Optimization Techniques Section 3

M. Fatih Amasyalı

Mehmet Fatih AMASYALI Optimization Techniques Lecture Notes

YILDIZ TECHNICAL UNIVERSITY COMPUTER ENG DEP

Approximating Derivatives

- In many instances, the finding f'(x) is difficult or impossible to encode. The Finite difference Newton method approximates the derivative:
- Forward difference

 $f'(x)\approx (f(x+delta)-f(x))/delta$

Backward difference

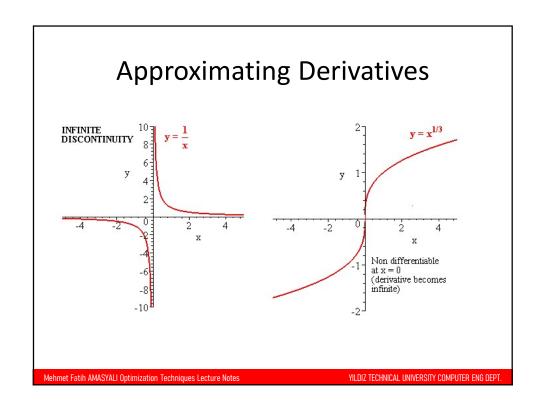
 $f'(x)\approx (f(x)-f(x-delta))/delta$

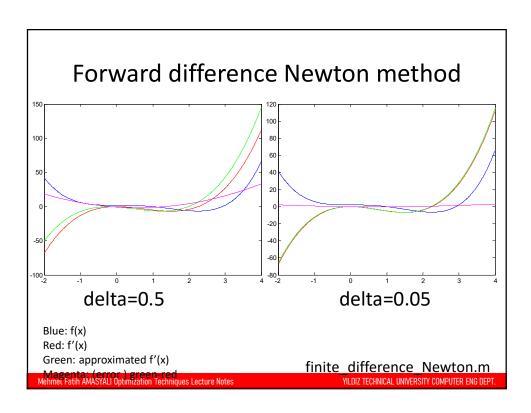
• Central difference

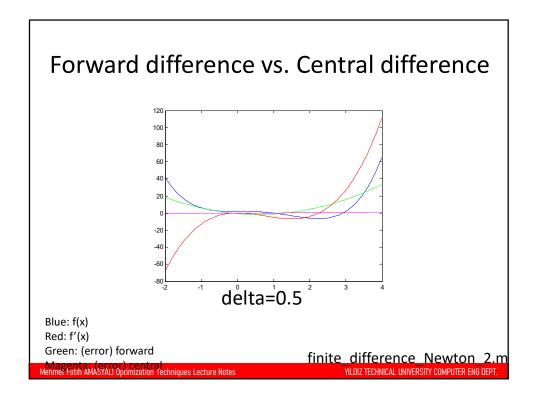
 $f'(x)\approx (f(x+delta/2)-f(x-delta/2))/$ delta The choice of delta matters.

Mehmet Fatih AMASYALI Ontimization Techniques Lecture Notes

YILDIZ TECHNICAL LINIVERSITY COMPLITER ENGINEET







Approximating higher order Derivatives

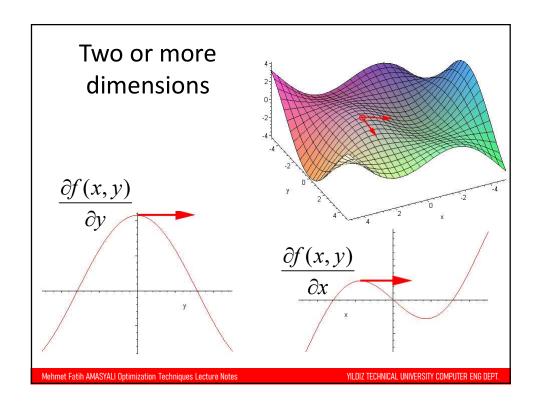
- According to the Central difference
- h=delta
- f'(x)=(f(x+h/2)-f(x-h/2))/h
- f''(x)=(f'(x+h/2)-f'(x-h/2))/h
- f'(x+h/2)=(f(x+h/2+h/2)-f(x+h/2-h/2))/h
- f'(x+h/2)=(f(x+h)-f(x))/h
- f'(x-h/2)=(f(x-h/2+h/2)-f(x-h/2-h/2))/h
- f'(x-h/2)=(f(x)-f(x-h))/h

Mehmet Fatih AMASYALI Ontimization Techniques Lecture Notes

Approximating higher order Derivatives

- f''(x)=(f'(x+h/2)-f'(x-h/2))/h
- f'(x+h/2)=(f(x+h)-f(x))/h
- f'(x-h/2)=(f(x)-f(x-h))/h
- f''(x) = (((f(x+h)-f(x))/h) ((f(x)-f(x-h))/h))/h
- $f''(x) = (f(x+h)-2*f(x)+f(x-h))/h^2$
- See the approximating to the partial derivatives: http://en.wikipedia.org/wiki/Finite_difference

Mehmet Fatih AMASYALI Optimization Techniques Lecture Notes



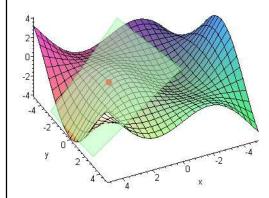
• <u>Definition</u>: The gradient of $f: R^n \to R$ is a function $\nabla f: R^n \to R^n$ given by

$$\nabla f(x_1,...,x_n) := \left(\frac{\partial f}{\partial x_1},..., \frac{\partial f}{\partial x_n}\right)^T$$

Mehmet Fatih AMASYALI Optimization Techniques Lecture Notes

YILDIZ TECHNICAL UNIVERSITY COMPUTER ENG DEPT

 The gradient defines (hyper) plane approximating the function



$$\Delta z = \frac{\partial f}{\partial x} \cdot \Delta x + \frac{\partial f}{\partial y} \cdot \Delta y$$

Mehmet Fatih AMASYALI Ontimization Techniques Lecture Notes

• Given the quadratic function

$$f(x)=(1/2) x^T q x + b^T x + c$$

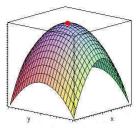
If *q* is positive definite, then *f* is a parabolic "bowl."

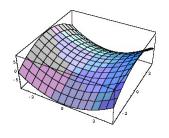
http://en.wikipedia.org/wiki/Positive-definite matrix

Mehmet Fatih AMASYALI Optimization Techniques Lecture Notes

YILDIZ TECHNICAL UNIVERSITY COMPUTER ENGIDEP

- Two other shapes can result from the quadratic form.
 - If q is negative definite, then f is a parabolic "bowl" up side down.
 - If q is indefinite then f is a saddle.





Sehmet Fatih AMASYALL Ontimization Techniques Lecture Notes

quadratic_functions.m

```
% quadratic functions in n dimensions
                                            x1=-5:0.5:5;
% f(x)=(1/2) * xT * q * x + bT * x + c
                                            z=zeros(length(x1),length(x1));
%f: Rn--> R
                                            for i=1:length(x1)
%q--> n*n
                                              for j=1:length(x2)
%b--> n*1
                                                x=[x1(i); x2(j)];
%c--> 1*1
                                                z(i,j)=(1/2)*x'*q*x+b'*x+c;
clear all;
                                            end
close all;
% n=2
                                            surfc(x1,x2,z)
q=[1 0.5; 0.5 -2];
                                            figure;
                                            contour(x1,x2,z)
b=[1;1];
c=0.5;
```

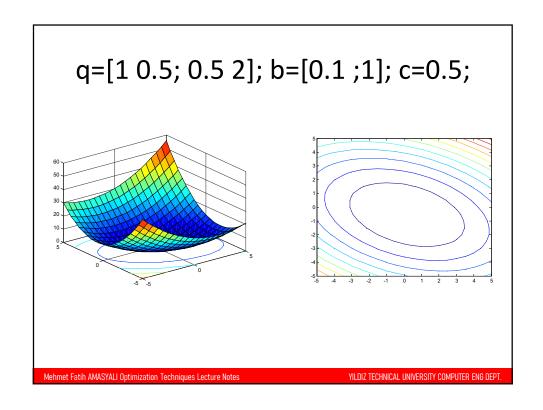
Mehmet Fatih AMASYALI Optimization Techniques Lecture Notes

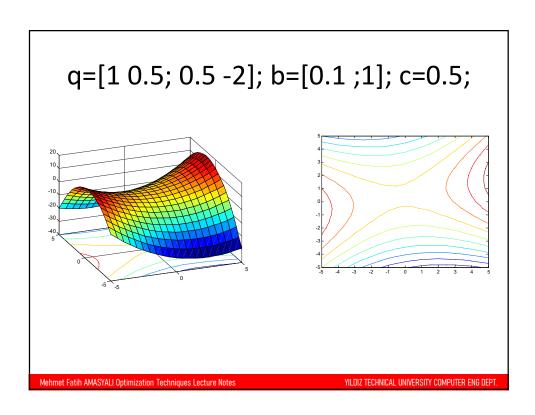
YILDIZ TECHNICAL UNIVERSITY COMPUTER ENG DEPT

quadratic_functions.m

```
 f(x) = (1/2) \ x^{\top} \ q \ x + b^{\top} \ x + c \qquad q = [\ 1\ 2\ ; 2\ 1] 
 \bullet \ x = [x_1 \ x_2 \ x_3 \ ... \ x_n]^{\top} \qquad b = [1\ ; 3] 
 \bullet \ q = [x_1^2 \ x_1 x_2 \ x_1 x_3 \ ... \ x_1 x_n \qquad c = 2 
 x_2 x_1 \ x_2^2 \ x_2 x_3 \ ... \ x_2 x_n \qquad f(x) = ? 
 x_n x_1 \ x_n x_2 \ x_n x_3 \ ... \ x_n^2] \qquad f(x) = (x_1^2 + 2x_1 x_2 + 2x_2 x_1 + x_2^2)/2 + x_1 + 3x_2 + 2 
 \bullet \ b = [x_1 \ x_2 \ ... \ x_n]^{\top} \qquad f(x) = (x_1^2 + 4x_1 x_2 + x_2^2)/2 + x_1 + 3x_2 + 2 
 \bullet \ c = constant \qquad \bullet \ f''(x) = q
```

Mehmet Fatih AMASYALI Ontimization Techniques Lecture Note:





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

- q,b,c?
- (½)*q = [1 4; 0 3] or [1 3; 1 3] or [1 2; 2 3] (symmetric) q= [2 4; 4 6]
- b = [0; 3]
- c = 2

Mehmet Fatih AMASYALI Optimization Techniques Lecture Note:

YILDIZ TECHNICAL LINIVERSITY COMPLITER ENGINED

• Hessian of f: the second derivative of f

$$\boldsymbol{F} = D^2 f = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2}(\boldsymbol{x}) & \frac{\partial^2 f}{\partial x_2 \partial x_1}(\boldsymbol{x}) & \cdots & \frac{\partial^2 f}{\partial x_n \partial x_1}(\boldsymbol{x}) \\ \frac{\partial^2 f}{\partial x_1 \partial x_2}(\boldsymbol{x}) & \frac{\partial^2 f}{\partial x_2^2}(\boldsymbol{x}) & \cdots & \frac{\partial^2 f}{\partial x_n \partial x_2}(\boldsymbol{x}) \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_1 \partial x_n}(\boldsymbol{x}) & \frac{\partial^2 f}{\partial x_2 \partial x_n}(\boldsymbol{x}) & \cdots & \frac{\partial^2 f}{\partial x_n^2}(\boldsymbol{x}) \end{bmatrix}$$

Mehmet Fatih AMASYALI Optimization Techniques Lecture Notes

$$f''(x) = q$$

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

```
\begin{array}{lll} \text{syms x1;} \\ \text{syms x2;} \\ \text{syms expr;} \\ \% \ \text{diff(expr,n,v)} \ \text{differentiate expr n times with respect to v} \ . \\ \text{expr=x1^2+3*x2^2+4*x1*x2+3*x2+2;} \\ \text{ddx=diff(expr,2,x1);} \\ \text{dx=diff(expr,1,x1);} \\ \text{dy=diff(expr,1,x2);} \\ \text{dxdy=diff(dx,1,x2);} \\ \text{ddy=diff(expr,2,x2);} \\ \text{q=[ddx dxdy; dxdy ddy]} \end{array} \qquad \qquad \begin{array}{l} \text{q=} \\ \text{q=} \\ \text{q=} \\ \text{q=} \end{array}
```

Mehmet Fatih AMASYALI Optimization Techniques Lecture Notes

YILDIZ TECHNICAL UNIVERSITY COMPUTER ENG DEPT

Quadratic functions in 2 dims.

Quadratic functions in 2 dims.

Opt. in 2 dims.

```
% gradient decent x = [x_1 \ x_2]^T

x_new = x_old - eps * df;

% [2,1] = [2,1] - [1,1]*[2,1]

% newton raphson

x_new = x_old - df/ddf;

x_new = x_old - inv(ddf)*df;

% [2,1] = [2,1] - [2,2]*[2,1]
```

Mehmet Fatih AMASYALI Optimization Techniques Lecture Notes

Opt. in N dims.

% gradient decent
$$x = [x_1 \ x_2 \ x_3 \ ... \ x_n]^T$$
 $x_new = x_old - eps * df;$
% $[n,1] = [n,1] - [1,1]*[n,1]$
% newton raphson
 $x_new = x_old - df/ddf;$
 $x_new = x_old - inv(ddf)*df;$
% $[n,1] = [n,1] - [n,n]*[n,1]$

Mehmet Fatih AMASYALI Optimization Techniques Lecture Notes

YILDIZ TECHNICAL UNIVERSITY COMPUTER ENG DEP

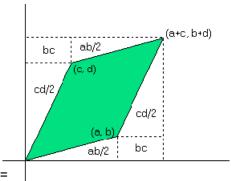
Matrix inversion

- A is a square matrix (n*n)
- I is the identity matrix (n*n)
- A*A-1=I
- A⁻¹ is the inversion of A
- A matrix has an inverse if the determinant |A|≠0

Mehmet Fatih AMASYALI Ontimization Techniques Lecture Notes

Geometric meaning of the determinant

- A=[a b; c d]
- det(A) is the area of the green parallelogram with vertices at (0,0), (a,b), (a+c,b+d), (c,d).



The area of the big rectengular= (a+c)*(b+d)=a*b+a*d+c*d+c*b

The area of the green parallelogram =

=a*b+a*d+c*d+c*b-2*c*b-2*(a*b)/2-2*(d*c)/2

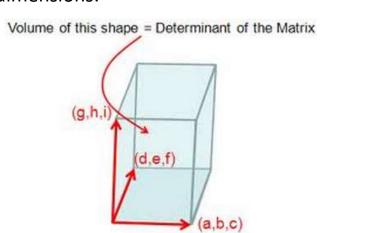
=a*d-c*b

Mehmet Fatih AMASYALI Optimization Techniques Lecture Notes

YILDIZ TECHNICAL LINIVERSITY COMPLITER ENGINEPT

Geometric meaning of the determinant

• In 3 dimensions:



Mehmet Fatih AMASYALI Ontimization Techniques Lecture Notes

Matrix inversion

- For a 2*2 matrix (A)= [a b; c d]
- A⁻¹ =[e f;gh]
- det(A)=a*d-c*b
- [a b; c d]*[e f; g h]=[10;01]

- a*e+b*g=1 a*f=-b*h
 a*f+b*h=0 f=-(b*h)/a
 c*e+d*g=0 -(c*b*h)/a+d*h=1
 h*(d-(c*b)/a)=1
- c*f+d*h=1
- h*(d-(c*b)/a)=1h=a/(a*d-c*b)

Mehmet Fatih AMASYALI Optimization Techniques Lecture Notes h=a/det(\(\bigcap_{\text{total}} \)

Matrix inversion

For a 2 x 2 matrix

$$A \equiv \begin{bmatrix} a & b \\ c & d \end{bmatrix},$$

the matrix inverse is

$$A^{-1} = \frac{1}{|A|} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$
$$= \frac{1}{a d - b c} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

h=a/det(A)

Matrix inversion

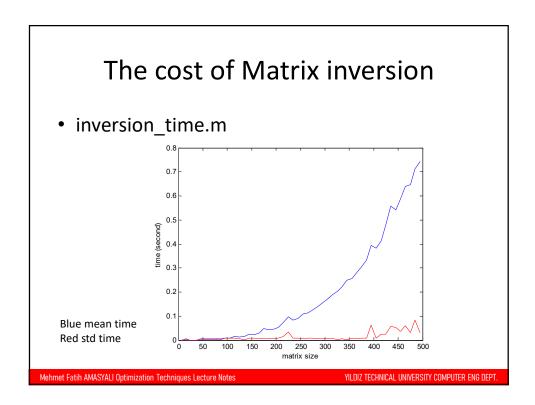
 For a 3×3 matrix the inverse may be written as:

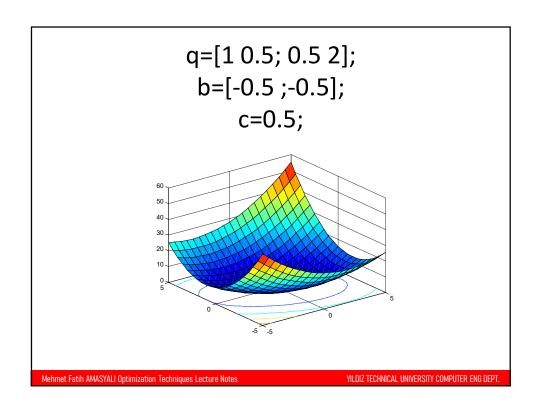
$$\mathbf{A} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$$

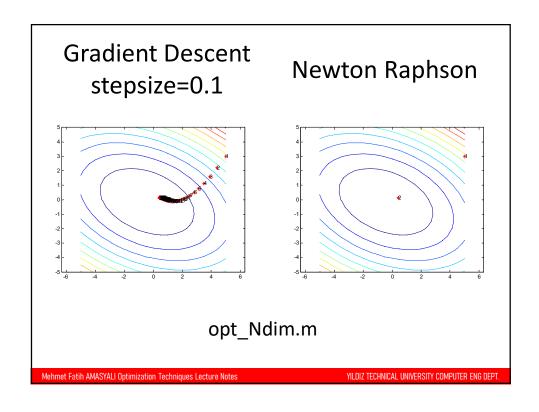
$$\mathbf{A}^{-1} = \frac{\begin{bmatrix} ei - fh & hc - ib & bf - ce \\ gf - di & ai - gc & dc - af \\ dh - ge & gb - ah & ae - db \end{bmatrix}}{|\mathbf{A}|}$$

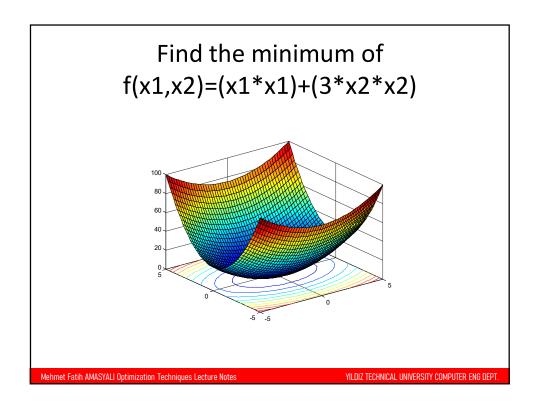
$$= \frac{\begin{bmatrix} ei - fh & hc - ib & bf - ce \\ gf - di & ai - gc & dc - af \\ dh - ge & gb - ah & ae - db \end{bmatrix}}{aei + bfg + cdh - gec - hfa - idb}$$

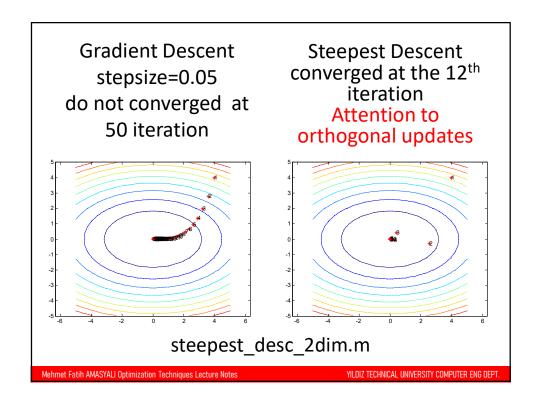
A general n*n matrix can be inverted using methods such as the Gauss-Jordan elimination, Gauss elimination or LU decomposition.

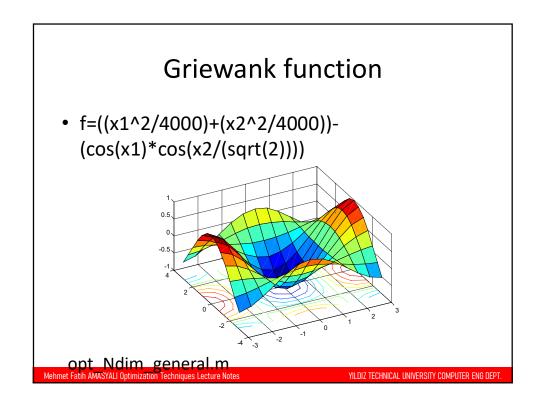


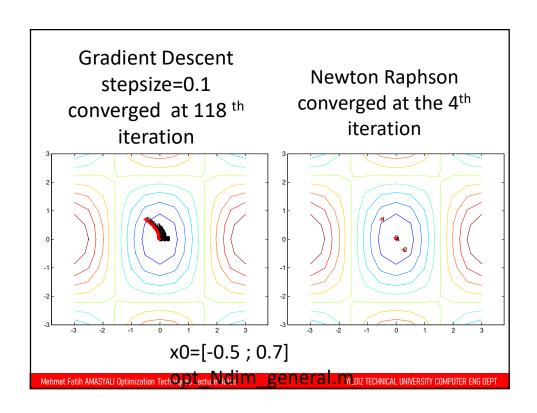


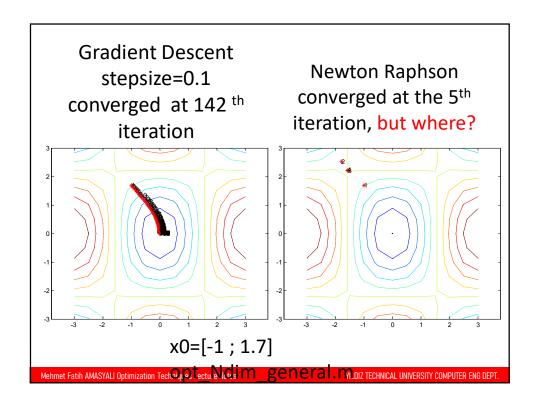


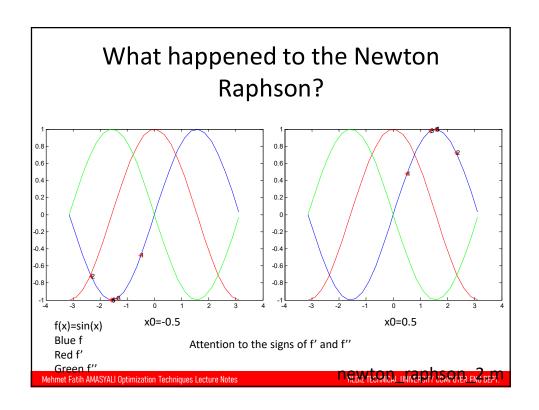


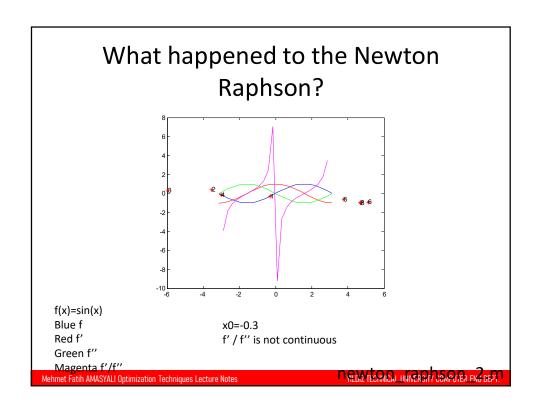


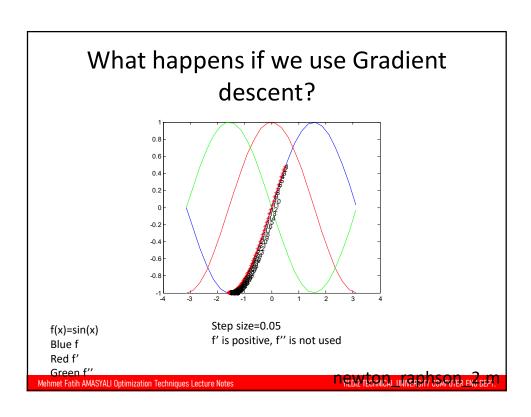


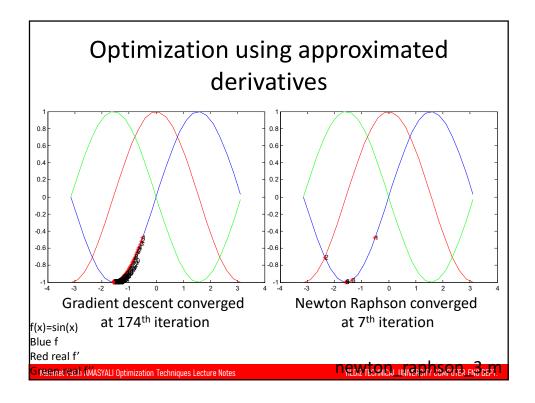












Some more comparisons

- opt Ndim general.m
- Nigthmares of a convex optimization, because of local minimums
- acckley f=(-20*exp(-0.2*sqrt((1/2)*(x1.^2+x2.^2))) -
- $\exp((1/2)*(\cos(2*pi*x1) + \cos(2*pi*x2))) +$
- $20 + \exp(1) + 5.7$);
- griewank f=((x1^2/4000)+(x2^2/4000))-(cos(x1)*cos(x2/(sqrt(2))));
- rastrigin f=10*2 + x1.^2 + x2.^2 10*cos(2*pi*x1) 10*cos(2*pi*x2);
- rosen f=100*(x1^2-x2)^2+(x1-1)^2;
- schwell f=(abs(x1)+abs(x2))+(abs(x1)*abs(x2));

Mehmet Fatih AMASYALL Ontimization Techniques Lecture Notes

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/Steepest_descent
- http://www.pitt.edu/~nak54/Unconstrained Optimization KN.pdf
- http://mathworld.wolfram.com/MatrixInverse.html
- http://lpsa.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
- Advanced Engineering Mathematics , Erwin Kreyszig, 10th Edition, John Wiley & Sons, 2011
- http://en.wikipedia.org/wiki/Finite_difference
- http://ocw.usu.edu/Civil and Environmental Engineering/Numerical Methods in Civil Engineering/NonLinearEquationsMatlab.pdf
- http://www-math.mit.edu/~djk/calculus_beginners/chapter09/section02.html
- http://stanford.edu/class/ee364a/lectures/intro.pdf

Mehmet Fatih AMASYALI Optimization Techniques Lecture Notes