Introduction	Evolutionary Algorithms	Initialization and Selection	Variation	EA Parameters	Typical EAs	EA-Design
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Mutation

- depends on the search space
- generates one offspring from one parent
- makes only small changes with high probability

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Mutation operators for $\{0,1\}^n$

- Standard Bit Mutation (parameter mutation-probability p_m) Copy x to y and invert every bit of y independently with probability p_m .
 - expected number of inverted bits $= p_m \cdot n$
 - $p_m \in (0; 1/2]$ to favor small changes
 - most often used mutation probability $p_m = 1/n$
- *b*-Bit Mutation (parameter *b*)

Copy x to y, choose randomly uniformly

b different positions in y,

and invert the bits of y at these positions

- b often very small, most often b = 1
- easier to analyze than standard-bit-mutation
- Behavior can vary greatly from standard-bit-mutation

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Mutation operators for \mathbb{R}^n

most often $\$ add random vector m on x to generate y

almost always $E(m) = 0^n$

often $m=(m_1',m_2',\cdots,m_n') \text{ where all } m'\in\mathbb{R}$

random choice of $m' \in \mathbb{R}$ where $\mathsf{E}\left(m'\right) = 0$

- restricted $m' \in [a; b]$, most often $m' \in [-a; a]$ uniformly
- unrestricted often normally distributed with probability density $\frac{1}{\sqrt{2\pi\sigma}}e^{-r^2/(2\sigma^2)} \quad \rightsquigarrow \mathsf{E}(m') = 0$, $\mathsf{Var}(m') = \sigma^2$ sometimes $\sigma = 1$ fixed and use $s \cdot m'$ instead of m'

How to choose \boldsymbol{s}

- most often s is not fixed
- Idea choose large s, when far away from the optimum
- Idea choose small s, when close to the optimum

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Mutation operators for S_n

- we don't discuss problem-specific mutation operators
- Exchange

Copy parent, choose $i \neq j \in \{1, 2, ..., n\}$ uniformly randomly. Swap elements with positions i and j.

• Jump

Copy parent, choose $i \neq j \in \{1, 2, ..., n\}$ uniformly randomly. Delete element at position i and insert it at position j (elements in-between are moved).

• Combination of exchange and jump

Choose $k \in \mathbb{N}_0$ randomly according to Poisson-distribution with parameter 1, i. e. Prob $(k = r) = \frac{1}{e \cdot r!}$. Do k + 1 iterations, where randomly uniformly either an exchange or a jump is done.

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Crossover

- depends on the search space
- usually generates one offspring from at least two parents
- usually generates offspring, that are 'similar' to the parents
- sometimes two parents generate exactly two offspring

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Crossover operators for $\{0,1\}^n$ (1)

k-point crossover (parameter k) Generate offspring y from parents x₁ and x₂. Choose k different crossover points p₁,..., pk ∈ {1, 2, ..., n − 1} with p₁ < p₂ < p₃... < pk. y = x₁[1]x₁[2]...x₁[p₁]x₂[p₁ + 1]...x₂[p₂]x₁[p₂ + 1]....
most often k very small, usually k = 2 or even k = 1

uniform crossover

Generate offspring y from parents x_1 and x_2 . For every position $i \in \{1, \ldots, n\}$ choose y_i randomly uniformly from either $x_1[i]$ or $x_2[i]$.

- $\forall i \colon x_1[i] = x_2[i] \Rightarrow y[i] = x_1[i]$
- generates uniformly one of the possible offspring of x_1 and x_2
- in general there are much more possible offspring than using *k*-point crossover

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Crossover operators for $\{0,1\}^n$ (2)

Genepool crossover

Generate offspring y from parents $x_1, x_2, \ldots, x_{\mu}$. Choose y[i] = 1 with probability $\sum_{j=1}^{\mu} x_j[i]/\mu$.

- often the whole population acts as parents
- theoretically motivated

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Crossover operators for \mathbb{R}^n

- k-point crossover works as in $\{0,1\}^n$
- uniform crossover works as in $\{0,1\}^n$
- arithmetic crossover

Generate offspring y from parents $x_1, x_2, \ldots, x_{\mu}$. Generate $y = \sum_{i=1}^{\mu} \alpha_i \cdot x_i$ with parameters $\alpha_1, \ldots, \alpha_{\mu}$ where $\sum_{i=1}^{\mu} \alpha_i = 1$.

- often $\alpha_i = 1/\mu$ for all i
- for $\alpha_i = 1/\mu$, y is centroid of parents
- for $\alpha_i = 1/\mu$, it's also called intermediate crossover
- arithmetic crossover is the only deterministic variation operator

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Crossover operators for S_n

- most often offspring y is generated from two parents x_1 , x_2
- frequent idea Choose two positions in x_1 , and sort elements in this interval according to their order in x_2 (concrete examples: PMX, CX).
- many problem-specific crossover operators (e.g. edge recombination or inver-over for TSP)
- no crossover operators successful over a wide range of applications