Machine Learning Algorithms

ML Algorithms
- Supervised ML → Regression, Classification
- Unsupervised ML → Clustering.

Regression

House price prediction

Independent: No.of rooms, Total Size, Location → x_i

⇓ O/P

Price → Dependent

Continuous

1.5m $y_i = y'$

1.65m

Classification

Binary or Multiclass Classificat.

No.of Play hour	No.of sleep hours	No.of study	Pass/Fail O/P
5hrs	7hrs	1hr.	Fail
–	–	–	–

Decision Tree

Random Forest

AdaBoost

Xgboost → Classification, Regression

1. Linear Regression [Regression]
2. Ridge Regression ["]
3. Lasso " [ ]
4. ElasticNet " ["]
5. Logistic Regression [classif.]

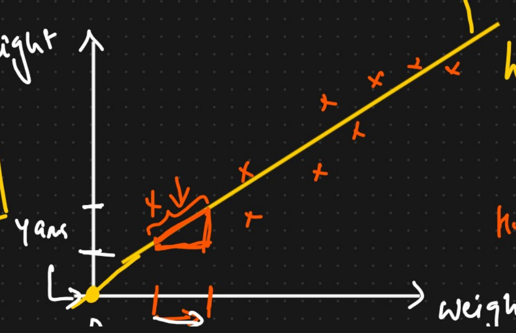
1. Simple Linear Regression

$y = mx + c$

$y = \beta_0 + \beta_1 x_1$

$h_\theta(x) = \theta_0 + \theta_1 x$

Hypothesis



$\boxed{\theta_0 = 0}$

Independent: Weight   O/P: Height

TRAIN DATASET → Sample of DATASET

↓ Training

Model

↓

$$\boxed{h_\theta(x) = \theta_0 + \theta_1 x}$$

New weight → Hypothesis → Height

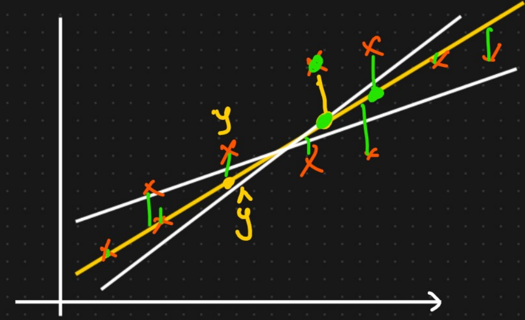
Equation of a straight line

$y = mx + c$

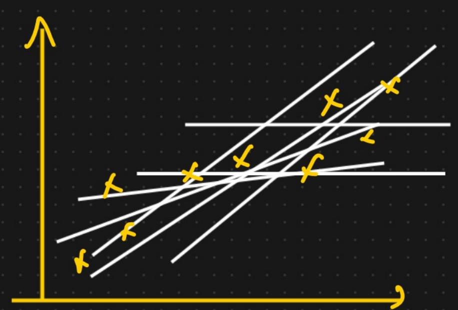
Aim

θ_0 = Intercept

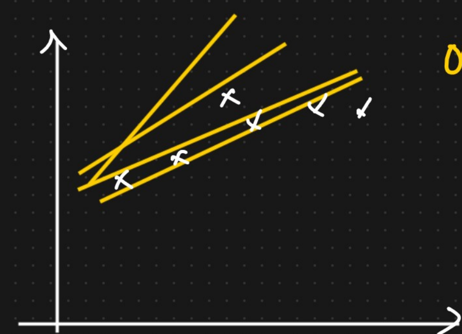
θ_1 = Coefficient or Slope



Less ERROR



No.



Optimization

$$h_\theta(x) = \theta_0 + \theta_1 x$$

$$\boxed{\hat{y} - y}$$

$$h_\theta(x) = \theta_0 + \theta_1 x$$

Cost function

Datapoint

$\hat{y}$

Error

Mean Squared Error

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x_i) - y^{(i)} \right)^2 \rightarrow \text{MSE}$$

What we need to solve (AIM) Final Goal

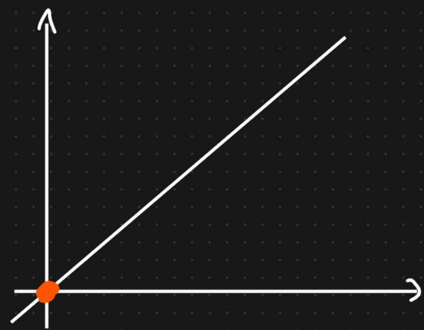
$$\underset{\theta_0, \theta_1}{\text{minimize}}\ J(\theta_0, \theta_1) \quad \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right)^2$$

Change θ_1 value

① $h_\theta(x) = \theta_0 + \theta_1 x$

if $\theta_0 = 0$

$$\boxed{h_\theta(x) = \theta_1 x}$$



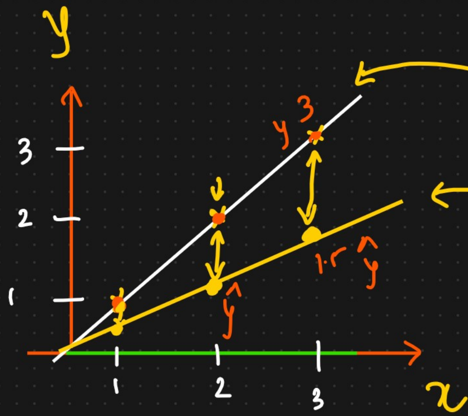
0.5×3

0.5×2

0.5×1

↓

$h_\theta(x) = \theta_1 x$



if $\theta_1 = 1$

if $\theta_1 = 0.5$

if $\theta_1 = 0$ →

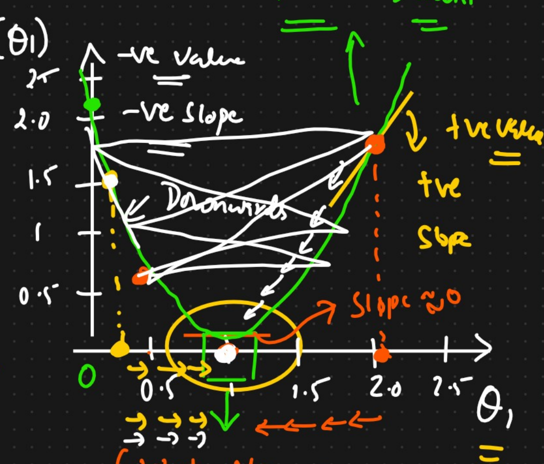
$\alpha R = 100\,000$

↗ Cost fn

MSE

$\alpha R = 0.001$

Gradient Descent



$$J(\theta_1) = \frac{1}{2m} \sum_{i=1}^{3} \left(h_\theta(x)^{(i)} - y^{(i)}\right)^2$$

$$= \frac{1}{2\times 3}\left[(1-1)^2 + (2-2)^2 + (3-3)^2\right]$$

$$= 0$$

$$\Rightarrow \frac{1}{2m} \sum_{i=1}^{m} (\hat{y} - y)^2$$

⇓

Quadratic Equation

⇓

$$\boxed{ax^2 + bx + c}$$

$$J(\theta_1) = \frac{1}{6}\left[(0.5-1)^2 + (1-2)^2 + (1.5-3)^2\right]$$

$$J(\theta_1) = 0.58$$

$$J(\theta_1) = \frac{1}{6}\left[(0-1)^2 + (0-2)^2 + (0-3)^2\right] \approx \boxed{2.3}$$

GRADIENT DESCENT CONVERGENCE Algorithm

repeat until convergence

{

$$\theta_j := \theta_j - \alpha \frac{\partial (J\theta_j)}{\partial \theta_j}$$

}

LR = 0.01

$\Rightarrow$ Coefficient updation formula

LR

Calculate Slope

$$\Rightarrow \theta_{new} = \theta_{old} - \alpha \boxed{\frac{\partial (J(\theta_{old}))}{\partial \theta_{old}}}$$

$$\Rightarrow \theta_{new} \approx \theta_{old} - \alpha(-ve)$$

$\theta_{new} \approx \theta_{old}$ + +ve value

$$\boxed{\theta_{new} >> \theta_{old}}$$

$\Rightarrow$

$\theta_{new} = \theta_{old} - \eta$ (+ve value)

$= \theta_{old} -$ (+ve) value

$$\boxed{\theta_{new} << \theta_{old}}$$

Gradient Descent [MSE]

$x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5 \quad y$

$$h_\theta(x) = \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \theta_4 x_4 + \theta_0$$

$\Downarrow$

Multi Linear Regression

Advantages

1. There is one global Minima ←
2. It is differentiable ←

Disadvantage

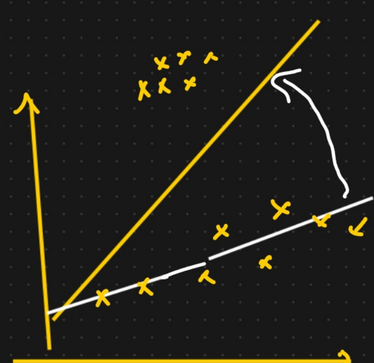
1. Not, Robust to outliers

Error

$$\frac{1}{2n}\sum_{i=1}^{n}(y-\hat{y})^2$$

Error

{MSE penalizes the Error}



x^2

$2x$

$$\frac{1}{2m}\sum_{i=1}^{m}\Big(\underbrace{h_\theta(x^{(i)}) - y}_{\text{error}}\Big)^2$$

② Mean Absolute Error

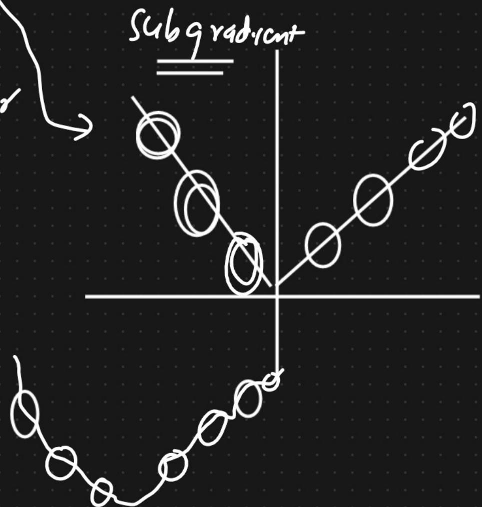
$\hat{y} = h_\theta(x^i)$

$$J(\theta_0,\theta_1) = \frac{1}{m}\sum_{i=1}^{m} |\hat{y} - y|$$

5 number summary → Remove the outlier

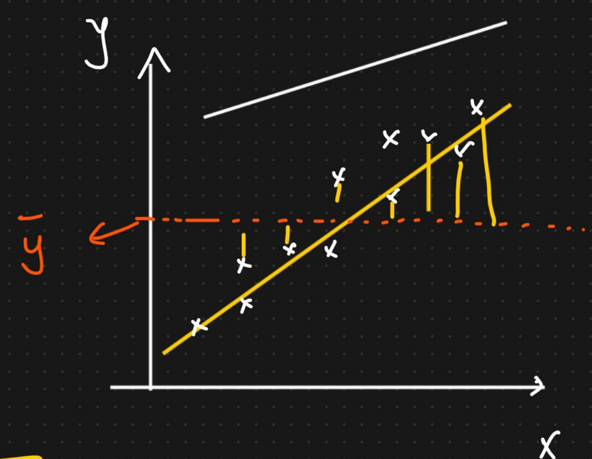
⇓

MSE



Performance Metrics

R^2 and Adjusted R^2



$$R^2 = 1 - \frac{SS_{Res}}{SS_{total}}$$

$\boxed{-ve}$??

$\boxed{0 \text{ to } 1}$

↑ Error

$$= 1 - \frac{\sum (y_i - \hat{y})^2}{\sum (y_i - \bar{y})^2} \begin{array}{l} \rightarrow \text{less} \\ \rightarrow \text{High} \end{array}$$

= 1 - Small number

= Higher Number

Adjusted R^2

House pricing

No.of room | Total size | location | Garden | Price

$R^2 = 89\% \Rightarrow 0.89$

$R^2 \approx 0.95$

$R^2 \approx 0.96$

Adjusted R^2

$R^2 = 0.87$

$R^2 = 0.89$

Adjusted $R^2 = 0.85$

Adjusted R^2

$$R^2_{adjusted} = 1 - \left[\frac{(1-R^2)(N-1)}{\boxed{N-p-1}}\right]$$

denominator

smaller

P = No.of predictors

N = No.of data points

$p=2$ $\quad R^2 = 90\%$ $\quad$ Adj $R^2 = 86\%$

$p=3$ $\quad R^2 = 91\%$ $\quad R^2$ Ad $= 82\%$

$p=2 \quad p=3$

$R^2 = 0.9 \qquad p=2 \qquad n=100$

$$1 - \left[\frac{(1-0.9)\times(100-1)}{100-2-1}\right]$$

$$= 1 - \left[\frac{0.1\times 99}{97}\right]$$

$$= 1 - \frac{9.9}{97} = 0.8979$$

$p=3$

$R^2 = 0.91$

$R^2 = 0.90$

Adjus $= 0.8979$.

$$R^2 = 1 - \left[\frac{(1-0.91)(100-1)}{100-3-1}\right]$$

>>

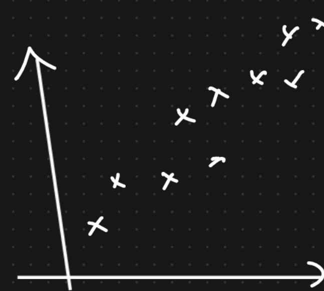
Adjusted R^2

$$= 1 - \left[\frac{(0.09)(99)}{96}\right] = 0.9071$$

Adjusted R^2 & $\boxed{R^2}$ $\Rightarrow$

$\Downarrow$

Difference higher



Linear Regression

1. There is a linear relationship with x & y
2. Independent feature should will have Normal Distribution
3. Always take care of multicollinearity.
3. Homoscedasticity = Same variance

$\boxed{f_1} \Leftrightarrow f_2$

4. Feature Scaling Required?? $\Rightarrow$ Yes
5. {Heteroscedasticity ?? $\rightarrow$ Assignment ??

Gradient = RMSE vs MSE }