

Regularization :-

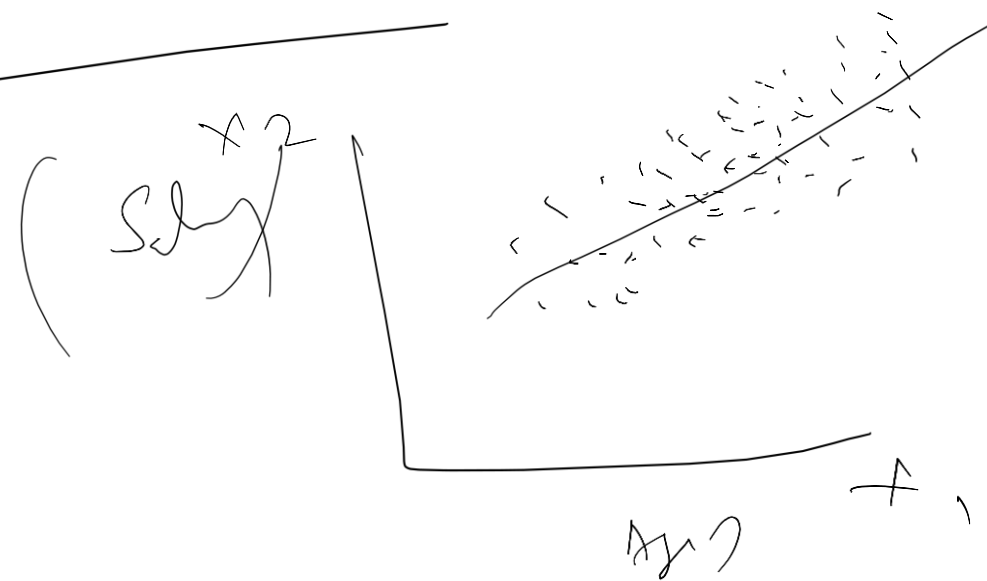
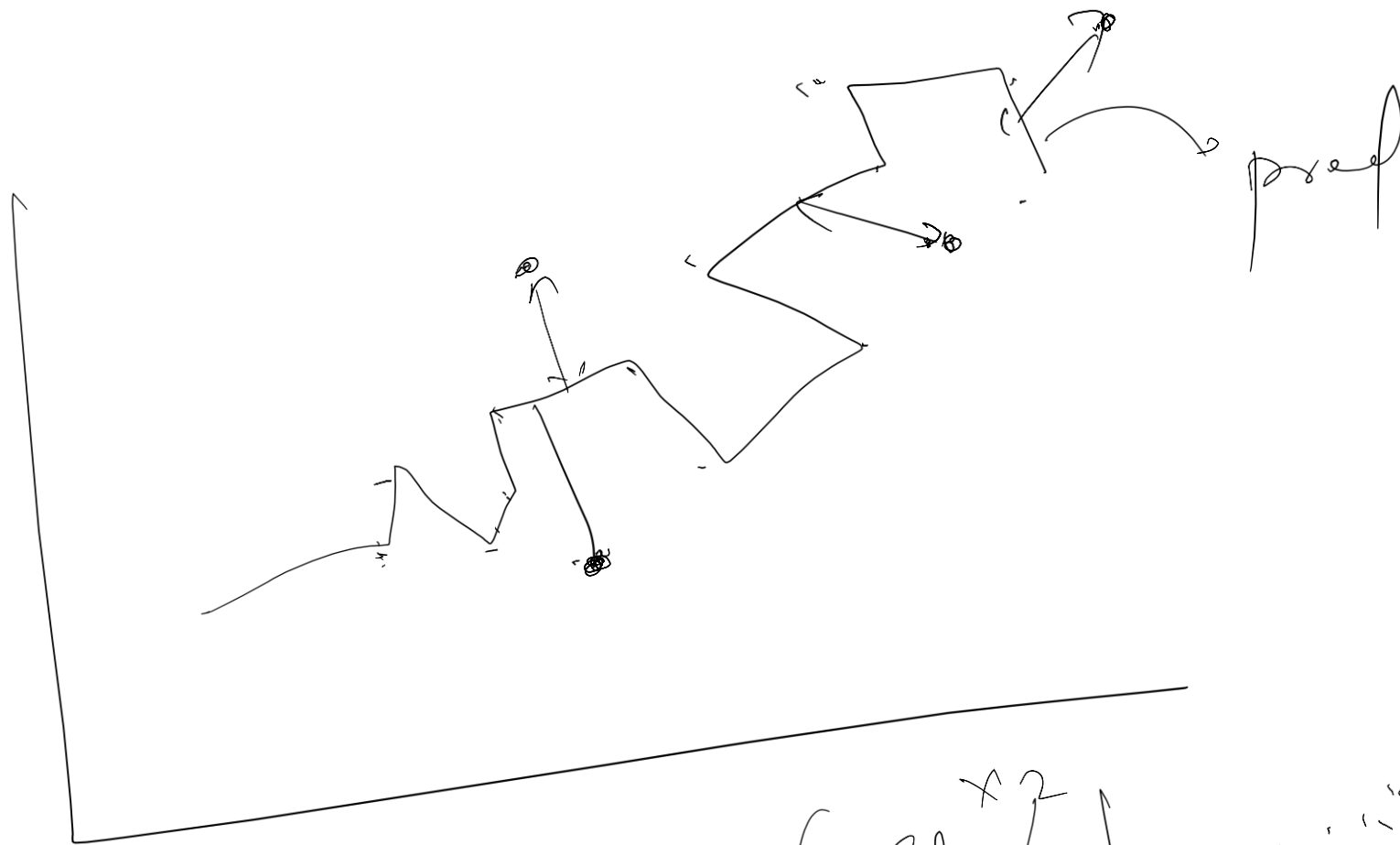
01/05/2025

Overfitting :-

Train error is less (eg 5% mape)
Test " " high (20% mape)

Underfitting :

Train error is high
Test error is high



✓ L1 \rightarrow LASSO

$\boxed{\text{Cov} \rightarrow \lambda = 0}$
 $\boxed{\lambda = 1}$ $\rightarrow 3 \times$

✓ L2 \rightarrow RIDGE

Elastic Net

$\boxed{\text{LASSO} + \text{RIDGE}}$

$$E = \sum (y - mx + b) + \lambda \sum |m_1 + m_2 + m_3|$$

Penalize the coeff that are high in magnitude

$$E = \sum y - m\alpha + b + \lambda \sum (m_1^2 + m_2^2 + m_3^2)$$

Elaborate Not.

$$(y - m\alpha + b) +$$

$$\underbrace{\lambda \sum |m_1 + m_2|}_{\text{Lasso}}$$

Lasso

2

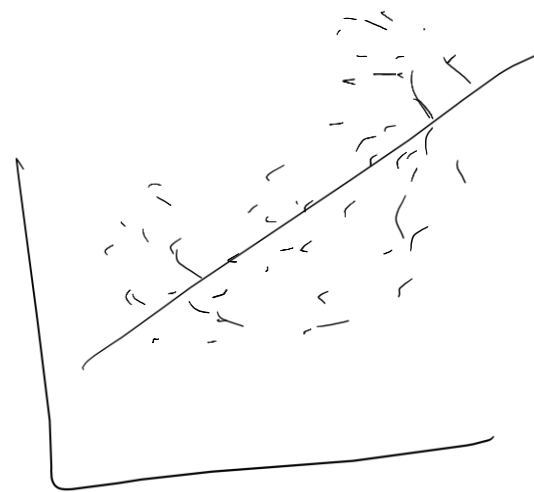
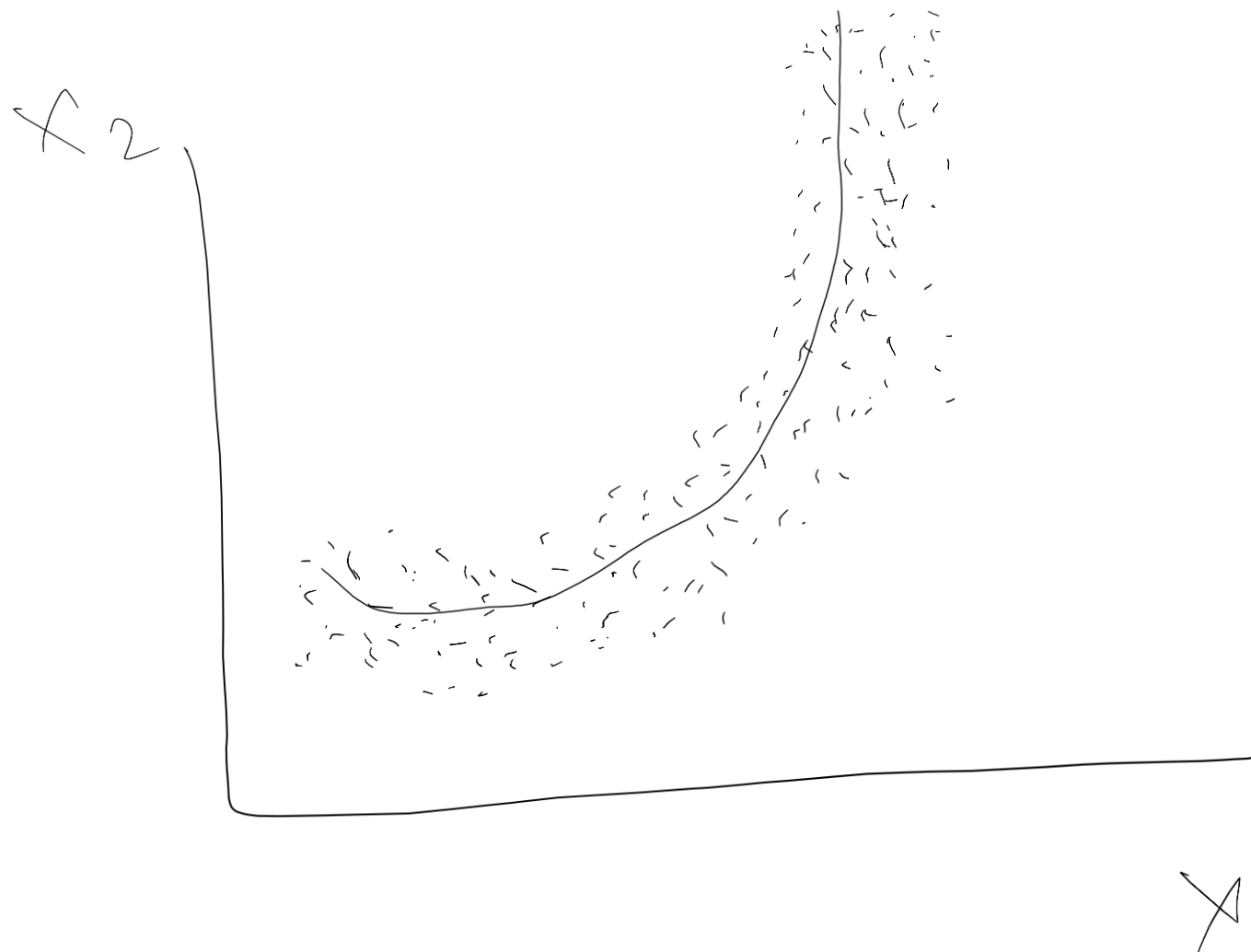
70%

30%

$$+ \underbrace{\lambda \sum (m_1^2 + m_2^2)}_{\text{Ridge}}$$

Ridge

ω_{eff}



$$y = mx + b \rightarrow$$

$$x^2 + 2x + 4 \rightarrow$$

$$x^3 + x^2 + 2x + 4 \rightarrow$$

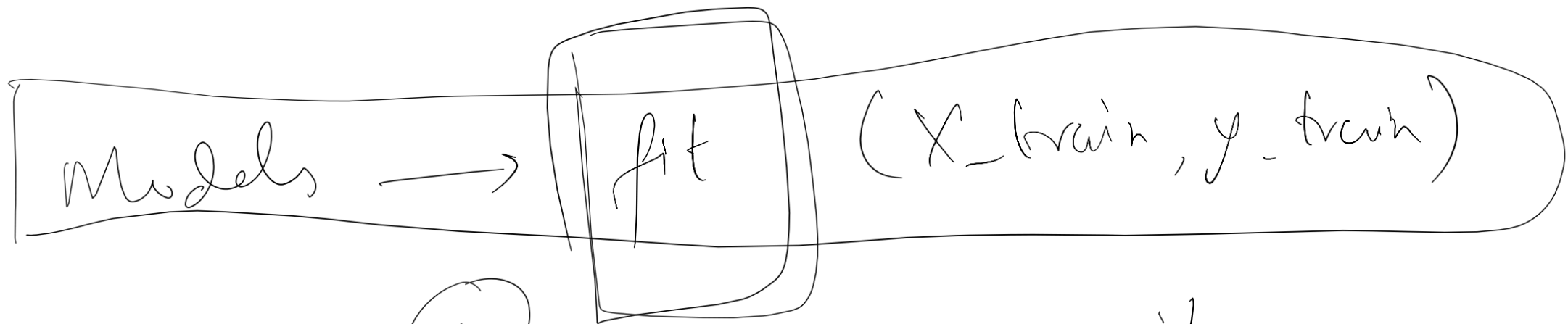
$$x^4 + x^3 + x^2 + 2x + 4 \rightarrow$$

simple line eqn

Quadratic eqn

Cubic eqn

Quartic eqn



Scaling: \rightarrow ① std scalar

i/p \Rightarrow

70% 70 \rightarrow Min Max scalar

X_{train} train \rightarrow

① fit_transform

$$\frac{X_i - \mu}{\sigma}$$

X_{test} test 30% 30

transform \times

$\mu = 2 \quad \sigma = 1$

$$y = mx + b \Rightarrow \text{Model}$$



poly-2

$$m_2 x^2 + \boxed{m_1 x_1} + b$$

Diagram illustrating a polynomial model with terms $m_2 x^2$, $m_1 x_1$ (enclosed in a box), and b . Arrows indicate relationships between the terms and the box.

$$+ \text{inter} \quad \boxed{\textcircled{3}} \quad \boxed{\textcircled{2}} \quad \boxed{m_3 x_1 + m_2 x_1 + m_1 x_1 + b}$$

Diagram illustrating a polynomial model with terms $m_3 x_1$, $m_2 x_1$, $m_1 x_1$, and b . The terms are grouped into boxes labeled 2 and 3, with an additional box containing the sum $m_3 x_1 + m_2 x_1 + m_1 x_1 + b$.

$$y = mx + b$$

$(n = 100)$

2 → Variable

$$= m_1 x_1 + m_2 x_2 + b$$

$(100, 2) \times 1 - 1V$
 $x_2 \rightarrow 2V$

Polynomial degree = 3

$$m_1 x_1 + m_2 x_1^2 + m_3 x_1^3 + m_1 x_2 + m_1 x_2^2 + m_1 x_2^3 + b$$

$m_1 \Rightarrow 0.02 \quad m_2 \Rightarrow 0.1 \quad (100, b)$

Regression: (Target \rightarrow Continuous)

└ Linear Regression

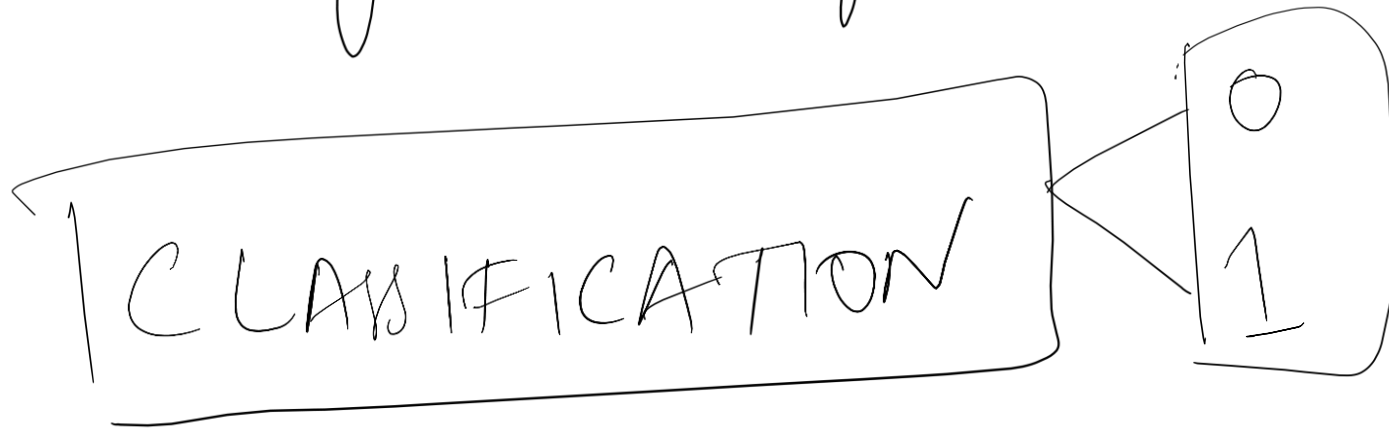
└ └ 1

└ └ 2

└ ElasticNet

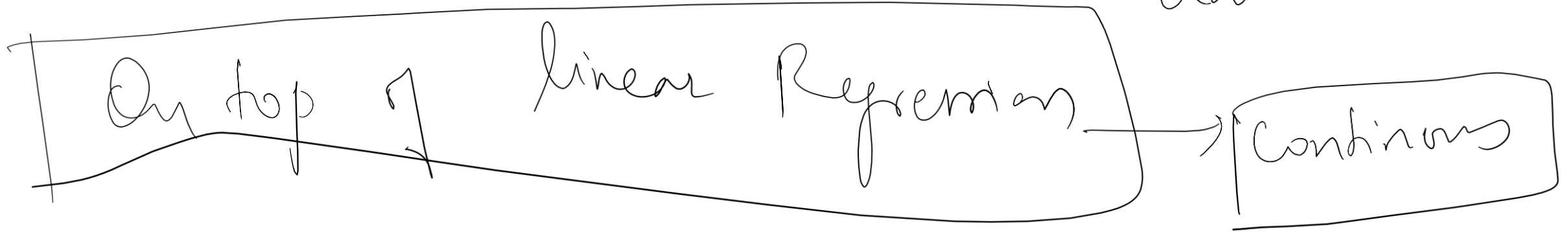
Logistic Regression:-

Target - Discrete



Binary (0, 1)

Multi-class (0, 1, 2, ...)



Classification model Applications:

- 1) Weather prediction → Rain / Not
 - 2) Email → Spam / Not
 - 3) Exam → Pass / Fail
 - 4) Online Fraud → fraudulent / Not
 - 5) Election - predict → Win / Not
 - 6) Credit / Loan → Give / Approve / Not
- Handwritten notes and diagrams:*
- Next to "Spam / Not": $(256, 256, 256)$ with R , B , G below them.
 - Next to "Pass / Fail": RGB with an arrow pointing to a small grid diagram.
 - Next to "fraudulent / Not": $B \rightarrow 0 - 256$ with an arrow pointing to the same grid diagram.
 - Next to "Win / Not": win with an arrow pointing to the grid diagram.
- The grid diagram is a 4x4 grid with the top row shaded. It is enclosed in a rounded rectangle.

Output of linear Regression:

$\langle -\infty, +\infty \rangle$

range $(0, +\infty)$

-2

0.13

-1

0.36

0

1

1

2.71

2

7.38

\downarrow
-5
exp
-5

Step: -> 1

exp

random = true

45.2

($-\infty$ to ∞)

(0 to ∞)

$x = 7000$

(0 to 1)

Step 2 ->

$$\frac{x}{x+1}$$

$$= \frac{7000}{7000+1}$$



(0, 1)

(0, 1)

0 1

$$y = mx + b$$

→ Linear Regression

$$y = (-\infty, \infty)$$

⇒ (0, 1) ⇒ Logistic Repr

$$\frac{e^{(mx+b)}}{e^{(mx+b)} + 1}$$

is P (0, 1)

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

$$\frac{\cancel{e^y}}{\cancel{e^y}} P = \frac{e^y}{e^y + 1} = \frac{\cancel{e^y} / \cancel{e^y}}{\frac{e^y + 1}{e^y}}$$

Both numerator & Denominator, \times by e^y

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

$$P(1 + e^{-y}) = 1 \Rightarrow P = \frac{1}{1 + e^{-y}}$$

$$p = \frac{1}{1 + e^{-(mn+b)}}$$

Number
Num $\rightarrow f \rightarrow (0, 1)$

Sigmoid fn \rightarrow D.L

$(0, 1)$

$$P = e^y / (e^y + 1)$$

$$P(e^y + 1) = e^y$$

$$Pe^y + P = e^y$$

\Rightarrow

$$P = e^y - Pe^y$$

$$P = e^y(1 - P)$$

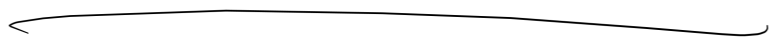
$$e^y = \frac{P}{1 - P}$$

Applying log on both sides

$$\cancel{\log(e^y)} = \log\left(\frac{p}{1-p}\right)$$

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

$$mx + b = \log\left(\frac{p}{1-p}\right)$$



$$p$$

part of success (0.7)

$$1 - p$$

"

"

"

$$1 - 0.7 = 0.3$$

$$(0, 1)$$

$$\frac{p}{1-p}$$

\Rightarrow

Odds

Continuous

$$\log(\text{odds}) = mx + b$$

\longleftrightarrow

$$(0 \dots 1)$$

$$\log\left(\frac{p}{1-p}\right) = \boxed{mx + b} \Rightarrow \text{Continue}$$

$$\log\left(\frac{p}{1-p}\right) = \boxed{-0.066 \times 0 + 1.8185}$$

$$= 1.8185$$

$$\frac{p}{1-p} = \exp(1.8185) = 6.16$$

$$m \Rightarrow -0.066$$

$$x \Rightarrow 0$$

$$b \Rightarrow 1.8185$$

$$\frac{p}{1-p}$$

$$= 6.16$$

$$p = 6.16 - 6.16p$$

$$p + 6.16p = 6.16$$

$$p(1 + 6.16) = 6.16$$

$$p = \frac{6.16}{7.16} = 0.86$$

Error :

Error

0 \longrightarrow 0 \longrightarrow 0

0 \longrightarrow 1 \longrightarrow 2

1 \longrightarrow 1 \longrightarrow 0

1 \longrightarrow 0 \longrightarrow 2

(Act)

(pred)

$$y = 1$$

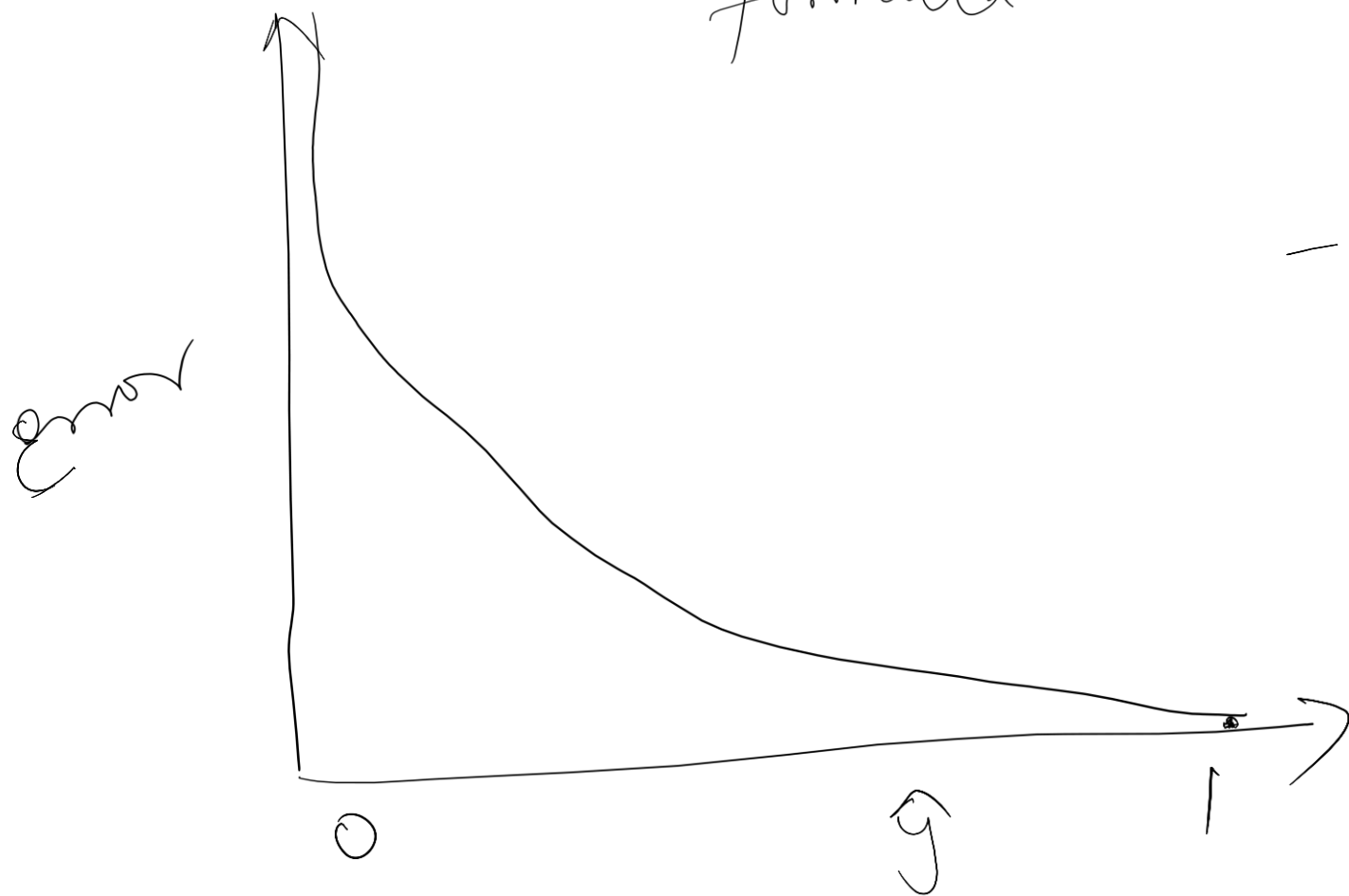
Formula = $-\log(y)$

$$-\log(1) = 0$$

$$-\log(0) = \infty$$

$$-\log(0.7) = 0.157$$

$$-\log(0.1) = 1$$

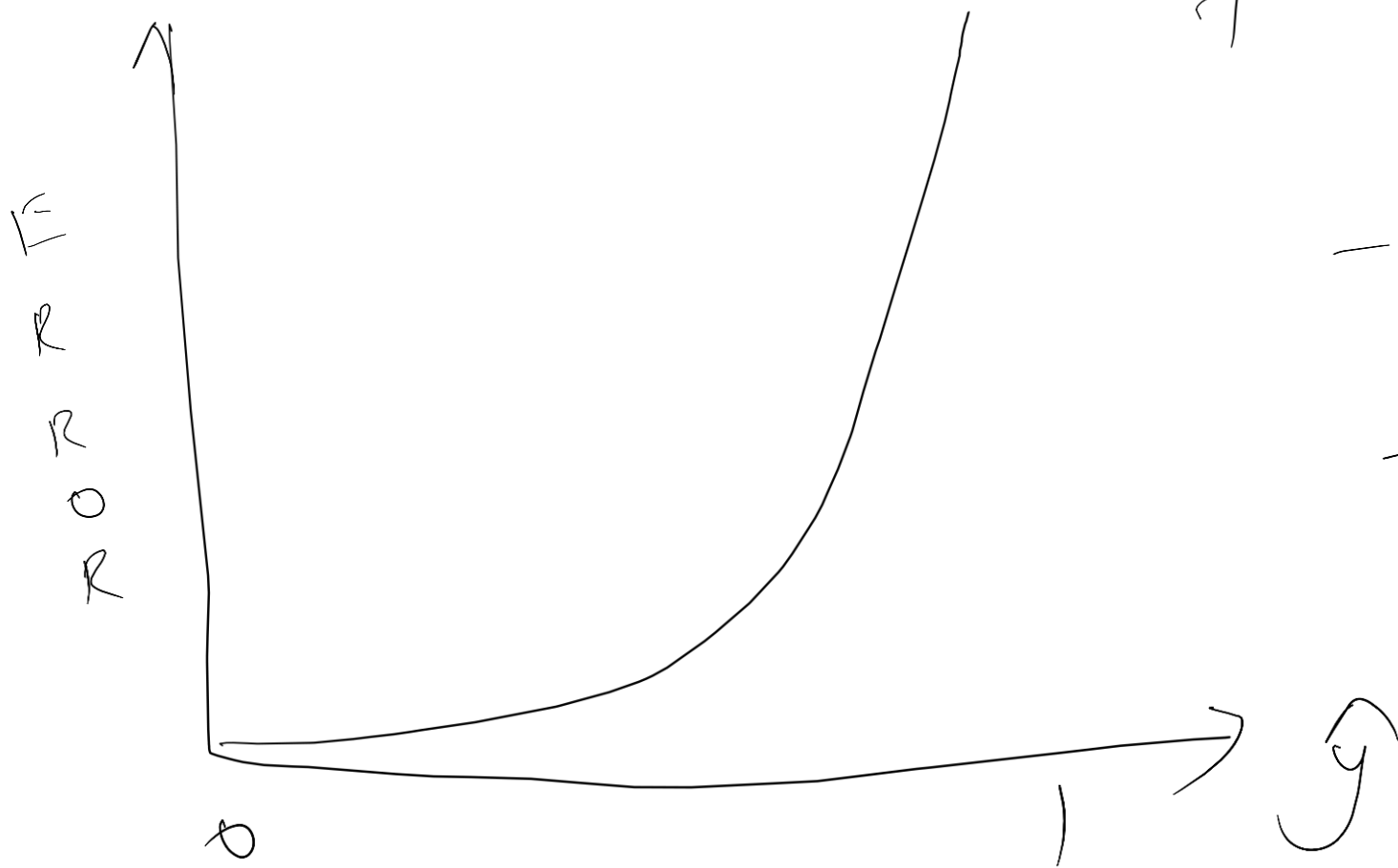


$$y = 0$$

$$\text{Formula} = -\log(1 - \hat{y})$$

$$-\log(1 - 1) = \infty$$

$$-\log(1 - 0) = 0$$



Cost function:

$$y = 1$$

\rightarrow

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

$$y = 0$$

\rightarrow

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

$$= \underbrace{[-y \log(\hat{y})]}_{y=1} - \underbrace{(1-y) \log(1-\hat{y})}_{y=0}$$

$$\text{Log Loss} \Rightarrow -y \log(ma + b) - (1-y) \log(1 - (ma + b))$$