

# Optimization Techniques

## Section 2

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## Steepest Descent

- Exact step size
- $x_{\text{new}} = x_{\text{old}} - \text{eps} * df;$
- Eps is calculated as:
  - $z(\text{eps}) = x - \text{eps} * df$
  - Find eps point where  $f'(z(\text{eps})) = 0$

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## Steepest Descent

- Find the minimum point of  $f(x)=x^2$
- $z(\text{eps})=x-\text{eps} \cdot 2 \cdot x = x(1-2 \cdot \text{eps})$  = search direction
- $f(z(\text{eps}))$ = the value of  $f$  at a point on the search direction
- Find  $\text{eps}$  value which is minimum of  $f(z(\text{eps}))$ ,  $f'(z(\text{eps}))=0$
- $f(z(\text{eps}))=(x(1-2 \cdot \text{eps}))^2=x^2(1-2 \cdot \text{eps})^2$
- $f(z(\text{eps}))=x^2(1-4 \cdot \text{eps}+4 \cdot \text{eps}^2)$
- $f'(z(\text{eps}))=x^2(-4+8 \cdot \text{eps})=0$
- $\text{eps}=1/2$
- $X_{n+1}=X_n-\text{eps} \cdot df=X_n-\text{eps} \cdot 2 \cdot X_n=X_n-X_n=0$
- **Wherever you start, the minimum point is found at one iteration !**

## Steepest Descent

- Find the minimum point of  $f(x)=x^4$
- $z(\text{eps})=x-\text{eps} \cdot 4 \cdot x^3$  = search direction
- If we know that the minimum point of  $f(z(\text{eps}))$  is 0 ( But, we do not know, in reality)
- $\text{eps} \cdot 4 \cdot x^3=x$  than,
- $\text{eps}=1/(4 \cdot x^2)$
- $X_{n+1}=X_n-\text{eps} \cdot 4 \cdot x^3=X_n-(1/(4 \cdot X_n^2)) \cdot 4 \cdot X_n^3=X_n-X_n=0$
- **Wherever you start, the minimum point is found at one iteration !**

## Steepest Descent in 2 dims.

- Find the iteration equation to find the minimum of  $f(x_1, x_2) = x_1^2 + 3x_2^2$
- $df = [2x_1 \ ; \ 6x_2]$
- $t = \epsilon$
- $z(t)$  have 2 dims as  $x$
- $z(t) = [x_1 \ ; \ x_2] - t \cdot df$
- $z(t) = [x_1; x_2] - [2x_1t; 6x_2t]$
- $z(t) = [x_1(1-2t) \ ; \ x_2(1-6t)]$
- $f(z(t)) = (x_1^2)(1-2t)^2 + 3(x_2^2)(1-6t)^2$

## Steepest Descent in 2 dims.

- $f(z(t)) = (x_1^2)(1-2t)^2 + 3(x_2^2)(1-6t)^2$
- $df(z(t))/dt = f'(z(t)) =$
- $= (x_1^2) \cdot 2(1-2t) \cdot (-2) + 3(x_2^2) \cdot 2(1-6t) \cdot (-6)$
- $= (x_1^2) \cdot (-4)(1-2t) - 36(x_2^2)(1-6t)$
- $= (x_1^2) \cdot (-4 + 8t) - (x_2^2) \cdot (36 - 216t)$
- $= -4(x_1^2) + (x_1^2) \cdot 8t - 36(x_2^2) + 216t(x_2^2)$
- $= 0$  because  $f'(z(t)) = 0$
- $(x_1^2) \cdot 8t + 216t(x_2^2) = 4(x_1^2) + 36(x_2^2)$
- $t = (4(x_1^2) + 36(x_2^2)) / ((x_1^2) \cdot 8 + 216(x_2^2))$
- $t = ((x_1^2) + 9(x_2^2)) / (2(x_1^2) + 54(x_2^2))$

## Steepest Descent in 2 dims.

- So the iteration equation is
  - $X_{n+1} = X_n - t * [2 * x_1; 6 * x_2]$  where
- $$t = ((x_1^2) + 9 * (x_2^2)) / (2 * (x_1^2) + 54 * (x_2^2))$$

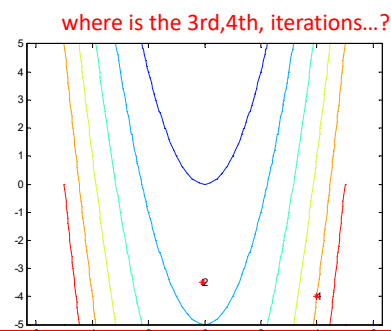
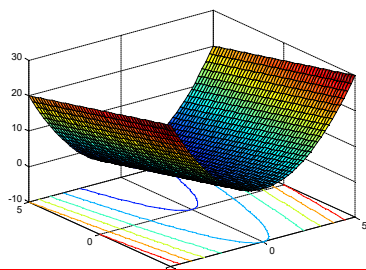
## Steepest Descent Examples

- $f(x) = x_1^2 + x_2^2$
- $df = [2 * x_1; 2 * x_2]$
- $z(t) = [x_1; x_2] - t * df$
- $z(t) = [x_1; x_2] - [2 * x_1 * t; 2 * x_2 * t]$
- $z(t) = [x_1 * (1 - 2 * t); x_2 * (1 - 2 * t)]$
- $f(z(t)) = (x_1^2) * (1 - 2 * t)^2 + (x_2^2) * (1 - 2 * t)^2$
- $f(z(t)) = ((1 - 2 * t)^2) * (x_1^2 + x_2^2)$
- $f'(z(t)) = (x_1^2 + x_2^2) * (8 * t - 4) = 0$
- $t = 1/2$
- $z(t) = [x_1; x_2] - t * [2 * x_1; 2 * x_2]$
- $z(t) = [x_1; x_2] - [x_1; x_2] = [0; 0]$
- **Wherever you start, the minimum point is found at one iteration!**

## Steepest Descent Examples

- $f(x) = x_1^2 + x_2^2$ ,  $t = 1/2$
- $f(x) = x_1^2 - x_2$ ,  $t = 0.5 + 1/(8 \cdot x_1^2)$

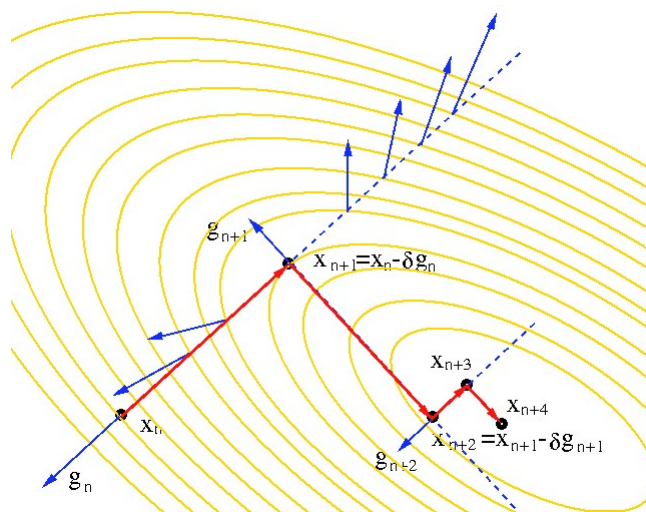
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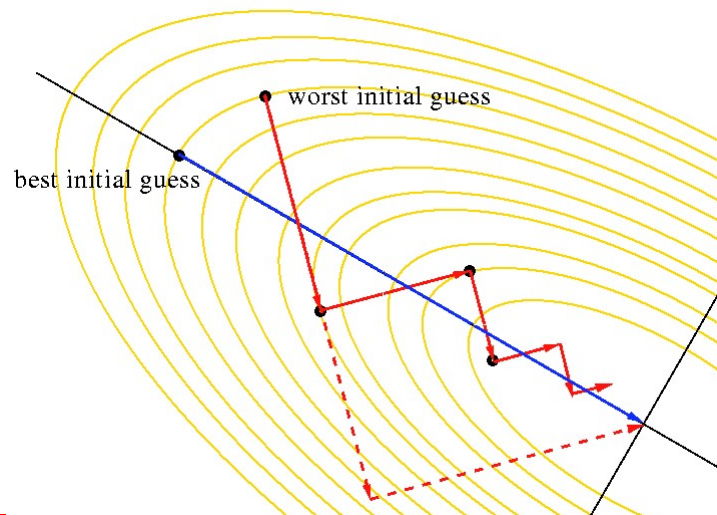
the new search direction will always be perpendicular to the previous direction.



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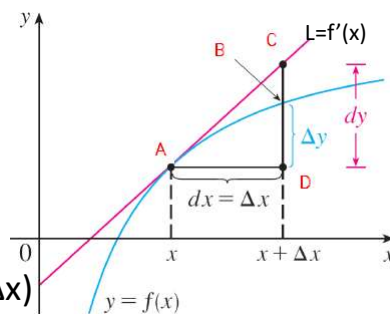


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## Linear Approximation

- Assuming the function is linear at a point.



$$f(x+\Delta x) \approx L(x+\Delta x)$$

$$\lim_{(\Delta x \rightarrow 0)} (f(x+\Delta x) - L(x+\Delta x)) = 0$$

$$L(x+\Delta x) = f(x) + dy = f(x) + \Delta x f'(x) \text{ since } f'(x) = dy/dx$$

New point:  $\text{dom}x = x + \Delta x$ ,

$$\Delta x = \text{dom}x - x, f(\text{dom}x) \approx f(x) + (\text{dom}x - x)f'(x)$$

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## Linear Approximation Example 1

- $(1.0002)^{50} \approx ?$
- $f(x) = x^{50}$
- $f(x+\Delta x) \approx f(x) + \Delta x f'(x)$
- $\text{dom}x = 1.0002, x=1, \Delta x = 0.0002$
- $f(1+0.0002) \approx f(1) + 0.0002 f'(1)$
- $f(1+0.0002) \approx f(1) + 0.0002 * 50 * 1^{49}$
- $f(1+0.0002) \approx 1 + 0.0002 * 50 * 1 = 1.01$

## Linear Approximation Example 2

- Find the linear approximation for  $x$  tends to 1 where  $f(x) = \ln x$ .
- $f(x+\Delta x) \approx f(x) + \Delta x f'(x)$
- $\text{dom}x = x+\Delta x, \Delta x = \text{dom}x - x, x=1, f'(x) = 1/x$
- $f(\text{dom}x) \approx \ln 1 + f'(1) (\text{dom}x - 1) = \text{dom}x - 1$
- $\ln x \approx x - 1$ , for  $x$  close to 1
  
- For  $x$  tends to 2
- $\Delta x = \text{dom}x - x, x=2$
- $f(\text{dom}x) \approx \ln 2 + f'(2) (\text{dom}x - 2) = \ln 2 + (\text{dom}x - 2)/2$
- $\ln x \approx \ln 2 + (x - 2)/2$ , for  $x$  close to 2

## For a better approximation

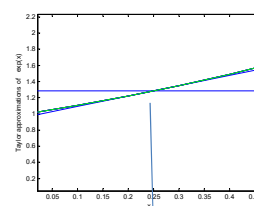
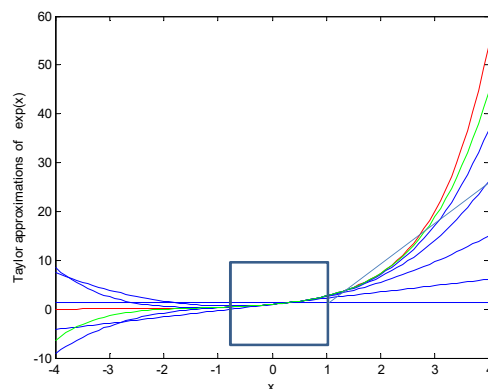
- 1<sup>st</sup> order Taylor: (linear approx.)  

$$f(x+\Delta x) \approx f(x) + \Delta x f'(x)$$
- 2<sup>nd</sup> order Taylor: (non-linear approx.)  

$$f(x+\Delta x) \approx f(x) + \Delta x f'(x) + \frac{1}{2} f''(x) \Delta x^2$$
- ...
- N<sup>th</sup> order Taylor: (non-linear approx.)  

$$f(x+\Delta x) \approx \sum (f^{(i)'}(x) \Delta x^i) / i! \quad i=0 \dots N$$

## Function approx. with Taylor



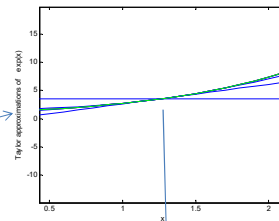
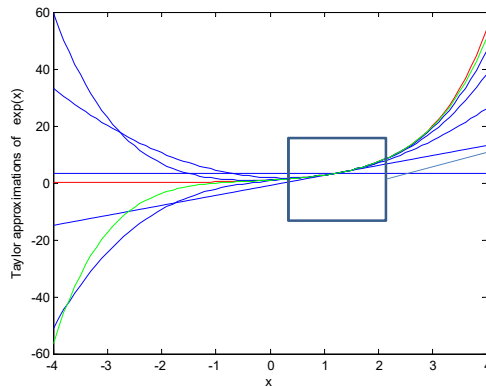
All approximations passes from (0.25, f(0.25))

- $f(x)=\exp(x)$ ,  $N=0:5$ ,  $X=0.25$
- Red: real f, Blues and green: approximations
- Green: The last approx.

approx\_taylor.m



## Function approx. with Taylor



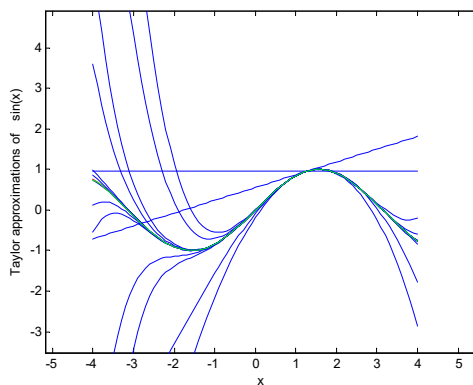
All approximations passes from (1.25, f(1.25))

- $f(x)=\exp(x)$ ,  $N=0:5$ ,  $X=1.25$
- Red: real f, Blues and green: approximations
- Green: The last approx.

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approx\_taylor.m

## Function approx. with Taylor



- $f(X)=\sin(x)$
- $X=1.25$
- $N=0:15$
- Red: real f
- Blues and green: approximations
- Green: The last approx.

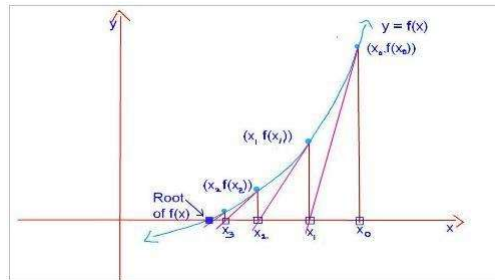
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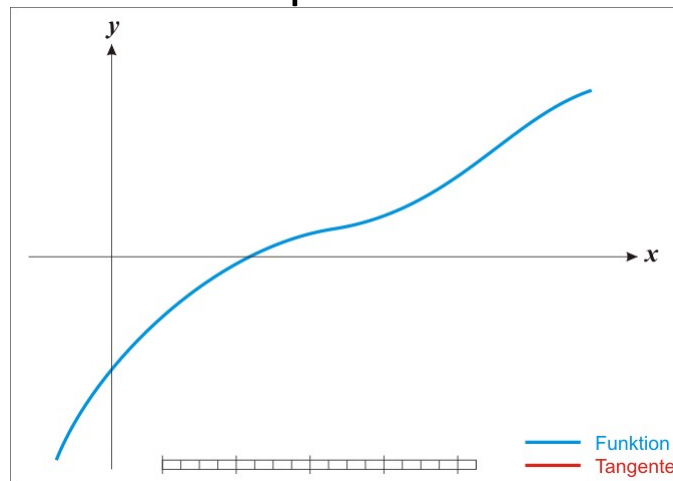
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## Finding a root of $f(x)$ iteratively (find a point $x$ where $f(x)=0$ ) Newton Raphson 1<sup>st</sup> order

- $f'(x_n) = f(x_n) / (x_n - x_{n+1})$
- $x_n - x_{n+1} = f(x_n) / f'(x_n)$
- $x_{n+1} = x_n - f(x_n) / f'(x_n)$   
 $n = 0, 1, 2, 3, \dots$
- If we require the root correct up to 6 decimal places, we stop when the digits in  $x_{n+1}$  and  $x_n$  agree till the 6<sup>th</sup> decimal place.



## Newton Raphson- 1<sup>st</sup> order



## Example

- Find  $\text{sqrt}(2)$
- Means find the root of  $x^2-2=0$
- $x_0=1$
- $x_{n+1} = x_n - f(x_n)/f'(x_n)$
- $x_{n+1} = x_n - (x_n^2 - 2)/(2 * x_n)$
- $x_0=1$   
 $x_1=1.5$   
 $x_2=1.41667$   
 $x_3=1.41422$   
 $x_4=1.41421$   
 if the current improvement (0.00001) is insignificant, we can say  $\text{sqrt}(2) = 1.41421$ , if not go on the iterations.

## Taylor Series - Newton Raphson 2nd order

- 1<sup>st</sup> order Taylor:  

$$f(x+\Delta x) \approx f(x) + \Delta x f'(x) \quad (1)$$
- According to 1<sup>st</sup> order Taylor, to find  $f(x+\Delta x)=0$ ,  

$$\Delta x = -f(x)/f'(x)$$
- To find  $f(x+\Delta x)'=0$ , take derivative of (1)  

$$f'(x+\Delta x) \approx f'(x) + \Delta x f''(x)$$

$$\Delta x = -f'(x)/f''(x) \leftarrow \text{Newton Raphson 2nd order}$$

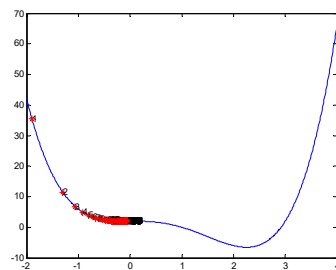
$$x_{n+1} = x_n - f(x_n) / f'(x_n)$$

$$\Delta x = x_{n+1} - x_n$$

## Newton Raphson

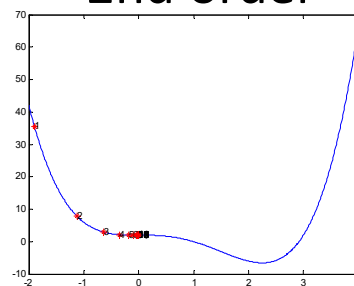
- Generally faster converge, because it uses more information (2nd derivative)
- No explicit step size selection
- 1st order :  $x_{\text{new}} = x_{\text{old}} - f/df$ ; ( $f(x)=0$ )
- 2nd order :  $x_{\text{new}} = x_{\text{old}} - df/ddf$ ; ( $f'(x)=0$ )
- instead of  $x_{\text{new}} = x_{\text{old}} - \text{eps} * df$ ; (gradient descent)

Gradient Descent  
Step size=0.01  
Starting point=-1.9



Does not converge with 200 iterations

Newton Raphson  
2nd order

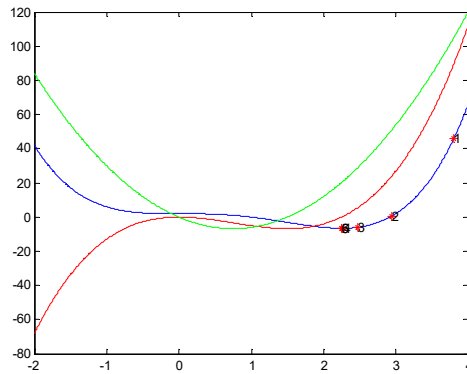


Converged at 20 iterations

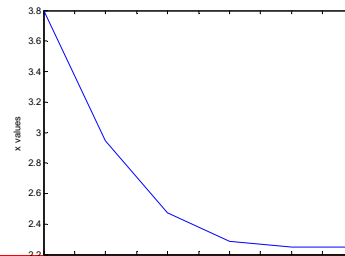
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## newton\_raphson\_1.m

### 2nd order finds $f'(x)=0$



- Blue  $f$
- Red  $f'$
- Green  $f''$

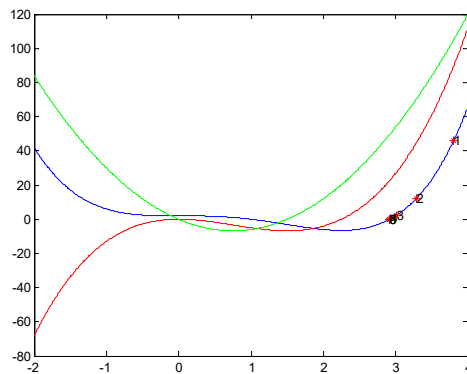


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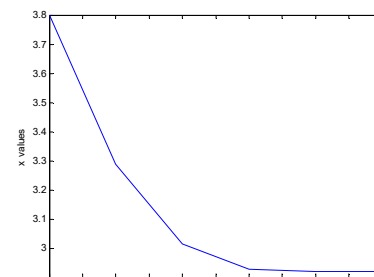
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## newton\_raphson\_1.m

### 1st order finds $f(x)=0$



- Blue  $f$
- Red  $f'$
- Green  $f''$

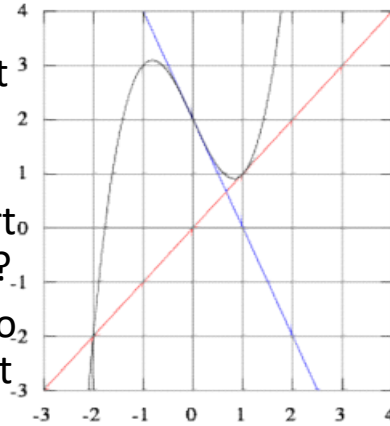


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## Newton Raphson 1st order -Cycle problem

- The tangent lines of  $x^3 - 2x + 2$  at 0 and 1 intersect the x-axis at 1 and 0 respectively.
- What happened if we start at a point in (0,1) interval?
- If we start at 0.1, it goes to 1, then it goes to 0, then it goes to 1 ...



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## Newton Raphson

- Faster convergence (lower iteration number)
- But, more calculation for each iteration

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## References

- <http://math.tutorvista.com/calculus/newton-raphson-method.html>
- <http://math.tutorvista.com/calculus/linear-approximation.html>
- [http://en.wikipedia.org/wiki/Newton's\\_method](http://en.wikipedia.org/wiki/Newton's_method)
- [http://en.wikipedia.org/wiki/Steepest\\_descent](http://en.wikipedia.org/wiki/Steepest_descent)
- [http://www.pitt.edu/~nak54/Unconstrained\\_Optimization\\_KN.pdf](http://www.pitt.edu/~nak54/Unconstrained_Optimization_KN.pdf)
- <http://mathworld.wolfram.com/MatrixInverse.html>
- <http://ipsa.swarthmore.edu/BackGround/RevMat/MatrixReview.html>
- <http://www.cut-the-knot.org/arithmetic/algebra/Determinant.shtml>
- Matematik Dünyası, MD 2014-II, Determinantlar
- [http://www.sharetechnote.com/html/EngMath\\_Matrix\\_Main.html](http://www.sharetechnote.com/html/EngMath_Matrix_Main.html)
- Advanced Engineering Mathematics , Erwin Kreyszig, 10th Edition, John Wiley & Sons, 2011
- [http://en.wikipedia.org/wiki/Finite\\_difference](http://en.wikipedia.org/wiki/Finite_difference)
- [http://ocw.usu.edu/Civil\\_and\\_Environmental\\_Engineering/Numerical\\_Methods\\_in\\_Civil\\_Engineering/NonLinearEquationsMatlab.pdf](http://ocw.usu.edu/Civil_and_Environmental_Engineering/Numerical_Methods_in_Civil_Engineering/NonLinearEquationsMatlab.pdf)
- [http://www-math.mit.edu/~djik/calculus\\_beginners/chapter09/section02.html](http://www-math.mit.edu/~djik/calculus_beginners/chapter09/section02.html)
- <http://stanford.edu/class/ee364a/lectures/intro.pdf>
- <http://fourier.eng.hmc.edu/e176/lectures/NM/node28.html>