## Multidimensional Newton's Method

In multidimensional Newton's Method, we'll assume that we have a function  $y = f(x_1, \ldots, x_n)$  for which we're trying to determine the roots of the gradient,

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

In that case, the function file (Matlab or Python) for f should actually output three items:

- $f(\mathbf{x})$  (which is a real number)
- $\nabla f(\mathbf{x})$  (which is a vector)
- $Hf(\mathbf{x})$ , or the Hessian of f, which is a matrix of all of the second derivatives of f:

$$(Hf(\mathbf{x})_{ij} = \frac{\partial^2 f}{\partial x_i \partial x_j}(\mathbf{x})$$

With that, recall that multidimensional Newton's method for the gradient of f is given by:

$$\mathbf{x}_{i+1} = \mathbf{x}_i - Hf^{-1}(\mathbf{x}_i)(\nabla f(\mathbf{x}))^T$$

(where we're assuming the gradient is a row, so the transpose as shown above is a column).

## Computations

For numerical stability, it is often recommended that we don't actually compute the inverse matrix. Rather, consider the following: If we define a new vector  $\delta$  to be our update term:

$$\vec{\delta} = H f^{-1}(\mathbf{x}_i) \nabla f(\mathbf{x}_i)^T$$

Then the vector solves the system of equations:

$$Hf(\mathbf{x}_i)\vec{\delta} = \nabla f(\mathbf{x}_i)^T$$

(again, the right hand side of the equation is a column vector). So in the code, you'll see us solving this equation.

Here's the code for that

function out=MultiNewton(F,x0,numits,tol)

```
for k=1:numits
  [g,gradg,hessg]=F(x0);
  if cond(hessg)>1000000
     error('The Hessian Matrix is not invertible');
  end
```

```
delta=hessg\gradg; % Assumes gradg is a column vector
   xnew=x0-delta;
   d=norm(gradg);
   if d<tol
      out=xnew;
      break
   end
   x0=xnew;
end
fprintf('Newton used %d iterations\n',k);
out=xnew;
  Here's a quick example. First, the function file:
function [y,dy,hy]=testfunc(x)
  A test function for Newton's Method:
%
%
  The input is the VECTOR x (with elements x, y below)
```

dy = Gradient = [x^3-x; y] (The gradient will output as a COLUMN)

Now the function call would be something like

 $y = (1/4)x^{4} - (1/2)x^{2} + (1/2)y^{2}$ 

 $hy = Hessian = [3x^2-1, 0; 0, 1]$ 

 $y=(1/4)*x(1)^{4}-(1/2)*x(1)^{(2)}+(1/2)*x(2)^{2};$ 

```
yout=MultiNewton(@testfunc,[-3;2],100,1e-6);
```

And the output will be: "Newton used 8 iterations", and yout would be (-1, 0).

## Example in Python

dy=[x(1)^3-x(1); x(2)]; hy=[3\*x(1)^2-1, 0;0,1];

% %

%

%

```
import numpy as np
def f(z):
    x, y = z
    w=(1/4)*x**4-(1/2)*x**2+(1/2)*y**2
    dw=np.array([x**3-x, y])
```

```
hw=np.array([
         [3*x**2-1,0],
         [0,1]
         ])
    return w, dw, hw
def newton_method(f, grad_f, hess_f, x0, tol=1e-6, max_iter=20):
    x = np.array(x0, dtype=float)
    for i in range(max_iter):
        g, gradg, hessg = f(x)
        if np.linalg.cond(hessg)>1000000
            print(f"Error- Hessian is not invertible")
            return x
        if np.linalg.norm(grad) < tol:</pre>
            print(f"Converged in {i} iterations")
            return x
        delta = np.linalg.solve(hess, grad)
        x = x - delta
        print(f"Iter {i+1}: x = \{x\}, f(x) = \{f(x)\}")
    print("Did not converge")
    return x
# Initial guess
x0 = [2.0, 2.0]
minimum = newton_method(f, grad_f, hess_f, x0)
```

```
print(f"Found minimum at {minimum}, f(x) = {f(minimum)}")
```