Optimization Techniques Section 2

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Steepest Descent

- Exact step size
- x_new = x_old eps * df;
- Eps is calculated as:
 - -z(eps)=x-eps*df
 - Find eps point where f'(z(eps))=0

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Steepest Descent

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

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Steepest Descent

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

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Steepest Descent in 2 dims.

- Find the iteration equation to find the minimum of $f(x_1,x_2)=x_1^2+3*x_2^2$
- df=[2*x1;6*x2]
- t=eps
- z(t) have 2 dims as x
- z(t)=[x1;x2]-t*df
- z(t)=[x1;x2]-[2*x1*t; 6*x2*t]
- z(t)=[x1*(1-2*t); x2*(1-6*t)]
- $f(z(t)) = (x1^2)^*(1-2^t)^2 + 3^*(x2^2)(1-6^t)^2$

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Steepest Descent in 2 dims.

- $f(z(t)) = (x1^2)^*(1-2^t)^2 + 3^*(x2^2)(1-6^t)^2$
- df(z(t))/dt=f'(z(t))=
- = $(x1^2)^2(1-2^t)^*(-2)+3^*(x2^2)^2(1-6^t)^*(-6)$
- = $(x1^2)^*(-4)^*(1-2^*t)-36^*(x2^2)^*(1-6^*t)$
- = $(x1^2)*(-4+8*t)-(x2^2)*(36-216*t)$
- =- $4*(x1^2)+(x1^2)*8*t-36*(x2^2)+216*t*(x2^2)$
- =0 because f'(z(t))=0
- (x1^2)*8*t+216*t*(x2^2)=4*(x1^2)+36*(x2^2)
- $t = (4*(x1^2)+36*(x2^2)) / ((x1^2)*8+216*(x2^2))$
- $t = ((x1^2) + 9*(x2^2)) / (2*(x1^2) + 54*(x2^2))$

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Steepest Descent in 2 dims.

- So the iteration equation is
- $X_{n+1}=X_n-t^*[2*x1; 6*x2]$ where

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t = ((x1^2) + 9*(x2^2)) / (2*(x1^2) + 54*(x2^2))
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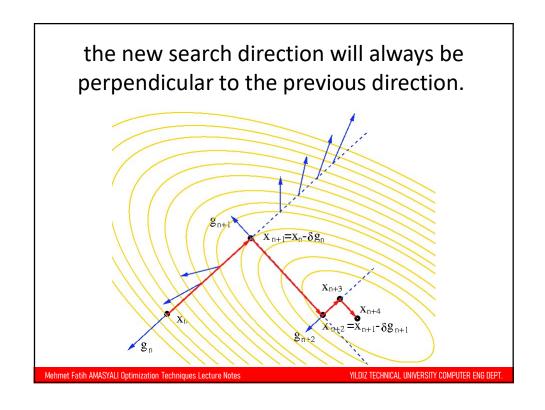
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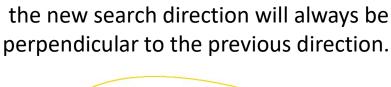
Steepest Descent Examples

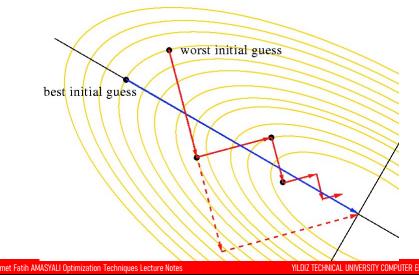
- f(x)=x1^2+x2^2
- df=[2*x1; 2*x2]
- z(t)=[x1;x2]-t*df
- z(t)=[x1;x2]-[2*x1*t; 2*x2*t]
- z(t)=[x1*(1-2*t); x2*(1-2*t)]
- $f(z(t))=(x1^2)*(1-2*t)^2+(x2^2)(1-2*t)^2$
- f(z(t))=((1-2*t) ^2)(x1^2+ x2^2)
- $f'(z(t))=(x1^2 + x2^2)*(8*t 4)=0$
- t=1/2
- z(t)=[x1; x2]-t* [2*x1; 2*x2]
- z(t)=[x1;x2]-[x1;x2]=[00]
- Wherever you start, the minimum point is found at one

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Steepest Descent Examples f(x)=x1^2+x2^2, t=1/2 f(x) =x1^2-x2, t= 0.5+1/(8*x1^2) steepest_desc_2dim_2.m

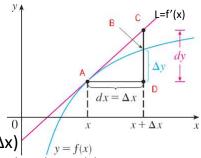






Linear Approximation

• Assuming the function is linear at a point.



 $f(x+\Delta x) \approx L(x+\Delta x)$ y = f(x) $\lim_{(\Delta x \to 0)} (f(x+\Delta x) - L(x+\Delta x)) = 0$

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

New point: $domx=x+\Delta x$,

Ax=domx-x, f(domx) ≈ f(x)+(domx-x)f'(x)

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Linear Approximation Example 1

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

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Linear Approximation Example 2

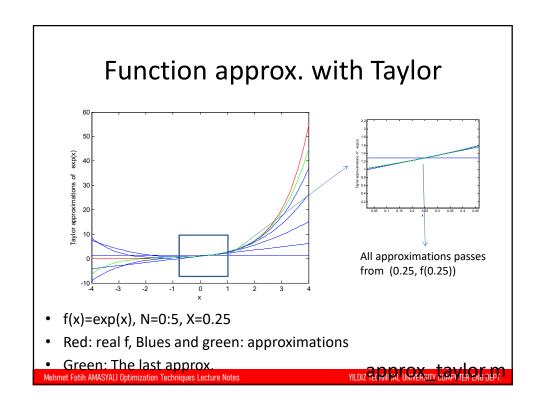
- Find the linear approximation for x tends to 1 where f(x) = ln x.
- $f(x+\Delta x) \approx f(x) + \Delta x f'(x)$
- domx=x+ Δx , Δx = domx-x, x=1, f'(x)=1/x
- $f(domx) \approx ln \ 1 + f'(1) (domx 1) = domx 1$
- $\ln x \approx x-1$, for x close to 1
- For x tends to 2
- $\Delta x = dom x x$, x = 2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

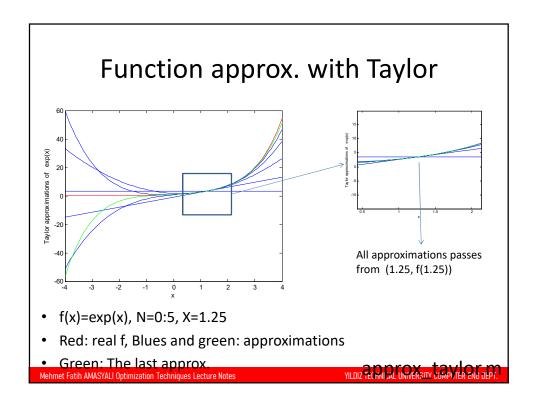
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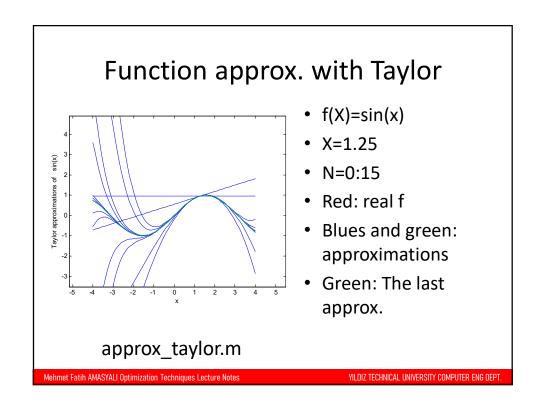
For a better approximation

- 1st order Taylor: (linear approx.) $f(x+\Delta x) \approx f(x) + \Delta x f'(x)$
- 2nd order Taylor: (non-linear approx.) $f(x+\Delta x) \approx f(x) + \Delta x f'(x) + \frac{1}{2} f''(x) \Delta x^2$
- ...
- Nth order Taylor: (non-linear approx.)
- $f(x+\Delta x) \approx \sum (f^{(i)'}(x) \Delta x^i)/i!$ i=0...N

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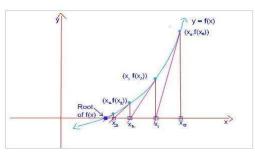




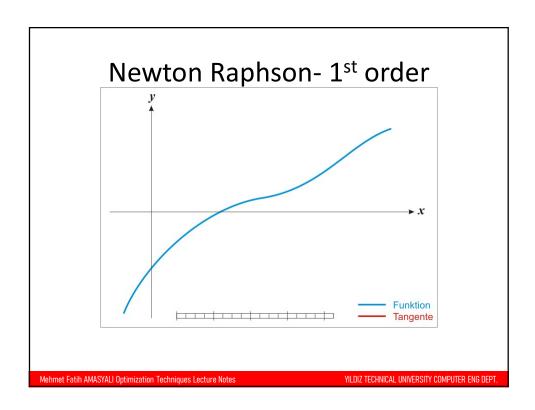


Finding a root of f(x) iteratively (find a point x where f(x)=0) Newton Raphson 1st order

- $f'(x_n) = f(x_n) / (x_n x_{n+1})$
- $x_n x_{n+1} = f(x_n) / f'(x_n)$
- $x_{n+1} = x_n f(x_n) / f'(x_n)$ n = 0,1,2,3....
- 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^{th} decimal place.



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Example

- Find sqrt(2)
- Means find the root of x²-2=0
- $x_0=1$
- $x_{n+1} = x_n f(x_n) / f'(x_n)$
- $x_{n+1} = x_n (x_n * x_n 2)/(2 * x_n)$
- x₀=1
 x₁=1.5
 x₂=1.41667
 x₃=1.41422

 x_4 =1.41421 if the current improvement (0.00001) is insignificant, we can say sqrt(2) =1.41421, if not go on the iterations.

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Taylor Series - Newton Raphson 2nd order

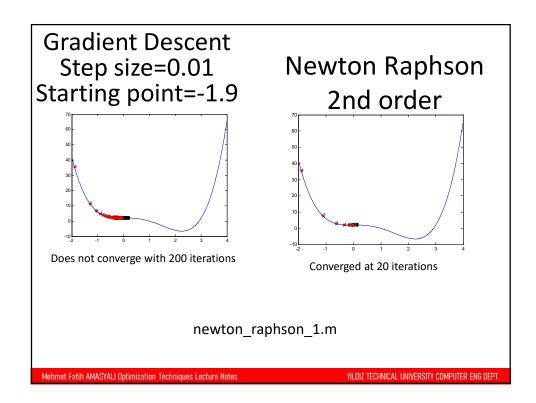
- 1st order Taylor: $f(x+\Delta x) \approx f(x) + \Delta x f'(x)$ (1)
- According to 1st order Taylor, to find $f(x+\Delta x)=0$, $\Delta x=-f(x)/f'(x)$
- To find $f(x+\Delta x)'=0$, take derivative of (1) $f'(x+\Delta x) \approx f'(x) + \Delta x f''(x)$ $\Delta x=-f'(x)/f''(x) \leftarrow \text{Newton Raphson 2nd order}$ $x_{n+1} = x_n - f(x_n) / f'(x_n)$ $\Delta x = x_{n+1} - x_n$

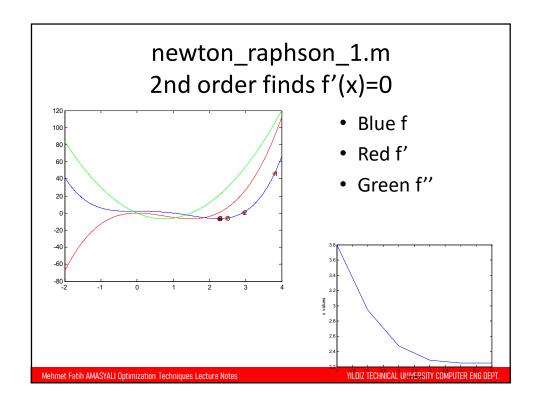
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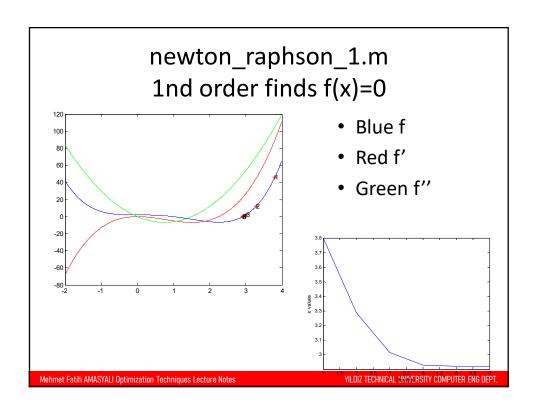
Newton Raphson

- Generally faster converge, because it uses more information (2nd derivative)
- No explicit step size selection
- 1st order : x_new = x_old f/df; (f(x)=0)
- 2nd order : x_new = x_old df/ddf; (f'(x)=0)
- instead of x_new = x_old eps * df; (gradient descent)

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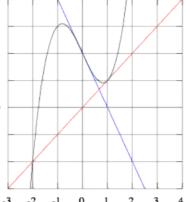






Newton Raphson 1st order -Cycle problem

- The tangent lines of x^3 2x + 2 at 0 and 1 intersect x^3 the x-axis at 1 and 0 x^3 respectively.
- What happened if we starto at a point in (0,1) interval?
- If we start at 0.1, it goes to₂
 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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