

# Problem Set 1

## 1 Conditions for Normal Equation

Prove the following theorem: The matrix  $A^T A$  is invertible if and only if the columns of  $A$  are linearly independent.

该题即证明： $A^T A$ 可逆  $\Leftrightarrow A$ 线性无关。

### 充分性：

已知 $A^T A$ 可逆，若 $A$ 线性无关，则有： $AX = 0$ 仅有唯一解 $X = 0$ 。

所以要证明充分性，即证明在 $A^T A$ 可逆的条件下， $AX = 0$ 有唯一解 $X = 0$ 即可。

若 $AX = 0$ ，则有： $A^T AX = 0$ ，由于 $A^T A$ 可逆，故该等式有唯一解 $X = 0$ 。

即： $AX = 0$ 有唯一解 $X = 0$ 。

故充分性得证。

### 必要性：

已知 $A$ 线性无关，若 $A^T A$ 可逆，则有： $A^T AX = 0$ 有唯一解 $X = 0$ 。

所以要证明必要性，即证明在 $A$ 线性无关的条件下， $A^T AX = 0$ 有唯一解 $X = 0$ 即可。

若 $A^T AX = 0$ ，则有： $X^T A^T AX = 0$ ，即： $(AX)^T AX = 0$ ，故 $AX = 0$ 。

由于 $A$ 线性无关，故 $X = 0$ 。

即 $A^T AX = 0$ 有唯一解 $X = 0$ 。

故必要性得证。

或者也可由可逆矩阵的相关性质简单证明：

若 $A^T A$ 可逆，则 $A^T$ 、 $A$ 均可逆，故 $A$ 线性无关。

若 $A$ 线性无关，则 $A$ 、 $A^T$ 均可逆，故 $A^T A$ 可逆。

## 2 Newton's Method for Computing Least Squares

In this problem, we will prove that if we use Newton's method solve the least squares optimization problem, then we only need one iteration to converge to the optimal parameter  $\theta^*$

(a) Find the Hessian of the cost function  $J(\theta) = \frac{1}{2} \sum_{i=1}^m (\theta^T x^{(i)} - y^{(i)})^2$

首先对 $J(\theta)$ 求 $\theta_j$ 的偏导：

$$\frac{\partial J(\theta)}{\partial \theta_j} = \sum_{i=1}^m (\theta^T x^{(i)} - y^{(i)}) x_j^{(i)}$$

再求得 $\theta_k$ 的偏导：

$$\frac{\partial^2 J(\theta)}{\partial \theta_j \partial \theta_k} = \sum_{i=1}^m \frac{\partial}{\partial \theta_k} (\theta^T x^{(i)} - y^{(i)}) x_j^{(i)} = \sum_{i=1}^m x_j^{(i)} x_k^{(i)} = (X^T X)_{jk}$$

因此， $J(\theta)$ 的Hessian即为 $H = X^T X$ 。

(b) Show that the first iteration of Newton's method gives us  $\theta^* = (X^T X)^{-1} X^T \vec{y}$ , the solution to our least square problem. ( $\vec{y}$  denotes the vector of the features.)

对于给定的 $\theta^{(0)}$ ，由牛顿法：

$$\begin{aligned} \theta^{(1)} &= \theta^{(0)} - H^{-1} \nabla_{\theta} J(\theta^{(0)}) \\ &= \theta^{(0)} - (X^T X)^{-1} (X^T X \theta^{(0)} - X^T \vec{y}) \\ &= \theta^{(0)} - \theta^{(0)} + (X^T X)^{-1} X^T \vec{y} \\ &= (X^T X)^{-1} X^T \vec{y} \end{aligned}$$

### 3 Prediction using Linear Regression

The sales of a company (in million dollars) for each year are shown in the table below.

x (year)	2005	2006	2007	2008	2009
y (sales)	12	19	29	37	45

(a) Find the least square regression line  $y = ax + b$

对题中数据进行处理，得到：

x (year)	0	1	2	3	4
y (sales)	12	19	29	37	45

X、Y：

$$X = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{bmatrix} \quad Y = \begin{bmatrix} 12 \\ 19 \\ 29 \\ 37 \\ 45 \end{bmatrix}$$

由least square公式 $\theta = (X^T X)^{-1} X^T Y$ 计算 $\theta$ ：

$$(X^T X)^{-1} = \left( \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 2 & 3 & 4 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{bmatrix} \right)^{-1} = \left( \begin{bmatrix} 5 & 10 \\ 10 & 30 \end{bmatrix} \right)^{-1} = \begin{bmatrix} \frac{3}{5} & -\frac{1}{5} \\ -\frac{1}{5} & \frac{1}{10} \end{bmatrix}$$

$$X^T Y = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 2 & 3 & 4 \end{bmatrix} \begin{bmatrix} 12 \\ 19 \\ 29 \\ 37 \\ 45 \end{bmatrix} = \begin{bmatrix} 142 \\ 368 \end{bmatrix}$$

$$\theta = (X^T X)^{-1} X^T Y = \begin{bmatrix} \frac{3}{5} & -\frac{1}{5} \\ -\frac{1}{5} & \frac{1}{10} \end{bmatrix} \begin{bmatrix} 142 \\ 368 \end{bmatrix} = \begin{bmatrix} \frac{58}{5} \\ \frac{42}{5} \end{bmatrix}$$

即: least square regression line 为:  $y = \frac{42}{5}x + \frac{58}{5}$ 。

(b) Use the least squares regression line as a model to estimate the sales of the company in 2012.

当year为2012时, x应为:  $2012 - 2005 = 7$ :

将  $x = 7$  带入least square regression line:

$$y = \frac{42}{5} \times 7 + \frac{58}{5} = \frac{352}{5} \approx 70.4$$

## 4 Logistic Regression

Consider the average empirical loss for logistic regression:

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m \log(1 + e^{-y^{(i)} \theta^T x^{(i)}}) = -\frac{1}{m} \sum_{i=1}^m \log(h_{\theta}(y^{(i)} x^{(i)}))$$

where  $y^{(i)} \in \{-1, 1\}$   $h_{\theta}(x) = g(\theta^T x)$  and  $g(z) = 1/(1 + e^{-z})$ . Find the Hessian H of this function, and show that for any vector z, it holds true that

$$z^T H z \geq 0$$

Hint: You might want to start by showing the fact that  $\sum_i \sum_j z_i x_i x_j z_j = (\sum_i z_i x_i)^2 \geq 0$ .

对  $J(\theta)$  求  $\theta_j$  的偏导:

$$\begin{aligned} \frac{\partial J(\theta)}{\partial \theta_j} &= -\frac{1}{m} \sum_{i=1}^m \frac{1}{h_{\theta}(y^{(i)} x^{(i)})} \cdot \frac{\partial h_{\theta}(y^{(i)} x^{(i)})}{\partial \theta_j} \\ &= -\frac{1}{m} \sum_{i=1}^m \frac{1}{h_{\theta}(y^{(i)} x^{(i)})} \cdot \frac{\exp(-y^{(i)} \theta^T x^{(i)}) y^{(i)} x_j^{(i)}}{(1 + \exp(-y^{(i)} \theta^T x^{(i)}))^2} \\ &= -\frac{1}{m} \sum_{i=1}^m \frac{1}{h_{\theta}(y^{(i)} x^{(i)})} \cdot h_{\theta}^2(y^{(i)} x^{(i)}) \cdot \frac{1 - h_{\theta}(y^{(i)} x^{(i)})}{h_{\theta}(y^{(i)} x^{(i)})} \cdot y^{(i)} x_j^{(i)} \\ &= -\frac{1}{m} \sum_{i=1}^m (1 - h_{\theta}(y^{(i)} x_j^{(i)})) y^{(i)} x_j^{(i)} \end{aligned}$$

再求对  $\theta_k$  的偏导:

$$\begin{aligned}
\frac{\partial^2 J(\theta)}{\partial \theta_j \partial \theta_k} &= -\frac{1}{m} \sum_{i=1}^m \left( -\frac{\exp(-y^{(i)} \theta^T x^{(i)}) y^{(i)} x_k^{(i)}}{(1 + \exp(-y^{(i)} \theta^T x^{(i)}))^2} \right) y^{(i)} x_j^{(i)} \\
&= \frac{1}{m} \sum_{i=1}^m h_{\theta}^2(y^{(i)} x^{(i)}) \cdot \frac{1 - h(y^{(i)} x^{(i)})}{h_{\theta}(y^{(i)} x^{(i)})} (y^{(i)})^2 x_j^{(i)} x_k^{(i)} \\
&= \frac{1}{m} \sum_{i=1}^m h_{\theta}(y^{(i)} x^{(i)}) (1 - h_{\theta}(y^{(i)} x^{(i)})) (y^{(i)})^2 x_j^{(i)} x_k^{(i)}
\end{aligned}$$

得到:  $H = (\frac{1}{m} \sum_{i=1}^m h_{\theta}(y^{(i)} x^{(i)}) (1 - h_{\theta}(y^{(i)} x^{(i)}))) (y^{(i)})^2 X^T X$

由于  $h(x) \in (0, 1)$ , 有:  $h_{\theta}(y^{(i)} x^{(i)}) > 0$ ,  $(1 - h_{\theta}(y^{(i)} x^{(i)})) > 0$ , 且  $(y^{(i)})^2 > 0$ , 因此H的系数均为正数, Hessian矩阵中各项的正负性取决于X。

对于任意向量z, 有:

$$z^T H z = (\frac{1}{m} \sum_{i=1}^m h_{\theta}(y^{(i)} x^{(i)}) (1 - h_{\theta}(y^{(i)} x^{(i)}))) (y^{(i)})^2 z^T X^T X z$$

要判断上式的正负性, 即判断  $z^T X^T X z$  的正负性, 而对于该矩阵中的每一项, 有:

$$\sum_i \sum_j z_i x_i x_j z_j = (x^T z)^2 \geq 0$$

故  $z^T X^T X z \geq 0$ , 原题得证。