# Machine Learning Homework 01 Solution

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- Suppose X be a zero-mean Gaussian random variable with variance  $\sigma_X^2$ . Let  $Y=X^2$ 
  - 1. What is the pdf of *Y*?

$$\Pr\{Y \le y\} = \Pr\{X^2 \le y\} = \Pr\{-\sqrt{y} \le X \le \sqrt{y}\} = \int_{-\sqrt{y}}^{\sqrt{y}} f_X(x) dx$$

The pdf of Y is

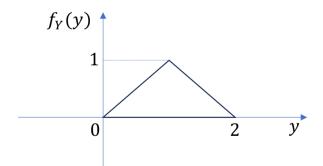
$$f_Y(y) = \frac{\partial \Pr\{Y \le y\}}{\partial y} = f_X(\sqrt{y}) \left(\frac{1}{2\sqrt{y}}\right) - f_X(-\sqrt{y}) \left(-\frac{1}{2\sqrt{y}}\right) = \frac{1}{\sqrt{2\pi\sigma_X^2 y}} \exp\{-y/\sigma_X^2\}$$

2. Please calculate  $E\{Y\}$  and  $E\{Y^2\}$ 

$$E\{Y\} = \sigma_X^2$$

$$E\{Y^2\} = 3\sigma_X^4$$

- Suppose  $X_1$  and  $X_2$  be uniform random variables over (0,1) and  $X_1$  and  $X_2$  are independent
- Let  $Y = X_1 + X_2$ 
  - 1. what is the pdf of Y?
  - 2. Please calculate  $E\{Y\}$  and  $E\{Y^2\}$



$$E\{Y\} = 1$$

$$E\{Y^2\} = \frac{1}{3} + 2 * \frac{1}{2} * \frac{1}{2} + \frac{1}{3} = \frac{14}{12} = \frac{7}{6}$$

- Suppose  $y=[y_1,y_2,y_3]^T$  and  $x=[x_1,x_2]^T$  in which  $y_1=x_1^2-2x_2^2,y_2=-3x_1^2+2x_1x_2+x_2^2$  and  $y_3=x_1^2+x_2^2$ 
  - 1. Please find  $\frac{\partial y}{\partial x}$

$$\begin{bmatrix} 2x_1 & -6x_1 + 2x_2 & 2x_1 \\ 4x_2 & 2x_1 + 2x_2 & 2x_2 \end{bmatrix}$$

• Let 
$$A = \begin{bmatrix} -1 & 2 & 3 \\ 2 & 0 & -1 \\ 3 & -1 & 5 \end{bmatrix}$$
 and  $\mathbf{x} = [x_1, x_2, x_3]^T$ 

1. Let y = Ax. Please find  $\frac{\partial y}{\partial x}$ 

$$A = \begin{bmatrix} -1 & 2 & 3 \\ 2 & 0 & -1 \\ 3 & -1 & 5 \end{bmatrix}$$

2. Let 
$$y = x^T A x$$
. Please find  $\frac{\partial y}{\partial x}$ 

2A*x* 

• Suppose we have a dataset

x	(1,2)	(3,2)	(0,3)	(4,1)	(2,0)	(2,3)
label	Class 1	Class 2	Class 1	Class 2	Class 1	Class 2

- Now we have a new data  $x_{new} = (2,2)$
- Use KNN with k=3 to classify this new data
  - 1. Minkowski distance with p = 1
  - 2. Minkowski distance with p = 2
  - 3. Minkowski distance with  $p = \infty$

	(1,2)	(3,2)	(0,3)	(4,1)	(2,0)	(2,3)	
$x_{new} = (2,2)$	Class 1	Class 2	Class 1	Class 2	Class 1	Class 2	
p = 1	1	1	3	3	2	1	Class 2
p = 2	1	1	$\sqrt{5}$	$\sqrt{5}$	2	1	Class 2
$p = \infty$	1	1	2	2	2	1	Class 1

ID	Study Hours/Day	Eat Lunch?	Money on pocket	Age	Have Afternoon Tea?
1	3	No	50	18	No
2	8	Yes	100	19	Yes
3	4	No	130	20	Yes
4	10	No	120	22	No
5	9	Yes	40	18	Yes

- Construct a decision tree with depth 3 to predict whether a person will have afternoon tea
  - 1. Use information gain
  - 2. Use gini index
  - 3. Use information gain ratio

- Information gain
  - the first level:
    - study hour/day
      - less than 3

$$\left(-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}\right) - \left(\frac{1}{5}(0) + \frac{4}{5}\left(-\frac{3}{4}\log_2\frac{3}{4} - \frac{1}{4}\log_2\frac{1}{4}\right)\right) = 0.3219$$

• less than 5

$$\left(-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}\right) - \left(\frac{2}{5}\left(-\frac{1}{2}\log_2\frac{1}{2} - \frac{1}{2}\log_2\frac{1}{2}\right) + \frac{3}{5}\left(-\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3}\right)\right) = 0.02$$

$$\left(-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}\right) - \left(\frac{2}{5}\left(-\frac{1}{2}\log_2\frac{1}{2} - \frac{1}{2}\log_2\frac{1}{2}\right) + \frac{3}{5}\left(-\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3}\right)\right) = 0.02$$

- Information gain
  - the first level:
    - study hour/day
      - less than 10  $\left( -\frac{3}{5}\log_2\frac{3}{5} \frac{2}{5}\log_2\frac{2}{5} \right) \left( \frac{1}{5}(0) + \frac{4}{5}\left( -\frac{2}{4}\log_2\frac{2}{4} \frac{2}{4}\log_2\frac{2}{4} \right) \right) = 0.1710$
    - eat Lunch?

$$\left(-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}\right) - \left(\frac{2}{5}\left(0\right) + \frac{3}{5}\left(-\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3}\right)\right) = 0.42$$

- Information gain
  - the first level:
    - money on pocket
      - less than 50?  $\left( -\frac{3}{5} \log_2 \frac{3}{5} \frac{2}{5} \log_2 \frac{2}{5} \right) \left( \frac{1}{5} (0) + \frac{4}{5} (1) \right) = 0.171$
      - less than 100?

$$\left(-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}\right) - \left(\frac{2}{5}\left(1\right) + \frac{3}{5}\left(-\frac{2}{3}\log_2\frac{1}{3} - \frac{2}{3}\log_2\frac{1}{3}\right)\right) = 0.02$$

• less than 120?

$$\left(-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}\right) - \left(\frac{2}{5}\left(1\right) + \frac{3}{5}\left(-\frac{2}{3}\log_2\frac{1}{3} - \frac{2}{3}\log_2\frac{1}{3}\right)\right) = 0.02$$

- Information gain
  - the first level:
    - money on pocket
      - less than 130?  $\left( -\frac{3}{5} \log_2 \frac{3}{5} \frac{2}{5} \log_2 \frac{2}{5} \right) \left( \frac{1}{5} (0) + \frac{4}{5} (1) \right) = 0.171$

- Information gain
  - the first level:
    - age

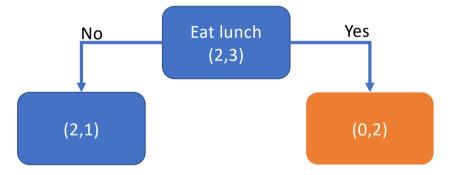
• less than 19 
$$\left( -\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5} \right) - \left( \frac{2}{5}(1) + \frac{3}{5}\left( -\frac{2}{3}\log_2\frac{1}{3} - \frac{2}{3}\log_2\frac{1}{3} \right) \right) = 0.02$$

• less than 20

$$\left(-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}\right) - \left(\frac{2}{5}\left(1\right) + \frac{3}{5}\left(-\frac{2}{3}\log_2\frac{1}{3} - \frac{2}{3}\log_2\frac{1}{3}\right)\right) = 0.02$$

$$\left(-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}\right) - \left(\frac{1}{5}(0) + \frac{4}{5}\left(-\frac{3}{4}\log_2\frac{1}{4} - \frac{1}{4}\log_2\frac{1}{4}\right)\right) = 0.3219$$

- Information gain
  - the first level:
    - we can split on eat lunch





- Information gain
  - the second level (the left child):

ID	Study Hours/Day	Eat Lunch?	Money on pocket	Age	Have Afternoon Tea?
1	3	No	50	18	No
3	4	No	150	20	Yes
4	10	No	120	22	No

- Information gain
  - the second level (the left child):
    - study hour/day
      - less than 4

$$\left(-\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3}\right) - \left(\frac{1}{3}(0) + \frac{2}{3}(1)\right) = 0.2516$$

$$\left(-\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3}\right) - \left(\frac{1}{3}(0) + \frac{2}{3}(1)\right) = 0.2516$$

- Information gain
  - the second level (the left child):
    - money on pocket
      - less than 120

$$\left(-\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3}\right) - \left(\frac{1}{3}(0) + \frac{2}{3}(1)\right) = 0.2516$$

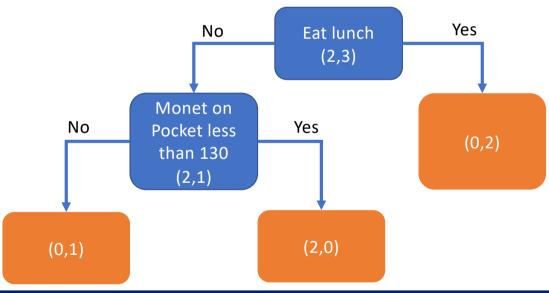
$$\left(-\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3}\right) - \left(\frac{1}{3}(0) + \frac{2}{3}(0)\right) = 0.9183$$

- Information gain
  - the second level (the left child):
    - age
      - less than 20

$$\left(-\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3}\right) - \left(\frac{1}{3}(0) + \frac{2}{3}(1)\right) = 0.2516$$

$$\left(-\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3}\right) - \left(\frac{1}{3}(0) + \frac{2}{3}(1)\right) = 0.2516$$

- Information gain
  - the second level (the left child):
    - we split on money on pocket less than 150



# Problem 07 (Linear regression)



x	1	3	5	7	9
у	2	5	4	4	8

• Determine the best predicted model when  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x$ 

Suppose we have the following dataset

x	1	3	5	7	9
у	2	5	4	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x$ 

Recall 
$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

Step 01: Forming  $\Phi$ , namely X in the simplest linear Regression Model

$$\Phi = \begin{bmatrix} 1 & 1 \\ 1 & 3 \\ 1 & 5 \\ 1 & 7 \\ 1 & 9 \end{bmatrix} = X$$

Suppose we have the following dataset

x	1	3	5	7	9
у	2	5	4	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x$ 

Recall 
$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

Step 02: Forming y

$$\mathbf{y} = \begin{bmatrix} 2 \\ 5 \\ 4 \\ 4 \\ 8 \end{bmatrix}$$

Suppose we have the following dataset

x	1	3	5	7	9
у	2	5	4	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x$ 

Recall 
$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$
  
Step 03: Calculate  $\Phi(\Phi^T \Phi)^{-1} \Phi^T \mathbf{v}$  name

Recall  $\mathbf{w}_{\mathrm{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$ Step 03: Calculate  $\Phi(\Phi^T \Phi)^{-1} \Phi^T \mathbf{y}$ , namely  $(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$  in the simplest linear regression model

$$\mathbf{X}^{T}\mathbf{X} = \begin{bmatrix} 1 & 1 \\ 1 & 3 \\ 1 & 5 \\ 1 & 7 \\ 1 & 9 \end{bmatrix}^{T} \begin{bmatrix} 1 & 1 \\ 1 & 3 \\ 1 & 5 \\ 1 & 7 \\ 1 & 7 \end{bmatrix} = \begin{bmatrix} 5 & 25 \\ 25 & 165 \end{bmatrix} \qquad \mathbf{X}^{T}\mathbf{y} = \begin{bmatrix} 1 & 1 \\ 1 & 3 \\ 1 & 5 \\ 1 & 7 \\ 1 & 9 \end{bmatrix}^{T} \begin{bmatrix} 2 \\ 5 \\ 4 \\ 4 \\ 8 \end{bmatrix} = \begin{bmatrix} 23 \\ 137 \end{bmatrix}$$



x	1	3	5	7	9
у	2	5	4	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x$ 

Recall 
$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

Step 03: Calculate  $\Phi(\Phi^T\Phi)^{-1}\Phi^Ty$ , namely  $(X^TX)^{-1}X^Ty$  in the simplest

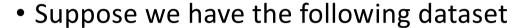
linear regression model

$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} = \begin{bmatrix} 5 & 25 \\ 25 & 165 \end{bmatrix}^{-1} \begin{bmatrix} 23 \\ 137 \end{bmatrix} = \begin{bmatrix} 1.85 \\ 0.55 \end{bmatrix}$$



$$\hat{y}(x, w_0, w_1) = 1.85 + 0.55x$$

# Problem 08 (Linear regression)



x	1	3	5	7	9
у	2	5	4	4	8

Determine the best predicted model when

$$\hat{y}(x, w_0, w_1) = w_0 + w_1 x + w_2 x^2$$

Suppose we have the following dataset

x	1	3	5	7	9
у	2	5	4	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x + w_2 x^2$ 

Recall 
$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

Step 01: Forming  $\Phi$ , namely X in the simplest linear Regression Model

$$\Phi = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 3 & 9 \\ 1 & 5 & 25 \\ 1 & 7 & 49 \\ 1 & 9 & 81 \end{bmatrix} = X$$

Suppose we have the following dataset

x	1	3	5	7	9
у	2	5	4	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x + w_2 x^2$ 

Recall 
$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

Step 02: Forming y

$$\mathbf{y} = \begin{bmatrix} 2 \\ 5 \\ 4 \\ 4 \\ 8 \end{bmatrix}$$

Suppose we have the following dataset

x	1	3	5	7	9
у	2	5	3	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x + w_2 x^2$ 

Recall 
$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$
  
Step 03: Calculate  $\Phi(\Phi^T \Phi)^{-1} \Phi^T \mathbf{y}$ , namely  $(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$  in the simplest linear regression model

$$\Phi^{T}\Phi = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 3 & 9 \\ 1 & 5 & 25 \\ 1 & 7 & 49 \\ 1 & 9 & 81 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 3 & 9 \\ 1 & 5 & 25 \\ 1 & 7 & 49 \\ 1 & 9 & 81 \end{bmatrix} = \begin{bmatrix} 5 & 25 & 165 \\ 25 & 165 & 1225 \\ 165 & 1225 & 9669 \end{bmatrix}$$

Suppose we have the following dataset

x	1	3	5	7	9
у	2	5	4	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x + w_2 x^2$ 

Recall 
$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

Step 03: Calculate  $\Phi(\Phi^T\Phi)^{-1}\Phi^Ty$ , namely  $(X^TX)^{-1}X^Ty$  in the simplest

linear regression model

$$\Phi^{T} \mathbf{y} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 3 & 9 \\ 1 & 5 & 25 \\ 1 & 7 & 49 \\ 1 & 9 & 81 \end{bmatrix}^{T} \begin{bmatrix} 2 \\ 5 \\ 4 \\ 4 \\ 8 \end{bmatrix} = \begin{bmatrix} 23 \\ 137 \\ 991 \end{bmatrix}$$

Suppose we have the following dataset

x	1	3	5	7	9
у	2	5	3	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x + w_2 x^2$ 

Recall 
$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

Step 03: Calculate  $\Phi(\Phi^T\Phi)^{-1}\Phi^Ty$ , namely  $(X^TX)^{-1}X^Ty$  in the simplest

linear regression model

$$\mathbf{w}_{\text{opt}} = (\Phi^T \Phi)^{-1} \Phi^T \mathbf{y} = \begin{bmatrix} 5 & 25 & 165 \\ 25 & 165 & 1225 \\ 165 & 1225 & 9669 \end{bmatrix}^{-1} \begin{bmatrix} 23 \\ 137 \\ 991 \end{bmatrix} = \begin{bmatrix} 2.7607 \\ 0.0143 \\ 0.0536 \end{bmatrix}$$



$$\hat{y}(x, w_0, w_1) = 2.7607 + 0.0143x + 0.0536x^2$$

# Problem 09 (Linear regression)

Suppose we have the following dataset

$x = (x_1, x_2)$	(1,1)	(1,3)	(5,2)	(7,4)	(9,2)
у	2	5	4	4	8

Determine the best predicted model when

$$\hat{y}(x, w_0, w_1) = w_0 + w_1 x_1 + w_2 x_2$$

Suppose we have the following dataset

$x = (x_1, x_2)$	(1,1)	(1,3)	(5,2)	(7,4)	(9,2)
у	2	5	4	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x_1 + w_2 x_2$ 

Recall 
$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

Step 01: Forming  $\Phi$ , namely X in the simplest linear Regression Model

$$\Phi = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 3 \\ 1 & 5 & 2 \\ 1 & 7 & 4 \\ 1 & 9 & 2 \end{bmatrix} = X$$

Suppose we have the following dataset

$x = (x_1, x_2)$	(1,1)	(1,3)	(5,2)	(7,4)	(9,2)
у	2	5	4	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x_1 + w_2 x_2$ 

Recall 
$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

Step 02: Forming y

$$\mathbf{y} = \begin{bmatrix} 2^{1} \\ 5 \\ 4 \\ 4 \\ 8 \end{bmatrix}$$

Suppose we have the following dataset

$x = (x_1, x_2)$	(1,1)	(1,3)	(5,2)	(7,4)	(9,2)
у	2	5	4	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x_1 + w_2 x_2$ 

Recall  $\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$ Step 03: Calculate  $\Phi(\Phi^T \Phi)^{-1} \Phi^T \mathbf{y}$ , namely  $(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$  in the simplest linear regression model

$$\Phi^{T}\Phi = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 3 \\ 1 & 5 & 2 \\ 1 & 7 & 4 \\ 1 & 9 & 2 \end{bmatrix}^{T} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 3 \\ 1 & 5 & 2 \\ 1 & 7 & 4 \\ 1 & 9 & 2 \end{bmatrix} = \begin{bmatrix} 5 & 23 & 12 \\ 23 & 157 & 60 \\ 12 & 60 & 34 \end{bmatrix}$$

Suppose we have the following dataset

$x = (x_1, x_2)$	(1,1)	(1,3)	(5,2)	(7,4)	(9,2)
у	2	5	4	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x_1 + w_2 x_2$ 

Recall 
$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

Recall  $\mathbf{w}_{\mathrm{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$ Step 03: Calculate  $\Phi(\Phi^T \Phi)^{-1} \Phi^T \mathbf{y}$ , namely  $(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$  in the simplest

linear regression model

$$\Phi^{T} \mathbf{y} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 3 \\ 1 & 5 & 2 \\ 1 & 7 & 4 \\ 1 & 9 & 2 \end{bmatrix}^{T} \begin{bmatrix} 2 \\ 5 \\ 4 \\ 4 \\ 8 \end{bmatrix} = \begin{bmatrix} 23 \\ 127 \\ 57 \end{bmatrix}$$

Suppose we have the following dataset

$x = (x_1, x_2)$	(1,1)	(1,3)	(5,2)	(7,4)	(9,2)
у	2	5	3	4	8

The simplest linear regression model suggests  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x_1 + w_2 x_2$ 

Recall 
$$\mathbf{w}_{\text{opt}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

Step 03: Calculate  $\Phi(\Phi^T\Phi)^{-1}\Phi^Ty$ , namely  $(X^TX)^{-1}X^Ty$  in the simplest

ression model 
$$\mathbf{w}_{\text{opt}} = (\Phi^T \Phi)^{-1} \Phi^T \mathbf{y} = \begin{bmatrix} 5 & 23 & 12 \\ 23 & 157 & 60 \\ 12 & 60 & 34 \end{bmatrix}^{-1} \begin{bmatrix} 23 \\ 127 \\ 57 \end{bmatrix} = \begin{bmatrix} 2.7730 \\ 0.4178 \\ -0.0395 \end{bmatrix}$$



$$\hat{y}(x, w_0, w_1) = 2.7730 + 0.4178x_1 - 0.0395x_2$$

# Problem 10 (Linear regression)

- This is a programming problem
- Suppose  $y=3+2x+0.2x^2+n$  in which n is a zero-mean Gaussian noise with variance  $\sigma_N^2$
- Suppose the predicted model is  $\hat{y}(x, w_0, w_1) = w_0 + w_1 x + w_2 x^2$
- Determine the optimal weights when
  - 1.  $\sigma_N = 0.01$
  - 2.  $\sigma_N = 0.1$
  - 3.  $\sigma_N = 1$
  - 4.  $\sigma_N = 2$

# Problem 10 (Linear regression)

- Procedure to generate your own dataset
  - step 1: uniformly generate a random variable between 0 and 8 and let this be x
  - step 2: generate a zero-mean Gaussian noise with variance  $\sigma_N^2$  and let this be n
  - step 3: let  $y = 3 + 2x + 0.2x^2 + n$
  - step 4: add (x, y) to your own dataset
  - use this procedure to have a dataset containing 40 pairs of x and y

### Note that

- 1. Please plot the regression function along with the data points on the same graph
- 2. You should also submit your code