Recommendation Systems

Stony Brook University
CSE545, Spring 2019

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

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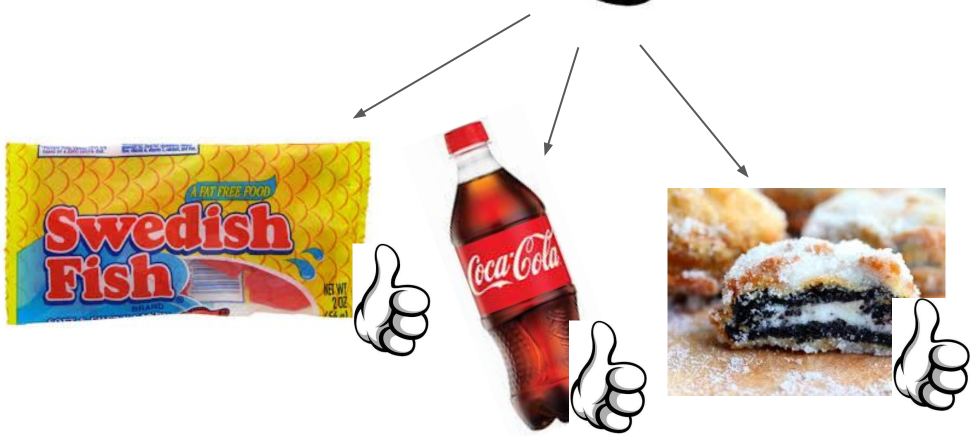
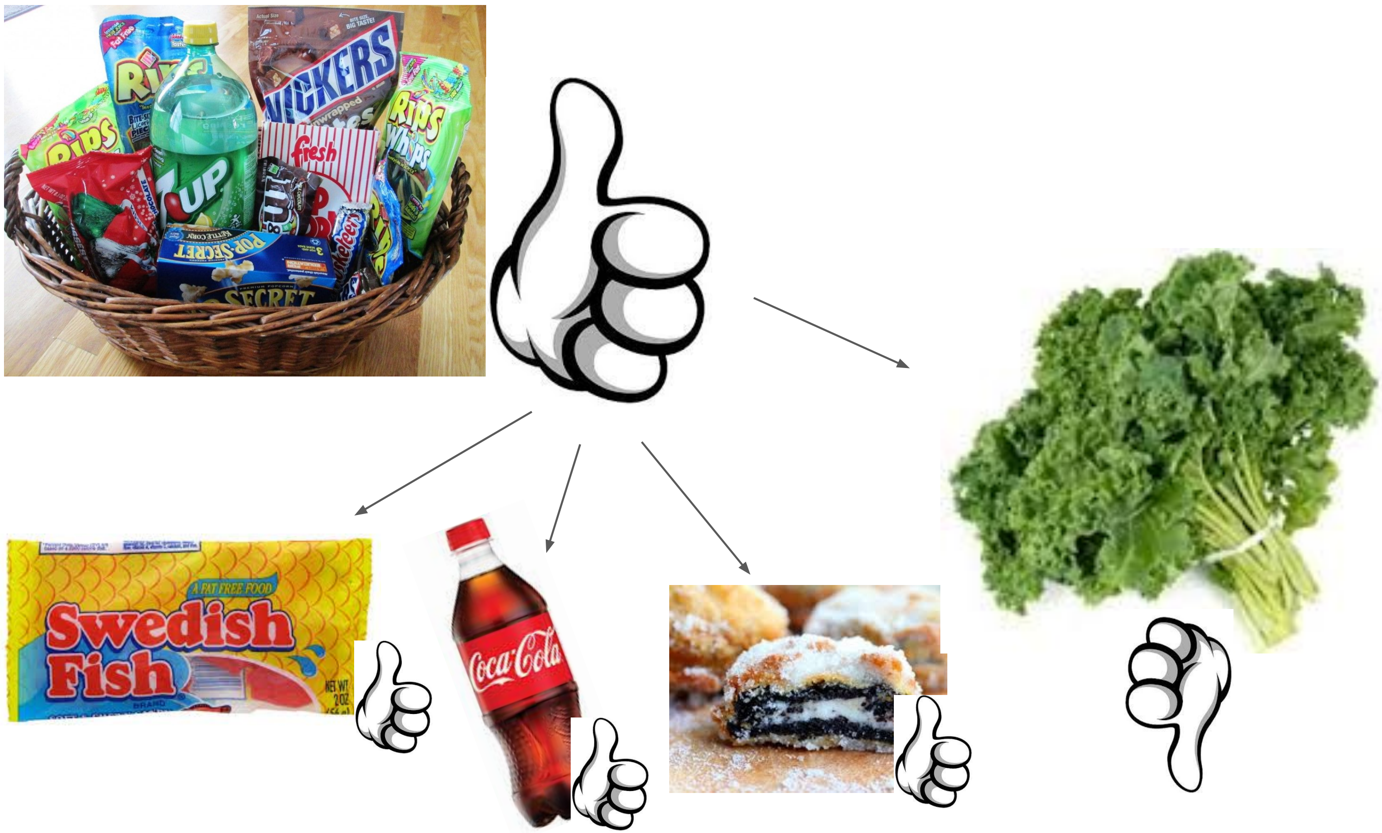


Recommendation Systems



Recommendation Systems

Past User Ratings

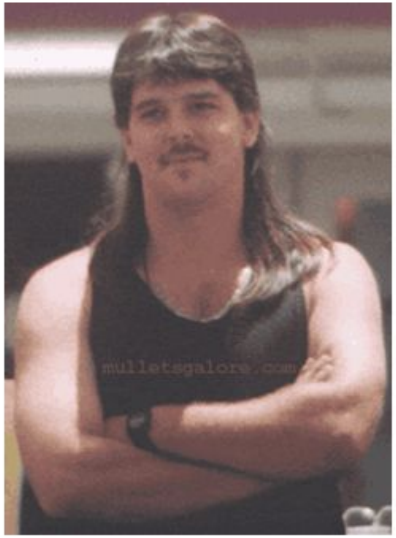
Recommendation Systems

Why Big Data?

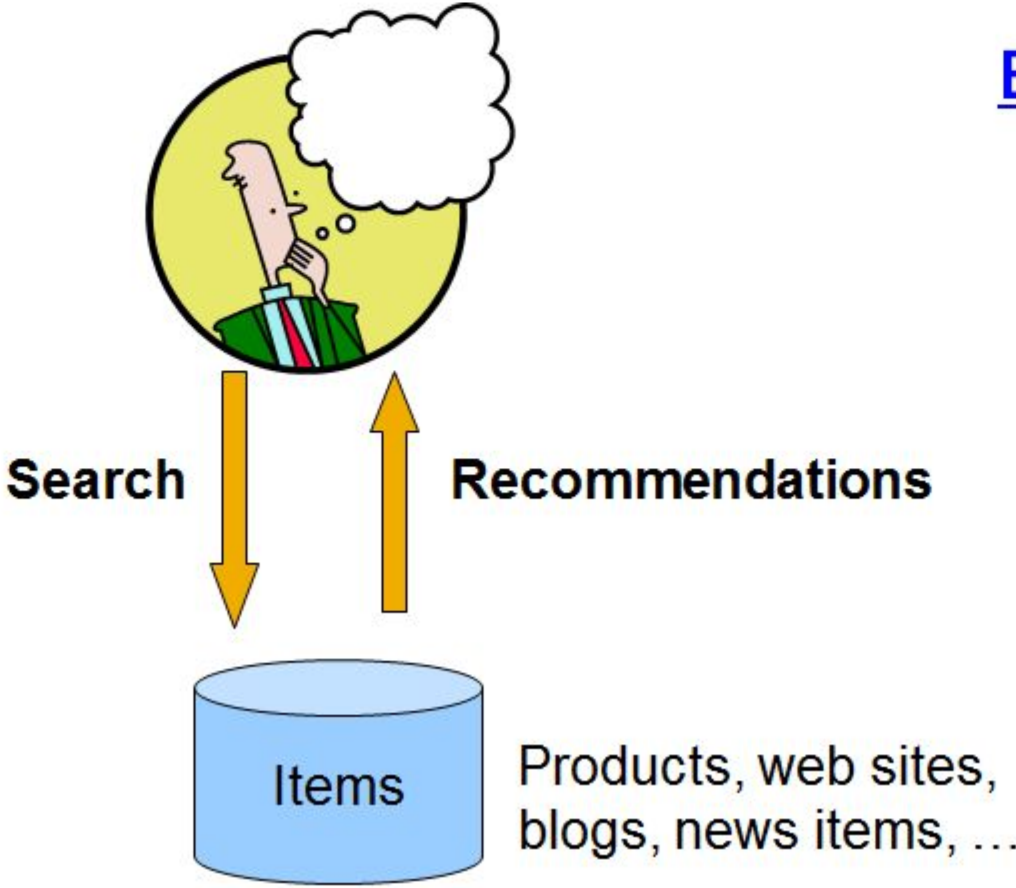
- Data with many potential features (and sometimes observations)

- An application of techniques for finding similar items
  - locality sensitive hashing
  - dimensionality reduction

Recommendation System: 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**



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

Enabled by Web Shopping

- Does Wal-Mart have everything you need?

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(thelongtail.com)

Enabled by 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

(thelongtail.com)

Enabled by Web Shopping

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A Model for Recommendation Systems

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	

A Model for Recommendation Systems

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

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

Recommendation Systems

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

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3. Evaluation

Common Approaches

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

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Utility Matrix:

movies

f1, f2, f3, f4, … fp

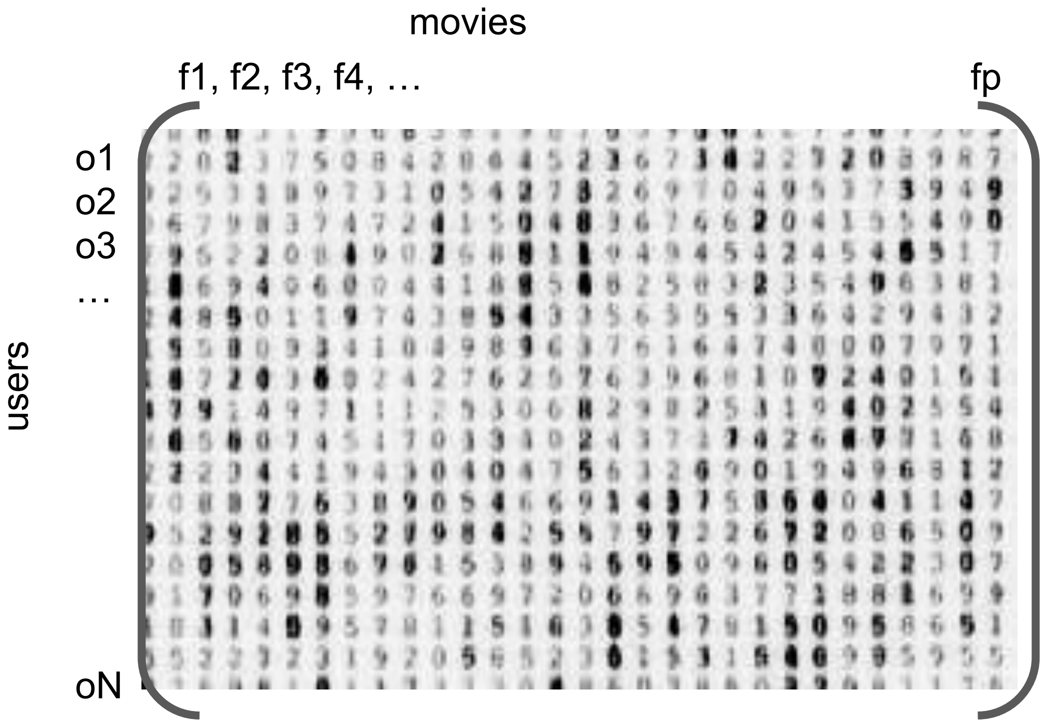
users

o1
o2
o3
…
oN

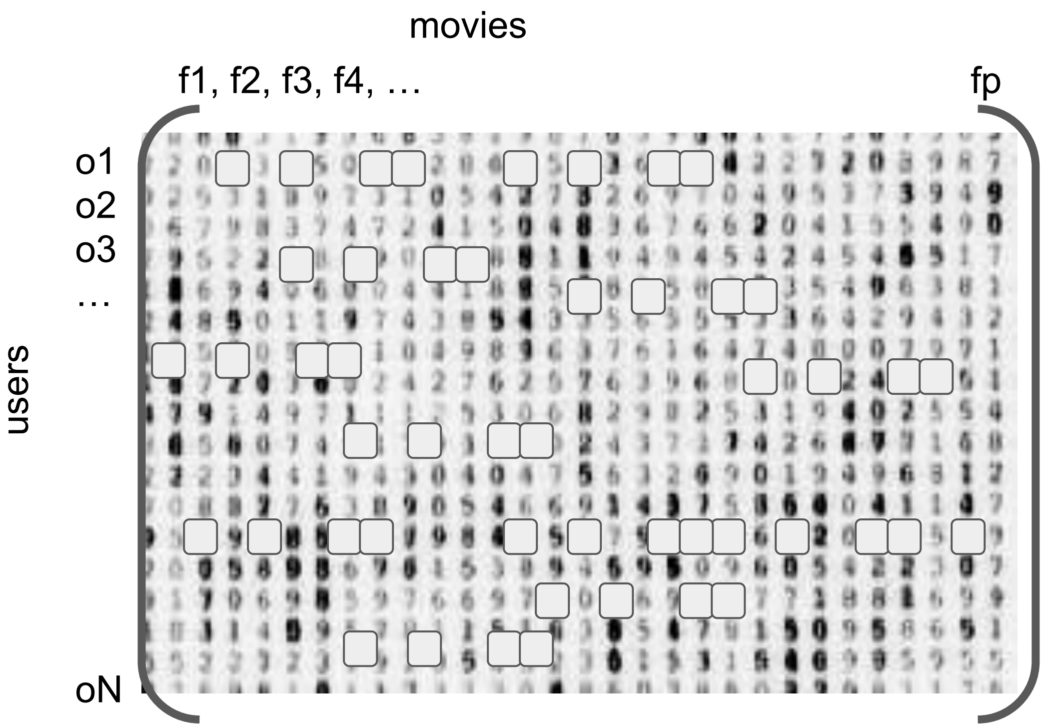
rows:
N observations

columns:
p features

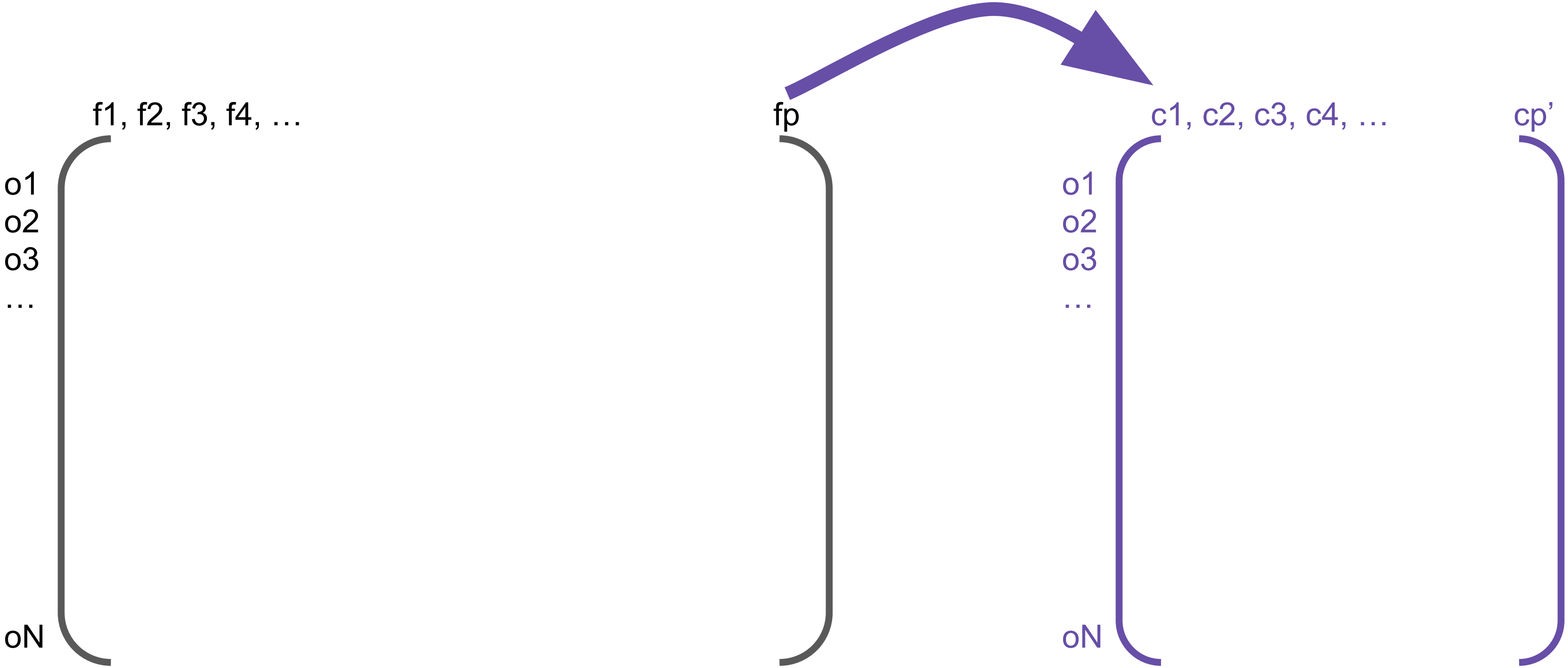
Goal: Complete Matrix



Problem: Given Incomplete Matrix



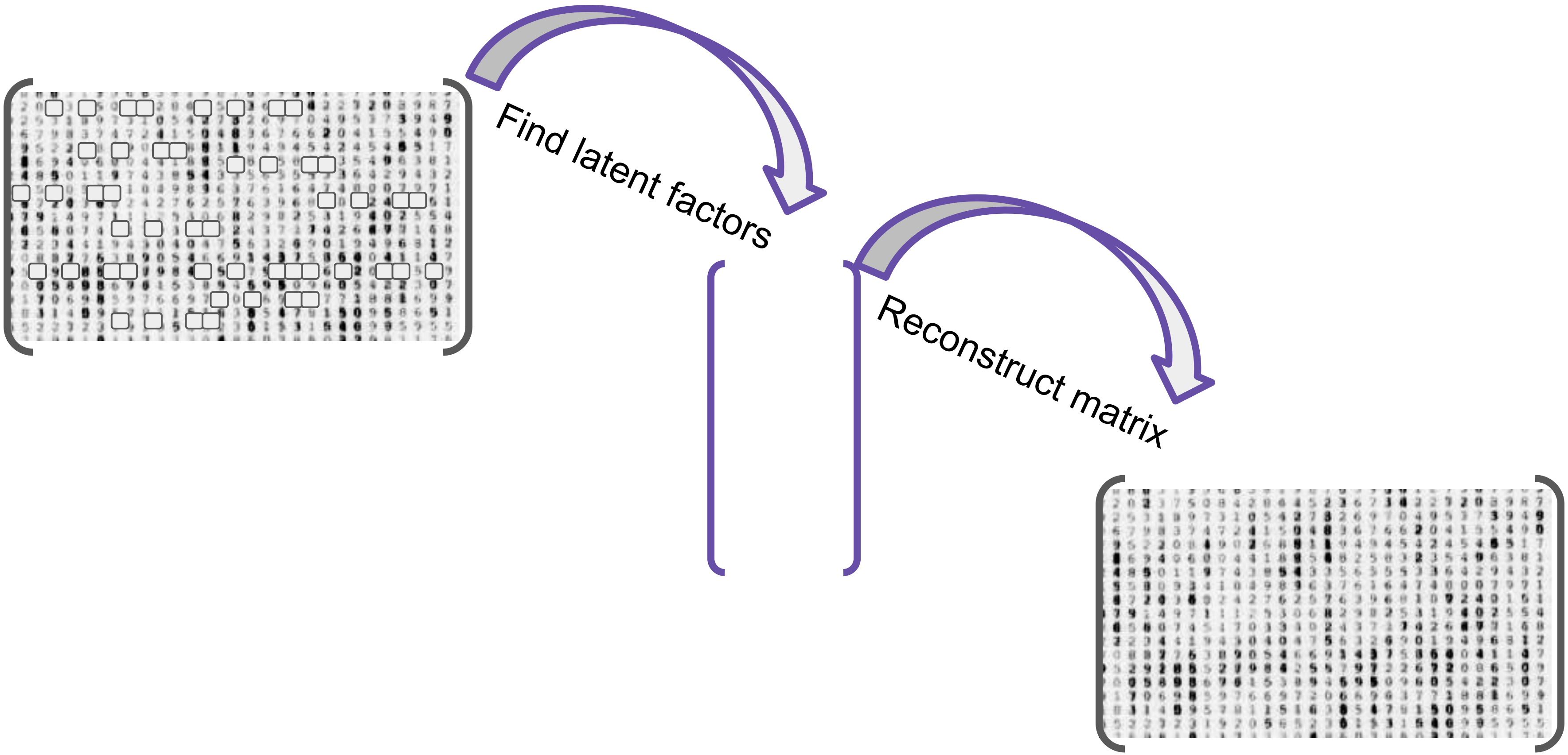
Complete Matrix using Latent Factors



Dimensionality reduction

Try to best represent but with on p’ columns.

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, U: "left singular vectors",
D: "singular values" (diagonal), V: "right singular vectors"

Projection (dimensionality reduced space) in 3 dimensions:

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

To reduce features in new dataset:

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

Dimensionality Reduction - PCA

Linear approximates of data in r dimensions.

Found via *Singular Value Decomposition:*

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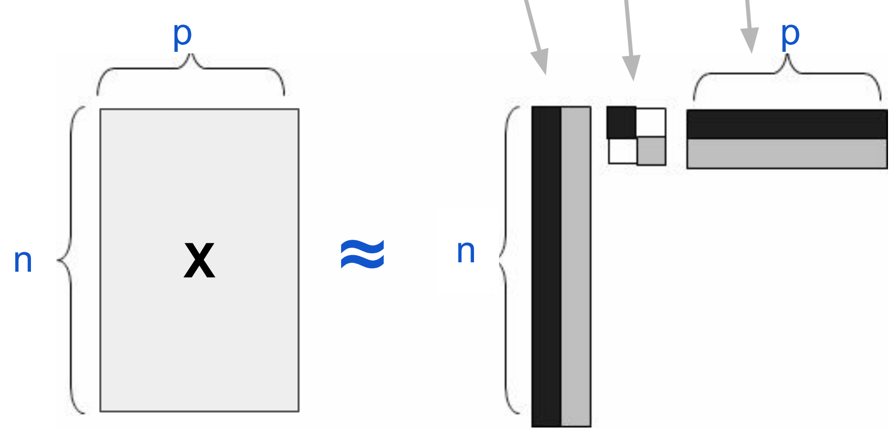

Dimensionality Reduction - PCA - Example

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

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

Users to movies matrix

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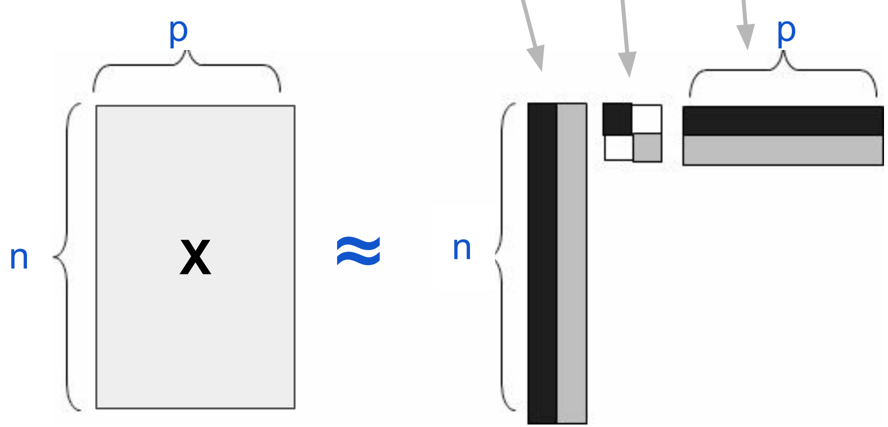


Dimensionality Reduction – PCA

- **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

s.

X: original ma … lar vectors”,

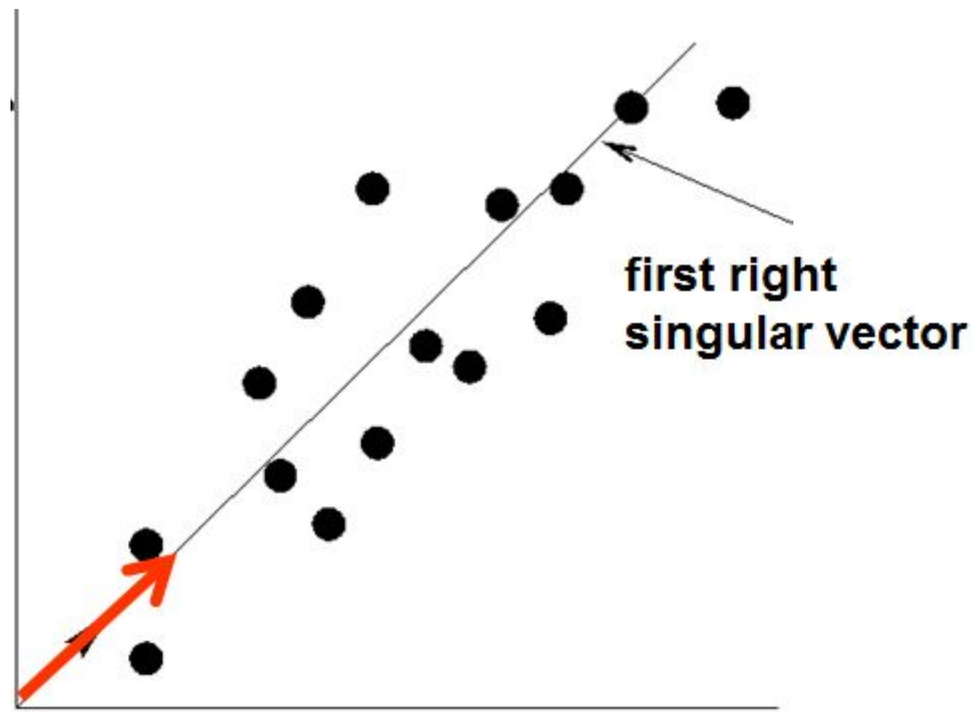
D: “singular va … ular vectors”

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 - Example

$$X_{[n \times p]} = U_{[n \times r]} D_{[r \times r]} V_{[p \times r]}^T$$



Recommendation Systems

Common Approaches

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

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Content-based Rec Systems

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

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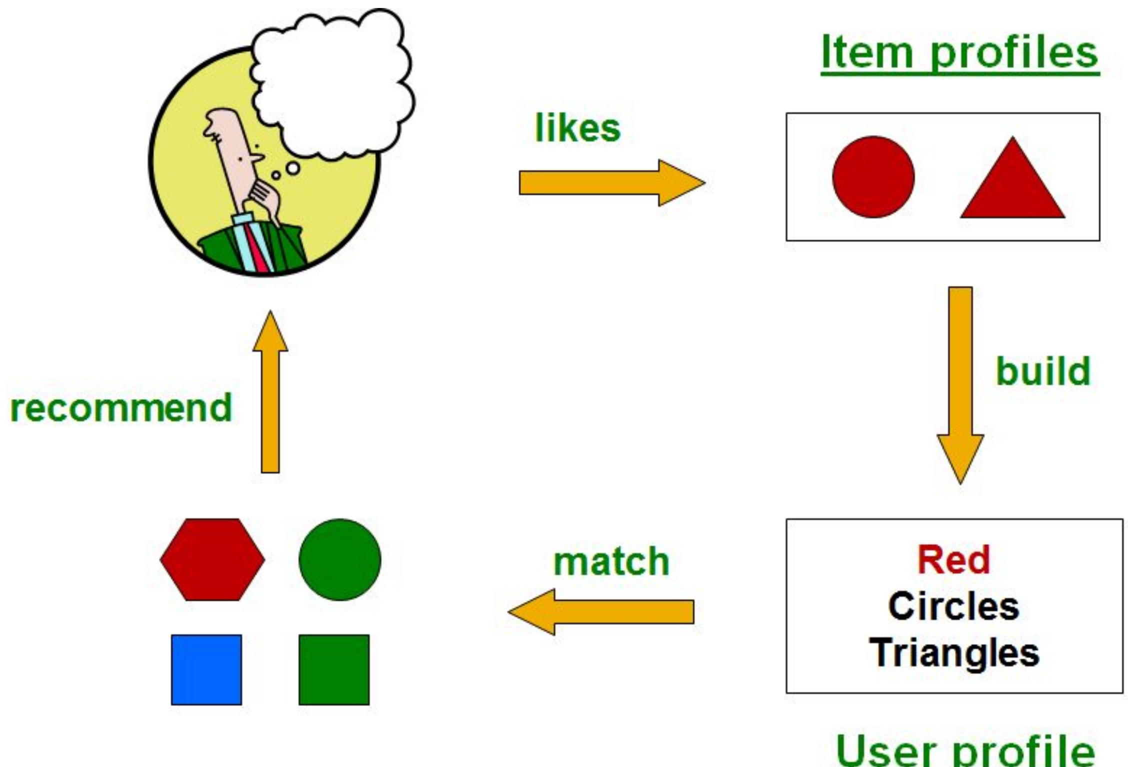

J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

Content-based Rec Systems

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

1. `Build profiles of items (set of features);` examples:

    shows: producer, actors, theme, review

    people: friends, posts

pick words with tf-idf

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   average all item profiles
   variation: weight by difference from their average

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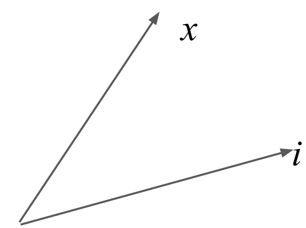
    average all item profiles of items they've purchased

    variation: weight by difference from their average ratings

3. `Predict ratings for new items;` approach:

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



Why Content Based?

- Only need users history
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(not exploiting other users judgments)

Collaborative Filtering Rec Systems

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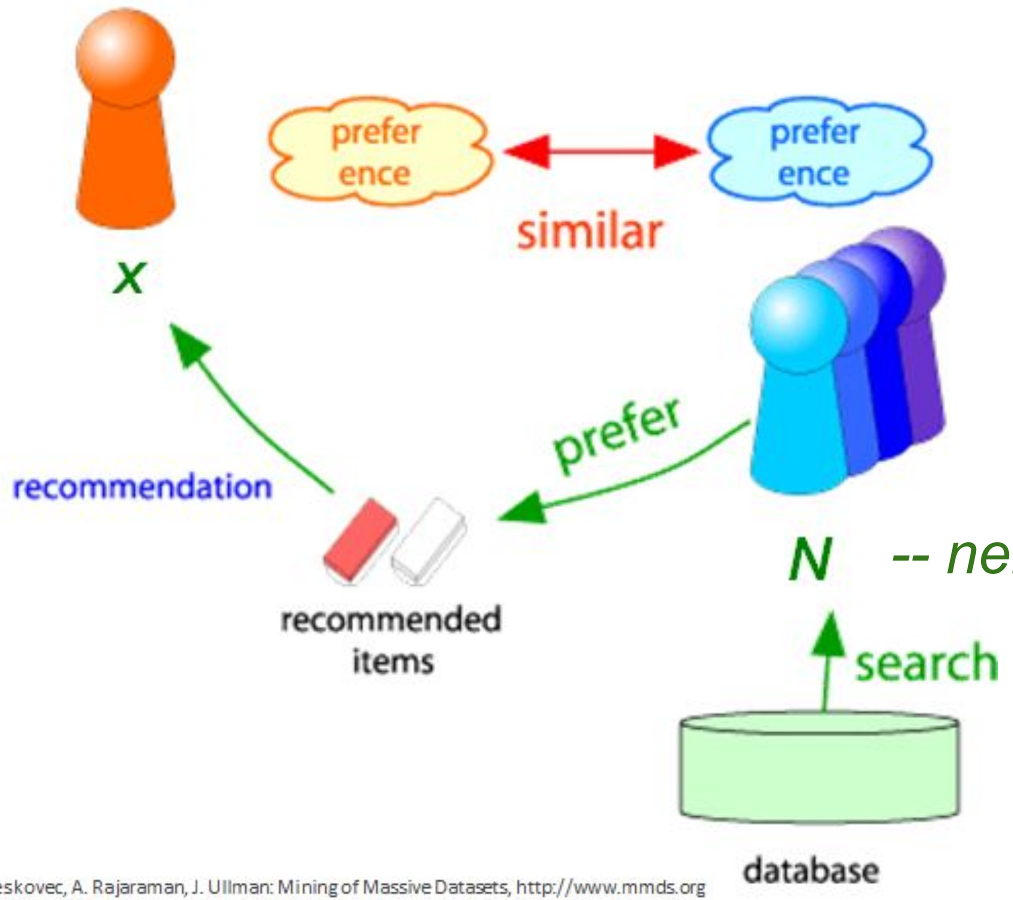

-- *neighborhood*

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Collaborative Filtering Rec Systems

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General Idea:

1) Find similar users = "neighborhood"

2) Infer rating based on how similar users rated

Collaborative Filtering Rec Systems

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Given: *user, x*; *item, i*; *utility matrix, u*

1. Find neighborhood, *N* # set of *k* users most similar to *x* who have also rated *i*

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   Two Challenges: (1) user bias, (2) missing values

Collaborative Filtering Rec Systems

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   Solution: subtract user's mean, add zeros for missing

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Given: user, x;   item, i;   utility matrix, u
0. Update u: mean center, missing to 0
1.  Find neighborhood, N # set of k users most similar to
                              x who have also rated i
    -- sim(x, other) = cosine_sim(u[x], u[other])
    -- threshold to top k (e.g. k = 30)
```

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2. Predict utility (rating) of *i* based on *N*
   -- 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 Rec Systems

"User-User collaborative filtering"

```
Given: user, x;   item, i;   utility matrix, u
0. Update u: mean center, missing to 0
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Collaborative Filtering Rec Systems

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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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Given:  user, x;   item, i;   utility matrix, u
0. Update u: mean center, missing to 0
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                                  i also rated by x
    -- sim(i, other) = cosine_sim(u[i], u[other])
    -- threshold to top k (e.g. k = 30)
2. Predict utility (rating) by x based on N
    -- average, weighted by sim
```

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

Item-Item v 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, Bob likes classical + rock,

but Mary may still have same rock preferences as Bob

Item-Item v User-User

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e.g. Mary likes jazz + rock, Bob likes classical + rock,
but Mary may still have same rock preferences as Bob

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

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	

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

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)
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**

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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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

Options for Parallelizing

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. 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.
    (more here.)

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.