

		Item			
		W	X	Y	Z
User	A		4.5	2.0	
	B	4.0		3.5	
	C		5.0		2.0
	D		3.5	4.0	1.0

Rating Matrix

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		Item			
		W	X	Y	Z
User	A	1.2	0.8		
	B	1.4	0.9		
	C	1.5	1.0		
	D	1.2	0.8		

User Matrix

X

		Item			
		W	X	Y	Z
	A	1.5	1.2	1.0	0.8
	B	1.7	0.6	1.1	0.4

Item Matrix

$$X_{N \times M} \approx U_{N \times K} \times V_{K \times M}^T$$

$$x_{n,m} = u_n^T v_m = \sum_{k=1}^K u_{n,k} v_{m,k}$$

$$L = \sum_{(m,n) \in \Omega} (x_{n,m} - u_n^T v_m)^2$$

$$L^{reg} = \sum_{(m,n) \in \Omega} (x_{n,m} - u_n^T v_m)^2 + \sum_{n=1}^N \lambda_u \|u_n\|_2^2 + \sum_{m=1}^M \lambda_v \|v_m\|_2^2$$

$$w = (X^T X + \lambda I_{d+1})^{-1} X^T y$$

$$\arg \min_{v_m} \sum_{n \in \Omega_{c_n}} (x_{n,m} - u_n^T v_m)^2 + \lambda_v \|v_m\|_2^2$$

$$v_m^{\hat{}} = (U^T U + \lambda_v I_K)^{-1} U^T x_m \quad \text{Dimensions are given below,}$$

$$[K \times 1] = ([K \times N] \times [N \times K] + [K \times K]) \times [K \times N] \times [N \times 1]$$

But we cannot take all of  $U^T U$  as there are missing entries.

$$[K \times 1] = ([K \times |\Omega_{cm}|] \times [|\Omega_{cm}| \times K] + [K \times K]) \times [K \times |\Omega_{cm}|] \times [|\Omega_{cm}| \times 1]$$

This is equivalent to,

$$v_m^{\hat{}} = \left( \sum_{n \in \Omega_{cm}} u_n u_n^T + \lambda_v I_K \right)^{-1} \sum_{n \in \Omega_{cm}} x_{n,m} u_n$$

$$[K \times 1] = \left( \sum_{n \in \Omega_{cm}} [K \times 1] \times [1 \times K] + [K \times K] \right) \sum_{n \in \Omega_{cm}} x_{n,m} [K \times 1]$$

Similarly,

$$\arg \min_{u_n} \sum_{m \in \Omega_{r_n}} (x_{n,m} - u_n^T v_m)^2 + \lambda_u \|u_n\|_2^2$$

$$u_n^{\hat{}} = (V^T V + \lambda_u I_K)^{-1} V^T x_n$$

$$u_n^{\hat{}} = \left( \sum_{m \in \Omega_{r_n}} v_m v_m^T + \lambda_u I_K \right)^{-1} \sum_{m \in \Omega_{r_n}} x_{n,m} v_m$$

Dyadic data, each

$$L_{reg} = \|y - Xw\| + \lambda \|w\|_2^2$$

$$\frac{\partial L_{reg}}{\partial w} = -2 \sum_{i=1}^n (y_i - x_i^T w) x_i + 2 \lambda w$$

2 will be absorbed into  $\eta$

If no analytical solution

Gradient descent

1. Start with an initial value of  $w = w^{(0)}$
2. Update  $w$  by moving along the gradient of the loss function  $L$ 

$$w^{(t)} = w^{(t-1)} - \eta \frac{\partial L}{\partial w}$$
3. Repeat until converge