Recommendation System

Collaborative Filtering

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Why Recommender?

"We are leaving the age of information and entering the age of recommendation."

—— Chris Anderson in "The Long Tail"

The Age of Recommendation

Search:

User → Items

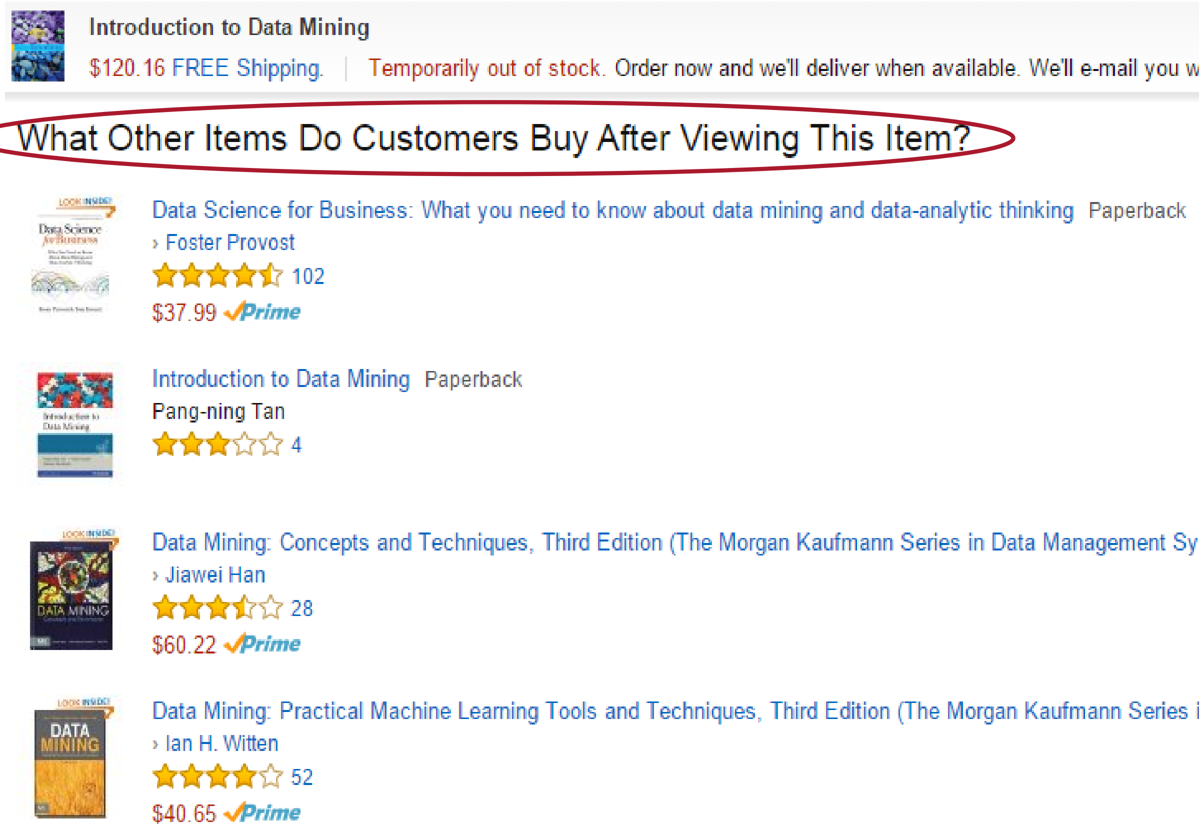
Recommend:

Items → User

Amazon: A personalized online store

Picture from: amazon.com

Amazon: A personalized online store



Picture from: amazon.com

Recommender System

- **Recommendation systems (RS) help to match users with items**
  - Ease information overload
  - Sales assistance (guidance, advisory, persuasion,…)

> *RS are software agents that elicit the interests and preferences of individual consumers [...] and make recommendations accordingly.*
> *They have the potential to support and improve the quality of the decisions consumers make while searching for and selecting products online.*
>
> » (Xiao & Benbasat 2007[1])

- **Different system designs / paradigms**
  - Based on availability of exploitable data
  - Implicit and explicit user feedback
  - Domain characteristics

Recommender Problem

A good recommender

- Show programming titles to a software engineer and baby toys to a new mother.
- Don’t recommend items user already knows or would find anyway.
- Expand user’s taste without offending or annoying him/her…

Challenges

- Huge amounts of data, tens of millions of customers and millions of distinct catalog items.
- Results are required to be returned in real time.
- New customers have limited information.
- Old customers can have a glut of information.
- Customer data is volatile.

Amazon's solution

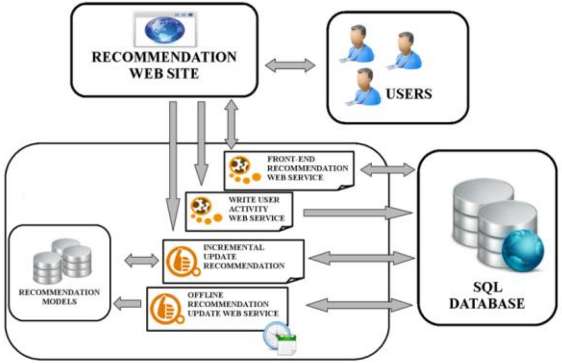
1. Amazon Recommendation Engine

- Amazon's model that implements recommendation algorithm.
- Recommendation algorithm is designed to personalize the online store for each customer.

2. Algorithm feature

- Most recommendation algorithms start by finding a set of similar customers whose purchased and rated items overlap the user's purchased and rated items.
- The Amazon's item-to-item collaborative filtering is focusing on finding similar items instead of similar customers.

3. Recommendation Engine Workflow



Traditional Recommendation Algorithms

Two mostly used traditional algorithms:

1. User Based Collaborative Filtering

2. Cluster Models

User Based Collaborative Filtering

Approach

- Represents a customer as an N-dimensional vector of items
- Vector is positive for purchased or positively rated items and negative for negatively rated items
- Based on cosine similarity: finds similar customers/users

$$similarity(\vec{A}, \vec{B}) = \cos(\vec{A}, \vec{B}) = \frac{\vec{A} \bullet \vec{B}}{\|\vec{A}\| * \|\vec{B}\|}$$

- Generates recommendations based on a few customers who are most similar to the user
- Rank each item according to how many similar customers purchased it

Problems

- **computationally expensive**, ***O(MN)*** in the worst case, where
  - M is the number of customers and
  - N is the number of items
- **dimensionality reduction** can increase the performance, BUT, also **reduce the quality of the recommendation**
- For very large data sets, such as **10 million customers and 1 million items**, the algorithm encounters **severe performance and scaling issues**

Cluster Models

Approach

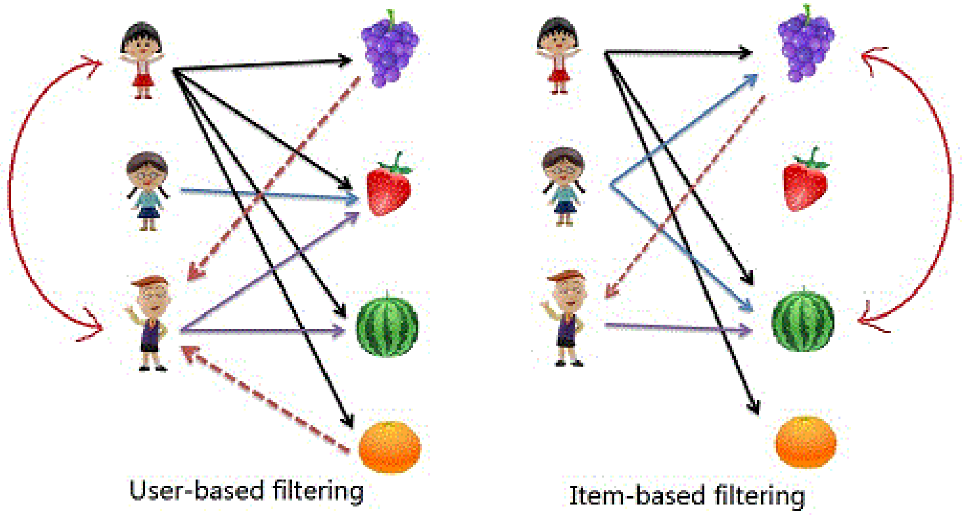
- Divide the customer base into many segments and treat the task as a classification problem
- Assign the user to the segment containing the most similar customers
- Uses the purchases and ratings of the customers in the segment to generate recommendations
- Cluster models have **better online scalability and performance** than collaborative filtering because they compare the user to a controlled number of segments rather than the entire customer base.

Problems

- **Quality of the recommendation is low**
- The recommendations are less relevant because the similar customers that the cluster models find are not the most similar customers
- **To improve quality**, it **needs online segmentation**, which is almost as **expensive as** finding similar customers using **collaborative filtering**

Amazon’s Item-to-Item CF

- **Difference with User-to-User CF**



Amazon’s Item-to-Item CF

Similarity of item i with item 17

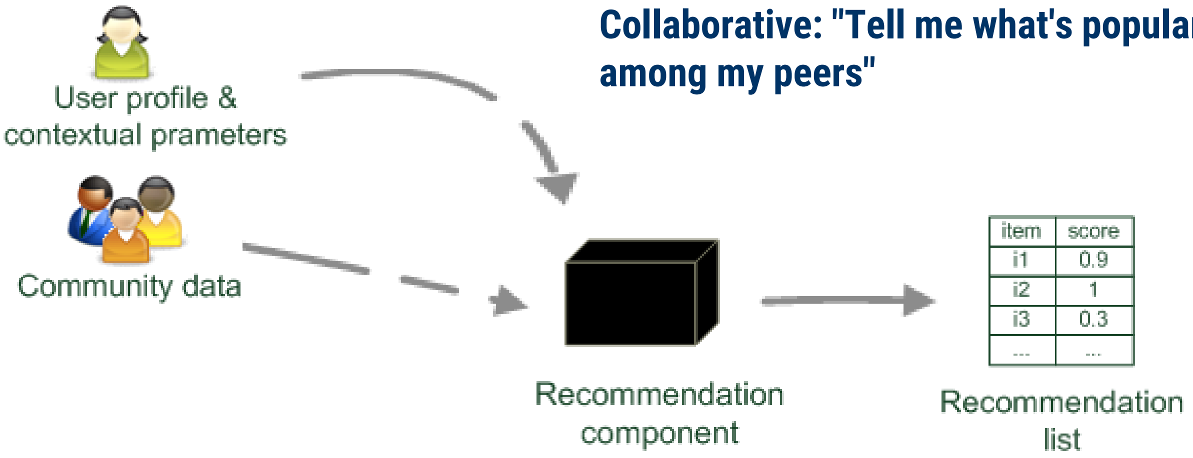
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
,1	,3	,6	,1	,3	,4	,3	,3	,2	,6	,2	,5	,4	,5	,5	,3	1	,3	,5	,4	,2	,4	,4	,5

Items

Users

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
a			1		4	5			4		3					2			4		2				
b			4							3							5	1		3					
c		5		4			4						3		5					4		5			
d								3				5				3			4		2			3	
e		3					5			4	5				5					1			5	4	
f			4				1		3	5		4	1		5	4	4		4				3		
g	2	4				4		2			5		1	4	5		4	2	4		5			4	
h			2		1		4		3	5		4	2		5	4	5						5		
i		1					3			5				5		4	4		5			4		3	
j			4			4				5			1		5		4		4				4		
k		5				4			2		5		1	5		4		2		4				2	
l					3			3				4	1		4		4	2	4					3	
m	5		3					5	3		5	4		5	5	3			4	4	5	4		4	
n			1		4	5				4	5		1	5		4		3		4		4	3		
o			4			4				5		4		5			4	2		5		5		3	
p				4			5								5	4		2	4	4	5	4		2	
q					3			3					1	5		4	4		4			4		3	
r		4			1	4		2					2		5		4				5	4		4	
s			2		4		4			5			1			4		2	4		4		5		
t		1		4			3					4		5	5		4			4				3	
u			2		1		4		3				1		5	4		2	4		5	4			
v					4	5				4	3		5			2					2			5	
w				2			2		3			5			4	5		4	2		3	4			
x	4			5				3		3				4	5					1					
y			1			3				2	3						3	3		5		4			

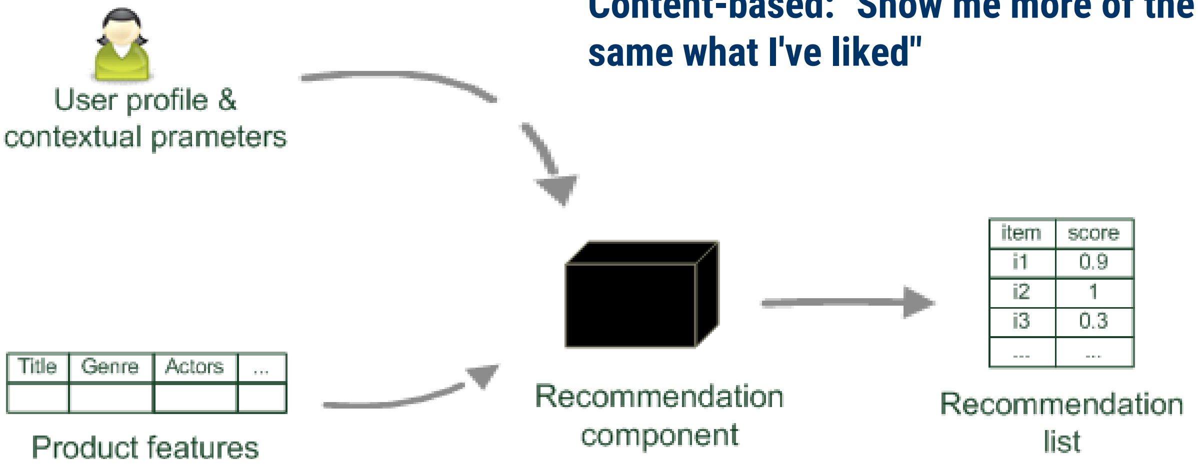
Collaborative Filtering based recommender systems



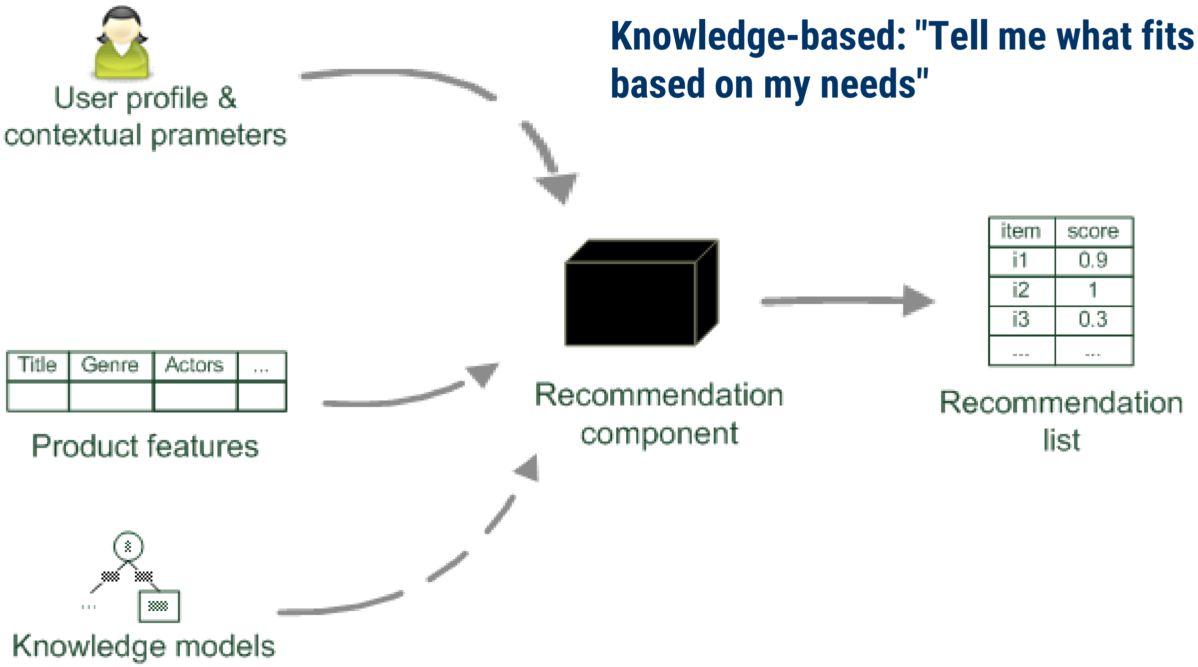
Collaborative: "Tell me what's popular among my peers"

Content based recommender systems

Content-based: "Show me more of the same what I've liked"



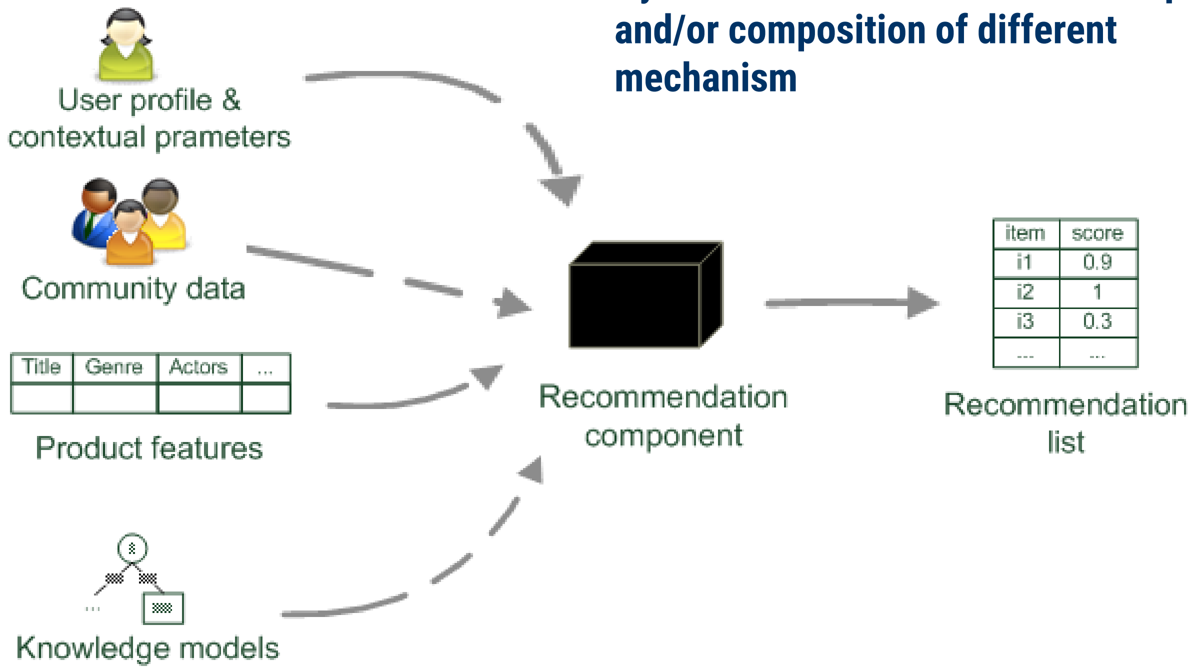
Knowledge based recommender systems



Knowledge-based: "Tell me what fits based on my needs"

Hybrid recommender systems

Hybrid: combinations of various inputs and/or composition of different mechanism



Collaborative Filtering (CF)

- **The most prominent approach to generate recommendations**
  - used by large, commercial e-commerce sites
  - well-understood, various algorithms and variations exist
  - applicable in many domains (book, movies, DVDs, ..)
- **Approach**
  - use the "wisdom of the crowd" to recommend items

- **Basic assumption and idea**
  - Users give ratings to catalog items (implicitly or explicitly)
  - Customers who had similar tastes in the past, will have similar tastes in the future

Pure CF Approaches

- **Input**
  - Only a matrix of given user–item ratings
- **Output types**
  - A (numerical) prediction indicating to what degree the current user will like or dislike a certain item
  - A top-N list of recommended items

User-based nearest-neighbor collaborative filtering (1)

- **The basic technique**
  - Given an "active user" (Alice) and an item i not yet seen by Alice
    - find a set of users (peers/nearest neighbors) who liked the same items as Alice in the past **and** who have rated item i
    - use, e.g. the average of their ratings to predict, if Alice will like item i
    - do this for all items Alice has not seen and recommend the best-rated
- **Basic assumption and idea**
  - If users had similar tastes in the past they will have similar tastes in the future
  - User preferences remain stable and consistent over time

User-based nearest-neighbor collaborative filtering (2)

- **Example**
  - A database of ratings of the current user, Alice, and some other users is given:

	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

  - Determine whether Alice will like or dislike *Item5*, which Alice has not yet rated or seen

User-based nearest-neighbor collaborative filtering (3)

- **Some first questions**
  - How do we measure similarity?
  - How many neighbors should we consider?
  - How do we generate a prediction from the neighbors' ratings?

	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

Measuring user similarity (1)

- **A popular similarity measure in user-based CF: Pearson correlation**

  a, b : users

  $r_{a,p}$: rating of user a for item p

  P : set of items, rated both by a and b

  - Possible similarity values between -1 and 1

$$\boldsymbol{sim(a,b)} = \frac{\sum_{p \in P}(r_{a,p} - \bar{r}_a)(r_{b,p} - \bar{r}_b)}{\sqrt{\sum_{p \in P}(r_{a,p} - \bar{r}_a)^2}\sqrt{\sum_{p \in P}(r_{b,p} - \bar{r}_b)^2}}$$

Measuring user similarity (2)

- **A popular similarity measure in user-based CF: Pearson correlation**

  a, b : users

  $r_{a,p}$: rating of user a for item p

  P : set of items, rated both by a and b

  – Possible similarity values between -1 and 1

	Item1	Item2	Item3	Item4	Item5	
Alice	5	3	4	4	?	
User1	3	1	2	3	3	sim = 0,85
User2	4	3	4	3	5	sim = 0,00
User3	3	3	1	5	4	sim = 0,70
User4	1	5	5	2	1	sim = -0,79

Making predictions

- A common prediction function:

$$\boldsymbol{pred(a,p) = \overline{r_a} + \frac{\sum_{b \in N} sim(a,b) * (r_{b,p} - \overline{r_b})}{\sum_{b \in N} sim(a,b)}}$$

- Calculate, whether the neighbors' ratings for the unseen item i are higher or lower than their average
- Combine the rating differences – use the similarity with a as a weight
- Add/subtract the neighbors' bias from the active user's average and use this as a prediction

Item-based collaborative filtering

- **Basic idea:**
  - Use the similarity between items (and not users) to make predictions
- **Example:**
  - Look for items that are similar to Item5
  - Take Alice's ratings for these items to predict the rating for Item5

	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

The cosine similarity measure

- **Produces better results in item-to-item filtering**
- **Ratings are seen as vector in n-dimensional space**
- **Similarity is calculated based on the angle between the vectors**

$$sim(\vec{a}, \vec{b}) = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}| * |\vec{b}|}$$

- **Adjusted cosine similarity**
  - take average user ratings into account, transform the original ratings
  - U: set of users who have rated both items a and b

$$sim(\vec{a}, \vec{b}) = \frac{\sum_{u \in U}(r_{u,a} - \overline{r_u})(r_{u,b} - \overline{r_u})}{\sqrt{\sum_{u \in U}(r_{u,a} - \overline{r_u})^2} \sqrt{\sum_{u \in U}(r_{u,b} - \overline{r_u})^2}}$$

Making predictions

- A common prediction function:

$$pred(u,p) = \frac{\sum_{i \in ratedItem(u)} sim(i,p) * r_{u,i}}{\sum_{i \in ratedItem(u)} sim(i,p)}$$

- Neighborhood size is typically also limited to a specific size
- Not all neighbors are taken into account for the prediction
- An analysis of the MovieLens dataset indicates that "in most real-world situations, a neighborhood of 20 to 50 neighbors seems reasonable" (Herlocker et al. 2002)

Explicit ratings

- Probably the most precise ratings
- Most commonly used (1 to 5, 1 to 7 Likert response scales)
- Research topics
  - Optimal granularity of scale; indication that 10-point scale is better accepted in movie dom.
  - An even more fine-grained scale was chosen in the joke recommender discussed by Goldberg et al. (2001), where a continuous scale (from −10 to +10) and a graphical input bar were used
    - No precision loss from the discretization
    - User preferences can be captured at a finer granularity
    - Users actually "like" the graphical interaction method
  - Multidimensional ratings (multiple ratings per movie such as ratings for actors and sound)
- Main problems
  - Users not always willing to rate many items
    - number of available ratings could be too small → sparse rating matrices → poor recommendation quality
  - How to stimulate users to rate more items?

Implicit ratings

- Typically collected by the web shop or application in which the recommender system is embedded
- When a customer buys an item, for instance, many recommender systems interpret this behavior as a positive rating
- Clicks, page views, time spent on some page, demo downloads …
- Implicit ratings can be collected constantly and do not require additional efforts from the side of the user
- Main problem
  - One cannot be sure whether the user behavior is correctly interpreted
  - For example, a user might not like all the books he or she has bought; the user also might have bought a book for someone else
- Implicit ratings can be used in addition to explicit ones; question of correctness of interpretation

Data sparsity problems

- **Cold start problem**
  - How to recommend new items? What to recommend to new users?
- **Straightforward approaches**
  - Ask/force users to rate a set of items
  - Use another method (e.g., content-based, demographic or simply non-personalized) in the initial phase
  - Default voting: assign default values to items that only one of the two users to be compared has rated (Breese et al. 1998)
- **Alternatives**
  - Use better algorithms (beyond nearest-neighbor approaches)
  - Example:
    - In nearest-neighbor approaches, the set of sufficiently similar neighbors might be too small to make good predictions
    - Assume "transitivity" of neighborhoods

Thank You