

Linear Regression from scratch

ACM AI SIG: Srinivasa Perisetla

Little bit About me...

Srinivasa Perisetla

2nd Year CSE Major

Hobbies: Basketball, Lifting Weights,
Coding



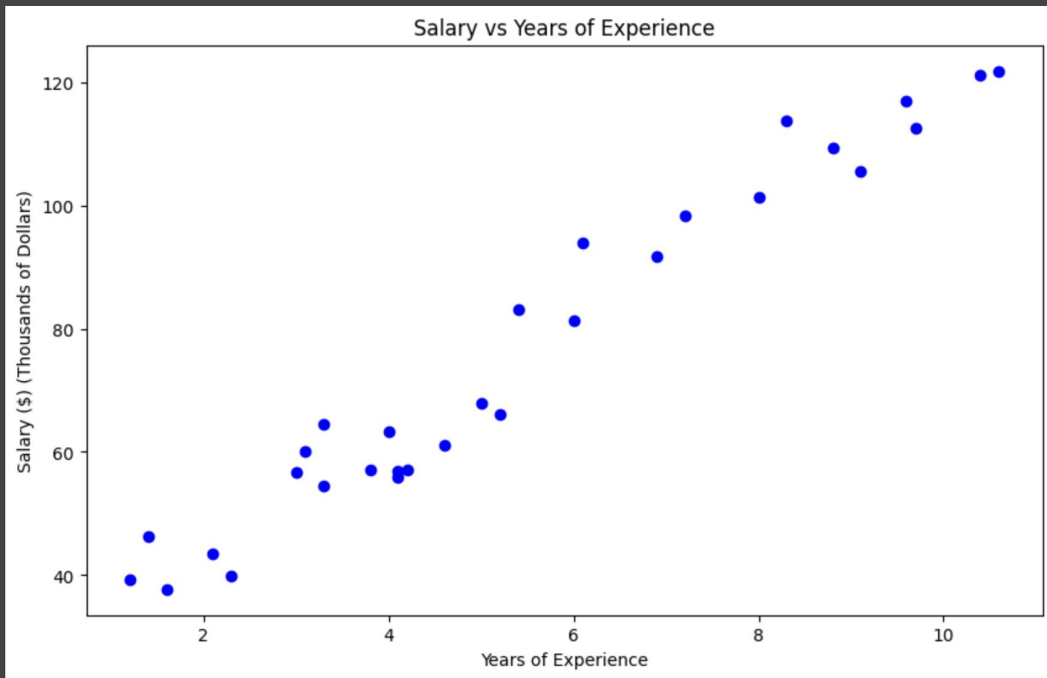
Intro To Linear Regression

Say we have a Graph
representing:

X: # of years of Experience

Y: Amount of Salary \$





How would a human draw a best fitted line?



How would a human draw a best fitted line?

Best Fit Line

This Line can be represented as

$$Y = mX + b$$

This can be used to predict the salary based off the # years of Experience

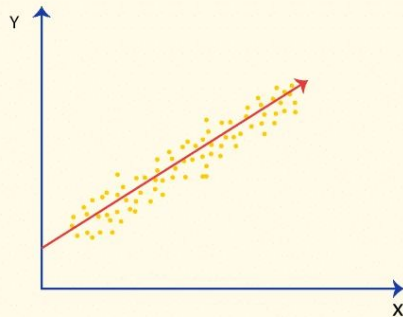


How can a computer come up with the best fit line

$$Y = mX + b$$

- If we can tune the parameters m and b to reduce the amount of error (difference) between the line and the actual point

**Linear
Regression**



How can we measure Error

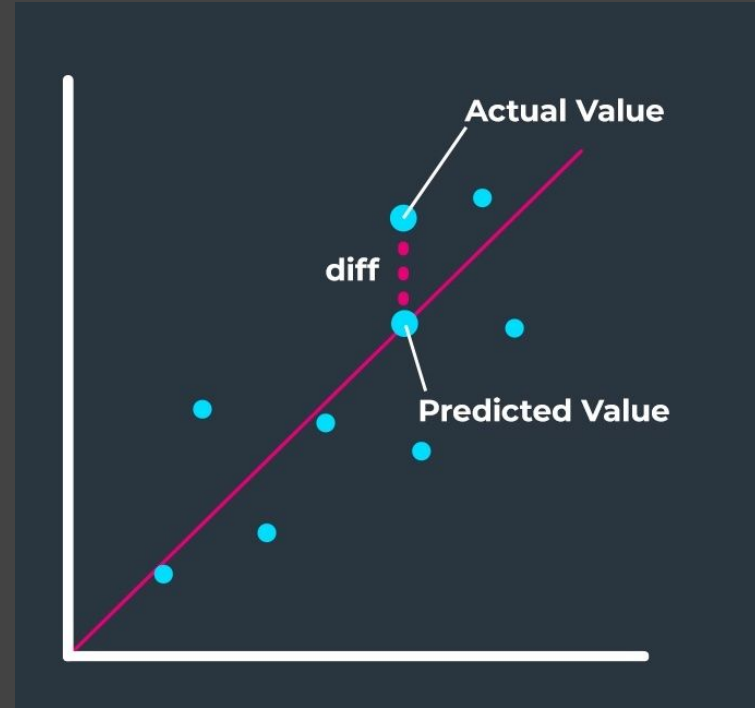
Goal: find m and b in the equation which gives the least amount of error

Error: $(y_i - \hat{y}_i)$

y_i = Actual value

\hat{y}_i = Predicted value from the line

Essentially the difference in distance between the points and the line



Measuring total error

Mean Squared Error

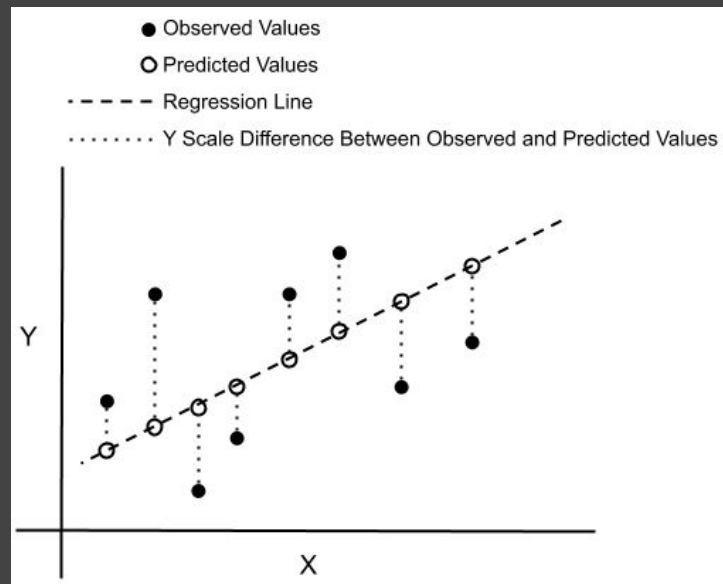
Square the differences:

- Penalize Larger Errors
- Get rid of Negative Error

Sum all of the errors up and take average

This gives the total error!

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$



Measuring total error

Mean Squared Error

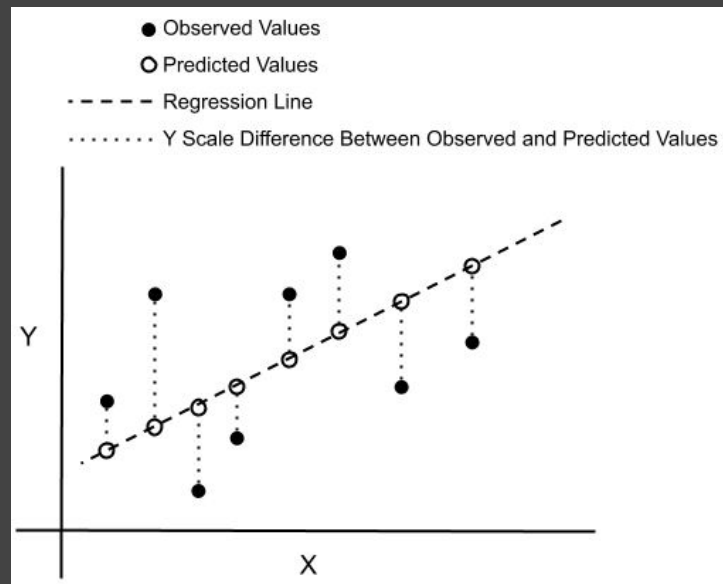
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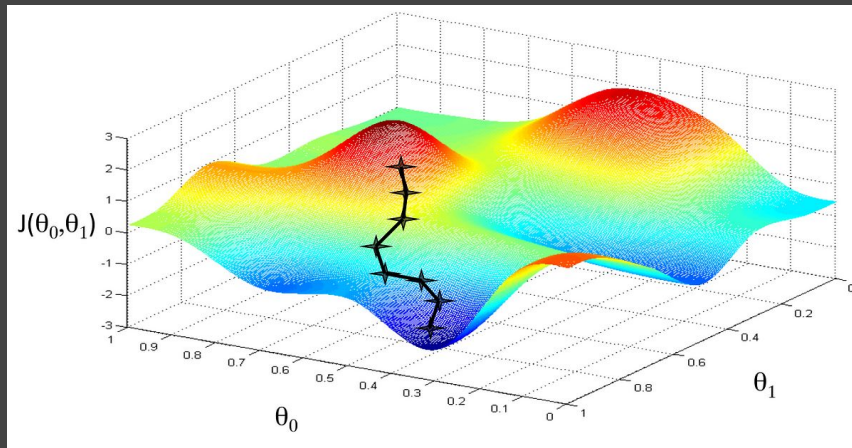
How can we reduce the error?

$$Y = mX + b$$

We have total error (MSE)

Perform Gradient Descent
Algorithm

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$



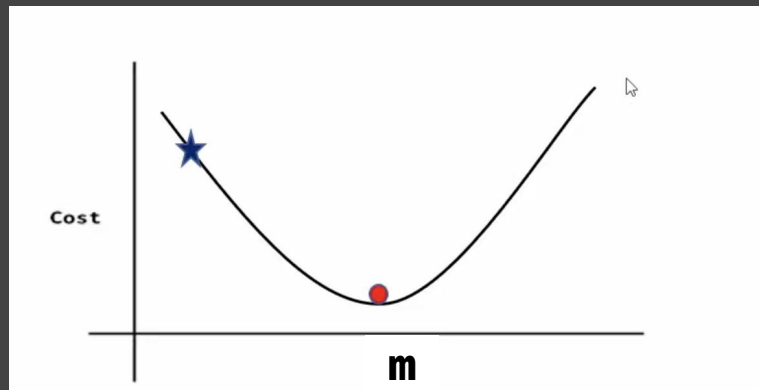
Gradient Descent Algorithm

Our total Error can be graphed as a Function vs m and b (3 dimensions)

Let's look at Total Error vs m for simplicity (2 Dimensions)

We want to traverse to the global minimum

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$



Gradient Descent Algorithm

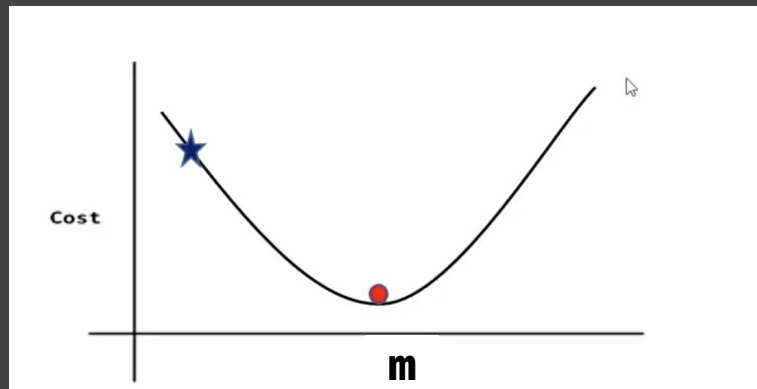
Find the Derivative $\partial E / \partial m$

- Derivative gives the maximum change in Error per change in variable (steepest ascent)

We need steepest descent ($-\partial E / \partial m$)

Then change the current m with the Derivative

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$



Calculating Derivative $\partial E / \partial m$

$$\hat{y} = mx + b$$

$$E = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$E = \frac{1}{n} \sum_{i=1}^n (y_i - (mx_i + b))^2$$

Calculating Derivative $\partial E / \partial m$

$$E = \frac{1}{n} \sum_{i=1}^n (y_i - mx_i - b)^2$$

$$\frac{\partial E}{\partial m} = \frac{1}{n} \sum_{i=1}^n 2 (y_i - mx_i - b) \cdot (-x_i)$$

Final Calculated Derivatives $\partial E/\partial m$ and $\partial E/\partial b$

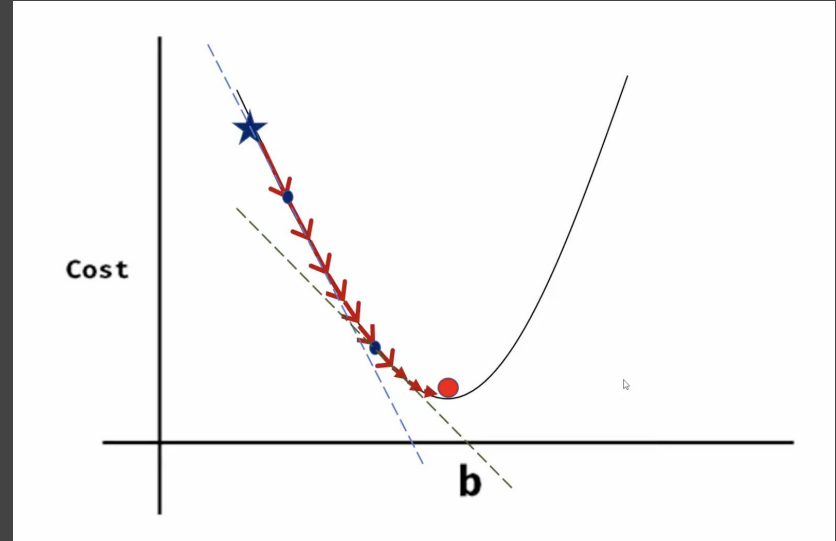
$$\frac{\partial E}{\partial m} = -\frac{2}{n} \sum_{i=1}^n x_i (y_i - mx_i - b)$$

$$\frac{\partial E}{\partial b} = -\frac{2}{n} \sum_{i=1}^n (y_i - mx_i - b)$$

Backpropogation

```
m = m - learning_rate *  $\partial E / \partial m$   
b = b - learning_rate *  $\partial E / \partial b$   
Learning_rate = 0.001
```

This is so the algorithm takes small steps towards the minimum

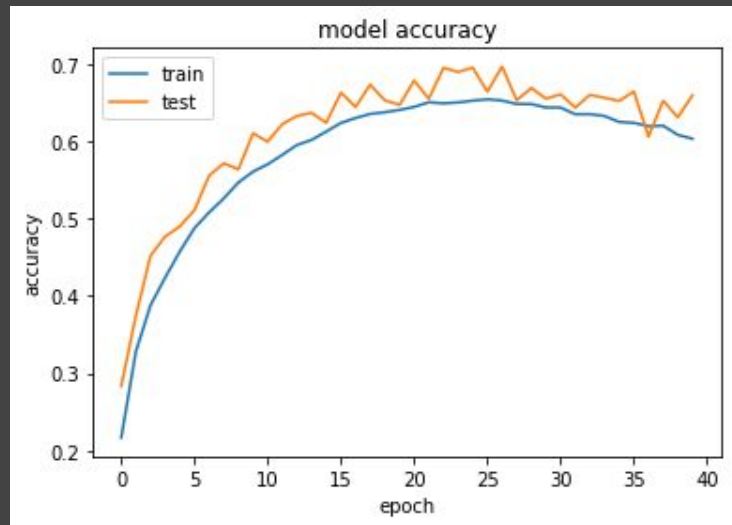


Training / Epochs

Train model for 100 Epochs

Epoch – 1 complete pass through entire training data set

Multiple Epochs are needed for effective training



Finished Model

$$Y = mX + b$$

Found values of m and b that reduces the Error (distance between points and line)



Lets Code Linear Regression from Scratch!

Scan the QR Code for Github Link and follow along!
