

# Social Recommendation

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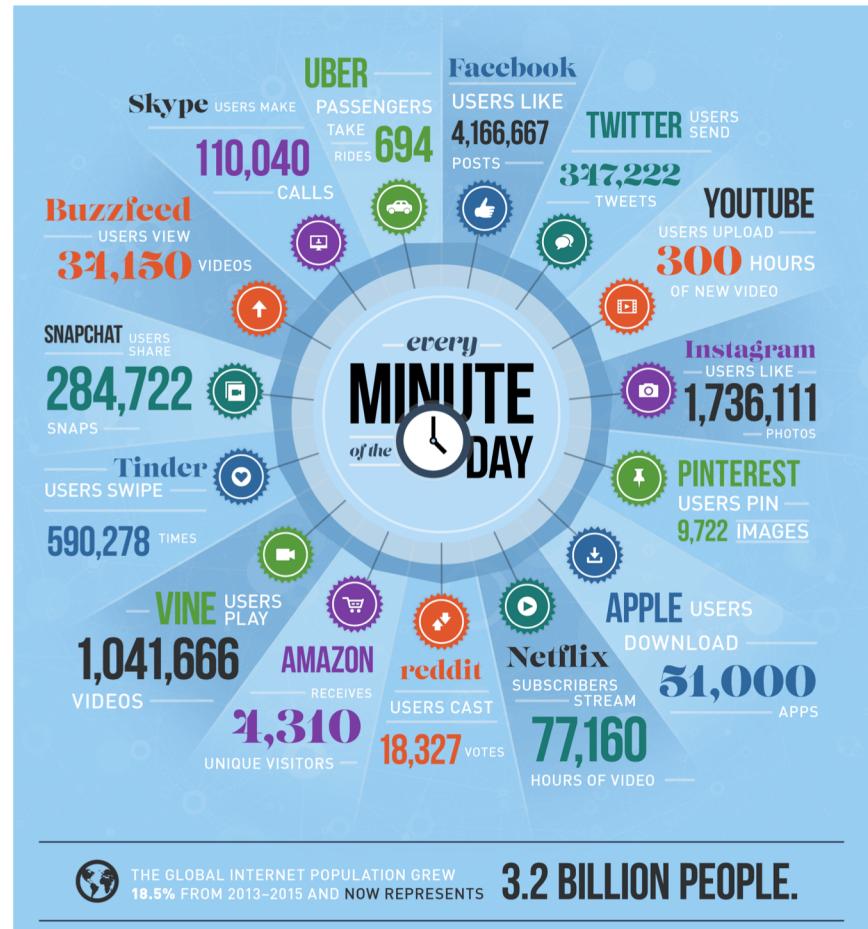
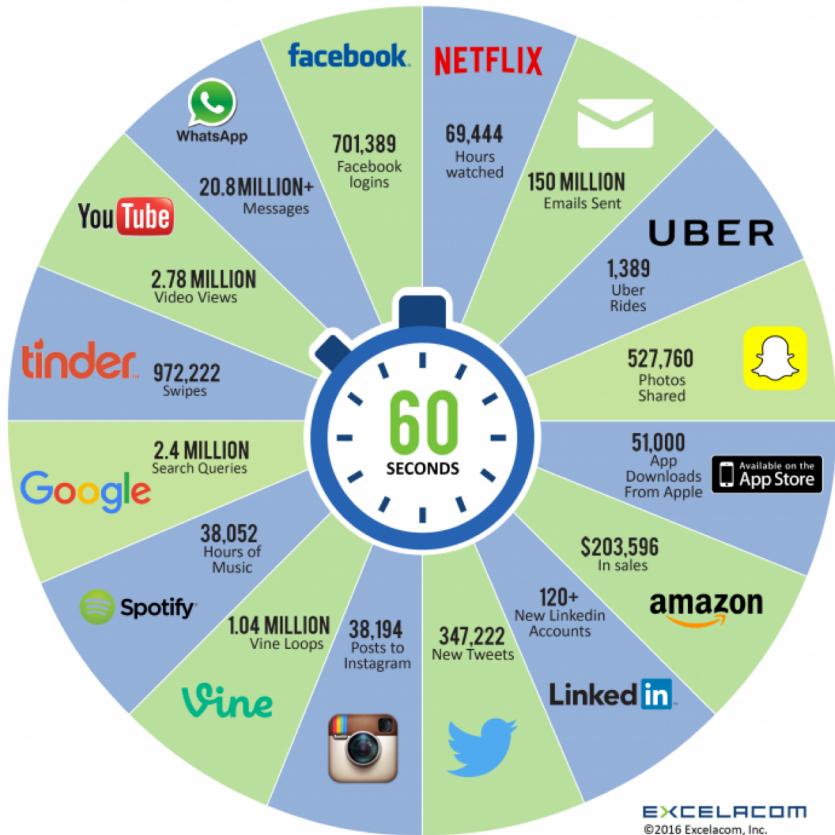
Homepage: <https://sites.google.com/site/yangdingqi/>

# Outline

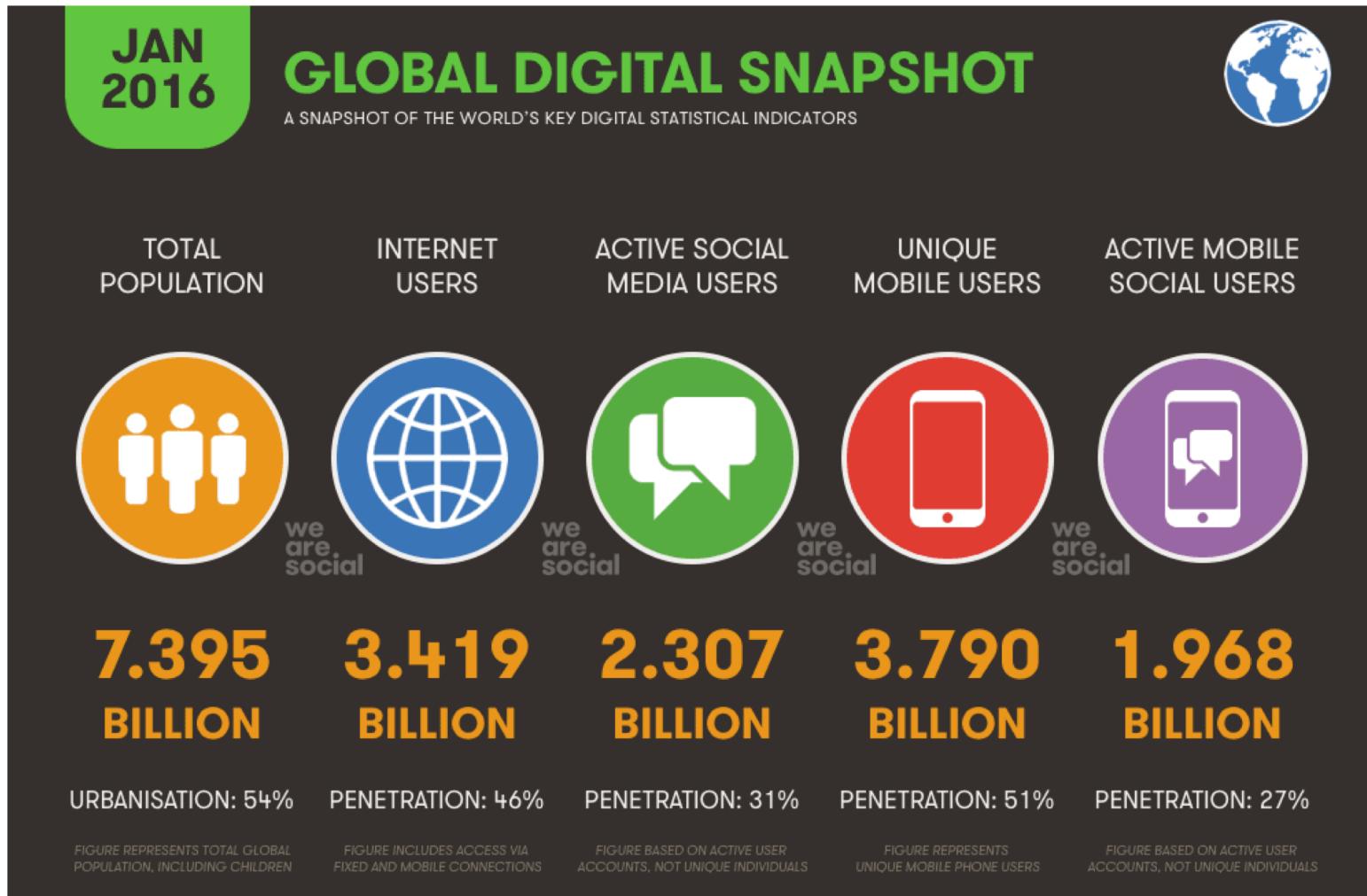
- **Introduction to Recommendation Systems**
- **Recommendation Techniques**
  - Content-based filtering
  - Collaborative filtering
    - Memory-based methods
    - Model-based methods (Matrix factorization)
- **Social Recommendation**
  - Social relationship in recommendation
- **Concluding remarks**

# An Internet Minute

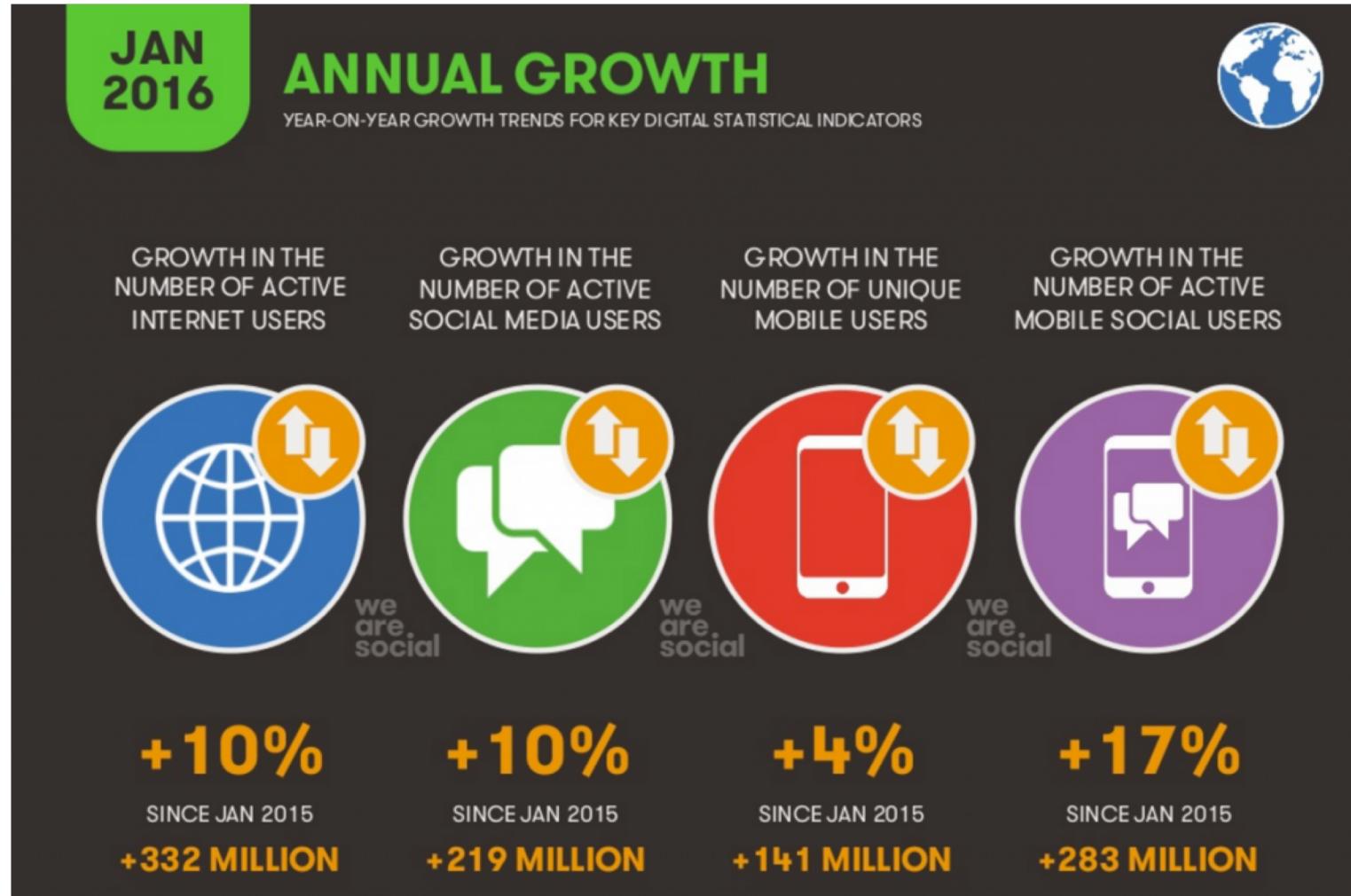
## 2016 What happens in an INTERNET MINUTE?



# Social Media Statistics

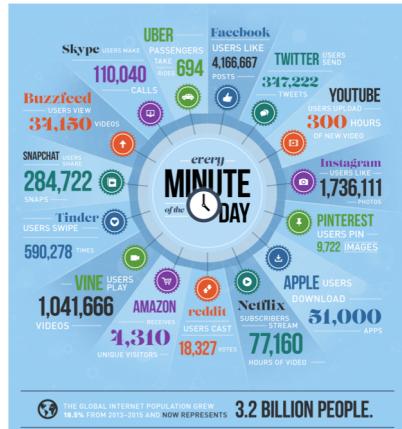


# Social Media Statistics



# Social Media Statistics

## ■ Okay, so many users and much data, then what ?



Benji · a year ago

Hooray for tons of data! 99% of which is total useless rubbish!

2 ^ | v · Reply · Share ›

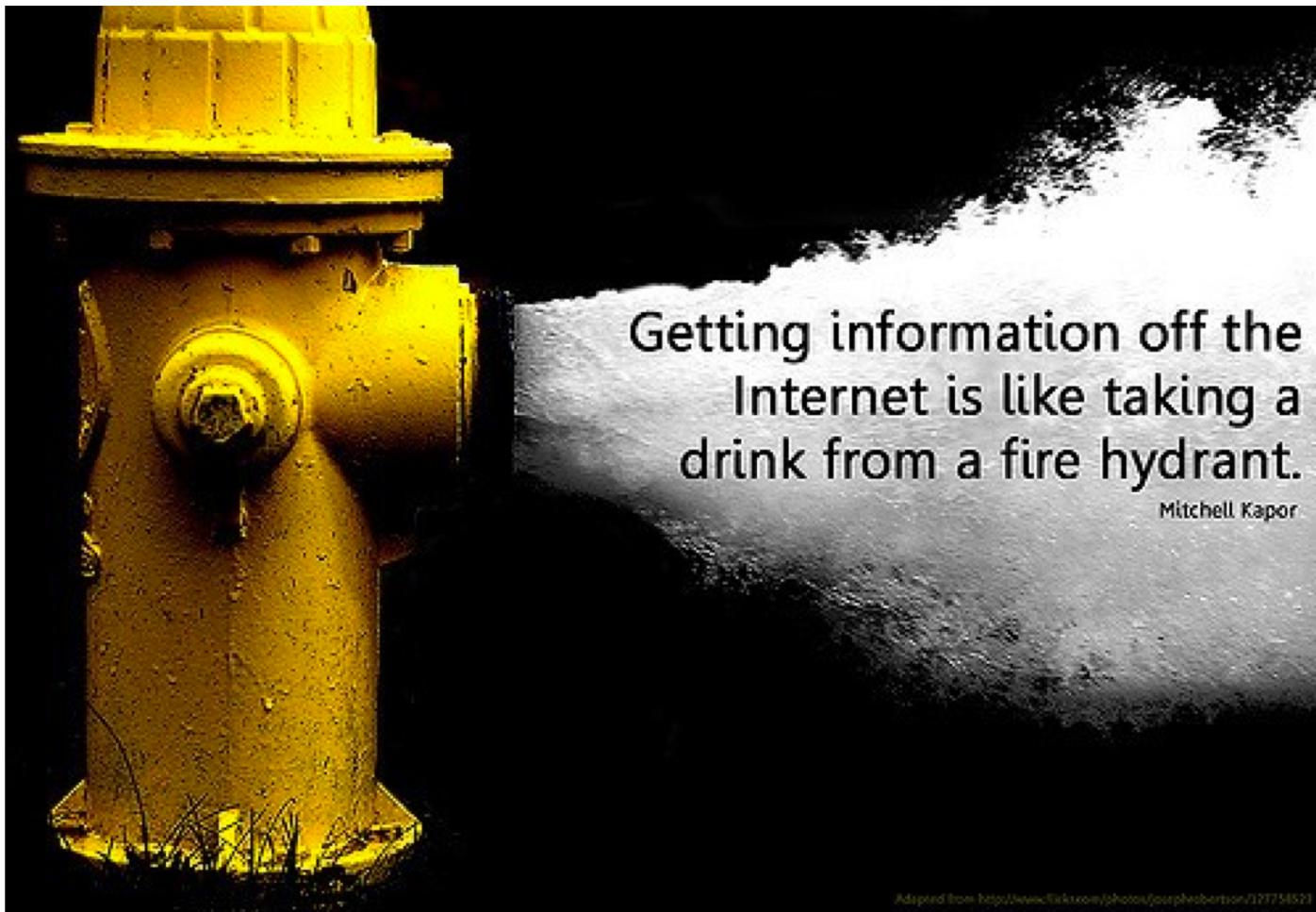


Pat Hennel · 20 days ago

Astounding amounts of data are generated every minute, which means that the possibilities are endless for those who use this data for BI. The goal for any enterprise is to zero in on the data that is meaningful and relevant. Failure to do that could result in poor quality insights, which could also result in a loss of revenue.

^ | v · Reply · Share ›

# Information Overload



Getting information off the Internet is like taking a drink from a fire hydrant.

Mitchell Kapor

Adapted from <http://www.flickr.com/photos/youphobis/12175182>

# Real Life Examples

Amazon.com: Social Computing, Behavioral Modeling, and Prediction: Huan Liu, John J. Salerno, Michael J. Young: Books  
<http://www.amazon.com/Social-Computing-Behavioral-Modeling-Prediction/>

Apple Yahoo! Google Maps YouTube Wikipedia News (26) Popular

Amazon.com: Social Comp...

**Social Computing, Behavioral Modeling, and Prediction (Hardcover)**

by [Huan Liu](#) (Editor), [John J. Salerno](#) (Editor), [Michael J. Young](#) (Editor)  
Key Phrases: [social network analysis](#), [electronic institutions](#), [cognitive modeling](#), [New York](#), [Cambridge University Press](#), [Virtual World](#) (more...)  
No customer reviews yet. [Be the first.](#)

List Price: \$129.00  
Price: **\$129.00** & this item ships for **FREE** with **Super Saver Shipping**. [Details](#)

**In Stock.**  
Ships from and sold by **Amazon.com**. Gift-wrap available.

Want it delivered Thursday, February 19? Order it in the next 14 hours and 52 minutes, and choose One-Day Shipping at checkout. [Details](#)  
**12 new** from \$95.29   **4 used** from \$103.33

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Amazon Prime Free Trial required. Sign up when you check out. [Learn More](#)

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**16 used & new** from \$95.29  
Have one to sell? [Sell yours](#)

**Frequently Bought Together**  
Customers buy this book with [Social Network Analysis: A Handbook](#) by John P Scott  
**Price For Both: \$174.85**

# Real Life Examples

The screenshot shows the product page for the book "Social Computing, Behavioral Modeling, and Prediction" on Amazon.com. The page includes a "Frequently Bought Together" section, a main product image, and a "Customers Who Bought This Item Also Bought" section. A red circle highlights the "Customers Who Bought This Item Also Bought" section, and another red circle highlights the price and rating information for one of the recommended items.

**Frequently Bought Together**

Customers buy this book with [Social Network Analysis: A Handbook](#) by John P Scott

**Price For Both: \$174.85**

[Add both to Cart](#)

**Customers Who Bought This Item Also Bought**

Image	Title	Author	Rating	Price
	Predictably Irrational: The Hidden Forces That Shape Our Lives	Dan Ariely	★★★★★ (184)	\$16.34
	Models and Methods in Social Network Analysis ...	Peter J. Carrington	★★★★★ (1)	\$31.49
	Complex Adaptive Systems: An Introduction to Co... by	John H. Miller	★★★★★ (7)	\$23.35
	Generative Social Science: Studies in Agent-Bas...	Joshua M. Epstein	★★★★★ (5)	\$42.00

**Editorial Reviews**

**Product Description**

Social computing concerns the study of social behavior and context based on computational systems. Behavioral modeling reproduces the social behavior, and allows for experimenting with and deep understanding of behavior, patterns, and potential

# Real Life Examples

**Today's Recommendations For You**

Here's a daily sample of items recommended for you. Click here to [see all recommendations](#).

Page 1 of 25

[Invincible](#)  ~ Michael Jackson  
★★★★★ (880) \$7.99

[In Search of Sunrise, Vol. 7: Asia](#)  ~ DJ Tiesto  
★★★★★ (53) \$15.99

[Fallen](#)  ~ Evanescence  
★★★★★ (2,447) \$8.99

[Amar Es Combatir](#)  ~ Maná  
★★★★★ (55) \$8.49

# Real Life Examples

## YAHOO! MOVIES

**Recommendations For You** Receive Recommendations by Email

**Movies in Theaters: 94089**

**Burn After Reading (R)**  
[Showtimes & Tickets](#) | [Add to My Lists](#)

Yahoo! Users: **B-** 4794 ratings  
The Critics: **B** 14 reviews

[X Don't Recommend Again](#) [★ Seen It? Rate It!](#)



**Pride and Glory (R)**  
[Showtimes & Tickets](#) | [Add to My Lists](#)

Yahoo! Users: **A-** 59 ratings  
The Critics: **C+** 6 reviews

[X Don't Recommend Again](#) [★ Seen It? Rate It!](#)



**Fight Club (R)**  
[Showtimes & Tickets](#) | [Add to My Lists](#)

Yahoo! Users: **B+** 52392 ratings  
The Critics: **B** 12 reviews

[X Don't Recommend Again](#) [★ Seen It? Rate It!](#)



**Lakeview Terrace (PG-13)**  
[Showtimes & Tickets](#) | [Add to My Lists](#)

Yahoo! Users: **B** 3229 ratings  
The Critics: **C** 12 reviews

[X Don't Recommend Again](#) [★ Seen It? Rate It!](#)



**Vicky Cristina Barcelona (PG-13)**  
[Showtimes & Tickets](#) | [Add to My Lists](#)

Yahoo! Users: **B** 1923 ratings  
The Critics: **B+** 13 reviews

[X Don't Recommend Again](#) [★ Seen It? Rate It!](#)



**The Duchess (PG-13)**  
[Showtimes & Tickets](#) | [Add to My Lists](#)

Yahoo! Users: **B+** 953 ratings  
The Critics: **B-** 10 reviews

[X Don't Recommend Again](#) [★ Seen It? Rate It!](#)



[See All Recommendations](#)



# Real Life Examples



# Real Life Examples

Songs from friends and similar people

[▶ Play All](#)  [Buy all](#)



[▶ Victims by The Oppressed](#)  
**New!** Traditional Byrd69



[▶ Skinhead Girl by The Oppressed](#)  
**New!** Traditional Byrd69



[▶ King Of The Jungle by Last Resort](#)  
**New!** Traditional Byrd69



[▶ Violence In Our Minds by Last Resort](#)  
**New!** Traditional Byrd69



[▶ Violence by The Templars](#)  
**New!** Traditional Byrd69

[View all](#) | [invite more friends](#)

iLike™

# Recommendation Systems

## ■ Content-based Filtering

- Recommend items based on key-words
- More appropriate for information retrieval

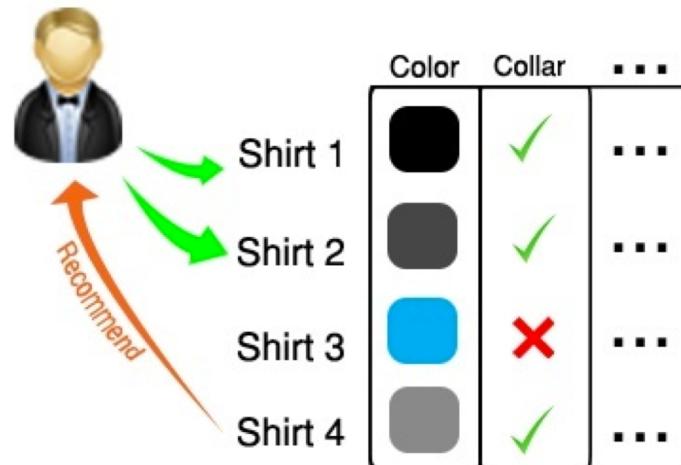
## ■ Collaborative Filtering (CF)

- Look at users with similar rating styles
- Look at similar items for each item

# Content-based Filtering

## ■ Matching user preference with content

- Requirement
  - Some information describing items (e.g., genre of movies)
  - Some sort of user profile describing the user's preference
- “Similarity” is computed based on the item attributes
- The task: Match a user with the content that may interest the user.



# Collaborative Filtering: The Tasks

## ■ Which item should be recommended?

- Predict the unknown rating

		Items						
		$i_1$	$i_2$	$i_3$	$i_4$	$i_5$	$i_6$	$i_7$
Users	$u_1$	4		4	3	3	5	
	$u_2$		3		2			
	$u_3$		2		5			1
	$u_4$		5		1		3	
	$u_5$	5		4		4		1
	$u_6$	?		3		4	2	1

Underling assumption: personal tastes are correlated -  
Active user will prefer those items which the similar users prefer.

# Netflix Prize

## ■ Netflix Prize : a movie recommendation challenge

- 1 Million USD for the best performing recommendation algorithm



## Leaderboard

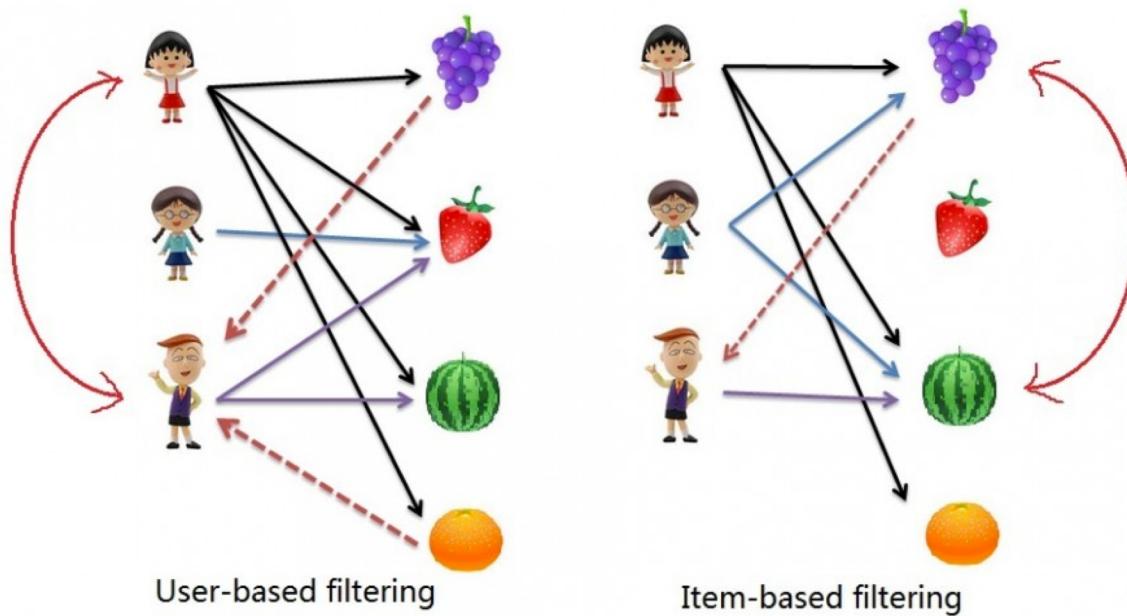
Showing Test Score. [Click here to show quiz score](#)

Display top  leaders.

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
<b>Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos</b>				
1	<a href="#">BellKor's Pragmatic Chaos</a>	0.8567	10.06	2009-07-26 18:18:28
2	<a href="#">The Ensemble</a>	0.8567	10.06	2009-07-26 18:38:22
3	<a href="#">Grand Prize Team</a>	0.8582	9.90	2009-07-10 21:24:40
4	<a href="#">Opera Solutions and Vandelay United</a>	0.8588	9.84	2009-07-10 01:12:31
5	<a href="#">Vandelay Industries !</a>	0.8591	9.81	2009-07-10 00:32:20
6	<a href="#">PragmaticTheory</a>	0.8594	9.77	2009-06-24 12:06:56
7	<a href="#">BellKor in BigChaos</a>	0.8601	9.70	2009-05-13 08:14:09
8	<a href="#">Dace</a>	0.8612	9.59	2009-07-24 17:18:43

# Collaborative Filtering

- A method of making automatic predictions (filtering) about the interests of a user by collecting preferences or taste information from many users (collaborating).



# Collaborative Filtering

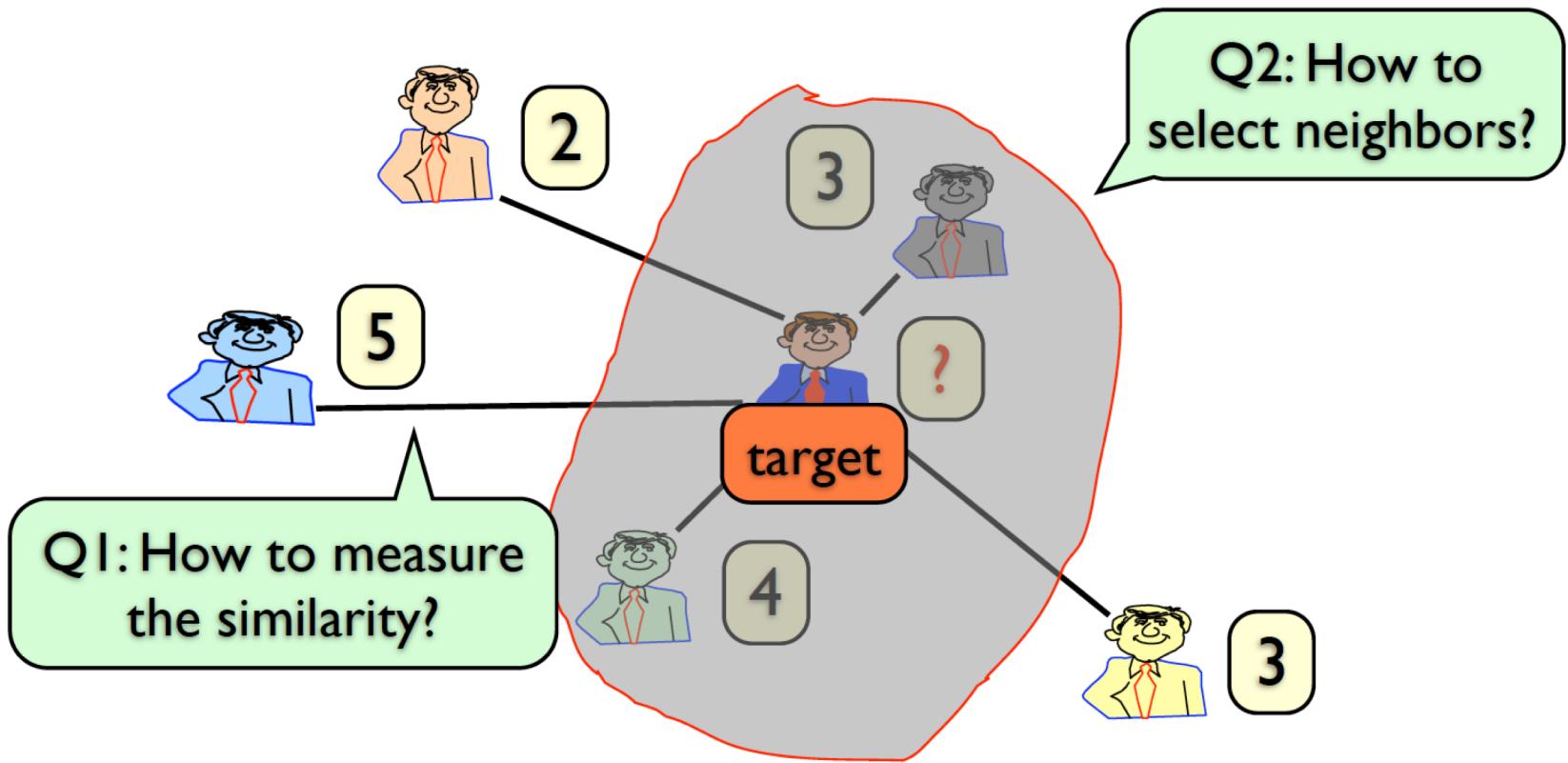
## ■ Memory-based (Neighborhood-based)

- User-based
- Item-based

## ■ Model-based

- Matrix Factorization
- Clustering Methods
- Bayesian Methods
- etc.

# User-User Similarity



# User-based Collaborative Filtering

		Items						
		4		3	3	3	1	
			3		2			
			2		5			1
			5		1		3	
		5		4		4		1
Users		?		3		4	2	1

# User-based Collaborative Filtering

- Predict the ratings of active users based on the ratings of similar users found in the user-item matrix
- Similarity between two users
  - Pearson correlation coefficient

$$S_{ij} = \frac{\sum_{k \in I} (R_{ik} - \bar{R}_i) \cdot (R_{jk} - \bar{R}_j)}{\sqrt{\sum_{k \in I} (R_{ik} - \bar{R}_i)^2} \sqrt{\sum_{k \in I} (R_{jk} - \bar{R}_j)^2}}$$

Items

- Cosine similarity

$$S_{ij} = \frac{\sum_{k \in I} R_{ik} \cdot R_{jk}}{\sqrt{\sum_{k \in I} R_{ik}^2} \sqrt{\sum_{k \in I} R_{jk}^2}}$$

- I: items rated by both users

	Users	4	3	3	3	1	
	4	3	2				Items
	3	2	5				Items
	2	5				1	Items
	1	1				3	Items
	5	4	4	4	1	Items	Items
	5	4	4	4	1	Items	Items
	?	3	4	2	1	Items	Items

# User-based Collaborative Filtering

## ■ Pearson correlation coefficient

$$S_{ij} = \frac{\sum_{k \in I} (R_{ik} - \bar{R}_i) \cdot (R_{jk} - \bar{R}_j)}{\sqrt{\sum_{k \in I} (R_{ik} - \bar{R}_i)^2} \sqrt{\sum_{k \in I} (R_{jk} - \bar{R}_j)^2}}$$

- $I$ : items rated by both users

		Items					
		4	3	3	3	1	
		3		2			
		2		5			1
		5		1		3	
5		4		4		1	
?		3		4	2	1	

$$\bar{R}_i = 3, \bar{R}_j = 2.67$$

$$S_{ij} = \frac{1 * 0.33 + 1 * 1.33 + (-2) * (-1.67)}{\sqrt{1^2 + 1^2 + (-2)^2} \sqrt{0.33^2 + 1.33^2 + (-1.67)^2}}$$

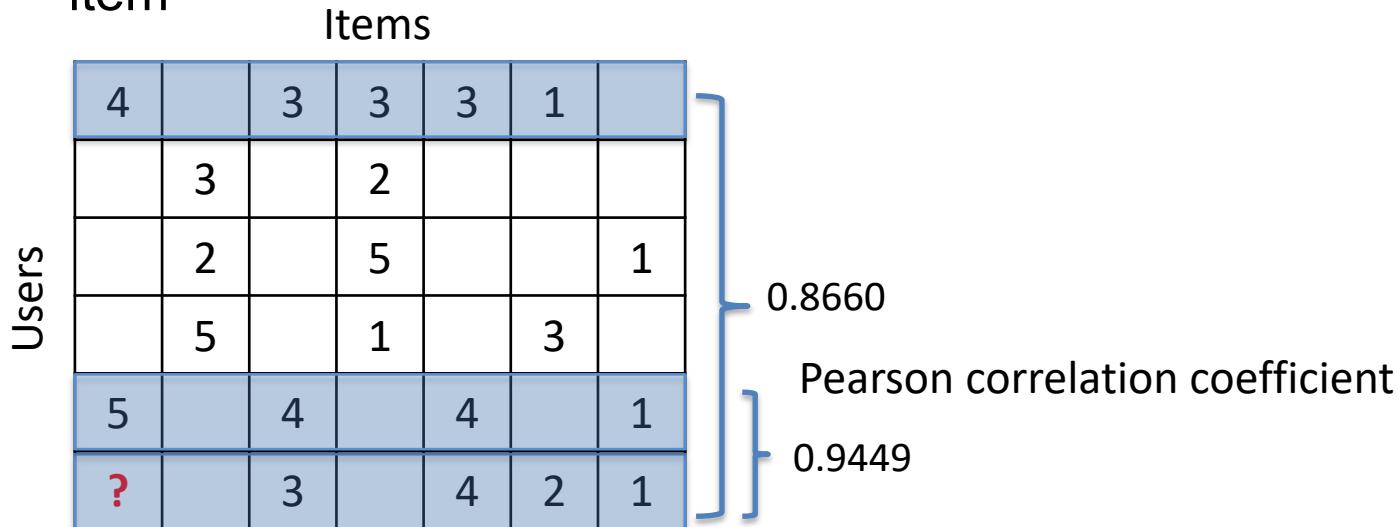
$$S_{ij} = 0.9449$$

# User-based Collaborative Filtering

## ■ Weighted average rating:

$$\hat{R}_{i,k} = \bar{R}_i + \frac{\sum_{u_j \in N_i} S_{ij}(R_{jk} - \bar{R}_j)}{\sum_{u_j \in N_i} S_{ij}}$$

- where  $N_i$  is the set of users (neighbors) who have rated the k-th item



$$\hat{R}_{i,k} = 2.5 + \frac{0.8660 * (4 - 2.8) + 0.9449 * (5 - 3.5)}{0.8860 + 0.9449} = 3.8565$$

# Item-Item Similarity

- Search for similarities among items
- Item-Item similarity is more stable than user-user similarity
  - People change their preference over time, but items rarely change their features.

		Items						
		4		3	3	3	1	
		3		2				
		2		5				1
		5		1			3	
		5		4		4		1
Users		?		3		4	2	1

# Item-based Collaborative Filtering

## ■ Similar as in user-user similarity but on item vectors

- Pearson correlation coefficient
- Cosine similarity
- Look for users who rated both items

		Items					
		4	3	3	3	1	
Users	4	3	3	3	1		
	3	2					
	2	5				1	
	5	1			3		
	5	4	4		1		
	?	3		4	2	1	

$$S_{ij} = \frac{\sum_{k \in I} (R_{ik} - \bar{R}_i) \cdot (R_{jk} - \bar{R}_j)}{\sqrt{\sum_{k \in I} (R_{ik} - \bar{R}_i)^2} \sqrt{\sum_{k \in I} (R_{jk} - \bar{R}_j)^2}}$$

$$\hat{R}_{i,k} = \bar{R}_i + \frac{\sum_{u_j \in N_i} S_{ij} (R_{jk} - \bar{R}_j)}{\sum_{u_j \in N_i} S_{ij}}$$

# Collaborative Filtering

## ■ Memory-based (Neighborhood-based)

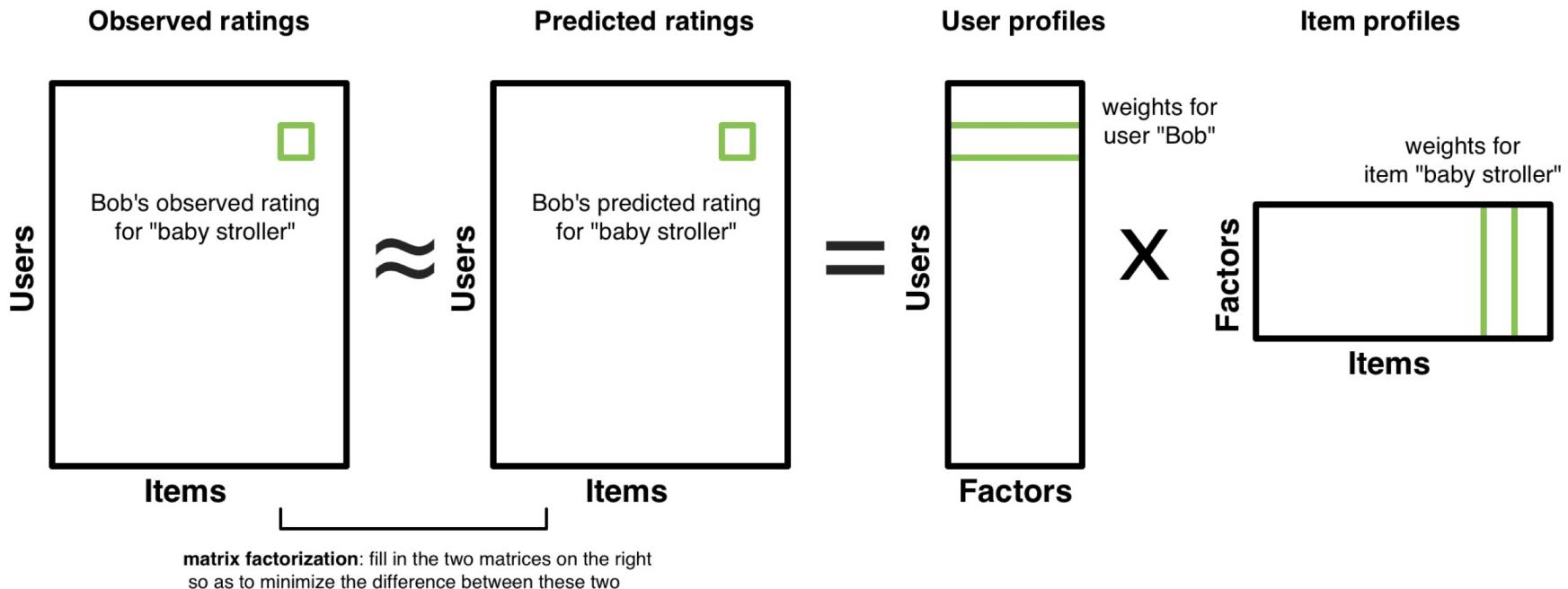
- User-based
- Item-based

## ■ Model-based

- Matrix Factorization
- Clustering Methods
- Bayesian Methods
- etc.

# Matrix Factorization

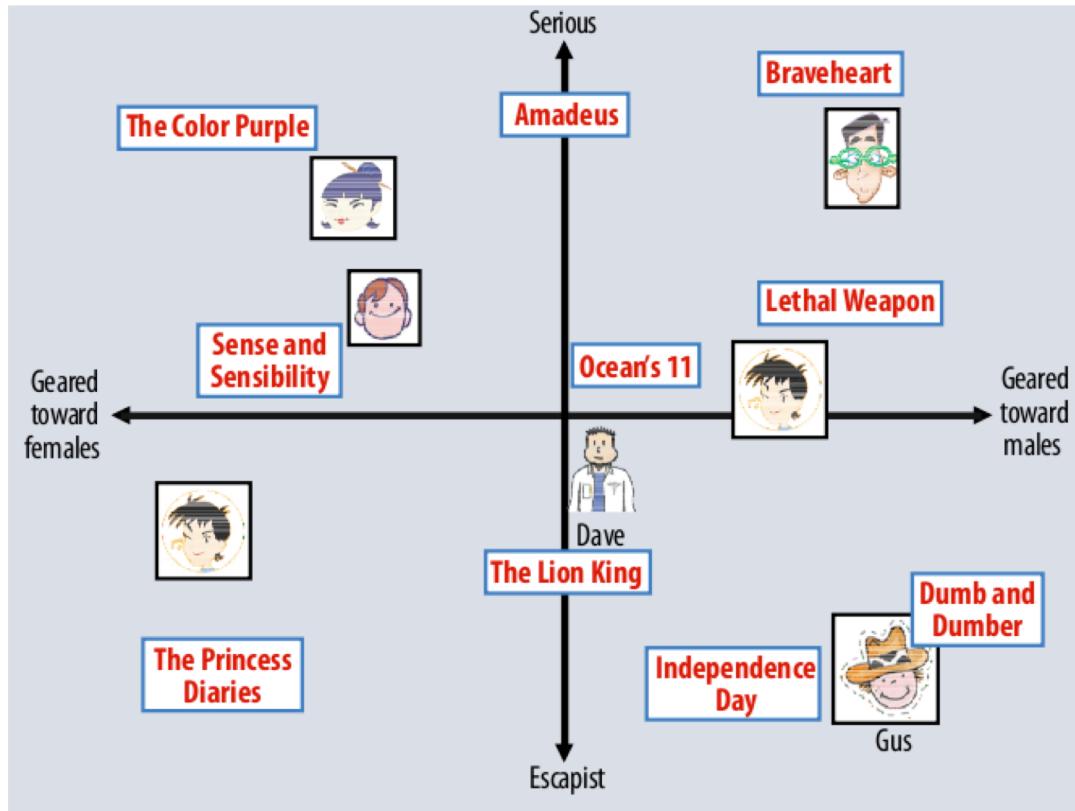
- Matrix factorization: characterizes both items and users by vectors of factors inferred from item rating patterns.



# Matrix Factorization

## ■ Interpretation of latent factors

- However, latent factors are practically often implicit and inexplicable.



# Matrix Factorization

	$i_1$	$i_2$	$i_3$	$i_4$	$i_5$	$i_6$	$i_7$	$i_8$
$u_1$	5	2		3		4		
$u_2$	4	3			5			
$u_3$	4		2			2	4	
$u_4$								
$u_5$	5	1	2		4	3		
$u_6$	4	3		2	4		3	5

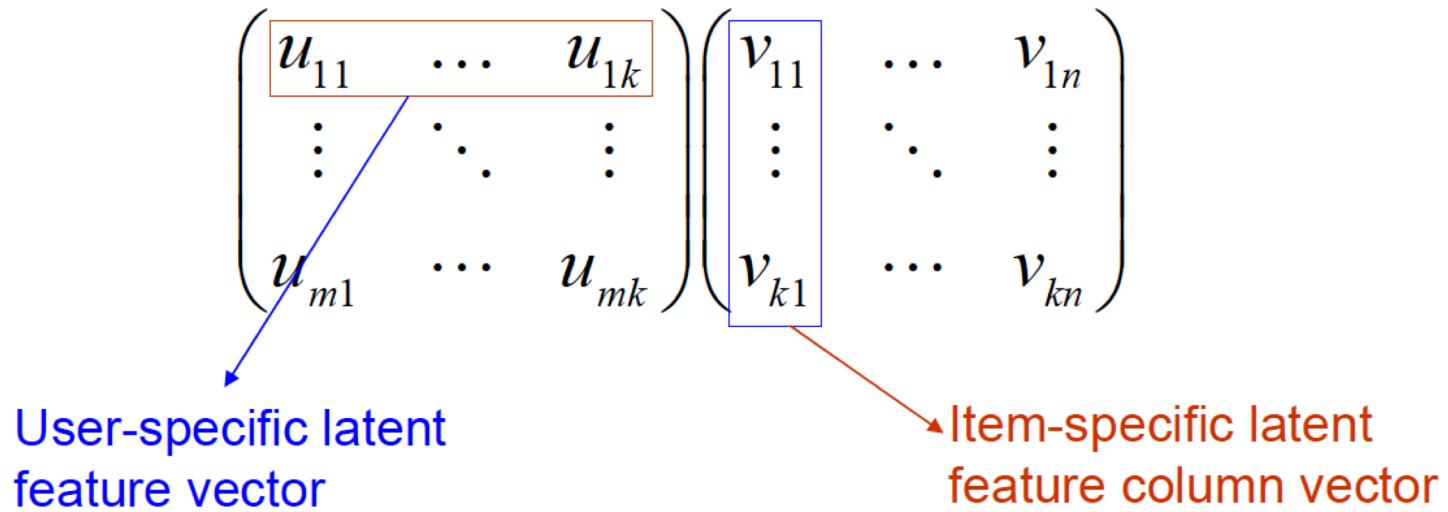
	$i_1$	$i_2$	$i_3$	$i_4$	$i_5$	$i_6$	$i_7$	$i_8$
$u_1$	5	2	2.5	3	4.8	4	2.2	4.8
$u_2$	4	3	2.4	2.9	5	4.1	2.6	4.7
$u_3$	4	1.7	2	3.2	3.9	3.0	2	4
$u_4$	4.8	2.1	2.7	2.6	4.7	3.8	2.4	4.9
$u_5$	5	1	2	3.4	4	3	1.5	4.6
$u_6$	4	3	2.9	2	4	3.4	3	5

$$U = \begin{bmatrix} 1.55 & 1.22 & 0.37 & 0.81 & 0.62 & -0.01 \\ 0.36 & 0.91 & 1.21 & 0.39 & 1.10 & 0.25 \\ 0.59 & 0.20 & 0.14 & 0.83 & 0.27 & 1.51 \\ 0.39 & 1.33 & -0.43 & 0.70 & -0.90 & 0.68 \\ 1.05 & 0.11 & 0.17 & 1.18 & 1.81 & 0.40 \end{bmatrix} \quad V = \begin{bmatrix} 1.00 & -0.05 & -0.24 & 0.26 & 1.28 & 0.54 & -0.31 & 0.52 \\ 0.19 & -0.86 & -0.72 & 0.05 & 0.68 & 0.02 & -0.61 & 0.70 \\ 0.49 & 0.09 & -0.05 & -0.62 & 0.12 & 0.08 & 0.02 & 1.60 \\ -0.40 & 0.70 & 0.27 & -0.27 & 0.99 & 0.44 & 0.39 & 0.74 \\ 1.49 & -1.00 & 0.06 & 0.05 & 0.23 & 0.01 & -0.36 & 0.80 \end{bmatrix}$$

# Matrix Factorization

## ■ Matrix Factorization in Collaborative Filtering

- To fit the product of two (low rank) matrices to the observed rating matrix.
- To find two latent user and item feature matrices.
- To use the fitted matrix to predict the unobserved ratings.



# Matrix Factorization

## ■ Optimization Problem

Given a  $m \times n$  rating matrix  $R$ , to find two matrices  $U \in \mathbb{R}^{l \times m}$  and  $V \in \mathbb{R}^{l \times n}$ ,

$$R \approx U^T V,$$

where  $l < \min(m, n)$ , is the number of factors

# Matrix Factorization

## ■ Models

- SVD-like Algorithm
- Regularized Matrix Factorization (RMF)
- Probabilistic Matrix Factorization (PMF)
- Non-negative Matrix Factorization (NMF)

# SVD-like Algorithm

## ■ Minimizing

$$\frac{1}{2} \|R - U^T V\|_F^2$$

## ■ For collaborative filtering

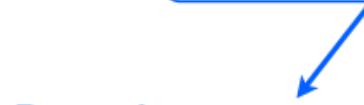
$$\min_{U, V} \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^n I_{ij} (R_{ij} - U_i^T V_j)^2$$

where  $I_{ij}$  is the indicator function that is equal to 1 if user  $u_i$  rated item  $v_j$  and equal to 0 otherwise.

# Regularized Matrix Factorization

- Minimize the loss based on the observed ratings with regularization terms to avoid over-fitting problem

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

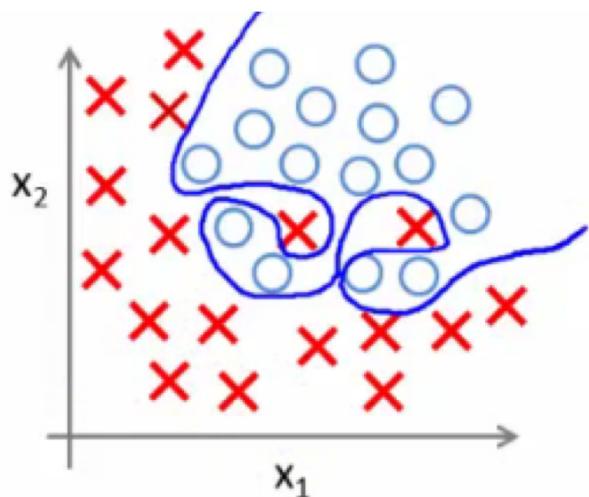
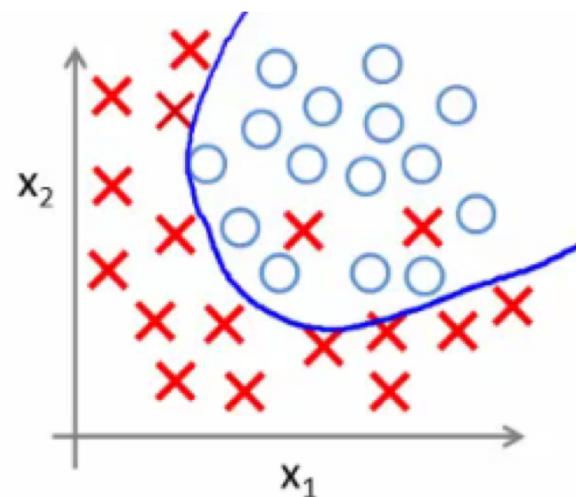
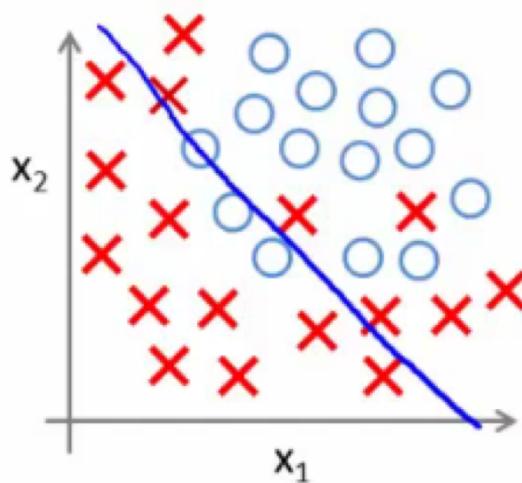
Regularization terms

where  $\lambda_1, \lambda_2 > 0$

- The problem can be solved by simple stochastic gradient descent algorithm.

# What is the Over-Fitting Problem?

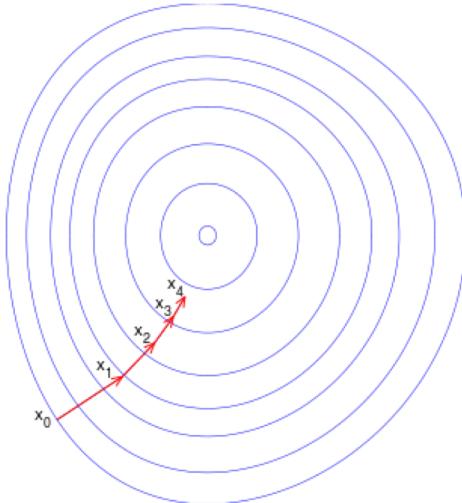
- Over-fitting: a statistical model describes random error or noise instead of the underlying relationship.



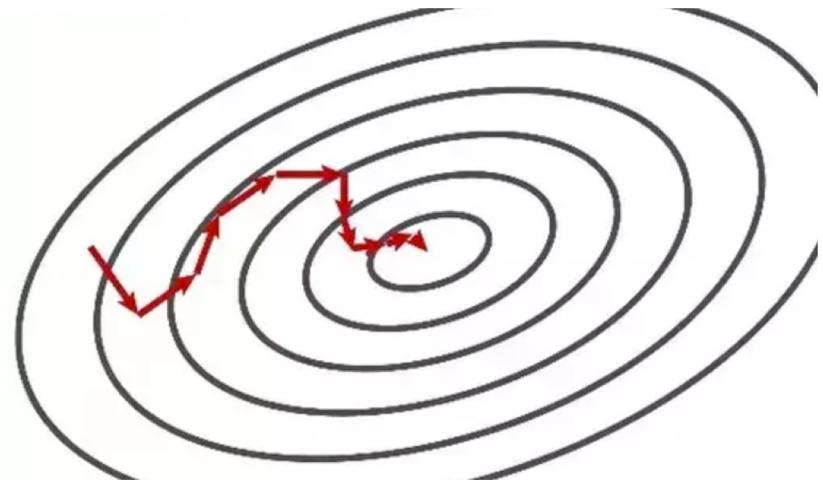
# Stochastic Gradient Descent (SGD)

- A stochastic approximation of the gradient descent optimization method.
- An objective function written as a sum of differentiable functions

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



Gradient descent



Stochastic gradient descent

# SGD for Matrix Factorization

## ■ A close look at objective loss function

$$e_{i,j} = \frac{1}{2}(R_{i,j} - \sum_k U_{k,i}V_{k,j})^2 + \frac{\lambda_1}{2}\|U\|^2 + \frac{\lambda_2}{2}\|V\|^2$$

## ■ Computing the partial derivative w.r.t. U and V

$$\frac{\partial e_{i,j}}{\partial U_{k,i}} = -(R_{i,j} - \sum_k U_{k,i}V_{k,j})V_{k,j} + \lambda_2 U_{k,i}$$

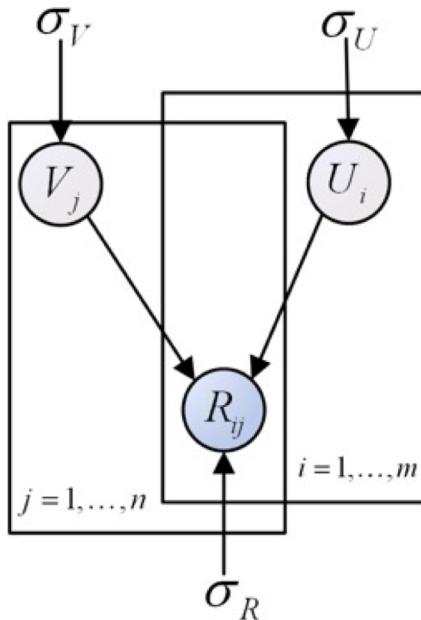
$$\frac{\partial e_{i,j}}{\partial V_{k,j}} = -(R_{i,j} - \sum_k U_{k,i}V_{k,j})U_{k,i} + \lambda_2 V_{k,j}$$

## ■ Update U and V accordingly

$$U_{k,i} = U_{k,i} - \alpha \frac{\partial e_{i,j}}{\partial U_{k,i}} \quad V_{k,j} = V_{k,j} - \alpha \frac{\partial e_{i,j}}{\partial V_{k,j}}$$

# Probabilistic Matrix Factorization

- Assume zero-mean Gaussian priors on user and item feature:
- Define a conditional distribution over the observed ratings as:



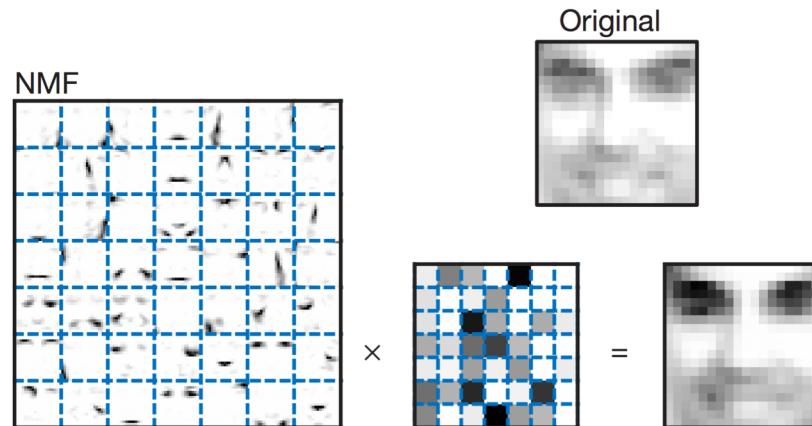
$$p(U|\sigma_U^2) = \prod_{i=1}^m \mathcal{N}(U_i|0, \sigma_U^2 \mathbf{I})$$

$$p(V|\sigma_V^2) = \prod_{j=1}^n \mathcal{N}(V_j|0, \sigma_V^2 \mathbf{I})$$

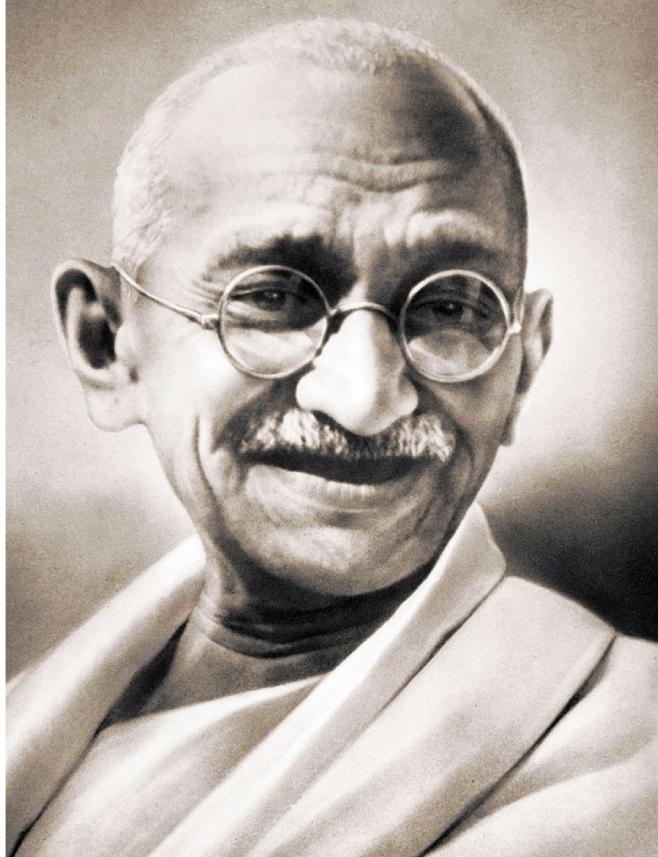
$$p(R|U, V, \sigma_R^2) = \prod_{i=1}^m \prod_{j=1}^n \left[ \mathcal{N} \left( R_{ij} | g(U_i^T V_j), \sigma_R^2 \right) \right]^{I_{ij}^R}$$

# Non-negative Matrix Factorization

- Given an observed matrix  $\mathbf{Y}$ , to find two non-negative matrices  $\mathbf{U}$  and  $\mathbf{V}$
- What is the advantage of the non-negative constraint?
  - Intuition and interpretation (particularly for images)
  - No obvious advantages for recommendation



# Social Recommendations



*“Interdependence is and ought to be as much the ideal of man as self-sufficiency.  
Man is a social being.”*

# Challenges in Recommendation Systems

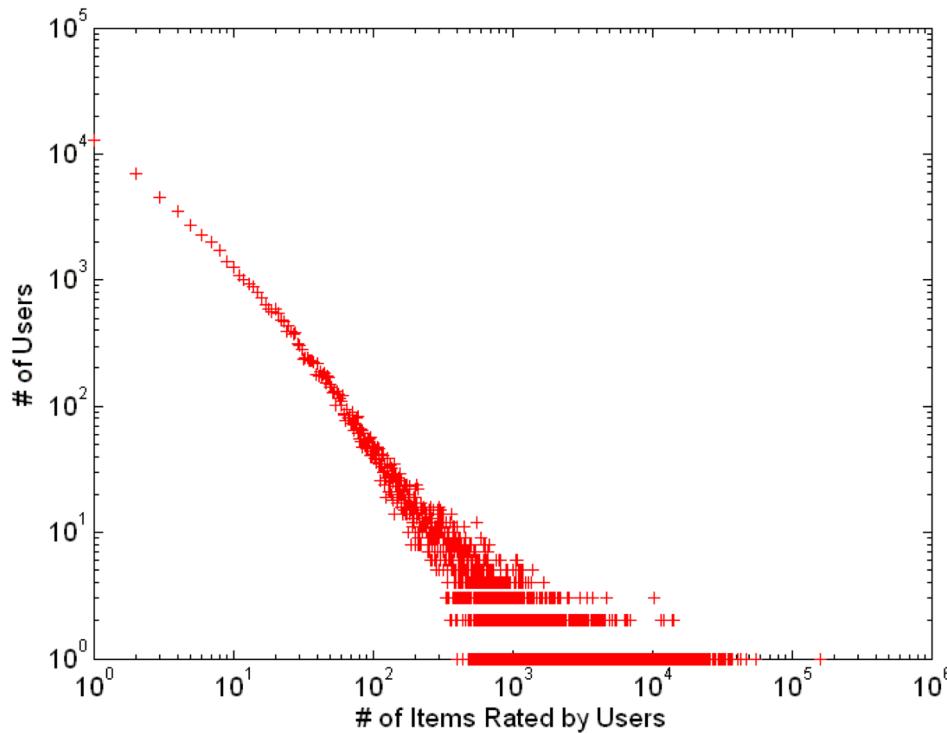
## ■ Data sparsity problems

0	0	0	0	0	0	0	0	4	0	0
0	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	5	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	6	0	0	0	0
0	0	0	0	0	2	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	3
0	0	8	0	0	0	0	0	0	0	0

# Data Sparsity Problem

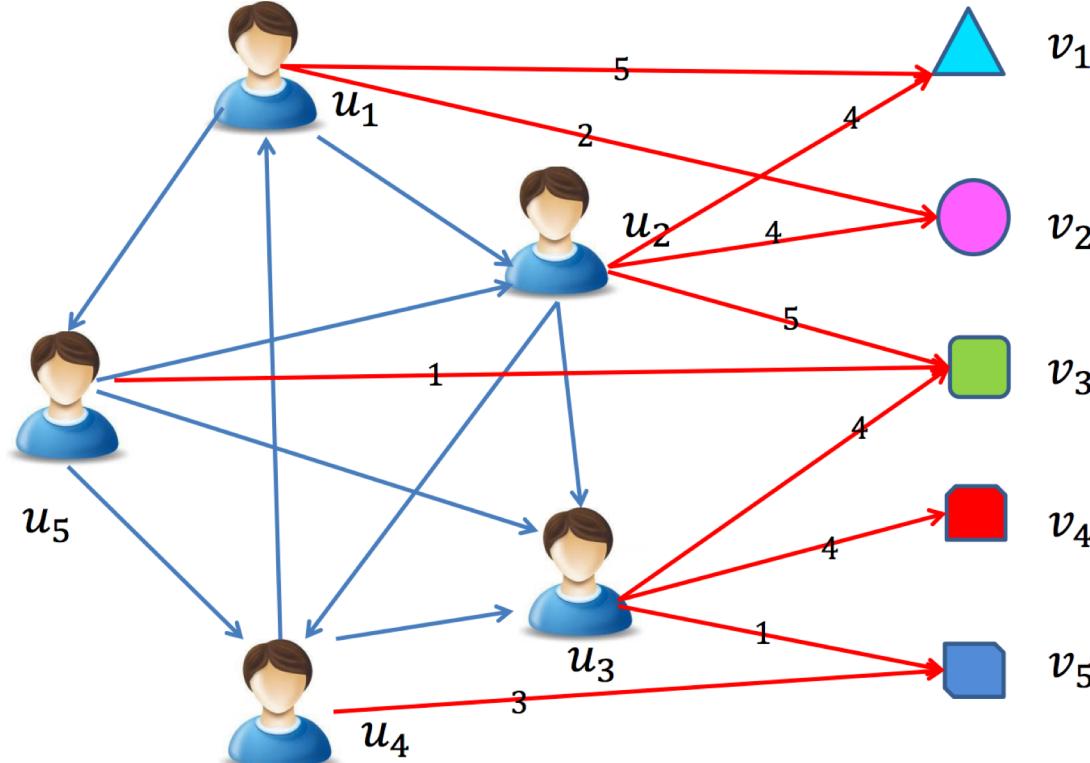
## ■ Epinions Dataset

- 114,222 users/ 754,987 items/ 13,385,713 ratings
- Density: 0.0155%



# Social Recommendations

- If links between users and items are sparse, can we use user social links for recommendation?



# Social Recommendations

Traditional Recommendation

	$i_1$	$i_2$	$i_3$	$i_4$	$i_5$	$i_6$	$i_7$
$u_1$	4		3	3	3	1	
$u_2$		3		2			
$u_3$		2		5			1
$u_4$		5		1		3	
$u_5$	5		4		4		1
$u_6$	?		3		4	2	1



Social Relationship

	$u_1$	$u_2$	$u_3$	$u_4$	$u_5$	$u_6$
$u_1$						1
$u_2$			1	1	1	
$u_3$	1					1
$u_4$	1				1	
$u_5$	1			1		
$u_6$	1		1			

# Social Recommendations

- **Intuition:** Users usually resort to their friends for recommendation. Thus, their preference might be similar to each other.

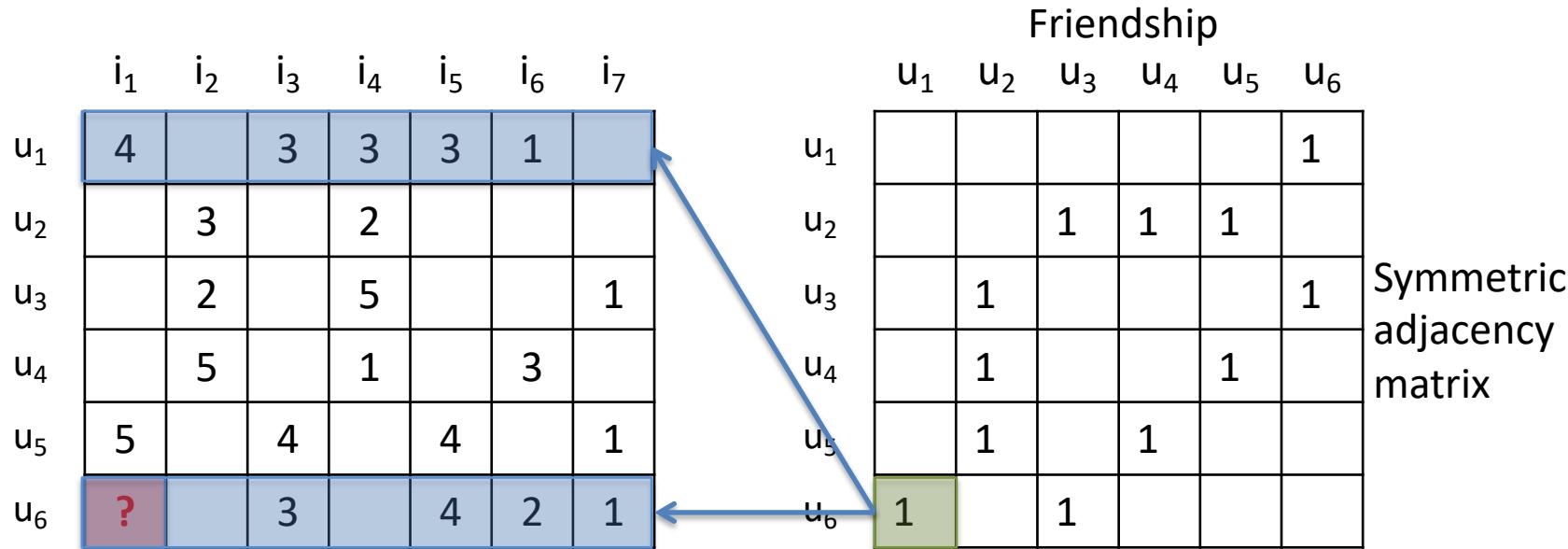


*a social recommendation CF model = a basic CF model + a social information model*

# Memory based Social Recommendation

## ■ Considering social information when computing user-user similarity

- Friend-based social relationship
  - Consider friends (bi-directional relationship) as correlated users



# Memory based Social Recommendation

## ■ Considering social information when computing user-user similarity

- Trust-based social relationship
  - Consider trust (uni-directional relationship) between users
    - E.g. Twitter followers/followings

	$i_1$	$i_2$	$i_3$	$i_4$	$i_5$	$i_6$	$i_7$
$u_1$	4		3	3	3	1	
$u_2$		3		2			
$u_3$		2		5			1
$u_4$		5		1		3	
$u_5$	5		4		4		1
$u_6$	?		3		4	2	1

Trust-based Relationship

	$u_1$	$u_2$	$u_3$	$u_4$	$u_5$	$u_6$
$u_1$		1			1	
$u_2$			1		1	
$u_3$						1
$u_4$		1			1	
$u_5$				1		1
$u_6$	1			1		

Asymmetric adjacency matrix

# Memory based Social Recommendation

- Considering social information when computing user-user similarity
  - Trust-based social relationship
    - More complex trust modeling



Celebrity



Domain expert



Authorities

# Model-based Social Recommendation

- Matrix factorization + Social relationship
- Three categories (depending on how social information is used)
  - Ensemble methods
  - Regularization methods
  - Co-factorization methods

# Ensemble Methods

## ■ Assumption:

- Users and their social networks should have similar ratings on items, and a missing rating for a given user is predicted as a linear combination of ratings from the user and her social network.

$$R_{ij} = U_i \times V_j + F_1 \times V_j + \dots + F_n \times V_j$$

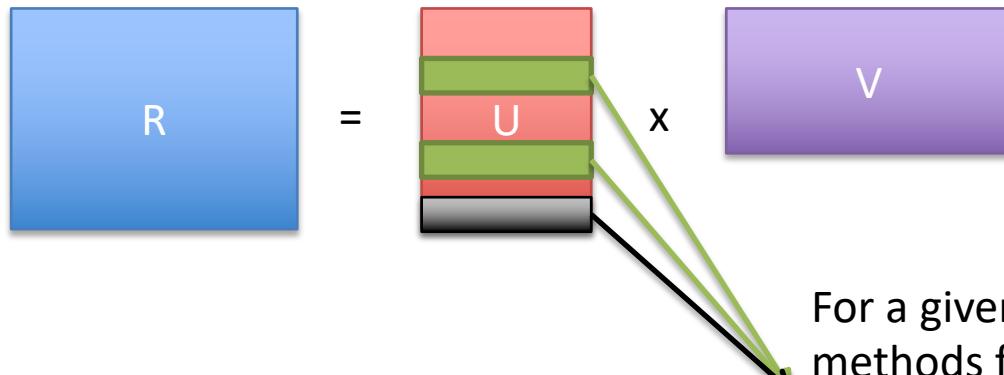
- Same objective function with different formulation of  $R_{ij}$

$$\hat{R}_{ij} = \mathbf{u}_i^\top \mathbf{v}_j + \beta \sum_{\mathbf{u}_k \in \mathcal{N}_i} \mathbf{s}_{ik} \mathbf{u}_k^\top \mathbf{v}_j$$

# Regularization Methods

## ■ Assumption:

- A user's preference should be similar to that of her social network

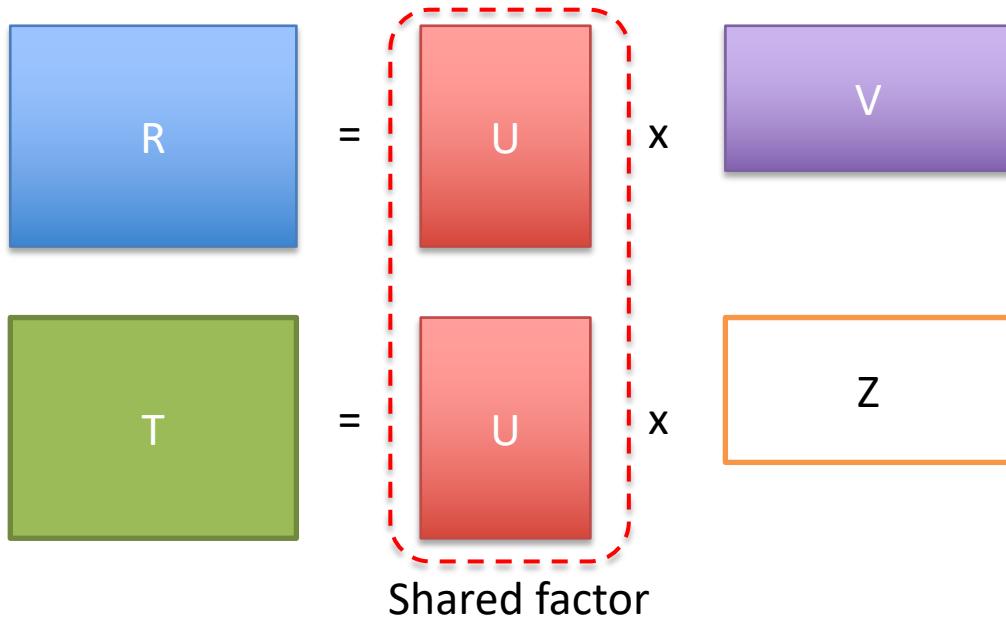


For a given user  $u_i$ , regularization methods force her preference  $u_i$  to be closer to that of users in  $u_i$ 's social network.

# Co-factorization Methods

## ■ Assumption:

- The  $i$ -th user  $u_i$  should share the same user preference vector  $u_i$  in the rating space (rating information) and the social space (social information).

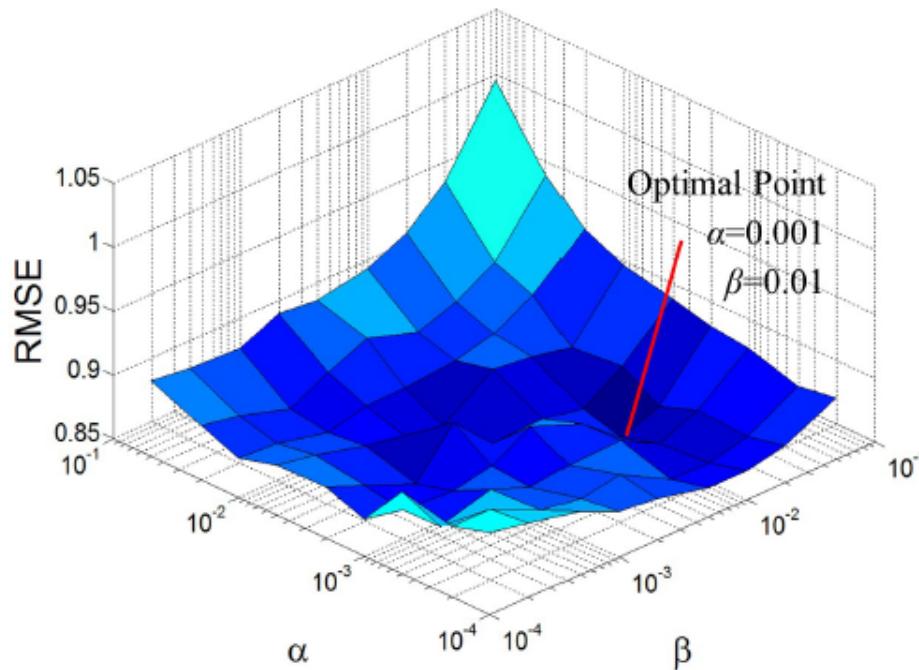


Co-factorization in the user-item matrix  $\mathbf{R}$  and the user-user social relation matrix  $\mathbf{T}$  by sharing the same user preference latent factor

# Example of Performance

## ■ POI recommendation in Foursquare

- $\alpha$  and  $\beta$  control how much the social and item (POIs) influence the matrix factorization process, respectively.



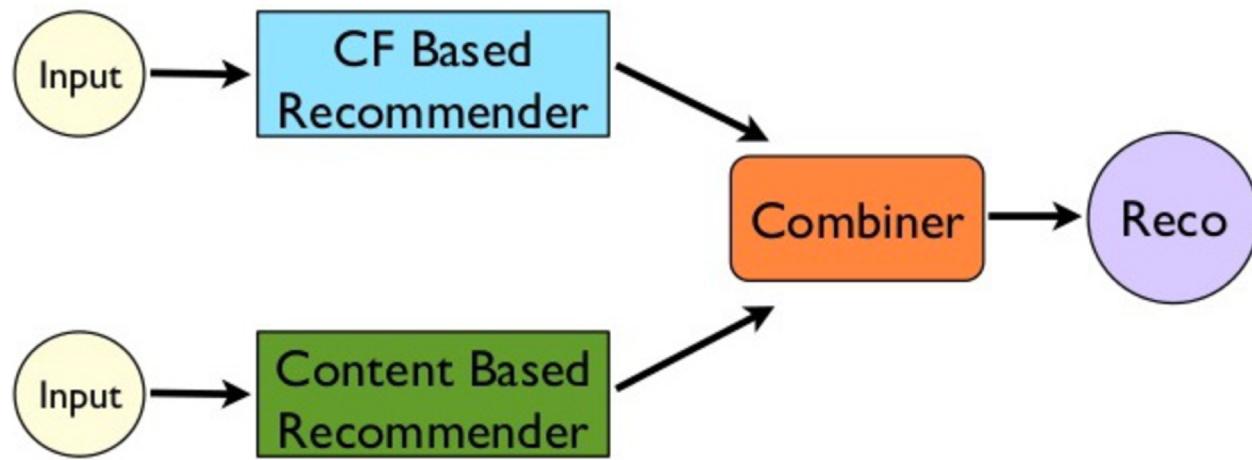
(a) New York restaurant dataset.

# Advanced Topics on Recommendations

- Hybrid Recommendation
- Top-N (ranking-based) recommendation
- Context in recommendation
- Privacy

# Hybrid Recommendation

- Merging the results from content-based recommendation and collaborative filtering



# Top-N (ranking-based) Recommendation

## ■ Rating prediction:

- Predict individual ratings of users on items as accurate as possible

## ■ Ranking prediction:

- Predict ranking of items that a user may be interested in.

	i <sub>1</sub>	i <sub>2</sub>	i <sub>3</sub>
u <sub>1</sub>	1	2	5

Real rating from u<sub>1</sub>

	i <sub>1</sub>	i <sub>2</sub>	i <sub>3</sub>
Prediction 1	3	4	5

*Same MAE, but different ranking loss*

	i <sub>1</sub>	i <sub>2</sub>	i <sub>3</sub>
Prediction 2	1	4	3

# Context in recommendation

## ■ Spatiotemporal context

- More constraints
  - Geographical distance
  - Temporal suitability (e.g., opening hour)
- Spatiotemporal user preference modeling



*It's **Friday 20:00 pm**, Jim is at **[40.71448, -74.00598]**, which places should we recommend to him?*

# Privacy issues

- **Releasing a user's rating information may cause serious privacy leakage.**
  - Inference attacks on identity, gender, income level, politic views, etc.
- **Privacy-preserving data publishing**
  - Add a certain level of noise to user rating such that the privacy is protected while the noise-added ratings can still be used for recommendation

# Conclusion

## ■ Why do we need recommendation systems?

- Information overload -> Searching pertinent information is hard!

## ■ Recommendation Techniques

- Content-based recommendation
- Collaborative-based recommendation
  - Memory-based methods
  - Model-based methods

## ■ Social Recommendation

- Social relationship in recommendation

## ■ Advanced Topics in Recommendation