Lecture 4:
Real-Coded Genetic Algorithms

Drawbacks of Binary Coded GAs

- Hamming cliffs
  - Moving to a neighboring solution requires changing many bits which introduces encumbrance to the gradual search in the continuous search space

Example 0 1 1 1 1 → 1 0 0 0 0

Drawback of Binary Coded GAs

- Difficulty in achieving arbitrary precision
  - Fixed string length limits the precision of the solution
  - Appropriate length of the string is not known a priori

- Uneven schema importance
  - For example, the schema 1*** is more significant than the schema ***1

Real Coded GAs

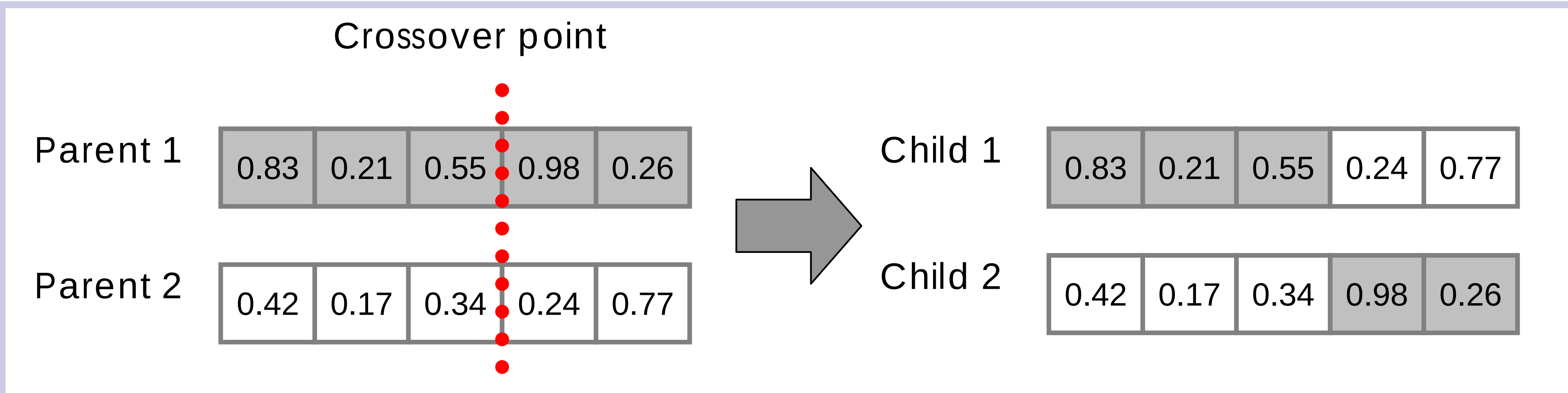
- Algorithm is simple and straightforward
- Selection operator is based on the fitness values and any selection operator for the binary-coded GAs can be used
- Crossover and mutation operators for the real-coded GAs need to be redefined

Crossover Operators for Real Coded GAs

- Single point crossover
- Linear crossover
- Blend crossover
- Simulated binary crossover

Single-Point Crossover

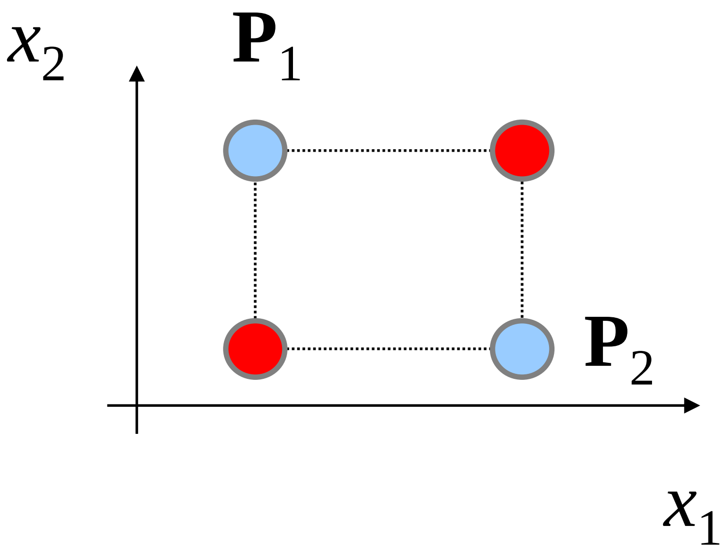
- Similar to the crossover operator used in the binary-coded GAs



- According to the number of crossover points, there are also two-point, three-point and *n*-point crossover

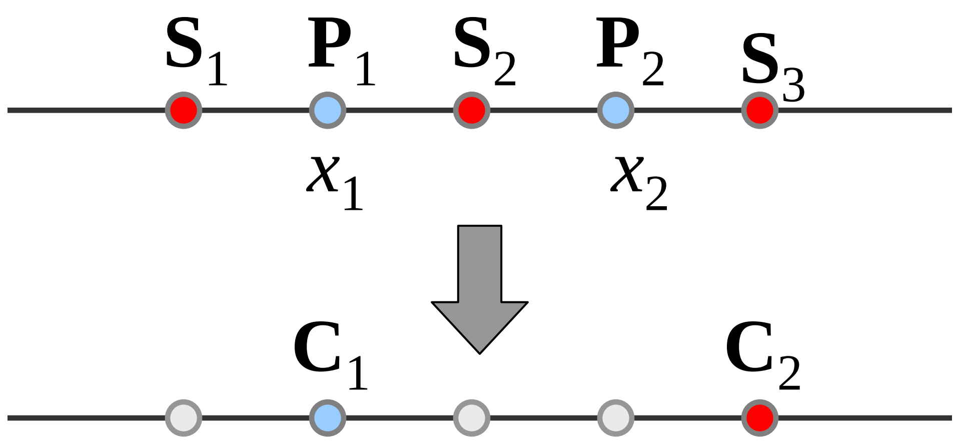
Single-Point Crossover

- Problematic in the real-coded GAs.



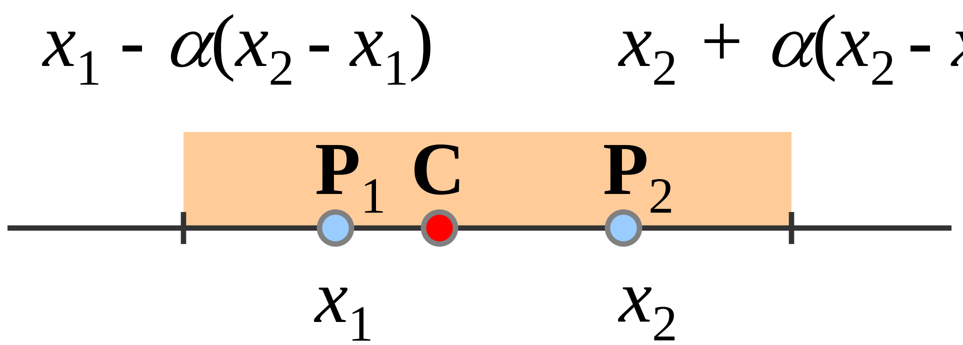
Linear Crossover

- Given the two parents x_1 and x_2, create three solutions $0.5x_1+0.5x_2$, $1.5x_1-0.5x_2$, and $-0.5x_1+1.5x_2$
- Choose two best solutions among the five solutions and they become the children



Blend Crossover

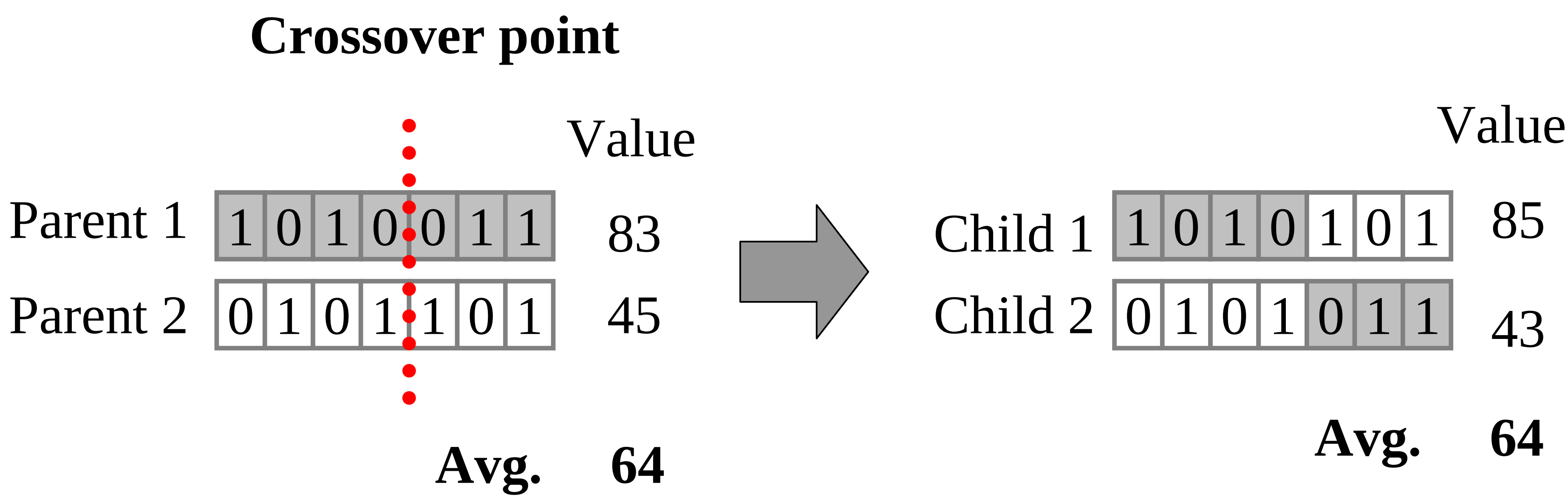
- Given the two parents x_1 and x_2 where $x_1 < x_2$, the blend crossover randomly selects a child in the range $[x_1-\alpha(x_2-x_1),\ x_2+\alpha(x_2-x_1)]$



- It is often suggested that a good choice of α is 0.5

Simulated Binary Crossover (SBC)

- Simulates the single-point crossover operator of the binary-coded GAs



Properties of Binary Crossover

- Gene values of children have same distance from the average gene value of parents
- Each point of the chromosome has the same probability to be selected as a crossover point
- The crossover in the lower bit results in small change in the gene value
- Children are more likely to be near the parents

Goal of SBC

- Simulated binary crossover uses probability density function that simulates the single-point crossover in binary-coded GAs

SBC Algorithm

- Select two parents x_1 and x_2
- Generate a random number $u \in [0,1)$
- Calculate β

$$\beta = \begin{cases} (2u)^{\frac{1}{\eta_c+1}}, & \text{if } u \le 0.5 \\ \left(\dfrac{1}{2(1-u)}\right)^{\frac{1}{\eta_c+1}}, & \text{otherwise} \end{cases}$$

where η_c is the distribution index

SBC Algorithm (Cont.)

- Compute offspring as

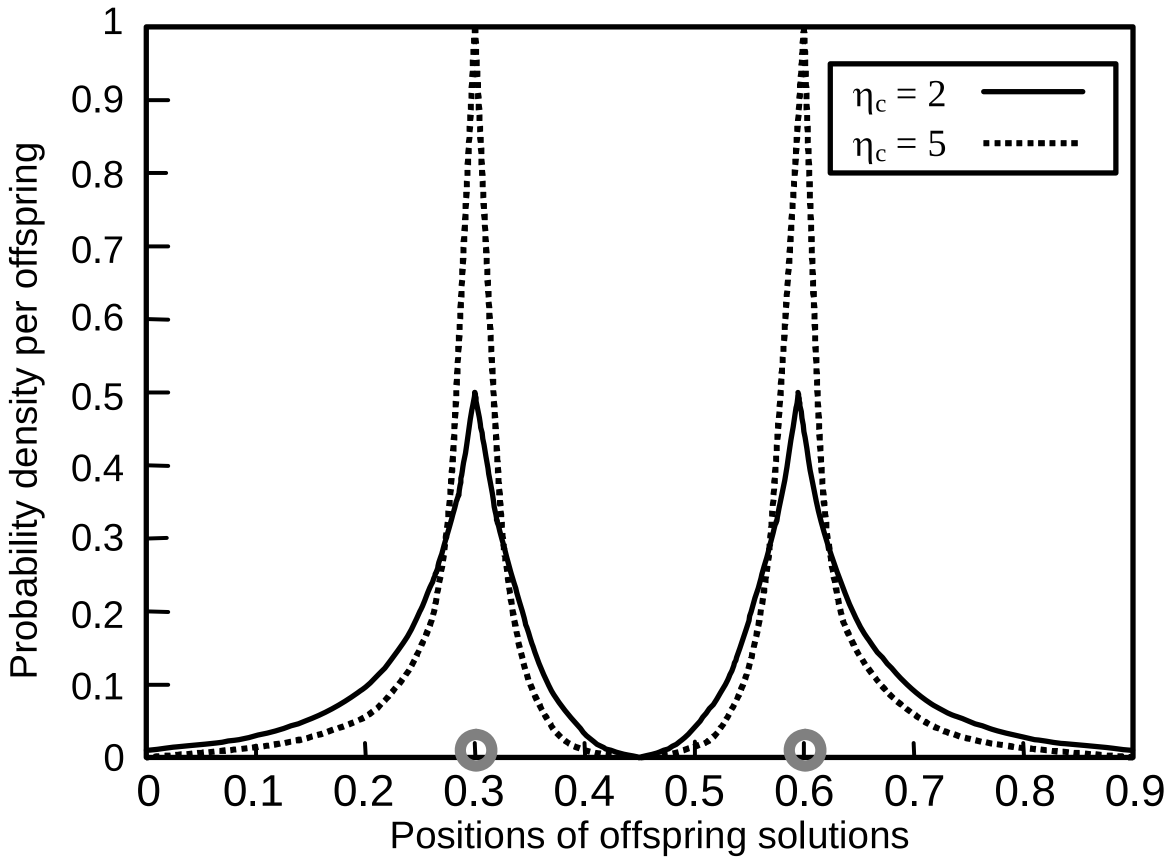
$$x_1^{\text{new}} = 0.5\left[(1+\beta)x_1 + (1-\beta)x_2\right]$$
$$x_2^{\text{new}} = 0.5\left[(1-\beta)x_1 + (1+\beta)x_2\right]$$

- Note

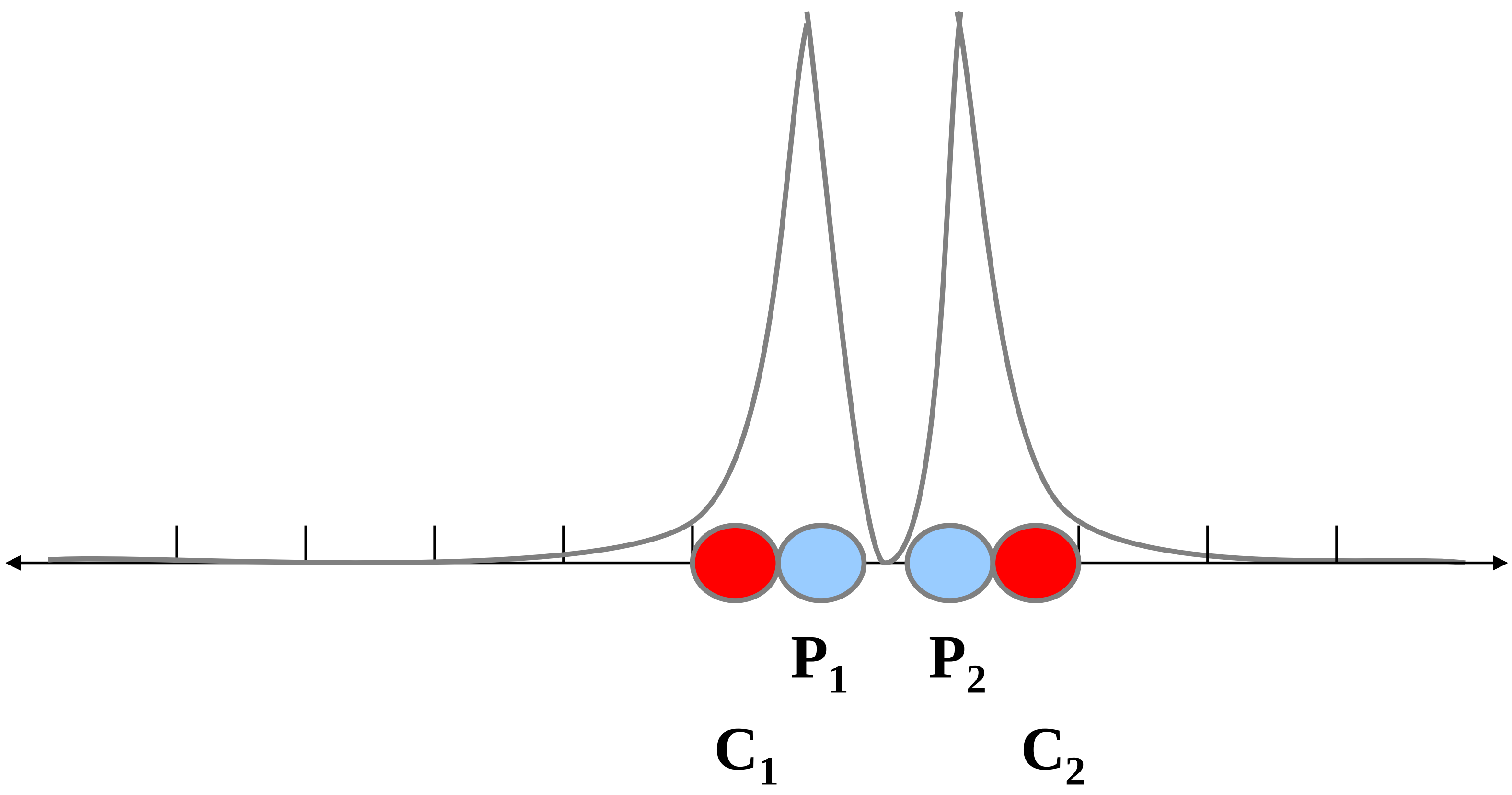
$$\frac{x_1^{\text{new}} + x_2^{\text{new}}}{2} = \frac{x_1 + x_2}{2}$$

SBC Distribution Index

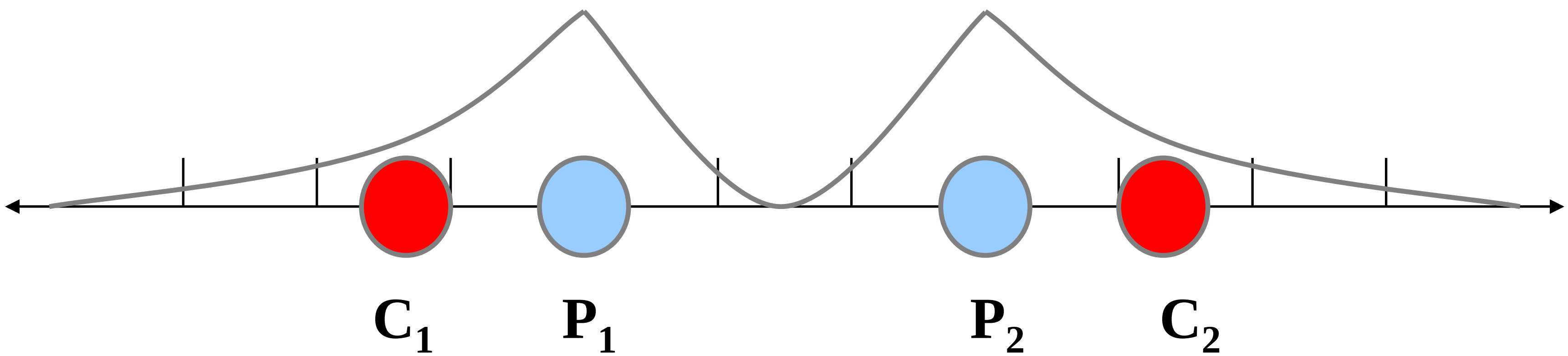
- Large η_c tends to generate children closer to the parents
- Small η_c allows the children to be far from the parents



SBC With Similar Parents



SBC With Different Parents

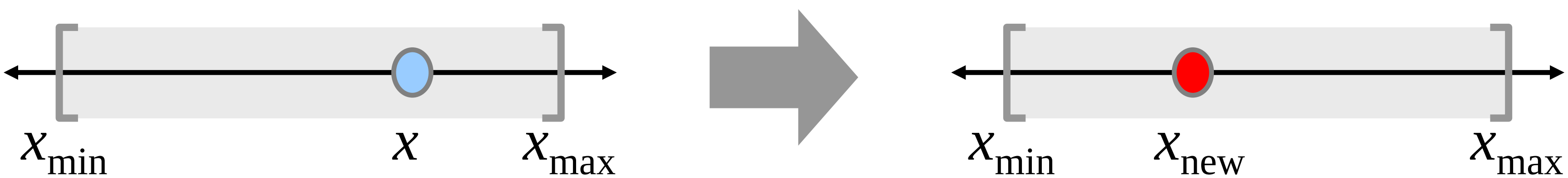


Mutation Operators for Real-Coded GAs

- Random mutation
- Non-uniform Mutation
- Normally distributed mutation

Random Mutation

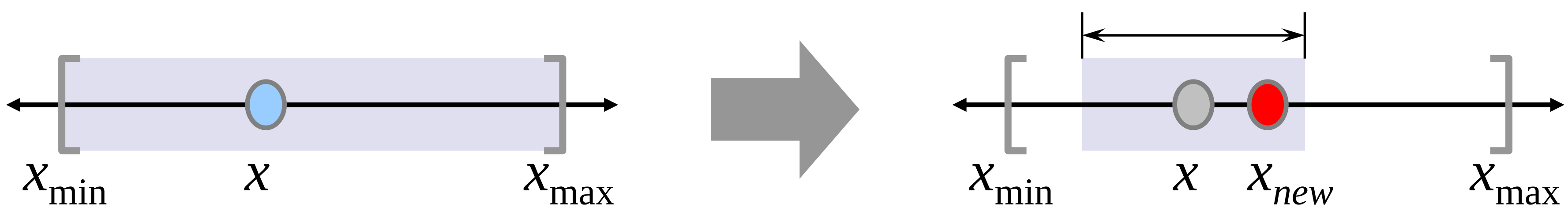
- Random mutation generates a solution randomly within the entire parameter range



- Generated solution has no relationship to the original solution

Alternate Random Mutation

- The random mutation generates a solution randomly within a vicinity of the original solution



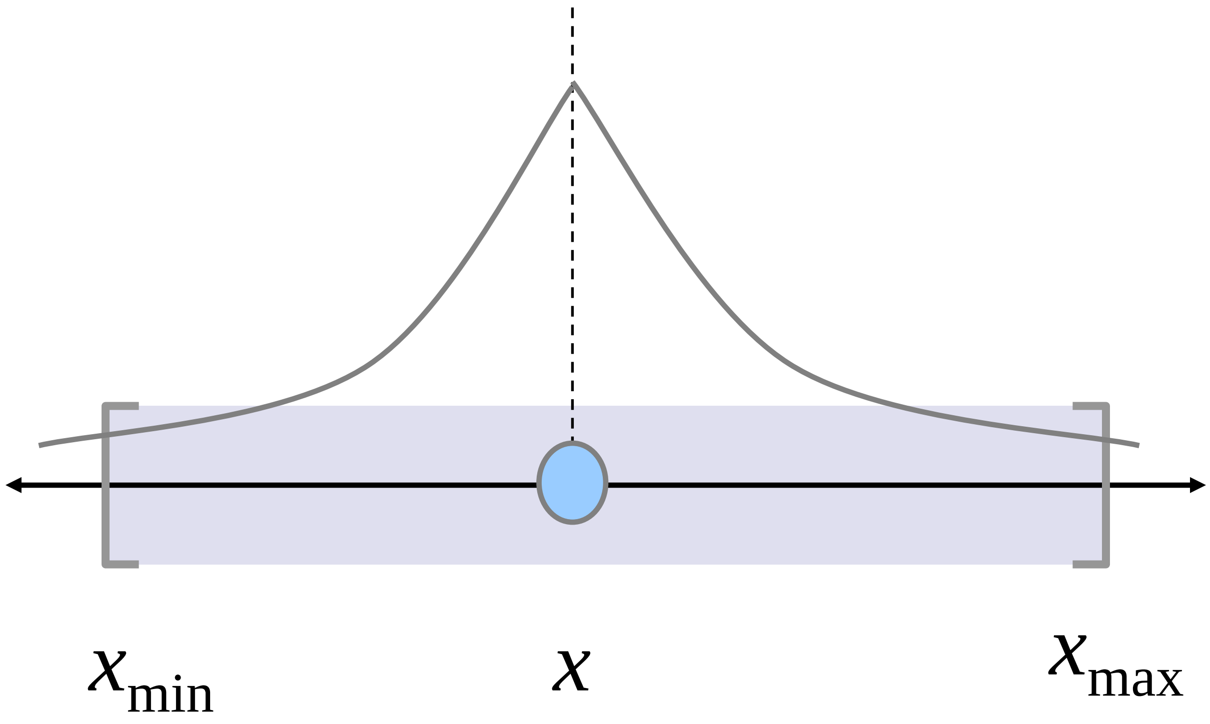
Non-Uniform Mutation

- Non-uniform mutation is expressed as

$$x_{\mathrm{new}} = x + \tau\left(x_{\max} - x_{\min}\right)\left(1 - r^{\left(1-t/t_{\max}\right)^{b}}\right)$$

- τ takes -1 or 1, each with a probability of 0.5
- r is a random number in [0, 1]
- $t_{\max}$ is the maximum number of generations
- t is the current generation number
- b is the design parameter

Non Uniform Mutation



Non-Uniform Mutation

- Mutated solution is more likely to be close to the original solution
- As the generation number increases, mutated solutions are generated closer to the original solution
- Illegal mutated gene values are adjusted to make them feasible, that is, within the allowed range

Normally Distributed Mutation

- Perturb the gene value using a zero-mean Gaussian distribution

$$x_{new} = x + N(0, \sigma)$$