→ Logistic Regression

Reg / Class
cont / discrete
↓
binary

Agenda

linear → what ✓
how → line best-fit ✓
implement ✓

↓

logistic → analogous

↳ ✓
↳ ✓

classes
week
labels
target
→ 0 or 1

doubt/clear

image → truck, cars —

use-case? housing loan → bank → who?

0 1

NPA

~~mcum~~

← CIBIL →

58 → ~~60~~

what has user history → history repeats itself

age income credit baddebt

$\underbrace{\text{age} \quad \text{income}}_{\text{cont}}$ $\underbrace{\text{credit} \quad \text{baddebt}}_{\text{categorical}}$

CT	target
–	0 ✓
–	1: def
–	0
–	1

analogous

credit → month pay pay bill

100

bill x_1	x_2 pay	y_1 CT	target	thresh
		$\frac{\text{pay}}{\text{bill}}$ →	1	$> 0.5 \Rightarrow 0$
		0 to 1	categorical	$< 0.5 \Rightarrow 1$

target

$(-\alpha, +\alpha)$

analogous

CT → Linear reg

$$\boxed{y_1 = \beta_0 + \beta_1 x_1 + \beta_2 x_2 - - - \beta_{100} x_{100}}$$

$\Downarrow$ transform

categorical

CF

Prob Brand — 0.3 = p

NF — 0.7 = $1-p$

cont

linear $z = \sum_{i=0}^{n} \beta_i x_i$ → sigmoid f^n $x_0 = 1$

Prob $y = \dfrac{1}{1+e^{-z}}$ $z = -\infty$ to $+\infty$

class A → +ve $\dfrac{1}{1+e^{\infty}} = 0$ $1 = \dfrac{1}{1+e^{-\infty}}$

class B → −ve

$$\log\left(\frac{p}{1-p}\right) = z \qquad \mathbb{R}$$

$$\frac{p}{1-p} = e^{z} \Rightarrow \frac{1-p}{p} = e^{-z}$$

$$= \frac{1}{p} - 1 = e^{-z}$$

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

$$\frac{1}{1 + \frac{1}{e^{z}}}$$

$$\frac{e^{z}}{1+e^{z}} \qquad \Rightarrow p = \frac{1}{1+e^{-z}}$$

fraudulent txn → +ve — business

-ve

p =

model → +ve class

sigmoid

$1-p$ — -ve class

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

x_{100}

0
1
0
0
0
0
1

$$\boxed{\log\left(\frac{p}{1-p}\right) = z}$$

-ve class

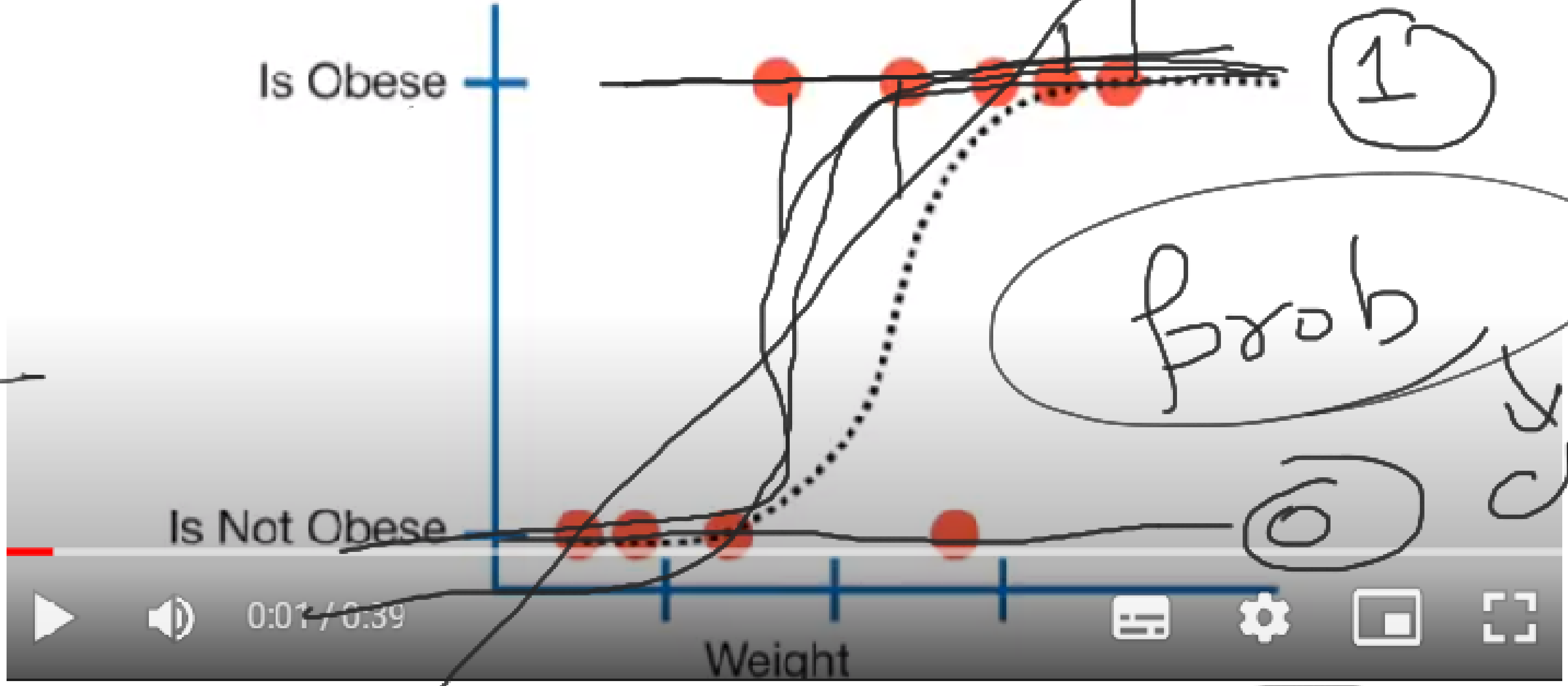
$1-p$

logit

cancer → +ve

fraud analytics

Logistic Regression



1

0

Prob

classifica

1 → trueclass

B Prob

~~cont 20~~

Linear reg

$z = -\infty, \infty$

$z = \sum w_i x_i$ → linear reg

$(0, 1)$

$\hat{y} = \frac{1}{1+e^{-z}}$ → sigmoid

$\frac{1}{\infty}$

0

$\hat{y} = \frac{1}{1+e^{-\infty}} \to 0$ $= 1$

$z = \infty$

$z = -\infty$

$> 0.5 = 1$

$< 0.5 = 0$

major

$$\Sigma(y_i - \hat{y}_i)^2$$

$(y - \hat{y})^2$ → penalize higher var

best

(p) + $(1-p)$ ← care

"y" $(1-y)$ → actual class ← care

care

CF

MLE

$$CF = \Sigma\, y_i \log p_i + (1-y_i)\log(1-p_i)$$

cost f^n

CF ↓ (0 - 1) $p < 1$

$$\downarrow CF = \sum \left[\underbrace{y_i \log(p_i)}_{I} + \underbrace{(1 - y_i)\log(1 - p_i)}_{II} \right] \quad (p_i)$$

	y_i	y_p	p_i
A ✓ ⇒	1 ⟷	1	
II B × ⇒	0 ⟷	1	$p_i \uparrow$
C × ⇒	1 ⟷	0	$1 - p_i \downarrow$
D ✓ ⇒	0	0	$p_i \downarrow$

A → more -ve → good ✓ ⇓

D → more -ve → good ✓ ⇓

B ⇒ less -ve → penalizing ✓

C → less -ve → penalizing

$(1 - p_i) \uparrow$

$$\ell(w) = \sum_{i=1}^{N} y_i log(h_w(x_i)) + (1 - y_i) log(1 - h_w(x_i))$$

$$= \sum_{i=1}^{N} y_i log(\frac{1}{1 + e^{-w^T x_i}}) + (1 - y_i) log(\frac{e^{-w^T x_i}}{1 + e^{-w^T x_i}})$$

$$= \sum_{i=1}^{N} -y_i log(1 + e^{-w^T x_i}) + (1 - y_i)(-w^T x_i - log(1 + e^{-w^T x_i}))$$

$$= \boxed{\sum_{i=1}^{N} (y_i - 1)(w^T x_i) - log(1 + e^{-w^T x_i})}$$

$log\left(\frac{e^{-z}}{1+e^{-z}}\right)$

$log\, e^{-z}$

$- log(1+$

$(y_i - 1)z - log(1+e^{-z}$

$W_i = W_i + \alpha \frac{\partial L}{\partial W_i}$

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \longrightarrow p = \frac{1}{1+e^{-z}}$$

$$\frac{\partial \ell(w)}{\partial w_j} = \sum_{i=1}^{N} (x_{ij}) \left(y_i - \frac{1}{1 + e^{-w^T x_i}} \right)$$

$$\sum_{i=1}^{n} \left(y - \left(\beta_0 + \beta_1 X \right) \right) . X$$

1000 $\xrightarrow{80:20}$ train 800 test 200

least error

train

$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2$

GD

.fit(feature, target)

parameters

.pred(f-ey

y_pred

$y = mx + c$

linear

Logisi

X_train

pred train → .pred(X-train) → brain train

pred test → .pred(X-test) → pre

Rewind → train — ~~test~~ answer target

100

80 → 20 → Pre board ⇒ Boards

generalize

train brain

100%

~~mug~~

~~Loss~~

~~student~~

never!

??

Real data

Best ⇒ lifetime

BEST!

---

what? Evaluation metric → % marks

question ✓

0

1

~~Loss~~

Regression

test

train

R^2, adj R^2, mse, mae, mape — class

~~search~~

EM

-ve → 0
+ve → 1

bias

act pred

1	1	✓	50
0	1	×	5
1	0	×	20
0	0	✓	25

act pred

accuracy = How many correct / Total datapt

0/1

0/1

1000

test

100 → act

+ve	-ve
70	30

50	20	25	5
pred +ve	-ve	-ve	+ve

target

-ve
+ve

Mon

use case

actual	pred
70 (1)	50 – +ve
	20 – -ve
30 (0)	25 → -ve
	5 → +ve

accuracy

$\frac{50+25}{100}$

Class → 0 | 1

confusion

Predict

Actual	Predicted 0	Predicted 1
Actual 0	TN	FP
Actual 1	FN	TP

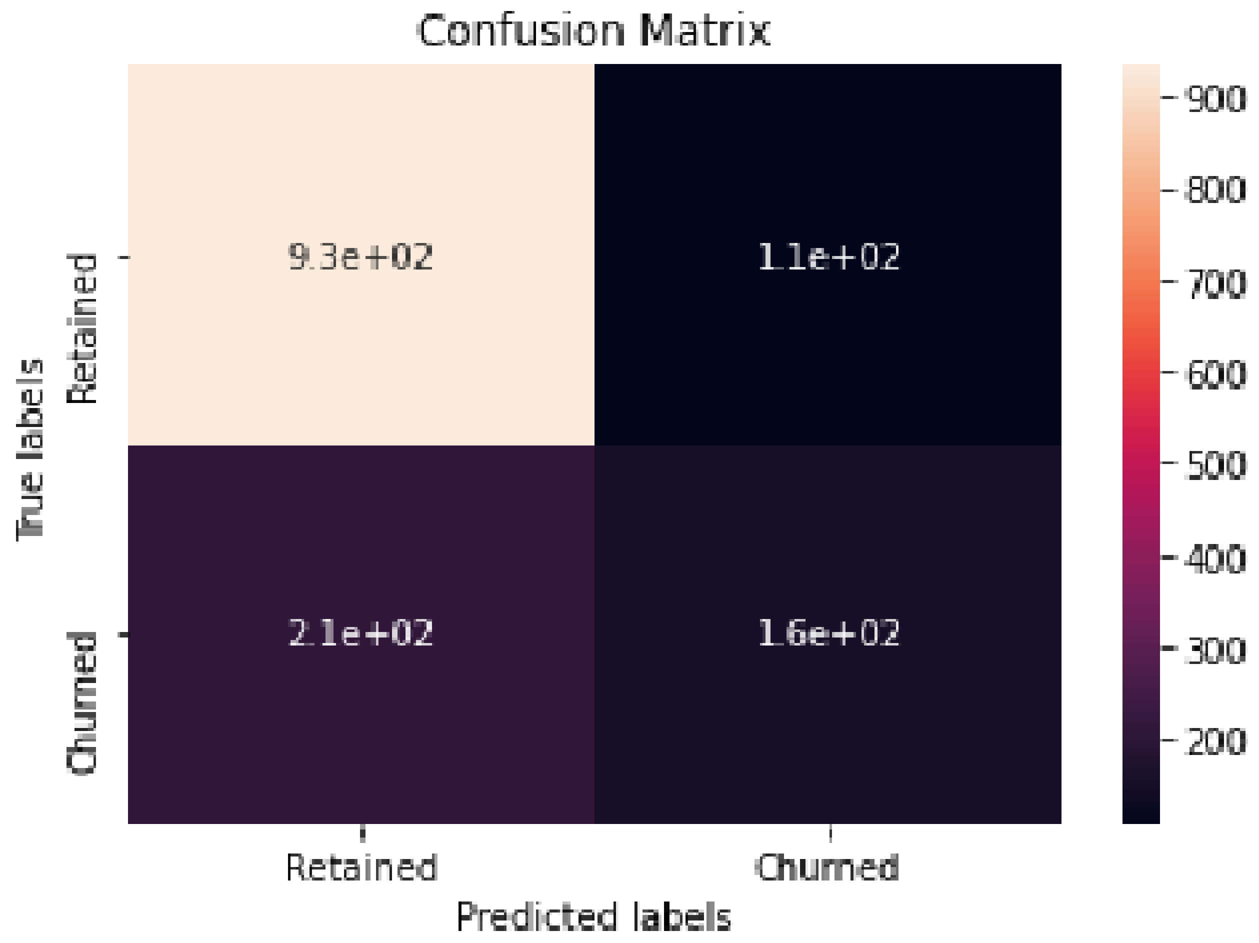
$\frac{T / F}{4}$ P / N

wrdu

predicted class model

+ve / -ve

0 → -ve



Actual

Pred	0	1
0	TN	FN
1	FP	TP

T/F

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

Is pred ✓/✗

T F

Pred ?

EM → Accuracy

FN

$P/(1-P)$

Precision

Precise are we in pred +ve

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

Metric

Recall

out of actual +ve how many recall success

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

	Predicted 0	Predicted 1
Actual 0	TN	FP
Actual 1	FN	TP

luv → $\frac{1}{1000}$

IITJEE

score

Model → % accuracy $\frac{\text{right}}{\text{attempt}}$

Model

EM train ⇒ EM test → under done

	Predicted 0 -ve	Predicted 1 +ve
Actual 0 -ve	TN	FP
Actual 1 +ve	FN	TP

Precision

↓ train

↓ test

underfit

↑ train

↓ test

Overfit

P, R

Actual +ve class

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

error

$$\frac{1}{F1} = \frac{\frac{1}{P} + \frac{1}{R}}{2}$$

$$F1 = \frac{2PR}{P + R}$$