

**Taylor's Theorem:**

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

where  $x_0 \leq \xi(x) \leq x$   
 $P_n(x) = f(x) - R_n(x) \leftarrow$  truncation error/remainder

**Single floating point operation:** relative error  $|1-p^*/p|$  is very small:  $<b^{1-k}(\text{chopping}), <0.5b^{1-k}(\text{rounding})$  (b=base) but increases w/more fl() operations.

**Problem Conditioning:** ill conditioned if exact solution changes greatly with small changes in data. Only well-conditioned if for ALL small  $\varepsilon_i, \{r_i\} \approx \{r_i\}$

$$\text{data } \{d_i\} \xrightarrow{\text{Exact Arithmetic}} \text{computed solution } \{r_i\}$$

$$\text{perturbed data } \{\hat{d}_i\} = \{d_i + \varepsilon_i\} \xrightarrow{\text{Exact Arithmetic}} \text{exact solution } \{\hat{r}_i\}$$

With  $|\varepsilon_i/d_i|$  small.

**Algorithm Stability:** an algorithm is stable if it determines a computed solution (using floating-point arithmetic) that is close to the exact solution of some small perturbation of the given problem.

**Stable** if ANY data  $\{\hat{d}_i\} \approx \{d_i\}, \{\hat{r}_i\} \approx \{r_i\}$

Only **unstable** if NO data  $\{\hat{d}_i\} \approx \{d_i\}, \{\hat{r}_i\} \approx \{r_i\}$

$$\text{data } \{d_i\} \xrightarrow{\text{Floating Point}} \text{computed solution } \{r_i\}$$

$$\text{perturbed data } \{\hat{d}_i\} = \{d_i + \varepsilon_i\} \xrightarrow{\text{Exact Arithmetic}} \text{exact solution } \{\hat{r}_i\}$$

With  $|\varepsilon_i/d_i|$  small.

**Bisection Method:** used to compute a zero of any function f(x) that is continuous on any interval [a,b] for which  $f(a) \times f(b) < 0$  has linear convergence ( $\alpha = 1$ )

- a and b are two initial approximations
- new approximation is the midpoint of [a,b],  $c = (a+b)/2$
- if  $f(c) = 0$ , stop
- otherwise, a new interval that is half the length of the previous interval is determined:
  - if  $f(a) \times f(c) < 0$  set  $b \leftarrow c$
  - if  $f(b) \times f(c) < 0$  set  $a \leftarrow c$
- repeat until  $[a,b]$  is sufficiently small - c will be close to a zero of f(x)
- if tolerance is specified, stop when  $(b-a)/2 < \varepsilon$

Max absolute error of successive approx:

$$|p - p_n| \leq \frac{b-a}{2^n}, \quad p_n = \text{mid}(a,b)$$

# of iterations N to achieve absolute error  $< \varepsilon$ :

$$N > \frac{\ln(b-a) - \ln(\varepsilon)}{\ln(2)}$$

**Newton's Method:** if p is a zero of f(x), and  $p_0$  is an approximate of p

$$p_n = p_{n-1} - \frac{f(p_{n-1})}{f'(p_{n-1})}$$

- always converges if the initial approximation  $p_0$  is sufficiently close to the root p
  - converges quadratically ( $\alpha = 2$ ) if p is a simple zero (multiplicity,  $m = 1$ ) otherwise linear
- $f \in C^3[a,b]$  means  $f(x), f'(x), f''(x)$  all exist and are continuous on  $[a,b]$ ,  $p \in [a,b]$  is a root of  $f(x) = 0, f'(p) \neq 0$

**Multiplicity**

- If a zero exists at p for f(x), keep taking derivatives until  $f^m(p) \neq 0$
- m = multiplicity
- If  $m = 1$ , then p is a simple zero of f(x)

**Secant Method:**

$$p_{n+1} = p_n - f(p_n) \frac{p_n - p_{n-1}}{f(p_n) - f(p_{n-1})}$$

Error in k<sup>th</sup> approx.:

$$\frac{e_k}{e_{n+1}} \approx \left| \frac{p_k - p}{e_{n+1}} \right|$$

Order of convergence,  $\alpha = \frac{(1+\sqrt{5})}{2} \approx 1.618$  for a simple zero

**Horner's Algorithm:** Given a polynomial

$$P(x) = \sum_{i=0}^n a_i x^i$$

and a value  $x_0$ , it evaluates  $P(x_0)$  and  $P'(x_0)$

Given  $a_0, a_1, \dots, a_n$  and  $x_0$ , compute:

$$\begin{aligned} b_n &= a_n & c_n &= b_n \\ b_{n-1} &= a_{n-1} + b_n x_0 & c_{n-1} &= b_{n-1} + c_n x_0 \\ b_1 &= a_1 + b_2 x_0 & c_1 &= b_1 + c_2 x_0 = P'(x_0) \\ b_0 &= a_0 + b_1 x_0 = P(x_0) \end{aligned}$$

$P(x) = (x - x_0)Q(x) + b_0$

original polynomial:

$$P(x) = a_n x^n + a_{n-1} x^{n-1} + \dots + a_1 x + a_0$$

deflated polynomial:

$$Q(x) = b_1 + b_2 x + b_3 x^2 + \dots + b_n x^{n-1}$$

**Newton's Method w/Horner's Algorithm and Polynomial Deflation:**

- to approx. a zero of P(x)
- choose an initial approx.  $p_0$

i = N: use Horner's Algorithm to evaluate  $\{b_n \dots b_0\}$  and  $\{c_n \dots c_0\}$  so  $b_0 = P(p_{N+1})$  and  $c_1 = P'(p_{N+1})$

compute  $p_N \leftarrow p_{N+1} - b_0/c_1$

$p_N$  is the approx. to a zero of P(x)

deflated polynomial is  $Q(x) = b_1 + b_2 x + b_3 x^2 + \dots + b_n x^{N-1}$

**Muller's Method:**

$$P(x) = a(x - x_2)^2 + b(x - x_2) + c$$

\*P(x) and f(x) are equal at  $x_0, x_1, x_2$

$$c = f(x_2)$$

$$b = \frac{(x_0 - x_2)^2 [f(x_1) - f(x_2)] - (x_1 - x_2)^2 [f(x_0) - f(x_2)]}{(x_0 - x_2)(x_1 - x_2)(x_0 - x_1)}$$

$$a = \frac{(x_1 - x_2)[f(x_0) - f(x_2)] - (x_0 - x_2)[f(x_1) - f(x_2)]}{(x_0 - x_2)(x_1 - x_2)(x_0 - x_1)}$$

to determine the next approx.  $x_3$ .

$$x_3 = x_2 - \frac{2c}{b + \text{sign}(b)\sqrt{b^2 - 4ac}}$$
 Make the denominator as small as

possible to make  $x_3$  as close to  $x_2$  as possible.

then reinitialize  $x_0, x_1, x_2$  to be  $x_1, x_2, x_3$  and repeat

Order of convergence = 1.84 for simple zero

**Polynomial Interpolation:**

- let  $y = f(x)$  and  $y_i = f(x_i)$  for given values  $x_i$
- then  $P(x_i) = y_i$  interpolates f(x)
- general form (n=2):

$$P(x) = \frac{(x - x_1)(x - x_2)}{(x_0 - x_1)(x_0 - x_2)} y_0 + \frac{(x - x_0)(x - x_2)}{(x_1 - x_0)(x_1 - x_2)} y_1 + \frac{(x - x_0)(x - x_1)}{(x_2 - x_0)(x_2 - x_1)} y_2$$

- or linear interpolation (n=1)

$$P(x) = \frac{(x - x_1)}{(x_0 - x_1)} y_0 + \frac{(x - x_0)}{(x_1 - x_0)} y_1$$

**Error Term of Polynomial Interpolation:**

$$f(x) = P(x) + \frac{f^{(n+1)}(\xi(x))}{(n+1)!} (x - x_0)(x - x_1) \dots (x - x_n)$$

where P(x) is the interpolation polynomial and  $x_0, x_1, \dots, x_n$  are distinct points, therefore:

$$|f(x) - P(x)| \leq \frac{1}{(n+1)!} \max |f^{(n+1)}(\xi(x))| \max |x - x_0| \dots |x - x_n|$$

- to determine max, either use inspection or take derivative and set it equal to 0
- assume  $f(x) \in C^{(n+1)}[a,b]$

**Runge Phenomenon:**

- as  $n \rightarrow \infty$ ,  $f(x) - P_n(x) \rightarrow \infty$ ,  $P_n(x)$  diverges from f(x) for all values of x such that  $0.726 \leq x \leq 1$  (except at the points of interpolation  $x_i$ )
- consider the error term for polynomial interpolation as an example of this

**Lagrange Interpolation Polynomials:**

$$f(x_k) = P(x_k) \text{ for } k = 0, 1, 2, \dots, n$$

$$P(x) = f(x_0)L_{n,0}(x) + \dots + f(x_n)L_{n,n}(x) = \sum_{k=0}^n f(x_k)L_{n,k}(x)$$

$$L_{n,k}(x) = \frac{(x - x_0) \dots (x - x_{k-1})(x - x_{k+1}) \dots (x - x_n)}{(x_k - x_0)(x_k - x_1) \dots (x_k - x_{k-1})(x_k - x_{k+1}) \dots (x_k - x_n)}$$

$$L_{n,k}(x) = \prod_{\substack{i=0 \\ i \neq k}}^n \frac{(x - x_i)}{(x_k - x_i)}$$

Order of Convergence:

$$\lim_{n \rightarrow \infty} \frac{|p_{n+1} - P|}{|p_n - P|} = \lambda \quad \lambda \text{ is positive} \rightarrow \alpha \text{ is order of convergence}$$

**Cubic Spline Interpolation:**

S(x) is a cubic spline interpolant for f(x) if:

- (a) S(x) is a cubic polynomial, denoted by  $S_j(x)$ , on each subinterval  $[x_j, x_{j+1}]$ ,  $0 \leq j \leq n-1$
- (b)  $S_j(x_j) = f(x_j)$ , for  $0 \leq j \leq n-1$  and  $S_{n-1}(x_n) = f(x_n)$
- (c)  $S_{j+1}(x_{j+1}) = S_j(x_{j+1})$ , and  $0 \leq j \leq n-2$
- (d)  $S'_{j+1}(x_{j+1}) = S'_j(x_{j+1})$ , for  $0 \leq j \leq n-2$
- (e)  $S''_{j+1}(x_{j+1}) = S''_j(x_{j+1})$ , for  $0 \leq j \leq n-2$
- (f) and either one of:
  - (i)  $S''(x_0) = S''(x_n) = 0$  (free/natural boundary condition)
  - (ii)  $S'(x_0) = f'(x_0)$  and  $S'(x_n) = f'(x_n)$  (clamped boundary condition)

There are infinite solutions for conditions (a)-(e) with 4n-2 conditions to be satisfied in 4n unknowns. If (f) is satisfied, there are only 4n conditions in 4n unknowns and a unique S(x).

**Numerical Differentiation Formulas:**

Given f(x) and  $\hat{x}$ . Write a Lagrange interpolating polynomial, then differentiate it and its error term. Solve  $f'(\hat{x})$ .

$$f'(x) = \sum_{k=0}^n f(x_k) \mathcal{L}_k'(x) + f^{(n+1)}(\xi(x)) \frac{d}{dx} \left[ \frac{(x - x_0) \dots (x - x_n)}{(n+1)!} \right]$$

simplified error term when  $x = x_i$ :

$$f^{(n+1)}(\xi(x)) \frac{d}{dx} \left[ \frac{(x - x_0) \dots (x - x_i) \dots (x - x_n)}{(n+1)!} \right]_{x=x_i} = \frac{f^{(n+1)}(\xi(x))}{(n+1)!} \left[ \prod_{\substack{k=0 \\ k \neq j}}^n (x_j - x_k) \right]$$

For  $n = 1, j = 0$ :

$$f'(x_0) = \frac{f(x_1) - f(x_0)}{x_1 - x_0} \text{ with error term } \frac{f''(\xi(x_0))}{2} (x_0 - x_1)$$

For  $n = 2$  (middle of 3 data points),  $j = 1$ :

$$f'(x_1) = f(x_0) \left[ \frac{x_1 - x_2}{(x_0 - x_1)(x_0 - x_2)} \right] + f(x_1) \left[ \frac{2x_1 - x_1 - x_2}{(x_1 - x_0)(x_1 - x_2)} \right] + f(x_2) \left[ \frac{x_1 - x_0}{(x_2 - x_0)(x_2 - x_1)} \right]$$

with error term  $\frac{f''(\xi(x_1))}{6} (x_1 - x_0)(x_1 - x_2)$  where  $\xi_1$  lies between  $x_0$

and  $x_2$

For equally spaced data,  $x_1 - x_0 = x_2 - x_1 = h$ :

$$f'(x_1) = \frac{1}{2h} (f(x_2) - f(x_0)) - \frac{h^2}{6} f''(\xi_1) \text{ where } x_0 - h \leq \xi_1 \leq x_0 + h$$

For  $n = 2, j = 0$  or  $2$  (equally spaced data):

$$f'(x_0) = \frac{1}{2h} (-3f(x_0) + 4f(x_0 + h) - f(x_0 + 2h)) + \frac{h^2}{3} f''(\xi_0)$$

where  $x_0 \leq \xi_0 \leq x_0 + 2h$

**Numerical Differentiation Using Taylor's Theorem:**

$$f(x_0 + h) = f(x_0) + hf'(x_0) + \frac{h^2}{2} f''(x_0) + \frac{h^{n+1}}{(n+1)!} f^{(n+1)}(\xi_1)$$

for  $-h$ , etc, replace all h by  $-h$ . Write Taylor for all points, do

linear combination to cancel as many derivatives as possible.

**Richardson's Extrapolation:**

Case 1:

$$M = N_1(h) + K_1 h + K_2 h^2 + K_3 h^3 \dots$$

M = exact value,  $N_1(h)$  = computed approx. using stepsize h,  $K_1, K_2, \dots$  = truncation error of O(h)

Use same formula to approx M, but replace h by h/2 (or h/some value). Determine linear combination of two formulas for M so that largest term in truncation error (O(h)) cancels out. N calculation for extrapolation table:

$$N_j \left( \frac{h}{2^j} \right) = N_{j-1} \left( \frac{h}{2^{j-1}} \right) + \frac{N_{j-1} \left( \frac{h}{2^{j-1}} \right) - N_{j-1} \left( \frac{h}{2^j} \right)}{2^{j-1} - 1} \text{ for } j \geq 2$$

Case 2:

$$M = N_1(h) + K_1 h + K_2 h^2 + K_3 h^3 \dots$$

M has truncation error of O(h<sup>2</sup>).

Replace h by h/2 (or h/some value) and follow steps in case 1.

N calculation for extrapolation table:

$$N_j \left( \frac{h}{2^j} \right) = N_{j-1} \left( \frac{h}{2^{j-1}} \right) + \frac{N_{j-1} \left( \frac{h}{2^{j-1}} \right) - N_{j-1} \left( \frac{h}{2^j} \right)}{4^{j-1} - 1} \text{ for } j \geq 2$$

has truncation error of O(h<sup>2j</sup>).

**Newton-Cotes Closed Quadrature Formulas:**

Trapezoidal rule (n=1):

$$\int_a^b f(x) dx \approx \frac{h}{2} [f(x_0) + f(x_1)] - \frac{h^3}{12} f''(\xi)$$

$h = x_1 - x_0$  degree = 1

Simpson's rule (n=2):

$$\int_a^b f(x) dx \approx \frac{h}{3} [f(x_0) + 4f(x_1) + f(x_2)] - \frac{h^5}{90} f^{(4)}(\xi)$$

$h = (b-a)/2$  degree = 3

Simpsons Rule: (deg of precision is 3)

| $f(x)$         | $\int_a^b f(x) dx$    | $\frac{h}{3} \left[ f(a) + 4f\left(\frac{a+b}{2}\right) + f(b) \right]$                           |
|----------------|-----------------------|---|
| 1              | $\frac{b-a}{2}$       | $\frac{b-a}{3} [1 + 4(1) + 1] = b-a$  |
| x              | $\frac{b^2 - a^2}{2}$ | $\frac{b-a}{6} \left[ a^2 + 4\left(\frac{a+b}{2}\right)^2 + b^2 \right] = \frac{b^3 - a^3}{3}$    |
| x <sup>2</sup> | $\frac{b^3 - a^3}{3}$ | $\frac{b-a}{6} \left[ a^3 + 4\left(\frac{a+b}{2}\right)^3 + b^3 \right] = \frac{b^4 - a^4}{4}$    |
| x <sup>3</sup> | $\frac{b^4 - a^4}{4}$ | $\frac{b-a}{6} \left[ a^4 + 4\left(\frac{a+b}{2}\right)^4 + b^4 \right] = \frac{b^5 - a^5}{5}$    |
| x <sup>4</sup> | $\frac{b^5 - a^5}{5}$ | $\frac{b-a}{6} \left[ a^5 + 4\left(\frac{a+b}{2}\right)^5 + b^5 \right] \neq \frac{b^6 - a^6}{6}$ |

**Composite Simpson's Rule:**

m applications of Simpson's rule on [a,b] requires [a,b]

be subdivided into an even # (2m) of subintervals each of length:

$$h = \frac{b-a}{2m}$$

$$\int_a^b f(x) dx \approx \frac{h}{3} \left[ f_0 + 2 \sum_{j=1}^{m-1} f_{2j} + 4 \sum_{j=1}^m f_{2j-1} + f_{2m} \right]$$

Case m = 2:

Requires 5 quadrature points, 4 subintervals.

$$\int_a^b f(x) dx \approx \frac{h}{3} [f_0 + 4f_1 + 2f_2 + 4f_3 + f_4]$$

Case m = 4:

Requires 9 quadrature points, 8 subintervals.

$$\int_a^b f(x) dx \approx \frac{h}{3} [f_0 + 4f_1 + 2f_2 + 4f_3 + 2f_4 + 4f_5 + 2f_6 + 4f_7 + f_8]$$

Truncation error:

$$E_{2m}(f) = -\frac{(b-a)h^4}{180} f^{(4)}(\mu)$$

**Romberg Integration:** is the application of Richardson's Extrapolation

to the composite trapezoidal rule approximations

$$R_{k,1} \text{ is the composite trapezoidal rule approx. to } \int_a^b f(x) dx$$

using  $2^{k-1}$  sub intervals

$$R_{k,j} = R_{k,j-1} + \frac{R_{k,j-1} - R_{k-1,j-1}}{4^{j-1} - 1}$$
  
for  $k = 2, 3, \dots$  and  $j = 2, 3, \dots, k$   
(use for columns 2,3,...)

$$\begin{aligned} R_{1,1} &= \frac{h}{2} [f_0 + f_1] \\ R_{2,1} &= h \left[ \frac{f_0}{2} + f_1 + \frac{f_2}{2} \right] \\ R_{3,1} &= h \left[ \frac{f_0}{2} + f_1 + f_2 + f_3 + \frac{f_4}{2} \right] \end{aligned}$$

$$R_{2,2} = R_{2,1} + \frac{R_{2,1} - R_{1,1}}{3}$$

Truncation Error: First column = O(h<sup>2</sup>), Second Column = O(h<sup>4</sup>), Third O(h<sup>6</sup>) ...

Error Term, First column:  $-\frac{b-a}{12} h^2 f''(\mu)$  , where  $a < \mu < b$

**Adaptive Quadrature:**

$$S_1 = \text{(non-composite) Simpson's rule approx to } \int_a^b f(x) dx$$

$S_2$  = composite Simpson's rule approx using 2 applications of Simpson's rule

$$\int_a^b f(x) dx \approx S_2 - \frac{h^5}{1440} f^{(4)}(\bar{\mu}) \approx S_2 + \frac{1}{15} (S_2 - S_1)$$

$$\left| \int_a^b f(x) dx - S_2 \right| \approx \frac{1}{15} |S_2 - S_1|$$

If  $|S_2 - S_1| < 1.5\varepsilon$ ,  $\left| \int_a^b f(x) dx - S_2 \right| < \varepsilon$

else, select smaller h and repeat.

**DE Equations:** An initial-value problem has a unique solution if  $f(t, y(t))$  is continuous on  $D = \{(t, y) | a \leq t \leq b, -\infty < y < \infty\}$  and if  $f$  satisfies a **Lipshitz** condition on  $D$ :

$$|f(t, y_1) - f(t, y_2)| \leq L |y_1 - y_2| \text{ for some constant } L \text{ and all } (t, y_i) \in D$$

**Euler's Method:** is obtained from this truncated Taylor polynomial approx. by replacing  $y(t_{i+1})$  by its numerical approx.  $w_{i+1}$ , and similarly replacing  $y(t_i)$  by  $w_i$ :

$$w_0 = \alpha \quad (\text{initial condition})$$

$$w_{i+1} = w_i + h \cdot f(t_i, w_i)$$

Geometric interpretation of Euler's Method:

$$w_0 = \alpha = y(t_0)$$

$$w_1 = w_0 + h \cdot f(t_0, w_0) = w_0 + h \cdot y'(t_0)$$

$$\frac{w_1 - w_0}{h} = y'(t_0)$$

$$w_2 = w_1 + h \cdot f(t_1, w_1)$$

**Global Truncation Error** at  $t_i$  is  $|y_i - w_i|$

If the global truncation error is  $O(h^k)$ , numerical method for computing  $w_i$  is said to be of the order  $k$ , the larger the order of  $k$ , the faster the rate of convergence.

A difference method is said to be convergent (wrt the differential equation it approx.) if:

$$\lim_{h \rightarrow 0} \max_{1 \leq i \leq N} |y_i - w_i| = 0$$

$$\max_{1 \leq i \leq N} |y_i - w_i| \leq \frac{hM}{2L} [e^{L(b-a)} - 1]$$

Euler's method is of order 1.

**Local Truncation Error:** the error incurred in one step of a numerical method assuming that the value at the previous mesh point is exact.

For Euler's Method,

$$v_{i+1} = y(t_i) + h \cdot f(t_i, y(t_i))$$

$$|y_{i+1} - v_{i+1}| = \left| \frac{h^2}{2} y''(\xi_i) \right| \leq \frac{h^2}{2} M \quad , \quad y''(\xi_i) \leq M$$

Local truncation error is  $O(h^2)$

If the local truncation error is  $O(h^{k+1})$  then the global is  $O(h^k)$  - method is order  $k$

**Disadvantages of Eulers:** not sufficiently accurate.

Global truncation is  $O(h)$ , means that  $h$  must be small for high accuracy approx.

**Taylor's Method of order n**

$$w_{i+1} = w_i + h \cdot f(t_i, w_i) + \frac{h^2}{2} f'(t_i, w_i) + \dots + \frac{h^n}{n!} f^{(n-1)}(t_i, w_i) \quad , \quad \text{int } n \geq 1$$

Truncation error is  $O(h^{n+1})$ : just above remainder term:

$$\frac{|h^{n+1}|}{(n+1)!} |y^{(n+1)}(\xi_i)|$$

Global Truncation is  $O(h^n)$ , so order  $n$

Euler's method is just special case where  $n = 1$

**Runge-Kutta:**

Advantage of Taylor method: high order (high accuracy) truncation error.

Disadvantage: high derivatives

R-K are higher order formulas that require function evaluations of only  $f(t, y(t))$ , and not its derivatives, by using Taylor for 2 variables.

**General form:**

$$w_{i+1} = w_i + \sum_{j=1}^m a_j k_j$$

Where

$$k_1 = h \cdot f(t_i, w_i) \quad \text{and} \quad k_j = h \cdot f\left(t_i + \alpha_j h, w_i + \sum_{i=1}^{j-1} \beta_{ji} k_i\right)$$

Choose parameters  $\{\alpha_j\}, \{\beta_{ji}\}$  so that the general R-K formula is identical to the Taylor series expansion

$$y_{i+1} = y_i + h y'_i + \frac{h^2}{2} y''_i + \dots$$

**Runge-Kutta-Fehlberg:**

Variable stepsize implementation of R-K that insures that the global truncation error is within  $\epsilon$ .

$$|y(t_{i+1}) - w_{i+1}| < \epsilon$$

The global truncation error is estimated by finding 2 approximations, using 2 different R-K formulas,  $w_{i+1}$  with  $O(h^{n+1})$  and  $\tilde{w}_{i+1}$  with  $O(h^{n+2})$ . The global error estimate is:  $|\tilde{w}_{i+1} - w_{i+1}|/h$

**Direct Methods for Solving Linear Systems**

$Ax=b$ ,  $n$  equations,  $n$  unknowns

case 1

$$a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = b_1$$

$$a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n = b_2$$

$$\vdots$$

$$a_{n1}x_1 + a_{n2}x_2 + \dots + a_{nn}x_n = b_n$$

or case 2,  $P(x) = a_n + a_{n-1}x + a_{n-2}x^2$

$$\begin{bmatrix} 1 & x_0 & x_0^2 \\ 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \end{bmatrix} \cdot \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} f(x_0) \\ f(x_1) \\ f(x_2) \end{bmatrix}$$

forward elimination

$$m_{21} = \frac{a_{21}}{a_{11}}, \quad E_2 \leftarrow E_2 - m_{21}E_1$$

$$m_{31} = \frac{a_{31}}{a_{11}}, \quad E_3 \leftarrow E_3 - m_{31}E_1$$

$$m_{32} = \frac{a_{32}}{a_{12}}, \quad E_3 \leftarrow E_3 - m_{32}E_2$$

Make upper triangular and back substitute

Algorithm

forward elimination

For  $i=1$  to  $n-1$

For  $j=(i+1)$  to  $n$

$$\text{mult} \leftarrow a_{ij}/a_{ii}$$

For  $k=i+1$  to  $n$

$$a_{ik} \leftarrow a_{ik} - \text{mult} \cdot a_{ii}$$

$$b_j \leftarrow b_j - \text{mult} \cdot b_i$$

Back substitution

$$x_n \leftarrow b_n/a_{nn}$$

For  $i=n-1$  to 1

$$x_i \leftarrow \left[ b_i - \sum_{j=i+1}^n a_{ij} x_j \right] / a_{ii}$$

Fails with divide by zero ( $a_{ii}=0$ )

Partial Pivoting to reduce error

Find largest pivot

$$p \leftarrow i$$

for  $k=1$  to  $n$

if  $|a_{ki}| > |a_{pi}|$  then  $p \leftarrow k$

row swap if necessary

if  $p \neq i$

For  $k=i$  to  $n$

$$\text{temp} \leftarrow a_{ik}$$

$$a_{ik} \leftarrow a_{pk}$$

$$a_{pk} \leftarrow \text{temp}$$

$$\text{temp} \leftarrow b_i$$

$$b_i \leftarrow b_p$$

$$b_p \leftarrow \text{temp}$$

continue with gaussian

Requires  $n^3/3$  mults/divides (adds/subs as well)

Matlab  $Ax=b$  type A\b for Gaussian with PPivot

$$\det A = (-1)^m a_{11} a_{22} \dots a_{nn} \quad \text{where } m = \# \text{ of row swaps}$$

To find inverse solve  $A[I]$

Better method, if need  $A^{-1}b$ , solve for  $x$  in  $Ax=b$

If  $A^{-1}B$  is needed, more efficient to solve  $AX=B$  for  $X$

Stability

Stable if there exists small perturbations

E.e such that  $\hat{x}$  is close to the exact solution

$(A+E)y=b+e$

small perturbation means  $\frac{\|E\|}{\|A\|}, \frac{\|e\|}{\|b\|}$  are small

$$\|A\| = \sqrt{\sum \sum a_{ij}^2} \quad \|x\| = \sqrt{\sum x_i^2}$$

Gaussian elimination with PPivoting is almost always stable

Condition of problem  $Ax=b$

Ill-conditioned if there exists one small perturbation of the data

$(A+E)y=b+e$  for which the exact value of  $y$

Can be measured by the condition number of  $A$ :

$$\|A\| \|A^{-1}\|$$

Matlab  $\text{cond}(A)$

**Various Formulae:**

Matrix algebra:  $Ax=B \rightarrow x=A^{-1}B$

Taylor approximations:

$$\sin(x) \approx x - \frac{x^3}{6} \quad e^x \approx 1 + x + \frac{x^2}{2} + \frac{x^3}{6} + \frac{x^4}{24} + \dots + \frac{x^n}{n!}$$

$$\cos(x) \approx 1 - \frac{1}{2}x^2 + \frac{1}{24}x^4 - \frac{1}{720}x^6$$

$$\sum_{k=1}^n k = \frac{n(n+1)}{2} \quad \sum_{k=1}^n k^2 = \frac{n(n+1)(2n+1)}{6}$$

**Trig Identities:**

$$\sin 2\theta = 2 \sin \theta \cos \theta$$

$$\sin(a-b) = \sin a \cos b - \cos a \sin b$$

$$\cos(a-b) = \cos a \cos b + \sin a \sin b$$

$$\cos 2\theta = \cos^2 \theta - \sin^2 \theta = 2 \cos^2 \theta - 1 = 1 - 2 \sin^2 \theta$$

**Examples:**

Determine second order ( $n=2$ ) Taylor polynomial approx for  $f(x)=x^{1/4}$  expanded about  $x_0=1$ . Include remainder term.

$$f(x) = f(x_0) + f'(x_0)(x-x_0) + \frac{f''(x_0)}{2!}(x-x_0)^2 + \frac{f'''(x_0)}{3!}(x-x_0)^3$$

$$f(x_0) = 1 \quad f'(x_0) = \frac{1}{4} x_0^{-3/4} = \frac{1}{4}$$

$$f''(x_0) = -\frac{3}{16} x_0^{-7/4} = -\frac{3}{16} \quad f'''(x_0) = \frac{21}{64} x_0^{-11/4} = \frac{21}{64}$$

$$\therefore f(x) = 1 + \frac{1}{4}(x-1) - \frac{3}{32}(x-1)^2 + \frac{7}{128}(\xi(x))^{-11/4}(x-1)^3$$

Determine a good upper bound for the truncation error of the Taylor poly approx. above when  $0.95 \leq x \leq 1.06$  by bounding the remainder term. Give 4 sig digits.

$$|f(x) - P(x)| \leq \max \left| \frac{7}{128} (\xi(x))^{-11/4} (x-1)^3 \right|$$

$$\leq \frac{7}{128} \left| (0.95)^{-11/4} (1.06-1)^3 \right| \leq 1.360 \cdot 10^{-5}$$

Let  $P(x)=x^4+x^2-3$ . If Muller's method is used to approx. a zero of  $P(x)$  using initial approx. 0,1,2, give the Lagrange form of the interpolating polynomial.

$$x_0 = 0, x_1 = 1, x_2 = 2$$

$$L_0(x) = \frac{(x-x_1)(x-x_2)}{(x_0-x_1)(x_0-x_2)} = \frac{(x-1)(x-2)}{(-1)(-2)}$$

$$L_1(x) = \frac{(x-x_0)(x-x_2)}{(x_1-x_0)(x_1-x_2)} = \frac{(x)(x-2)}{(1)(-1)}$$

$$L_2(x) = \frac{(x-x_0)(x-x_1)}{(x_2-x_0)(x_2-x_1)} = \frac{(x)(x-1)}{(2)(1)}$$

$$f(x_0) = P(x_0) = -3$$

$$f(x_1) = P(x_1) = -1$$

$$f(x_2) = P(x_2) = 17$$

$$\therefore P(x) = -3L_0(x) - L_1(x) + 17L_2(x)$$

What values of  $x$ , where  $x > 1$  is the following expression subject to subtractive cancellation (which will produce a very inaccurate result using floating point arithmetic)?

$$f(x) = \sqrt{x} - \sqrt{x-1}$$

$x$  large and positive

How should  $f(x)$  be evaluated in floating point arithmetic in order to avoid subtractive cancellation?

$$f(x) = (\sqrt{x} - \sqrt{x-1}) * \frac{\sqrt{x} + \sqrt{x-1}}{\sqrt{x} + \sqrt{x-1}} = \frac{1}{\sqrt{x} + \sqrt{x-1}}$$

Apply Newton's method to  $f(x) = x^2 - \frac{1}{c}$  in order to determine

$$\text{an iterative formula for computing } \frac{1}{\sqrt{c}}$$

$$f(x) = x^2 - \frac{1}{c} \quad f'(x) = 2x$$

$$P_n = P_{n-1} - \frac{P_{n-1}^2 + \frac{1}{c}}{2P_{n-1}} = \frac{P_{n-1}^2 + \frac{1}{c}}{2P_{n-1}} \text{ or } \frac{1}{2} \left( P_{n-1} + \frac{1}{cP_{n-1}} \right)$$

$$f(x_0 + h) = f(x_0) + hf'(x_0) + \frac{h^2}{2!} f''(x_0) + \frac{h^3}{3!} f'''(x_0) + \dots$$

Use this form of Taylor's theorem to determine the quadratic approx to  $\sin(1+h)$ .

$$\sin(1+h) \approx \sin(1) + h \cos(1) + \frac{h^2}{2} (-\sin(1))$$

Apply the Newton-Raphson method to  $f(x) = x^2 - \frac{R}{x}$  in order

$$\text{to determine an iterative formula for computing } \sqrt[3]{R}$$

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)} = x_n - \frac{x_n^2 - \frac{R}{x_n}}{2x_n + \frac{R}{x_n^2}} = x_n - \left( \frac{x_n^3 - R}{2x_n^3 + R} \right) \left( \frac{x_n^2}{2x_n^3 + R} \right)$$

$$= x_n \left( 1 - \frac{x_n^3 - R}{2x_n^3 + R} \right) = x_n \left( \frac{2x_n^3 + R - x_n^3 + R}{2x_n^3 + R} \right) = x_n \left( \frac{x_n^3 + 2R}{2x_n^3 + R} \right)$$

A good approx to a zero of  $P(x)=x^4+x^3-6x^2-7x-7$  is  $x_0=2.64$ . If  $x_0$  is used as an approx to a zero of  $P(x)$ , use synthetic division (Homer's algorithm) to determine the associated deflated polynomial.

$$a_0 = -7, a_1 = -7, a_2 = -6, a_3 = 1, a_4 = 1$$

$$b_4 = a_4 = 1$$

$$b_3 = a_3 + b_4 x_0 = 3.64$$

$$b_2 = a_2 + b_3 x_0 = 3.6096$$

$$b_1 = a_1 + b_2 x_0 = 2.529344$$

$$b_0 = -0.322532$$

$$\therefore \text{deflated polynomial is } x^3 + 3.64x^2 + 3.6096x + 2.529344$$

If  $a, b, c, d, e, f$  have known values then  $\begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} e \\ f \end{bmatrix}$

is a system of 2 linear equations in the 2 unknowns  $x, y$ .

If  $ad-bc \neq 0$ , then the solution is  $x = \frac{de-bf}{ad-bc}$  and

$y = \frac{af-ce}{ad-bc}$ . Consider the system:

$$\begin{bmatrix} 0.96 & -1.23 \\ 4.91 & -6.29 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} -0.27 \\ -1.38 \end{bmatrix} \quad \text{Show that the problem of}$$

computing the solution  $\begin{bmatrix} x \\ y \end{bmatrix}$  is ill conditioned.

Almost any perturbation of the 6 constants in the data will do. For

$$\text{example, } \begin{bmatrix} 0.961 & -1.23 \\ 4.89 & -6.29 \end{bmatrix} \begin{bmatrix} \hat{x} \\ \hat{y} \end{bmatrix} = \begin{bmatrix} -0.27 \\ -1.38 \end{bmatrix} \text{ has the exact solution}$$

$$\approx \begin{bmatrix} -0.03 \\ 0.196 \end{bmatrix}, \text{ whereas the given system has solution } \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

$$\text{Let } f(x) = -\frac{1}{2}x - \frac{x^2}{3} - \frac{x^3}{24} \cdot f(x) \text{ is accurate when } x \text{ is close to}$$

0. Show that the computation of  $f(f(0.123))$  is unstable.

given problem  $\rightarrow$  computed solution

$$x = 0.123 \quad -0.4629$$

perturbed problem

$$\hat{x} = 0.123 + \epsilon \quad \rightarrow \quad f(\hat{x}) \approx -\frac{1}{2}\hat{x} - \frac{\hat{x}^2}{3} - \frac{\hat{x}^3}{24} \text{ for } x \text{ close to } 0$$

$$f(\hat{x}) = -\frac{1}{2}\hat{x} - \frac{\hat{x}^2}{3} - \frac{(\hat{x}^3 + \epsilon^3)}{24}$$

$$f(\hat{x}) = -0.54163 - 0.34358\epsilon + O(\epsilon^2)$$

$$f(\hat{x}) \approx -0.5416 \text{ for all } \epsilon \text{ such that } \left| \frac{\epsilon}{0.123} \right| \text{ is small.}$$

Since this is not close to  $-0.4629$  for all small  $\epsilon$ , the computation is unstable.

$$f(f(w*x - f(y*z))) \text{ for } w=16.00, x=43.61, y=12.31,$$

$$z=56.68$$

Using idealized, rounding, floating point arithmetic (base 10,  $k=4$ ), the above equation evaluates to 0.1. The exact value is 0.0292. Use the definition of stability to show (by using only a perturbation in  $y$ ) that the computation is stable.

To show that it's stable, find a value  $\epsilon$  for which the exact value of

$(16.00)(43.61) - (12.31 + \epsilon)(56.68)$  is approx equal to 1. Solving for  $\epsilon$

$$\text{gives } \epsilon = \frac{16*43.61 - 0.1}{56.68} - 12.31 = -0.0012491$$

Thus, for example, if  $y = 12.31$  is perturbed to  $\hat{y} = y + \epsilon = 12.31 - 0.00125$

then the exact value of  $w*x - \hat{y}*z = 0.10005$ , which is close to 0.1.

And since  $\left| \frac{\epsilon}{0.123} \right| = \frac{0.00125}{0.123}$  is small, the computation is stable.



```
ezplot('0.5*exp(x/3)-sin(x)', [-4, 5])
fplot('3*x^3-x-1', [-1 2], 'r')
```

**fzero** to compute the zeros of f(x):  
fzero('0.5\*exp(x/3)-sin(x)', [-5, -3])  
Change bounds for each interval a zero is located.

**Polynomial Operations:**

The coefficients of a polynomial are stored in a vector *p* (**starting with the coefficient of the highest power of x**).

$p(x) = x^3 - 2x - 5$   
p = [1 0 -2 -5];  
r = roots(p)  
Will compute and store all of the roots of the polynomial in r.  
Alternate format: r = roots([1 0 -2 -5])  
If r is any vector, p = poly(r), will result in p being a vector whose entries are the coefficients of a polynomial *p(x)* that has as its roots the entries of r.

Example:  
r = [1 2 3 4];  
p = poly(r)  
Results in p = [1 -10 35 -50 24],  
 $p(x) = x^4 - 10x^3 + 35x^2 - 50x + 24$   
The function *polyval* evaluates a polynomial at a specified value. If p = [1 -10 35 -50 24], then polyval(p, -1) gives the value of  $p(x) = x^4 - 10x^3 + 35x^2 - 50x + 24$  at x = -1, namely 120. MATLAB uses HORNER'S ALGORITHM for *polyval*.

The MATLAB function INTERP1 can be used to do linear and cubic polynomial interpolation. If X denotes a vector of values, Y = F(X) a set of corresponding function values, then z = interp1(X, Y, x) or z = interp1(X, Y, x, 'linear'). z = interp1(X, Y, x, 'cubic') determines z based on a cubic polynomial approximation.

For the cubic spline with clamped boundary conditions, the data to be interpolated should be stored in vectors, X and Y, where Y has 2 more entries than X and the first and last entries of Y are the two boundary conditions. If *S(x)* denotes the cubic spline interpolant, and z is a given number, then the value of *S(z)* can be computed by entering spline(X, Y, z). To determine the coefficients of the spline, first determine the pp (piecewise polynomial) form of the spline by entering pp = spline(X, Y). Then enter [breaks, coefs] = unmkpp(pp). breaks: a vector of the knots (or nodes) of the spline, coefs: an array, the i-th row of which contains the coefficients of the i-th spline

**Quad** - Numerically evaluate integral, adaptive Simpson quadrature. Use array operators .\*, ./ and .^ using tol = 10<sup>-5</sup>

```
int_0.1^2 sin(1/x) dx
[Q, fnc] = quad (@f, 0.1, 2, 10^-5)
function y=f(x)
    y = sin(1./x);
```

**Ode45:** is variable stepsize Runge-Kutta method that uses two Runge-Kutta formulas of orders 4 and 5. Solve non-stiff differential equations, medium order method.

```
y'(t) = -y(t) - 5e^-t sin(5t) , y(0) = 1 on [0,3]
[t, y] = ode45('r', [0 3], 1)
function z=f(t,y)
    z = -y-5*exp(-t)*sin(5*t);
```

**Linspace:** Linearly spaced vector.

Linspace(X1, X2) generates a row vector of 100 linearly equally spaced points between X1 and X2.  
Linspace(X1, X2, N) generates N points between X1 and X2. For N < 2, Linspace returns X2.

**Gaussian Elimination Algorithm**

(forward elimination)  
For i=1,2,...,n-1 do  
    For j=i+1,i+2,...,n do  
        mult ← a<sub>ij</sub>/a<sub>ii</sub>  
        for k=i+1,i+2,...,n do  
            a<sub>jk</sub> ← a<sub>jk</sub>-mult\*a<sub>ik</sub>  
        b<sub>j</sub> ← b<sub>j</sub>-mult\*b<sub>i</sub>  
    end  
end  
(back substitution)  
x<sub>n</sub> ← b<sub>n</sub>/a<sub>nn</sub>  
for i=n-1,n-2,...,1 do  
    x<sub>i</sub> ← [b<sub>i</sub>-sum(a<sub>ij</sub>x<sub>j</sub>, from j=i+1 to n)]/a<sub>ii</sub>

**Gaussian Elimination with partial pivoting**

(forward elimination)  
for i=1,2,...,n-1 do  
    (find the largest pivot)  
    p ← i  
    for k=i+1,i+2,...,n do  
        if |a<sub>ki</sub>| > |a<sub>pi</sub>| then  
            p ← k  
        end  
    end  
    if p != i then  
        for k=i,i+1,...,n do  
            temp ← a<sub>ik</sub>  
            a<sub>ik</sub> ← a<sub>pk</sub>  
            a<sub>pk</sub> ← temp  
        end  
        temp ← b<sub>i</sub>  
        b<sub>i</sub> ← b<sub>p</sub>  
        b<sub>p</sub> ← temp  
    end  
    for j=i+1,i+2,...,n do  
        mult ← a<sub>ji</sub>/a<sub>ii</sub>  
        for k=i+1,i+2,...,n do  
            a<sub>jk</sub> ← a<sub>jk</sub>-mult\*a<sub>ik</sub>  
        end  
        b<sub>j</sub> ← b<sub>j</sub>-mult\*b<sub>i</sub>  
    end  
end  
(back-substitution)  
x<sub>n</sub> ← b<sub>n</sub>/a<sub>nn</sub>  
for i=n-1,n-2,...,1 do  
    x<sub>i</sub> ← [b<sub>i</sub>-sum(a<sub>ij</sub>x<sub>j</sub>, from j=i+1 to n)]/a<sub>ii</sub>

**Bisection Method**  
function p = **bisection**(p0, p1, N, tol)

```
i=1;
FA=f(a);
while i<=N
    p=a+(b-a)/2;
    FP=f(p);
    if ((FP==0)||((b-a)/2<TOL))
        return;
    end
    i=i+1;
    if FA*FP>0
        a=p;
        FA=FP;
    else
        b=p;
    end
end
fprintf('failed to converge in %g',Nzero),fprintf(' iterations\n')
```

Polynewton computes one zero of a polynomial.

Input variables:  
*n* the polynomial degree  
*a* a vector of the coefficients of the polynomial *P(x)*  
*pzero* the initial approximation to a zero  
*Nzero* the maximum number of iterations allowed  
*tol* relative error tolerance used to test for convergence and the output variables are  
*p* the final computed approximation to a zero of *P(x)*  
*b* the final vector of values *b* computed by Horner's algorithm, from which the deflated polynomial can be obtained.

```
polynewton(4, [-3.3 -1 0 2 5], 1.3, 20, 1e-8);
Will output to the screen each computed approximation to the zero.
[x, y] = polynewton(4, [-3.3 -1 0 2 5], 1.3, 20, 1e-8);
Will output to the screen each computed approximation to a zero,
will store the final computed approximation in the variable x, and
will store the final computed vector of values b from Horner's
algorithm in the vector y.
```

```
function [p,b] = polynewton(n, a, pzero, Nzero, tol)
i=1;
while i<=Nzero
    [b, c] = horner(pzero, n, a);
    p = pzero - b(1)/c(2);
    fprintf('i = %g',i),fprintf(' approximation = %18.10f\n',p)
    if abs(1-pzero/p)<tol
        return
    end
    i=i+1;
    pzero=p;
end
fprintf('failed to converge in %g',Nzero),fprintf(' iterations\n')
```

**Horner:** to evaluate the polynomial. Input – location x0, degree n, coefficients a. Outputs: b = P(x0), c = P'(x0)

```
function [b, c] = horner(x0, n, a)
b(n+1)=a(n+1);
c(n+1)=a(n+1);
for j = n: -1: 2
    b(j) = a(j) + b(j+1)*x0;
    c(j) = b(j) + c(j+1)*x0;
end
b(1) = a(1) + b(2)*x0;
```

Composite Trapezoidal Rule: Input – upper and lower limits of the integral a and b, max # of iterations maxiter, and tolerance tol.

```
function trap(a, b, maxiter, tol)
m = 1;
x = linspace(a, b, m+1);
y = f(x);
approx = trapz(x, y);
disp(' m integral approximation');
fprintf(' %5.0f %16.10f\n', m, approx);
for i = 1 : maxiter
    m = m*2;
    oldapprox = approx;
    x = linspace(a, b, m+1);
    y = f(x);
    approx = trapz(x, y);
    fprintf(' %5.0f %16.10f\n', m, approx);
    if abs(1-oldapprox/ approx) < tol
        return
    end
end
fprintf('The iteration did not converge in %g', maxiter), fprintf(' iterations.')
```

**Secant:** To find the zero of the function. Input – initial approx. p0, p1, tolerance tol, and max # of iterations N.  
function p = **secant**(p0, p1, N, tol)

```
i=2;
q0=f(p0);
q1=f(p1);
while i<=N
    p=p1-q1*(p1-p0)/(q1-q0);
    if abs(p-p1)<tol
        return;
    end
    i=i+1;
    p0=p1;
    q0=q1;
    p1=p;
    q1=f(p);
end
fprintf('failed to converge in %g',Nzero),fprintf(' iterations\n')
```

Use *polyval* to evaluate *q(x)* at the first zero of *q(x)* computed by MATLAB in (a). This should give a result very close to 0.

```
r = [1 1 1 1 1 1 1];
p = poly(r)
roots_of_p = roots(p)
q = p + [0 0 0.001 0 0 0 0]
qr = roots(q)
```

polyval(q,qr(1))

Use INTERP1 to approximate z = P(1.3), where P(x) is the piecewise linear interpolating polynomial to y = sin x at the 11 equally-spaced points

```
for i = 1:11
    x(i)=(i-1)*pi/20;
    y(i)=sin(x(i));
end

z = interp1(x, y, 1.3, 'linear');
fprintf(' z = %18.10f\n',z);
fprintf(' sin(1.3) = %18.10f\n',sin(1.3));
fprintf(' abs(sin(1.3)-z) = %18.10f\n',abs(sin(1.3)-z));
```

**Assignment #3**

plot a graph of the function

```
>> ezplot('0.5*exp(x/3)-sin(x)',[-4,5])
```

fzero to compute the 3 zeros of  
>> fzero('0.5\*exp(x/3)-sin(x)',[-5,-3])  
ans = -3.3083

h=fzero('10\*(0.5\*pi^1/2-1^2\*asin(x/1)-x\*sqrt(1^2-x^2))-12.4',[0,1])  
h = 0.1662; >> r=1; >> x=-h; x = 0.8338

**Newton.m**

To find a zero of the function. Input – Initial approx. pzero, maximum iterations Nzero, tolerance tol.  
function p = **newton**(pzero,Nzero,tol)

```
i=1;
while i <= Nzero
    p = pzero-f(pzero)/fp(pzero);
    fprintf('i = %g',i),fprintf(' approximation = %18.10f\n',p)
    if abs(1-pzero/p)<tol
        return
    end
    i=i+1;
    pzero=p;
end
fprintf('failed to converge in %g',Nzero),fprintf(' iterations\n')
f.m
function y=f(x)
y=32*(x-sin(x))-35;
fp.m
function y=f(x)
y=32*(1-cos(x));
```

Newtons method to find reciprocal

$$f(x) = \frac{1}{x} - R$$
$$f'(x) = \frac{1}{-x^2}$$
$$p = p_0 - \frac{f(p_0)}{f'(p_0)}$$
$$p = p_0 - \frac{\frac{1}{p_0} - R}{-\frac{1}{p_0^2}}$$
$$p = p_0 + p_0 - R \cdot p_0^2$$
$$p = 2 \cdot p_0 - R \cdot p_0^2$$

**Multiplicity of the roots.**

```
function test_mult(x)
root = newton (pi/2, 40, 1e-8);
fprintf('\nroot used = %18.10f\n',root);
for i = 0:x
    fprintf('m = %g',i),fprintf(' p = %18.10f\n',f_diff(root,i));
end
```

**Matlab version of Newtons method for computing 1/R**

```
function p = reciprocal(R,pzero,Nzero,tol)
i=1;
while i<=Nzero
    p=2*pzero-R*pzero*pzero;
    fprintf('i = %g',i),fprintf(' approximation = %18.10f\n',p)
    y(i)=p;
    if abs(1-pzero/p)<tol
        return
    end
    i=i+1;
    pzero=p;
end
fprintf('failed to converge in %g',Nzero),fprintf(' iterations\n')
```