

# Introduction to Simulation - Lecture 9

## Multidimensional Newton Methods

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Thanks to Deepak Ramaswamy, Jaime Peraire, Michal  
Rewienski, and Karen Veroy

# Outline

- Quick Review of 1-D Newton
  - Convergence Testing
- Multidimensional Newton Method
  - Basic Algorithm
  - Description of the Jacobian.
  - Equation formulation.
- Multidimensional Convergence Properties
  - Prove local convergence
  - Improving convergence

Problem: Find  $x^*$  such that  $f(x^*) = 0$

Use a Taylor Series Expansion

$$\cancel{f(x^*)} = f(x) + \frac{\partial f(x)}{\partial x}(x^* - x) + \frac{\partial^2 f(\tilde{x})}{\partial x^2}(x^* - x)^2$$

If  $x$  is close to the exact solution

$$\frac{\partial f(x)}{\partial x}(x^* - x) \approx -f(x)$$

# 1-D Reminder

## Newton Algorithm

$x^0 = \text{Initial Guess}, k = 0$

Repeat {

$$\frac{\partial f(x^k)}{\partial x}(x^{k+1} - x^k) = -f(x^k)$$

$$k = k + 1$$

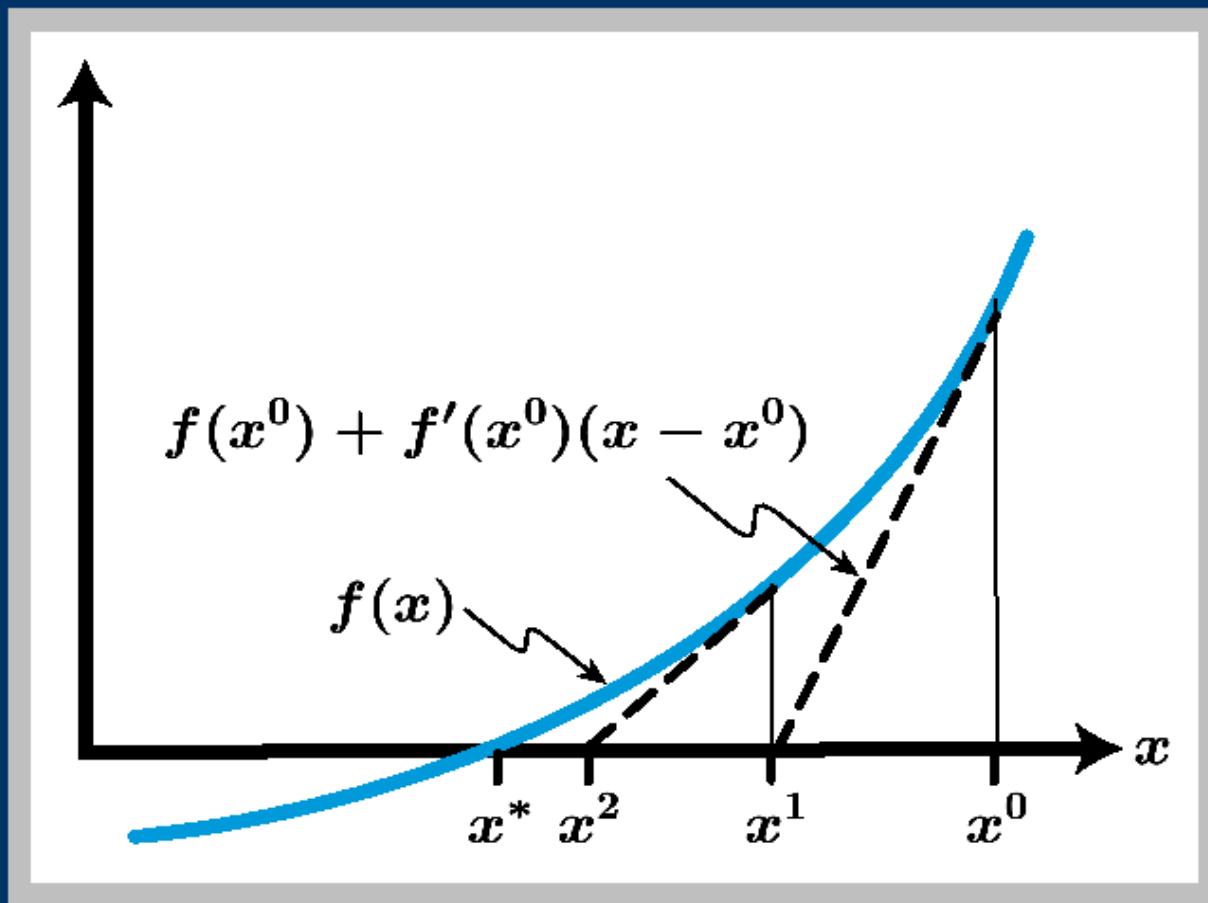
} Until ?

$$\|x^{k+1} - x^k\| < \text{threshold} ? \quad \|f(x^{k+1})\| < \text{threshold} ?$$

# 1-D Reminder

## Newton Algorithm

### Algorithm Picture

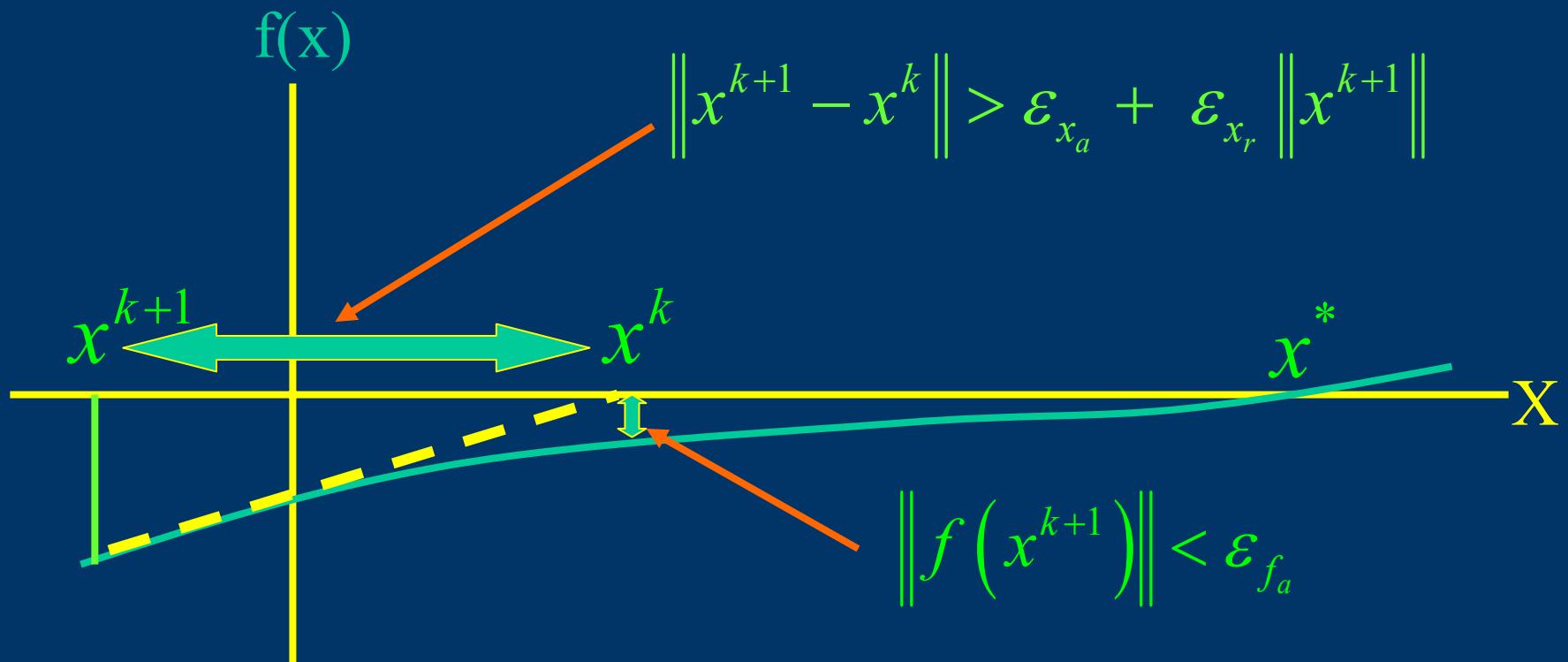


# 1-D Reminder

## Newton Algorithm

### Convergence Checks

Need a "delta-x" check to avoid false convergence

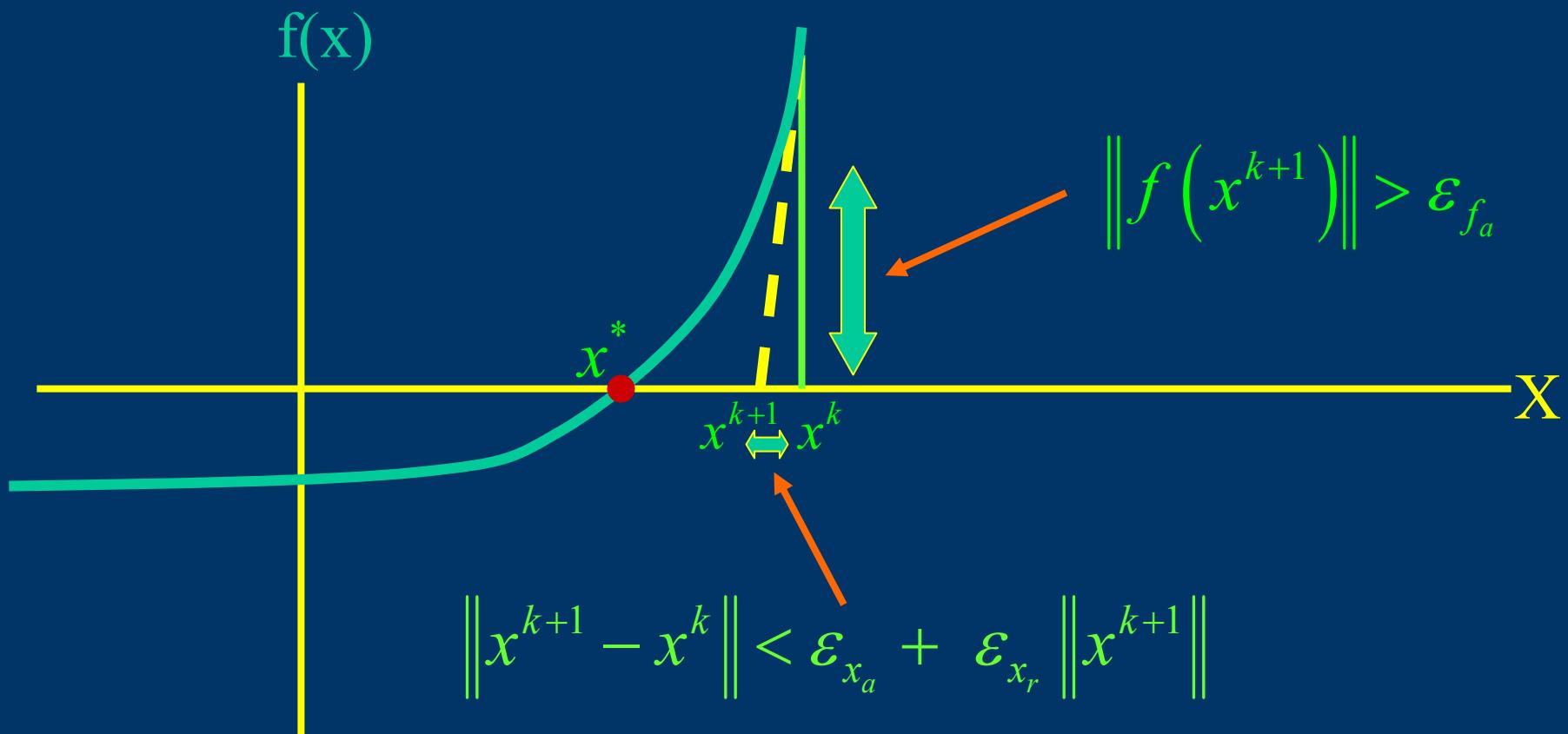


# 1-D Reminder

## Newton Algorithm

### Convergence Checks

Also need an " $f(x)$ " check to avoid false convergence

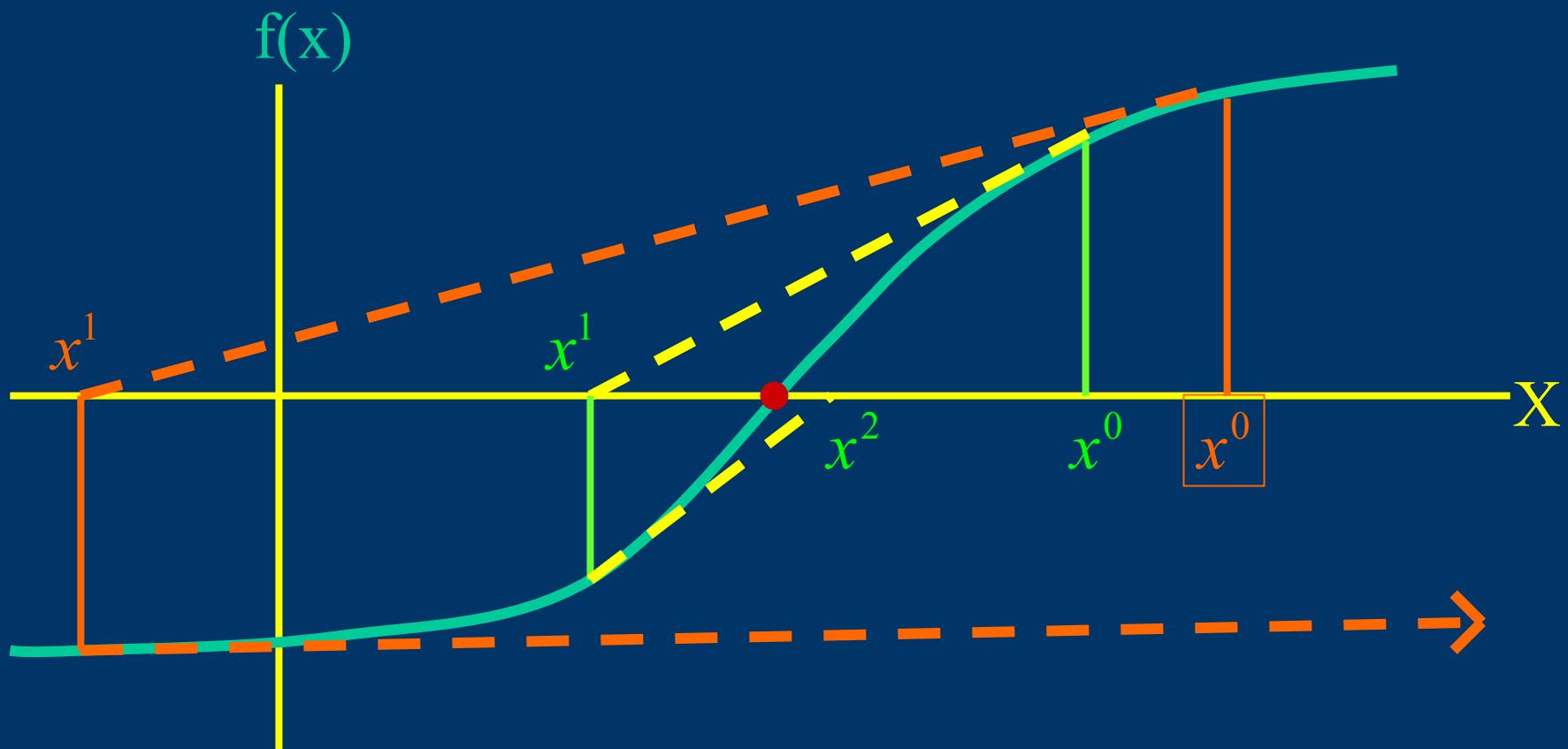


# 1-D Reminder

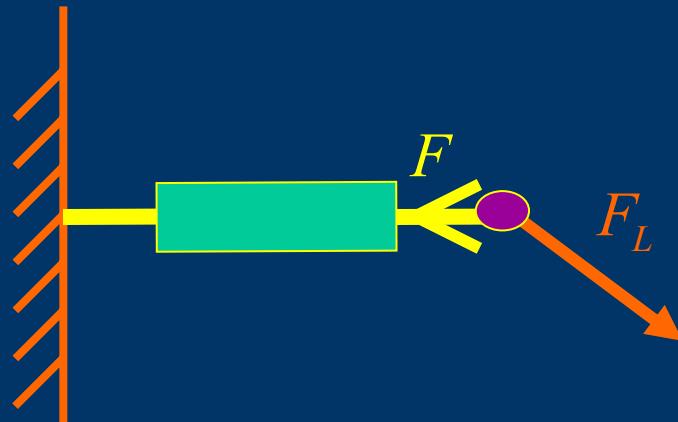
## Newton Algorithm

### Local Convergence

Convergence Depends on a Good Initial Guess



# Multidimensional Newton Method



$$l = \sqrt{x^2 + y^2}$$

$$F = EA_c \frac{(l_o - l)}{l_o} = \varepsilon(l_o - l)$$

$$f_x = \frac{x}{l} F = \frac{x}{l} \varepsilon(l_o - l)$$

$$f_y = \frac{y}{l} F = \frac{y}{l} \varepsilon(l_o - l)$$

## Example Problem

### Strut and Joint

$$F(\vec{x}) = \begin{cases} f_x + F_{L_x} = 0 \\ f_y + F_{L_y} = 0 \end{cases}$$

OR

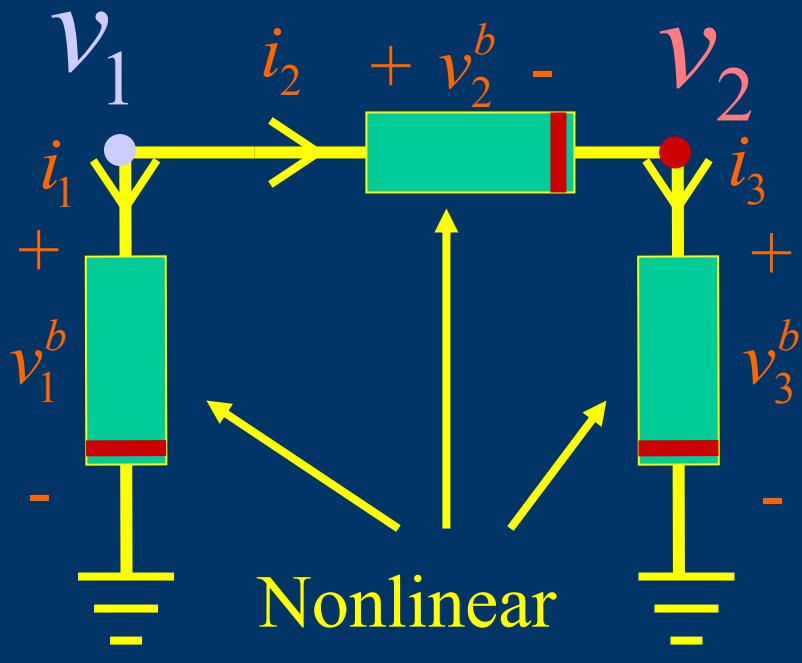
$$\frac{x}{l} \varepsilon(l_o - l) + F_{L_x} = 0$$

$$\frac{y}{l} \varepsilon(l_o - l) + F_{L_y} = 0$$

# Multidimensional Newton Method

## Example Problem

### Nonlinear Resistors



$$i = g(v)$$

### Nodal Analysis

$$\text{At Node 1: } i_1 + i_2 = 0$$

$$\Rightarrow g(v_1) + g(v_1 - v_2) = 0$$

$$\text{At Node 2: } i_3 - i_2 = 0$$

$$\Rightarrow g(v_3) - g(v_1 - v_2) = 0$$

Two coupled  
nonlinear equations  
in two unknowns

# Multidimensional Newton Method

## General Setting

Problem: Find  $x^*$  such that  $F(x^*) = 0$   
 $x^* \in \mathbb{R}^N$  and  $F: \mathbb{R}^N \rightarrow \mathbb{R}^N$

Use a Taylor Series Expansion

$$\cancel{F(x^*)^0} = F(x) + \underbrace{J_F(x)}_{\substack{\text{Jacobi} \\ \text{an} \\ \text{Matrix}}} (x^* - x) + H.O.T.$$

If  $x$  is close to the exact solution

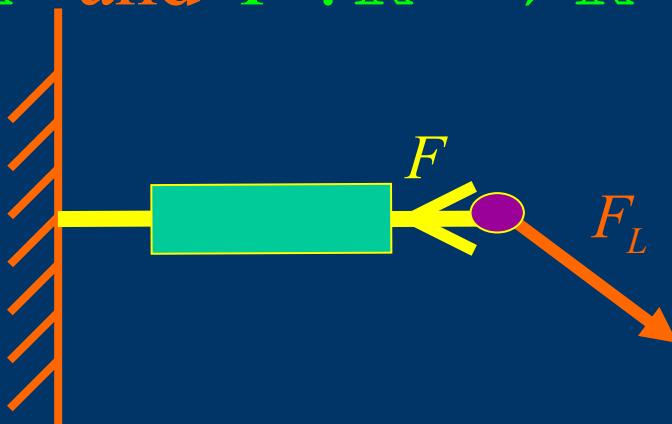
$$J_F(x)(x^* - x) \approx -F(x)$$

# Multidimensional Newton Method

## Nodal Analysis

### Strut and Joint

$$x^* \in \mathbb{R}^2 \text{ and } F : \mathbb{R}^2 \rightarrow \mathbb{R}^2$$



$$\frac{x}{l} \varepsilon(l_o - l) + F_{L_x} = 0$$

$$\frac{y}{l} \varepsilon(l_o - l) + F_{L_y} = 0$$

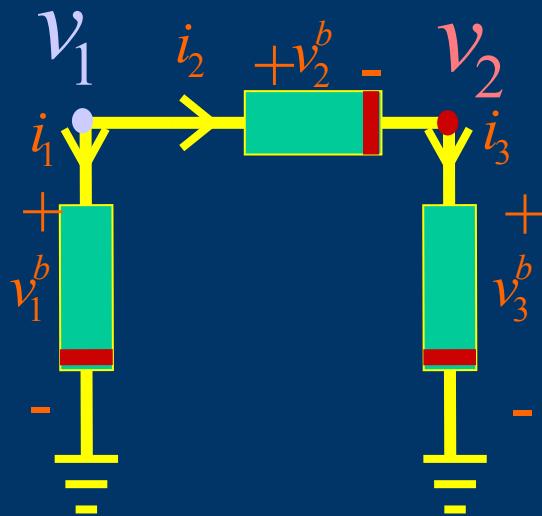
$$J_F(\vec{x}) = \begin{bmatrix} ? & ? \\ ? & ? \end{bmatrix}$$

# Multidimensional Newton Method

## Nodal Analysis

### Nonlinear Resistor

$$x^* \in \mathbb{R}^2 \text{ and } F : \mathbb{R}^2 \rightarrow \mathbb{R}^2$$



$$\text{At Node 1: } i_1 + i_2 = 0$$

$$\Rightarrow F_1(\vec{v}) = g(v_1) + g(v_1 - v_2) = 0$$

$$\text{At Node 2: } i_3 - i_2 = 0$$

$$\Rightarrow F_2(\vec{v}) = g(v_3) - g(v_1 - v_2) = 0$$

$$J_F(\vec{x}) = \begin{bmatrix} ? & ? \\ ? & ? \end{bmatrix}$$

# Multidimensional Newton Method

## Jacobian Matrix

$$J_F(x) \Delta x \approx F(x + \Delta x) - F(x)$$

$$J_F(x) \Delta x \equiv \begin{bmatrix} \frac{\partial F_1(x)}{\partial x_1} & \dots & \frac{\partial F_1(x)}{\partial x_N} \\ \vdots & \ddots & \vdots \\ \frac{\partial F_N(x)}{\partial x_1} & \dots & \frac{\partial F_N(x)}{\partial x_N} \end{bmatrix} \begin{bmatrix} \Delta x_1 \\ \vdots \\ \Delta x_N \end{bmatrix}$$

# Multidimensional Newton Method

## Jacobian Matrix

### Singular Case

Suppose  $J_F(x)$  is singular?

$$J_F(x)\Delta x = \begin{bmatrix} \frac{\partial F_1(x)}{\partial x_1} & \dots & \frac{\partial F_1(x)}{\partial x_N} \\ \vdots & \ddots & \vdots \\ \frac{\partial F_N(x)}{\partial x_1} & \dots & \frac{\partial F_N(x)}{\partial x_N} \end{bmatrix} \begin{bmatrix} \Delta x_1 \\ \vdots \\ \Delta x_N \end{bmatrix} = 0$$

What does it mean?

# Multidimensional Newton Method

## Newton Algorithm

$x^0$  = Initial Guess,  $k = 0$

Repeat {

Compute  $F(x^k)$ ,  $J_F(x^k)$

Solve  $J_F(x^k)(x^{k+1} - x^k) = -F(x^k)$  for  $x^{k+1}$

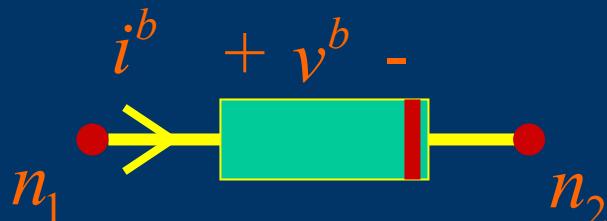
$k = k + 1$

} Until  $\|x^{k+1} - x^k\|$ ,  $\|f(x^{k+1})\|$  small enough

# Multidimensional Newton Method

## Computing the Jacobian and the Function

Consider the contribution of one nonlinear resistor  
Connected between nodes  $n_1$  and  $n_2$



$$i^b = g(v^b)$$

Summing currents at Node  $n_1$ :  $F_{n_1}(v) = g(v_{n_1} - v_{n_2}) + \dots$

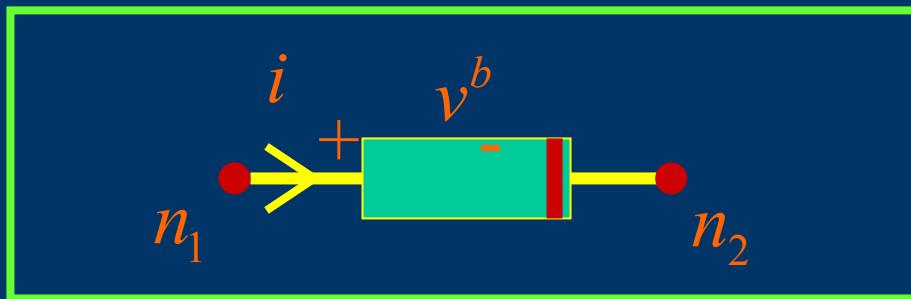
Summing currents at Node  $n_2$ :  $F_{n_2}(v) = -g(v_{n_1} - v_{n_2}) + \dots$

Differentiating at Node  $n_1$ :  $\frac{\partial F_{n_1}(v)}{\partial v_{n_1}} = \underbrace{\frac{\partial g(v_{n_1} - v_{n_2})}{\partial v_{n_1}}}_{\frac{\partial g}{\partial v}} + \dots$      $\frac{\partial F_{n_1}(v)}{\partial v_{n_2}} = \underbrace{\frac{\partial g(v_{n_1} - v_{n_2})}{\partial v_{n_2}}}_{-\frac{\partial g}{\partial v}} + \dots$

# Multidimensional Newton Method

## Computing the Jacobian and the Function

Stamping a  
Resistor



$$\begin{bmatrix} n_1 \\ \vdots \\ n_1 \\ \vdots \\ n_2 \\ \vdots \\ n_2 \end{bmatrix} \underbrace{\begin{bmatrix} n_1 & & & & & & \\ \vdots & \vdots & & & & & \\ \frac{\partial g(v_{n_1} - v_{n_2})}{\partial v} & & -\frac{\partial g(v_{n_1} - v_{n_2})}{\partial v} & & & & \\ \vdots & \vdots & \vdots & & & & \\ -\frac{\partial g(v_{n_1} - v_{n_2})}{\partial v} & & \frac{\partial g(v_{n_1} - v_{n_2})}{\partial v} & & & & \\ \vdots & \vdots & \vdots & & & & \\ \vdots & \vdots & \vdots & & & & \end{bmatrix}}_{J_F(v)} \begin{bmatrix} n_1 \\ \vdots \\ g(v_{n_1} - v_{n_2}) \\ \vdots \\ -g(v_{n_1} - v_{n_2}) \\ \vdots \\ F(v) \end{bmatrix} n_2$$

# Multidimensional Newton Method

## More Complete Newton Algorithm

$x^0$  = Initial Guess,  $k = 0$

Repeat {

Compute  $F(x^k)$ ,  $J_F(x^k)$

Zero  $J_F$  and  $F$

for each element

Compute element currents and derivatives

Sum currents to  $F$ , sum derivatives to  $J_F$

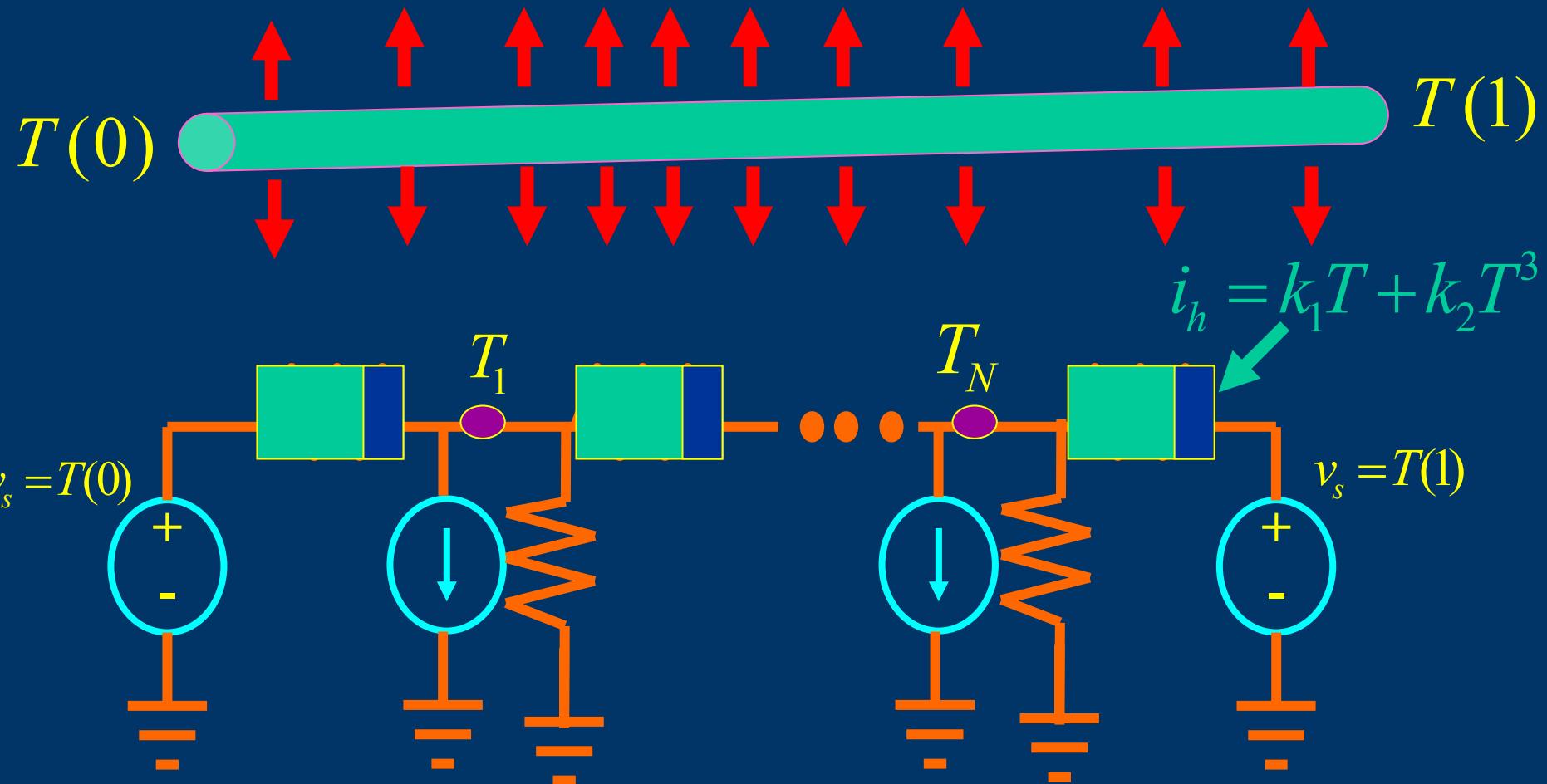
Solve  $J_F(x^k)(x^{k+1} - x^k) = -F(x^k)$  for  $x^{k+1}$

$k = k + 1$

} Until  $\|x^{k+1} - x^k\|$ ,  $\|f(x^{k+1})\|$  small enough

# Multidimensional Newton's Method

## Example: Heat Flow in leaky bar



What is the Jacobian?

# Multidimensional Newton Method

## Multidimensional Convergence Theorem

### Theorem Statement

#### Main Theorem

If

- a)  $\|J_F^{-1}(x^k)\| \leq \beta$  (Inverse is bounded)
- b)  $\|J_F(x) - J_F(y)\| \leq \ell \|x - y\|$  (Derivative is Lipschitz Cont)

Then Newton's method converges given a sufficiently close initial guess

# Multidimensional Newton Method

# Multidimensional Convergence Theorem

## Key Lemma

If  $\|J_F(x) - J_F(y)\| \leq \ell \|x - y\|$  (Derivative is Lipschitz Cont)

Then  $\|F(x) - F(y) - J_F(y)(x - y)\| \leq \frac{\ell}{2} \|x - y\|^2$

**There is no multidimensional mean value theorem.**

# Multidimensional Newton Method

## Multidimensional Convergence Theorem

### Theorem Proof

By definition of the Newton Iteration and the assumed bound on the inverse of the Jacobian

$$\|x^{k+1} - x^k\| = \|J_F^{-1}(x^k)F(x^k)\| \leq \beta \|F(x^k)\|$$

Again applying the Newton iteration definition

$$\|x^{k+1} - x^k\| \leq \beta \left\| F(x^k) - \underbrace{F(x^{k-1}) - J_F(x^{k-1})(x^k - x^{k-1})}_0 \right\|$$

Finally using the Lemma

$$\|x^{k+1} - x^k\| \leq \frac{\beta \ell}{2} \|x^k - x^{k-1}\|^2$$

# Multidimensional Newton Method

## Multidimensional Convergence Theorem

Theorem Proof Continued

Reorganizing the equation

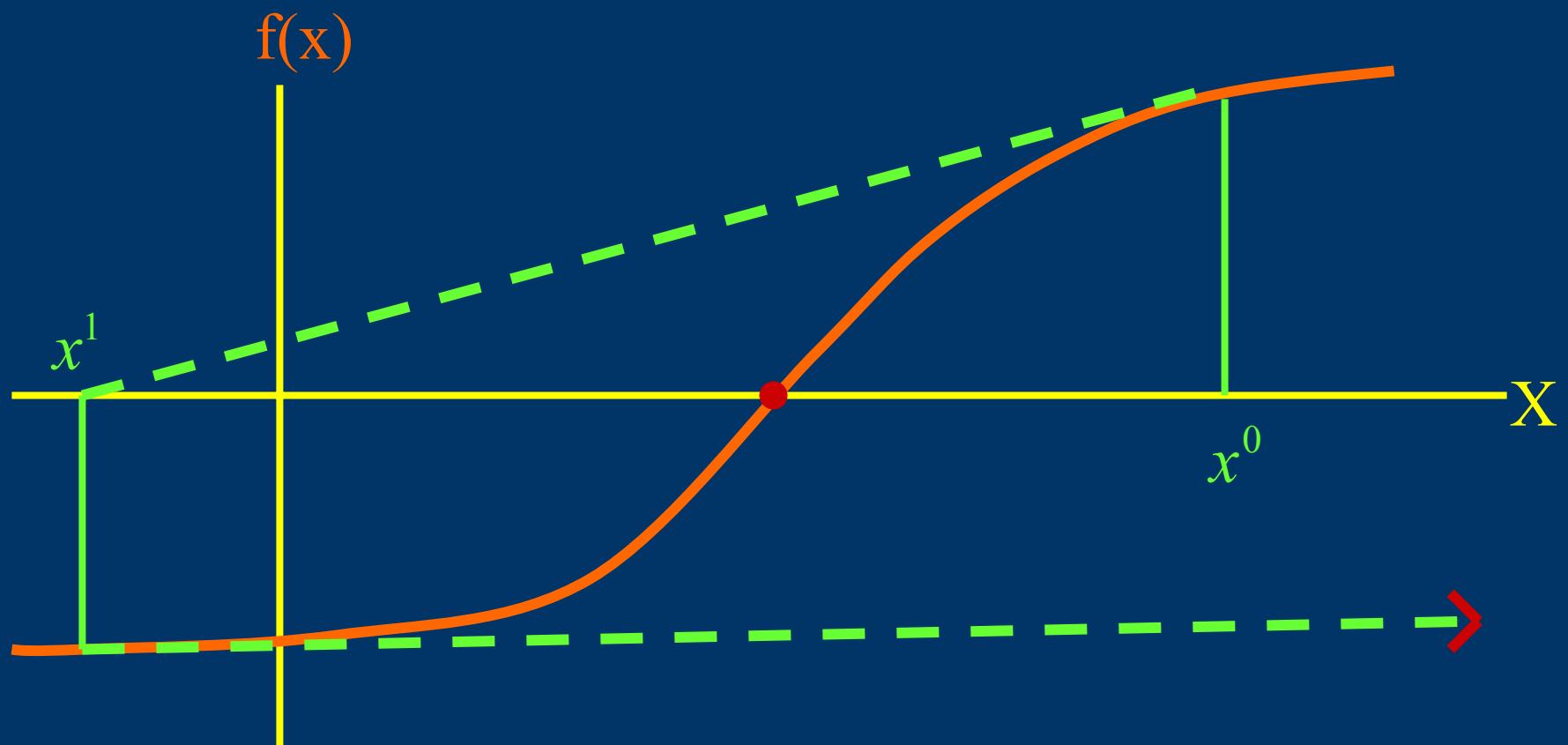
$$\|x^{k+1} - x^k\| \leq \left( \frac{\beta\ell}{2} \|x^k - x^{k-1}\| \right) \|x^k - x^{k-1}\|$$

If  $\left( \frac{\beta\ell}{2} \|x^1 - x^0\| \right) \leq \gamma < 1$

$$\|x^{k+1} - x^k\| \leq \gamma^k \Rightarrow \sum_{k=0}^{\infty} (x^{k+1} - x^k) + x^0 \text{ converges}$$

# Non-converging Case

## 1-D Picture



Must Somehow Limit the changes in  $X$

# Newton Method with Limiting

## Newton Algorithm

Newton Algorithm for Solving  $F(x) = 0$

$x^0$  = Initial Guess,  $k = 0$

Repeat {

Compute  $F(x^k)$ ,  $J_F(x^k)$

Solve  $J_F(x^k) \Delta x^{k+1} = -F(x^k)$  for  $\Delta x^{k+1}$

$x^{k+1} = x^k + \text{limited}(\Delta x^{k+1})$

$k = k + 1$

} Until  $\|\Delta x^{k+1}\|$ ,  $\|F(x^{k+1})\|$  small enough

# Newton Method with Limiting

## Limiting Methods

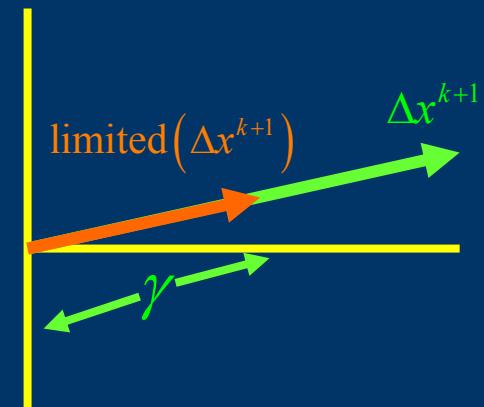
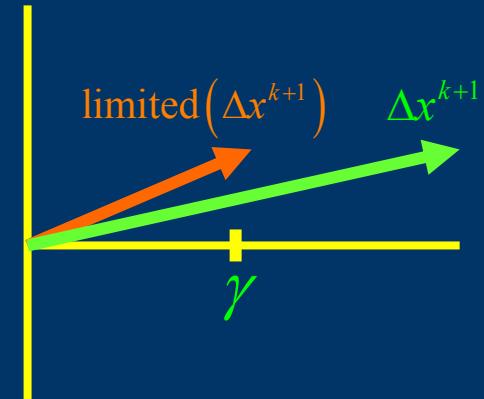
- Direction Corrupting

$$\text{limited}(\Delta x^{k+1})_i = \begin{cases} \Delta x_i^{k+1} & \text{if } |\Delta x_i^{k+1}| < \gamma \\ \gamma \text{ sign}(\Delta x_i^{k+1}) & \text{otherwise} \end{cases}$$

- NonCorrupting

$$\text{limited}(\Delta x^{k+1}) = \alpha \Delta x^{k+1}$$

$$\alpha = \min \left\{ 1, \frac{\gamma}{\|\Delta x^{k+1}\|} \right\}$$



Heuristics, No Guarantee of Global Convergence

# Newton Method with Limiting

# Damped Newton Scheme

## General Damping Scheme

Solve  $J_F(x^k) \Delta x^{k+1} = -F(x^k)$  for  $\Delta x^{k+1}$

$$x^{k+1} = x^k + \alpha^k \Delta x^{k+1}$$

## Key Idea: Line Search

Pick  $\alpha^k$  to minimize  $\|F(x^k + \alpha^k \Delta x^{k+1})\|_2^2$

$$\|F(x^k + \alpha^k \Delta x^{k+1})\|_2^2 \equiv F(x^k + \alpha^k \Delta x^{k+1})^T F(x^k + \alpha^k \Delta x^{k+1})$$

Method Performs a one-dimensional search in  
Newton Direction

# Newton Method with Limiting

## Damped Newton

### Convergence Theorem

If

a)  $\|J_F^{-1}(x^k)\| \leq \beta$  (Inverse is bounded)

b)  $\|J_F(x) - J_F(y)\| \leq \ell \|x - y\|$  (Derivative is Lipschitz Cont)

Then

There exists a set of  $\alpha^k$ 's  $\in (0, 1]$  such that

$$\|F(x^{k+1})\| = \|F(x^k + \alpha^k \Delta x^{k+1})\| < \gamma \|F(x^k)\| \text{ with } \gamma < 1$$

Every Step reduces F-- Global Convergence!

# Newton Method with Limiting

## Damped Newton

### Nested Iteration

$x^0$  = Initial Guess,  $k = 0$

Repeat {

    Compute  $F(x^k)$ ,  $J_F(x^k)$

    Solve  $J_F(x^k) \Delta x^{k+1} = -F(x^k)$  for  $\Delta x^{k+1}$

    Find  $\alpha^k \in (0,1]$  such that  $\|F(x^k + \alpha^k \Delta x^{k+1})\|$  is minimized

$x^{k+1} = x^k + \alpha^k \Delta x^{k+1}$

$k = k + 1$

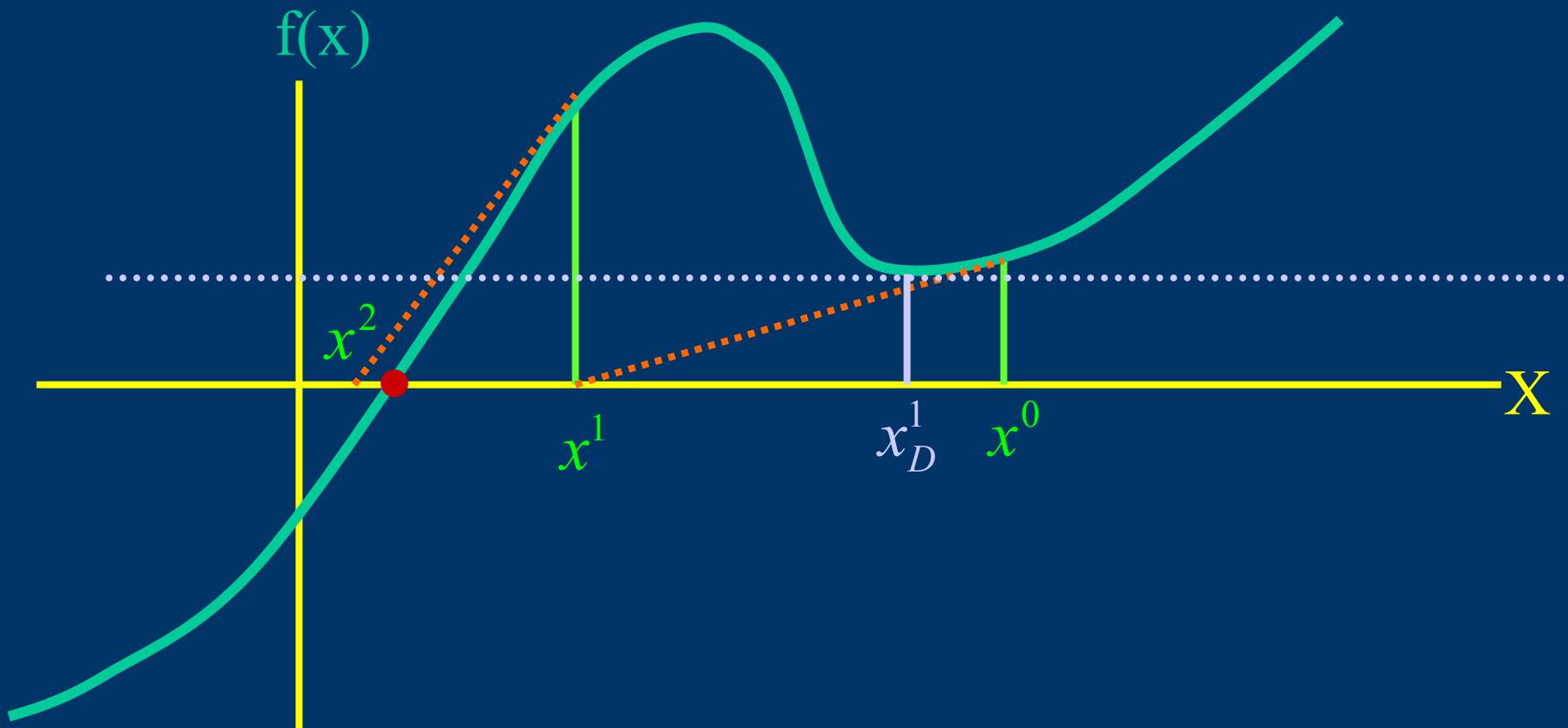
} Until  $\|\Delta x^{k+1}\|$ ,  $\|F(x^{k+1})\|$  small enough

How can one find the damping coefficients?

# Newton Method with Limiting

## Damped Newton

### Singular Jacobian Problem



Damped Newton Methods “push” iterates to local minimums  
Finds the points where Jacobian is Singular

# Summary

- Quick Review of 1-D Newton
  - Convergence Testing
- Multidimensional Newton Method
  - Basic Algorithm
  - Description of the Jacobian.
  - Jacobian Construction.
  - Local Convergence Theorem
- Damped Newton Method
  - Nested Algorithm with line search
  - Global convergence **IF** Jacobian nonsingular