ACM40290: Numerical Algorithms

Nonlinear Equations

Dr Barry Wardell School of Mathematics and Statistics University College Dublin

Problem: find the roots, **x**, of a vector-valued function

$$\mathbf{f}: \mathbb{R}^n \to \mathbb{R}^n$$
 so that $\mathbf{f}(\mathbf{x}) = 0$

For example, if n=2 we might consider solving the problem

$$\mathbf{f}: \left\{ \begin{array}{l} x_1 - x_2^2 + 1 = 0 \\ 3x_1x_2 + x_2^3 = 0 \end{array} \right.$$

We are very familiar with scalar (n=1) nonlinear equations Simplest case is a quadratic equation

$$\left[ax^2 + bx + c = 0\right]$$

We can write down a closed-form solution[†], the quadratic formula

$$x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

†A closed-form expression involves only a finite number of "well-known" functions, e.g. +, -, ×, ÷, trigonometric functions, logarithms, etc.

Our n=2 example has similarly trivial solutions

$$\begin{bmatrix} x_1 - x_2^2 + 1 = 0 \\ 3x_1x_2 + x_2^3 = 0 \end{bmatrix} \Rightarrow \begin{bmatrix} x_1 = x_2^2 - 1 \\ x_1 = x_2^2 - 1 \end{bmatrix} \Rightarrow \begin{bmatrix} (4x_2^2 - 3)x_2 = 0 \\ (4x_2^2 - 3)x_2 = 0 \end{bmatrix}$$

$$\{-1,0\}$$

$$\{x_1,x_2\} = \{-\frac{1}{4},\sqrt{\frac{3}{4}}\}$$

$$\{-\frac{1}{4},-\sqrt{\frac{3}{4}}\}$$

What about the more general case?

- * In fact, there are closed-form solutions for arbitrary cubic and quartic polynomials (Ferrari & Cardano, ~1540).
- * Important mathematical result (Galois, Abel) is that there is no closed-form solution for fifth or higher order polynomial equations.
- * Hence, even for the simplest type of nonlinear equation (polynomials on \mathbb{R}), the only hope is to employ an iterative algorithm.
- * An iterative method should converge in the limit where the number of iterations goes to infinity, and ideally yields an accurate approximation after a small number of iterations.

Problem: find the roots, **x**, of a vector-valued function

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For many real problems n may be large, $n \sim 10,000$ is not uncommon.

Use an iterative algorithm to generate a sequence of vectors that converge to the solution.

Minimisation and Optimisation

Closely related to both of these problems is the question of minimising a function

$$g(\mathbf{x}): \mathbb{R}^n \to \mathbb{R}$$

Such a problem can take one of two forms:

- 1. Unconstrained optimisation: minimise g(x).
- 2. Constrained optimisation: minimise g(x) with an additional condition f(x) = 0 or possibly $f(x) \ge 0$.

This is a distinct problem, which we will come back to later.

Converting Equations to Fixed Point Form

We wish to solve f(x) = 0 iteratively. We need to transform the equation f(x) = 0 to the fixed-point form

$$x = T(x)$$

so that we can apply successive approximations which converge to a fixed point of *T*. Assume

$$\left| x_{k+1} = T(x_k) \right|$$

generates $\{x_0, x_1, x_2, x_3, ..., x_k, ...\} \rightarrow x$.

Converting Equations to Fixed Point Form

Many possible transformations

*
$$T(x) = x - f(x)$$
 (Rarely works because *T* is rarely a contraction mapping)

*
$$T(x) = x - G(x) f(x), 0 < |G(x)| < \infty$$

* etc.

We will look at a set of algorithms that have been well tested and analysed.

Iteratively Solving Nonlinear Equations

We are going to consider iterations of the form:

$$x_{k+1} = T(x_k), \quad k = 0, 1, 2, \dots$$
 (*)

for solving nonlinear equations.

For example, Heron's method for solving $x^2 - a = 0$ (i.e. for computing square roots) is:

$$x_{k+1} = \frac{1}{2} \left(x_k + \frac{a}{x_k} \right)$$

This uses
$$T_{\text{Heron}}(x) = \frac{1}{2} \left(x + \frac{a}{x} \right)$$

Suppose α is such that $T(\alpha) = \alpha$, then we call α a **fixed point** of T.

For example, we see that \sqrt{a} is a fixed point of $T_{\rm Heron}$ since

$$T_{\text{Heron}}(\sqrt{a}) = \frac{1}{2} \left(\sqrt{a} + \frac{a}{\sqrt{a}} \right) = \sqrt{a}$$

An iteration of the form (*) "terminates" once a fixed point is reached, since if $T(x_k) = x_k$ then we get $x_{k+1} = x_k$.

Also, if $x_{k+1} = T(x_k)$ converges as $k \to \infty$, it must converge to a fixed point: Let $\alpha \equiv \lim_{k \to \infty} x_k$, then

$$\alpha = \lim_{k \to \infty} x_k = \lim_{k \to \infty} T(x_k) = T\left(\lim_{k \to \infty} x_k\right) = T(\alpha)$$

But in order to use an iteration to compute fixed points in practice, we must be able to guarantee that it will converge...

You may recall from other modules that a function T satisfies a Lipschitz condition in an interval [a, b] if $\exists L \in \mathbb{R}_{>0}$ such that

$$|T(x) - T(y)| \le L|x - y|, \quad \forall x, y \in [a, b]$$

If L < 1, then T is called a **contraction**.

Theorem: Suppose that $T(\alpha) = \alpha$ and that T is a contraction on $[\alpha - A, \alpha + A]$. Suppose also that $|x_0 - \alpha| \le A$. Then the fixed point iteration converges to α .

Proof:

$$|x_k - \alpha| = |T(x_{k-1}) - T(\alpha)| \le L |x_{k-1} - \alpha|,$$

which implies

$$|x_k - \alpha| \le L^k |x_0 - \alpha|$$

and, since L < 1, $|x_k - \alpha| \rightarrow 0$ as $k \rightarrow \infty$.

(Note that $|x_0 - \alpha| \le A$ implies that all iterates are in $[\alpha - A, \alpha + A]$.

Recall that if $T \in C^1[a, b]$, we can obtain a Lipschitz constant based on T':

$$L = \max_{\theta \in (a,b)} |T'(\theta)|$$

We now use this result to show the if $|T'(\alpha)| < 1$, then there is a neighbourhood of α on which T is a contraction.

This tells us that we can verify convergence of a fixed point iteration scheme by checking the gradient of *T*.

By continuity of T' (and hence continuity of |T'|), for any $\epsilon > 0$, $\exists \ \delta > 0$ such that for $x \in (\alpha - \delta, \alpha + \delta)$:

$$| |T'(x)| - |T'(\alpha)| | \leq \epsilon$$

This implies

$$\max_{x \in (\alpha - \delta, \alpha + \delta)} |T'(x)| \le |T'(\alpha)| + \epsilon$$

Suppose $|T'(\alpha)| < 1$ and set $\epsilon = \frac{1}{2} (1 - |T'(\alpha)|)$, then there is a neighbourhood on which T is Lipschitz with $L = \frac{1}{2} (1 - |T'(\alpha)|)$

Then L < 1 and hence T is a contraction in a neighbourhood of α .

Furthermore, as $k \rightarrow \infty$,

$$\frac{|x_{k+1} - \alpha|}{|x_k - \alpha|} = \frac{|T(x_k) - T(\alpha)|}{|x_k - \alpha|} \to |T'(\alpha)|$$

Hence, asymptotically, error decreases by a factor of $|T'(\alpha)|$ after each iteration.

Order of Convergence

We assume that any iterative algorithm for zero-finding generates a sequence $\{x_0, x_1, ..., x_k, ...\} \rightarrow x$, the solution to f(x) = 0, and that the error at stage k is defined as

$$e_k = |x_k - x|$$
, error at stage k .

Therefore, we may view an iterative algorithm as generating a sequence of errors

$$\{e_0, e_1, \ldots, e_k, \ldots\} \to 0.$$

In theory this sequence is infinite but in practice finite precision forces us to stop at some stage k when $e_k \le \epsilon$, for some chosen ϵ .

Order of Convergence

Definition (Order of Convergence)

Let $\{x_0, x_1, ..., x_k, ...\} \rightarrow x$, and $e_k = |x_k - x|$. If there exists a number p and a constant $C \neq 0$ such that

$$\lim_{k \to \infty} \frac{e_k}{e_{k-1}^p} = C$$

then *p* is called the *Order of Convergence* of $\{x_k\}$.

We assume that $e_k < 1$, for all k. A more usable definition is

$$e_k = Ce_{k-1}^p$$

where *C* possibly depends on *k*, but can be bounded above by a constant.

Sequences with p = 1 are said to have *Linear Convergence*, while sequences with p > 1 have *Super-Linear Convergence*.

Convergence of Successive Approximation

Consider the sequence $\{x_k = T(x_{k-1})\}$ and assume it converges to a fixed point x = T(x). Assume further that at the fixed point the derivatives T'(x), T''(x), ..., $T^{(n)}(x)$ exist. Expanding $T(x_k)$ in a Taylor series about the fixed point x, we get

$$T(x_k) = T(x) + \frac{1}{1!}T'(x)(x_k - x) + \frac{1}{2!}T''(x)(x_k - x)^2 + \dots + \frac{1}{n!}T^{(n)}(x)(x_k - x)^n + R_{n+1}$$

or

$$T(x_k) - T(x) = \frac{1}{1!}T'(x)(x_k - x) + \frac{1}{2!}T''(x)(x_k - x)^2 + \dots + \frac{1}{n!}T^{(n)}(x)(x_k - x)^n + R_{n+1}$$

Now $|T(x_k) - T(x)| = |x_{k+1} - x| = e_{k+1}$. Hence we get, using the triangle inequality,

$$|e_{k+1} \le |T'(x)|e_k + \frac{1}{2}|T''(x)|e_k^2 + \dots + \frac{1}{n!}|T^{(n)}(x)|e_k^n + |R_{n+1}|$$

Convergence of Successive Approximation

1.If
$$T'(x) \neq 0$$
 then $e_{k+1} \approx T'(x) e_k$,

2.If
$$T'(x) = 0$$
, $T''(x) \neq 0$ then $e_{k+1} \approx T''(x) e_k^2$,

3.If
$$T'(x) = T''(x) = \dots = T^{(n-1)}(x) = 0$$
,
 $T^{(n)}(x) \neq 0$ then $e_{k+1} \approx T^{(n)}(x) e_k^n$,

1st order convergence

2nd order convergence

n-th order convergence

Example: Square Root \sqrt{a}

$$x_{k+1} = \frac{1}{2} \left(x_k + \frac{a}{x_k} \right) \equiv T(x_k)$$

The mapping T(x) = (x + a/x)/2 has a fixed point $x = \sqrt{a}$. The derivative is $T'(x) = (1-a/x^2)/2$. This gives $T'(\sqrt{a}) = (1-a/a)/2 = 0$. Hence this algorithm has **second order convergence**, at least.

k	0	1	2	3	4	5	6
x_k	1.0	2.5	2.05	2.0006098	2.0000001	2.0000000	2.0000000
e_k	1	0.5	0.05	0.000609	9.2×10 ⁻⁸	2.15×10 ⁻¹⁵	1.16×10 ⁻³⁰

The effect of second order convergence is to double the number of correct digits at each iteration or $e_k \approx e_{k-1}^2 \approx e_0^{2^k}$. If $e_0 = 2^{-1}$ then $e_k \approx e_0^{2^k} = 2^{-2^k}$. For k = 6 we get $e_k = 2^{-64} \approx 10^{-20}$. This means that k = 6 iterations are sufficient to give full IEEE double precision.

Algorithms for Solving Nonlinear Equations

- * Iterative algorithms for non-linear equations fall into two broad categories:
 - 1. Locally convergent and fast.
 - 2. Globally convergent and slow.
- * A good algorithm should:
 - 1. Be easy to use, preferably using only information on f, not on its derivative.
 - 2. Be reliable, i.e., it should find a root close to an initial guess and not go off to become chaotic.
- * There is no ideal method. MATLAB uses a combination of methods to find the root. We will study a few of these.

Algorithms for Solving Nonlinear Equations

- Bisection algorithm
- * Newton's (Newton-Raphson) method
- Secant algorithm
- * Multipoint secant algorithms (e.g. Muller's three-point algorithm, inverse quadratic interpolation)