



Numerical Methods Formulas

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Preliminaries

- **True Error (E_t):** $E_t = \text{True Value} - \text{Approximate Value}$
- **Approximate Error (E_a):** $E_a = \text{Current Approx.} - \text{Previous Approx.}$
- **Absolute Error:** $|\text{Error}|$
- **Relative Error:** $\epsilon = \frac{|\text{Error}|}{|\text{Reference Value}|} \times 100\%$
(Ref. can be True or Approx. value)

Solution of Nonlinear Equations $f(x) = 0$

- **Fixed point iteration Method:** $x_{i+1} = g(x_i)$, where $x = g(x)$ is equivalent to $f(x) = 0$. Converges if $|g'(x)| < 1$ near root.
- **Bisection Method:** Given $[a, b]$ with $f(a)f(b) < 0$, $x_m = \frac{a+b}{2}$. New interval $[a, x_m]$ or $[x_m, b]$.
- **False Position Method (Regula Falsi):** Given $[a, b]$ with $f(a)f(b) < 0$, $x_r = b - \frac{f(b)(a-b)}{f(a)-f(b)}$. Update a or b .
- **Newton-Raphson Method:** $x_{i+1} = x_i - \frac{f(x_i)}{f'(x_i)}$
- **Convergence of N-R:** $M = 1$: Quadratic, $M > 1$: Linear
- **Accelerated Newton Raphson Method:** For root of multiplicity m : $x_{i+1} = x_i - m \frac{f(x_i)}{f'(x_i)}$
- **Convergence of Accel. N-R:** Quadratic
- **Secant Method:** $x_{i+1} = x_i - \frac{f(x_i)(x_{i-1}-x_i)}{f(x_{i-1})-f(x_i)}$

Analytical Solution of Linear Systems

- **Upper and Lower Triangular Linear Systems:** Solve by back-substitution (Upper) or forward-substitution (Lower).
- **Gaussian Elimination and Pivoting:** Use elementary row operations to achieve row echelon form (Upper Triangular). Pivoting swaps rows to avoid division by small/zero elements.
- **LU Decomposition and Permutation matrices:** $A = LU$ or $PA = LU$, where L is lower triangular (unit diagonal often), U is upper triangular, P is permutation matrix.
- **Solution of linear systems with LU decomposition:** Solve $Ax = b$ by first solving $Ly = Pb$ (forward sub.), then $Ux = y$ (back sub.).

Iterative Solution Methods for Linear Systems

- **Diagonally Dominant:** $|a_{diagonal}| > \sum_{j \neq i} |a_{others}|$ in each row.
- **Gauss Jacobi Method:** Use same values for each iter.
- **Gauss Seidel Method:** Use most recent values.

Iterative Solution Method for Nonlinear Systems: Newton's Method

- **Newton's Method for Systems:** Iterate $\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} - J(\mathbf{x}^{(k)})^{-1} \mathbf{f}(\mathbf{x}^{(k)})$, where Jacobian Matrix: $J_{ij} = \frac{\partial f_i}{\partial x_j}$.

Üniversite Numerik Analiz konu anlatımı ve soru çözümleri için QR'ı okut.

Buraya tıkla, konu anlatımı ve soru çözümlerini izle.

Ya da buraya tıkla ve interaktif formül sayfasına git.



Interpolation and Polynomial Approximation

- **Lagrange Polynomials:** $P_n(x) = \sum_{i=0}^n y_i L_{n,i}(x)$, where $L_{n,i}(x) = \prod_{j=0, j \neq i}^n \frac{x-x_j}{x_i-x_j}$
 - **Newton's Divided Difference table:** $P_n(x) = f[x_0] + f[x_0, x_1](x - x_0) + \dots + f[x_0, \dots, x_n] \prod_{i=0}^{n-1} (x - x_i)$.
- Differences: $f[x_i, \dots, x_j] = \frac{f[x_{i+1}, \dots, x_j] - f[x_i, \dots, x_{j-1}]}{x_j - x_i}$

Curve Fitting

- **Least-squares Line:** $y = a_0 + a_1x$. Solve normal equations: $\begin{pmatrix} n & \sum x_i \\ \sum x_i & \sum x_i^2 \end{pmatrix} \begin{pmatrix} a_0 \\ a_1 \end{pmatrix} = \begin{pmatrix} \sum y_i \\ \sum x_i y_i \end{pmatrix}$
- **Least-squares Parabola:** $y = a_0 + a_1x + a_2x^2$. Solve corresponding normal equations (3x3 system).
- **Data Linearization:** Transform model to linear form, e.g., $y = ae^{bx} \rightarrow \ln y = \ln a + bx$; $y = ax^b \rightarrow \log y = \log a + b \log x$.
- **Bezier Curve Fitting:** Parametric curve $P(t) = \sum_{i=0}^n P_i B_{i,n}(t)$, where P_i are control points and $B_{i,n}(t) = \binom{n}{i} t^i (1-t)^{n-i}$ are Bernstein polynomials.
- **Interpolation by Spline Functions:** Piecewise polynomials (e.g., cubic splines) joined at knots with continuity conditions on function and derivatives.

Numerical Differentiation

- **Approximating the Derivative:** Use finite differences based on Taylor series.
- **Forward Difference:** $f'(x_i) \approx \frac{f(x_{i+1}) - f(x_i)}{h}$
- **Backward Difference:** $f'(x_i) \approx \frac{f(x_i) - f(x_{i-1}))}{h}$
- **Central Difference:** $f'(x_i) \approx \frac{f(x_{i+1}) - f(x_{i-1}))}{2h}$ (More accurate)
- **Second Derivative (Central):** $f''(x_i) \approx \frac{f(x_{i+1}) - 2f(x_i) + f(x_{i-1}))}{h^2}$

Numerical Integration (Quadrature)

- **Trapezoidal Method:** $\int_a^b f(x)dx \approx \frac{h}{2} [f(x_0) + 2 \sum_{i=1}^{n-1} f(x_i) + f(x_n)]$, $h = \frac{b-a}{n}$
- **Mid-Point Method:** $\int_a^b f(x)dx \approx h \sum_{i=0}^{n-1} f(x_i + h/2)$, $h = \frac{b-a}{n}$
- **Simpson's 1/3 Method (n even):** $\int_a^b f(x)dx \approx \frac{h}{3} [f(x_0) + 4 \sum_{i=1, \text{odd}}^{n-1} f(x_i) + 2 \sum_{i=2, \text{even}}^{n-2} f(x_i) + f(x_n)]$
- **Simpson's 3/8 Method (n multiple of 3):** $\int_a^b f(x)dx \approx \frac{3h}{8} [f(x_0) + 3 \sum_{i=1, 4, 7, \dots}^{n-2} (f(x_i) + f(x_{i+1})) + 2 \sum_{i=3, 6, 9, \dots}^{n-3} f(x_i) + f(x_n)]$

Numerical Solution of ODEs

- **Euler's method:** For $y'(x) = f(x, y)$, $y(x_0) = y_0$: $y_{i+1} = y_i + hf(x_i, y_i)$, where $h = x_{i+1} - x_i$.

Eigenvalues and Eigenvectors

- **Analytical solution:** Solve characteristic equation $\det(A - \lambda I) = 0$ for eigenvalues λ . Solve $(A - \lambda I)\mathbf{v} = \mathbf{0}$ for eigenvectors $\mathbf{v}$.
- **Power Method:** Finds dominant eigenvalue (λ_1) and eigenvector. Iterate $\mathbf{y}^{(k+1)} = A\mathbf{x}^{(k)}$, $\mathbf{x}^{(k+1)} = \mathbf{y}^{(k+1)} / \|\mathbf{y}^{(k+1)}\|_\infty$. Eigenvalue estimate $\lambda_1 \approx \|\mathbf{y}^{(k+1)}\|_\infty / \|\mathbf{x}^{(k)}\|_\infty$ or Rayleigh quotient.
- **Inverse Power Method:** Finds eigenvalue closest to shift σ . Iterate $(A - \sigma I)\mathbf{y}^{(k+1)} = \mathbf{x}^{(k)}$, $\mathbf{x}^{(k+1)} = \mathbf{y}^{(k+1)} / \|\mathbf{y}^{(k+1)}\|_\infty$. Eigenvalue $\lambda \approx \sigma + 1/(\text{eigenvalue estimate from Power Method applied to } (A - \sigma I)^{-1})$.