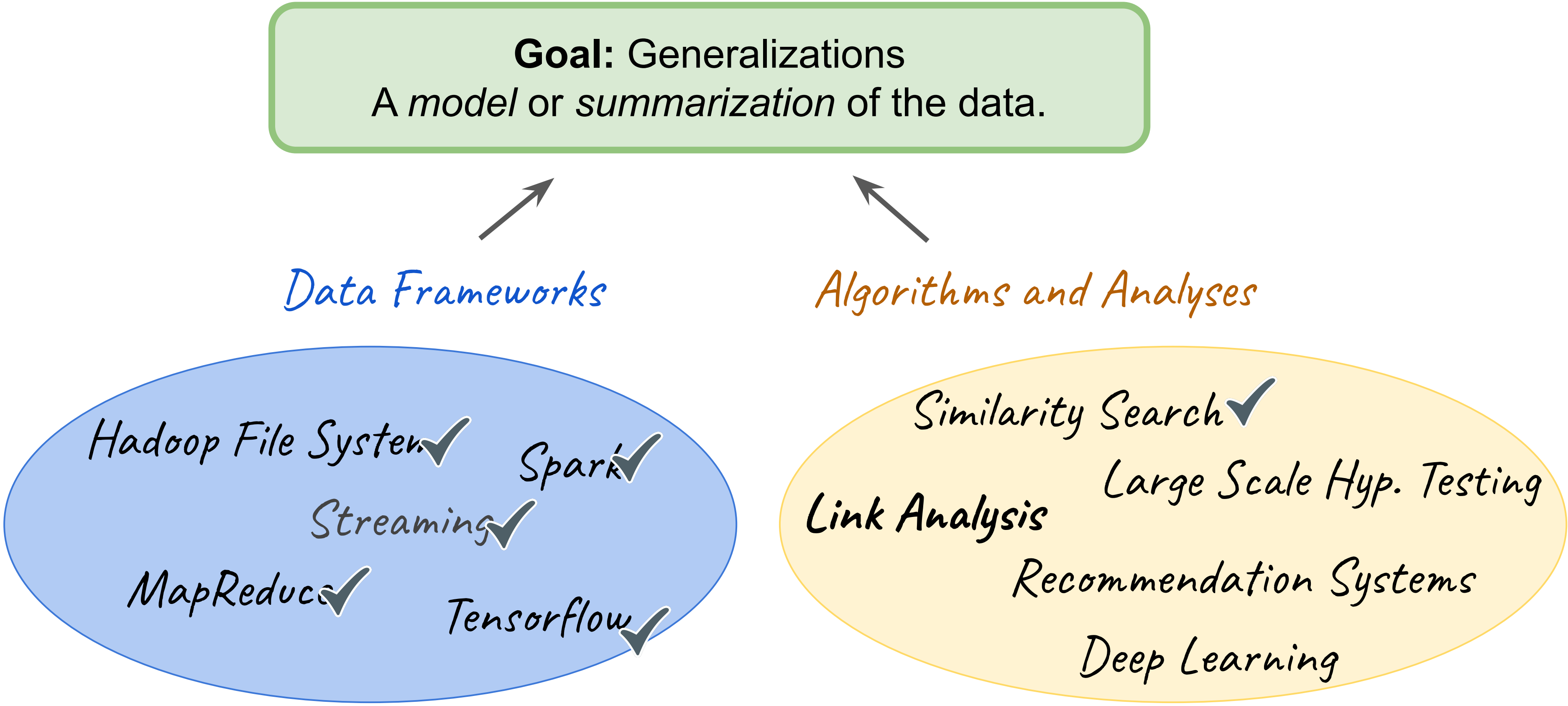
Recommendation Systems

CSE545 - Spring 2022

Stony Brook University

H. Andrew Schwartz

Big Data Analytics, The Class



Goal: Generalizations
A *model* or *summarization* of the data.

Data Frameworks

- Hadoop File System ✓
- Spark ✓
- Streaming ✓
- MapReduce ✓
- Tensorflow ✓

Algorithms and Analyses

- Similarity Search ✓
- Large Scale Hyp. Testing
- Link Analysis
- Recommendation Systems
- Deep Learning

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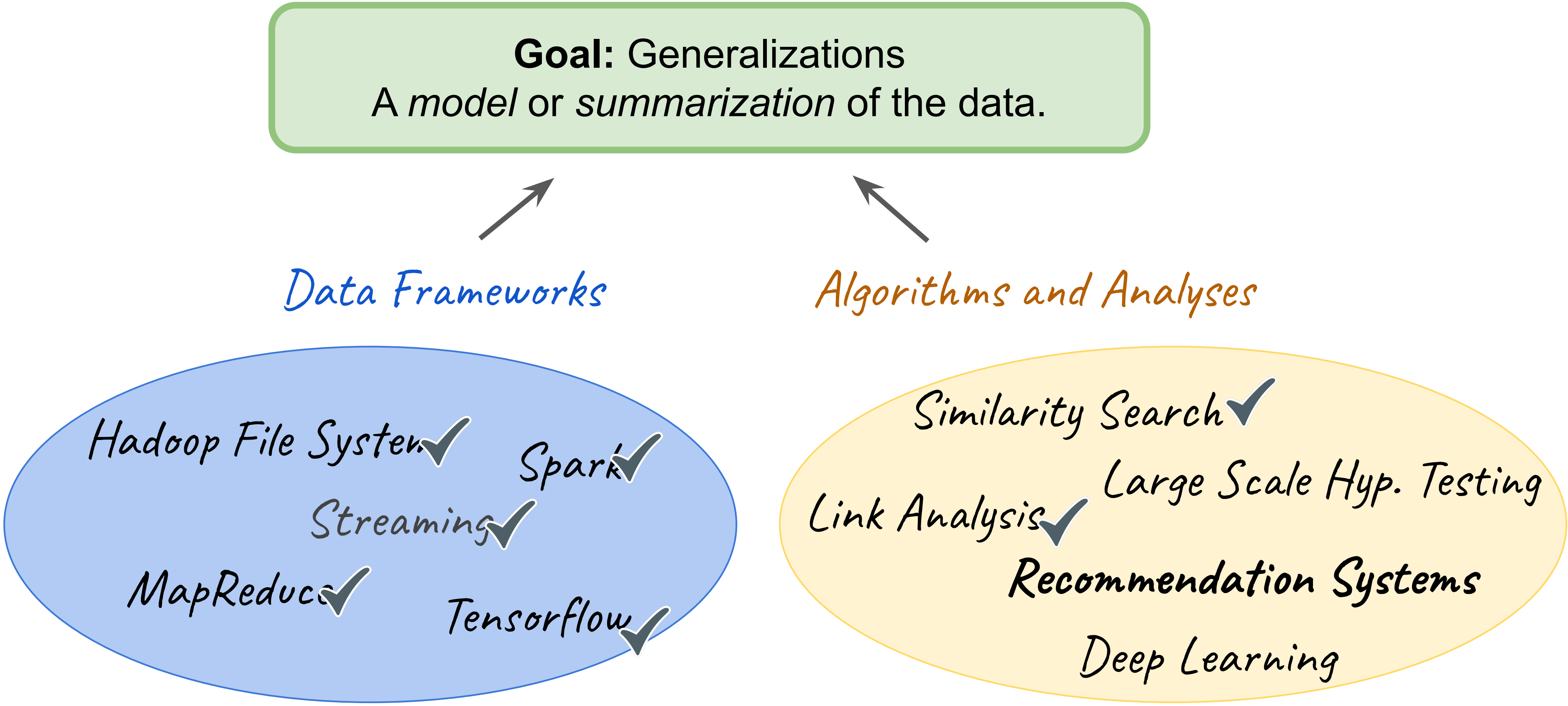

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- **Recommendation Systems**
- Deep Learning

Recommendation Systems

- What other item will this **user** like? (based on previously liked items)
- How much will user like item X?

Recommendation Systems

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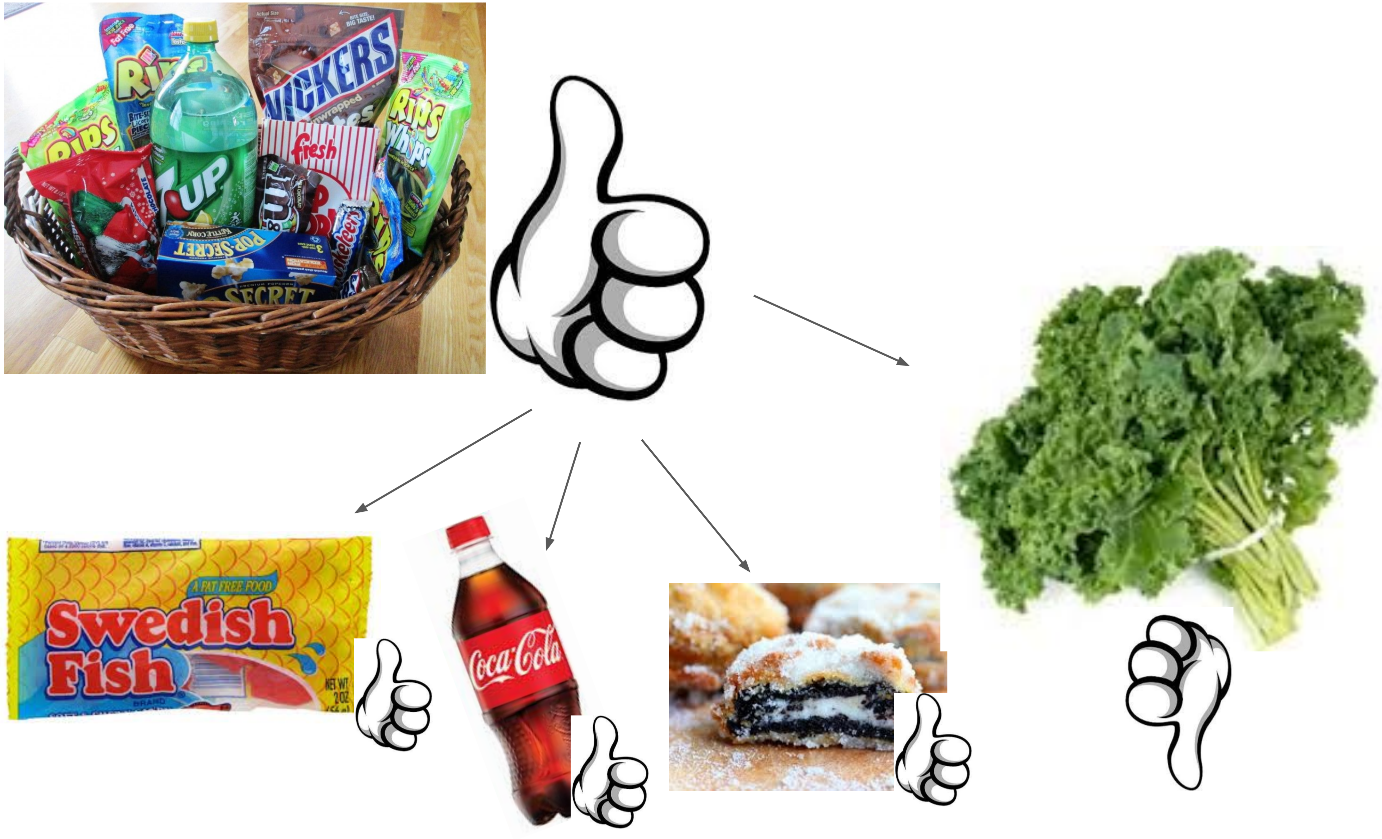
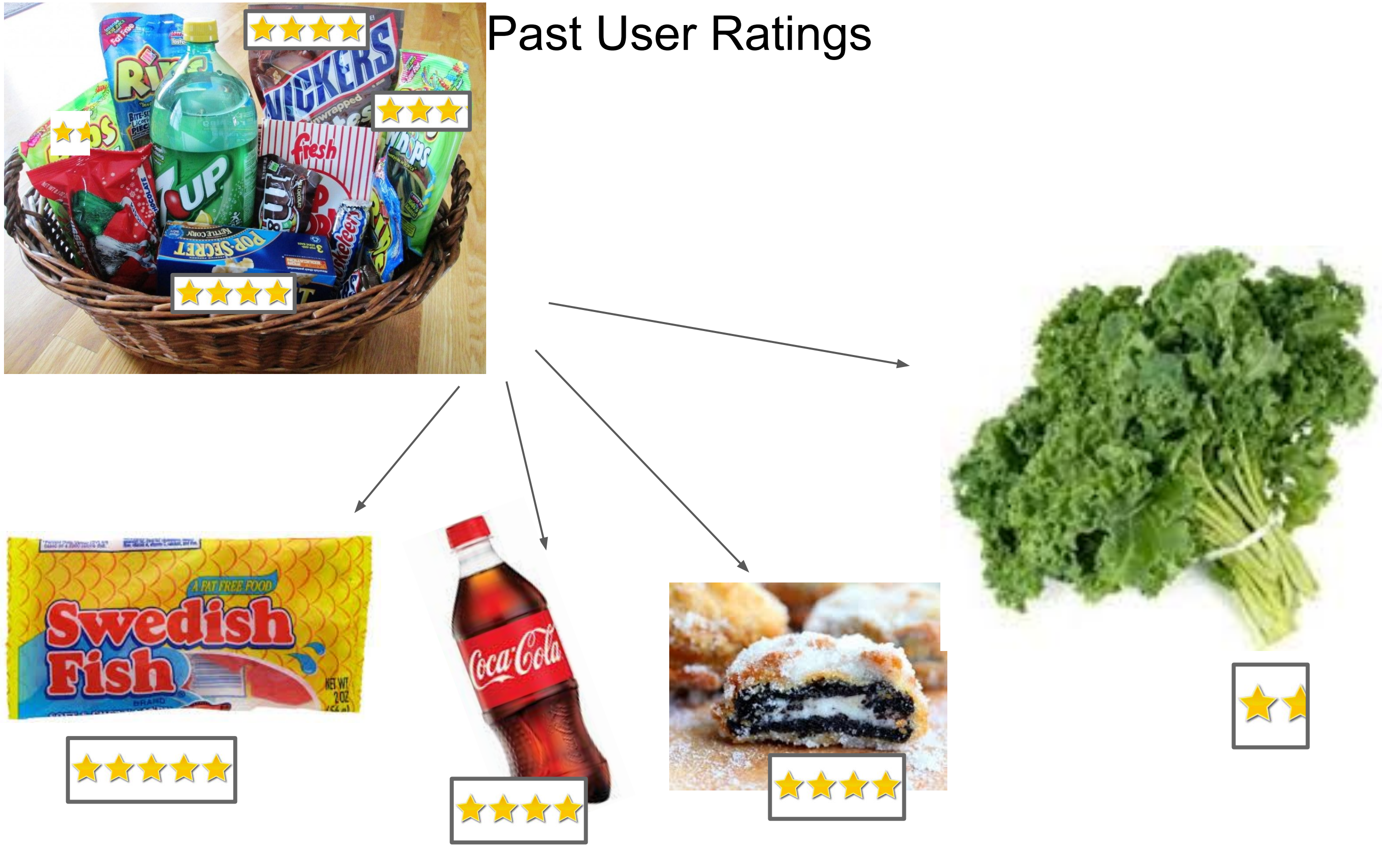
Recommendation Systems



Recommendation Systems



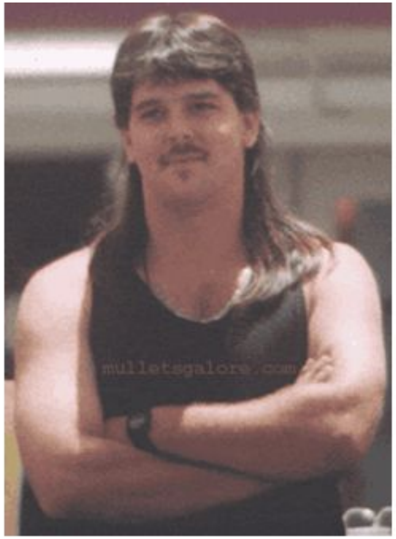
Past User Ratings

Recommendation Systems

Why Big Data?

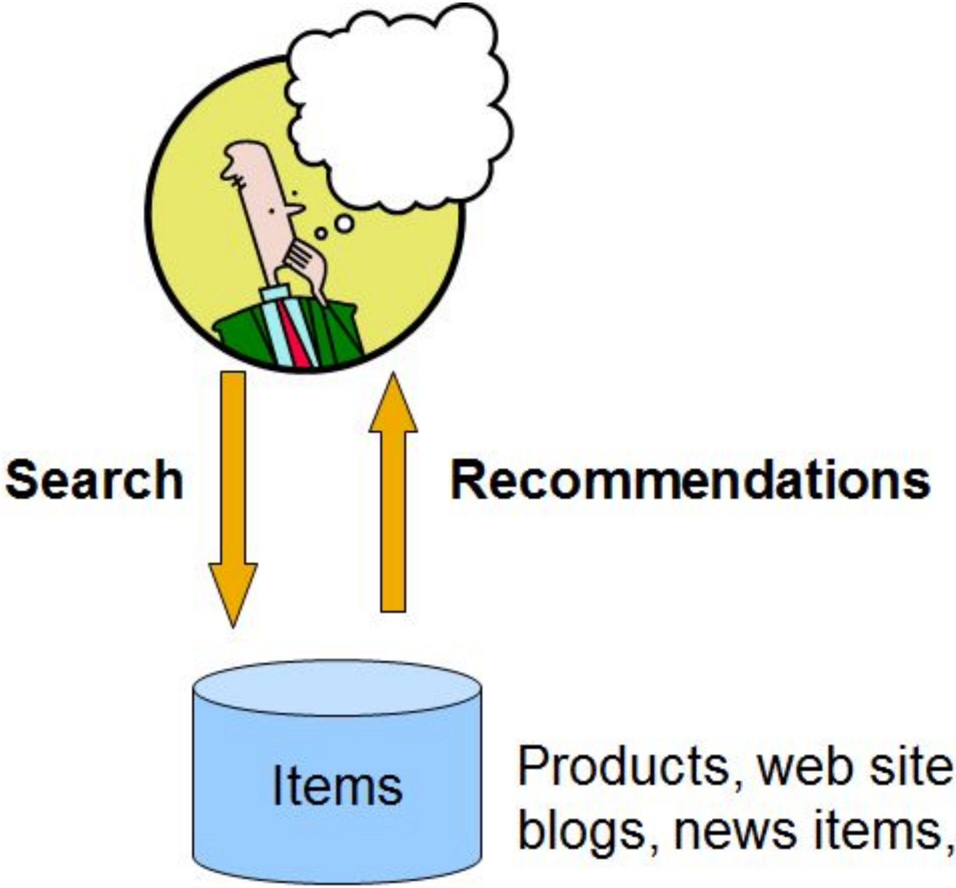
- Data with many potential features (and sometimes observations)
- An application of techniques for finding similar items
  - locality sensitive hashing
  - dimensionality reduction

Recommendation Systems: Example



- **Customer X**
  - Buys Metallica CD
  - Buys Megadeth CD

- **Customer Y**
  - Does search on Metallica
  - Recommender system suggests Megadeth from data collected about customer **X**



Products, web sites, blogs, news items, …

Examples:

amazon.com

PANDORA

StumbleUpon

del.icio.us

NETFLIX

movielens
helping you find the *right* movies

last.fm
the social music revolution

Google News

YouTube

XBOX LIVE

Origins: Web Shopping

- Does Wal-Mart have everything you need?

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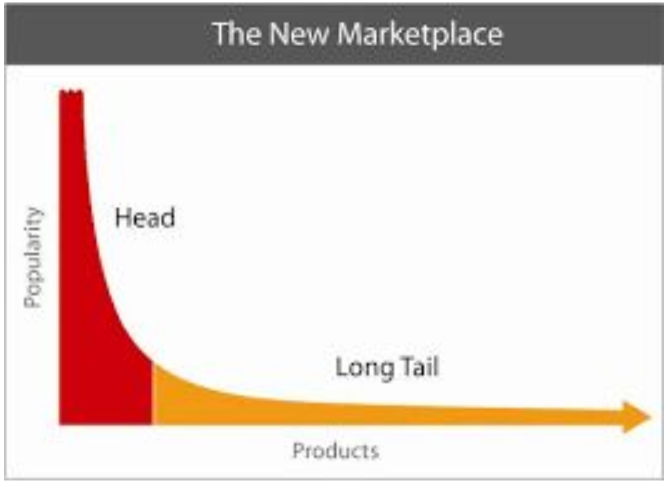


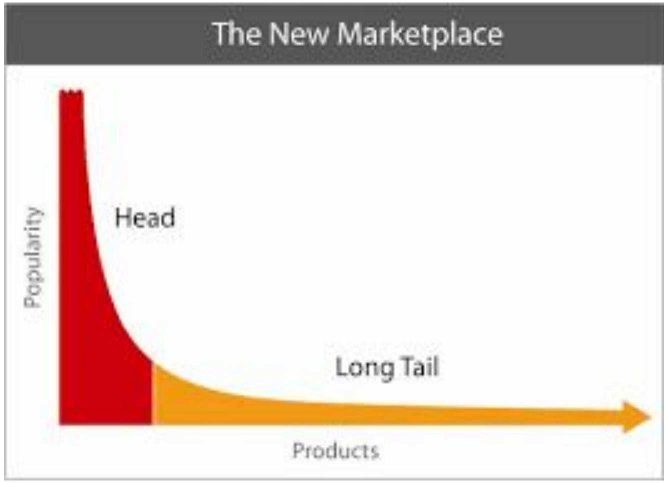
(thelongtail.com)

Origins: Web Shopping

- Does Wal-Mart have everything you need?

- A lot of products are only of interest to a small population (i.e. “long-tail products”).
- However, most people buy many products that are from the long-tail.

- Web shopping enables more choices
  - Harder to search
  - Recommendation engines to the rescue



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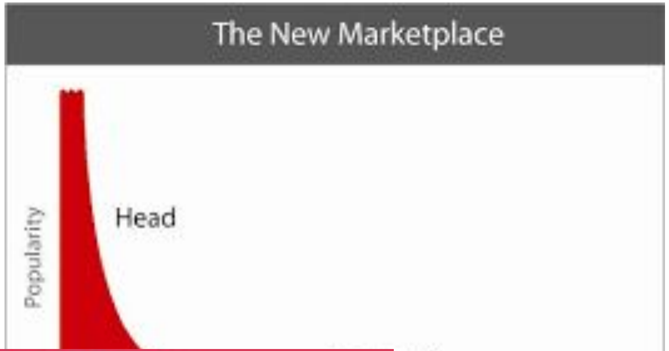

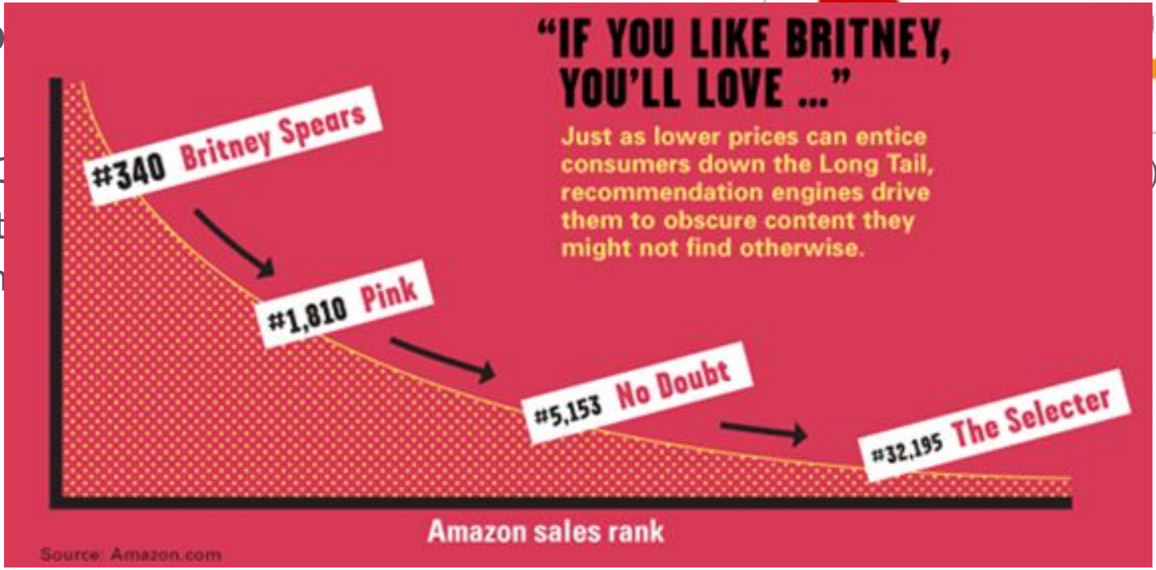

“IF YOU LIKE BRITNEY, YOU’LL LOVE …”

Just as lower prices can entice consumers down the Long Tail, recommendation engines drive them to obscure content they might not find otherwise.

Source: Amazon.com

Rec Systems Model

Given: *users*, *items, utility matrix*

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user	Game of Thrones	Fargo	Brooklyn Nine-Nine	Silicon Valley	Walking Dead
A	4	5	3		3
B	5			4	2
C			5	2	

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Rec Systems Model

Problems to tackle:

1. Gathering ratings

2. Extrapolate unknown ratings
   a. Explicit: based on user ratings and reviews
      (problem: only a few users engage in such tasks)
   b. Implicit: Learn from actions (e.g. purchases, clicks)
      (problem: hard to learn low ratings)

3. Evaluation

Rec Systems Model

Common Approaches

1. Content-based
2. Collaborative
3. Latent Factor

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Based on similarity of items to past items that they have rated.

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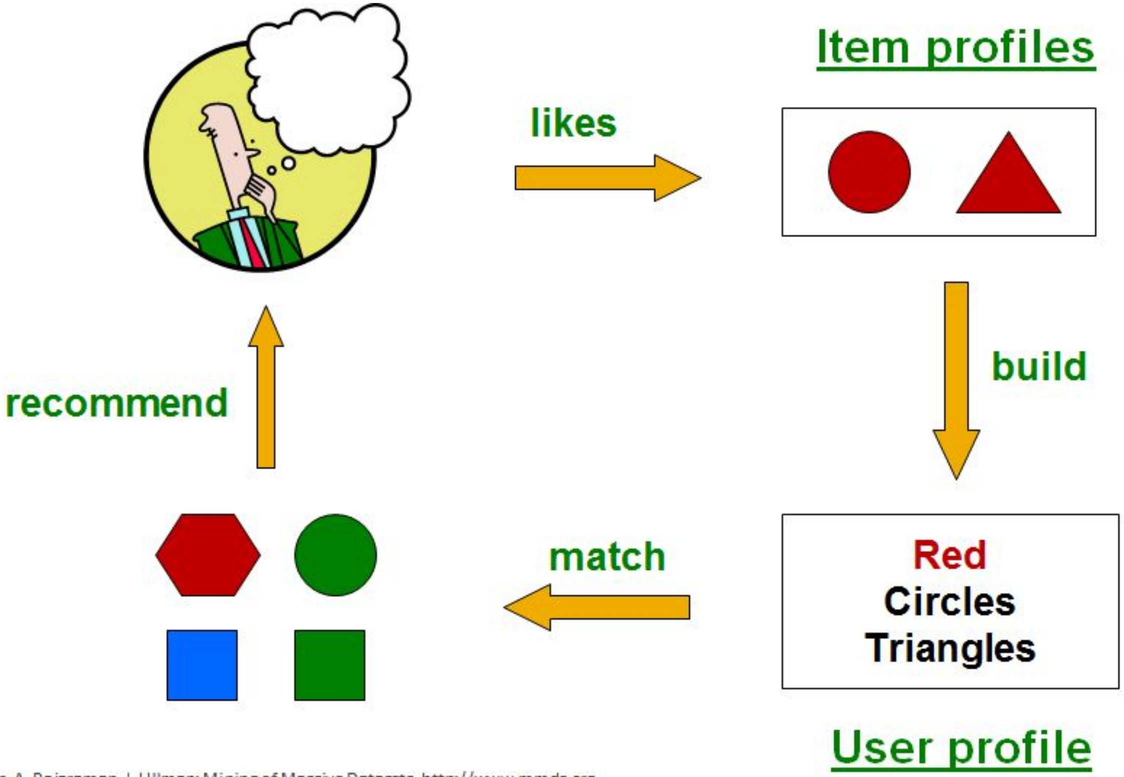

J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

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Based on similarity of items to past items that they have rated.

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    people: friends, posts

pick words with tf-idf

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   average all item profiles of items they've purchased

   variation: weight by difference from their average

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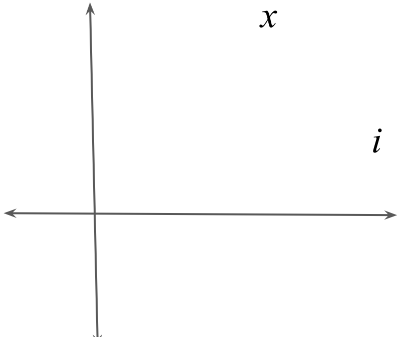
    find similarity between user and items



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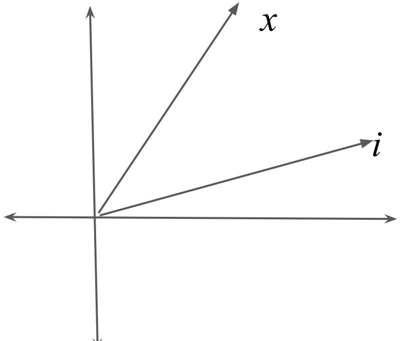
$$utility(user, i) = \cos(x, i) = \frac{x \cdot i}{||x|| \cdot ||i||}$$



Distance Metrics (for Similarity)

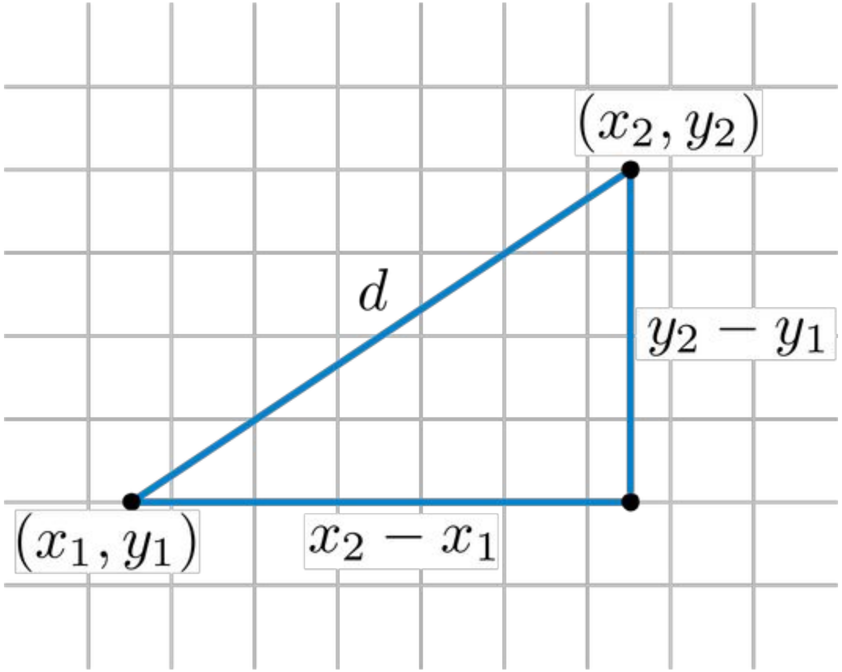
finding *near-neighbors* in *high-dimensional space*

Typical properties of a distance metric, *d*:

d(a, a) = 0

d(a, b) = d(b, a)

d(a, b) ≤ d(a,c) + d(c,b)



(http://rosalind.info/glossary/euclidean-distance/)

Distance Metrics (for Similarity)

finding *near-neighbors* in *high-dimensional space*

There are other metrics of similarity. e.g:

- Euclidean Distance
- Cosine Distance

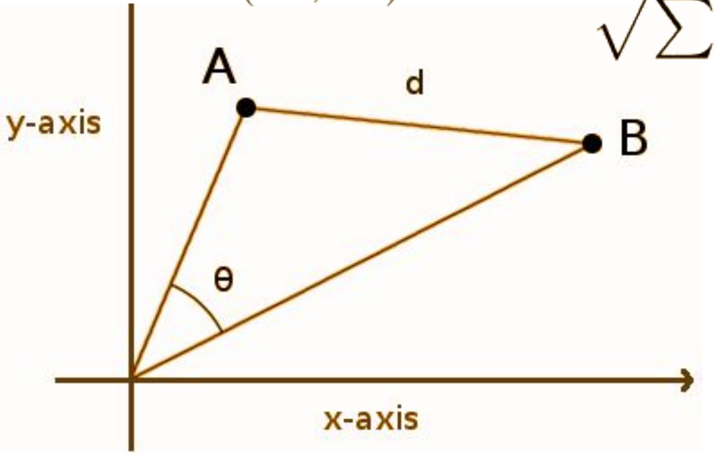
…

- Edit Distance
- Hamming Distance

$$distance(X,Y) = \sqrt{\sum_{i}^{n}(x_i - y_i)^2}$$

("L2 Norm")

$$distance(X,Y) = 1 - \frac{\sum x_i y_i}{\sqrt{\sum x_i^2}\sqrt{\sum y_i^2}}$$



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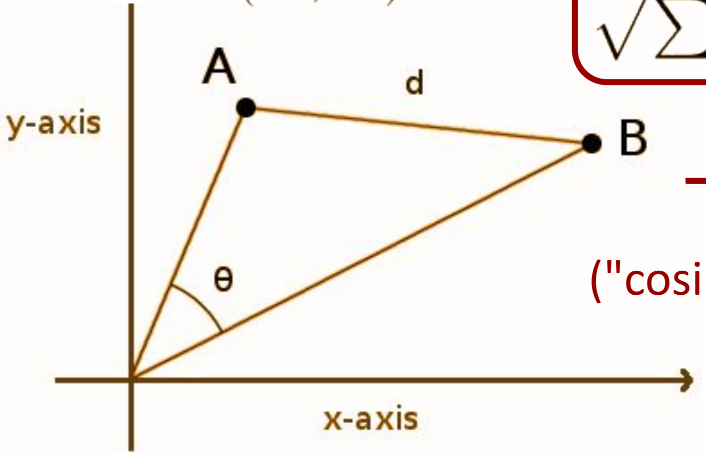

$$\frac{X \cdot Y}{||X||\,||Y||}$$

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(not exploiting other users judgments)

Collaborative Filtering

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Rec Systems

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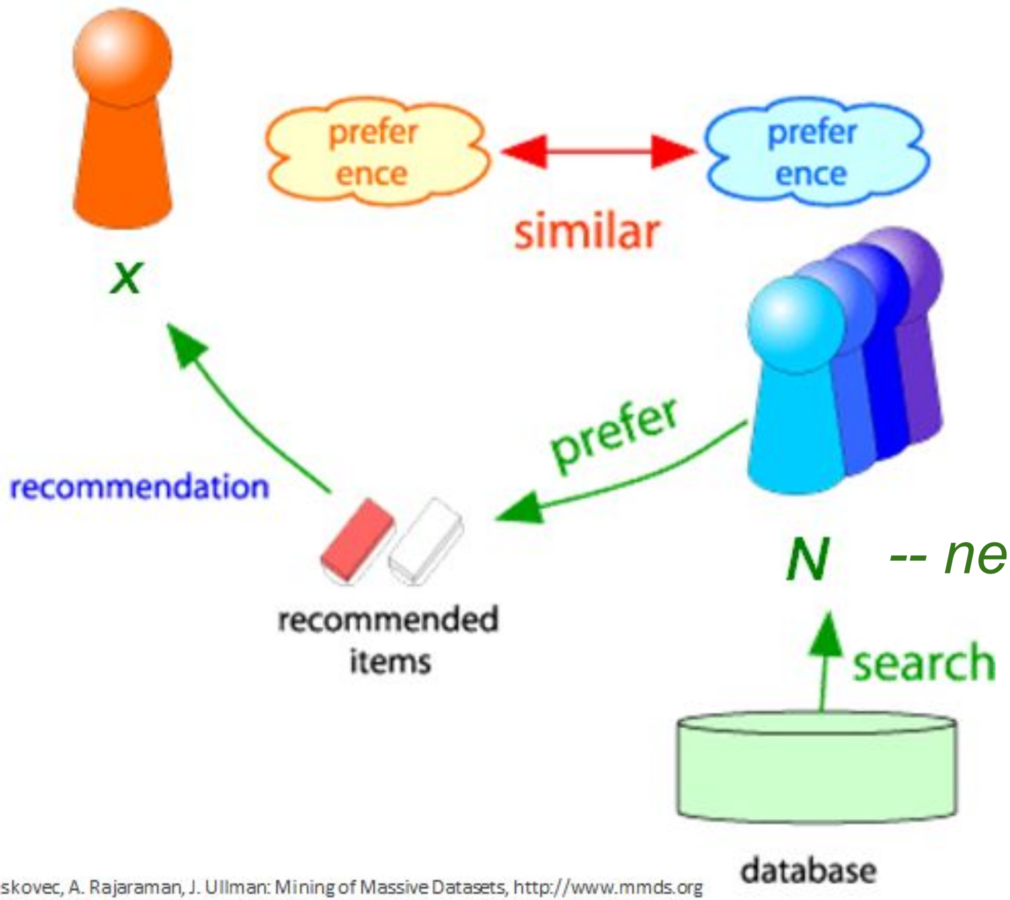

-- neighborhood

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General Idea:

1) Find similar users = "neighborhood"

2) Infer rating based on how similar users rated

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Given:  user, x;   item, i;   utility matrix, u
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Solution: subtract user's mean, add zeros for missing

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    -- threshold to top k (e.g. k = 30)
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    -- average, weighted by sim
```

$$utility(x,i) = \frac{\sum_{y \in N} Sim(x,y) \cdot utility(y,i)}{\sum_{y \in N} Sim(x,y)}$$

Collaborative Filtering

“User-User collaborative filtering”

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Given:  user, x;   item, i;   utility matrix, u
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Item-Item:

Flip rows/columns of utility matrix and use same methods.
(i.e. estimate rating of item i, by finding similar items, j)

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1.  Find neighborhood, N # set of k items most similar to
                                   i also rated by x
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    -- threshold to top k (e.g. k = 30)
2. Predict utility (rating) by x based on N
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```

$$\text{utility}(x,i) = \frac{\sum_{j\in N} Sim(i,j)\cdot \text{utility}(x,j)}{\sum_{j\in N} Sim(i,j)}$$

item-item vs user-user

Item-item often works better than user-user. Why?

Users tend to be more different from each other than items are from other items.

e.g. Mary likes jazz + rock, Coleman likes classical + rock,

but Mary may still have same rock preferences as Bob

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e.g. Mary likes jazz + rock, Coleman likes classical + rock,
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In other words, users span genres but items usually do not.

Item-Item: Example

movies	1	2	3	4	5	6	7	8	9	10	11	12
1	1		3			5			5		4	
2			5	4			4			2	1	3
3	2	4		1	2		3		4	3	5	
4		2	4		5			4			2	
5			4	3	4	2					2	5
6	1		3		3			2			4	

□ - unknown rating 🟨 - rating between 1 to 5

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movies

	1	2	3	4	**5**	6	7	8	9	10	11	12
1	1		3		?	5			5		4	
2			5	4			4			2	1	3
3	2	4		1	2		3		4	3	5	
4		2	4		5			4			2	
5			4	3	4	2					2	5
6	1		3		3			2			4	

🟥 - estimate rating of movie **1** by user **5**

J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

Item-Item: Example

movies	1	2	3	4	**5**	6	7	8	9	10	11	12	**sim(1,m)**
1	1		3		?	5			5		4		**1.00**
2			5	4			4			2	1	3	**-0.18**
3	2	4		1	2		3		4	3	5		**0.41**
4		2	4		5			4			2		**-0.10**
5			4	3	4	2					2	5	**-0.31**
6	1		3		3			2			4		**0.59**

Same as cosine sim when subtracting the mean

Neighbor selection:
Identify movies similar to movie **1**, **rated by user 5**

Here we use Pearson correlation as similarity:

1) Subtract mean rating m_i from each movie i

$m_1 = (1+3+5+5+4)/5 = \mathbf{3.6}$

row 1: *[-2.6, 0, -0.6, 0, 0, 1.4, 0, 0, 1.4, 0, 0.4, 0]*

2) Compute cosine similarities between rows

Item-Item: Example

movies

	1	2	3	4	5	6	7	8	9	10	11	12	sim(1,m)
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3	2	4		1	2		3		4	3	5		0.41
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5			4	3	4	2					2	5	-0.31
6	1		3		3			2			4		0.59

Compute similarity weights:

$s_{1,3}=0.41$, $s_{1,6}=0.59$

Item-Item: Example

movies

	1	2	3	4	5	6	7	8	9	10	11	12	sim(1,m)
1	1		3		?	5			5		4		1.00
2			5	4			4			2	1	3	-0.18
3	2	4		1	2		3		4	3	5		0.41
4		2	4		5			4			2		-0.10
5			4	3	4	2					2	5	-0.31
6	1		3		3			2			4		0.59

***utility*(1, 5) = (0.41*2 + 0.59*3) / (0.41+0.59)**

$$\text{utility}(x,i) = \frac{\sum_{j \in N} Sim(i,j) \cdot \text{utility}(x,j)}{\sum_{j \in N} Sim(i,j)}$$

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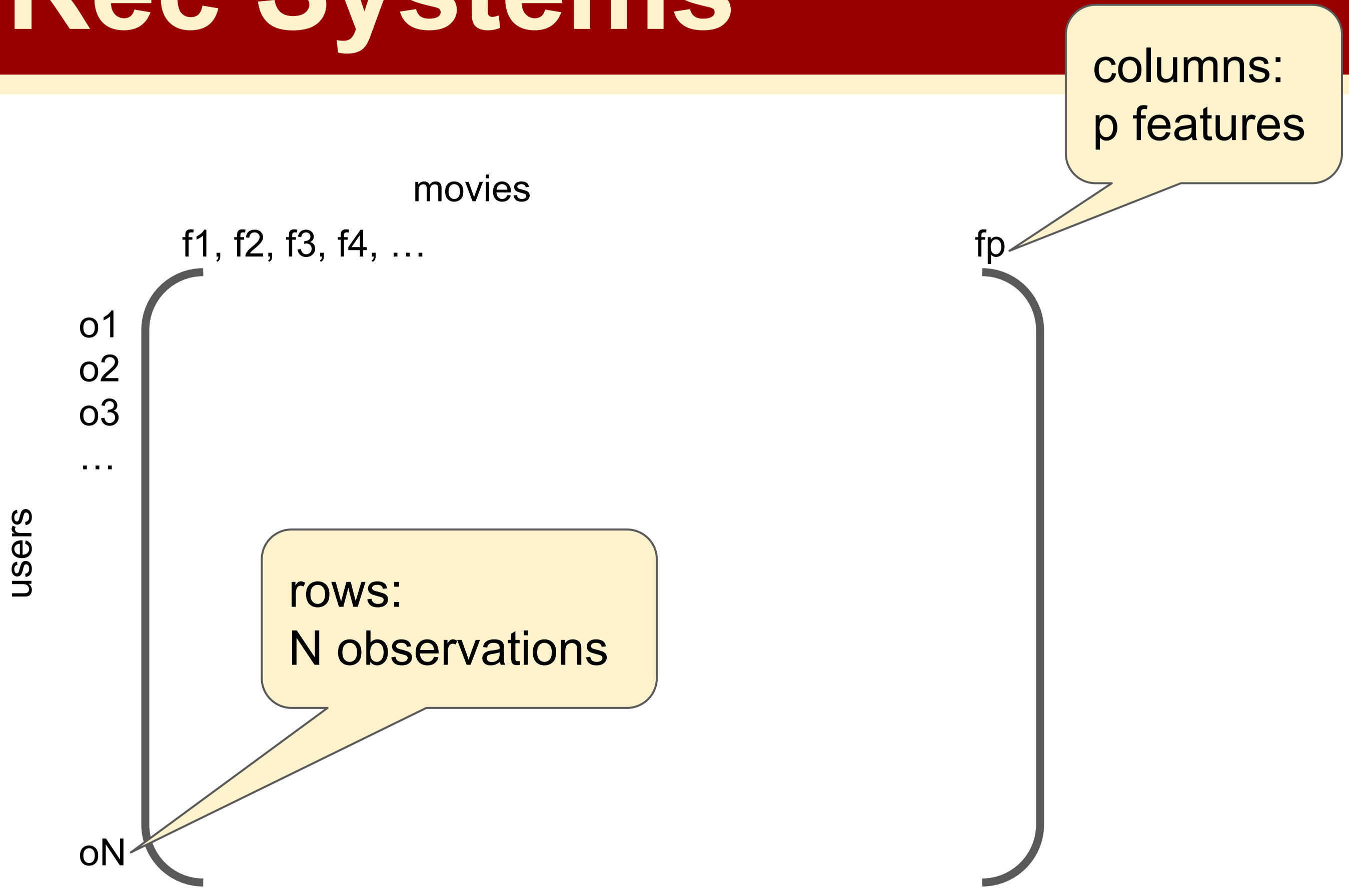
Rec Systems



movies

f1, f2, f3, f4, … fp

columns:
p features

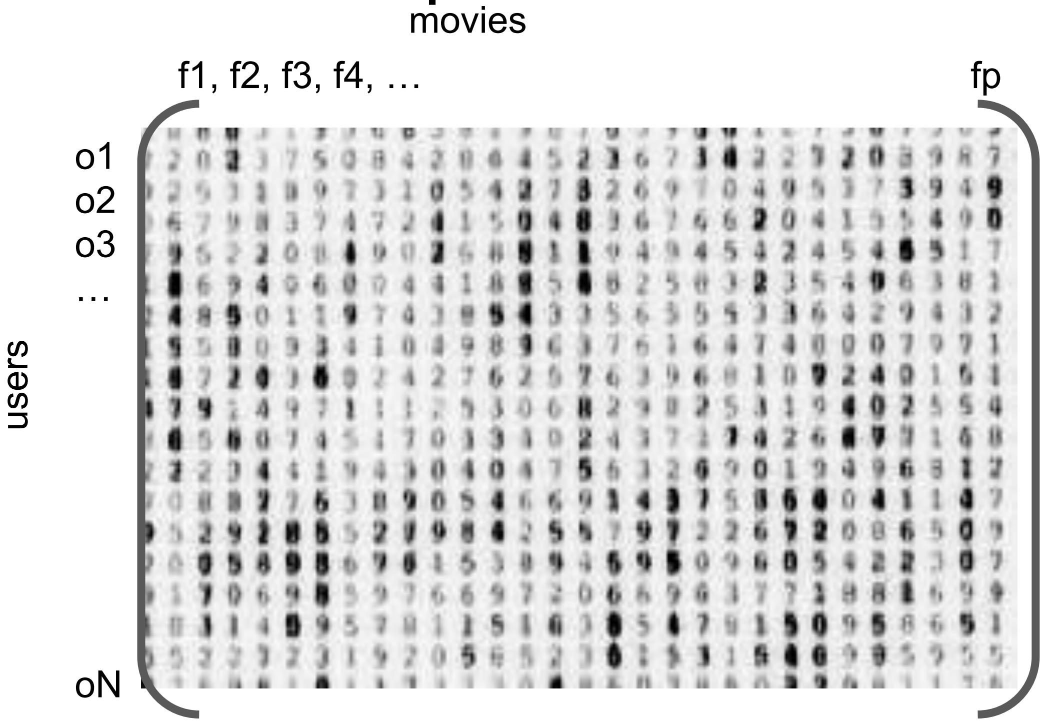
users

o1
o2
o3
…
oN

rows:
N observations

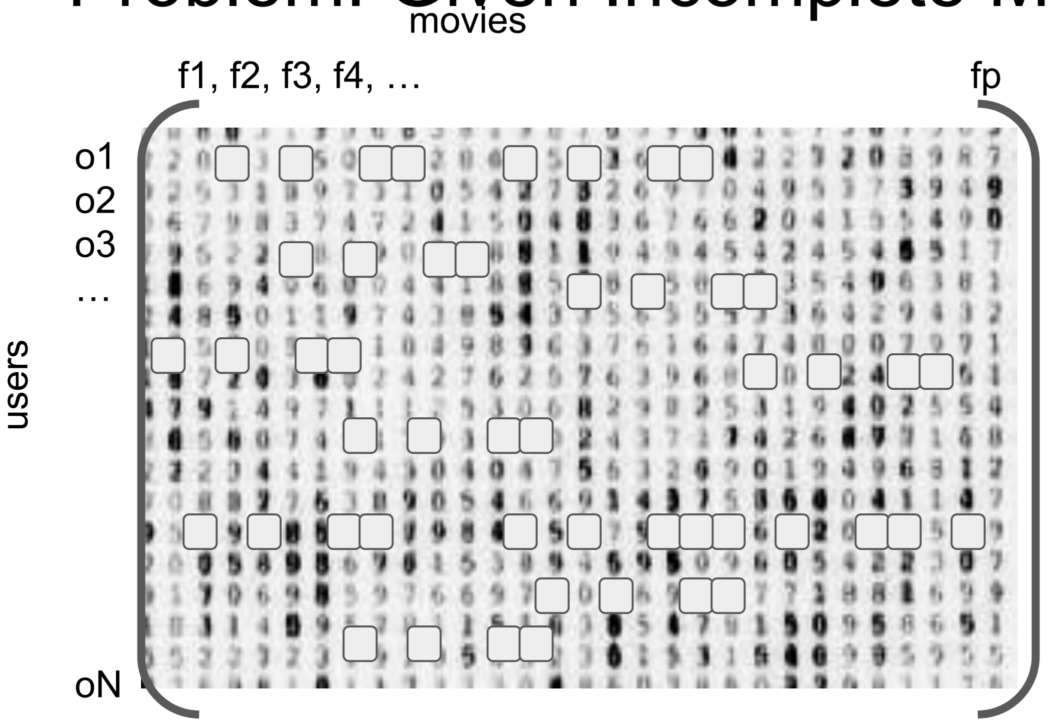
Rec Systems

Goal: Complete Matrix



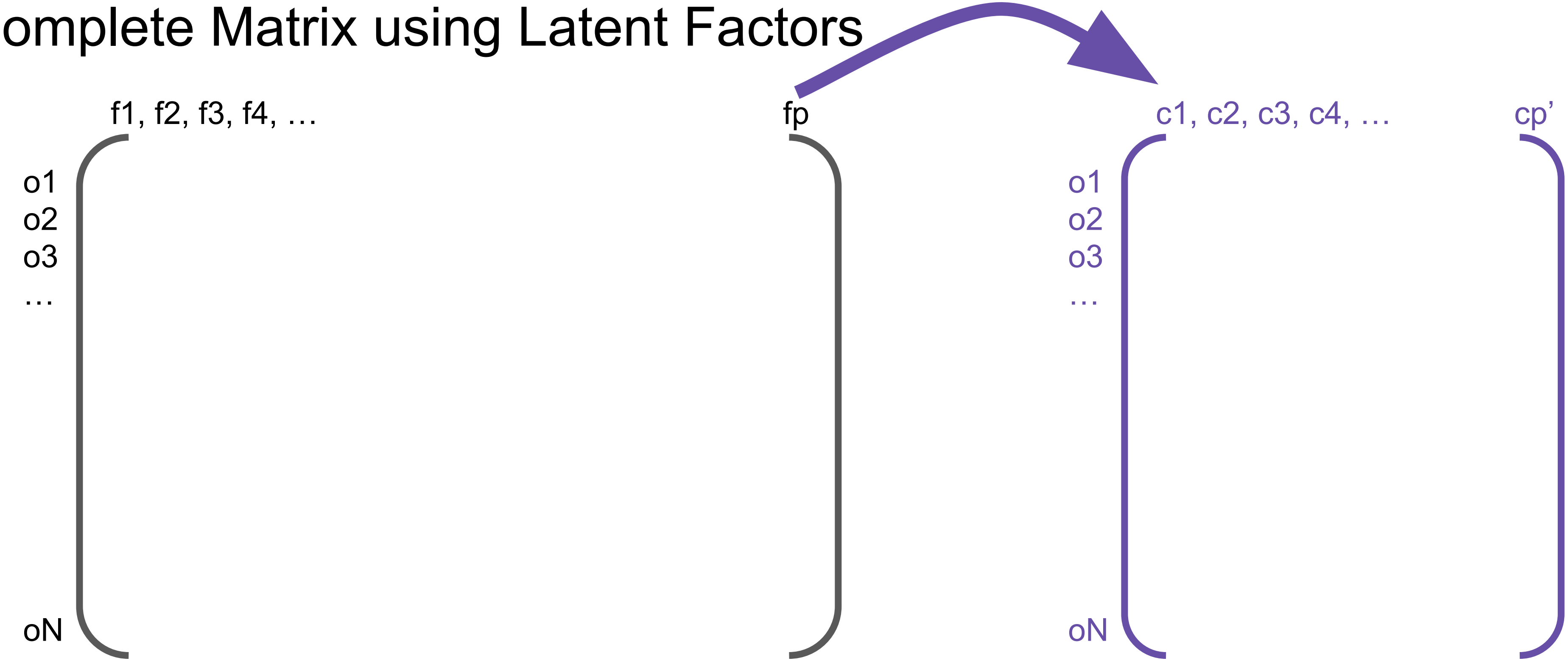
Rec Systems

Problem: Given Incomplete Matrix



Rec Systems

Complete Matrix using Latent Factors

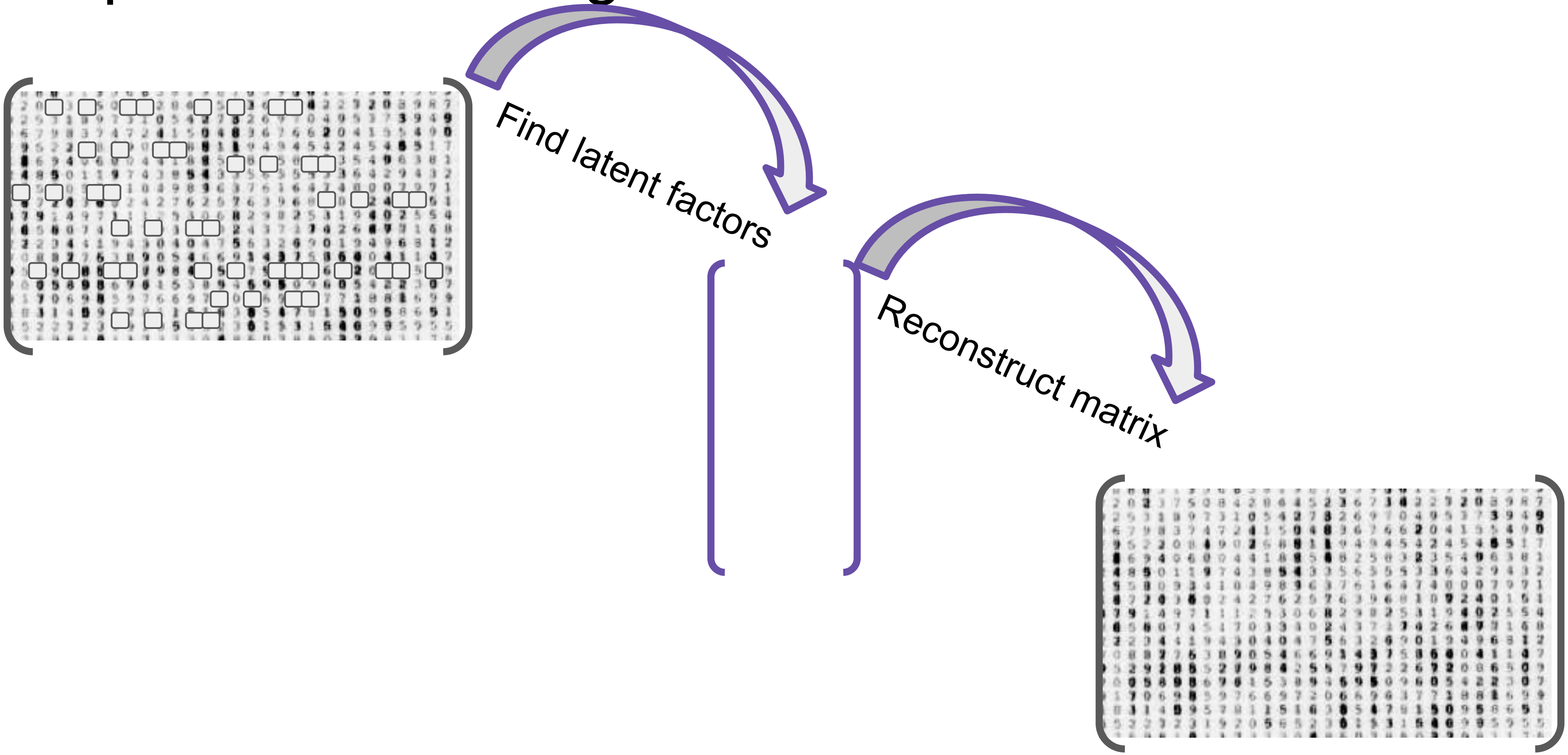


Dimensionality reduction

Try to best represent but with on p’ columns.

Rec Systems

Complete Matrix using Latent Factors



Dimensionality Reduction PCA

Linear approximates of data in *r* dimensions.

Found via *Singular Value Decomposition:*

$$X_{[nxp]} = U_{[nxr]} D_{[rxr]} V_{[pxr]}^{T}$$

X: original matrix,

D: “singular values” (diagonal),

U: “left singular vectors”,

V: “right singular vectors”

Projection (dimensionality reduced space) in 3 dimensions:

$$(U_{[nx3]} D_{[3x3]} V_{[px3]}^{T})$$

To reduce features in new dataset:

$$X_{new} V = X_{new\_small}$$

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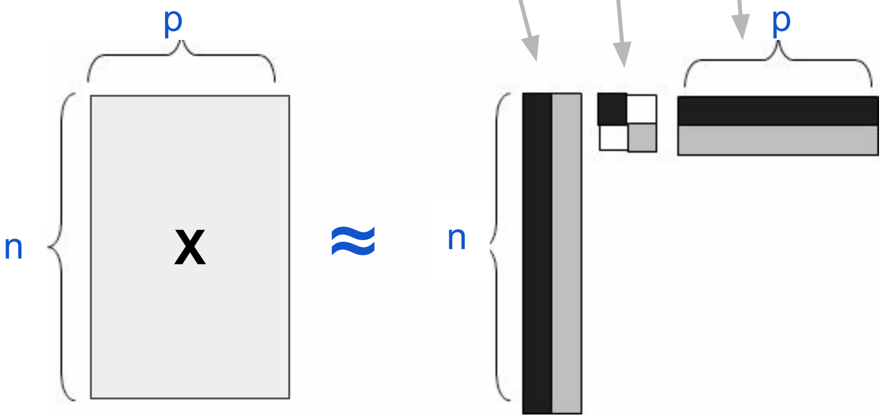
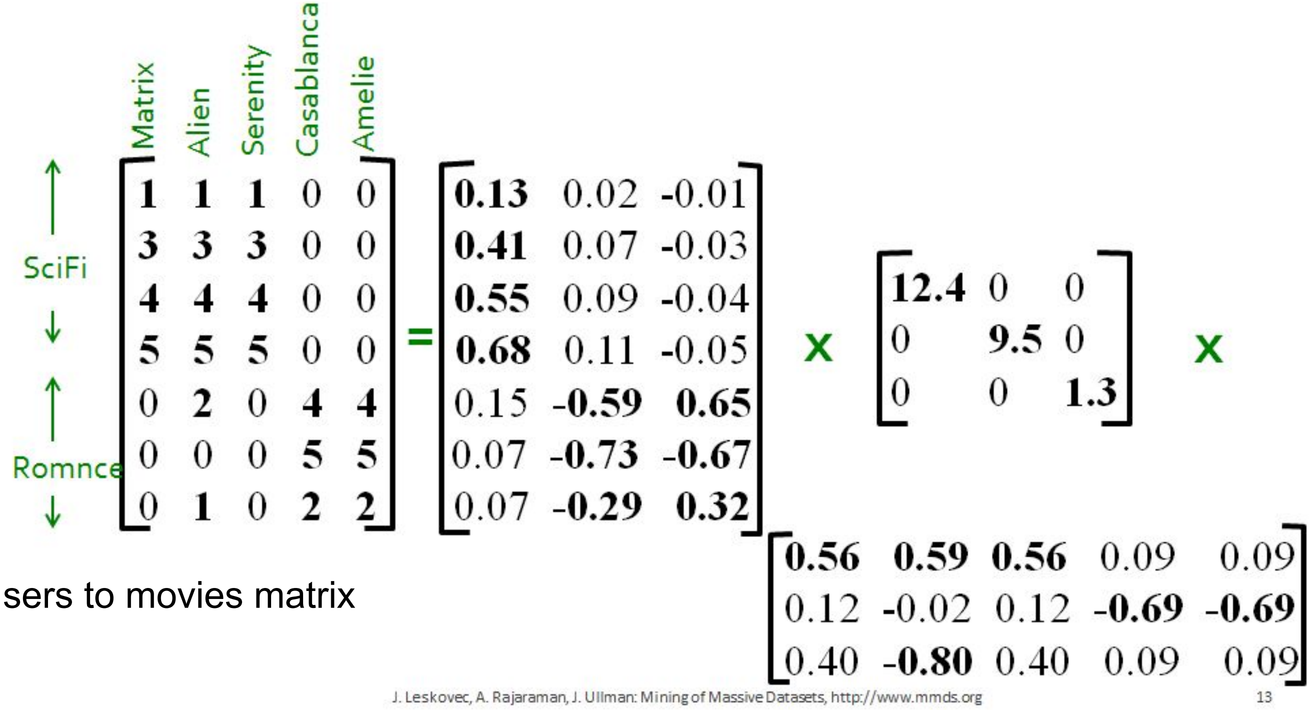


Dimensionality Reduction PCA

$$X_{[nxp]} = U_{[nxr]}\, D_{[rxr]}\, V_{[pxr]}^{T}$$



$$\begin{array}{c|ccccc}
 & \text{Matrix} & \text{Alien} & \text{Serenity} & \text{Casablanca} & \text{Amelie} \\
\hline
\uparrow\ \text{SciFi} & \mathbf{1} & \mathbf{1} & \mathbf{1} & 0 & 0 \\
 & \mathbf{3} & \mathbf{3} & \mathbf{3} & 0 & 0 \\
 & \mathbf{4} & \mathbf{4} & \mathbf{4} & 0 & 0 \\
\downarrow & \mathbf{5} & \mathbf{5} & \mathbf{5} & 0 & 0 \\
\uparrow\ \text{Romnce} & 0 & \mathbf{2} & 0 & \mathbf{4} & \mathbf{4} \\
 & 0 & 0 & 0 & \mathbf{5} & \mathbf{5} \\
\downarrow & 0 & \mathbf{1} & 0 & \mathbf{2} & \mathbf{2}
\end{array}
=
\begin{bmatrix}
\mathbf{0.13} & 0.02 & -0.01 \\
\mathbf{0.41} & 0.07 & -0.03 \\
\mathbf{0.55} & 0.09 & -0.04 \\
\mathbf{0.68} & 0.11 & -0.05 \\
0.15 & \mathbf{-0.59} & \mathbf{0.65} \\
0.07 & \mathbf{-0.73} & \mathbf{-0.67} \\
0.07 & \mathbf{-0.29} & \mathbf{0.32}
\end{bmatrix}
\times
\begin{bmatrix}
\mathbf{12.4} & 0 & 0 \\
0 & \mathbf{9.5} & 0 \\
0 & 0 & \mathbf{1.3}
\end{bmatrix}
\times
\begin{bmatrix}
\mathbf{0.56} & \mathbf{0.59} & \mathbf{0.56} & 0.09 & 0.09 \\
0.12 & -0.02 & 0.12 & \mathbf{-0.69} & \mathbf{-0.69} \\
0.40 & \mathbf{-0.80} & 0.40 & 0.09 & 0.09
\end{bmatrix}$$

Users to movies matrix

J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org 13

Dimensionality Reduction PCA

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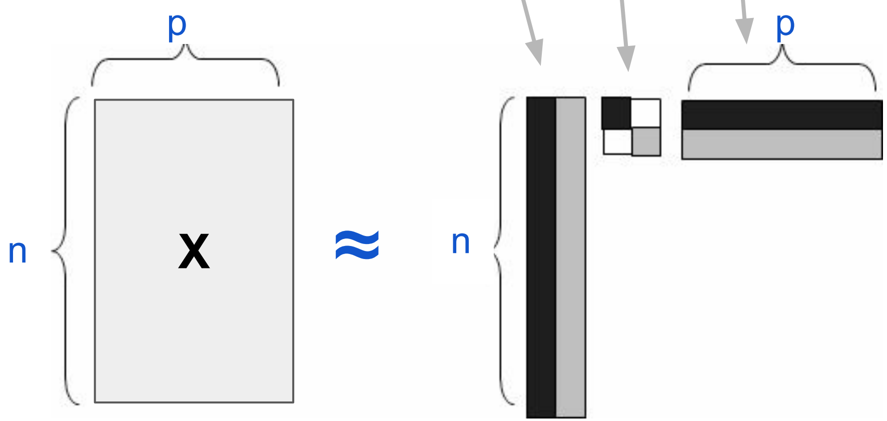
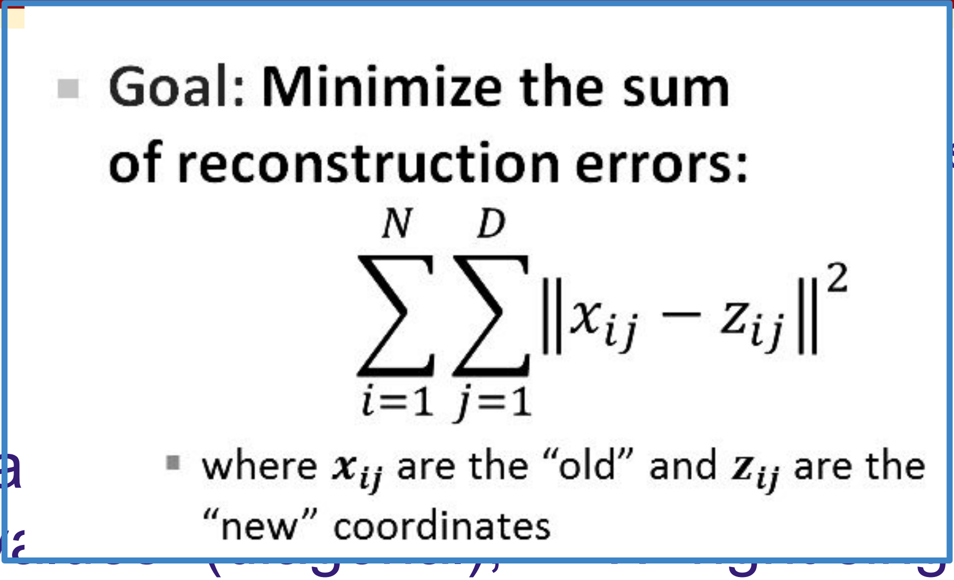


Dimensionality Reduction PCA

s.



- Goal: Minimize the sum of reconstruction errors:

$$\sum_{i=1}^{N}\sum_{j=1}^{D}\left\|x_{ij}-z_{ij}\right\|^{2}$$

  - where $\boldsymbol{x}_{ij}$ are the “old” and $\boldsymbol{z}_{ij}$ are the “new” coordinates

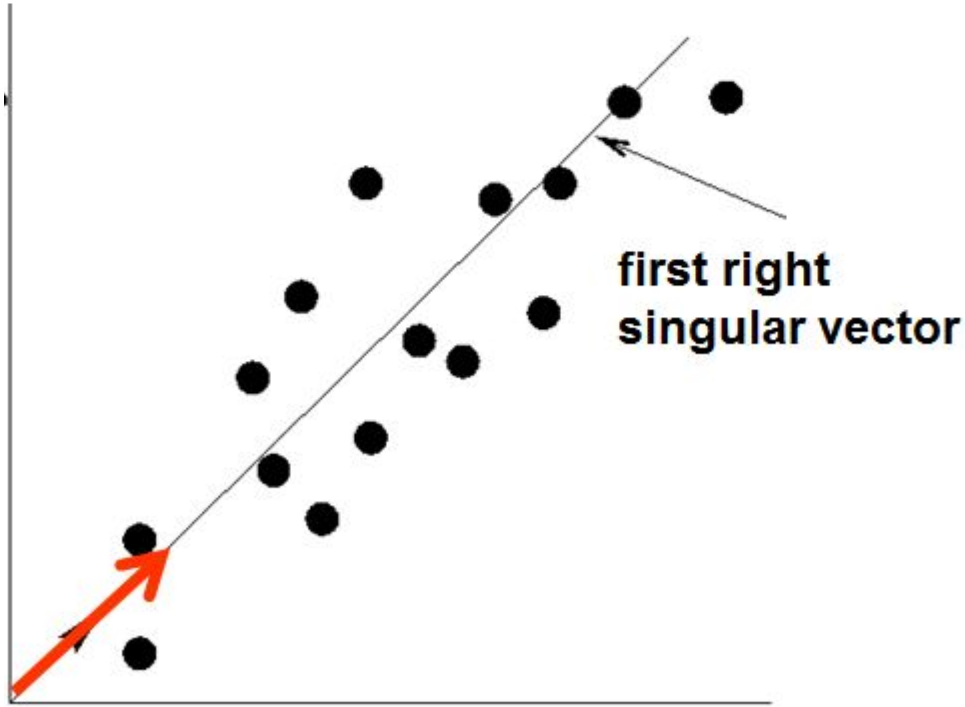
X: original ma lar vectors”,
D: “singular va ular vectors”

To check how well the original matrix can be reproduced:

$Z_{[nxp]} = U\,D\,V^{T}$, How does Z compare to original X?

Dimensionality Reduction PCA

$$X_{[nxp]} = U_{[nxr]} D_{[rxr]} V_{[pxr]}^{T}$$



PCA - Parallelized

1. Approximate solutions to PCA (very large speedups with little drawback!):
    a. **Stochastic Sampling** (also sometimes called "randomized" which is ambiguous): Only using a sample rows (i.e. only some users for recommendation systems)

    b. **Truncated SVD:** Only optimizing for minimizing reconstruction error based on up to r dimensions (full SVD solves for up to min(n, p) dimensions and then you just truncate the result for the lower rank version). One you do this, by the way, using a smaller sample becomes much less of a problem.

    c. **Limiting power iterations to a few iterations:** Power iterations from pagerank solves for the first principle component. This can be extended to multiple components.
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2. Distribute the matrix operations. Complex; not as flexible (usually done across processors within node)
3. Data Parallelism: As in other instances stochastic or mini-batch gradient descent.

Rec Systems

Common Approaches

1. Content-based
2. Collaborative
3. Latent Factor

Problems to tackle:

1. Gathering ratings
2. Extrapolate unknown ratings
   a. Explicit: based on user ratings and reviews (problem: only a few users engage in such tasks)
   b. Implicit: Learn from actions (e.g. purchases, clicks) (problem: hard to learn low ratings)
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