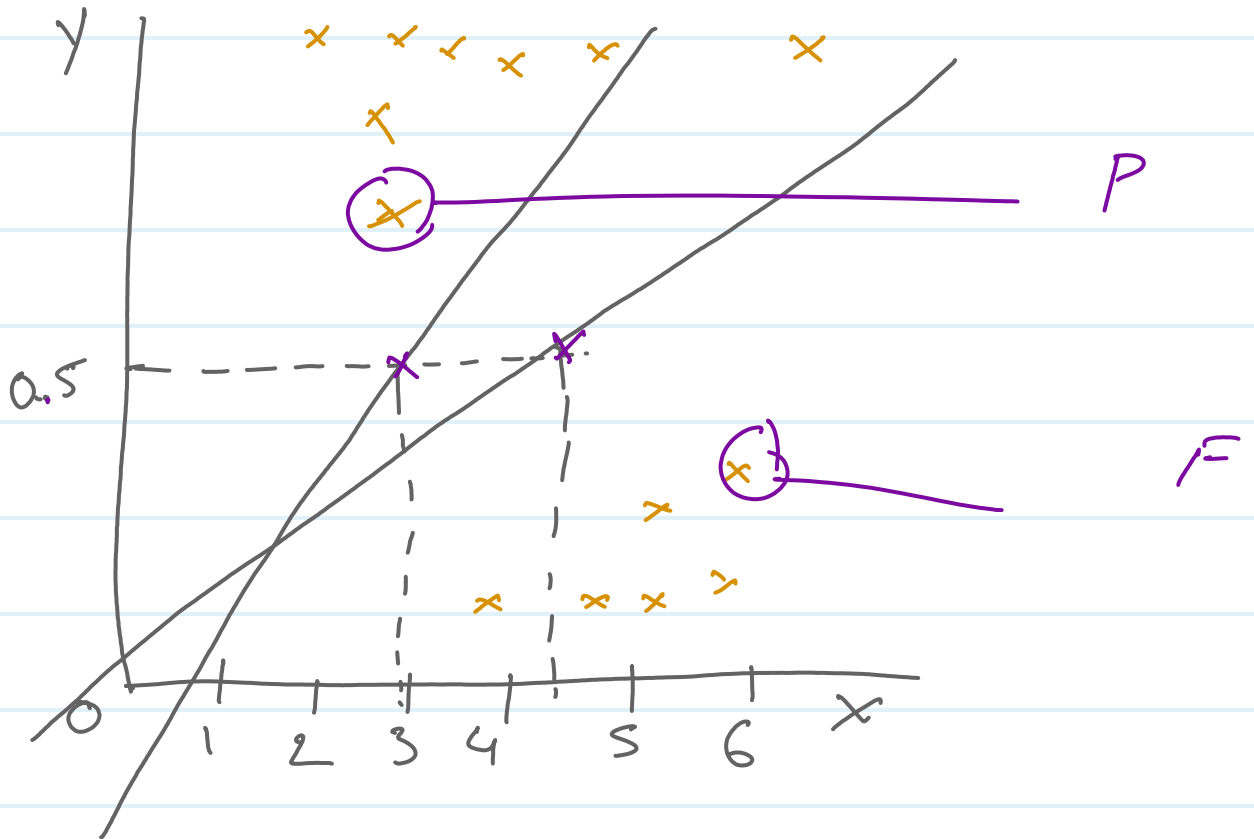


Logistic Regression



Line eqn $h_{\theta}(x) = \theta_0 + \theta_1 x$

but here we apply sigmoid function on line eqn.

Step-I $z = h_{\theta}(x) = \theta_0 + \theta_1 x$

Step-II

$$\text{Sigmoid function} = \frac{1}{1 + e^{-z}}$$

$$z = \theta_0 + \theta_1 x$$

We get always 0 and 1 value after applying this formula.

Cost function -

$$J(\theta_0, \theta_1) = \frac{1}{m} \sum_{i=1}^m [h_{\theta}(x)^{(i)} - y^{(i)}]^2$$

This is convex function of Linear Regress.



Linear Reg - one global minima

logistic - local minima

logistic cost funt -

$$J(\theta_0, \theta_1) = \frac{1}{m} \sum_{i=1}^m [h_{\theta}(x)^i - (y^i)]^2$$

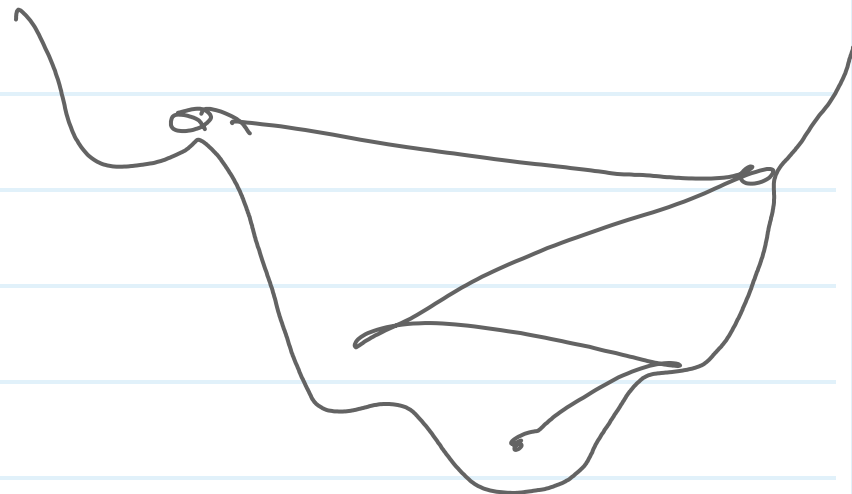
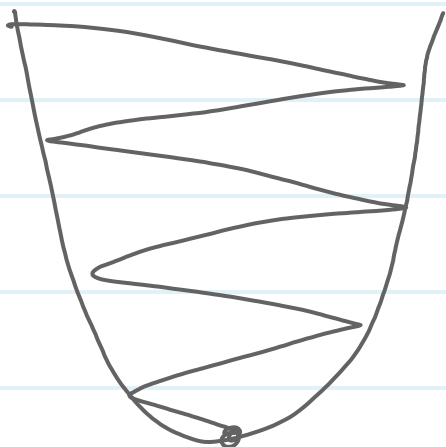
$$h_{\theta}(x) = \sigma(\theta_0 + \theta_1 x)$$

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

$$\sigma = \frac{1}{1+e^{-z}}$$

$$\frac{1}{1+e^{-z}} = \frac{1}{1+e^{-(\theta_0 + \theta_1 x)}}$$

This is non-convex function.



* Repeat Conversion theorem

$$[J = 0 \text{ and } 1]$$

$$\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$$

α is learning rate

Note - ① Logistic Regression can use for Binary or multiclass classification.

② Only solve class. problem

③ sigmoid function is key of logistic regner

④ usually it gives best model for Binary class classification.

model evaluation

Performance metrics

- ① Confusion matrix
- ② Accuracy score
- ③ Precision
- ④ Recall
- ⑤ F-Beta score

① Confusion matrix

F_1	F_2	\checkmark	\hat{x}
-	-	0	1
-	-	1	1
-	-	0	0
-	-	1	1
-	-	1	1
-	-	0	1
-	-	1	0
-	-	0	1

\hat{y} Predict
1
0

y Actual

	1	0
1	3	2
0	1	1

Y

	1	0
X	1	0
	T.P	F.P.
	0	T.N
	F.N.	

② Accuracy score! -

$$= \frac{TP + TN}{TP + FP + FN + TN}$$

$$= \frac{3 + 1}{3 + 2 + 1 + 1}$$

$$\Rightarrow \frac{4}{7} = 5.7$$

③ Precision

$$= \frac{TP}{TP + FP}$$

$$= \frac{3}{3 + 2} = \frac{3}{5} \Rightarrow 0.6$$

④ Recall

$$= \frac{TP}{TP + FN}$$

$$= \frac{3}{3 + 1} = \frac{3}{4} \Rightarrow 0.75$$

⑤ F-Beta Score

$$= \frac{(1 - \beta^2) \times \text{Precision} \times \text{Recall}}{\beta^2 \times (\text{Precision} + \text{Recall})}$$

① If F_P and F_N both are imp

$$\beta = 1$$

$$\begin{aligned} F_1 \text{ score} &= \frac{(1 + \beta) \times P \times R}{\beta^2 \times (P + R)} \\ &= \frac{(1 + 1) \times 0.6 \times 0.75}{1^2 \times (0.6 + 0.75)} \\ &= \frac{2 \times 0.45}{1.35} \\ &= 0.33 \end{aligned}$$

② If F_P is more imp. than F_N

$$\beta = 0.5$$

$$\begin{aligned} &= \frac{[1 + (0.5)^2] \times 0.6 \times 0.75}{(0.5)^2 \times (0.6 + 0.75)} \\ &= \frac{(1 + 0.25) \times 0.45}{0.25 \times 1.35} \end{aligned}$$

$$\Rightarrow \frac{0.5625}{0.3375}$$

$$\Rightarrow 1.66$$

(ii) If FN is more imp. FP

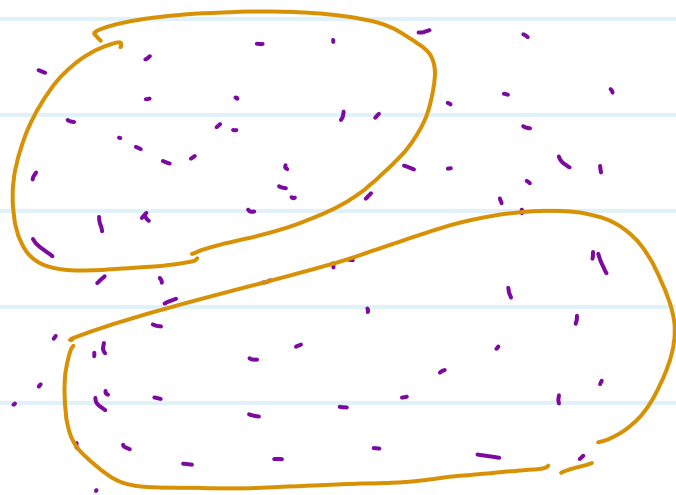
$$\beta = \lambda$$

$$= \frac{1 + 4(p \times R)}{4 \times (p + R)}$$

$$=$$

* Unsupervised ML

* K-mean clustering



It is centroid based clustering

Height weight

185 72

170 56

168 60

179 68

182 72

188 77

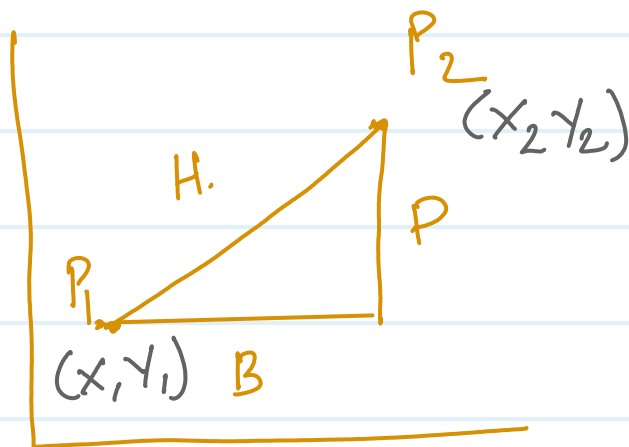
180 71

160 70

183 84

180 88

167 76





$$AC^2 = \sqrt{AB^2 + BC^2}$$

formula

$$D(P_1, P_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

* Important point

① centroid ~

② Distance ~

③ mean ~

Step-① Random centroid. choose

2-centroid

① 185 - 72

② 170 - 56

Step ②

3rd

C_1

C_2

3rd

$(185, 72)$

$(170, 56)$

$(168, 60)$

$$D(C_1, 3^{\text{rd}}) = \sqrt{(168 - 185)^2 + (60 - 72)^2}$$

$$= 20.80$$

$$D(C_2, 3^{\text{rd}}) = \sqrt{(168 - 170)^2 + (60 - 56)^2}$$

$$= \underline{\underline{4.4}}$$

3rd point distance is less for $C-2$, so it will belong to $C-2$

$C-2$ update

$$C_2 = \frac{170 + 168}{2}, \frac{60 + 56}{2}$$

$$C_2 = (169, 58)$$

$$\underline{\underline{4^{th}}} = (179, 68)$$

$$\begin{aligned} D(C_1, 4^{th}) &= \sqrt{(179-185)^2 + (68-72)^2} \\ &= \sqrt{36+16} \\ &= 7.21 // \end{aligned}$$

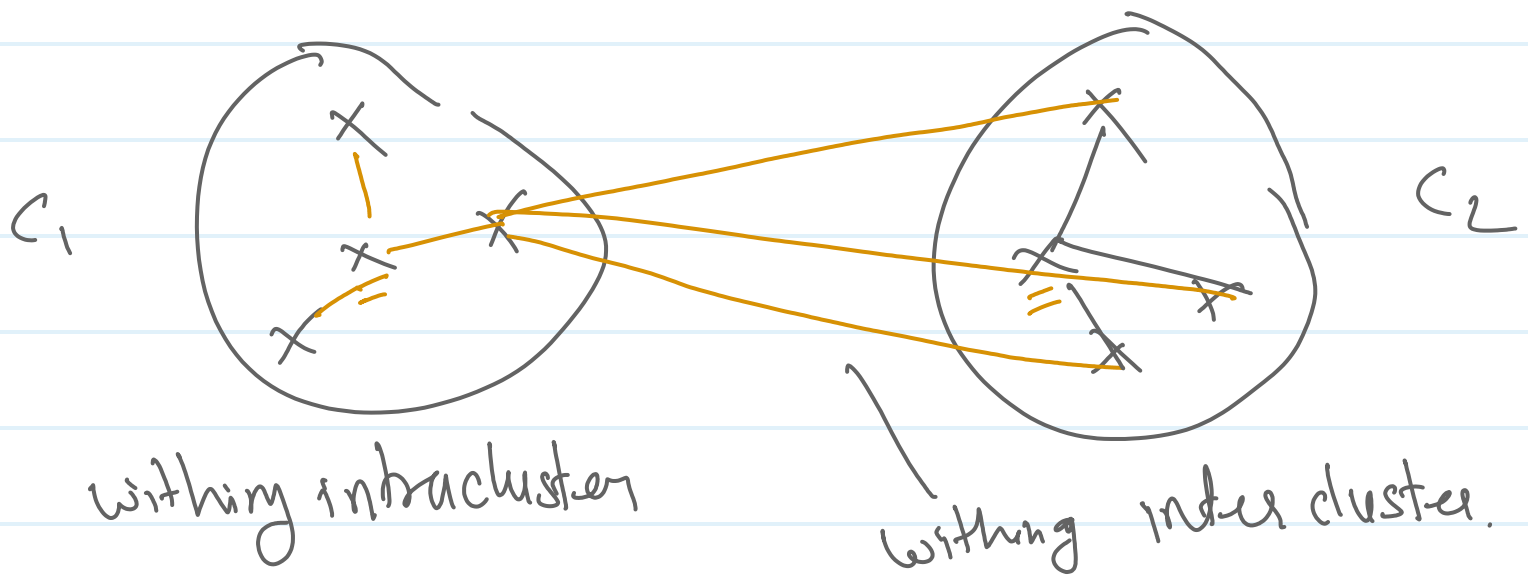
$$\begin{aligned} D(C_2, 4^{th}) &= \sqrt{(179-169)^2 + (68-58)^2} \\ &= \sqrt{(10)^2 + (10)^2} \\ &= \sqrt{200} \\ &\Rightarrow 14.14 \end{aligned}$$

4th point since distance is less for C-1 so it belong to C-1

C_1 - update

$$C_1 = \frac{185+169}{2}, \frac{72+58}{2}$$

$$C_1 \Rightarrow (177, 70)$$



★ model evaluation

- ① Dunn Indexing
- ② Silhout score.

① Dunn Indexing -

$$= \frac{\max \text{dist. } (x_i, x_j)}{\max \text{dist } (y_i, y_j)}$$

② Silhout score

$$= \frac{b_i - a_i}{\max(b_i - a_i)}$$

a_i = within same cluster (Intra)

b_i = within other cluster (Inter)

Range of Silhouette score

-1 to +1

↑
worst

↑
best