## The nonlinear boundary value problem

The general nonlinear boundary value problem is

$$
\begin{gathered}
y^{\prime \prime}(x)=f\left(x, y(x), y^{\prime}(x)\right) \\
y(a)=\alpha \\
y(b)=\beta
\end{gathered}
$$

In the method of finite differences we seek an approximate solution to this boundary value problem by setting up a grid of $N+2$ equally spaced points $x_{i}$ with $x_{0}=a$ and $x_{N+1}=b$ :

$$
\begin{aligned}
h & =\frac{b-a}{N+1} \\
x_{i} & =a+i h
\end{aligned}
$$

The method seeks to compute estimates for $y\left(x_{i}\right)$ at each of the interior points $x_{i}$ for $i$ ranging from 1 to $N$ by replacing the derivative terms with finite difference estimates and solving a set of equations. Specifically, we replace the term $y^{\prime \prime}\left(x_{i}\right)$ with an $O\left(h^{2}\right)$ centered difference formula

$$
y^{\prime \prime}\left(x_{i}\right)=\frac{y\left(x_{i+1}\right)-2 y\left(x_{i}\right)+y\left(x_{i-1}\right)}{h^{2}}-\frac{h^{2}}{12} y^{(4)}\left(\xi_{i}\right)
$$

and we replace the term $y^{\prime}\left(x_{i}\right)$ with an $O\left(h^{2}\right)$ centered difference formula

$$
y^{\prime}\left(x_{i}\right)=\frac{y\left(x_{i+1}\right)-y\left(x_{i-1}\right)}{2 h}-\frac{h^{2}}{6} y^{(3)}\left(\eta_{i}\right)
$$

Making these substitutions gives

$$
\frac{y\left(x_{i+1}\right)-2 y\left(x_{i}\right)+y\left(x_{i-1}\right)}{h^{2}}=f\left(x_{i}, y\left(x_{i}\right), \frac{y\left(x_{i+1}\right)-y\left(x_{i-1}\right)}{2 h}\right)
$$

If $f\left(x, y, y^{\prime}\right)$ is a nonlinear function, this is a coupled, nonlinear system of equations in the $N$ unknowns $y\left(x_{i}\right)$. If we let $w_{i}$ be the solution of this equation for $y\left(x_{i}\right)$ for each of these $i$ values with $w_{0}=\alpha$ and $w_{N+1}=\beta$, we get a coupled system of nonlinear equations in $w_{1}$ through $w_{N}$ :

$$
-\frac{w_{i+1}-2 w_{i}+w_{i-1}}{h^{2}}+f\left(x_{i}, w_{i}, \frac{w_{i+1}-w_{i-1}}{2 h}\right)=0
$$

Our problem has now degenerated to a root-finding problem. We seek the root of a function

$$
\mathbf{g}(\mathbf{w})=\left[\begin{array}{c}
g_{1}\left(w_{1}, w_{2}, \ldots, w_{N}\right) \\
g_{2}\left(w_{1}, w_{2}, \ldots, w_{N}\right) \\
\vdots \\
g_{N}\left(w_{1}, w_{2}, \ldots, w_{N}\right)
\end{array}\right]
$$

where

$$
g_{k}\left(w_{1}, w_{2}, \ldots, w_{N}\right)=-\frac{w_{k+1}-2 w_{k}+w_{k-1}}{h^{2}}+f\left(x_{k}, w_{k}, \frac{w_{k+1}-w_{k-1}}{2 h}\right)
$$

and $w_{0}=\alpha$ and $w_{N+1}=\beta$.

## Solving the system of equations

To solve the nonlinear root-finding problem we employ Newton's method for functions from $\mathbb{R}^{n}$ to $\mathbb{R}^{n}$.

$$
\mathbf{w}^{(k)}=\mathbf{w}^{(k-1)}-J^{-1}\left(\mathbf{w}^{(k-1)}\right) \mathbf{g}\left(\mathbf{w}^{(k-1)}\right)
$$

where the Jacobian matrix is

$$
J(\mathbf{x})=\left[\begin{array}{cccc}
\frac{\partial g_{1}(\mathbf{w})}{\partial w_{1}} & \frac{\partial g_{1}(\mathbf{w})}{\partial w_{2}} & \cdots & \frac{\partial g_{1}(\mathbf{w})}{\partial w_{N}} \\
\frac{\partial g_{2}(\mathbf{w})}{\partial w_{1}} & \frac{\partial g_{2}(\mathbf{w})}{\partial w_{2}} & \cdots & \frac{\partial g_{2}(\mathbf{w})}{\partial w_{N}} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial g_{N}(\mathbf{w})}{\partial w_{1}} & \frac{\partial g_{N}(\mathbf{w})}{\partial w_{2}} & \cdots & \frac{\partial g_{N}(\mathbf{w})}{\partial w_{N}}
\end{array}\right]
$$

One fact working to our advantage here is that $g_{j}(\mathbf{w})$ is independent of $w_{k}$ for $k<j-1$ and $k>j+1$. This means that the Jacobian matrix is tri-diagonal.

Another optimization we can make here is to note that we don't have to compute the inverse of the Jacobian to compute the term

$$
J^{-1}\left(\mathbf{w}^{(k-1)}\right) \mathbf{g}\left(\mathbf{w}^{(k-1)}\right)
$$

instead, we can solve the equation

$$
J\left(\mathbf{w}^{(k-1)}\right) \mathbf{z}=\mathbf{g}\left(\mathbf{w}^{(k-1)}\right)
$$

for $\mathbf{z}$ and then compute

$$
\mathbf{w}^{(k)}=\mathbf{w}^{(k-1)}-\mathbf{z}
$$

Since the Jacobian matrix is tri-diagonal, we can apply a Crout factorization to it to get

$$
J\left(\mathbf{w}^{(k-1)}\right)=L U
$$

and then solve

$$
L \mathbf{y}=\mathbf{g}\left(\mathbf{w}^{(k-1)}\right)
$$

and

$$
U \mathbf{z}=\mathbf{y}
$$

## Summary of the method

Fix $w_{0}=\alpha$ and $w_{N+1}=\beta$ and set $w_{1}$ through $w_{N}$ to starting values. (Interpolating linearly between $\alpha$ and $\beta$ is a good choice.) This generates $\mathbf{w}^{(0)}$.

Now repeat the following steps until $\left\|\mathbf{g}\left(\mathbf{w}^{(k)}\right)\right\|$ drops below a desired tolerance.

1. Compute the tridiagonal Jacobian matrix $J\left(\mathbf{w}^{(k-1)}\right)$.
2. Use Crout factorization to obtain

$$
J\left(\mathbf{w}^{(k-1)}\right)=L U
$$

3. Use back substitution to solve for $\mathbf{y}$ :

$$
L \mathbf{y}=\mathbf{g}\left(\mathbf{w}^{(k-1)}\right)
$$

4. Use back substitution to solve for $\mathbf{z}$ :

$$
U \mathbf{z}=\mathbf{y}
$$

5. Compute

$$
\mathbf{w}^{(k)}=\mathbf{w}^{(k-1)}-\mathbf{z}
$$

## Extrapolation

For the same reasons as applied in the linear case, these results can be improved by extrapolation. The technique is exactly the same: we compute a set of $w_{i}$ values for a given step size $h$, and then compute a second set for a step size of $h / 2$ and throw away every other $w_{i}$. We then form extrapolated $w_{i}$ values

$$
y\left(x_{i}\right)=\frac{4 w_{i}(h / 2)-w_{i}(h)}{3}+O\left(h^{4}\right)
$$

