

# Regularization :-

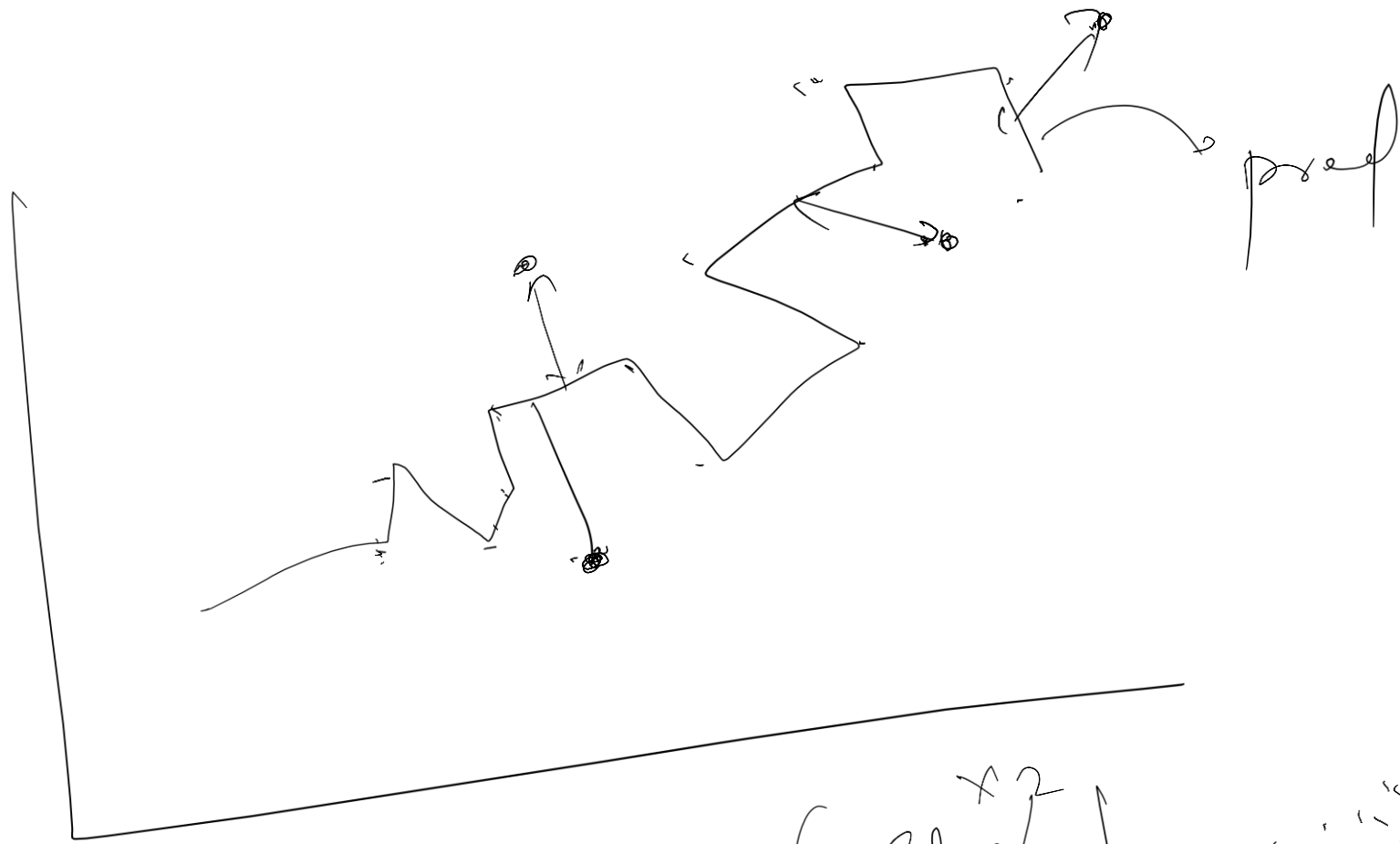
01/05/2025

Overfitting :-

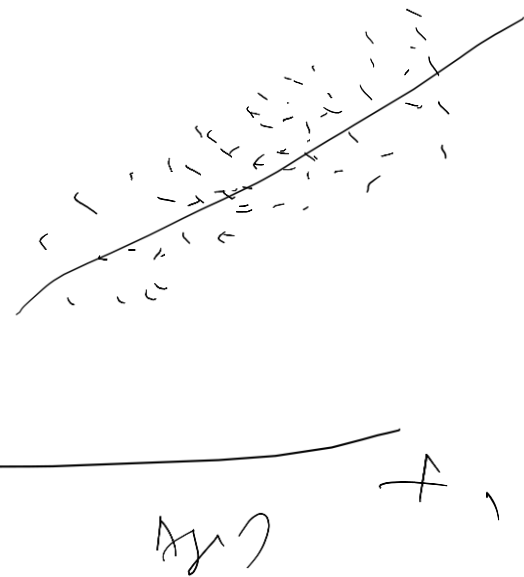
Train error is less (eg 5% mape)  
Test " " high (20% mape)

Underfitting :

Train error is high  
Test error is high



(Sly<sup>x2</sup>)



✓ L1 → LASSO

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

✓ L2 → 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

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

Elaborate Nat.

$$(y - m a + b) +$$

$$\lambda \sum |m_1 + m_2|$$

Lasso

2

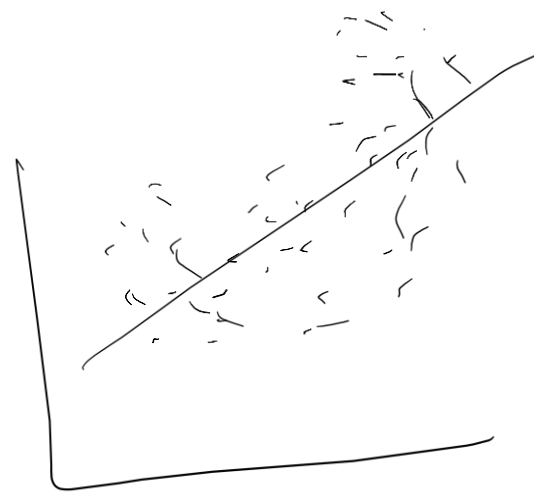
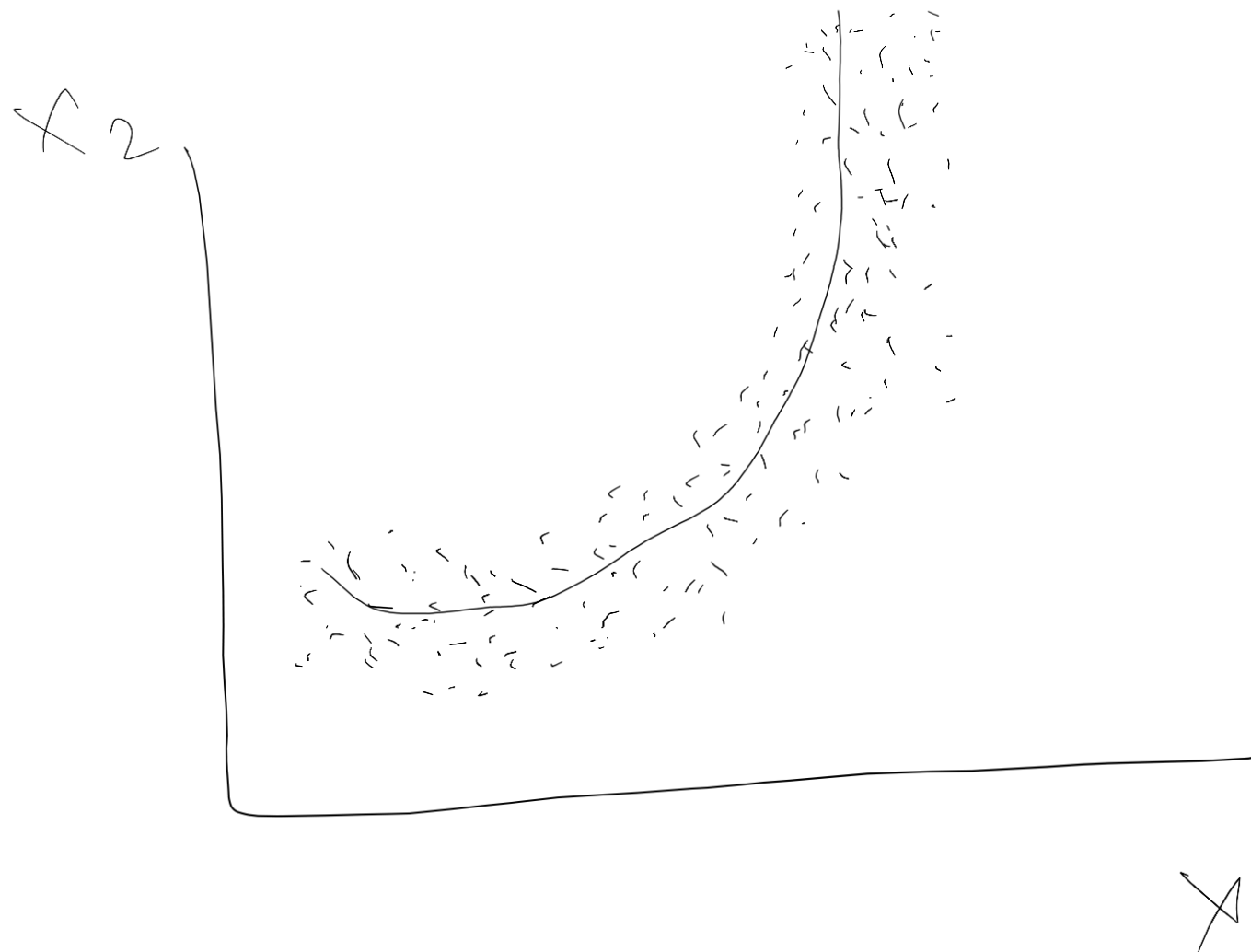
70%

30%

$$\lambda \sum (m_1^2 + m_2^2)$$

Ridge

ω<sub>eff</sub>



$$y = mx + b \rightarrow$$

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

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

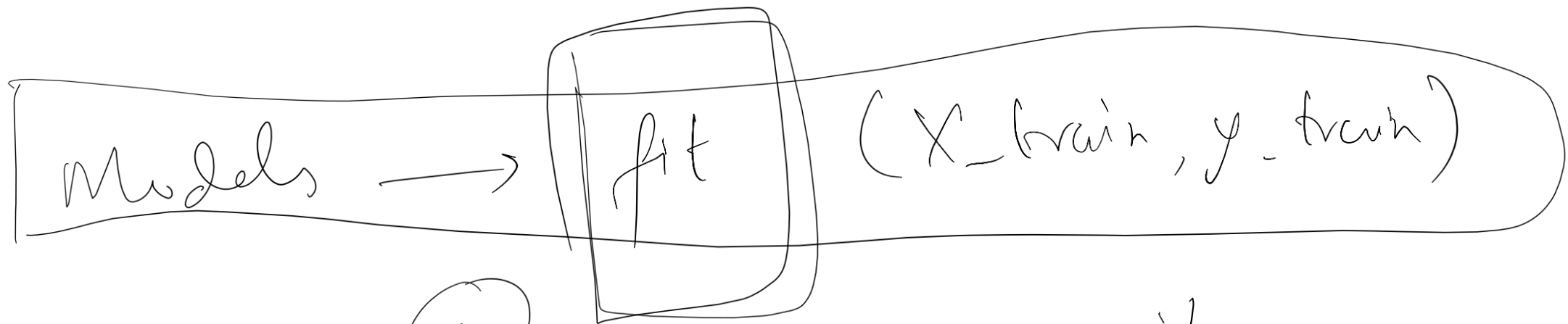
$$x^4 + x^3 + x^2 + 2x + 4 \rightarrow$$

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  $\rightarrow$

① fit\_transform  $\rightarrow$  5  
2  $\rightarrow$  6  
3  $\rightarrow$  4

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

X test 30% 30

transform X

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

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



25

Handwritten diagram illustrating a sequence of operations or components:

- Box 1 (left):  $m_3 x_1 + b$
- Box 2 (middle):  $m_2 x_1 +$
- Box 3 (right):  $m_3 x_1 + \text{infer}$  (with an arrow pointing to Box 2)

Additional annotations include a 'b' to the left of Box 3 and various scribbles and arrows indicating relationships between the boxes.



$$y = mx + b$$

$(n = 100)$

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

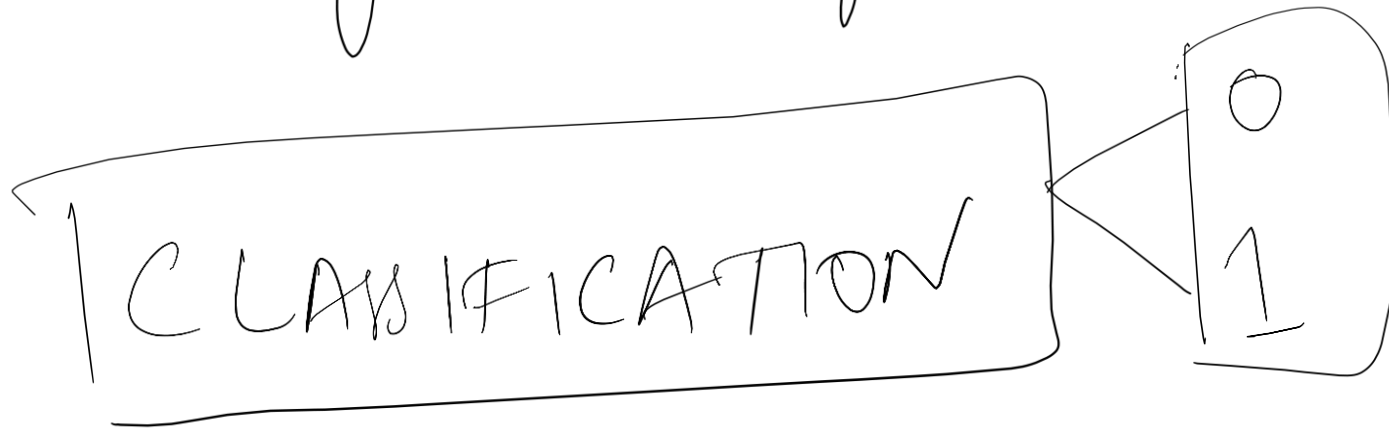
└ └ 1

└ └ 2

└ ElasticNet

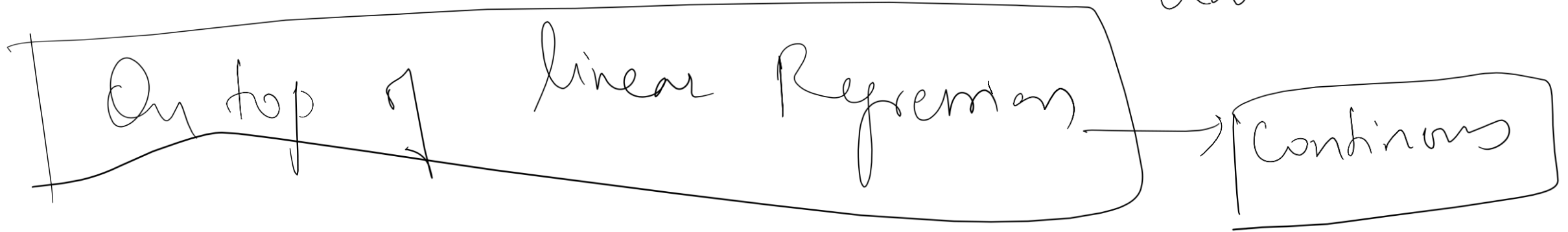
# Logistic Regression:-

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 of squares, with the top-left square shaded black.

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

$\downarrow$   $\begin{array}{|c|} \hline \exp^{-5} \\ \hline \end{array}$

Step: -> 1

exp

random = true

45.2

( $-\infty$  to  $\infty$ )

(0 to  $\infty$ )

$x = 7000$

(0 to 1)

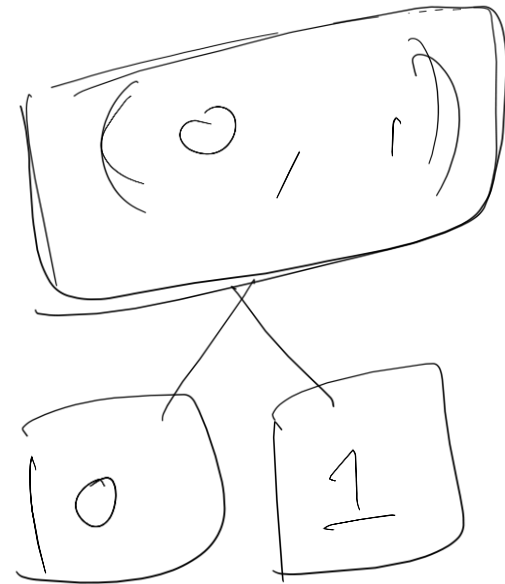
Step 2 ->

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

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



(0, 1)



$$y = mx + b$$

→ Linear Regression

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

⇒ (0, 1) ⇒ Logistic Repr

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

$\hat{P}$  (0, 1)

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

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

Both numerator & Denominator,  $\times$  by  $e^y$

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

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



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



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

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

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

$\Rightarrow$

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

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

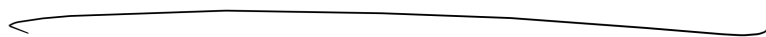
Applying log on both sides

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

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

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

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



$$p$$

part of success (0.7)

$$1 - p$$

"

"

"

$$1 - 0.7 = 0.3$$

$$(0, 1)$$

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

$\Rightarrow$

Odds

Continuous

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



$$(0 \dots 1)$$

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

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

$$= 1.8185$$

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

$$m \Rightarrow -0.066$$

$$x \Rightarrow 0$$

$$b \Rightarrow 1.8185$$

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

$$= 6.16$$

$$p = 6.16 - 6.16p$$

$$p + 6.16p = 6.16$$

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

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