

**MA3457/CS4033:**  
***Numerical Methods***  
***for Calculus and***  
***Differential Equations***

**Course Materials**

**PART II**

**B'14**  
**2014-2015**

# Approximation – Key Idea

**Function approximation** is closely related to the idea of function interpolation.

In F.A., **we do not require the approximating function to match the given data exactly.**

This helps avoid some of the difficulties observed with interpolation:

- when trying to match a large amount of data,
- when working with “noisy” data (or data containing *error in measurements*),
- etc.

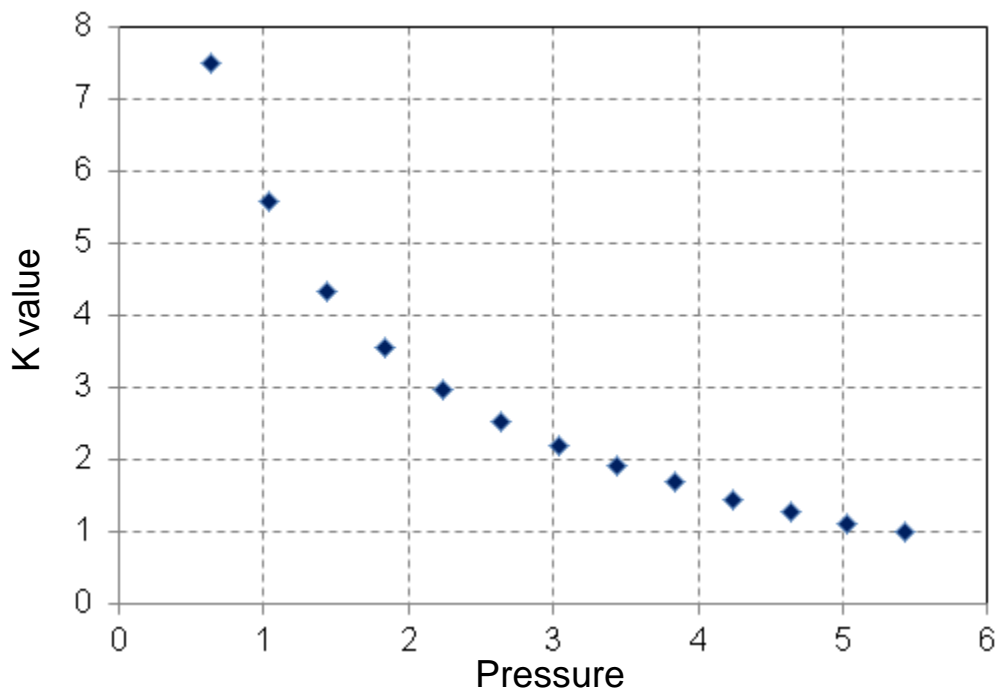
There are many applications in which:

a functional form is known and **the best function of that form (accommodating the data point) is required.**

In situations like this, *approximation is an ultimate choice.*

# Introductory Illustration

## Equilibrium Constant of a Reaction vs Pressure



Experimental Data:

Pressure:

[0.635 1.035 1.435 1.835 2.235 2.635 3.035 3.435 3.835 4.235 4.635 5.035 5.435]

K value:

[ 7.5 5.58 4.35 3.55 2.97 2.53 2.2 1.93 1.7 1.46 1.28 1.11 1.0 ]

**Question: What function does represent this behavior?**

# Concept of the Method of Least Squares

The most common approach to “best fit” approximation is **to minimize the sum of the squares of the differences between the data values and the values of the approximating function:**

$$\text{Minimize } \{(\text{Data value } 1 - \text{approx. } f)^2 + \dots + (\text{Data value } n - \text{approx. } f)^2\}$$

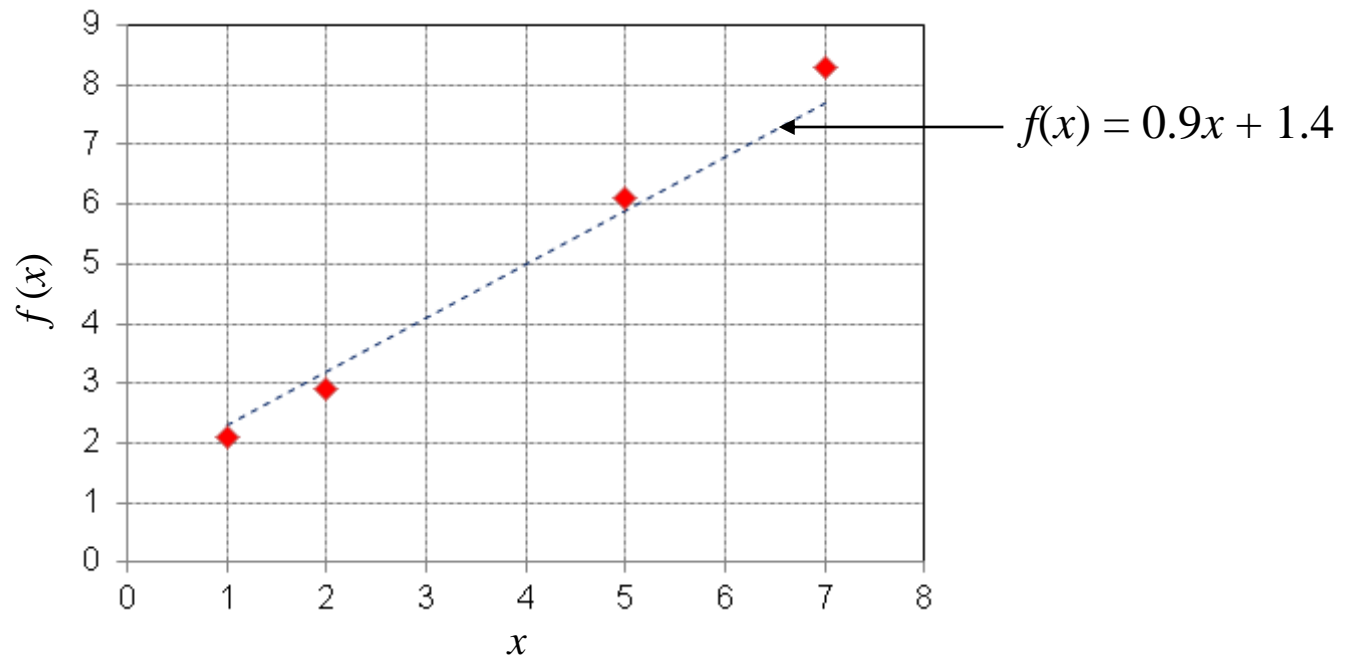
**Advantages** in using **the square of the differences**

*(rather than the difference, or the absolute value of the difference, or some other measure of the error):*

- positive differences do not cancel negative differences;
- differentiation is not difficult, and
- small differences become smaller and larger differences are magnified.

# Linear Least Squares Approximation

## Example – Four Data Points



$x_i$	$y_i$	$ax_i+b$	$d_i=y_i-(ax_i+b)$
1	2.1	1.9791	0.1209
2	2.9	3.0231	-0.1231
3	6.1	6.1549	-0.0549
4	8.3	8.2429	0.0571

# Linear LS Approximation – MATLAB Script

LIBRARY OF MATLAB PROCEDURES

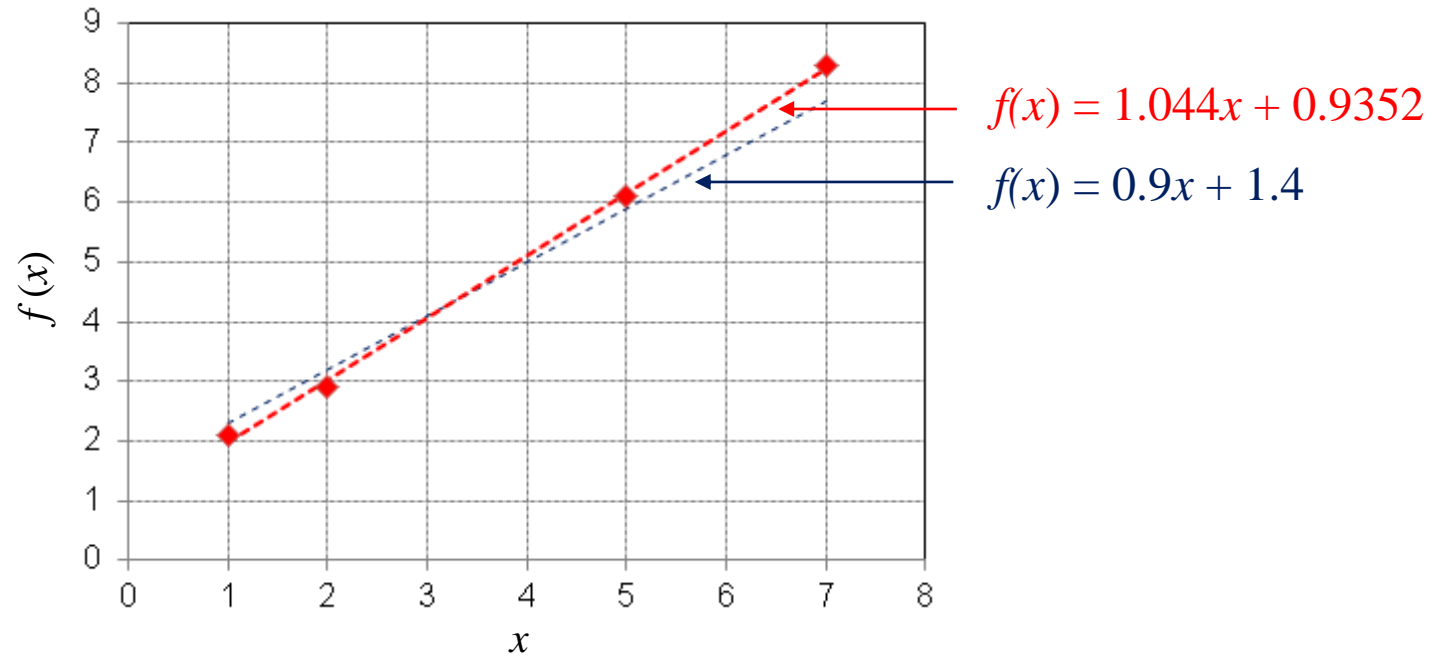
**Lin\_LS**

Gives the linear least squares approximation

```
function s = Lin_LS(x, y)
%
% Linear Regression Function
%
% Input x and y as row or column vectors
% (they are converted to column form is necessary)
%
m = length(x); x = x(:); y = y(:);
sx = sum(x); sy = sum(y);
sxx = sum(x.*x); sxy = sum(x.*y);
%
a = (m*sxy - sx*sy) / (m*sxx - sx^2)
b = (sxx*sy - sxy*sx) / (m*sxx - sx^2)
%
table = [x y (a*x+b) (y-(a*x+b))];
disp('      x          y          a*x+b      y-(a*x+b)')
disp(table), err = sum(table(:, 4) .^ 2)
s(1) = a; s(2) = b;
```

# Linear Least Squares Approximation

## Example – Four Data Points



# Quadratic LS Approximation – MATLAB Script

## LIBRARY OF MATLAB PROCEDURES

### Quad\_LS

Gives the quadratic least squares approximation

```
function z = Quad_LS(x, y)
%
% Quadratic Regression Function
%
% Input x and y as row or column vectors
%
n = length(x); x = x(:); y = y(:);
%
sx = sum(x); sx2 = sum(x.^2);
sx3 = sum(x.^3); sx4 = sum(x.^4);
sy = sum(y); sxy = sum(x.*y);
sx2y = sum(x.*x.*y);
A = [ sx4 sx3 sx2,
      sx3 sx2 sx,
      sx2 sx n]
r = [sx2y sxy sy]'
z = A\r;
%
a = z(1), b = z(2), c = z(3)
%
table = [x y (a*x.^2+b*x+c) (y-(a*x.^2+b*x+c))];
disp('pi=a*x.^2+b*x+c')
disp('      x      y      pi      y-pi')
disp(table)
err = sum(table(:, 4).^2)
```



# Cubic LS Approximation

The *Normal Equations* to Determine the Coefficients for the “Best Fit” Cubic Function

$$\begin{aligned} a \sum_{i=1}^n x_i^6 + b \sum_{i=1}^n x_i^5 + c \sum_{i=1}^n x_i^4 + d \sum_{i=1}^n x_i^3 &= \sum_{i=1}^n x_i^3 y_i \\ a \sum_{i=1}^n x_i^5 + b \sum_{i=1}^n x_i^4 + c \sum_{i=1}^n x_i^3 + d \sum_{i=1}^n x_i^2 &= \sum_{i=1}^n x_i^2 y_i \\ a \sum_{i=1}^n x_i^4 + b \sum_{i=1}^n x_i^3 + c \sum_{i=1}^n x_i^2 + d \sum_{i=1}^n x_i &= \sum_{i=1}^n x_i y_i \\ a \sum_{i=1}^n x_i^3 + b \sum_{i=1}^n x_i^2 + c \sum_{i=1}^n x + d \sum_{i=1}^n 1 &= \sum_{i=1}^n y_i \end{aligned}$$

# MATLAB Function `polyfit`

Built-in MATLAB function `polyfit` finds the coefficients of the polynomial of a specified  $n$ -th degree that best fits a set of data, in a least squares sense:

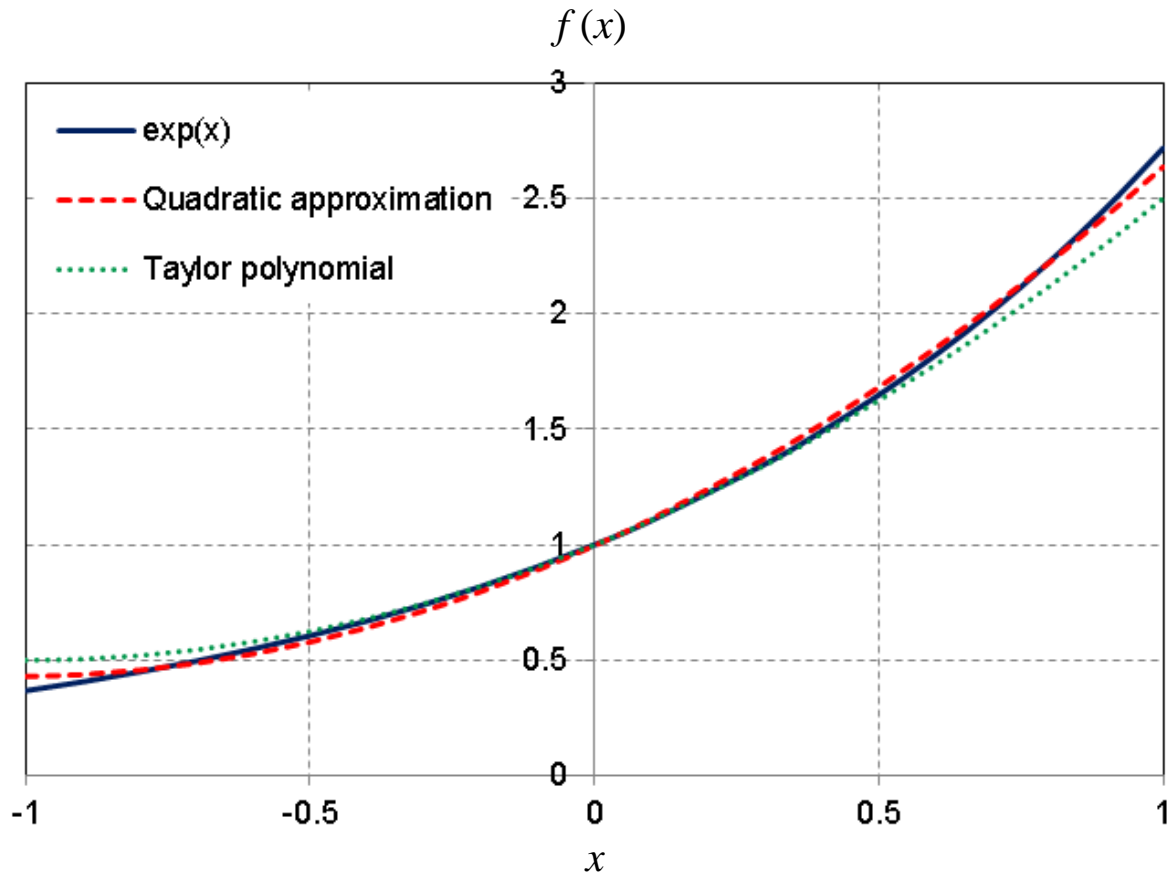
```
> [p, S] = polyfit(x, y, n)
```

where `x` and `y` are vectors containing the data, and  
`n` is the degree of the polynomial desired.

The function returns the coefficients of the polynomial in the vector `p`.

The returned structure `S` can be used (with the function `polyval`) to obtain error bound.

# Continuous LS Approximation



Quadratic approximation:  $p(x) = 0.5368x^2 + 1.1037x + 0.9963$

Taylor polynomial:  $t(x) = 0.5x^2 + x + 1$

# Continuous LSA & Matrix [P]

$$[P][z] = [q]$$

➤ In some applications, matrix [P] may be *ill-conditioned*.

This term “ill-conditioned matrix” is linked with the *matrix condition number*  $k(\mathbf{A})$  of a square matrix  $\mathbf{A}$  defined as

$$k(\mathbf{A}) = \|\mathbf{A}\| \|\mathbf{A}^{-1}\|$$

where  $\|\cdot\|$  is any valid matrix norm. The condition number is a measure of stability or sensitivity of a matrix to numerical operations.

Example of an ill-conditioned matrix:

✓ Hilbert Matrix, i.e., a matrix defined as  $H_{ij} = 1/(i+j-1)$ .

- Matrices with condition numbers near 1 are said to be *well-conditioned*.
- Matrices with condition numbers *much greater than one* (such as around  $10^5$  for a 5x5 Hilbert matrix) are said to be *ill-conditioned*.