CE 601: Numerical Methods

Lecture 13

System of Non-Linear Equations (Contd..) & Polynomial Approximations

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System of Non-Linear Equations

 For a system of two non-linear equations any iterative scheme should follow

$$\begin{pmatrix}
\frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \\
\frac{\partial g}{\partial x} & \frac{\partial g}{\partial y}
\end{pmatrix}^{(s)} \begin{cases}
\Delta x \\
\Delta y
\end{pmatrix}^{(s)} = -\begin{cases} f \\
g \end{cases}^{(s)}$$

i.e.
$$[J]^{(s)} \{\Delta x\}^{(s)} = \{f_j\}^{(s)}$$

and $x^{(s+1)} = x^{(s)} + \Delta x^{(s)}$
 $y^{(s+1)} = y^{(s)} + \Delta y^{(s)}$

Newton's method for solving system of non-linear equations

• Consider any n-dimensional non-linear x_2 systems $\{x_i\} = 1$.

•

 \mathcal{X}_n

Let there be n non-linear equations,

$$f_1(x_1, x_2, \dots, x_n) = 0$$

$$f_2(x_1, x_2, ..., x_n) = 0$$

•

$$f_n\left(x_1, x_2, \dots, x_n\right) = 0$$

Now, the first equation,

$$f_1(x_1, x_2, x_4, \dots, x_n) = 0$$

We have,
$$x_j^{(s+1)} = x_j^{(s)} + \Delta x_j^{(s)}$$

 \therefore The function using modified values of $\{x\}$ can be repeated as such,

$$f_1\left(\left\{x\right\}^{(s)} + \left\{\Delta x\right\}^{(s)}\right) = f_1\left(\left\{x\right\}^{(s)}\right) + \frac{\partial f_1}{\partial x_1} \Delta x_1 + \frac{\partial f_1}{\partial x_2} \Delta x_2 + \dots + \frac{\partial f_1}{\partial x_n} \Delta x_n = 0$$

(After truncating first order terms)

$$\frac{\partial f_1}{\partial x_1} \Delta x_1 + \frac{\partial f_1}{\partial x_2} \Delta x_2 + \dots + \frac{\partial f_1}{\partial x_n} \Delta x_n = -f_1^{(s)}$$

$$\frac{\partial f_2}{\partial x_1} \Delta x_1 + \frac{\partial f_2}{\partial x_2} \Delta x_2 + \dots + \frac{\partial f_2}{\partial x_n} \Delta x_n = -f_2^{(s)}$$

$$\vdots$$

$$\frac{\partial f_n}{\partial x_1} \Delta x_1 + \frac{\partial f_n}{\partial x_2} \Delta x_2 + \dots + \frac{\partial f_n}{\partial x_n} \Delta x_n = -f_n^{(s)}$$

You can write,

$$\frac{\partial f_n}{\partial x_1} \Delta x_1 + \frac{\partial f_n}{\partial x_2} \Delta x_2 + \dots + \frac{\partial f_n}{\partial x_n} \Delta x_n = -f_n^{(s)} \\
\text{where } \Delta x_j = x_j^{(s+1)} - x_j^{(s)}; i = 1, 2, \dots, n.$$

$$\frac{\partial f_n}{\partial x_1} \Delta x_1 + \frac{\partial f_n}{\partial x_2} \Delta x_2 + \dots + \frac{\partial f_n}{\partial x_n} \Delta x_n = -f_n^{(s)} \\
\frac{\partial f_n}{\partial x_1} \frac{\partial f_1}{\partial x_2} \dots \frac{\partial f_1}{\partial x_n} \\
\vdots \\
\frac{\partial f_n}{\partial x_1} \frac{\partial f_2}{\partial x_2} \dots \frac{\partial f_n}{\partial x_n}$$

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$$\vdots \\
\frac{\partial f_n}{\partial x_1} \frac{\partial f_n}{\partial x_2} \dots \frac{\partial f_n}{\partial x_n}$$

$$\vdots \\
\frac{\partial f_$$

where $[J] \rightarrow$ Jacobian Matrix.

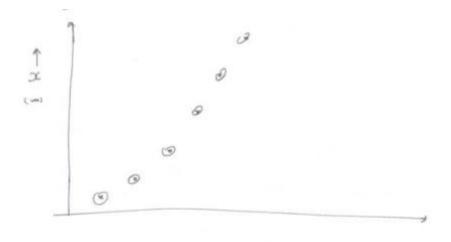
- Please note that in the expression given above, the Jacobian [J] is evaluated in each iteration. Therefore it is time consuming.
- O In modified Newton-Raphson method, the Jacobian [J] is evaluated only for the first matrix and then it is retained subsequently. This may increase the number of iterations little bit. However, it is faster as [J] is not evaluated in every iteration.
- The non-linear solution technique, we would like to stop it here, The steps are mentioned.
 You are requested to understand conceptually.

Polynomial approximation & Interpolation

- As a scientist (or engineer) you may be required to handle lots of data. The data may be
 - Experimental observations/measurements etc.
 - Field information
 - Computed values etc.
- Q. What will you do with such available data?
- e.g. Let us measure the distance moved by a car for few seconds, when it starts moving from its initial points (x = 0) at (t = 0).

Time, t	Distance, x
(sec)	(metre)
0.00	0.0
10.00	50.00
20.00 30.00	150.00 300.00
40.00 50.00	500.00 750.00
60.00	1000.00
70.00	1250.00
80.00	1500.00

- Note these are observed values or experimental observations.
- The measurements are discrete.
- You can also transfer these observations on a graph paper with x vs. t – plane.



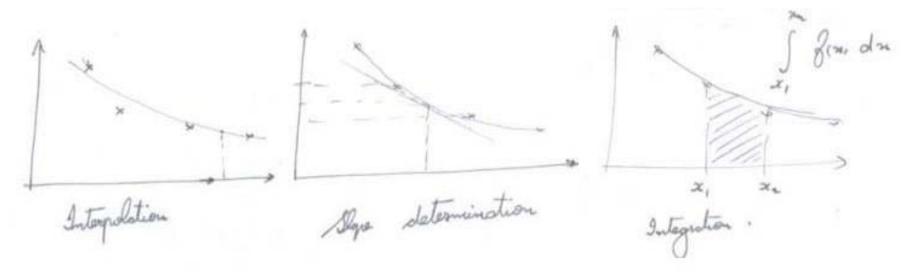
- The data set consist of discrete values at every 10 seconds. What if someone wants to know the distance travelled by the car after 37 seconds or 23 seconds.
- From the observation, you can see that 'x' is 'f(t)'. But we
 don't know the mathematical form of the function. If
 that is available, there is no need to proceed further.
- However the lack of knowledge of this mathematical form need to be compensated to interpret the data.

The Method

- Using the observed data, fit an approximate function (or polynomial) that passes through the concerned points.
- Some of the function you have approximated for the given data may happen to be an exact function. If not use some known functions or approximations.

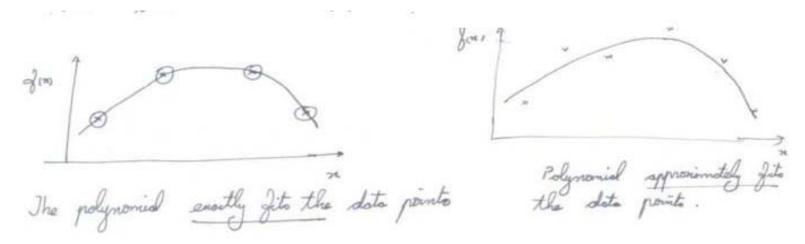
- Using these approximate function for 'x' with respect to 't', evaluate x at t=23 sec. or t=39 sec. etc.
- This approximate function is used to infer nay value of 'x' for time between 0 to 80 seconds.
 This is called <u>Interpolation</u>.
- If we want to find distances beyond 80 seconds, then use the same approximate function but the method will called <u>Extrapolation</u>.
- There are many types of approximating functions
 - > Polynomials
 - ➤ Trigonometric functions
 - > Exponential functions etc.

- Q. How do you decide what should be your approximating function?
- While selecting any approximate function, you should note that
 - > It is easy to evaluate
 - > Easy to differentiate
 - > Easy to integrate etc.
- Q. What will you do by approximating a function?
 - You can do interpolation
 - You can do extrapolation
 - Find the slope of the curve generated by these data points.
 - Find area within certain data points etc.



Approximations Using Polynomials

 We are now trying to fit an approximate function to the given observations using polynomials.



• As the approximated function is a polynomial $f(x) = P_n(x)$

$$\checkmark P_1(x) = a_0 + a_1 x$$

-> you require two points (x_0, f_0) and (x_1, f_1)

✓ For a nth polynomial:

$$P_n(x) = a_0 + a_1 x + a_2 x^2 + ... + a_n x^n$$

requires $(n+1)$ number of data points.

- ✓ For (n+1) data pints or observations, you can fit any polynomials ranging from $P_1(x)$ to $P_n(x)$.
 - \square However the $P_n(x)$ will be <u>unique</u>.
- ✓ In the objective of approximating $f(x) \approx P_n(x)$, we can have differentiation,

$$f'(x) \approx dP_n(x)/dx = P_n'(x)$$

 $f''(x) \approx P_n''(x)$, etc.

Integartion,
$$I = \int P_n(x) dx = P_{n+1}(x)$$

• The error involved in nth degree polynomial:

Taylor's series:

$$f(x) = f(x_0) + f'(x_0)(x - x_0) + \frac{1}{2!}f''(x_0)(x - x_0)^2 + \cdots$$

When $f(x) \approx P_n(x)$, the error involved is:

$$\frac{1}{(n-1)!} f^{(n+1)}(\xi) (x - x_0)^{n+1} \text{ for } x_0 \le \xi \le x.$$

- Polynomials are one of the best tools for approximating functions
 - Direct-fit polynomials
 - Approximate fit polynomials
- We have discussed about Nested Algorithm that can be used to represent nth degree polynomials.

i.e.
$$P_n(x) = a_0 + x (a_1 + x (a_2 + ... + x (a_{n-1} + x a_n))...)$$

- This form of expressions requires
 - $\rightarrow n$ additions
 - $\rightarrow n$ multiplications

So, 2n operations.

- Now this nested algorithms of polynomials can be used for the objectives of polynomials i.e.
 - To interpolate
 - To differentiate
 - o To integrate
- Say now if we want to find the function f(x=M). We will approximate $f(M) \approx P_n(M)$.
- How will you evaluate $P_n(M)$?
- One methodology is, $P_n(x) = (x-M)Q_{n-1}(x) + R$ $Q_{n-1}(x) \rightarrow (n-1)^{th}$ degree polynomial $R \rightarrow \text{remainder}$
- For evaluating $Q_{n-1}(x)$ polynomial, the synthetic division can be used

$$Q_{n-1}(x) = b_1 + x (b_2 + x (b_3 + ... + x (b_{n-1} + x b_n))...)$$

where $b_n = a_n$
 $b_i = a_i + x b_{i+1}$; $i = n-1, n-2, ..., 1, 0$

- From the basic factor theorem: $P_n(M) = 0 + R$ and $R = b_0 = a_0 + x$ b_1
- Now as $P_n(x) = (x-M)Q_{n-1}(x) + R$
- If we want to find derivative of f(x) at x=M, then $f'(M) \approx P_n'(M)$ However, $P_n'(x) = Q_{n-1}(x) + (x-M)Q_{n-1}'(x)$ So, at x=M, $P_n'(M) = Q_{n-1}(M)$
- That is the first derivative to be evaluated is nothing but the (n-1)th degree polynomial.

$$Q_{n-1}(x) = b_1 + x (b_2 + x (b_3 + ... + x (b_{n-1} + x b_n))...)$$

where $b_n = a_n$; $b_i = a_i + x b_{i+1}$; $i = n-1, n-2, ..., 1$
 $b_0 = R = a_0 + x b_1$.

i.e. whatever remainder is there, that will give the interpolated value for f(M), as $f(x) \approx P_n(x)$.