

Hw2.3
2018年10月28日 星期日 上午1:13

In Piazza #74.
 $w_{ij} = N(u_i \cdot v_j, \sigma^2)$
 $y_{ij} = w_{ij} + \epsilon_{ij}$
 ϵ_{ij} is a parameter
 and σ is a parameter
 should be estimated.

② $\log \max_{u_i, v_j} P(u_i, v_j)$
 $= \log \max_{u_i, v_j} \sum_{i,j} P(u_i, v_j)$
 $= \log \min_{u_i, v_j} \sum_{i,j} \log P(u_i, v_j)$
 $\hat{r}_{ij} = u_i \cdot v_j + \epsilon_{ij}$
 $R = \frac{1}{n \cdot d} \sum_{i,j} u_i \cdot v_j + \frac{\sigma^2}{n \cdot d}$
 $N(u_i \cdot v_j, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(u_i \cdot v_j - R)^2}{2\sigma^2}}$
 $\arg\max_{u_i, v_j} \sum_{i,j} \frac{1}{2} \left(u_i^2 v_j^2 - 2u_i v_j R + R^2 \right)$

$\frac{\partial F}{\partial u_i} = 0$

$\arg\max_{u_i} \sum_{j=1}^k \frac{1}{2} \left(u_i^2 v_j^2 - 2u_i v_j R + R^2 \right)$

(iv) prove convex, $f: \mathbb{R}^d \rightarrow \mathbb{R}$
 for any two points $x, x' \in \mathbb{R}^d$ & $\beta \in [0, 1]$.
 $f(\beta x + (1-\beta)x') \leq \beta f(x) + (1-\beta)f(x')$

① for u_i .

$f(x) = \sum_{j=1}^k u_i^2 v_j^2 - 2u_i v_j R + R^2$
 $f(x') = \sum_{j=1}^k u_i'^2 v_j^2 - 2u_i' v_j R + R^2$
 choose different v_j :
 $f(\beta x + (1-\beta)x') = \sum_{j=1}^k \left[(\beta u_i + (1-\beta)u_i')^2 v_j^2 - 2\beta u_i v_j (\beta u_i + (1-\beta)u_i') + 2\beta^2 u_i^2 v_j^2 \right]$
 $\beta f(x) + (1-\beta)f(x') = \sum_{j=1}^k \left[\beta u_i^2 v_j^2 + (1-\beta)u_i'^2 v_j^2 + 2\beta u_i v_j (\beta u_i + (1-\beta)u_i') + 2\beta^2 u_i^2 v_j^2 \right]$
 $? \quad \beta^2 u_i^2 + (1-\beta)^2 u_i'^2 + 2\beta(1-\beta) u_i u_i' \geq \beta u_i^2 + (1-\beta) u_i'^2$

② similarly for u_i' .

v). Similarly:
 $f(x) = \sum_{j=1}^k u_i^2 v_j^2 - 2u_i v_j R + R^2$
 $f(x') = \sum_{j=1}^k u_i'^2 v_j^2 - 2u_i' v_j R + R^2$

$\beta u_i^2 + (1-\beta) u_i'^2$
 $= \beta^2 u_i^2 + 2\beta(1-\beta) u_i u_i' + (1-\beta)^2 u_i'^2$
 $= \beta^2 u_i^2 + u_i'^2 - 2\beta u_i^2 + \beta^2 u_i'^2 + 2\beta(1-\beta) u_i u_i'$
 $- \beta u_i'^2$

$L-R = \beta(1-\beta) u_i^2 - \beta(1-\beta) u_i'^2 + 2\beta(1-\beta) u_i u_i'$

$\alpha \in \beta$
 $\sum_{i=1}^n (L-R) = \sum_{i=1}^n u_i^2 - u_i'^2 + 2u_i u_i'$

$\arg\min_{u_i, v_j} \sum_{i=1}^n \sum_{j=1}^k u_i^2 v_j^2 - 2u_i v_j R + R^2$

prove convex, $f: \mathbb{R}^d \rightarrow \mathbb{R}$
 for any two points $x, x' \in \mathbb{R}^d$ & $\beta \in [0, 1]$.
 $f(\beta x + (1-\beta)x') \leq \beta f(x) + (1-\beta)f(x')$

④ prove jointly convex.

$f(x) = \sum_{i,j} u_i^2 v_j^2 - 2u_i v_j R + R^2$
 $f(x') = \sum_{i,j} u_i'^2 v_j^2 - 2u_i' v_j R + R^2$
 $f(\beta x + (1-\beta)x') = \left[\beta u_i v_j + (1-\beta) u_i' v_j \right] R + \sum_{i,j} u_i^2 v_j^2$

See online: in movies
 estimate how new client like movie.
 o.

f existing clients.
 with client $x \in \mathbb{R}^d$.

$y_{ij} = N(u_i \cdot v_j, \sigma^2)$

\downarrow
 u_i
 v_j
 σ

(v), $\arg\max_{u_i} \sum_{j=1}^k \frac{1}{2} \left(u_i^2 v_j^2 - 2u_i v_j R + R^2 \right)$

$\frac{\partial f}{\partial u_i} = -2 \sum_{j=1}^k (u_i v_j - R) = 0$
 no constraint?
 $\therefore u_i = \frac{1}{\sum_{j=1}^k v_j} R$

similarly, $v_j = \frac{1}{\sum_{i=1}^n u_i} R$

(vi), $\arg\max_{u_i} \sum_{j=1}^k \frac{1}{2} \left(u_i^2 v_j^2 - 2u_i v_j R + R^2 \right)$

$\frac{\partial f}{\partial u_i} = -2 \sum_{j=1}^k (u_i v_j - R) = 0$
 $\therefore u_i = \frac{1}{\sum_{j=1}^k v_j} R$

(vii)

$r_{ij} = N(u_i \cdot v_j, \sigma^2)$
 New client: $v_j = N(\tilde{u}_i \cdot \tilde{v}_j, \sigma^2)$
 don't know.
 or \tilde{v}_j

$\sum_{j=1}^k -\frac{\partial}{\partial u_i} (u_i v_j) + \sum_{j=1}^k (2r_{ij} v_j) = 0$
 $\sum_{j=1}^k r_{ij} v_j = 0$
 $\therefore u_i = \frac{\sum_{j=1}^k r_{ij}}{\sum_{j=1}^k v_j} \tilde{v}_j$

$[f(u_i) + (1-\beta)f(u_i')]^2$
 $\beta u_i^2 + (1-\beta)u_i'^2$

$f(x) = x^2$
 $f(x') = x'^2$
 $f(\beta x + (1-\beta)x') = [\beta x + (1-\beta)x']^2$
 $= \beta^2 x^2 + (1-\beta)^2 x'^2$