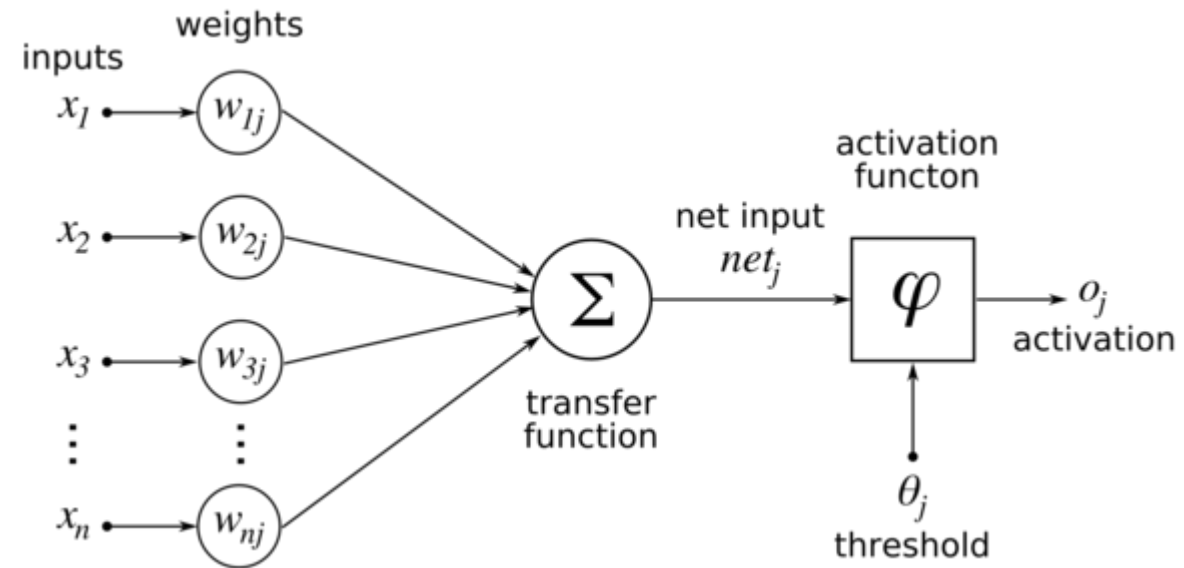


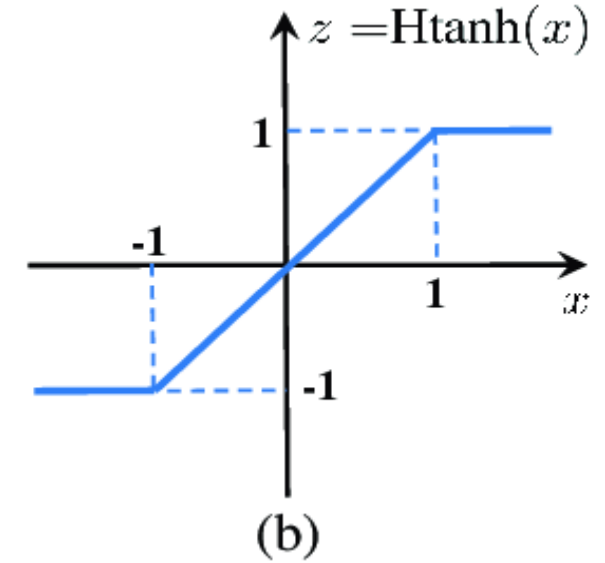
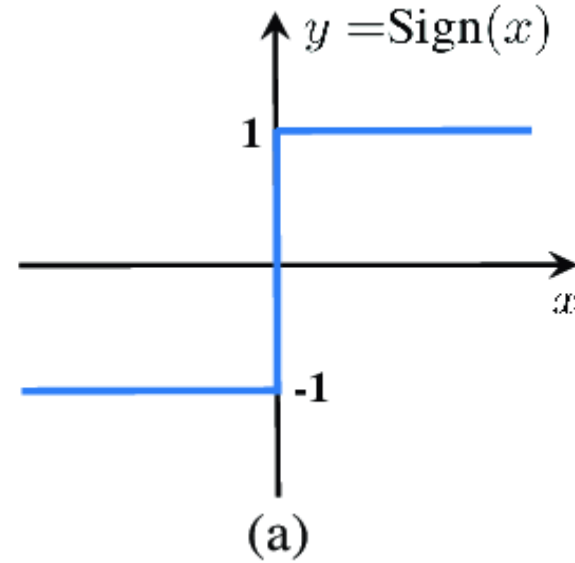
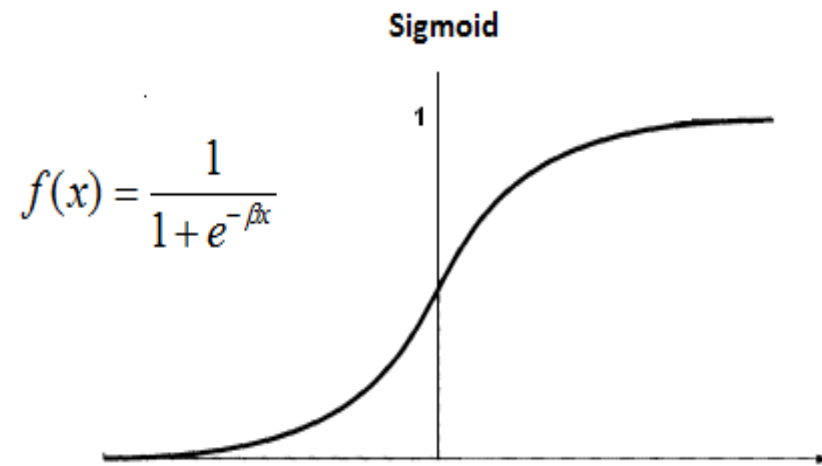
Logistic Regression

- *Supervised Learning*
- *Classification*
- *Binary*
- *Multi-nominal*

Neural Networks



Activation Functions



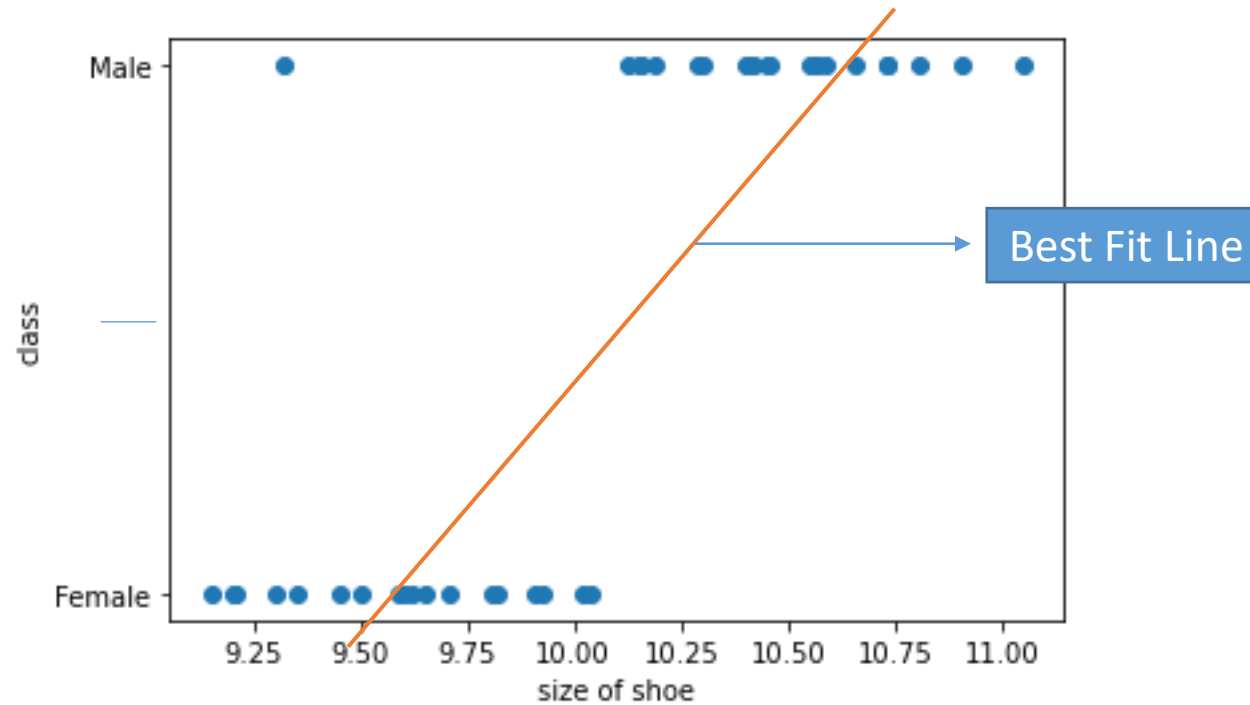
Activation Functions

Sigmoid vs Softmax

The sigmoid function is used for the two-class logistic regression, whereas the softmax function is used for the multiclass logistic regression.

The main advantage of using Softmax is the output probabilities range. The range will 0 to 1, and the sum of all the probabilities will be equal to one. If the softmax function used for multi-classification model it returns the probabilities of each class and the target class will have the high probability.

Linear Regression



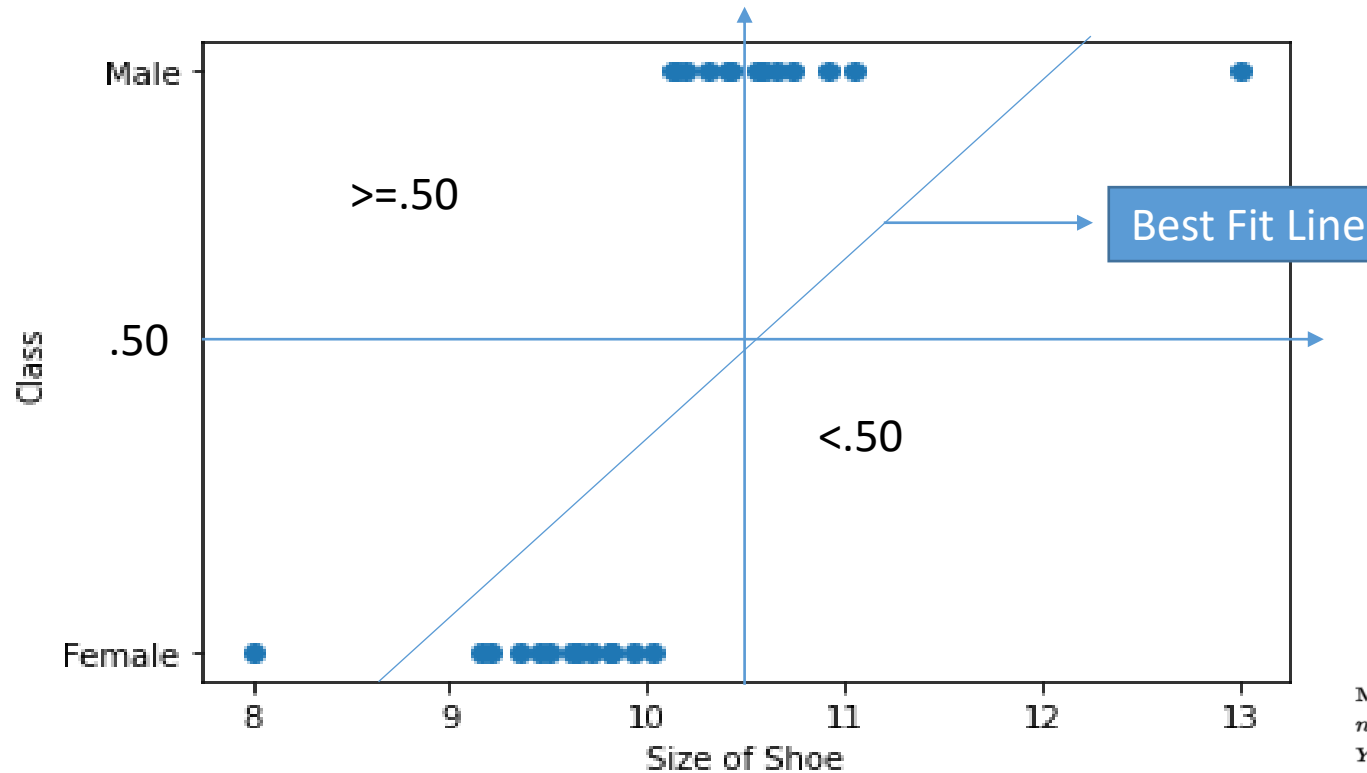
$$Y = MX + C$$

M = Slope

C = Intercept

X = Data Point

Linear Regression



$$Y = MX + C$$

M = Slope

C = Intercept

X = Data Point

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

MSE = mean squared error
 n = number of data points
 Y_i = observed values
 \hat{Y}_i = predicted values

Logistic Regression

$$\log\left(\frac{y}{1-y}\right) = mx + c$$

1. Raising e to the power on both sides of the equation

$$\left(\frac{y}{1-y}\right) = e^{mx+c}$$

2. One divided by both sides of the equation

$$\left(\frac{1-y}{y}\right) = e^{-mx+c}$$

$$3. \left(\frac{1}{y} - 1\right) = e^{-(mx+c)}$$

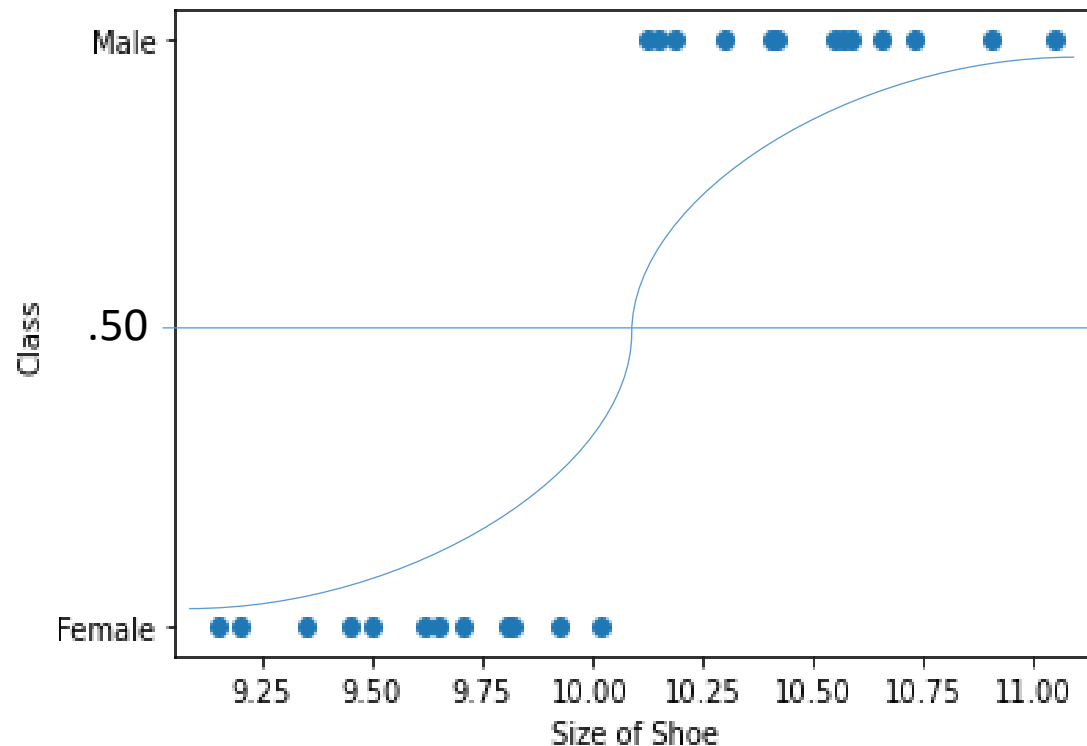
$$4. \frac{1}{y} = 1 + e^{-(mx+c)}$$

$$5. 1 = y(1 + e^{-(mx+c)})$$

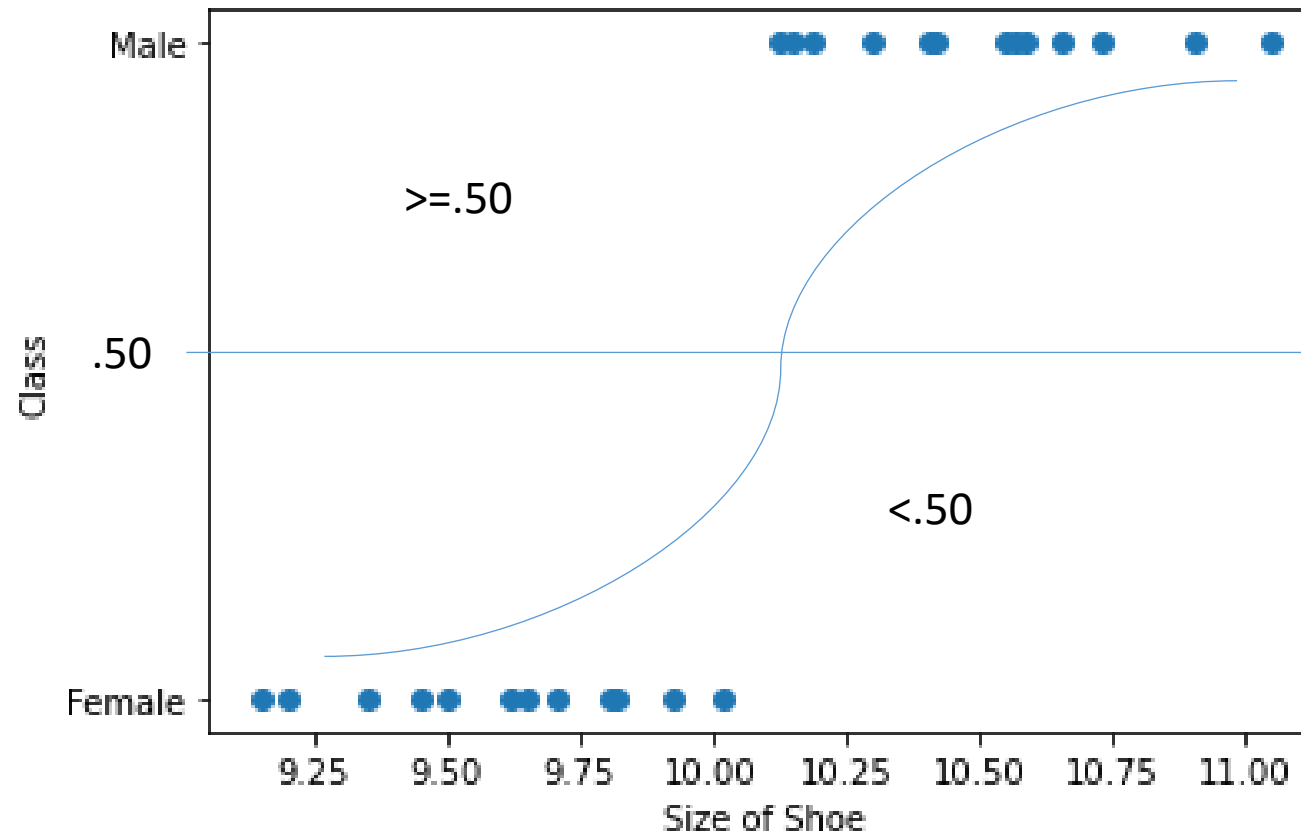
$$6. y = \frac{1}{1 + e^{-(mx+c)}}$$

Logistic Regression

Logistic regression is a linear classifier, so you'll use a linear function $f(\mathbf{x}) = b_0 + b_1x_1 + \dots + b_r x_r$, also called the **Logit**. The variables b_0, b_1, \dots, b_r are the estimators of the regression coefficients, which are also called the predicted weights or just coefficients.



Logistic Regression



$$\text{Logit}(x) = MX + C$$

M = Slope

C = Intercept

X = Data Point

$$\text{sigmoid}_x = \frac{1}{1+e^{-x}}$$

Linear vs Logistic Regression

