Convex Optimization - Gradient Descent

Optimization

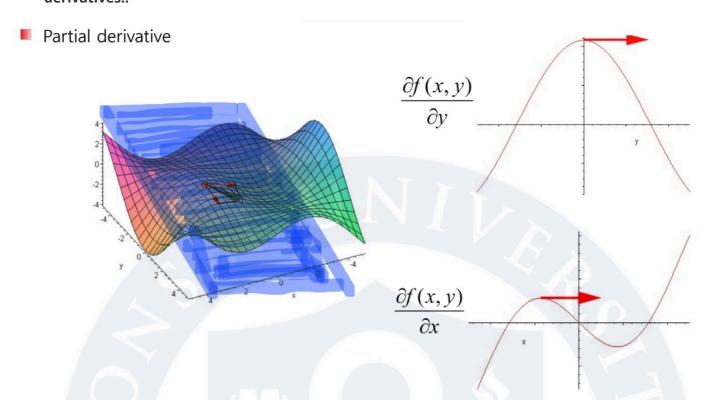
- Find value of decision variables that make object function have minimum(maximum) value.
- In machine learning, object function becomes Cost function which have to be minimized.
- e.g. : MSE, Entrophy, etc.

Gradient

• $\nabla f(x)$: Vector whose components are partial derivatives of f at some point x

$$abla f(x) = \left(rac{\partial f}{\partial x_1}, \cdots, rac{\partial f}{\partial x_p}
ight)^T$$

- Which can be interpreted as direction and magnitude in which the function moves
- If we want to minimize objective function, We have to update variable in **negative direction of derivatives!!**



Algorithm

• Objective : $\min_{\theta} J(\theta)$

ullet Parameter : $heta = [heta_0.\, heta_1 \cdots heta_p]$

Algorithm

1. Set t=0 and choose the learning rate(step size) lpha

2. Compute $\nabla J(\theta)$

3. Set $\dot{ heta^{(t+1)}} := \dot{ heta^{(t)}} - lpha
abla J(heta)$

4. Repeat 2~3 until abla J(heta) = 0

Example - linear regression

Functions

$$J(heta) = rac{1}{2m} \sum_{i=1}^m (\hat{y}_i - y_i)^2 \ \hat{y}_i = heta_0 + heta_1 x_{i1} + \dots + heta_p x_{ip}$$

• where $j \neq 0$

$$\frac{\partial J}{\partial \theta_j} = \frac{\partial}{\partial \theta_j} \frac{1}{2m} \sum_{i} (\hat{y}_i - y_i)^2$$

$$= 2 \cdot \frac{1}{2m} \sum_{i} (\hat{y}_i - y_i) \frac{\partial}{\partial \theta_j} (\hat{y}_i - y_i)$$

$$= \frac{1}{m} \sum_{i} (\hat{y}_i - y_i) x_{ij}$$

$$\frac{\partial J}{\partial \theta_0} = \frac{1}{m} \sum_{i} (\hat{y}_i - y_i)$$

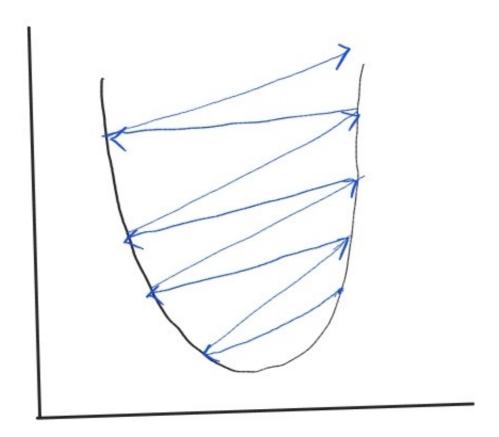
Repeat until converge

$$egin{aligned} heta_0 &:= heta_0 - lpha rac{1}{m} \sum (\hat{y}_i - y) \ heta_j &:= heta_1 - lpha rac{1}{m} \sum (\hat{y}_i - y) x_{ij} \end{aligned}$$

Learning rate

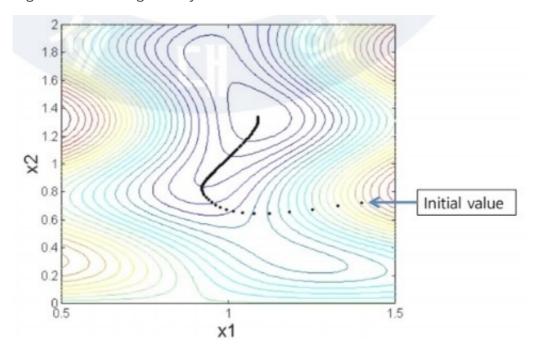
• If α is too high: It can diverge

• If α is too low : It is very slow to be converge



Steepest Descent

• Disadvantage of GD: converge is very slow



- If direction is not changed, there is no need to slowly update parameters
 - $\rightarrow \text{recalculate learning rate every step!!}$
- Algorithm
 - 1. Set t=0

- 2. Compute abla J(heta)3. Compute learning $\mathrm{rate} lpha_i = \operatorname*{argmin}_{\alpha \geq 0} f(x_i lpha
 abla J(heta))$
- 4. Set $heta^{(t+1)} := heta^{(t)} lpha
 abla J(heta)$
- 5. Repeat 2~4 until abla J(heta) = 0

