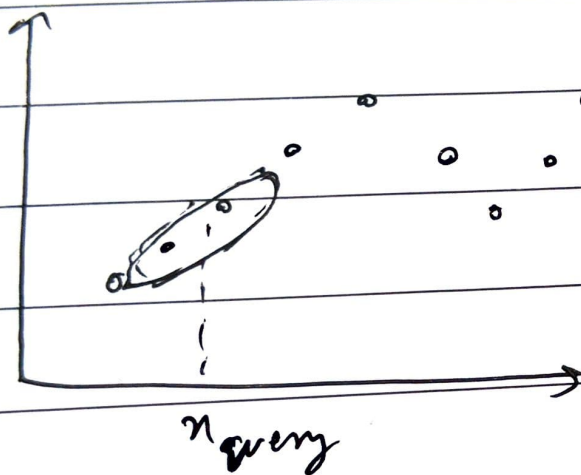


Locally weighted Regression (LOWESS)

Idea:

It is not going to learn parameter / function for the curve like linear reg.



According to query:

- (i) Neighbours of the query point will have more weight.
- (ii) Far away points will have less weight.
- (iii) weight will dec as we move away from point.

In LR:

$$h_{\theta}(x) = \theta^T x$$

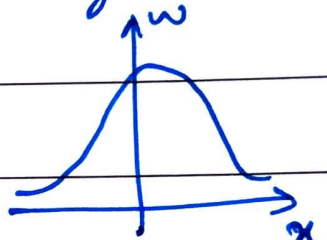
$$\text{loss} = \sum_i (y^i - h_{\theta}(x^i))^2$$

Microsoft Student Partners | 2020

$n \rightarrow$ If data pts have n from 1 to 100, algo will fit linear model for all points i.e. total 100 models.

* In loss, we are going to have weighted loss.

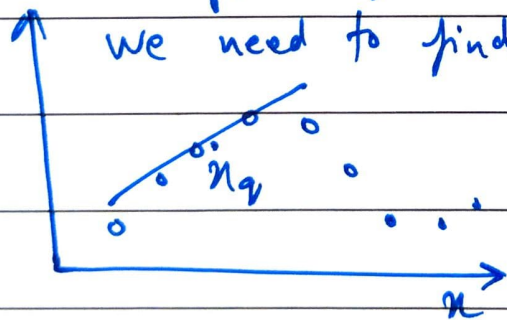
$$\text{loss} = \sum_i \underbrace{w^{(i)}}_{\text{Only new thing added}} (y^{(i)} - h_\theta(x^{(i)}))^2$$

$$w^{(i)} = e^{-\left(\frac{x^{(i)} - n}{2\tau}\right)^2}$$


$x^{(i)} \rightarrow$ Any given pt. in dataset

$n \rightarrow$ Query points (usually but not always the data pts in your sample)

we need to find slope & bias at this pt.



* Pts. which are closer to n_q have more weight in determining the slope at that point.

$\tau \rightarrow$ Bandwidth parameter
(controls how quickly weight falls)

Notice, $(x^{(i)} - x)$ is distance,
the $w^{(i)}$ will be:

* $\boxed{e^{-\infty} = 0}$ if they are far

* $x^{(i)} - x = 0$ if $x^{(i)} = x$
 $e^0 = 1$

$w^{(i)}$ will lie btw $(0, 1)$

So, we are adding more value to loss
if points $x^{(i)} - x$ are close and less
value if they are far away by multiplying
 $w^{(i)}$ in loss.

* It is a non-parametric algorithm.
Not going to learn any parameters.

OR: for every query point, learn some
parameters

You can now use various methods to
minimize loss function.

Closed form solution for loss:

$$\text{loss} = \sum_{i=1}^{m \text{ (examples)}} w^{(i)} [h_0(x^{(i)}) - y^{(i)}]^2$$

$$= (X\theta - y)^T W (X\theta - y) = J(\theta)$$

$$W = \begin{bmatrix} w_1 & 0 & \dots & 0 \\ 0 & w_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & w_m \end{bmatrix} \quad \left[\begin{array}{l} \text{matrix of} \\ \text{all weights} \end{array} \right]$$

Find, $\nabla_{\theta} J(\theta) = 0$

$$\theta = (X^T W X)^{-1} X^T W Y$$

(Closed form solⁿ for least squares)