智能系统原理与开发
第10章 智能推荐算法

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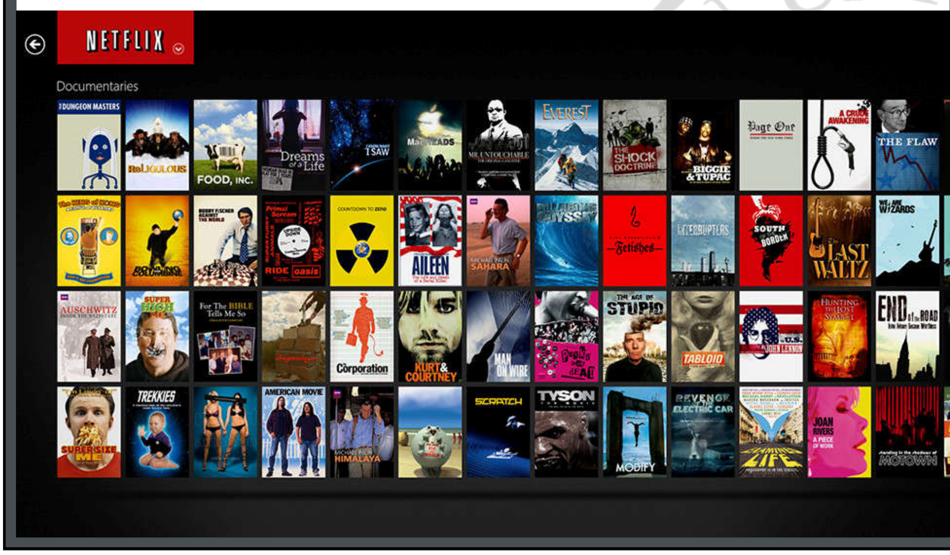
Collaborative Filtering



Memory-based CF

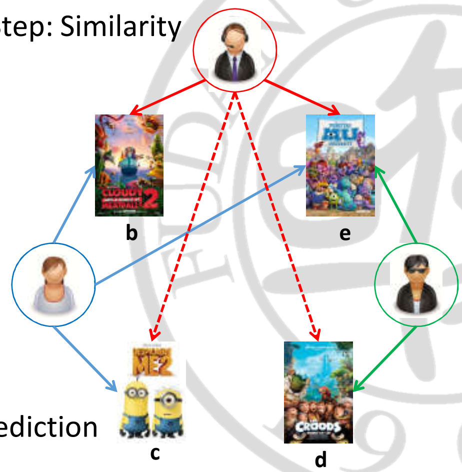
- 1st Step: Collect preference data
  - Represented as a Preference Matrix (bipartite graph)
  - An entry denotes a user’ s preference on an item
- 2nd Step: Find neighboring users/items
  - Compute Similarity between users/items
  - Determine neighboring users/items for the target user
- 3rd Step: Recommend unrated items
  - Predict unrated ratings based on neighbors’ ratings
  - Recommend highly ranked items to the target user

User-based CF

1st Step: Data

	a	b	c	d	e	f
A	4					3
B		3	4		3	
C		3			4	
D	4		5			4
E				2	5	

2nd Step: Similarity



3rd Step: Prediction

User-based CF

- Given Preference Matrix **X** and the target user
- Each user is represented as an *M*-dim vector $\mathbf{x}_u$
  - $\mathbf{x}_u = [x_{u,1}, x_{u,2}, \cdots, x_{u,M}]$ corresponds to the *u*th row in **X**
  - $x_{u,m}$ denotes the rating user *u* provides to item *m*
- User similarity
  - Only calculate on the overlapped items between two users
  - Pearson correlation coefficient and cosine

$$\mathrm{sim}(u,v)=\frac{\sum_{m\in I_u\cap I_v}(x_{u,m}-\bar{x}_u)(x_{v,m}-\bar{x}_v)}{\sqrt{\sum_{m\in I_u\cap I_v}(x_{u,m}-\bar{x}_u)^2}\sqrt{\sum_{m\in I_u\cap I_v}(x_{v,m}-\bar{x}_v)^2}}$$

User-based CF

- User-User Similarity Computation

$$\mathrm{sim}(u,v)=\frac{\sum_{m\in I_u\cap I_v}(x_{u,m}-\bar{x}_u)(x_{v,m}-\bar{x}_v)}{\sqrt{\sum_{m\in I_u\cap I_v}(x_{u,m}-\bar{x}_u)^2}\sqrt{\sum_{m\in I_u\cap I_v}(x_{v,m}-\bar{x}_v)^2}}$$

$$\mathrm{sim}(C,A)=0$$

$$\mathrm{sim}(C,B)=\frac{(3-3.5)(2-3)+(4-3.5)(3-3)}{\sqrt{(3-3.5)^2+(4-3.5)^2}\sqrt{(2-3)^2+(3-3)^2}}=0.7$$

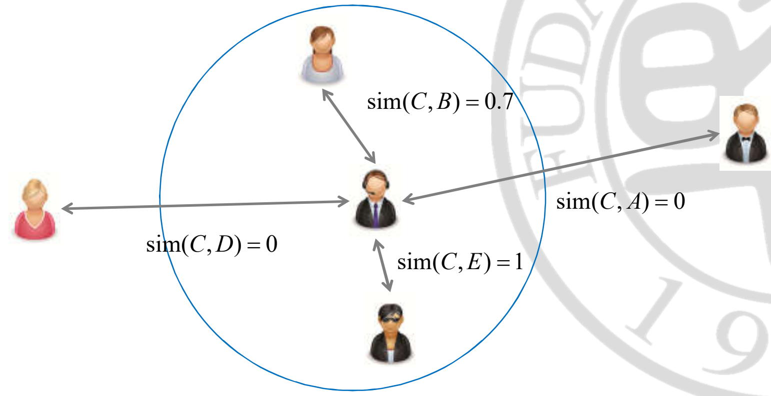
$$\mathrm{sim}(C,D)=0$$

$$\mathrm{sim}(C,E)=\frac{(4-3.5)(5-3.5)}{\sqrt{(4-3.5)^2}\sqrt{(5-3.5)^2}}=1$$

	a	b	c	d	e	f
A	4					3
B		2	4		3	
C		3			4	
D	4		5			4
E				2	5	

User-based CF

- *K*-Nearest Neighbors
  - Top-*K* similar users to the target user



User-based CF

- Rating Prediction

$$\hat{x}_{u,m}=\bar{x}_u+\frac{\sum_{v\in N_u}\mathrm{sim}(u,v)(x_{v,m}-\bar{x}_v)}{\sum_{v\in N_u}|\mathrm{sim}(u,v)|}$$

$$\hat{x}_{C,c}=3.5+\frac{0.7(4-3)}{|0.7|}=4.5$$

$$\hat{x}_{C,d}=3.5+\frac{1(2-3.5)}{|1|}=2$$

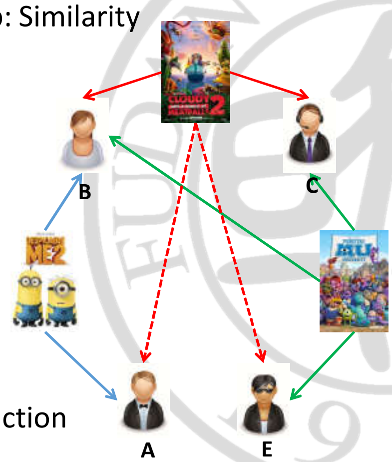
	a	b	c	d	e	f
A	4					3
B		2	4		3	
C		3	4.5	2	4	
D	4		5			4
E				2	5	

Item-based CF

1st Step: Data

	a	b	c	d	e	f
A	4					3
B		3	4		3	
C		3			4	
D	4		5			4
E				2	5	

2nd Step: Similarity



3rd Step: Prediction

Item-based CF

- Given Preference Matrix **X** and the target item
- Each item is represented as an N-dim vector $\mathbf{x}_m$
  - $\mathbf{x}_m = [x_{m,1}, x_{m,2}, \cdots, x_{m,N}]^T$ corresponds to the mth column in **X**
  - $x_{m,u}$ denotes the rating user u provides to item m
- Item similarity
  - Only calculate on the overlapped users between two items
  - Cosine and Pearson correlation coefficient

$$\text{sim}(m,m') = \frac{\sum_{u \in U_m \cap U_{m'}} x_{m,u} x_{m',u}}{\sqrt{\sum_{u \in U_m \cap U_{m'}} x_{m,u}^2}\sqrt{\sum_{u \in U_m \cap U_{m'}} x_{m',u}^2}}$$

Item-based CF

- Item-Item Similarity Computation

$$\mathrm{sim}(m,m') = \frac{\sum_{u \in U_m \cap U_{m'}} x_{m,u} x_{m',u}}{\sqrt{\sum_{u \in U_m \cap U_{m'}} x_{m,u}^2} \sqrt{\sum_{u \in U_m \cap U_{m'}} x_{m',u}^2}}$$

$$\mathrm{sim}(b,a) = 0$$

$$\mathrm{sim}(b,c) = \frac{3 \times 4}{\sqrt{3^2}\sqrt{4^2}} = 1$$

$$\mathrm{sim}(b,d) = 0$$

$$\mathrm{sim}(b,e) = \frac{3 \times 3 + 3 \times 4}{\sqrt{3^2 + 3^2}\sqrt{3^2 + 4^2}} \approx 1$$

$$\mathrm{sim}(b,f) = 0$$

	a	b	c	d	e	f
A	4					3
B		3	4		3	
C		3			4	
D	4		5			4
E				2	5	

Item-based CF

- Rating Prediction

$$\widehat{x}_{m,u} = \frac{\sum_{m' \in I_m} \mathrm{sim}(m,m') x_{m',u}}{\sum_{m' \in I_m} |\mathrm{sim}(m,m')|}$$

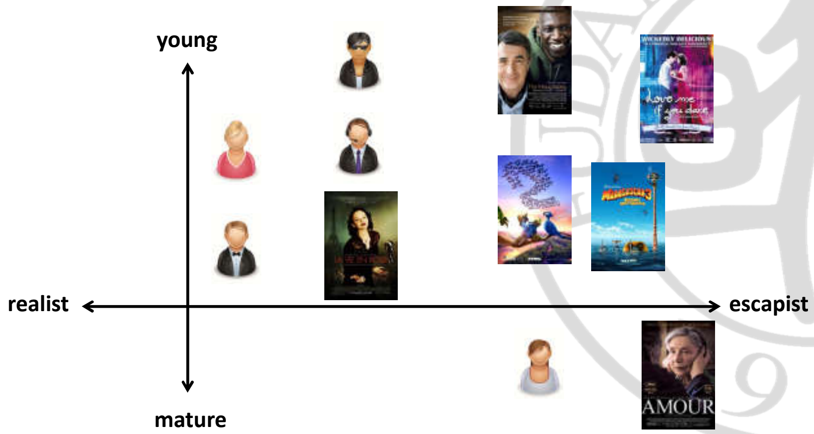
$$\widehat{x}_{b,D} = \frac{1 \times 5}{|1|} = 5$$

$$\widehat{x}_{b,E} = \frac{1 \times 5}{|1|} = 5$$

	a	b	c	d	e	f
A	4					3
B		3	4		3	
C		3			4	
D	4	5	5			4
E		5		2	5	

Model-based CF

- Latent variable view – matrix factorization approach



Model-based CF

- Matrix Factorization

realist/ escapist	young/ mature
-2.1	-0.4
-1.9	-0.6
-2.0	-0.1
-2.1	-0.1
-2.0	1.2

$\times$

-1.9	-1.7	-2.0	-1.7	-1.9	-1.8	realist/ escapist
-0.1	0.2	-0.3	-1.0	1.0	0.1	young/ mature

Assume two latent variables (features)

Rank - 2 matrix factorization : $\hat{\mathbf{X}} = \mathbf{F}\mathbf{G}^{\mathrm{T}} \in R^{5\times 6}$

User feature matrix : $\mathbf{F} \in R^{5\times 2}$

Item feature matrix : $\mathbf{G} \in R^{6\times 2}$

Model-based CF

- Preference (Rating) Matrix Reconstruction
  - Predict missing ratings in the rating matrix

4		5			3
	3	4		3	
3.8	3			4	
4			3.7		4
			2	5	

$\sim$

-2.1	-0.4
-1.9	-0.6
-2.0	-0.1
-2.1	-0.1
-2.0	1.2

$\times$

-1.9	-1.7	-2.0	-1.7	-1.9	-1.8
-0.1	0.2	-0.3	-1.0	1.0	0.1

- Remaining problems
  - Why we can assume rank-K matrices (K latent variables)?
  - How to compute rank-K matrices (user/item feature matrices)?

Model-based CF

- Why K latent variables?
  - We don't know exact number of features in advance
  - We can assume there are indeed L (>>K) features, so

$$\text{User feature matrix}: \mathbf{F}_0 \in R^{N\times L}$$
$$\text{Item feature matrix}: \mathbf{G}_0 \in R^{M\times L}$$

  - We do a linear projection to $\mathbf{F}_0$ and $\mathbf{G}_0$ (feature reduction)

$$\text{Projection matrix}: \mathbf{A} \in R^{L\times L}, \mathbf{A}^{\mathrm{T}}\mathbf{A} = \mathbf{I}$$
$$\text{User feature matrix}: \mathbf{F} = \mathbf{F}_0\mathbf{A}_{1:K} \in R^{N\times K}$$
$$\text{Item feature matrix}: \mathbf{G} = \mathbf{G}_0\mathbf{A}_{1:K} \in R^{M\times K}$$

  - Now we can directly compute $\mathbf{F}$ and $\mathbf{G}$ (without noisy features)

Model-based CF

- How to get rank-K feature matrices
  - Low-rank matrix factorization problem
  - Minimize the reconstruction and the observed preference matrix
- Regularized risk minimization
  - Many ML methods can be applied

$$\text{Given the preference matrix } \mathbf{X} \in R^{N \times M} \text{ and rank } K$$
$$\min_{\{\mathbf{F} \in R^{N \times K}, \mathbf{G} \in R^{M \times K}\}} \left\| \left(\mathbf{X} - \mathbf{F}\mathbf{G}^{\mathrm{T}}\right) \circ \mathbf{W} \right\|_F^2 + \lambda (\|\mathbf{F}\|_F^2 + \|\mathbf{G}\|_F^2)$$
$$\text{where } \mathbf{W} \in \{0,1\}^{N \times M} \text{ indicates observed entries in } \mathbf{X}$$

Model-based CF

- Probabilistic Matrix Factorization (PMF)
  - Assume user/item features and ratings are generated from Gaussians

$$p(\mathbf{X} \mid \mathbf{F}, \mathbf{G}) = \prod_{w_{u,m}=1} p\left(x_{u,m} \mid \mathbf{f}_u^{\mathrm{T}} \mathbf{g}_m, \sigma_R^2\right)$$
$$p(\mathbf{F} \mid \mathbf{0}) = \prod_{u=1}^{N} p\left(\mathbf{f}_u \mid \mathbf{0}, \sigma_F^2\right)$$
$$p(\mathbf{G} \mid \mathbf{0}) = \prod_{m=1}^{M} p\left(\mathbf{g}_m \mid \mathbf{0}, \sigma_G^2\right)$$

  - Probabilistic interpretation of the optimization problem

$$\max_{\{\mathbf{F},\mathbf{G}\}} \ln\left[p(\mathbf{X} \mid \mathbf{F}, \mathbf{G}) p(\mathbf{F} \mid \mathbf{0}) p(\mathbf{G} \mid \mathbf{0})\right]$$
$$\Rightarrow \min_{\{\mathbf{F},\mathbf{G}\}} \sum_{w_{u,m}=1} \left(x_{u,m} - \mathbf{f}_u^{\mathrm{T}} \mathbf{g}_m\right)^2 + c_1 \sum_{u=1}^{N} \|\mathbf{f}_u\|^2 + c_2 \sum_{m=1}^{M} \|\mathbf{g}_m\|^2$$
$$\Rightarrow \min_{\{\mathbf{F},\mathbf{G}\}} \left\| \left(\mathbf{X} - \mathbf{F}\mathbf{G}^{\mathrm{T}}\right) \circ \mathbf{W} \right\|_F^2 + c_1 \|\mathbf{F}\|_F^2 + c_2 \|\mathbf{G}\|_F^2$$

[1] Salakhutdinov & Mnih: Probabilistic Matrix Factorization, NIPS 2008.

Model-based CF

- Singular Value Decomposition (SVD)
  - Most straightforward way to matrix factorization
  - But SVD is not defined for missing entries
  - Use average rating to stuff missing entries
  - Inaccurate for sparse matrices (tries to fit too many stuff entries)

4	3.7	5	3.7	3.7	3
3.7	3	4	3.7	3	3.7
3.7	3	3.7	3.7	4	3.7
4	3.7	3.7	3.7	3.7	4
3.7	3.7	3.7	2	5	3.7

Filled matrix : $\widetilde{\mathbf{X}} \in R^{N \times M}$

User feature matrix : $\mathbf{F} \in R^{N \times K}$

Item feature matrix : $\mathbf{G} \in R^{M \times K}$

SVD : $\widetilde{\mathbf{X}} = \mathbf{USV}^{\mathrm{T}} = \left(\mathbf{U}\sqrt{\mathbf{S}}\right)\left(\sqrt{\mathbf{S}}\mathbf{V}\right)^{\mathrm{T}} = \mathbf{FG}^{\mathrm{T}}$

Model-based CF

- Alternative Least Squares (ALS)
  - Optimize **F** assuming **G** is known
  - Optimize **G** assuming **F** is known
  - Each step is a standard least square problem
  - Converge to a local minimum over alternative iterations

$$\min_{\{\mathbf{F} \in R^{N \times K}, \mathbf{G} \in R^{M \times K}\}} \left\| \left(\mathbf{X} - \mathbf{FG}^{\mathrm{T}}\right) \circ \mathbf{W} \right\|_F^2 + \lambda \left(\|\mathbf{F}\|_F^2 + \|\mathbf{G}\|_F^2 \right)$$

$$\Rightarrow \begin{cases} \min_{\mathbf{F} \in R^{N \times K}} \left\| (\mathbf{X} - \mathbf{F}\widehat{\mathbf{G}}^{\mathrm{T}}) \circ \mathbf{W} \right\|_F^2 + \lambda \|\mathbf{F}\|_F^2 \\ \min_{\mathbf{G} \in R^{M \times K}} \left\| (\mathbf{X} - \hat{\mathbf{F}}\mathbf{G}^{\mathrm{T}}) \circ \mathbf{W} \right\|_F^2 + \lambda \|\mathbf{G}\|_F^2 \end{cases}$$

Model-based CF

- Alternative Least Squares (ALS)

$$
\begin{aligned}
&\min_{\mathbf{F}\in R^{N\times K}} \left\| \left(\mathbf{X}-\mathbf{F}\hat{\mathbf{G}}^{\mathrm{T}}\right)\circ \mathbf{W} \right\|_F^2 + \lambda \|\mathbf{F}\|_F^2 \\
&\Rightarrow \min_{\mathbf{f}_u\in R^K} \sum_{w_{u,m}=1} \left(x_{u,m}-\mathbf{f}_u^{\mathrm{T}}\hat{\mathbf{g}}_m\right)^2 + \lambda \|\mathbf{f}_u\|^2, \text{ for } u\in U \\
&\Rightarrow \mathbf{f}_u \leftarrow \left(\lambda + \sum_{w_{u,m}=1} \hat{\mathbf{g}}_m \hat{\mathbf{g}}_m^{\mathrm{T}}\right)^{-1} \sum_{w_{u,m}=1} \hat{\mathbf{g}}_m x_{u,m}
\end{aligned}
$$

$$
\begin{aligned}
&\min_{\mathbf{G}\in R^{M\times K}} \left\| \left(\mathbf{X}-\hat{\mathbf{F}}\mathbf{G}^{\mathrm{T}}\right)\circ \mathbf{W} \right\|_F^2 + \lambda \|\mathbf{G}\|_F^2 \\
&\Rightarrow \min_{\mathbf{g}_m\in R^K} \sum_{w_{u,m}=1} \left(x_{u,m}-\hat{\mathbf{f}}_u^{\mathrm{T}}\mathbf{g}_m\right)^2 + \lambda \|\mathbf{g}_m\|^2, \text{ for } m\in I \\
&\Rightarrow \mathbf{g}_m \leftarrow \left(\lambda + \sum_{w_{u,m}=1} \hat{\mathbf{f}}_u \hat{\mathbf{f}}_u^{\mathrm{T}}\right)^{-1} \sum_{w_{u,m}=1} \hat{\mathbf{f}}_u x_{u,m}
\end{aligned}
$$

Model-based CF

- Stochastic Gradient Descent (SGD)
  - Minimize an objective in the form of a sum of differentiable functions
  - All ratings in the rating matrix are shuffled and fed in sequentially
  - Each time a user/item feature vector is optimized on a single rating

$$
\begin{aligned}
&\min_{\{\mathbf{F}\in R^{N\times K},\mathbf{G}\in R^{M\times K}\}} \left\| \left(\mathbf{X}-\mathbf{F}\mathbf{G}^{\mathrm{T}}\right)\circ \mathbf{W} \right\|_F^2 + \lambda\left(\|\mathbf{F}\|_F^2 + \|\mathbf{G}\|_F^2 \right) \\
&\Rightarrow \min_{\{\mathbf{F},\mathbf{G}\}} \sum_{w_{u,m}=1} \left(x_{u,m}-\mathbf{f}_u^{\mathrm{T}}\mathbf{g}_m\right)^2 + \lambda\left(\sum_{u=1}^{N} \|\mathbf{f}_u\|^2 + \sum_{m=1}^{M} \|\mathbf{g}_m\|^2 \right) \\
&\Rightarrow \begin{cases} \mathbf{f}_u \leftarrow (1-\alpha\lambda)\mathbf{f}_u - \alpha \mathbf{g}_m \left(x_{u,m}-\mathbf{f}_u^{\mathrm{T}}\mathbf{g}_m\right) \\ \mathbf{g}_m \leftarrow (1-\alpha\lambda)\mathbf{g}_m - \alpha \mathbf{f}_u \left(x_{u,m}-\mathbf{f}_u^{\mathrm{T}}\mathbf{g}_m\right) \end{cases}, \text{ for all } \{x_{u,m}\}
\end{aligned}
$$

Model-based CF

- SVD++[1]: Netflix Winner's Method
  - An improvement of SVD
  - Consider user bias b_u and item bias b_m

$$
\begin{aligned}
&\min_{\{\mathbf{F}\in R^{N\times K},\mathbf{G}\in R^{M\times K}\}} \left\| \left(\mathbf{X}-\mathbf{F}\mathbf{G}^{\mathrm{T}}\right)\circ \mathbf{W} \right\|_F^2 + \lambda\left(\|\mathbf{F}\|_F^2 + \|\mathbf{G}\|_F^2 \right) \\
&\Rightarrow \min_{\{\mathbf{F},\mathbf{G}\}} \sum_{w_{u,m}=1} \left(x_{u,m} - \left(\mu + b_u + b_m + \mathbf{f}_u^{\mathrm{T}}\mathbf{g}_m\right)\right)^2 \\
&\qquad + \lambda\left(\sum_{u=1}^{N} \|\mathbf{f}_u\|^2 + \sum_{m=1}^{M} \|\mathbf{g}_m\|^2 + \sum_{u=1}^{N} \|b_u\|^2 + \sum_{m=1}^{M} \|b_m\|^2 \right)
\end{aligned}
$$

[1] Koren: Factorization meets the neighborhood: a multifaceted collaborative filtering model, KDD 2008

Model-based CF

- SVD++: Netflix Winner's Method
  - Stochastic Gradient Descent solution

$$
\begin{aligned}
&\min_{\{\mathbf{F},\mathbf{G}\}} \sum_{w_{u,m}=1} \left(x_{u,m} - \left(\mu + b_u + b_m + \mathbf{f}_u^{\mathrm{T}}\mathbf{g}_m\right)\right)^2 \\
&\qquad + \lambda\left(\sum_{u=1}^{N} \|\mathbf{f}_u\|^2 + \sum_{m=1}^{M} \|\mathbf{g}_m\|^2 + \sum_{u=1}^{N} \|b_u\|^2 + \sum_{m=1}^{M} \|b_m\|^2 \right) \\
&\Rightarrow \begin{cases}
\mathbf{f}_u \leftarrow (1-\alpha\lambda)\mathbf{f}_u - \alpha \mathbf{g}_m \delta_{u,m} \\
\mathbf{g}_m \leftarrow (1-\alpha\lambda)\mathbf{g}_m - \alpha \mathbf{f}_u \delta_{u,m} \\
b_u \leftarrow (1-\alpha\lambda)b_u - \alpha \delta_{u,m} \\
b_m \leftarrow (1-\alpha\lambda)b_m - \alpha \delta_{u,m}
\end{cases}, \text{for all } \{x_{u,m}\} \\
&\text{where } \delta_{u,m} = x_{u,m} - \left(\mu + b_u + b_m + \mathbf{f}_u^{\mathrm{T}}\mathbf{g}_m\right)
\end{aligned}
$$

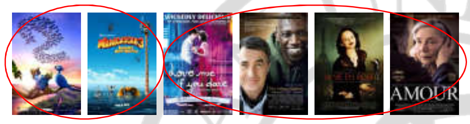
Block Models for Network Data

- Block-structure view
  - Co-clustering approach

4	3			5	
4	4				
		3	3	4	
		3	4		
			5		2

Block Models for Network Data

- Co-clustering



1	0
1	0
0	1
0	1
0	1

3.7	5
3.7	3.4

1	1	0	0	0	0
0	0	1	1	1	1

Assume two user and two item groups

Matrix tri-factorization : $\hat{\mathbf{X}} = \mathbf{PBQ}^{\mathrm{T}} \in R^{5\times 6}$

User membership matrix : $\mathbf{F} \in [0,1]^{5\times 2}$

Item membership matrix : $\mathbf{G} \in [0,1]^{6\times 2}$

Group-level rating matrix : $\mathbf{B} \in R^{2\times 2}$

Block Models for Network Data

- Matrix Reconstruction
  - Predict missing ratings in the preference matrix

4	3			5	
4	4				
3.7		3	3	4	
		3	4	3.4	
			5		2

~

1	0
1	0
0	1
0	1
0	1

3.7	5
3.7	3.4

1	1	0	0	0	0
0	0	1	1	1	1

Block Models for Network Data

- Clustering users and items separately
  - Most straightforward way for co-clustering
  - Clustering one side using the other side as features
  - Any clustering algorithm can be applied (e.g., *K*-Means)

1	0	0	0	0	1
0	1	1	1	1	0

1	0
0	1
0	1
1	0
0	1

4		5			3
	3	4		3	
	3			4	
4					4
			2	5	

4		5			3
	3	4		3	
	3			4	
4					4
			2	5	

Block Models for Network Data

- Group-level rating matrix
  - Each entry is the average rating of a user-item joint group

4	3			5	
4	4				
		3	3	4	
		3	4		
			5		2

⇨

3.7	5
3.7	3.4

$$\mathbf{B}_{1,1} = (3+4+4+4)/4 = 3.7$$
$$\mathbf{B}_{1,2} = 5/1 = 5$$
$$\mathbf{B}_{2,1} = (2+3\times 4+4\times 5+5\times 2)/12 = 3.7$$
$$\mathbf{B}_{2,2} = (2+3+3+3+4+4+5)/7 = 3.4$$

Block Models for Network Data

- Flexible Mixture Model[1] (FMM)
  - From hard-membership to soft-membership
  - Each user/item has a distribution over K user/ L item groups

$$\hat{\mathbf{X}} = \mathbf{PBQ}^{\mathrm{T}} \text{ where } \mathbf{B}_{k,l} = \sum\nolimits_r rp(r \mid k,l)$$

User u's membership in user group k : $\mathbf{P}_{u,k} = p(k \mid u)$

$$p(k \mid u) \propto p(u \mid k)p(k)$$

Item m's membership in item group l : $\mathbf{Q}_{m,l} = p(l \mid m)$

$$p(l \mid m) \propto p(m \mid l)p(l)$$

[1] Si & Jin: Flexible mixture model for collaborative filtering, ICML 2003

Block Models for Network Data

$\mathrm{E-Step:}$

$$p(k,l \mid x_{u,m}) = \frac{p(x_{u,m} \mid k,l)\,p(u \mid k)\,p(k)\,p(m \mid l)\,p(l)}{\sum_{k,l} p(x_{u,m} \mid k,l)\,p(u \mid k)\,p(k)\,p(m \mid l)\,p(l)}$$

$\mathrm{M-Step:}$

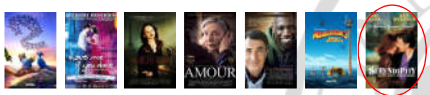
$$p(k) = \frac{\sum_l \sum_{w_{u,m}=1} p(k,l \mid x_{u,m})}{\sum_{(u,m)} w_{u,m}}, \quad p(l) = \frac{\sum_k \sum_{w_{u,m}=1} p(k,l \mid x_{u,m})}{\sum_{(u,m)} w_{u,m}}$$

$$p(u \mid k) = \frac{\sum_l \sum_{w_{v,m}=1 \cap v=u} p(k,l \mid x_{v,m})}{p(k) \sum_{(u,m)} w_{u,m}}, \quad p(m \mid l) = \frac{\sum_k \sum_{w_{u,m'}=1 \cap m'=m} p(k,l \mid x_{u,m'})}{p(l) \sum_{(u,m)} w_{u,m}}$$

$$p(r \mid k,l) = \frac{\sum_{w_{u,m}=1 \cap x_{u,m}=r} p(k,l \mid x_{u,m})}{\sum_{w_{u,m}=1} p(k,l \mid x_{u,m})}$$

Cold-Start Problem

- Cold-Start Problem in Collaborative Filtering



New item

	4		5			3	
		3	4		3		
		3			4		
	4					4	
				2	5		
New user							

Cold-Start Problem

- A major limitation of CF
  - A reason that real-world RSs adopts hybrid strategies
- Solutions for user cold-start
  - Demography-based
  - Popularity-based (most popular items)
  - Social relationship based (friends' preference)
  - Implicit preference based (e.g., browsed items)
- Solutions for item cold-start
  - Content-based
  - Ratings borrowed from items of the same category

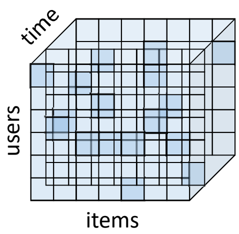
Temporal Changes

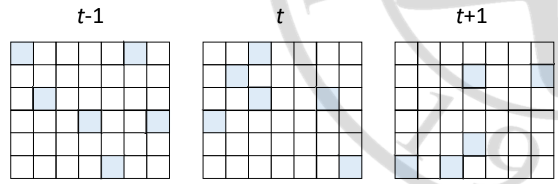
- A major challenge of CF
  - Real RSs usually take into account temporal factors
- Causes of temporal changes from users
  - Changing bias
  - Changing interest
  - Changing context
- Causes of temporal changes from items
  - Seasonal effects (Valentine's day, Mid-autumn day)
  - Trending (fashions, digital products)

Temporal CF

- Temporal CF Problem
  - Each timestamp has a rating matrix
  - Can be represented as a tensor

user	movie	date	rate
1	34	11-04-02	3
1	296	09-05-02	4
2	11	18-01-02	5
2	59	23-02-02	4
2	124	03-04-02	2

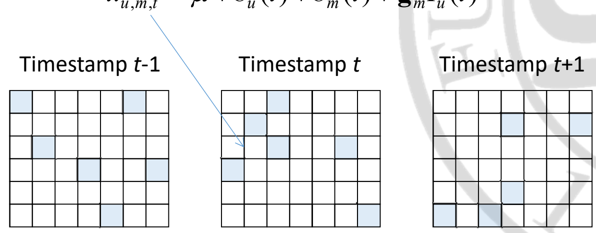




Temporal CF

- TimeSVD++[1]: Netflix Winner's Method
  - An improvement of SVD++ for temporal CF
  - TimeSVD++ considers time-dependent factors: user rating bias $b_u(t)$, item rating bias $b_m(t)$, and user feature vector $\mathbf{f}_u(t)$

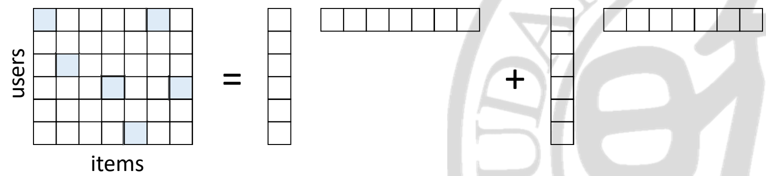
$$x_{u,m,t} = \mu + b_u(t) + b_m(t) + \mathbf{g}_m^{\mathrm{T}} \mathbf{f}_u(t)$$



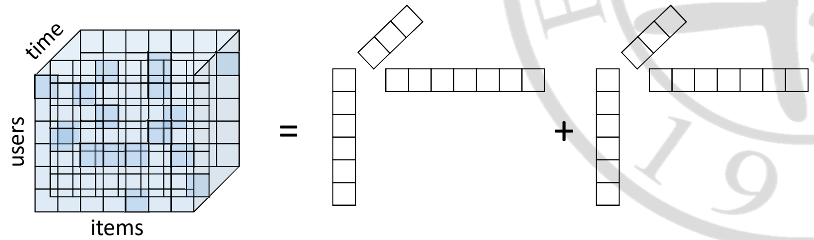
[1] Y. Koren: Collaborative Filtering with Temporal Dynamics, KDD 2009

Temporal CF

- Matrix Factorization



- Tensor Factorization



Noise Problem

- Spammer Detection (malicious users)
  - Promote certain items with misleading information
  - Usually formulate as a classification problem to detect malicious users

- Shilling Detection (malicious users)
  - A group of colluded users inserting untruthful profiles to promote or degrade certain items
  - Fake profiles are usually generated according to certain distributions
  - Usually formulate as a clustering or principal component analysis problem to detect colluded users

Noise Problem

- Natural Noise Detection (nonmalicious users)
  - Difficult to detect because no patterns
  - Difficult to define natural noisy users
  - Difficult to quantify the noise

- Solutions: Consistency of Preference
  - The larger the difference, the more likely a user is to be noisy
  - E.g., consistency between observed and predicted ratings
  - E.g., consistency between multiple ratings on same items

Implicit Feedback

- Implicit Feedback Data
  - Click-through records, purchased records, etc.
  - Easy and cheap to obtain
  - Large amount
  - Noisy

1		1			1
	1	1		1	
	1			1	
1					1
			1	1	

Implicit Feedback

- Characteristics of Implicit Feedbacks
  - Simple (usually binary data)
  - Abundant
  - Noisy
  - Sequential
- A Better Approach – Online Learning
  - Binary data is simpler for online learning
  - Performance can be reinforced using noisy but abundant data
  - Sequential arrived data is natural for online learning

Project: Collaborative Filtering

- Dataset:
  - Public available datasets for collaborative filtering (e.g., https://movielens.org/)
  - Or user rating data collected by yourself
- Method:
  - Use User-based CF or Probabilistic Matrix Factorization for collaborative filtering
- Experiments:
  - Obtain the rating prediction results for evaluate the performance
  - And discuss the limitations of the method you used based on the observations from the results

Thanks

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