

# HW 2

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①.  $L(y_i | x_i, w) = y_i \log(\sigma(w^T x_i)) + (1 - y_i) \log(\sigma(-w^T x_i))$

Derive the gradient of  $L(y_i | x_i, w)$  respect to  $w_j$

According to the derivative of sigmoid function

$$\sigma'(x) = \sigma(x)(1 - \sigma(x))$$

$\therefore$  For first, assume  $z = \sigma(w^T x_i)$

$$\therefore \frac{\partial}{\partial w_j} \log(\sigma(w^T x_i)) = \frac{\partial}{\partial z} \frac{\partial z}{\partial w_j} \quad \text{chain rule}$$

$$= \frac{1}{z} \cdot \sigma(w^T x_i) \cdot (1 - \sigma(w^T x_i)) \cdot \frac{\sigma(w^T x_i)}{\sigma w_j}$$

$$= (1 - \sigma(w^T x_i)) \cdot x_{ij}$$

For second part, using the same way

$$\begin{aligned} & (1 - y_i) \log \sigma(-w^T x_i) \frac{\partial}{\partial w_j} \\ &= (1 - y_i) \frac{1}{\sigma(-w^T x_i)} \sigma(-w^T x_i) \cdot (1 - \sigma(-w^T x_i)) \cdot -x_{ij} \\ &= (1 - y_i) \cdot (1 - \sigma(-w^T x_i)) \cdot -x_{ij} \end{aligned}$$

$$\therefore \frac{\partial \mathcal{L}(y_i | x_i; w)}{\partial w_j} = y(1 - \sigma(w^T x)) \cdot x_{ij} + (1-y) \cdot (1 - \sigma(-w^T x_i)) \cdot -x_{ij}$$

$$= y(1 - \sigma(w^T x)) \cdot x_{ij} + (1-y) \sigma(w^T x_i) \cdot -x_{ij}$$

$$= x_{ij} (y - y \cancel{\sigma(w^T x)} - \sigma(w^T x_i) + y \cancel{\sigma(w^T x)})$$

$$= x_{ij} (y - \sigma(w^T x_i))$$

③

$$f(w) = \frac{1}{2} \|w\|_2^2 + C \sum_{i=1}^n \max(0, 1 - y_i(w^T x_i + b))$$

$$\text{find } \frac{\partial}{\partial w_j} f(w)$$

for gradient of hinge loss

if  $L = 0$ , then the gradient is 0

if  $L > 0$ ,

$$\begin{aligned} & (1 - y_i(w^T x_i + b)) \frac{\partial}{\partial w} \\ &= -x_{ij} y_i \end{aligned}$$

$$\therefore \frac{\partial f(w)}{\partial w} = w_j - C \sum y_i x_{ij} \quad \text{if hinge loss greater than 0}$$

$$\frac{\partial f(w)}{\partial w} = w_j \quad \text{if hinge loss is equal to 0}$$

## HW2

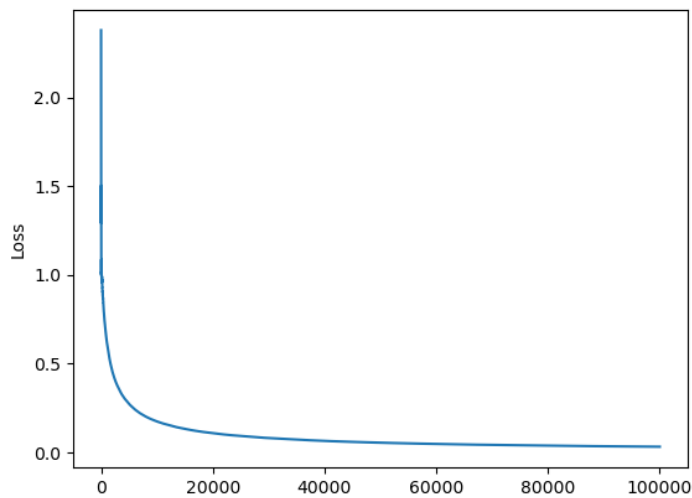
### Question2

- Logistic Regression

eta_value	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Fold 7	Fold 8	Fold 9	Fold 10	Mean	Std
0.001	0.00125	0.00625	0.0125	0.0125	0.01875	0.0125	0.00625	0	0.00625	0.03125	0.0118	0.008125
0.01	0.01875	0.0125	0.0125	0.0125	0.01875	0.0125	0.0125	0	0.01252	0.03125	0.01437	0.007421
0.1	0.025	0.00625	0.0125	0.01875	0.01875	0.01875	0	0.0125	0.0375	0.01875	0.016875	0.0097

Which value of  $\eta$  is optimal?

- Best  $\eta$  for **logistic regression** with eta 0.001: MSE is 0.005



According to training average loss plot, the loss keep going lower until 5000 iteration. If I using Gradient Decent, the loss will be more smoother.

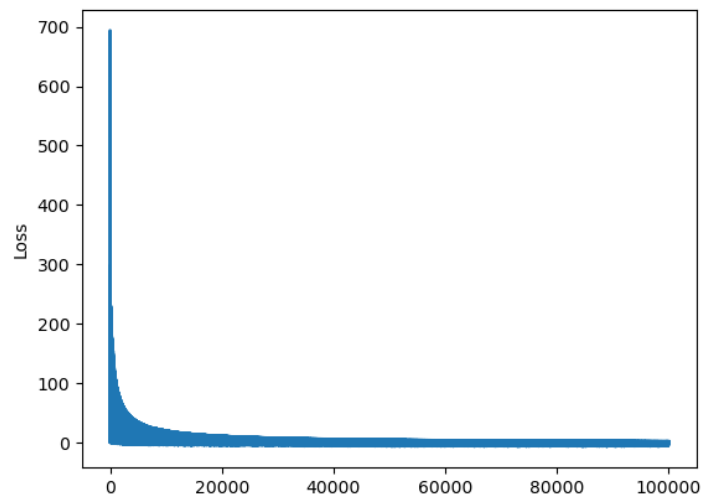
### Question4

- SVM

C	Learning Rate	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Fold 7	Fold 8	Fold 9	Fold 10	Mean	Std
1	1e-05	0.075	0.025	0.05	0.05	0.075	0.075	0.075	0	0.075	0.15	0.065	0.03741657
10	1e-05	0.075	0.05	0.05	0.05	0.075	0.075	0.075	0	0.025	0.125	0.06	0.03201562
100	1e-05	0.05	0.025	0.05	0.025	0.075	0.05	0	0	0.05	0.125	0.0575	0.03172144
1	0.0001	0.075	0.025	0.05	0.05	0.075	0.075	0.075	0	0.05	0.15	0.0625	0.0375
10	0.0001	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0	0.05	0.125	0.0525	0.02839454
100	0.0001	0.05	0.075	0.05	0.05	0.05	0.05	0.075	0	0.05	0.125	0.0575	0.02968586
1	0.001	0.05	0.025	0.025	0.05	0.1	0.075	0.075	0.05	0.075	0.15	0.0675	0.03544362
10	0.001	0.075	0.025	0.05	0.05	0.075	0.075	0.05	0	0.025	0.125	0.055	0.03316625
100	0.001	0.1	0.075	0.005	0.025	0.05	0.075	0.075	0.025	0.075	0.175	0.0725	0.041

Which value of  $\eta$  and C are optimal?

- Best  $\eta$  for **logistic regression** with eta 0.00001 and C 100: MSE is 0.02 and zero\_one loss is 0.005



According to training average loss plot, the loss keep going lower until 2000 ~ 4000 iteration. Also, the training loss is very noisy. If I using Gradient Decent, the loss will be more smoother.