

# A system of nonlinear equations

## Newton's method

# Outline

- Matlab toolbox
- Newton's method for nonlinear system solving
  - Updating rule
  - Matlab implementation

```
function F = myfun(x)
    F(1) = x(1)^2 + x(2)^2 - 1;
    F(2) = x(1)^2 - x(2)^2;
return
```

$$f_1(x_1, x_2) = x_1^2 + x_2^2 - 1$$
$$f_2(x_1, x_2) = x_1^2 - x_2^2$$

# symbols

```
s1='x1^2+x2^2-1';
```

```
s2='x1^2-x2^2';
```

```
x1=sym('x1')
```

```
x2=sym('x2')
```

# Inline Function

```
f=inline([sym(s1);sym(s2)]);  
f(0,0)
```

# fsolve

```
x=fsolve(@(x) [x(1)^2+x(2)^2-1  
x(1)^2-x(2)^2],[1 1])
```

x =

0.7071      0.7071

```
s1='x1^2+x2^2-1';  
s2='x1^2-x2^2';
```

```
x1=sym('x1')  
x2=sym('x2')  
f=inline([sym(s1);sym(s2)]);  
f(x(1),x(2))
```

```
ans =  
1.0e-11 *  
0.2282  
0
```

zeros

# Jacobian

```
A=jacobian([sym(s1);sym(s2)],[x1 x2]);
```

```
j=inline(A);
```

```
j(1,1)
```

$$f_1(x_1, x_2) = X_1^2 + X_2^2 - 1$$

$$f_2(x_1, x_2) = X_1^2 - X_2^2$$

```
A =
```

```
[ 2*x1, 2*x2]
```

```
[ 2*x1, -2*x2]
```

# fsolve

<https://www.mathworks.com/help/optim/ug/fsolve.htm>  
mathwork

$$\begin{aligned} e^{-e^{-(x_1+x_2)}} - x_2(1+x_1^2) &= 0 \\ x_1 \cos(x_2) + x_2 \sin(x_1) - \frac{1}{2} &= 0. \end{aligned}$$

Write a function that computes the left-hand side of these two equations.

```
function F = root2d(x)
F(1) = exp(-exp(-(x(1)+x(2)))) - x(2)*(1+x(1)^2);
F(2) = x(1)*cos(x(2)) + x(2)*sin(x(1)) - 0.5;
```

- [1] Coleman, T.F. and Y. Li, "An Interior, Trust Region Approach for Nonlinear Minimization Subject to Bounds," *SIAM Journal on Optimization*, Vol. 6, pp. 418-445, 1996.
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- [4] Levenberg, K., "A Method for the Solution of Certain Problems in Least-Squares," *Quarterly Applied Mathematics* 2, pp. 164-168, 1944.
- [5] Marquardt, D., "An Algorithm for Least-squares Estimation of Nonlinear Parameters," *SIAM Journal Applied Mathematics*, Vol. 11, pp. 431-441, 1963.
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***A method for the solution of certain non-linear problems in least squares***

## An Algorithm for Least-Squares Estimation of Nonlinear Parameters

Donald W. Marquardt

*Journal of the Society for Industrial and Applied Mathematics*, Vol. 11, No. 2 (Jun., 1963), 431-441.

Stable URL:

<http://links.jstor.org/sici?&sici=0368-4245%28196306%2911%3A2%3C431%3AAAFLEO%3E2.0.CO%3B2-7>

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# Nonlinear systems

A system of nonlinear equations

$$F(x_1, x_2, \dots, x_n) = \begin{bmatrix} f_1(x_1, x_2, \dots, x_n) \\ f_2(x_1, x_2, \dots, x_n) \\ \vdots \\ \vdots \\ f_n(x_1, x_2, \dots, x_n) \end{bmatrix}$$

$f_1, f_2, \dots, f_n$  are coordinate functions of F

# Example

---

$$3x_1 - \cos(x_2 x_3) - \frac{1}{2} = 0$$

$$x_1^2 - 81(x_2 + 0.1)^2 + \sin(x_3) + 1.06 = 0$$

$$e^{-x_1 x_2} + 20x_3 + \frac{1}{3}(10\pi - 3) = 0$$

# myfun

```
function F = myfun(x)
    F(1) = 3*x(1)-cos(x(2)*x(3))-1/2;
    F(2) = x(1).^2 -81*(x(2)+0.1).^2+sin(x(3))+1.06;
    F(3) = exp(-x(1)*x(2))+20*x(3)+1/3*(10*pi-3);
return
```

# Example

---

$$x_1^2 + x_2^2 + x_3^2 = 4$$

$$2x_1 - x_2 + x_3 = 1$$

$$x_1 + 3x_2 - x_3 = 3$$

# Neural dynamics

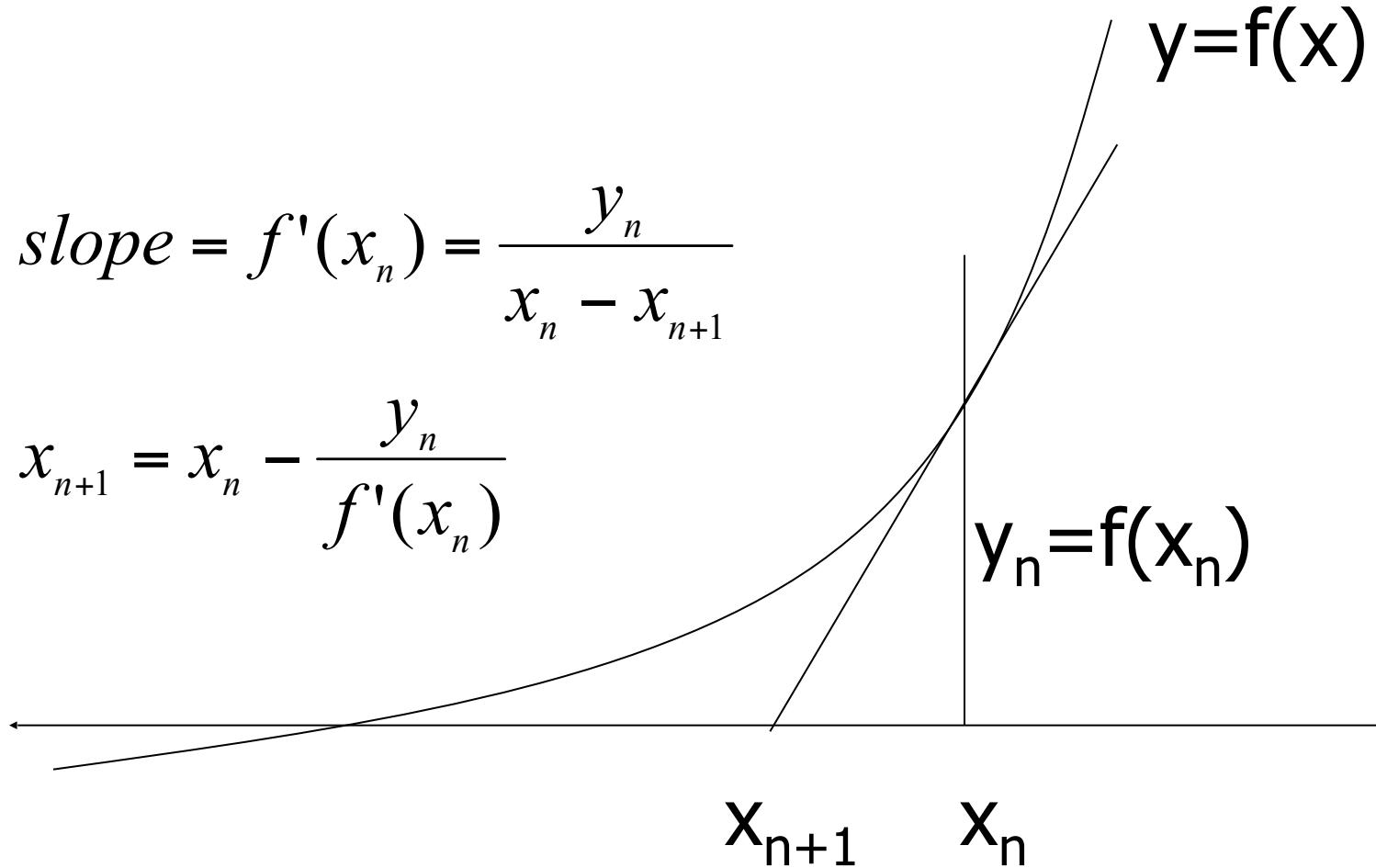
---

$$x_i = \tanh(a_i^T \mathbf{x}), \text{ for all } i$$

# Newton's method -Tangent line

$$slope = f'(x_n) = \frac{y_n}{x_n - x_{n+1}}$$

$$x_{n+1} = x_n - \frac{y_n}{f'(x_n)}$$



# Updating rule

$x$  : scalar

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$$

$x$  : vector

$$\mathbf{x}_{n+1} = \mathbf{x}_n - [J(\mathbf{x}_n)]^{-1} F(\mathbf{x}_n)$$

# Taylor series

- Second order expansion at  $\mathbf{x} = \mathbf{x}_n$

$$F(\mathbf{x} + \Delta\mathbf{x}) \approx F(\mathbf{x}) + J(\mathbf{x})\Delta\mathbf{x} + \frac{1}{2}\Delta\mathbf{x}^T H(\mathbf{x})\Delta\mathbf{x}$$

Jacobi matrix

Hessian matrix

$$\mathbf{x} \leftarrow \mathbf{x}_n, \quad \Delta\mathbf{x} \leftarrow \mathbf{x} - \mathbf{x}_n,$$

$$F(\mathbf{x}) \approx F(\mathbf{x}_n) + J(\mathbf{x}_n)(\mathbf{x} - \mathbf{x}_n) + \frac{1}{2}(\mathbf{x} - \mathbf{x}_n)^T H(\mathbf{x}_n)(\mathbf{x} - \mathbf{x}_n)$$

# Hessian Matrix

$$H(\mathbf{x}) = \begin{bmatrix} \frac{\partial^2 f_1(\mathbf{x})}{\partial x_1^2} & \frac{\partial^2 f_1(\mathbf{x})}{\partial x_1 \partial x_2} & \dots & \frac{\partial^2 f_1(\mathbf{x})}{\partial x_1 \partial x_n} \\ \frac{\partial^2 f_2(\mathbf{x})}{\partial x_1 \partial x_2} & \frac{\partial^2 f_2(\mathbf{x})}{\partial x_2^2} & \dots & \frac{\partial^2 f_2(\mathbf{x})}{\partial x_1 \partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f_n(\mathbf{x})}{\partial x_n \partial x_1} & \frac{\partial^2 f_n(\mathbf{x})}{\partial x_n \partial x_2} & \dots & \frac{\partial^2 f_n(\mathbf{x})}{\partial x_n^2} \end{bmatrix}$$

# Jacobi matrix

$$J(\mathbf{x}) = \begin{bmatrix} \frac{\partial f_1(\mathbf{x})}{\partial x_1} & \frac{\partial f_1(\mathbf{x})}{\partial x_2} & \cdots & \frac{\partial f_1(\mathbf{x})}{\partial x_n} \\ \frac{\partial f_2(\mathbf{x})}{\partial x_1} & \frac{\partial f_2(\mathbf{x})}{\partial x_2} & \cdots & \frac{\partial f_2(\mathbf{x})}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_n(\mathbf{x})}{\partial x_1} & \frac{\partial f_n(\mathbf{x})}{\partial x_2} & \cdots & \frac{\partial f_n(\mathbf{x})}{\partial x_n} \end{bmatrix}$$

# First order expansion

- Set zero to

$$F(\mathbf{x}) \approx F(\mathbf{x}_n) + J(\mathbf{x}_n)(\mathbf{x} - \mathbf{x}_n)$$

$$F(\mathbf{x}_n) + J(\mathbf{x}_n)(\mathbf{x} - \mathbf{x}_n) = 0 \implies \mathbf{x} = \mathbf{x}_n - J^{-1}(\mathbf{x}_n)F(\mathbf{x}_n)$$

# Newton's method

$$\mathbf{x}_{n+1} = \mathbf{x}_n - [J(\mathbf{x}_n)]^{-1} F(\mathbf{x}_n)$$

$$J(\mathbf{x}) = \begin{bmatrix} \frac{\partial f_1(\mathbf{x})}{\partial x_1} & \frac{\partial f_1(\mathbf{x})}{\partial x_2} & \dots & \frac{\partial f_1(\mathbf{x})}{\partial x_n} \\ \frac{\partial f_2(\mathbf{x})}{\partial x_1} & \frac{\partial f_2(\mathbf{x})}{\partial x_2} & \dots & \frac{\partial f_2(\mathbf{x})}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_n(\mathbf{x})}{\partial x_1} & \frac{\partial f_n(\mathbf{x})}{\partial x_2} & \dots & \frac{\partial f_n(\mathbf{x})}{\partial x_n} \end{bmatrix}$$

# Flow Chart

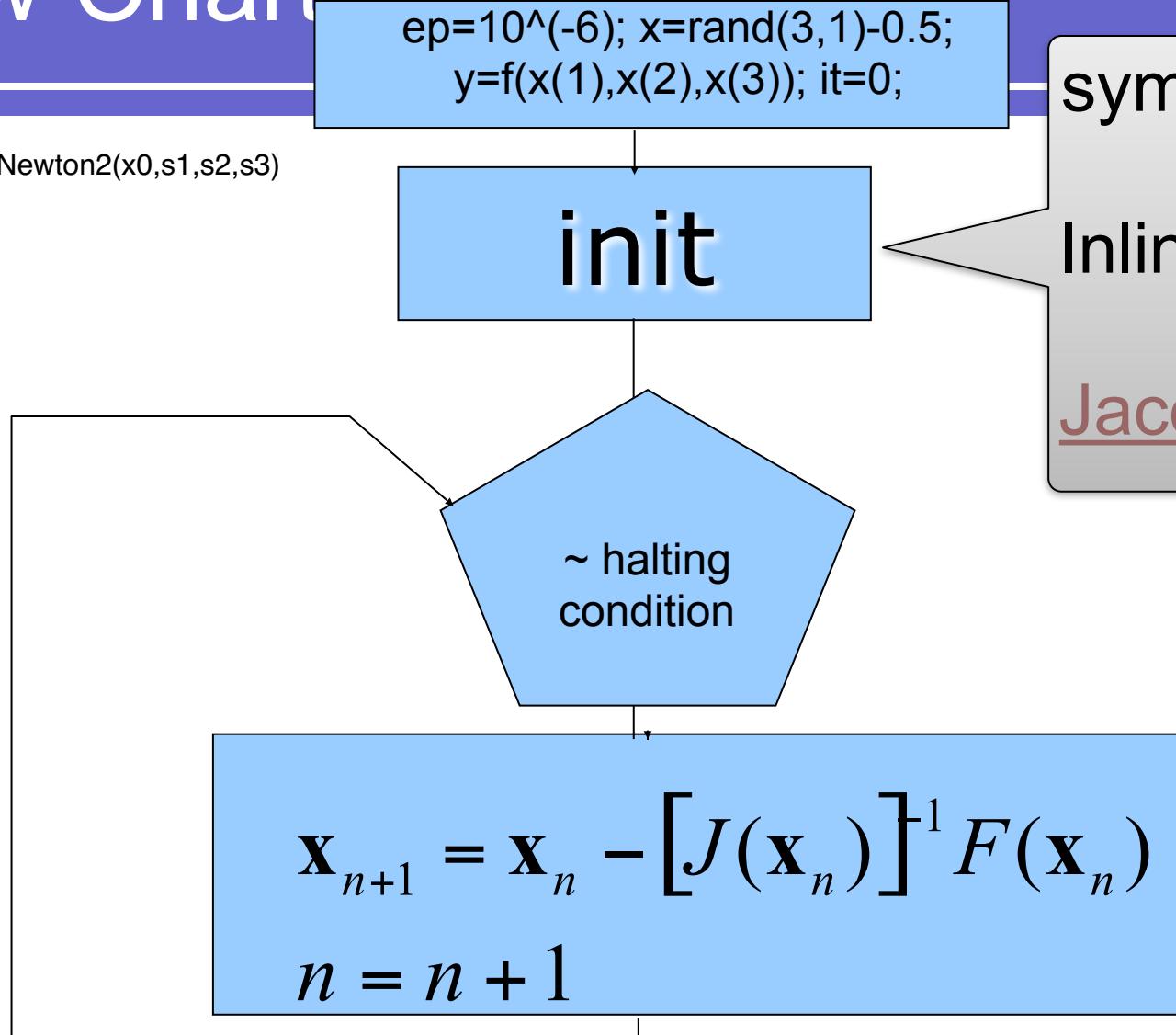
```
function x=Newton2(x0,s1,s2,s3)
```

```
ep=10^(-6); x=rand(3,1)-0.5;  
y=f(x(1),x(2),x(3)); it=0;
```

symbols

Inline function

Jacobian



```
s1='3*x1-cos(x2*x3)-1/2';
s2='x1^2 -81*(x2+0.1)^2+sin(x3)+1.06';
s3='exp(-x1*x2)+20*x3+1/3*(10*pi-3)';
x1=sym('x1')
x2=sym('x2')
X3=sym('x3')
```

# inline Function

```
f=inline([sym(s1);sym(s2) ;sym(s3)]);  
f(0,0,0)
```

# Jaconian

```
A=jacobian([sym(s1);sym(s2) ;sym(s3)],[x1  
x2 x3]);  
j=inline(A);  
j(1,1,1)
```

# Symbols, inline and Jacobian

```
s1='3*x1-cos(x2*x3)-1/2';  
s2='x1^2 -81*(x2+0.1)^2+sin(x3)+1.06';  
s3='exp(-x1*x2)+20*x3+1/3*(10*pi-3)';  
x1=sym('x1');x2=sym('x2');x3=sym('x3');  
f=inline([sym(s1);sym(s2) ;sym(s3)]);  
A=jacobian([sym(s1);sym(s2) ;sym(s3)], [x1 x2 x3]);  
j=inline(A);
```

symbols

Inline function

Jacobian

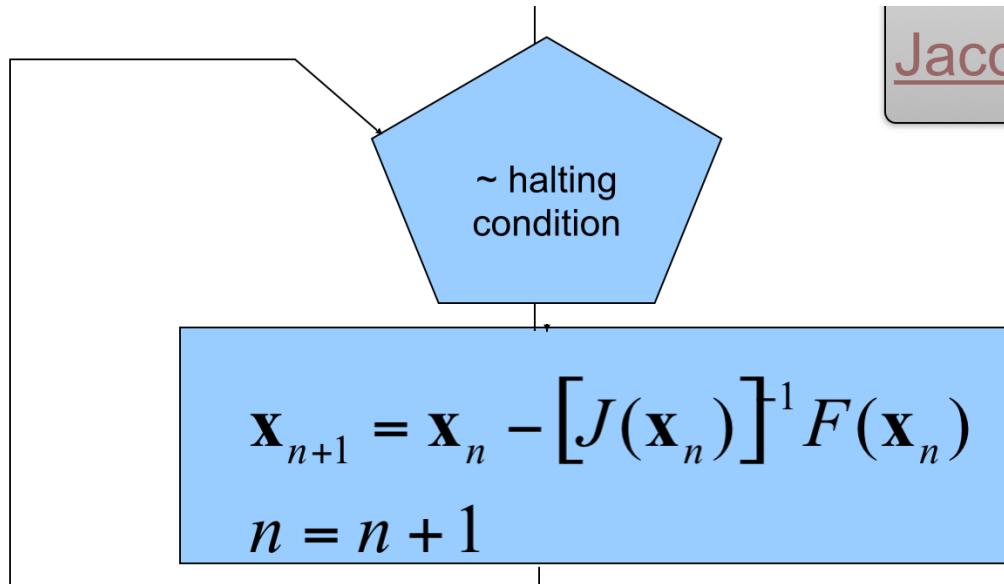
# Init

```
ep=10^(-6); x=rand(3,1)-0.5;  
y=f(x(1),x(2),x(3)); it=0;
```

```

while sum(abs(y)) > ep & it < 100
x=x-inv(j(x(1),x(2),x(3)))*y;
y=f(x(1),x(2),x(3))
it=it+1
end
x

```



- Implement the Newton's method for solving a three-variable nonlinear system
- Test your matlab codes with the following nonlinear system

$$3x_1 - \cos(x_2 x_3) - \frac{1}{2} = 0$$

$$x_1^2 + x_2^2 + x_3^2 = 4$$

$$x_1^2 - 81(x_2 + 0.1)^2 + \sin(x_3) + 1.06 = 0$$

$$2x_1 - x_2 + x_3 = 1$$

$$e^{-x_1 x_2} + 20x_3 + \frac{1}{3}(10\pi - 3) = 0$$

$$x_1 + 3x_2 - x_3 = 3$$

```
load mnist_uint8;
train_x = double(train_x) / 255;
test_x = double(test_x) / 255;
train_y = double(train_y);
test_y = double(test_y);
X=[];
for i=1:10
A = train_x;
b = train_y(:,i)==1;
AA=A'*A;
bb=A'*b;
x=CG_lin(AA,bb);
b_hat=A*x>0.5;
er_train=b-b_hat;
b_test=(test_x*x)>0.5;
er_test=b_test-test_y(:,i)==1;
fprintf('%d er_train %d er_test %d\n',i-1,sum(abs(er_train))/length(er_train),sum(abs(er_test))/length(er_test));
X=[X x];
end
train_y_hat=train_x*X;
r=count_er(train_y,train_y_hat)

test_y_hat=test_x*X;
r=count_er(test_y,test_y_hat)
```

```
function r=count_er(y,y_hat)
[v ind_y]=max(y');
[v ind_y_hat]=max(y_hat');
r=sum(ind_y~=ind_y_hat)/length(ind_y);
```

Let  $y=f(x)$  denote a mapping realized by a deep neural network

$$f(x) = W_3 * \tanh(W_2 * \tanh(W_1 x))$$

where  $W_1$ ,  $W_2$  and  $W_3$  denote matrixes,  $x$  denotes a stimulus vector and  $y$  denotes an output vector. For example,  $x$  is a handwritten digit and  $y$  is a unit vector for representing a label. Consider training and testing sets of MNIST. Discuss how to train  $W_1$ ,  $W_2$  and  $W_3$  by the Newton method.