Session : Genetic Algorithm

Course Title: Computational Intelligence
Course Code: 19CSE422A

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Objectives of this Session

I wish to provide a foundation to:

1. Generic GAs
2. GA operators (crossover and mutation)
3. Variants of GA (CGAs and SSGAs)
4. Engineering applications of GAs

Intended Outcomes of this Session

At the end of this session, the student will be able to:

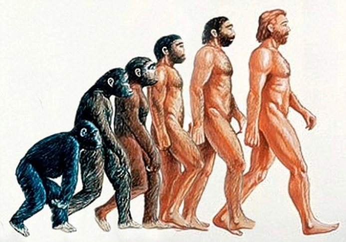
1. Implement a canonical GA to solve a given optimization problem
2. Classify GAs based on various figures of merit
3. Compare among the various types of GAs
4. Relate the GA operators with those in biological genetics
5. Perform one-point, two-point and uniform crossover on given chromosomes
6. Perform random and in-order mutation on given chromosomes
7. Illustrate the various GA operators

Recommended Resources for this Session

1. Engelbrecht, A. P. (2007). *Computational intelligence: An introduction*. Chichester, England, John Wiley & Sons.
2. De Jong, K. A. (2012). *Evolutionary Computation: A Unified Approach*. New York, USA, Bradford Books.
3. Konar, A. (2005). *Computational Intelligence: Principles, Techniques and Applications*. Secaucus, NJ, USA, Springer-Verlag New York, Inc.
4. Q. Wu, N. Rao, J. Barhen, S. Iyengar, V. Vaishnavi, H. Qi, and K. Chakrabarty. (2004). On computing mobile agent routes for data fusion in distributed sensor networks.*IEEE Transactions on Knowledge Data Eng.*, vol. 16, no. 6, pp. 740753.

Genetic Algorithms

- Popularized by John Holland, University of Michigan, in 1970



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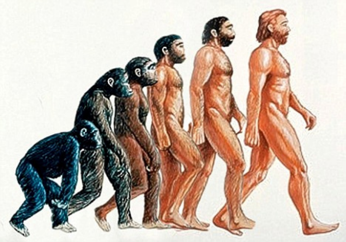

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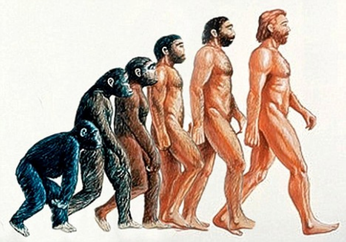

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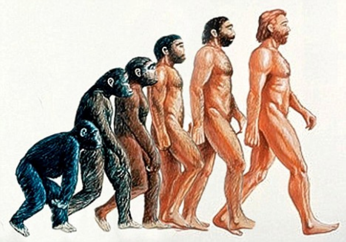

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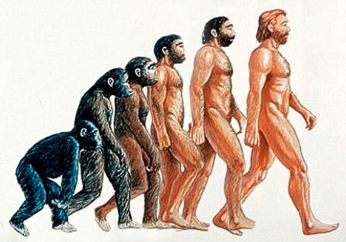

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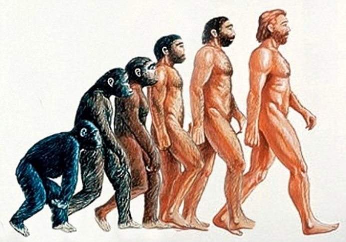

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- A chromosome is made from N genes that represent the parameters to be optimized
- Represents a **species that evolves with time**

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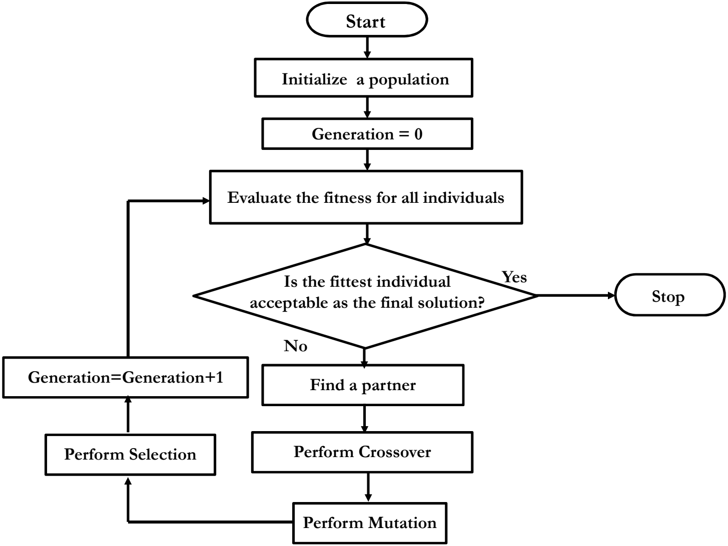
- The driving operators of a GA are selection (to model survival of the fittest) and recombination through crossover operator (to model reproduction)
- In the canonical GA the following were used:
  - A bitstring chromosome representation
  - Proportional selection
  - One-point crossover
  - Uniform mutation (as a background operator with little importance)

Flowchart of a Generic GA



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- In selection of parents, the following should be considered:
  - The same individual should not be used as both parents
  - The same individual should not take part in more than o

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- In the case of two offspring, similar replacement strategies can be used

Crossover for Binary Gene Representation

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Crossover for Binary Gene Representation

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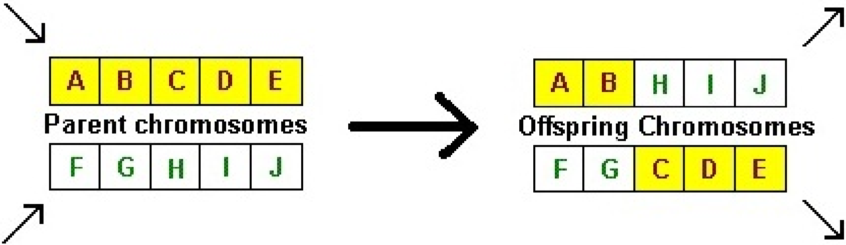
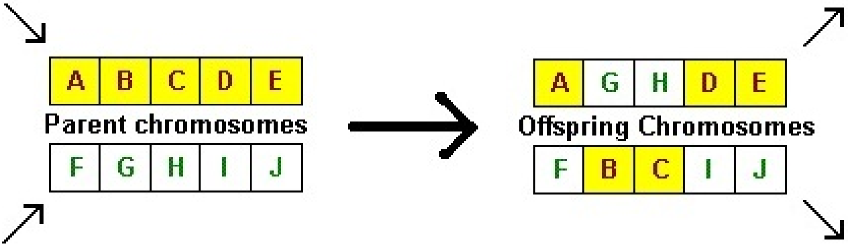
- **Two-point crossover:** Two bit positions are randomly selected, and the bitstrings between these points are swapped
- **Uniform crossover:** An n_x-dimensional mask is created randomly. Here, p_x is the bit-swapping probability. If $p_x = 0.5$, then each bit has an equal chance to be swapped

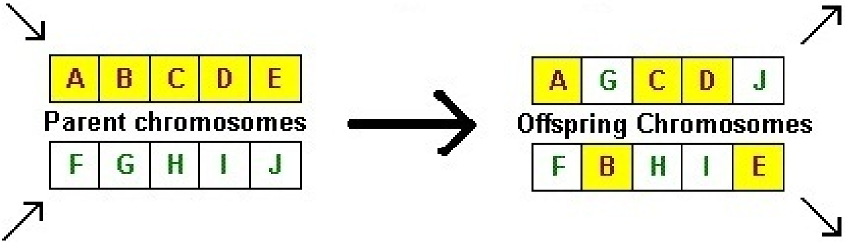
One Point Crossover



Two Point Crossover



Uniform Crossover



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- A solution to the problem of finding best values for these control parameters is to use dynamically changing parameters
- In addition to p_m and p_c, the choice of the best evolutionary operators to use is also problem dependent

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- Selection process is described by how a parent is selected, and how it decides if offspring will replace parents, and which parents to replace
- Two classes based on the replacement strategy: **Generational genetic algorithms (GGA)** and **steady state genetic algorithms (SSGA)**

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- GGAs have a zero generation gap, while SSGAs generally have large generation gaps

Replacement Strategies for SSGAs

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- Replace random: The offspring replaces a randomly selected individual of the current population
- Kill tournament: A group of individuals is randomly selected, and the worst individual of this group is replaced with the offspring
- Replace oldest: A first-in-first-out strategy is followed by replacing the oldest individual of the current population

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- Elitist strategies: The best individual is excluded from selection
- Parent-offspring competition: A selection strategy decides if an offspring replaces one of its own parents

Genetic Operators

- **Selection Operator:** A child that has better fitness than the population minimum is added to the population, and the parent having minimum fitness is removed

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- **Selection Operator**: A child that has better fitness than the population minimum is added to the population, and the parent having minimum fitness is removed

- **Crossover Operator:** Two point crossover is used with a large crossover probability ($p_c \geq 0.9$)

Genetic Operators

- **Mutation:** Two mutation points are selected randomly and the values of these two points are exchanged with a small crossover probability ($p_m \leq 0.1$)

Before Mutation:

0	1	2	3	7	5	6	8	9	11	10	**Level 1**
1	1	1	0	1	1	0	1	0	1	0	**Level 2**

After Mutation:

0	1	2	3	9	5	6	8	7	11	10	**Level 1**
1	1	1	0	0	1	0	1	1	1	0	**Level 2**

Genetic Operators

- **Inversion:** Two mutation points are selected randomly and the order of nodes between these two points is reversed

Before Inversion:

0	1	2	3	9	5	6	8	7	11	10	Level 1
1	1	1	0	0	1	0	1	1	1	0	Level 2

After Inversion:

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  - Optimal Routing
- Robotics
  - Optimal Path Planning
  - Swarm Robotics

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- ✗ Reported to have a tendency to converge to sub-optimal solution

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- Popular crossover operators: One-point, Two-point and uniform
- Popular mutation operators: Random and In-order
- Interactive evolution involves a human user on-line into the selection and variation processes
- Application of GA include: Design, Control Engineering, Power Systems, Distributed Networks, Robotics and many others

Any Questions?

Thank You