# Root Estimation using Newton-Raphson 

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## 1. Univariate Case

Consider the Taylor Series of a function, $f$, of one variable, $x$ :
$f(x+d x)=f(x)+\frac{\partial f}{\partial x} \cdot d x+\frac{1}{2} \cdot \frac{\partial^{2} f}{\partial x^{2}} \cdot(d x)^{2}+\cdots$

As an approximation:
$f(x+d x) \approx f(x)+\frac{\partial f}{\partial x} . d x$

We can use this relation to find the value of $d x$ such that $f(x+d x) \approx 0$ ie. the value $x+d x$ will be close to the 'root' of $f$.

If $f(x+d x) \approx 0$ then:
$0 \approx f(x)+\frac{\partial f}{\partial x} \cdot d x$
$\therefore-f(x) \approx \frac{\partial f}{\partial x} \cdot d x$
$\therefore-\frac{f(x)}{\frac{\partial f}{\partial x}} \approx d x$
$\therefore d x \approx-\frac{f(x)}{\frac{\partial f}{\partial x}}$

So, we can use this value of $d x$ to find $x+d x$, ie:
$x+d x \approx x-\frac{f(x)}{\frac{\partial f}{\partial x}}$

This new value of $x\left(x_{\text {new }}\right)$ :
$x_{\text {new }}=x+d x \approx x-\frac{f(x)}{\frac{\partial f}{\partial x}}$
gives rise to a new value of $f\left(f_{\text {new }}\right)$ :
$f_{\text {new }}=f\left(x_{\text {new }}\right)=f(x+d x) \approx f\left(x-\frac{f(x)}{\frac{\partial f}{\partial x}}\right)$
which will be closer to 0 than $f(x)$ was. Of course if the value of $f_{\text {new }}$ is not as close to 0 as we would like, we can just set the value of $x$ to be $x_{\text {new }}$ and perform the process again, ie.:
$x_{\text {new }}=x_{\text {old }}-\frac{f\left(x_{\text {old }}\right)}{f^{l}\left(x_{\text {old }}\right)}$
where $f^{\prime}\left(x_{\text {old }}\right)=\left.\frac{\partial f}{\partial x}\right|_{x=x_{\text {old }}}$

We can keep on iterating like this until our value for $f_{\text {new }}$ is "close enough" to 0 , ie. within our desired tolerance. This is the essence of the Newton-Raphson algorithm for finding the root of a function.

In applying Newton-Raphson there is one practical problem: determining $f^{\prime}(x)$. Quite often the functional form of $f$ is not known, eg. $f(x)$ could simply be the value in a cell of a complex spreadsheet. Not knowing the equation for $f(x)$ means not being able to determine $f^{\prime}(x)$. In such a situation, however, $f^{\prime}(x)$ can be approximated using the difference operator:
$f^{\prime}(x) \approx \frac{f(x+d x)-f(x)}{d x}$

The smaller $d x$ is, the closer the difference operator will come to the true value for $f^{\prime}(x)$.

The Newton-Raphson algorithm, therefore, can be stated as:

1. Start with an initial value for $x$, being a guess as to what the root of the function is;
2. Set $x_{\text {old }}=x$;
3. Calculate fold $=f\left(x_{\text {old }}\right)$;
4. Compare fold with 0 to see how far away from 0 we are;
5. If $f_{\text {old }}$ is close enough to 0 then stop - we have found that $x_{\text {old }}$ is close enough to the real root of $f$.
6. If fold is not close enough to 0 then calculate $f^{\prime}(x)$. This requires two separate calculations: one to calculate $f(x+h)$ and the other to calculate $f^{\prime}(x)$;
7. Calculate $x_{\text {new }}$ from the values of $f^{\prime}(x)$, foid and $x_{\text {old }}$ we have just determined above, using the formula specified above;
8. Set $x_{\text {old }}=x_{\text {new }}$;
9. Go to step 3 with this new value of $x_{\text {oid }}$.

## 2. Multivariate Case

The above univariate case can be extended to the multivariate case quite simply. Consider the two variable case: $f\left(x_{1}, x_{2}\right)$. Again, we start with the Taylor Series expansion of $f$, but this time with two variables, $x_{1}$ and $x_{2}$ :
$f\left(x_{1}+d x_{1}, x_{2}+d x_{2}\right)=f\left(x_{1}, x_{2}\right)+\frac{\partial f}{\partial x_{1}} \cdot d x_{1}+\frac{\partial f}{\partial x_{2}} \cdot d x_{2}+\cdots$

Again, as an approximation:
$f\left(x_{1}+d x_{1}, x_{2}+d x_{2}\right) \approx f\left(x_{1}, x_{2}\right)+\frac{\partial f}{\partial x_{1}} \cdot d x_{1}+\frac{\partial f}{\partial x_{2}} \cdot d x_{2}$
If $f\left(x_{1}+d x_{1}, x_{2}+d x_{2}\right) \approx 0$ then:
$0 \approx f\left(x_{1}, x_{2}\right)+\frac{\partial f}{\partial x_{1}} \cdot d x_{1}+\frac{\partial f}{\partial x_{2}} \cdot d x_{2}$
$\therefore-f\left(x_{1}, x_{2}\right) \approx \frac{\partial f}{\partial x_{1}} \cdot d x_{1}+\frac{\partial f}{\partial x_{2}} \cdot d x_{2}$

In matrix notation:
$\therefore-f\left(x_{1}, x_{2}\right) \approx\left[\begin{array}{ll}\frac{\partial f}{\partial x_{1}} & \frac{\partial f}{\partial x_{2}}\end{array}\right]\left[\begin{array}{l}d x_{1} \\ d x_{2}\end{array}\right]$

The problem here, of course, is that we have one equation but two unknowns resulting in an infinite number of solutions. Therefore, in order to have a unique solution we require two equations, ie. two different functions which both depend on $x_{1}$ and $x_{2}$. If this is the case then we have the equations:
$-f_{1}\left(x_{1}, x_{2}\right) \approx\left[\frac{\partial f_{1}}{\frac{\partial f_{1}}{\partial x_{1}}} \frac{\partial}{\partial x_{2}}\right] \cdot\left[\begin{array}{l}d x_{1} \\ d x_{2}\end{array}\right]$
$-f_{2}\left(x_{1}, x_{2}\right) \approx\left[\begin{array}{ll}\frac{\partial f_{2}}{\partial x_{1}} & \frac{\partial f_{2}}{\partial x_{2}}\end{array}\right] \cdot\left[\begin{array}{l}d x_{1} \\ d x_{2}\end{array}\right]$
which simplifies to:
$-\left[\begin{array}{l}f_{1}\left(x_{1}, x_{2}\right) \\ f_{2}\left(x_{1}, x_{2}\right)\end{array}\right] \approx\left[\begin{array}{ll}\frac{\partial f_{1}}{\partial x_{1}} & \frac{\partial f_{1}}{\partial x_{2}} \\ \frac{\partial f_{2}}{\partial x_{1}} & \frac{\partial f_{2}}{\partial x_{2}}\end{array}\right] \cdot\left[\begin{array}{l}d x_{1} \\ d x_{2}\end{array}\right]$
or
$-\mathrm{f} \approx \mathrm{J} . \mathrm{dx}$
where $\mathbf{f}$ is the vector of $f_{\mathrm{i}}(\mathbf{x}), \mathbf{J}$ is the Jacobian matrix and $\mathbf{d x}$ is the vector of $x_{\mathrm{i}} \mathrm{s}$. Rearranging for $\mathbf{d x}$ gives:
$\mathrm{dx} \approx-\mathrm{J}^{-1} \mathbf{f}$
and the resulting vector from
$\mathbf{x}-\mathbf{J}^{-1} \mathbf{f}$
provides our estimates of $x_{i}+d x_{i}$ which we can use to generate $f_{\text {new }}$ which can then be tested to see if each $f_{i}$ is close enough to the target value to make $\mathbf{x}-\mathbf{J}^{\mathbf{- 1}} \mathbf{f}$ our estimate of the root of $\mathbf{f}$.

The problem with multivariate Newton-Raphson is that the more variates there are, the more calculations need to be done. When we had one variate, we needed to calculate the estimate of $f^{\prime}(x)$ which involved 2
calculations: $f(x+d x)$ and $f^{\prime}(x)$. With the bivariate case presented above we now have to calculate 4 partial derivatives, with each partial derivative requiring 2 calculations, ie. a total of 8 calculations to get $\mathbf{J}$. A trivariate case has 9 partial derivatives in its Jacobian matrix, ie. 18 calculations for $\mathbf{J}$. Generalizing we see that for the $n$-variate case, the calculation of $\mathbf{J}$ requires $2 n^{2}$ separate calculations to be done. And this is before we even start to invert J. Consequently, while Newton-Raphson lends itself well to the multivariate case, in its application we must be mindful of the computational effort required.

