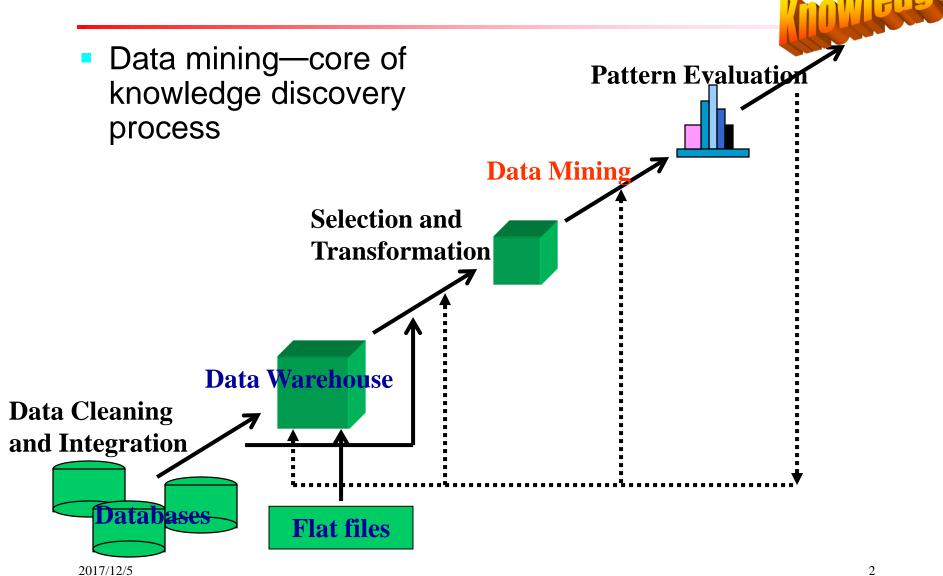
Data Mining

Ying Liu, Prof., Ph.D

University of Chinese Academy of Sciences

Review



Outline

- What is Recommender System?
- Recommendation Algorithms
- Evaluation of Recommender Systems

Motivation

- Which digital camera should I buy?
- Where should I spend my holiday?
- Which movie should I see?
- Whom should I follow?
- Where should I find interesting news article?

Motivation

- 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
- Solution
 - > Recommendation: automatically come up with a short list of items that fits user's interests!

Examples

Book recommendation in Amazon



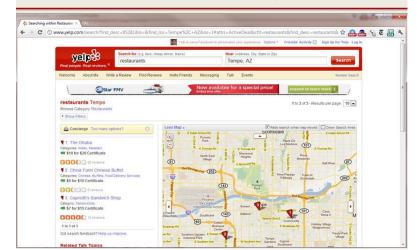
Product Recommendation in ebay



Video clip recommendation in YouTube



Restaurant Recommendation in Yelp



Recommender Systems

- Idea: Use historical data such as the user's past preferences or similar users' past preferences to predict future likes
- Basic assumption
 - Users' preferences are likely to remain stable, and change smoothly over time
 - Users with similar tastes have similar ratings for an item
- By watching the past users' or groups' preferences, try to predict their future likes
 - Then we can recommend items of interest to them

Recommender Systems

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!

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Content-based Methods

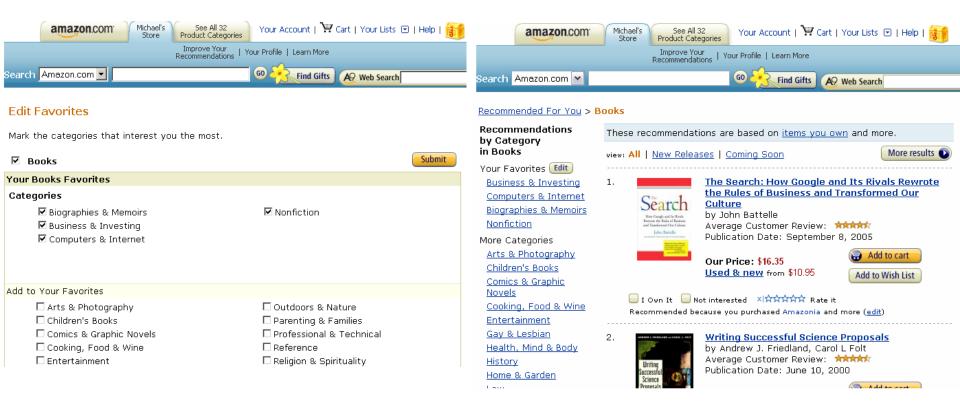
- Content-based methods are based on the fact that a user's interest should match the description of the items that she should be recommended
- The more similar the item's description to that of the user's interest, the more likely the user finds the item's recommendation interesting
- Core idea: Find the similarity between the user and all of the existing items

Content-based Methods

Steps

- 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

Example



Content-based Algorithm

- 1. Represent both user profiles and item descriptions by vectorizing them using a set of k keywords
- 2. Vectorize (e.g., using TF-IDF) both users and items and compute their similarity

$$I_i = (i_{i,1}, i_{i,2}, \dots, i_{i,k})$$
 $U_i = (u_{i,1}, u_{i,2}, \dots, u_{i,k}).$

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

3. Recommend the top most similar items to the

Collaborative Filtering

Assumption

User-based CF

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

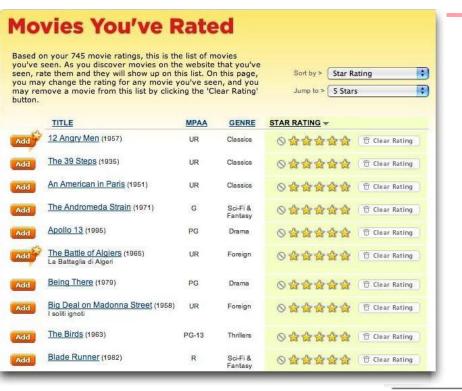
	11	12	13	14
U 1	1	2	4	4
3	1	2	4	o.
U3	2	5	2	2
U4	5	2	3	3

Item-based CF

 Items that have received similar ratings previously from users are likely to receive similar ratings from future users (itembased CF)

	11	12	/3	A
U1	1	2	4	4
U2	1	2	4	?
U3	2	5	2	2
U4	5	2	3	3

Example



Value	Graphic representation	Textual representation
5	* * * * * *	Excellent
4	* * * *	Very good
3	* * *	Good
2	4 4	Fair
1	A	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

Collaborative Filtering

- Rating matrix
 - 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
 - Play lists or music listened to, for a music Rec system
 - The amount of time users spent on a webpage

Collaborative Filtering Algorithm

Steps

- 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

Collaborative Filtering Algorithm

Measure Similarity between Users (or Items)

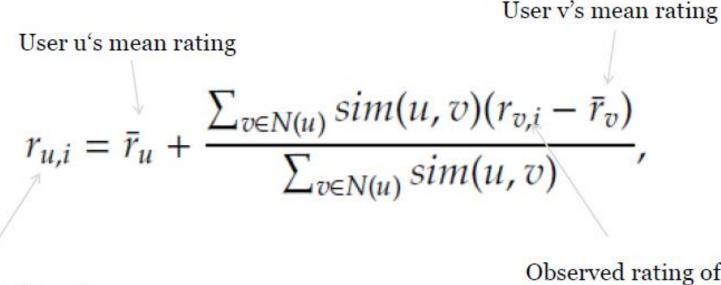
$$sim(U_i, U_j) = cos(U_i, U_j) = \frac{U_i \cdot U_j}{\|U_i\| \|U_j\|} = \frac{\sum_k r_{i,k} r_{j,k}}{\sqrt{\sum_k r_{i,k}^2} \sqrt{\sum_k r_{j,k}^2}}$$

Pearson Correlation Coefficient

$$sim(U_{i}, U_{j}) = \frac{\sum_{k} (r_{i,k} - \bar{r}_{i})(r_{j,k} - \bar{r}_{j})}{\sqrt{\sum_{k} (r_{i,k} - \bar{r}_{i})^{2}} \sqrt{\sum_{k} (r_{j,k} - \bar{r}_{j})^{2}}}$$

Collaborative Filtering Algorithm

Updating the ratings:



Predicted rating of user *u* for item *i*

Observed rating of user v for item i

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

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

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

User_based CF, Example

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Outline

- What is Recommender System?
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- Evaluation of Recommender Systems

Evaluation is Challenging

- Different algorithms may be better or worse on different datasets (applications)
 - Many algorithms are designed specifically for datasets
 - 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" in "predicting"
 - Other properties also have important effect on user satisfaction and performance

Evaluation is Challenging

It is challenge in deciding what combination of measures should be used in comparative evaluation

Predictive Accuracy Metrics

Mean Absolute Error (MAE) measures the average absolute deviation between a predicted rating (p) and the user's true rating (r)

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

- NMAE = MAE/ $(r_{max}-r_{min})$
- Root Mean Square Error (RMSE) is similar to MAE, but places more emphasis on larger deviation

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

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

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

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

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

$$= 2.28$$

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}	$N_{\rm m}$	$N_{\rm r}$
Irrelevant	Nis	$N_{ m in}$	N _i
Total	N_s	N_n	N

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

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

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) : concordant

 (i_1, i_3) : concordant

 (i_1, i_4) : concordant

 (i_2, i_3) : discordant

 (i_2, i_4) : discordant

 (i_3, i_4) : concordant

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