20/3/24

43. # Logistic Regression

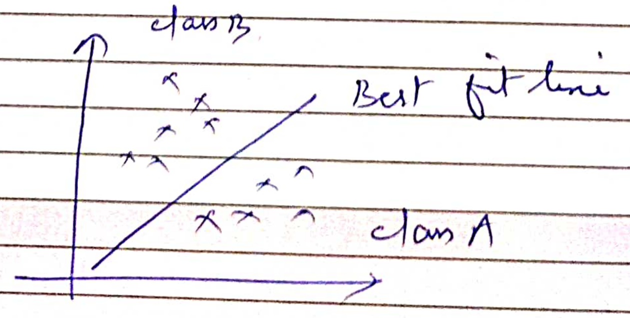
we used this algo for classification.

ML → supervised ML → Regression
supervised ML → classification → target col → categorical col
(1) binary category
(2) multiclass category
ML → unsupervised ML

most of the time we use logistic reg for binary category & for multiclass category we have a method called OVR. (One vs Rest)

study time	Pass or Fail (1 ← → 0)
0	0
1	0
2	0
3	0
4	1
5	1
6	0
7	0
8	1
9	1

we have 2 class pass or fail
∴ it is binary category



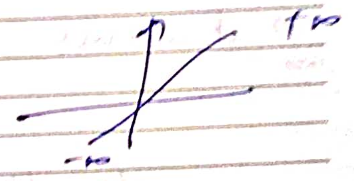
why linear reg is not used?

Ans ① outlier - if my line little bit is going to deviate in that case it will be a major impact on accuracy.

② in linear reg we have numeric value lies from $-\infty$ to $+\infty$.

but in classification eg:- (0,1), (0,1,2, ... n)
we can apply linear reg by having threshold value but it will impact our accuracy. as it has range of $(-\infty, +\infty)$ so we can pass it to sigmoid fun which will squash the value.

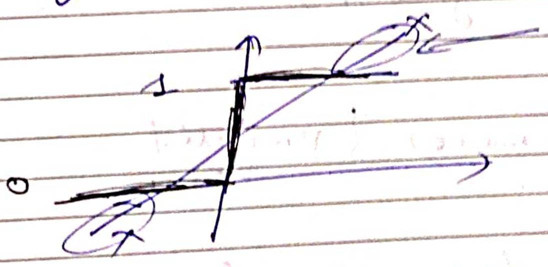
$y = mx + c \Rightarrow [-\infty, +\infty]$



$\Downarrow$

sigmoid

$sig(y) \Rightarrow (0, 1]$



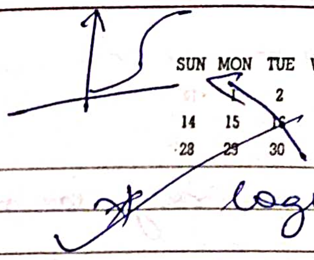
infinite take nahi jayega

$$\text{sigmoid fun} = \frac{1}{1+e^{-x}}$$

$$= \frac{1}{1+e^{-(mx+c)}} \Rightarrow (0,1]$$

logistic reg

SUN	MON	TUE	WED	THU	FRI	SAT	SUN	MON	TUE	WED	THU
	1	2	3	4	5	6	7	8	9	10	11
14	15	16	17	18	19	20	21	22	23	24	25
28	29	30	31								



09.00 linear reg. — logistic reg.

10.00 $f(x) = \frac{1}{n} \sum_{i=1}^{n} (y - \hat{y})^2$ — $f(x) = \frac{1}{n} \sum_{i=1}^{n} (y - \hat{y})^2$

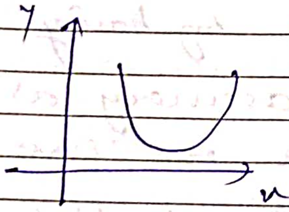
11.00 $\hat{y} = mx + c$ — $\hat{y} = \frac{1}{1+e^{-x}}$

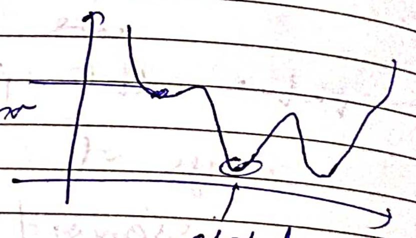
12.00 $= \frac{1}{1+e^{-(mx+c)}}$

13.00 Eg for x^2

14.00

15.00





16.00

17.00

→ it will use loss fun. — → it will use log loss fun

18.00

log loss fun.

$$\boxed{f(x) = y_i \log(\hat{y}_i) - (1 - y_i) \log(1 - \hat{y}_i)}$$

parabola curve

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

Value range from (0 - 1)

y_i = actual value.

if $y_i = 1$ we will get $-\log(1-\hat{y})$

$y_i = 0$ " " " $-\log(\hat{y})$

conversion theorem

$$m_{new} = m_{old} - \eta \frac{\partial L}{\partial m} \leftarrow \text{loss fun. derivative}$$

$$= m_{old} - \eta \frac{\partial \text{ log loss}}{\partial m}$$

L_1 = logloss + lasso reg penalty $\lambda|m|$

L_2 = logloss + Ridge reg $\lambda(m)^2$

Elastic = logloss + $(L_1 + L_2)$ $\lambda|m| + \lambda(m)^2$

Logit Function?

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x$$