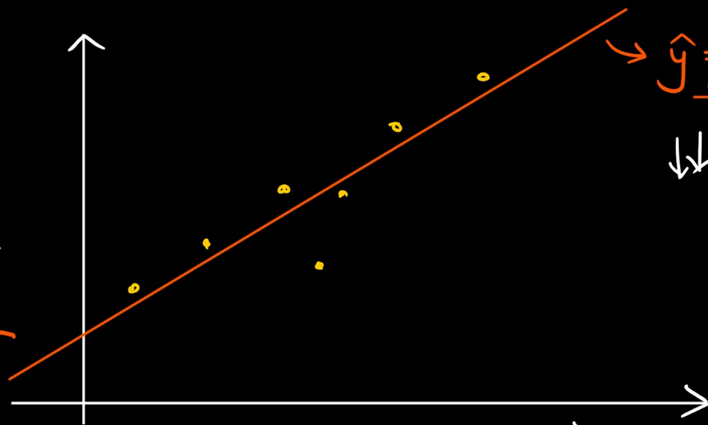
Logistic Regression → Binary classification

↓

Classification → categories → Diabetes Prediction

0 (A)

1 (B)

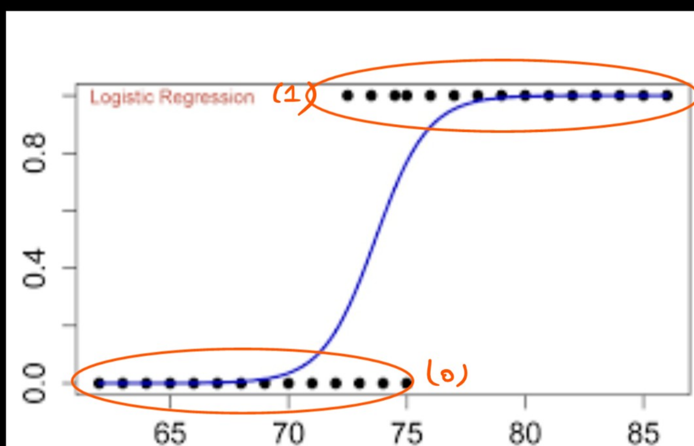


weight ↑

height →

$\hat{y} = mx + c$

$\downarrow\downarrow (y - \hat{y}) \to$ Residuals



Probability

(Binary Classification)

sigmoid activation function ⇒

$$f(z) = \frac{1}{1 + e^{-z}}$$

$$f(\hat{y}) = \frac{1}{1 + e^{-\hat{y}}}$$

$$f(\hat{y}) = \frac{1}{1 + e^{-(mx+c)}}$$

$$f(\hat{y}) = \frac{1}{1 + \frac{1}{e^{(mx+c)}}}$$

$$f(\hat{y}) = \frac{1}{\dfrac{e^{mx+c} + 1}{e^{mx+c}}}$$

$$P(A) = f(\hat{y}) = \frac{e^{mx+c}}{e^{mx+c} + 1}$$

$P(A) + P(B) = 1$

$$P(B) = 1 - P(A)$$

$$P(B) = 1 - \frac{e^{mx+c}}{e^{mx+c} + 1}$$

$$P(B) = \frac{1}{e^{(mx+c)} + 1}$$

$$\frac{P(A)}{P(B)} = \frac{\dfrac{e^{mx+c}}{\cancel{e^{mx+c} + 1}}}{\dfrac{1}{\cancel{e^{mx+c} + 1}}}$$

$$\frac{\sigma(\hat{y})}{1-\sigma(\hat{y})} = \frac{P(A)}{P(B)} = e^{mx+c}$$

$$\hat{y} = mx+c$$

$$\log_e\left(\frac{P(A)}{P(B)}\right) = \log_e e^{mx+c}$$

$$\log_e\left(\frac{P(A)}{P(B)}\right) = mx+c$$

$$\boxed{\log_e\left(\frac{P(A)}{P(B)}\right) = \hat{y}}$$

$P(A) = 0.8$
$P(B) = 0.2$

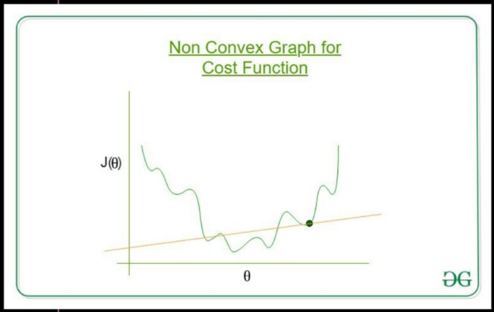
$$\hat{y} = \log_e\left(\frac{0.8}{0.2}\right) = 1.386$$

>0 —— Positive Class

$P(A) = 0.2$
$P(B) = 0.8$

$$\hat{y} = \log_e\left(\frac{0.2}{0.8}\right) = -1.386$$

<0 —— Negative Class



Cost function

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

sigmoid

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \frac{1}{1+e^{-(mx+c)}}\right)^2$$

Plot ⟶ non- Convex curve

limited to binary - classification task

log - loss function

$$Cost(\hat{y}, y) = \begin{cases} -\log_e(\hat{y}) & ; \ y = 1 \\ -\log_e(1-\hat{y}) & ; \ y = 0 \end{cases}$$

Actual Scenario ⟶ $y = 1$

Wrong Classification ⟵ $\hat{y} = 0$ ⟶ $-\log_e(0) = -\infty$

Correct Classification ⟵ $\hat{y} = 1$ ⟶ $-\log_e(1) = 0$

Actual scenario $\quad y = 0$

$\hat{y} = 0$ (correct classification)

$\hookrightarrow -\log_e(1-\hat{y}) = -\log_e(1) = 0$

$\hat{y} = 1$ (wrong classification) $= -\log_e(1-1) =$

$-\log_e(0) = \infty$

predicted value

$$\text{cost}(\hat{y}, y) = -\boxed{\sum_{i=1}^{n} y_i \log(\hat{y}_i)} - \boxed{(1-y_i)\log(1-\hat{y}_i)}$$

Actual value

$y_i = 1$

$y_i = 0$

Confusion Matrix (Binary Classification)

		Actual Values: Positive	Actual Values: Negative
Predicted Values	Positive	TP	FP
	Negative	FN	TN

Data Imbalance ← Accuracy → $\frac{TP + TN}{TP + FP + FN + TN}$

Diabetic
- 0 → 1000
- 1 → 200

Healthcare

↑↑ Recall → $\frac{TP}{TP + FN\downarrow\downarrow}$

FN →
Prediction → 0
actual → 1

Specificity → $\frac{TN}{FP + TN}$

Actual → 0
Prediction → 1

↑↑ Precision → $\frac{TP}{TP + FP\downarrow\downarrow}$

Spam email classification

$$\text{f1-Score} \Rightarrow \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$