



ITMO UNIVERSITY

Saint Petersburg, Russia

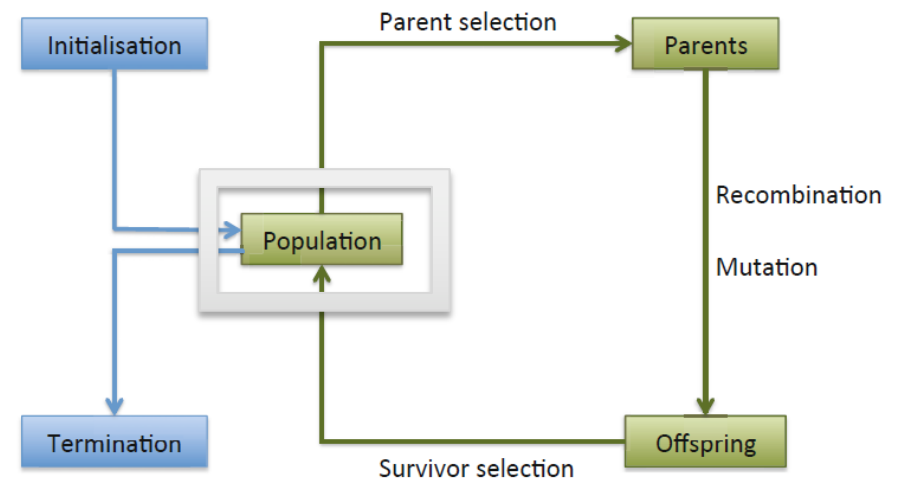
# Lecture 2: Representation of individuals

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# Components of EAs

- ✓ **Representation of individuals**
- ✓ Population of individuals
- ✓ Evaluation function (fitness function)
- ✓ Parent selection mechanism
- ✓ Variation operators (recombination, mutation)
- ✓ Survivor selection mechanism
- ✓ Terminate conditions



# Representations

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- ✓ The first stage of building any evolutionary algorithm is to decide on a genetic representation of a candidate solution to a problem
- ✓ Common types of representation:
  - Binary
  - Integer values
  - Real values
  - Permutation
  - Tree representation

# Binary representation

1	0	1	0	0	0	0	1	0
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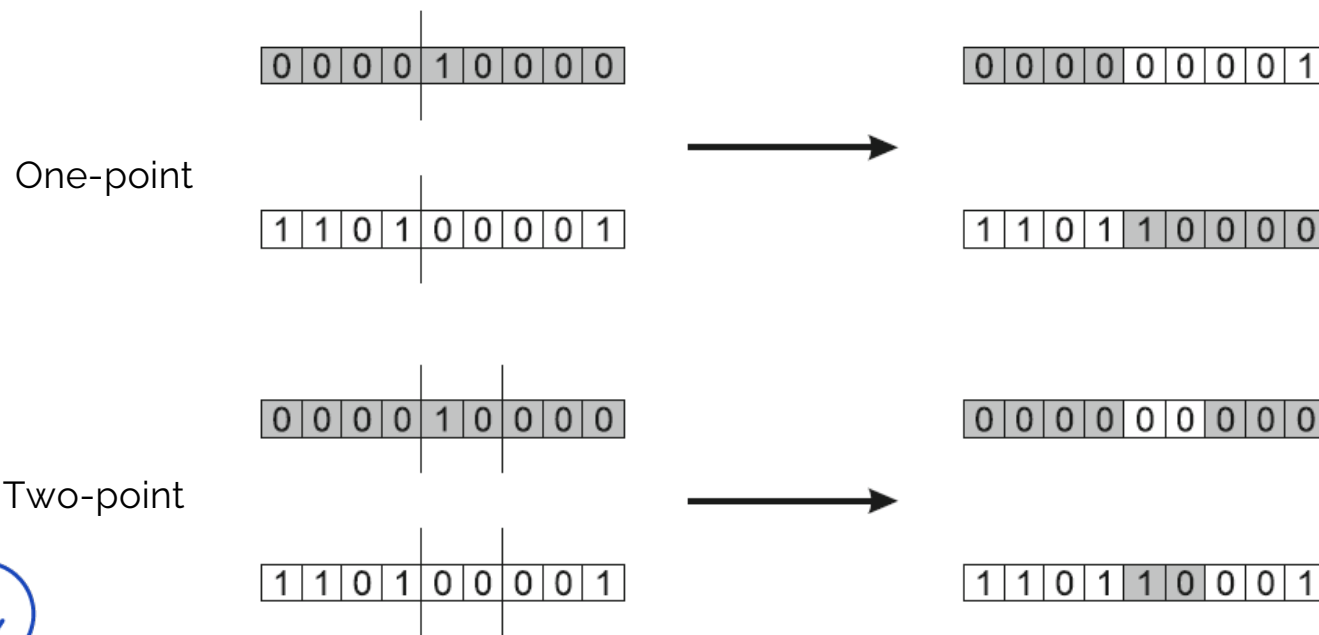
Integer 332 is represented as a binary genotype

**Mutation** may flip some bits in genotype



# Binary crossover

- ✓ Original crossover operator is one-point crossover
- ✓ This can be easily extended to n-point crossover



# Uniform crossover

- ✓ Child may receive genes uniformly

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

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



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

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

# Crossover or mutation

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- ✓ Decade long debate: which one is better / necessary / main-background
- ✓ Answer:
  - it depends on the problem, but
  - in general, it is good to have both
  - both have another role
  - mutation-only-EA is possible, crossover-only-EA would not work

# Crossover OR mutation

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- ✓ Only crossover can combine information from two parents
- ✓ Only mutation can introduce new information (genes)

There is co-operation AND competition between them

- ✓ Crossover is explorative, it makes a *big* jump to an area somewhere “in between” two (parent) areas
- ✓ Mutation is exploitative, it creates random *small* diversions, thereby staying near (in the area of ) the parent



# Integer representation

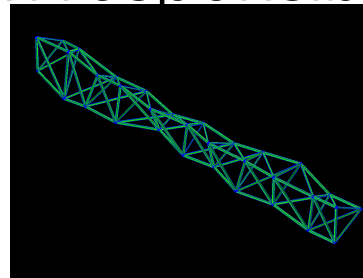
- ✓ Nowadays it is generally accepted that it is better to encode numerical variables directly (integers, floating point variables)
- ✓ Some problems naturally have integer variables, e.g. image processing parameters
- ✓ Others take categorical values from a fixed set e.g. {blue, green, yellow, pink}
- ✓ N-point / uniform crossover operators work
- ✓ Extend bit-flipping mutation to make
  - “creep” i.e. more likely to move to similar value
    - Adding a small (positive or negative) value to each gene with probability  $p$
  - Random resetting (esp. categorical variables)
    - With probability  $p_m$  a new value is chosen at random
- ✓ Same recombination as for binary representation

# Real-valued (floating-point) representation

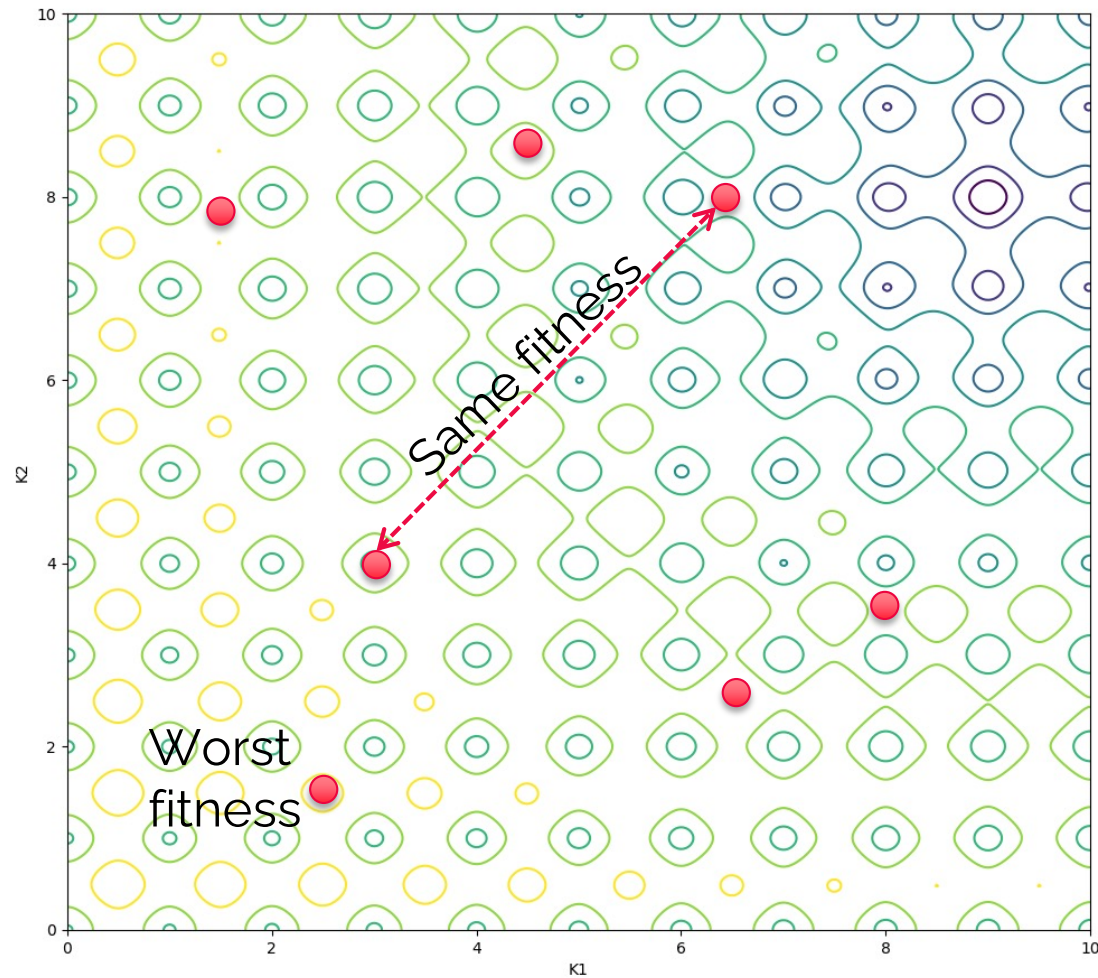
- ✓ Genotype for a solution with is now a vector of real values

0.5	0.9	0.1	1.5	0.6
-----	-----	-----	-----	-----

- ✓ Floating-point ignores discretization and considers genes as continuous values
- ✓ Real valued representation is widely used
- ✓ For example: satellite holder can be encoded as a set of float values, which responsible for different angles and spar lengths



# Population



- ✓ Randomly generated points:  $[(x_1, x_2), \dots]$

# Mutation

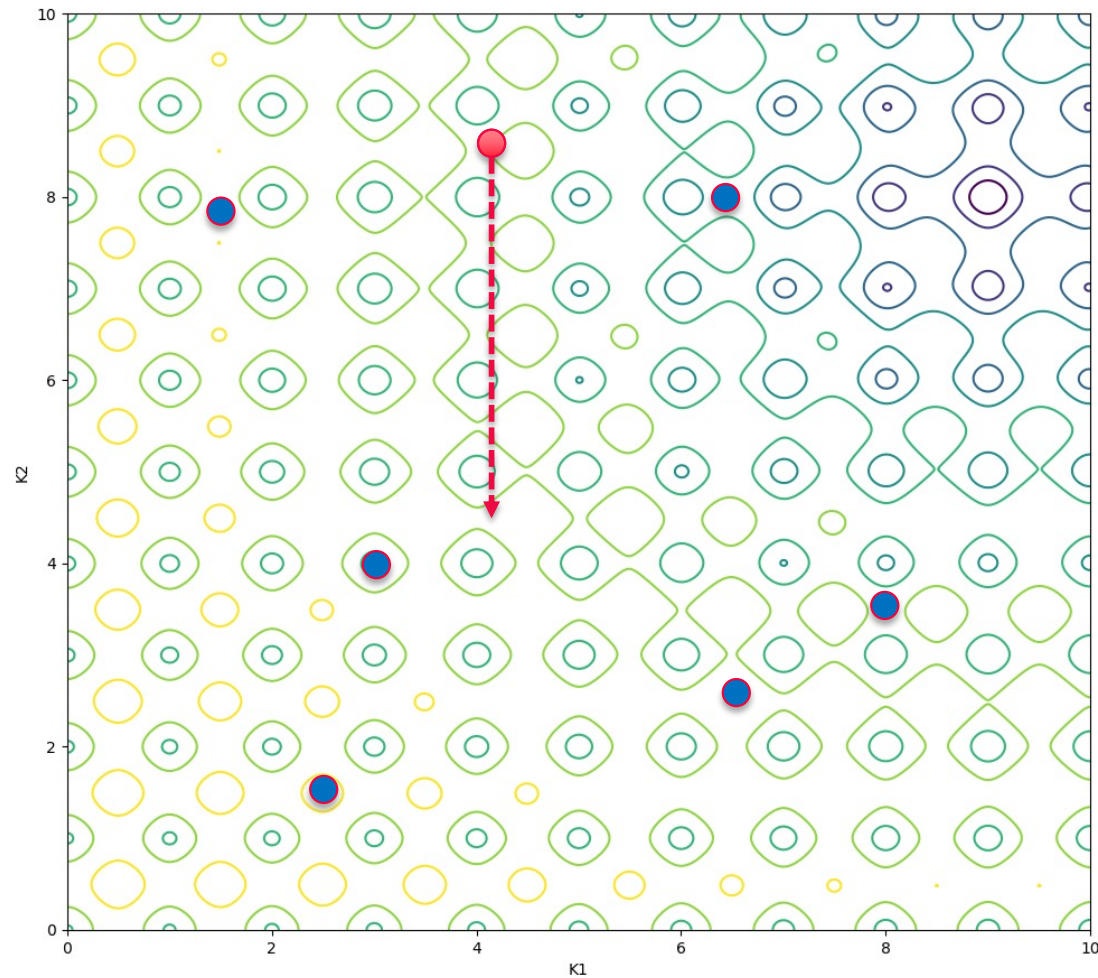
- ✓ For real-valued representation it is common to change value of each gene randomly within its domain given by lower and upper bounds

$$\langle x_1, \dots, x_n \rangle \rightarrow \langle x'_1, \dots, x'_n \rangle, \text{ where } x_i, x'_i \in [L_i, U_i]$$

Two types of mutations can be defined:

- uniform
- nonuniform

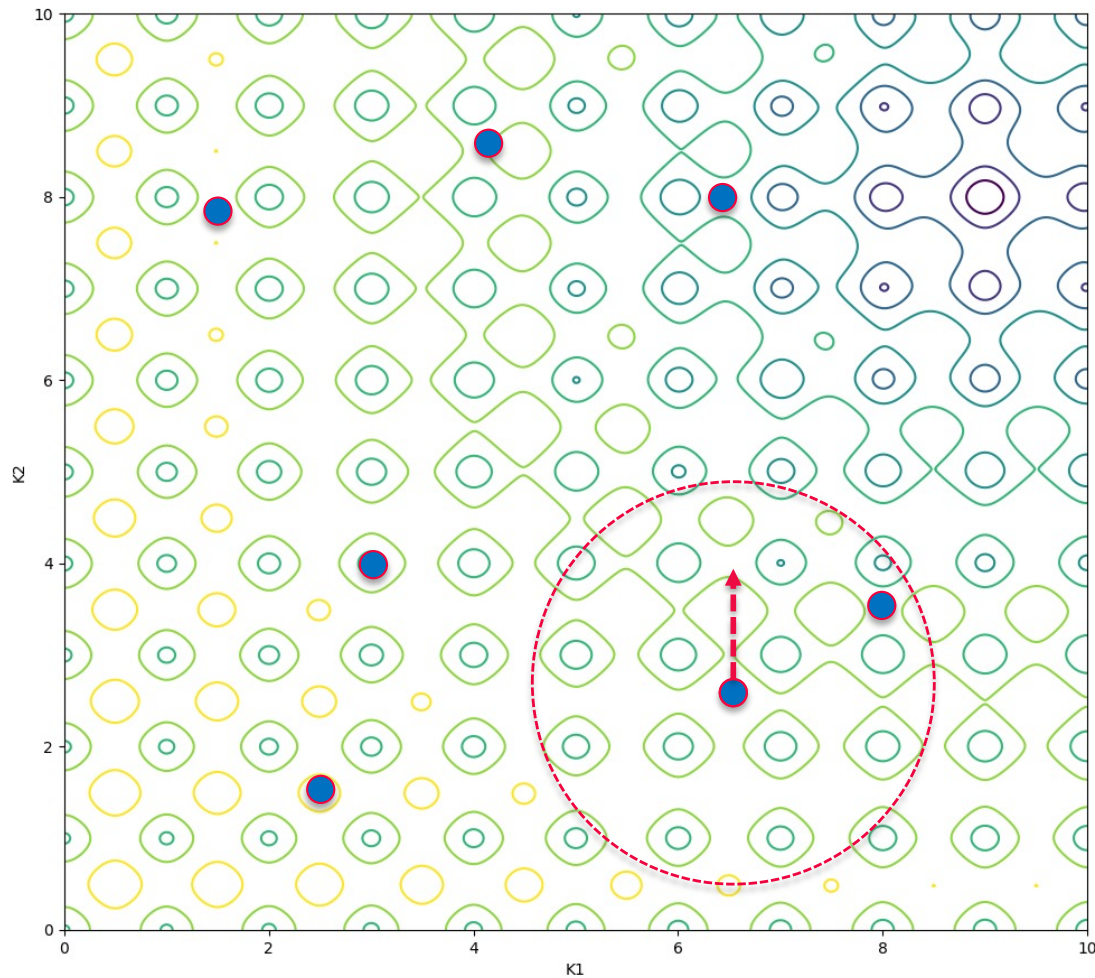
# Uniform mutation



- ✓ Uniform random value from range  $[L_i, U_i]$ .

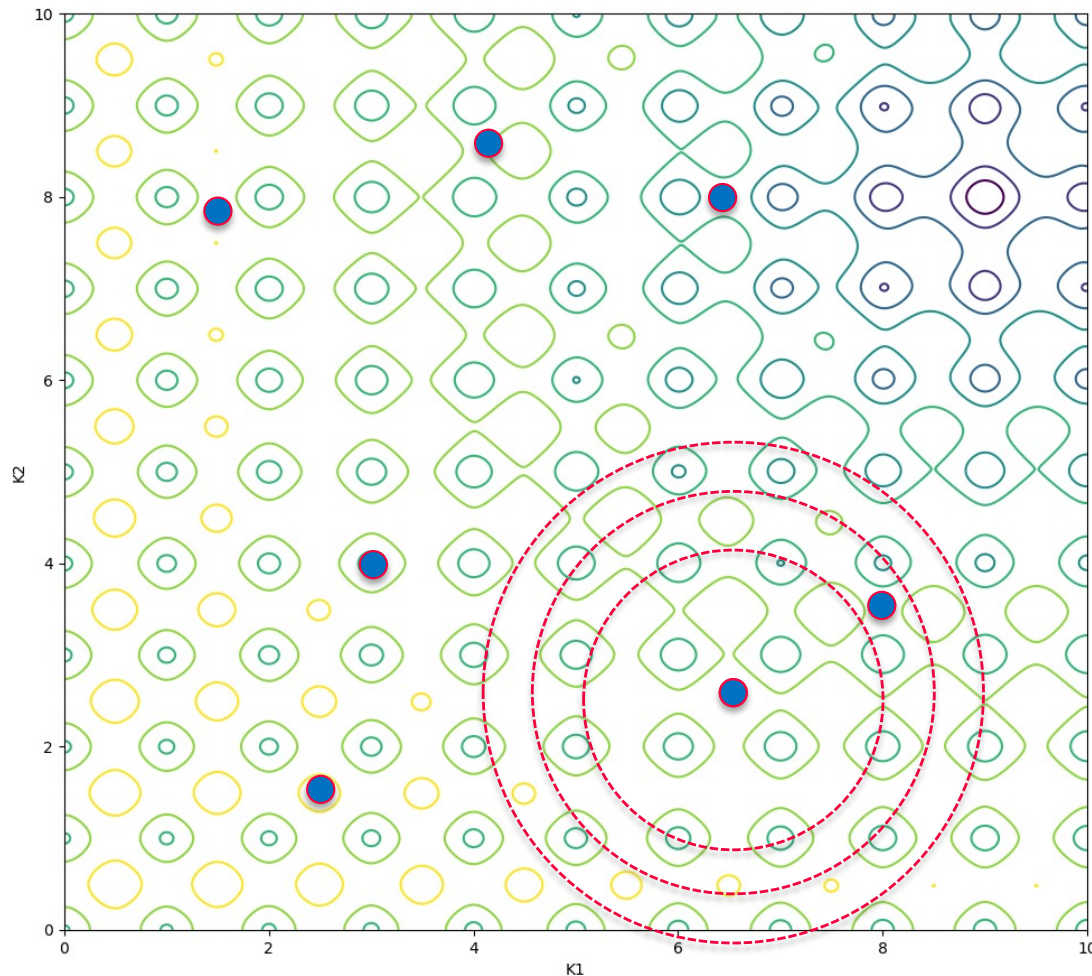


# Nonuniform mutation



- ✓ Nonuniform creep mutation.
- ✓  $x'_i = x_i + N(0, \sigma)$

# Uniform mutation $N(0, \sigma)$



How to choose  $\sigma$ ?

- ✓ Hand-tuned by problem range
- ✓ Hyper-parameter

# Self-adaptive mutation

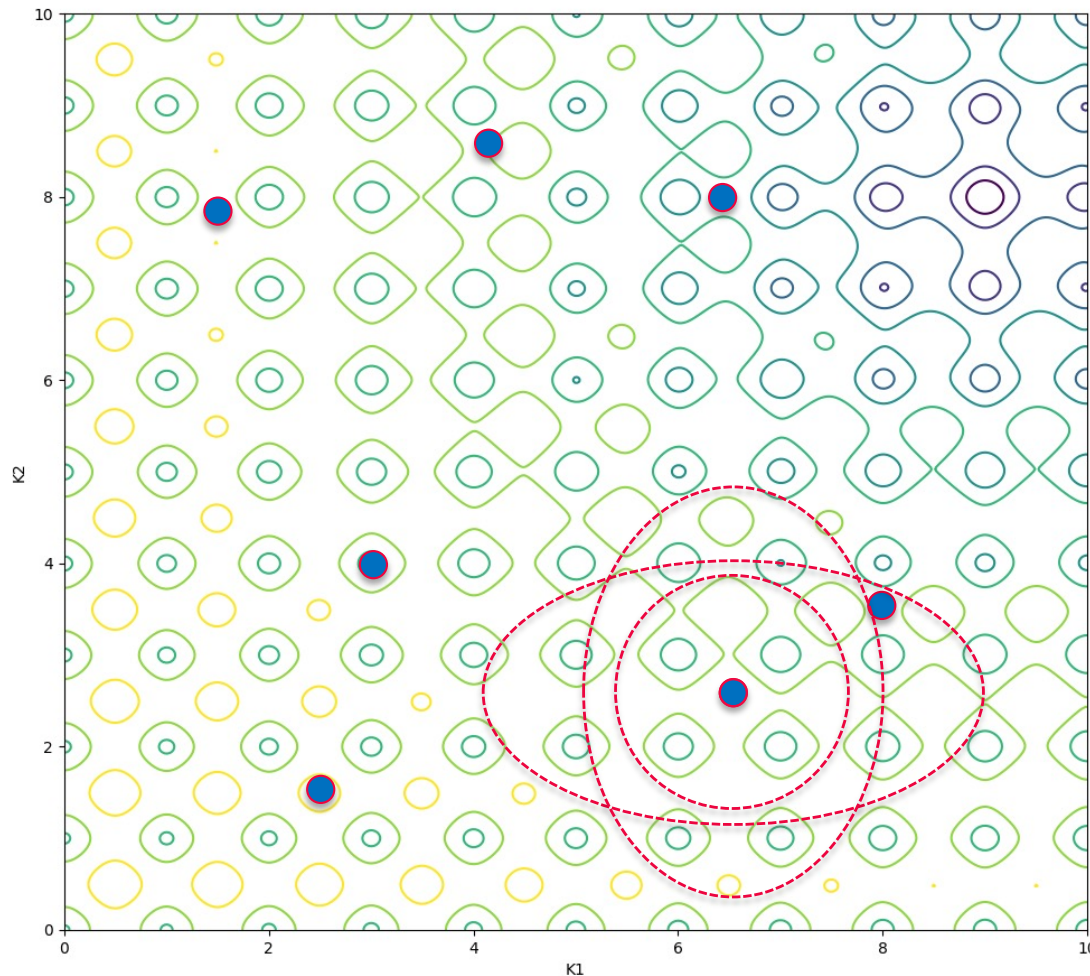
- ✓ Nonuniform mutation is done by adding some random variables from a Gaussian distribution with specified std.
- ✓ Concept of self-adaptive mutation is that std evolves with solutions
- ✓  $\langle X_1, \dots, X_n, \sigma \rangle$



# Self adaptive mutation

- ✓ Mutate  $\sigma$  first
- ✓ Mutation effect:  $\langle x, \sigma \rangle \rightarrow \langle x', \sigma' \rangle$
- ✓ Order is important:
  - first  $\sigma \rightarrow \sigma'$
  - then  $x \rightarrow x' = x + N(0, \sigma')$
- ✓ Reversing mutation order this would not work
  - Primary:  $x'$  is good if  $f(x')$  is good
  - Secondary:  $\sigma'$  is good if the  $x'$  it created is good

# Nonuniform mutation $N(0, \sigma)$



How to choose  $\sigma$ ?

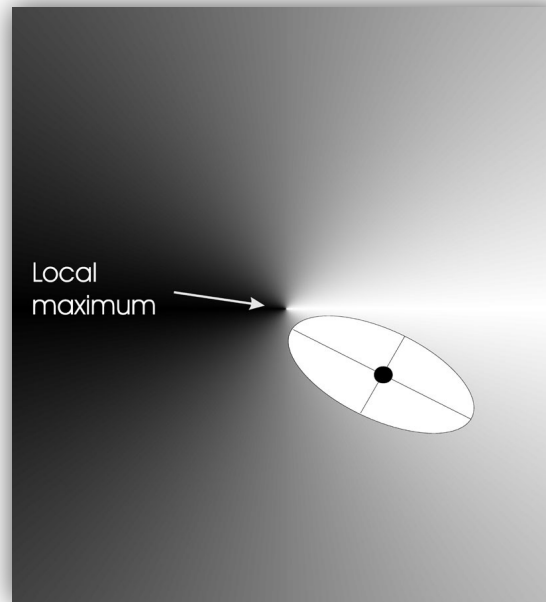
- ✓ Hand-tuned by problem range
- ✓ Hyper-parameter
- ✓ Hyper-parameters for each x value:  
 $N(0, \sigma_1, \sigma_2)$

# Uncorrelated mutation with n stds

- ✓ Chromosomes:  $\langle x_1, \dots, x_n, \sigma_1, \dots, \sigma_n \rangle$ 
  - $\sigma'_i = \sigma_i \cdot \exp(\tau' \cdot N(0,1) + \tau \cdot N_i(0,1))$
  - $x'_i = x_i + \sigma'_i \cdot N_i(0,1)$
- ✓ Two learning rate parameters:
  - $\tau'$  overall learning rate
  - $\tau$  coordinate wise learning rate

# Correlated mutation

- ✓ Mutants with equal likelihood



- ✓ Ellipse: mutants having the same chance to be created

# Correlated mutation

- ✓ Chromosomes:  $\langle x_1, \dots, x_n, \sigma_1, \dots, \sigma_n, \alpha_1, \dots, \alpha_k \rangle$   
where  $k = n \cdot (n-1)/2$
- ✓ Covariance matrix  $C$  is defined as:
  - $c_{ii} = \sigma_i^2$
  - $c_{ij} = 0$  if  $i$  and  $j$  are not correlated
  - $c_{ij} = \frac{1}{2} \cdot (\sigma_i^2 - \sigma_j^2) \cdot \tan(2 \alpha_{ij})$  if  $i$  and  $j$  are correlated
- ✓ Note the numbering / indices of the  $\alpha$ 's

# Correlated mutation

The mutation mechanism is then:

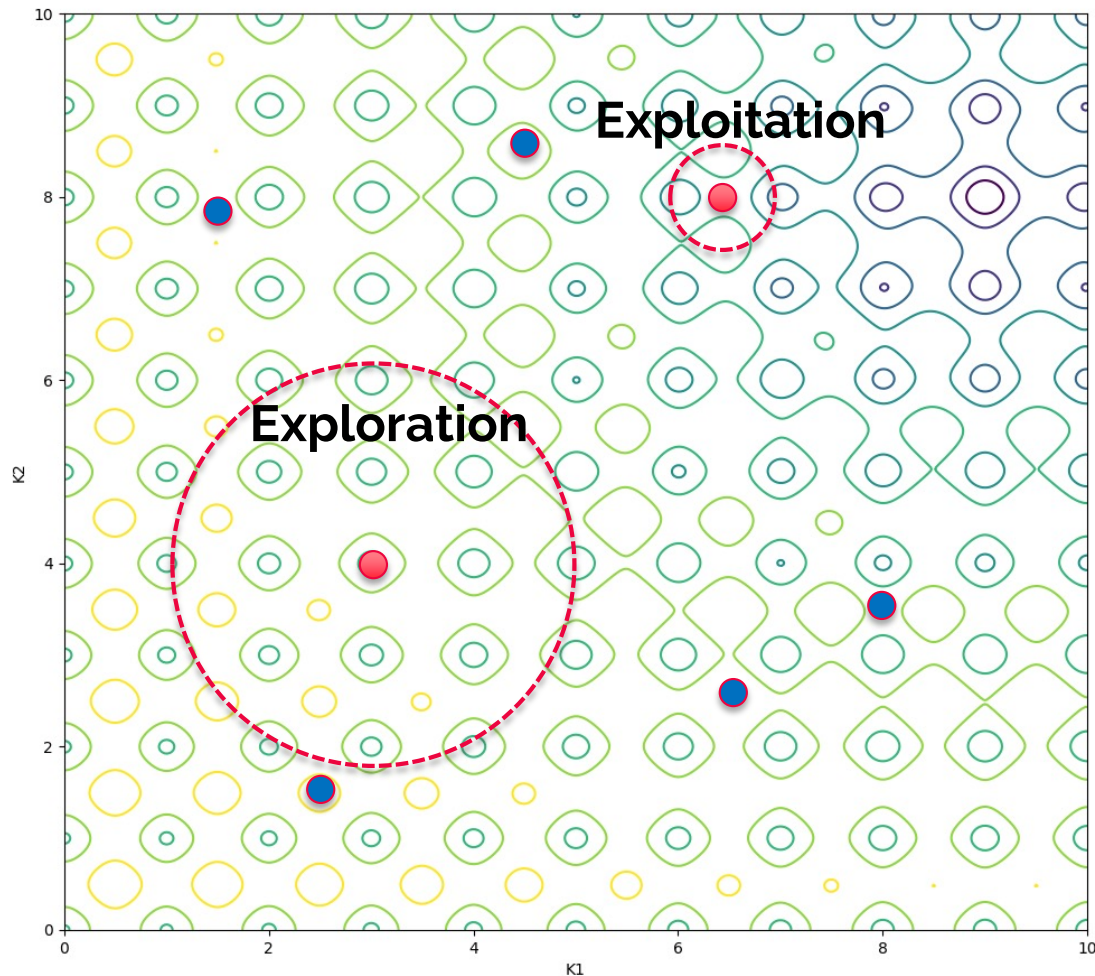
✓  $\sigma'_i = \sigma_i \cdot \exp(\tau' \cdot N(0,1) + \tau \cdot N_i(0,1))$

✓  $\alpha'_j = \alpha_j + \beta \cdot N(0,1)$

✓  $\mathbf{x}' = \mathbf{x} + N(\mathbf{0}, \mathbf{C}')$

- $\mathbf{x}$  stands for the vector  $\langle x_1, \dots, x_n \rangle$
- $\mathbf{C}'$  is the covariance matrix  $\mathbf{C}$  after mutation of the  $\alpha$  values

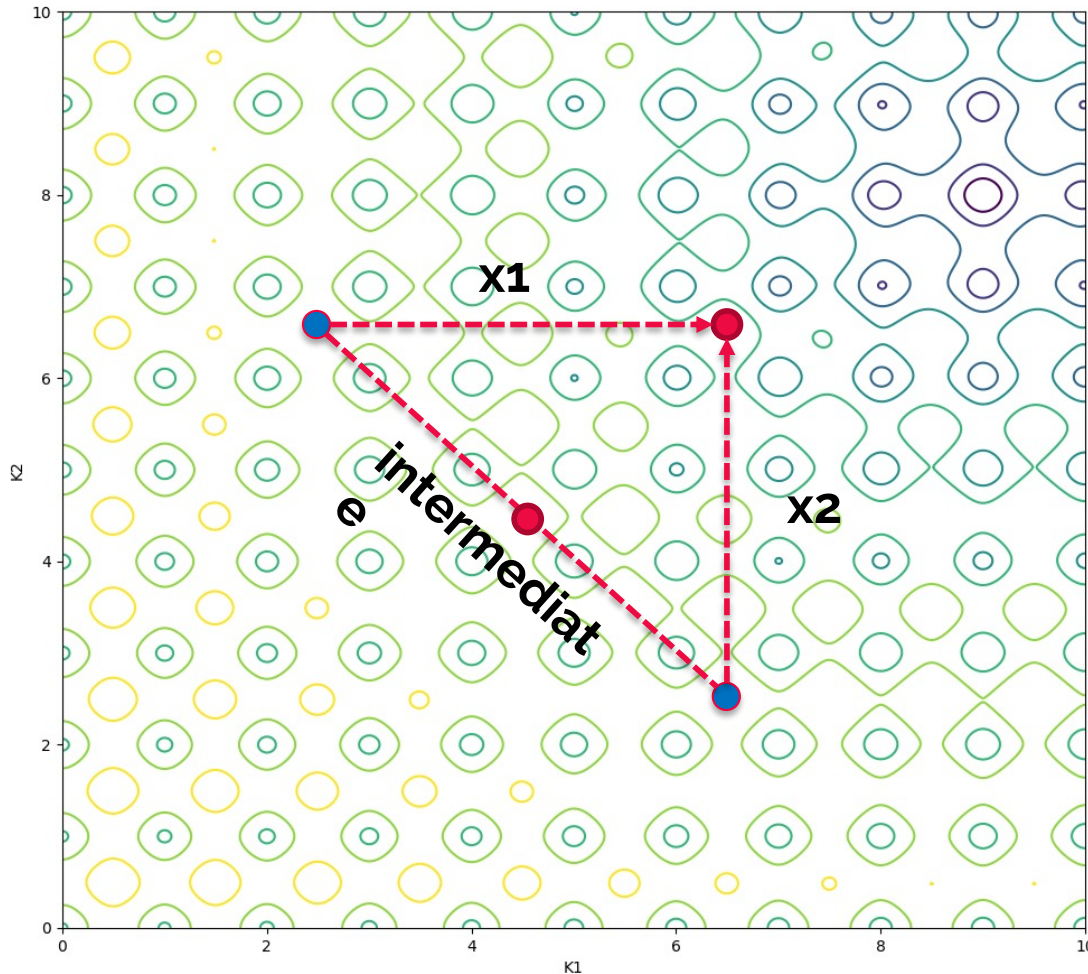
# Exploration vs Exploitation



- ✓ Exploration
  - Global search
- ✓ Exploitation
  - Local search

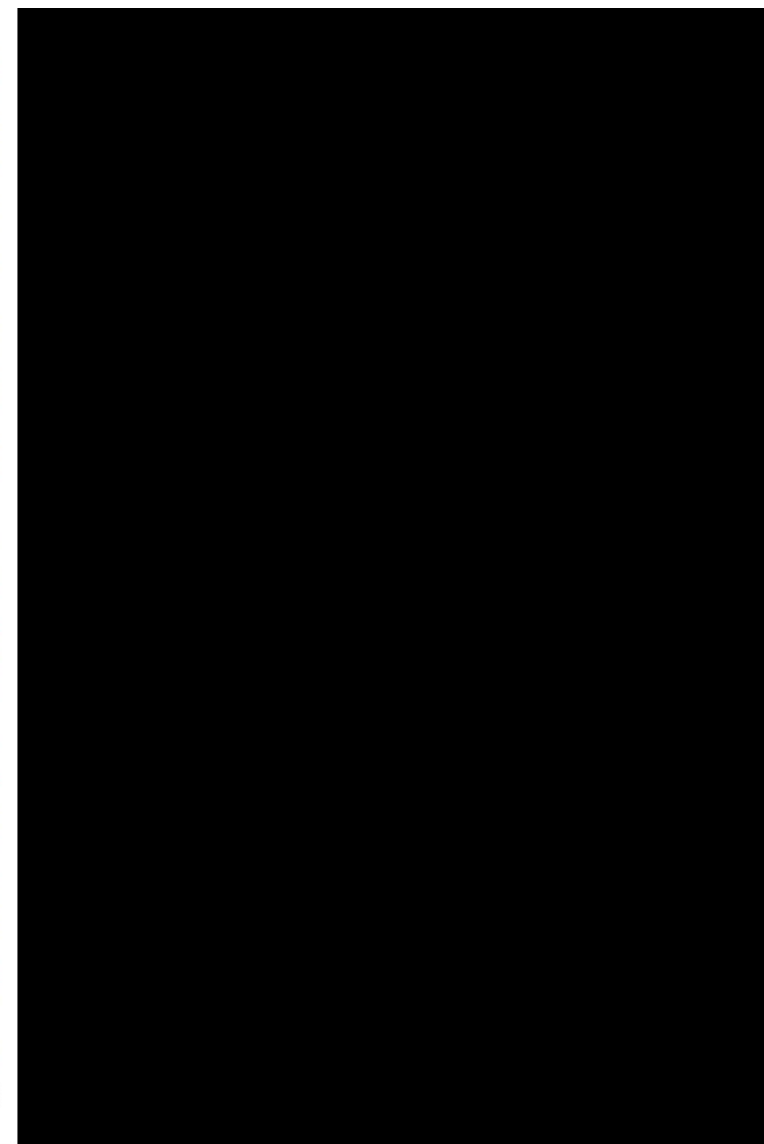
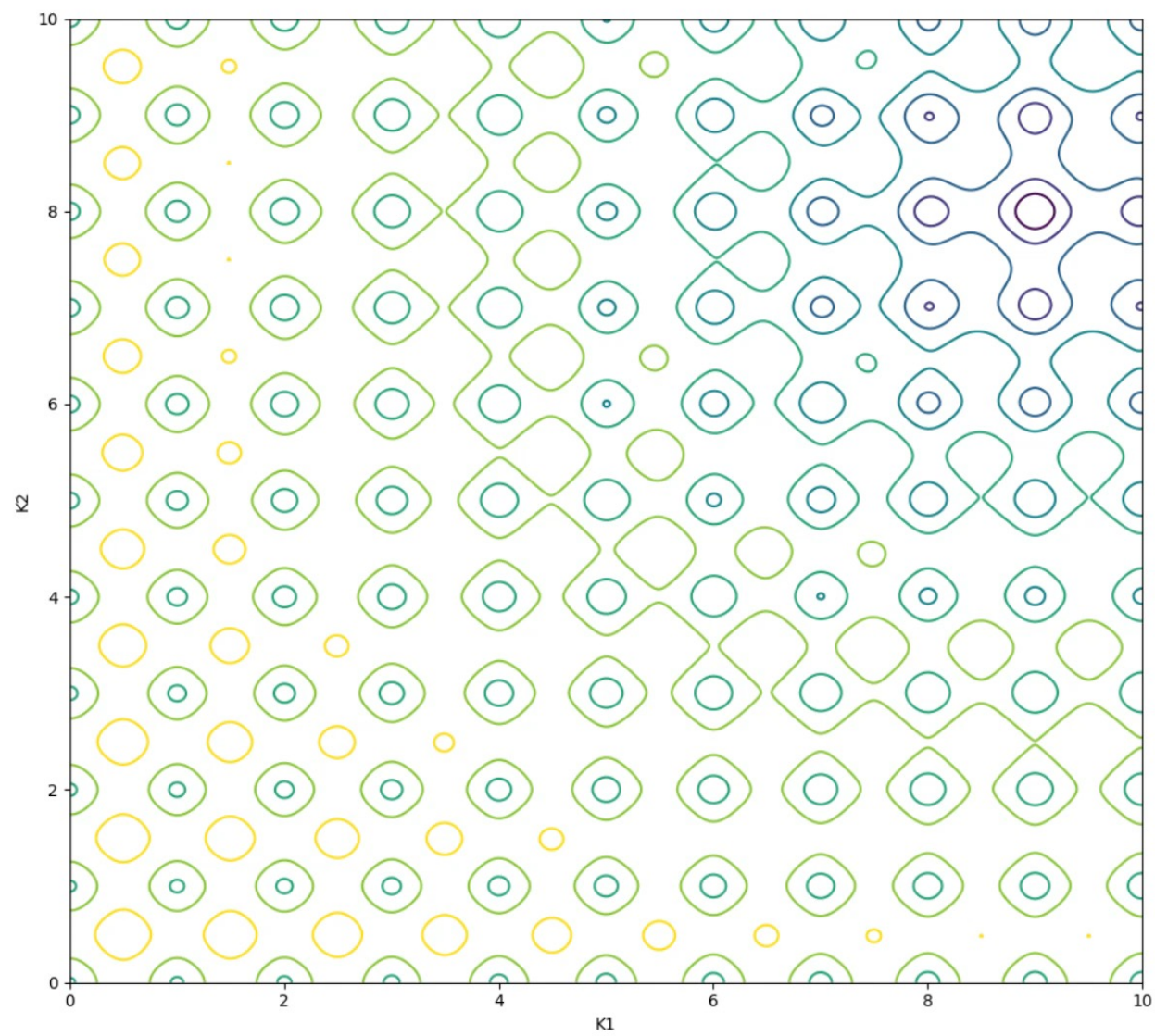


# Crossover



- ✓ Discrete:
  - each gene value in offspring  $z$  comes from one of its parents  $(x, y)$  with equal probability:  $z_i = x_i$  or  $y_i$
- ✓ Intermediate
  - $z_i = \alpha x_i + (1 - \alpha) y_i$  where  $\alpha: 0 \leq \alpha \leq 1$ .





# Representations

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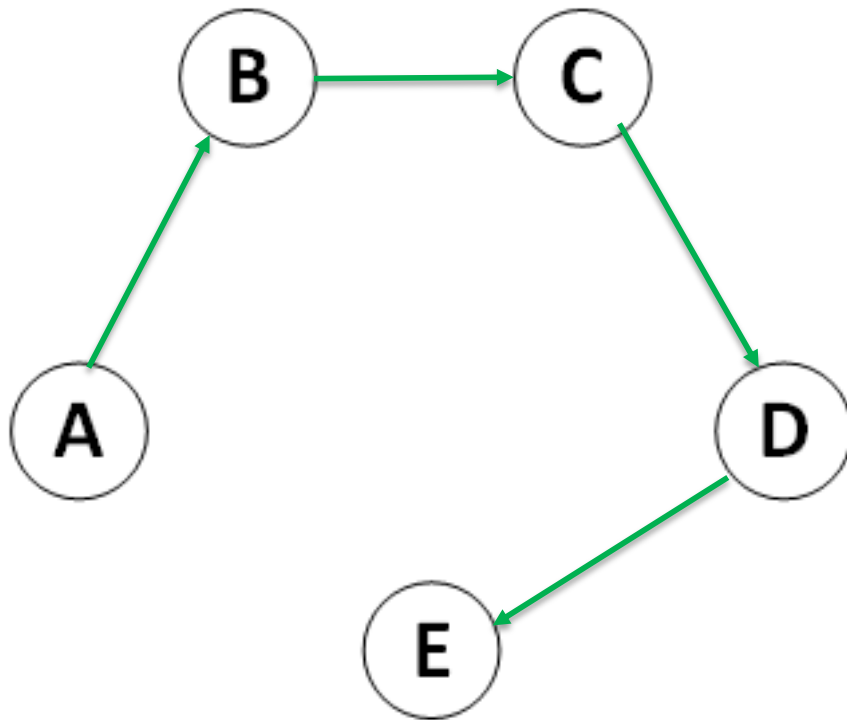
- ✓ The first stage of building any evolutionary algorithm is to decide on a genetic representation of a candidate solution to a problem
- ✓ Common types of representation:
  - Binary
  - Integer values
  - Real values
  - **Permutation**
  - Tree representation

# Permutation representations

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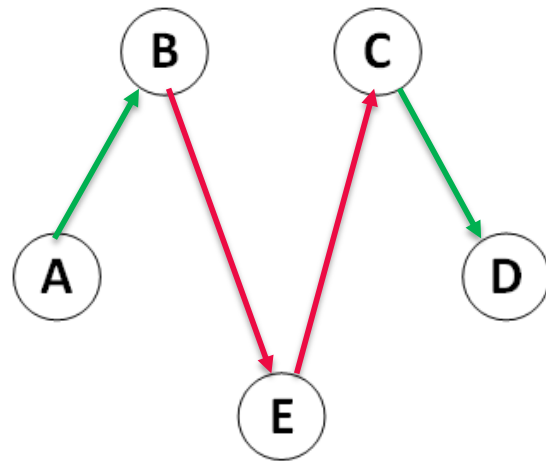
- ✓ Ordering/sequencing problems form a special type
- ✓ Task is (or can be solved by) arranging some objects in a certain order
- ✓ Example: Travelling Salesman Problem (TSP) :  
important thing is which elements occur next to each other

# Traveling salesman problem

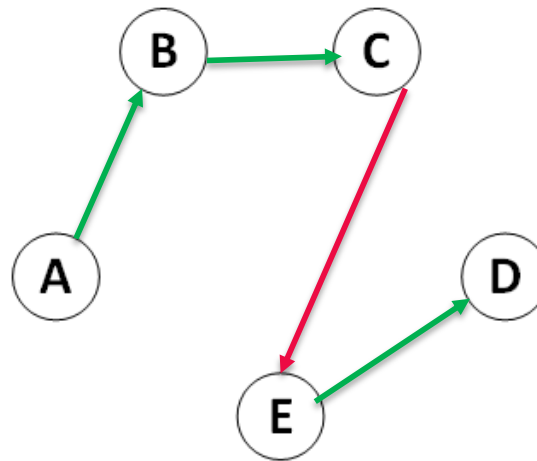


- ✓ 5 cities
- ✓ Need to find the shortest path

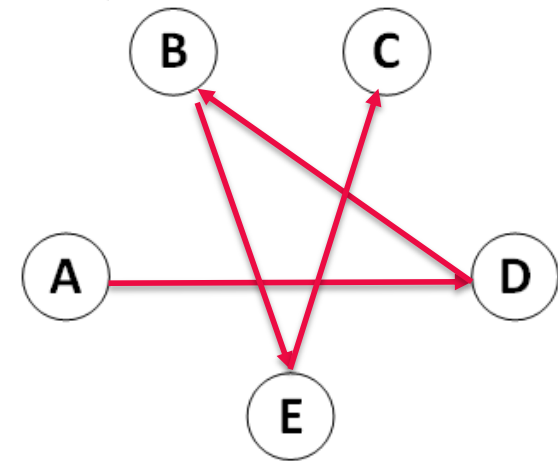
# Population



[A, B, E, C, D]



[A, B, C, E, D]



[A, D, B, E, C]

# Permutation Representations: Mutation

- ✓ Normal mutation operators lead to inadmissible solutions
  - e.g. bit-wise mutation: let gene  $i$  have value  $j$
  - changing to some other value  $k$  would mean that  $k$  occurred twice and  $j$  no longer occurred

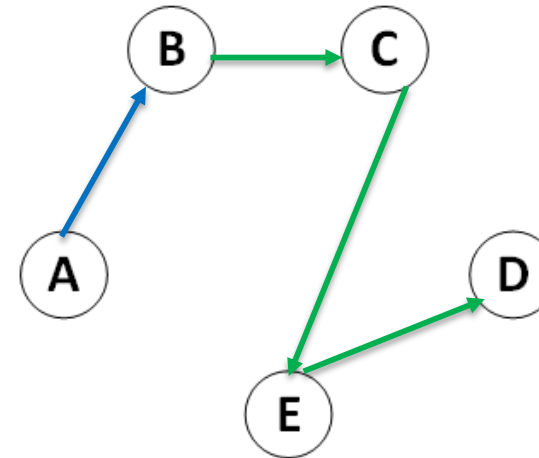
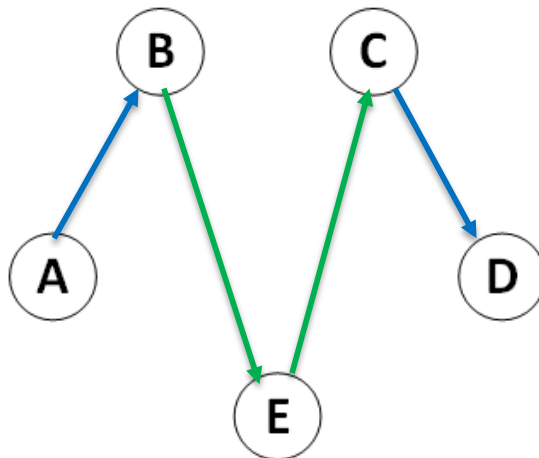
[A B C D E]  $\longrightarrow$  [A B C D A]

[A B C D E]  $\longrightarrow$  [A C B D E]

- ✓ Therefore must change at least two values
- ✓ Mutation parameter now reflects the probability that some operator is applied once to the whole string, rather than individually in each position

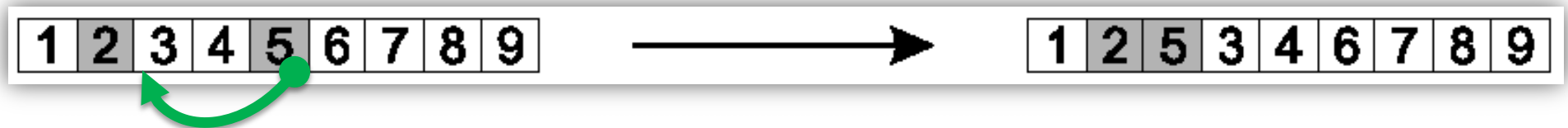
## Permutation Representations: Swap mutation

- ✓ Pick two alleles at random and swap their positions



## Permutation Representations: Insert Mutation

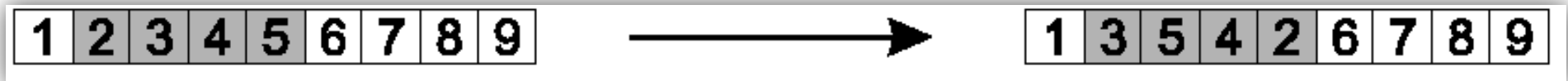
- ✓ Pick two allele values at random
- ✓ Move the second to follow the first, shifting the rest along to accommodate
- ✓ Note that this preserves most of the order and the adjacency information





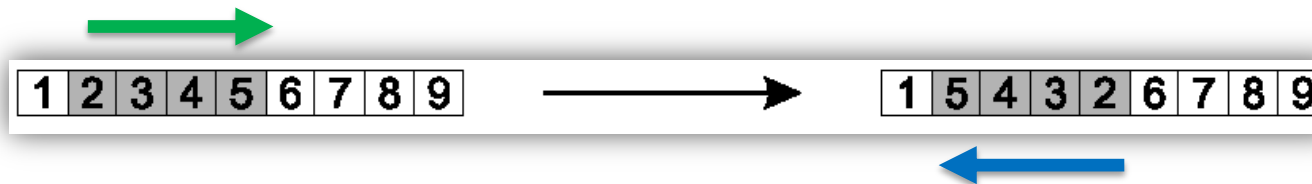
## Permutation Representations: Scramble mutation

- ✓ Pick a subset of genes at random
- ✓ Randomly rearrange the alleles in those positions



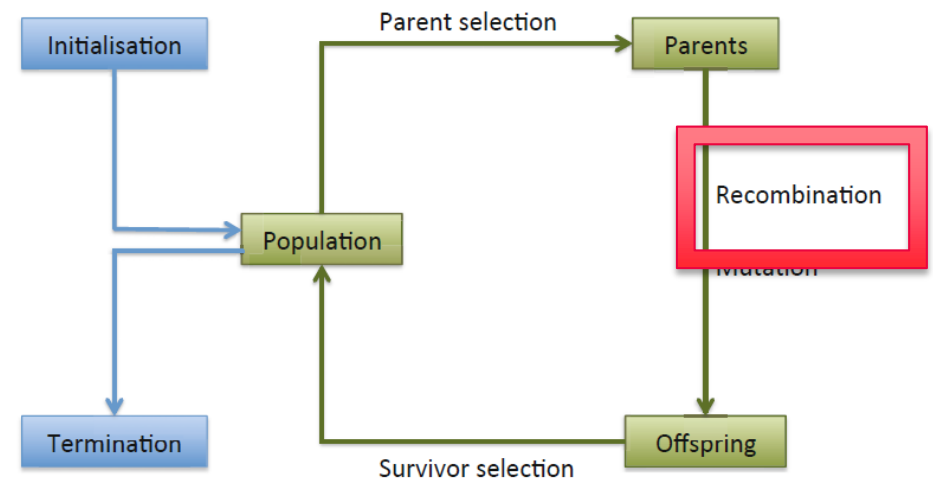
## Permutation Representations: Inversion mutation

- ✓ Pick two alleles at random and then invert the substring between them.
- ✓ Preserves most adjacency information (only breaks two links) but disruptive of order information



# Components of EAs

- ✓ Representation of individuals
- ✓ Population of individuals
- ✓ Evaluation function (fitness function)
- ✓ Parent selection mechanism
- ✓ Variation operators (**recombination**, mutation)
- ✓ Survivor selection mechanism
- ✓ Terminate conditions



## Permutation Representations: Crossover operators

- ✓ “Normal” crossover operators will often lead to inadmissible solutions



- ✓ Many specialised operators have been devised which focus on combining order or adjacency information from the two parents

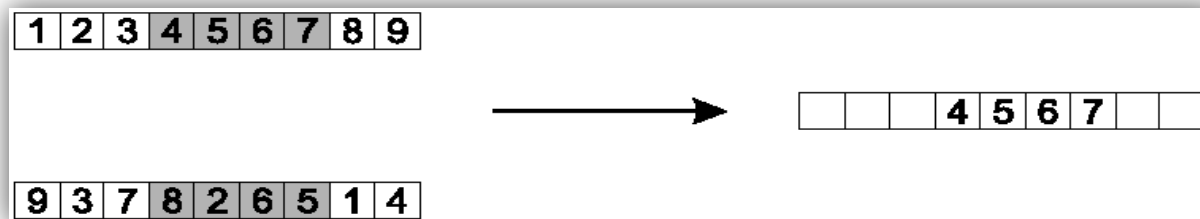
## Permutation Representations: Order 1 crossover (1/2)

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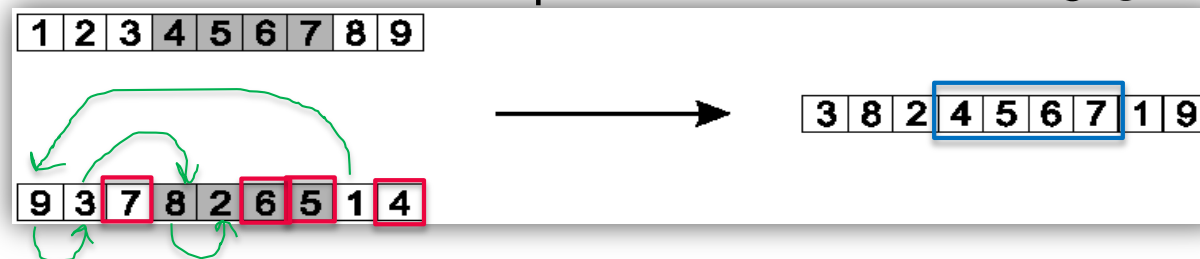
- ✓ Idea is to preserve relative order that elements occur
- ✓ Informal procedure:
  - 1. Choose an arbitrary part from the first parent
  - 2. Copy this part to the first child
  - 3. Copy the numbers that are not in the first part, to the first child:
    - starting right from cut point of the copied part,
    - using the **order** of the second parent
    - and wrapping around at the end
  - 4. Analogous for the second child, with parent roles reversed

## Permutation Representations: Order 1 crossover (2/2)

- ✓ Copy randomly selected set from first parent



- ✓ Copy rest from second parent in order 1,9,3,8,2



# Representations

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- ✓ The first stage of building any evolutionary algorithm is to decide on a genetic representation of a candidate solution to a problem
- ✓ Common types of representation:
  - Binary
  - Integer values
  - Real values
  - Permutation
  - **Tree representation**

# Tree Representation (1/6)

✓ Trees are a universal form, e.g. consider

✓ Arithmetic formula:  $2 \cdot \pi + \left( (x + 3) - \frac{y}{5 + 1} \right)$

✓ Logical formula:

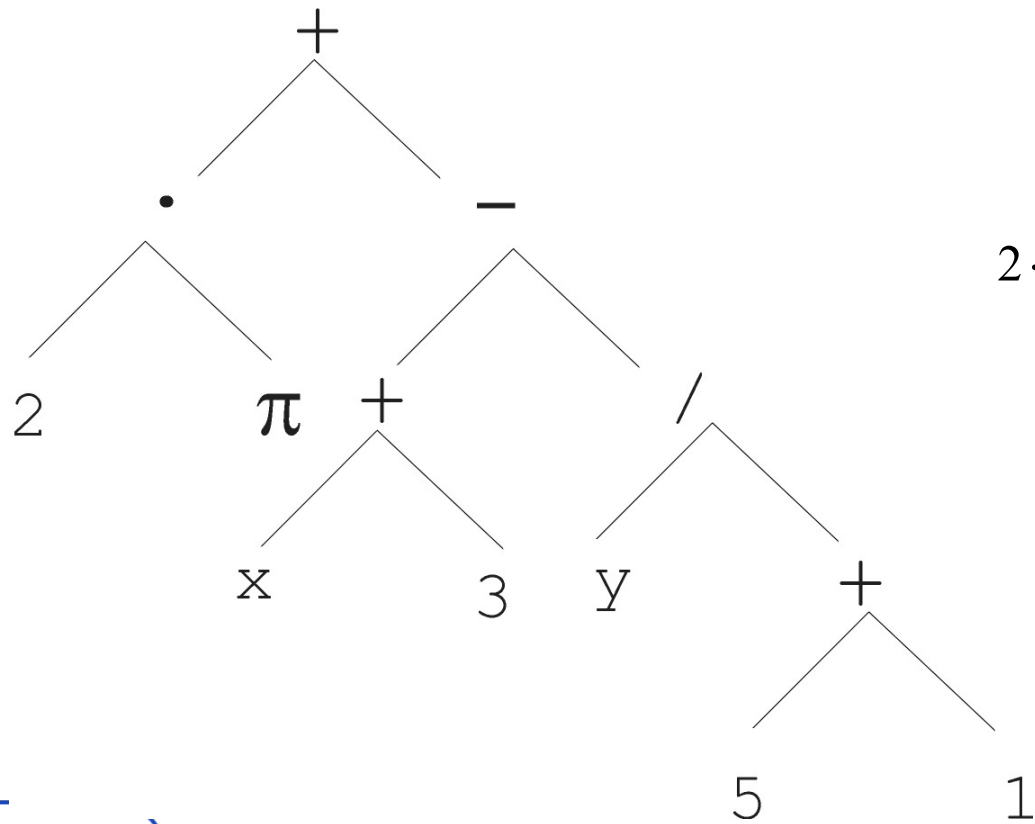
$(x \wedge \text{true}) \rightarrow ((x \vee y) \vee (z \leftrightarrow (x \wedge y)))$

✓ Program:

```
i = 1;
while (i < 20)
{
    i = i + 1
}
```

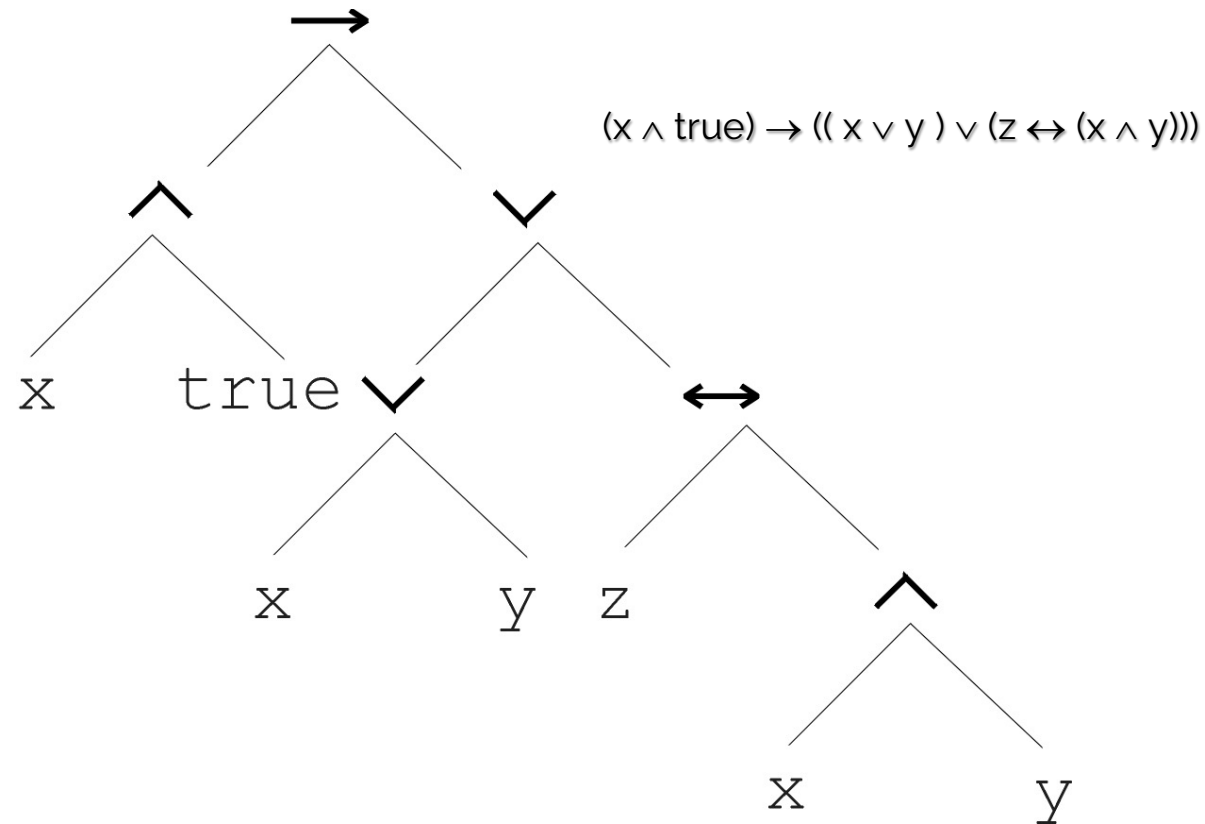


## Tree Representation (2/6)



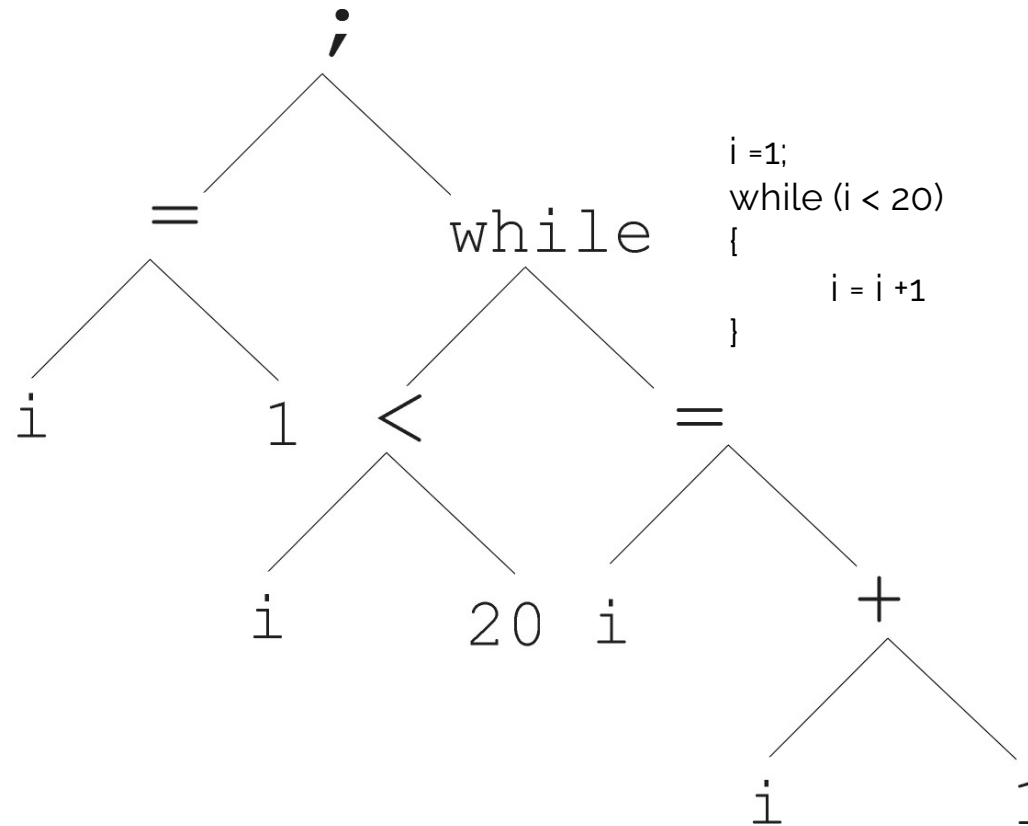
$$2 \cdot \pi + \left( (x + 3) - \frac{y}{5 + 1} \right)$$

## Tree Representation (3/6)



# Tree Representation (4/6)

Genetic  
programming



## Tree Representation (5/6)

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- ✓ In GA, ES, EP chromosomes are linear structures (bit strings, integer string, real-valued vectors, permutations)
- ✓ Tree shaped chromosomes are non-linear structures
- ✓ In GA, ES, EP the size of the chromosomes is fixed
- ✓ Trees in GP may vary in depth and width

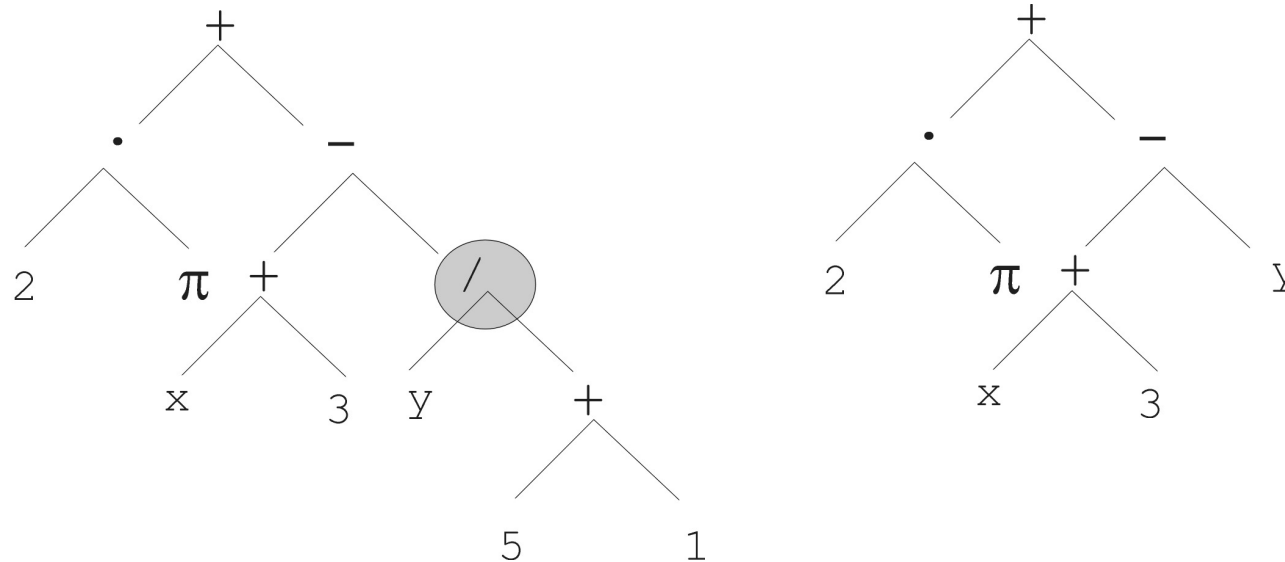
# Tree Representation (6/6)

- ✓ Symbolic expressions can be defined by
  - Terminal set  $T$
  - Function set  $F$  (with the arities of function symbols)
- ✓ Adopting the following general recursive definition:
  - Every  $t \in T$  is a correct expression
  - $f(e_1, \dots, e_n)$  is a correct expression if  $f \in F$ ,  $\text{arity}(f)=n$  and  $e_1, \dots, e_n$  are correct expressions
  - There are no other forms of correct expressions
- ✓ In general, expressions in GP are not typed (closure property: any  $f \in F$  can take any  $g \in F$  as argument)

Function set	$\{+, -, \cdot, /\}$
Terminal set	$\mathbb{R} \cup \{x, y\}$

## Tree Representation: Mutation (1/2)

- ✓ Most common mutation: replace randomly chosen subtree by randomly generated tree



## Tree Representation: Mutation (2/2)

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- ✓ Mutation has two parameters:
  - Probability  $p_m$  to choose mutation
  - Probability to choose an internal point as the root of the subtree to be replaced
- ✓ Remarkably  $p_m$  is advised to be 0 (Koza'92) or very small, like 0.05 (Banzhaf et al. '98)
- ✓ The size of the child can exceed the size of the parent

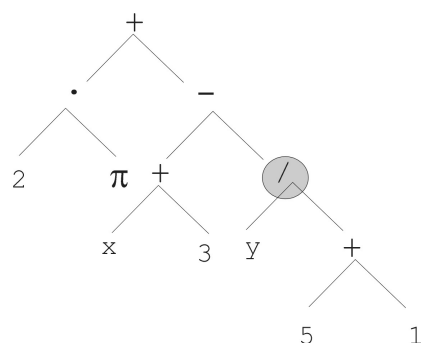
## Tree Representation: Recombination (1/2)

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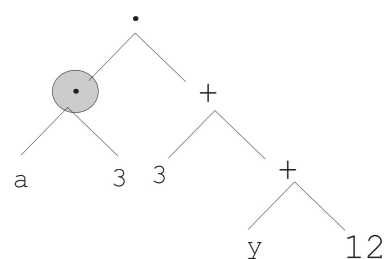
- ✓ Most common recombination: exchange two randomly chosen subtrees among the parents
- ✓ Recombination has two parameters:
  - Probability  $p_c$  to choose recombination
  - Probability to choose an internal point within each parent as crossover point
- ✓ The size of offspring can exceed that of the parents



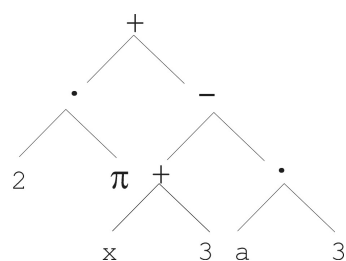
# Tree Representation: Recombination (2/2)



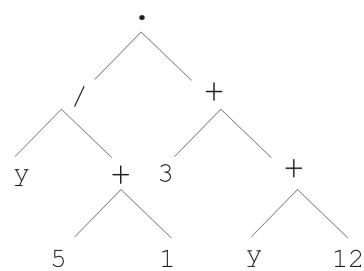
Parent 1



Parent 2



Child 1



Child 2

# Lab2

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- ✓ Function optimization
- ✓ Need to implement Factory, Mutation and Crossover
- ✓ Fitness function estimates n dimensional double array with values from -5.0 to 5.0
- ✓ Max possible fitness is 10.0.



# Thank you for your attention!

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