

HW 1

1. 经验风险: $\min_{f \in \mathcal{F}} \frac{1}{N} \sum_{i=1}^N L(y_i, f(x_i)) \Rightarrow \min_{f \in \mathcal{F}} \frac{1}{N} \sum_{i=1}^N (-\log P(y_i | x_i))$
 $= \max_{f \in \mathcal{F}} \frac{1}{N} \log \left(\underbrace{\prod_{i=1}^N P(y_i | x_i)}_{\text{求最大值}} \right)$

极大似然估计: $\max_{f \in \mathcal{F}} \prod_{i=1}^N P(y_i | x_i)$ 可见两者等价.

2. $\exp(sx) \leq \frac{b-x}{b-a} \exp(sa) + \frac{x-a}{b-a} \exp(sb)$.

$$E\{\exp(sX)\} \leq \frac{b-E(X)}{b-a} \exp(sa) + \frac{E(X)-a}{b-a} \exp(sb)$$

$$= \frac{b}{b-a} \exp(sa) - \frac{a}{b-a} \exp(sb)$$

$$= \exp\left\{sa + \ln\left(1 + \frac{a - \exp(s(b-a))a}{b-a}\right)\right\}$$

$$\frac{1}{2} L(s(b-a)) = sa + \ln\left(1 + \frac{a - \exp(s(b-a))a}{b-a}\right)$$

$$L(x) = \frac{a}{b-a} x + \ln\left(1 + \frac{a - \exp(x)a}{b-a}\right)$$

$$L'(x) = \frac{a}{b-a} + \frac{b-a}{b - \exp(x)a} \cdot \frac{-a}{b-a} \exp(x) = \frac{a}{b-a} + \frac{-a}{b - \exp(x)a} \exp(x)$$

$$L''(x) = \left[\frac{-a}{b - \exp(x)a} + \frac{a}{[b - \exp(x)a]^2} \cdot (-a \exp(x)) \right] \cdot \exp(x)$$

$$L''(0) = \frac{-a}{b-a} + \frac{-a^2}{(b-a)^2} = -\left(\frac{a}{b-a} + \frac{1}{2}\right)^2 + \frac{1}{4} \leq \frac{1}{8}$$

当且仅当 $a+b=0$ 时取等.

$$L(0) = 0, \quad L'(0) = \frac{a}{b-a} + \frac{-a}{b-a} = 0$$

Taylor 展开: $L(x) = L(0) + L'(0)x + \frac{L''(0)}{2}x^2 + o(x^2)$

由 Taylor 中值定理, $\exists 0 \leq \theta \leq 1$ 使 $L(x) = L(0) + L'(0)x + \frac{1}{2} L''(\theta x) x^2 \leq \frac{1}{8} x^2$.

$$\therefore E(\exp(sX)) \leq \exp\left\{\frac{1}{8} s^2 (b-a)^2\right\} \text{ 得证.}$$

3. (1) 问题背景: 关于信贷风险, 根据用户行为预测该用户是否会在将来还款逾期.

(2) 因变量: 该用户是否曾经发生过逾期行为.

自变量: 该用户的行为 (如月收入、月消费额、单笔最高支出等).

(3) 机器学习建模: 这是一个二分类问题, 可以使用决策树、随机森林、逻辑回归、SVM 等分类器进行建模. 在数据集上训练后即可得到模型.

4. (a) $y = (y_1, y_2, \dots, y_m)'$, $x = (x_1, x_2, \dots, x_n)'$.

$$A = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{pmatrix}_{m \times n}$$

$$y = Ax \Rightarrow y_i = \sum_{j=1}^m \sum_{j=1}^n a_{ij} x_j.$$

$$\therefore \frac{\partial y_i}{\partial x_j} = a_{ij} \quad (\text{因为 } A \text{ 与 } x \text{ 无关}).$$

$$\therefore \frac{\partial y}{\partial x^T} = \begin{pmatrix} \frac{\partial y_1}{\partial x_1} & \dots & \frac{\partial y_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_m}{\partial x_1} & \dots & \frac{\partial y_m}{\partial x_n} \end{pmatrix}_{m \times n} = (a_{ij})_{m \times n} = A. \quad \text{得证.}$$

(b) $\alpha = y^T A x = (y^T A)_{1 \times n} x = x^T A^T y = \alpha^T$. (α 是标量, 故 $\alpha = \alpha^T$).

本来根据 (a) 的结论, $\frac{\partial \alpha}{\partial x^T} = y^T A$, 但是在本题中 $y = \varphi(x)$, 还需要对 y 进行求导.

$$\frac{\partial \alpha}{\partial x^T} = y^T A + \frac{\partial \alpha}{\partial y} \cdot \frac{\partial y}{\partial x^T} = y^T A + x^T A^T \left(\frac{\partial y}{\partial x^T} \right). \quad \text{得证.}$$

(c) 本题对应 (b) 中 $y = x$ 的情况.

$$\therefore \frac{\partial \alpha}{\partial x^T} = x^T A + x^T A^T \cdot I = x^T (A + A^T). \quad \text{得证.}$$

$$(d) \frac{\partial \alpha}{\partial z^T} = \frac{\partial \alpha}{\partial x} \cdot \frac{\partial x}{\partial z^T} + \frac{\partial \alpha}{\partial y} \cdot \frac{\partial y}{\partial z^T}$$

$$= y^T A \left(\frac{\partial x}{\partial z^T} \right) + x^T A^T \left(\frac{\partial y}{\partial z^T} \right) \quad \text{得证.}$$

(e) $AA^{-1} = I$.

$$A^{-1} \frac{\partial A}{\partial \alpha} + \frac{\partial A^{-1}}{\partial \alpha} A = 0$$

$$\text{同乘 } A^{-1}, \quad A^{-1} \cdot \frac{\partial A}{\partial \alpha} \cdot A^{-1} + \frac{\partial A^{-1}}{\partial \alpha} A \cdot A^{-1} = 0. \Rightarrow \frac{\partial A^{-1}}{\partial \alpha} = -A^{-1} \cdot \frac{\partial A}{\partial \alpha} \cdot A^{-1}. \quad \text{得证.}$$

5. $\min_a \sqrt{(x_a - y)^T (x_a - y)}$.

$$\text{令 } S = (x_a - y)^T (x_a - y) = a^T X^T X a - 2a^T X^T y + y^T y.$$

对目标函数 S 关于 a 求导.

$$\frac{\partial S}{\partial a^T} = 2X^T X a - 2X^T y. \quad \text{令 } \frac{\partial S}{\partial a^T} = 0. \quad \text{则 } X^T X a = X^T y. \quad \text{两边同左乘 } (X^T X)^{-1}. \quad (\text{因为 } X^T X \text{ 满秩}).$$

$$\therefore \hat{a} = (X^T X)^{-1} X^T y.$$