

# Lecture 5: Systems of nonlinear equations

COMP5930M Scientific Computation

# Today

Notation

Newton's method

The Jacobian matrix

Efficiency

Next

## Notation

- ▶ Single equation in a single unknown

$$F(x) = 0$$

- ▶  $n$  equations in  $n$  unknowns

$$\mathbf{F}(\mathbf{x}) = \mathbf{0}$$

$\mathbf{x}$  is a vector  $\{x_1, x_2, \dots, x_n\}$  of  $n$  unknown values

$\mathbf{F}$  is a set  $\{F_1(\mathbf{x}), F_2(\mathbf{x}), \dots, F_n(\mathbf{x})\}$  of  $n$  nonlinear equations

## The nonlinear problem

Find the  $n$ -dimensional point  $\{x_j^*\}$ ,  $j = 1, 2, \dots, n$   
such that the set of functions

$$F_i(x_j^*) = 0, \quad i = 1, 2, \dots, n \text{ simultaneously}$$

## Example: $n = 2$ system

Find  $(x_1^*, x_2^*)$  such that  $F_1(x_1^*, x_2^*) = 0$  and  $F_2(x_1^*, x_2^*) = 0$  simultaneously

$$U = [x_1, x_2]$$

$$F_1(x_1, x_2) = 3x_1^2 + 4x_1x_2$$

$$F_2(x_1, x_2) = x_1^2 + 2x_1x_2^2$$

$$F(U) = 0$$

$$0$$

## Example: $n = 2$ system

$$\begin{aligned}\frac{\partial F_1}{\partial x_1} &= 6x_1 + 4x_2, & \frac{\partial F_1}{\partial x_2} &= 4x_1 \\ \frac{\partial F_2}{\partial x_1} &= 2x_1 + 2x_2^2, & \frac{\partial F_2}{\partial x_2} &= 4x_1x_2\end{aligned}$$

## Newton's Method

- ▶ Assume we have access to the set of functions  $\mathbf{F}(\mathbf{x})$
- ▶ Assume we know an initial state  $\mathbf{x}_0$

These first two are the minimum information necessary

- ▶ Assume we have access to all the partial derivatives of  $\mathbf{F}$  with respect to  $\mathbf{x}$

$$\frac{\partial F_i}{\partial x_j}, \quad i = 1, 2, \dots, n, \quad j = 1, 2, \dots, n$$

## Derivation of Newton's method in the vectorial case

Given current iterate  $\mathbf{x}_k$ , find an increment  $\delta \in \mathbb{R}^n$  s.t.

$$\mathbf{F}(\mathbf{x}_k + \delta) = 0. \quad (1)$$

If the function  $\mathbf{F}$  is differentiable at  $\mathbf{x}_k$ , we can linearise it:

$$\mathbf{F}(\mathbf{x}_k + \delta) = \mathbf{F}(\mathbf{x}_k) + \frac{\partial \mathbf{F}}{\partial \mathbf{x}}(\mathbf{x}_k)\delta + o(|\delta|^2).$$



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Dropping the second order terms, we can solve for  $\delta$  from (1):

$$\mathbf{x}_{k+1} - \mathbf{x}_k = \delta = - \left[ \frac{\partial \mathbf{F}}{\partial \mathbf{x}}(\mathbf{x}_k) \right]^{-1} \mathbf{F}(\mathbf{x}_k).$$

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## The algorithm

Generate a sequence of approximations  $\mathbf{x}_1, \mathbf{x}_2, \dots$  using

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \left( \frac{\partial \mathbf{F}}{\partial \mathbf{x}}(\mathbf{x}_k) \right)^{-1} \mathbf{F}(\mathbf{x}_k)$$

starting from an initial guess  $\mathbf{x}_0$ .

## The Jacobian Matrix

The  $n \times n$  matrix of partial derivatives is called the Jacobian, **J**,  
where  $J_{ij} = \frac{\partial F_i}{\partial x_j}$

Newton's Method is more compactly written as

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \mathbf{J}(\mathbf{x}_k)^{-1} \mathbf{F}(\mathbf{x}_k)$$

This implies the solution of an  $n \times n$  linear system at every step

This is a costly part of the algorithm

## Rewrite as 2-step algorithm

$$\begin{aligned}\mathbf{J}(\mathbf{x}_k)\delta &= -\mathbf{F}(\mathbf{x}_k) \\ \mathbf{x}_{k+1} &= \mathbf{x}_k + \delta\end{aligned}$$

Notes:

- ▶ Step 2 is trivial in this basic form
- ▶ Step 1 is a linear algebra problem: system of  $n \times n$  linear equations with  $\mathbf{J}$  a known  $n \times n$  matrix at each iteration

## Computational cost

	Function calls	Algorithmic
Evaluate $\mathbf{J}$	?	$n^2$
Solve $\mathbf{J}\delta = -\mathbf{F}$	1	$n^3$
Update $\mathbf{x}_{k+1}$	0	$n$

## Evaluating the Jacobian in practice

- ▶ Analytical Jacobian may be expensive to evaluate
- ▶ Numerical approximation of Jacobian requires  $2n^2$  evaluations
- ▶ Quasi-Newton methods rely on approximation of Jacobian that is updated at each step

## Evaluating the Jacobian numerically

- ▶ We require  $n^2$  values to fill the Jacobian matrix
- ▶ Numerical approximation term-by-term

$$\frac{\partial F_i}{\partial x_j} \approx \frac{F_i(x_1, \dots, x_j + \delta_j, \dots, x_n) - F_i(x_1, \dots, x_n)}{\delta_j}$$

- ▶ Efficient implementation
  - ▶ Can simultaneously perturb all the  $F_i$  with respect to  $x_j$
  - ▶ Equivalent to  $n$  Matlab function calls
    - where a function call evaluates all the  $F_i$



## Jacobian for the $n = 2$ system

```
% Vectorised version of the function F(x1,x2)
F=@(x1,x2)([3*x1.^2 + 4.*x1.*x2;
            x1.^2 + 2*x1.*x2.^2]);
```

- ```
% Optimal choice of perturbation parameter h
h = 10 * sqrt(eps);
```

```
% Call F(x1,x2) once and store
Fx = F(x1,x2);
```

```
% Numerical Jacobian based on difference approximation
dFnum = [ (F(x1+h,x2) - Fx) / h ...
          (F(x1,x2+h) - Fx) / h ];
```

## Computational cost



|                                        | Function calls | Algorithmic |
|----------------------------------------|----------------|-------------|
| Evaluate $\mathbf{J}$                  | $n$            | $n^2$       |
| Solve $\mathbf{J}\delta = -\mathbf{F}$ | 1              | $n^3$       |
| Update $\mathbf{x}_{k+1}$              | 0              | $n$         |

## Problems?

- ▶ More difficult to make the algorithm robust overall
  - ▶ There is no bisection method in higher dimensions
- ▶ For this reason damped Newton-like methods are preferred
  - ▶ Take steps in the direction  $\frac{\delta}{\|\delta\|}$  but control the step size to avoid divergence when the Jacobian  $\partial \mathbf{F} / \partial \mathbf{x} \approx \mathbf{0}$ .
  - ▶ In some circumstances this allows global convergence of Newton-type algorithms

## Next time...

### Tutorial

- ▶ Solving nonlinear systems with MATLAB
- ▶ Problems with convergence of non-damped Newton's method

### Lecture

- ▶ Line-search algorithms for Newton's method
- ▶ Computational algorithms for systems