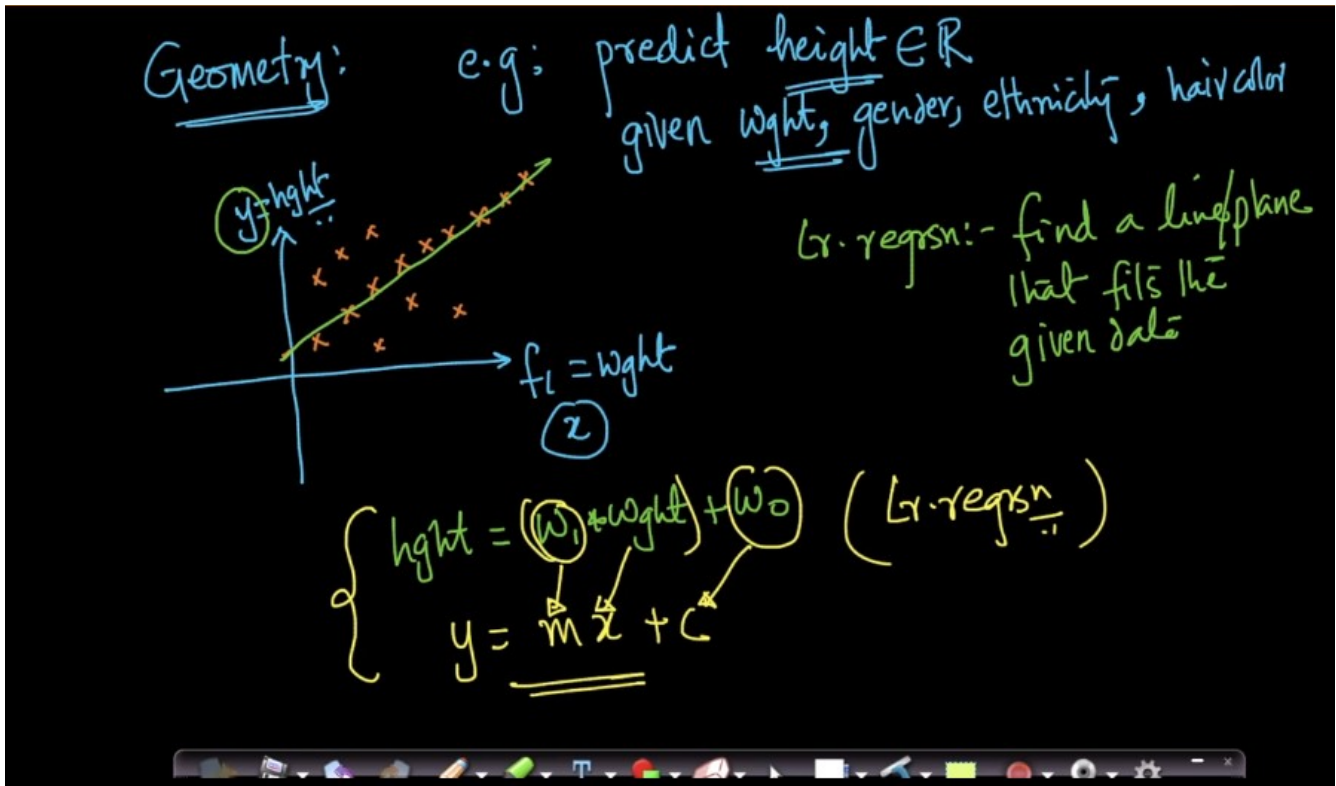
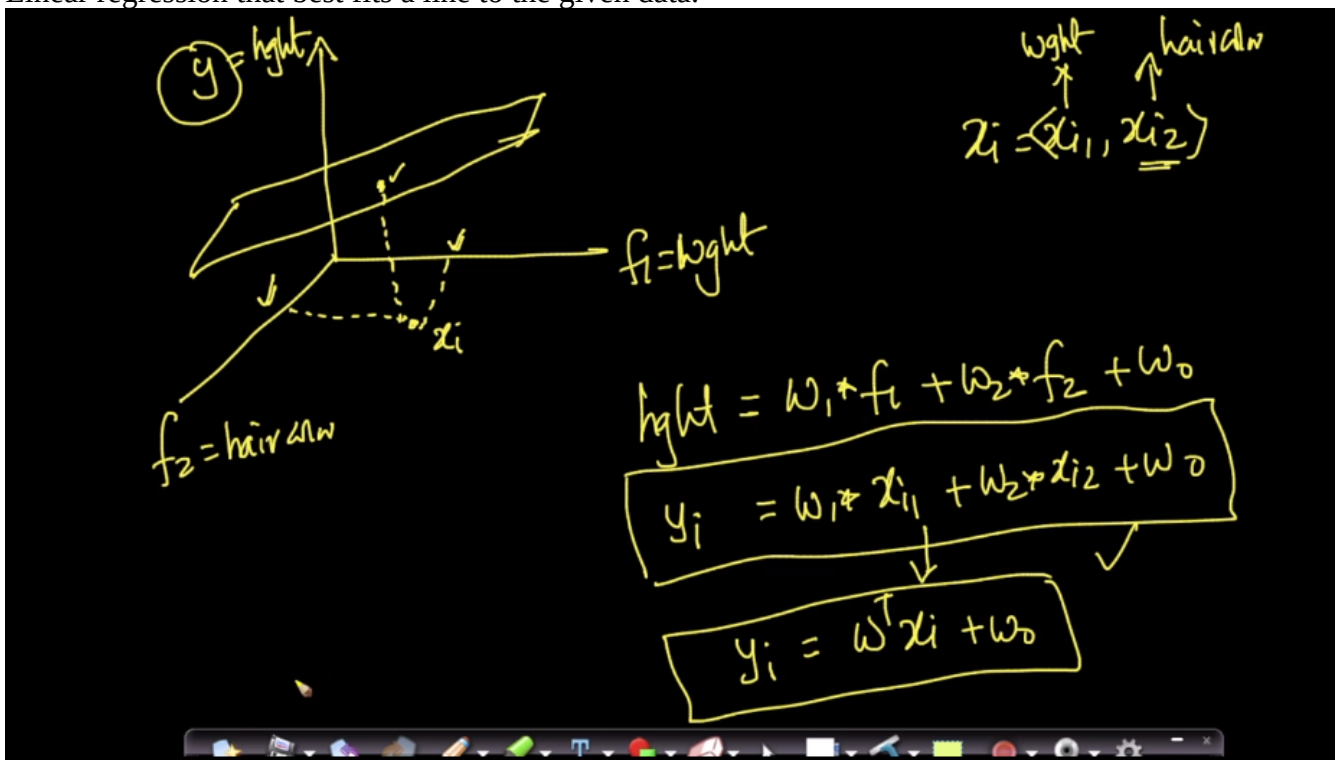


## Linear Regression:

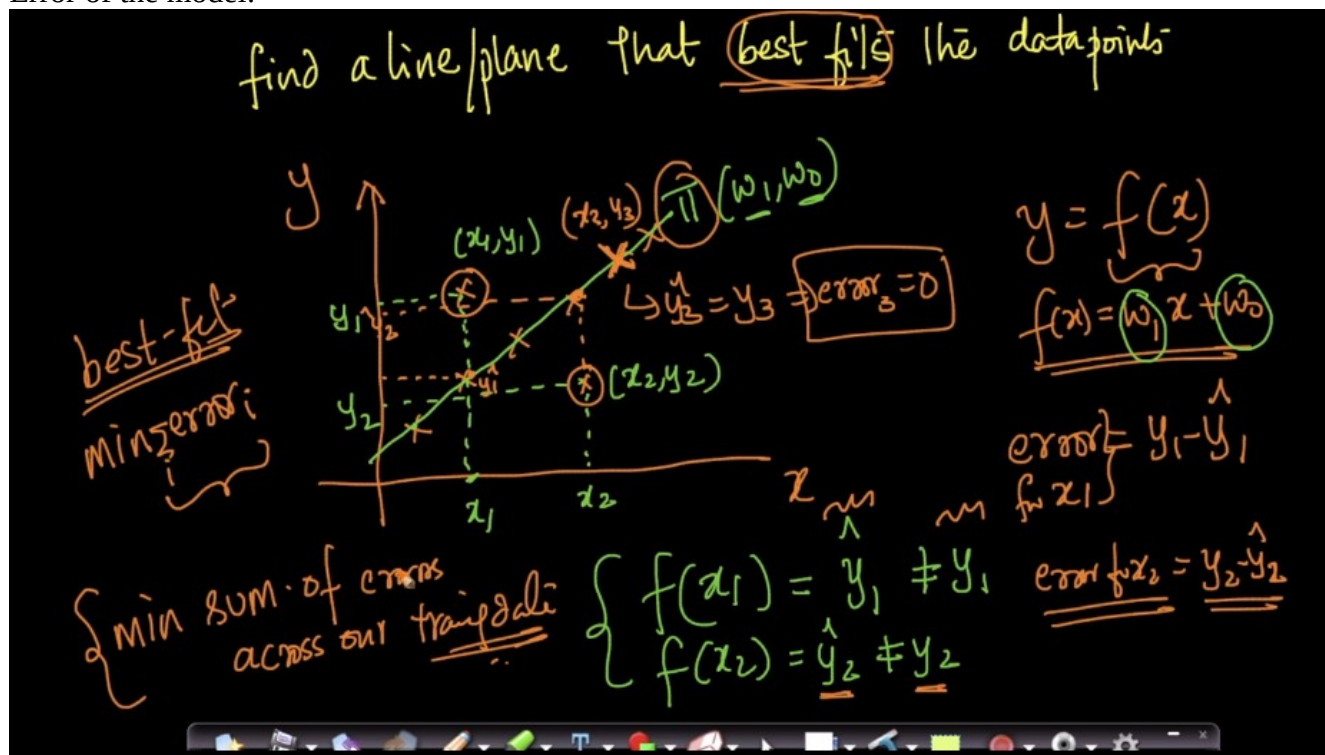


Linear regression in higher dimensional space has hyper plane to predict.

Linear regression that best fits a line to the given data.

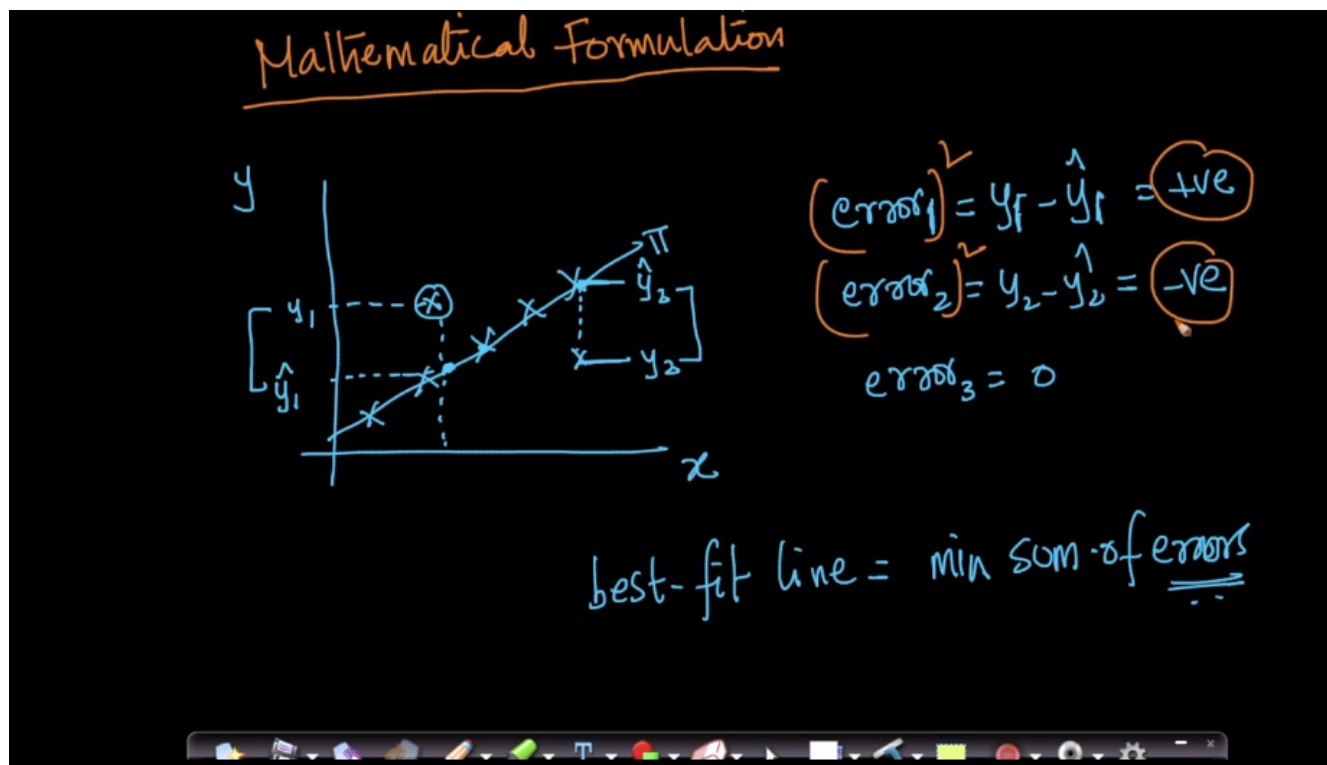


Error of the model:



Mathematical formulation:

Error for the extreme points..



The mathematical formulation is to find the  $(W, W_0)$  that minimize the difference between the actual and predicted value of  $y$ .

Linear regression is also referred to as OLS (Ordinary Least Squares).

$\text{Lr. regnsn} \rightarrow \underline{\text{OLS}}, \underline{\text{LLS}}$ 
 $\pi: \boxed{w^T x + w_0 = 0}$

$$\begin{cases} (w^*, w_0^*) = \underset{\substack{w, w_0 \\ \text{vector} \quad \text{scalar}}}{\text{argmin}} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \\ \hat{y}_i = f(x_i) = w^T x_i + w_0 \end{cases}$$

$\text{optmzn-prob} \rightarrow (w^*, w_0^*) = \underset{w, w_0}{\text{argmin}} \sum_{i=1}^n \underbrace{\left\{ y_i - \underbrace{(w^T x_i + w_0)}_{\text{sq-loss}} \right\}^2}_{\text{Lr}}$

Same like we need to use Regularization to the Linear regression.

regularization:

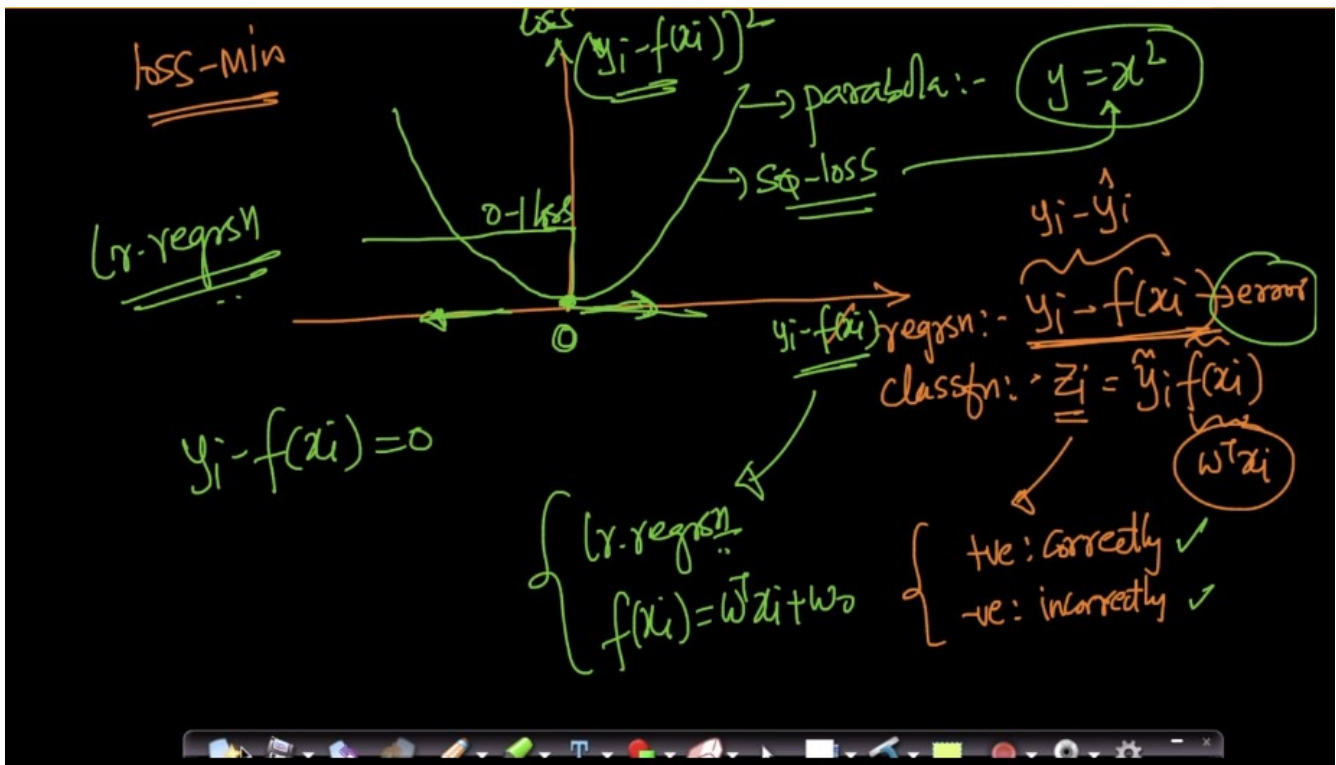
$$(w^*, w_0^*) = \underset{w, w_0}{\text{argmin}} \sum_{i=1}^n \underbrace{\left\{ y_i - (w^T x_i + w_0) \right\}^2}_{\text{sq-loss}} + \underbrace{\lambda \|w\|_2^2}_{\text{L2-reg.}}$$

Logistic regnsn

$$\text{L2-reg or L1-reg or elastic net}$$

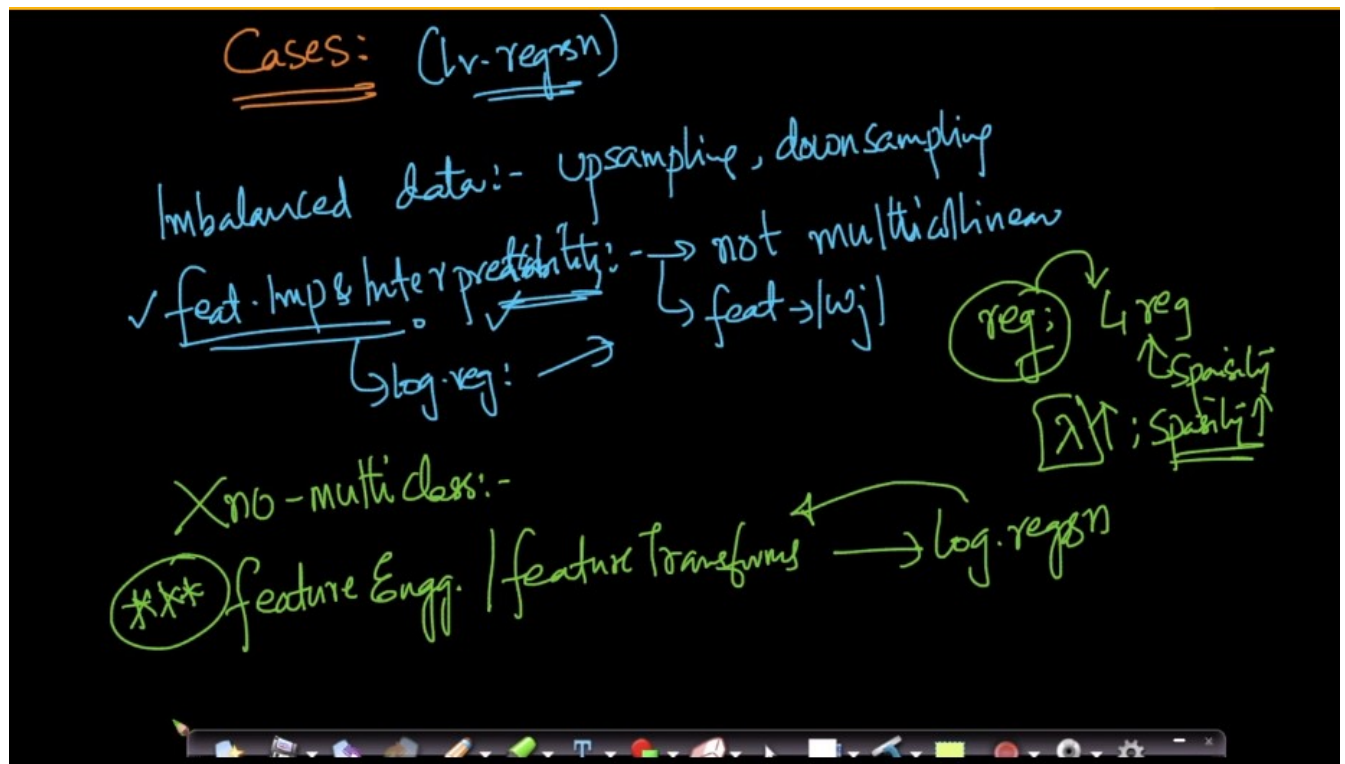
$\checkmark$  prob. interpton: (GLM)
$$\underline{P(y_i | x_i) = N(\mu, \sigma^2)}$$

Loss minimization:



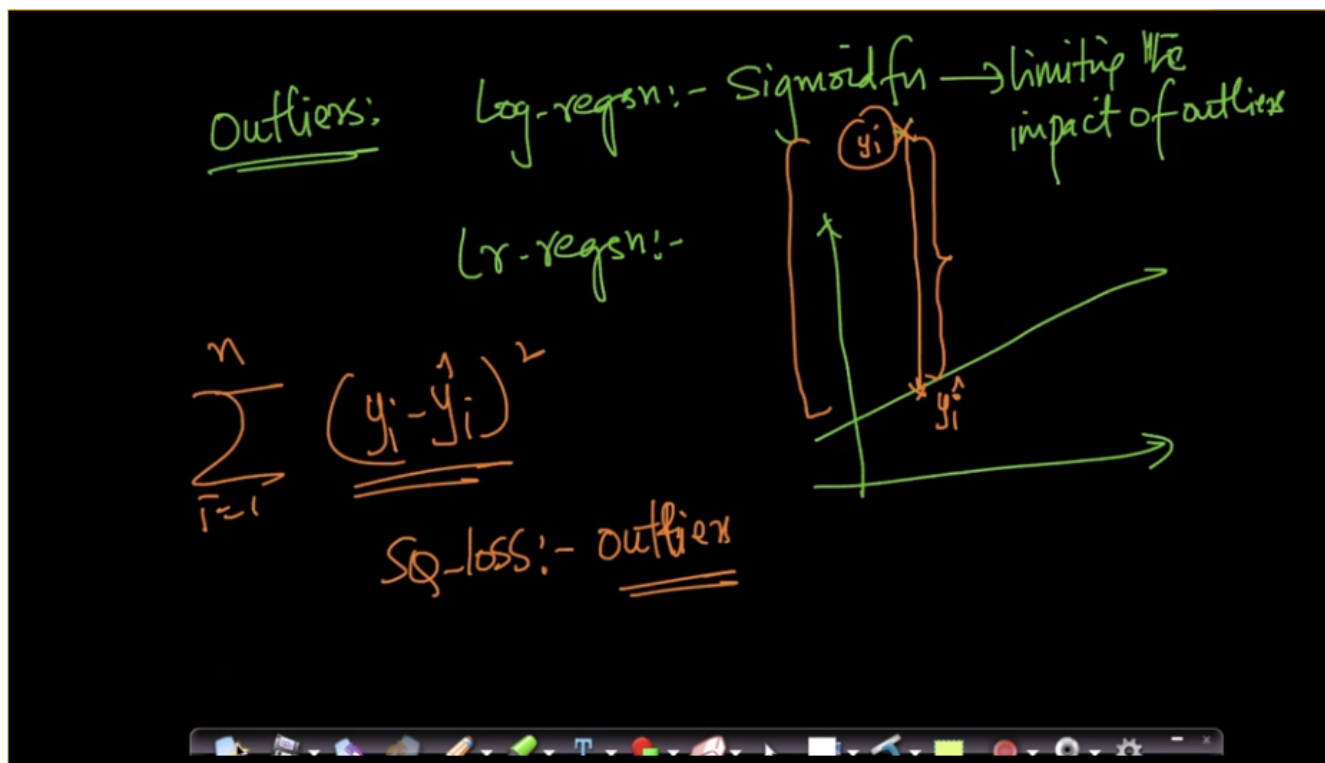
Using Loss minimization frame work, If we take SQ loss we get Linear regression, OLS, LLS.

Real world Cases:

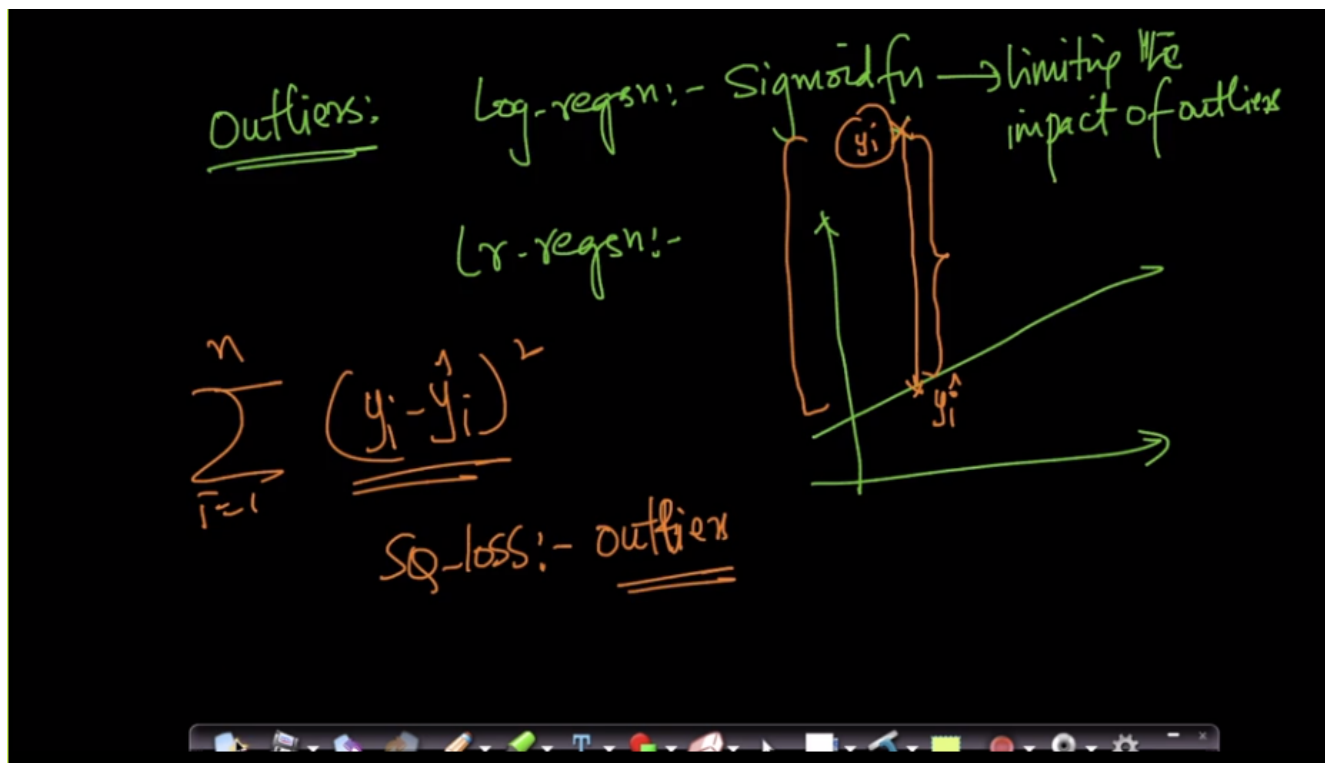




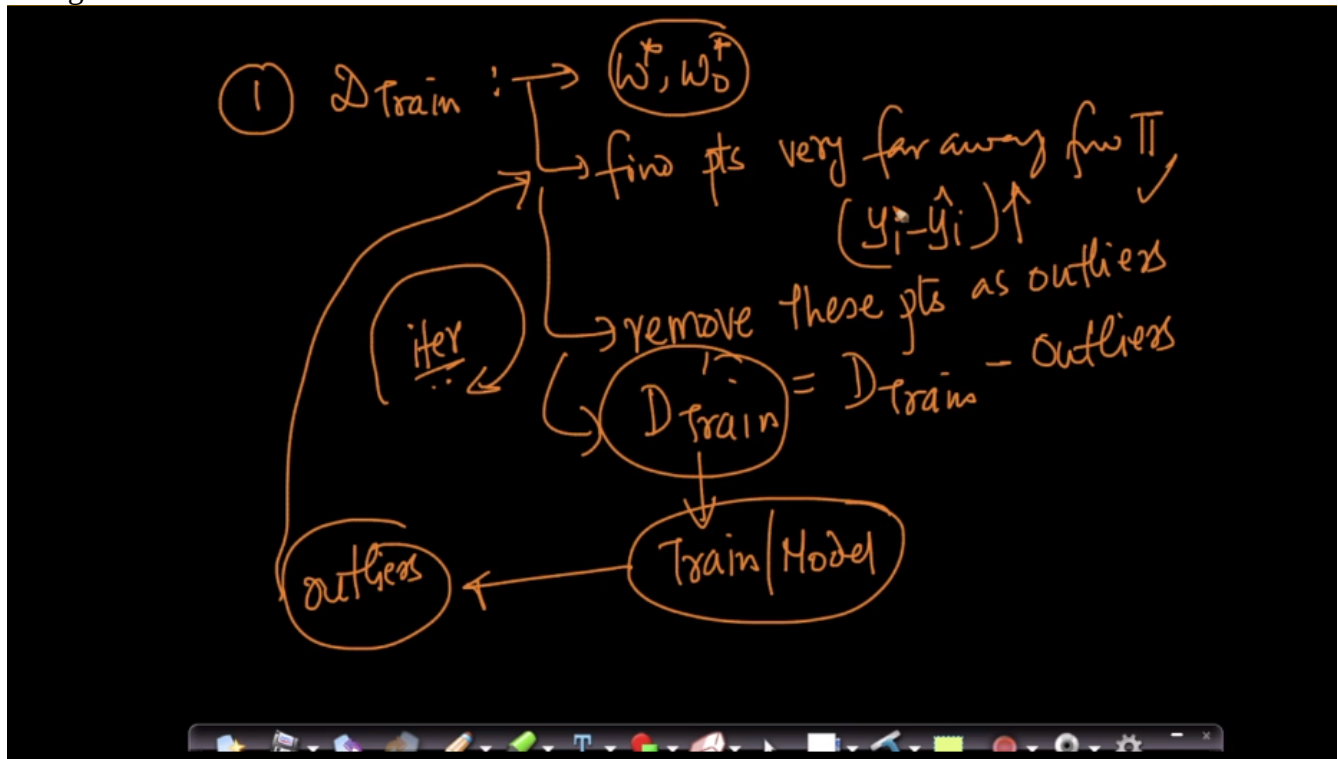
Outliers effect on the linear regression:



Outliers can mess up the Linear regression:



Using all of the train data we will find the  $W^*$  and  $W_0^*$



Iteratively remove the outliers from the data.

This is called RANSAC.