House prices

1) Implement by hand equations of derivative using LaTeX (I will use similar format in LibreOffice/ODF, sorry)

$$f_{x} = \frac{\partial f}{\partial x} = \lim_{h \to 0} \frac{f(x+h, y) - f(x, y)}{h}$$
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2) Writing equations for housings:

$$dw \, linear : \frac{\delta}{\delta \, W} [W \cdot x + b] = x$$

$$dx \, linear : \frac{\delta}{\delta \, x} [W \cdot x + b] = W$$

$$db \, linear : \frac{\delta}{\delta \, b} [W \cdot x + b] = 1$$

3) Cost function

We will use mean squared error cost function:

$$J(\theta_0, \theta_1) = L_{MSE} = \frac{1}{N} \cdot \sum_{i=0}^{N} (h_{\theta}(x_i) - y_i)^2$$

where $h_{\theta}(x_i) = \theta_0 + \theta_1 \cdot x_i$ (is our model)

We need to minimize cost function's result.

4) Gradient descent

The goal of this is to update θ_0 , b and θ_1 , W to minimize cost function result.

$$\theta_0 := \theta_0 - \alpha \cdot \frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1)$$
$$b := b - \alpha \cdot \frac{\partial}{\partial b} J(b, W)$$

$$\begin{aligned} &\boldsymbol{\theta}_{1} \!:=\! \boldsymbol{\theta}_{1} \!-\! \boldsymbol{\alpha} \!\cdot\! \! \frac{\partial}{\partial \boldsymbol{\theta}_{1}} J(\boldsymbol{\theta}_{0}, \! \boldsymbol{\theta}_{1}) \\ &\boldsymbol{W} \!:=\! \boldsymbol{W} \!-\! \boldsymbol{\alpha} \!\cdot\! \! \frac{\partial}{\partial \boldsymbol{W}} J(\boldsymbol{b}, \! \boldsymbol{W}) \end{aligned}$$

but to simultaneously update both variables we need to assign them to temporary variables first, so b doesn't affect calculation of the W.

 α - is a learning rate, which defines how fast we are going to change b and W.

By intuition what is going to happen – partial derivative of the cost function will be a positive slope (will return a positive number) if the mse will on the right side of the local minima, as a result we will subtract a slope value multiplied by learning rate from W (or b). Otherwise we will add it. In ideal situation once MSE is 0 – we don't move anymore.

So let's try to figure out partial derivatives:

For θ_0 or b:

$$\frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1) = \frac{\partial}{\partial \theta_0} \cdot \frac{1}{N} \cdot \sum_{i=0}^{N} (h_{\theta}(x_i) - y_i)^2 = \frac{\partial}{\partial \theta_0} \cdot \frac{1}{N} \cdot \sum_{i=0}^{N} (\theta_0 + \theta_1 x_i - y_i)^2 = \frac{2}{N} \sum_{$$

equals to:

$$\frac{2}{N} \sum_{i=0}^{N} (\theta_0 + \theta_1 x_i - y_i) \cdot 1 = \frac{2}{N} \sum_{i=0}^{N} (b + W \cdot x_i - y_i) \cdot 1$$

and for θ_1 or W:

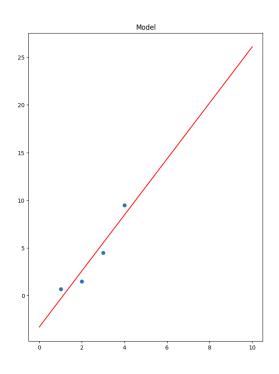
$$\frac{\partial}{\partial \theta_1} J(\theta_0, \theta_1) = \frac{\partial}{\partial \theta_1} \cdot \frac{1}{N} \cdot \sum_{i=0}^N (h_{\theta}(x_i) - y_i)^2 = \frac{\partial}{\partial \theta_1} \cdot \frac{1}{N} \cdot \sum_{i=0}^N (\theta_0 + \theta_1 x_i - y_i)^2 = \frac{2}{N} \sum$$

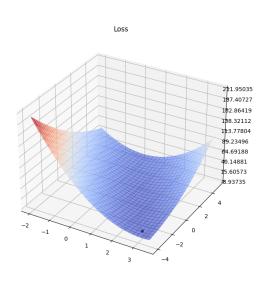
equals to:

$$\frac{2}{N} \sum_{i=0}^{N} (\theta_0 + \theta_1 x_i - y_i) \cdot x_i = \frac{2}{N} \sum_{i=0}^{N} (b + W \cdot x_i - y_i) \cdot x_i$$

For linear model:

w=2.939305864784624 b=-3.2979591578193053 loss=1.103000695674468 learning_rate=0.000149000000000007





For sigmoid model:

$$\frac{1}{1+e^{-x}}$$

We need to find a gradient descent:

$$\boldsymbol{\theta}_0 \colon= \boldsymbol{\theta}_0 - \boldsymbol{\alpha} \cdot \frac{\partial}{\partial \boldsymbol{\theta}_0} \boldsymbol{J}(\boldsymbol{\theta}_0, \boldsymbol{\theta}_1)$$

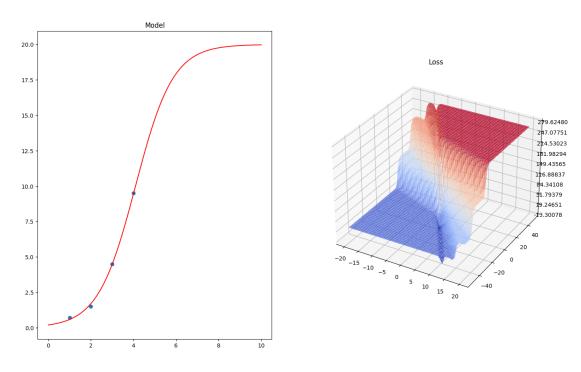
$$b := b - \alpha \cdot \frac{\partial}{\partial b} J(b, W)$$

$$\boldsymbol{\theta}_{1} \!:=\! \boldsymbol{\theta}_{1} \!-\! \boldsymbol{\alpha} \!\cdot\! \frac{\partial}{\partial \boldsymbol{\theta}_{1}} \boldsymbol{J}(\boldsymbol{\theta}_{0}, \!\boldsymbol{\theta}_{1})$$

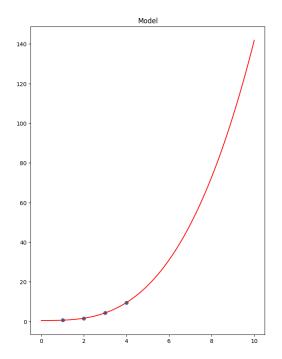
$$W := W - \alpha \cdot \frac{\partial}{\partial W} J(b, W)$$

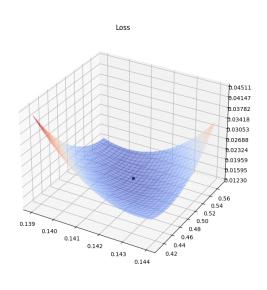
$$\frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1) = \frac{\partial}{\partial \theta_0} \cdot \frac{1}{N} \cdot \sum_{i=0}^{N} (h_{\theta}(x_i) - y_i)^2$$
where $h_{\theta}(x) = \frac{1}{1 + e^{-(\theta_0 + \theta_1 \cdot x)}} = \frac{1}{1 + e^{-(b + W \cdot x)}}$
let's substitute $a = b + W \cdot x$ so $h_{\theta}(x) = \frac{1}{1 + e^{-a}}$

w=1.1346432286934436 b=-4.648250084920094 loss=0.014018803935005443 learning_rate=0.000149000000000007



I don't find sigmoid logical here because there is no chance that 10 floor building may cost same as 100 floor. What about cubic $b+W\cdot x^3$? Where b would shift line vertically and W would regulate its width. That was my intuition on how to fit the line.





And it worked. That's much better.