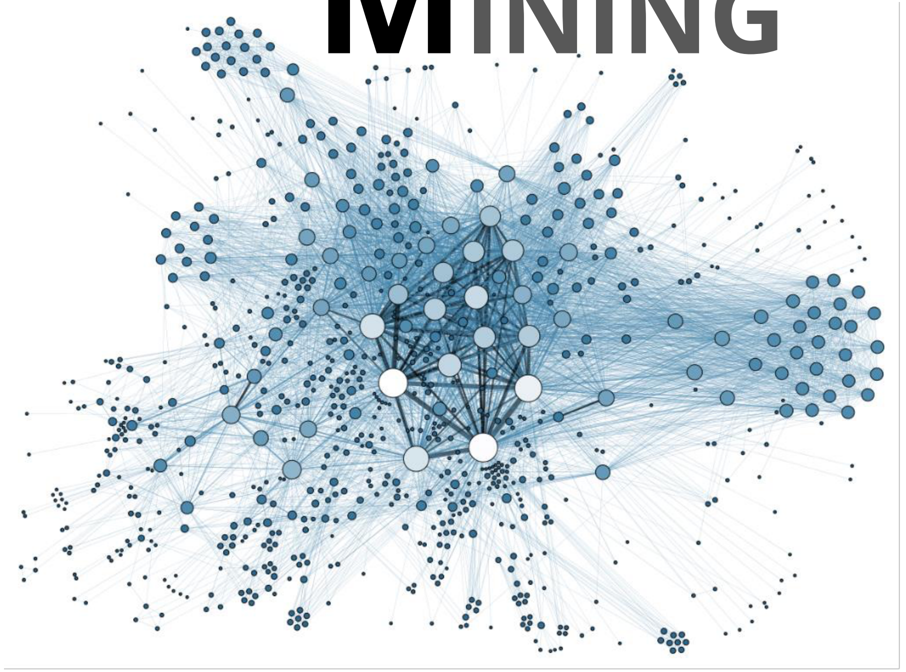
Social Media Mining

Recommendation in Social Media



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Please feel free to include these slides in your own material, or modify them as you see fit. If you decide to incorporate these slides into your presentations, please include the following note:

> R. Zafarani, M. A. Abbasi, and H. Liu, *Social Media Mining: An Introduction*, Cambridge University Press, 2014.
> Free book and slides at **http://socialmediamining.info/**

or include a link to the website:
http://socialmediamining.info/

Difficulties of Decision Making

- Which digital camera should I buy?
- Where should I spend my holiday?
- Which movie should I rent?
- Whom should I follow?
- Where should I find interesting news article?
- Which movie is the best for **our family**?

- If interested, see two recent conference tutorials
  - SIGKDD2014, Recommendation in Social Media
  - RecSys2014, Personalized Location Recommendation

When Does This Problem Occur?

- There are many choices
- There are no obvious advantages among them
- We do not have enough resources to check all options (**information overload**)
- We do not have enough knowledge and experience to choose, or
  – I'm lazy, but don't want to miss out on good stuff
  – Defensive decision making

Goal of Recommendation:
To come up with a short list of items that fits user's interests

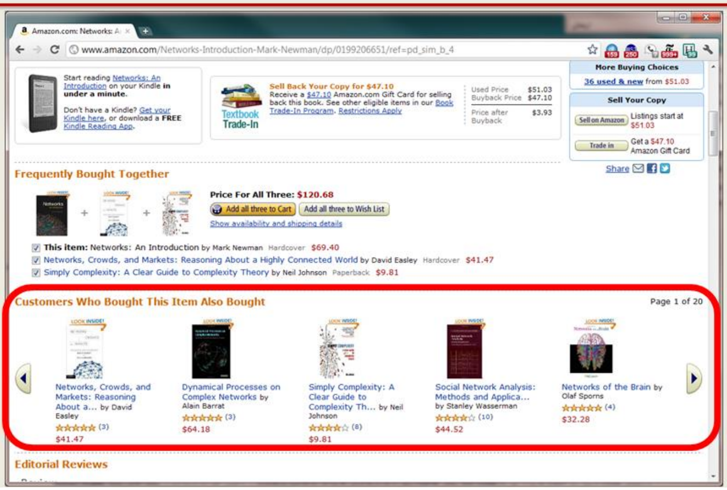
Common Solutions to the Problem

- Consulting friends
- Obtaining information from a trusted third party
- Hiring a team of experts
- Search the Internet
- Following the crowd
  - Pick the item from top-n lists
  - Best sellers on Amazon

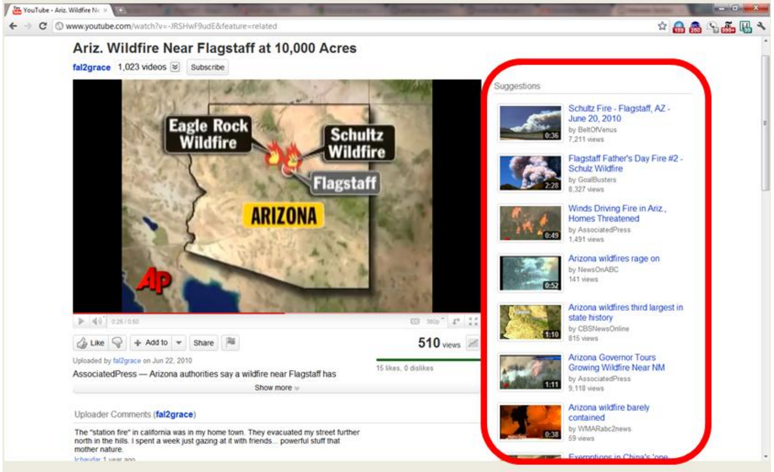
- **Can we automate all of the above?**
  - **Using a recommender algorithm**
  - **Also known as recommender systems**

Recommender Systems - Examples

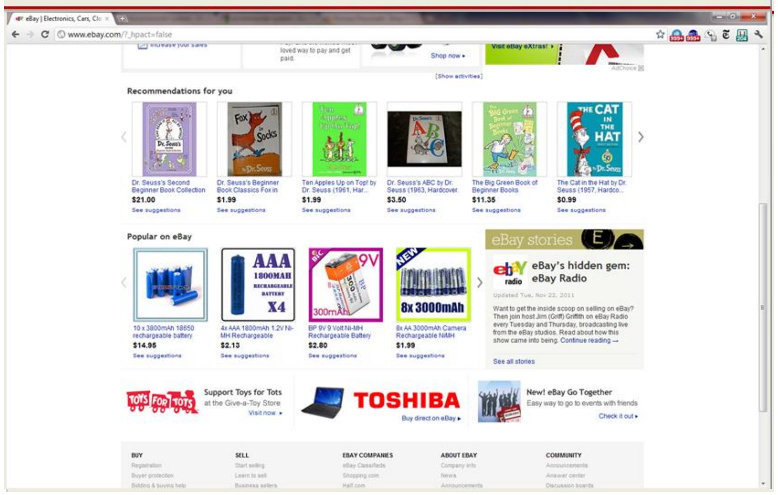
Book recommendation in Amazon



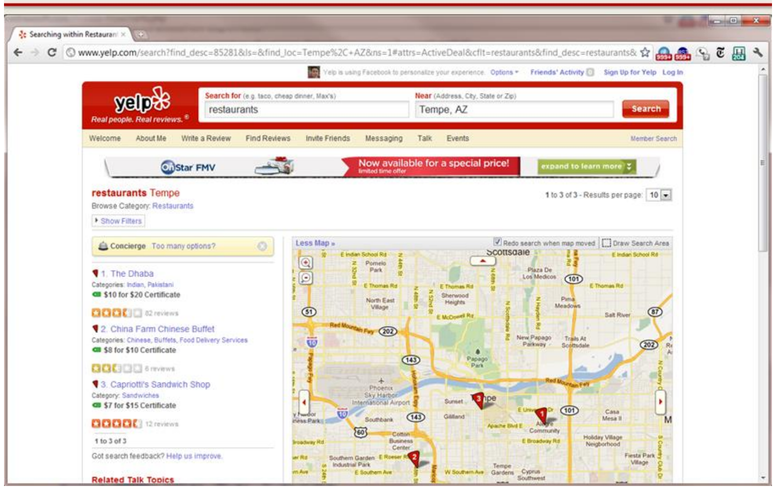
Video clip recommendation in YouTube



Product Recommendation in ebay



Restaurant Recommendation in Yelp



Main Idea behind Recommender Systems

Use historical data such as the user's past preferences or similar users' past preferences to predict future likes

- Users' preferences are likely to remain stable, and change smoothly over time.
  - By watching the past users' or groups' preferences, we try to predict their future interests
  - Then we can recommend items of interest to them

- Formally, a recommender system takes a set of users U and a set of items I and learns a function f such that:

$$f : U \times I \to \mathbb{R}$$

Recommendation vs. Search

- One way to get answers is using search engines
- Search engines find results that match the query provided by the user
- The results are generally provided as a list ordered with respect to the relevance of the item to the given query
- Consider the query "**best 2014 movie to watch**"
  - The same results for an 8 year old and an adult

Search engines' results are not customized

Challenges of Recommender Systems

- **The Cold Start Problem**
  - Recommender systems use historical data or information provided by the user to recommend items, products, etc.
  - When user join sites, they still haven't bought any product, or they have no history.
  - It is hard to infer what they are going to like when they start on a site.

- **Data Sparsity**
  - When historical or prior information is insufficient.
  - Unlike the cold start problem, this is in the system as a whole and is not specific to an individual.

Challenges of Recommender Systems

- **Attacks**
  - **Push Attack**: pushing ratings up by making fake users
  - **Nuke attack**: DDoS attacks, stop the whole recommendation systems
- **Privacy**
  - Using one's private info to recommend to others.
- **Explanation**
  - Recommender systems often recommend items with no explanation on why these items are recommended

Classical Recommendation Algorithms

- **Content-based algorithms**
- **Collaborative filtering**

Content-Based Methods

Assumption: a user's interest should match the description of the items that the user should be recommended by the system.

– The more similar the item's description to that of the user's interest, the more likely that the user finds the item's recommendation interesting.

Goal: find the similarity between the user and all of the existing items is the core of this type of recommender systems

Content-based Recommendation: An Example

Book Database

Title	Genre	Author	Type	Price	Keywords
The Night of the Gun	Memoir	David Carr	Paperback	29.90	press and journalism, drug addiction, personal memoirs, New York
The Lace Reader	Fiction, Mystery	Brunonia Barry	Hardcover	49.90	American contemporary fiction, detective, historical
Into the Fire	Romance, Suspense	Suzanne Brockmann	Hardcover	45.90	American fiction, murder, neo-Nazism
...					

User Profile

Title	Genre	Author	Type	Price	Keywords
...	Fiction, Suspense	Brunonia Barry, Ken Follett	Paperback	25.65	detective, murder, New York

Content-based Recommendation Algorithm

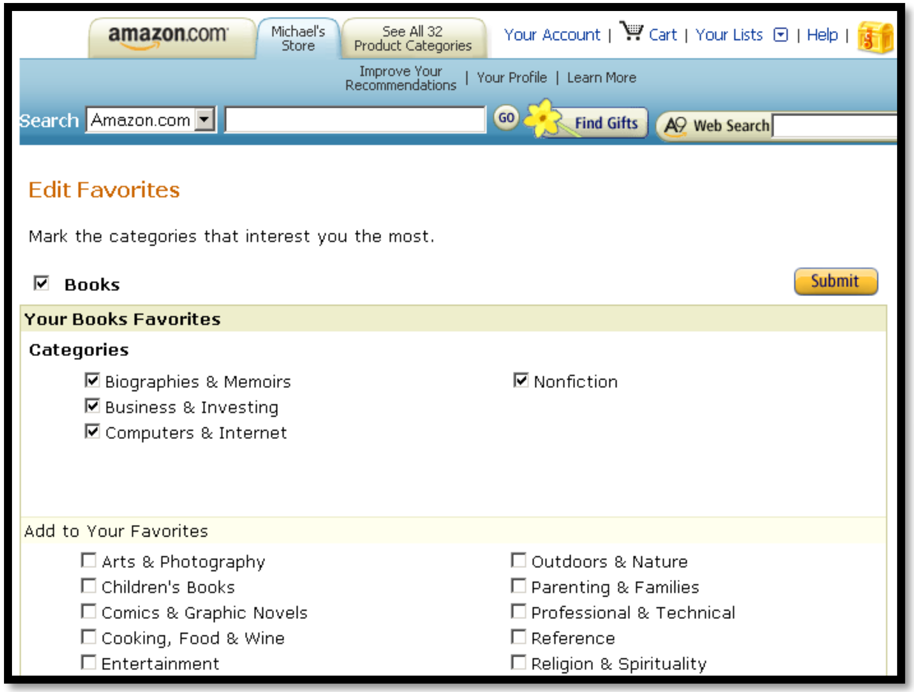
1. Describe the items to be recommended

2. Create a profile of the user that describes the types of items the user likes

3. Compare items with the user profile to determine what to recommend

The profile is often created, and updated automatically in response to feedback on the desirability of items that are presented to the user

Content-based Recommendation: Example



User Profile

Items Recommended

More formally

- We represent user profiles and item descriptions by vectorizing them using a set of k keywords
- We can vectorize (e.g., using **TF-IDF**) both users and items and compute their similarity

$$I_j = (i_{j,1}, i_{j,2}, \ldots, i_{j,k}) \quad U_i = (u_{i,1}, u_{i,2}, \ldots, u_{i,k})$$

$$sim(U_i, I_j) = cos(U_i, I_j) = \frac{\sum_{l=1}^{k} u_{i,l} i_{j,l}}{\sqrt{\sum_{l=1}^{k} {u_{i,l}}^2} \sqrt{\sum_{l=1}^{k} {i_{j,l}}^2}}$$

We can recommend the top most similar items to the user

Content-Based Recommendation Algorithm

Algorithm 9.1 Content-based recommendation

Require: User i's Profile Information, Item descriptions for items $j \in \{1, 2, \ldots, n\}$, k keywords, r number of recommendations.

1: **return** r recommended items.
2: $U_i = (u_1, u_2, \ldots, u_k)$ = user i's profile vector;
3: $\{I_j\}_{j=1}^n = \{(i_{j,1}, i_{j,2}, \ldots, i_{j,k})$ = item j's description vector$\}_{j=1}^n$;
4: $s_{i,j} = sim(U_i, I_j), 1 \leq j \leq n$;
5: Return top r items with maximum similarity $s_{i,j}$.

- We compute the topmost similar items to a user *j* and then recommend these items in the order of similarity

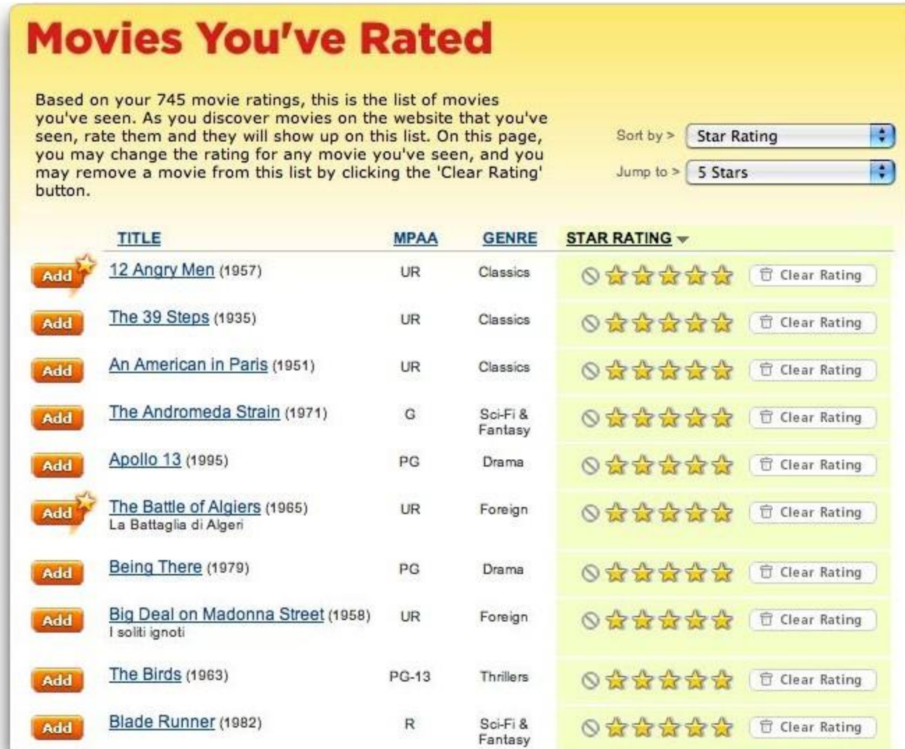
Collaborative Filtering

Collaborative filtering: the process of selecting information or patterns using techniques involving collaboration among multiple agents, viewpoints, data sources, etc.

Advantage: we don't need to have additional information about the users or content of the items

– Users' rating or purchase history is the only information that is needed to work

Rating Matrix: An Example



Value	Graphic representation	Textual representation
5	☆ ☆ ☆ ☆ ☆	Excellent
4	☆ ☆ ☆ ☆	Very good
3	☆ ☆ ☆	Good
2	☆ ☆	Fair
1	☆	Poor

Table 9.1: User-Item Matrix

	Lion King	Aladdin	Mulan	Anastasia
John	3	0	3	3
Joe	5	4	0	2
Jill	1	2	4	2
Jane	3	?	1	0
Jorge	2	2	0	1

Rating Matrix

Users rate (rank) items (purchased, watched)

Explicit ratings:

- entered by a user directly
- i.e., “Please rate this on a scale of 1-5”

Implicit ratings:

- Inferred from other user behavior
- E.g., Play lists or music listened to, for a music Rec system
- The amount of time users spent on a webpage

Collaborative Filtering

Types of Collaborative Filtering Algorithms:

- **Memory-based**: Recommendation is directly based on previous ratings in the stored matrix that describes user-item relations
- **Model-based**: Assumes that an underlying model (hypothesis) governs how users rate items.
  - This model can be approximated and learned.
  - The model is then used to recommend ratings.
  - **Example**: users rate low budget movies poorly

Memory-Based Collaborative Filtering

Two memory-based methods:

User-based CF

Users with similar **previous** ratings for items are likely to rate future items similarly

	I1	I2	I3	I4
U1	1	2	4	4
U2	1	2	4	?
U3	2	5	2	2
U4	5	2	3	3

Item-based CF

Items that have received similar ratings **previously** from users are likely to receive similar ratings from future users

	I1	I2	I3	I4
U1	1	2	4	4
U2	1	2	4	?
U3	2	5	2	2
U4	5	2	3	3

Collaborative Filtering: Algorithm

1. Weigh all users/items with respect to their similarity with the current user/item
2. Select a subset of the users/items (**neighbors**) as recommenders
3. Predict the rating of the user for specific items using neighbors' ratings for the same (or similar) items
4. Recommend items with the highest predicted rank

Measuring Similarity between Users (or Items)

Cosine Similarity

$$sim(U_u, U_v) = cos(U_u, U_v) = \frac{U_u \cdot U_v}{||U_u||\ ||U_v||} = \frac{\sum_i r_{u,i} r_{v,i}}{\sqrt{\sum_i {r_{u,i}}^2}\sqrt{\sum_i {r_{v,i}}^2}}.$$

Pearson Correlation Coefficient

$$sim(U_u, U_v) = \frac{\sum_i (r_{u,i} - \bar{r}_u)(r_{v,i} - \bar{r}_v)}{\sqrt{\sum_i (r_{u,i} - \bar{r}_u)^2}\sqrt{\sum_i (r_{v,i} - \bar{r}_v)^2}}$$

User-based Collaborative Filtering

- User-based collaborative filtering
  – The system finds the most similar user (users) to the current user and uses their preferences for recommendation

- The user-based approach is not as popular as the item-based approach
  – **Why?** With large number of users, even the smallest change in the user data is likely to reset the entire group of similar users

User-based CF

Updating the ratings:

User v's mean rating

User u's mean rating

$$r_{u,i} = \bar{r}_u + \frac{\sum_{v \in N(u)} sim(u,v)(r_{v,i} - \bar{r}_v)}{\sum_{v \in N(u)} sim(u,v)}$$

Predicted rating of user u for item i

Observed rating of user v for item i

User-based CF, Example

	Lion King	Aladdin	Mulan	Anastasia
John	3	0	3	3
Joe	5	4	0	2
Jill	1	2	4	2
Jane	3	?	1	0
Jorge	2	2	0	1

Predict Jane's rating for Aladdin

1- Calculate average ratings

$$\bar{r}_{John} = \frac{3+3+0+3}{4} = 2.25$$

$$\bar{r}_{Joe} = \frac{5+4+0+2}{4} = 2.75$$

$$\bar{r}_{Jill} = \frac{1+2+4+2}{4} = 2.25$$

$$\bar{r}_{Jane} = \frac{3+1+0}{3} = 1.33$$

$$\bar{r}_{Jorge} = \frac{2+2+0+1}{4} = 1.25$$

2- Calculate user-user similarity

$$sim(Jane, John) = \frac{3\times 3 + 1\times 3 + 0\times 3}{\sqrt{10}\sqrt{27}} = 0.73$$

$$sim(Jane, Joe) = \frac{3\times 5 + 1\times 0 + 0\times 2}{\sqrt{10}\sqrt{29}} = 0.88$$

$$sim(Jane, Jill) = \frac{3\times 1 + 1\times 4 + 0\times 2}{\sqrt{10}\sqrt{21}} = 0.48$$

$$sim(Jane, Jorge) = \frac{3\times 2 + 1\times 0 + 0\times 1}{\sqrt{10}\sqrt{5}} = 0.84$$

User-based CF, Example- continued

3- Calculate Jane's rating for Aladdin, Assume that neighborhood size = 2

$$
\begin{aligned}
r_{Jane,Aladdin} &= \bar{r}_{Jane} + \frac{sim(Jane, Joe)(r_{Joe,Aladdin} - \bar{r}_{Joe})}{sim(Jane, Joe) + sim(Jane, Jorge)} \\
&\quad + \frac{sim(Jane, Jorge)(r_{Jorge,Aladdin} - \bar{r}_{Jorge})}{sim(Jane, Joe) + sim(Jane, Jorge)} \\
&= 1.33 + \frac{0.88(4 - 2.75) + 0.84(2 - 1.25)}{0.88 + 0.84} = 2.33
\end{aligned}
$$

Item-based CF

Calculate the similarity between items and then predict new items based on the past ratings for similar items

$$r_{u,i} = \bar{r}_i + \frac{\sum_{j \in N(i)} sim(i,j)(r_{u,j} - \bar{r}_j)}{\sum_{j \in N(i)} sim(i,j)}$$

Item i's mean rating

i and j are two items

Item-based CF, Example

1- Calculate average ratings

$$\bar{r}_{Lion\,King} = \frac{3+5+1+3+2}{5} = 2.8$$

$$\bar{r}_{Aladdin} = \frac{0+4+2+2}{4} = 2.$$

$$\bar{r}_{Mulan} = \frac{3+0+4+1+0}{5} = 1.6$$

$$\bar{r}_{Anastasia} = \frac{3+2+2+0+1}{5} = 1.6$$

2- Calculate item-item similarity

$$sim(Aladdin, Lion\,King) = \frac{0\times 3+4\times 5+2\times 1+2\times 2}{\sqrt{24}\sqrt{39}} = 0.84$$

$$sim(Aladdin, Mulan) = \frac{0\times 3+4\times 0+2\times 4+2\times 0}{\sqrt{24}\sqrt{25}} = 0.32$$

$$sim(Aladdin, Anastasia) = \frac{0\times 3+4\times 2+2\times 2+2\times 1}{\sqrt{24}\sqrt{18}} = 0.67$$

3- Calculate Jane's rating for Aladdin, Assume that neighborhood size = 2

$$\begin{aligned} r_{Jane,Aladdin} &= \bar{r}_{Aladdin} + \frac{sim(Aladdin, Lion\,King)(r_{Jane,Lion\,King} - \bar{r}_{Lion\,King})}{sim(Aladdin, Lion\,King) + sim(Aladdin, Anastasia)} \\ &\quad + \frac{sim(Aladdin, Anastasia)(r_{Jane,Anastasia} - \bar{r}_{Anastasia})}{sim(Aladdin, Lion\,King) + sim(Aladdin, Anastasia)} \\ &= 2 + \frac{0.84(3-2.8) + 0.67(0-1.6)}{0.84+0.67} = 1.40 \end{aligned}$$

Recommendation to a Group

Recommendation to Groups

- Find content of interest to all members of a group of socially acquainted individuals
- Examples:
  - A movie for friends to watch together
  - A travel destination for a family to spend a break
  - A good restaurant for colleagues to have lunch
  - A music to be played in a public area

Tasks of a Group Recommender System

- Acquiring preferences
- Generating recommendations
- Explaining recommendations
- Helping group members to achieve consensus

Aggregation Strategies

Maximizing Average Satisfaction

- Average everyone's ratings and choose the max

$$R_i = \frac{1}{n}\sum_{u \in G} r_{u,i}$$

Least Misery

- This approach tries to minimize the dissatisfaction among group's members (max of all mins)

$$R_i = \min_{u \in G} r_{u,i}$$

Most Pleasure

- The maximum of individuals' maximum ratings is taken as group's rating

$$R_i = \max_{u \in G} r_{u,i}$$

Recommendation to Group, an Example

Table 9.3: User-Item Matrix

	Soda	Water	Tea	Coffee
John	1	3	1	1
Joe	4	3	1	2
Jill	2	2	4	2
Jorge	1	1	3	5
Juan	3	3	4	5

Average Satisfaction

$$R_{Soda} = \frac{1+2+3}{3} = 2.$$
$$R_{Water} = \frac{3+2+3}{3} = 2.66$$
$$R_{Tea} = \frac{1+4+4}{3} = 3.$$
$$R_{Coffee} = \frac{1+2+5}{3} = 2.66$$

Least Misery

$$R_{Soda} = \min\{1,2,3\} = 1$$
$$R_{Water} = \min\{3,2,3\} = 2$$
$$R_{Tea} = \min\{1,4,4\} = 1$$
$$R_{Coffee} = \min\{1,2,5\} = 1$$

Most Pleasure

$$R_{Soda} = \max\{1,2,3\} = 3$$
$$R_{Water} = \max\{3,2,3\} = 3$$
$$R_{Tea} = \max\{1,4,4\} = 4$$
$$R_{Coffee} = \max\{1,2,5\} = 5$$

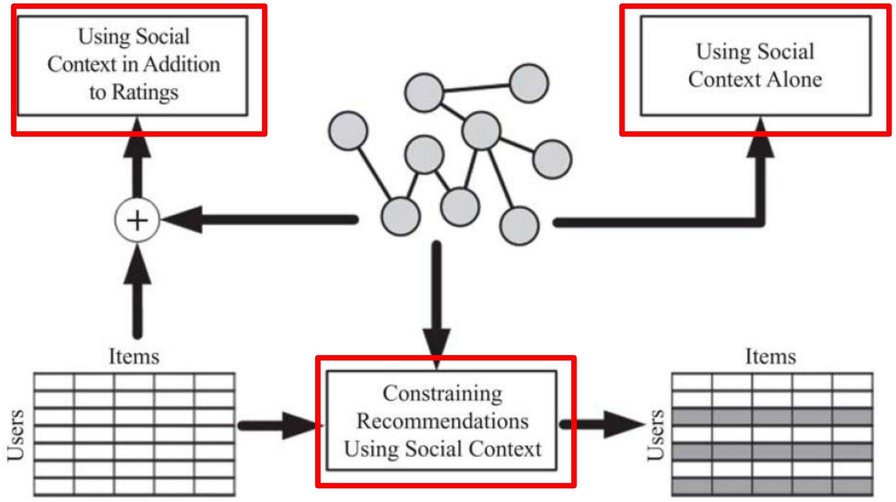
Recommendation Using Social Context

- Recommendation using social context alone
- Extending classical methods with social context
- Recommendation constrained by social context

Information Available in Social Context

- In social media, in addition to ratings of products, there is additional information
  – E.g., the friendship network

- This information can be used to improve recommendations
  - Assuming that friends have an impact on the ratings ascribed by the individual.
  - This impact can be due to homophily, influence, or confounding



I. Recommendation Using Social Context Alone

- Consider a network of friendships for which no user-item rating matrix is provided.
- In this network, we can still recommend users from the network to other users for friendship.
- This is an example of friend recommendation in social networks [**Next Chapter**!]

3. Recommendation Constrained by Social Context

- In classical recommendation,
  - To estimate ratings, we determine similar users or items.
  - Any user similar to the individual can contribute to the predicted ratings for the individual.

- We can limit the set of individuals that can contribute to the ratings of a user to the set of friends of the user.
  - $S(i)$ is the set of k most similar **friends** of an individual

$$r_{u,i} = \bar{r}_u + \frac{\sum_{v \in S(u)} sim(u,v)(r_{v,i} - \bar{r}_v)}{\sum_{v \in S(u)} sim(u,v)}$$

Example

$$A = \begin{array}{c} \\ John \\ Joe \\ Jill \\ Jane \\ Jorge \end{array} \begin{array}{c} \begin{array}{ccccc} John & Joe & Jill & Jane & Jorge \end{array} \\ \begin{bmatrix} 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \end{bmatrix} \end{array}$$

	Lion King	Aladdin	Mulan	Anastasia
John	4	3	2	2
Joe	5	2	1	5
Jill	2	5	?	0
Jane	1	3	4	3
Jorge	3	1	1	2

Average Ratings

$$\bar{r}_{John} = \frac{4+3+2+2}{4} = 2.75.$$

$$\bar{r}_{Joe} = \frac{5+2+1+5}{4} = 3.25.$$

$$\bar{r}_{Jill} = \frac{2+5+0}{3} = 2.33.$$

$$\bar{r}_{Jane} = \frac{1+3+4+3}{4} = 2.75.$$

$$\bar{r}_{Jorge} = \frac{3+1+1+2}{4} = 1.75.$$

User Similarity

$$sim(Jill, John) = \frac{2\times 4 + 5\times 3 + 0\times 2}{\sqrt{29}\sqrt{29}} = 0.79$$

$$sim(Jill, Joe) = \frac{2\times 5 + 5\times 2 + 0\times 5}{\sqrt{29}\sqrt{54}} = 0.50$$

$$sim(Jill, Jane) = \frac{2\times 1 + 5\times 3 + 0\times 3}{\sqrt{29}\sqrt{19}} = 0.72$$

$$sim(Jill, Jorge) = \frac{2\times 3 + 5\times 1 + 0\times 2}{\sqrt{29}\sqrt{14}} = 0.54$$

$$r_{Jill,Mulan} = \bar{r}_{Jill} + \frac{sim(Jill, Jane)(r_{Jane,Mulan} - \bar{r}_{Jane})}{sim(Jill, Jane) + sim(Jill, Jorge)} + \frac{sim(Jill, Jorge)(r_{Jorge,Mulan} - \bar{r}_{Jorge})}{sim(Jill, Jane) + sim(Jill, Jorge)}$$

$$= 2.33 + \frac{0.72(4 - 2.75) + 0.54(1 - 1.75)}{0.72 + 0.54} = 2.72$$

Evaluation of Recommender Systems

Evaluating Recommender Systems is difficult

- Different algorithms may be better or worse on different datasets (applications)
  - Many algorithms are designed specifically for datasets where there are many more users than items or vice versa.
  - Similar differences exist for rating density, rating scale, and other properties of datasets
- The goals to perform evaluation may differ
  - Early evaluation work focused specifically on the "accuracy" of algorithms in "predicting" withheld ratings.
  - Other properties different from accuracy also have important effect on user satisfaction and performance
- There is a significant challenge in deciding what combination of measures should be used in comparative evaluation

Evaluating Recommender Systems

- A myriad of algorithms are proposed, **but**
  - Which one is the best in a given application domain?
  - What are the success factors of different algorithms?
  - Comparative analysis based on an optimality criterion?

Main questions are:

- Is a RS efficient with respect to specific criteria like accuracy, user satisfaction, response time, etc.
- Do customers like/buy recommended items?
- Do customers buy items they otherwise would have not?
- Are they satisfied with a recommendation after purchase?

How Do We Evaluate Recommenders

- Application outcomes
  - Add-on sales
  - Click-through rates
  - The number of products purchased
    - And not returned!

- Research measures
  - User satisfaction

- Metrics
  - To anticipate the above beforehand (offline)

Accuracy Metrics

- **Predictive accuracy**
  - *How close* are the recommender system's predicted ratings are to the true user ratings?

- **Classification accuracy**
  - The ratio with which a recommender system makes correct vs. incorrect decisions about whether an item is good.
  - Classification metrics are thus appropriate for tasks such as *Find Good Items* when users have binary preferences.

- **Rank accuracy**

I. Predictive accuracy - Metrics measure error rate

- **Mean Absolute Error (*MAE*).** The average absolute deviation between a predicted rating (p) and the user's true rating (r)
  - $NMAE = MAE/(r_{max} - r_{min})$

$$MAE = \frac{\sum_{ij} |\hat{r}_{ij} - r_{ij}|}{n}$$

- **Root Mean Square Error (*RMSE*).** Similar to *MAE*, but places more emphasis on larger deviation

$$RMSE = \sqrt{\frac{1}{n}\sum_{i,j}(\hat{r}_{ij} - r_{ij})^2}$$

Evaluation Example

Item	Predicted Rating	True Rating
1	1	3
2	2	5
3	3	3
4	4	2
5	4	1

$$MAE = \frac{|1-3| + |2-5| + |3-3| + |4-2| + |4-1|}{5} = 2$$

$$NMAE = \frac{MAE}{5-1} = 0.5$$

$$RMSE = \sqrt{\frac{(1-3)^2 + (2-5)^2 + (3-3)^2 + (4-2)^2 + (4-1)^2}{5}}$$

$$= 2.28$$

II. Classification Accuracy: Precision and Recall

Precision: a measure of exactness, determines the fraction of relevant items retrieved out of all items retrieved

$$P = \frac{N_{rs}}{N_s}$$

Recall: a measure of completeness, determines the fraction of relevant items retrieved out of all relevant items

$$R = \frac{N_{rs}}{N_r}$$

	Selected	Not Selected	Total
Relevant	N_{rs}	N_{rn}	N_r
Irrelevant	N_{is}	N_{in}	N_i
Total	N_s	N_n	N

Evaluating Relevancy, Example

	Selected	*Not Selected*	*Total*
Relevant	9	15	24
Irrelevant	3	13	16
Total	12	28	40

$$P = \frac{9}{12} = 0.75$$

$$R = \frac{9}{24} = 0.375$$

$$F = \frac{2 \times 0.75 \times 0.375}{0.75 + 0.375} = 0.5$$

III. Evaluating Ranking of Recommendation

- **Spearman's Rank Correlation**

$$\rho = 1 - \frac{6\sum_{i=1}^{n}(x_i - yi)^2}{n^3 - n}$$

- **Kendall's τ**
  - Compares concordant the items of the recommended ranking list against the ground truth ranking list
    - If the two orders are consistent, it is concordant
    - E.g., for top 4 items in ranking list, there are 4×3/2=6 pairs

$$\tau = \frac{c-d}{\binom{n}{2}}$$

    - c is the number of concordants
    - d is the number of disconcordants