# CS 277, Data Mining

# Recommender Systems

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Thanks to Yehuda Koren and Jure Leskovec for contributing material for many of these slides.

# Reading on Recommender Systems (on Web page)

- Good overviews
  - Recommender systems, Melville and Sindwhani, Encyclopaedia of Machine Learning, 2010 (a good starting point)
  - Chapter on recommendation algorithms from the online text Mining of Massive Data Sets, Rajaraman, Leskovec, and Ullman.
  - Amazon.com recommendations: item-to-item collaborative filtering, Linden, Smith, and York, 2003 (overview of the basic components of Amazon's recommender system)

- Matrix Factorization
  - Matrix factorization techniques for recommender systems, Koren, Bell, Volinsky, IEEE Computer, 2009
  - Advances in collaborative filtering, Koren and Bell, chapter from the Recommender Systems Handbook, 2011

- Other Aspects
  - Recommender systems: from algorithms to user experience, Konstain and Riedl, 2012 (emphasizes that the user experience is important, not just predictive accuracy)
  - Factorization machines with libFM, S. Rendle, 2012, with associated publicly-available software for libFM

# "Ratings" Data

- Data with users u and items i
  - E.g., items are products purchases, movies viewed, songs listened to, etc

- Can represent as an N x M sparse binary matrix
  - N = number of users, M = number of items

- Entries $r_{ui}$

  **Explicit Ratings**: $r_{ui}$ = user u's rating of item i (e.g. on a scale of 1 to 5)

  **Implicit Ratings**: $r_{ui}$ = 1 if user u purchased/read/listened to item i

  $r_{ui}$ = 0 if no purchase or rating

  (note that 0 means a user's preference is unknown, not that they don't like the item)

- Automated recommender systems
  - Given a user and their ratings (if any) recommend to this user other items that the user may be interested in

# Examples of Recommender Systems

- Shopping
  - Amazon, eBay
- Movie and music recommendations:
  - Netflix, YouTube, Last.fm, Pandora
- News
  - New York Times, Yahoo! front page
- Reading
  - Goodreads
- Digital libraries
- Web page/blog recommendations

# So why do we need Automated Recommendations?

- Many “sellers” moving to online stores
  - For music and movies for example, virtually all sales are now online

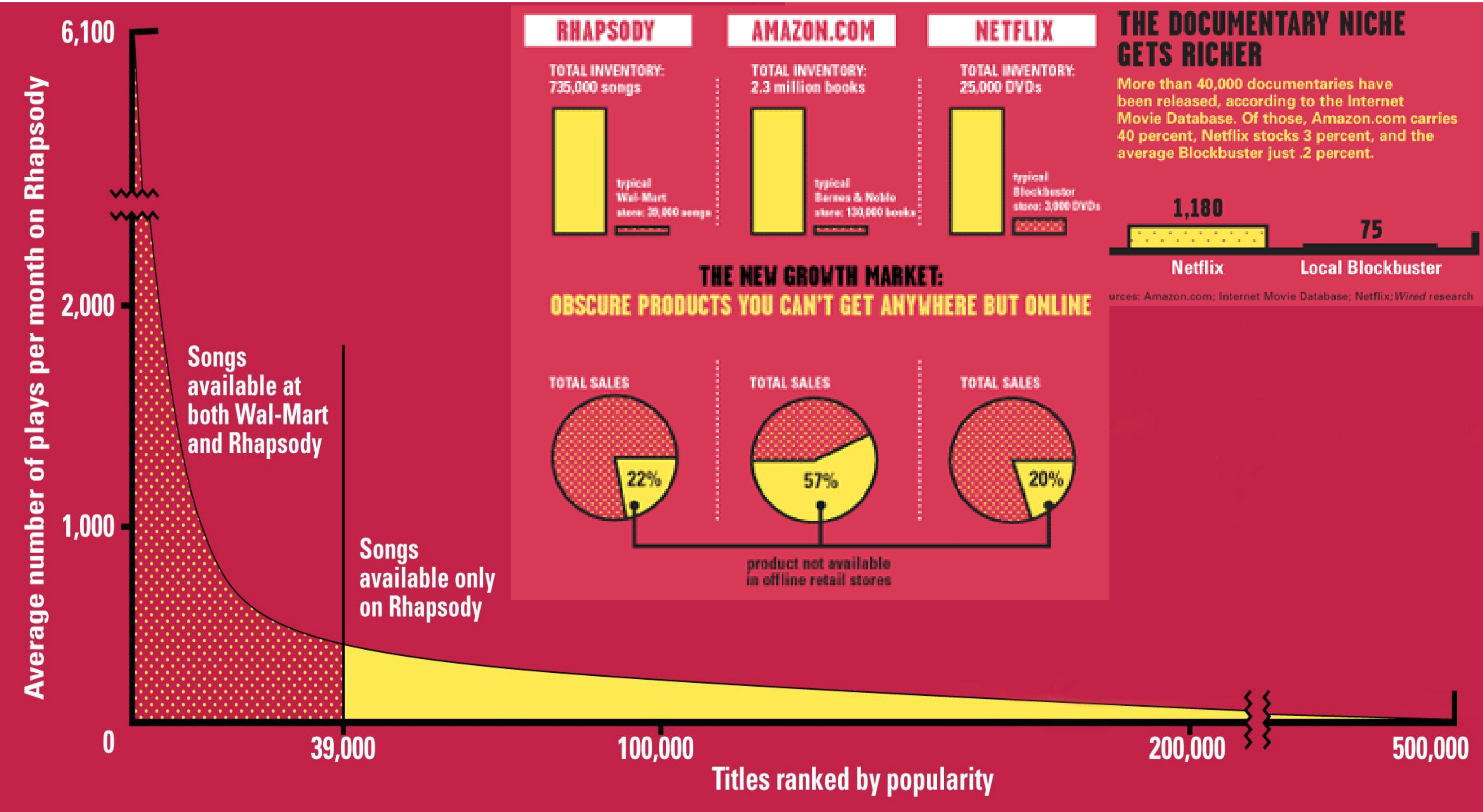
- Online store can stock many more items than a “brick and mortar” store

- But this brings a problem: how do customers find products they like when there are potentially millions of products?
  - Approach: Automated Recommendations

- Simple approaches:
  - Hand-crafted/editorial lists (e.g., for online newspapers)
  - Most-popular lists

- Personalized approaches
  - Recommendations personalized to each user, e.g., Amazon, Netflix, Facebook, etc

# Business Aspects of “The Long Tail”




Sources: Erik Brynjolfsson and Jeffrey Hu, MIT, and Michael Smith, Carnegie Mellon; Barnes & Noble; Netflix; RealNetworks

Source: Chris Anderson (2004)

# Example: Netflix Movie Ratings

100,000 movies

40 million users

| | | | | | |
|---|---|---|---|---|---|
| 1 | 3 | 4 | | | |
| | 3 | 5 | | | 5 |
| | | 4 | 5 | | 5 |
| | | 3 | | | |
| | | 3 | | | |
| 2 | | | 2 | | 2 |
| | | | | 5 | |
| | 2 | 1 | | | 1 |
| | 3 | | | 3 | |
| 1 | | | | | |

# The $1 Million Question

# Million Dollars Awarded Sept 21$^{st}$ 2009

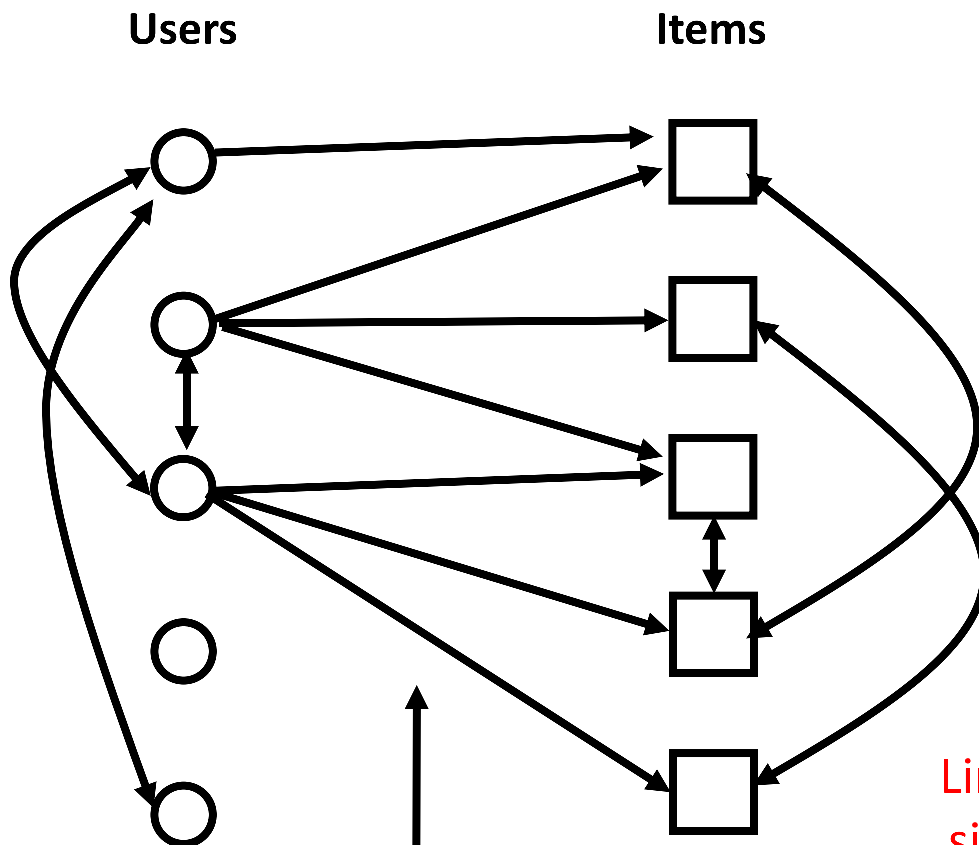
# Additional Content/Side Information

- Often have additional information about users and/or items

- Examples of additional user information
  - Search queries
  - Pages browsed
  - Demographics
  - Social network (connections to other users)

- Examples of additional item information
  - Item attributes, e.g., size, sales numbers
  - Item descriptions (e.g., in text format)
  - Item relationships (e.g., as a hierarchy)

# The Recommender Space as a Bipartite Graph




Links derived from similar attributes, explicit connections

User-User Links

Item-Item Links

Observed preferences

(Ratings, purchases, page views, play lists, bookmarks, etc)

Links derived from similar attributes, similar content, explicit cross references

# Challenges for Recommender Systems

- Data Sparsity
  - Users with very little historical data and few user attributes
  - Items with little or no content information

- "Cold Start" problem
  - How can we make  recommendations for new users? And new items?

# Gathering Ratings Data

- Explicit Ratings
  - E.g., Netflix movie ratings from 1 to 5
  - Difficult in practice: users often don't want to spend time assigning ratings
  - Bias and Variance in ratings
    - Research in cognitive science tells us that humans are not very good at consistently making judgements on a numerical scale
      (Easier for users to make A versus B judgements)
    - Bias: some users may consistently provide ratings lower than others
    - Variance: users may assign different ratings to the same item at different times

- Implicit Ratings
  - Ratings = user actions
  - E.g., purchased an item, listened to a song, viewed a movie for longer than k minutes
  - Issue here is that action need not imply preference, e.g., purchasing an item does not necessarily indicate a high or low preference

# Train/Test Setup (for Explicit Ratings)

Items

Training Users

| | | | | | |
|---|---|---|---|---|---|
| 1 | 3 | 4 | | | |
| | 3 | 5 | | | 5 |
| | | 4 | 5 | | 5 |
| | | 3 | | | |
| | | 3 | | | |
| 2 | | | 2 | | 2 |
| | | | | 5 | |
| | 2 | 1 | | | 1 |
| | 3 | | | 3 | |
| 1 | | | | | |

Test User

| | | | | | |
|---|---|---|---|---|---|
| 1 | | 3 | | 2 | 1 |

Predict each rating for a test user given all their other known ratings and the test data

# Evaluation Metrics

- Mean squared/absolute error in predicting all ratings for all test users
  - Assumes that all predictions are equally useful
  - E.g.,

$$\text{MSE} = 1/|R| \sum_{(u,i)\, \varepsilon\, R} ( r_{ui} - p_{ui} )^2$$

where $r_{ui}$ is the actual rating by user u of item i,
$p_{ui}$ is the algorithms prediction of user u's rating of item i,
and R is the set of ratings being used in the test set

- Precision-based metrics
  - E.g., rank the predictions and measure the precision of the top K predictions
  - Puts more emphasis on predicting positively rated items

# Evaluation with (Implicit) Binary Purchase Data

- Cautionary note:
  - It is not clear that prediction on historical data is a meaningful way to evaluate recommender algorithms, especially for purchasing
  - Consider:
    - User purchases products A, B, C
    - Algorithm ranks C highly given A and B
    - However, what if the user would have purchased C anyway?

      i.e., making this recommendation would have had no impact
      (or possibly a negative impact!)
  - What we would really like to do is reward recommender algorithms that lead the user to purchase products that they would not have purchased without the recommendation
    - This can't be done based on historical data alone
  - Requires direct "live" experiments (which is often how companies evaluate recommender algorithms)

# General Approaches to Automated Recommender Systems

1. Content-based Recommendations
   – Use attributes/features of items to recommend similar items
   – Ignores ratings data

2. Collaborative filtering
   – Use ratings matrix to recommend items, ignores item and user content data
   – 2 broad types:
     (1) Nearest-neighbor methods
     (2) Matrix factorization methods

3. Hybrid methods
   – Combine both content and ratings data (often provides “state of the art” performance)

# Content-Based Recommender Systems

# Content-Based Recommendation Algorithms

- Approach:
  - recommend items to user U that are similar to previous items that user U liked
  - Does not use ratings of other users when making predictions for user U

- "Similarity" is computed from item attributes, e.g.,
  - Similarity of movies by actors, director, genre
  - Similarity of text by words, topics
  - Similarity of music by genre, year

# Content-Based Recommendations

- Represent all items in some feature space
  - Item feature vectors $\underline{x}_1$, ..... $\underline{x}_M$
- "Map" any user into this same space (based on items they have rated)
  - User U has a feature vector $\underline{x}_U$
- Compute similarity of user's feature vector $\underline{x}_U$ to each item feature vector $\underline{x}_i$
- Definition of Sim($\underline{x}_U$ , $\underline{x}_i$ ) is critical

# Example: Text-Based Content

Items = documents,

Features = words or phrases

- Represent each document as as "bag of words"
- i.e., a vector with the counts of how often each word occurs in the document

Can use TF-IDF from information retrieval to weight features:

$TF_{ij}$ = frequency of term (feature) ***j*** in doc (item) ***i***

$n_i$ = number of docs that mention term ***i***

$N$ = total number of docs

$$IDF_i = \log \frac{N}{n_i}$$

"Downweights" terms that are more common

**TF-IDF score:** $w_{ij} = TF_{ij} \times IDF_i$

# Example: Text-Based Content

feature vector for item i, $\underline{x}_i$ = vector of words represented by their **TF-IDF** scores

feature vector for user u, $\underline{x}_u$ ?

can be computed as the average of the TF-IDF items rated by that user, weighted by the user's ratings

Prediction:

e.g., rank items using cosine similarity Cos ($\underline{x}_u$ , $\underline{x}_i$ ) $= \frac{xu \cdot xi}{||xu|| \cdot ||xi||}$

# Advantages of the Content-Based Approach

+ Only uses data from user U
  - So no need for data from other users
  - Easy to apply with few users

+ Can accommodate new items with no ratings
  - New items can be included as long as we can compute their feature vector

+ Can handle users with unique/unusual preferences

+ Can provide explanations
  - E.g., by listing the content features that caused an item to be recommended

# Weaknesses of the Content-Based Approach

- Items must have useful features on which to base similarity
- Finding which features are relevant to user tastes may be difficult
- Cannot make recommendations for new users
- May be sensitive to
  - similarity metric
  - definition of user features

# Collaborative Filtering for Recommender Systems:

# Nearest-Neighbor Algorithms

# User-User Neighborhood-Based Collaborative Filtering

- Idea: make recommendations for **active user a** based on finding similar users to user **a**
  - Let $\mathbf{K_a}$ be the set of K nearest-neighbors for user **a**
  - Generate predictions for **a** as a weighted combination of $\mathbf{K_a}$'s ratings

- Define similarity weight $\mathbf{w_{a,u}}$ between user **a** and user **u**,
  - e.g., linear correlation coefficient is often used:

$$w_{a,u} = \frac{\sum_{i \in I} (r_{a,i} - \overline{r}_a)(r_{u,i} - \overline{r}_u)}{\sqrt{\sum_{i \in I} (r_{a,i} - \overline{r}_a)^2 \sum_{i \in I} (r_{u,i} - \overline{r}_u)^2}}$$

where I is the set of items rated by **both** users, $\mathbf{r_{u,i}}$ is rating given by u to item I, and $\overline{r}_u$ is the mean rating of user u across items in set I

# User-User Neighborhood-Based Collaborative Filtering

## Prediction Step

$$p_{a,i} = \overline{r}_a + \frac{\sum_{u \in K} (r_{u,i} - \overline{r}_u) \times w_{a,u}}{\sum_{u \in K} w_{a,u}}$$

Where **$p_{a,i}$** is the prediction of rating for item **i** for user **a**,

$\overline{r}_u$ is the average rating of user u

**$w_{a,u}$** is the similarity weight between user **a** and user **u**,

**K** is the set of nearest users to **a**, as determined by **$w_{a,u}$**

Basically we are computing “deltas” for each user in **a**’s neighborhood, weighted by how similar these users are in general to **a**.

# Extensions/Options

- Significance weighting:
  - The active user can have highly correlated neighbors based on a very few co-rated items
  - This may yield poor predictions
  - Downweighting the similarity weight by a “significance weighting factor” can help here

- Downweight commonly rated items
  - Some items are rated/purchased by everyone, e.g., a Oscar-winning movie
  - These items are often not that useful as less common items
  - Can multiple original ratings by TF-IDF weighting, log $(n / n_i)$ where $n_i$ is the number of users who rated item i
  - Will tend to downweight the more common items (i.e., with high $n_i$ values)

- Various other heuristic modifications….

# User-User Near Neighbor Algorithm

1. For an active user **a**, find the K-nearest neighbor users using $\mathbf{w_{a,u}}$

2. Use the prediction equation to generate predicted rankings on all items

Naïve Time Complexity = O( N M ),
where N = number of users, M = number of items

More realistically:
Time Complexity = O( N r + M) where r = average # items rated by users

This is still too slow to perform in real-time,
e.g., Amazon ~ 100 million customers, ~ 10 million items

# Speed-Up Options for User-User Collaborative Filtering

- Reducing N
  - Randomly sample customers
  - Remove customers with few purchases (large fraction)
- Reducing M
  - Remove rarely purchased items
  - Do dimension reduction
- Cluster customers or items or both…

All of these methods tend to reduce the quality of neighbor-based collaborative filtering methods

Note also that it is usually not practical to do significant user-user computations offline since there is constantly new (and relevant) user data being generated

# Item-Item Collaborative Filtering

Match a user's rated items to similar items

- Tends to scale better than user-user CF methods (see Linden et al, Amazon paper)
- Items are fewer and potentially more stable than users

Similarity between items i and j computed using:

$$w_{i,j} = \frac{\sum_{u \in U} (r_{u,i} - \bar{r}_i)(r_{u,j} - \bar{r}_j)}{\sqrt{\sum_{u \in U} (r_{u,i} - \bar{r}_i)^2} \sqrt{\sum_{u \in U} (r_{u,j} - \bar{r}_j)^2}}$$

where U = set of users who have rated both items i and j

$\bar{r}_i$ = the average rating of item i across all users in set U

This can be computed offline

# Item-Item Collaborative Filtering

We can now predict the rating for item i by user a as follows:

$$p_{a,i} = \frac{\sum_{j \in K} r_{a,j} w_{i,j}}{\sum_{j \in K} |w_{i,j}|}$$

where K is the neighborhood set of k items, from the set rated by user a, that are most similar to item i

# Toy Example of Item-Item Collaborative Filtering

users

| 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

Figures and example courtesy of Jure Leskovec, Stanford

# Toy Example of Item-Item Collaborative Filtering

users

| 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**

Figures and example courtesy of Jure Leskovec, Stanford

# Toy Example of Item-Item Collaborative Filtering

**users**

| movies | 1 | 2 | 3 | 4 | **5** | 6 | 7 | 8 | 9 | 10 | 11 | 12 | $w_{1,j}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | | 3 | | ? | 5 | | | 5 | | 4 | | **1.00** |
| 2 | | | | | | | | | | | | 3 | **-0.18** |
| 3 | | | | | | | | | | | | | **0.41** |
| 4 | | | | | | | | | | | | | **-0.10** |
| 5 | | | 4 | 3 | 4 | 2 | | | | | 2 | 5 | **-0.31** |
| 6 | 1 | | 3 | | 3 | | | 2 | | | 4 | | **0.59** |

**Using Pearson correlation as similarity:**

**1)** Subtract mean rating $r_i$ from each movie ***i***

$r_1 = (1+3+5+5+4)/5 = \mathbf{3.6}$

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

**2)** Compute correlation between rows

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

Figures and example courtesy of Jure Leskovec, Stanford

# Toy Example of Item-Item Collaborative Filtering

users

| movies | 1 | 2 | 3 | 4 | **5** | 6 | 7 | 8 | 9 | 10 | 11 | 12 | $w_{1,j}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 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** |

**Find the 2 nearest neighbors, with similarity weights**
**$w_{13}$=0.41, $w_{16}$=0.59**

Figures and example courtesy of Jure Leskovec, Stanford

# Toy Example of Item-Item Collaborative Filtering

users

movies

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | | 3 | | **2.6** | 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 | |

**Predict by taking weighted average:**

**$P_{1,5}$ = (0.41*2 + 0.59*3) / (0.41+0.59) = 2.6**

$$p_{a,i} = \frac{\sum_{j \in K} r_{a,j} w_{i,j}}{\sum_{j \in K} |w_{i,j}|}$$

Figures and example courtesy of Jure Leskovec, Stanford

# Comparing User-User and Item-Item Methods

- Research studies indicate that item-item may produce more accurate ratings than user-user: why?
  - More stability across items than users (?)
  - More unusual/idiosyncratic users than items (?)
  - Item dimensionality is smaller (fewer items than users): so more data per item than per user

- Algorithmic advantage of Item-Item
  - Offline
    - build item similarity list
    - Can save time by skipping pairs of items with no common customers
  - Online predictions for an active user
    - Can be done relatively quickly
    - Depends on number of items rated by a user, and number of similar items

  - See paper by Linden, Smith, York on Amazon's item-item recommender system
    (note, there may be typos in their derivation of O(M+N) complexity for on 2nd page)

# Advantages/Weaknesses of Collaborative Filtering

- Advantages
  - Works for any kind of item – no features needed
  - Simple to implement – no feature engineering

- Weaknesses:
  - Not idea for “Cold Start”
    - needs to have users already in system to work
  - Cannot recommend items that have not already been rated
    - e.g., new items, unusual items
  - Popularity bias
    - Hard to make recommendations to someone with unique tastes
    - Can tend to recommend popular items

# Hybrid Methods

- Combine content-based and collaborative filtering
  - E.g., simply implement both methods and combine predictions linearly
  - Weights can be learned by cross-validation

- Integrate content features into collaborative filtering
  - Item features for new items
  - User features for new users

…. When we discuss matrix factorization we will discuss a systematic way to do this

# Next Lecture

- Matrix factorization approaches to recommender systems
- Stochastic gradient and related ideas
- The Netflix Prize competition