سیستم های

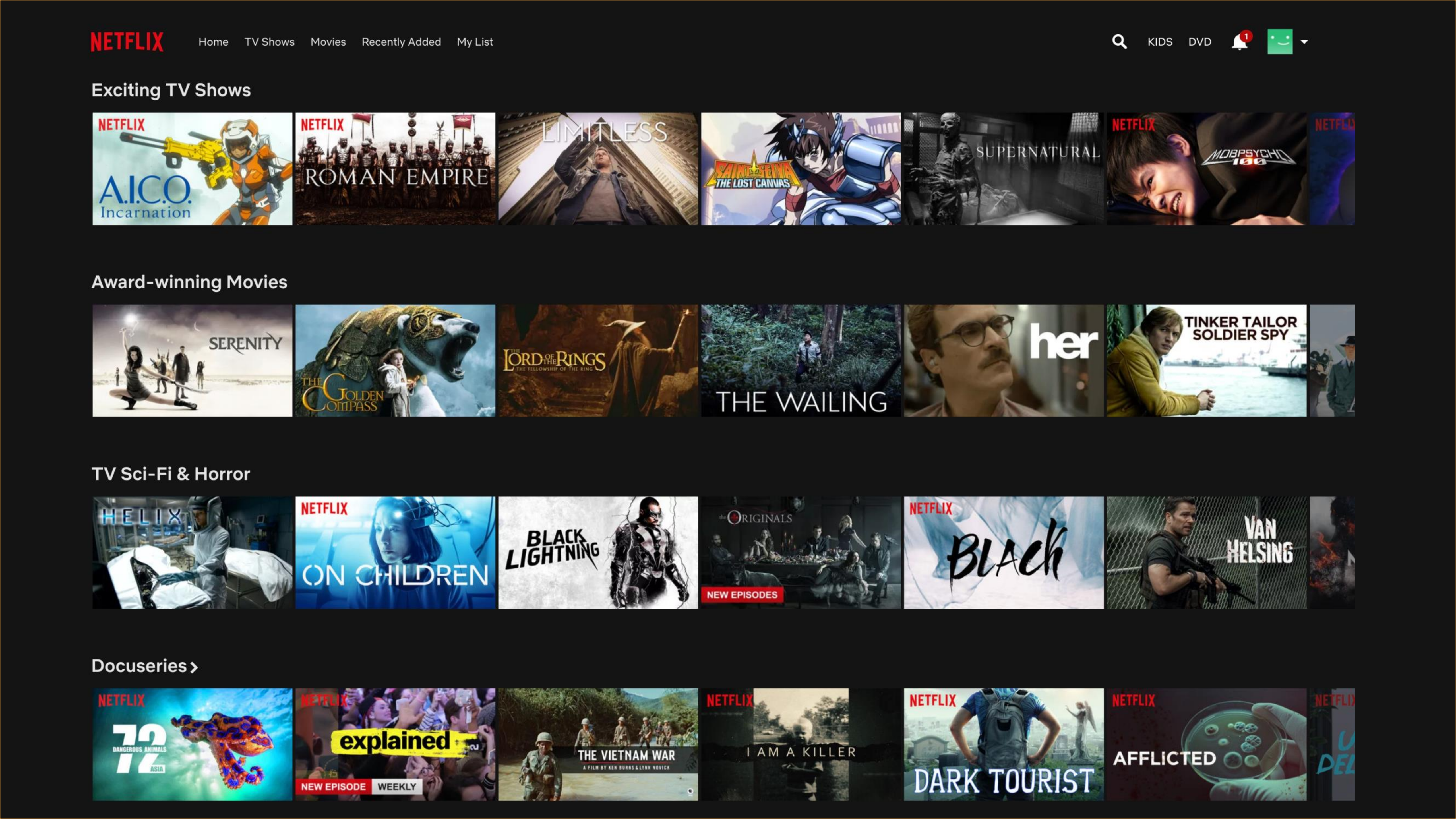
توصیه گر

محمد دهقانی

data-hub

معرفی

۱. مدیر دیتاهاب
۲. لیسانس نرم افزار از دانشگاه اصفهان و ارشدIT تربیت مدرس
۳. کارشناس سابق پردازش متن شرکت لایف وب
۴. سابقه همکاری با شرکت های داده پردازی آرون و توانمند
۵. سابقه تدریس در مرکز علوم شناختی(IPM) و دانشگاه های شریف، اصفهان، امیرکبیر، شهرکرد، علوم پزشکی تهران و کنفرانس وب پژوهی
۶. دارای بیش از ۳ مقاله ژورنالی
۷. مترجم کتاب یادگیری ماشین
۸. نویسنده کتاب تحلیل عواطف با استفاده از تکنیک های یادگیری ماشین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LIMITLESS
SAINT SEIYA THE LOST CANVAS
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SERENITY
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THE FELLOWSHIP OF THE RING
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TINKER TAILOR SOLDIER SPY
TV Sci-Fi & Horror
HELIX
NETFLIX
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BLACK LIGHTNING
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NEW EPISODES
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explained
NEW EPISODE
WEEKLY
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I AM A KILLER
NETFLIX
DARK TOURIST
NETFLIX
AFFLICTED

35% of the purchases on Amazon are the result of their recommender system, according to McKinsey.

Recommendations are responsible for 70% of the time people spend watching videos on YouTube.

75% of what people are watching on Netflix comes from recommendations, according to McKinsey.

Recommendation Engine – Examples

Facebook–"People You May Know"

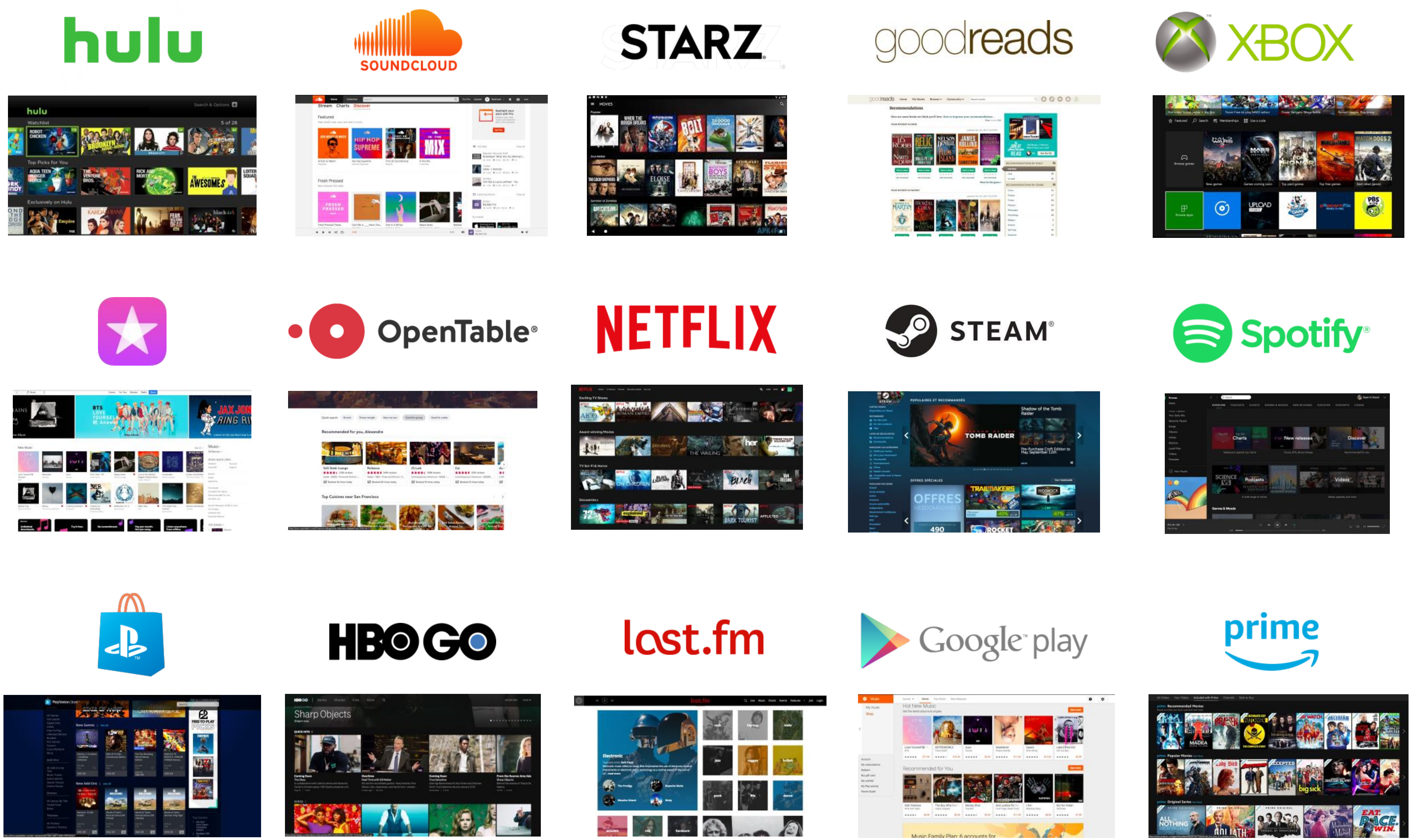
YouTube–"Recommended Videos"

Netflix–"Other Movies You May Enjoy"

Amazon–"Customer who bought this item also bought …"

LinkedIn–"Jobs You May Be Interested In"

Pinterest–"Recommended Images"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STARZ
goodreads
XBOX
OpenTable
NETFLIX
STEAM
Spotify
HBO GO
last.fm
Google play
prime

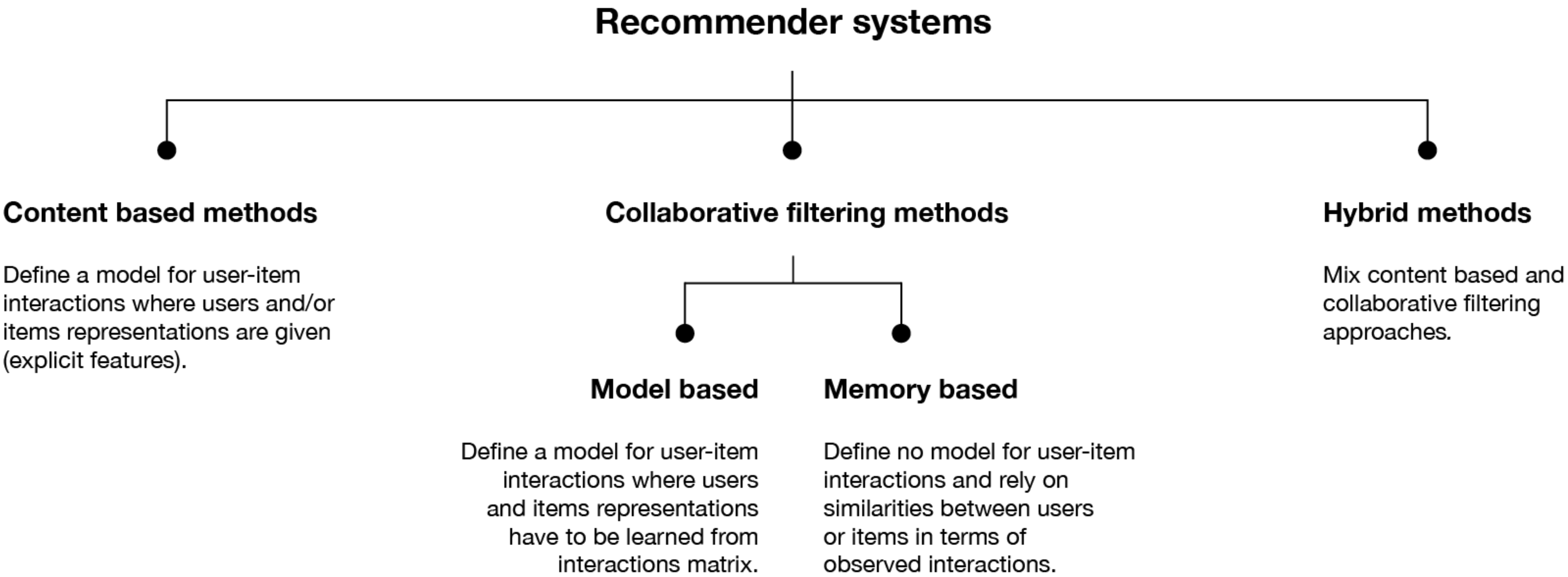
Plan for Today

1. Collaborative Filtering

2. Content-Based

3. In Production

Category


Recommender systems
Content based methods
Define a model for user-item interactions where users and/or items representations are given (explicit features).
Collaborative filtering methods
Model based
Define a model for user-item interactions where users and items representations have to be learned from interactions matrix.
Memory based
Define no model for user-item interactions and rely on similarities between users or items in terms of observed interactions.
Hybrid methods
Mix content based and collaborative filtering approaches.

Most popular items

Most popular items

- This is a blazing fast and dirty approach.
- The things is, there is no personalization involved with this approach.
- Surprisingly, such approach still works in places like news portals.

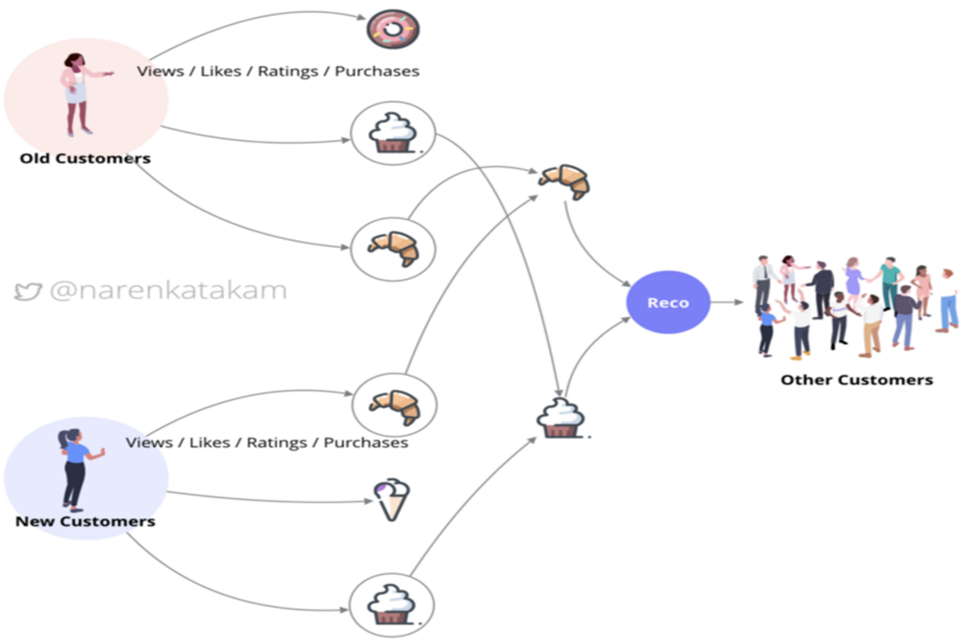


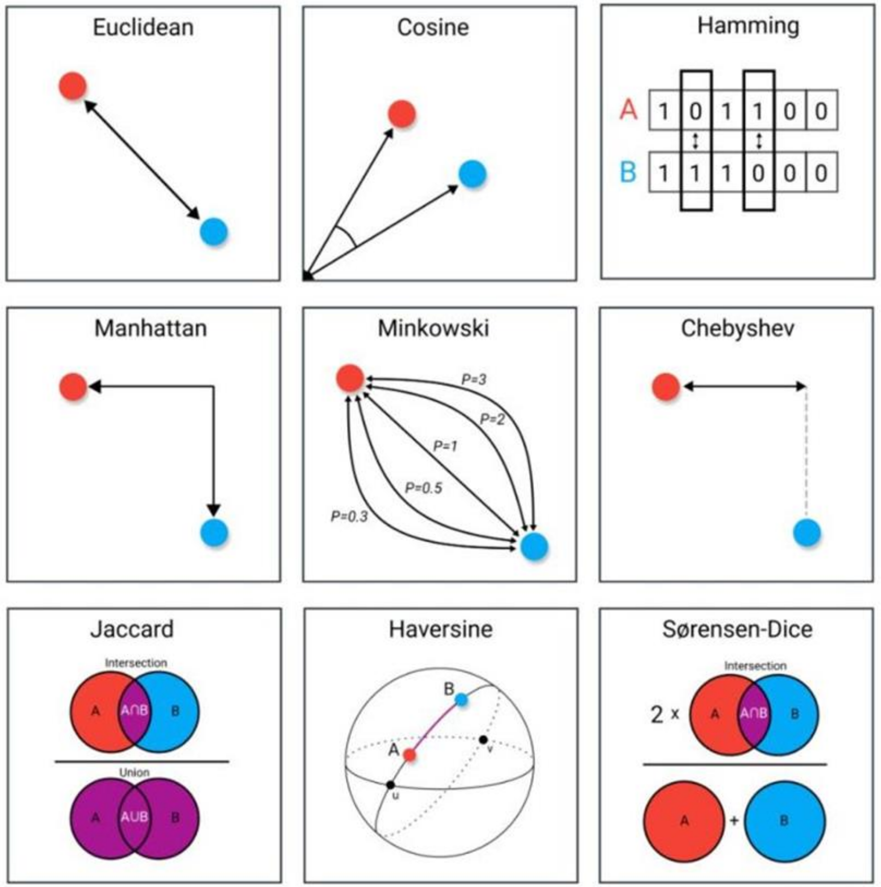
Fig.1: Popularity Filtering Model

Collaborative Filtering

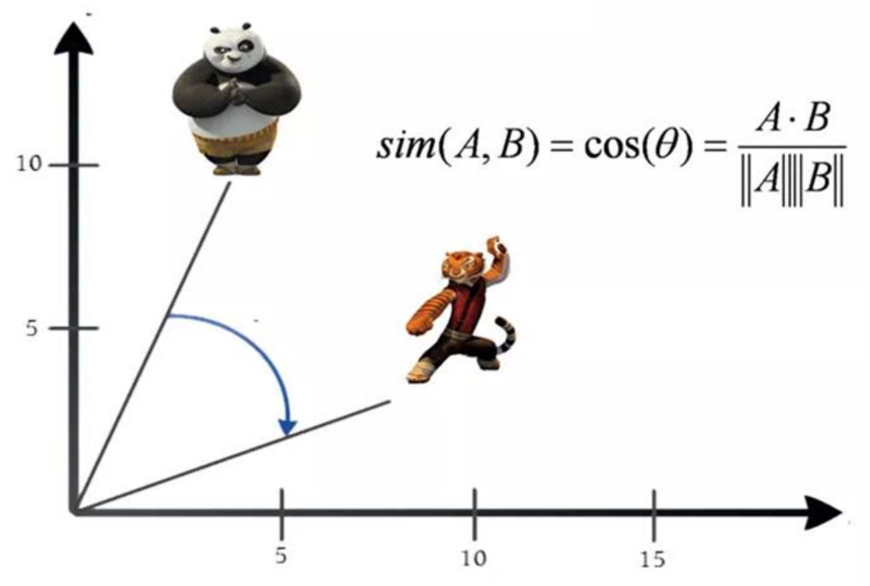
1. Collaborative Filtering – **Similarity Function**

Real function that quantify the similarity between two objects.

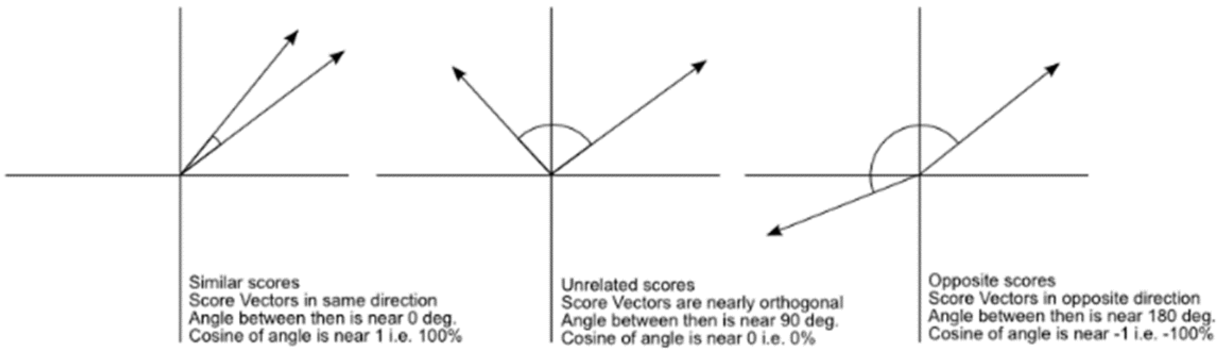
$\text{sim}(a, b) = \dots$



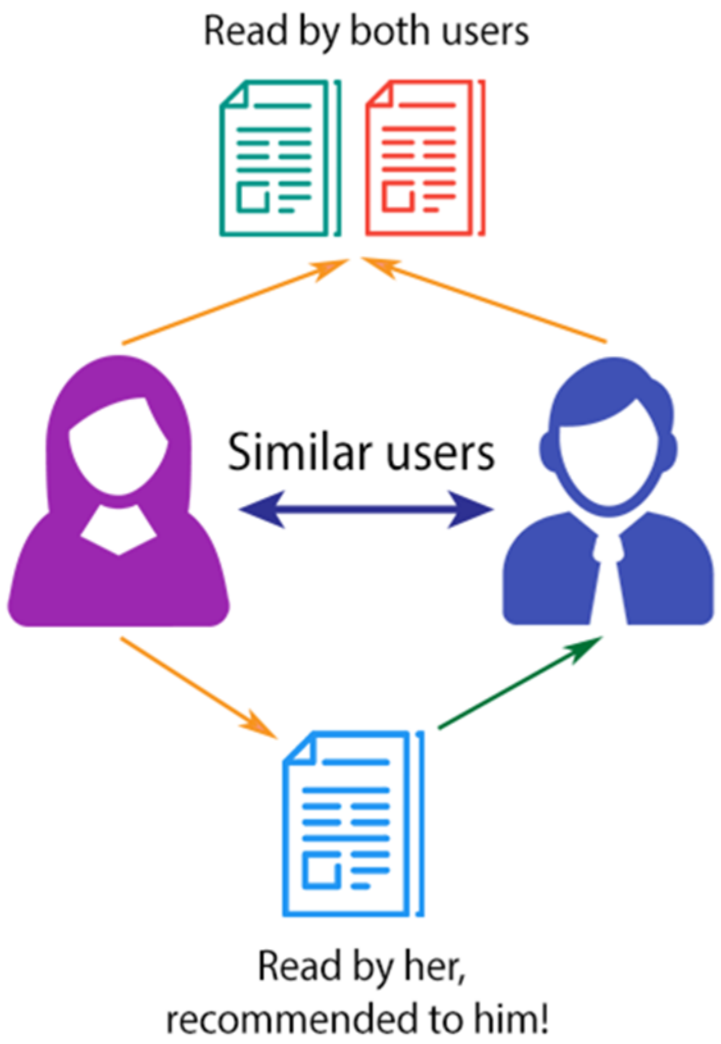
1. Collaborative Filtering – **Similarity Function**



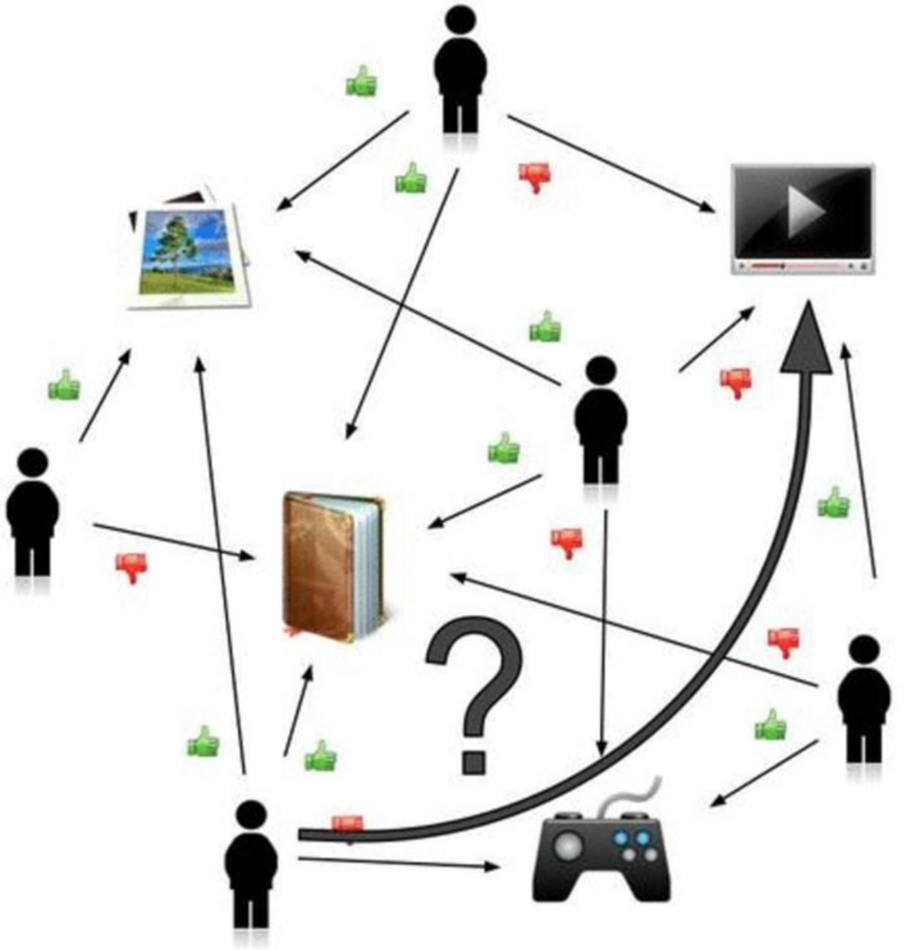
$$sim(A,B) = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|}$$

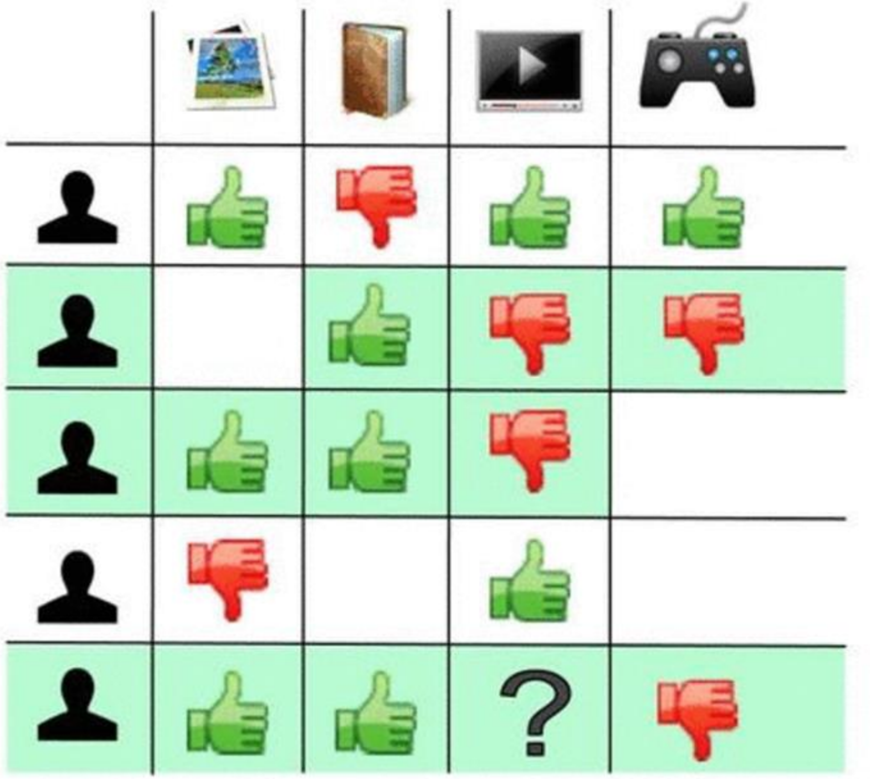


1. Collaborative Filtering



1. Collaborative Filtering





https://en.wikipedia.org/wiki/Collaborative_filtering

1. Collaborative Filtering – **Rating Matrix**

Rating data:

$$D_{(\,\cdot\,,\,\cdot\,)} = 4 \quad \in \{\varnothing, 1, 2, 3, 4, 5\}$$

2		2	4	5	
5		4			1
		5		2	
	1		5		4
		4			2
4	5		1		

1. Collaborative Filtering – **User-User**

2		2	4	5	
5		4			1
		5		2	
	1		5		4
		4			2
4	5		1		

	0	1	2	3	4	5
0	1.000000	0.396780	0.530558	0.440867	0.255551	0.264520
1	0.396780	1.000000	0.573068	0.095238	0.621059	0.476190
2	0.530558	0.573068	1.000000	0.000000	0.830455	0.000000
3	0.440867	0.095238	0.000000	1.000000	0.276026	0.238095
4	0.255551	0.621059	0.830455	0.276026	1.000000	0.000000
5	0.264520	0.476190	0.000000	0.238095	0.000000	1.000000

1. Collaborative Filtering – **User-User**

2		2	4	5	
5		4			1
		5		2	
	1		5		4
		4			2
4	5	2.5	1		

Rating prediction: $\hat{y}_{u,i} = \sum \text{sim}(u',u) r_{u'i}$

5 0.264520 0.476190 0.000000 0.238095 0.000000 1.000000

0.264520*2 + 0.476190*4 + 0*5 + 0.238095*0 + 0*4 + 1*0

2.43 ≈ 2.5

1. Collaborative Filtering – User-User **Benefits**

- "People who bought that also bought that"

- Good when #items >> #users

1. Collaborative Filtering – User-User **Challenges**

- Sparsity
- Don’t scale – Nearest Neighbors requires computation that grows with the number of users and items
- Model Too Simplistic – Accuracy of recommendation may be poor

1. Collaborative Filtering – **Item-Item**

2		2	4	5	
5		4			1
		5		2	
2.6	1	2.15	5		4
		4			2
4	5		1		

0.58*1 + 0.28*5 + 0.16*4
2.62 ≈ 2.6

0*1 + 0.16*5 + 0.34*4
2.16 ≈ 2.15

1.00	0.58	0.46	0.28	0.28	0.16
0.58	1.00	0.00	0.30	0.00	0.17
0.46	0.00	1.00	0.16	0.48	0.34
0.28	0.30	0.16	1.00	0.57	0.67
0.28	0.00	0.48	0.57	1.00	0.00
0.16	0.17	0.34	0.67	0.00	1.00

What about mean? 2.62/5

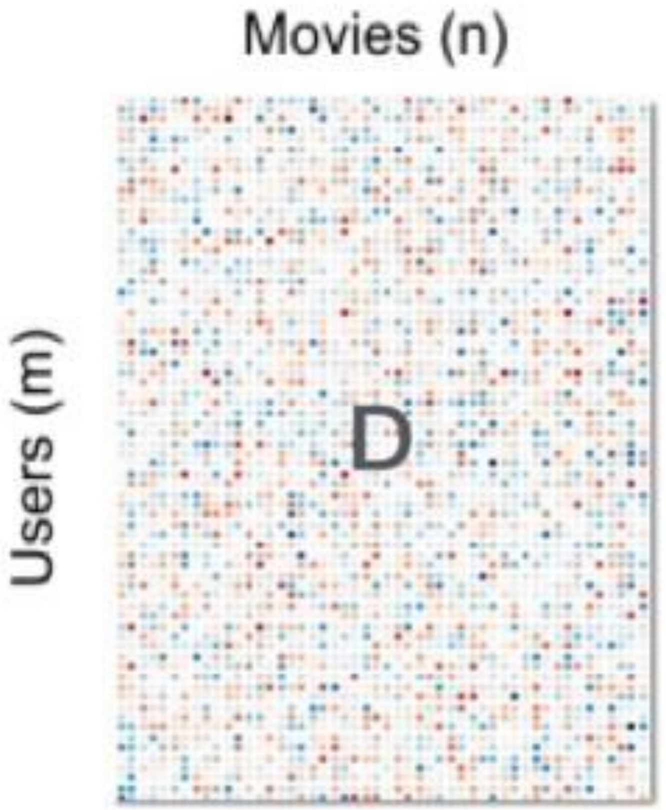
1. Collaborative Filtering – Item-Item **Benefits**

- “If you like this you might also like that”
- Good when #users >> #items
- Very fast after the item-item table has been pre-computed

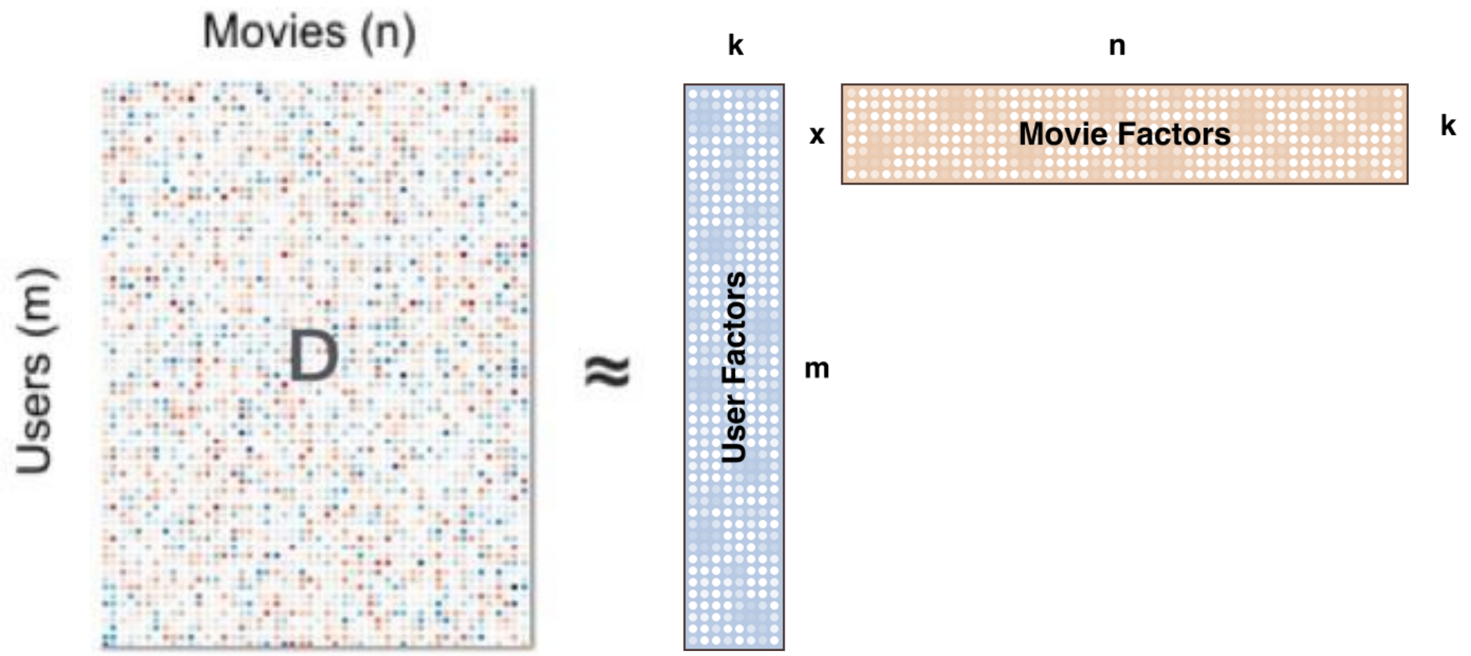
1. Collaborative Filtering – Item-Item **Challenges**

- Bottleneck – similarity computation
- Space complexity – dense item-item similarity matrix
- Model Too Simplistic – Accuracy of recommendation may be poor

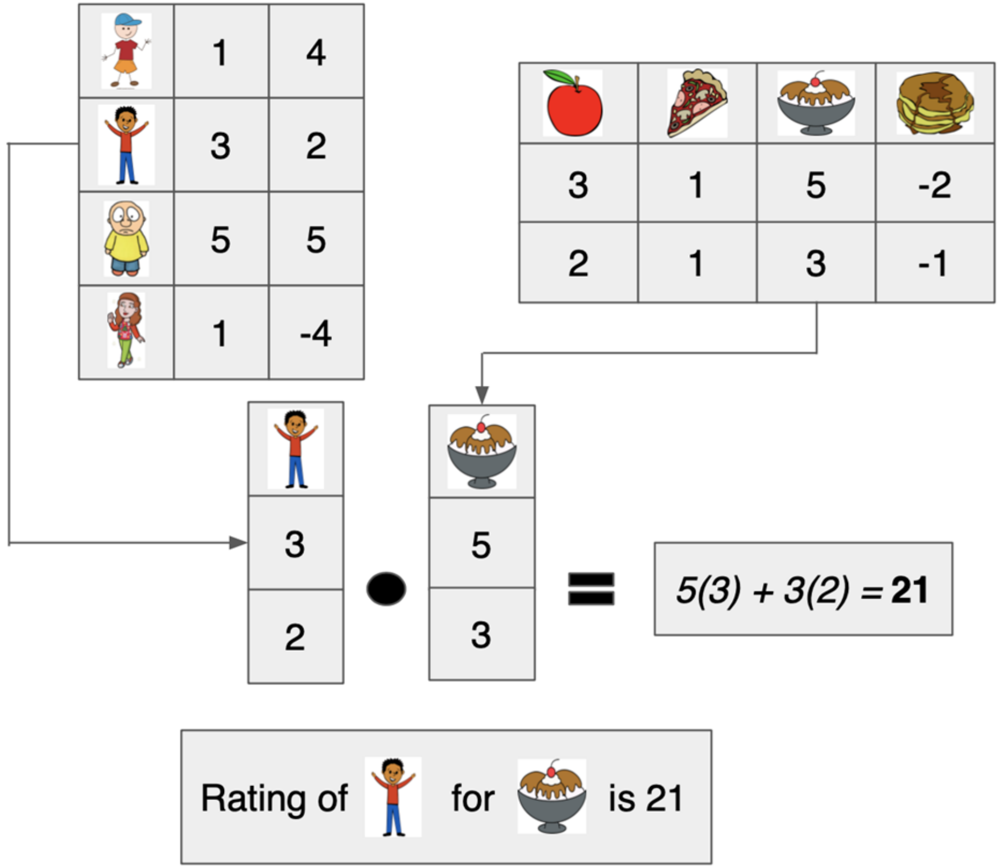
1. Collaborative Filtering – **User-Item**



1. Collaborative Filtering – **User-Item**



1. Collaborative Filtering – **User-Item**



1. Collaborative Filtering – **User-Item**

U*I = U*d   d*I

Item

User	W	X	Y	Z
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*

4*2

User Matrix

X

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

2*4

Item Matrix

we’ll feed our model with the vector [1.2, 0.8].[1.2,0.6] and force its output to equal 4.5

1. Collaborative Filtering – **Matrix Factorization**

- SGD – Stochastic Gradient Descent
- SVD – Truncated Singular Value Decomposition
- ALS – Alternating Least Square

1. Collaborative Filtering – User-Item **Benefits**

similar

- Fast after U and I are pre-computed
- Can learn more about users with U
- Can learn more about items with I

1. Collaborative Filtering – User-Item **Challenges**

- Sparsity
- Need to re-learn everything every time a new user or new item or new rating enter the game

1. Collaborative Filtering – Sparsity Example, the **Netflix Prize**

- 17,770 Movies

- 480,189 Users

- 100,480,507 Ratings How

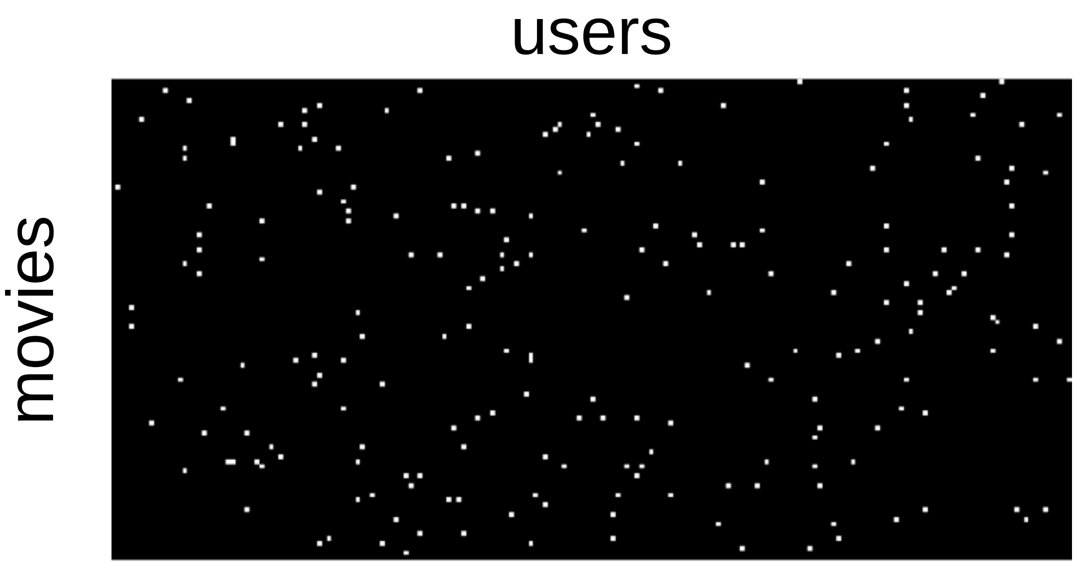
dense is our Matrix?

$$\frac{Ratings}{Movies \times Users} = \frac{100,480,507}{17,770 \times 480,189} \times 100 = 1.18\%$$

1. Collaborative Filtering – Sparsity Example, the **Netflix Prize**

- 17,770 Movies
- 480,189 Users
- 100,480,507 Ratings

How dense is our Matrix ?



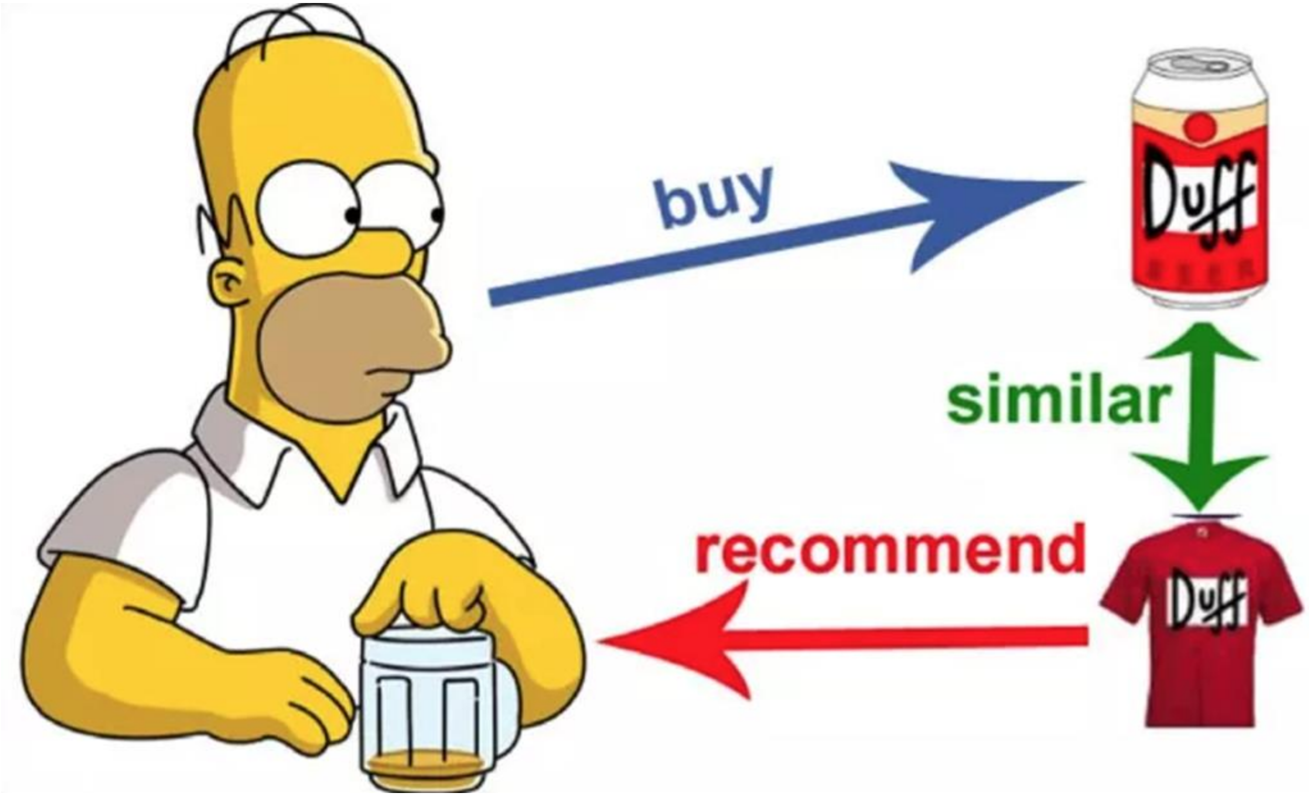
$$\frac{Ratings}{Movies \times Users} = \frac{100,480,507}{17,770 \times 480,189} \times 100 = 1.18\%$$

Content based filtering

2. Content based filtering(Content Extraction)

Based on “what does the user like about an item”:

- Meta-data extraction
- Clustering
- Similarity/distance between objects



2. Content based filtering– **Item-Item Similarity**

- Allow to compute similarities between items

- Does not require rating dataset

- The previous item-item recommendation algorithm still works

- No item cold start

- User attributes mitigate user cold start

In Production

4. In Production – Current Problematics

Data quality –implicit feedback; etc.

Sparsity – increase in size with items / users

Cold start problem – user cold start; item cold start

Recommendation speed – O(#items) algorithms not possible

4. In Production – Solutions

Data quality

Unbiased consumer app where the users enter their tastes(transfer learning)

Sparsity

User interaction: Ask each user to rate the most informative items

Cold start problem

Hybrid models with deep content extraction to recommend new items without ratings

Recommendation speed

Use GPU & TPU ☺

Use ligther method

4. In Production – Tools

LightFM

☺ open source: https://github.com/lyst/lightfm
☺ hybrid: matrix factorization + context

Deep Learning?

😐 way less tools than Computer Vision or NLP
😐 no pre-trained model available – you need large dataset and GPUs
😐 TensorFlow and PyTorch support for sparse data is limited

#DONTFORGETUS

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