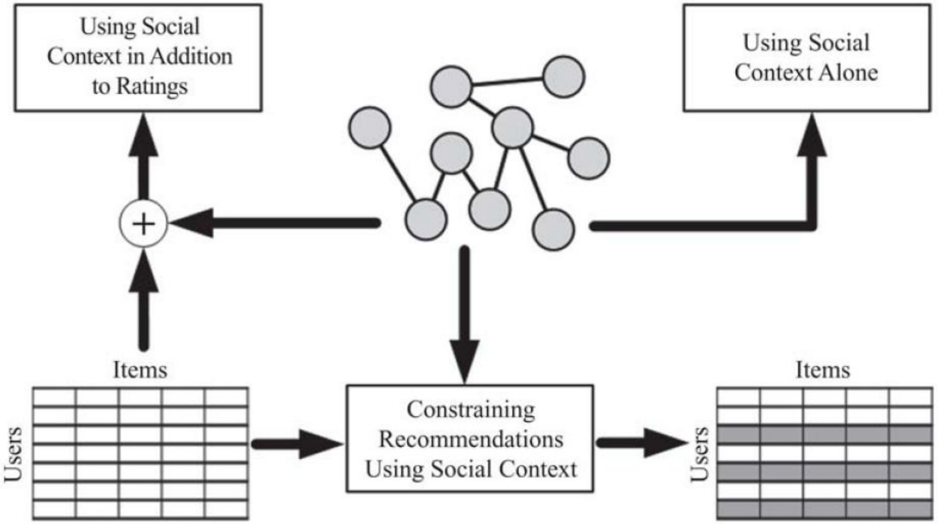
Recommendation Using Social Context

- 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 available, such as the friendship network among individuals.
- This information can be used to improve recommendations, based on the assumption that an individual's friends have an impact on the ratings ascribed to the individual.
- This impact can be due to homophily, influence, or confounding



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.

Extending Classical Methods

- Social information can be used in addition to a user-item rating matrix to improve recommendation.
- Social information can be added by assuming that users that are connected (i.e., friends) have similar tastes in rating items.

$$R = U^T V \qquad R \in \mathbb{R}^{n\times m}, U \in \mathbb{R}^{k\times n}, V \in \mathbb{R}^{k\times m}$$

$$\min_{U,V} \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{m} I_{ij}(R_{ij} - U_i^T V_j)^2$$

$$\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{m} I_{ij}(R_{ij} - U_i^T V_j)^2 + \frac{\lambda_1}{2}||U||_F^2 + \frac{\lambda_2}{2}||V||_F^2$$

U – n users k tastes, and
V – m items and k tastes
I_{ij} - 1 if i rated j

What is k in content-based recommendation?

Modeling Social Information in Recommendation

- The taste for user *i* is close to that of all his friends $j \in F(i)$

$$\sum_{i=1}^{n} \sum_{j \in F(i)} sim(i,j) \|U_i - U_j\|_F^2$$

- sim(i, j) denotes the similarity between user *i* and *j* (e.g., cosine similarity or Pearson correlation between their ratings) and F(i) denotes the friends of *i*

$$\min_{U,V} \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{m} I_{ij}(R_{ij} - U_i^T V_j)^2 + \beta \sum_{i=1}^{n} \sum_{j \in F(i)} sim(i,j) \|U_i - U_j\|_F^2$$
$$+ \frac{\lambda_1}{2} \|U\|_F^2 + \frac{\lambda_2}{2} \|V\|_F^2$$

Recommendation Constrained by Social Context

- In classical recommendation, to estimate ratings of an item, we determine similar users or items. In other words, 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

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

	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

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

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

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

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

$$\begin{aligned} r_{Jill,Mulan} &= \bar{r}_{Jill} + \frac{sim(Jill, Jane)(r_{Jane,Mulan} - \bar{r}_{Jane})}{sim(Jill, Jane) + sim(Jill, Jorge)} \\ &+ \frac{sim(Jill, Jorge)(r_{Jorge,Mulan} - \bar{r}_{Jorge})}{sim(Jill, Jane) + sim(Jill, Jorge)} \\ &= 2.33 + \frac{0.72(4-2.75) + 0.54(1-1.75)}{0.72+0.54} = 2.72 \end{aligned}$$

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, serendipity, online conversion, ...
  - 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
  - Predictive accuracy metrics measure *how close* the recommender system's predicted ratings are to the true user ratings
- Classification accuracy
  - Classification metrics measure 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

Predictive accuracy - Metrics measure error rate

- Mean Absolute Error (*MAE*) measures 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*) is 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

Consider the following table with both the predicted ratings and true ratings of five items

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

$$
\begin{aligned}
MAE &= \frac{|1-3| + |2-5| + |3-3| + |4-2| + |4-1|}{5} = 2 \\
NMAE &= \frac{MAE}{5-1} = 0.5 \\
RMSE &= \sqrt{\frac{(1-3)^2 + (2-5)^2 + (3-3)^2 + (4-2)^2 + (4-1)^2}{5}} \\
&= 2.28
\end{aligned}
$$

Relevance: 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

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

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

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

Evaluating Ranking of Recommendation

- Spearman's Rank Correlation
  - $\rho = 1 - \frac{6\sum_{i=1}^{n}(x_i - y_i)^2}{n^3 - n}$
- Kendall's τ
  - It checks the concordant the items of the recommended ranking list against the ground truth ranking list
    - If the two orders are consistent, it is concordant
    - For top 4 items in ranking list, there are 4*3/2=6 pairs
  - $\tau = \frac{c-d}{\binom{n}{2}}$

    where c is the number of concordants and d of disconcordants

Ranking, Example

Consider a set of four items $I = \{i_1, i_2, i_3, i_4\}$ for which the predicted and true rankings are as follows

	Predicted Rank	*True Rank*
i_1	1	1
i_2	2	4
i_3	3	2
i_4	4	3

Pair of items and their status {concordant/discordant} are

$$(i_1, i_2) : \textit{concordant}$$
$$(i_1, i_3) : \textit{concordant}$$
$$(i_1, i_4) : \textit{concordant}$$
$$(i_2, i_3) : \textit{discordant}$$
$$(i_2, i_4) : \textit{discordant}$$
$$(i_3, i_4) : \textit{concordant}$$

$$\tau = \frac{4-2}{6} = 0.33$$

Beyond Accuracy, Relevance, and Rank

- Coverage
  - Measure of the domain of items in the system over which the system can form predictions or make recommendations
- Novelty and Serendipity
  - Helping users to find a surprisingly interesting item he might not have otherwise discovered
- Confidence
  - How sure is the RS that its recommendation is accurate?
- Diversity
- Risk
- Robustness
- Privacy
- Adaptivity
- Scalability

Recommendation Explanation

The digital camera X is the best for you because …

Confidence

- Why would someone distrust a recommendation?
  - Can I trust the provider?
  - How does this work, anyway?
  - Does the system know enough about me?
  - Does the system know enough about the item it is recommending?
  - How sure is it?

The Confidence Challenge

- Why should users believe recommendations?
- When should users believe them?
- Approaches
  - Confidence indicators
  - Explain the recommendations
    - Reveal data and processes
    - Corroborating data, track records
  - Offer opportunities to correct mistaken data

Explanations in recommender systems

- Motivation
  - "The digital camera *Profishot* is a must-buy for you because . . . ."
  - Why should recommender systems should deal with explanations at all?
  - The answer is related to the two parties providing and receiving recommendations:
    - A selling agent may be interested in promoting some particular products
    - A buying agent is concerned about making the right buying decision
- Additional information to explain if the system's output follows some given objectives

Objectives of explanations

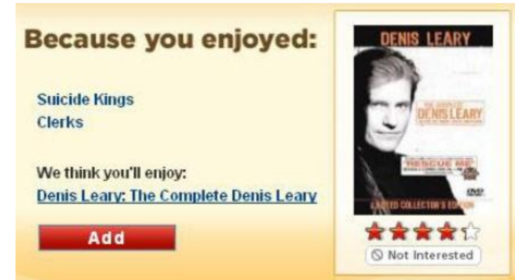
- Transparency
  - Provide information such that the user can comprehend the reasoning used to generate a specific recommendation
- Validity
  - Explanations can be generated in order to allow a user to check the validity of a recommendation
- Trustworthiness
  - Explanations aiming to build trust in recommendations reduce the uncertainty about the quality of a recommendation
- Comprehensibility
  - Explanations targeting comprehension support the user by relating her known concepts to the concepts employed by the recommender
- Education
  - Deep knowledge about the domain helps the customer rethink her preferences and evaluate the pros and cons of different solutions

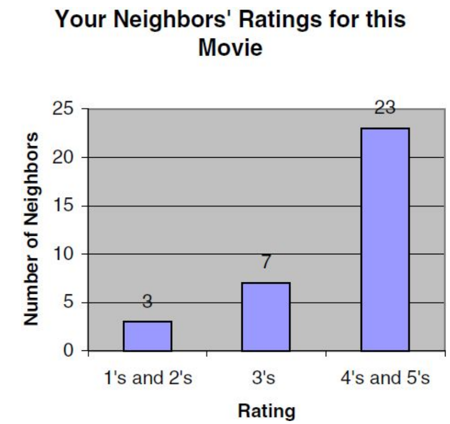
More Objectives of Explanations

- Persuasiveness
  - In this sense persuasive explanations for recommendations aim to change the user's buying behavior
- Effectiveness
  - The support a user receives for making high-quality decisions
- Efficiency
  - A system's ability to support users in order to reduce the decision-making effort e.g. time
- Satisfaction
  - Explanations can attempt to improve the overall satisfaction stemming from the use of a recommender system.
- Relevance
  - Additional information may be required in conversational recommenders. Explanations can be provided to justify why additional information is needed from the user

Examples

- Similarity between items
- Similarity between users
- Tags
  - Tag relevance (for items)
  - Tag preference (of users)





Explanation types

- Nearest neighbor explanation
  - Customers who bought item X also bought items Y,Z
  - Item Y is recommended because you rated related item X
- Content based explanation
  - This story deals with topics X,Y which belong to your topic of interest
- Social-network based explanation
  - People leverage their social network to reach information and make use of trust relationships to filter information.
    - Your friend X wrote that blog
    - 50% of your friends liked this item (while only 5% disliked it)