



Machine Learning

CHAPTER 9 Genetic Algorithms



9.1 动机

—模拟生物进化

—不断变异、重组当前最好假设生成后续的假设

—GA 特点:

—进化具有很好的鲁棒性

—假设空间中，假设的各个部分相互作用，每个假设对适应度的影响难以建模

—易于并行计算



9.2 Genetic Algorithms

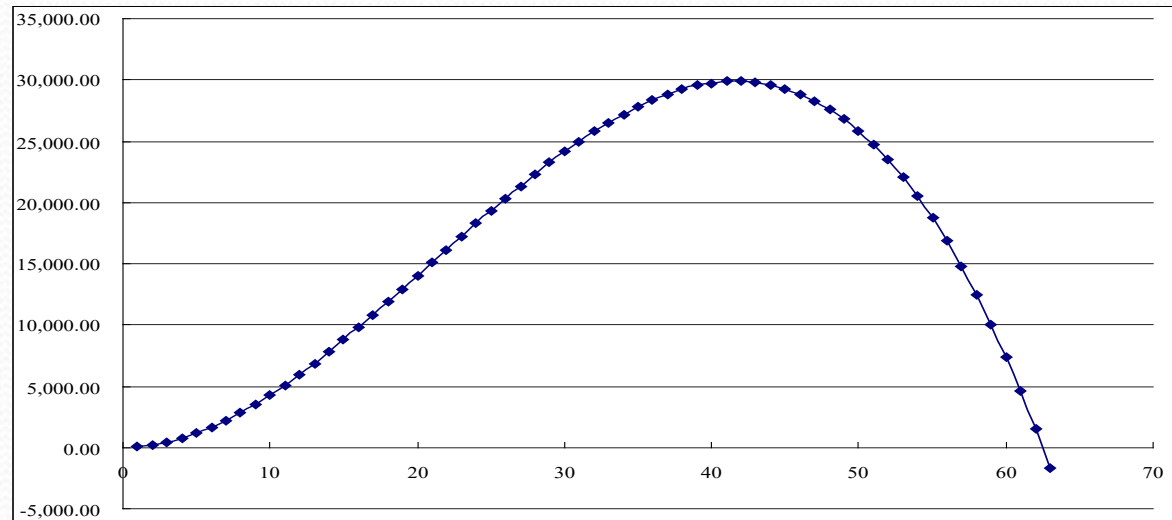
- 假设适应度 (Hypothesis fitness)
 - Fitness
 - Best hypothesis has the highest fitness
- 算法结构:
 - 迭代更新种群 (population)
 - 对种群的每个成员进行评估
 - 产生新的种群

Let's start from a problem

Max $F(X) = -0.83X^3 + 52X^2 - 8.5X + 8$

Subject to: $0 \leq X \leq 61$

$X \in \text{Integer}$



■ □ □ □ ?

■ □ □ □ , □ □ □ □ □ □ □ □

■ □ □ □ (□ □ , □ □ □ □) □

■ □ □ , □ □ □ □ □ □

■ □ □ ?

A dumb solution

A “blind generate and test” algorithm:

Repeat

- Generate a random possible solution

- Test the solution and see how good it is

Until solution is good enough

Can we use this dumb idea?

- Sometimes - yes:
 - if there are only a few possible solutions
 - and you have enough time
- For most problems - no:
 - many possible solutions
 - with no time to try them all

A “less-dumb” idea (GA)

产生一组随机解

Repeat

- 评估集合中的每一个解(rank them)

- 删除集合中的不良解

- 复制部分优良解

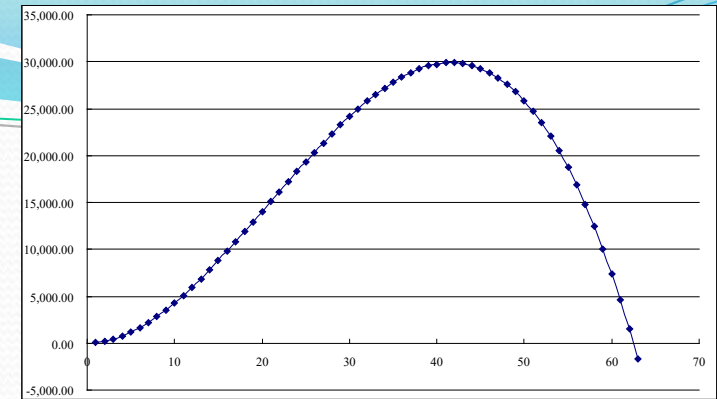
- 对部分解进行小的改变

Until best solution is good enough


$$\text{Max } F(X) = -0.83X^3 + 52X^2 - 8.5X + 8$$

$$\text{Subject to: } 0 \leq X \leq 61$$

$$X \in \text{Integer}$$



Step 1: Encoding (编码)

		X		$F(X)$						
<i>pop 1</i>	<table border="1"><tr><td>1</td><td>0</td><td>1</td><td>0</td><td>1</td><td>1</td></tr></table>	1	0	1	0	1	1	43		29799.69
1	0	1	0	1	1					
<i>pop 2</i>	<table border="1"><tr><td>0</td><td>0</td><td>0</td><td>1</td><td>1</td><td>0</td></tr></table>	0	0	0	1	1	0	6		1649.72
0	0	0	1	1	0					
<i>pop 3</i>	<table border="1"><tr><td>1</td><td>0</td><td>0</td><td>0</td><td>1</td><td>1</td></tr></table>	1	0	0	0	1	1	35	27824.25	
1	0	0	0	1	1					

Step 2: Generate population (产生群体)

pop 1	0	1	1	1	0	1	29
pop 2	1	0	1	0	1	0	42
pop 3	0	1	1	1	1	1	31
pop 4	0	1	0	1	0	1	21
pop 5	1	0	0	1	1	1	39
...
...
pop 19	0	1	0	0	0	1	17
pop 20	0	0	1	1	1	1	15

Step2 Selection (选择)

	<i>X</i>							<i>F(X)</i>	<i>survival rate</i>
Pop 1	0	1	1	1	0	1	29	23250.63	5.77%
Pop 2	1	0	1	0	1	0	42	29885.96	7.41%
Pop 3	0	1	1	1	1	1	31	24989.97	6.20%
Pop 4	0	1	0	1	0	1	21	15074.87	3.74%
Pop 5	1	0	0	1	1	1	39	29533.73	7.33%
Pop 6	1	0	1	1	1	1	47	28303.41	7.02%
Pop 7	0	1	0	1	0	1	21	15074.87	3.74%
Pop 8	0	1	0	0	0	1	17	10813.71	2.68%
Pop 9	0	0	1	1	1	1	15	8779.25	2.18%
Pop 10	1	1	0	1	1	1	55	18749.25	4.65%
Pop 11	0	1	1	1	0	1	29	23250.63	5.77%
Pop 12	0	1	0	1	1	1	23	17221.89	4.27%
Pop 13	1	0	1	0	1	1	43	29799.69	7.39%
Pop 14	0	1	1	0	1	0	26	20350.92	5.05%
Pop 15	1	0	0	0	1	1	35	27824.25	6.90%
Pop 16	0	0	1	1	1	1	15	8779.25	2.18%
Pop 17	0	1	0	1	1	1	23	17221.89	4.27%
Pop 18	0	0	0	1	0	1	5	1161.75	0.29%
Pop 19	1	0	1	0	1	1	43	29799.69	7.39%
Pop 20	0	1	1	1	0	1	29	23250.63	5.77%

$$\text{Survival Rate} = \frac{\text{fitness}}{\text{sum}(\text{fitness})}$$

Step 3: Crossover (交叉)

pop 1	0	1	1	1	0	1	29
pop 2	1	0	1	0	1	0	42
pop 3	0	1	1	1	1	1	31
pop 4	0	1	0	1	0	1	21
pop 5	1	0	0	1	1	1	39
...
...
pop 19	0	1	0	0	0	1	17
pop 20	0	0	1	1	1	1	15

*Randomly
select
parents*

Parent 1

0	1	1	1	0	1
---	---	---	---	---	---

Parent 2

1	0	0	1	1	1
---	---	---	---	---	---

Crossover point



Offspring 1

0	1	1	1	1	1
---	---	---	---	---	---

X F(X)

31 24989.97

Offspring 2

1	0	0	1	0	1
---	---	---	---	---	---

37 28839.51

Step 4: Mutation (变异)

		X	$F(X)$			X	$F(X)$												
Offspring 1	<table><tr><td>0</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td></tr></table>	0	1	1	1	1	1	31	24989.97										
0	1	1	1	1	1														
Offspring 2	<table><tr><td>1</td><td>0</td><td>0</td><td>1</td><td>0</td><td>1</td></tr></table>	1	0	0	1	0	1	37	28839.51	→	<table><tr><td>1</td><td>0</td><td>0</td><td>1</td><td>1</td><td>1</td></tr></table>	1	0	0	1	1	1	39	29533.73
1	0	0	1	0	1														
1	0	0	1	1	1														
Offspring 3	<table><tr><td>0</td><td>0</td><td>1</td><td>0</td><td>1</td><td>0</td></tr></table>	0	0	1	0	1	0	10	4293.00										
0	0	1	0	1	0														
.....																			
Offspring 20	<table><tr><td>0</td><td>0</td><td>0</td><td>1</td><td>1</td><td>0</td></tr></table>	0	0	0	1	1	0	6	1649.72										
0	0	0	1	1	0														

↑

Randomly select mutation point

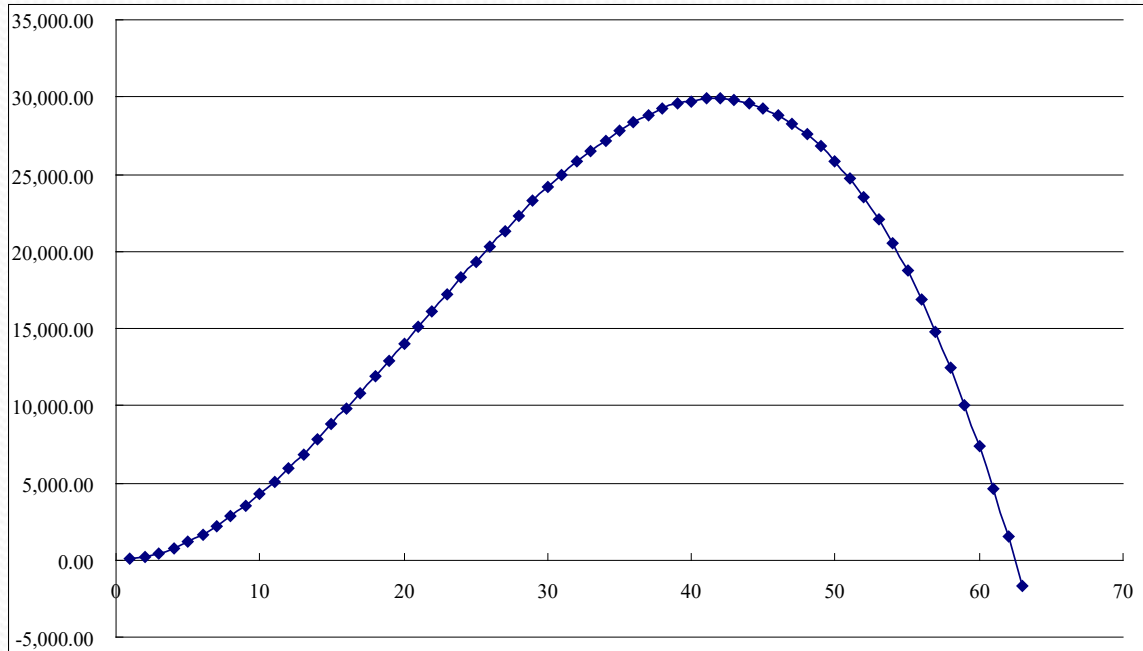
Step 5: Next round-back to Step2

When converged!

	X						$F(X)$	
Pop 1	1	0	1	0	1	0	42	29885.96
Pop 2	1	0	1	0	1	0	42	29885.96
Pop 3	1	0	1	0	1	0	42	29885.96
Pop 4	1	0	1	0	1	0	42	29885.96
Pop 5	1	0	1	0	1	0	42	29885.96
Pop 6	1	0	1	0	1	0	42	29885.96
Pop 7	1	0	1	0	1	0	42	29885.96
Pop 8	1	0	1	0	1	0	42	29885.96
Pop 9	1	0	1	0	1	0	42	29885.96
Pop 10	1	0	1	0	1	0	42	29885.96
Pop 11	1	0	1	0	1	0	42	29885.96
Pop 12	1	0	1	0	1	0	42	29885.96
Pop 13	1	0	1	0	1	0	42	29885.96
Pop 14	1	0	1	0	1	0	42	29885.96
Pop 15	1	0	1	0	1	0	42	29885.96
Pop 16	1	0	1	0	1	0	42	29885.96
Pop 17	1	0	1	0	1	0	42	29885.96
Pop 18	1	0	1	0	1	0	42	29885.96
Pop 19	1	0	1	0	1	0	42	29885.96
Pop 20	1	0	1	0	1	0	42	29885.96

$$F(X) = 0.83X^3 + 52X^2 - 8.5X + 8$$

Subject to: $0 \leq X \leq 61$
 $X \in \text{integer}$





A prototypical genetic algorithm

—GA(Fitness, fitness_threshold, p,r,m)

Fitness: 适应度函数;

fitness_threshold:终止判据的阈值

p:群体中包含的假设数量;

r:通过交叉替换成员的比例;

m:变异率



initialize population : P

Evaluate : For each h in P, compute Fitness(h)

while[max Fitness(h)] < Fitness_threshold do

{

create a new generation, P_s :

1. **Select**: select $(1-r)p$ members of P to add to P_s .

$$\Pr(h_i) = \text{Fitness}(h_i) / \sum \text{Fitness}(h_j)$$

2. **Crossover**: select $r*p/2$ pairs of hypotheses from P.

applying the crossover operator. Add all offspring to P_s

3. **Mutate**: choose m percent of the members of P_s .

invert one randomly selected bit in its representation.

4. update: $P = P_s$

5. Evaluate: for each h in P, compute Fitness(h)

}

Return the hypothesis from P that has the highest fitness

Parameters of GA

- GA has following parameters:
 - Crossover rate（交叉率）
 - Mutation rate（变异率）
 - Population size（群体大小）
 - Encoding（编码）
 - Crossover and mutation type（交叉、变异类型）
 - Selection（选择）
- 参数如何确定，无确定方法.
 - 根据具体问题, 实验确定



9.2.1 Representing Hypotheses

- 假设表示为位串
 - 易于被遗传算子操作
- Example: 编码 if-then 规则
 - If wind=strong, then playTennis =yes
 - Attribute coding (属性编码)
 - Wind: Strong, weak
 - 两位长位串: **10**
 - 规则中未被约束的属性编码
 - Outlook=111



9.2.1 Representing Hypotheses

- rule coding
 - concatenating the corresponding bit strings
 - 111 10 10
- Representation of sets of rules:
 - concatenating bit strings of individual rules
- 语法正确的位串应能表示有意义的假设
 - 111 10 11?

9.2.2 Genetic operators



- The most common operators : crossover and mutation
- The crossover (交叉) operator:

- Produces two new offspring from two parents strings by copying selected bits from each parent

- crossover mask:

- Single point crossover

$A \square 1011011100 \quad 1111111100 \quad A' \square 1011011111$
 $B \square 0001110011 \quad \longrightarrow \quad B' \square 0001110000$

- Two-point crossover

$A: 1011011100 \quad 0001111100 \quad A' \square 0001011111$
 $B \square 0001110011 \quad \longrightarrow \quad B' \square 1011110000$

- Uniform crossover

$A: 1011001100 \quad 0001101100 \quad A' \square 0001011111$
 $B \square 0001110011 \quad \longrightarrow \quad B' \square 1011100000$



9.2.2 Genetic operators (2)

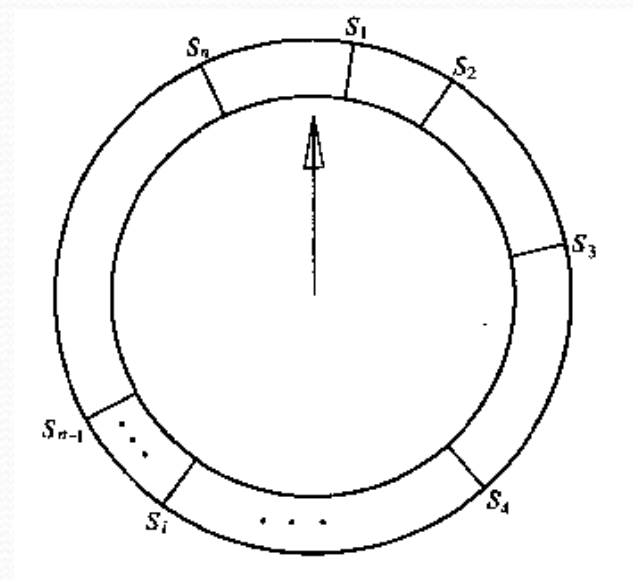
—Mutation operator:

- Produces offspring from a single parent and produces small changes to the bit string
- Mutation is often performed after crossover has been applied



9.2.3 Fitness Function and Selection

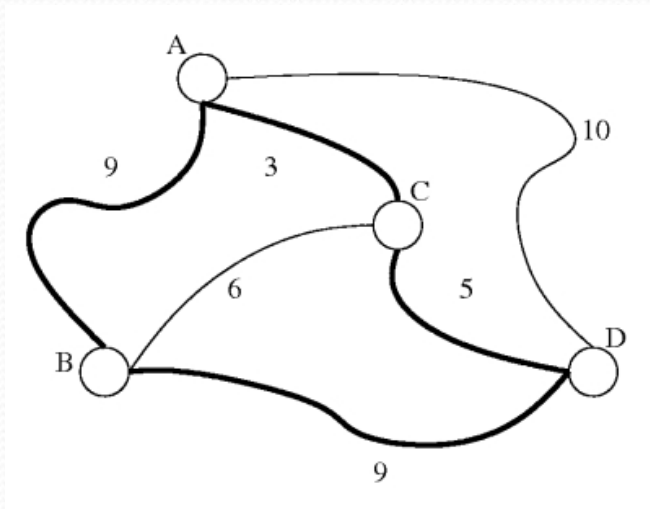
- 适应度函数定义了候选假设的排序准则
- 选择假设的概率方法
 - 适应度比例选择(roulette wheel selection)
 - 锦标赛选择
 - Randomly select two h
 - $p, (1-p) \rightarrow h_{\text{high}}, h_{\text{low}}$
 - A more diverse population
 - 排序选择
 - Sorted by fitness
 - Probability is proportional to its rank



TSP

- **The decision version of this problem has been proven to be NP-Complete!**
- **Existing solutions:**
 - heuristics,
 - cutting-plane methods,
 - branch-and-cut
- **How to solve it by GA?**

(1) Encoding



	<i>1st city on tour</i>	<i>2nd city on tour</i>	<i>last city on tour</i>
City #			

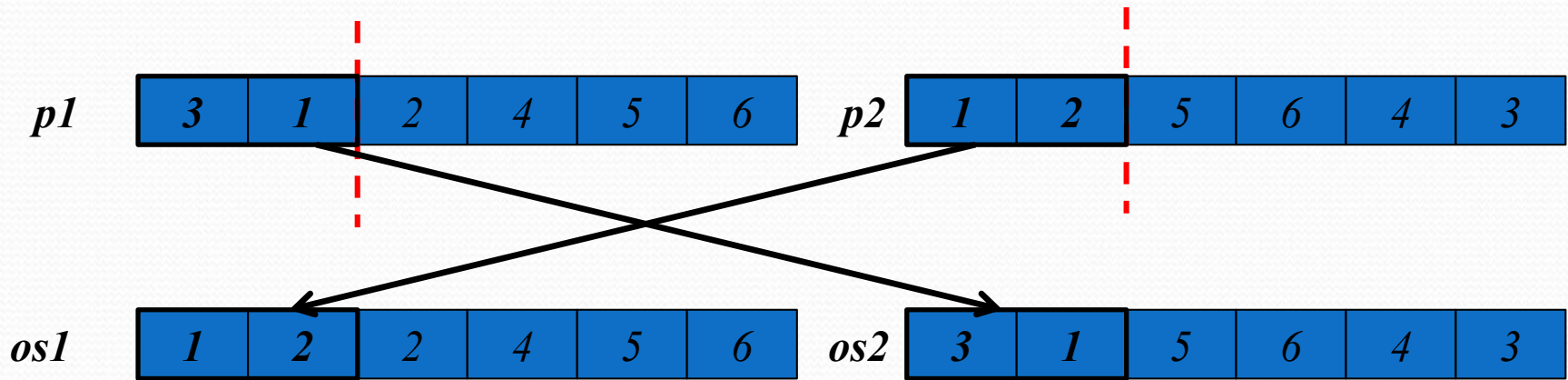
—For example, we have 6 cities, and a tour is 3-1-2-4-5-6

<i>3</i>	<i>1</i>	<i>2</i>	<i>4</i>	<i>5</i>	<i>6</i>
----------	----------	----------	----------	----------	----------

(2) Fitness Evaluation

- Given a chromosome, simply calculate the total distance.
- The shorter the distance, the higher the fitness of the chromosome

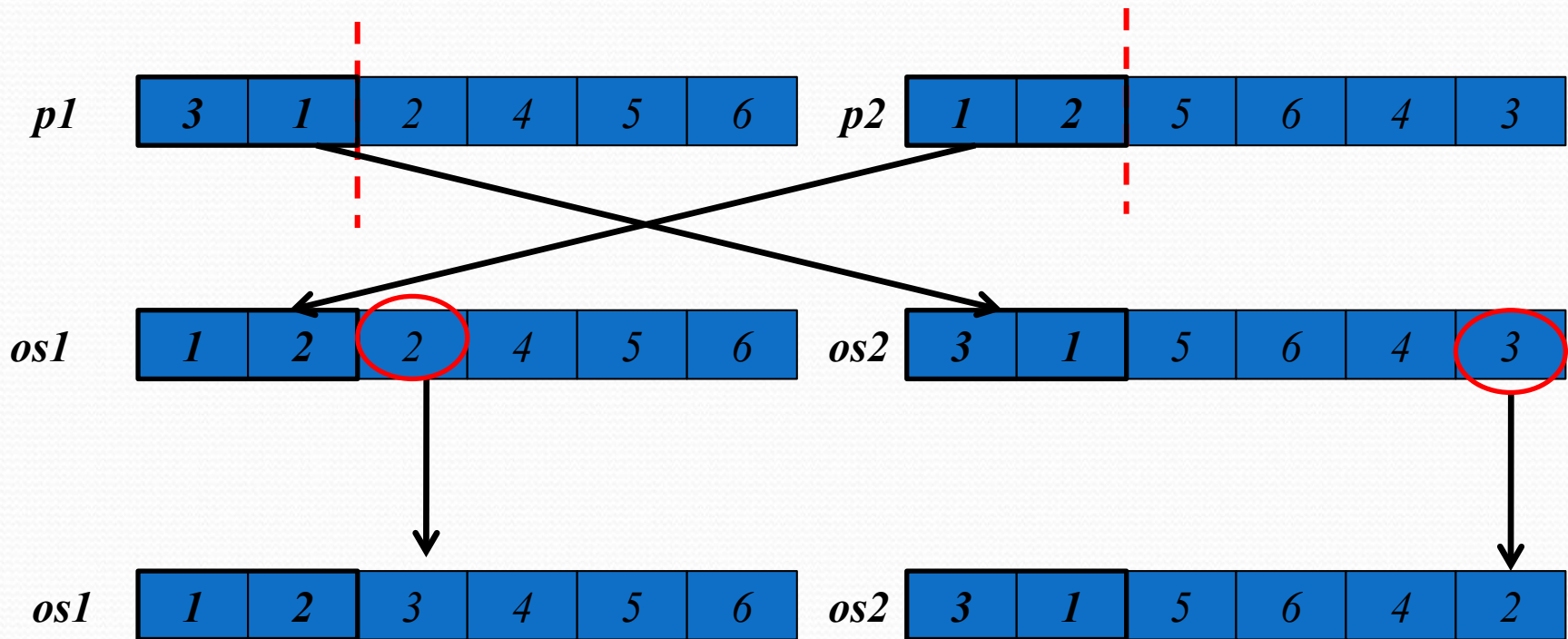
(3) Cross-over



—Do you find any problem?

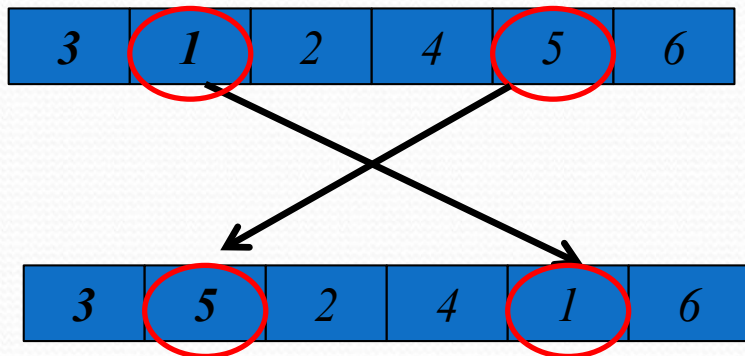
How to solve this problem?

Repair operator

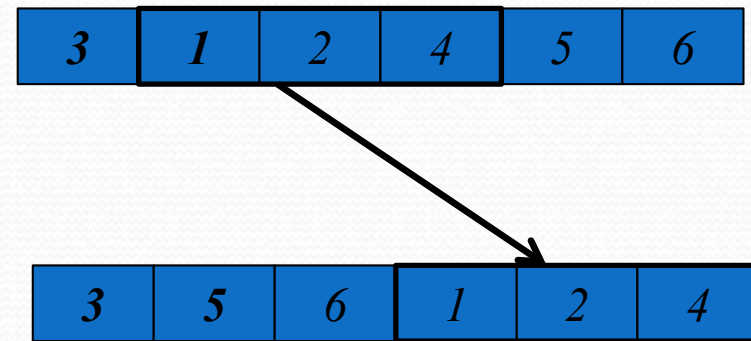


(3) Mutation

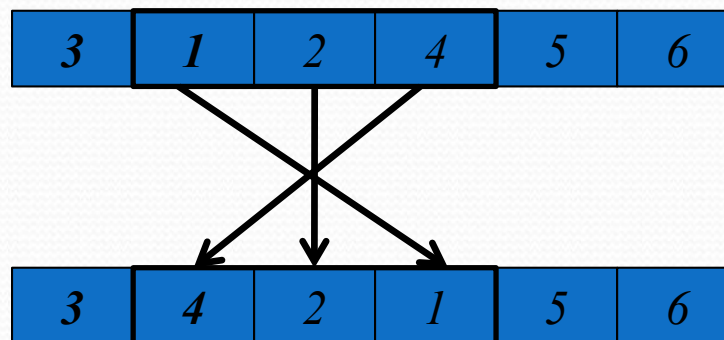
— Exchange mutation



— Displacement mutation



— Simple inversion mutation





9.4 Hypothesis Space Search

- GAs 使用随机柱状搜索寻找最大适应度假设
 - The gradient descent search moves smoothly from one h to a new h
 - GA搜索的移动可能非常突然
 - less likely to fall into the local minima
- 实际应用困难: 拥挤问题 (crowding)
 - 高适应度值个体迅速繁殖, 群体包含过多相似个体
 - 降低种群多样性, 减慢进化过程



Hypothesis space search (2)

—避免拥挤的策略

—修改选择函数

- 使用锦标赛或排序选择

—适应度共享

- 根据相似性个体的数量，降低个体的适应度

—限制可重组生成后代的个体种类

- 只允许最相似的个体进行重组
- 按空间分配个体，仅允许相邻个体重组

Summary

—遗传算法优点:

1. 无需先验知识或计算误差函数的梯度信息
2. 可设计多目标函数
3. 并行性
4. 可很容易地用于对庞大、难以理解的假设空间进行搜索
5. 可广泛应用于优化问题的求解

Summary

遗传算法的缺点:

1. 问题的表示
2. 适应度函数的定义
3. 过早收敛
4. 参数的选择问题: 如种群大小, 变异率, 交叉率, 选择的策略等
5. 无法应用梯度信息
6. 终止条件难判断
7. 频繁计算适应度, 计算量较大