

Broyden's method Summary

Newton's method for systems:

$$\vec{p}_{n+1} = \vec{p}_n - J^{-1}(\vec{p}_n) \vec{F}(\vec{p}_n) \quad (1.1)$$

$O(n^2)$ funct. evaluations to form $J(\vec{p}_n)$.

$O(n^3)$ operations to solve system:

$$J(\vec{p}_n) \vec{y}_{n+1} = -\vec{F}(\vec{p}_n) \quad (1.2)$$

Where

$$\vec{y}_{n+1} = \vec{p}_{n+1} - \vec{p}_n. \quad (1.3)$$

Broyden's idea is to construct a matrix A_k at every iteration step k , such that it only requires

$O(n)$ funct. evaluations. to construct it.

$O(n^2)$ operations. to solve system:

$$\vec{x}^{(k+1)} = \vec{x}^{(k)} - A_k^{-1} \vec{F}(\vec{x}^{(k)}) \quad (1.4)$$

Brayden's method is inspired in Secant method

Secant method replace $f'(p_n)$ in formula ^{Newt}

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

by $f'(p_n) \rightarrow \frac{f(p_n) - f(p_{n-1})}{p_n - p_{n-1}}$ (avoid computation of derivatives)

Brayden's method replaces $J(\vec{p}_n)$ in (1.1)

by

Step k : $\rightarrow$ Only $\mathcal{O}(n)$ functional evaluation.

$$A_k = A_{k-1} + \frac{\vec{F}(\vec{x}^{(k)}) - \vec{F}(\vec{x}^{(k-1)}) - A_{k-1}(\vec{x}^{(k)} - \vec{x}^{(k-1)})}{\|\vec{x}^{(k)} - \vec{x}^{(k-1)}\|^2} (\vec{x}^{(k)} - \vec{x}^{(k-1)})^T \quad (2.1)$$

Motivation for definition of A_k in following pages.

First goal of having only $\mathcal{O}(n)$ functional evaluations is accomplished by A_k .

ONLY-QNS

It can be proved that the inverse of A_k is given by (pages QN6-QN7)

$$A_k^{-1} = A_{k-1}^{-1} - \frac{[A_{k-1}^{-1} (\vec{F}(\vec{x}^{(k)}) - \vec{F}(\vec{x}^{(k-1)})) - (\vec{x}^{(k)} - \vec{x}^{(k-1)})] (\vec{x}^{(k)} - \vec{x}^{(k-1)})^T A_{k-1}^{-1}}{(\vec{x}^{(k)} - \vec{x}^{(k-1)})^T A_{k-1}^{-1} (\vec{F}(\vec{x}^{(k)}) - \vec{F}(\vec{x}^{(k-1)}))}$$

only n^2 operations: matrix $\times$ vector
 $n \times n$ $n \times 1$

Implementation:

Broyden's method requires two initial guess (similar to secant method).

Step 1: $\vec{x}^0$ initial guess

Compute $J(\vec{x}^0)$. And $F(\vec{x}^0)$

Step 2: Compute $\vec{x}^1$ using Newton's method

But, first compute the inverse

$$J^{-1}(\vec{x}^0)$$

and then obtain

$$\vec{x}^{(1)} = \vec{x}^0 - J^{-1}(\vec{x}^0) F(\vec{x}^0)$$

Step 3:

Use $\bar{x}^0$, $\bar{x}^{(1)}$ and $J^{-1}(\bar{x}^0)$ to define A_1^{-1}

In fact, if

$$\begin{aligned}\bar{s}^1 &= \bar{x}^1 - \bar{x}^0 \rightarrow n \text{ functional evaluations.} \\ \bar{y}^1 &= F(\bar{x}^1) - F(\bar{x}^0) \\ \bar{p}^1 &= J^{-1}(\bar{x}^0) \bar{y} \rightarrow n^2 \text{ operations}\end{aligned}$$

Then,

$$A_1^{-1} = J^{-1}(\bar{x}^0) + \frac{(\bar{s}^1 - \bar{p}^1) * \bar{s}^{1T} * J^{-1}(\bar{x}^0)}{\bar{s}^{1T} * \bar{p}^1}$$

Step 4:

Compute $\bar{x}^2$

$$\bar{x}^2 = \bar{x}^1 - A_1^{-1} \bar{F}(\bar{x}^1) \rightarrow n^2 \text{ operations.}$$

STEP 5:

Repeat the previous steps. and obtain

A_k^{-1} from A_{k-1}^{-1} and then $\bar{x}^{k+1}$

$$A_k^{-1} = A_{k-1}^{-1} + \frac{(\bar{s}^k - \bar{p}^k) * (\bar{s}^k)^T A_{k-1}^{-1}}{(\bar{s}^k)^T \bar{p}^k}$$

and

$$\bar{x}^{k+1} = \bar{x}^k - A_k^{-1} \bar{F}(\bar{x}^k)$$

where $\bar{s}^k = \bar{x}^k - \bar{x}^{k-1}$, $\bar{y}^k = F(\bar{x}^k) - F(\bar{x}^{k-1})$
and $\bar{p}^k = A_{k-1}^{-1} \bar{y}^k$.

Exercise 10.1 (3)

Find the roots of

$$X_1^2 - 10X_1 + X_2^2 + 8 = 0$$

$$X_1 X_2 + X_1 - 10X_2 + 8 = 0$$

Initial guess: $\bar{X}^0 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$.

Step 1: Computation of

$$J(1) = \begin{bmatrix} -9 & 1 \\ 5/4 & -19/2 \end{bmatrix}$$

$$\tilde{F}(1) = \begin{bmatrix} 7/2 \\ 29/8 \end{bmatrix}$$

Step 2: $J^{-1}(1) = \begin{bmatrix} -38/337 & -4/337 \\ -5/337 & -36/337 \end{bmatrix}$

$$\bar{X}^{(1)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix} - J^{-1}(1) \tilde{F}(1) = \begin{pmatrix} 0.937685 \\ 0.939169 \end{pmatrix}$$

Step 3: Definition of A_1'

$$\bar{S}' = \bar{X}' - \bar{X}^0 = \begin{pmatrix} 295/674 \\ 148/337 \end{pmatrix}, \quad \hat{p}' = J^{-1}(\bar{X}^0) (F(\bar{X}') - F(\bar{X}^0))$$

$$\text{or } \hat{p}' = \begin{pmatrix} 0.3899 \\ 0.3936 \end{pmatrix}$$

Then,

$$A_1^{-1} = J^{-1}(1) + \frac{(\hat{S}' - \hat{p}')(\hat{S}')^T J^{-1}(1)}{(\hat{S}')^T \hat{p}'}$$

or

$$A_1^{-1} = \begin{bmatrix} -0.12 & -0.02 \\ -0.02 & -0.11 \end{bmatrix}, \quad \tilde{F} \begin{pmatrix} 0.938 \\ 0.9391 \end{pmatrix} =$$

Step 4:

$$\hat{X}^{(2)} = \begin{pmatrix} 0.9912 \\ 0.9902 \end{pmatrix} - A_1^{-1} \begin{pmatrix} 0.3844 \\ 0.3731 \end{pmatrix} =$$

$$\text{or } \hat{X}^{(2)} = \begin{pmatrix} 0.991154 \\ 0.990153 \end{pmatrix}$$

10.3 Quasi-Newton Methods.

They are inspired in the "Secant Method" which is used instead of Newton to reduce number of operations due to computation of $f'(x)$.

Newton Iteration:

$$p_n = g(p_{n-1}) = p_{n-1} - \frac{f(p_{n-1})}{f'(p_{n-1})}, \quad n \geq 1$$

p_0 initial guess.

Secant Method:

$$p_n = g(p_{n-1}) = p_{n-1} - \frac{f(p_{n-1})}{\frac{f(p_{n-1}) - f(p_{n-2})}{p_{n-1} - p_{n-2}}}, \quad n \geq 1$$

p_0, p_1 initial guess

$f'(p_{n-1})$ is replaced by $\frac{f(p_{n-1}) - f(p_{n-2})}{p_{n-1} - p_{n-2}}$

Recall that

$$f'(p_{n-1}) = \lim_{x \rightarrow p_{n-1}} \frac{f(x) - f(p_{n-1})}{x - p_{n-1}} \approx \overset{\text{for } x \text{ close to } p_{n-1}}{\frac{f(x) - f(p_{n-1})}{x - p_{n-1}}}$$

If $x = p_{n-2}$, then

$$f'(p_{n-1}) \approx \frac{f(p_{n-2}) - f(p_{n-1})}{p_{n-2} - p_{n-1}} = \frac{f(p_{n-1}) - f(p_{n-2})}{p_{n-1} - p_{n-2}}$$

- Newton has quadratic convergence or $\lim_{n \rightarrow \infty} \frac{|p_n - p|}{|p_{n-1} - p|^2} = \alpha$

- Secant method

is order ≈ 1.62
or it has superlinear convergence

$$\lim_{n \rightarrow \infty} \frac{|p_n - p|}{|p_{n-1} - p|^{1.62}} = \lambda.$$

Counting operations. Computational cost.

i) Gauss Elimination: $A_{n \times n}$

To eliminate each entry below diagonal (in total $\frac{n(n-1)}{2}$) takes

$$\left(\begin{array}{c} n(n-1)/2 \\ \hline n(n-1)/2 \end{array} \right)$$

n operations.

Then G-E requires $\frac{n(n-1)}{2} \cdot n = O(n^3)$ operations.

ii) Computation of the Jacobian at each Newt. iteration requires n^2 funct. evaluation (1 funct. evaluation per entry)

iii) Evaluation of the vector $\vec{F}(\vec{x})$ in Newt. iteration for nonlinear systems

$$\left\{ \begin{array}{l} - \boxed{J(\vec{x}^k) \vec{y}^{(k)} = -\vec{F}(\vec{x}^k)} \end{array} \right. \quad (2.1)$$

$$\left\{ \begin{array}{l} - \boxed{\vec{x}^{(k+1)} = \vec{x}^k + \vec{y}^k} \end{array} \right. \quad (2.2)$$

requires n function evaluations.

$$\boxed{\vec{x}^{(k+1)} = \vec{x}^k - J(\vec{x}^k)^{-1} \vec{F}(\vec{x}^k)} \quad (2.3)$$

So

$$1 \text{ Newt. iteration} \approx \begin{cases} O(n^2 + n) \\ n^3 \end{cases} \begin{matrix} \text{Evaluations} \\ \text{operations} \end{matrix}$$

Most attractive feature of Newt. method : Quadratic Convergence.

Broyden's Method

Jacobian matrix is approximated by a

matrix A_k at every iteration step : $\boxed{\vec{X}^{(k+1)} = \vec{X}^{(k)} - A_k^{-1} \vec{F}(\vec{X}^{(k)})}$

i) computation of A_k : only requires $O(n)$ evaluations, instead of $O(n^2)$ of Newton method per iteration.

ii) Computation of the inverse of A_k requires $O(n^2)$ operations, instead of $O(n^3)$ operations required by Newton method to solve linear system at each iteration.

Summarizing,

	Newt	Broyden
Constructing matrix	$O(n^2)$	$O(n)$
# Opers. to solve linear system	$O(n^3)$	$O(n^2)$
order of convergence	Order 2	Superlinear

$$\lim_{k \rightarrow \infty} \frac{\|\vec{X}^k - \vec{p}\|}{\|\vec{X}^{k-1} - \vec{p}\|} = 0$$

$$\text{but } \lim_{k \rightarrow \infty} \frac{\|\vec{X}^k - \vec{p}\|}{\|\vec{X}^{k-1} - \vec{p}\|^2} = \infty$$

Broyden method replaces $J(\vec{x}^k)$ by a matrix A_k

$$\vec{x}^{(k+1)} = \vec{x}^{(k)} - A_k^{-1} \vec{F}(\vec{x}^k) \quad (4.1)$$

Construction of A_k at each iteration and $\vec{x}^{(1)} = \vec{x}^{(0)} - J(\vec{x}^0)^{-1} \vec{F}(\vec{x}^0)$

Process starts with $\textcircled{a} A_0 = J(\vec{x}^0)$. Then, to obtain A_1 two conditions are required

$$A_1 (\vec{x}^{(1)} - \vec{x}^{(0)}) = F(\vec{x}^1) - F(\vec{x}^0) \quad (4.2)$$

Not enough $\nearrow$ and $A_1 \hat{z} = J(\vec{x}^0) \hat{z}$, when $\hat{z} \cdot (\vec{x}^1 - \vec{x}^0) = 0 \quad (4.3)$

It can be shown that (4.2) and (4.3) defines A_1 uniquely.

$$A_1 \equiv J(\vec{x}^0) + \frac{[F(\vec{x}^1) - F(\vec{x}^0) - J(\vec{x}^0)(\vec{x}^1 - \vec{x}^0)] (\vec{x}^1 - \vec{x}^0)^T}{\|\vec{x}^{(1)} - \vec{x}^{(0)}\|_2^2}$$

Check conds. (4.2) and (4.3).

A_1 is now used to compute $\vec{x}^{(2)}$

$$\vec{x}^{(2)} = \vec{x}^{(1)} - A_1^{-1} \vec{F}(\vec{x}^{(1)})$$

At step k : $\vec{x}^{(k)}$ is computed

Assuming $\vec{x}^{(k)}$ and A_{k-1} are known

$$A_k = A_{k-1} + \frac{[F(\vec{x}^k) - \tilde{F}(\vec{x}^{k-1}) - A_{k-1}(\vec{x}^k - \vec{x}^{k-1})](\vec{x}^k - \vec{x}^{k-1})^T}{\|\vec{x}^k - \vec{x}^{k-1}\|_2^2}$$

and

$$\vec{x}^{k+1} = \vec{x}^{(k)} - A_k^{-1} \tilde{F}(\vec{x}^k)$$

$\rightarrow n$ function evaluations only.

It still requires $\mathcal{O}(n^3)$ operations for matrix inversion of A_k^{-1}

Not Enough!

Sherman-Morrison Formula

1) A nonsingular

2) $\vec{x}, \vec{y}$ two vectors such that $\vec{y}^T A^{-1} \vec{x} \neq -1$

Then, $A + \vec{x} \vec{y}^T$ is nonsingular and

$$(A + \vec{x} \vec{y}^T)^{-1} = A^{-1} - \frac{A^{-1} \vec{x} \vec{y}^T A^{-1}}{1 + \vec{y}^T A^{-1} \vec{x}}$$

Thm. 10.8 (Sherman Morrison Formula)

If ① A is nonsingular.

② $\vec{u}, \vec{w}$ two vectors such that $\vec{w}^T A^{-1} \vec{u} \neq -1$

Then,

$A + u w^T$ is nonsingular and

$$(A + u w^T)^{-1} = A^{-1} - \frac{A^{-1} \vec{u} \vec{w}^T A^{-1}}{1 + \vec{w}^T A^{-1} \vec{u}} \quad (6.0)$$

Application to obtain Broyden's method

At Step k , Broyden's method matrix is given by

$$(6.1) \quad A_k = A_{k-1} + \frac{[\vec{F}(\vec{x}^k) - \vec{F}(\vec{x}^{k-1}) - A_{k-1}(\vec{x}^k - \vec{x}^{k-1})](\vec{x}^k - \vec{x}^{k-1})^T}{\|\vec{x}^k - \vec{x}^{k-1}\|_2^2}$$

$$\text{If } \vec{u} = \frac{[\vec{F}(\vec{x}^k) - \vec{F}(\vec{x}^{k-1}) - A_{k-1}(\vec{x}^k - \vec{x}^{k-1})]}{\|\vec{x}^k - \vec{x}^{k-1}\|_2^2}$$

and

$$\vec{w} = (\vec{x}^k - \vec{x}^{k-1})$$

Then (6.1) reduces to

$$A_k = A_{k-1} + \vec{u} \vec{w}^T$$

Applying S-M formula (6.0)

$$A_k^{-1} = (A_{k-1} + \tilde{u} \tilde{w}^T) = A_{k-1}^{-1} - \frac{A_{k-1}^{-1} \tilde{u} \tilde{w}^T A_{k-1}^{-1}}{1 + \tilde{w}^T A_{k-1}^{-1} \tilde{u}}$$

Now,

$$A_{k-1}^{-1} \tilde{u} \tilde{w}^T A_{k-1}^{-1} = A_{k-1}^{-1} \left(\frac{[\tilde{F}(\tilde{x}^k) - \tilde{F}(\tilde{x}^{k-1}) - A_{k-1}(\tilde{x}^k - \tilde{x}^{k-1})]}{\|\tilde{x}^k - \tilde{x}^{k-1}\|_2^2} (\tilde{x}^k - \tilde{x}^{k-1})^T \right) A_{k-1}^{-1}$$

or

$$A_{k-1}^{-1} \tilde{u} \tilde{w}^T A_{k-1}^{-1} = \frac{[A_{k-1}^{-1} (\tilde{F}(\tilde{x}^k) - \tilde{F}(\tilde{x}^{k-1})) - (\tilde{x}^k - \tilde{x}^{k-1})] (\tilde{x}^k - \tilde{x}^{k-1})^T A_{k-1}^{-1}}{\|\tilde{x}^k - \tilde{x}^{k-1}\|_2^2}$$

$$\text{and } 1 + \tilde{w}^T A_{k-1}^{-1} \tilde{u} = 1 + (\tilde{x}^k - \tilde{x}^{k-1})^T A_{k-1}^{-1} \left(\frac{\tilde{F}(\tilde{x}^k) - \tilde{F}(\tilde{x}^{k-1}) - A_{k-1}(\tilde{x}^k - \tilde{x}^{k-1})}{\|\tilde{x}^k - \tilde{x}^{k-1}\|_2^2} \right)$$

or

$$1 + \tilde{w}^T A_{k-1}^{-1} \tilde{u} = \frac{\cancel{\|\tilde{x}^k - \tilde{x}^{k-1}\|_2^2} + (\tilde{x}^k - \tilde{x}^{k-1})^T A_{k-1}^{-1} (\tilde{F}(\tilde{x}^k) - \tilde{F}(\tilde{x}^{k-1})) - \cancel{\|\tilde{x}^k - \tilde{x}^{k-1}\|_2^2}}{\|\tilde{x}^k - \tilde{x}^{k-1}\|_2^2}$$

Therefore,

$$A_k^{-1} = A_{k-1}^{-1} - \frac{[A_{k-1}^{-1} (\tilde{F}(\tilde{x}^k) - \tilde{F}(\tilde{x}^{k-1})) - (\tilde{x}^k - \tilde{x}^{k-1})] (\tilde{x}^k - \tilde{x}^{k-1})^T A_{k-1}^{-1}}{(\tilde{x}^k - \tilde{x}^{k-1})^T A_{k-1}^{-1} (\tilde{F}(\tilde{x}^k) - \tilde{F}(\tilde{x}^{k-1}))}$$

only n^2 operations
(matrix) times a (vector)_n
n x n