CMSC5733 Social Computing

Irwin King

The Chinese University of Hong Kong

king@cse.cuhk.edu.hk

©2013 All Rights Reserved.



Information and more Information!





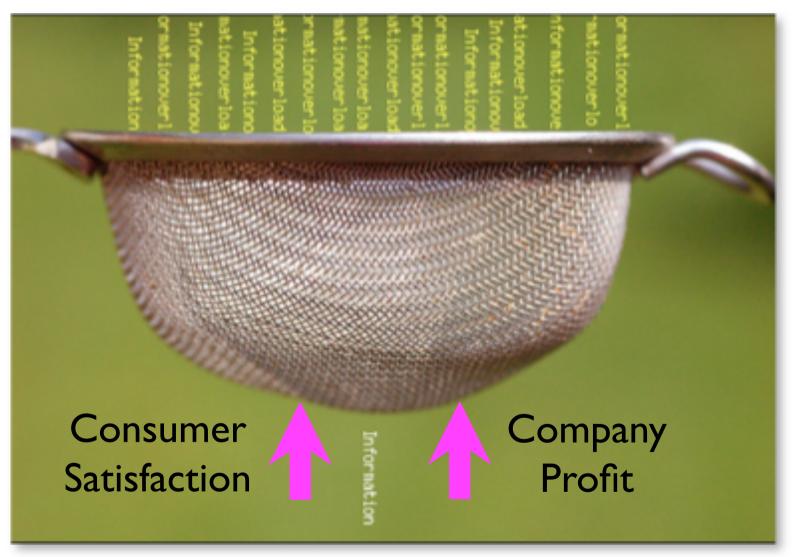
Information Overload



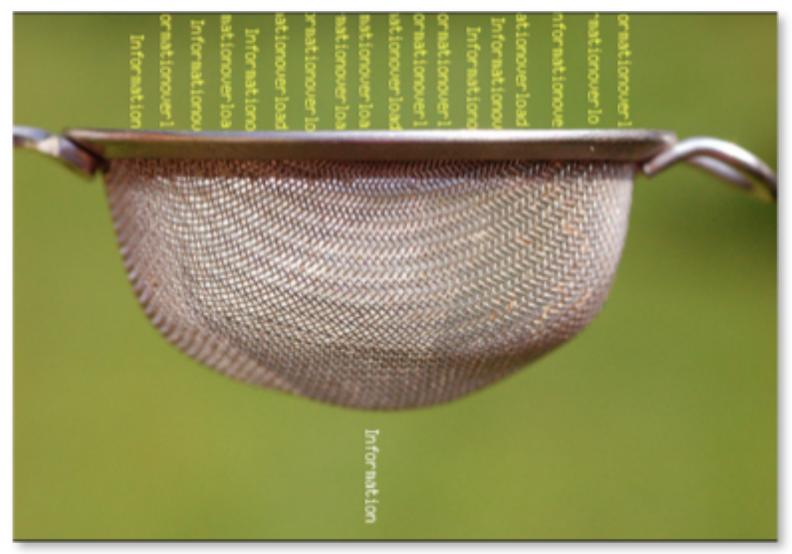
















amazon.com	Hello. <u>Sign in</u> to Your Amazon.c	in to get personalized recommendation con.com 😥 Today's Deals Gifts			ns. New customer? <u>Start here</u> . s & Wish Lists Gift Cards		FREE 2-Day Shipping: See detail Your Digital Items Your Account Hel		
Shop All Departments 🛛 💙	Search Book		•			<u>@</u>	∖ ∕ Cart	Wish List	
Books	Advanced Search	Browse Subjects	New Releases	Bestsellers	The New York Times® Bestsellers	Libros	en español Ba	Irgain Books Text	tbooks
Click to LOOK	ces the	Wide V Irwin King Be the first List Price: Price:	Veb [Hardo (Editor), <u>Rica</u> to review this i \$99.00	this item s) (0) hips for FREE with Supe	 r	Sign in to tu	Add to Cart or urn on 1-Click orde or Add to Cart with E Two-Day Shipping	

In Stock.

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

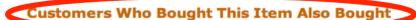
Only 2 left in stock--order soon (more on the way).

Want it delivered Thursday, July 21? Order it in the next 0 hours and 19 minutes, and choose One-Day Shipping at checkout. Details

18 new from \$14.62 13 used from \$14.62



FREE Two-Day Shipping for Students. Learn more





World Wide Web

2 Springer

Share your own customer images

Search inside this book



required. Sign up when you

check out. Learn More

Add to Wish List

More Buying Choices

31 used & new from \$14.62 Have one to sell? Sell yours here

Share 🖂 🖬 💟





Today's Recommendations For You

Here's a daily sample of items recommended for you. Click here to see all recommendations.



Invincible 🔽 ~ Michael Jackson



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



Fallen ♥ ~ Evanescence



AMAR ES COMBATIR Amar Es Combatir 🖓 ~ Maná



The Chinese University of Hong Kong, CMSC5733 Social Computing, Irwin King

Page 1 of 25

YAHOO! MOVIES

My Movies: gabe_ma Edit Profile

Recommendations For You

Movies in Theaters: 94089



Showtimes & Tickets | Add to My Lists Yahoo! Users: B- 4794 ratings The Critics: B 14 reviews

Burn After Reading (R)

🔞 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

🔞 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

😢 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

🛛 😢 Don't Recommend Again 🙄 Seen It? Rate It!

Lakeview Terrace (PG-13) Showtimes & Tickets | Add to My Lists

Yahoo! Users:B3229 ratingsThe Critics:C12 reviews

🔞 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

🔞 Don't Recommend Again 😳 Seen It? Rate It!

See All Recommendations

Receive Recommendations by Email





The Chinese University of Hong Kong, CMSC5733 Social Computing, Irwin King

AL P +

	gs from friends and similar people	
A.	Victims by The Oppressed New! Traditional Byrd69	
A.	Skinhead Girl by The Oppressed New! Traditional Byrd69	
A.	King Of The Jungle by Last Resort New! Traditional Byrd69	
A.	Violence In Our Minds by Last Resort New! Traditional Byrd69	
A.	Violence by The Templars New! Traditional Byrd69	
view a	ll invite more friends	



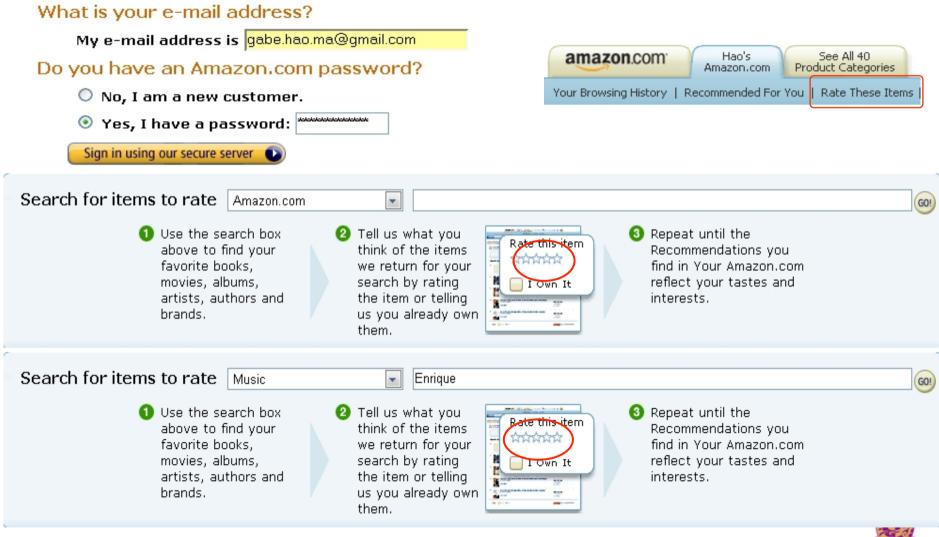
5-scale Ratings

:	Search for i	tems to rate Music Enrique	60!
:	Search resu	ults for <mark>Enrique</mark> in Music:	
1.		Escape Saved ~ Enrique Iglesias ×I☆☆☆☆☆ Your tags: I Own It Add (What's this?) I Own It	
2.	MRQUE	Enrique ~ Enrique Iglesias Your tags: Add (What's this?)	
3.	7	Seven Saved ~ Enrique Iglesias 시☆☆☆☆☆ Your tags: I Own It Add (What's this?) I Own It	



5-scale Ratings

Sign In





On The Menu

- Introduction
- Basic Techniques
 - Collaborative filtering
 - Matrix factorization
- Different Models
 - Social graph
 - Social ensemble
 - Social distrust
 - Website recommendation



Basic Approaches

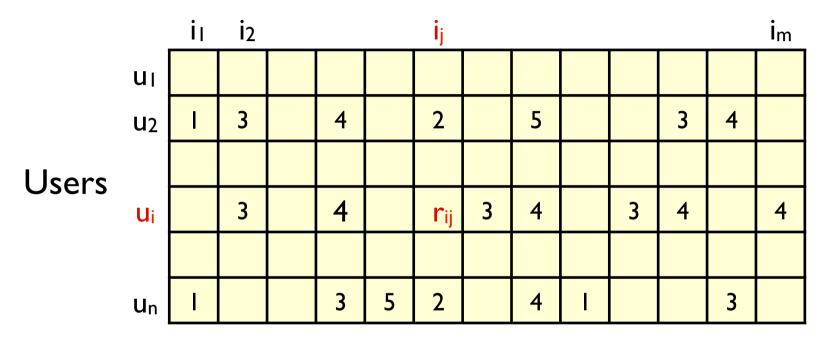
- Content-based Filtering
 - Recommend items based on key-words
 - More appropriate for information retrieval
- Collaborative Filtering (CF)
 - Look at users with similar rating styles
 - Look at similar items for each item

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



Framework

Items



•The tasks

- Find the unknown rating!
- Which item(s) should be recommended? The Chinese University of Hong Kong, CMSC5733 Social Computing, Irwin King

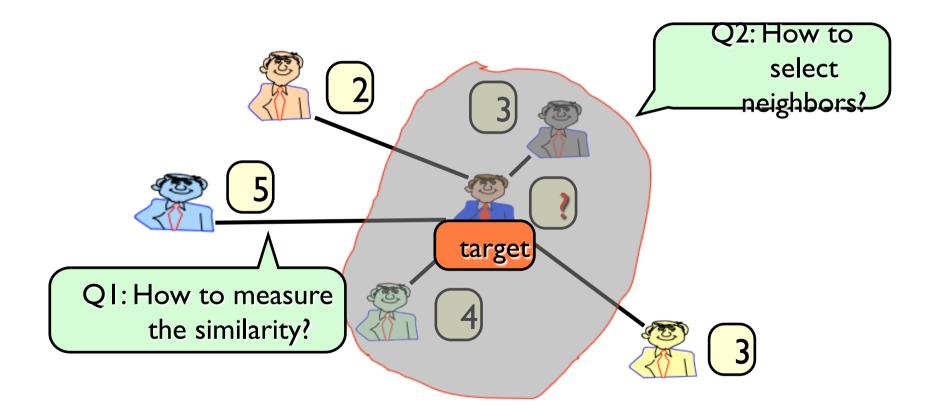


Collaborative Filtering

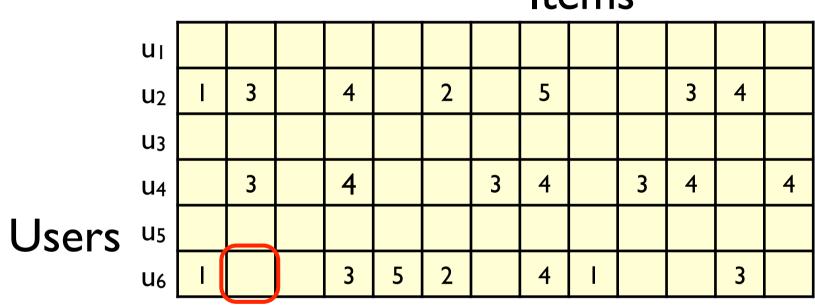
- Memory-based (Neighborhood-based)
 - User-based
 - Item-based
- Model-based
 - Clustering Methods
 - Bayesian Methods
 - Matrix Factorization
 - etc.



User-User Similarity



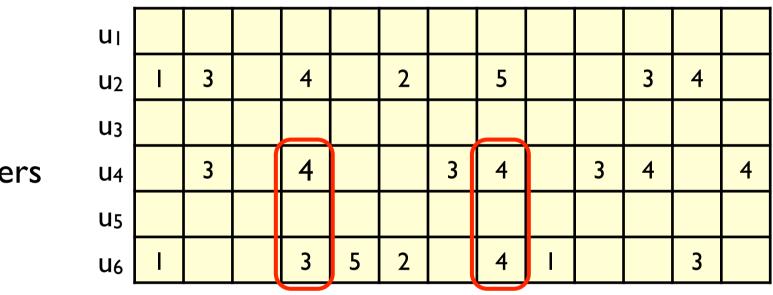




ltems

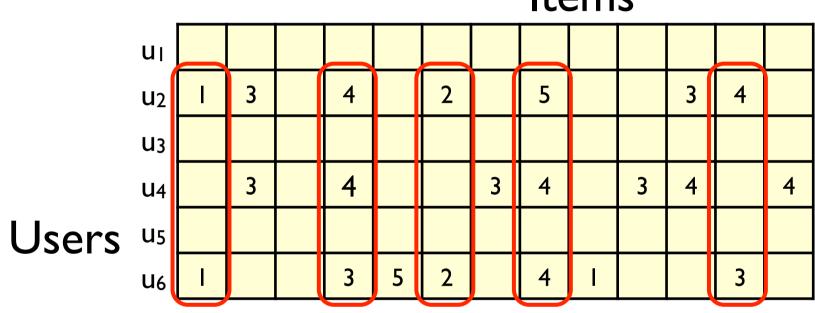


Items



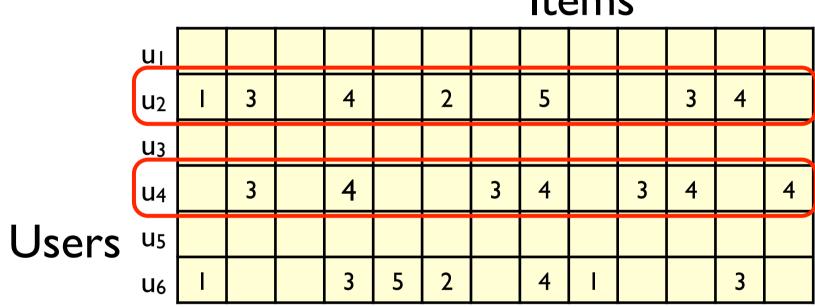
Users





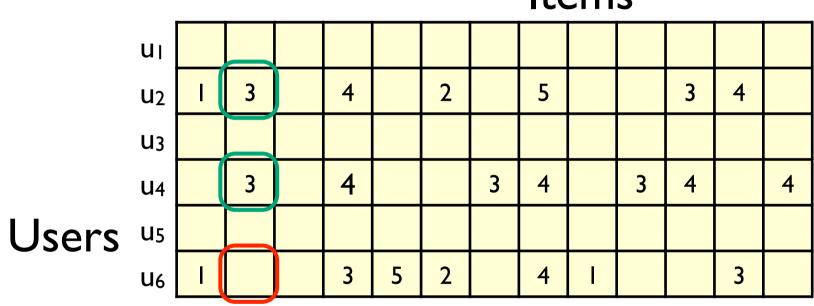
ltems





Items





ltems



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

$$w(a,i) = \frac{\sum_{j} (r_{aj} - \bar{r}_a)(r_{ij} - \bar{r}_i)}{\sqrt{\sum_{j} (r_{aj} - \bar{r}_a)^2 \sum_{j} (r_{ij} - \bar{r}_i)^2}} \quad j \in I(a) \cap I(i)$$

Cosine measure

$$c(a,i) = \frac{r_a \cdot r_i}{||r_a||_2 * ||r_i||_2}$$

Nearest Neighbor Approaches

[Sarwar, 00a]

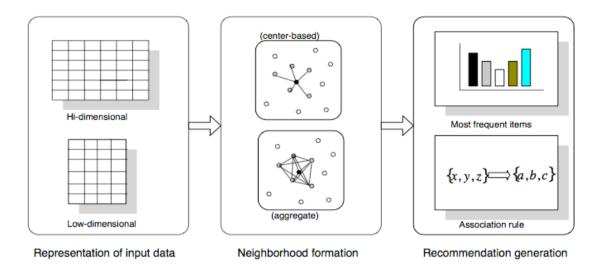


Figure 1: Three main parts of a Recommender System.

- Identify highly similar users to the active one
 - All with a measure greater than a threshold
- Best K ones $r_{aj} = \bar{r}_a + \frac{\sum_i w(a,i)(r_{ij} - \bar{r}_i)}{\sum_i w(a,i)}$ • Prediction The Chinese University of Hong Kong, CMSC5733 Social Computing, Irwin King



Collaborative Filtering

- Memory-based Method (Simple)
 - User-based Method [Xue et al., SIGIR '05]
 - Item-based [Deshpande et al., TOIS '04]
- Model-based (Robust)
 - Clustering Methods [Hkors et al, CIMCA '99]
 - Bayesian Methods [Chien et al., IWAIS '99]
 - Aspect Method [Hofmann, SIFIR '03]
 - Matrix Factorization [Sarwar et al., WWW '01]



Collaborative Filtering

- Memory-based (Neighborhood-based)
 - User-based
 - Item-based
- Model-based
 - Clustering Methods
 - Bayesian Methods
 - Matrix Factorization
 - etc.



Item-Item Similarity

- Search for similarities among items
- Item-Item similarity is more stable than user-user similarity



Correlation-based Method

[Sarwar, 2001]

- Same as in user-user similarity but on item vectors
- Pearson correlation coefficient
 - Look for users who rated both items

$$s_{ij} = \frac{\sum_{u} (r_{uj} - \bar{r}_j)(r_{ui} - \bar{r}_i)}{\sqrt{\sum_{u} (r_{uj} - \bar{r}_j)^2 \sum_{u} (r_{ui} - \bar{r}_i)^2}}$$

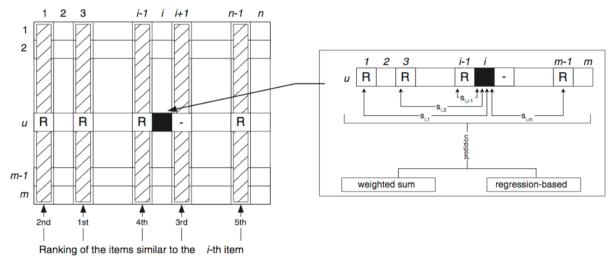
• u: users rated both items
$$u: users rated both items$$

The Chinese University of Hong Kong, CMSC5733 Social Computing, Irvin King

Correlation-based Method

[Sarwar, 2001]

Calculate item similarity, then determine its k-most similar items



• Predict rating for a given user-item pair as a weighted sum over similar items that he rated $r_{ai} = \frac{\sum_{j} s_{ij} r_{aj}}{\sum_{j} s_{ij}}$ items that he rated $u_a = \frac{2}{3}$ items that he

Collaborative Filtering

- Memory-based (Neighborhood-based)
 - User-based
 - Item-based
- Model-based
 - Clustering Methods
 - Bayesian Methods
 - Matrix Factorization
 - etc...



	i_1	i_2	i ₃	i4	i ₅	i ₆	i_{7}	i ₈
u_1	5	2		3		4		
u_2	4	3			5			
<i>u</i> ₃	4		2				2	4
u4								
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_{γ}	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
<i>u</i> ₃	4	1.7	2	3.2	3.9	3.0	2	4
<i>u</i> 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

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



- Matrix Factorization 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.

$$Y \approx UV = \begin{pmatrix} u_{11} & \dots & u_{1k} \\ \vdots & \ddots & \vdots \\ u_{m1} & \dots & u_{mk} \end{pmatrix} \begin{pmatrix} v_{11} & \dots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{k1} & \cdots & v_{kn} \end{pmatrix}$$

User-specific latent
feature vector Item-specific latent
feature column vector



- Optimization Problem
 - Given a *m x 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



- 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.



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

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

where $\lambda_1, \lambda_2 > 0$

• The problem can be solved by simple gradient descent algorithm.



- Algorithm for RMF
 - Not convex & local optimal
 - Gradient-decent algorithm
 - Gradient computation with randomly initialized U and V

$$\frac{\partial L}{\partial u_{il}} = \lambda u_{il} - \sum_{j \mid (i,j) \in S} (y_{ij} - \widehat{y_{ij}}) v_{jl}$$
$$\frac{\partial L}{\partial v_{il}} = \lambda v_{il} - \sum_{j \mid (i,j) \in S} (y_{ij} - \widehat{y_{ij}}) u_{jl}$$

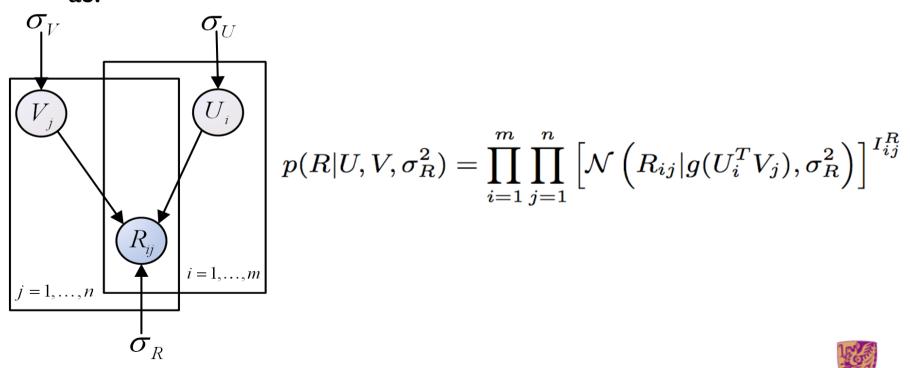
• Update *U* and *V* alternatively

$$u_{il}^{(t+1)} = u_{il}^{(t)} - \tau \frac{\partial L}{\partial u_{il}^{(t)}}$$
$$v_{jl}^{(t+1)} = v_{jl}^{(t)} - \tau \frac{\partial L}{\partial v_{jl}^{(t)}}$$

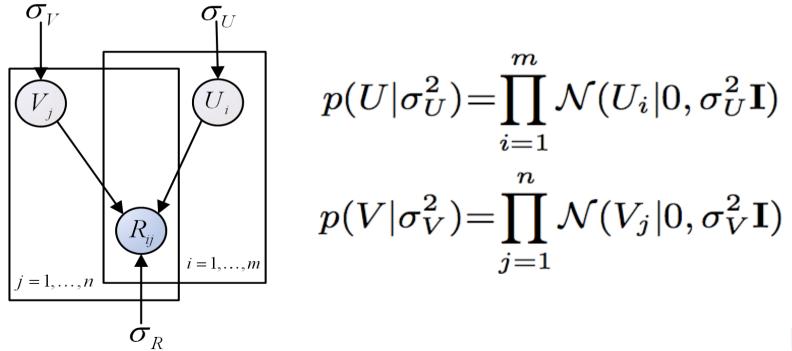
au is the step size of gradient decent.



- PMF
 - Define a conditional distribution over the observed ratings as:



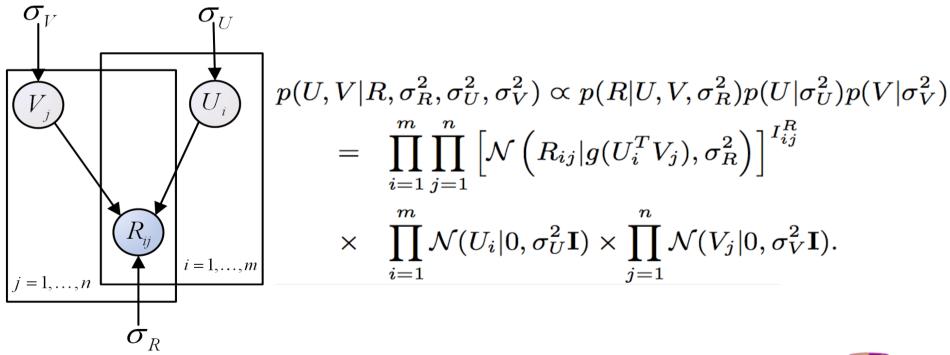
- PMF
 - Assume zero-mean spherical Gaussian priors on user and item feature:





• PMF

• Bayesian inference





RMF and PMF

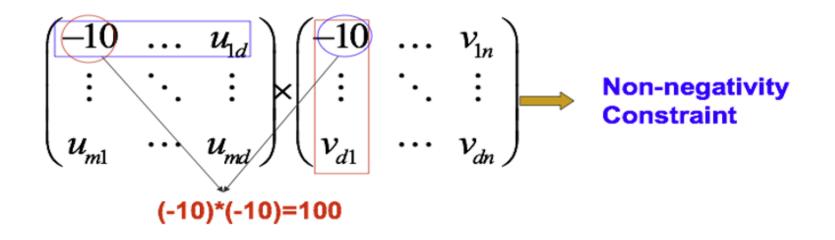
• PMF is the probabilistic interpretation of RMF

PMF and RMF have the same optimization objective function



Non-negative Matrix Factorization

- NMF
 - Non-negative constraints on all entries of matrices U and V





Non-negative Matrix Factorization

- NMF
 - Given an observed matrix Y, to find two non-negative matrices U and V
 - Two types of loss functions
 - Squared error function

$$\sum_{ij} \left(R_{ij} - U_i^T V_j \right)^2$$

• Divergence

$$D(R||U^{T}V) = \sum_{ij} (R_{ij} \log \frac{R_{ij}}{U_{i}^{T}V_{j}} - R_{ij} + U_{i}^{T}V_{j})$$

Solving by multiplicative updating rules



Non-negative Matrix Factorization

- Multiplicative updating rules
 - For divergence objective function

$$u_{il} \leftarrow u_{il} \frac{\sum_{j} v_{jl} y_{ij} / (\widehat{y_{ij}})}{\sum_{a} v_{al}}$$
$$v_{il} \leftarrow v_{il} \frac{\sum_{j} u_{jl} y_{ij} / (\widehat{y_{ij}})}{\sum_{a} u_{al}}$$

