

# Numerical Analysis

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Week 11, Lecture-I-II

A word cloud titled "Methods" in large blue font. Other words in the cloud include: error, regression, integration, non-linear, Gauss, Raphson, equations, analytical, finite, ma, simp, p, roots, and engineering.

Newton OOTS  
environmental  
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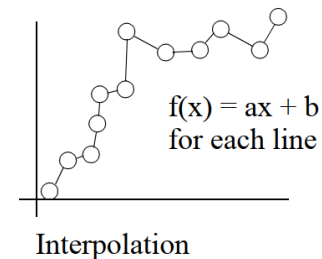
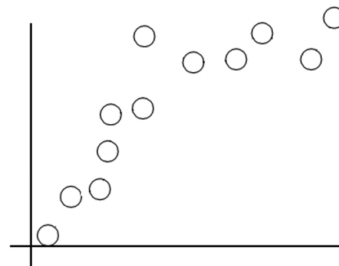
- **Introduction:** Numerical analysis and background, definitions of computer number systems, floating point representation, representation of numbers in different bases, and round-off errors.
- **Root Finding:** Bisection method, fixed-point iteration, Newton's method, the secant method and their error analysis and order of convergence (Newton's method and Secant method).
- **Direct Methods for Solving Linear Systems:** Gaussian elimination, LU decomposition, pivoting strategies, and  $PA=LU$ -factorization,.....
- **Polynomial:** Polynomial interpolation, Lagrange interpolation, Piecewise interpolation, divided differences interpolation, and curve fitting in interpolation (Application: Regression).....
- **Integration:** Numerical differentiation, numerical integration, and composite numerical integration.....
- **Ordinary Differential Equations:** Euler's Method, and Runge-Kutta methods.....

- ❖ **Interpolation and Curve Fitting**
- ❖ **Newton's Divided Difference Interpolating Polynomial**
- ❖ **Linear Regression**

## Interpolation and Curve Fitting

### Interpolation

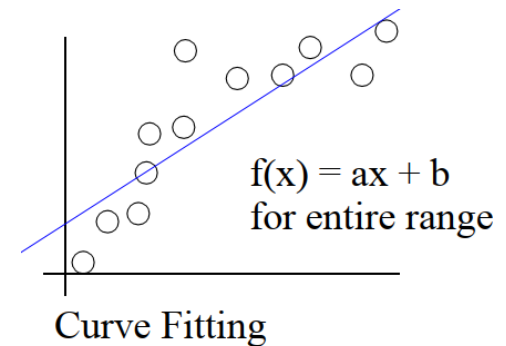
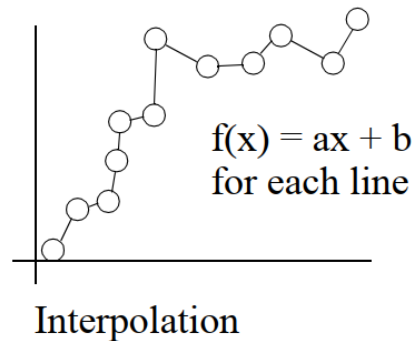
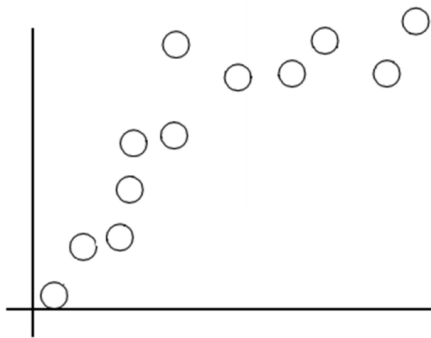
- ❑ The method of finding a value between known values of data points.
  - It determines a polynomial that gives the exact value at the data points
- ❑ If there is small number of data points
  - A single polynomial is enough
- ❑ If there is large number of data points
  - Different polynomials are used in the intervals between the points.
  - If data is reliable, we can plot it and connect the dots. This is piece-wise linear interpolation.
- ❑ Since its really a group of small s, connecting one point to the next it doesn't work very well for data that has built in random error (scatter).



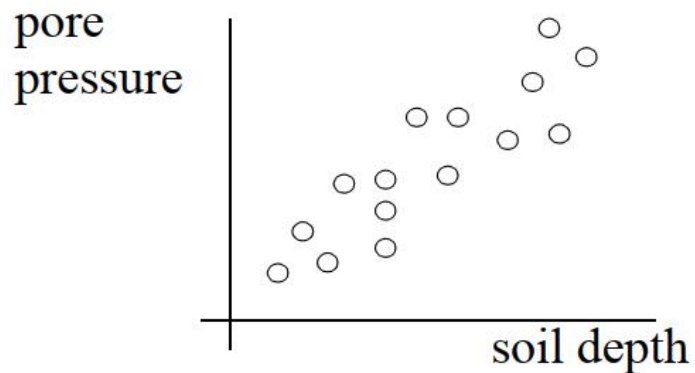
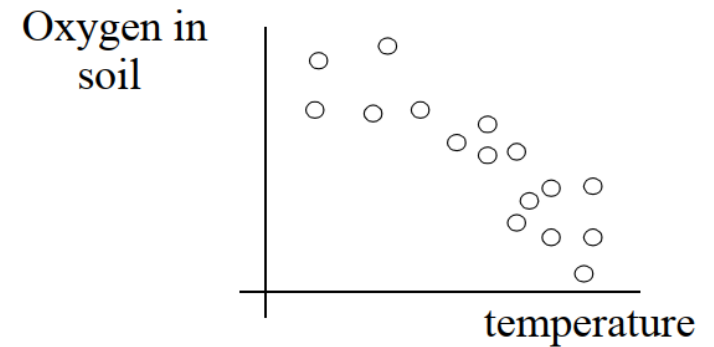
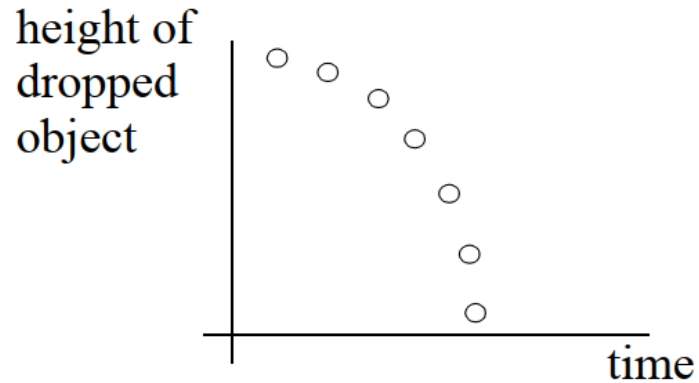
## Interpolation and Curve Fitting

### Curve Fitting

- ❑ Capturing the trend in the data by assigning a single function across the entire range.
- ❑ Objective of curve fitting
  - To identify a function that fits the overall data points.
  - The function does not have to give the exact value at any single point, but fits the data well overall.
  - It can be used typically when the values of data points have some error.
- ❑ Curve fitting can be carried out with many types of functions and with polynomials of various orders.
- ❑ A straight line is described generically by  $f(x) = ax + b$ .



## Interpolation and Curve Fitting



## □ Interpolation

- Lagrange Interpolation Polynomials
- Piecewise Interpolation Polynomials
- Newton's Divided Difference Interpolating Polynomial

## □ Regression

- Linear Regression
- Polynomial Regression

## **Newton's Divided Difference Interpolating Polynomial**



## Newton's Divided Difference Interpolating Polynomial

### □ What is divided differences

- Suppose that  $P_n(x)$  is the  $n$ th Lagrange polynomial that agrees with the function  $f$  at the distinct numbers  $x_0, x_1, x_2, \dots, x_n$ . The divided differences of  $f$  with respect to  $x_0, x_1, x_2, \dots, x_n$  are used to express  $P_n(x)$  in the form.

$$P_n(x) = a_0 + a_1(x - x_0) + a_2(x - x_0)(x - x_1) + \dots + a_n(x - x_0) \dots (x - x_{n-1})$$

For appropriate constants  $a_0, a_1, a_2, \dots, a_n$ .

- To determine the first of these constants,  $a_0$ , note that if  $P_n(x)$  is written in the form of the above equation, then evaluating  $P_n(x)$  at  $x_0$  leaves only the constant term  $a_0$ ; that is

$$x_0: \quad a_0 = P_n(x_0) = f(x_0).$$

- Similarly, when  $P(x)$  is evaluated at  $x_1$ , the only nonzero terms in the evaluation of  $P_n(x_1)$  are the constant and linear terms,

$$\begin{aligned} \text{at } x_1: \quad f(x_0) + a_1(x_1 - x_0) &= P_n(x_1) = f(x_1) \\ \Rightarrow a_1 &= \frac{f(x_1) - f(x_0)}{x_1 - x_0}. \end{aligned}$$

## Newton's Divided Difference Interpolating Polynomial

## Newton's Divided Difference Interpolating Polynomial

### □ Generating the divided differences table

$x$	$f(x)$	First divided differences	Second divided differences	Third divided differences
$x_0$	$f[x_0]$			
		$f[x_0, x_1] = \frac{f[x_1] - f[x_0]}{x_1 - x_0}$		
$x_1$	$f[x_1]$		$f[x_0, x_1, x_2] = \frac{f[x_1, x_2] - f[x_0, x_1]}{x_2 - x_0}$	
		$f[x_1, x_2] = \frac{f[x_2] - f[x_1]}{x_2 - x_1}$		$f[x_0, x_1, x_2, x_3] = \frac{f[x_1, x_2, x_3] - f[x_0, x_1, x_2]}{x_3 - x_0}$
$x_2$	$f[x_2]$		$f[x_1, x_2, x_3] = \frac{f[x_2, x_3] - f[x_1, x_2]}{x_3 - x_1}$	
		$f[x_2, x_3] = \frac{f[x_3] - f[x_2]}{x_3 - x_2}$		$f[x_1, x_2, x_3, x_4] = \frac{f[x_2, x_3, x_4] - f[x_1, x_2, x_3]}{x_4 - x_1}$
$x_3$	$f[x_3]$		$f[x_2, x_3, x_4] = \frac{f[x_3, x_4] - f[x_2, x_3]}{x_4 - x_2}$	
		$f[x_3, x_4] = \frac{f[x_4] - f[x_3]}{x_4 - x_3}$		$f[x_2, x_3, x_4, x_5] = \frac{f[x_3, x_4, x_5] - f[x_2, x_3, x_4]}{x_5 - x_2}$
$x_4$	$f[x_4]$		$f[x_3, x_4, x_5] = \frac{f[x_4, x_5] - f[x_3, x_4]}{x_5 - x_3}$	
		$f[x_4, x_5] = \frac{f[x_5] - f[x_4]}{x_5 - x_4}$		
$x_5$	$f[x_5]$			

## Newton's Divided Difference Interpolating Polynomial

### □ Zeroth divided difference

$$f[x_i] = f(x_i). \quad \text{at } x_0: a_0 = P_n(x_0) = f(x_0).$$

### □ First divided difference

$$f[x_i, x_{i+1}] = \frac{f[x_{i+1}] - f[x_i]}{x_{i+1} - x_i}. \quad \text{at } x_1: f(x_0) + a_1(x_1 - x_0) = P_n(x_1) = f(x_1)$$
$$\Rightarrow a_1 = \frac{f(x_1) - f(x_0)}{x_1 - x_0}.$$

### □ Second divided difference

$$f[x_i, x_{i+1}, x_{i+2}] = \frac{f[x_{i+1}, x_{i+2}] - f[x_i, x_{i+1}]}{x_{i+2} - x_i}.$$

### □ kth divided difference

$$f[x_i, x_{i+1}, \dots, x_{i+k}] = \frac{f[x_{i+1}, x_{i+2}, \dots, x_{i+k}] - f[x_i, x_{i+1}, \dots, x_{i+k-1}]}{x_{i+k} - x_i}.$$

$$f(x) = f[x_0] + f[x_0, x_1](x - x_0) + f[x_0, x_1, x_2](x - x_0)(x - x_1)$$
$$+ f[x_0, x_1, x_2, x_3](x - x_0)(x - x_1)(x - x_2) \dots$$

## Newton's Divided Difference Interpolating Polynomial

### □ What is the notation of divided differences

- Another form of Newton's Forward Difference Formula is constructed by using operator  $\Delta$ .
- We now introduce the divided-difference notation, which is related to Aitken's  $\Delta^2$  notation

### □ First divided difference

$$\Delta f_0 = \frac{f_1 - f_0}{x_1 - x_0} \quad \Delta f_1 = \frac{f_2 - f_1}{x_2 - x_1} \quad \Delta f_2 = \frac{f_3 - f_2}{x_3 - x_2}$$

### □ Second divided difference

$$\Delta^2 f_0 = \frac{\Delta f_1 - \Delta f_0}{x_2 - x_0} \quad \Delta^2 f_1 = \frac{\Delta f_2 - \Delta f_1}{x_3 - x_1} \quad \Delta^2 f_2 = \frac{\Delta f_3 - \Delta f_2}{x_4 - x_2}$$

### □ Third divided difference

$$\Delta^3 f_0 = \frac{\Delta^2 f_1 - \Delta^2 f_0}{x_3 - x_0} \quad \Delta^3 f_1 = \frac{\Delta^2 f_2 - \Delta^2 f_1}{x_4 - x_1}$$

$$f(x) = f_0 + \Delta f_0(x - x_0) + \Delta^2 f_0(x - x_0)(x - x_1) + \Delta^3 f_0(x - x_0)(x - x_1)(x - x_2) \dots\dots$$

## Newton's Divided Difference Interpolating Polynomial

**Question:** Using newton's divided difference formula to find  $f(x)$ , given

$$x : 0 \quad 2 \quad 3 \quad 6$$

$$f(x) : 648 \quad 704 \quad 729 \quad 792$$

**Also find  $f(4)$  and  $f'(4)$**

**Solution:** The divided difference table for given data

X	$f = f(x)$	First divided difference	Second divided difference	Third divided difference
0	648	$\Delta f_0 = \frac{704 - 648}{2 - 0} = 28$ $\Delta f_1 = \frac{729 - 704}{3 - 2} = 25$ $\Delta f_2 = \frac{792 - 729}{6 - 3} = 21$	$\Delta^2 f_0 = \frac{25 - 28}{3 - 0} = -1$	$\Delta^3 f_0 = 0$
2	704			
3	729		$\Delta^2 f_1 = \frac{21 - 25}{6 - 2} = -1$	
6	792			

## Newton's Divided Difference Interpolating Polynomial

By newton's divided difference interpolation formula

$$f(x) = f[x_0] + f[x_0, x_1](x - x_0) + f[x_0, x_1, x_2](x - x_0)(x - x_1) \\ + f[x_0, x_1, x_2, x_3](x - x_0)(x - x_1)(x - x_2) \dots\dots$$

OR

$$f(x) = f_0 + \Delta f_0(x - x_0) + \Delta^2 f_0(x - x_0)(x - x_1) + \Delta^3 f_0(x - x_0)(x - x_1)(x - x_2) \dots\dots$$

$$f(x) = 648 + 28(x - 0) + (-1)(x - 0)(x - 2)$$

$$f(x) = -x^2 + 30x + 648$$

Now we should find the required  $f(4)$  and  $f'(4)$

$$f(4) = -4^2 + 30(4) + 648$$

$$f(4) = -16 + 120 + 648$$

$$f(4) = 752$$

$$f'(x) = -2x + 30$$

$$f'(4) = -2(4) + 30$$

$$f'(4) = 22$$

## Linear Regression



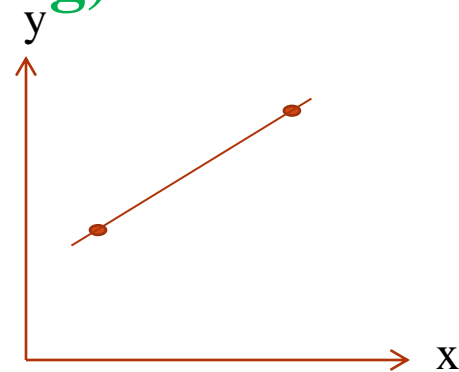
## Linear Regression (Linear Curve Fitting)

### ❑ Curve fitting using a linear equation

$$f(x) = ax + b$$

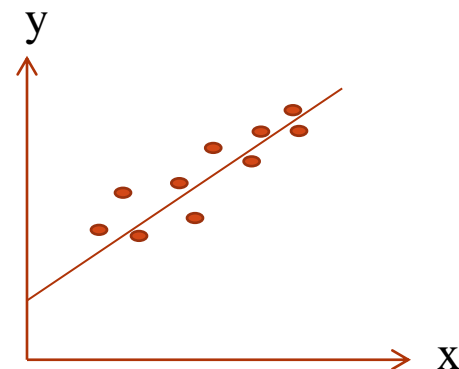
### ❑ With two data points

- The constant can be determined that gives the exact values at the points.



### ❑ With more than two data points

- Constant a and b are determined such that the line has the **best fit overall (?)**.

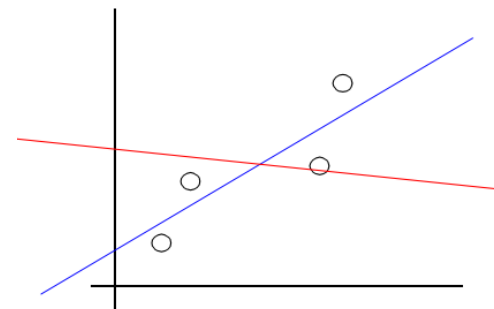


### ❑ What makes a particular straight line a 'good' fit?

## Linear Regression

### ❑ Measuring how good is fit

- To quantify the overall agreement between the points and the function



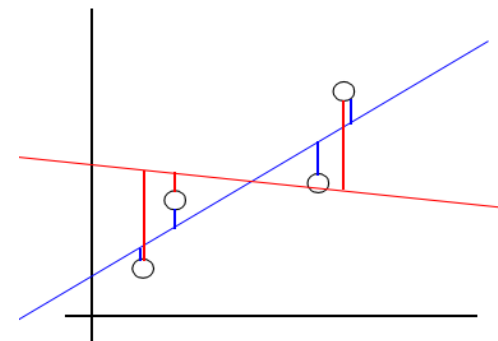
### ❑ Why does the blue line appear to us to fit the trend better?

### ❑ Method

- Calculate the error (**residual**, the difference between a data point and the predicted value)
- Calculate a total error using the residuals

$$r_i = y_i - f(x_i)$$

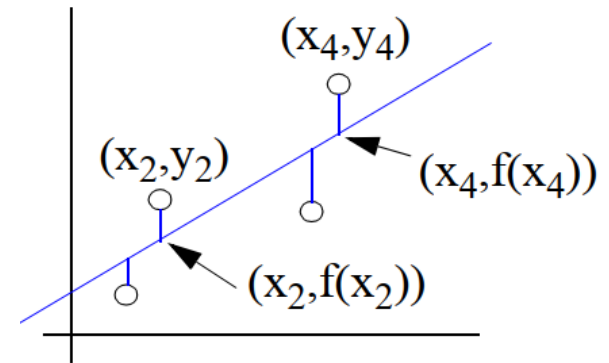
- The one line that provides a minimum error is then the 'best' straight line .



## Linear Regression

### Quantifying error in a curve fit

- Both the positive and negative error have the same value.
- we can do both of these things by squaring the distance.



### Linear Regression

- A procedure to determine the coefficients  $a$  and  $b$ .
- Best fit
  - The smallest possible total error calculated by adding the squares of the residuals.

$$err = \sum (d_i)^2 = (y_1 - f(x_1))^2 + (y_2 - f(x_2))^2 + (y_3 - f(x_3))^2 + (y_4 - f(x_4))^2$$

- Our fit is a straight line, so now substitute  $f(x) = ax + b$

$$err = \sum_{i=1}^{\text{\# data points}} (y_i - f(x_i))^2 = \sum_{i=1}^{\text{\# data points}} (y_i - (ax_i + b))^2$$

## Linear Regression

### □ Least Square approach

- This is called the **least squares approach**, since we minimize the square of the error.

$$\text{minimize } err = \sum_{i=1}^{\text{\# data points} = n} (y_i - (ax_i + b))^2$$

$$\frac{\partial err}{\partial a} = -2 \sum_{i=1}^n x_i (y_i - ax_i - b) = 0$$

$$\frac{\partial err}{\partial b} = -2 \sum_{i=1}^n (y_i - ax_i - b) = 0$$

- Solve for the a and b so that the previous two equations both = 0 and re-write these two equations .

$$a \sum x_i^2 + b \sum x_i = \sum (x_i y_i)$$

$$a \sum x_i + b * n = \sum y_i$$

## Linear Regression

### □ Matrix form

$$\begin{bmatrix} n & \sum x_i \\ \sum x_i & \sum x_i^2 \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} \sum y_i \\ \sum (x_i y_i) \end{bmatrix}$$

- we have the data points  $(x_i, y_i)$  for  $i=1,2,\dots,n$ , so we have all the summation terms in the matrix, but we don't have  $a$  and  $b$
- Find  $a$  and  $b$  using Gaussian elimination.

$$A = \begin{bmatrix} n & \sum x_i \\ \sum x_i & \sum x_i^2 \end{bmatrix}, \quad X = \begin{bmatrix} b \\ a \end{bmatrix}, \quad B = \begin{bmatrix} \sum y_i \\ \sum (x_i y_i) \end{bmatrix}$$

$$AX = B$$

- The coefficients  $a$  and  $b$  can be solved using matrix inversion.

$$X = A^{-1} * B$$

## Linear Regression

**Example:** Fit a straight line  $f(x)=ax+b$  to the following data

i	1	2	3	4	5	6
x	0	0.5	1.0	1.5	2.0	2.5
y	0	1.5	3.0	4.5	6.0	7.5

**Solution** Solve for the a and b

$$a\sum x_i^2 + b\sum x_i = \sum (x_i y_i) \quad a\sum x_i + b*n = \sum y_i$$

- First we find values for all the summation terms

$$n = 6$$

$$\sum x_i = 7.5, \quad \sum y_i = 22.5, \quad \sum x_i^2 = 13.75, \quad \sum x_i y_i = 41.25$$

$$\begin{bmatrix} n & \sum x_i \\ \sum x_i & \sum x_i^2 \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} \sum y_i \\ \sum (x_i y_i) \end{bmatrix}$$

## Linear Regression

- Put these values in the matrix.

$$\begin{bmatrix} 6 & 7.5 \\ 7.5 & 13.75 \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 22.5 \\ 41.25 \end{bmatrix}$$

$$\begin{bmatrix} b \\ a \end{bmatrix} = \text{inv} \begin{bmatrix} 6 & 7.5 \\ 7.5 & 13.75 \end{bmatrix} * \begin{bmatrix} 22.5 \\ 41.25 \end{bmatrix}$$
$$X = A^{-1} * B$$

- The solution is

$$\begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ 3 \end{bmatrix}$$

- Put these values in the straight line linear equation

$$f(x) = ax + b$$

$$f(x) = 3x + 0$$

## Linear Regression

**Example:** Fit a straight line  $f(x)=ax+b$  to the following data

$$x = [0 \quad .5 \quad 1 \quad 1.5 \quad 2 \quad 2.5], \quad y = [-0.4326 \quad -0.1656 \quad 3.1253 \quad 4.7877 \quad 4.8535 \quad 8.6909]$$

**Solution** Solve for the a and b

$$a \sum x_i + b * n = \sum y_i \longrightarrow \text{Eq (1)} \quad a \sum x_i^2 + b \sum x_i = \sum (x_i y_i) \longrightarrow \text{Eq (2)}$$

$x_i$	$y_i$	$x_i^2$	$x_i y_i$
0	-0.4326	0	0
0.5	-0.1656	0.25	-0.0828
1	3.1253	1	3.1253
1.5	4.7877	2.25	7.18155
2	4.8535	4	9.707
2.5	8.6909	6.25	21.72725
$\sum x_i = 7.5$	$\sum y_i = 20.8593$	$\sum x_i^2 = 13.75$	$\sum x_i y_i = 41.7411$



## Linear Regression

Put the last row values in equation 1 and 2

$$a \sum x_i + b * n = \sum y_i$$

$$7.5a + 6b = 20.8593$$

$$a = \frac{20.8593 - 6b}{7.5} \longrightarrow \text{Eq (3)}$$

Put the value of b in equation 3

$$a = \frac{20.8593 - 6 \frac{41.7411 - 13.75a}{7.5}}{7.5}$$

$$a = 3.581$$

Put the value of a in equation 4

$$b = \frac{41.7411 - 13.75(3.581)}{7.5}$$

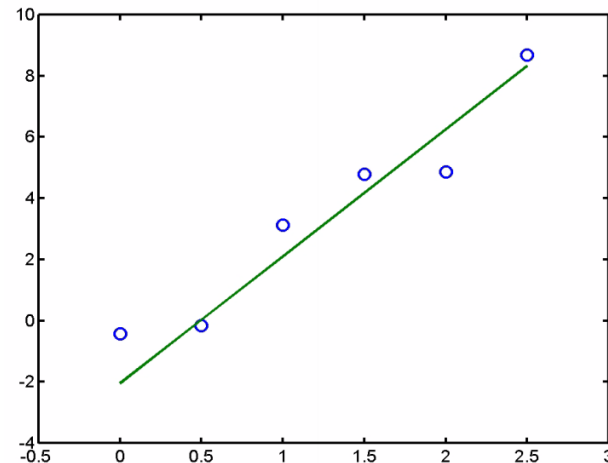
$$b = -0.999$$

$$a \sum x_i^2 + b \sum x_i = \sum (x_i y_i)$$

$$13.75a + 7.5b = 41.7411$$

$$b = \frac{41.7411 - 13.75a}{7.5} \longrightarrow \text{Eq (4)}$$

$$f(x) = 3.581x - 0.999$$



*Thank  
You !*