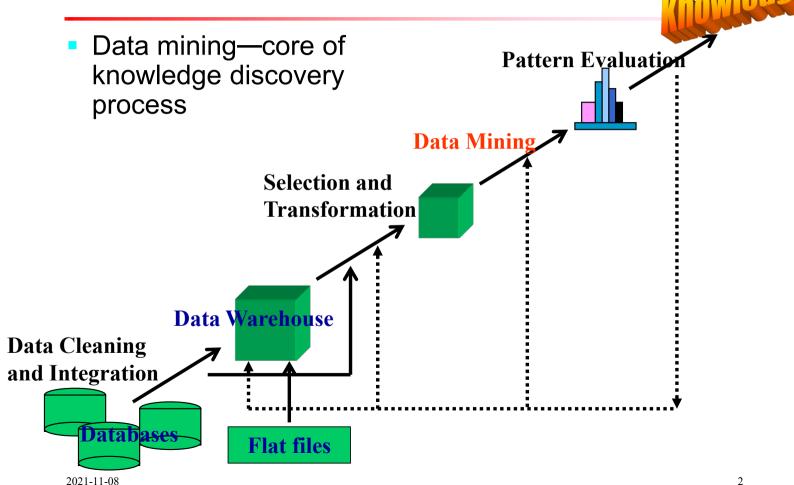
Data Mining

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Review



Outline

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

Motivation

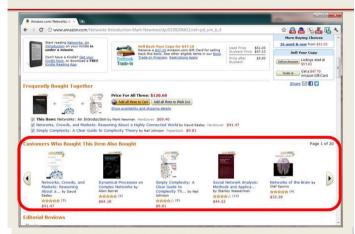
- Which digital camera should I buy?
- Where should I spend my holiday?
- Which movie should I see?
- Whom should I follow?
- Where should I find interesting news article?

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!

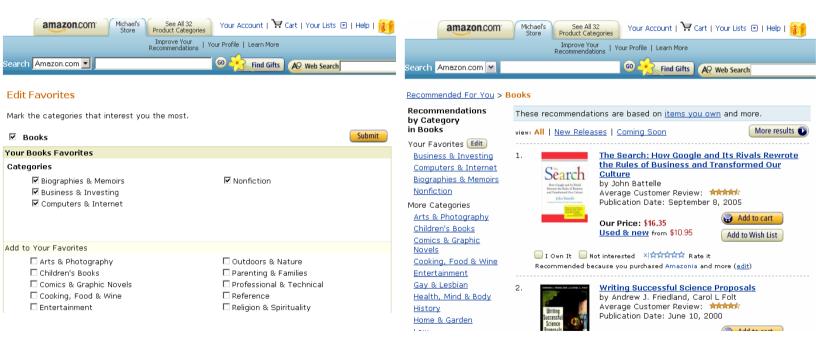
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Content-based Methods

- 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

Example



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

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

$$I_{j} = (i_{j,1}, i_{j,2}, \dots, i_{j,k}) \qquad \qquad U_{i} = (u_{i,1}, u_{i,2}, \dots, u_{i,k}).$$

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

3. Recommend the top most similar items to the

2021-1**USE**

Collaborative Filtering

Assumption

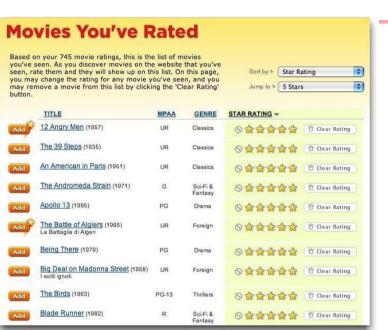
- User-based CF
 - Users with similar previous ratings for items are likely to rate future items similarly

		11	12	13	14
4	51	1	2	4	4
	슞	1	2	4	d.
	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)

	I1	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	\$	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:

User u's mean rating

User v'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*

9+20+16 Example

$$\frac{1}{\sqrt{3}} = \frac{4}{\sqrt{3}} = 1.5$$

 $\overline{r_5} = \frac{10}{4} = 2.5$ Predict Jane's rating for Aladdin

1- Calculate average ratings

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

$$5+4+0+2$$

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

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

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

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

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

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

$$sim(Jane, Joe) = \frac{\sqrt{10}\sqrt{27}}{\sqrt{10}\sqrt{29}} = 0.88$$

$$sim(Jane, Joe) = \frac{1}{\sqrt{10}\sqrt{29}} = 0.88$$

 $sim(Jane, Jill) = \frac{3 \times 1 + 1 \times 4 + 0 \times 2}{\sqrt{10}\sqrt{21}} = 0.48$
 $sim(Jane, Jorge) = \frac{3 \times 2 + 1 \times 0 + 0 \times 1}{\sqrt{10}\sqrt{5}} = 0.84$

$$Sim(U2, U1) = \frac{3+25+12}{150} = 210.96$$

Example

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

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

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Vu m - 11 09

11 0.76 (1 2 7) + 0-98 (3-10

22

096 x 0.98

Outline

- What is Recommender System?
- Recommendation Algorithms
- 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

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

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

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

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}	$N_{ m m}$ 把著便遊送	$N_{\rm r}$
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 推答的 无顺序

Spearman's Rank Correlation

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

- \blacksquare 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

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

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	
7	i_2	$\sqrt{2}$	4	-> discordant
	i_3	3	2	-7 0113 CON OWN (
Č	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

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