

Lecture 2 | Linear Regression and Gradient Descent

🕒 Date de création	@December 14, 2024 5:18 PM
🏷️ Étiquettes	

Notes

Gradient Descent

To apply gradient, we need:

- start with some random θ
- keep changing θ to minimize $J(\theta)$

Since we start θ randomly maybe you end in different places at the end (but still lower than the beginning).

We apply gradient until convergence. and in each iteration you update for $j = 0, 1, 2, 3...$

Batch Gradient Descent

This gradient is called Batch Gradient Descent and it's negative side is that in large dataset it becomes slower.

Stochastic Gradient Descent

```

Repeat {
    for j = 1 to m {
         $w_i := w_i - lr(w_{oxi} - y_i)x_{ji}$ 
    }
}

```

Suppose we have 100 million examples, GD one step requires you run through all data.

SGD updates at every iterations (for every single element).

If you're using Linear Regression Algorithm, It's possible in one step go to the local minima (normal equation).

Quotes

Questions

▼ How compute PD $J(\theta)$

PD = Partial Derivative

$(h_{\theta}(x) - y)$. $PD_{\theta_j}(\theta_0 x_0 + \theta_1 x_1 + \dots - y)$, and we know that, for all values that aren't θ_j the values of PD_{θ_j} is zero.

So, the final result is $(h_{\theta}(x) - y) * x_j$

▼ How is a step in gradient descent?

$$\theta_j = \theta_j - lr * \sum_{i=0, m} (h_{\theta}(x^{i}) - y^{i})x_j^{i}$$

▼ How find the Global Minima for Linear Regression in one single step?

Normal Equation

$$X^T \Theta = X^T y$$

$$\Theta = (X^T)^{-1} X^T y$$