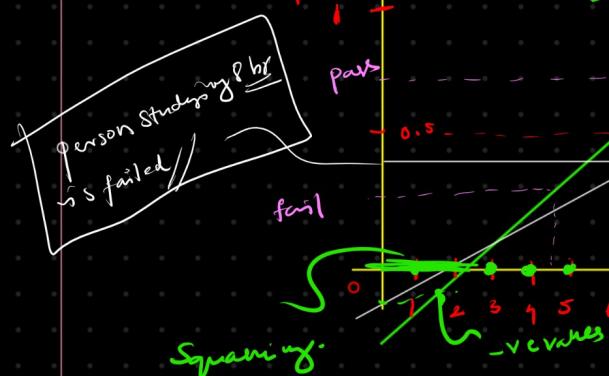


Logistic Regression (Binary classification)

* can linear regression solve binary classification.



Squaring

* But when we introduce any new datapoint or outliers from our best fit line will change

* how if we'll predict using the new best fit line the output will not be the same.

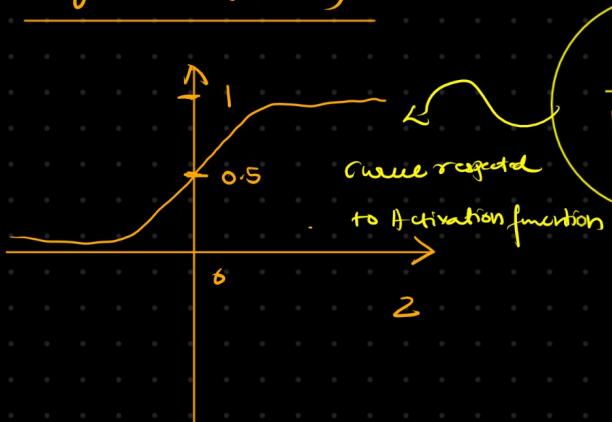
study hours	result
1 hour	fail
3 hours	fail
4 hours	fail
5 hours	fail
6 hours	pass
8 hours	pass
12 hours	pass

Let's say we

have this dataset
try to solve this
using linear
regression.

* why we can't use
+ outliers (best fit line
changes)

Sigmoid activation



curve regarded
to Activation function

$$\frac{1}{1+e^{-x}}$$

* we gonna use this to squash the
the best fit line

* we create best fit line upon that
we gonna apply sigmoid function

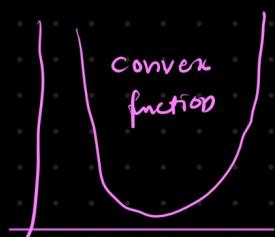
$$h_{\theta}(x) = \sigma(\theta_0 + \theta_1 x)$$

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

logistic regression
hypothesis

Linear regression cost function

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=0}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$



convex
function

logistic Regression Cf

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=0}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

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

non convex function

global minimum

local minimum

the θ will be
stagnant at here
 $\rightarrow \theta$ will not move

Convergence algorithms

Repeat

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

↓
So we use log loss

$$Cost(h_\theta(x^{(i)}), y^{(i)}) = \begin{cases} -\log h_\theta(x) & \text{if } y=1 \\ -\log(1-h_\theta(x)) & \text{if } y=0 \end{cases}$$

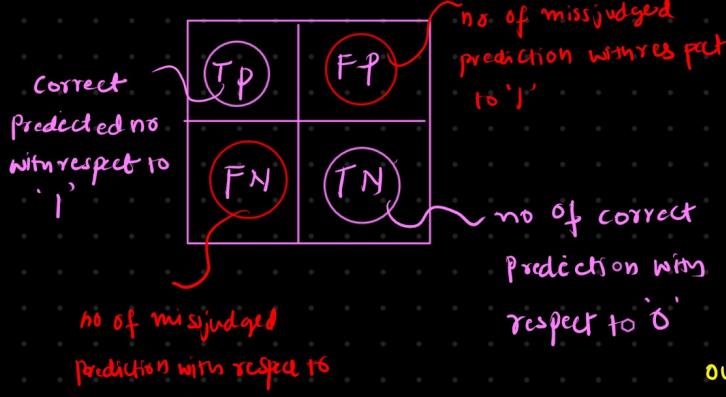
$$\text{log loss} = -\frac{1}{N} \sum_{i=1}^N [y_i \log h_\theta(x) + (1-y_i) \log(1-h_\theta(x))]$$

convex function //

Performance metrics

① Confusion matrix

		actual values	
		1	0
predicted values	1	2	2
	0	2	1



dataset

—
—
—
—
—
—
—
—
—

y
○
○
1
1
0
1
1
1

\hat{y}
1
1
1
0
0
0
0
1

95
5

accuracy

$$\text{accuracy} = \frac{T_p + T_n}{T_p + F_p + F_n + T_n}$$

correct predictions //
total predictions //

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

$$\text{accuracy} = \frac{3}{7}$$

② Precision & recall

Dataset

→ 1000 datapoints
↓

900 - (1)
100 - (0)

imbalanced
dataset.

how if we calculate

$$\text{accuracy} = 90.1$$

$$\text{Accuracy} \rightarrow \frac{T_n + T_p}{T_n + F_n + F_p + T_p}$$

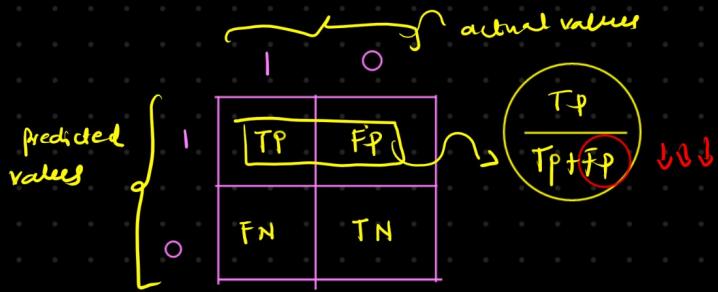
$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

out of all the actual values how many are predicted right

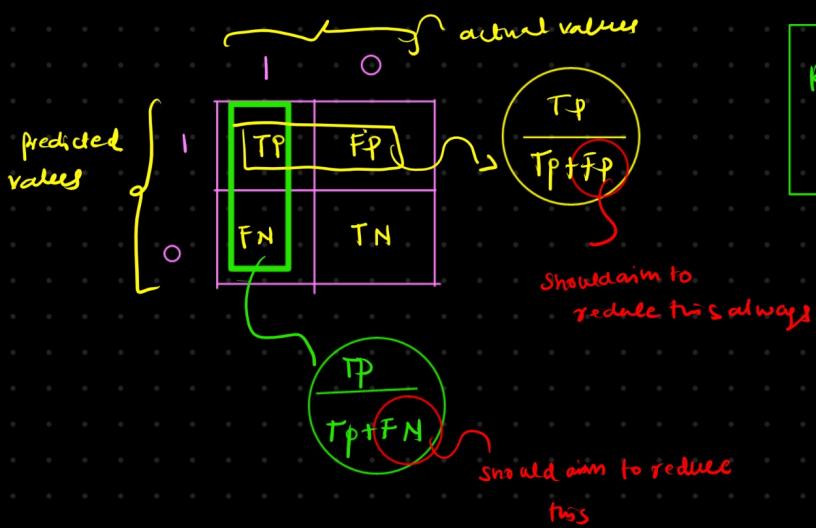
$\text{To.} = \frac{\text{900}}{1000}$

So the model consider predicting 0 is an error because it is not trained on 0's much

so, we use precision



ii) recall



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

out of all the predicted values how many were right,

use case

tomorrow my stock will crash or not

		crash	not crash
crash	crash	TP	FP
	not crash	FN	TN
			<u>Recall</u>

$$3. F\text{-beta score} : (1+\beta^2) \frac{\text{Precision} + \text{Recall}}{\text{Precision} + \text{Recall}}$$

→ if both F_p & F_N is important

$$\boxed{F\text{score} = 2 \times \frac{\text{Precision} + \text{Recall}}{\text{Precision} + \text{Recall}}}$$

→ if F_p is more important

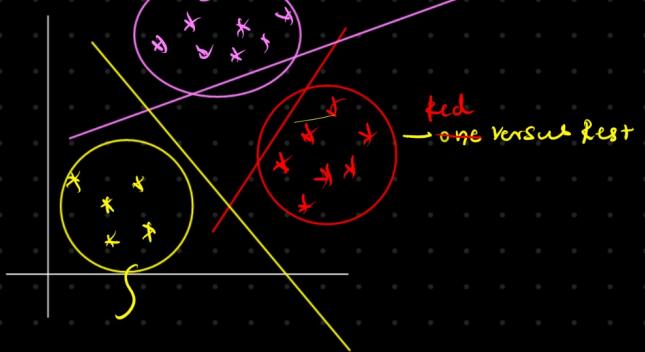
$$\boxed{F_{0.5}\text{ score} = (1+0.25) \frac{P \times R}{P + R}}$$

→ if F_N is important.

$$\boxed{F_2\text{ score} = (1+4) \frac{P \times R}{P + R}}$$

purple versus test

diagnostic regression (one versus rest) [OVR]



f_1	f_2	f_3	output	O_1	O_2	D_3
—	—	—	O_1	1	0	0
—	—	—	O_2	0	1	0
—	—	—	O_3	0	0	1
—	—	—	O_2	0	1	0
—	—	—	O_1	1	0	0

on new test data

$$M_1 = 0.25$$

$$M_2 = 0.20$$

$$M_3 = 0.55$$

$$p(0.25, 0.20, 0.55) \rightarrow M_3 \text{ output //}$$

Onch O+
Oday.

ROC and AUC

threshold-values = [0, 0.2, 0.4, 0.6, 0.8]

* what is the threshold ?? (Based on the project)

output y	\hat{y}_{prob}	$\hat{y}(0)$	$\hat{y}(0.2)$
1	0.8	1	1
0	0.96	1	1
1	0.4	1	1
1	0.3	1	1
0	0.2	1	0
1	0.7	1	1

$$\text{True-positive-Rate} = \frac{TP}{TP + FN}$$

$$\text{False-positive-Rate} = \frac{FP}{FP + TN}$$

↳

* based on this we will plot the graph

