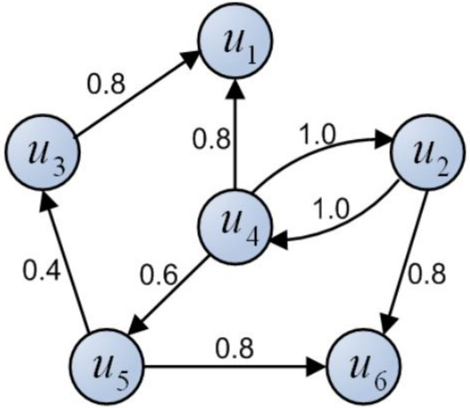
Trust Aware Recommendation Systems

Problem



(a) Social Network Graph

	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

(b) User-Item Matrix

	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

(c) Predicted User-Item Matrix

Co-factorization Methods

- The underlying assumption of systems in this group is that the i-th user u_i should share the same user preference vector u_i in the rating space (rating information) and the trust relation space.
- Systems in this group perform a co-factorization in the user-item matrix and the user-user trust relation matrix by sharing the same user preference latent factor.

Sorec

$$\min \sum_{i=1}^{n} \sum_{u_k \in \mathcal{F}_i} (\mathbf{S}_{ik} - \mathbf{U}_i^\top \mathbf{Z}_k)^2,$$

$$\min_{\mathbf{U},\mathbf{V},\mathbf{Z}} \|\mathbf{W} \odot (\mathbf{R} - \mathbf{U}^\top \mathbf{V})\|_F^2 + \alpha \sum_{i=1}^{n} \sum_{u_k \in \mathcal{F}_i} (\mathbf{S}_{ik} - \mathbf{U}_i^\top \mathbf{Z}_k)^2$$
$$+ \lambda(\|\mathbf{U}\|_F^2 + \|\mathbf{V}\|_F^2 + \|\mathbf{Z}\|_F^2),$$

Sorec

$$\mathcal{L}(R, C, U, V, Z) =$$

$$\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}(r_{ij} - g(U_i^T V_j))^2 + \frac{\lambda_C}{2}\sum_{i=1}^{m}\sum_{k=1}^{m} I_{ik}^{C}(c_{ik}^{*} - g(U_i^T Z_k))^2$$

$$+ \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_V}{2}\|V\|_F^2 + \frac{\lambda_Z}{2}\|Z\|_F^2, \qquad (9)$$

Sorec

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial U_i} &= \sum_{j=1}^{n} I_{ij}^{R} g'(U_i^T V_j)(g(U_i^T V_j) - r_{ij})V_j \\
&+ \lambda_C \sum_{j=1}^{m} I_{ik}^{C} g'(U_i^T Z_k)(g(U_i^T Z_k) - c_{ik}^{*})Z_k + \lambda_U U_i, \\
\frac{\partial \mathcal{L}}{\partial V_j} &= \sum_{i=1}^{m} I_{ij}^{R} g'(U_i^T V_j)(g(U_i^T V_j) - r_{ij})U_i + \lambda_V V_j, \\
\frac{\partial \mathcal{L}}{\partial Z_k} &= \lambda_C \sum_{i=1}^{m} I_{ik}^{C} g'(U_i^T Z_k)(g(U_i^T Z_k) - c_{ik}^{*})U_i + \lambda_Z Z_k, (10)
\end{aligned}
$$

Ensemble Methods

The basic idea of ensemble methods is that users and their trust 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 trust network.

STE

$$\hat{\mathbf{R}}_{ij} = \mathbf{u}_i^\top \mathbf{v}_j + \beta \sum_{u_k \in \mathcal{F}_i} \mathbf{S}_{ik} \mathbf{U}_k^\top \mathbf{V}_j,$$

$$\min_{\mathbf{U},\mathbf{V}} \|\mathbf{W} \odot ((\mathbf{R} - \mathbf{U}^\top \mathbf{V}) - \beta \mathbf{S} \mathbf{U}^\top \mathbf{V})\|_F^2 + \lambda(\|\mathbf{U}\|_F^2 + \|\mathbf{V}\|_F^2).$$

STE

$$\mathcal{L}(R, S, U, V)$$
$$= \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij}^{R} (R_{ij} - g(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j))^2$$
$$+ \frac{\lambda_U}{2} ||U||_F^2 + \frac{\lambda_V}{2} ||V||_F^2, \qquad (13)$$

STE

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial U_i} =& \alpha \sum_{j=1}^{n} I_{ij}^{R} g'(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j) V_j \\
& \times (g(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j) - R_{ij}) \\
& + (1-\alpha) \sum_{p \in \mathcal{B}(i)} \sum_{j=1}^{n} I_{pj}^{R} g'(\alpha U_p^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(p)} S_{pk} U_k^T V_j) \\
& \times (g(\alpha U_p^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(p)} S_{pk} U_k^T V_j) - R_{pj}) S_{pi} V_j + \lambda_U U_i, \\
\frac{\partial \mathcal{L}}{\partial V_j} =& \sum_{i=1}^{m} I_{ij}^{R} g'(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j) \\
& \times (g(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T V_j) - R_{ij}) \\
& \times (\alpha U_i + (1-\alpha) \sum_{k \in \mathcal{T}(i)} S_{ik} U_k^T) + \lambda_V V_j, \qquad (14)
\end{aligned}
$$

Regularization Methods

Regularization methods focus on a user's preferences and assume that a user's preferences should be similar to that of her trust network.

SocialMF

$$\min \sum_{i=1}^{n} (\mathbf{u}_i - \sum_{u_k \in \mathcal{N}_i} \mathbf{T}_{ik} \mathbf{u}_k)^2,$$

$$\min_{\mathbf{U},\mathbf{V}} \|\mathbf{W} \odot (\mathbf{R} - \mathbf{U}^\top \mathbf{V})\|_F^2 + \alpha \sum_{i=1}^{n} (\mathbf{u}_i - \sum_{u_k \in \mathcal{N}_i} \mathbf{T}_{ik} \mathbf{u}_k)^2$$

$$+ \lambda(\|\mathbf{U}\|_F^2 + \|\mathbf{V}\|_F^2)$$

SocialMF

$$\mathcal{L}(R,S,U,V) = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}\Big(R_{ij} - g\big(\alpha U_i^T V_j + (1-\alpha)\sum_{k\in\mathcal{T}(i)} S_{ik}U_k^T V_j\big)\Big)^2 + \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_V}{2}\|V\|_F^2, \qquad (13)$$

SocialMF

$$\frac{\partial \mathcal{L}}{\partial U_u} = \sum_{i=1}^{M} I_{u,i}^{R} V_i g'(U_u^T V_i)(g(U_u^T V_i) - R_{u,i}) + \lambda_U U_u$$

$$+\lambda_T (U_u - \sum_{v \in N_u} T_{u,v} U_v)) - \lambda_T \sum_{\{v|u \in N_v\}} T_{v,u} \Big(U_v - \sum_{w \in N_v} T_{v,w} U_w \Big) \tag{13}$$

$$\frac{\partial \mathcal{L}}{\partial V_i} = \sum_{u=1}^{N} I_{u,i}^{R} U_v g'(U_u^T V_i)(g(U_u^T V_i) - R_{u,i}) + \lambda_V V_i \tag{14}$$

Regularization Methods: SocialMF

One advantage of these approaches is that they indirectly model the propagation of tastes in social networks, which can be used to mitigate cold-start problem and increase the coverage of items for recommendations.

Going Forward

Structured Approach

- Identify a social phenomenon. (Either new or unnoticed)
- Check if it falls within the confines of the problem.
- Check if it was already proposed.
- Try to see if it can be modelled in one of the existing domains (Co-factorization methods, Ensemble methods, Regularization methods)
- Prototype and verify.

Thanks!

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