

作业8

2017年5月6日

8:22

$$\begin{aligned} 1, \quad & \textcircled{1} \text{ 计算 } X_j^{(1)} & (A+1)B + (B+1) \cdot 1 \\ & \textcircled{2} \text{ 计算 } S_j^{(1)} & B \cdot 1 \\ & \textcircled{3} \text{ 计算 } W_j^{(1)} & (A+1)B + (B+1) \cdot 1 \end{aligned}$$

$$\text{总计算量} \quad 2AB + 5B + 2$$

$$\begin{aligned} 2-3 \quad & d^{(0)} + 1 = 10 & d^{(1)} = 1 \\ & \sum_{i=1}^{L-1} (d^{(i)} + 1) = 36 & (d^{(i)} \geq 1) \\ & T = \sum_{i=0}^{L-1} (d^{(i)} + 1) \cdot d^{(i+1)} \end{aligned}$$

使用程序暴力求解, $d^{(1)} = 2, d^{(2)} = 13$ 时, 有 $T_{\max} = 510$
 $d^{(1)} = d^{(2)} = \dots = d^{(8)} = 1$ 时, 有 $T_{\min} = 46$
 暂未找到更好的最优比方法

$$\begin{aligned} 4, \quad \text{err}_n(w) &= \|x_n - ww^T x_n\|^2 \\ &= (x_n - ww^T x_n)^T (x_n - ww^T x_n) \\ &= (x_n^T - x_n^T ww^T) (x_n - ww^T x_n) \\ &= x_n^T x_n - 2x_n^T ww^T x_n + x_n^T ww^T ww^T x_n \end{aligned}$$

$$\begin{aligned} \text{记 } a &= x_n^T w = w^T x_n & \frac{\partial a}{\partial w} &= x_n \\ b &= w^T w & \frac{\partial b}{\partial w} &= 2w \end{aligned}$$

$$\nabla_w \text{err}_n(w) = \nabla_w (-2a^2 + a^2 b)$$

$$\begin{aligned} &= (-4a + 2ab) \frac{\partial a}{\partial w} + a^2 \frac{\partial b}{\partial w} \\ &= -4w^T x_n x_n + 2w^T x_n w^T w x_n + 2(w^T x_n)^2 w \end{aligned}$$

$$5, \quad \bar{\text{err}}_n(w) = \frac{1}{N} \sum_{n=1}^N \|x_n - ww^T (x_n + \epsilon_n)\|^2$$

$$\begin{aligned} &= \frac{1}{N} \sum_{n=1}^N (x_n - ww^T (x_n + \epsilon_n))^T (x_n - ww^T (x_n + \epsilon_n)) \\ &= \frac{1}{N} \sum_{n=1}^N (x_n - ww^T x_n - ww^T \epsilon_n)^T (x_n - ww^T x_n - ww^T \epsilon_n) \\ &= \frac{1}{N} \sum_{n=1}^N (x_n - ww^T x_n)^T (x_n - ww^T x_n) - \epsilon_n^T ww^T (x_n - ww^T x_n) \\ &\quad - (x_n - ww^T x_n) ww^T \epsilon_n + \epsilon_n^T ww^T ww^T \epsilon_n \end{aligned}$$

$$\epsilon_n \sim \mathcal{N}(0, 1)$$

$$-(x_n - w w^T x_n) w w^T \varepsilon_n + \varepsilon_n' w w^T w w^T \varepsilon_n$$

$$\varepsilon_n \sim N(0, 1)$$

$$\begin{aligned} E(E_n w) &= \frac{1}{N} \sum_{n=1}^N \|x_n - w w^T x_n\| + E\left(\frac{1}{N} \sum_{n=1}^N \varepsilon_n^T w w^T w w^T \varepsilon_n\right) \\ \Omega(w) &= E\left(\frac{1}{N} \sum_{n=1}^N \varepsilon_n^T w w^T w w^T \varepsilon_n\right) \\ &= \frac{1}{N} \sum_{n=1}^N E(\varepsilon_n^T w w^T w w^T \varepsilon_n) \\ &= w^T w \cdot \frac{1}{N} \sum_{n=1}^N E(\varepsilon_n^T w w^T \varepsilon_n) \\ &= w^T w \cdot \frac{1}{N} \sum_{n=1}^N E\left(\sum_{i=1}^d \varepsilon_{ni}^2 w_i^2\right) \\ &= w^T w \cdot \frac{1}{N} \sum_{n=1}^N \sum_{i=1}^d w_i^2 E(\varepsilon_{ni}^2) \\ &= w^T w \cdot \frac{1}{N} \sum_{n=1}^N \sum_{i=1}^d w_i^2 (E(\varepsilon_{ni}^2) + \text{var}(\varepsilon_{ni})) \\ &= w^T w \cdot \frac{1}{N} \sum_{n=1}^N \sum_{i=1}^d w_i^2 = w^T w \cdot \frac{1}{N} \sum_{n=1}^N w^T w = (w^T w)^2 \end{aligned}$$

6. $g_{\text{lin}}(x) = \text{sign}(\|x - x_-\|^2 - \|x - x_+\|^2)$ (距离 x_+ 较小, 为 +1)

$$\begin{aligned} &= \text{sign}((x - x_-)^T (x - x_-) - (x - x_+)^T (x - x_+)) \\ &= \text{sign}(2(x_+ - x_-)^T x + \|x_-\|^2 - \|x_+\|^2) \end{aligned}$$

故 $w = 2(x_+ - x_-)$ $b = \|x_-\|^2 - \|x_+\|^2$

7. $\beta_+ \exp(-\|x - \mu_+\|^2) + \beta_- \exp(-\|x - \mu_-\|^2) \geq 0$

$$\Rightarrow \frac{\exp(-\|x - \mu_+\|^2)}{\exp(-\|x - \mu_-\|^2)} \geq -\frac{\beta_-}{\beta_+}$$

$$\Rightarrow \|x - \mu_-\|^2 - \|x - \mu_+\|^2 \geq \ln\left(-\frac{\beta_-}{\beta_+}\right)$$

$$\Rightarrow 2(\mu_+ - \mu_-)^T x + \|\mu_-\|^2 - \|\mu_+\|^2 - \ln\left(-\frac{\beta_-}{\beta_+}\right) \geq 0$$

故 $w = 2(\mu_+ - \mu_-)$
 $b = \|\mu_-\|^2 - \|\mu_+\|^2 - \ln\left(-\frac{\beta_-}{\beta_+}\right)$

8. $\text{RBF}(x, \mu) = [x = \mu]$

$$\begin{aligned} \text{则 } z_h &= [\text{RBF}(x_h, x_1), \text{RBF}(x_h, x_2), \dots, \text{RBF}(x_h, x_N)] \\ &= [0, 0, \dots, 1, \dots, 0] \\ &\quad \uparrow \\ &\quad h \end{aligned}$$

故 $z = I$

$$\beta = (z^T z)^{-1} z^T y = y \quad \text{即 } \beta_h = y_h$$

9. 损失函数 $\sum_{m=1}^M (\sum_{(x_n, r_{nm}) \in D_m} (r_{nm} - w_m^T v_n)^2)$

对 w_m 求偏导 $\sum_{(x_n, r_{nm}) \in D_m} 2(r_{nm} - w_m^T v_n)(-v_n)$

注意到 $v_n = 1$, 令上式为 0, 则 $w_m = \frac{\sum_n r_{nm}}{\sum_n 1}$

故 w_m 为第 m 部电影评分的平均值

10. $\max_m v_{N+1}^T w_m = \max_m (\frac{1}{N} \sum_{n=1}^N v_n)^T w_m$

$= \max_m \frac{1}{N} \sum_{n=1}^N v_n^T w_m = \max_m \frac{1}{N} \sum_{n=1}^N r_{nm}$

即为 m 部电影中, 平均打分最高的

11~18 部电影

12. $\bar{z}_m = (0.0, 0.1, 0.16, 0.15, 0.14)$ 先升后降

14. $\bar{z}_{out} = (0.394, 0.288, 0.316, 0.322, 0.303)$ 比较稳定

16. $\bar{z}_m = (0.45, 0.45, 0.02, 0.0, 0.0)$ 下降

18. $\bar{z}_{out} = (0.467, 0.448, 0.288, 0.396, 0.344)$ 先降后升

19~20 部电影

20. $\bar{z}_m = (2.676, 2.268, 1.997, 1.801, 1.662)$ 逐渐减小