## Recommender system

Wang Jianfang

王建芳(in Chinese)

September 1, 2020

## Plan

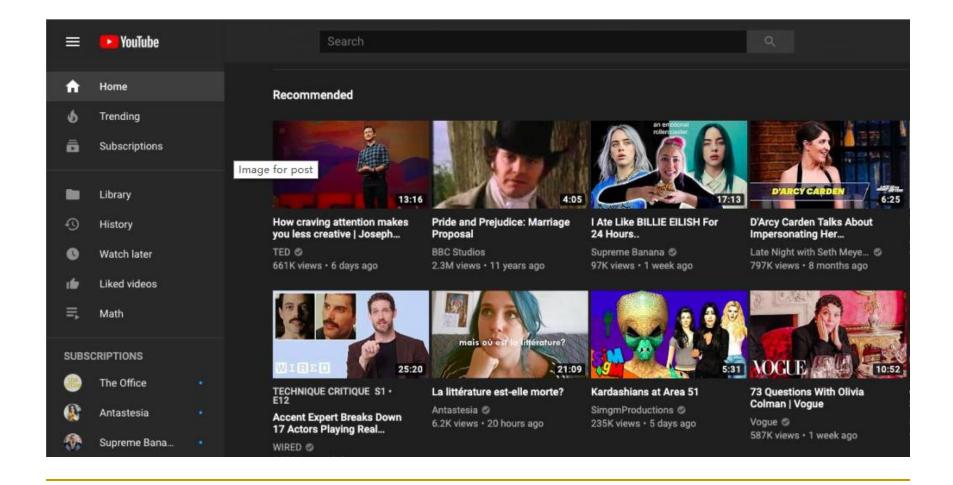
24(Lesson)+24(Lab.)

Time/Day	Monday	Tuesday	Wednesday	Thursday
8.00-9.50				Recommender system (Chen Feng, Wang Jianfang) (1-6,202)
10.10-12.00		Recommender system (Chen Feng, Wang Jianfang) (1-6,110)		

## Agenda

- Concepts
- Collaborative Filtering
- Algorithms (user-based)
- Evaluation Metrics
- Practise

### Entertainment

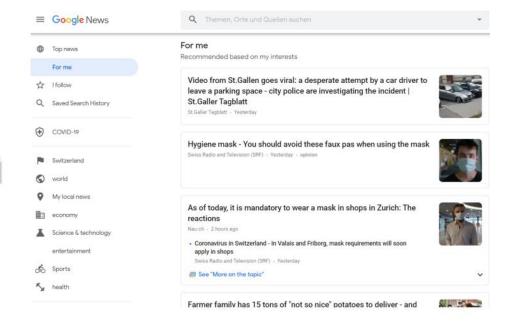


## Entertainment



## News Recommendation





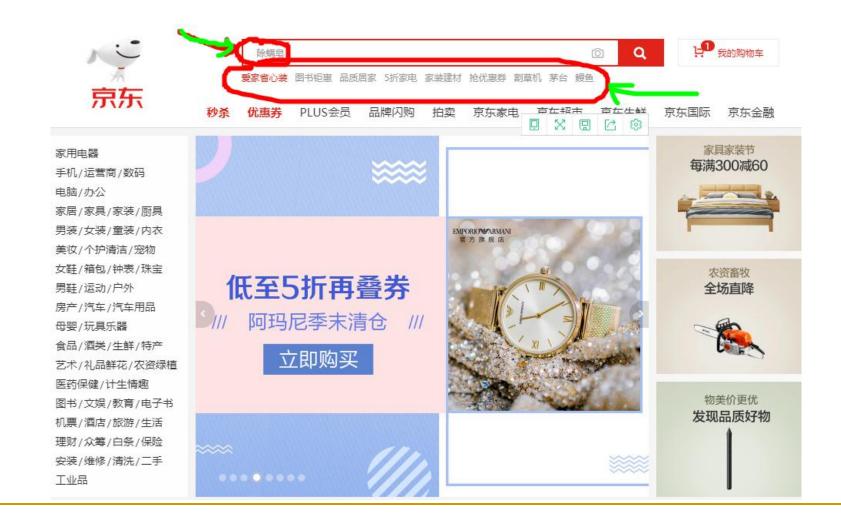
## Online Shopping



# Online Shopping



## Online Shopping



Why are recommender systems so pervasive?

#### Benefits for customers

- Ease information overload
- Sales assistance (guidance, advisory, persuasion,...)
- ...

#### Benefits for industry

- Improve user experience
- Increase sales
- ...

# History

Toward the next generation of recommender systems: a survey of the state-ofthe-art and possible extensions

Adomavicius, Gediminas, and Alexander Tuzhilin. 2005

Recommendation	Recommendation	on Technique	
Approach	Heuristic-based	Model-based	
Content-based	Commonly used techniques:  TF-IDF (information retrieval)  Clustering Representative research examples:  Lang 1995  Balabanovic & Shoham 1997  Pazzani & Billsus 1997	Commonly used techniques:  Bayesian classifiers  Clustering  Decision trees  Artificial neural networks  Representative research examples:  Pazzani & Billsus 1997  Mooney et al. 1998  Mooney & Roy 1999  Billsus & Pazzani 1999, 2000  Zhang et al. 2002	
Collaborative	Commonly used techniques:  Nearest neighbor (cosine, correlation)  Clustering Graph theory Representative research examples: Resnick et al. 1994 Hill et al. 1995 Shardanand & Maes 1995 Breese et al. 1998 Nakamura & Abe 1998 Aggarwal et al. 1999 Delgado & Ishii 1999 Pennock & Horwitz 1999 Sarwar et al. 2001	Commonly used techniques:  Bayesian networks Clustering Artificial neural networks Linear regression Probablistic models Representative research examples: Billsus & Pazzani 1998 Breese et al. 1998 Ungar & Foster 1998 Chien & George 1999 Getoor & Sahami 1999 Pennock & Horwitz 1999 Goldberg et al. 2001 Kumar et al. 2001 Pavlov & Pennock 2002 Shani et al. 2002 Yu et al. 2002 Yu et al. 2003, 2004 Hofmann 2003, 2004 Marlin 2003 Si & Jin 2003	
Hybrid	Combining content-based and collaborative components using:  Linear combination of predicted ratings  Various voting schemes  Incorporating one component as a part of the heuristic for the other	Combining content-based and collaborative components by:  • Incorporating one component as a part of the model for the other  • Building one unifying model Representative research examples:	

# History

TABLE 2: Overview of collaborative filtering techniques.

#### A Survey of Collaborative Filtering Techniques Xiaoyuan Su and Taghi

Xiaoyuan Su and Ta M. Khoshgoftaar 2009

CF categories	Representative techniques	Main advantages	Main shortcomings	
Memory-based CF	"Neighbor-based CF (item-based/user-based CF algorithms with Pearson/vector	*easy implementation *new data can be added easily and incrementally	*are dependent on human ratings *performance decrease when data are sparse	
	cosine correlation) *Item-based/user-based top-N recommendations	*need not consider the content of the items being recommended	"cannot recommend for new users and items	
	recommendations	*scale well with co-rated items	*have limited scalability for large datasets	
	*Bayesian belief nets CF *clustering CF	*better address the sparsity, scalability and other problems	*expensive model-building	
Model-based CF	*MDP-based CF *latent semantic CF	*improve prediction performance	*have trade-off between prediction performance and scalability	
	* sparse factor analysis  *CF using dimensionality reduction techniques, for example, SVD, PCA	*give an intuitive rationale for recommendations	*lose useful information for dimensionality reduction techniques	
Hybrid recommenders	*content-based CF recommender, for example, Fab	* overcome limitations of CF and content-based or other recommenders	* have increased complexity and expense for implementation	
	*content-boosted CF	*improve prediction performance	"need external information that usually not available	
	"hybrid CF combining memory-based and model-based CF algorithms, for example, Personality Diagnosis	* overcome CF problems such as sparsity and gray sheep	ATTIC COSTO AS ASSESSED MARRIED	

### Netflix Prize

The Netflix Prize was an open competition for the best collaborative filtering algorithm to predict user ratings for films, based on previous ratings without any other information about the users or films.

On September 21, 2009 we awarded the \$1M Grand Prize to team "BellKor's Pragmatic Chaos".



https://www.netflixprize.com/

## Collaborative Filtering (CF)

- The most prominent approach to generate recommen dations
  - used by large, commercial e-commerce sites
  - well-understood, various algorithms and variations exist
  - applicable in many domains (book, movies, DVDs, ..)
- Approach
  - use the "wisdom of the crowd" to recommend items
- Basic assumption and idea
  - Users give ratings to catalog items (implicitly or explicitly)
  - Customers who had similar tastes in the past, will have similar tastes in the future

## Pure CF Approaches

- Input
  - Only a matrix of given user—item ratings
- Output types
  - A (numerical) prediction indicating to what degree the current user will like or dislike a certain it em
  - A top-N list of recommended items

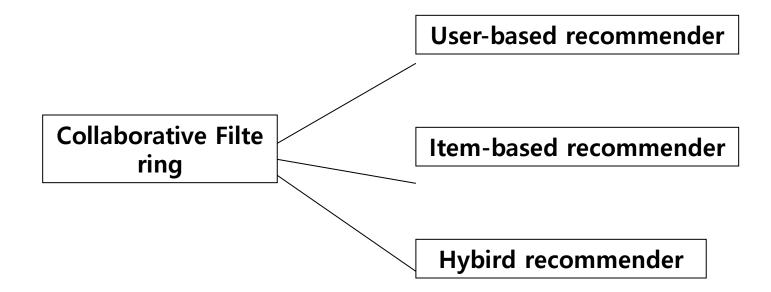
## Concepts

- Collaborative Filtering
  - The process of information filtering by collecting human judgments (ratings)
  - "word of mouth"
- User
  - Any individual who provides ratings to a system
- Items
  - Anything for which a human can provide a rating

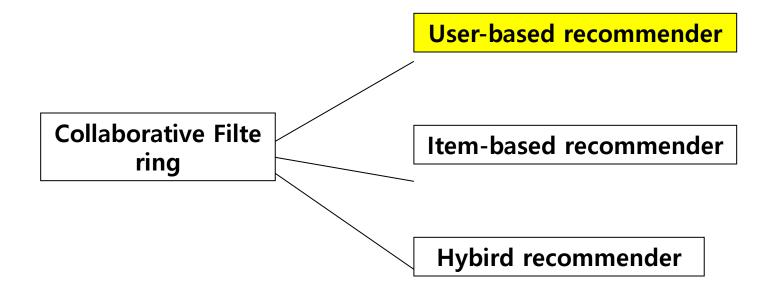
### Uses for CF: Domains

- Many items
- Many ratings
- Many more users than items recommended
- Users rate multiple items
- For each user of the community, there are other u sers with common needs or tastes
- Item evaluation requires personal taste
- Items persists
- Taste persists
- Items are homogenous

# Algorithms



# Algorithms



## Algorithms: User-Based

#### User-Based Nearest Neighbor

- Neighbor = similar users
- Generate a prediction for an item i by analyzing ratings for i from users in u's neighborhood

$$pred(u,i) = \overline{r}_u + \frac{\sum_{n \subset neighbors(u)} sim(u,n) \cdot (r_{ni} - \overline{r}_n)}{\sum_{n \subset neighbors(u)} sim(u,n)}$$

## Algorithms: Item-Based

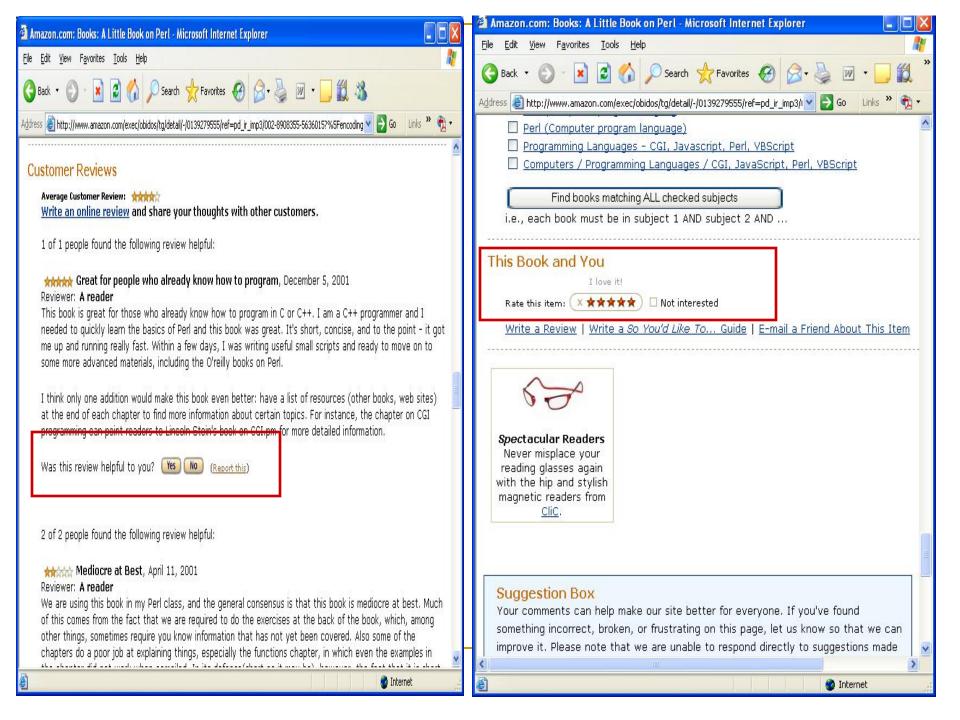
#### Item-Based Nearest Neighbor

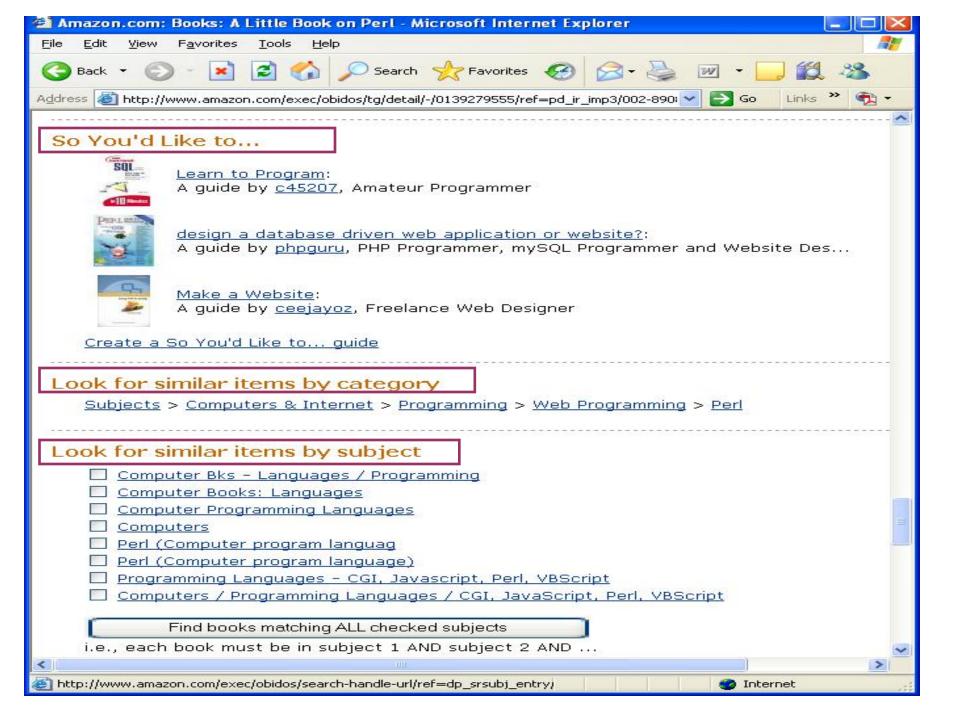
- Generate predictions based on similarities between items.
- ullet Prediction for a user u and item i is composed of a weight ed sum of the user u's ratings for items most similar to i.

$$pred (u,i) = \frac{\sum_{j \in ratedItems (u)} sim(i,j) \cdot r_{ui}}{\sum_{j \in ratedItems (u)} sim(i,j)}$$

## Practical Issues: Ratings

- Explicit vs. Implicit ratings
  - Explicit ratings
    - Users rate themselves for an item
    - Most accurate descriptions of a user's preference
    - Challenging in collecting data
  - Implicit ratings
    - Observations of user behavior
    - Can be collected with little or no cost to user
    - Ratings inference may be imprecise.





## Practical Issues: Ratings

- Rating Scales
  - Scalar ratings
    - Numerical scales
    - 1-5, 1-7, etc.
  - Binary ratings
    - Agree/Disagree, Good/Bad, etc.
  - Unary ratings
    - Good, Purchase, etc.
    - Absence of rating indicates no information

# User-based nearest-neighbor coll aborative filtering (1)

#### The basic technique

- Given an "active user" (Alice) and an item i not yet seen by Alice
  - find a set of users (peers/nearest neighbors) who liked the same items as Alice in the past and who have rated item i
  - use, e.g. the average of their ratings to predict, if Alice will like item i
  - do this for all items Alice has not seen and recommend the best-rated

#### Basic assumption and idea

- If users had similar tastes in the past they will have similar tastes in the future
- User preferences remain stable and consistent over time

# User-based nearest-neighbor coll aborative filtering (2)

#### Example

A database of ratings of the current user, Alice, and some other users is given:

	ltem1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

Determine whether Alice will like or dislike *Item5*, which Alice has not yet rated or seen

# User-based nearest-neighbor coll aborative filtering (3)

- Some first questions
  - How do we measure similarity?
    - How many neighbors should we consider?
  - How do we generate a prediction from the neighbors' ratings?

	ltem1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1



## Measuring user similarity (1)

A popular similarity measure in user-based CF: Pearson correlation

a, b: users

 $r_{a,p}$ : rating of user a for item p

P: set of items, rated both by a and b

- Possible similarity values between -1 and 1

$$sim(a,b) = \frac{\sum_{p \in P} (r_{a,p} - \bar{r}_a)(r_{b,p} - \bar{r}_b)}{\sqrt{\sum_{p \in P} (r_{a,p} - \bar{r}_a)^2} \sqrt{\sum_{p \in P} (r_{b,p} - \bar{r}_b)^2}}$$

## Measuring user similarity (2)

#### A popular similarity measure in user-based CF: Pearson correlation

a, b: users

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P: set of items, rated both by a and b

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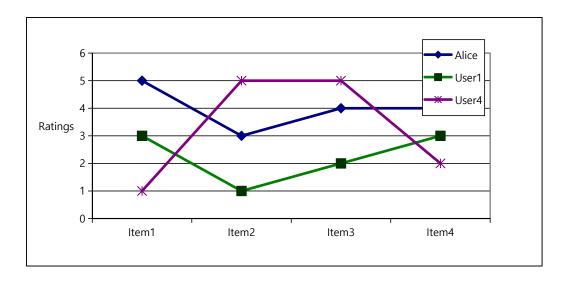
	ltem1	Item2	Item3	Item4	Item5
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User3	3	3	1	5	4
User4	1	5	5	2	1



sim = 0.85 sim = 0.00 sim = 0.70sim = -0.79

### Pearson correlation

Takes differences in rating behavior into account



- Works well in usual domains, compared with alternative measures
  - such as cosine similarity

## Making predictions

A common prediction function:

$$pred(a,p) = \overline{r_a} + \frac{\sum_{b \in N} sim(a,b) * (r_{b,p} - \overline{r_b})}{\sum_{b \in N} sim(a,b)}$$



- Calculate, whether the neighbors' ratings for the unseen item i are higher or lower than their average
- Combine the rating differences use the similarity with a as a weight
- Add/subtract the neighbors' bias from the active user's average and use this as a prediction

## similarity function

Pearson

$$sim(a,b) = \frac{\sum_{p \in P} (r_{a,p} - \bar{r}_a)(r_{b,p} - \bar{r}_b)}{\sqrt{\sum_{p \in P} (r_{a,p} - \bar{r}_a)^2} \sqrt{\sum_{p \in P} (r_{b,p} - \bar{r}_b)^2}}$$

Cosine Similarity

$$w_{uv} = \frac{|N(u) \cap N(v)|}{|N(u) \cup N(v)|}$$

Jaccard

$$w_{uv} = \frac{|N(u) \cap N(v)|}{\sqrt{|N(u)||N(v)|}}$$

# similarity function

Pearson

$$sim(a,b) = \frac{\sum_{p \in P} (r_{a,p} - \bar{r}_a)(r_{b,p} - \bar{r}_b)}{\sqrt{\sum_{p \in P} (r_{a,p} - \bar{r}_a)^2} \sqrt{\sum_{p \in P} (r_{b,p} - \bar{r}_b)^2}}$$

Pearson(simpler)

$$r = \frac{\sum XY - \frac{\sum X\sum Y}{N}}{\sqrt{(\sum X^2 - \frac{(\sum X)^2}{N})(\sum Y^2 - \frac{(\sum Y)^2}{N})}}$$

Pearson(simpler)

$$r = \frac{\sum XY - \frac{\sum X\sum Y}{N}}{\sqrt{(\sum X^{2} - \frac{(\sum X)^{2}}{N})(\sum Y^{2} - \frac{(\sum Y)^{2}}{N})}}$$

X rating is [1, 2, 3], Y rating is [2, 5, 6]. what t is the person similarity.

## Pratise

How to get the similarity?

$$sim(a,b) = \frac{\sum_{p \in P} (r_{a,p} - \bar{r}_a)(r_{b,p} - \bar{r}_b)}{\sqrt{\sum_{p \in P} (r_{a,p} - \bar{r}_a)^2} \sqrt{\sum_{p \in P} (r_{b,p} - \bar{r}_b)^2}}$$

	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
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sim = 0.85 sim = 0.00 sim = 0.70sim = -0.79

## similarity function

Pearson

$$sim(a,b) = \frac{\sum_{p \in P} (r_{a,p} - \bar{r}_a)(r_{b,p} - \bar{r}_b)}{\sqrt{\sum_{p \in P} (r_{a,p} - \bar{r}_a)^2} \sqrt{\sum_{p \in P} (r_{b,p} - \bar{r}_b)^2}}$$

 Pearson correlation coefficient formula is used to calculate the correlation coefficient of XY to verify y the correctness of the code

$$\rho_{X,Y} = \frac{COV(X,Y)}{\sigma_X \sigma_Y} = \frac{E\left[(X - \mu_X)(X - \mu_Y)\right]}{\sigma_X \sigma_Y} = \frac{E\left(XY\right) - E(X)E(Y)}{\sqrt{E\left[X^2\right] - E\left[X\right]^2} \sqrt{E\left[Y^2\right] - E\left[Y\right]^2}}$$

## Homework

ex1. gaining the Pearson similarity by the detail process.
 (Alice with user1, user2,user3,user4).

	ltem1	Item2	Item3	Item4	Item5		
Alice	5	3	4	4	?		
User1	3	1	2	3	3		sim = 0,85
User2	4	3	4	3	5		sim = 0,00
User3	3	3	1	5	4		sim = 0,70
User4	1	5	5	2	1	-	sim = -0,79

ex2. reading the file(1.1-collaborative filtering.pdf), and memeory the user-based collaborative filtering algorithm mainly consists of two steps, and understand the Cosine Similarity.

ex3. setup Anaconda3 software.

## Questions and Comments?

## Thank you!!