

Analytics and Visualization of Big Data

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Lecture 18: Recommendation Systems



AUBURN UNIVERSITY

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Department of Industrial and Systems Engineering

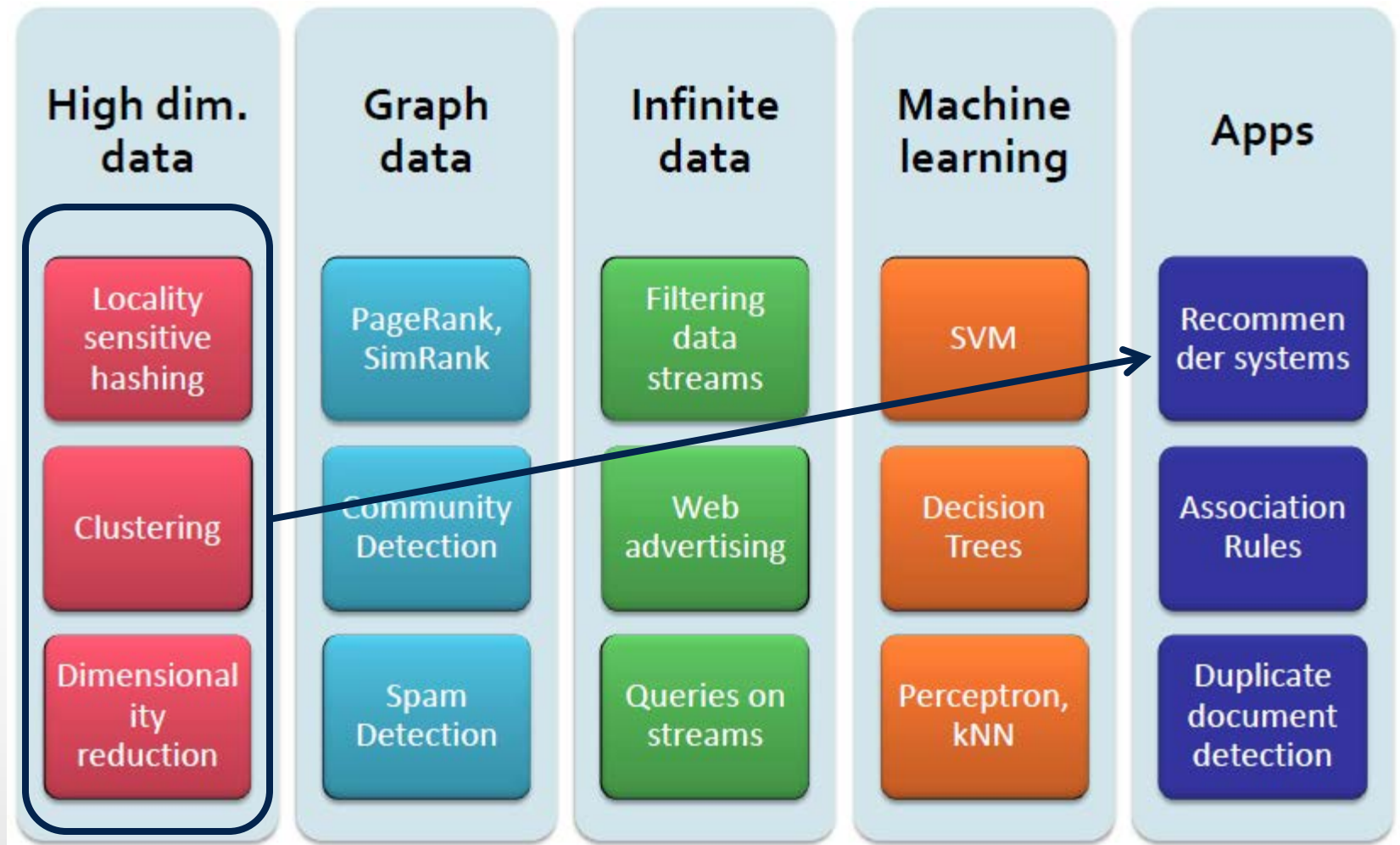
Spring 13

- Explain the basics behind the hardware and software needed for “big data” analytics.
- Analyze high-dimensional data.
- Develop visualizations that makes the data “sing” 😊.
- Describe the components of successful search engines.
- Mine the web using structured and unstructured data.
- Train algorithms that can be used to extract new knowledge from data.



Spring Break Refresher: Analytics Based on Data Type

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A Model for Recommendation Systems

- The Utility Matrix
- Physical vs. Online Worlds
- Applications
- Populating the Utility Matrix

Content-based Recommendations

- Item Profiles
- Discovering Features of Docs
- User Profiles
- Recommending Items Based on Content

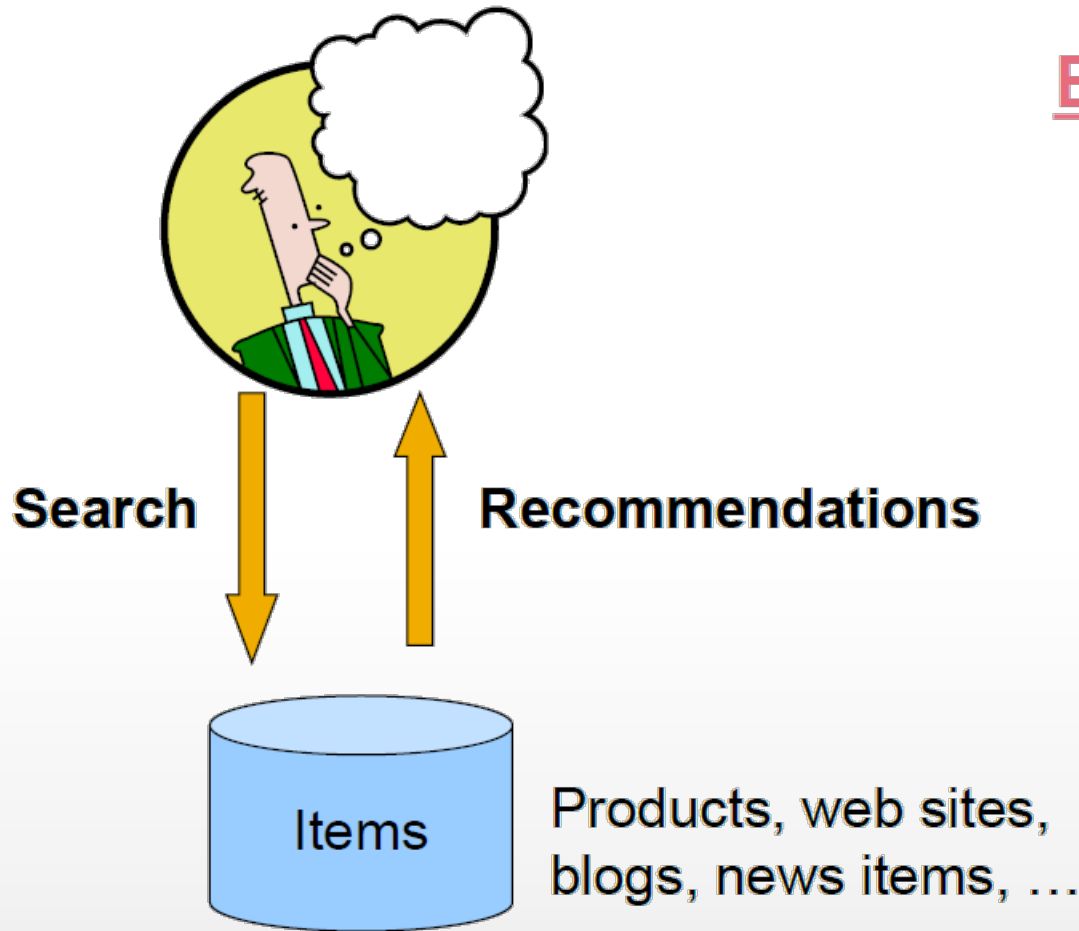
Collaborative Filtering

- Discussing its Main Idea (Only)



Recommendation Systems

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Examples:

amazon.com.



moviелens
helping you find the *right* movies

last.fm
the social music revolution

Google
News

YouTube



Source: Jure Leskovic, Stanford CS246, Lecture Notes, see <http://cs246.stanford.edu>

The Utility Matrix

- In RS, there are two classes of entities:
 - Users
 - Items
- The data itself is represented as a **utility matrix**
- The **utility matrix** is typically very sparse

	HP1	HP2	HP3	TW	SW1	SW2	SW3
<i>A</i>	4			5	1		
<i>B</i>	5	5	4				
<i>C</i>				2	4	5	
<i>D</i>		3					3



- Properties of the Matrix:
 - Rows = elements of the universal set
 - Columns = sets
- 1 if and only if the token is a member of the set
- Column similarity is the Jaccard similarity of the corresponding sets (rows with value 1)
- Typical matrix is sparse

<i>Element</i>	S_1	S_2	S_3	S_4
<i>a</i>	1	0	0	1
<i>b</i>	0	0	1	0
<i>c</i>	0	1	0	1
<i>d</i>	1	0	1	1
<i>e</i>	0	0	1	0



Physical World

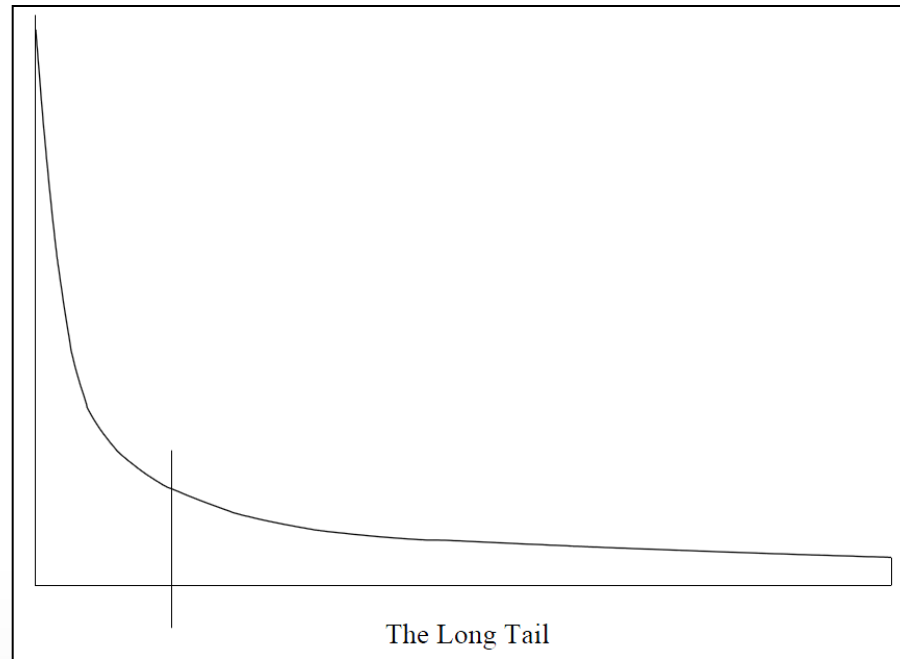
- Limited by shelf space
- Choice of products is based on aggregate #s
- Recommendation systems are fairly simple; recommend hits

Online World

- Essentially unlimited
- Choice of products is ~ infinite
- Recommendation systems can be tailored to a single customer

The Properties of the Online World → New Paradigm in Marketing and New Opportunities (How?)





The long tail: physical institutions can only provide what is popular, while on-line institutions can make everything available

- **More choice necessitates better filters**
 - Recommendation engines
 - How **Into Thin Air** made **Touching the Void** a bestseller:
<http://www.wired.com/wired/archive/12.10/tail.html>



Read <http://www.wired.com/wired/archive/12.10/tail.html> to learn more!

- Traditional Applications
 - Product Recommendations
 - Movie Recommendations
 - News Article Recommendations
- IE Applications
 - ????
 - ????

Your Recent History (What's this?)

Recently Viewed Items

-  **Reliability and Optimal...**
Hongzhou Wang
Hardcover
-  **Reliability and Optimal...**
Hongzhou Wang
Paperback
-  **Planning for Big Data**
Edd Dumbill
Kindle Edition

Continue Shopping: Customers who shopped for items in your recent history also shopped for



The Little Book of BIG DATA...
Noreen Burlingame

★☆☆☆☆ (3)
Kindle Edition
\$4.95

[Fix this recommendation](#)



NoSQL Distilled: A Brief Guide...
Martin Fowler

★★★★★ (24)
Kindle Edition
\$17.27

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A Simple Introduction to DATA...
Lars Nielsen

★★★★☆ (2)
Kindle Edition
\$4.95

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Big Data - An Introduction
Subu Raj

Kindle Edition
\$2.99

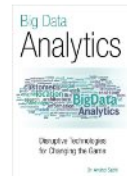
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Scalability Rules: 50 Principles...
Martin L. Abbott

★★★★☆ (14)
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\$15.39

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Big Data Analytics: Disruptive...
Arvind Sathi

★★★★★ (4)
Kindle Edition
\$9.99

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[View and Edit Your Browsing History](#)

1. Gathering “known” ratings for matrix
2. Extrapolate unknown ratings from known ratings
 - Mainly interested in high unknown ratings
3. Evaluating extrapolation methods



- **Explicit**

- Ask people to rate items
- Doesn't work well in practice – people can't be bothered

- **Implicit**

- Learn ratings from user actions
 - E.g., purchase implies high rating
- What about low ratings?

Source: Jure Leskovic, Stanford CS246, Lecture Notes, see <http://cs246.stanford.edu>



2) Extrapolating the Empty Cells in the Utility Matrix

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Key problem: matrix U is sparse

- Most people have not rated most items
- **Cold start:**
 - New items have no ratings
 - New users have no history

Three approaches to recommender systems:

- Content-based
- Collaborative
- Hybrid

Our Focus in Class



A Model for Recommendation Systems

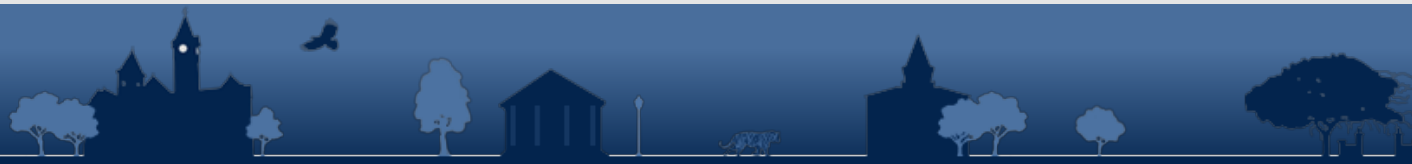
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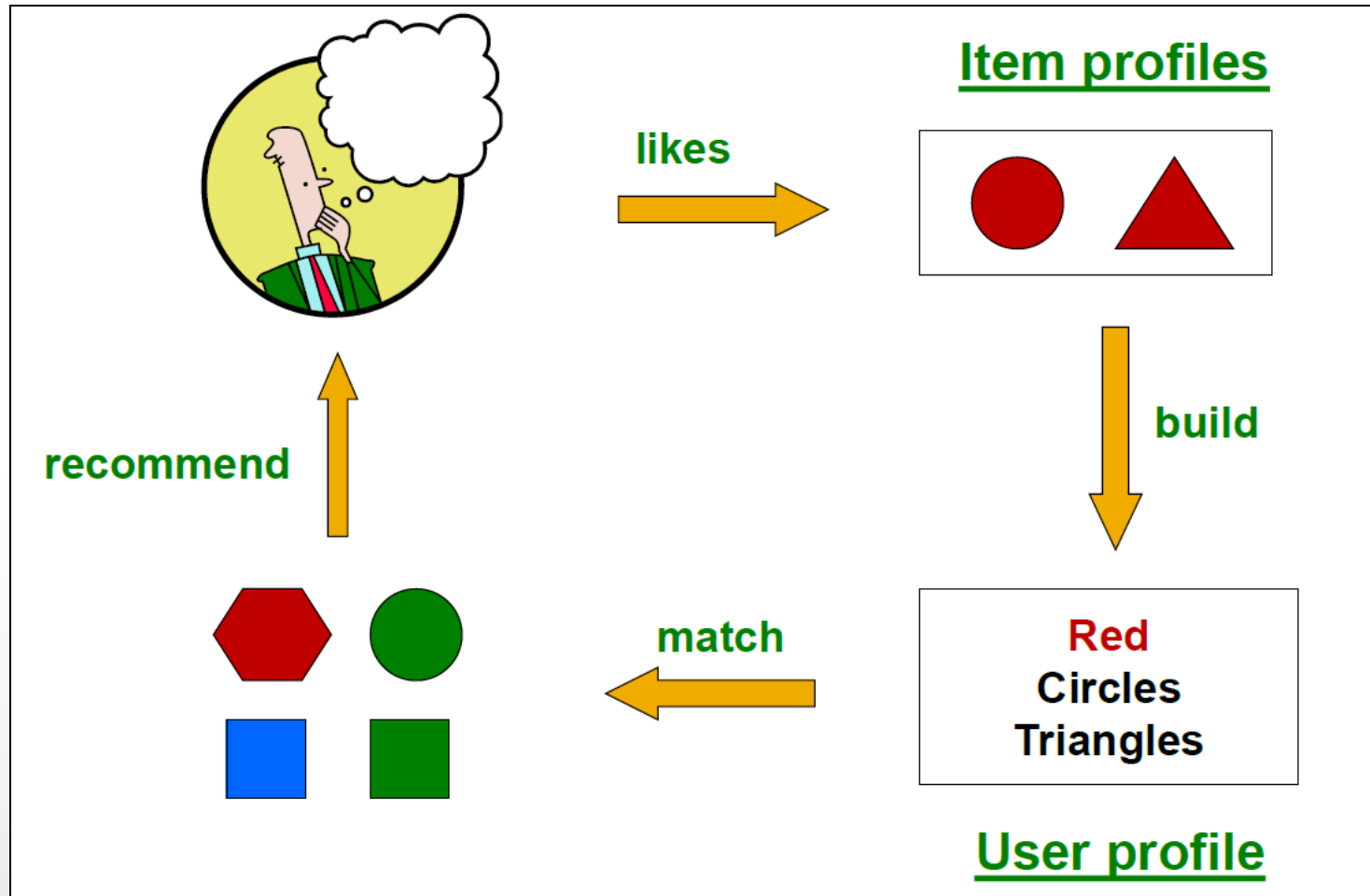


Main idea: Recommend items to customer x similar to previous items rated highly by customer x

Example:

- **Movie recommendations:** Recommend movies with same actor(s), director, genre, ...
- **Websites, blogs, news:** Recommend other sites with “similar” content
- **Images: How do you compare images?**





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- For each item, create an **item profile**
- Profile is a set (vector) of features
 - Movies: author, title, actor, director,...
 - Text: set of “important” words in document
- How to pick important features?
 - Usual heuristic from text mining is TF-IDF (Term frequency * Inverse Doc Frequency)
 - Term ... feature
 - Document ... item
- **Question: Now what?**



- **+: No need for data on other users**
 - No cold-start or sparsity problems
- **+: Able to recommend to users with unique tastes**
- **+: Able to recommend new and unpopular items**
 - No first-rater problem
- Can provide explanations of recommended items by listing content-features that caused an item to be recommended



- –: Finding the appropriate features is hard E.g., images, movies, music
- –: **Overspecialization** Never recommends items outside user's content profile
 - People might have multiple interests
 - Unable to exploit quality judgments of other users
- –: **Recommendations for new users** How to build a user profile?



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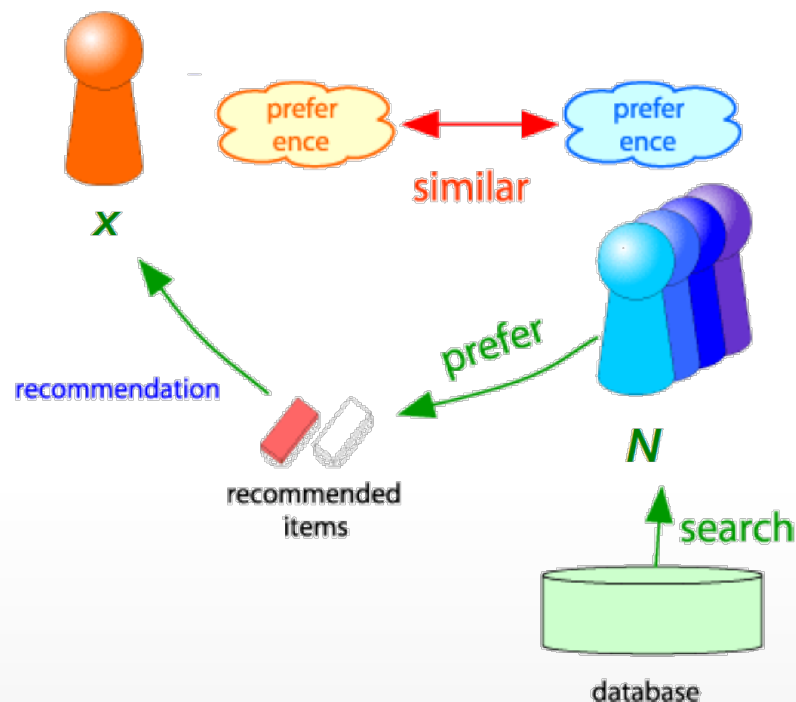
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Collaborative Filtering

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- Consider user x
- Find set N of other users whose ratings are “**similar**” to x ’s ratings
- Estimate x ’s ratings based on ratings of users in N



- **Works for any kind of item**
 - No feature selection needed
- **Cold Start:**
 - Need enough users in the system to find a match
- **Sparsity:**
 - Hard to find users that have rated the same items
- **First rater:**
 - Cannot recommend an item that has not been previously rated
 - New items, Esoteric items
- **Popularity bias:**
 - Cannot recommend items to someone with unique taste
 - Tends to recommend popular items





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