

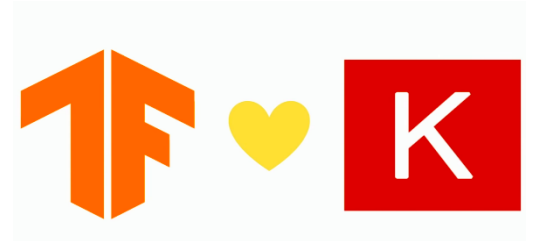
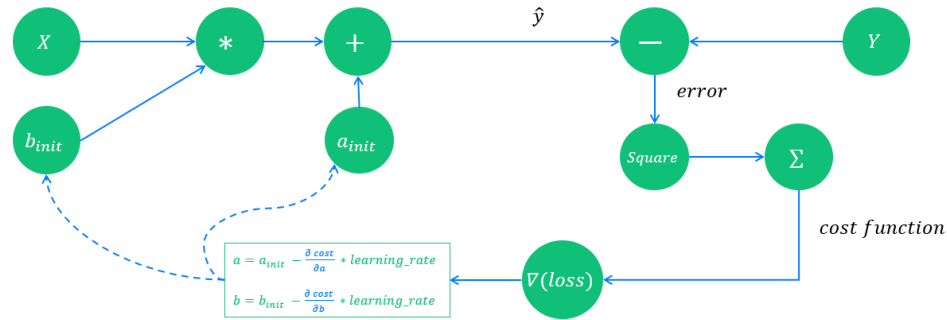
# Linear Model

**Srikanth Dakoju**

GitHub: <https://github.com/srikanthdakoju/custom-regression-training-tensorflow2>

Udemy: <https://www.udemy.com/course/draft/3075150/?referralCode=B685C9F6A839572F40CA>

# What you will learn



TensorFlow  
Keras

Advanced  
TensorFlow  
(Custom Training)

Model  
Architecture  
(Perceptron)

$\nabla f(b, W)$

Gradient  
Descent  
Algorithm

$$\hat{y} = b + W * X$$

Linear  
Regression

# Fitting Linear Model

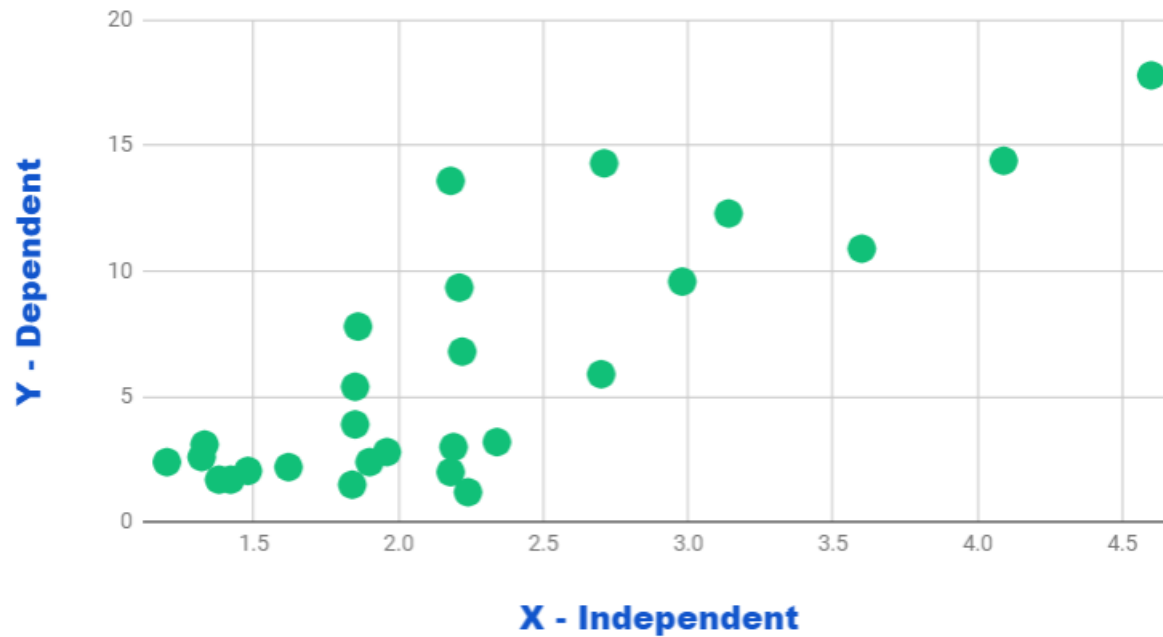
# Consider Data

X	Y
1.42	1.7
1.86	7.8
1.48	2.05
3.14	12.3
2.21	9.35
1.96	2.8
1.2	2.4
1.9	2.4
4.09	14.4
2.98	9.59
2.19	3
1.84	1.5
2.18	13.6
1.33	3.1
2.18	2
2.22	6.8
2.24	1.2
1.62	2.2
1.32	2.6
1.85	5.4
1.85	3.9
2.7	5.9
3.6	10.9
4.6	17.8

# Consider Data

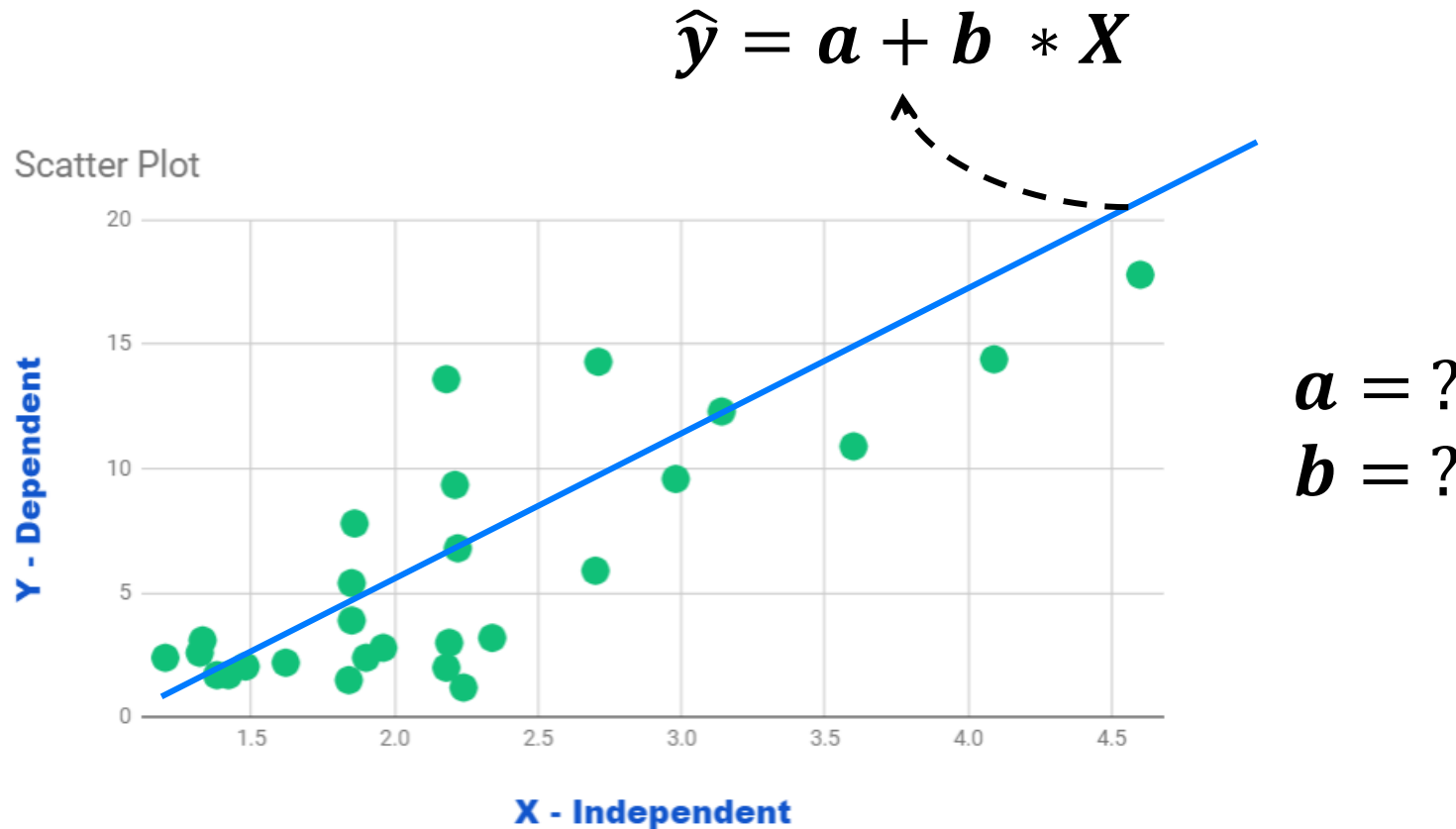
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Scatter Plot



# Linear Regression

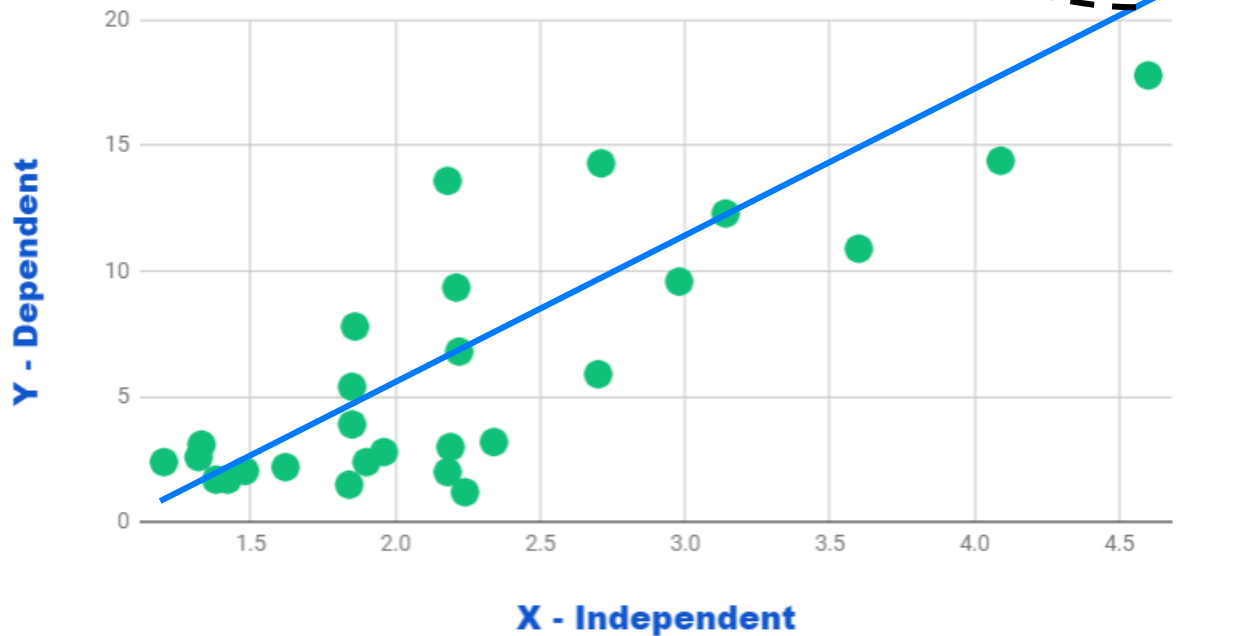
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# Linear Regression

$$\hat{y} = a + b * X$$

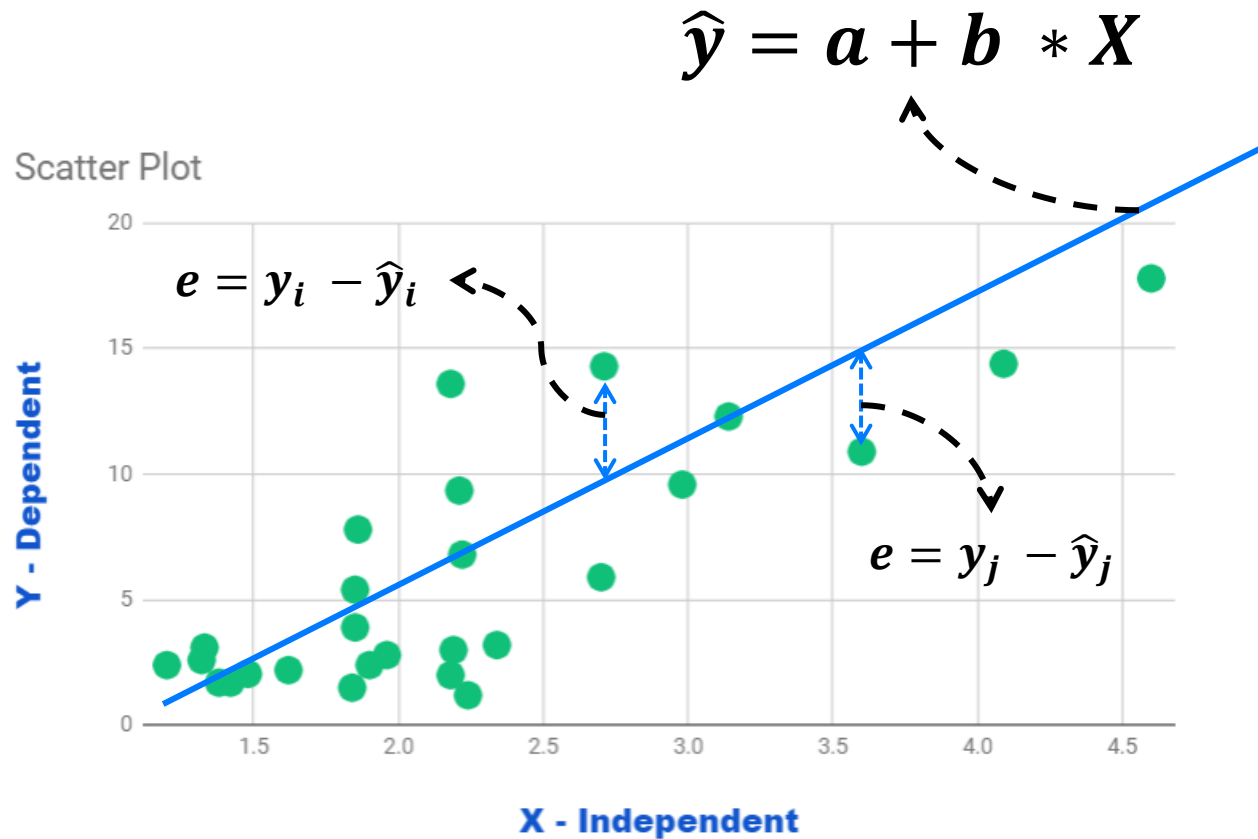
Scatter Plot



Linear Regression is a line, which will identify the relation between independent and dependent variable.

Such a way that line show has minimum **sum of squared error** or mean squared error

# Linear Regression

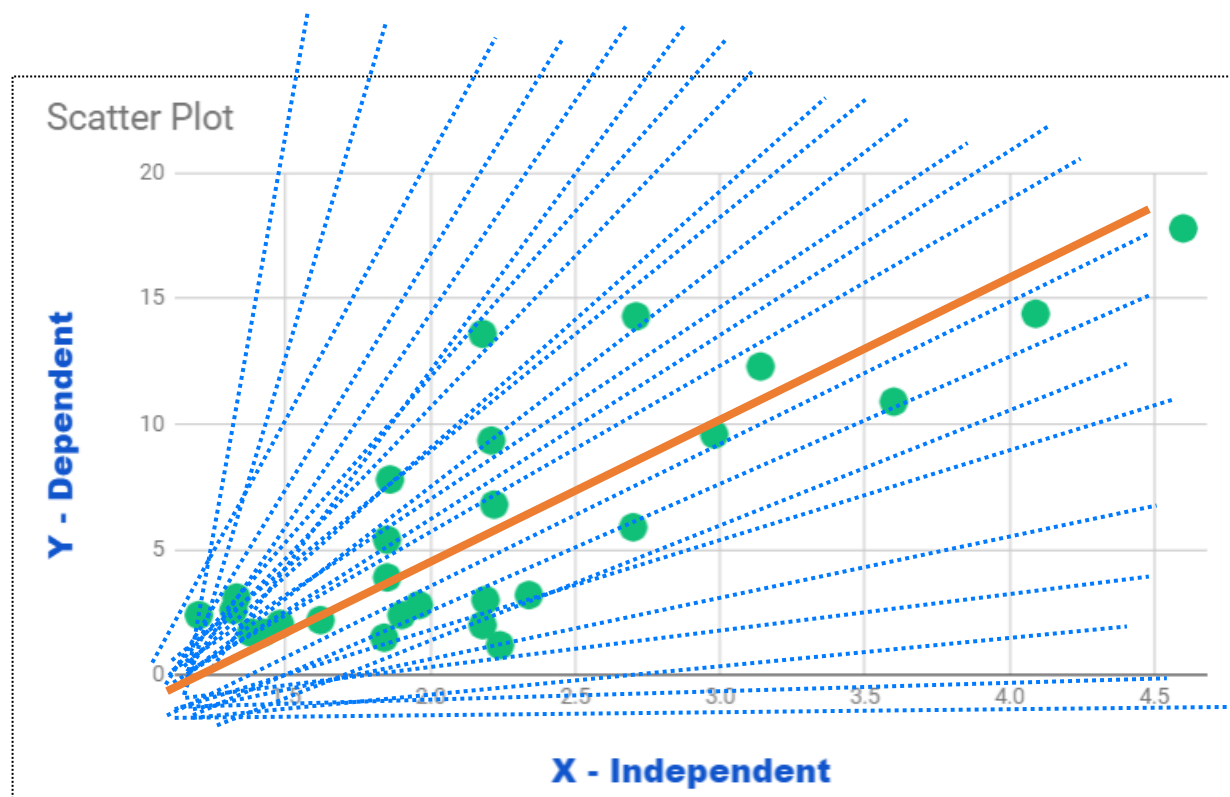


$$e = y_i - \hat{y}_i$$

$$SSE = \sum_i (y_i - \hat{y}_i)^2$$



# Linear Regression



$$\hat{y} = a + b * X$$

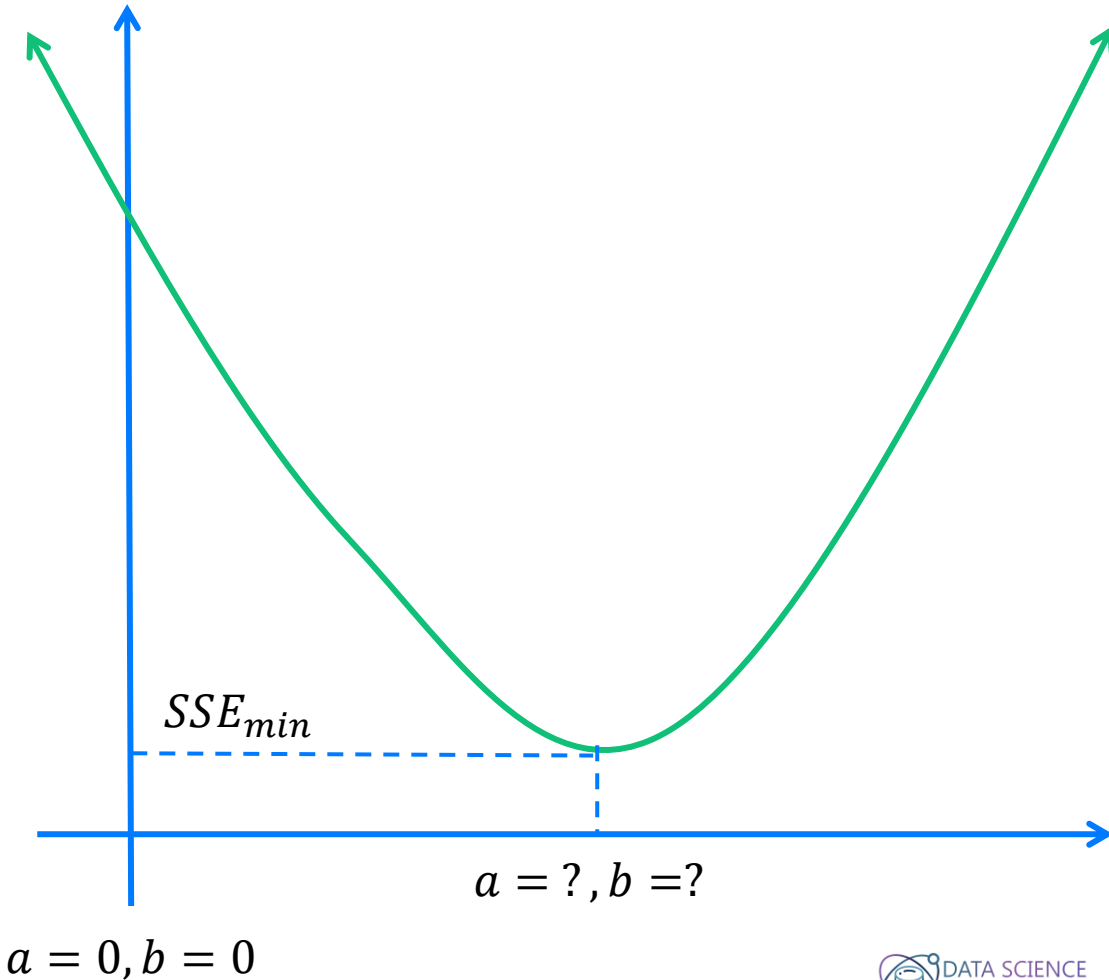
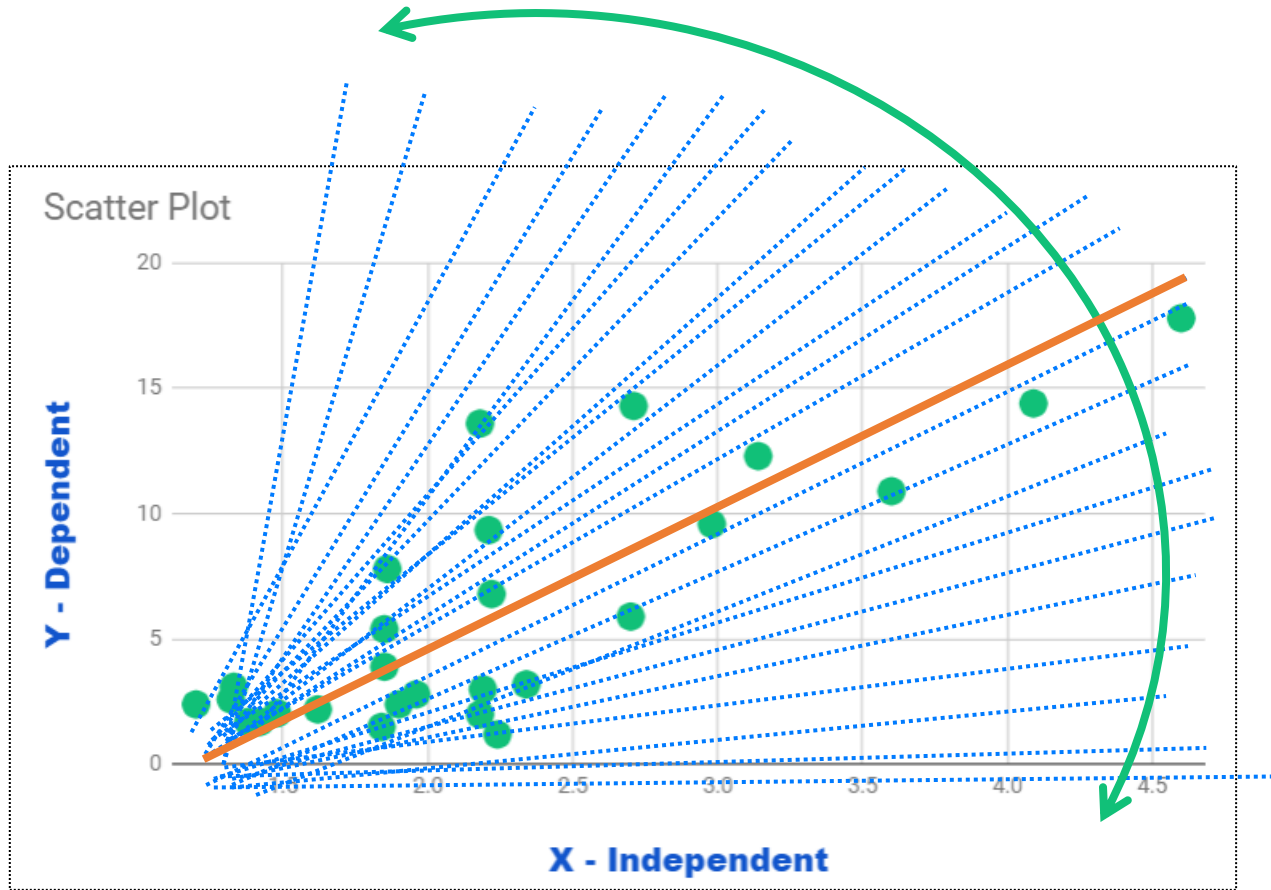
Select the line with minimum SSE

# Gradient Descent

# Linear Regression

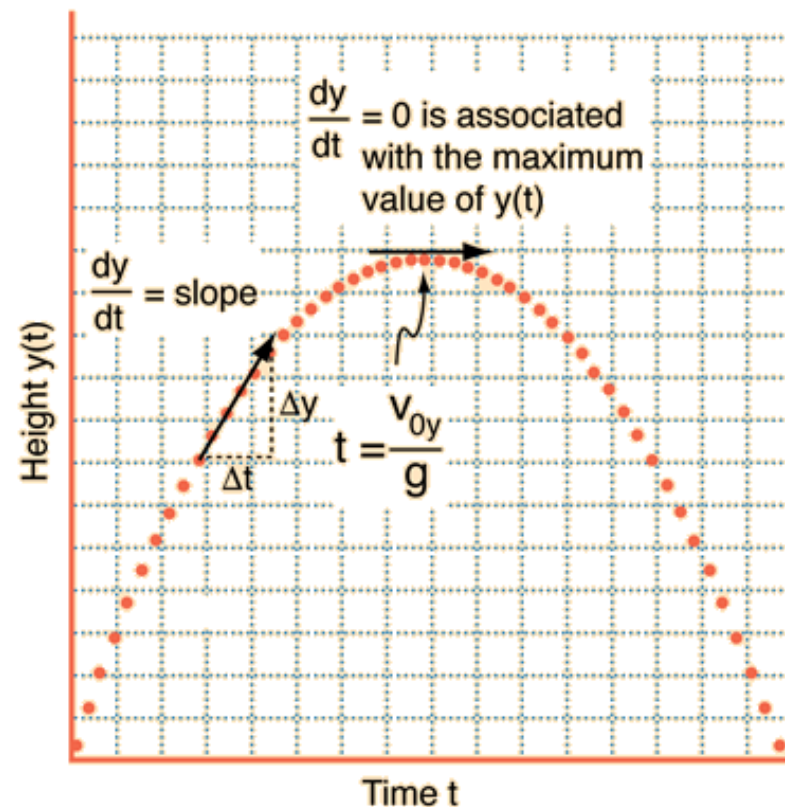
$$\hat{y} = a + b * X$$

*Sum of Squared Error (SSE)*



# Calculus – Maxima and Minima

One of the great powers of calculus is in the determination of the maximum or minimum value of a function. Take  $f(x)$  to be a function of  $x$ . Then the value of  $x$  for which the [derivative](#) of  $f(x)$  with respect to  $x$  is equal to zero corresponds to a maximum, a minimum or an inflexion point of the function  $f(x)$ .



$$y(t) = v_{0y} t - \frac{1}{2}gt^2$$

$$\frac{dy}{dt} = v_{0y} - gt = 0$$

$$\frac{d^2y}{dt^2} = -g$$

The fact that the second derivative is negative guarantees that the condition

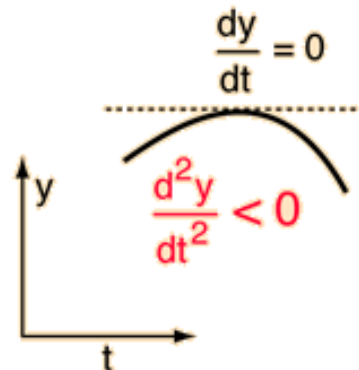
$$\frac{dy}{dt} = 0$$

corresponds to a maximum.

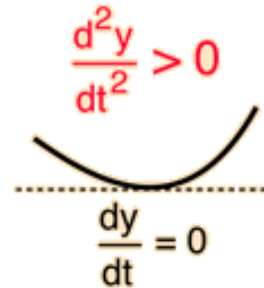
# Calculus – Maxima and Minima

The derivative of a function can be geometrically interpreted as the [slope of the curve](#) of the mathematical function  $y(t)$  plotted as a function of  $t$ . The derivative is positive when a function is increasing toward a maximum, zero (horizontal) at the maximum, and negative just after the maximum. The second derivative is the rate of change of the derivative, and it is negative for the process described above since the first derivative (slope) is always getting smaller. The second derivative is always negative for a "hump" in the function, corresponding to a maximum.

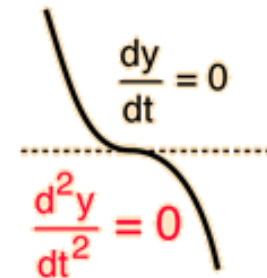
The second derivative demonstrates whether a point with zero first derivative is a maximum, a minimum, or an inflexion point.



For a **maximum**, the second derivative is negative. The slope of the curve ( first derivative) is at first positive, then goes through zero to become negative.



For a **minimum**, the second derivative is positive. The slope of the curve = first derivative is at first negative, then goes through zero to become positive.

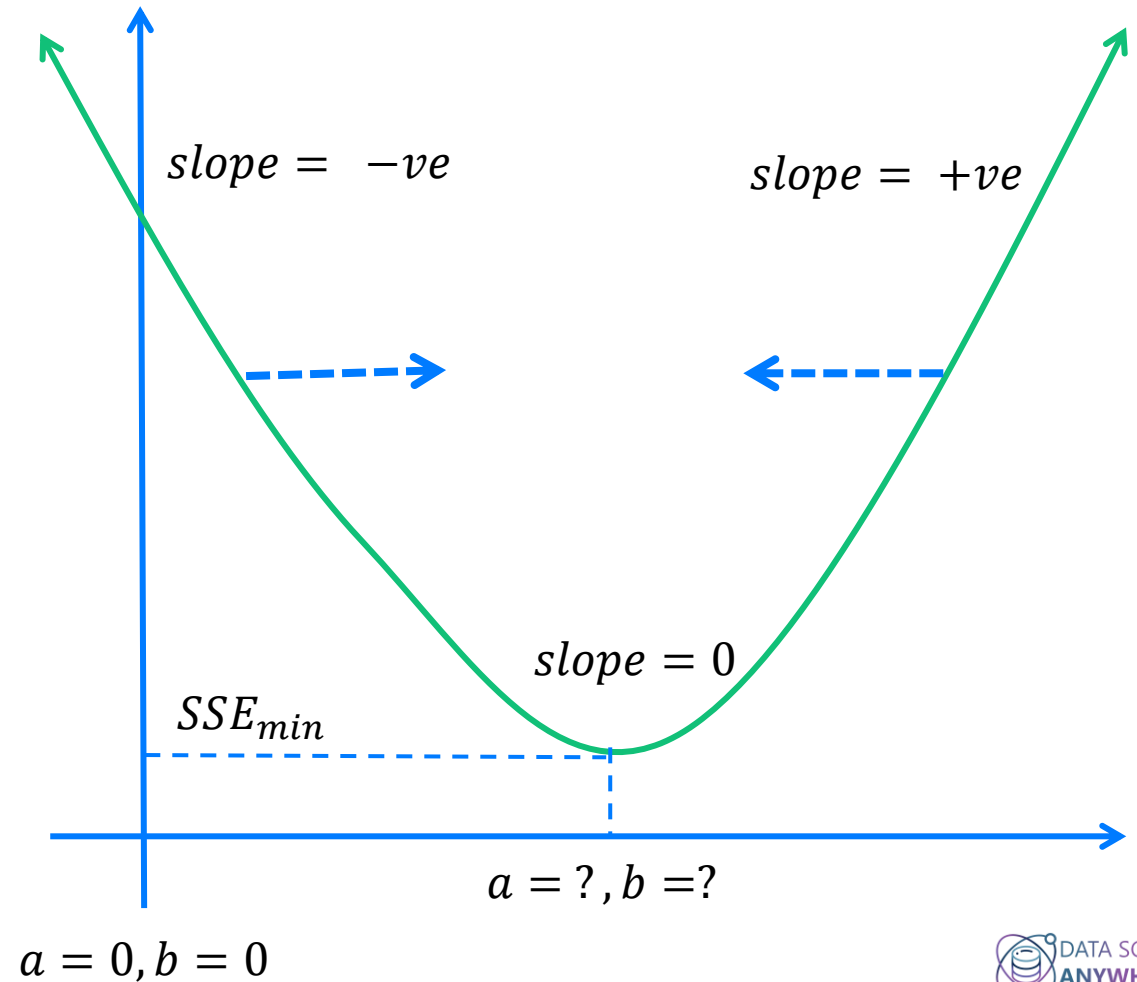


For an **inflexion point**, the second derivative is zero at the same time the first derivative is zero. It represents a point where the curvature is changing its sense. Inflexion points are relatively rare in nature.

# Gradient Descent

$$\hat{y} = a + b * X$$

Sum of Squared Error (SSE)



# Gradient Descent

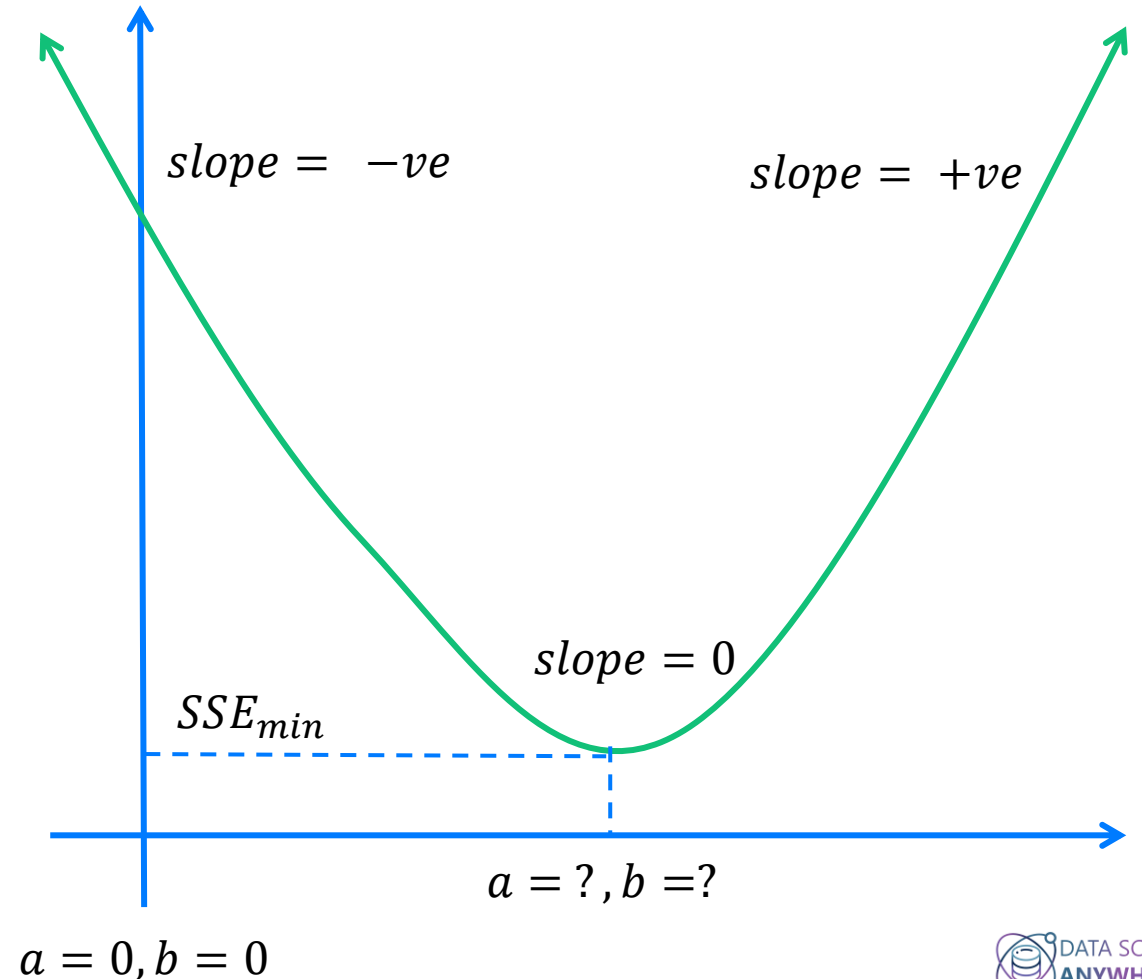
$$\hat{y} = a + b * X$$

Sum of Squared Error (SSE)

$$SSE = \sum_i (y_i - \hat{y}_i)^2$$

$$= \sum_i (y_i - (a + b * X_i))^2$$

$$f(a, b) = \sum_i (y_i - (a + b * X_i))^2$$



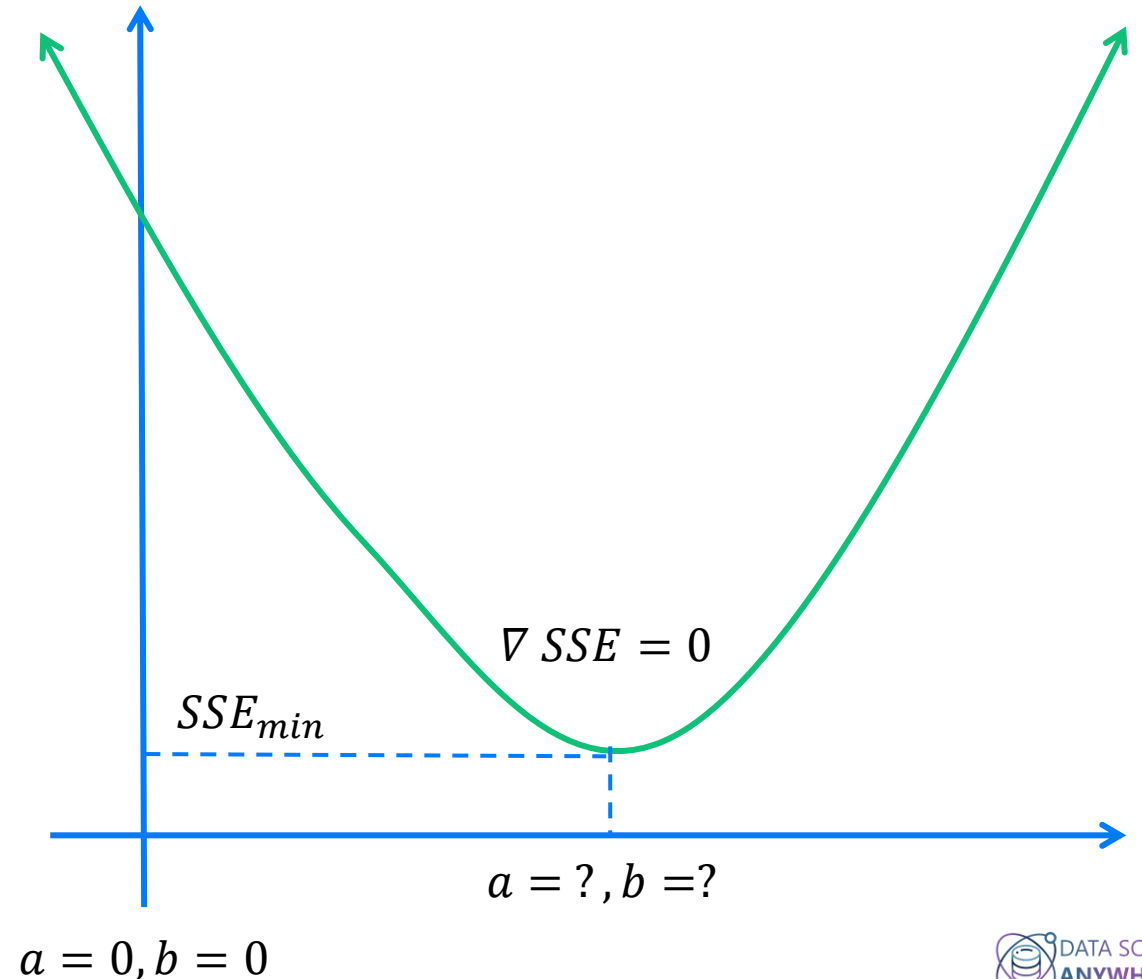
# Gradient Descent

$$f(a, b) = \text{cost} = \sum_i (y_i - (a + b * X_i))^2$$

*Sum of Squared Error (SSE)*

$$\nabla f(a, b) = \begin{pmatrix} \frac{\partial \text{cost}}{\partial a} \\ \frac{\partial \text{cost}}{\partial b} \end{pmatrix}$$

Gradient



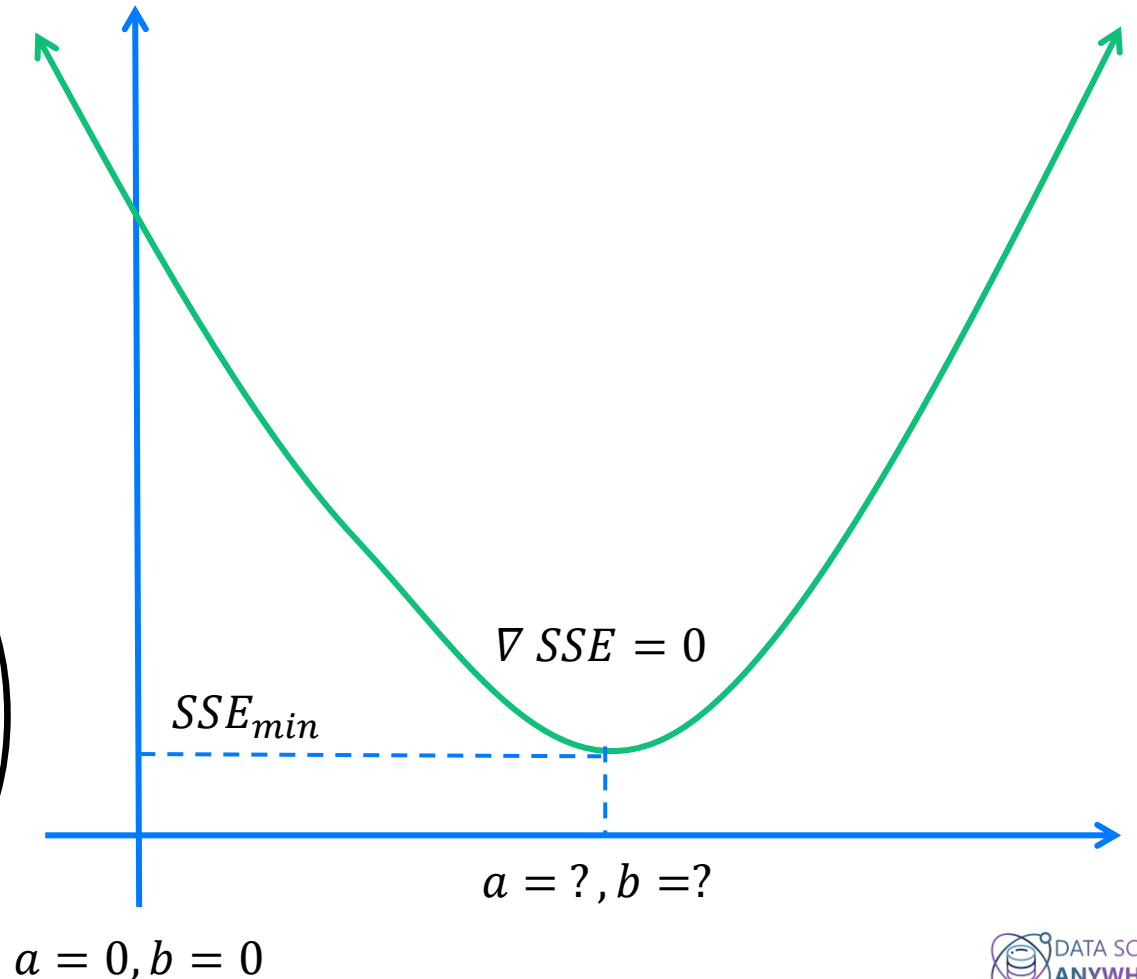


# Gradient Descent

$$f(a, b) = \text{cost} = \sum_i (y_i - (a + b * X_i))^2$$

*Sum of Squared Error (SSE)*

$$\nabla f(a, b) = \begin{pmatrix} \frac{\partial \text{cost}}{\partial a} \\ \frac{\partial \text{cost}}{\partial b} \end{pmatrix} = \begin{pmatrix} \sum_i -2X_i (y_i - a - b * X_i) \\ \sum_i -2 (y_i - a - b * X_i) \end{pmatrix}$$



# Gradient Descent

$$\nabla f(a, b) = \begin{pmatrix} \frac{\partial \text{cost}}{\partial a} \\ \frac{\partial \text{cost}}{\partial b} \end{pmatrix} = \begin{pmatrix} \sum_i -2X_i (y_i - a - b * X_i) \\ \sum_i -2 (y_i - a - b * X_i) \end{pmatrix}$$

# Gradient Descent

$$\nabla f(a, b) = \begin{pmatrix} \frac{\partial \text{cost}}{\partial b} \\ \frac{\partial \text{cost}}{\partial a} \end{pmatrix} = \begin{pmatrix} \sum_i -2X_i (y_i - a - b * X_i) \\ \sum_i -2 (y_i - a - b * X_i) \end{pmatrix}$$

$$a = a_{init} - \frac{\partial \text{cost}}{\partial a} * \text{learning\_rate}$$

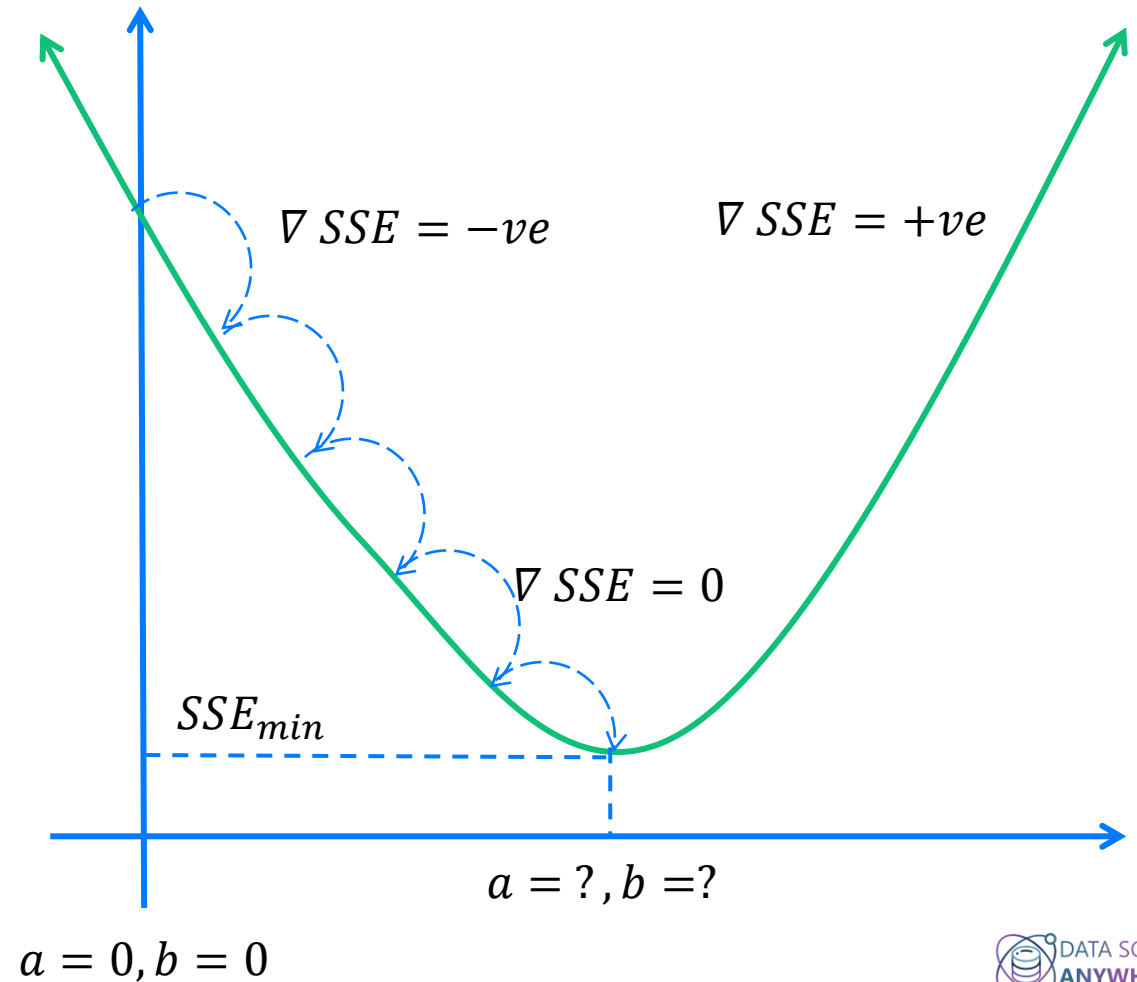
$$b = b_{init} - \frac{\partial \text{cost}}{\partial b} * \text{learning\_rate}$$

# Gradient Descent

$$a = a_{init} - \frac{\partial \text{cost}}{\partial a} * \text{learning\_rate}$$

$$b = b_{init} - \frac{\partial \text{cost}}{\partial b} * \text{learning\_rate}$$

Sum of Squared Error (SSE)



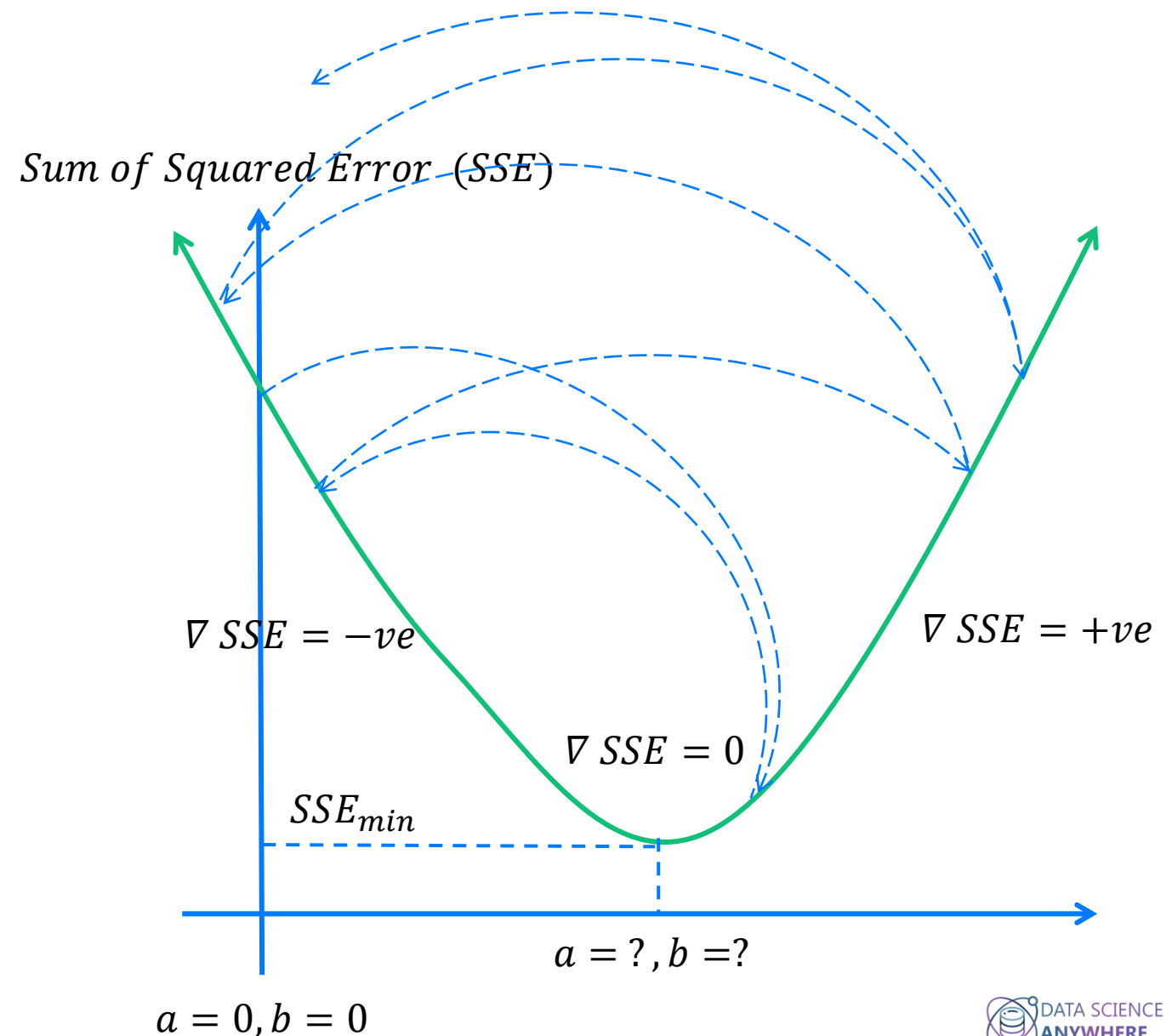
# Learning Rate

Learning Rate = (0 – 1)

$$a = a_{init} - \frac{\partial \text{cost}}{\partial a}$$

$$b = b_{init} - \frac{\partial \text{cost}}{\partial b}$$

Without learning rate or for large learning rate, model will become **unstable**.



# Gradient Descent

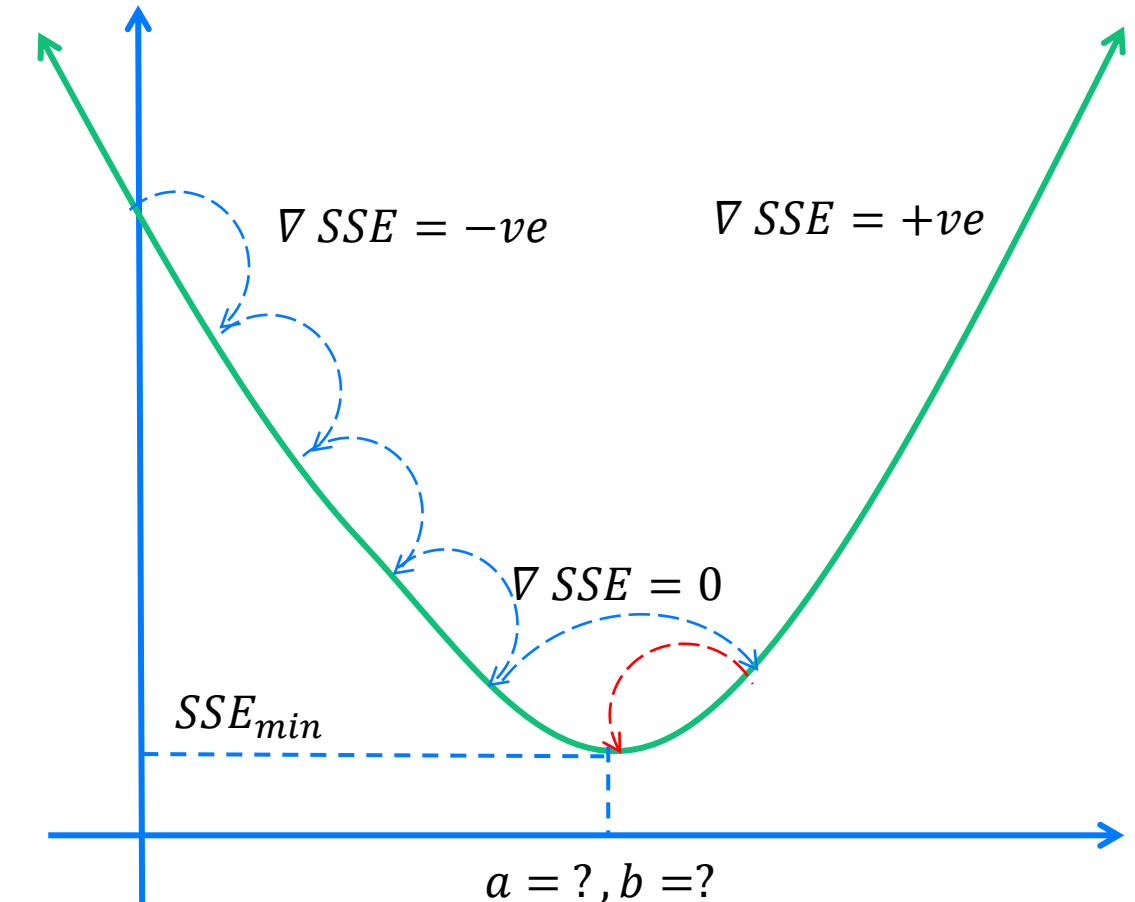
*Learning Rate* = (0 – 1)

- Small learning rate takes longer steps and converges granatee
- Large learning some time takes small steps but may diverge

$$a = a_{init} - \frac{\partial \text{cost}}{\partial a} * \text{learning\_rate}$$

$$b = b_{init} - \frac{\partial \text{cost}}{\partial b} * \text{learning\_rate}$$

*Sum of Squared Error (SSE)*



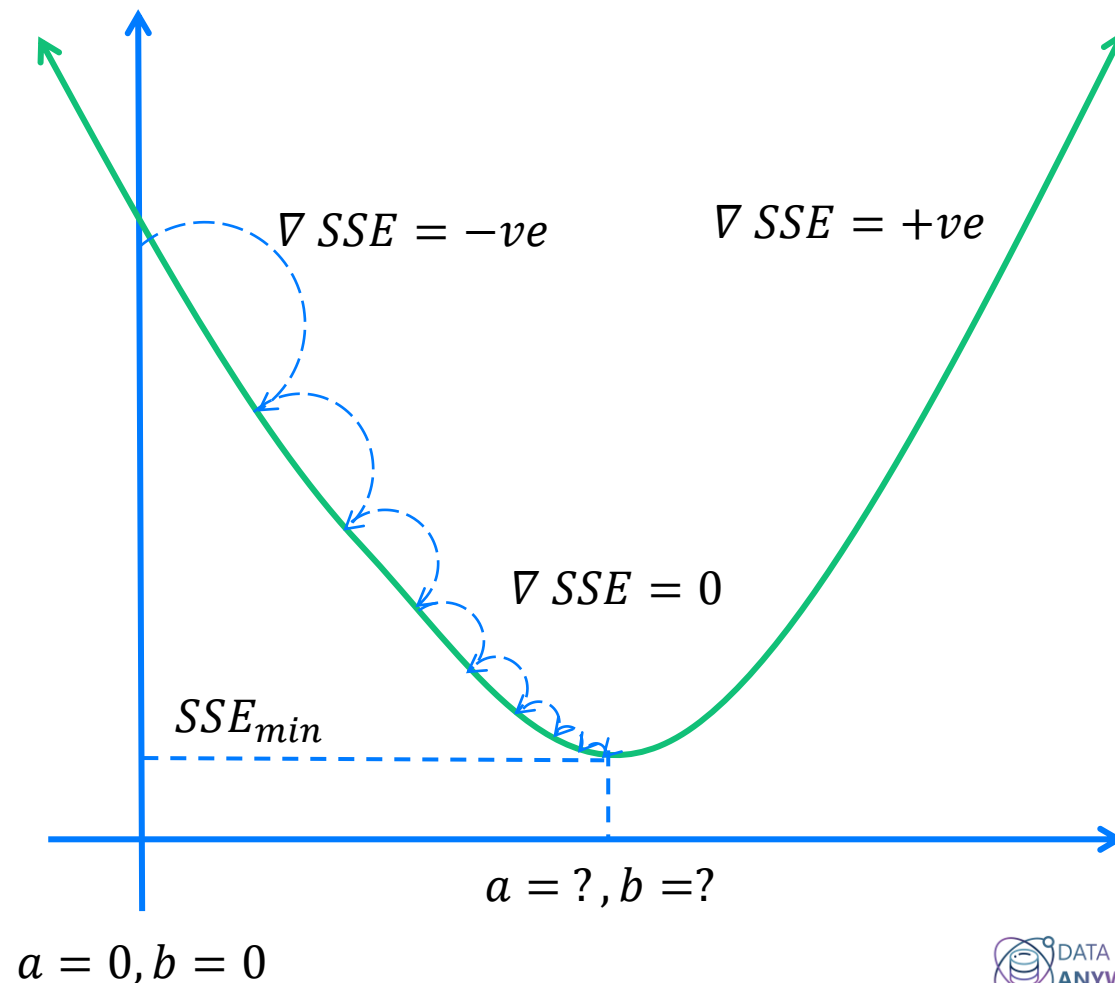
$a = 0, b = 0$

# Adam Optimizer

*Learning Rate* = (0 – 1)

- Initially starts with large learning rate as epochs increase learning rate become smaller and smaller.
- Get optimal value with less epochs

*Sum of Squared Error (SSE)*



# Model Architecture

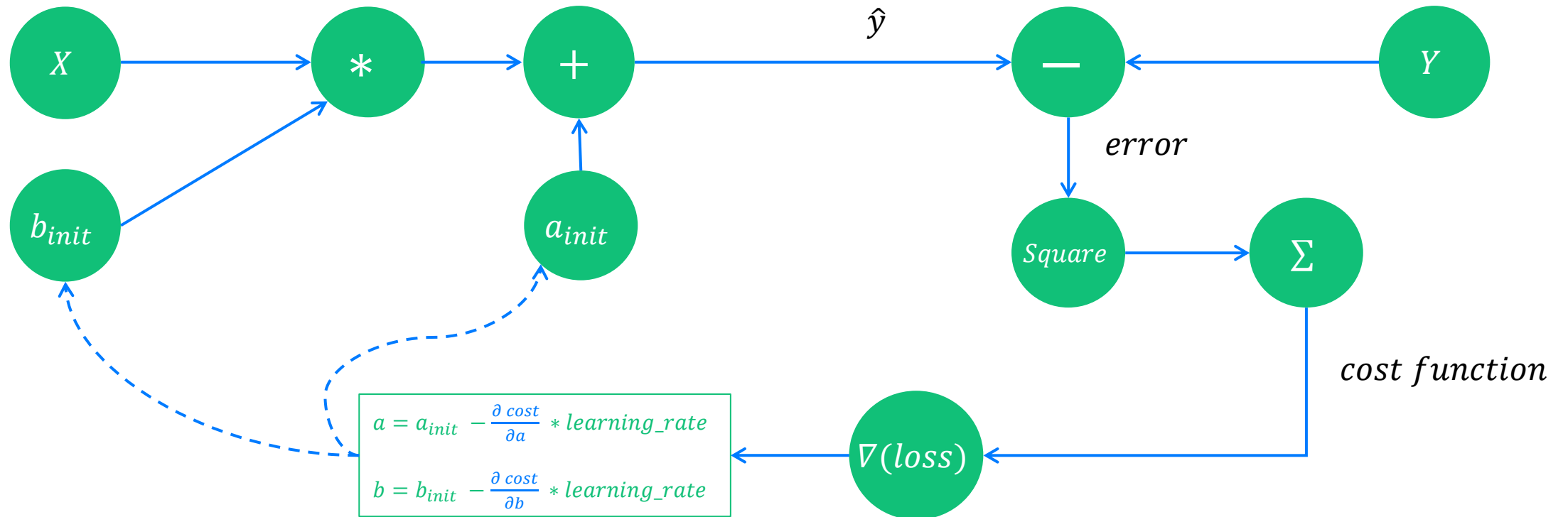
Reference: [https://www.tensorflow.org/tutorials/customization/custom\\_training](https://www.tensorflow.org/tutorials/customization/custom_training)



# Linear Model Architecture (Neuron)

TensorFlow 2.x 

$$\hat{y} = a + b * X$$

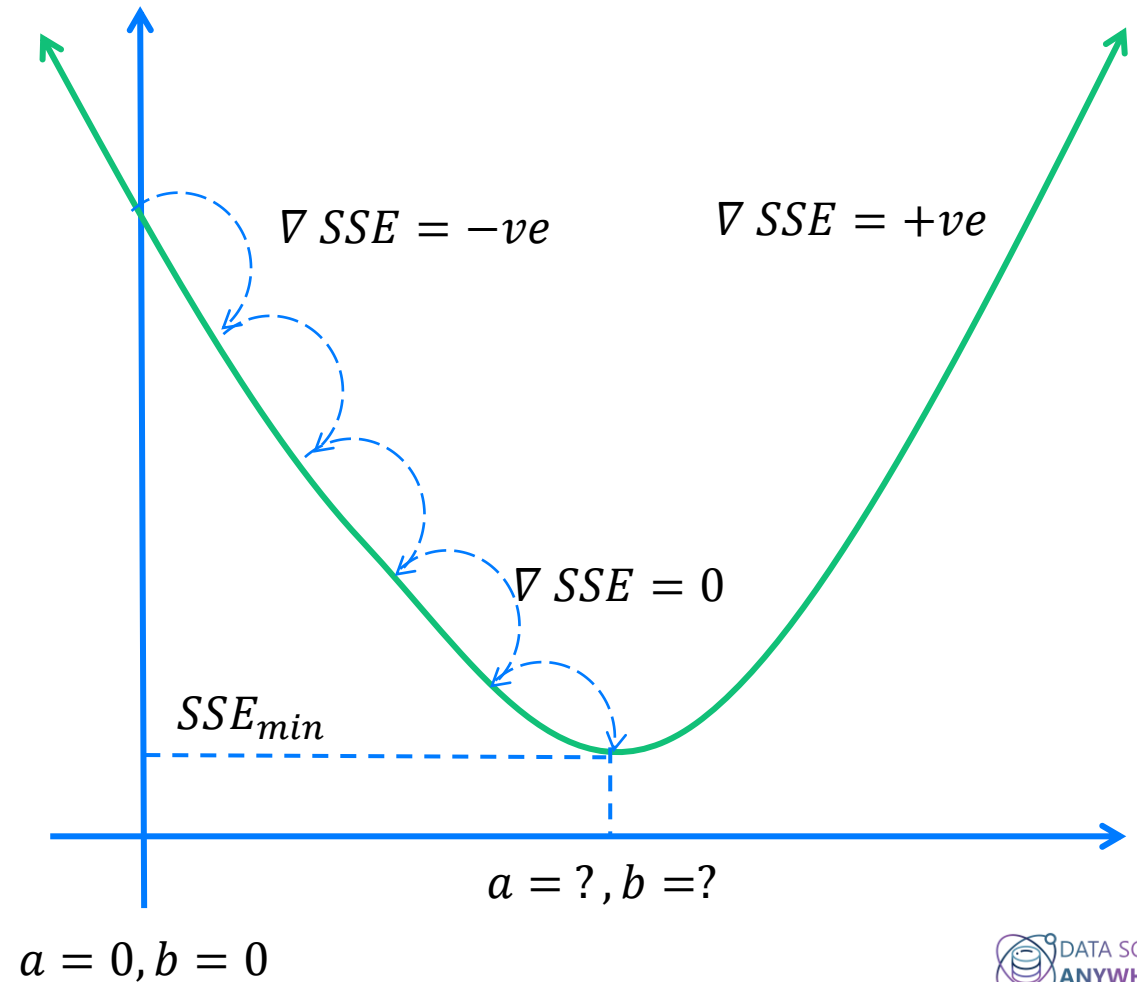


# Gradient Descent

$$a = a_{init} - \frac{\partial \text{cost}}{\partial a} * \text{learning\_rate}$$

$$b = b_{init} - \frac{\partial \text{cost}}{\partial b} * \text{learning\_rate}$$

Sum of Squared Error (SSE)



**Srikanth**

GitHub: <https://github.com/srikanthdakoju/custom-regression-training-tensorflow2>

**Jupyter Notebook:** <https://colab.research.google.com/drive/1i0nm4swR64QFBP2hPPI4Gn8GsPZR3f17?usp=sharing>

website: <http://www.datascienceanywhere.com>