Rootfinding: Secant Method

Lecture 12

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• Given two guesses x_{k-1} and x_k , the next guess at the root is where the line through $f(x_{k-1})$ and $f(x_k)$ crosses the x axis.



Given:

- $x_{k-1} =$ previous guess $x_k =$ current guess
- Approximate the first derivative with: $f'(x_k) \approx \frac{f(x_k) - f(x_{k-1})}{x_k - x_{k-1}}$

Substitute $f'(x_k)$ into Newton's method.

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}$$

Becomes:

$$x_{k+1} = x_k - f(x_k) \left[\frac{x_k - x_{k-1}}{f(x_k) - f(x_{k-1})} \right]$$

Two versions of formula are the equivalent in exact math:

•
$$x_{k+1} = x_k - f(x_k) \left[\frac{x_k - x_{k-1}}{f(x_k) - f(x_{k-1})} \right]$$

• $x_{k+1} = \frac{f(x_k)x_{k-1} - f(x_{k-1})x_k}{f(x_k) - f(x_{k-1})}$

Which is better computationally?

• Cancellation?

Secant Algorithm

Initialize
$$x_1 = *, x_2 = *$$

for $k = 2,3, ...$
 $x_{k+1} = x_k - f(x_k) (x_k - x_{k-1})/(f(x_k) - f(x_{k-1}))$
if converged stop
end

Secant Example

Solve:

$$x - x^{\frac{1}{3}} - 2 = 0$$

k	x_{k-1}	x_k	$f(x_k)$	
0	4	3	-0.44224957	
1	3	3.51734262	-0.00345547	
2	3.51734262	3.52141665	0.00003163	
3	3.52141665	3.52137970	-2.034 10 ⁻⁹	
4	3.52137959	3.52137971	-1.332 10 ⁻¹⁵	
5	3.52137971	3.52137971	0.0	

Secant Example

- Conclusions:
 - Converges almost as quickly as Newton's method (r = 1.62).
 - There is no need to compute f'(x).
 - The algorithm is simple.
 - Two initial guesses are necessary
 - Iterations are not guaranteed to stay inside an ordinal bracket.

Divergence of Secant Method



Since

$$x_{k+1} = x_k - f(x_k) \left[\frac{x_k - x_{k-1}}{f(x_k) - f(x_{k-1})} \right]$$

the new guess, x_{k+1} , will be far from the old guess whenever $f(x_k) \approx f(x_{k-1})$ and $|f(x_k)|$ is not small.

Summary

- Plot f(x) before searching for roots
- Bracketing finds coarse interval containing roots and singularities
- Bisection is robust, but converges slowly
- Newton's Method
 - Requires f(x) and f'(x)
 - Iterates are not confined to initial bracket.
 - Converges rapidly (r = 2).
 - Diverges if f'(x) = 0 is encountered.
- Secant Method
 - Uses f(x) values to approximate f'(x)
 - Iterates are not confined to initial bracket.
 - Converges almost as rapidly as Newton's method (r = 1.62).
 - Diverges if f'(x) = 0 is encountered.

Systems of Equations

- Single valued function of 1 variable.
- What about higher dimensions?

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

$$f_2(x_1, x_2, \dots, x_n) = 0$$

:

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

Systems of Equations

$$F(X)=0$$

Where

$$F = [f_1, f_2, \dots, f_n]^T$$
$$X = [x_1, x_2, \dots, x_n]^T$$

Newton's method becomes:

 $X^{(k+1)} = X^{(k)} - \left[F'(X^{(k)})\right]^{-1} F(X^{(k)})$

Systems of Equations

- $F'(x^{(k)})$ is the Jacobian Matrix.
- Made up of the partial derivatives of F evaluated at $X^{(k)}$
- $X^{(0)}$ is the initial solution vector
- The inverse of the Jacobian Matrix is not computed but rather the related system of equations solved.

• 3 equations in 3 variables

$$f_1(x_1, x_2, x_3) = 0$$

$$f_2(x_1, x_2, x_3) = 0$$

$$f_3(x_1, x_2, x_3) = 0$$

• Use Taylor series expansion $f_i(x_1 + h_1, x_2 + h_2, x_3 + h_3)$ $= f_i(x_1, x_2, x_3) + h_1 \frac{\partial f_i}{\partial x_1} + h_2 \frac{\partial f_i}{\partial x_2} + h_3 \frac{\partial f_i}{x_3}$ $+ \cdots$

- Let $X^{(0)} = [x_1^{(0)}, x_2^{(0)}, x_3^{(0)}]^T$ be the initial approximate solution.
- Let $H = [h_1, h_2, h_3]^T$ be a correction vector such that $X^{(0)} + H$ is a better approximate solution.
- Discard the higher order terms in the Taylor expansion and ...

$$0 \approx F(X^{(0)} + H) \approx F(X^{(0)}) + F'(X^{(0)})H$$

Where:

$$F'^{(X^{(0)})} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \frac{\partial f_1}{\partial x_3} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \frac{\partial f_2}{\partial x_3} \\ \frac{\partial f_3}{\partial x_1} & \frac{\partial f_3}{\partial x_2} & \frac{\partial f_3}{\partial x_3} \end{bmatrix}$$

- Assume $F'(X^{(0)})$ is nonsingular.
- Solving for $H = -[F'(X^{(0)})]^{-1}F(X^{(0)})$
- $X^{(1)} = X^{(0)} + H$ is a better approximation.
- In general

$$X^{(k+1)} = X^{(k)} - \left[F'(X^{(k)})\right]^{-1} F(X^{(k)})$$

1. Solve $[F'(X^{(k)})]H^{(k)} = -F(X^{(k)})$ 2. Update

$$X^{(k+1)} = X^{(k)} + H^{(k)}$$

Numerical Example

- $f_1(x, y) = 2x^2 + 3x 4 y = 0$
- $f_2(x, y) = x^2 + 2x + 3 y = 0$

$$F'(x) = \begin{bmatrix} 4x + 3, & -1 \\ 2x + 2, & -1 \end{bmatrix}$$

Numerical Example

•
$$x_0 = 1, y_0 = 1$$

k	х	У	f_1	f_2	Δx	Δy
0	1.0	1.0	-0.0	-5.0	1.6667	11.6667
1	2.6667	12.6667	-5.5556	-2.7778	-0.4386	-0.4386
2	2.2281	12.2281	-0.3847	-0.1924	-0.3526	-0.3526
3	2.1928	12.1928	-0.0025	-0.0013	-0.0002	-0.0002
4	2.1926	12.1926	-1.06e-07	-5.33e-08	-9.89e-09	-9.89e-09

Numerical Example



Roots of Polynomials

- Complications arise due to
 - Repeated roots
 - Complex roots
 - Sensitivity of roots to small perturbations in the polynomial coefficients (conditioning).



Algorithms for Finding Polynomial Roots

- Bairstow's method
- Müller's method
- Laguerre's method
- Jenkin's–Traub method
- Companion matrix method

roots Function

The built-in roots function in numpy uses the companion matrix method

- No initial guess
- Returns all roots of the polynomial
- Solves eigenvalue problem for companion matrix

Write polynomial in the form:

$$c_0 x^n + c_1 x^{n-1} + \dots + c_{n-1} x + c_n = 0$$

Then for a 3rd order polynomial:

```
>>> coeff = [3.2, 2, 1]
```

```
>>> np.roots(coeff)
```

array([-0.3125+0.46351241j, -0.3125-0.46351241j])

What is a Companion Matrix

Eigenvalues of:

$$\begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -c_0 & -c_1 & -c_2 & -c_3 \end{bmatrix}$$

Are the same as the roots of: $\lambda^4 + c_3\lambda^3 + c_2\lambda^2 + c_1\lambda + c_0 = 0$

Companion Matrix

To see this, recall $Ax = \lambda x$ is the equation satisfied by eigenvalues of A.

Write this as $(A - \lambda I)x = 0$.

Then the matrix

$$(A - \lambda I)x = \begin{bmatrix} -\lambda & 1 & 0 & 0\\ 0 & -\lambda & 1 & 0\\ 0 & 0 & -\lambda & 1\\ -c_0 & -c_1 & -c_2 & -\lambda - c_3 \end{bmatrix}$$

is singular and the determinant is zero. Because most of the elements are zero the determinant can be computed.

$$f(x) = x^2 - 10x + 25$$

Companion Matrix:

$$\begin{bmatrix} 0 & 1 \\ -25 & 10 \end{bmatrix}$$

```
>>> coef = [1.0,-10.0,25.0]
>>> np.roots(coef)
array([ 5., 5.])
>>> coef = [-25.0,10.0];
```

```
>>> A = scipy.array([[0.,1.],coef]);
```

```
>>> scipy.linalg.eig(A,right=False);
```

```
array([ 5.+0.j, 5.+0.j])
```

- Fractal: A mathematical pattern (geometric object) that is reproducible at any level of magnification or reduction.
- Fractal: A term used by Benoit Mandelbrot to refer to geometric objects with fractional dimensions rather than integer dimensions. Also used "fractal" to refer to shapes that are self-similar: they look the same at any zoom level.

Scientifically used to describe highly irregular objects

- fractal image compression
- Seismology
- Cosmology
- life sciences:
 - clouds and fluid turbulence
 - trees
 - coastlines
- More interesting observations:
 - New music/New art
 - Video games/graphics
 - Chaos theory
 - the Butterfly effect: small changes produces large effects

Fractal Generated Terrain



Recall Complex Numbers: $z \in C$ means

$$z = x + iy$$

where $i = \sqrt{-1}$

- Things to notice:
 - still think of the x-y plane, but now it's in C^1 instead of R^2
 - $-f(z) = z^{2} + 1 \text{ has 2 roots } z_{1,2} = \pm i$ -f(z) = z^{3} + 1 has 3 roots $z_{1} = 1, z_{2,3} = \frac{-1 \pm i\sqrt{3}}{2}$

 $-f(z) = z^4 + 1$ has 4 roots $z_{1,2} = -1, z_{3,4} = \pm i$

- Take a complex function like $f(z) = z^3 + 1$
- Pick a bunch of initial guesses z_0 as the roots
- Run Newton's Method
- The initial guesses z_0 will each converge to one of n = 3 roots
- Color each guess in the plane depending on the root to which it converged.

