

# Introduction to Machine Learning

– Prof. Balaraman Ravindran | IIT Madras

## Problem Solving Session (Week-2)

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# Week-2 Contents

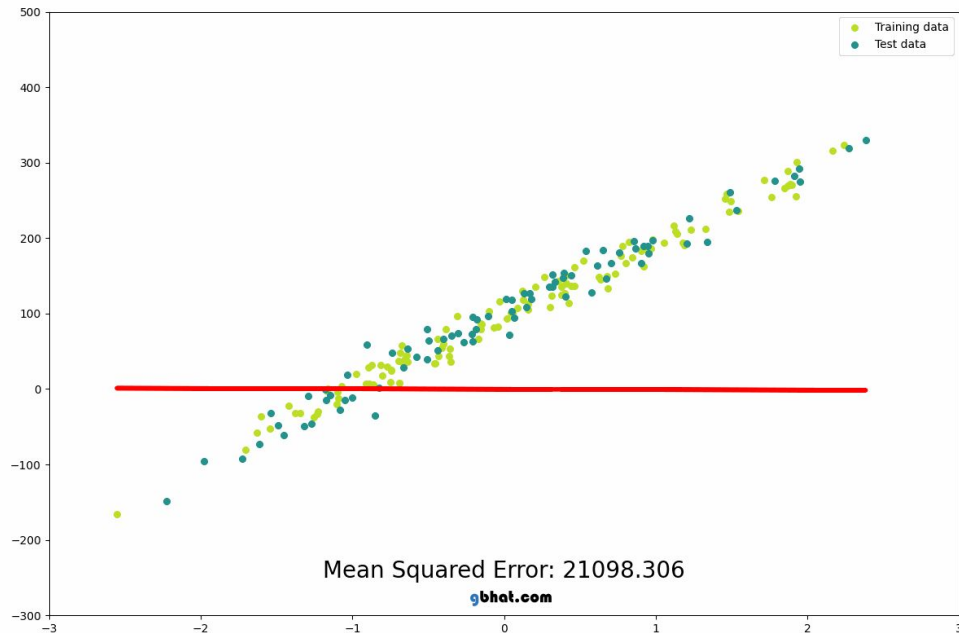
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1. Linear Regression
2. Multiple Regression
3. Subset Selection
4. Ridge and Lasso Regression
5. Principal Component Regression
6. Partial Least Square

# Linear Regression

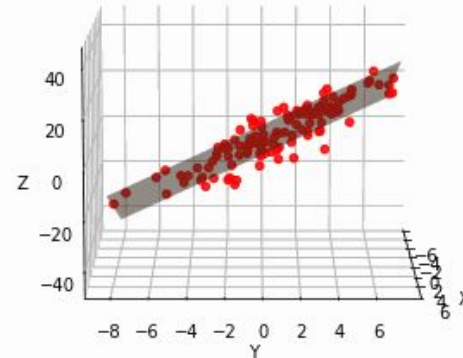
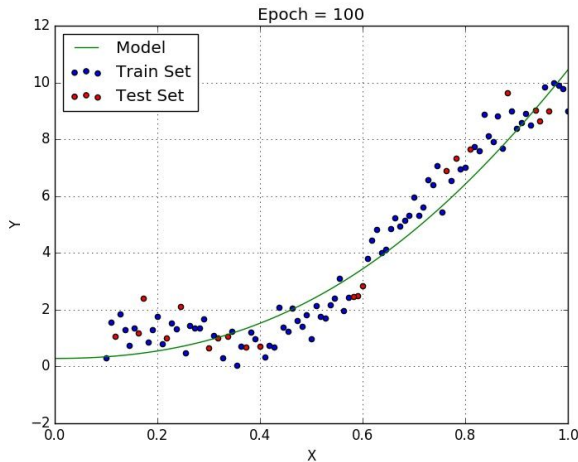
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- Predicts a dependent variable using one independent variable
- Equation:  $y = \beta_0 + \beta_1 x + \varepsilon$
- Solved using Ordinary Least Squares (OLS)



# Multiple Regression

- Extends Linear Regression to multiple predictors
- Equation:  $y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon$



# Regression

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- Models the relationship between dependent and independent variables by fitting a linear equation:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

where:

- $\mathbf{Y}$  is the output (dependent variable)
- $\mathbf{X}$  is the input (independent variables)
- $\boldsymbol{\beta}$  are the model parameters
- $\boldsymbol{\varepsilon}$  is the error term

# Least Squares Error Function

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- The goal of linear regression is to minimize the squared error:
- $\text{Error} = (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})^2 = (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})^T (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})$  [As  $\mathbf{P}^2 = \mathbf{P}^T\mathbf{P}$ ]
- This represents the sum of squared differences between actual and predicted values.

# Expanding the Error Function

- Using the matrix identity

$$(A - B)^T (A - B) = A^T A - A^T B - B^T A + B^T B$$

- $(Y - X\beta)^T (Y - X\beta)$  expands to:  $Y^T Y - Y^T (X\beta) - (X\beta)^T Y + \beta^T X^T X \beta$ 
  - $Y^T (X\beta)$  is scalar so equal to its transpose

$$Y^T Y - (X\beta)^T Y - (X\beta)^T Y + \beta^T X^T X \beta$$

$$Y^T Y - 2\beta^T X^T Y + \beta^T X^T X \beta$$

- This is a quadratic function in  $\beta$ .

# Finding Optimal $\beta$

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- To minimize the error function, take its derivative w.r.t.  $\beta$  and set it to zero:

$$\partial/\partial\beta (\mathbf{Y}^T \mathbf{Y} - 2\beta^T \mathbf{X}^T \mathbf{Y} + \beta^T \mathbf{X}^T \mathbf{X} \beta) = 0$$

- Solving for  $\beta$  gives:

$$\beta = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y}$$



# Sample Question: Regression

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x1	x2	x3	y
2	3	5	10
4	2	1	8
3	4	2	11
5	1	3	9
1	5	4	7

# Sample Question: Linear Regression

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x1	y
2	10
4	8
3	11
5	9
1	7



X (5 x 2)	
1	2
1	4
1	3
1	5
1	1

Y (5 X 1)
10
8
11
9
7

Step-1: Define X and Y

# Sample Question: Linear Regression

$\mathbf{X}^T$ (2 x 5)	1	1	1	1	1
	2	4	3	5	1

$\mathbf{X}$ (5 x 2)	
1	2
1	4
1	3
1	5
1	1



$\mathbf{a}$ (2 x 2)	5	15
	15	55



$\mathbf{a}^{-1}$ (2 x 2)	1.1	-0.3
	-0.3	0.1

Step-2: Calculate  $\mathbf{a}^{-1} = (\mathbf{X}^T \mathbf{X})^{-1}$

# Sample Question: Linear Regression

$\mathbf{X^T}$ (2 x 5)	1	1	1	1	1
	2	4	3	5	1

$\mathbf{Y}$ (5 X 1)
10
8
11
9
7



$\mathbf{b}$ (2 x 1)	45
	137

Step-3: Calculate  $\mathbf{b} = \mathbf{X^T Y}$

# Sample Question: Linear Regression

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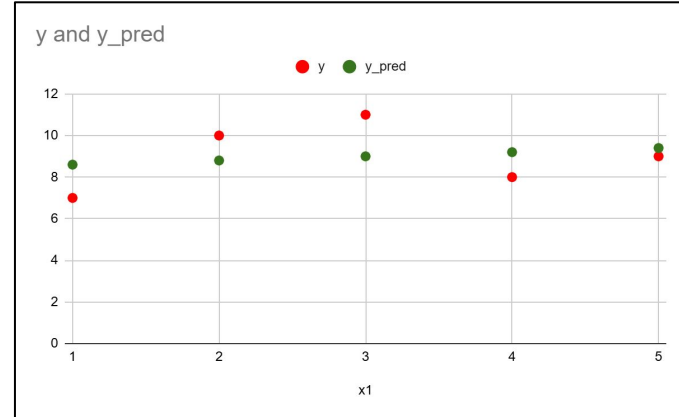
$\mathbf{a}^{-1}$ (2 x 2)	1.1	-0.3
	-0.3	0.1

$\mathbf{b}$ (2 x 1)	45
	137



$\boldsymbol{\beta}$ (2 x 1)	8.4
	0.2

$$y = 8.4 + 0.2x$$



Step-4: Calculate  $\boldsymbol{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y} = \mathbf{a}^{-1} \mathbf{b}$

# Sample Question: Regression

---

x1	x2	x3	y
2	3	5	10
4	2	1	8
3	4	2	11
5	1	3	9
1	5	4	7

# Sample Question: Multiple Regression

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X (5 x 4)			
1	2	3	5
1	4	2	1
1	3	4	2
1	5	1	3
1	1	5	4

Y (5 X 1)
10
8
11
9
7

Step-1: Define X and Y

# Sample Question: Linear Regression

$\mathbf{X}^T$ (4 x 5)	1	1	1	1	1
	2	4	3	5	1
	3	2	4	1	5
	5	1	2	3	4

X (5 x 4)			
1	2	3	5
1	4	2	1
1	3	4	2
1	5	1	3
1	1	5	4

Step-2:  
Calculate  
 $\mathbf{a}^{-1} = (\mathbf{X}^T \mathbf{X})^{-1}$



$\mathbf{a}$ (4 x 4)	5	15	15	15
	15	55	36	39
	15	36	55	48
	15	39	48	55



$\mathbf{a}^{-1}$ (4 x 4)	60.95	-9.1875	-7.5	-3.5625
	-9.1875	1.4218	1.125	30.51562
	-7.5	1.125	1	0.375
	-3.5625	0.5156	0.375	0.2968



# Sample Question: Linear Regression

— — —

$\mathbf{X}^T$ (4 x 5)	1	1	1	1	1
	2	4	3	5	1
	3	2	4	1	5
	5	1	2	3	4



$\mathbf{b}$ (4 x 1)	45
	137
	134
	135

$\mathbf{Y}$ (5 X 1)
10
8
11
9
7

Step-3: Calculate  $\mathbf{b} = \mathbf{X}^T \mathbf{Y}$

# Sample Question: Linear Regression

<b>a</b> <sup>-1</sup> (4 x 4)	60.95	-9.1875	-7.5	-3.5625
	-9.1875	1.4218	1.125	30.51562
	-7.5	1.125	1	0.375
	-3.5625	0.5156	0.375	0.2968

<b>b</b> (4 x 1)	45
	137
	134
	135



<b>β</b> (4 x 1)	-1.875
	1.718
	1.25
	0.6562

$$y = -1.875 + 1.718 x_1 + 1.25 x_2 + 0.6562 x_3$$

Step-4: Calculate  $\beta = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y} = \mathbf{a}^{-1} \mathbf{b}$

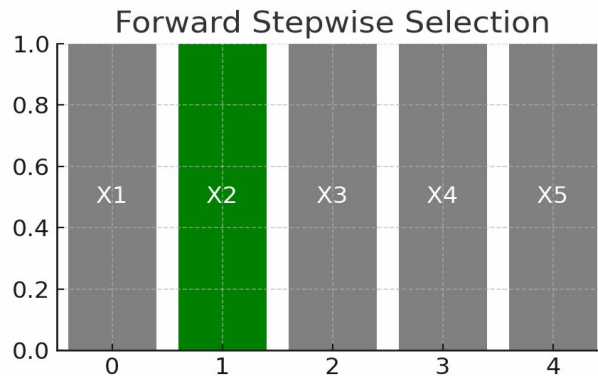
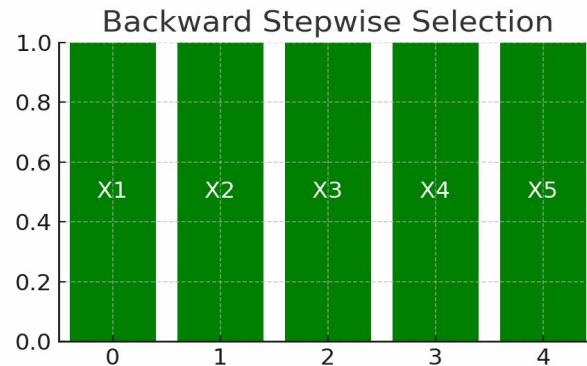
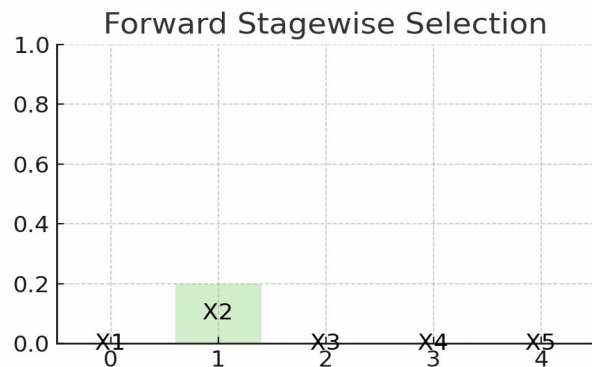
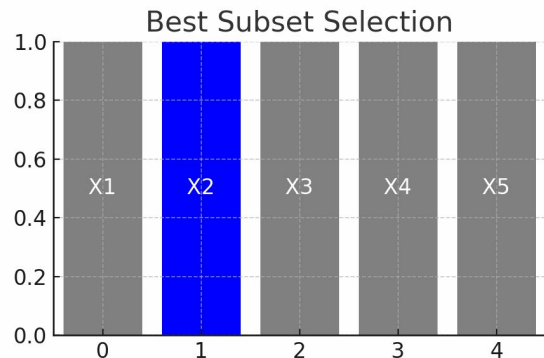
# Sample Question: Regression (Output)

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x1	x2	x3	y	y_pred	Error
2	3	5	10	8.592	1.9824
4	2	1	8	8.1532	0.023
3	4	2	11	9.5914	1.9841
5	1	3	9	9.9336	0.8716
1	5	4	7	8.7178	2.950
Average error = 1.562					

# Subset Selection Methods

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# Subset Selection Methods

**Forward  
Stepwise  
Selection**

**Higher bias,  
lower variance**

**Iteratively add  
predictors**

**Backward  
Stepwise  
Selection**

**Balanced**

**Iteratively  
remove  
predictors**

**Forward  
Stagewise  
Selection**

**Lower bias,  
moderate  
variance**

**Iteratively  
update  
coefficients**

# Ridge vs Lasso Regression

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## Ridge Regression

### L2 regularization

Shrinks coefficients towards zero, but never exactly to zero

$$\text{Min} (\Sigma(y - X\beta)^2 + \lambda \Sigma \beta^2)$$

## Lasso Regression

### L1 regularization

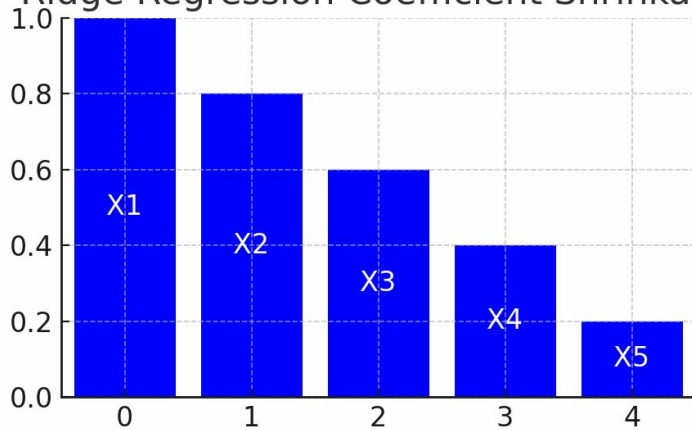
Can shrink coefficients exactly to zero, feature selection

$$\text{Min} (\Sigma(y - X\beta)^2 + \lambda \Sigma |\beta|)$$

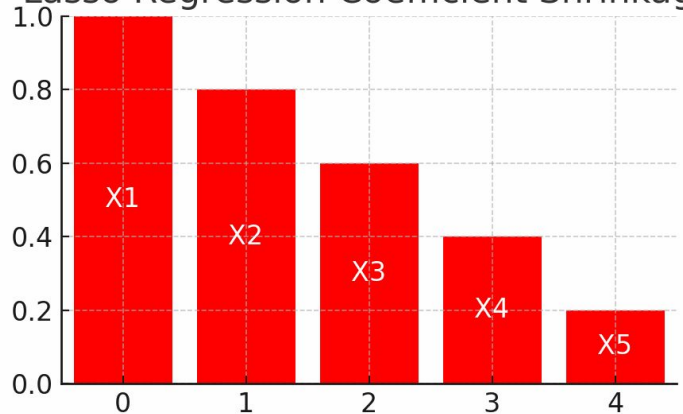
# Ridge vs Lasso Regression

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Ridge Regression Coefficient Shrinkage

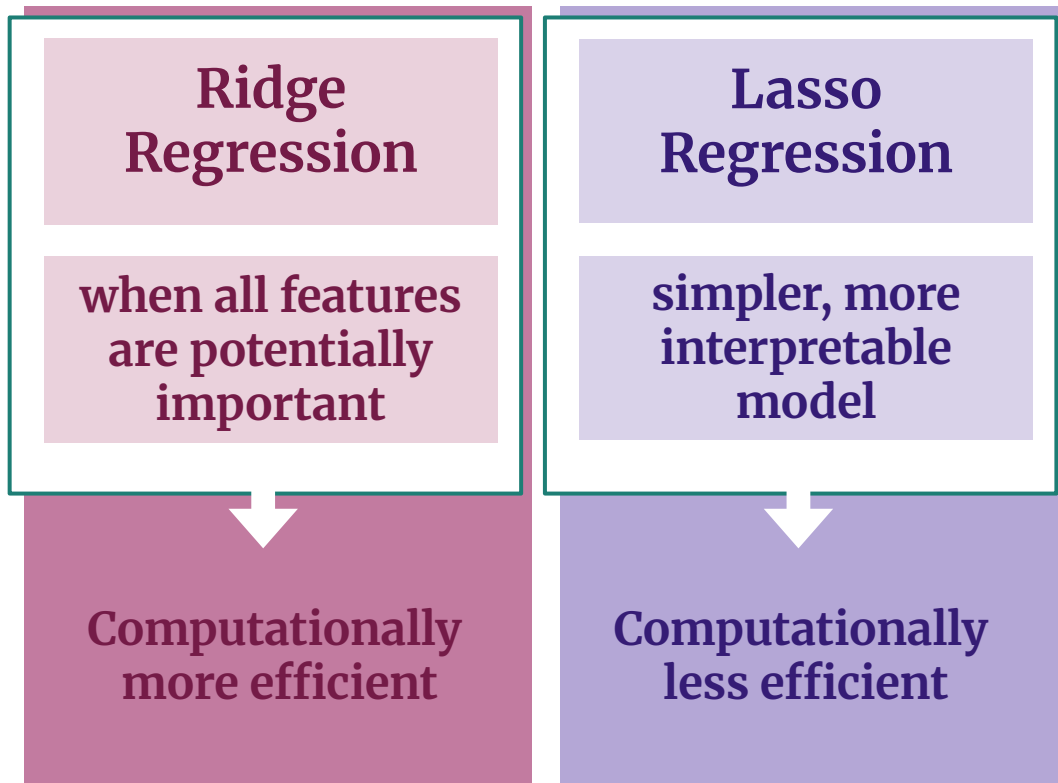


Lasso Regression Coefficient Shrinkage



# Choosing Between Ridge and Lasso

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# Sample Question: Ridge Regression

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x1	x2	x3	y
2	3	5	10
4	2	1	8
3	4	2	11
5	1	3	9
1	5	4	7

# Sample Question: Ridge Regression

$\mathbf{X}^T$ (4 x 5)	1	1	1	1	1
	2	4	3	5	1
	3	2	4	1	5
	5	1	2	3	4

$\mathbf{X}$ (5 x 4)			
1	2	3	5
1	4	2	1
1	3	4	2
1	5	1	3
1	1	5	4



$\mathbf{X}^T \mathbf{X}$ (4 x 4)	5	15	15	15
	15	55	36	39
	15	36	55	48
	15	39	48	55

$\mathbf{I}'$ (4 x 4)	0	0	0	0
	0	1	0	0
	0	0	1	0
	0	0	0	1



$\lambda=1$  (for simplicity)

$\mathbf{a}$ (4 x 4)	5	15	15	15
	15	56	36	39
	15	36	56	48
	15	39	48	56



$\mathbf{a}^{-1}$ (4 x 4) (Calculate)
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Step-2: Calculate  $\mathbf{a}^{-1} = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}')^{-1}$

# Sample Question: Linear Regression

— — —

$\mathbf{X}^T$ (4 x 5)	1	1	1	1	1
	2	4	3	5	1
	3	2	4	1	5
	5	1	2	3	4



$\mathbf{b}$ (4 x 1)	45
	137
	134
	135

$\mathbf{Y}$ (5 X 1)
10
8
11
9
7

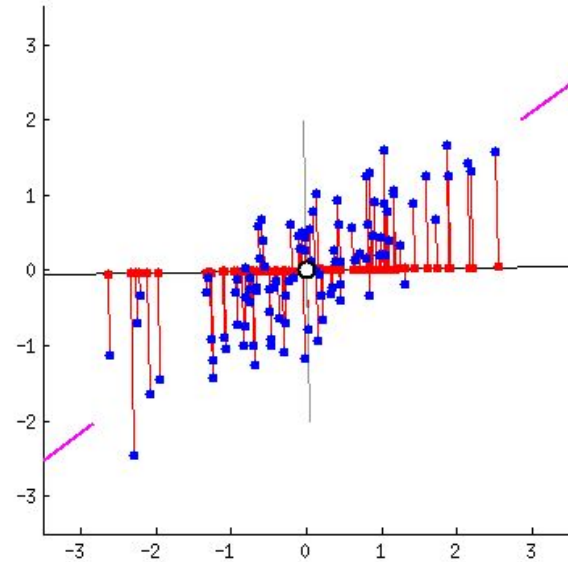
Step-3: Calculate  $\mathbf{b} = \mathbf{X}^T \mathbf{Y}$

Step-4: Calculate  $\boldsymbol{\beta} = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I})^{-1} \mathbf{X}^T \mathbf{Y} = \mathbf{a}^{-1} \mathbf{b}$   
(Calculate yourself)

# Principal Component Regression (PCR)

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- Uses PCA to reduce dimensionality before regression
- Addresses multicollinearity issues
- Regression is performed on principal components rather than original variables



# PCR Method

— — —

- **Standardize the data:** Center and scale both predictor (X) and response (Y)
- **Perform PCA on predictors:**
  - Compute the covariance matrix of X
  - Calculate eigenvectors and eigenvalues
  - Rank eigenvectors by descending eigenvalues
  - Select top k principal components (PCs)
- **Project data onto PCs:** Transform X into the new PC space.
- **Perform OLS regression:** Use the selected PCs as predictors for Y.
- **Transform coefficients back:** Convert PC coefficients to original variable space.

# Sample Question: PC Regression

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x1	x2	x3	y
2	3	5	10
4	2	1	8
3	4	2	11
5	1	3	9
1	5	4	7

# Sample Question: PC Regression

— — —

Original Data	x1	x2	x3	y
	2	3	5	10
	4	2	1	8
	3	4	2	11
	5	1	3	9
	1	5	4	7
Mean	3	3	3	9
Std	1.58	1.58	1.58	1.58

Scaled Data			
z1	z2	z3	y
-0.63	0	1.26	4.42
0.63	-0.63	-1.26	3.16
0	0.63	-0.63	5.05
1.26	-1.26	0	3.79
-1.26	1.26	0.63	2.52

Step-1: Standardized data

# Sample Question: PCR

$\mathbf{X}^T$ (3 x 5)	-0.63	0.63	0	1.26	-1.26
	0	-0.63	0.63	-1.26	1.26
	1.26	-1.26	-0.63	0	0.63

$\mathbf{X}$ (5 x 3)		
-0.63	0	1.26
0.63	-0.63	-1.26
0	0.63	-0.63
1.26	-1.26	0
-1.26	1.26	0.63



$\mathbf{A}$ (3 x 3)	1	-0.9	-0.6
	-0.9	1	0.3
	-0.6	0.3	1

Step-2: Calculate covariance matrix

$$\mathbf{A} = (1/n-1)(\mathbf{X}^T \mathbf{X})$$

$n=5$



# Sample Question: Linear Regression

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Step-3: Calculate Eigen value and eigen vector of A using solution of  $|A-\lambda I|=0$

Solve:

$$-\lambda^3 + 3\lambda^2 - 1.74\lambda + 0.064=0$$

$$\lambda_1= 2.23, \lambda_2= 0.726 \text{ and } \lambda_3= 0.039$$

For eigenvector  $v$ , solve  $(A-\lambda I)v=0$

# Sample Question: Linear Regression

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Step-4: Select top-K eigenvectors

Step-5: Calculate  $PC_i = X V_i$

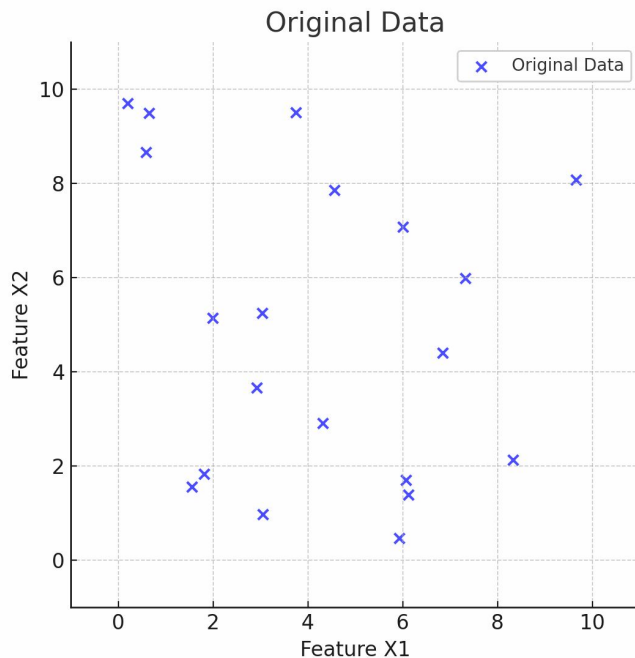
Step-6: Apply Regression on PC

Step-7: Convert PC coefficients to original variable space using  $V_i$

# Partial Least Squares (PLS) Regression

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- **Similar to PCR but maximizes covariance between predictors and response**
- **Works well for high-dimensional data with correlated predictors**

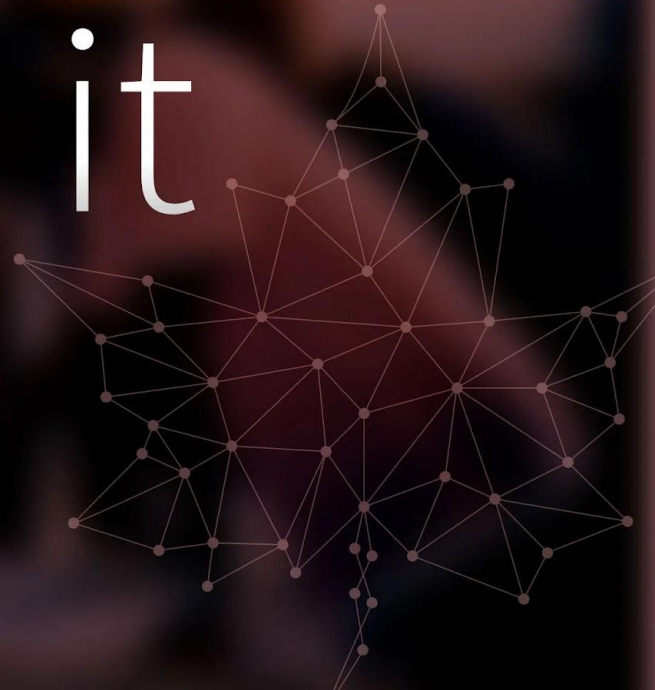


# PLS Method

- Standardize the data (center and scale variables).
- Find components that maximize the covariance between X and Y spaces.
- Project the data onto these components.
- Perform regression using the projected data.

## Assignment-2 (Cs-46- 2025) (Week-2)

Let's <sup>SOLVE</sup> = it



# Question-1

— — —

01:00

In a linear regression model  $y = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_p x_p$ , what is the purpose of adding an intercept term ( $\theta_0$ )?

- a) To increase the model's complexity
- b) To account for the effect of independent variables.
- c) To adjust for the baseline level of the dependent variable when all predictors are zero.
- d) To ensure the coefficients of the model are unbiased

# Question-1- Correct answer

— — —

In a linear regression model  $y = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_p x_p$ , what is the purpose of adding an intercept term ( $\theta_0$ )?

- a) To increase the model's complexity
- b) To account for the effect of independent variables.
- c) To adjust for the baseline level of the dependent variable when all predictors are zero.
- d) To ensure the coefficients of the model are unbiased

**Correct options: (c)**

## Question-2

— — —

03:00

Which of the following is true about the cost function (objective function) used in linear regression?

- a) It is non-convex.
- b) It is always minimized at  $\theta = 0$ .
- c) It measures the sum of squared differences between predicted and actual values.
- d) It assumes the dependent variable is categorical.



## Question-2 – Correct answer

— — —

Which of the following is true about the cost function (objective function) used in linear regression?

- a) It is non-convex.
- b) It is always minimized at  $\theta = 0$ .
- c) It measures the sum of squared differences between predicted and actual values.
- d) It assumes the dependent variable is categorical.

**Correct options: (c)**

## Question-3

— — —

01:00

Which of these would most likely indicate that Lasso regression is a better choice than Ridge regression?

- a) All features are equally important
- b) Features are highly correlated
- c) Most features have small but non-zero impact
- d) Only a few features are truly relevant

# Question-3- Correct answer

— — —

Which of these would most likely indicate that Lasso regression is a better choice than Ridge regression?

- a) All features are equally important
- b) Features are highly correlated
- c) Most features have small but non-zero impact
- d) Only a few features are truly relevant

**Correct options: (d)**

## Question-4

— — —

01:00

Which of the following conditions must hold for the least squares estimator in linear regression to be unbiased?

- a) The independent variables must be normally distributed.
- b) The relationship between predictors and the response must be non-linear.
- c) The errors must have a mean of zero.
- d) The sample size must be larger than the number of predictors.

## Question-4 - Correct answer

— — —

Which of the following conditions must hold for the least squares estimator in linear regression to be unbiased?

- a) The independent variables must be normally distributed.
- b) The relationship between predictors and the response must be non-linear.
- c) The errors must have a mean of zero.
- d) The sample size must be larger than the number of predictors.

**Correct options: (c)**

# Question-5

— — —

01:00

When performing linear regression, which of the following is most likely to cause overfitting?

- a) Adding too many regularization terms.
- b) Including irrelevant predictors in the model.
- c) Increasing the sample size.
- d) Using a smaller design matrix.

# Question-5 - Correct answer

— — —

When performing linear regression, which of the following is most likely to cause overfitting?

- a) Adding too many regularization terms.
- b) Including irrelevant predictors in the model.
- c) Increasing the sample size.
- d) Using a smaller design matrix.

**Correct options: (b)**

# Question-6

— — —

01:00

You have trained a complex regression model on a dataset. To reduce its complexity, you decide to apply Ridge regression, using a regularization parameter  $\lambda$ . How does the relationship between bias and variance change as  $\lambda$  becomes very large? Select the correct option

- a) bias is low, variance is low.
- b) bias is low, variance is high.
- c) bias is high, variance is low.
- d) bias is high, variance is high.



## Question-6 - Correct answer

You have trained a complex regression model on a dataset. To reduce its complexity, you decide to apply Ridge regression, using a regularization parameter  $\lambda$ . How does the relationship between bias and variance change as  $\lambda$  becomes very large? Select the correct option

- a) bias is low, variance is low.
- b) bias is low, variance is high.
- c) bias is high, variance is low.
- d) bias is high, variance is high.

**Correct options: (c)**

# Question-7

— — —

03:00

Given a training data set of 10,000 instances, with each input instance having 12 dimensions and each output instance having 3 dimensions, the dimensions of the design matrix used in applying linear regression to this data is

- a)  $10000 \times 12$
- b)  $10003 \times 12$
- c)  $10000 \times 13$
- d)  $10000 \times 15$

# Question-7 – Correct answer

— — —

Given a training data set of 10,000 instances, with each input instance having 12 dimensions and each output instance having 3 dimensions, the dimensions of the design matrix used in applying linear regression to this data is

- a)  $10000 \times 12$
- b)  $10003 \times 12$
- c)  $10000 \times 13$
- d)  $10000 \times 15$

**Correct options: (c)**

# Question-8

— — —

01:00

The linear regression model  $y = a_0 + a_1x_1 + a_2x_2 + \dots + a_px_p$  is to be fitted to a set of  $N$  training data points having  $P$  attributes each. Let  $X$  be  $N \times (p+1)$  vectors of input values (augmented by 1's),  $Y$  be  $N \times 1$  vector of target values, and  $\theta$  be  $(p+1) \times 1$  vector of parameter values  $(a_0, a_1, a_2, \dots, a_p)$ . If the sum squared error is minimized for obtaining the optimal regression model, which of the following equation holds?

- (a)  $X^T X = X Y$
- (b)  $X \theta = X^T Y$
- (c)  $X^T X \theta = Y$
- (d)  $X^T X \theta = X^T Y$

## Question-8- Correct answer

— — —

The linear regression model  $y = a_0 + a_1x_1 + a_2x_2 + \dots + a_px_p$  is to be fitted to a set of  $N$  training data points having  $P$  attributes each. Let  $X$  be  $N \times (p+1)$  vectors of input values (augmented by 1's),  $Y$  be  $N \times 1$  vector of target values, and  $\theta$  be  $(p+1) \times 1$  vector of parameter values  $(a_0, a_1, a_2, \dots, a_p)$ . If the sum squared error is minimized for obtaining the optimal regression model, which of the following equation holds?

- (a)  $X^T X = X Y$
- (b)  $X \theta = X^T Y$
- (c)  $X^T X \theta = Y$
- (d)  $X^T X \theta = X^T Y$

**Correct options: (d)**

# Question-9

— — —

01:00

Which of the following scenarios is most appropriate for using Partial Least Squares (PLS) regression instead of ordinary least squares (OLS)?

- (a) When the predictors are uncorrelated and the number of samples is much larger than the number of predictors.
- (b) When there is significant multicollinearity among predictors or the number of predictors exceeds the number of samples.
- (c) When the response variable is categorical and the predictors are highly non-linear.
- (d) When the primary goal is to interpret the relationship between predictors and response, rather than prediction accuracy.

# Question-9- Correct answer

— — —

Which of the following scenarios is most appropriate for using Partial Least Squares (PLS) regression instead of ordinary least squares (OLS)?

- (a) When the predictors are uncorrelated and the number of samples is much larger than the number of predictors.
- (b) When there is significant multicollinearity among predictors or the number of predictors exceeds the number of samples.
- (c) When the response variable is categorical and the predictors are highly non-linear.
- (d) When the primary goal is to interpret the relationship between predictors and response, rather than prediction accuracy.

**Correct options: (b)**

# Question-10

— — —

01:00

Consider forward selection, backward selection and best subset selection with respect to the same data set. Which of the following is true?

- (a) Best subset selection can be computationally more expensive than forward selection
- (b) Forward selection and backward selection always lead to the same result
- (c) Best subset selection can be computationally less expensive than backward selection
- (d) Best subset selection and forward selection are computationally equally expensive
- (e) Both (b) and (d)



# Question-10- Correct answer

— — —

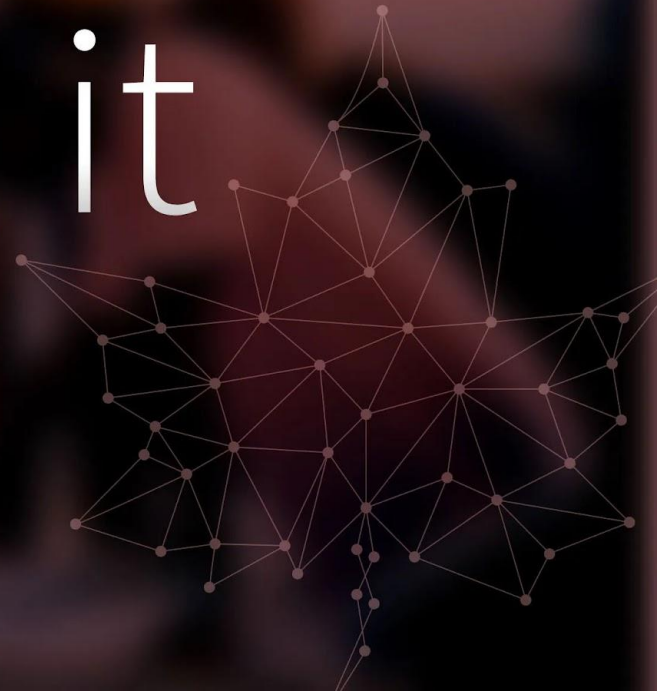
Consider forward selection, backward selection and best subset selection with respect to the same data set. Which of the following is true?

- (a) Best subset selection can be computationally more expensive than forward selection
- (b) Forward selection and backward selection always lead to the same result
- (c) Best subset selection can be computationally less expensive than backward selection
- (d) Best subset selection and forward selection are computationally equally expensive
- (e) Both (b) and (d)

**Correct options: (a)**

## Assignment-2 (Cs-101- 2024) (Week-2)

Let's <sup>SOLVE</sup> = it



# Question-1

— — —

01:00

State True or False: Typically, linear regression tend to underperform compared to k-nearest neighbor algorithms when dealing with high-dimensional input spaces.

- a) True
- b) False

# Question-1- Correct answer

— — —

State True or False: Typically, linear regression tend to underperform compared to k-nearest neighbor algorithms when dealing with high-dimensional input spaces.

a) True

b) False

**Correct options: (b)**

## Question-2

03:00

Given the following dataset, find the uni-variate regression function that best fits the dataset.

- a)  $f(x) = 1x + 4$
- b)  $f(x) = 1x + 5$
- c)  $f(x) = 1.5x + 3$
- d)  $f(x) = 2x + 1$

X	Y
2	5.5
3	6.5
4	9
10	18.5

## Question-2 – Correct answer

Given the following dataset, find the uni-variate regression function that best fits the dataset.

- a)  $f(x) = 1x + 4$
- b)  $f(x) = 1x + 5$
- c)  $f(x) = 1.5x + 3$
- d)  $f(x) = 2x + 1$

**Correct options: (c)**

## Question-3

---

01:00

Given a training data set of 500 instances, with each input instance having 6 dimensions and each output being a scalar value, the dimensions of the design matrix used in applying linear regression to this data is

- a)  $500 \times 6$
- b)  $500 \times 7$
- c)  $500 \times 6^2$
- d) None

## Question-3- Correct answer

Given a training data set of 500 instances, with each input instance having 6 dimensions and each output being a scalar value, the dimensions of the design matrix used in applying linear regression to this data is

- a) 500 x 6
- b) 500 x 7
- c) 500 x 62
- d) None

**Correct options: (b)**



# Question-4

— — —

01:00

Assertion A: Binary encoding is usually preferred over One-hot encoding to represent categorical data (eg. colors, gender etc)

Reason R: Binary encoding is more memory efficient when compared to One-hot encoding

- a) Both A and R are true and R is the correct explanation of A
- b) Both A and R are true but R is not the correct explanation of A
- c) A is true but R is false
- d) A is false but R is true

# Question-4 – Correct answer

— — —

Assertion A: Binary encoding is usually preferred over One-hot encoding to represent categorical data (eg. colors, gender etc)

Reason R: Binary encoding is more memory efficient when compared to One-hot encoding

- a) Both A and R are true and R is the correct explanation of A
- b) Both A and R are true but R is not the correct explanation of A
- c) A is true but R is false
- d) A is false but R is true

**Correct options: (d)**

# Question-5

— — —

01:00

Select the TRUE statement

- a) Subset selection methods are more likely to improve test error by only focussing on the most important features and by reducing variance in the fit.
- b) Subset selection methods are more likely to improve train error by only focussing on the most important features and by reducing variance in the fit.
- c) Subset selection methods are more likely to improve both test and train error by focussing on the most important features and by reducing variance in the fit.
- d) Subset selection methods don't help in performance gain in any way.

# Question-5 - Correct answer

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Select the TRUE statement

- a) Subset selection methods are more likely to improve test error by only focussing on the most important features and by reducing variance in the fit.
- b) Subset selection methods are more likely to improve train error by only focussing on the most important features and by reducing variance in the fit.
- c) Subset selection methods are more likely to improve both test and train error by focussing on the most important features and by reducing variance in the fit.
- d) Subset selection methods don't help in performance gain in any way.

**Correct options: (a)**

# Question-6

— — —

01:00

Rank the 3 subset selection methods in terms of computational efficiency

- a) Forward stepwise selection, best subset selection, and forward stagewise regression.
- b) Forward stepwise selection, forward stagewise regression and best subset selection.
- c) Best subset selection, forward stagewise regression and forward stepwise selection.
- d) Best subset selection, forward stepwise selection and forward stagewise regression.

# Question-6 – Correct answer

— — —

Rank the 3 subset selection methods in terms of computational efficiency:

- a) Forward stepwise selection, best subset selection, and forward stagewise regression.
- b) Forward stepwise selection, forward stagewise regression and best subset selection.
- c) Best subset selection, forward stagewise regression and forward stepwise selection.
- d) Best subset selection, forward stepwise selection and forward stagewise regression.

**Correct options: (b)**

# Question-7

— — —

03:00

Choose the TRUE statements from the following: (Multiple correct choice)

- a) Ridge regression since it reduces the coefficients of all variables, makes the final fit a lot more interpretable.
- b) Lasso regression since it doesn't deal with a squared power is easier to optimize than ridge regression.
- c) Ridge regression has a more stable optimization than lasso regression.
- d) Lasso regression is better suited for interpretability than ridge regression.

# Question-7 - Correct answer

— — —

Choose the TRUE statements from the following:

- a) Ridge regression since it reduces the coefficients of all variables, makes the final fit a lot more interpretable.
- b) Lasso regression since it doesn't deal with a squared power is easier to optimize than ridge regression.
- c) Ridge regression has a more stable optimization than lasso regression.
- d) Lasso regression is better suited for interpretability than ridge regression.

**Correct options: (c) (d)**



# Question-8

— — —

01:00

Which of the following statements are TRUE? Let  $x_i$  be the  $i$ -th datapoint in a dataset of  $N$  points. Let  $v$  represent the first principal component of the dataset. (Multiple answer questions)

a)  $v = \arg \max \sum_{i=1}^N (v^T x_i)^2 \text{ s.t. } |v| = 1$

b)  $v = \arg \min \sum_{i=1}^N (v^T x_i)^2 \text{ s.t. } |v| = 1$

c) Scaling at the start of performing PCA is done just for better numerical stability and computational benefits but plays no role in determining the final principal components of a dataset.

d) The resultant vectors obtained when performing PCA on a dataset can vary based on the scale of the dataset.

# Question-8- Correct answer

Which of the following statements are TRUE? Let  $x_i$  be the  $i$ -th datapoint in a dataset of  $N$  points. Let  $v$  represent the first principal component of the dataset. (Multiple answer questions)

a)  $v = \arg \max \sum_{i=1}^N (v^T x_i)^2 \text{ s.t. } |v| = 1$

b)  $v = \arg \min \sum_{i=1}^N (v^T x_i)^2 \text{ s.t. } |v| = 1$

c) Scaling at the start of performing PCA is done just for better numerical stability and computational benefits but plays no role in determining the final principal components of a dataset.

d) The resultant vectors obtained when performing PCA on a dataset can vary based on the scale of the dataset.

**Correct options: (a) (d)**



**THANK YOU**

# Suggestions and Feedback



**Next Session:**

**Tuesday:  
10-Aug-2025  
3:00 - 5:00 PM**