

# Least square Problem

- Suppose a polynomial

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \cdots + \beta_m x_i^m + \varepsilon_i \quad (i = 1, 2, \dots, n)$$

- In matrix form

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 & \cdots & x_1^m \\ 1 & x_2 & x_2^2 & \cdots & x_2^m \\ 1 & x_3 & x_3^2 & \cdots & x_3^m \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & x_n^2 & \cdots & x_n^m \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_n \end{bmatrix},$$

- It is a linear problem

$$\vec{y} = \mathbf{X} \vec{\beta} + \vec{\varepsilon}.$$

Note that X is **not square** but rectangular because n is not equal to m

# Solve via Inverse

$$\hat{\vec{\beta}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \vec{y},$$

It means best parameters to fit (least square criteria), in other word we are looking for the condition

$$\arg \min_{\beta} \|y - X\beta\|,$$

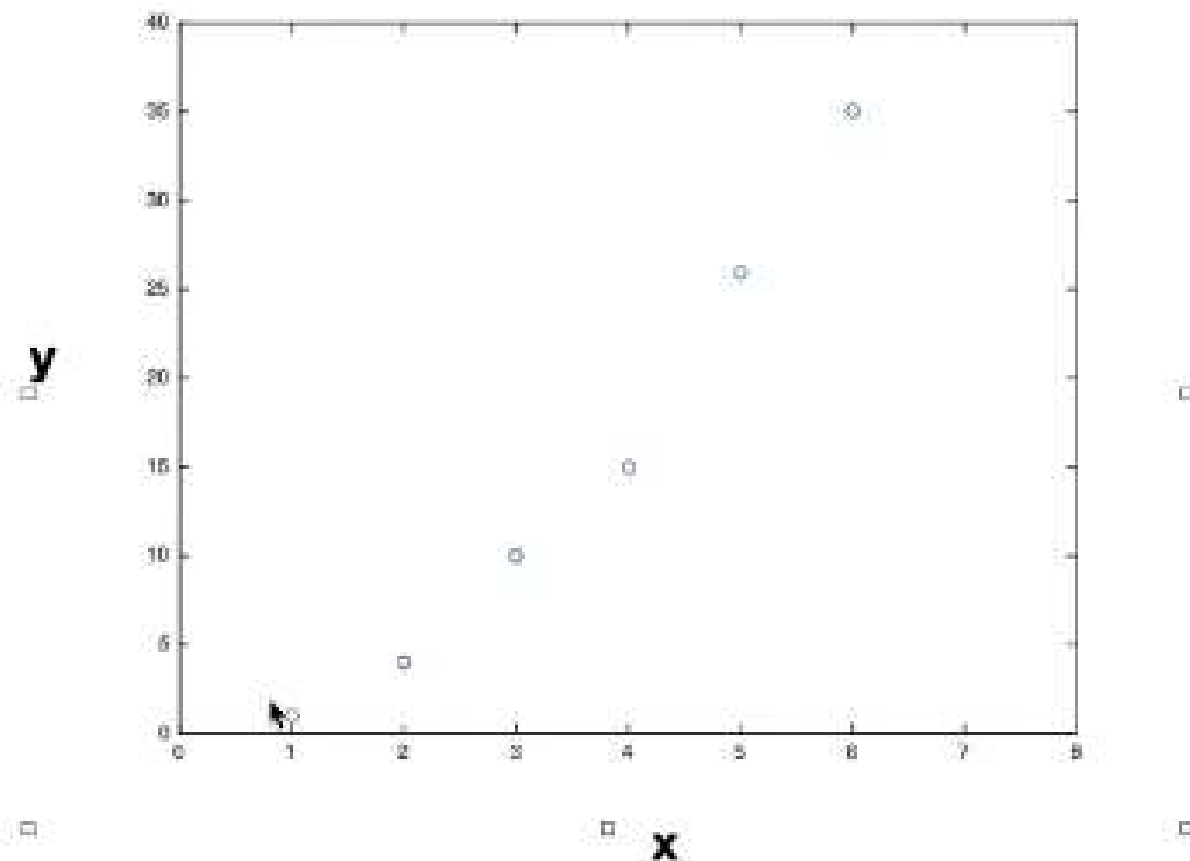
an **L<sup>2</sup> norm**, note that this norm will be zero for polynomial interpolation.

# Lets evaluate

- Calculate parameter  $\beta_0$ ,  $\beta_1$  and  $\beta_2$  (Regression problem)

## Data

<u>x</u>	<u>y</u>
1	1
2	4
3	10
4	15
5	26
6	35



# Lets evaluate

- Assembly the rectangular (not square) Vandermonde Matrix

Data	
<i>x</i>	<i>y</i>
1	1
2	4
3	10
4	15
5	26
6	35

$$\mathbf{X} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 4 \\ 1 & 3 & 9 \\ 1 & 4 & 16 \\ 1 & 5 & 25 \\ 1 & 6 & 36 \end{bmatrix}$$

$n \times m = 6 \times 3$ ,  $n$  data  $m$  unknown

# First

- Assembly the rectangular (not square) Vandermonde Matrix

$$\hat{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \vec{y},$$

$$\mathbf{X}^T = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 & 5 & 6 \\ 1 & 4 & 9 & 16 & 25 & 36 \end{bmatrix}$$

$$\mathbf{X} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 4 \\ 1 & 3 & 9 \\ 1 & 4 & 16 \\ 1 & 5 & 25 \\ 1 & 6 & 36 \end{bmatrix}$$

$$\mathbf{M} = \begin{bmatrix} 6 & 21 & 91 \\ 21 & 91 & 441 \\ 91 & 441 & 2275 \end{bmatrix} \text{ a } 3 \times 3 \text{ need to find the inverse}$$

# Lets evaluate Parameter

$$\hat{\vec{\beta}} = \underbrace{(\mathbf{X}^T \mathbf{X})^{-1}}_{\mathbf{M}} \mathbf{X}^T \vec{y},$$

$$\mathbf{M} = \begin{bmatrix} 6 & 21 & 91 \\ 21 & 91 & 441 \\ 91 & 441 & 2275 \end{bmatrix}$$

a 3x3 need to find the inverse  $\mathbf{M}^{-1}$

Using the LU decomposition above, resulted

$$\mathbf{L} = \begin{bmatrix} 6 & 0 & 0 \\ 21 & 17.5 & 0 \\ 91 & 122.5 & 37.33 \end{bmatrix}$$

$$\mathbf{U} = \begin{bmatrix} 1 & 3.5 & 15.17 \\ 0 & 1 & 7 \\ 0 & 0 & 1 \end{bmatrix}$$

# Upper Matrix

$$\mathbf{M}\mathbf{M}^{-1} = \mathbf{I}$$

$$\begin{bmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{bmatrix} \begin{bmatrix} m'_{11} & m'_{12} & m'_{13} \\ m'_{21} & m'_{22} & m'_{23} \\ m'_{31} & m'_{32} & m'_{33} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{L}\mathbf{U}\mathbf{M}^{-1} = \mathbf{I}$$

$$\begin{bmatrix} 6 & 0 & 0 \\ 21 & 17.5 & 0 \\ 91 & 122.5 & 37.33 \end{bmatrix} \begin{bmatrix} 1 & 3.5 & 15.17 \\ 0 & 1 & 7 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} m'_{11} & m'_{12} & m'_{13} \\ m'_{21} & m'_{22} & m'_{23} \\ m'_{31} & m'_{32} & m'_{33} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$\mathbf{L}$ 
 $\mathbf{D}$ 
 $\mathbf{I}$

# Lower Matrix

$$\mathbf{M}\mathbf{M}^{-1} = \mathbf{I}$$

$$\begin{bmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{bmatrix} \begin{bmatrix} m'_{11} & m'_{12} & m'_{13} \\ m'_{21} & m'_{22} & m'_{23} \\ m'_{31} & m'_{32} & m'_{33} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{L}\mathbf{D} = \mathbf{I}$$

$$\begin{bmatrix} 6 & 0 & 0 \\ 21 & 17.5 & 0 \\ 91 & 122.5 & 37.33 \end{bmatrix} \begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$



# D-Matrix

$$\begin{bmatrix} 6 & 0 & 0 \\ 21 & 17.5 & 0 \\ 91 & 122.5 & 37.33 \end{bmatrix} \begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

- By forward substitution

$$\begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{bmatrix} = \begin{bmatrix} 0.1667 & 0 & 0 \\ -0.2000 & 0.0571 & 0 \\ 0.2500 & -0.1875 & 0.0268 \end{bmatrix}$$

# The Inverse

$$\mathbf{U}\mathbf{M}^{-1} = \mathbf{D}$$

$$\begin{bmatrix} 1 & 3.5 & 15.17 \\ 0 & 1 & 7 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} m'_{11} & m'_{12} & m'_{13} \\ m'_{21} & m'_{22} & m'_{23} \\ m'_{31} & m'_{32} & m'_{33} \end{bmatrix} = \begin{bmatrix} 0.1667 & 0 & 0 \\ -0.2000 & 0.0571 & 0 \\ 0.2500 & -0.1875 & 0.0268 \end{bmatrix}$$

- By backward substitution

$$\begin{bmatrix} m'_{11} & m'_{12} & m'_{13} \\ m'_{21} & m'_{22} & m'_{23} \\ m'_{31} & m'_{32} & m'_{33} \end{bmatrix} = \begin{bmatrix} 3.2 & -1.95 & 0.2500 \\ -1.95 & 1.3696 & -0.1875 \\ 0.25 & -0.1875 & 0.0268 \end{bmatrix}$$

# Best Parameters

$$\mathbf{M}^{-1} = \begin{bmatrix} m'_{11} & m'_{12} & m'_{13} \\ m'_{21} & m'_{22} & m'_{23} \\ m'_{31} & m'_{32} & m'_{33} \end{bmatrix} = \begin{bmatrix} 3.2 & -1.95 & 0.2500 \\ -1.95 & 1.3696 & -0.1875 \\ 0.25 & -0.1875 & 0.0268 \end{bmatrix}$$

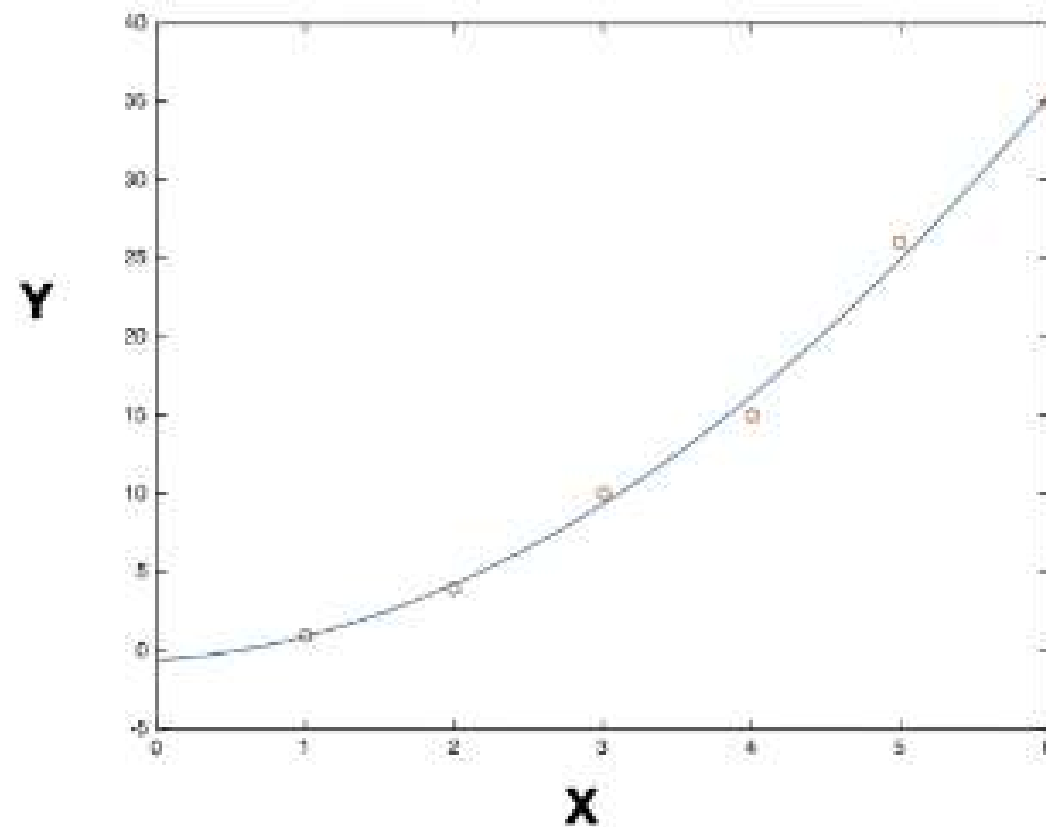
$$\hat{\vec{\beta}} = \begin{bmatrix} 3.2 & -1.95 & 0.2500 \\ -1.95 & 1.3696 & -0.1875 \\ 0.25 & -0.1875 & 0.0268 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 & 5 & 6 \\ 1 & 4 & 9 & 16 & 25 & 36 \end{bmatrix} \begin{bmatrix} 1 \\ 4 \\ 10 \\ 15 \\ 26 \\ 35 \end{bmatrix}$$

$$\hat{\vec{\beta}} = \begin{bmatrix} -0.6 \\ 0.6357 \\ 0.8929 \end{bmatrix}$$

# Plug in into polynomial

$$\hat{\vec{\beta}} = \begin{bmatrix} -0.6 \\ 0.6357 \\ 0.8929 \end{bmatrix}$$

$$y_i = -0.6 + 0.6357x_i + 0.8929x_i^2$$



```
import numpy as np

def crout(A):
    n = A.shape[0]

    U = np.zeros((n, n), dtype=np.double)
    L = np.zeros((n, n), dtype=np.double)

    for k in range(n):

        L[k, k] = A[k, k] - L[k, :] @ U[:, k]

        U[k, k:] = (A[k, k:] - L[k, :k] @ U[:, k:]) / L[k, k]
        L[(k+1):, k] = (A[(k+1):, k] - L[(k+1):, :] @ U[:, k]) / U[k, k]

    return L, U

A = np.array([[1, 4, 5], [6, 8, 22], [32, 5., 5]])
L,U=crout(A)
print(A)
print(L)
print(U)
print(L@U)
```