

RS

recommender systems

PG



28.9.2017

Source of background: www.wallpaperswide.com

What is recommender?


Hello M J Seckington. We have [recommendations](#) for you. ([Not M?](#))

M's Amazon.co.uk Deals of the Week Gift Certificates ▾ Gifts & Wish Lists ▾

Search

More to Explore


You looked at




[Giant Bath Duck](#)
£9.75

[Find similar items](#)


You might also consider



[Classic Bath Duck](#)
£1.50



[Medium Rubber Duck](#)
£1.49



[Small Rubber Duck](#)
£0.56

Why we need them?


Plenty of information available “out there”.




Popularity != ideal

Basic - recommend the most popular.


Trending



Primitive Technology: Mud Bricks
Primitive Technology ✓
14M views • 2 days ago



JAY-Z - Numb/Encore in the Live Lounge
BBCRadio1 VEVO
782K views • 3 days ago



Cristiano Ronaldo Reacts To My Football Videos
ChrisMD ✓
4.1M views • 3 days ago

NAJČÍTANEJŠIE NA SME

4 hod 24 hod 7 dní SME+ EN









1. Nie sme ovce, Gašpar preč, znelo na pochode proti korupcii (minúta po minúte) VIDEO 21 676
2. Štvrtý titul? O rok naň Sagan môže zabudnúť 14 270
3. Sagan či Hantuchová sa budú plateniu daní na Slovensku vyhýbať ťažšie 11 927
4. Českého turistu našli v Tatrách mŕtveho. Fatálne podcenil výstroj a počasie FOTO 11 258
5. Pozrite si záver MS z Bergenu, ktorý nebol v televízii VIDEO 10 298
6. Päťdesiatnici a stres: Po päťdesiatke začne stres zabíjať 7 565
7. Ešte v marci robil v obleku kľuky. Železná vôľa urobila z Jana Třísku Američana VIDEO 7 408
8. Nový vynález môže výrazne zlepšiť opravu výtlkov VIDEO 7 280

	1. Darebák jedna: Star Wars Story (2016)
	2. Finding Dory (2016)
	3. Captain America: Civil War (2016)
	4. The Secret Life of Pets (2016)
	5. The Jungle Book (2016)
	6. Deadpool (2016)
	7. Zootopia (2016)
	8. Batman v Superman: Dawn of Justice (2016)
	9. Jednotka samovrahov (2016)
	10. Sing (2016)

IMDb - Top 10 US Box office 2016



dataLys

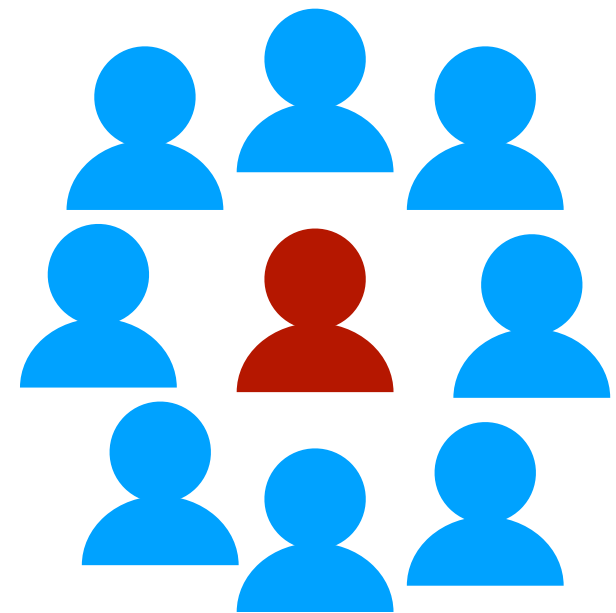
Rank	Rating	Title
1.	 98%	Moonlight (2016)
2.	 98%	Zootopia (2016)
3.	 94%	Arrival (2016)
4.	 96%	Manchester by the Sea (2016)
5.	 97%	Hell or High Water (2016)
6.	 95%	The Jungle Book (2016)
7.	 92%	La La Land (2016)
8.	 94%	Finding Dory (2016)
9.	 96%	Moana (2016)
10.	 98%	Love & Friendship (2016)

Rotten Tomatoes - Top 10 (rating)

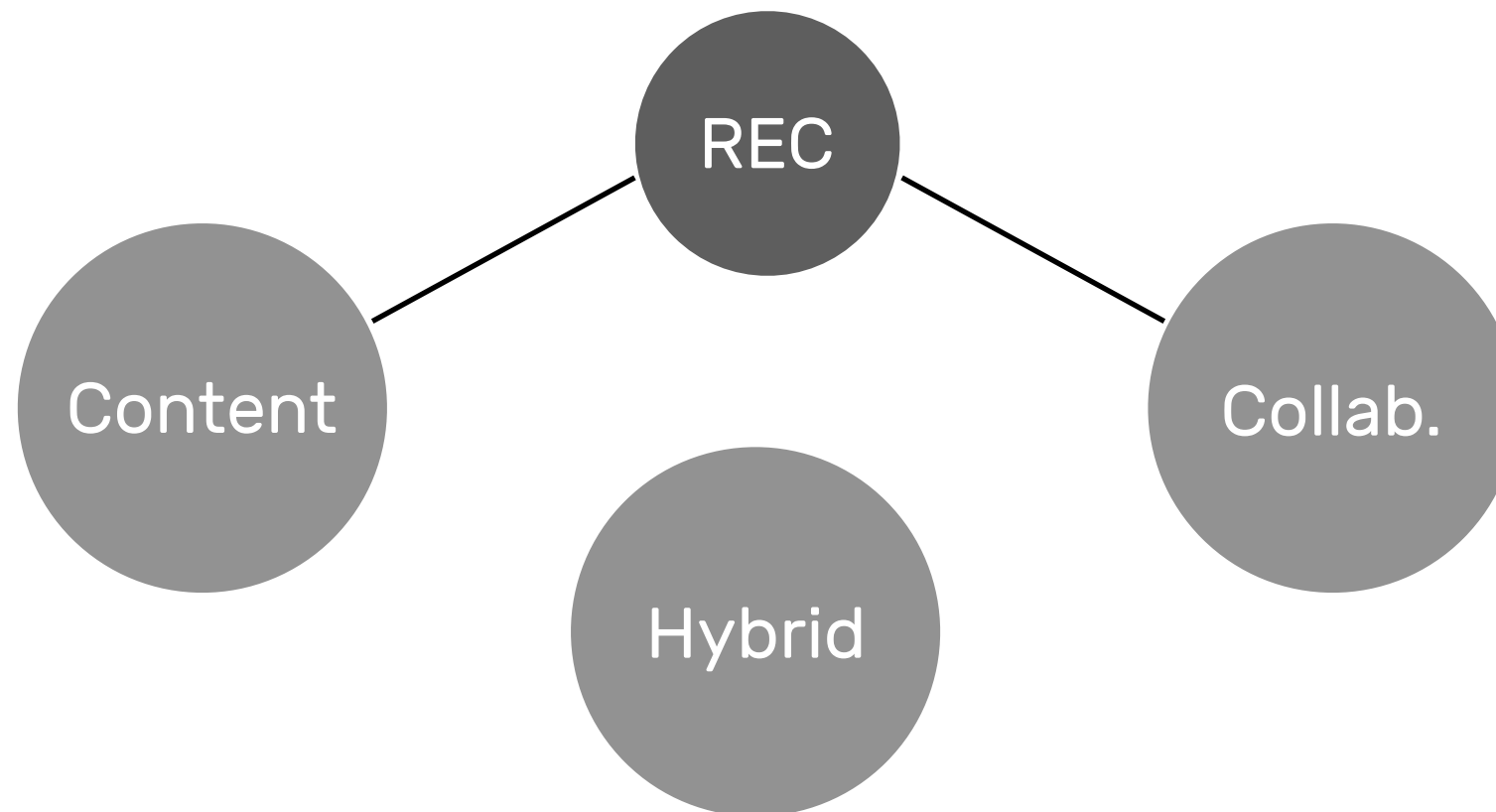
Personalization

Tailor recommender to *user preferences*.

How?



Recommendation techniques



What about data?

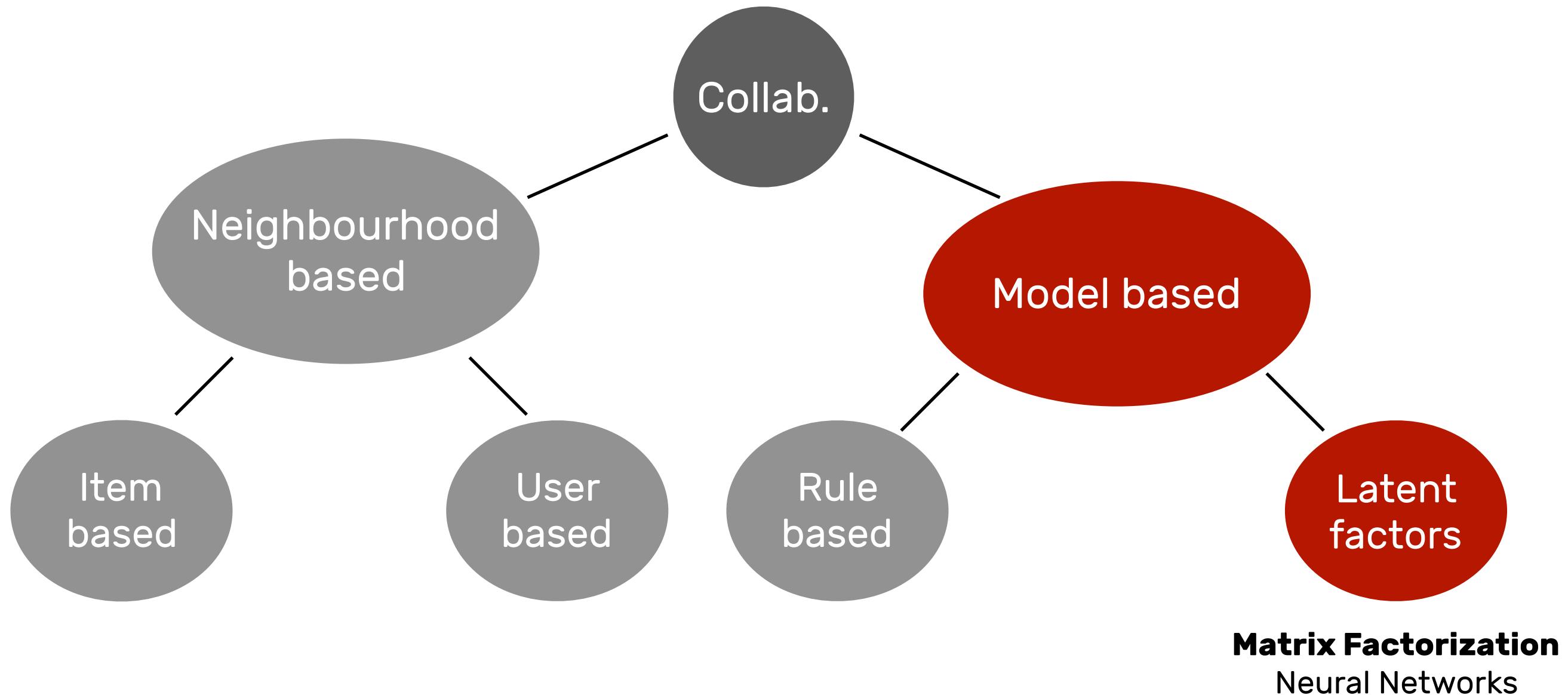
Implicit feedback

clicks, purchases, plays

Explicit feedback

ratings, likes, reviews

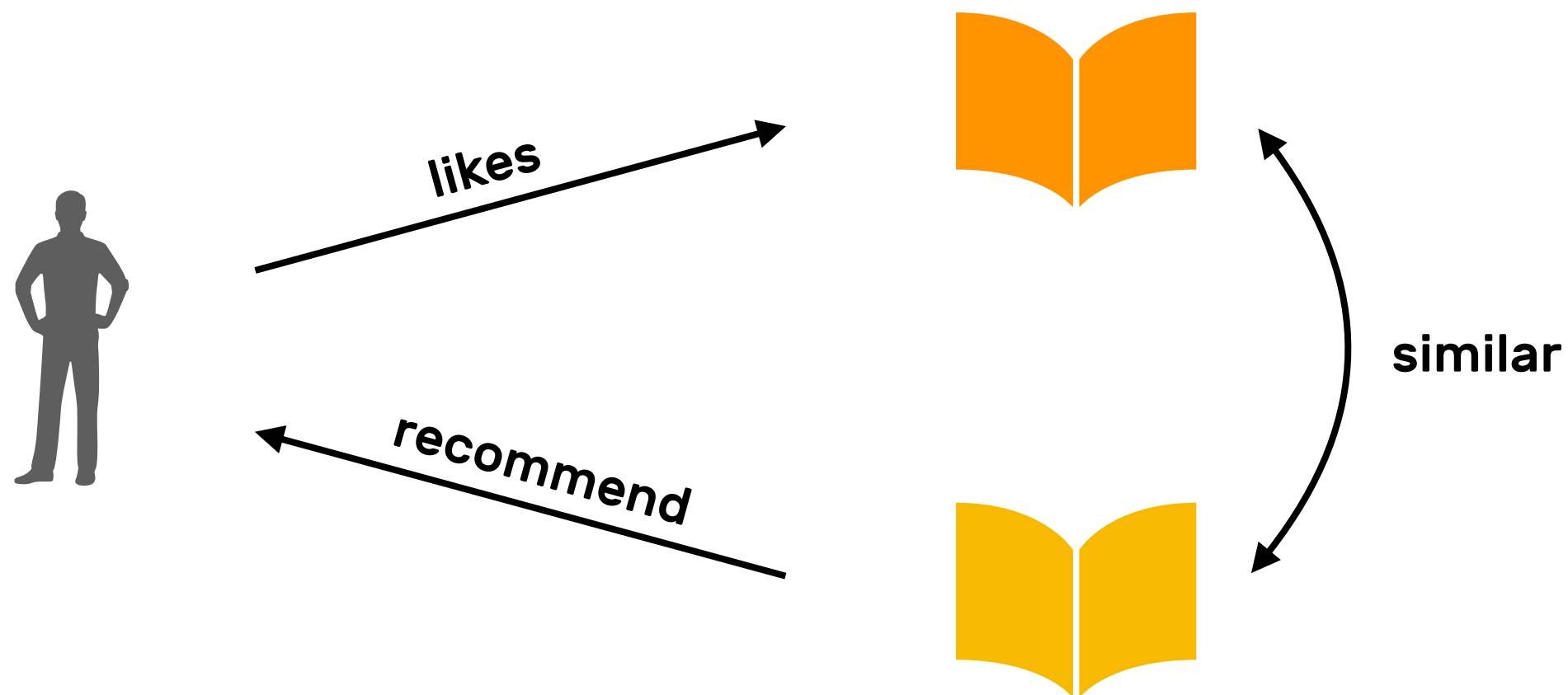
Recommendation techniques



Content-based

Utilize (textual) characteristics of items.

News, movies, books, ...



Collaborative filtering

Based on the items that users with the similar taste previously liked.

Two types:

neighbourhood-based,

model-based.

Problem: cold-start, similarity

Neighborhood-based

Focuses on the similarity between users or items.

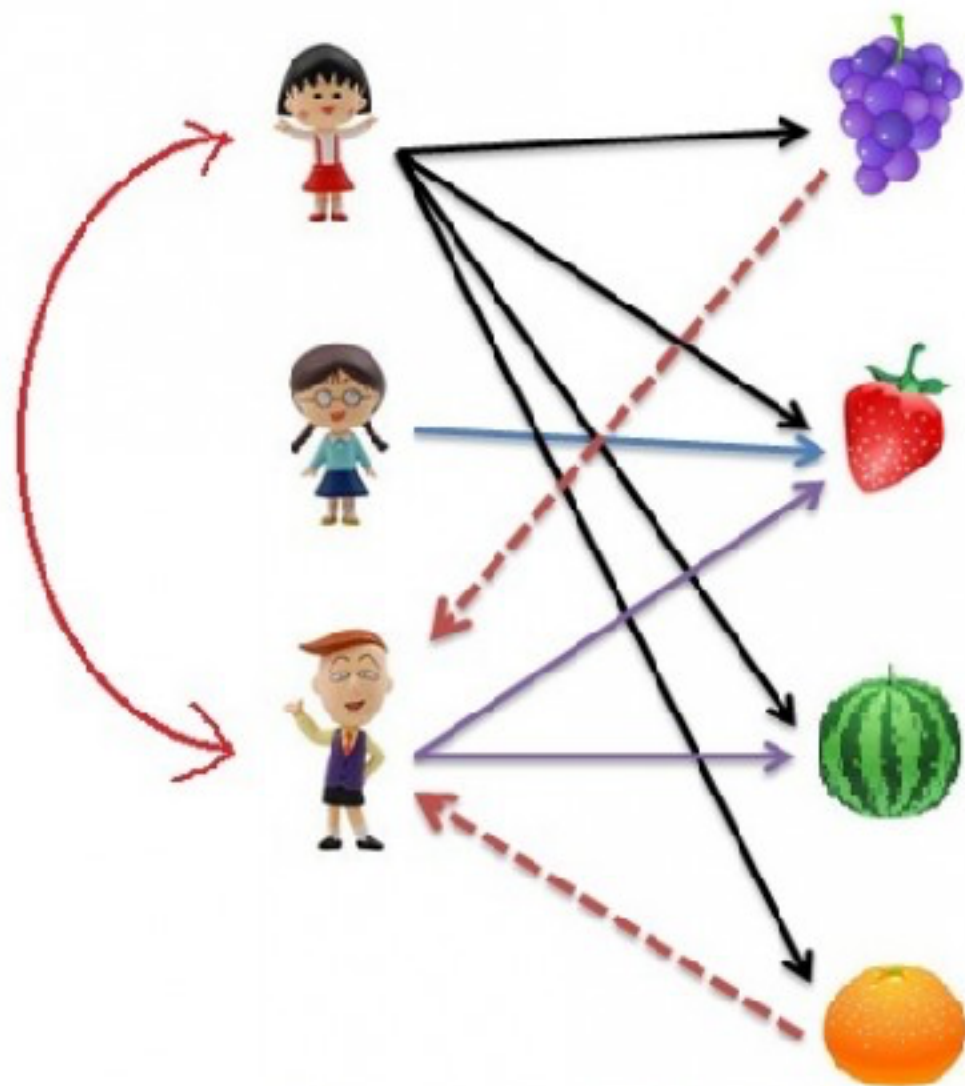
User-user:

find similar users to me and aggregate their ratings

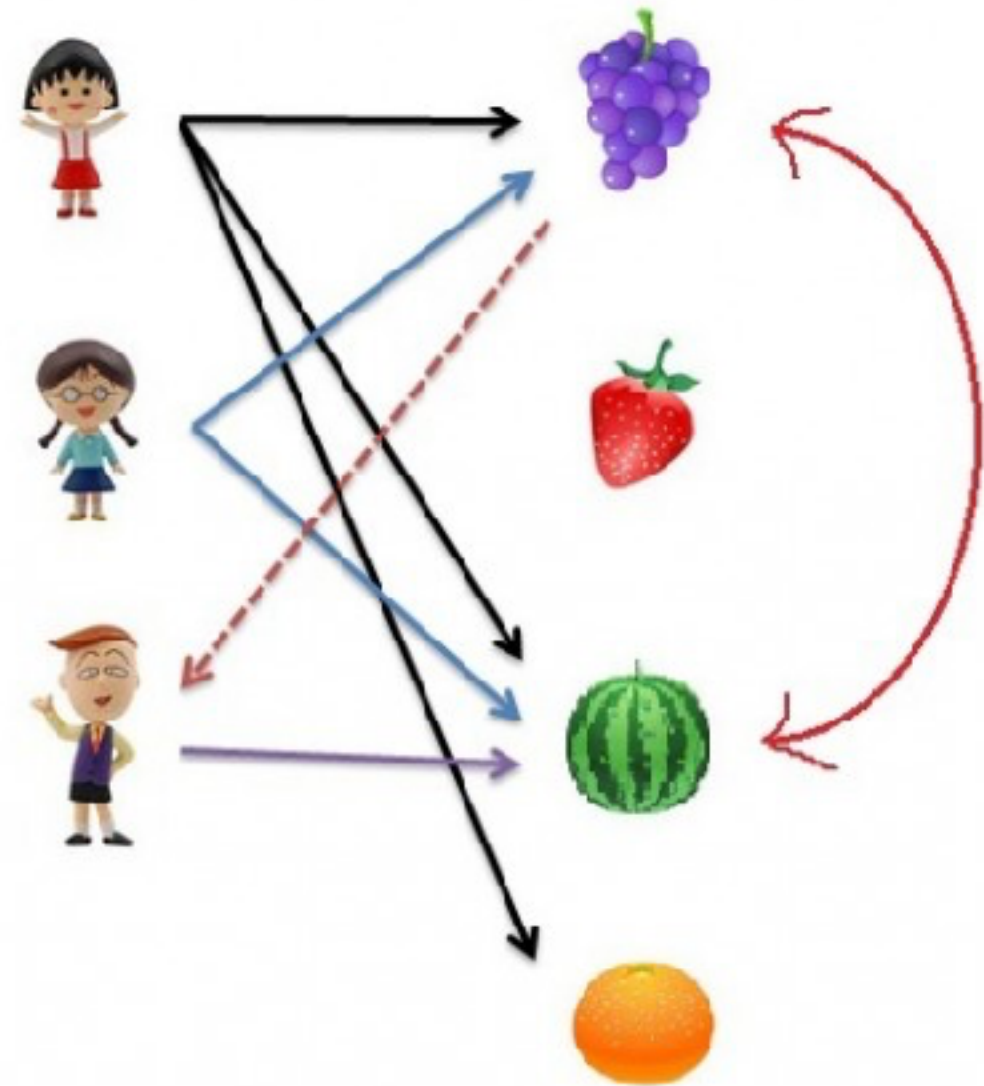
Item-item:

find items that are similar the items I rated

Neighborhood-based



User-based filtering



Item-based filtering

Model-based

Rule based

Latent factors

Matrix Factorization

Neural Networks

Matrix Factorization

		Item			
		W	X	Y	Z
User	A		4.5	2.0	
	B	4.0		3.5	
	C		5.0		2.0
	D		3.5	4.0	1.0

Rating Matrix

=

A	1.2	0.8
B	1.4	0.9
C	1.5	1.0
D	1.2	0.8

User Matrix

X

	W	X	Y	Z
	1.5	1.2	1.0	0.8
	1.7	0.6	1.1	0.4

Item Matrix

Source:

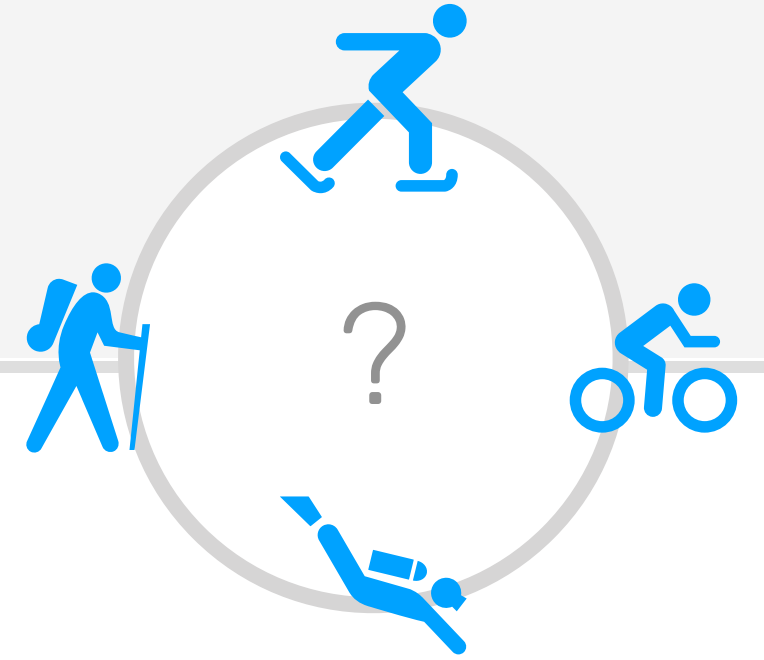
<http://jxieeducation.com/2016-06-26/Factorization-Machines-A-Theoretical-Introduction/>

Group RS

Recommending items for a group of people such that everyone *should* be satisfied.

Domains:
travel, restaurants, movies.

How to *aggregate*?



Context-aware RS

context = conditions or circumstances which affect something



Contextual features:

time, location, purchasing purpose, mood, ...

Hybrid

A combination of different recommendation techniques.

EXAMPLE:

Recommend with *content-based* to a new user.

After receiving a specific amount of ratings (for this user), continue with *collaborative filtering*.

Several combination strategies.

Resources

IR @ fit

Conferences: RecSys, UMAP

Useful datasets:

Grouplens (<https://grouplens.org/datasets/>)

YELP (<https://www.yelp.com/dataset/challenge>)

Sources

Ricci et al. Recommender Systems Handbook. 2015.