

Last time

9/26/23

Solving eigenvalue problem $A\vec{v} = \lambda\vec{v}$

for largest eigenvalue using 'power' method

We iterate

$$\vec{z}^{(k)} = A^k \vec{z}^{(0)}$$

Starting with a guess that needs to have
a component along \vec{v}_0

Rayleigh quotient $\mu(\vec{x}) = \frac{\vec{x}^T A \vec{x}}{\vec{x}^T \vec{x}}$

and normalize $\vec{q}^{(k)} = \frac{\vec{z}^{(k)}}{\|\vec{z}^{(k)}\|}$

$$\vec{z}^{(k)} = A \vec{q}^{(k-1)}$$

$$\vec{q}^{(k)} = \vec{z}^{(k)} / \|\vec{z}^{(k)}\|$$

$$\mu(\vec{q}^{(k)}) = [\vec{q}^{(k)}]^T A \vec{q}^{(k)}$$

Eventually $\mu(\vec{q}^{(k)}) \rightarrow \lambda_0 \quad \vec{q}^{(k)} \rightarrow \vec{v}_0$

Zeros and Minima (Chapter 5)

5-1

We often need to solve equations of the form $f(x) = 0$ where $f(x)$ is non-linear

Van der Waals equation of state $(p + a/v^2)(v - b) = RT$ $v = \frac{V}{\text{mole}}$

QM particle in finite well of width $2a$, height V_0

$$k \tan(ka) = \left[\frac{2mV_0}{\hbar^2} - k^2 \right]^{1/2}$$

Or worse: $\vec{f}(\vec{x}) = \vec{0}$

$$f_0(x_0, x_1, \dots, x_{n-1}) = 0$$

$$f_1(x_0, x_1, \dots, x_{n-1}) = 0$$

!

$$f_{n-1}(x_0, x_1, \dots, x_{n-1}) = 0$$

n non-linear equations w/ n unknowns

Also we want to solve or find minima of scalar ϕ

$$\min \phi(\vec{x}) = \min \phi(x_0, x_1, \dots, x_{n-1})$$

Our test problem $f(x) = e^{x-\sqrt{x}} - x = 0$

[see plot]

We observe roots around 1, 2.5

(1 is clearly exact)

Bisection Method

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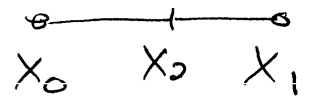
Assume you have 'bracketed' a root

\Rightarrow found an x_0 and x_1 such that

$f(x_0)$ and $f(x_1)$ have opposite signs

So the root must exist in interval (x_0, x_1)

Evaluate midpoint $x_2 = \frac{x_0 + x_1}{2}$



Evaluate $f(x_0)f(x_2)$

If $f(x_0)f(x_2) < 0$ root is in (x_0, x_2)

repeat with x_2 in place of x_1

If $f(x_0)f(x_2) > 0$ root is in (x_2, x_1)

repeat with x_2 in place of x_0

If we call $x_0 = a$ and $x_1 = b$ we generate

a series of iterations $x^{(0)} = x^0, x^{(1)}, x^{(2)}, \dots$

where each new iteration halves the interval

So if x^* is true root

$$|x^{(k)} - x^*| \leq \frac{1}{2} |x^{(k-1)} - x^*| \quad (\text{See Egn 5.16})$$

our iterations are linearly convergent

We choose to terminate iterations when 5-3
fractional change is less than tolerance

$$\frac{|x^{(k)} - x^{(k-1)}|}{|x^{(k)}|} \leq \epsilon \sim \text{small \#}$$

[See bisection.py]

Doesn't generalize well to higher dimensional problems

Newton's Method

Need $f(x)$ and $f'(x)$

Let $x^{(k-1)}$ be our last iteration (or first guess)

Taylor expand $f(x)$ around this point

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

where ξ is a point between x and $x^{(k-1)}$

Take $x = x^*$ so $f(x^*) = 0$. If $f(x)$
is linear (it isn't, but if it was)

$$f(x^*) = 0 = f(x^{(k-1)}) + (x^* - x^{(k-1)}) f'(x^{(k-1)})$$

$$\Rightarrow x^* = x^{(k-1)} - \frac{f(x^{(k-1)})}{f'(x^{(k-1)})}$$

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So when $f(x)$ is not linear we will iterate w/

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

Can show from our earlier equation with $x=x^*$ and keeping $f''(f)$ term that (lots of algebra!)

$$x^{(k)} - x^* = C (x^{(k-1)} - x^*)^2$$

where C depends on $f''(f)$ and $f'(x^{(k-1)})$
Method is quadratically convergent

Geometric interpretation and trouble on next pages

Approx $f(x)$ with tangent at $x^{(k-1)}, f(x^{(k-1)})$

get $x^{(k)}$ by point where tangent

crosses x axis

visional problems in a reasonably straightforward manner. At a big-picture level, Newton's method requires more input than the approaches we saw earlier: in addition to being able to evaluate the function $f(x)$, one must also be able to evaluate its first derivative, $f'(x)$. This is obviously trivial for our example above, where $f(x)$ is analytically known, but may not be so easy to access for the case where $f(x)$ is an externally provided (costly) routine. Furthermore, to give the conclusion ahead of time: there are many situations in which Newton's method can get in trouble, so it always pays to think about your specific problem instead of blindly trusting a canned routine. Even so, if you already have a reasonable estimate of where the root may lie, Newton's method is usually a fast and reliable solution.

5.2.5.1 Algorithm and Interpretation

We will assume that $f(x)$ has continuous first and second derivatives. Also, take $x^{(k-1)}$ to be the last iterate we've produced (or just an initial guess). Similarly to what we did in 5.2.6 above, we will now write down a Taylor expansion of $f(x)$ around $x^{(k-1)}$, then we go up to one order higher:

$$f(x) = f(x^{(k-1)}) + (x - x^{(k-1)}) f'(x^{(k-1)}) + \frac{1}{2} (x - x^{(k-1)})^2 f''(\xi) \quad (5.37)$$

where ξ is a point between x and $x^{(k-1)}$. If we now take $x = x^*$ then we have $f(x^*) = 0$. Further assume that $f(x)$ is linear (in which case $f''(\xi) = 0$), we get:

$$0 = f(x^{(k-1)}) + (x^* - x^{(k-1)}) f'(x^{(k-1)}) \quad (5.38)$$

which can be re-arranged to give:

$$x^* = x^{(k-1)} - \frac{f(x^{(k-1)})}{f'(x^{(k-1)})} \quad (5.39)$$

For a linear function, an initial guess can be combined with the values of the function and the first derivative (at that initial guess) to locate the root.

This motivates Newton's method: if $f(x)$ is non-linear, we still use the same formula as in 5.39, this time in order to evaluate not the root but our next iterate (which, we hope, is closer to the root):

$$x^{(k)} = x^{(k-1)} - \frac{f(x^{(k-1)})}{f'(x^{(k-1)})}, \quad k = 1, 2, \dots \quad (5.40)$$

As we did in the previous paragraph, we are here neglecting the second derivative term in the Taylor expansion. However if we are, indeed, converging, then $(x^{(k)} - x^{(k-1)})^2$ in 5.37 will actually be smaller than $x^{(k)} - x^{(k-1)}$, so all will be well.

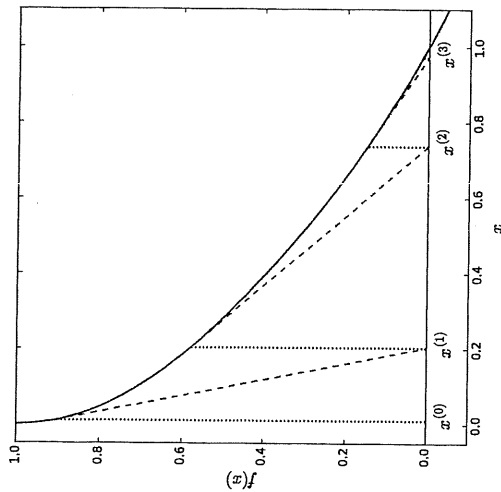


Illustration of Newton's method for our example function

Each $x^{(k)}$ is the point where the tangent intercepts the x axis and repeat. For our example, this process brings us very close to the root in just a few steps.

5.2.5.2 Convergence Properties

We now turn to the convergence properties of Newton's method. To orient the reader, what we will try to do is to relate $x^{(k)} - x^*$ to $x^{(k-1)} - x^*$, as per Eq. (5.16). We will employ our earlier Taylor expansion, Eq. (5.37), and take $x = x^*$, but this time without assuming that the second derivative vanishes. Furthermore, we assume that we are dealing with a simple root x^* , for which we therefore have $f'(x^*) \neq 0$; that means we can also assume $f''(x) \neq 0$ in the vicinity of the root. We have:

$$0 = f(x^{(k-1)}) + (x^* - x^{(k-1)}) f'(x^{(k-1)}) + \frac{1}{2} (x^* - x^{(k-1)})^2 f''(\xi) \quad (5.41)$$

where the left-hand side is the result of $f(x^*) = 0$.

Dividing by $f'(x^{(k-1)})$ and re-arranging, we find:

$$-\frac{f(x^{(k-1)})}{f'(x^{(k-1)})} - x^* + x^{(k-1)} = \frac{(x^* - x^{(k-1)})^2 f''(\xi)}{2f'(x^{(k-1)})} \quad (5.42)$$

The first and third terms on the left-hand side can be combined together to give $x^{(k)}$, as per Newton's prescription in Eq. (5.40). This leads to:

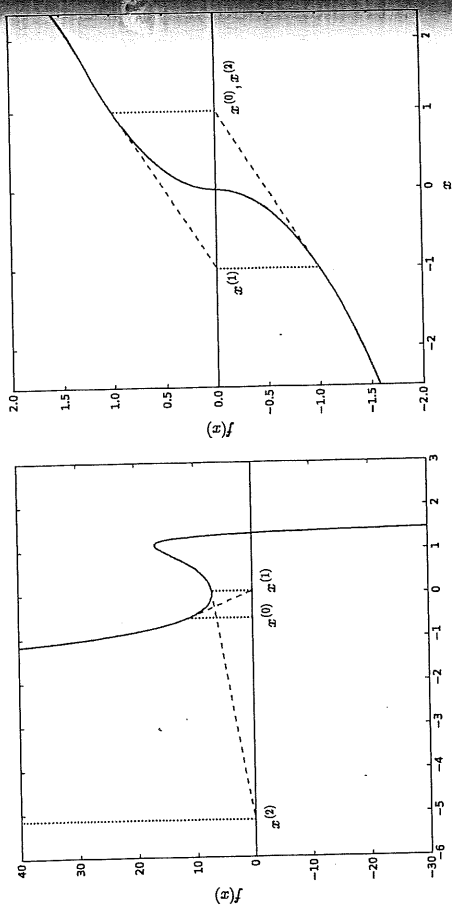


Fig. 5.8 Cases where Newton's method struggles

sides, our result is identical to that in Eq. (5.16), under the assumption that:

$$\frac{f''(\xi)}{2f'(x^{(k-1)})} \leq m \quad (5.44)$$

Since the right-hand side of Eq. (5.43) contains a square, we find that, using the notation of Eq. (5.16), $p = 2$, so if $m < 1$ holds then *Newton's method is quadratically convergent*, sufficiently close to the root.¹⁸ This explains why our iterates approached the root so rapidly in Fig. 5.7, even though we intentionally picked a poor starting point.

5.2.5.3 Multiple Roots and Other Issues

Of course, as already hinted at above, there are situations where Newton's method can misbehave. As it so happens, our starting point in Fig. 5.7 was *near* 0, but not actually 0. For our example function $f(x) = e^{x-\sqrt{x}} - x$, the first derivative has a \sqrt{x} in the denominator so picking $x^{(0)} = 0$ would have gotten us in trouble. This can easily be avoided by picking another starting point. There are other problems that relate not to our initial guess, but to the behavior of $f(x)$ itself.

An example is given in the left panel of Fig. 5.8. Our initial guess $x^{(0)}$ is perfectly normal and does not suffer from discontinuities, or other problems. However, by taking the tangent and finding the intercept with the x axis, our $x^{(1)}$ happens to be near a local extremum (minimum in this case); since $f'(x^{(k-1)})$ appears in the denominator in Newton's prescription in Eq. (5.40), a small derivative leads to a large step, considerably away from the root. Note that, for this misbehavior to arise, our previous iterate doesn't even need to be at the extremum, only in its neighborhood. It's worth observing that, for this case, the root $x^* \approx 1.4$ actually is found by Newton's method after a few dozen iterations: after about

Things are even worse in the case of the right panel of Fig. 5.8, where the function enters an infinite cycle. Here we start with a positive $x^{(0)}$, then the tangent line is negative (which happens to be the exact opposite of where we are), and then taking the tangent and finding the intercept brings us back to $x^{(2)} = x^{(0)}$. After that, the entire cycle keeps repeating, without ever reaching the root which we can see is at $x^* = 0$. Of course, this example is sort of a real-world application, the function would likely not be perfectly symmetric about the root which we can see is at $x^* = 0$.

Another problem arises when we are faced with a root that is not simple, in our study of the convergence properties for Newton's method recall, in our study of the convergence properties for Newton's method that $f'(x^*) \neq 0$. This is not the case when you are faced with a multiple root not only for the convergence study but also for the prescription contains the derivative in the denominator, so $f'(x^*) = 0$ can obviously be a problem. As an example, in Fig. 5.9 we are plotting the function:

$$f(x) = x^4 - 9x^3 + 25x^2 - 24x + 4$$

which has one root at $x^* \approx 0.21$, another one at $x^* \approx 4.79$, as we can see in Fig. 5.9. This is easier to see if we rewrite our function as:

$$f(x) = (x-2)^2(x^2-5x+1)$$

As it turns out, Newton's method can find the double root, but it is not what you'd expect to do so. Intriguingly, this is an example where the bisection method (bracketing methods) cannot help us: the function does not change sign at the root (i.e., the root is not bracketed). As you will find out when you solve for the root for this case converges linearly! If you would like to have it converge linearly (as is usually the case), you need to implement Newton's prescription in a different form, namely:

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

As opposed to Eq. (5.40). Problem 5.9 discusses the source of this misbehavior. Unfortunately, in practice we don't know ahead of time that we are dealing with a multiple root (or a triple root, etc.), so we cannot pick such a prefactor that would guarantee convergence. As you will discover in problem 5.10, a useful trick (with your knowledge of the multiplicity of the root) is to apply Newton's method not on the function $f(x)$ but on the function:

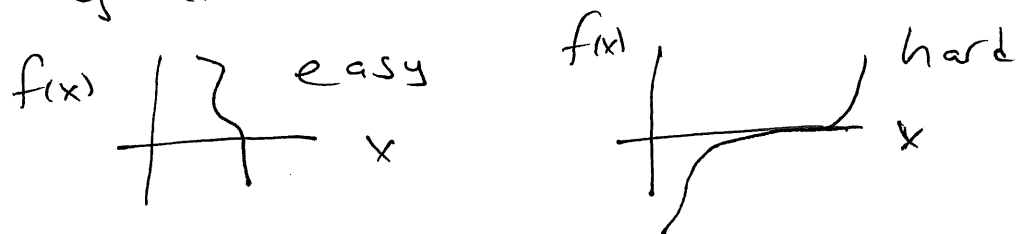
$$w(x) = \frac{f(x)}{f'(x)}$$

As you will show in that problem, $w(x)$ has a simple root at x^* , regardless of the root of $f(x)$ at x^* . Of course, there's no free lunch, and you have to be careful when evaluating $w(x)$ when evaluating the derivative of $f(x)$.

Note: We are trying to find where

5-5

$f(x)=0$. Obviously easier if crossing of y-axis occurs when f is 'steep'



$$x_{\text{est}} - x_{\text{true}} \approx \frac{1}{f'(x_{\text{true}})} [f(x_{\text{est}}) - f(x_{\text{true}})]$$

$$\kappa = 1/f'(x) \quad \text{condition number}$$

When $f'(x)$ large, κ is small and we should do well

$f'(x)$ small $\rightarrow \kappa$ large \rightarrow hard problem

Also double roots can be problematic (5.10)

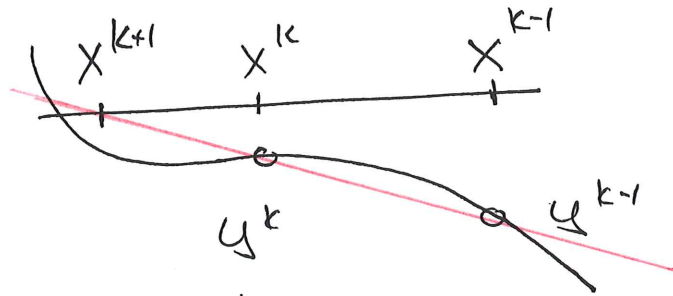
Secant Method: modification to Newton algorithm
estimate $f'(x)$ a la finite diff

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

$$f'(x^{(k-1)}) \approx \frac{f(x^{(k-1)}) - f(x^{(k-2)})}{x^{(k-1)} - x^{(k-2)}} \quad k=2, 3, \dots$$

Like a finite diff but spacing is not const. 5-6

Geometric
interpretation



Draw straight line between
 x^k, y^k and x^{k-1}, y^{k-1} and find x -int.

For points (x_0, y_0) (x_1, y_1)

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

Set $y = 0$

Solve for $x \equiv x^{k+1}$

$$\text{with } \begin{aligned} x_0 &= x^{k-1} & x_1 &= x^k \\ y_0 &= y^{k-1} & y_1 &= y^k \end{aligned}$$

[See Secant.py]

Other methods available

Ridders: bracketing; superlinear convergence

Fixed point: non-bracketing; simple; may not converge

Look at text examples for details

Systems of non-linear equation (5.4)

5-7

n simultaneous non-linear equations w/ n unknowns

$$\vec{f}(\vec{x}) = \vec{0}$$

n functions } n components

ex: $n=2$

$$f_0(x_0, x_1) = x_0^3 - 2x_0 + x_1^4 - 2x_1^2 + x_1 = 0$$

$$f_1(x_0, x_1) = x_0^3 + x_0 - 2x_1^3 - 2x_1^2 - 3/5 x_1 - .05 = 0$$

unknowns are x_0, x_1

We will generalize Newton's method

iterate over vectors $\vec{x}(k)$

First consider a single function component f_i

and we Taylor expand around iterate $\vec{x}^{(k-1)}$

$$f_i(\vec{x}) = f_i(\vec{x}^{(k-1)}) + (\nabla f_i(\vec{x}^{(k-1)}))^T (\vec{x} - \vec{x}^{(k-1)}) + O(\|\vec{x} - \vec{x}^{(k-1)}\|^2) \quad i=0, 1, \dots, n-1$$

$$\nabla f_i(\vec{x}) = \begin{bmatrix} \partial f_i / \partial x_0 \\ \partial f_i / \partial x_1 \\ \vdots \\ \partial f_i / \partial x_{n-1} \end{bmatrix}$$

evaluated at \vec{x}
in this case

$$\left[\nabla f_i(\vec{x}^{(k-1)}) \right]^T (\vec{x} - \vec{x}^{(k-1)}) = \sum_{j=0}^{n-1} \frac{\partial f_i}{\partial x_j} \bigg|_{x_j^{(k-1)}} (x_j - x_j^{(k-1)})$$

$$= \frac{\partial f_i}{\partial x_0} \bigg|_{x_0^{(k-1)}} (x_0 - x_0^{(k-1)}) + \frac{\partial f_i}{\partial x_1} \bigg|_{x_1^{(k-1)}} (x_1 - x_1^{(k-1)})$$

$$+ \dots + \frac{\partial f_i}{\partial x_{n-1}} \bigg|_{x_{n-1}^{(k-1)}} (x_{n-1} - x_{n-1}^{(k-1)})$$

For all components we use Jacobian matrix $J(\vec{x})$

$$\vec{J}(\vec{x}) = \begin{bmatrix} \nabla f_0(\vec{x}) & \nabla f_1(\vec{x}) & \dots & \nabla f_{n-1}(\vec{x}) \end{bmatrix}^T$$

column vectors

$$J_{ij} = \partial f_i / \partial x_j$$

$$\vec{f}(\vec{x}) = \vec{f}(\vec{x}^{(k-1)}) + J(\vec{x}^{(k-1)}) (\vec{x} - \vec{x}^{(k-1)}) + \mathcal{O}(\vec{x}^2)$$

shorthand

Assume we know solution $\vec{f}(\vec{x}^*) = \vec{0}$

$$\vec{0} = \vec{f}(\vec{x}^{(k-1)}) + J(\vec{x}^{(k-1)}) (\vec{x}^* - \vec{x}^{(k-1)})$$

iterative procedure

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

$$\Rightarrow \vec{A} \vec{x} = \vec{b}$$

we can evaluate these
 \Rightarrow just #ers