

# **Evolutionary Algorithms:**

## **Multiobjective Optimization, Genetic Programming**

**May 21, 2013**

**Prof. Chang Wook Ahn**



---

**S**ungkyunkwan **E**volutionary **A**lgorithms **L**ab.  
**S**chool of Info. & Comm. Eng.  
**S**ungkyunkwan University

---



# **E**volutionary **M**ultiobjective **O**ptimization





# Multiobjective Optimization (1)



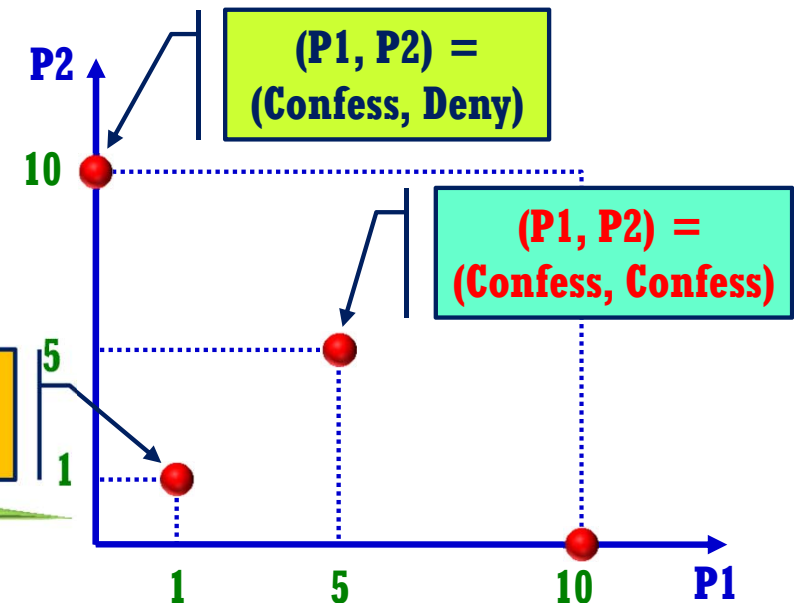
## ❖ Multiobjective Optimization - Concept

### ➤ Example: Prisoners Dilemma (PD) Problem

- ✓ **2 prisoners** are arrested for a crime.
- ✓ They can make a decision about two actions: **Confess, Deny**
- ✓ They have to make their own decision **simultaneously**
- ✓ They want to **minimize their prison years** under the conditions:



	P2: Confess	P2: Deny
P1: Confess	5, 5	0, 10
P1: Deny	10, 0	1, 1



The prisoners will make the decision of  $(P1, P2) = (Confess, Confess)$  as they don't trust each other!

$(P1, P2) = (Deny, Deny)$

Is this optimal?

What do you think about (Deny, Deny)?

Prison Years of the Prisoners



# Multiobjective Optimization (2)

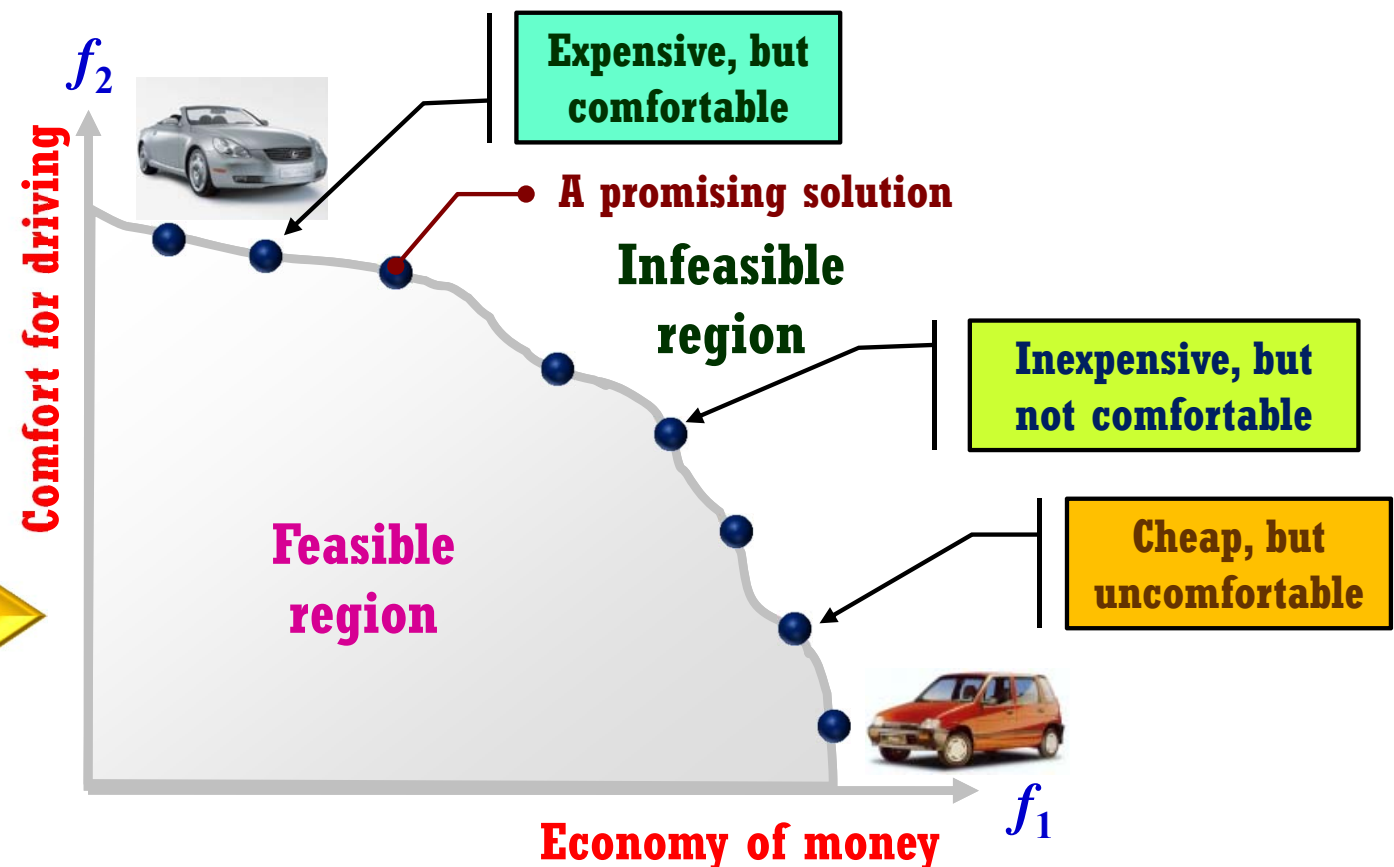


## ❖ What is the Aim of Multiobjective Optimization?

### ➤ Example: Car Buying Problem

- ✓ We want to buy a car in view of “Comfort for driving” and “Economy of money”
- ✓ But the **two objectives** are **conflicted**; thus, all possible solutions must be found!

In the Car Buying example, **all the circles** represent the **best solutions** when **simultaneously considering** “comfort for driving” and “economy of money”!





# Multiobjective Optimization (3)



## ❖ What are Multiobjective Optimization Problems (MOPs)?

- A Class of **Optimization Problems** that have several **Conflicting Objectives**
  - ✓ The aim is to **discover all** the possible **solutions** that are the **optimal/best** in view of *Multiple Conflicting Objectives*

### Single Objective Optimization

For a search space  $\Omega$

There is a function  $f : \Omega \mapsto \mathbb{R}$

The task is **to find**  $x^* = \arg \max_{x \in \Omega} f(x)$

**subject to**  $g_i(x) \leq 0, i = 1, \dots, m$

$h_i(x) = 0, j = 1, \dots, p$

Inequality  
Constraints

Equality Constraints

### Multiobjective Optimization

For a search space  $\Omega$

There are functions  $f_i : \Omega \mapsto \mathbb{R}$

**To find**  $x^* = \arg \max_{x \in \Omega} (f_1(x), \dots, f_n(x))$

**subject to**  $g_i(x) \leq 0, i = 1, \dots, m$

$h_i(x) = 0, j = 1, \dots, p$



# Multiobjective Optimization (4)

## ● Multiobjective Optimization Problems

➤ MOPs have several **conflicting objectives** to be **maximized** simultaneously

➤ **Due to the interdependence of the objectives**

✓ MOPs normally have a set of **alternative solutions**

➤ The solutions, known as **Pareto-optimal set**, are optimal in the sense that

✓ no solution is superior to them overall as no objective can be improved without degrading the others;

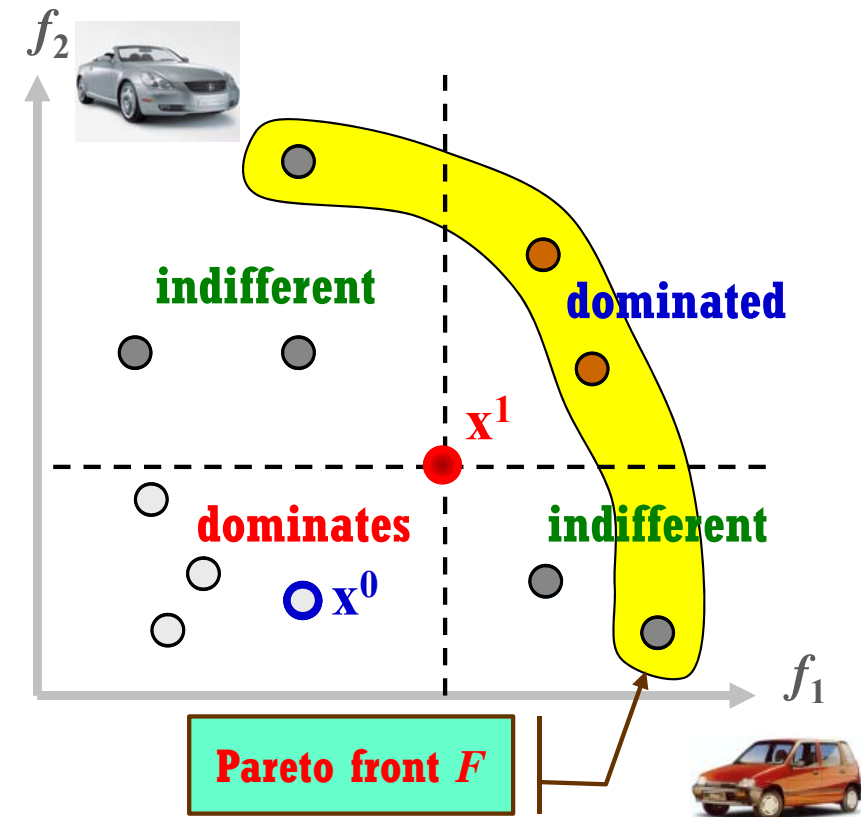
$$Q = \{\mathbf{x}^0 \in A \mid \neg \exists \mathbf{x}^1 \in \Omega_f : \mathbf{x}^1 \succ \mathbf{x}^0\}$$

where  $\mathbf{x}^1 \succ \mathbf{x}^0$  indicates that  $\mathbf{x}^1$  (Pareto) dominates  $\mathbf{x}^0$ .

$$\forall i : f_i(\mathbf{x}^0) \leq f_i(\mathbf{x}^1) \wedge \exists j : f_j(\mathbf{x}^0) < f_j(\mathbf{x}^1)$$

✓ The image of the Pareto-optimal set is defined as the **Pareto (optimal) front**

$$F = \{f_1(\mathbf{x}^0), f_2(\mathbf{x}^0), \dots, f_n(\mathbf{x}^0) \mid \mathbf{x}^0 \in Q\}$$





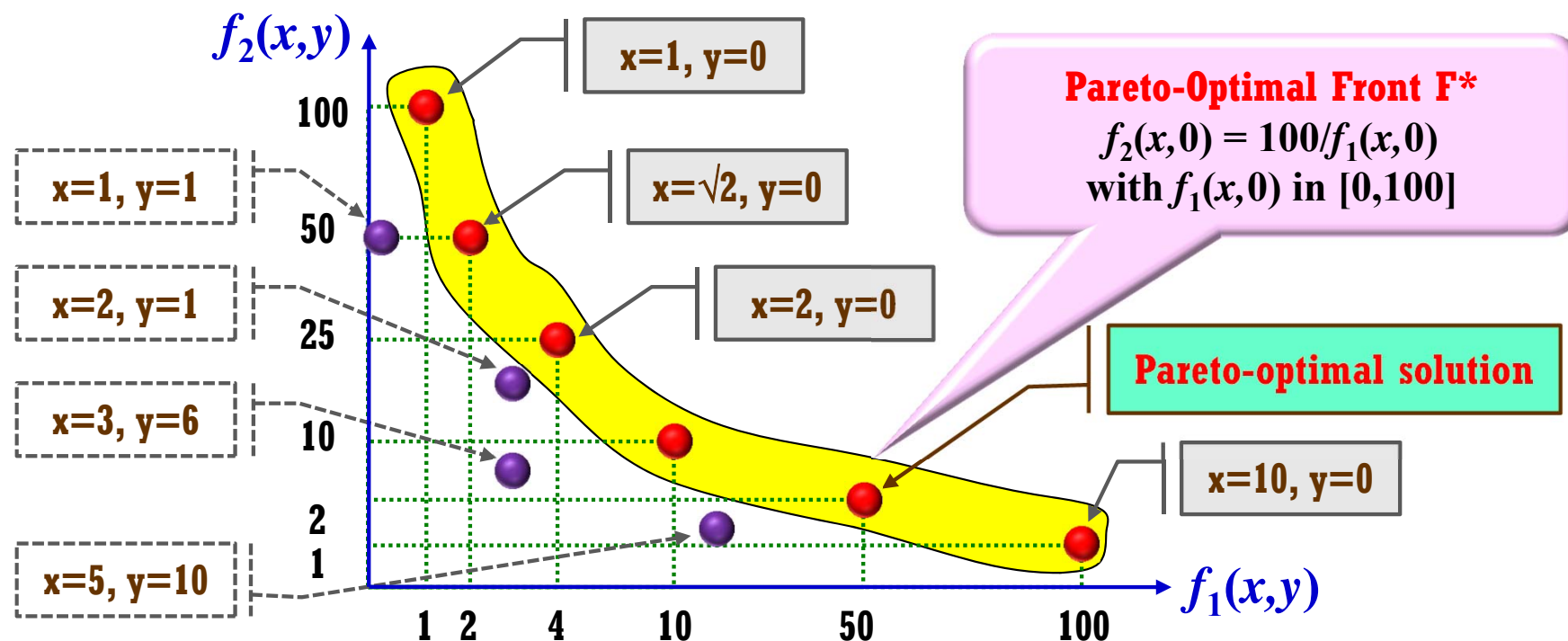
# Multiobjective Optimization (5)



## ❖ Example

- Find the Optimal Solutions w.r.t the Simultaneous Maximization of

$$f_1(x, y) = x^2 - y, \quad f_2(x, y) = \frac{100}{x^2 + y} \quad \text{where } 1 \leq x \leq 10, 0 \leq y \leq x^2$$





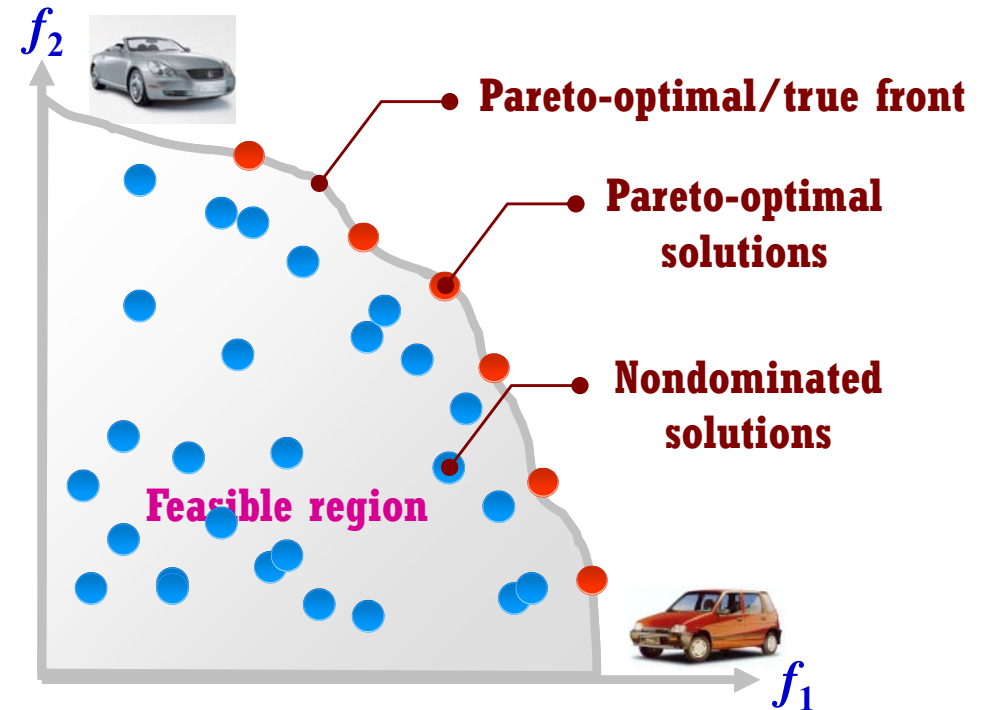
# Multiobjective Optimization (6)



## ● Goal of Multiobjective Optimization

- The aim is to find the *global* Pareto optimal set  $Q^*$ ;
  - ✓ i.e., Place the **nondominated set** on the **true Pareto front**  $F^*$

☞ But, achieving the goal is not practical since there can be infinite solutions



## ● Actual Goals

- **Higher Proximity**
  - Discover nondominated solutions that are **closer** to the true Pareto front
- **Better Diversity**
  - Discover nondominated solutions that are **uniformly distributed** over the true front



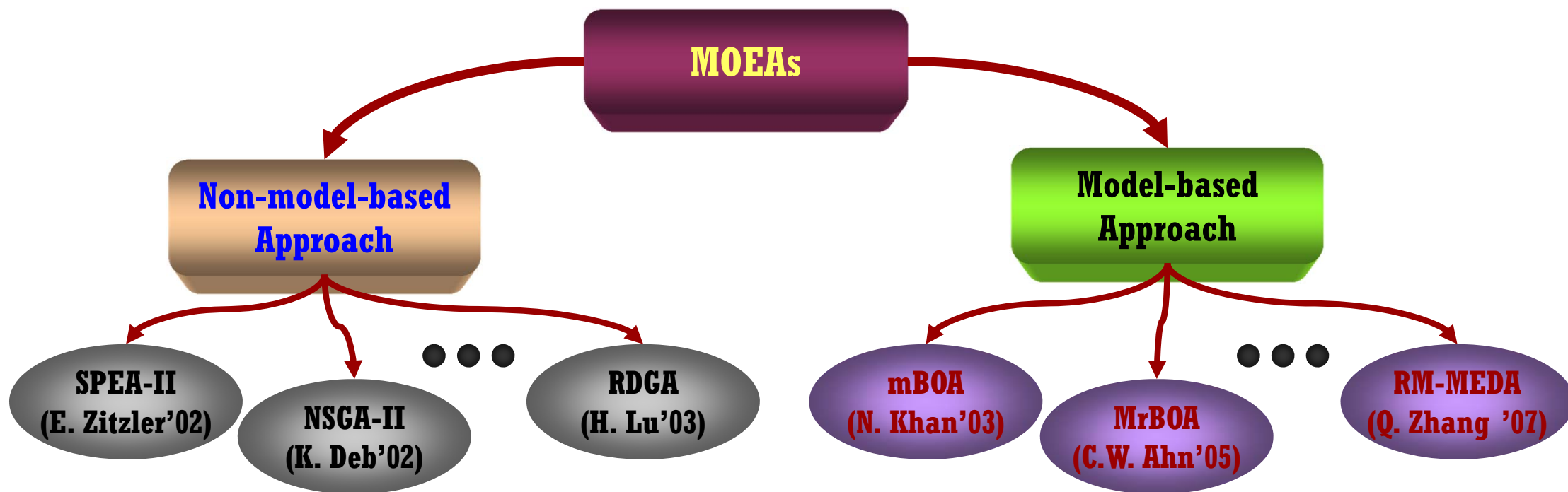


# Multiobjective Evolutionary Algo.



## ● Classification of Multi-Objective Evolutionary Algorithms (MOEAs)

- **Non-model-based approach:** NSGA (II), MOGA, SPEA (II), RDGA
  - Domination information, Sharing strategy, Elitism harmonization
  - It may be inefficient for some complicated problems
- **Model-based approach:** m(h)BOA, MIDEA, BMOA, MrBOA, RM-MEDA
  - All the benefits of non-model-based approach + EDAs' capability
  - It generally outperforms the non-model-based approach





# NSGA-II: Nondominated Sorting GA II



- Proposed by K. Deb, '02
- Basic framework of MOEAs

Population

$P_t$   
Parent

$O_t$   
Offspring

Nondominated  
Sorting

$F_1$

$F_2$

$F_3$

$F_4$

Crowding  
Distance  
Sorting

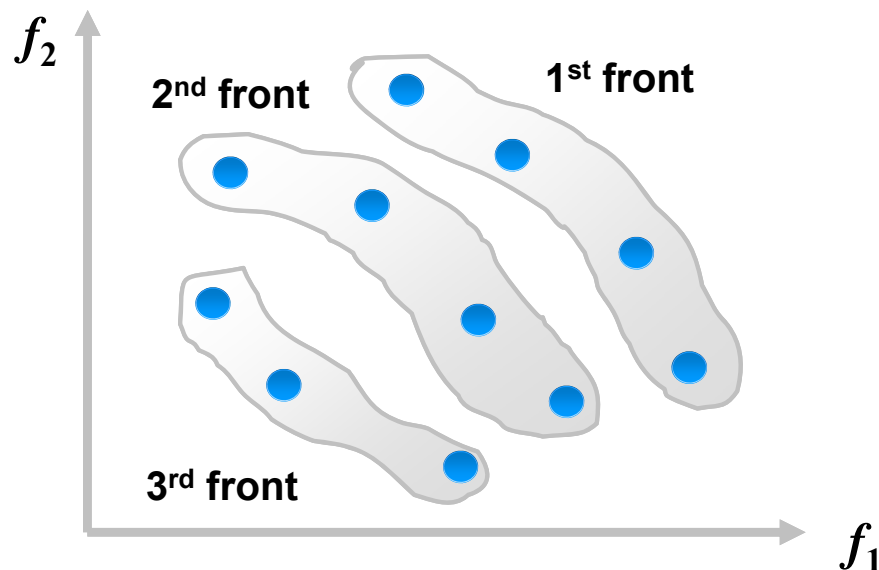
By  
Selection!

$P_{t+1}$   
Parent

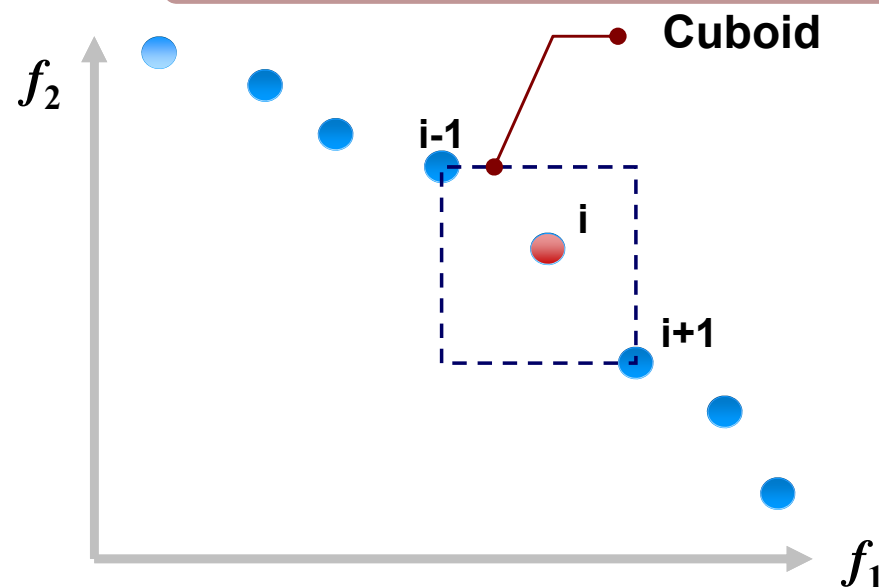
$O_{t+1}$   
Offspring

By Crossover  
& Mutation

Nondominated Sorting



Crowding Distance Sorting





# Robot Soccer System



## ❖ Path Planner for Robot Shooting Behavior (using NSGA-II)

### ➤ Key objectives of path planning in the robot shooting

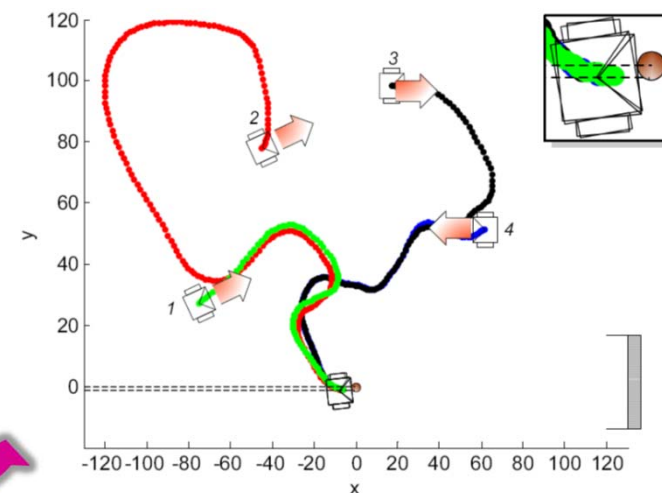
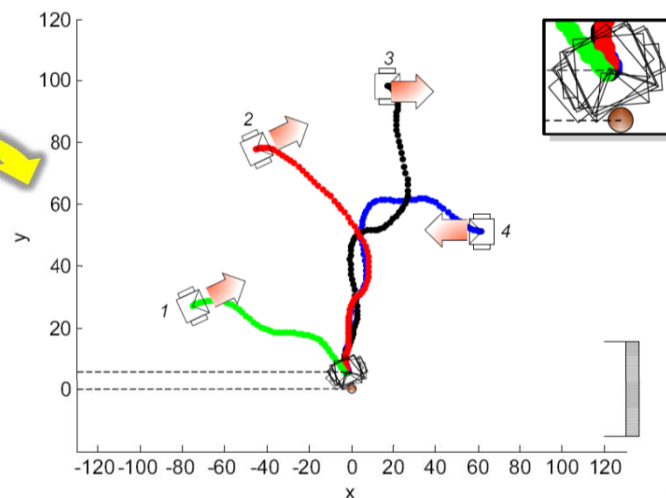
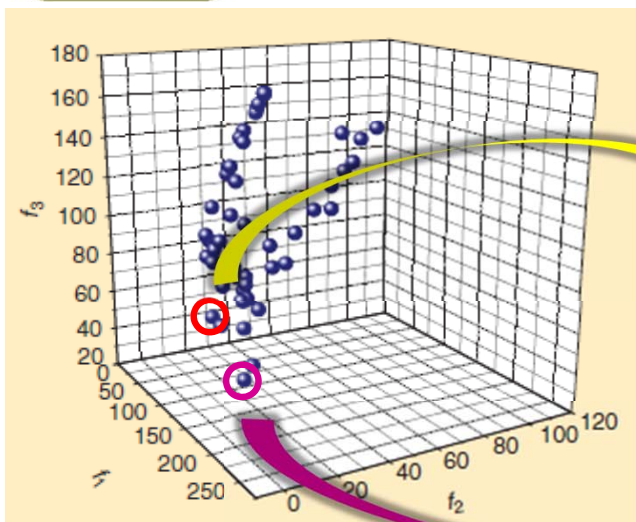
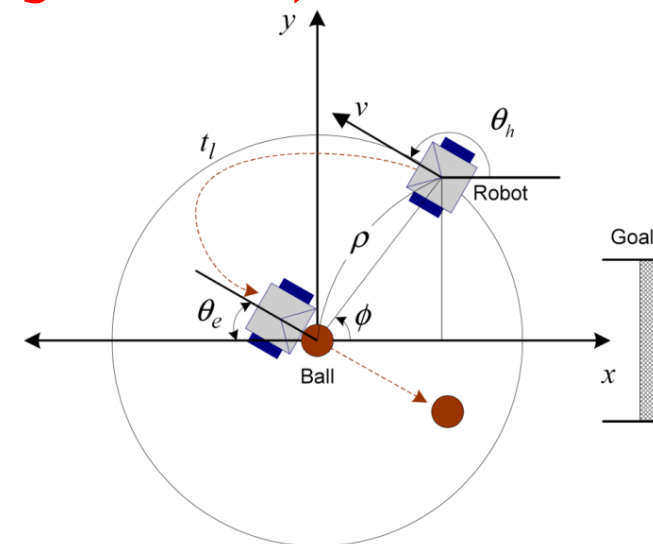
- ✓ Robot should approach to the ball as soon as possible
- ✓ Robot should kick the ball to the goal accurately

$$f_1 = K_t \cdot t_l \quad \text{(Elapsed time)}$$

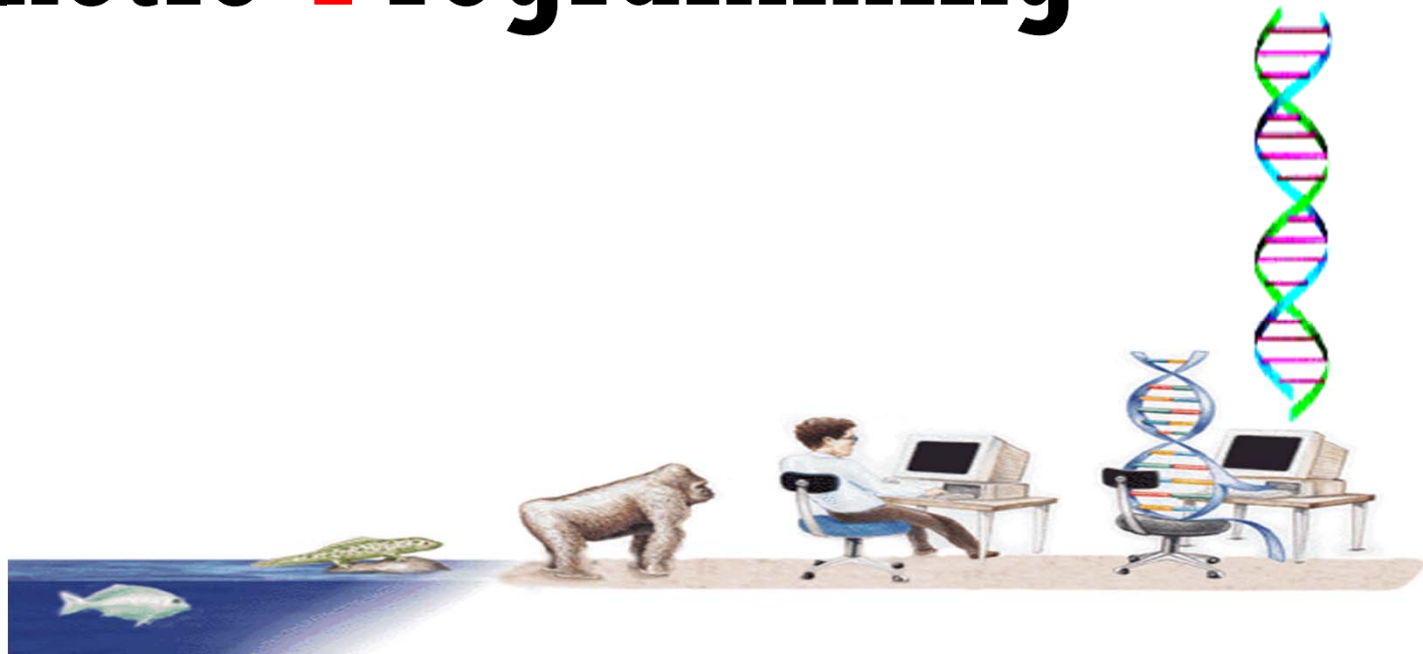
$$f_2 = K_\theta \cdot \theta_e \quad \text{(Heading direction error)}$$

$$f_3 = K_\phi \cdot |\pi - \phi| \quad \text{(Posture angle error when kicking a ball)}$$

Dependencies exist!  
Spending more time  
returns a more  
accurate position!



# Genetic Programming





# Genetic Programming (1)



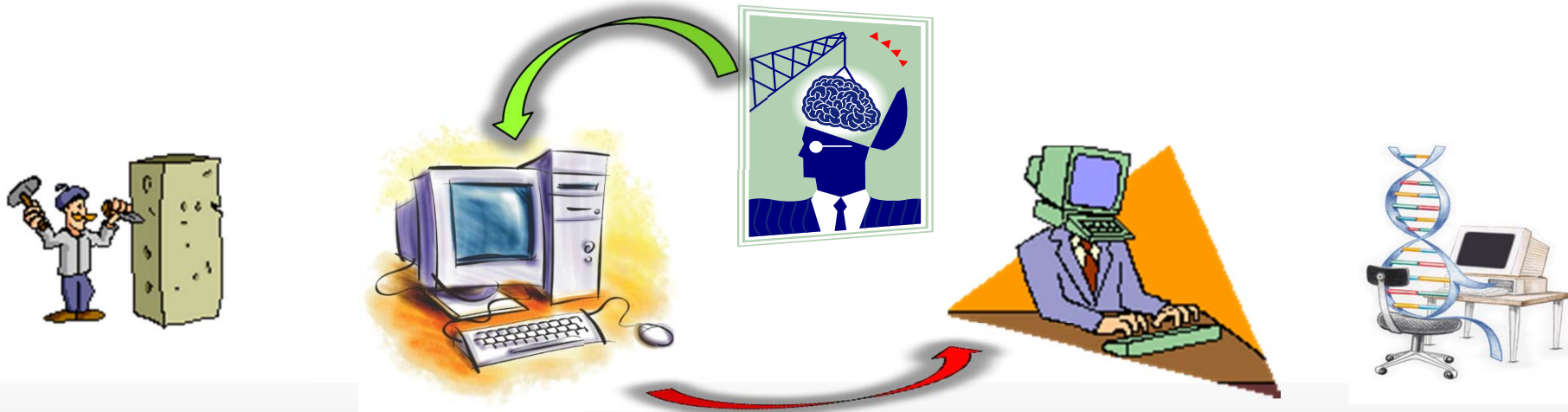
## ❖ From “Manual” to “Automatic/Intelligent”

### ➤ The Challenge

“How can computers learn to solve problems **without being explicitly programmed?**  
In other words, how can computers be made to do what is needed to be done,  
without being told exactly how to do it?” by Arthur Samuel (1959)

### ➤ Criterion for Success

“The aim is to get machines to exhibit behavior, which if done by humans, would  
be assumed to involve **the use of intelligence.**” by Arthur Samuel (1983)





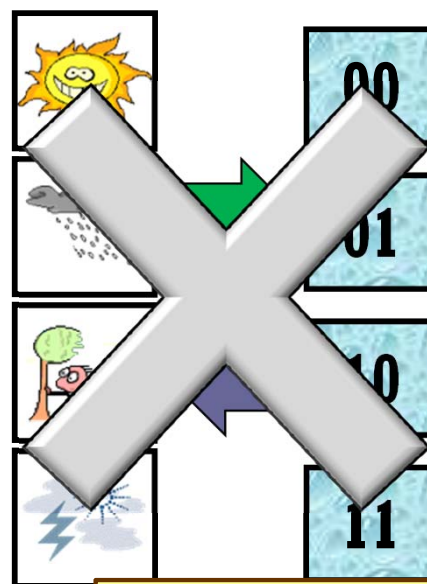
# Genetic Programming (1)



## ❖ A Computer Program in C

- Usually, C program codes are used for solving problem on computers
- But, numeric (e.g., binary) codes are used for doing tasks
- It is not flexible to solve problems on computers!
- Why not use the program codes directly?

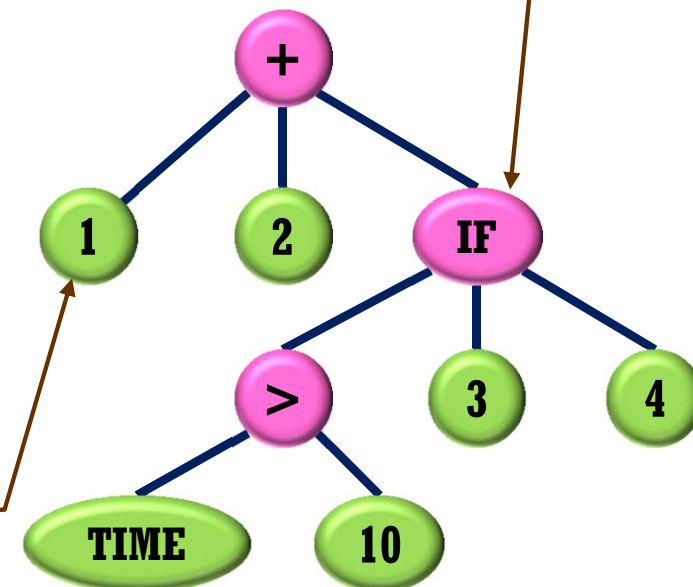
```
int foo (int time)
{
    int temp1, temp2;
    if (time > 10)
        temp1 = 3;
    else
        temp1 = 4;
    temp2 = temp1 + 1 + 2;
    return (temp2);
}
```



**Terminal node:**  
{X, Y, ..., random}

**Functional node:**  
{+, -, \*, %, IF-ELSE}

(+ 1 2 (IF (> TIME 10) 3 4))





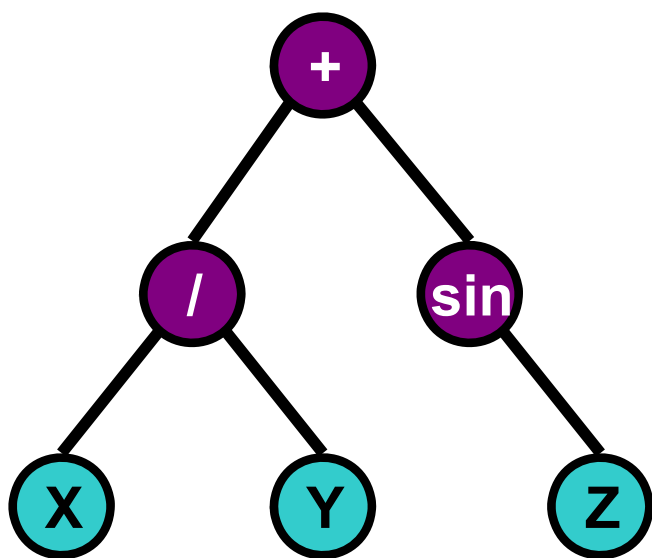
# Genetic Programming (2)



## ● What is Genetic Programming (GP)?

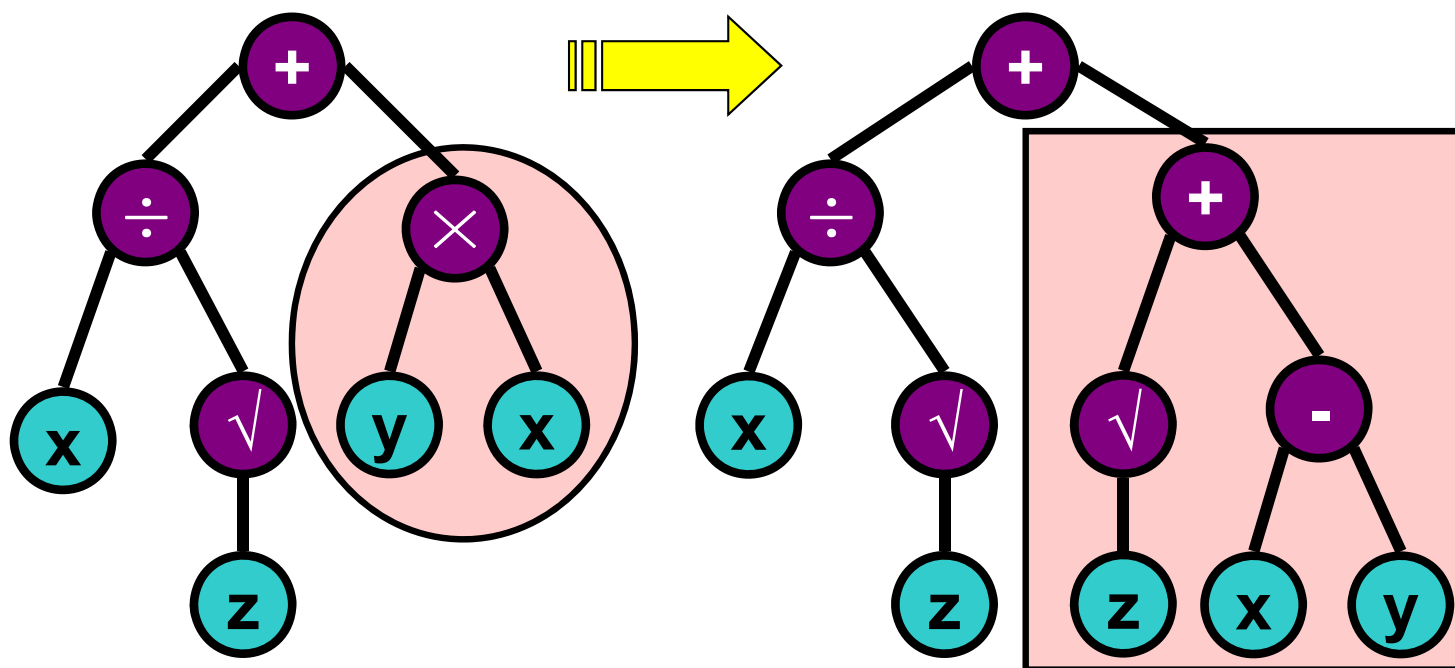
- **Breeding computer programs** to resolve problems
  - Key principle is very similar to GAs; but something different
    - 1) **Sameness**: Evolutionary procedures by selection and variation
    - 2) **Difference**: **Representation** by tree and graph (**non-linear representation**)
- All possible computer programs can be encoded!

### TREE REPRESENTATION



$$f(x,y,z) = x/y + \sin(z)$$

### MUTATION



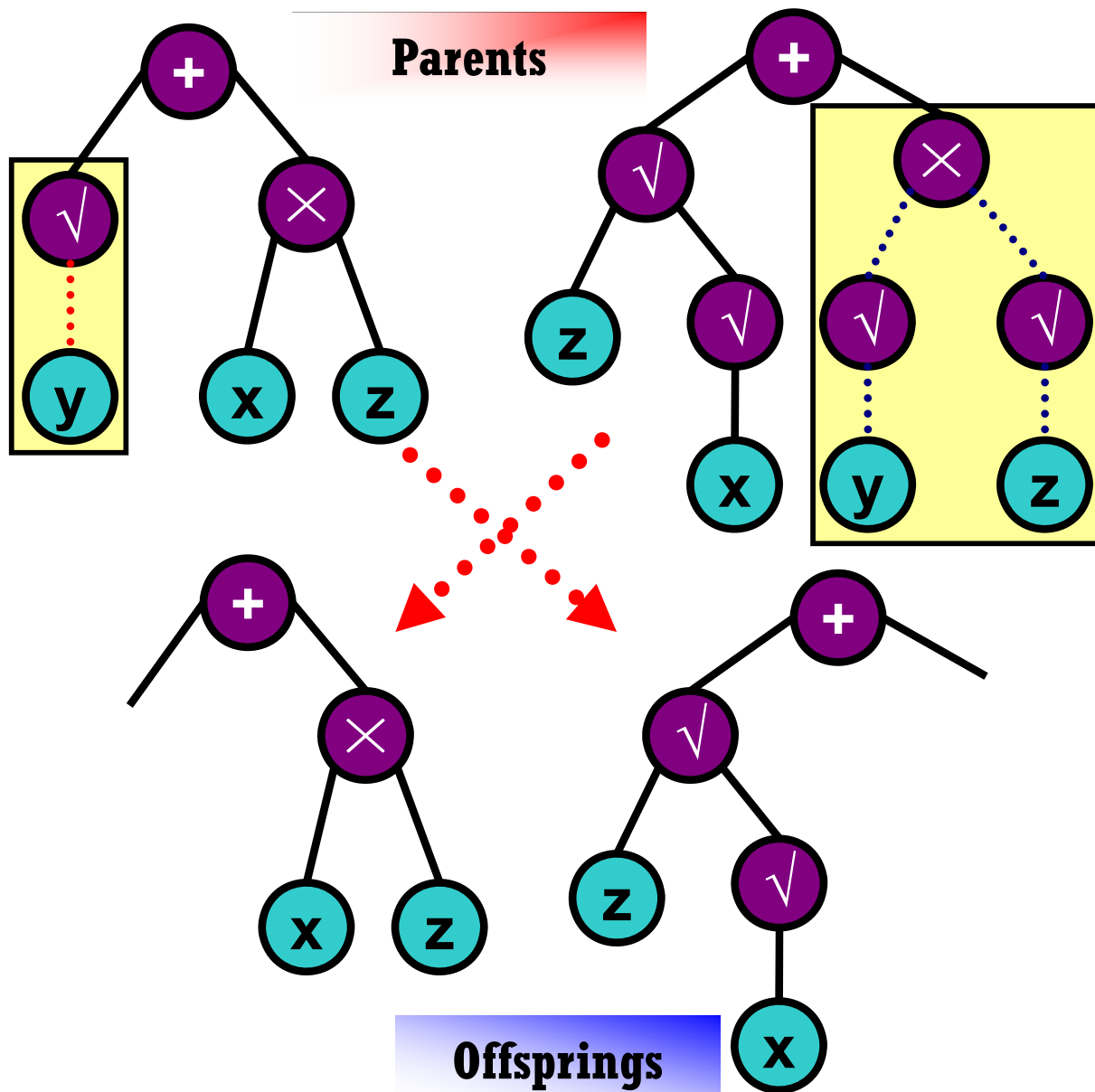




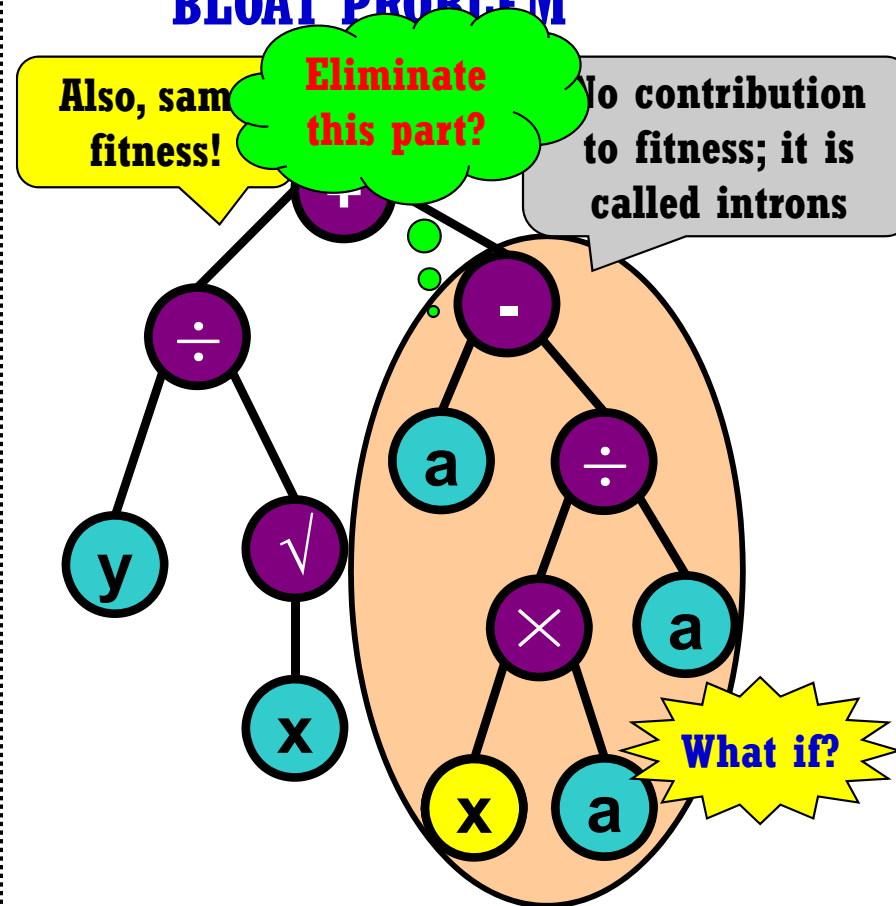
# Genetic Programming (3)



## CROSSOVER



## BLOAT PROBLEM



**Problem:** It is possible to grow rapidly in size over the course of a run while the fitness does not improve at all!  
→ Solving the problem is not easy.



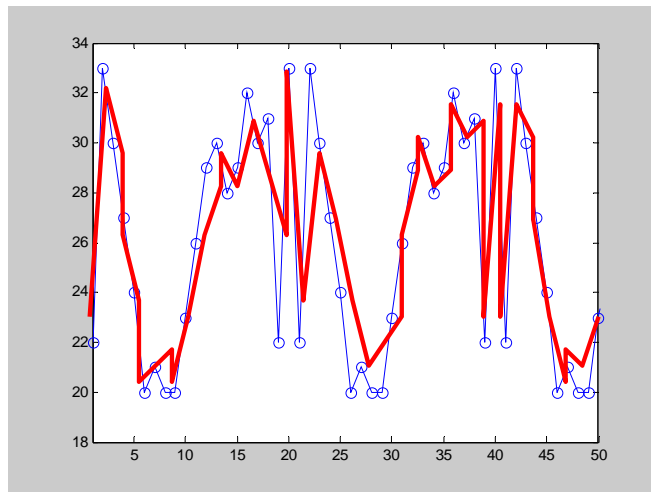
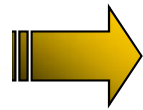
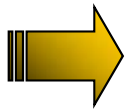


# GP-Based Prediction



## Time-Series Forecasting

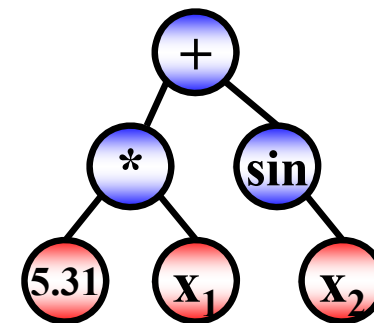
CRC40	6.380	10K01	➡ +1.86%
S&P120	4.315	10K01	➡ +1.69%
S&P250	4.042	10K01	➡ +1.55%
FTSE100	2.667	10K01	➡ +0.10%
INDICE ATM	4.450	10K01	➡ -0.66%



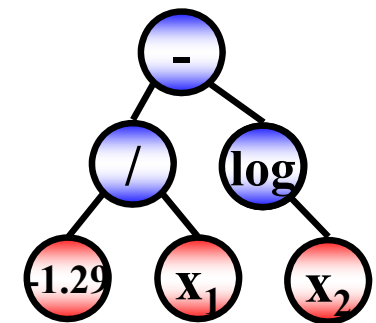
- Predicting some future outcomes from a set of historical events
- Stock prediction, Weather forecasting, etc.

## GP Approach

- Using a nonlinear-type function

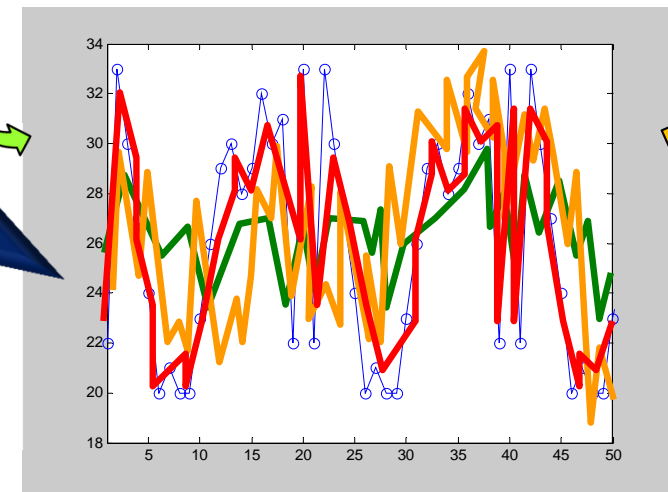


$$-5.31 * x_1 + \sin(x_2)$$



$$-5.31 * x_1 - \log(x_2)$$

By Selection,  
Crossover, &  
Mutation



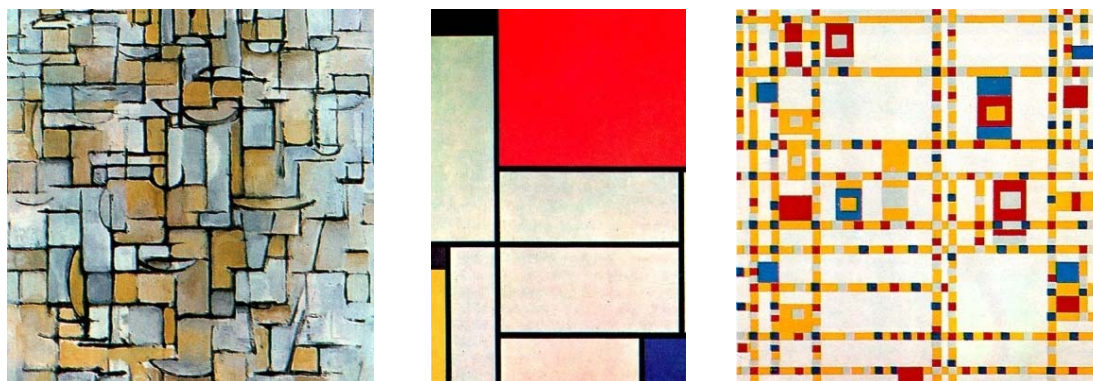
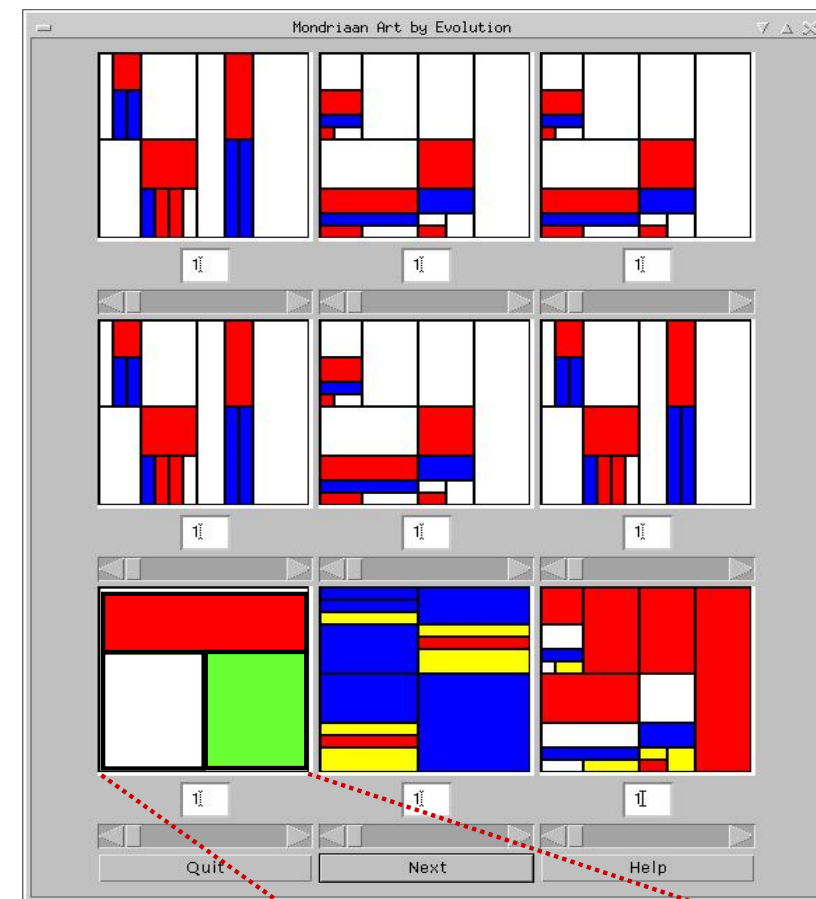


# GP-Based Evolutionary Art



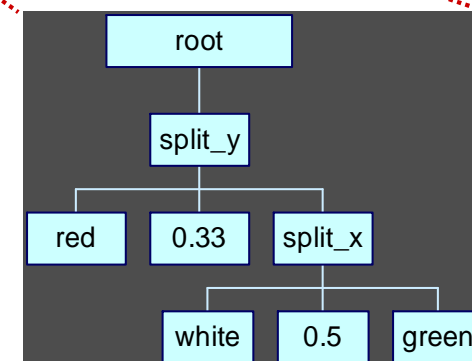
## ● Mondriaan Evolver (Craenen et al.)

- GUI shows population of 9 pictures
- User offers their grades
- Computer performs one evolutionary cycle
  - ✓ Selection based on the fitness  
(thus, create mating pool)
  - ✓ Crossover & mutation  
(thus, create new population)
- Repeat



Mondriaan's Arts

Mondriaan  
Representation





# Summary



## ❖ Multiobjective Evolutionary Algorithms (MOEAs)

- Generally, many problems consist of a set of **conflicting objectives**
- Naturally, EAs deal with **multiple solutions**, and hence **very suitable**
- MOEAs are **superior** to mathematical multiobjective schemes.
- ➔ MOEAs are **useful** for **resolving** diverse problems **in an attractive way**.

## ❖ Genetic Programming (GP)

- To develop **the breeding computer programs** for solving problems
- **Program codes** are directly **employed** as data structure
- The codes evolves in the **concept of GAs**.
- ➔ GP is very **flexible** and **powerful** to deal with many **real-world applications**.