

## Collaborative filtering.

Movie $x^{(i)}$	Alice ( $\theta^1$ )	Bob ( $\theta^2$ )	Carol ( $\theta^3$ )	Dave ( $\theta^4$ )	$x_1$ (romance)	$x_2$ (action)
$x^{(1)}$	<del>0</del>	<del>0</del>	0	0	?	?
$x^{(2)}$	5	?	?	0	?	?
...	?	4	0	?	?	?
...	0	0	5	4	...	...
...	0	0	5	?	...	...

$$\theta^{(1)} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \quad \theta^{(2)} = \begin{bmatrix} 0 \\ 5 \\ 0 \end{bmatrix} \quad \theta^{(3)} = \begin{bmatrix} 0 \\ 0 \\ 5 \end{bmatrix} \quad \theta^{(4)} = \begin{bmatrix} 0 \\ 0 \\ 5 \end{bmatrix}$$

$$\therefore x^{(1)} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

Given  $\theta^{(1)} \dots \theta^{(n_u)}$ , to learn  $x^{(1)}$ :

$$\min_{x^{(1)}} \frac{1}{2} \sum_{j: r(i,j)=1} \left( (\theta^{(j)})^T x^{(1)} - y^{(i,j)} \right)^2 + \frac{\lambda}{2} \sum_{k=1}^n (x_k^{(1)})^2$$

Squared error

Given  $\theta^{(1)} \dots \theta^{(n_u)}$ , to learn  $x^{(1)}, x^{(2)} \dots x^{(n_m)}$

$$\min_{x^{(1)}, \dots, x^{(n_m)}} \frac{1}{2} \sum_{i=1}^{n_m} \sum_{j: r(i,j)=1} \left( (\theta^{(j)})^T x^{(i)} - y^{(i,j)} \right)^2 + \frac{\lambda}{2} \sum_{i=1}^{n_m} \sum_{k=1}^n (x_k^{(i)})^2$$

for movie  $i$ :  
sum over all users who have watched that movie.

In the first algo,  
if you have movie ratings,  $x^{(1)}, \dots, x^{(nm)}$   
then predict  $\theta^{(1)}, \dots, \theta^{(n_u)}$

In 2nd,

if your users have  $\theta^{(1)}, \dots, \theta^{(n_u)}$   
can estimate  $x^{(1)}, \dots, x^{(nm)}$

↑ features for different movie.

Guess  $\theta \rightarrow x \rightarrow \theta \rightarrow x \dots$

So, we are putting both of them together as -

$$J(x^{(1)}, \dots, x^{(nm)}, \theta^{(1)}, \dots, \theta^{(n_u)}) = \frac{1}{2} \sum_{(i,j): r(i,j)=1} ((\theta^{(i)})^T x^{(j)} - y^{(i,j)})^2$$

$$+ \frac{\lambda}{2} \sum_{i=1}^{nm} \sum_{k=1}^n (x_k^{(i)})^2 + \frac{\lambda}{2} \sum_{j=1}^{n_u} \sum_{k=1}^n (\theta_{(k)}^{(j)})^2$$

~~$\theta \in \mathbb{R}^n$~~   
 ~~$x \in \mathbb{R}^n$~~  now  $\mathbb{R}^{n \times 1} \dots \left\{ \begin{array}{l} \theta_{(k)}^{(j)} \\ x_k^{(i)} \end{array} \right\}$

Algo

- 1) Initialize  $x^{(1)}, \dots, x^{(nm)}, \theta^{(1)}, \dots, \theta^{(n_u)}$  to small random values.
- 2) Minimize  $J(x^{(1)}, \dots, x^{(nm)}, \theta^{(1)}, \dots, \theta^{(n_u)})$  using gradient descent (or any advanced opt. algorithm) e.g. for every  $j=1 \dots n_u$   $i=1, \dots, nm$ :

$$\pi_k^{(i)} := x_k^{(i)} - \alpha \left( \sum_{j: r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)}) \theta_k^{(j)} + \lambda x_k^{(i)} \right)$$

$$\theta_k^{(i)} := \theta_k^{(j)} - \alpha \left( \sum_{i: r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)}) x_k^{(i)} + \lambda \theta_k^{(j)} \right)$$

- e) For a user with parameters  $\theta$  & a movie with learned features  $x$ , predict a score rating.  $\theta^T x$   
 $(\theta^T x)$

### Vectorization Example

(Low rank matrix Factorization)

Movie	Alice	Bob	Carol	Dave
Love at first sight	5	5	0	0
... ..	3	?	?	0
...	?	4	0	?
...	0	0	5	4
...	0	0	5	?

$$Y = \begin{bmatrix} 5 & 5 & 0 & 0 \\ 3 & ? & ? & 0 \\ ? & 4 & 0 & ? \\ 0 & 0 & 5 & 4 \\ 0 & 0 & 5 & ? \end{bmatrix}$$

$$n_m = 5$$

$$n_u = 4$$

$y^{(i,j)}$   
 ↑  
 movie      user

$$Y = \begin{bmatrix} 5 & 5 & 0 & 0 \\ 5 & ? & ? & 0 \\ ? & 4 & 0 & ? \\ 0 & 0 & 5 & 4 \\ 0 & 0 & 5 & 0 \end{bmatrix}$$

Predicted ratings

$$\begin{bmatrix} (\theta^{(1)})^T x^{(1)} & (\theta^{(2)})^T x^{(1)} & \dots & (\theta^{(n_u)})^T x^{(1)} \\ \vdots & \vdots & \ddots & \vdots \\ (\theta^{(1)})^T x^{(n_m)} & (\theta^{(2)})^T x^{(n_m)} & \dots & (\theta^{(n_u)})^T x^{(n_m)} \end{bmatrix}$$

$$\begin{matrix} (\theta^{(j)})^T x^{(i)} \\ \uparrow \quad \quad \uparrow \\ \text{user } j \quad \text{movie } i \end{matrix}$$

$$X = \begin{bmatrix} -x^{(1)}{}^T \\ -x^{(2)}{}^T \\ \vdots \\ -x^{(n_m)}{}^T \end{bmatrix}$$

$$\theta = \begin{bmatrix} -(\theta^{(1)})^T \\ -(\theta^{(2)})^T \\ \vdots \\ -(\theta^{(n_u)})^T \end{bmatrix}$$

$$\therefore X \theta^T$$

Low rank Matrix factorization

How to find movie  $j$  is related to movie  $i$

$$\|x^{(i)} - x^{(j)}\| \rightarrow \text{small}$$

$\therefore$  movie  $j$  is similar to  $i$ .

Mean Normalization

New user

$$Y = \begin{bmatrix} 5 & ? & 0 & 0 & ? \\ 5 & ? & ? & 0 & ? \\ ? & 4 & 0 & ? & ? \\ 0 & 0 & 5 & 4 & ? \\ 0 & 0 & 5 & 0 & ? \end{bmatrix}$$

$$\mu = \begin{bmatrix} 2.5 \\ 2.5 \\ 2 \\ 2.25 \\ 1.25 \end{bmatrix}$$

$$y = Y - \mu$$

$$\therefore Y =$$

$$\begin{bmatrix} 2.5 & 2.5 & -2.5 & -2.5 & ? \\ 2.5 & ? & ? & -2.5 & ? \\ ? & 2 & -2 & ? & ? \\ -2.25 & -2.25 & 2.75 & 1.75 & ? \\ -1.25 & -1.25 & 3.75 & -1.25 & ? \end{bmatrix}$$

← New user (Eve)

$$\downarrow \text{user } \theta^{(j)} \text{ \& } x^{(i)}$$

$\therefore$  For user  $j$ , on movie  $i$  predicts  
 $\rightarrow (\theta^{(j)})^T (x^{(i)}) + \mu_i$

Ex -

$$\theta^{(j)} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \therefore (\theta^{(j)})^T (x^{(i)}) + \mu_i$$