Cost Function

Linear Regression

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앞으로 우리는

$$f(x) = h_\theta(x)$$

예측 함수를 가설 함수라고 부를 예정

실제값과 가설함수의 차이

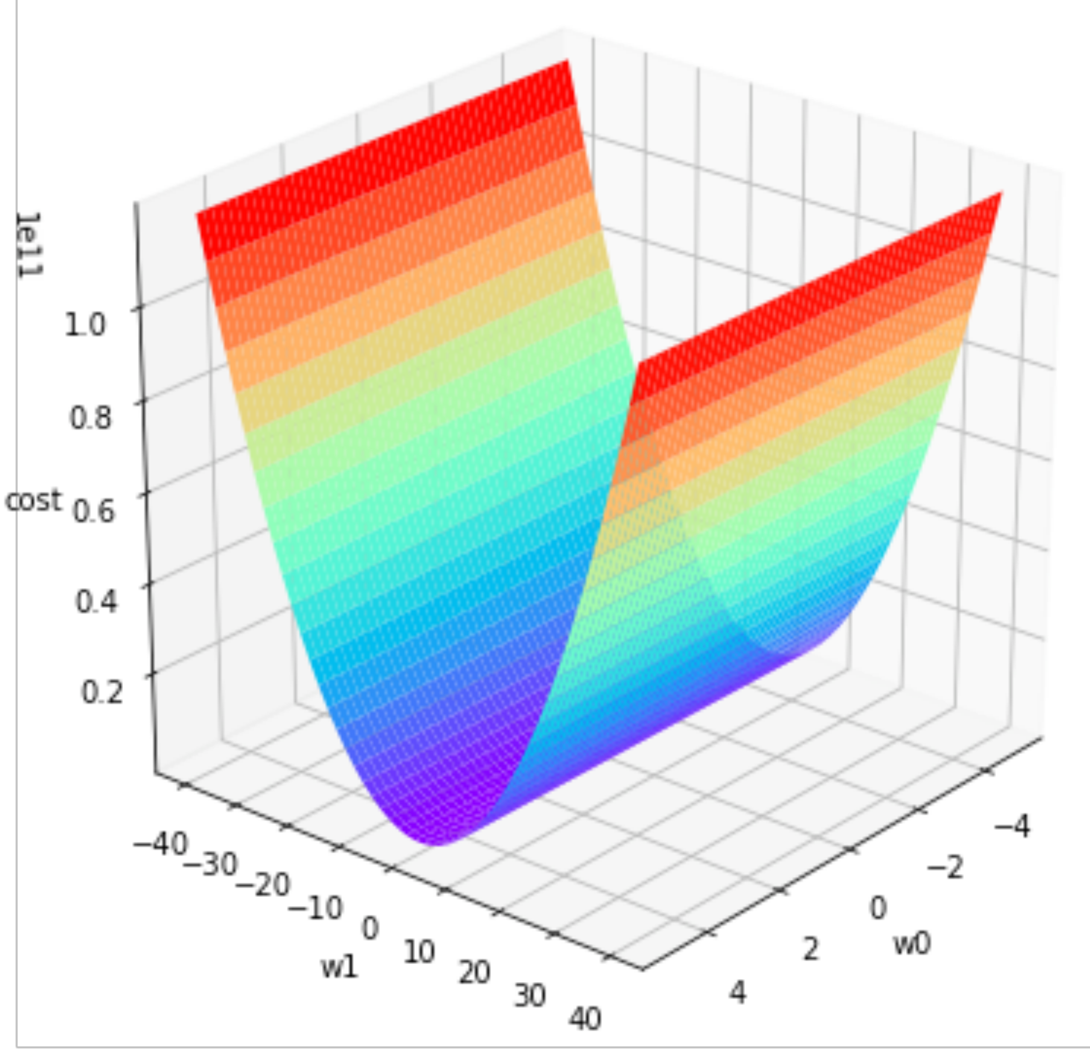
$$J(w_0, w_1) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2$$

Cost function이라고 부를 예정

Cost function에서 구하는 것

$$\arg\min_{\theta} \ \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2$$

cost function의 최소화를 위한 weight 값



1e11
1.0
0.8
cost
0.6
0.4
0.2
−40
−30
−20
−10
0
10
20
30
40
w1
−4
−2
0
2
4
w0

$$J(w_0, w_1) = \frac{1}{2m} \sum_{i=1}^{m} (w_1 x^{(i)} + w_0 - y^{(i)})^2$$

$$\frac{\partial J}{\partial w_0} = \frac{1}{m} \sum_{i=1}^{m} (w_1 x^{(i)} + w_0 - y^{(i)})$$

$$\frac{\partial J}{\partial w_1} = \frac{1}{m} \sum_{i=1}^{m} (w_1 x^{(i)} + w_0 - y^{(i)}) x^{(i)}$$

$$f(x) = \sum_{i=1}^{5} \frac{1}{2} x^2$$

$$\frac{df}{dx} = x + x + x + x + x$$

$$= \sum_{i=1}^{5} x$$

Derivate of $f(g(x))$

$$\frac{df}{dx} = \frac{df(u)}{du} \frac{du}{dx}, \text{let } u = g(x)$$

$$f = (2x - 1)^2, \frac{df}{dx} = 2(2x - 1) \times 2$$

Review: Scalar derivative rules

Rule	$f(x)$	Scalar derivative notation with respect to x	Example
Constant	c	0	$\frac{d}{dx}99 = 0$
Multiplication by constant	cf	$c\frac{df}{dx}$	$\frac{d}{dx}3x = 3$
Power Rule	x^n	nx^{n-1}	$\frac{d}{dx}x^3 = 3x^2$
Sum Rule	$f + g$	$\frac{df}{dx} + \frac{dg}{dx}$	$\frac{d}{dx}(x^2 + 3x) = 2x + 3$
Difference Rule	$f - g$	$\frac{df}{dx} - \frac{dg}{dx}$	$\frac{d}{dx}(x^2 - 3x) = 2x - 3$
Product Rule	fg	$f\frac{dg}{dx} + \frac{df}{dx}g$	$\frac{d}{dx}x^2x = x^2 + x2x = 3x^2$
Chain Rule	$f(g(x))$	$\frac{df(u)}{du}\frac{du}{dx}$, let $u = g(x)$	$\frac{d}{dx}ln(x^2) = \frac{1}{x^2}2x = \frac{2}{x}$

http://parrt.cs.usfca.edu/doc/matrix-calculus/index.html

weights의 최적값 컴퓨터가 찾는 방법

- 연립방정식 풀기 (normal equation)
- gradient descent

TEAMLAB

Human knowledge belongs to the world.