

Logistic reg

Approximations \rightarrow Mean \uparrow SSE \uparrow Best fit line
 SSE

Can I do better? \rightarrow Non-parametric (dogs vs cats)
 KNN (discrete prediction)
 (repeated class based discrete values)
 (real numbers) Continuous (Assumption) $(-\infty, \infty)$
 Logistic Regression (parametric method) $(0,1)$

9:26:

discrete values?

0 or 1

converting into probab.

0 \rightarrow Loss
 1 \rightarrow Win

odds of cricket

Team \Rightarrow 1002 matches
 won = 559 matches
 lost = 443 matches
 (∞ to ∞)

odds \Rightarrow $\frac{\text{No. of wins}}{\text{No. of defeats}}$

ratios of some event happen k Not

$\frac{559}{443} = 1.26$ happen.

$\rightarrow 0 \rightarrow \infty$

far away

10000

non-favourable

Probability
favourable

Total
Non + fav

$y \Rightarrow 0 \rightarrow 1$

Odds

Probability of a team
winning
Probability of a team
losing

$(-\infty, +\infty)$
 $\log(\text{odds})$
 $(0, \infty)$
 $\log(\text{odds})$ odds

$(0, 1)$
probability

Constrained

$(-\infty, +\infty) \rightarrow (0, \infty) \rightarrow (0, 1)$
inverse of $\log(e)$ $(-\infty, +\infty)$

$(-\infty, +\infty)$
max

$e \rightarrow (0, \infty)$

$\frac{e^{\text{predict}}}{e^{\text{pred}} + 1}$
 $[0, 0.001, 0.02, 0.2, 0.5, 1]$

$(-\infty, +\infty)$
 $[-300, -200, -100, 0, 100, 200, 300]$

1



$$y = mx + c = 0$$

$$\frac{1}{1+e^{-y}} = 0.5$$

Predict of probab. = $\frac{e^y}{1+e^y}$

$$\Rightarrow \frac{1}{1+e^{-y}}$$

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

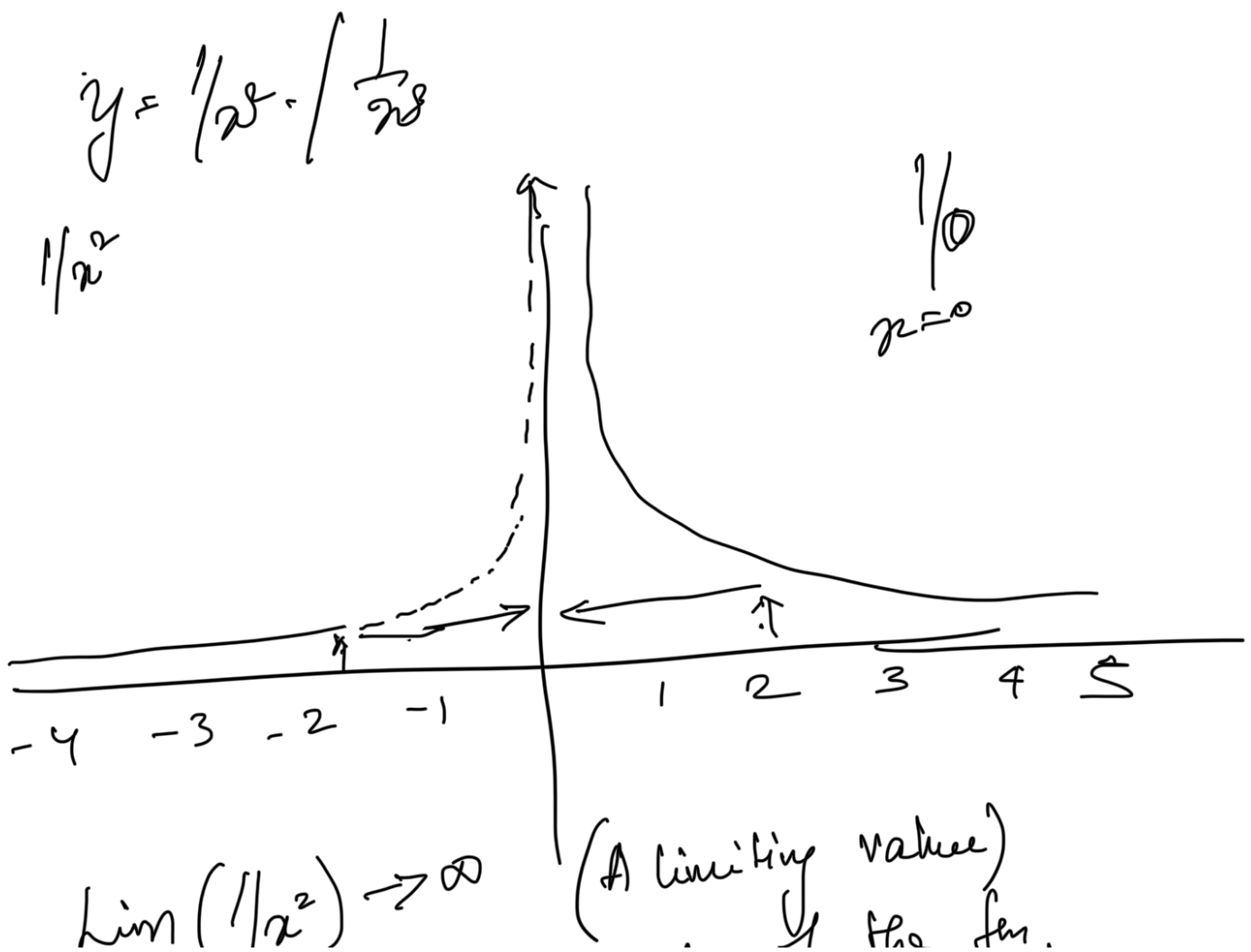
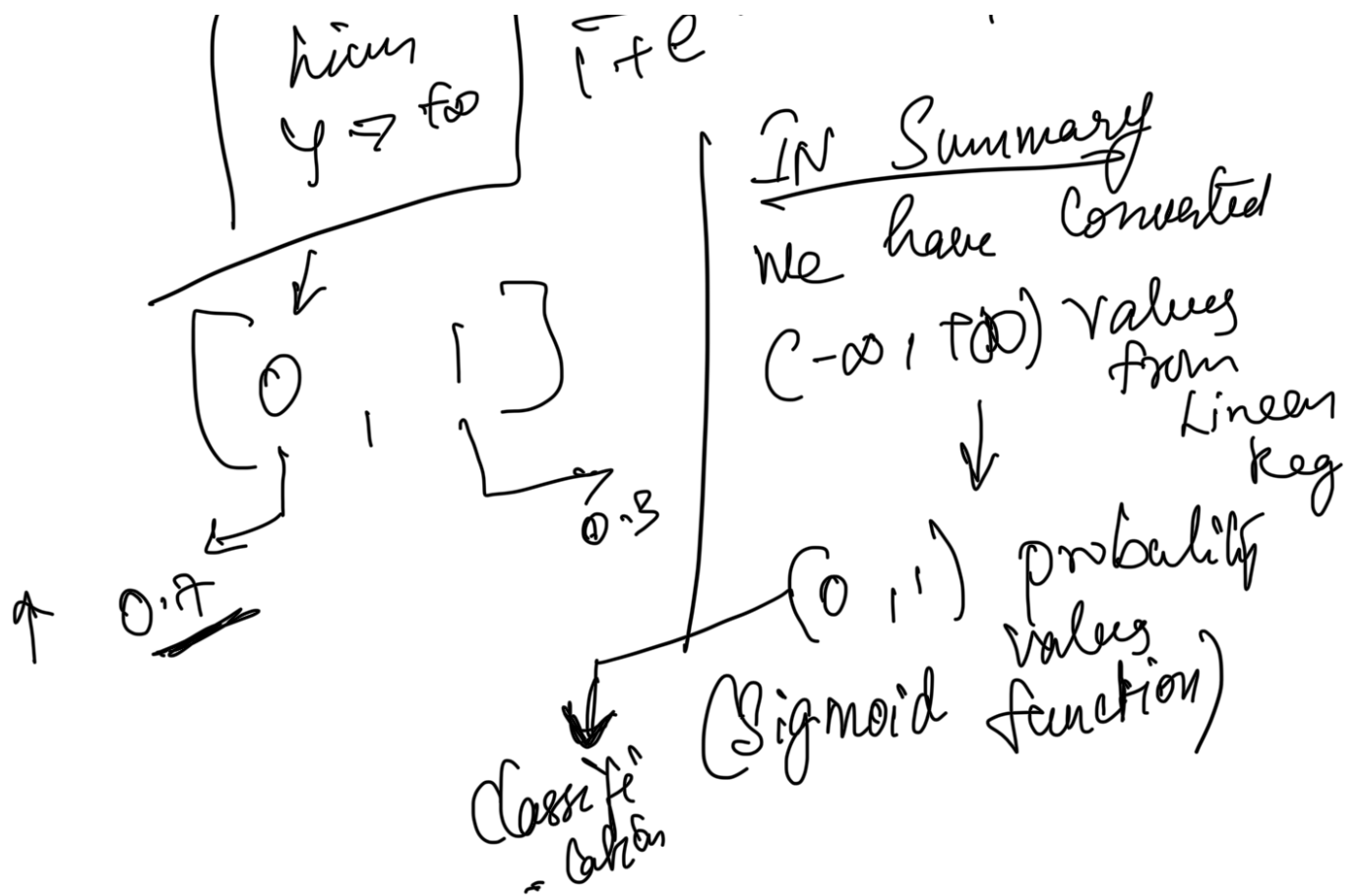
$$\sigma(-4) = \frac{1}{1+e^{-(-4)}} = \frac{1}{1+e^4}$$

$$\rightarrow 0.0179$$

~~Ex~~ $\lim_{y \rightarrow -\infty} \sigma(y) = \frac{1}{1+e^{-(-\infty)}} = \frac{1}{1+e^{\infty}}$

$$= 0$$

$\frac{1}{1+\infty} \Rightarrow \frac{1}{\infty} = 0$



$x \rightarrow 0$

the val. of y appears to a
as y_p partic. m

① loss function??

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m \text{cost}(\hat{y}_i, y_i)$$

Common Error

Class wise Error term

0 - 1 \Rightarrow 0.89 ↓

8000 / 8000

Requirements

① Classwise loss

② Blow up if its wrong
 ↳ reduce if predicts right

$y=0$

y	\hat{y}	loss
0	0	
0	1	

$\log(1-\hat{y})$

loss
 $y=0 \quad \hat{y}=0 \quad 0$
 $y=0 \quad \hat{y}(1) = 1 \uparrow$

Case 1

1 - 1 - 0

1 - 1 - 1

$$\begin{array}{l|l}
 y=0 & y=1 \\
 \hline
 \hat{y}=0 \Rightarrow \log(1-0) = 0 & -\log(1-0) \\
 \hat{y}=1 \Rightarrow \log(1-1) = -\infty & -\log(1-\hat{y})
 \end{array}$$

Can 2

$$\begin{array}{c}
 \downarrow \\
 (y=1 \Rightarrow \log(1) \Rightarrow -\log(\hat{y})) \\
 \downarrow \\
 - (y \log(\hat{y}) + (1-y) \log(1-\hat{y}))
 \end{array}$$

log loss

$$-\frac{1}{n} \sum_{i=0}^n [y_i \log(\hat{y}_i) + (1-y_i) \log(1-\hat{y}_i)]$$

Quantitative Metric Done !!!
Binary Cross Entropy (log loss)

Qualitative Metrics

		500	
		250/0	250/1
Actual		200/1	225/1
		50/0	25/1
Predicted	0	① 200	② 25
	1	③ 50	④ 225

Confusion Matrix \Rightarrow diagonal are all Correct preds

		Actual	
		Positive +ve	-ve
Predicted	Positive +ve	TP	FP
	Negative -ve	FN	TN

TP - True +ve
TN - True -ve

Accuracy of my model $= \frac{TP + TN}{FP + TP + FN + TN}$

Positive (1) Precision $= \frac{TP}{TP + FP}$

Negative (2) $= \frac{TN}{TN + FN}$

Sensitivity True $=$ Recall $= \frac{TP}{TP + FN}$ (TP Rate)

Specificity -ve $= \frac{TN}{TN + FP}$ (True Negative Rate)

F_1 - Score $= \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}$

Learn 1

A

Pred

Cat

