

Data Science & AI



Machine Learning



Supervised Learning

Lecture No.- 02



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Recap of Previous Lecture



Topic

Introduction

Topic

Regression & Its types

Topic

Topic

Topic

Topics to be Covered



Topic

Ridge

Topic

Lasso

Topic

Elastic

Topic

Regression

Topic

Cost Function

Machine Learning

- ① Multiple Linear Regression ✓
- ② R Squared, Adjusted R Squared [Metrics] → Correlation ✓
- ③ Types of Cost function
 - i) Mean Squared Error (MSE)
 - ii) Mean Absolute Error (MAE)
 - iii) Root Mean Squared Error (RMSE)✓
- ④ Overfitting, Underfitting } ✓
- ⑤ Ridge, Lasso, Elastic Net ML Algorithms } ✓



① Multiple Linear Regression

Simple Linear Regression $\rightarrow h_{\theta}(x) = \beta_0 + \beta_1 x_1$

β_0 is Intercept
 β_1 is Slope
 x_1 is I/p feature
Independent feature

We have 1 i/p feature

House Price Dataset

House Price Dataset

↓ O/P

No. of Rooms Size of Rooms Price

x_1 x_2

$$h_{\theta}(x) = \overset{\text{Intercept}}{\theta_0} + \theta_1 x_1 + \theta_2 x_2$$

$\theta_1 \rightarrow$ coefficient of x_1

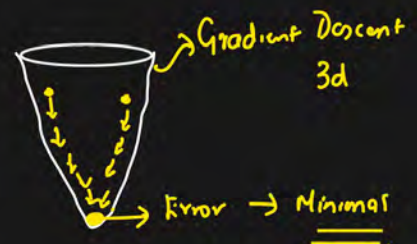
$\theta_2 \rightarrow$ Slope or coefficient of x_2 .

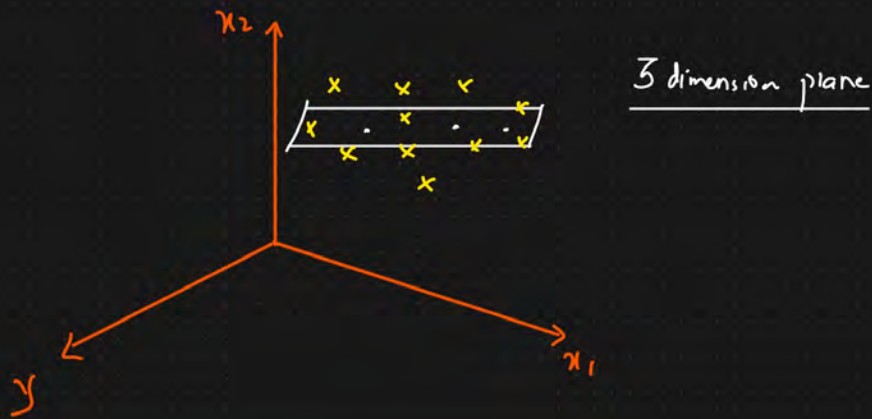
$$h_0(x) \rightarrow 1 \text{ unit } \uparrow \uparrow$$

$$0.5x_1 \quad 0.75x_2$$

$$\theta_1 = 0.5 \quad \theta_2 = 0.75$$

$$h_{\theta}(x) = \theta_0 + 0.5x_1 + 0.75x_2$$





$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \theta_4 x_4 \dots + \theta_n x_n$$

② Performance Metrics [R Squared, Adjusted R Squared]

① R Squared

$$R^2_{\text{squared}} = 1 - \frac{SS_{\text{Res}}}{SS_{\text{Total}}}$$



$$\left\{ \begin{aligned} SS_{Res} &= \text{Sum of Squares Residual [Error]} = \sum_{i=1}^n (y_i - \text{ho}(x)_i)^2 \quad \hookrightarrow \hat{y}_i \Rightarrow \text{predicted} \\ SS_{Total} &= \text{Sum of Square Total} = \sum_{i=1}^n (y_i - \bar{y})^2 \end{aligned} \right.$$

If best fit line $SS_{Total} \gg SS_{Res.}$

$$R^2_{\text{Squared}} = 1 - \frac{SS_{\text{Res}}}{SS_{\text{Total}}} \{ \text{small} \} \approx 1$$

If $SS_{RUs} \gg SS_{Total} \Rightarrow R \text{ Squared} \Rightarrow -ve \text{ value}$

$$[-\infty \leftrightarrow 1]$$

$$[0, 1]$$

House Size ↑ No. of Bedrooms ↑ Location ↑ No. of people ↓ Price ↑↑

$R^2_{\text{Squared}} = 0.76 \Rightarrow 76\%$

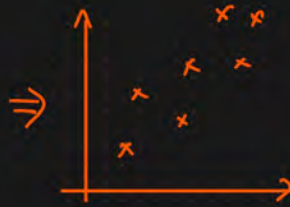
$R^2_{\text{Squared}} = 0.80 \uparrow\uparrow$

$R^2_{\text{Squared}} = 0.83 \uparrow\uparrow$

$R^2_{\text{Squared}} = 0.84 \uparrow\uparrow$

X	Y
2	3
3	4
5	6
7	8

X ↑ Y ↑
X ↓ Y ↓



⇒ Mathematically

Adjusted

$R_{\text{Squared}} = 0.82 \downarrow$

X	Y
1	5
2	4
3	3
4	2
5	1

X ↑ Y ↓
X ↓ Y ↑



① Covariance → It quantifies the relationship between X and Y

Variance (X) = $s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$



Covariance (X, Y) = $\text{Cov}(X, Y) = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$

↓

$\text{Cov}(X, X) = \text{Var}(X)$

-inf to +inf

X ↑ Y ↑
X ↓ Y ↓

X	Y
2	3
3	4
5	6
7	8

+ve

Covariance

X	Y
1	5
2	4
3	3
4	2
5	1

X ↑ Y ↓
X ↓ Y ↑

⇒ -ve Covariance



⇒ 0

Covariance

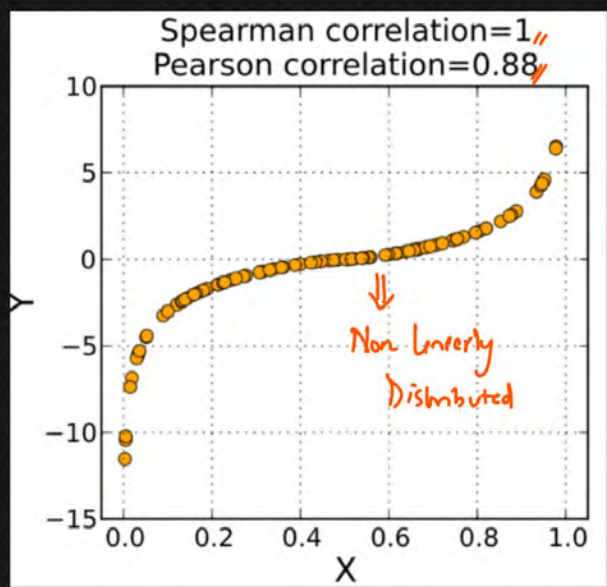
Covariance \div $-\infty \leftrightarrow +\infty$.



② Pearson Correlation Coefficient \div $[-1 \text{ to } 1]$

$$\rho_{X,Y} = \frac{\text{Cov}(X,Y)}{\sigma_X \sigma_Y} \Rightarrow -1 \text{ to } 1.$$

③ Spearman Rank Correlation $[-1 \text{ to } +1]$.



$$r_s = \rho_{R(X), R(Y)} = \frac{\text{cov}(R(X), R(Y))}{\sigma_{R(X)} \sigma_{R(Y)}},$$

\downarrow
 $X \uparrow Y \uparrow$
 $X \downarrow Y \downarrow$
 $\Rightarrow 1$

X	Y	R(X)	R(Y)
1	2	1	
5	3	2	
7	8	3	
9	1	4	

② Adjusted R squared

$$\text{Adjusted R squared} = \frac{1 - (1 - R^2)(N - 1)}{N - p - 1}$$

$N \rightarrow$ No. of data points.

$R^2 \rightarrow$ R squared

$p \rightarrow$ No. of Independent feature

④ Types of cost function

① Mean Squared Error (MSE) ✓

② Mean Absolute Error (MAE) ✓

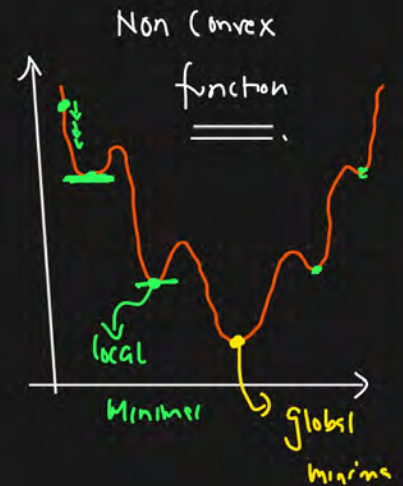
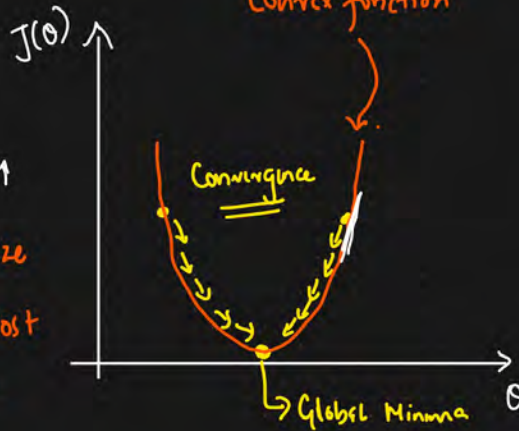
③ Root Mean Squared Error (RMSE) → Assignment

① Mean Squared Error (MSE)

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - h_{\theta}(x_i))^2 \rightarrow \text{Quadratic Equation}$$



MSE
penalize
the cost
fn



Advantage

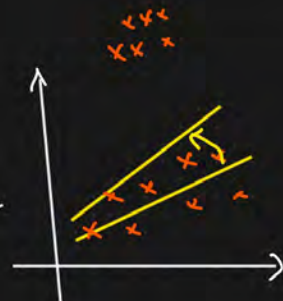
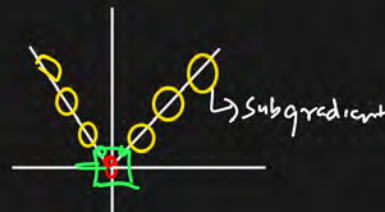
- ① Equation is differentiable
- ② It has only one local or global minima.

Disadvantage

- ① Not Robust to outliers
- ② Units gets changed

② Mean Absolute Error

$$MAE = \frac{1}{n} \sum_{i=1}^n |y - \hat{y}|$$



Advantage

- ① Robust to outliers

Disadvantage

- ① Convergence it will take time

② Unit are same

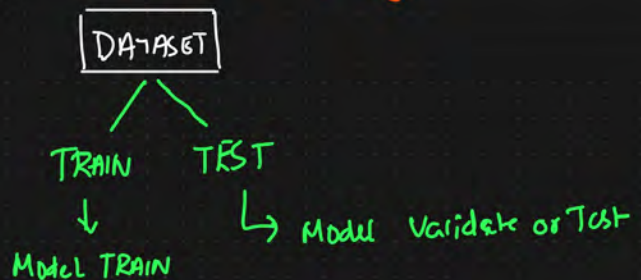
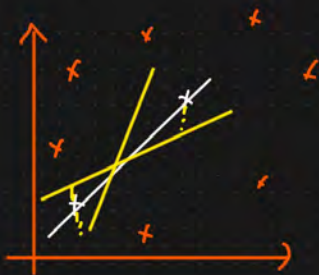
⑤ Root Mean Squared Error [Assignment].

$$RMSE = \sqrt{MSE}$$

⑧ Ridge, Lasso And Elastic Regression

$$\text{Cost fn} = \frac{1}{n} \sum_{i=1}^n (y_i - \text{hol}(x)_i)^2 \quad [MSE]$$

① Ridge Regression [L2 Regularization] → Reduce Overfitting ←



Overfitting = TRAIN → Acc ↑↑ ⇒ 93%.

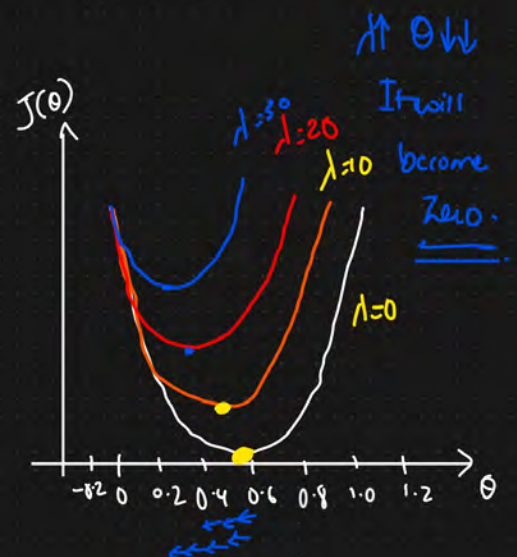
TEST → Acc ↓ ⇒ 50%.

$$\text{Cost fn} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \lambda \sum_{i=1}^n (\text{slope})^2$$

Annotations:

- ↓ 0 (under $\frac{1}{n}$)
- Hyperparameter (pointing to λ)
- ↓ (under \sum)
- ↓ (under n)
- ↓ (under $(\text{slope})^2$)

Values for λ : $\lambda = 1, 2, 3, 4, 5, 6, 7$



② Lasso Regression (L_1 Regularization) \rightarrow Feature Selection

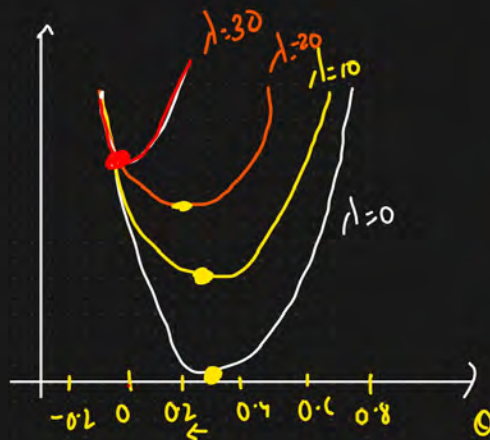
$$\text{Cost fn} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \boxed{\lambda \sum_{i=1}^n |\text{slope}|}$$

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

$$= 0.52 + 0.65x_1 + 1.5x_2 + 0.2x_3.$$

The least important feature is x_3 because the coefficient is less.

$\lambda \Rightarrow \{\text{Experimentation}\}$



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

$$= 0.52 + 0.65x_1 + 1.5x_2 + 0.2x_3.$$

$$0.52 + 0.50x_1 + 1.3x_2 + 0.1x_3$$

$$\boxed{h_{\theta}(x) = 0.52 + 0.40x_1 + 1.1x_2 + \cancel{0x_3}}$$

\downarrow
Coefficient
0

③ Elastic Net

$\left. \begin{array}{l} \rightarrow \text{Reduce Overfitting} \rightarrow \text{Ridge} \\ \rightarrow \text{Feature Selection} \rightarrow \text{Lasso} \end{array} \right\}$

$$\text{Cost fn} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \lambda_1 \sum_{i=1}^n (\text{slope})^2 + \lambda_2 \sum_{i=1}^n |\text{slope}|$$

\Downarrow
MSE

\Downarrow
+ Reduce Overfitting

\Downarrow
+ Feature Selection.



THANK - YOU

