Evolutionary Computation 2015: Introduction

Geoff Nitschke

Department of Computer Science
University of Cape Town, South Africa

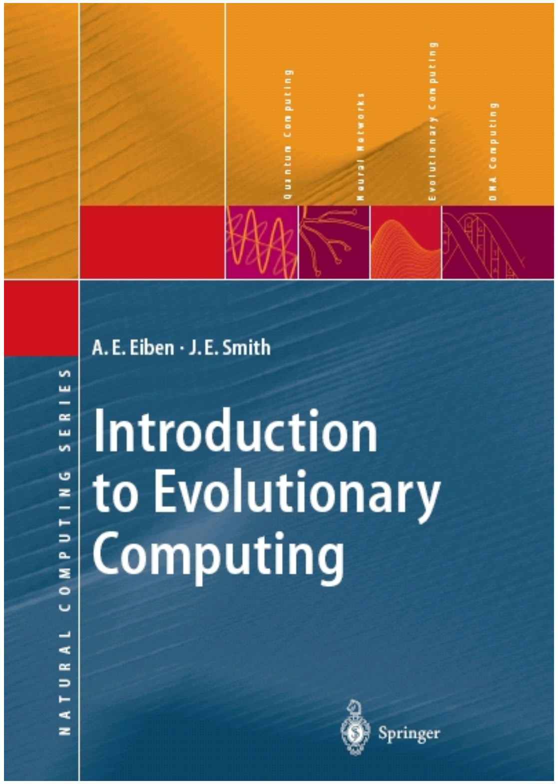
EC 2015: Lecture Outline

1. Introduction.
2. What is an Evolutionary Algorithm?
3. Genetic Algorithms.
4. Evolution Strategies.
5. Evolutionary Programming.
6. Genetic Programming.
7. Niching.
8. Multi-Objective Optimisation.
9. Co-Evolution
10. Working with Evolutionary Algorithms .

EC 2015: Module Outline

Recommended Text:

Eiben, A. and Smith, J. (2003). Introduction to Evolutionary Computing.



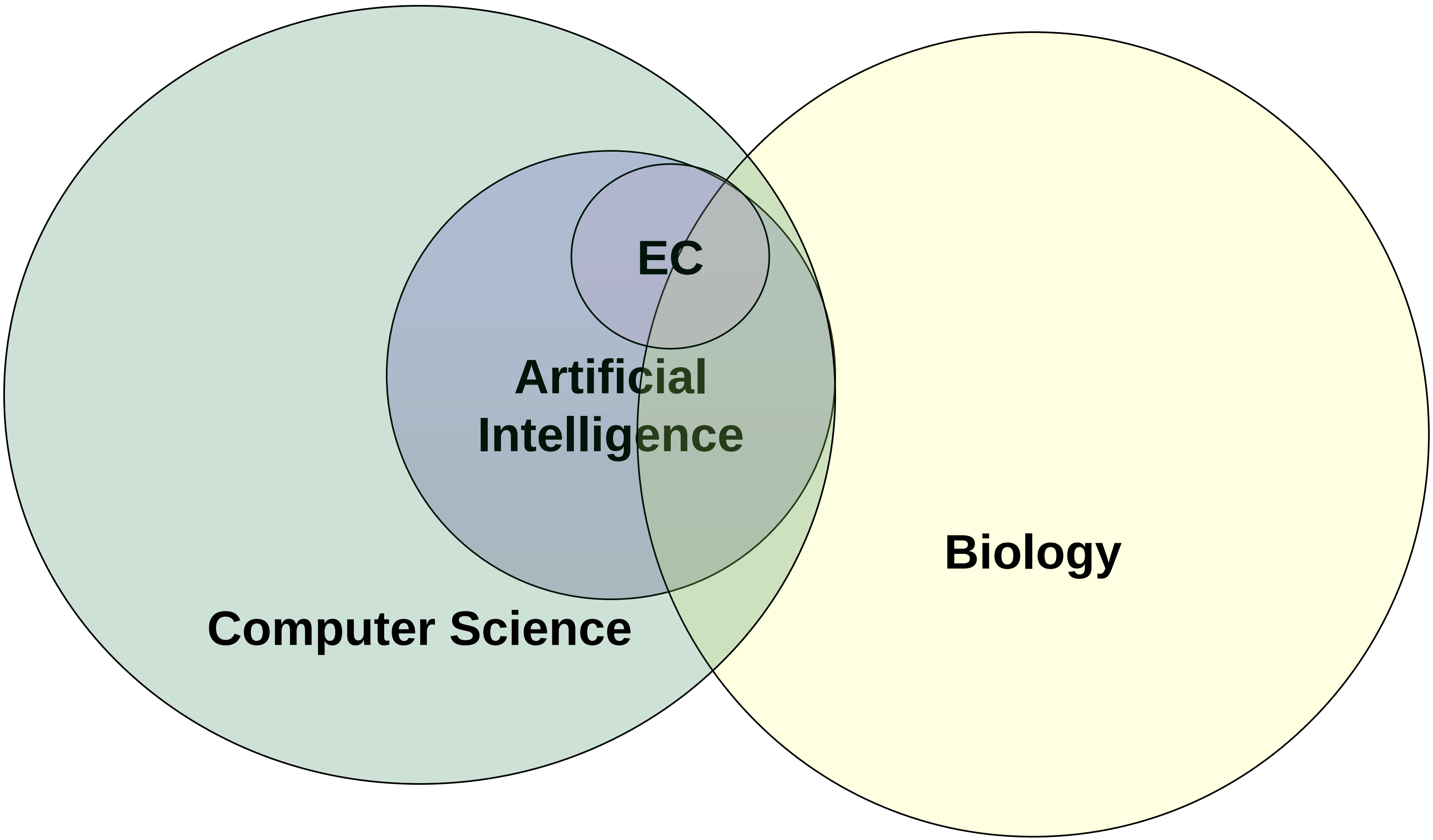
Evaluation:

- Practical assignment and presentation: 40%
- Written examination: 60%

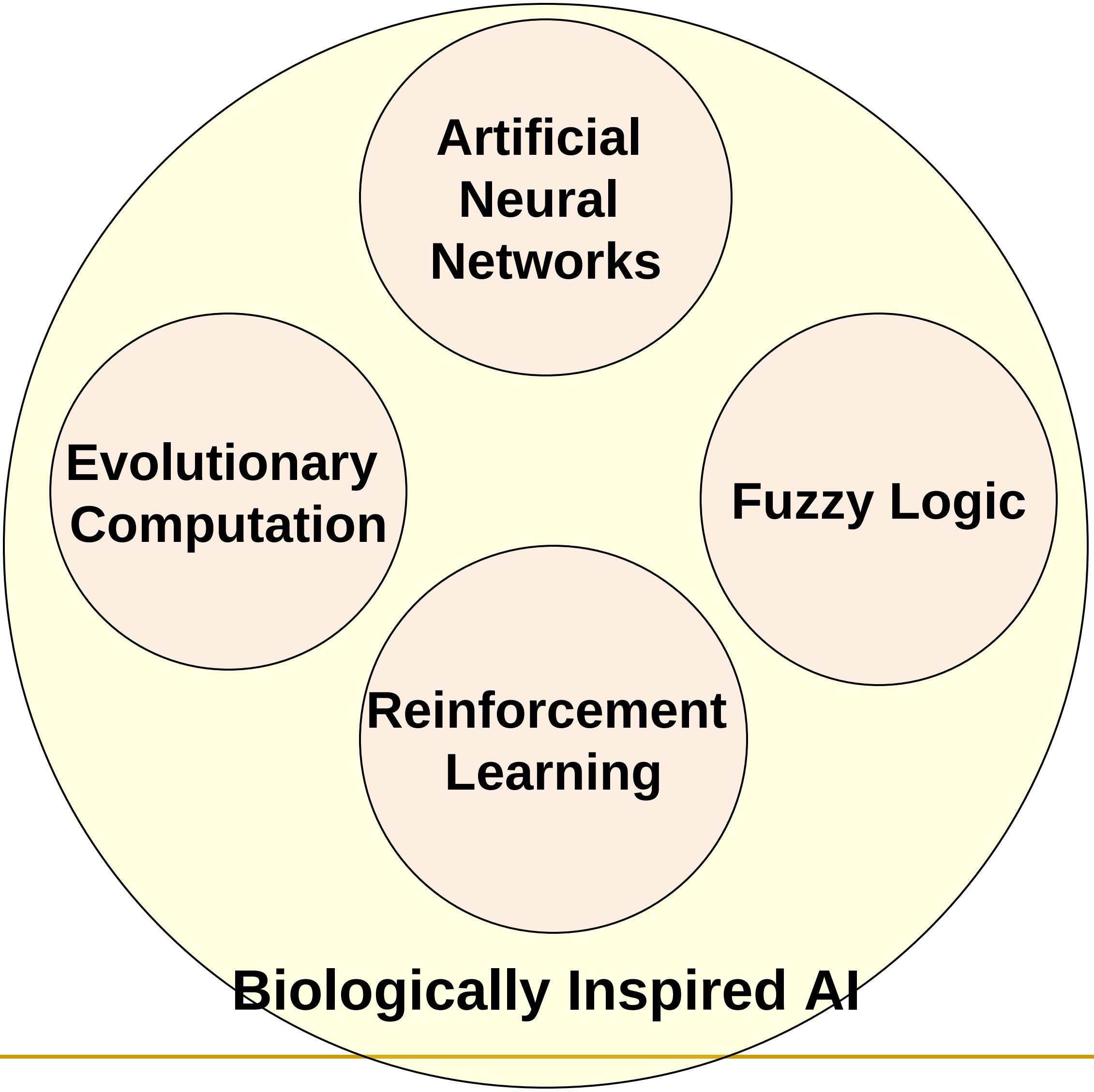
Website:

http://people.cs.uct.ac.za/~gnitschke/Teaching/EC.html

Where Does EC Fit In?



EC in the Context of AI



Approaches to AI

- **GOFAI:** Good Old Fashioned AI
(McCarthy, 1955; Haugeland, 1985).

- **New (Biologically Inspired) AI** (Brooks, 1989).

GOFAI: Central Hypothesis

- Knowledge can be represented by symbols and intelligence is reducible to symbol manipulation (Allen and Simon, 1963).
- AI is achieved by manipulation of symbols.
- Dominated AI paradigm until the late 20th century.
- **Philosophical Roots:**
  - Gottfried Leibniz (1646 – 1716): Attempted to create a logical calculus of all human ideas.
  - David Hume (1711 – 1776): Perception is reducible to "atomic impressions“.
  - Immanuel Kant (1724 – 1804): Experience is controlled by formal rules.

GOFAI and Symbols

- **Formal Logic:**
  - Symbols: AND, OR, NOT, A, B…
  - Expressions: TRUE or FALSE statements.
  - Process: Rules of logical deduction.

- **Chess:**
  - Symbols: The pieces.
  - Expressions: All possible board configurations.
  - Processes: The legal chess moves.

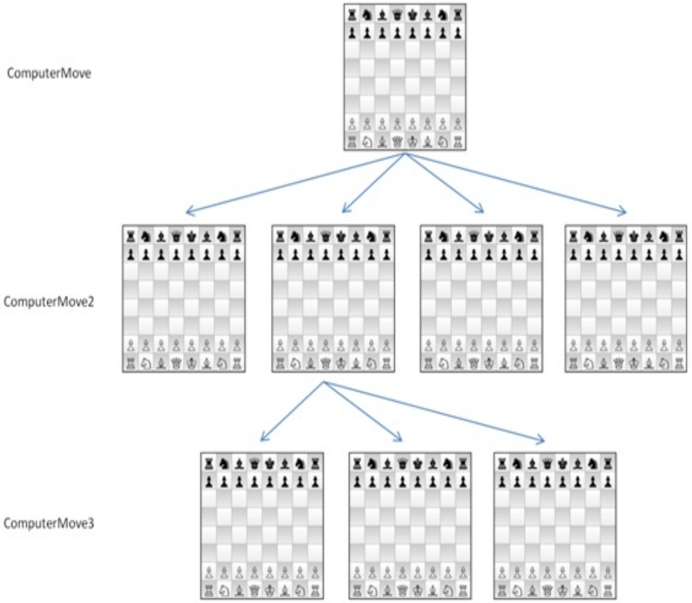
GOFAI and Symbols

- **Human Thought:**
  - Symbols: Encoded in our brains.
  - Expressions: Our thoughts.
  - Processes: The mental operations of thinking.

- **AI "Thought":**
  - Symbols: Data structures.
  - Expressions: Sets of data structures.
  - Processes: Programs that manipulate the data structures.

GOFAI Approaches

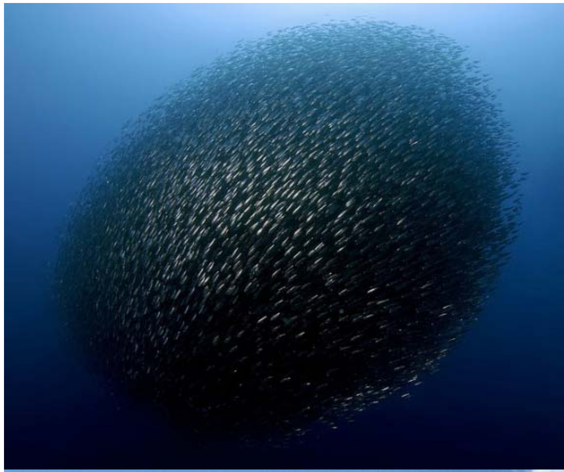
- **Top-Down Approach:** Hierarchical symbolic based architecture.

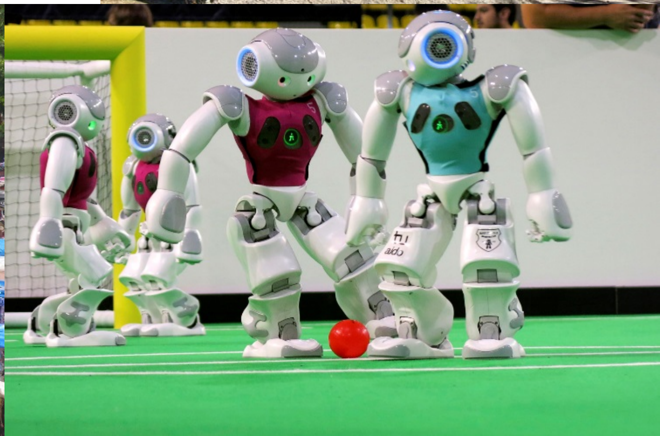


- **Some GOFAI Approaches:**
  - Finite State Machines (FSMs).
  - MINIMAX, Alpha-Beta Pruning.
  - Monte-Carlo Search.
  - Rule Based Systems.
  - …

New AI

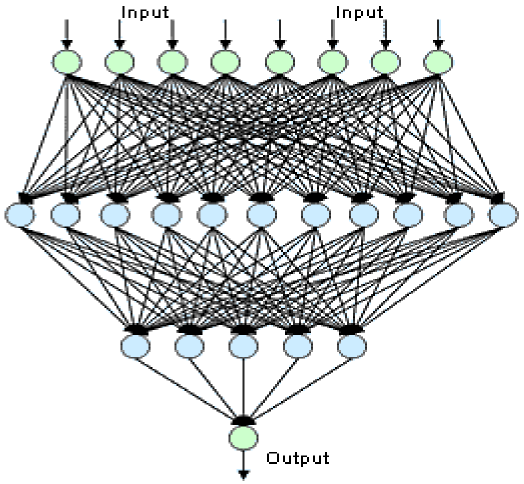
- Biologically inspired algorithm design.
- Bottom-Up (Synthetic) Approach: Individual components interact (*self-organise*) to produce global (*system-level*) behaviour.
- New AI models: How should simple components interact to produce "intelligent" behaviour?

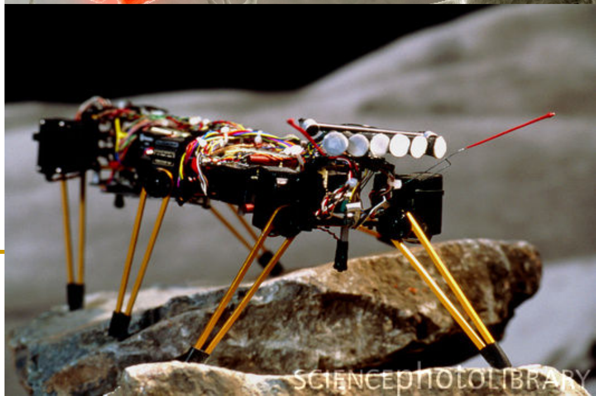




New AI Approaches

- Some New AI Approaches:
  - *Evolutionary Algorithms (EAs).*
  - *Artificial Neural Networks (ANNs).*
  - *Neuro-Evolution (NE) .*
  - *Reinforcement Learning (RL).*
  - *Swarm Intelligence (PSO).*



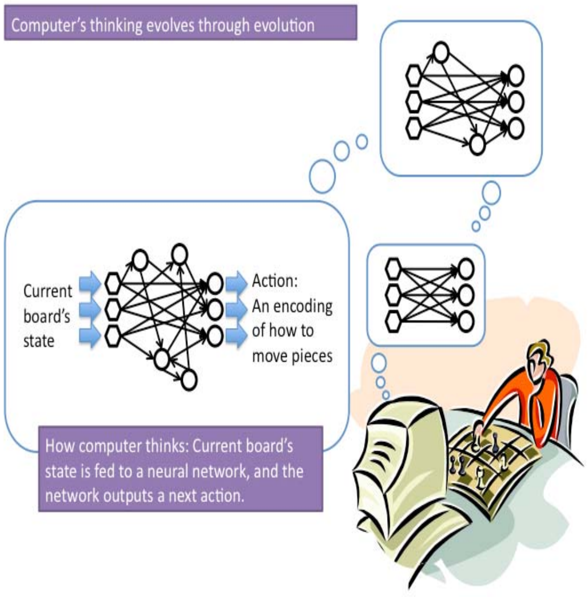


Motivations for EC

- Nature has been a constant source of inspiration for engineers and scientists.

- The best problem solver known in nature is:
  - Human brain.
  - Evolutionary mechanisms that created the human brain.

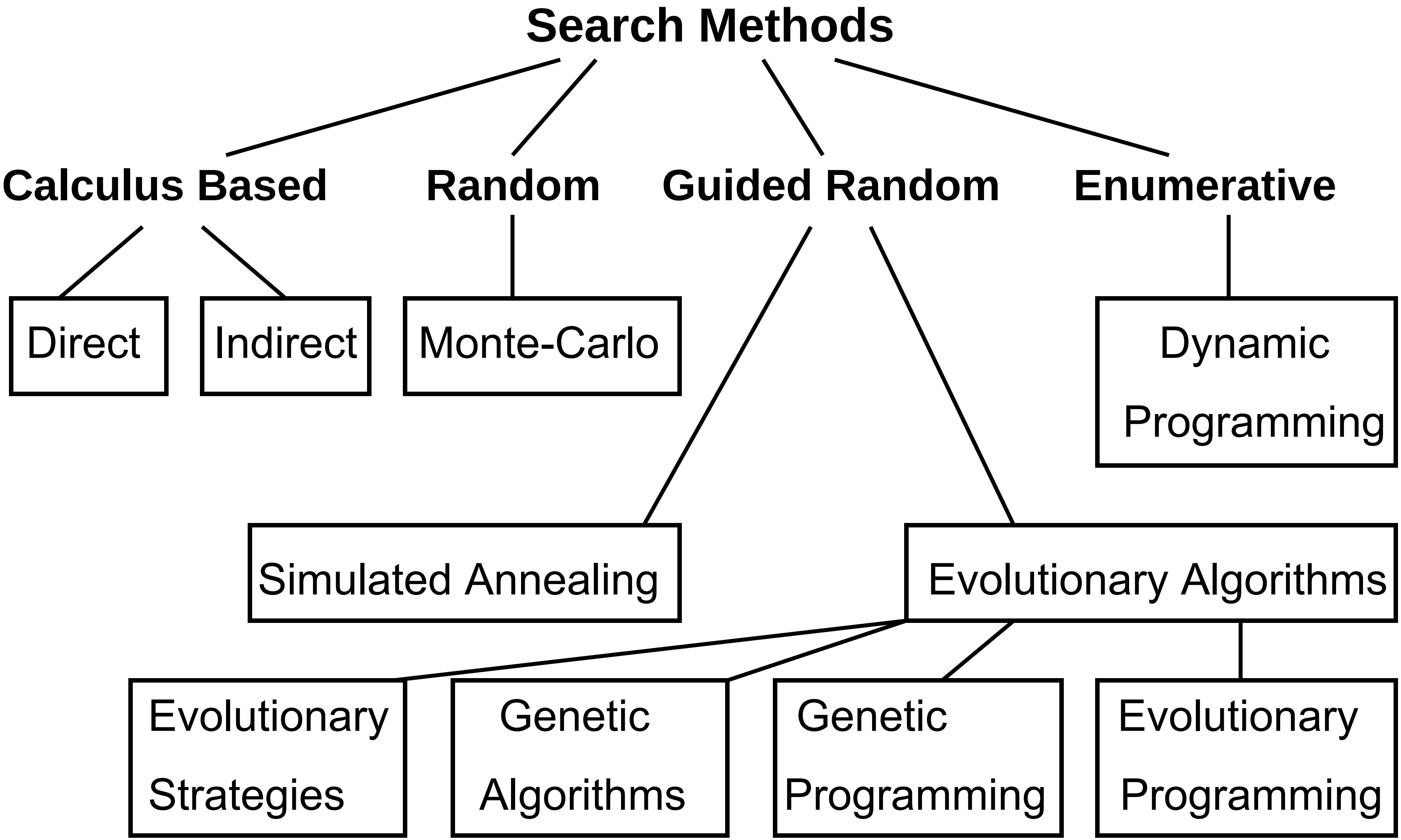
- Approach 1 → Neuro-Evolution.
- Approach 2 → Evolutionary Computation.



Motivation for EC

- Central Theme in Computer Science:
  Developing, testing, and analysing, algorithms to solve problems.
- EC / Evolutionary Algorithms (EAs):
  Automated design of solutions using the principles of evolution.
- Advantage:
  Complexity of problems to be solved increases.
- Disadvantage:
  Complexity of solution analysis also increases.
- EC: Is a generalised and robust problem solving methodology.

EC is a Search Method

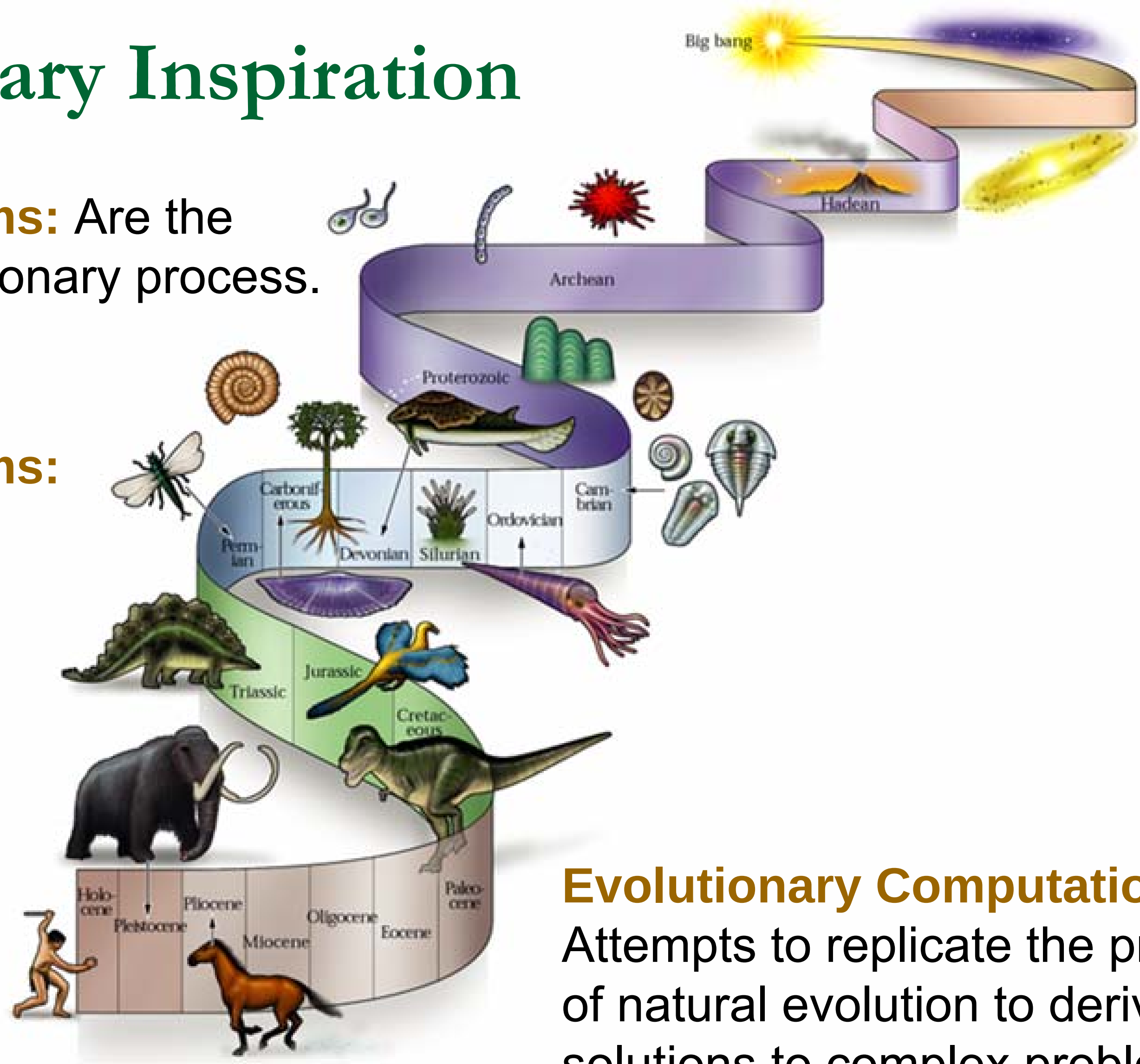


Evolutionary Inspiration

Biological systems: Are the result of an evolutionary process.

Biological systems:

- Robust
- Complex
- Adaptive

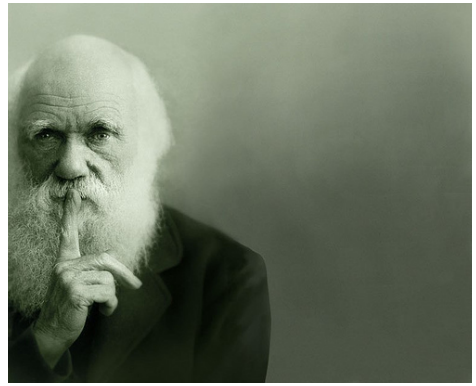


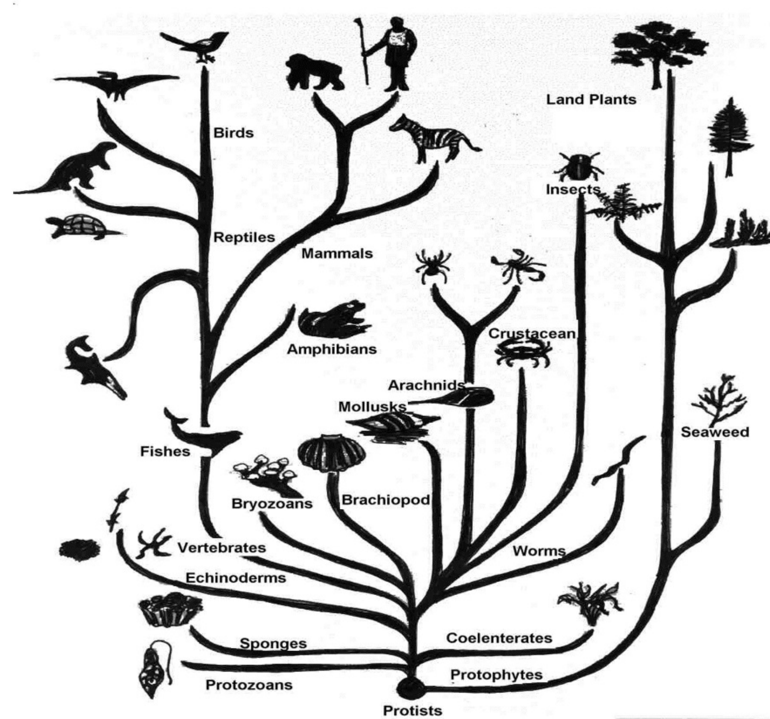
Evolutionary Computation: Attempts to replicate the process of natural evolution to derive solutions to complex problems.

Tenets of Evolution

“All species derive from common ancestors”

- Charles Darwin, 1859
On the Origin of Species





Population: Set of many individuals.

Diversity: Individuals have different characteristics.

Inheritance: Characteristics transmitted over generations.

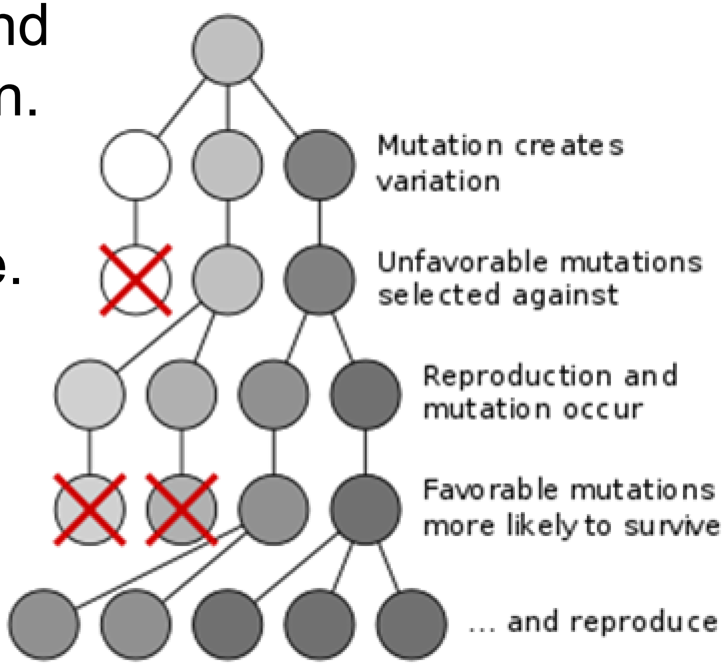
Selection: Individuals best suited to their environment produce offspring.

Variation: Offspring are *recombined* and *mutated* elements of parents.

Survival of the fittest: Population gradually improves over generations.

Darwinian Evolution I

- **All Environments:** Have finite resources.
  - Environments can only support a limited number of individuals.
- **All Lifeforms:** Have basic instincts and lifecycles geared towards reproduction.
- **Thus:** A form of selection is inevitable.
- **Individuals:** That effectively compete for resources, increase their chances of reproducing.



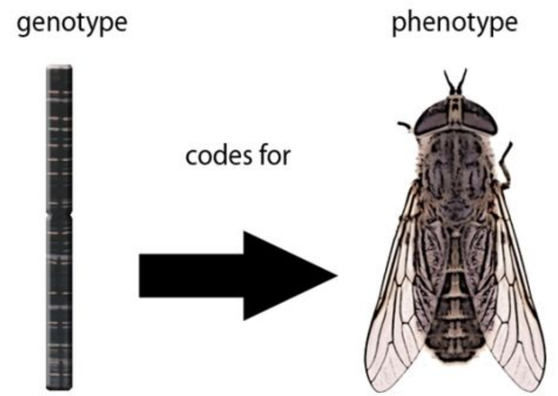
Genotype and Phenotype

Phenotype: Manifestation of the organism (appearance, behaviour, ...).

- Selection operates on the phenotype;
- Phenotype is affected by environment, development, and learning.

Genotype: Genetic material of an organism.

- Genotype is transmitted during reproduction.
- Genotype is affected by mutations.
- Selection does not operate directly on genotypes.



Genetics: Structure and operation of genes.

Functional genomics: Role of genes in an organism.

Darwinian Evolution II

- **Phenotypic traits:**
  - Behavioural and physical differences.
  - Phenotypes:
    - Partly determined by inheritance
    - Partly by developmental factors.
  - Unique to each individual.

- ***If* phenotypic traits:**
  - Lead to higher chances of reproduction.
  - Can be inherited.
  - *Then* they will tend to increase in subsequent generations.

Darwinian Evolution III

- **Population:** A diverse set of individuals.
- **Combination (and Recombination):** Of traits that are better adapted tend to be propagated in population.
  - **Individuals are “units of selection”.**
- **Variations:** Occur through random mutations – constant source of diversity – coupled with selection.
  - **Population is the “unit of evolution”.**

EC Metaphor I

<u>**EVOLUTION**</u>		<u>**PROBLEM SOLVING**</u>
Environment	⟷	Problem
Individual	⟷	Candidate Solution
Fitness	⟷	Quality

Fitness → Chance of survival and reproduction

Quality → Chance of seeding new solutions

EC Metaphor II

- ***Population*** of individuals in an environment with limited resources.
- ***Competition*** for resources causes selection of ***fitter*** individuals
  - Individuals better adapted to the environment.
- Fitter individuals are then the ***parents*** for a new generation
  - Created via ***recombination*** and ***mutation*** of genotypes.
- New generation individuals have their fitness evaluated:
  - They compete for survival in their environment.
- Over evolutionary time:
  - ***Selection*** gives rise to adaptation in the population
  - Individuals' fitness increases.

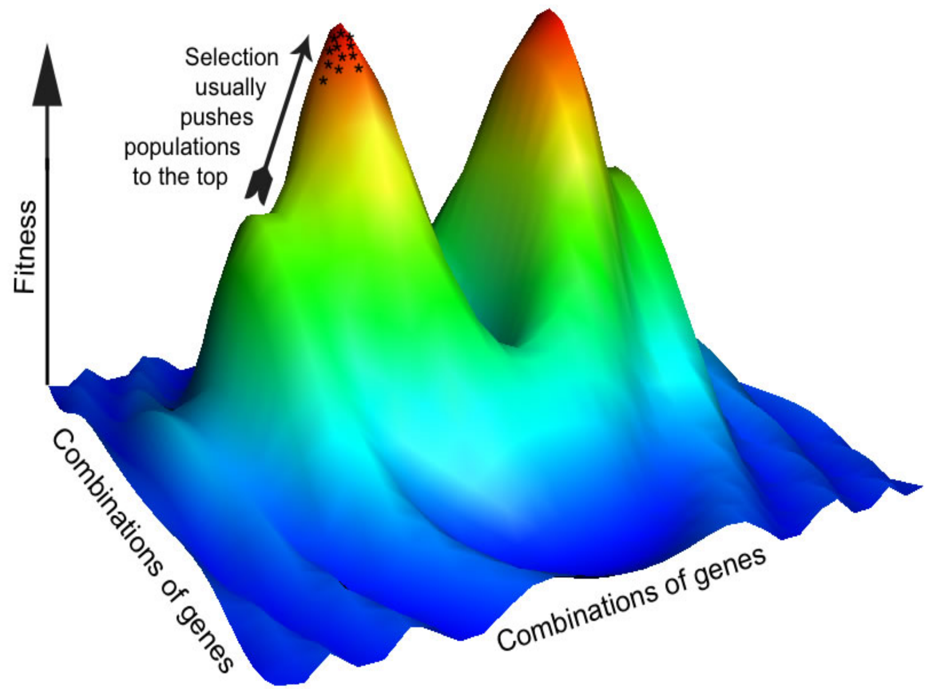
EC Metaphor III: Fitness Landscape

- **Consider:**
  n+1 dimensional gene space (*fitness landscape*);
  Vertical axis corresponds to fitness (Wright, 1932).

- **Individual (Genotype):**
  Composed of genes from different gene dimensions;

- **Genotype:**
  Represents a single point
  on the landscape.

- **Population:**
  Set of points moving across the
  landscape over evolutionary time.



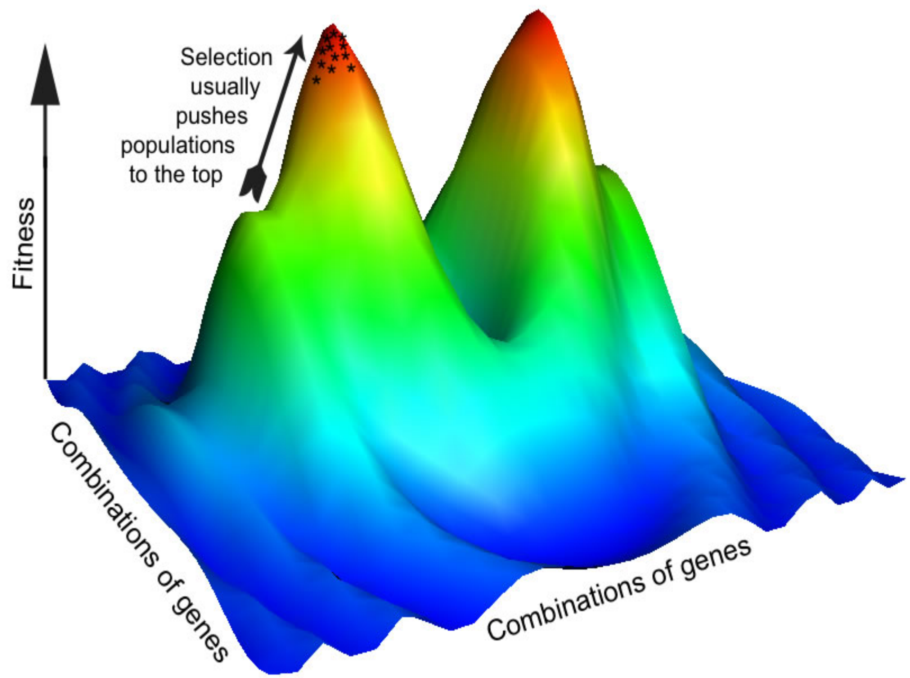
EC Metaphor III: Fitness Landscape

- **Genetic distance between individuals:**
  Determined by location of points.

- **Selection:**
  “Pushes” population up the fitness landscape.

- **Genetic drift:**
  Random variations in point set distribution (genotype population).

  Allows the population to jump out of “valleys” and off “low peaks” (local optima).



Brief History of EC Founders

1948: Turing proposes *genetical* (evolutionary) search.

1962: Bremermann publishes *optimization through evolution and recombination*.

1964: Rechenberg introduces *evolution strategies*.

1965: Fogel introduces *evolutionary programming*.

1975: Holland introduces *genetic algorithms*.

1992: Koza introduces *genetic programming*.

Different Types of EAs?

EA types have become defined by various genotype representations:

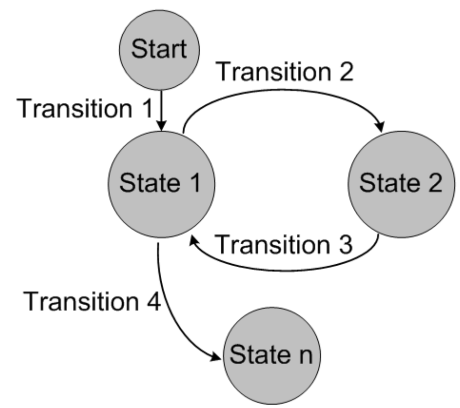
Binary strings: Genetic Algorithms (Holland, 1975).

$G = \{ 0, 1, 0, 0, 1, 1, 0, 1 \}$

Real-valued vectors: Evolution Strategies (Rechenberg, 1964).

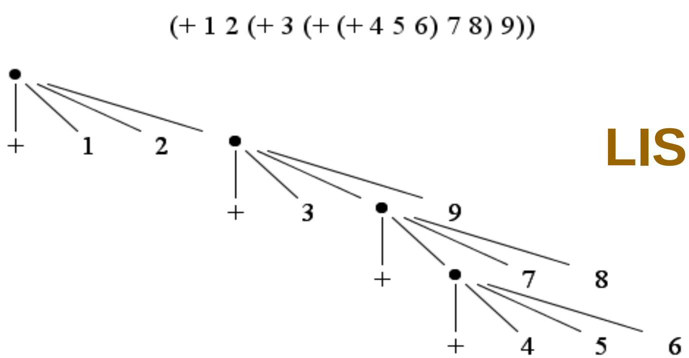
$G = \{ 3.05, 5.76, 8.53, 2.04, 0.59, 9.12, 3.86, 0.90 \}$

$G =$



Finite State Machines: Evolutionary Programming (Fogel *et al.* 1965).

$G =$

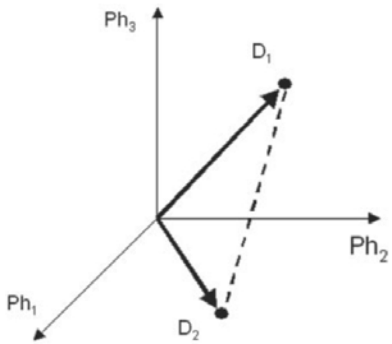


LISP trees: Genetic Programming (Koza, 1992).

Different Types of EAs?

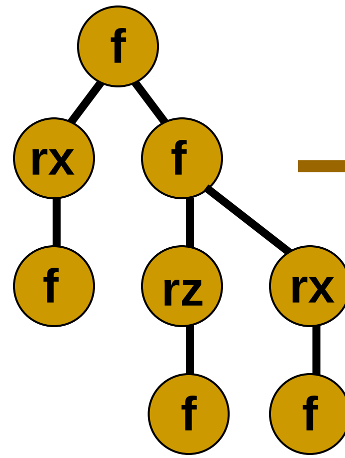
- Representational differences are largely irrelevant:
  - Select representation best suited to a given problem.
  - Select variation operators best suited to representation.
- Selection operators only use fitness:
  - Selection is independent of an EA's representation.

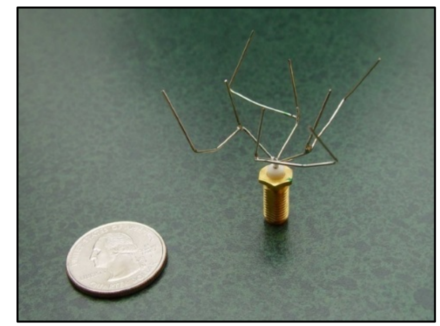
Representations



Candidate solutions (individuals) exist in *phenotype* space – Mapped from the *genotype* space.

Individuals are encoded as *genotypes* (existing in the *genotype* space):





Encoding: Phenotype → Genotype

(1 → N)

Decoding: Genotype → Phenotype

(1 → 1)

Representation =
Elements of genotype +
Genotype to phenotype mapping;

Genotypes: Composed of *Genes*. **Position on Genotype:** *Loci*. **Gene Value:** *Allele*.

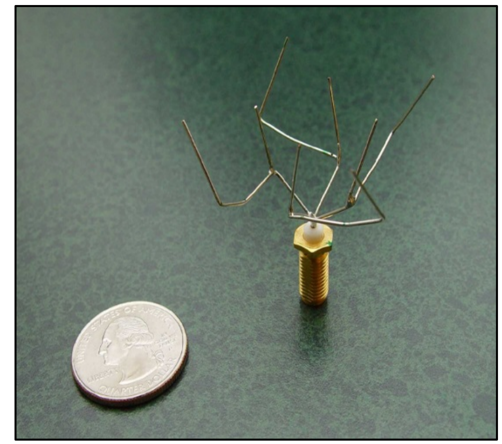
Human Design versus EC Design

NASA's Space Technology 5 (ST5) Mission – March 22, 2006: Three miniaturized satellites (*micro-sats*: ≈ 50cm across) measured the effects of solar activity on Earth's magnetosphere (Hornby *et al.* 2006).

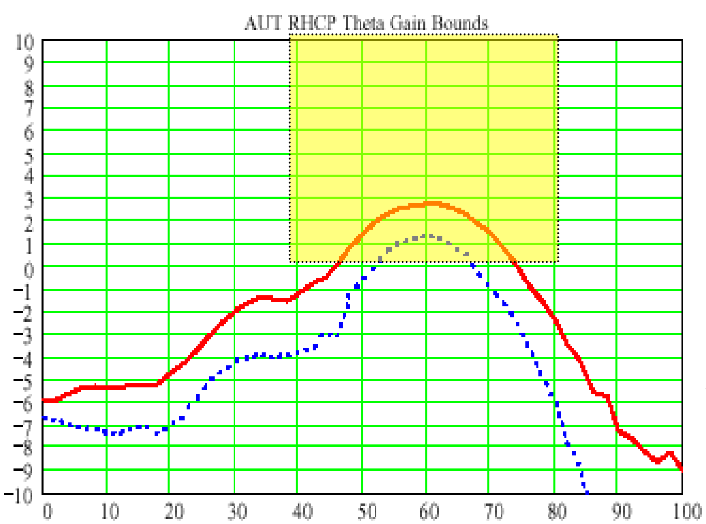
Human Design

Goal: Design an antenna to send data to a ground station. Specific communication and antenna shape and mass requirements.

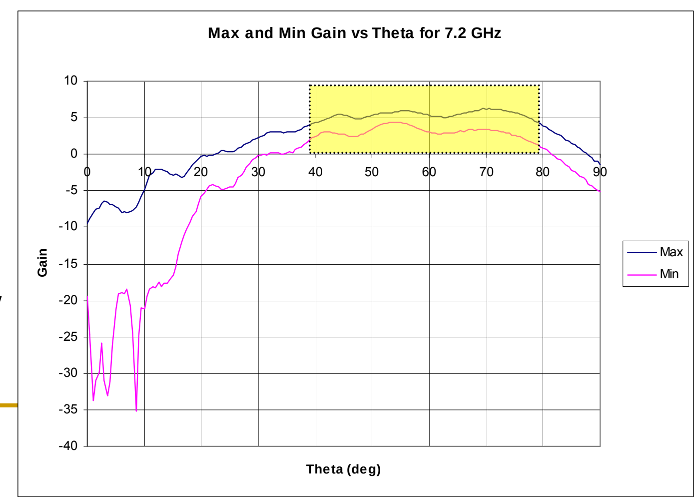
QHA (Quadrilar Helix Antenna): 38% efficiency was achieved, Evolved antenna: 93% efficiency.



Evolved Design

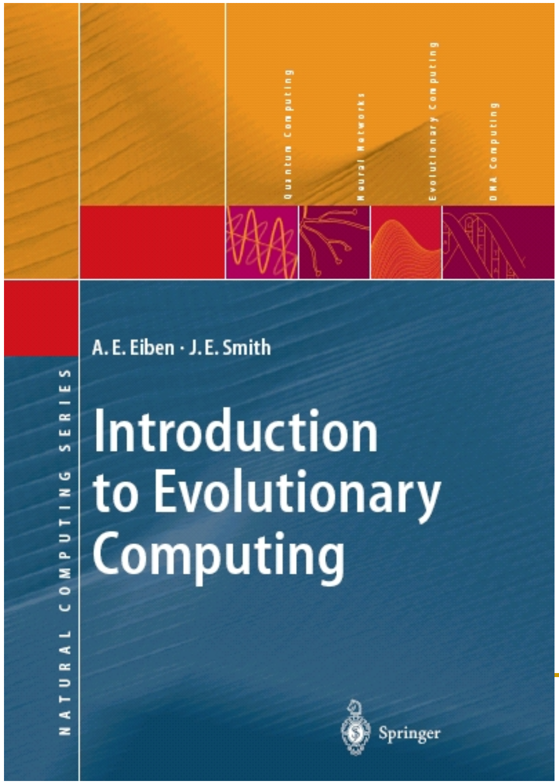


Faster Design Cycle: EA quickly redesigns novel antennae for new specifications.



Reading

- Hornby, G., Globus, A., Linden, D., and Lohn, J. (2006). Automated Antenna Design with Evolutionary Algorithms. In, *Proceedings of the 2006 AAIA Space Conference*, AAIA Press, San Jose, USA.
- Eiben, A. and Smith, J. (2003). Introduction to Evolutionary Computing: Introduction chapter.



Automated Antenna Design with Evolutionary Algorithms

Gregory S. Hornby
hornby@email.arc.nasa.gov
University of California Santa Cruz, Mailtop 269-3, NASA Ames Research Center, Moffett Field, CA

Al Globus
San Jose State University

Derek S. Linden
JEM Engineering, 8683 Cherry Lane, Laurel, Maryland 20707

Jason D. Lohn
NASA Ames Research Center, Mail Stop 269-1, Moffett Field, CA 94035

Whereas the current practice of designing antennas by hand is severely limited because it is both time and labor intensive and requires a significant amount of domain knowledge, evolutionary algorithms can be used to search the design space and automatically find novel antenna designs that are more effective than would otherwise be developed. Here we present automated antenna design and optimization methods based on evolutionary algorithms. We have evolved efficient antennas for a variety of aerospace applications and here we describe one proof-of-concept study and one project that produced flight antennas that flew on NASA's Space Technology 5 (ST5) mission.

I. Introduction

The current practice of designing and optimizing antennas by hand is limited in its ability to develop new and better antenna designs because it requires significant domain expertise and is both time and labor intensive. As an alternative, researchers have been investigating evolutionary antenna design and optimization since the early 1990s,[1–3] and the field has grown in recent years as computer speed has increased and electromagnetics simulators have improved. This techniques is based on evolutionary algorithms (EAs), a family stochastic search methods, inspired by natural biological evolution, that operate on a population of potential solutions using the principle of survival of the fittest to produce better and better approximations to a solution. Many antenna types have been investigated, including antenna arrays[4] and quadrifilar helical antennas.[5] In addition, evolutionary algorithms have been used to evolve antennas *in-situ*,[6] that is, taking into account the effects of surrounding structures, which is very difficult for antenna designers to do by hand due to the complexities of electromagnetic interactions. Most recently, we have used evolutionary algorithms to evolve an antenna for the three spacecraft in NASA's Space Technology 5 (ST5) mission[7] and are working on antennas for other upcoming NASA missions, such as one of the Tracking and Data Relay Satellites (TDRS). In the rest of this paper we will discuss our work on evolving antennas for both the ST5 and the TDRS missions.