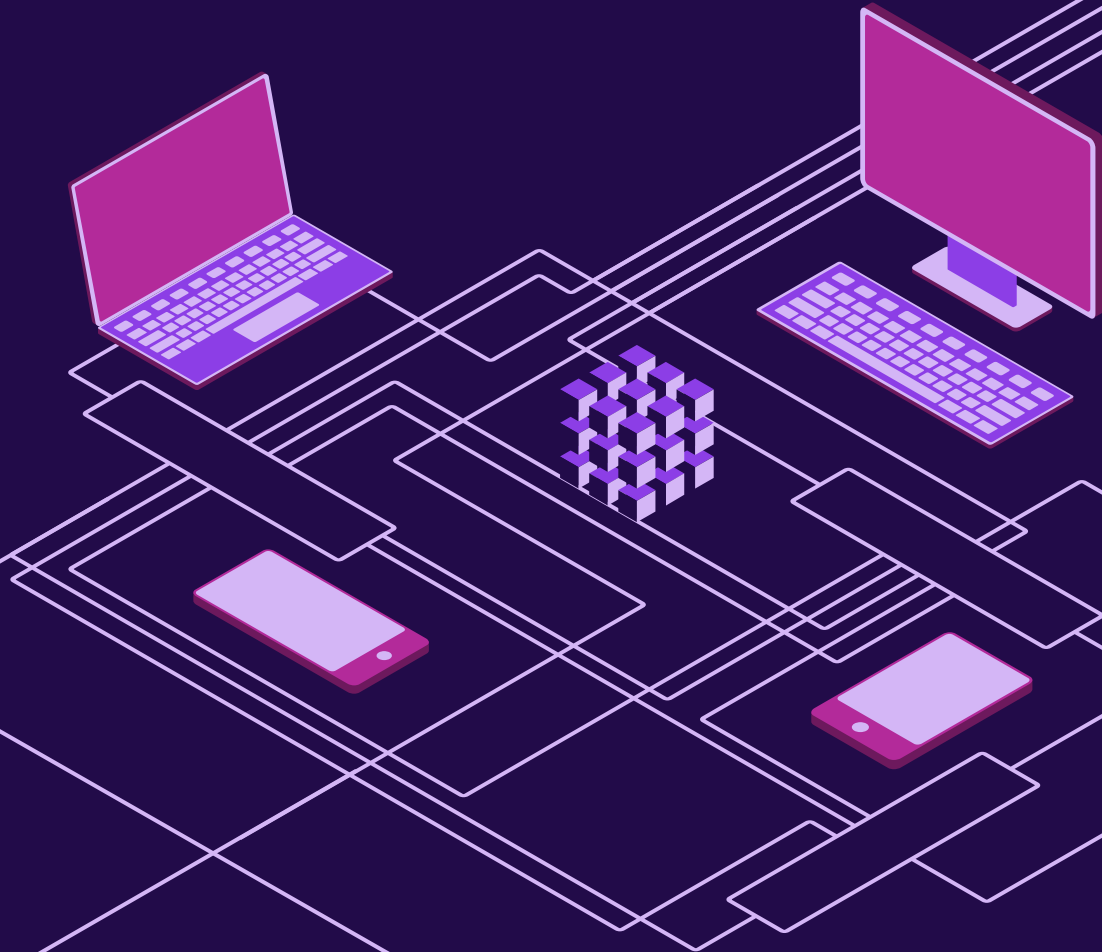
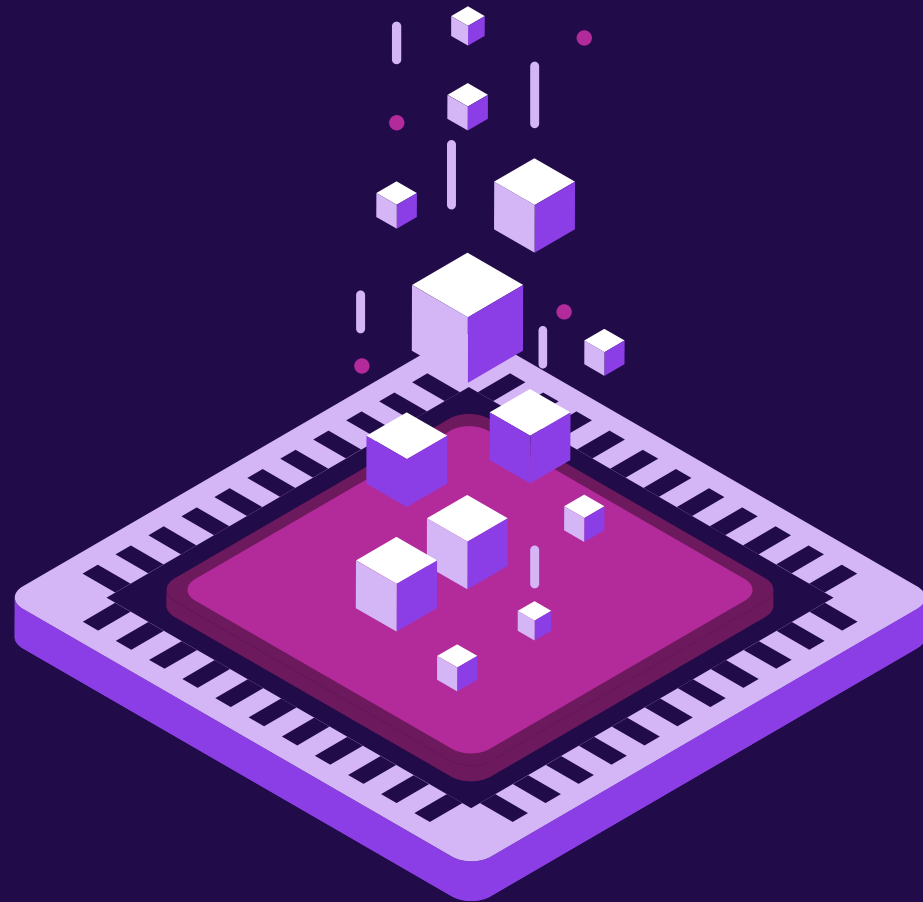


# LOGISTIC REGRESSION

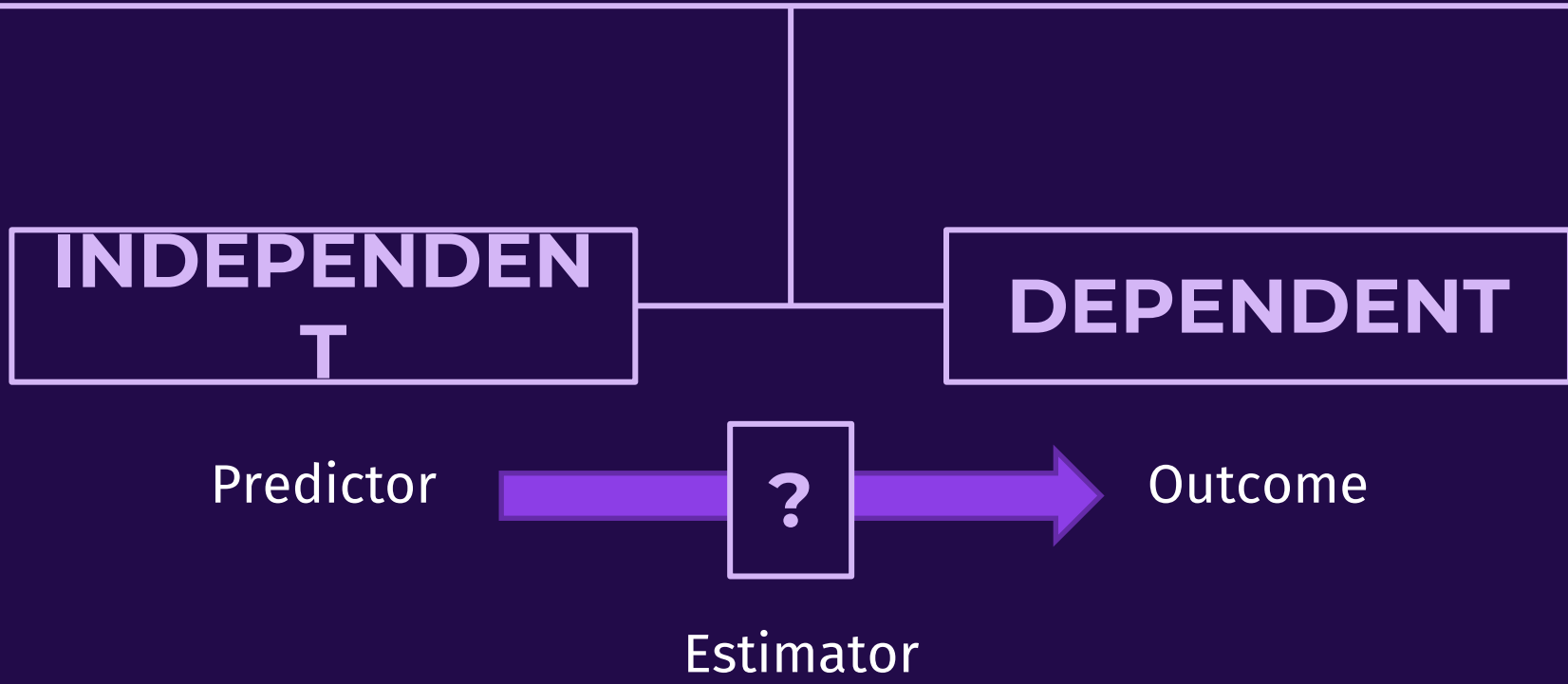
IN CLASSIFICATION MODEL





## WHAT IS REGRESSION?

Regress -> estimate  
**relationship** between  
variables



## SOME TYPES



### Linear

Assume linear relation



### Polynomial

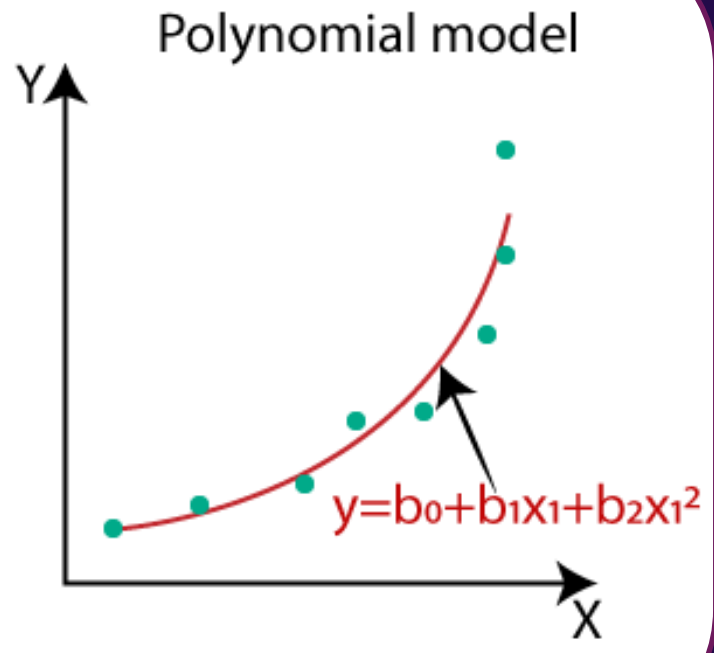
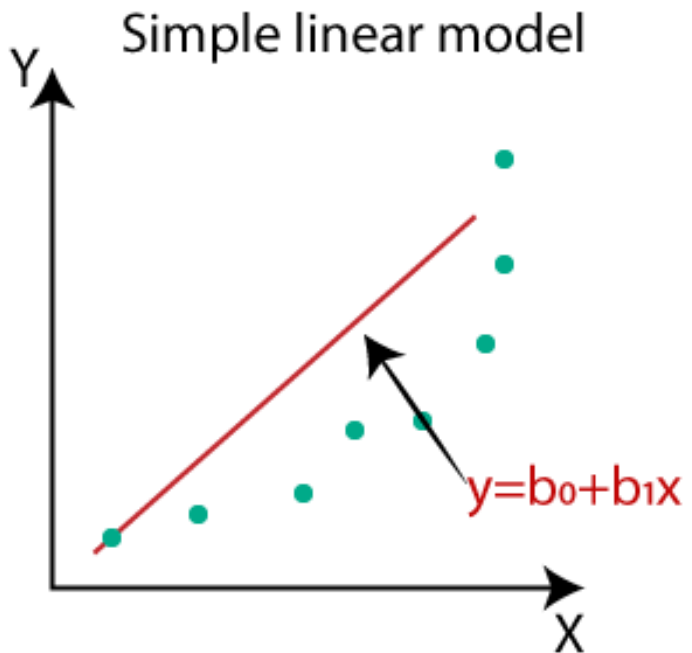
Assume polynomial  
relation



### Logistic

Assume logistic relation

# EXAMPLE



Source: Javatpoint.com

## WHAT IS LOGISTIC?

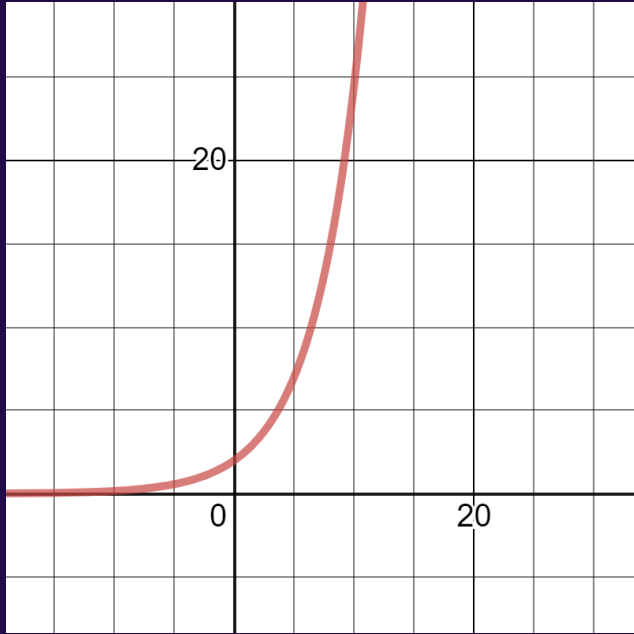
- Pierre Verhulst (1845-1847) developed a model of bounded population growth
- Verhulst named it “logistic model”, the reason is unknown.
- One guess is that this model can be used to predict the supplies an army requires

$$\frac{dy(x)}{dx} = a \cdot y(x)$$

$$\frac{dy(x)}{dx} = a \cdot y(x)(b - y(x))$$

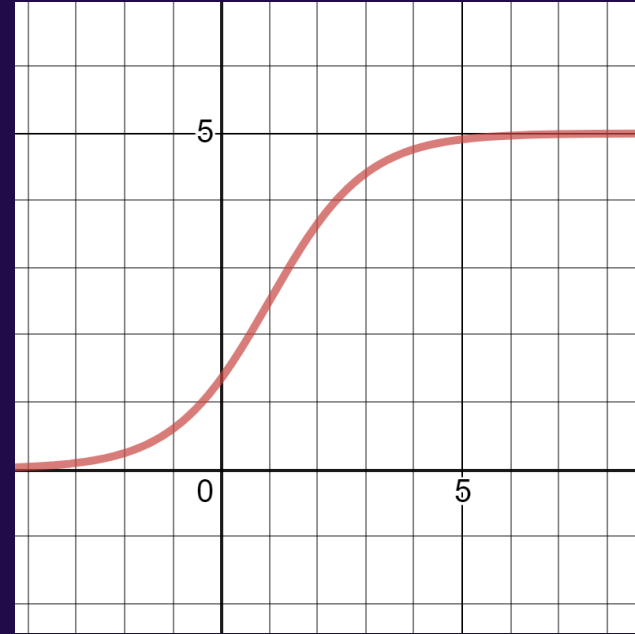
**Simple  
growth**

**Logistic**



**Simple  
growth**

$$y(x) = x_0 e^{kx}$$



**Logistic**

$$y(x) = \frac{b}{1 + e^{a(x-x_0)}}$$



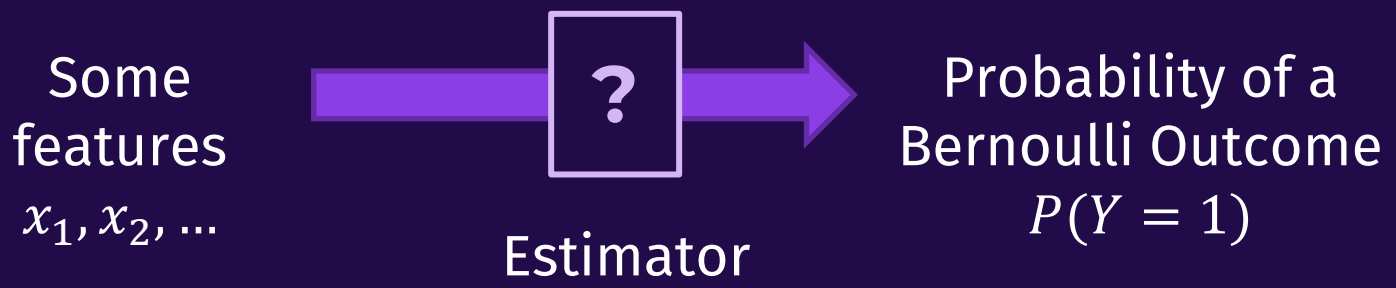
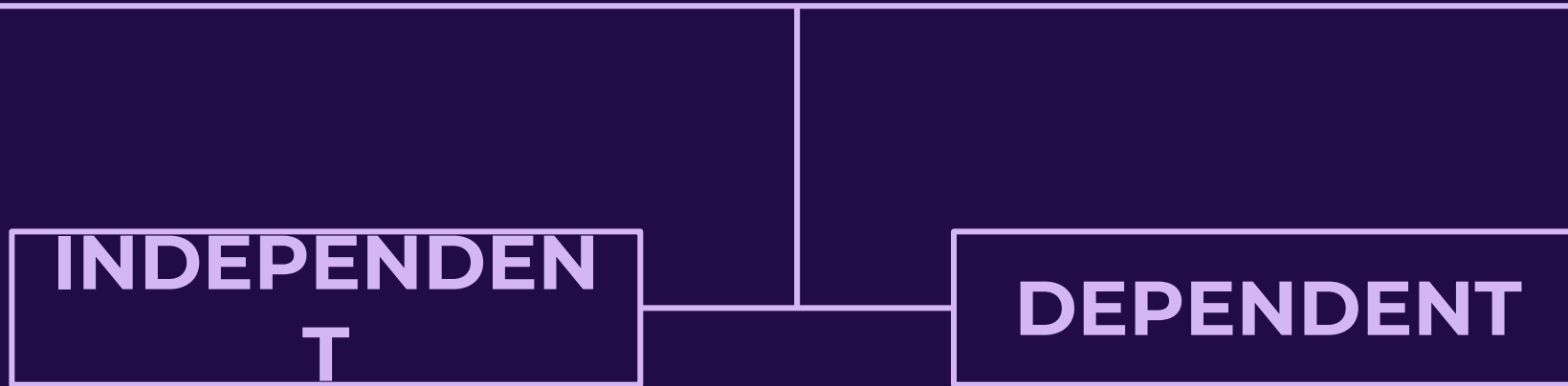
## WHY MUST LOGISTIC?

- Probability function must be  $(-\infty, \infty) \rightarrow [0,1]$
- Using polynomial regression would be computationally expensive
- One of the simplest functions met the criteria is logistic function

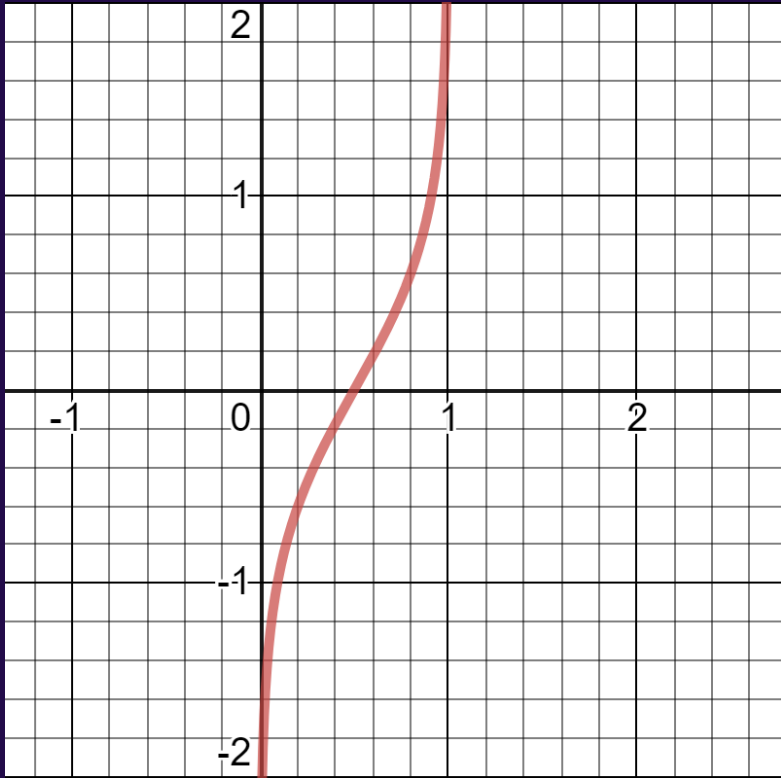


# BINARY CLASSIFICATION

We need a model that estimate some predictors to probability of Bernoulli outcome



$$P(Y = 1) = \Theta(x_1, x_2, \dots)$$

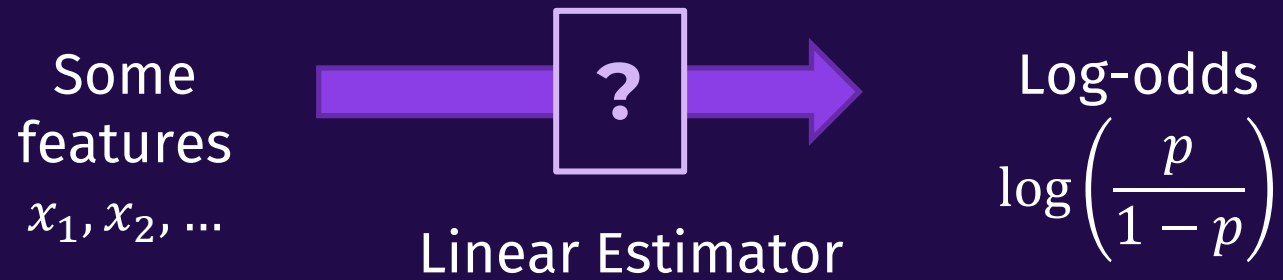
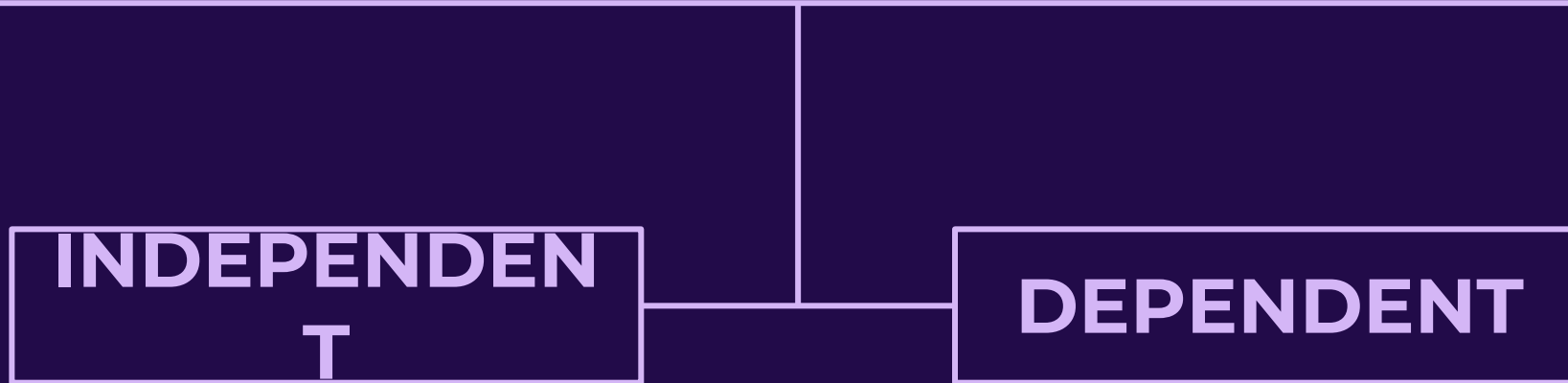


$$\log\left(\frac{p}{1-p}\right)$$

**Log-odds**

Odds:  
likelihood of outcome

Log-odds:  
logarithm of odds



$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots$$

## LOGISTIC = INVERSE OF THE LOG ODDS

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots$$

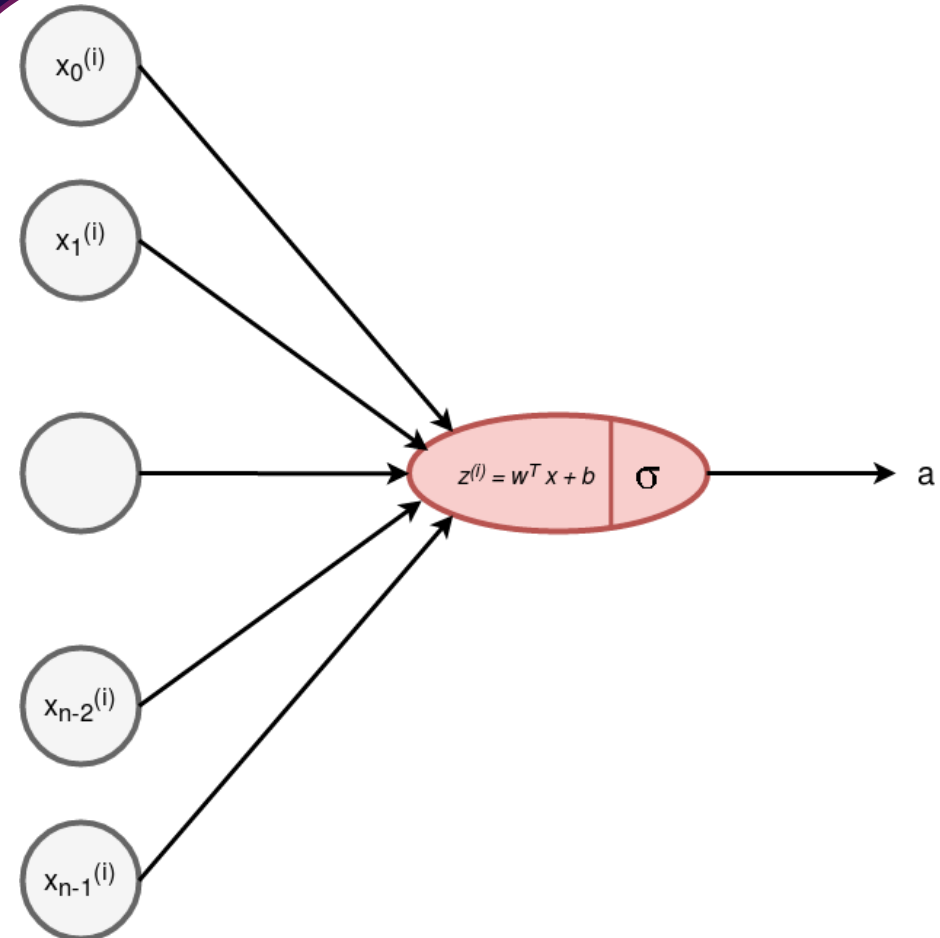
Inversed to

$$p = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots)}}$$

which is a logistic function!

## WRAP UP

- We actually do “linear regression” then “activates” it using a logistic function
- Sometimes the activator is called **sigmoid function**
- Sigmoid is all S-shaped functions and logistic is just one of it.



Source: vbvsharma.com

## LET'S GENERALIZE!

- Assume there are  $n$  outcomes.
- Let us choose a “pivot” outcome. For example,  $Y = n$
- Instead using odds, we will just take the ratio to one “pivot” outcome.
- So, for each  $Y = k \in \{1, 2, \dots, n - 1\}$ , we can regress its log-ratio:

$$\log \left( \frac{P(Y = k)}{P(Y = n)} \right) = B_k X$$

- Note that  $B_k X = \beta_{k0} + \beta_{k1} x_1 + \dots$



## LET'S GENERALIZE!

- Thus, we have

$$\log \left( \frac{P(Y = 1)}{P(Y = n)} \right) = B_1 X$$

$$\log \left( \frac{P(Y = 2)}{P(Y = n)} \right) = B_2 X$$

⋮

$$\log \left( \frac{P(Y = n - 1)}{P(Y = 1)} \right) = B_{n-1} X$$

## LET'S GENERALIZE!

- Little exponent manipulation yields

$$P(Y = 1) = P(Y = n)e^{B_2X}$$

$$P(Y = 2) = P(Y = n)e^{B_3X}$$

⋮

$$P(Y = n - 1) = P(Y = n)e^{B_nX}$$

- +

$$\sum_{k=1}^{n-1} P(Y = k) = P(Y = n) \sum_{k=1}^{n-1} e^{B_kX}$$

## LET'S GENERALIZE!

- We know that

$$P(Y = n) = 1 - \sum_{k=1}^{n-1} P(Y = k) = 1 - P(Y = 1) \sum_{k=1}^{n-1} e^{B_k X}$$

$$P(Y = n) = \frac{1}{1 + \sum_{k=1}^{n-1} e^{B_k X}}$$

Thus,

$$P(Y = k) = \frac{\sum_{k=1}^{n-1} e^{B_k X}}{1 + \sum_{k=1}^{n-1} e^{B_k X}}, k \in \{1, 2, \dots, n - 1\}$$

## LET'S GENERALIZE!

- Actually  $P(Y = n)$  can be known once the other  $P(Y = k)$  have been obtained.
- This makes  $B_n$  can't be uniquely identifiable
- So we can transform a new parameter  $B'_k = B_k - B_n$  and that will yield to

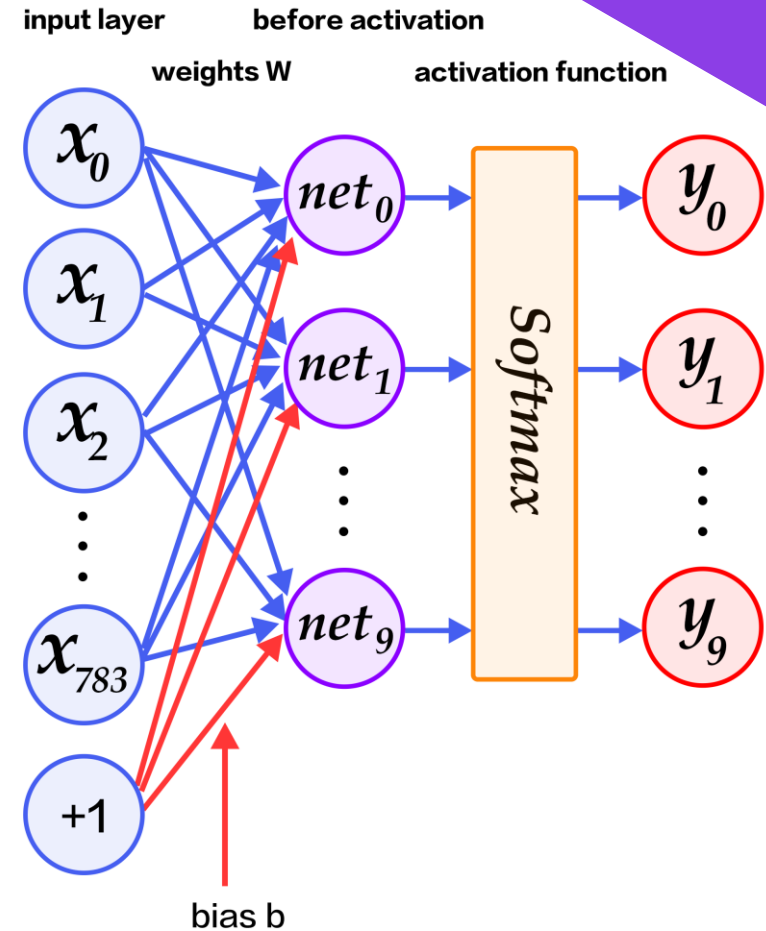
$$P(Y = k) = \frac{e^{B'_k X}}{\sum_{k=1}^n e^{B'_k X}}$$

$$P(Y = k) = \frac{e^{B'_k X}}{\sum_{k=1}^n e^{B'_k X}}$$

Yes, this is softmax function for categorical classification

# WRAP UP

- If we have  $k > 2$  category, we use softmax to activate the output.
- Softmax will be reduced to logistic function if  $k = 2$



**THANKS!**

Do you have any questions?

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