

Gradient Descenti May 12,2021 Gradient descent is algorithm that minimizes the cost function, i.e. We have  $J(O_0, O_1)$ , we want to find min  $J(O_0, O_1)$ . First start w/ some  $\Theta_0$ ,  $\Theta$ , leig,  $\Theta_0 = 0$ ,  $\Theta_1 = 0$ ) Then keep changing  $\Theta_0$ ,  $\Theta_1$  until  $\mathcal{J}(\Theta_0, \Theta_1)$  is a min. repeat until convergence  $\{\theta_j := \theta_j - \chi \frac{\partial}{\partial \theta_j}, T(\theta_0, \theta_1)\}$ temp():=0, -x & J(0, 0,) Do:=temp() X

temp():=0, -x & J(0, 0,)

temp():=temp() & Simultaneous update or else this

0,:=temp() & won't work properly

x-learning rate

:=-override value of variable

The Importance of Learning hate. Too small = lots of training iters needed Too large = overshoot, fail to converge &ESC190 exam QF &If O; is already at a local minima, gradient descent does nothing. As we approach a local min, the derivative term automatically gets smaller, so g.d. will take smaller steps, Ly the learning rate can be fixed

$$\frac{\partial}{\partial \theta_{j}} T(\theta_{0}, \theta_{1}) = \frac{\partial}{\partial \theta_{j}} \cdot \frac{1}{2m} \sum_{i=1}^{m} \left( h_{\theta}(x^{(i)}) - y^{(i)} \right)^{2}$$

$$= \frac{\partial}{\partial \theta_{j}} \cdot \frac{1}{2m} \sum_{i=1}^{m} \left( \theta_{0} + \theta_{1} \times x^{(i)} - y^{(i)} \right)^{2}$$

$$j = 0 : \frac{\partial}{\partial \theta_{0}} T(\theta_{0}, \theta_{1}) = \frac{1}{m} \sum_{i=1}^{m} \left( h_{\theta}(x^{(i)}) - y^{(i)} \right)$$

$$j = 1 : \frac{\partial}{\partial \theta_{1}} T(\theta_{0}, \theta_{1}) = \frac{1}{m} \sum_{i=1}^{m} \left( h_{\theta}(x^{(i)}) - y^{(i)} \right) \cdot x^{(i)}$$

Gradient Descent For Linear Regression!

$$\frac{\partial}{\partial \theta_{i}} \mathcal{T}(\theta_{0}, \theta_{i}) = \frac{\partial}{\partial \theta_{i}} \cdot \frac{1}{2m} \sum_{i=1}^{m} \left(h_{0}(x^{(i)}) - y^{(i)}\right)^{2}$$
 $= \frac{\partial}{\partial \theta_{i}} \cdot \frac{1}{2m} \sum_{i=1}^{m} \left(\theta_{0} + \theta_{i} \times x^{(i)} - y^{(i)}\right)^{2}$ 

repeat until convergence {

Oo!=Oo- x m ? (ho(x(1)) - y(1)) Simultaneously

Oi!=O,- x m ? (ho(x(1)) - y(1)), x(1)

Batch gradient descent is where each step

of gradient descent uses all the training examples

(S) (ho(x(1)) - y(1))

[E] (ho(x(1)) - y(1))