Session : Evolutionary Computing

Course Title: Computational Intelligence
Course Code: 19CSE422A

Course Leader:
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Objectives of this Session

I wish to provide a foundation to:

1. Evolutionary algorithms (EAs)
2. Biological inspiration to EAs
3. Paradigms of evolutionary computing (EC)
4. Chromosome representation in EC
5. Initial population in EC
6. Fitness function in EC
7. Selection operators in EC
8. Reproduction operators in EC
9. Stopping criteria in EC
10. EC optimization versus classical optimization

Intended Outcomes of this Session

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

1. Relate Evolutionary Algorithms (EAs) to biological evolution
2. Judge if a given problem can be approached using EAs
3. Compare traditional optimization with evolutionary computing-based optimization
4. Formulate a problem into optimization problem solvable by EA
5. List and outline the paradigms of evolutionary computing
6. Arrange the major operators in a generic EA in the form an algorithm
7. Summarize the importance of the initial population, selection operators, reproduction operators and stopping criteria
8. List the types of aforementioned operators and discuss their relative advantages
9. Choose a particular selection operator suitable for a given problem

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.

Algorithms in EC

- Genetic algorithms (GAs)
- Evolutionary programming (EP)
- Evolution strategies (ESs)
- Genetic programming (GP)
- Differential Evolution (DE)
- Cultural Evolution (CE)
- Coevolution (CoE)

Introduction to Evolution

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- Lamarckism rests on the concept of use and disuse: over time, individuals lose characteristics they do not require, and develop those which are useful by “exercising” them

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- A second part of Darwins theory states that, during production of a child organism, random events cause random changes to the child organisms characteristics
- If the new characteristics are a benefit, then the chances of survival for that organism are increased

Biological Evolution

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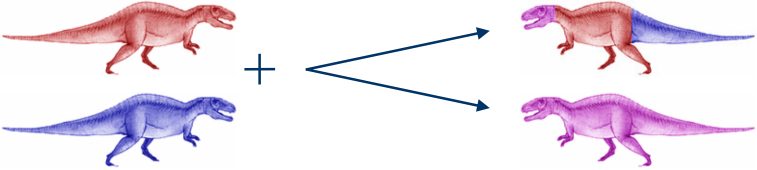
  - Reproduction



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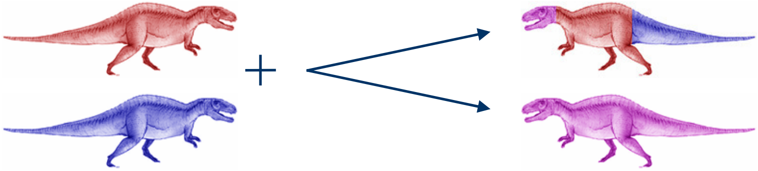
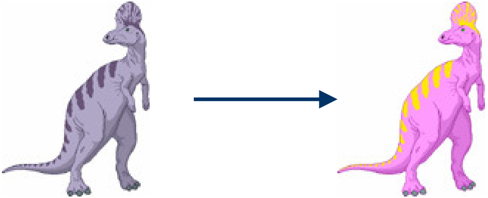


  - Mutations (random changes)



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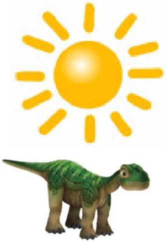

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- An EA is a stochastic search for an optimal solution to a given problem

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Steps in Generic Evolutionary Algorithm

1. Let $t = 0$ be the generation counter;
2. Create and initialize an n_x-dimensional population, $C(0)$, to consist of n_s individuals;
3. WHILE(stopping condition(s) not true)[a]
4. Evaluate the fitness, $f(x_i(t))$, of each individual, $x_i(t)$;
5. Perform reproduction to create offspring;
6. Select the new population, $C(t+1)$;
7. Advance to the new generation $t = t + 1$;

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- CoE has initially "dumb" individuals that evolve through cooperation, or in competition with one another, acquiring the necessary characteristics to survive

Representation: The Chromosome

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- A genotype describes the genetic composition of an individual. A phenotype describes the behavioral traits of an individual

Representation: An Example

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- **Population:** The number of chromosomes available to test

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1	0	1	1	1	0	1	0	0	0	1	1
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- A standard binary encoding scheme can be used to transform the individual $\mathbf{x} = (x_1, \ldots, x_j, \ldots, x_{nx})$, with $x_j \in \mathbb{R}$ to the binary-valued individual, $\mathbf{b} = (\mathbf{b}_1, \ldots, \mathbf{b}_j, \ldots, \mathbf{b}_{nx})$, where $\mathbf{b}_j = (b_{(j-1)}n_d + 1, \cdots, b_{jn_d})$, with $b_l \in \{0, 1\}$ and the total number of bits, $n_b = n_x n_d$

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- A small population results in lower time complexity per generation. But, the it take more generations to converge

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$\mathscr{S}_C$: Search space	Φ: Chromosome decoding function
Ψ: Objective function	Υ: Scaling function

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- **Dynamic and noisy problems:** Dynamic fitness functions are time-dependent. Noisy functions have additive noise component

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- Offspring are created using crossover and/or mutation operators. In crossover, "superior" individuals should get more opportunities to reproduce
- Mutation should focus on "weak" individuals because it brings better traits in them and increases their chances of survival

Selective Pressure

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- A high selective pressure limits the exploration abilities of the population

Selection Operators: Random Selection

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- Random selection has the lowest selective pressure

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- A probability distribution proportional to the fitness is created, and individuals are selected by sampling the distribution

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- Here, n_s is the population size and $\varphi(\mathbf{x}_i(t))$ is the probability that $\mathbf{x}_i$ will be selected
- **Roulette wheel selection** is a good example of proportional selection

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- Crossover: The process of creating one or more new individuals through the combination of genetic material randomly selected from two or more parents
- If selection focuses on the most-fit individuals, the selection pressure may cause premature convergence due to reduced diversity of the new population
- **Mutation:** The process of randomly changing the values of genes in a chromosome in order to introduce new genetic material into the population, thereby increasing genetic diversity

Reproduction Operators

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- The difference is in their search process and how they use the search surface information

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Any Questions?

Thank You