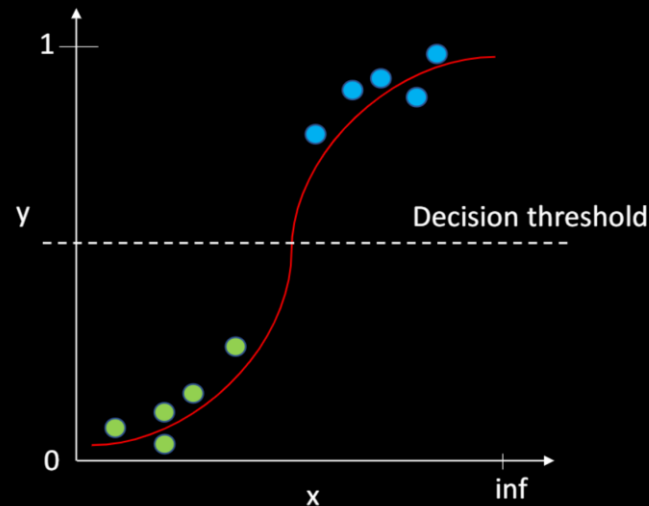


Training a Logistic Regression model



Logistic Regression

(used to solve Classification problems)

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Background

- Supervised Machine Learning
- Classification
- Sigmoid function
- Cost function
- Gradient descent

What is logistic regression?

$$y = w_0 + w_1x_1 + w_2x_2$$

$$y = w_0 + [w_1 \quad w_2][x_1 \quad x_2]^T$$

Input samples	Feature 1 (x1)	Feature 2 (x2)	Labels
1	50	32	1
2	10	22	1
3	55	39	1
4	34	67	0

$$\begin{matrix} y & = & w_0 & + & wx^T \\ \text{(scalar)} & & \text{(scalar)} & & \text{(1x2)*(2x1)} \\ & & & & \text{(scalar)} \end{matrix}$$

$$\begin{matrix} Y & = & W_0 & + & WX^T \\ \text{(1x4)} & & \text{(1x4)} & & \text{(1x2)*(2x4)} \end{matrix}$$

Process entire dataset at once

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

$$y_{predicted} = \begin{cases} 0 & \text{if } \bar{y} < 0.5 \\ 1 & \text{if } \bar{y} \geq 0.5 \end{cases}$$

Training the model

1. Start with a random set of parameters (W)
2. For epoch 1: N
 - i. For all samples in the training set (say, m number of samples)
 - i. Predict the output using a LR model based on the random set of weights
 - ii. Find the cost function (error between true and predicted output)
 - ii. Find average cost for all training samples
 - iii. Minimize the cost function (using gradient descent)
 - iv. Update model parameters
 - v. Repeat step 2 until convergence or for N iterations

$$C(\theta) = \begin{cases} -\log(\bar{y}), & \text{if } y_{true} = 1 \\ -\log(1 - \bar{y}), & \text{if } y_{true} = 0 \end{cases} \quad \text{Cost function for the LR}$$

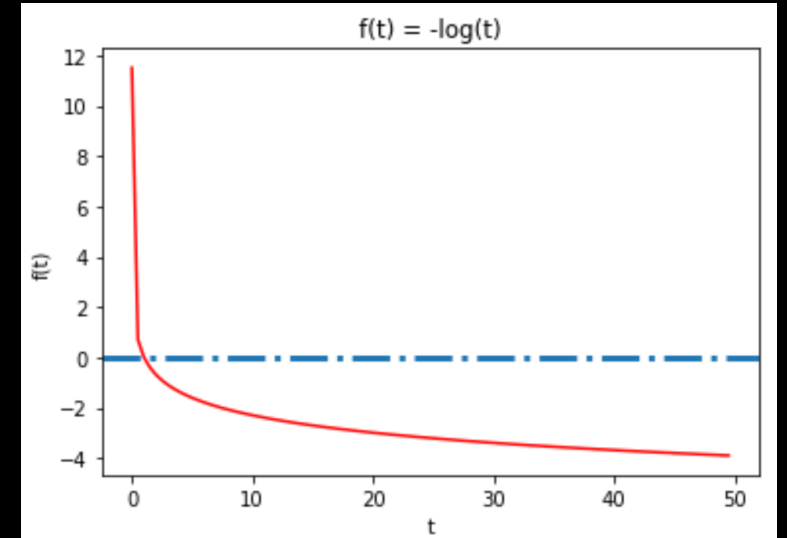
Cost function for LR

$$C(w) = \begin{cases} -\log(\bar{y}), & \text{if } y_{true} = 1 \\ -\log(1 - \bar{y}), & \text{if } y_{true} = 0 \end{cases}$$

$$J(w) = \frac{-1}{m} \sum_{i=0}^m [y_{true}^i \log(\bar{y}^i) + (1 - y_{true}^i) \log(1 - \bar{y}^i)]$$

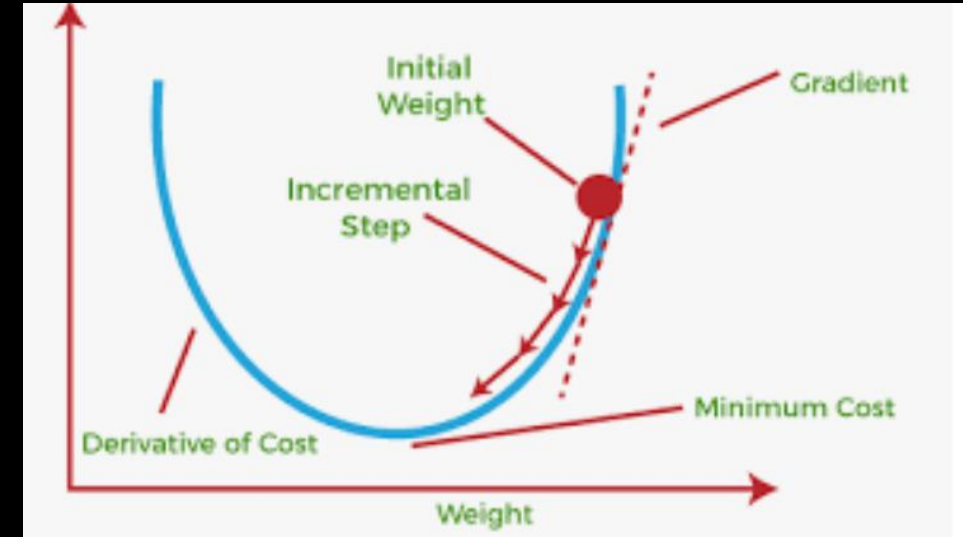
$$\frac{\partial}{\partial w_j} J(w) = \frac{1}{m} \sum_{i=1}^m (\bar{y}^i - y^i) x^i$$

Derivative of the cost function – used to update the parameters using gradient descent



Update parameters using gradient descent

$$\frac{\partial}{\partial w_j} J(w) = \frac{1}{m} \sum_{i=1}^m (\bar{y}^i - y^i) x^i$$



$$w_{new} = w - \alpha \frac{\partial}{\partial w} J(w)$$

After the model is trained, we will have the model parameters (W) and bias(W_0).

Let's code!