

# Loss Function

$$L(y, \hat{y}) = \text{Compare}(y, \hat{y})$$

$y$  - Target

$\hat{y}$  - Prediction

**Loss Function**



**Regression**



**Classification**

# Regression

$y$	$\hat{y}$	$y - \hat{y}$	$ y - \hat{y} $	$(y - \hat{y})^2$
120	154	-34	34	1156
100	113	-13	13	169
110	107	3	3	9
			16.((6))	444.((6))

# Regression

$y$	$\hat{y}$	$y - \hat{y}$	MAE	MSE
120	154	-34	34	1156
100	113	-13	13	169
110	107	3	3	9
			16.((6))	444.((6))

If:  $y_1 - \hat{y}_1 = x$   
 $y_2 - \hat{y}_2 = 2x$

$$\text{MAE}(y_1, \hat{y}_1) = x \quad \text{MSE}(y_1, \hat{y}_1) = x^2$$

$$\text{MAE}(y_2, \hat{y}_2) = 2x \quad \text{MSE}(y_2, \hat{y}_2) = 4x^2$$



If:  $y_1 - \hat{y}_1 = x$   
 $y_2 - \hat{y}_2 = 2x$

$$\text{MSE}(y_2, \hat{y}_2) = (2x)^2 = 4x^2$$

$$\text{MSE}(y_1, \hat{y}_1) = (x)^2 = x^2$$



# Classification

(Win = 1, Loss = 0)

$L(y, \hat{y})$  = Compare categories

$y$  = True category

$\hat{y}$  = Predicted category

# Classification

((Win = 1, Loss = 0))

## Binary Cross Entropy

$$L(y, \hat{y}) \equiv -\frac{1}{n} \sum_{i=1}^n (y_i \cdot \log \hat{y}_i + (1-y_i) \cdot \log(1-\hat{y}_i))$$

Averaging for all observations



Predictions are rounded using some threshold like 0.5

$$L(y_i, \hat{y}_i) \equiv -y_i \cdot \log \hat{y}_i - (1-y_i) \cdot \log(1-\hat{y}_i)$$

$$L(1, 0.3) \equiv 1.2$$

$$L(0, 0.8) \equiv 1.61$$

$$L(1, 0.9) \equiv -1 \cdot (-0.1) - 0 \cdot (-2.3)$$

## Multi-Class Classification

$$L(y, \hat{y}) = -\frac{1}{n} \sum_{i=1}^n \sum_{j=1}^C y_{ij} \cdot \log(\hat{y}_{ij})$$

$$L(y_i, \hat{y}_i) = - \sum_{j=0}^{C-1} y_{ij} \cdot \log(\hat{y}_{ij}) =$$

$$\equiv -0 \cdot \log(0.04) - 1 \cdot \log(0.1) - 0 \cdot \log(0.86)$$

$$\equiv 2.3$$

**Note:** cross entropy is a harder topic.  
We will refer to it separately!

Ex.  $C=3$

Labels = 0, 1, 2

$y_0: [1, 0, 0]$

$y_1: [0, 1, 0]$

$y_2: [0, 0, 1]$

$\hat{y}_0 = 0.04$

$\hat{y}_1 = 0.1$

$\hat{y}_2 = 0.86$

# Categorical Cross-Entropy

↓  
Sigmoid Binary

1 ✓ Belong.  
0 - Not belong.

$$CCE = -\frac{1}{N} \sum_{i=1}^N y_i \log(\hat{y}_i)$$

Actual. (above  $y_i$ )  
Softmax. (above  $\hat{y}_i$ )  
Prediction (below  $\hat{y}_i$ )

$$\frac{\log_e .7 + \log_e .8 + \log_e .9}{3}$$

11 (+ .66)

$$= .23$$

Data Points	Class <u>X</u>	Class <u>Y</u>	Class <u>Z</u>	Actual Class
1	<u>.7</u> X	.2 X 0	.3 X 0	<u>X</u> ✓
2 —	.1 X 0	.8 X	.2 X 0	Y ✓
3	.2 X 0	.1 X 0	.9 X	<u>Z</u> ✓



# Binary Cross-Entropy (Log Loss)

$$BCE = -\frac{1}{n} \sum_{i=1}^n \left[ \overset{\substack{1,0 \\ \text{Actual}}}{y_i} \log(\overset{\text{pred.}}{\hat{y}_i}) + (1 - y_i) \log(1 - \hat{y}_i) \right]$$

$\frac{1}{n} (\ln 2)^x$   
 $\leftarrow \frac{\ln(N)}{\log_2 N}$

$1 \times \log_e(.9) + (1-0) (\log_e(1-.7))$   
 $\ln .3$

Email	Actual label	Model Prediction
<b>A</b>	<b>1 (SPAM)</b>	<b>.9</b> $\rightarrow \ln(.9) +$
<b>B</b>	<b><u>0</u> (NOT SPAM)</b>	<b>.7</b> $\ln(.3) +$
<b>C</b>	<b><u>1</u> (SPAM)</b>	<b>.4</b> $\ln(.4)$