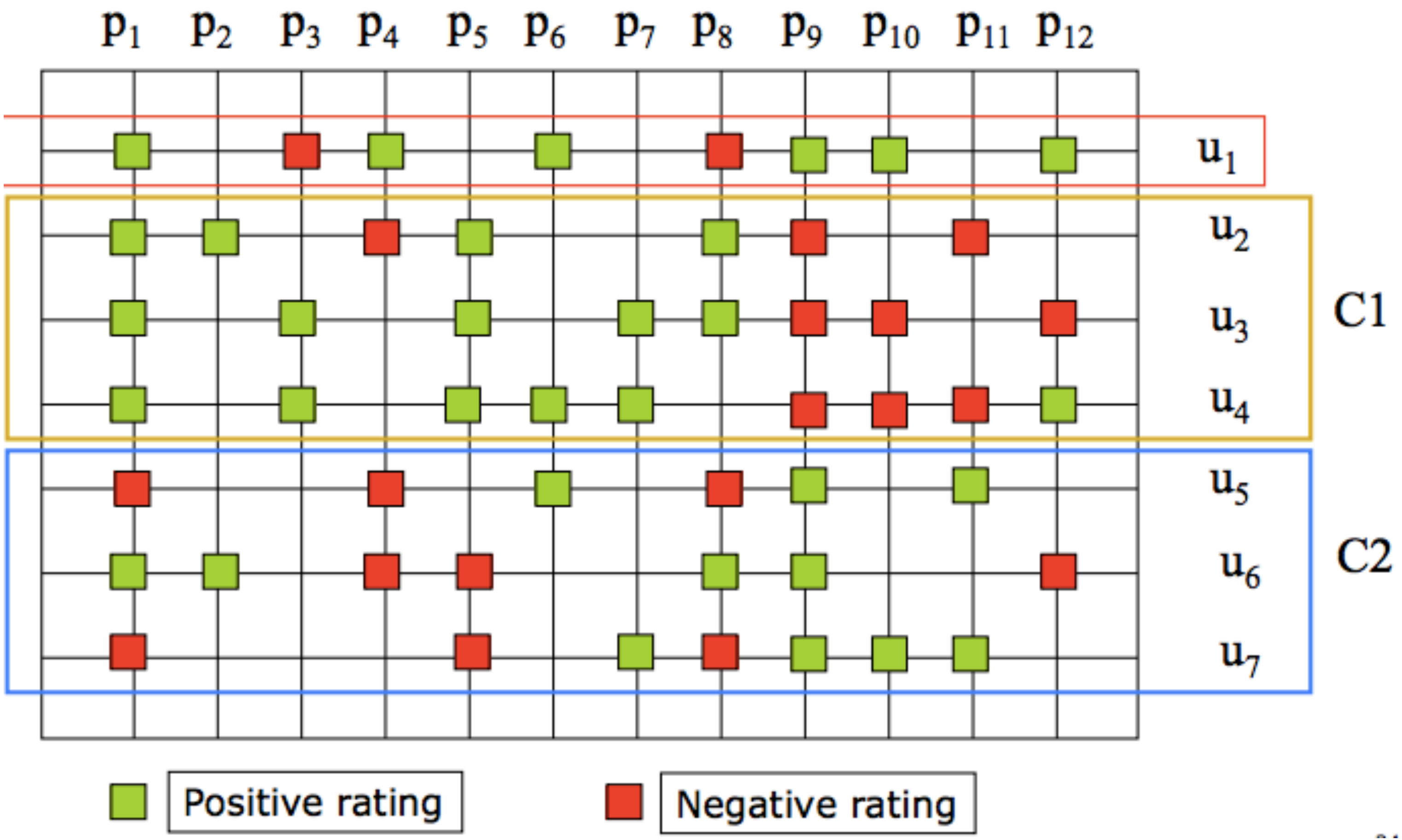
Worst case complexity is O(MN)[M- Number of customers, N - Number of product catalog].

USER-BASED CLUSTERING

Divide the customer base into many segments and assign the user to the segment containing the most similar customers.

The algorithm’s goal is to assign the user to the segment containing the most similar customers. It then uses the purchases and ratings of the customers in the segment to generate recommendations.

User-Based Cluster Example



PROS & CONS

- **Cluster models have better online scalability and performance than collaborative filtering because they compare the user to a controlled number of segments rather than the entire customer base.**
- **recommendations produced could be less relevant.**
- **online user–segment classification becomes almost as expensive as finding similar customers using collaborative filtering.**

ITEM-TO-ITEM COLLABORATIVE FILTERING

- Rather than matching the user to similar customers, item-to-item collaborative filtering matches each of the user’s purchased and rated items to similar items, then combines those similar items into a recommendation list.
- To determine the most-similar match for a given item, the algorithm builds a similar-items table by finding items that customers tend to purchase together.
- Given a similar-items table, the algorithm finds items similar to each of the user’s purchases and ratings, aggregates those items, and then recommends the most popular or correlated items. This computation is very quick, depending only on the number of items the user purchased or rated.

SIMILAR ITEMS

Similarity can be computed in a number of ways

- Using the user ratings
- Using some product description
- Using co-occurrence of items in a bag or in the set of a user past purchased products

Similarity of item i with item 17

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
.1	.3	.6	.1	.3	.4	.3	.3	.2	.6	.2	.5	.4	.5	.5	.3	1	.3	.5	.4	.2	.4	.4	.5

Items

Users

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
a			1		4	5			4		3					2			4		2				
b			4							3							5	1		3					
c		5		4			4						3		5					4		5			
d								3				5				3			4		2			3	
e		3					5			4	5				5					1			5	4	
f			4				1		3	5		4	1		5	4	4		4				3		
g	2	4				4		2			5		1	4	5		4	2	4		5			4	
h			2		1		4		3	5		4	2		5	4	5						5		
i		1					3			5				5		4	4		5			4		3	
j			4			4				5			1		5		4		4				4		
k		5				4			2		5		1	5		4		2		4				2	
l					3			3				4	1		4		4	2	4					3	
m	5		3					5	3		5	4		5	5	3			4	4	5	4		4	
n			1		4	5				4	5		1	5		4		3		4		4	3		
o			4			4				5		4		5			4	2		5		5		3	
p				4			5								5	4		2	4	4	5	4		2	
q					3			3					1	5		4	4		4			4		3	
r		4			1	4		2					2		5		4				5	4		4	
s			2		4		4			5			1			4		2	4		4		5		
t		1		4			3					4		5	5		4			4				3	
u			2		1		4		3				1		5	4		2	4		5	4			
v					4	5				4	3		5			2					2			5	
w				2			2		3			5			4	5		4	2		3	4			

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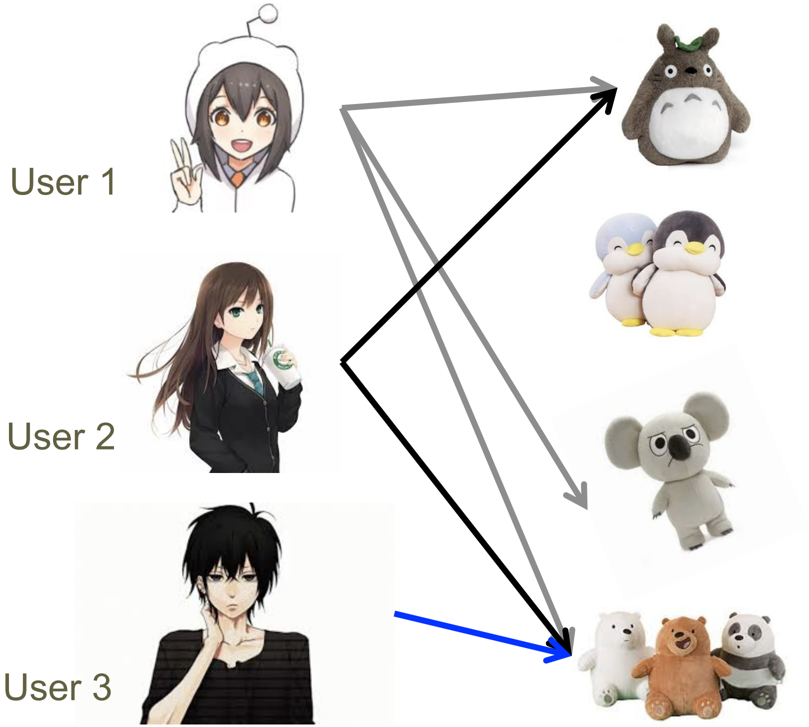
Book Description
This professional guidebook provides tips to create technically correct and highly marketable digital black-and-white photographs. Designed to instruct professional and experienced amateur photographers, this highly visual format features 100 landscape, portrait, and wedding images from 20 leading digital imaging experts. Advice is included for utilizing professional digital effects, selecting an appropriate SLR camera, and managing difficulties and rewards associated with creating high-end black-and-white digital images.

Find: Find Next Find Previous Highlight Match case

ITEM-BASED COLLABORATIVE FILTERING



What item would the RS recommends to User 3?

PROS

For item-to-item it is dependent only on how many items the user has purchased or rated. Thus, the algorithm is fast even for extremely large data sets. Because the algorithm recommends highly correlated similar items, recommendation quality is excellent.

MATRIX FACTORIZATION

Matrix Factorization

	M1	M2	M3	M4	M5
Comedy	3	1	1	3	1
Action	1	2	4	1	3

	Comedy	Action
A	✓	✗
B	✗	✓
C	✓	✗
D	✓	✓

	M1	M2	M3	M4	M5
	3	1	1	3	1
	1	2	4	1	3
	3	1	1	3	1
	4	3	5	4	4

Estimate Unknown Ratings

items

users

1		3			5			5		4	
		5		?		4			2	1	3
2	4		1	2		3		4	3	5	
	2	4		5			4			2	
		4	3	4	2					2	5
1		3		3			2			4	

~

~ users

.1	-.4	.2
-.5	.6	.5
-.2	.3	.5
1.1	2.1	.3
-.7	2.1	-2
-1	.7	.3

•

items

1.1	-.2	.3	.5	-2	-.5	.8	-.4	.3	1.4	2.4	-.9
-.8	.7	.5	1.4	.3	-1	1.4	2.9	-.7	1.2	-.1	1.3
2.1	-.4	.6	1.7	2.4	.9	-.3	.4	.8	.7	-.6	.1

A rank-3 SVD approximation

Estimate Unknown Ratings

$-0.5*(-2) + 0.6*0.3 + 0.5*2.4 = 2.4$

items

users

1		3			5			5		4	
		5		2.4		4			2	1	3
2	4		1	2		3		4	3	5	
	2	4		5			4			2	
		4	3	4	2					2	5
1		3		3			2			4	

~

users

.1	-.4	.2
-.5	.6	.5
-.2	.3	.5
1.1	2.1	.3
-.7	2.1	-2
-1	.7	.3

●

items

1.1	-.2	.3	.5	-2	-.5	.8	-.4	.3	1.4	2.4	-.9
-.8	.7	.5	1.4	.3	-1	1.4	2.9	-.7	1.2	-.1	1.3
2.1	-.4	.6	1.7	2.4	.9	-.3	.4	.8	.7	-.6	.1

A rank-3 SVD approximation

SUMMARY

Overview of recommender systems

Types of Recommender Systems – Collaborative Filtering and Content-based Filtering

Matrix Factorization

REFERENCES

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