

Homework week 5

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1 Question 1

$$\text{Let } X = \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1d} \\ 1 & x_{21} & x_{22} & \dots & x_{2d} \\ \dots & \dots & \dots & \dots & \dots \\ 1 & x_{n1} & x_{n2} & \dots & x_{nd} \end{bmatrix} = \begin{bmatrix} x_1^T \\ x_2^T \\ \dots \\ x_n^T \end{bmatrix}; W = \begin{bmatrix} w_0 \\ w_1 \\ \dots \\ w_d \end{bmatrix};$$
$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}; \hat{Y} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \dots \\ \hat{y}_n \end{bmatrix} = \begin{bmatrix} h_\theta(x_1^T W) \\ h_\theta(x_2^T W) \\ \dots \\ h_\theta(x_n^T W) \end{bmatrix} = \theta(XW)$$

We have:

$$L = -(y^T \log \hat{y} + (1 - y)^T \log(1 - \hat{y}))$$

$$\frac{\partial L}{\partial W} = \left(\frac{\partial \hat{y}}{\partial W} \right)^T \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial \hat{y}}{\partial W} = \frac{\partial \theta(XW)}{\partial W} = \frac{\partial \theta(XW)}{\partial XW} \frac{XW}{\partial W} = \frac{\partial \theta(XW)}{\partial XW} X$$

$$h_\theta(x) = \frac{1}{1 + e^{-x}}$$

$$\frac{\partial h_\theta(x)}{\partial x} = \frac{e^{-x}}{(1 + e^{-x})^2} = \frac{1}{1 + e^{-x}} * \frac{e^{-x}}{1 + e^{-x}} = (1 - h_\theta(x))h_\theta(x)$$

$$\frac{\partial \theta(XW)}{\partial W} = [[1 - \theta(XW)] \odot \theta(XW)]^T X = (1 - \hat{y}) \odot \hat{y} X$$

$$\frac{\partial L}{\partial \hat{y}} = -(y^T \frac{1}{\hat{y}} + (1 - y)^T \frac{-1}{1 - \hat{y}})$$

$$\begin{aligned}
\frac{\partial L}{\partial W} &= [(1 - \hat{y}) \odot \hat{y} X]^T ((1 - y)^T \frac{1}{1 - \hat{y}} - y^T \frac{1}{\hat{y}}) \\
&= X^T (1 - \hat{y}) \odot \hat{y} * ((1 - y)^T \frac{1}{1 - \hat{y}} - y^T \frac{1}{\hat{y}}) \\
&= X^T (\hat{Y}^T (1 - Y) - (1 - \hat{Y})^T Y) \\
&= X^T (\hat{Y} - \hat{Y}^T Y - Y + \hat{Y}^T Y) \\
&= X^T (\hat{Y} - Y)
\end{aligned}$$

2 Question 2

Logistic model for loan approved prediction:

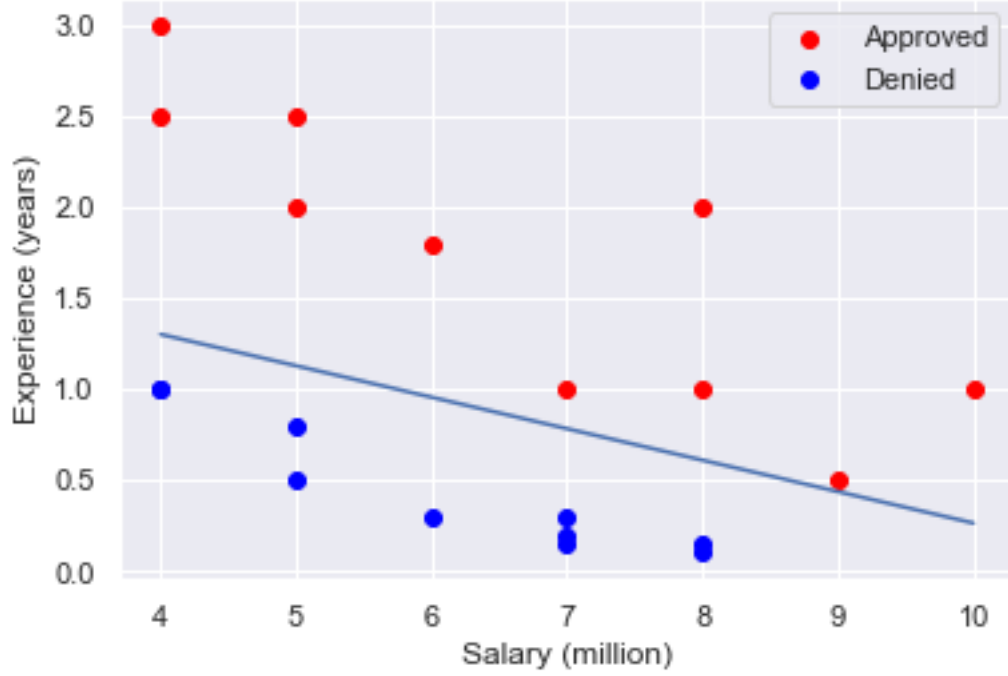
$$\theta = \frac{1}{1 + e^{-(7.252 + 0.629 * \text{Lương} + 3.642 * \text{Thời gian làm việc})}}$$

3 Question 3

Assume t is decision boundary

$$\begin{aligned}
&\Rightarrow \hat{y} \geq t \\
\Rightarrow \frac{1}{1 + e^{-X^T W}} &\geq t \\
&\Rightarrow \frac{1}{t} \geq 1 + e^{-X^T W} \\
&\Rightarrow \frac{1}{t} - 1 \geq e^{-X^T W} \\
&\Rightarrow \ln\left(\frac{1}{t} - 1\right) \geq -X^T W \\
&\Rightarrow X^T W \geq -\ln\left(\frac{1}{t} - 1\right)
\end{aligned}$$

Decision boundary for Question 2



4 Question 4

Binary Cross Entropy loss:

$$H = \frac{\partial^2 L}{\partial^2 W} = X^T \hat{y}(1 - \hat{y})X$$

We have: $\hat{y} \geq 0$ and $(1 - \hat{y}) \geq 0 \Rightarrow \hat{y}(1 - \hat{y}) \geq 0 \forall v \in R$

$$\begin{aligned} v^T H v &= v^T X^T \hat{y}(1 - \hat{y})X v \\ &= v^T X^T ((\hat{y}(1 - \hat{y}))^{\frac{1}{2}})^2 X v \\ &= \|(\hat{y}(1 - \hat{y}))^{\frac{1}{2}} X v\|_2^2 \geq 0 \forall v \end{aligned}$$

\Rightarrow Positive semi-definite \Rightarrow loss function is convex

MSE loss:

$$L = \|y - \hat{y}\|_2^2 \text{ where } \hat{y} = \frac{1}{1 + e^{-X^T \theta}}$$

$$\begin{aligned} \frac{\partial L}{\partial W} &= -2(y - \hat{y})\hat{y}(1 - \hat{y})X \\ &= -2(y\hat{y} - y\hat{y}^2 - \hat{y}^2 + \hat{y}^3)X \end{aligned}$$

$$\begin{aligned}
\frac{\partial^2 L}{\partial^2 W} &= -2(y - 2y\hat{y} - 2\hat{y} + 3\hat{y}^2)XX\hat{y}(1 - \hat{y}) \\
&= -2[3\hat{y}^2 - 2\hat{y}(y + 1) + y]X^2\hat{y}(1 - \hat{y})
\end{aligned}$$

If $y = 0$

$$H = -2[3\hat{y}(\hat{y} - \frac{2}{3})] \geq 0 \forall \hat{y} \in [\frac{2}{3}, 1]$$

If $y = 1$

$$H = 2[3(\hat{y} - \frac{1}{3})(\hat{y} - 1)] \geq 0 \forall \hat{y} \in [\frac{1}{3}, 1]$$

$\Rightarrow H$ is not semi-definite \Rightarrow MSE loss is not convex