

HOMEWORK 1

1 证明《统计学习方法》习题 1.2:

通过经验风险最小化推导极大似然估计。证明模型是条件概率分布，当损失函数是对数损失函数时，经验风险最小化等价于极大似然估计。

2 试利用 Hoeffding 引理证明 Hoeffding 不等式。Hoeffding 引理形式如下:

Lemma 1. *Let X be a random variable with $E(X) = 0$ and $P(X \in [a, b]) = 1$. Then it holds*

$$E\{\exp(sX)\} \leq \exp\{s^2(b-a)^2/8\}. \quad (0.1)$$

3 请列举一个实际中有监督学习的应用，请说明 (1) 问题背景、(2) 因变量和自变量分别是什么，以及 (3) 通过机器学习建模如何解决该实际问题。

4 Please read the background and then prove the following results.

Background:

Let $\mathbf{y} = \Psi(\mathbf{x})$, where \mathbf{y} is an m -element vector, and \mathbf{x} is an n -element vector. The symbol

$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_1}{\partial x_2} & \cdots & \frac{\partial y_1}{\partial x_n} \\ \frac{\partial y_2}{\partial x_1} & \frac{\partial y_2}{\partial x_2} & \cdots & \frac{\partial y_2}{\partial x_n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial y_m}{\partial x_1} & \frac{\partial y_m}{\partial x_2} & \cdots & \frac{\partial y_m}{\partial x_n} \end{bmatrix} \quad (0.2)$$

will denote the $m \times n$ matrix of first-order partial derivatives of the transformation from \mathbf{x} to \mathbf{y} . Such a matrix is called the Jacobian matrix of the transformation $\Psi()$.

Notice that if \mathbf{x} is actually a scalar then the resulting Jacobian matrix is a $m \times 1$ matrix; that is, a single column (a vector). On the other hand, if \mathbf{y} is actually a scalar then the resulting Jacobian matrix is a $1 \times n$ matrix; that is, a single row (the transpose of a vector).

Prove the results:

(a) Let $\mathbf{y} = \mathbf{A}\mathbf{x}$, where \mathbf{y} is $m \times 1$, \mathbf{x} is $n \times 1$, \mathbf{A} is $m \times n$, and \mathbf{A} does not depend on \mathbf{x} , then

$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}} = \mathbf{A} \quad (0.3)$$

(b) Let the scalar α be defined by $\alpha = \mathbf{y}^T \mathbf{A} \mathbf{x}$, where \mathbf{y} is $m \times 1$, \mathbf{x} is $n \times 1$, \mathbf{A} is $m \times n$, and \mathbf{A} is independent of \mathbf{x} and \mathbf{y} , then

$$\frac{\partial \alpha}{\partial \mathbf{x}} = \mathbf{y}^T \mathbf{A} \quad (0.4)$$

(c) For the special case in which the scalar α is given by the quadratic form $\alpha = \mathbf{x}^T \mathbf{A} \mathbf{x}$ where \mathbf{x} is $n \times 1$, \mathbf{A} is $n \times n$, and \mathbf{A} does not depend on \mathbf{x} , then

$$\frac{\partial \alpha}{\partial \mathbf{x}} = \mathbf{x}^T (\mathbf{A} + \mathbf{A}^T) \quad (0.5)$$

(d) Let the scalar α be defined by $\alpha = \mathbf{y}^T \mathbf{A} \mathbf{x}$, where \mathbf{y} is $m \times 1$, \mathbf{x} is $n \times 1$, \mathbf{A} is $m \times n$, and both \mathbf{y} and \mathbf{x} are functions of the vector \mathbf{z} , while \mathbf{A} does not depend on \mathbf{z} . Then

$$\frac{\partial \alpha}{\partial \mathbf{z}} = \mathbf{x}^T \mathbf{A}^T \frac{\partial \mathbf{y}}{\partial \mathbf{z}} + \mathbf{y}^T \mathbf{A} \frac{\partial \mathbf{x}}{\partial \mathbf{z}} \quad (0.6)$$

(e) Let \mathbf{A} be a nonsingular, $m \times m$ matrix whose elements are functions of the scalar parameter α . Then

$$\frac{\partial \mathbf{A}^{-1}}{\partial \alpha} = -\mathbf{A}^{-1} \frac{\partial \mathbf{A}}{\partial \alpha} \mathbf{A}^{-1} \quad (0.7)$$

(4) Please write \hat{a} as the solution of the minimization problem:

$$\min_a \|\mathbf{X}a - \mathbf{y}\| \quad (0.8)$$

where \mathbf{X} is a $n \times p$ matrix and \mathbf{y} is a $n \times 1$ vector. $\mathbf{X}^T \mathbf{X}$ is nonsingular.

提交时间：9 月 28 日，晚 20:00 之前。请预留一定的时间，迟交作业扣 3 分，作业抄袭 0 分。