Introduction to Evolutionary Computation

Inteligencia Artificial en los Sistemas de Control Autónomo

Universidad de Alcalá
ISG

Objectives

- Introduce biological evolution
- Introduce artificial evolution
- Justify the utility of artificial evolution from an engineering perspective
- Overview the components of an Evolutionary Algorithm

Bibliography

- Eiben, A.E. and Smith, J.E. *Introduction to Evolutionary Computing*. Springer 2003.
- Luke, S. *Essentials of Metaheuristics*. 2nd edition. Ed. Lulu, 2010. (Link)

Table of Contents

Biological background

Historical review (I)

Anaximander of Miletus (610 – 546 BC)

- First animals come from water
- Man come from fishes

Plato (428/427 – 348/347 BC)

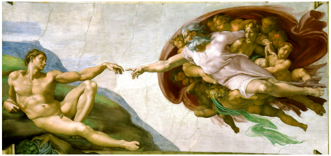
- Demiurgo created the cosmos
- Theory of Ideas

Aristotle (384 – 322 BC)

- Spontaneous generation
- Strong influence in Europe

Biological background

Historical review (II)



Creationism: God created all the species

- Literal interpretaton of the Genesis
- Species are hierarchical
- Man has a superior position

Main school in Europe for centuries

Biological background

Historical review (III)

Georges Louis Leclerc (1707 - 1788)

- Especulated that species change
- Noticied the similarities between men and apes
- Could not provide a theory

Jean-Baptiste Lamarck (1744 - 1829)

- First to propose a theory of evolution
- Transmutation of Species
- Use strengthens/weakens organs
- Heritability of acquired characteristics

Biological background

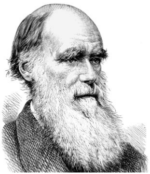
Historical review (IV)

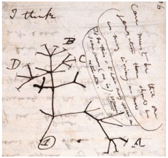
Charles Darwin (1809-1882)

- Published in ``On the Origin of the Species" in 1859

  ("On the Origin of Species by Means of Natural Selection, or the Preservation of Favoured Races in the Struggle for Life")

- Introduced natural selection ... and applies it to human being
  - Natural selection = Variability + selection
- Darwin did not explain the source of variation





Biological background

Historical review (V)

Gregor Mendel (1822 - 1884)

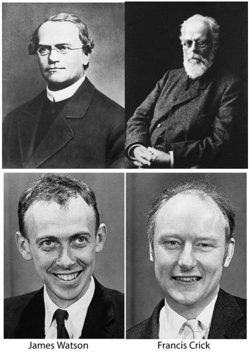
- Mendelian inheritance
- Recessive and dominant traits

August Weismann (1834 - 1914)

- Germ plasm theory
- Germ and somatic cells
- End of Lamarkism

J. Watson (1928) and F. Crick (1916 - 2004)

- Discovery of DNA
- Central Dogma of molecular biology



Biological background

Theory of Evolution

Neo-Darwinism: Darwin + Mendel + Weismann

- ... also called Theory of Evolution
- Variability + selection = evolution

There is variation among individuals

- Sexual reproduction, mutation and gene flow

There is a selection of those individuals

- Natural selection
- Artificial selection
- Sexual selection
- Genetic drift (deriva genética) (Link)

The *fittest* is the one that survives (not the strongest!)

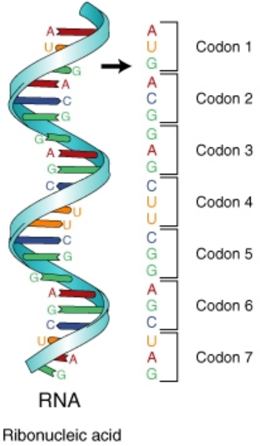
Biological background

Molecular Genetics (I)

Organisms are made by **proteins**

- Proteins are sequences of **aminoacids**
- They folder in a 3D structure
- 20 aminoacids

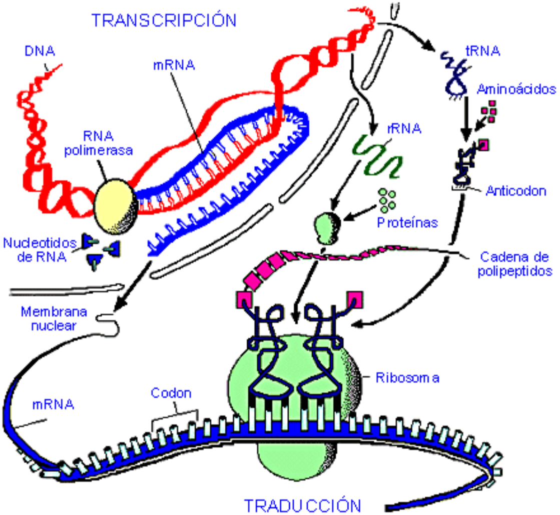
DNA codifies all the proteins in an organism



Biological background

Molecular Genetics (II)

Protein synthesis: Creation of proteins from DNA (video)



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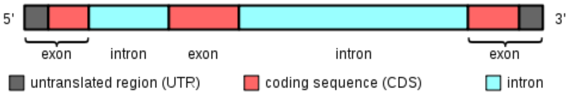
Biological background

Molecular Genetics (III)

Useful biological terms

Gene	ADN fragment that codifies one protein
Allele	The variant form of a gene
Genotype	The sequence of DNA
Phenotype	Characteristics of an individual
Exon	Part of a gene that is transcripted
Intron	Part of a gene that is not trascripted



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Biological background

Theory of Evolution from an algorithmic perspective

Given a population ...

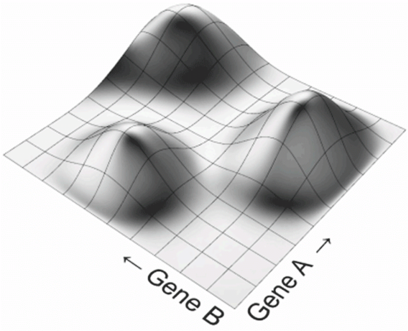
1. There are differences among individuals
2. Fittest individuals more likely to reproduce
3. Go to 1

We are interested in applying this to Engineering

How can we apply biological evolution to solve engineering problems?

Evolutionary Algorithms

Evolution as optimization



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Biological evolution is, in essence, an optimization algorithm

- ... it optimizes the survival probability
- Optimizing is to *search* the maximum

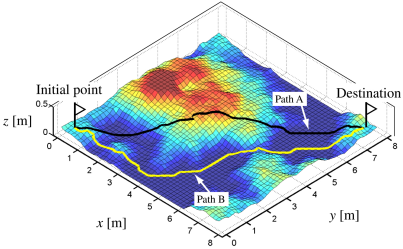
Evolutionary Algorithms

AI, search and optimization (I)

AI is much related to search a solution for a problem

- Search space
- Solution space

Almost any computational problem can be expressed as a search problem



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Evolutionary Algorithms

AI, search and optimization (II)

In AI, potential solutions are assessed

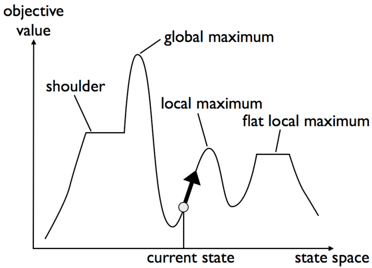
- Cost function
- Objective: Maximize cost function

The solution to any problem: **exhaustive search**

- Inviable in practice

How to find a solution efficiently?

- With domain knowledge
- With randomness: Metaheuristics



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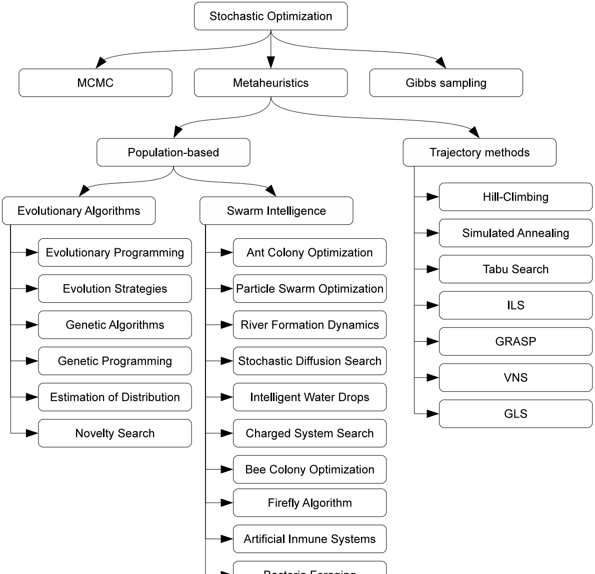
Evolutionary Algorithms

Metaheuristics



Again:

How can we apply biological evolution to solve engineering problems?

Evolutionary Algorithms

Basics (I)

Large number of Evolutionary Algorithms

- There is no ``canonical" algorithm
- They all imitate biological evolution

They use a population

- Each individual represents a (potential) solution
- Multiple **representations**

Population is modified

- Mutation (1 individual)
- Crossover (>1 individuals)
- Multiple **genetic operators**

Selection that imitates natural selection

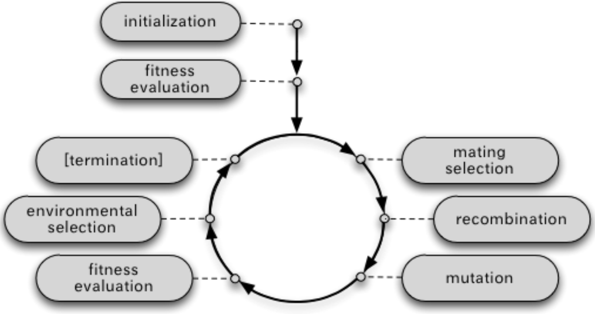
- Based on a **fitness** function

Iterative process

Evolutionary Algorithms

Basics (II)

Possible basic algorithm



Evolutionary Algorithms

Basics (III)

Initialization is usually random

- Random population
- Domain-dependent heuristics may be used
- Known solutions migh be injected into the initial population

Termination criteria

- Get a desired fitness
- Maximum number of iterations (or generations)
- Loss of genetic diversity
- Lack of fitness improvment

Evolutionary Algorithms

Exploration and explotation

Balance between explotation and exploration

- These are oposite objectives $\Rightarrow$ Need of trade-off

Exploration: Search of new regions (global search)

- Explore the search space
- Performed, mostly, by mutation

Explotation: Search of local (or global) maxima (local search)

- Exploit the adquired knowledge
- Performed, mostly, by crossover

EAs components

Components of an EA

Common components in any EA

- Representation
- Evaluation
- Selection
- Genetic operators

EAs components

Representation (I)

Main difference among EAs is the representation

- Strings: Genetic Algorithms (GA)
- Real vectors: Evolution Strategies (ES)
- State machine: Evolutive Programming (EP)
- Trees: Genetic Programming (GP)

These differences are, mostly, irrelevant

- Use the most natural representation
- Use the most natural genetic operators according to the representation

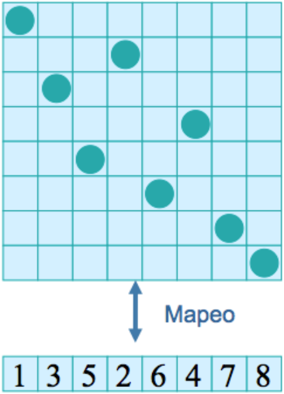
EAs components

Representation (II)

Example: 8 queens with a Genetic Algorithm

Phenotype: Board position

Genotype: Integer vector

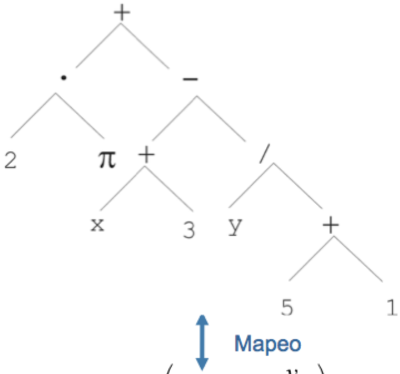


EAs components

Representation (III)

Example: Regression in Genetic Programming

Phenotype: Tree
Genotype: Formula



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

EAs components

Evaluation (I)

Individuals quality is assessed by a fitness function

- Individual = Potential solution

The fitness assigns a numerical value to a phenotype

- Caution, phenotype, not genotype
- Multiobjective algorithms use several fitnesses

Evaluation uses to be a bottleneck

- Many times it involves simulating a system

Minimize number of evaluations

EAs components

Evaluation (II)

Example: 8 queens

- The fitness may be the number of threaded pieces
- Objective: Minimize fitness (minimation problem)

Example: Regression

- The fitness may be the quadratic average error
- Objective: Minimize fitness (minimation problem)

EAs components

Selection (I)

Selection operator ``selects" individuals for reproduction

- Imitates natural selection
- Higher reproduction probability for high fitness individuals
  - Randomness helps avoiding local minima
- Selection is done in phenotipic space!
  - Selection does not take into account how representation is

Introduces selective pressure

EAs components

Selection (II)

High selective pressure reduces genetic diversity

- Faster evolution, higher probability of local maxima
- Eliminates low fitness individuals
  - Potentially valuable genetic material can be lost
- Selection operators: Tournment size n, roulette-wheel, rank-based, ...

Example: Tournment size n

- Take randomly n individuals
- Compute their fitness
- Select the highest fitness
- Variable selective pressure depending on n

EAs components

Selection (III)

Replacement strategy

- Select which individual replace

Two basic strategies

- Generational algorithms: Replace all the offspring
    - Iterations are named generations
    - Time is usually measured in generations
- Steady-stade: Replace part of the offscript
    - Criteria: Age, fitness, selection, etc
    - Lower memory consumption

Hybrid strategy: Elitism

- Replace the population, except the n fittest individuals
- n fittest individuals guaranteed to survive

EAs components

Genetic operators (I)

Genetic operators build new individuals

- Two basic operators: mutation and crossover

Open discussion (=research) about the role of mutation and crossover

- Mutation enhances exploration
- Crossover enhances explotation

Both are used

- Historial constrains

EAs components

Genetic operators (II)

Mutation operator

- It takes a genotype and returns another one
  - It has a stochastic behavior
  - Used to maintain genetic diversity
- Guarantees search space connectivity
- Mutation plays a disruptive role
  - Moves population to new regions

Example: 8 queens permutation operator

EAs components

Genetic operators (III)

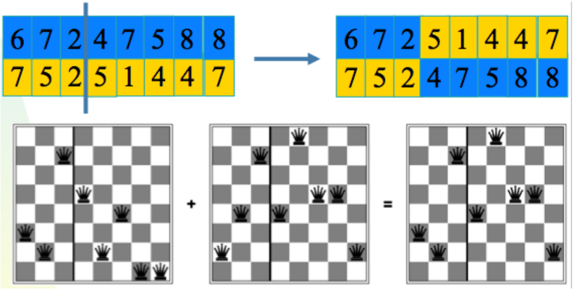
Crossover operator

- Fuse information from the parents (sexual reproduction)
  - Randomness has a place
- Offspring uses to be worse than its parents
  - With luck, good components of the parents are joined ...
  - ... and this is something that happens
- Crossover has a constructive role
  - Join preexistent components
  - Does not generate new genetic material
  - Encourages explotation

EAs components

Genetic operators (IV)

Example: 8 queens with one-point crossover

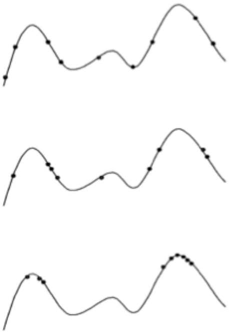


Working with an Evolutionary Algorithm

Search phases

Initial phase: Random distribution, high genetic diversity
Advanced phase: Begins to converge
Convergence: Around one or few points, low genetic diversity

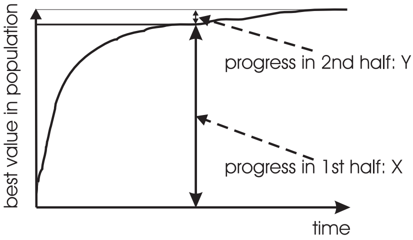
Premature convergence if population not located in global maxima

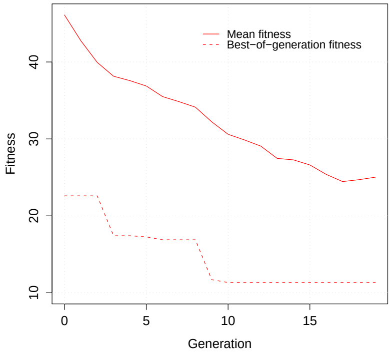


(Animation)

Working with an Evolutionary Algorithm

Fitness dynamics

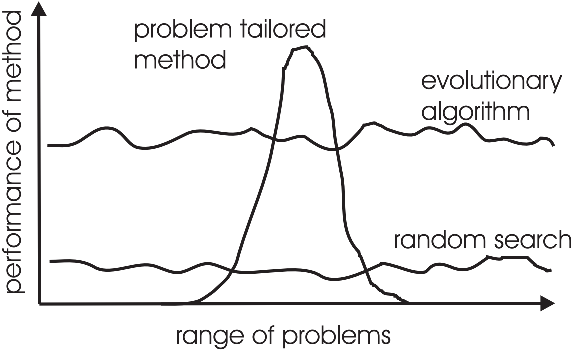




Few long runs or many short runs?

Working with an Evolutionary Algorithm

When EAs are useful



Working with an Evolutionary Algorithm

Advanced EAs

- Multiobjective Evolutionary Algorithms (MOEAs)
- Optimization with constrains
- Coevolution
- Dinamic optimization
- Islands models
- Memetic algorithms
- Hyperheuristics

Working with an Evolutionary Algorithm

Examples

- (Car design)
- (Genetic Algorithm Walkers)
- (Smart rockets)
- (Learn to walk)
- (Flexible Muscle-Based Locomotion for Bipedal Creatures)
- (MarI/O - Machine Learning for Video Games)
- (A genetic algorithm learns how to fight!)
- (Evolved Electrophysiological Soft Robots)