

# Optimization Techniques

## Section 1

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## What is optimization?

(mathematical) optimization problem

$$\begin{array}{ll} \text{minimize} & f_0(x) \\ \text{subject to} & f_i(x) \leq b_i, \quad i = 1, \dots, m \end{array}$$

- $x = (x_1, \dots, x_n)$ : optimization variables
- $f_0 : \mathbb{R}^n \rightarrow \mathbb{R}$ : objective function
- $f_i : \mathbb{R}^n \rightarrow \mathbb{R}, i = 1, \dots, m$ : constraint functions

**optimal solution**  $x^*$  has smallest value of  $f_0$  among all vectors that satisfy the constraints

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## Optimization example (Constraint Optimization)

- Find the largest possible rectangular area you can enclose, assuming you have L meters of fencing.
- $f(x) = x * ((L/2) - x)$

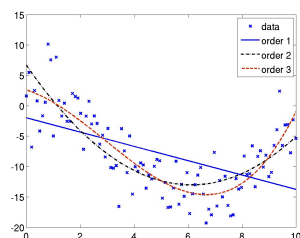
## Optimization examples

### portfolio optimization

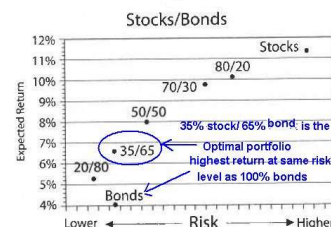
- variables: amounts invested in different assets
- constraints: budget, max./min. investment per asset, minimum return
- objective: overall risk or return variance

### data fitting

- variables: model parameters
- constraints: prior information, parameter limits
- objective: measure of misfit or prediction error



### Portfolio Optimization



## Optimization Techniques

- Derivative Techniques
  - Gradient descent
  - Newton Raphson
  - LM
  - BFGS
- Non Derivative Techniques
  - Hill climbing
  - Genetic algorithms
  - Simulated annealing

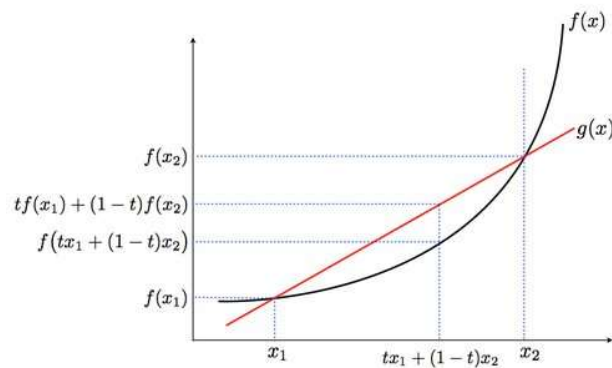
## Linear, nonlinear, convex functions

- $f$  is a function  $\mathbb{R}^n \rightarrow \mathbb{R}$
- For every  $x_1, x_2 \in \mathbb{R}^n$  ( $x_1, x_2$  are  $n$  dimensional points)
- $f$  is linear if
  - $f(x_1+x_2)=f(x_1)+f(x_2)$  and  $f(r*x_1)=r*f(x_1)$
- $f(x)=2*x$  is linear and affine.
- $f(x)=2*x+3$  is affine but not linear.
- A linear function fixes the origin, whereas an affine function need not do so. An affine function is the composition of a linear function with a translation.
- $f(x)=3$  is constant, but not linear.

## Linear, nonlinear, convex functions

- $f$  is convex if

$$\lambda f(x_1) + \beta f(x_2) \geq f(\lambda x_1 + \beta x_2), \text{ where } \lambda + \beta = 1, \lambda \geq 0, \beta \geq 0$$

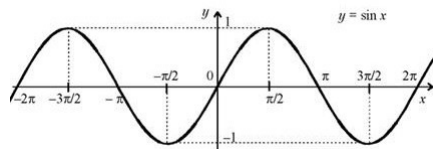


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## Linear, nonlinear, convex functions

- $f(x_1) = 3x_1 + 3$
- $f(x_1, x_2) = ax_1 + bx_2 + c$
- $f(x_1, x_2) = x_2^2 + x_1^2 + 3x_1$
- $f(x) = \sin(x)$  is convex when  $x \in [?, ?]$
- Concave?



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## How to find minimum point? Commonsense

- Use derivative
- Go to the negative direction of derivative
- But, step size?

## General Algorithm

- initial guess
- While (improvement is significant) and (maximum number of iterations is not exceeded)
  - improve the result

## Gradient Descent

- Using only derivative sign
- Using also magnitude of the derivative
- Effect of the step size
- Effect of the starting point
- Local minimum problem

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```
% The gradient descent algorithm with constant stepsize
% f(x)=x^2, with derivative f'(x)=2x
clear all;
close all;

% plot objective function
x=-5:0.01:5;
y=zeros(1,length(x));
for i=1:length(x)
    y(i)=x(i)^2;
end
plot(x,y);

x_old = 0;
x_new = -4.9;
% The algorithm starts at x=-4.9
eps = 0.05; % step size
precision = 0.00001; % stopping condition1
max_iter=200; % stopping condition2
Xs=zeros(1,max_iter);
Ys=zeros(1,max_iter);

i=1;
while abs(x_new - x_old) > precision && max_iter>=i
    Xs(i)=x_new;
    Ys(i)=x_new^2;
    hold on;
    plot(Xs(i),Ys(i),'r*');
    text(Xs(i),Ys(i),int2str(i));

    x_old = x_new;
    df= 2 * x_old;
    x_new = x_old - eps * sign(df); % gradient sign
    i=i+1;
end
figure;
plot(Xs(1:i-1));
xlabel('iteration');
ylabel('x values');
```

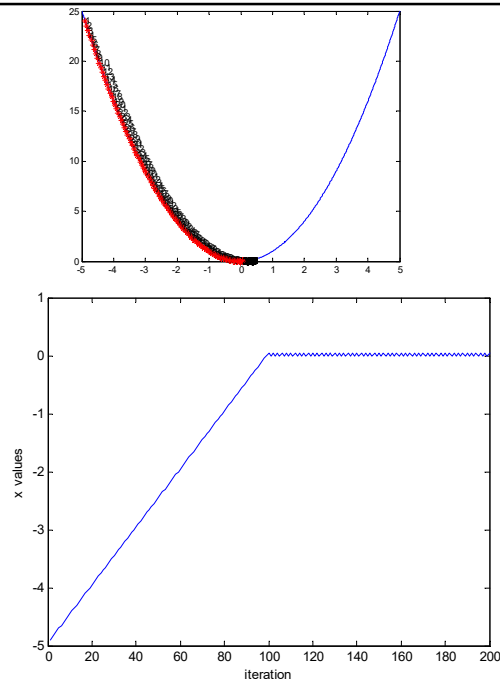
gradient\_desc\_1.m

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## Result

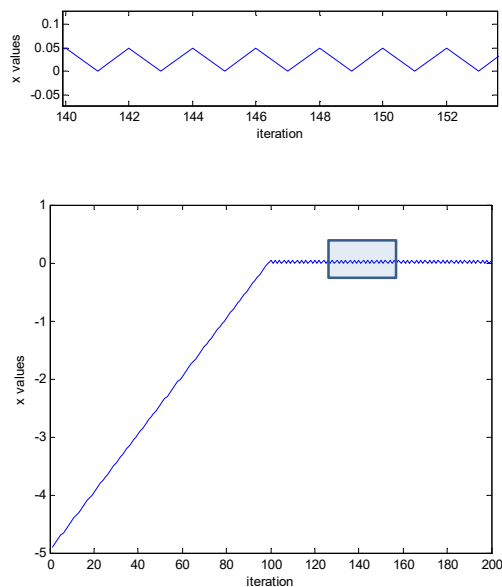
- $f(x)=x^2$
- $f'(x)=2*x$
- Max\_iter=200
- Constant step size =0.05
- Starting point=-4.9



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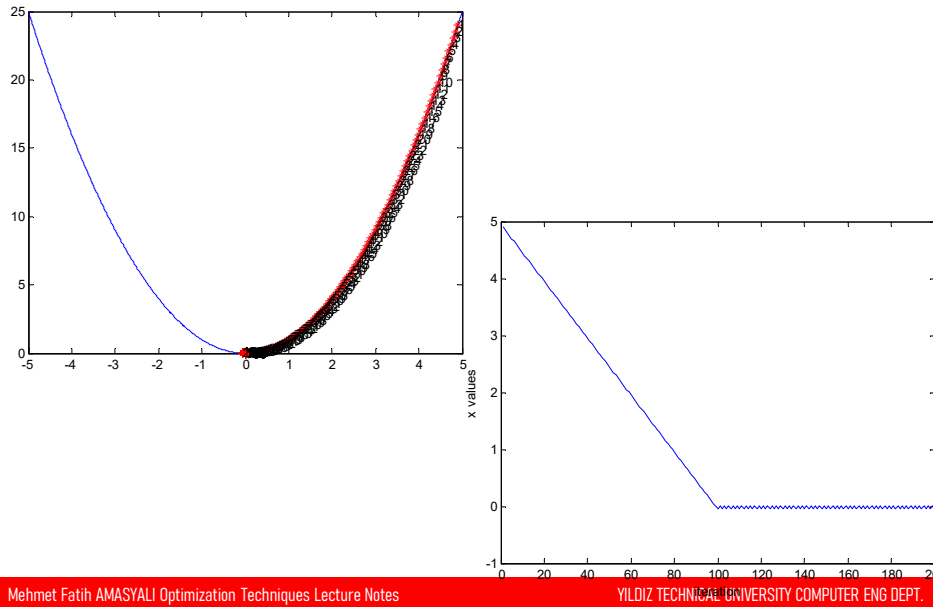
- It reaches the maximum iteration number
- It reached 0 at 100.iteration , then zig-zag.
- It selects 0 or 0.05 as the point  $f$  is minimum.



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## Starting point=4.9

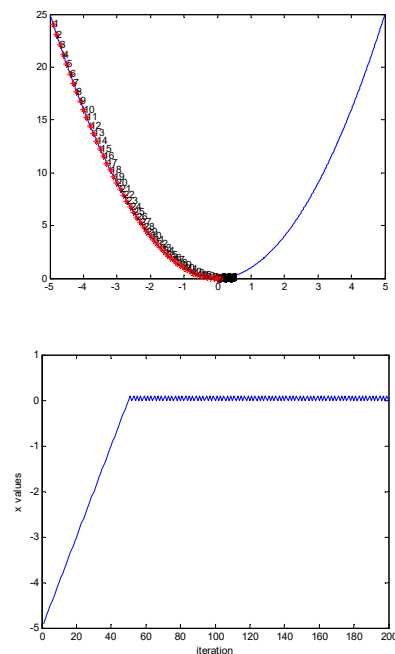


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## Step size=0.1

- It reaches the maximum iteration number
- It reached 0 at 50.iteration , then zig-zag.
- It selects 0 or 0.1 as the point f is minimum.



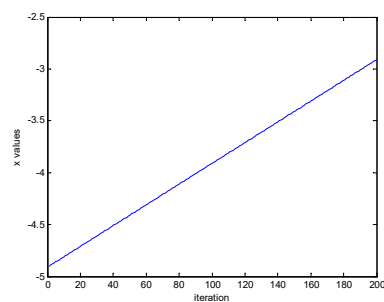
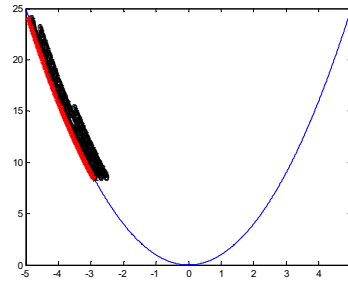
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## Step size=0.01

- It reaches the maximum iteration number
- It does not reached to 0.
- It selects -2.91 as the minimum point.
- It will zig-zag.



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## Gradient Descent

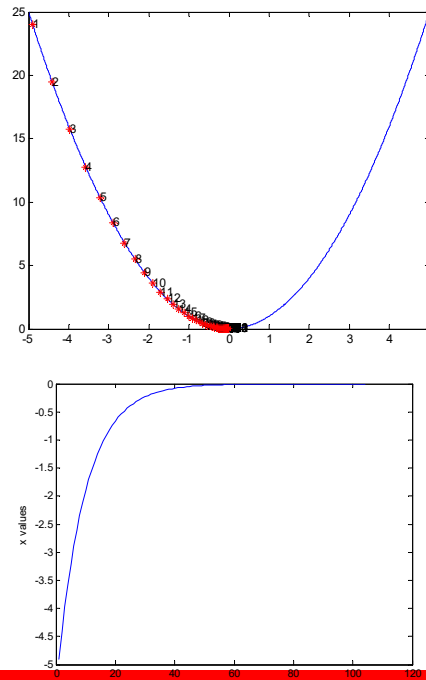
- Using also the magnitude of the derivative
- $x_{\text{new}} = x_{\text{old}} - \text{eps} * df;$
- instead of  $x_{\text{new}} = x_{\text{old}} - \text{eps} * \text{sign}(df);$
- Can we reduce the required number of iterations?

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## gradient\_desc\_2.m

- Step size=0.05
- Max\_iter=200
- The number of iteration is 120.
- It does not zig-zag.
- It selects  $0 \pm 10^{-5}$  the point f is minimum.

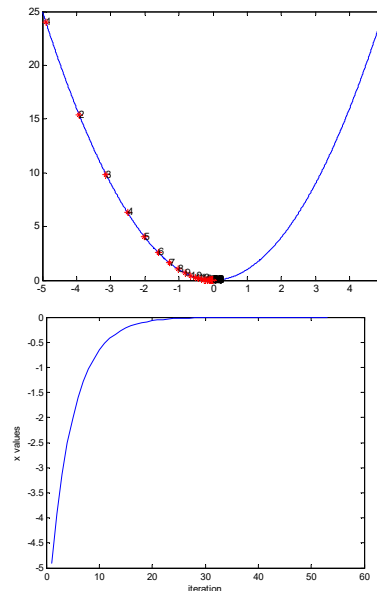


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## gradient\_desc\_2.m

- Step size=0.1
- Max\_iter=200
- The number of iteration is 60.
- It does not zig-zag.
- It selects  $0 \pm 10^{-5}$  the point f is minimum.

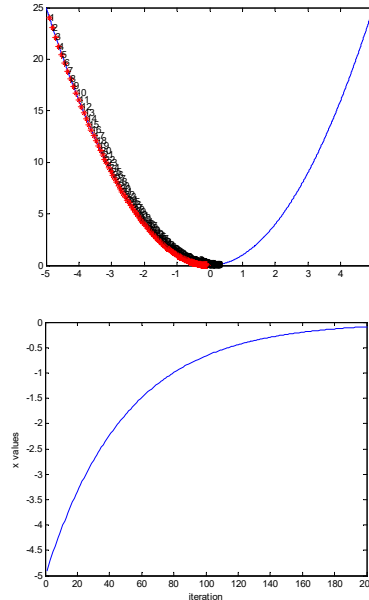


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### gradient\_desc\_2.m

- Step size=0.01
- Max\_iter=200
- It reaches the maximum iteration number.
- It does not zig-zag.
- It selects  $0 \pm 10^{-2}$  as the point  $f$  is minimum.
- It requires the more iteration.

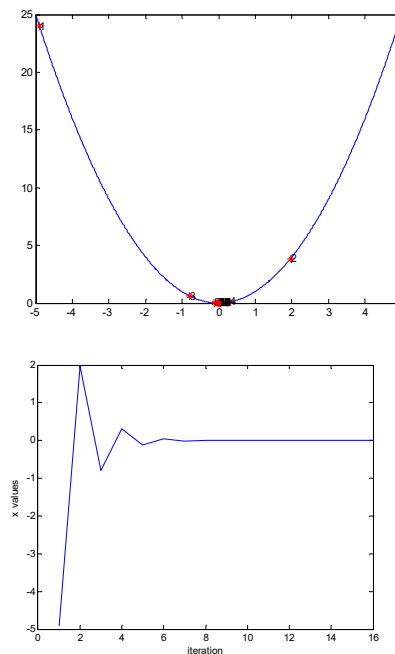


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### gradient\_desc\_2.m

- Step size=0.7
- Max\_iter=200
- The number of iteration is 16.
- It does not zig-zag.
- It selects  $0 \pm 10^{-5}$  the point  $f$  is minimum.

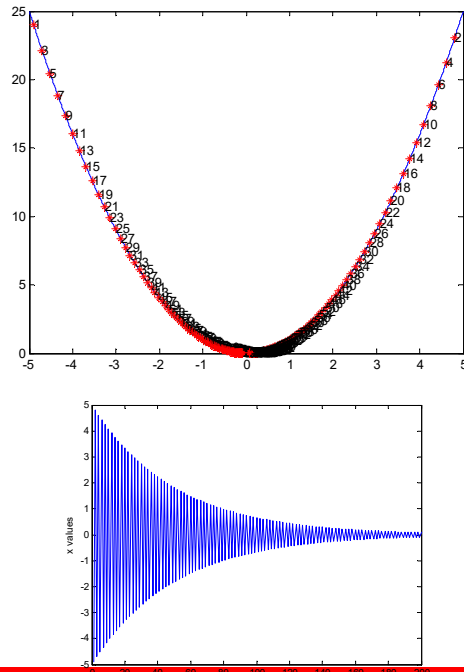


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### gradient\_desc\_2.m

- Step size=0.99
- Max\_iter=200
- It reached the maximum iteration number.
- It zig-zag, but zig-zag magnitude decreases.
- It selects  $0 \pm 10^{-1}$  the point f is minimum.
- It requires more iteration.

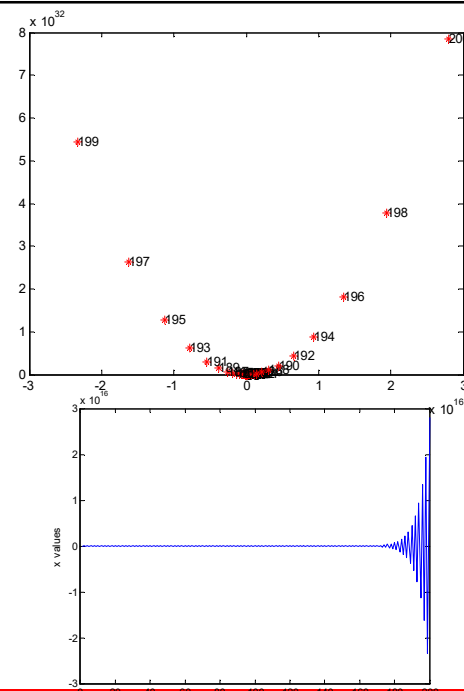


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### gradient\_desc\_2.m

- Step size=1
- Max\_iter=200
- It reached the maximum iteration number.
- It does not converge.



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## Starting point matters?

- $f(x)=x^4-3x^3+2$  with derivative  
 $f'(x)=4x^3-9x^2$
- It has two extreme points  $x=0$ ,  $x=9/4$
- gradient\_desc\_3.m

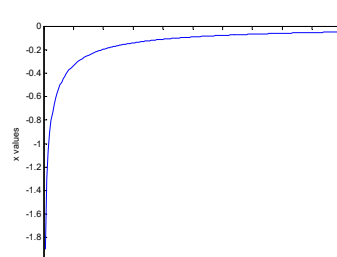
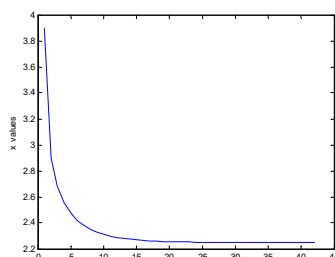
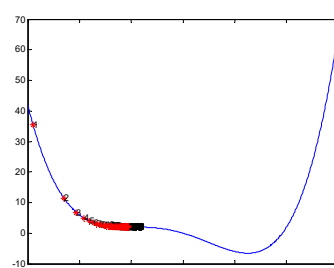
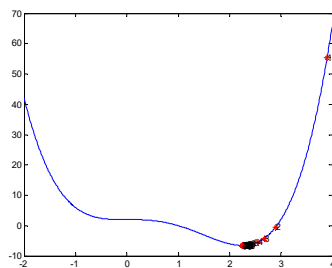
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Step size=0.01

Starting point=3.9

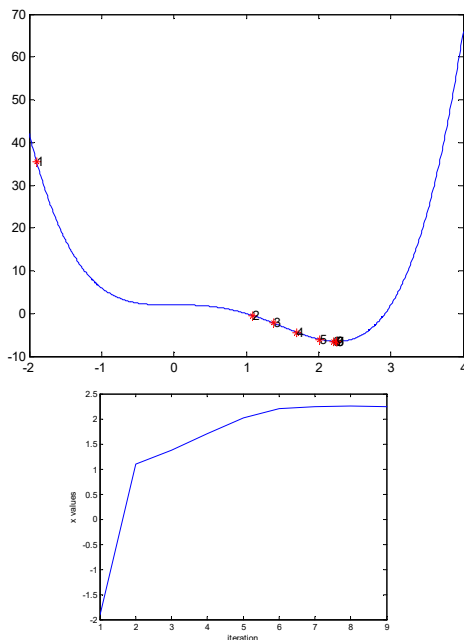
Starting point=-1.9



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- Step size=0.05 can handle plateau, but not guaranteed.
- Step size=0.1 is very big for this function, it does not converge



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## Gradient descent

- Static zig-zag (hopeless) vs. slow converge (with hope)
- Very Small step size  $\rightarrow$  slow converge, plateau problem
- Very big step size  $\rightarrow$  do not converge
- Big and small step sizes depend on the objective function.

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