Evolutionary Computing
Lecture 1
Introduction. Simple Genetic Algorithm

Danylo Tavrov

Outline

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Instructor

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  - 2019: Kyiv School of Economics, MA
  - 2022: University of California, Berkeley, MA in Economics
- Teaching at the Applied Mathematics Department since 2013 (with some breaks)
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- All materials are uploaded to a Github repository:
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  - Lecture slides
  - Literature, videos, and other useful stuff
- All lectures and one to one meetings are held in Zoom

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- We will have **three (four???)** lectures:
  - Introduction and basic facts about evolutionary algorithms
  - Genetic algorithms
  - Evolution strategies
  - Memetic algorithms (and some applications from personal experience)
- The idea of this small course is to help students analyze how evolutionary algorithms **can be used in their PhD theses**
- Therefore, instead of sections we will have **one to one** meetings, discussing specifics of everyone's work
- At the end of the class, each student will **present** his evolutionary algorithm
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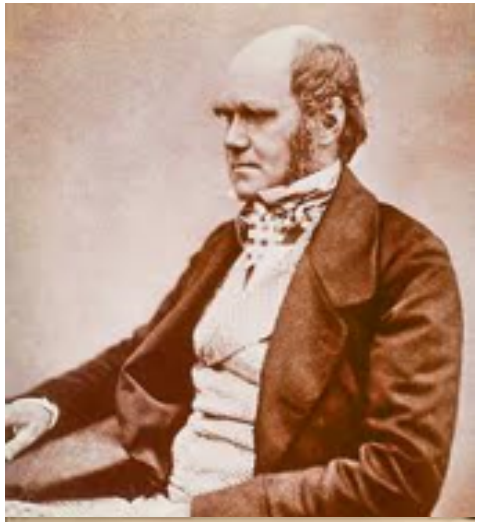
Theory of Evolution

- Evolution is the most fundamental theory in biology
- Many people don't understand evolution
- Evolutionary Computing is not a part of biology
- It only takes inspiration from the process of Darwinian evolution
- *Watch video*



ON

THE ORIGIN OF SPECIES

BY MEANS OF NATURAL SELECTION,

OR THE

PRESERVATION OF FAVOURED RACES IN THE STRUGGLE FOR LIFE.

By CHARLES DARWIN, M.A.,

LONDON:
JOHN MURRAY, ALBEMARLE STREET.
1859.

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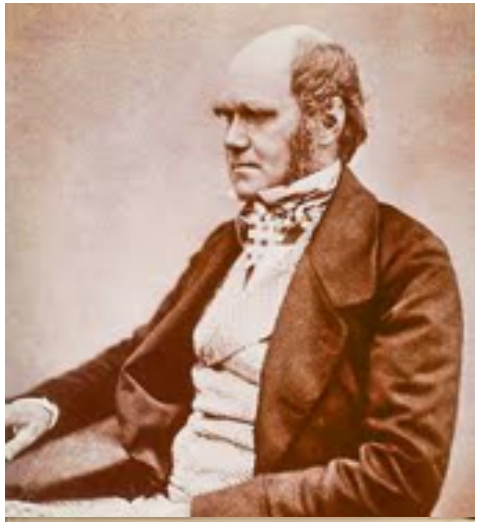

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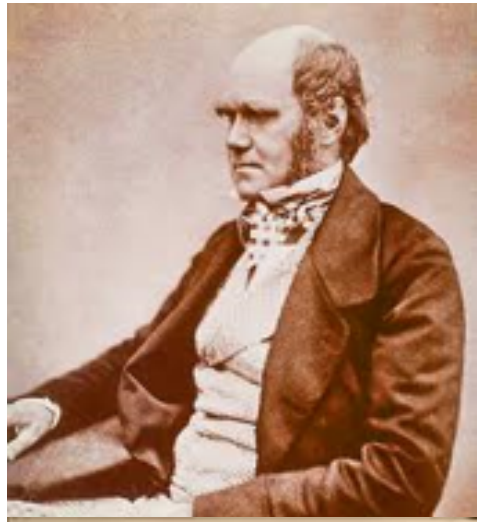

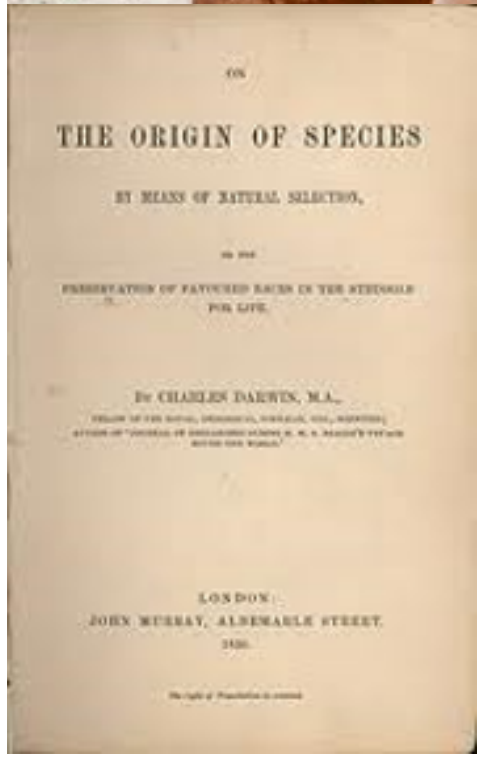

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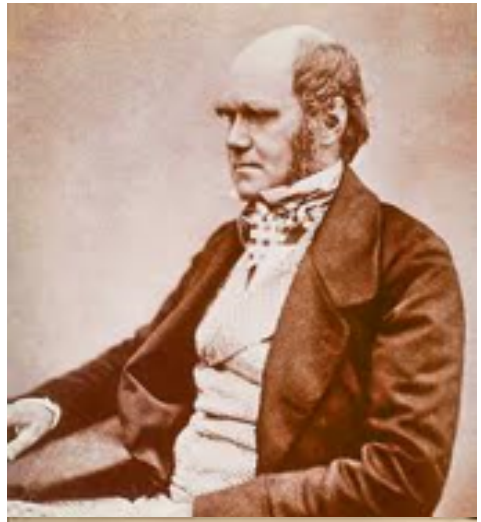

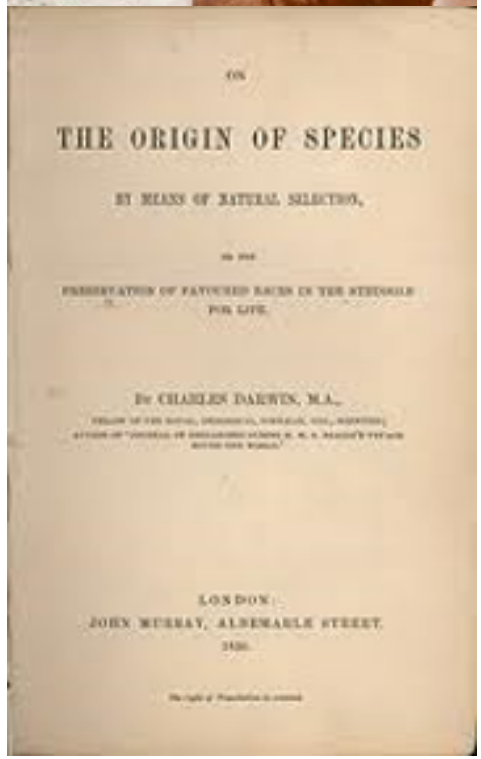
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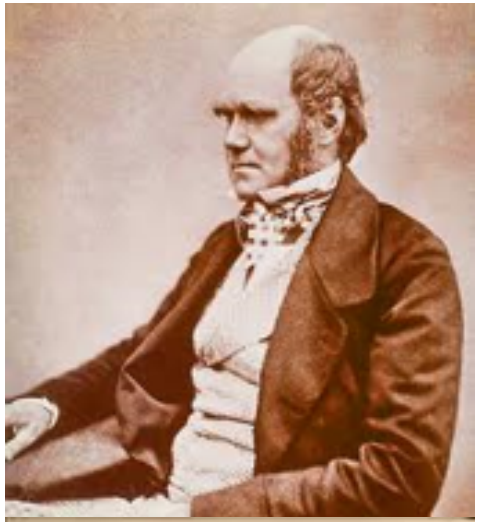


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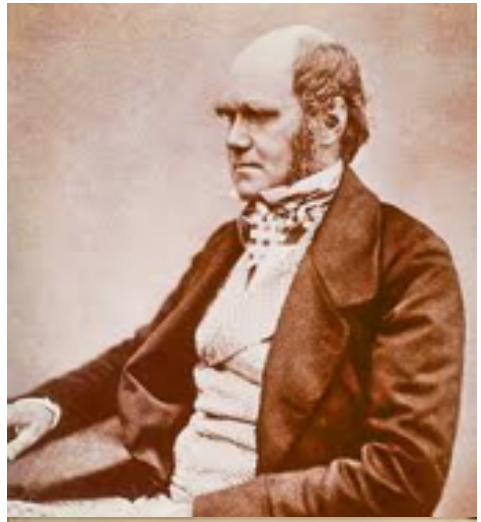

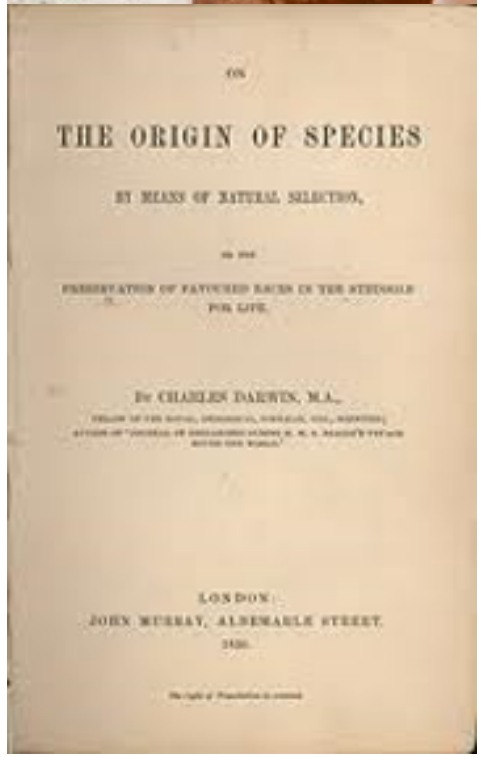
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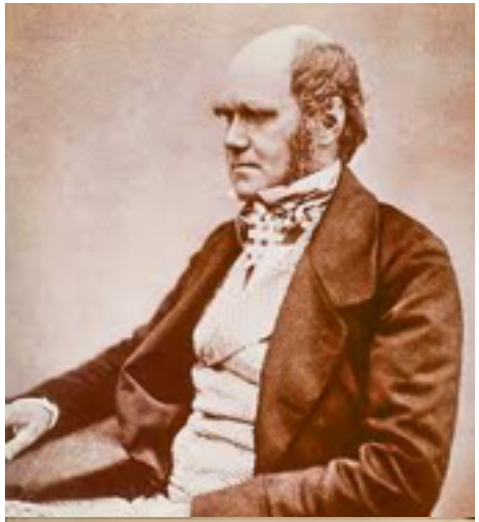


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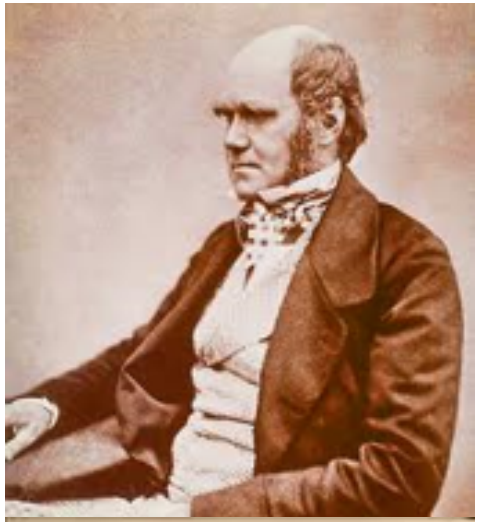


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Natural Selection

- All environments have finite resources, therefore some kind of **selection** is inevitable
- Those individuals that compete for the resources most effectively increase chance of reproduction
  - "Survival of the fittest," after Herbert Spencer, 1820–1903)
- Phenotypic traits can lead to higher chances of reproduction and can be inherited
- A **population** is a diverse set of **individuals**
- **Combinations of traits** that are better adapted (**fit**) tend to increase representation in population
- **Variations** occur through **random changes** during reproduction yielding constant source of diversity
- **Selective pressure** favors one trait over another

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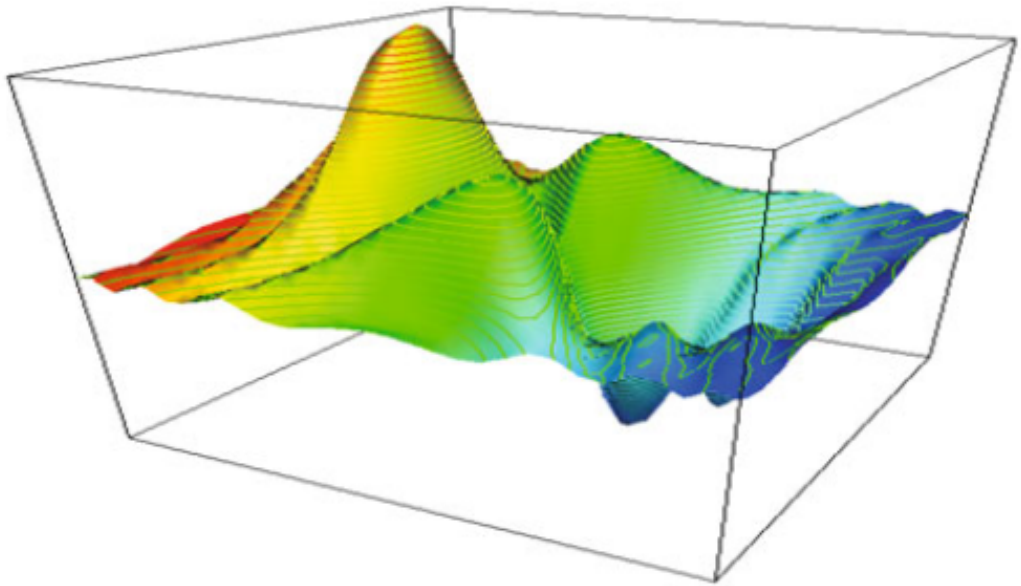
Fitness Landscape

- We can imagine a population with n traits as existing in a $(n+1)$-dimensional space (landscape)
  - With height corresponding to fitness of an individual
- Selection pushes the population up the landscape
- Eventually, the fitness of the whole population increases
- *Watch video*



Eiben, A.E., Smith, J.E.: Introduction to Evolutionary Computing. Springer-Verlag, Berlin, Heidelberg (2015), Fig. 2.2

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- We can imagine a population with n traits as existing in a $(n+1)$-dimensional space (landscape)
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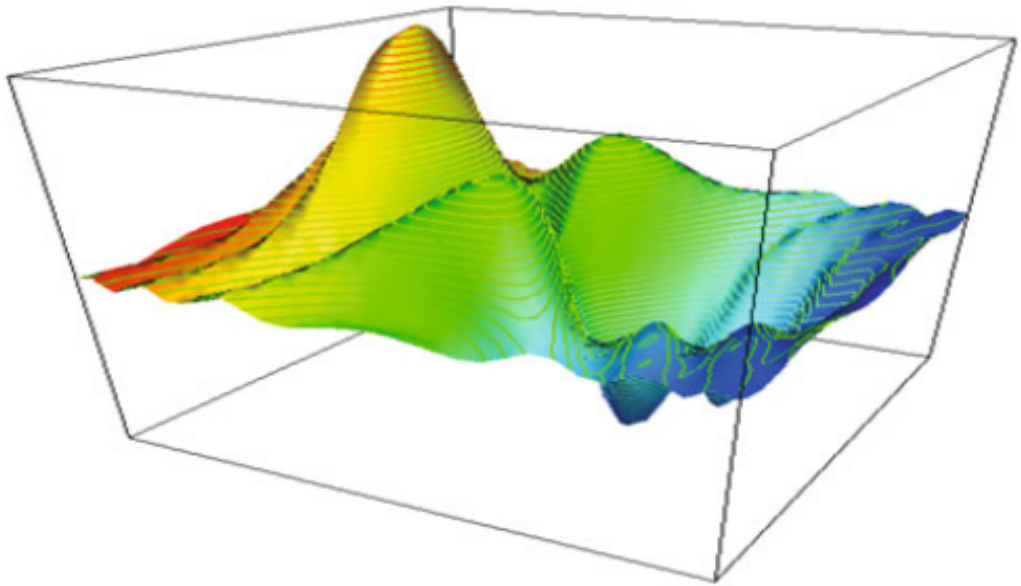

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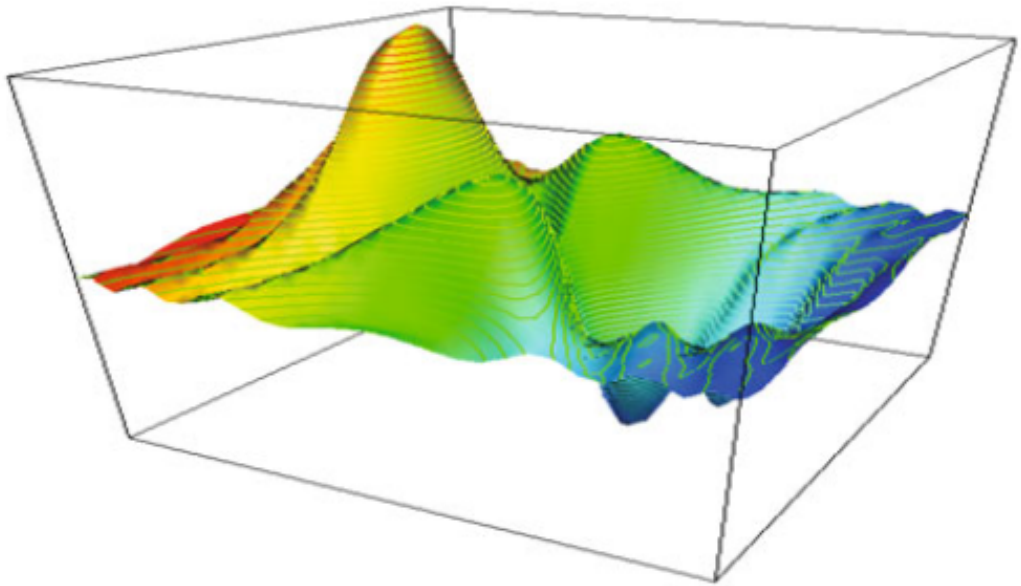

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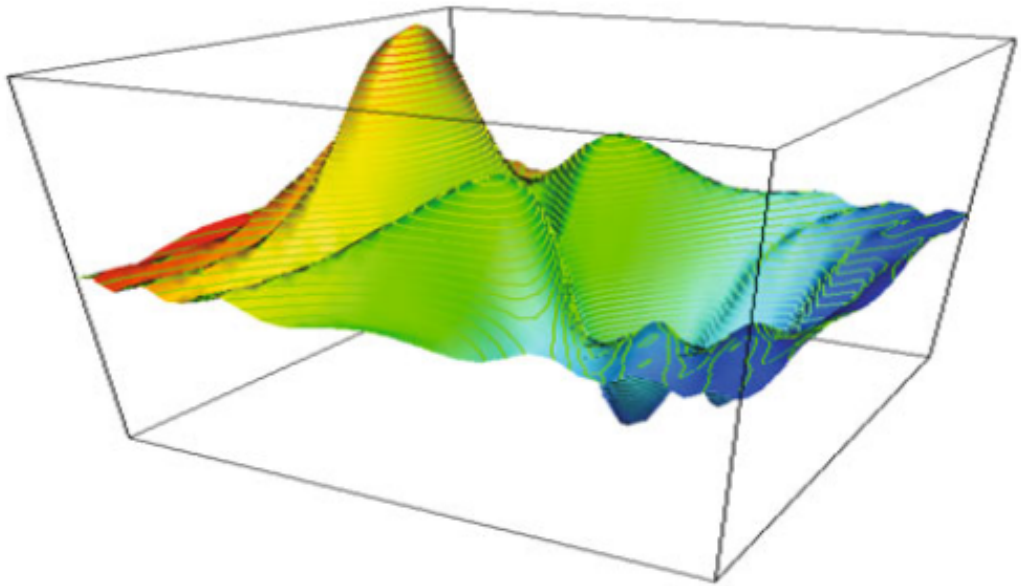

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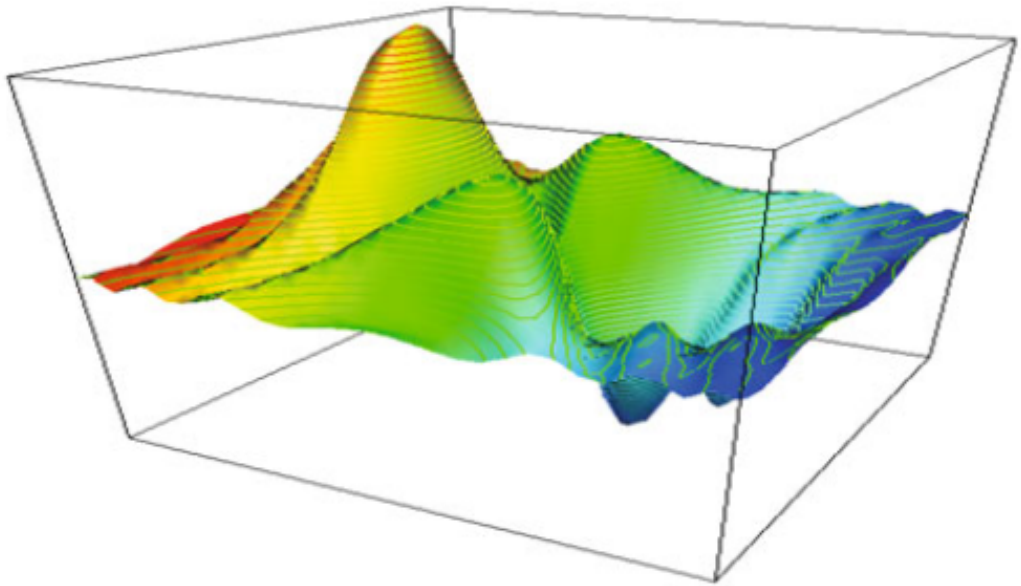

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Genetics and Reproduction

- Gametes (sperm and egg cells) contain 23 individual chromosomes (haploid cells)
- Gametes are formed by a special form of cell splitting called **meiosis**, during which the pairs of chromosome undergo **crossover**
  - Gametes are combined in a process called fertilization
  - New zygote rapidly divides creating many cells with the same genetic contents
  - Although all cells contain the same genes, they will behave differently (development)
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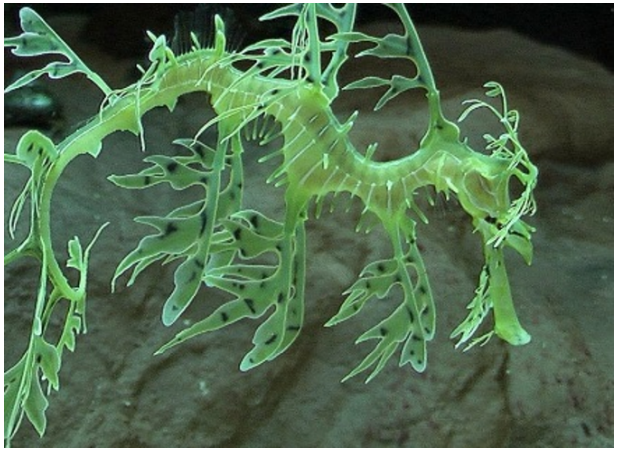
Some Interesting Examples



Phycodurus eques (leafy sea dragon)

Angraecum sesquipedale (Darwin's orchid) and *Xanthopan morganii* moth

Carausius morosus (stick insect)

Hemeroplanes Triptolemus ("snake caterpillar")

Evolution by Natural Selection Summary

- This is basically the accumulation in a population of heritable changes that allow the species to adapt to its environment
- Accumulation of changes is driven by selective pressure
- Combinations of traits that are better adapted tend to increase representation in population
- Most importantly, this is an **algorithmic process**
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- Evolutionary algorithms are **generate-and-test** algorithms
- We can map certain terminology from biology to computer science

Evolution	Problem Solving
Environment	Problem
Individual	Candidate solution
Fitness	Quality of a solution

- Candidate solutions (**individuals**) exist in a **phenotype** space
- They are enconded in **chromosomes**, which exist in a **genotype** space
- Chromosomes contain **genes**, which are located in (usually fixed) positions called **loci** (*sing. locus*) and have a value (**allele**)
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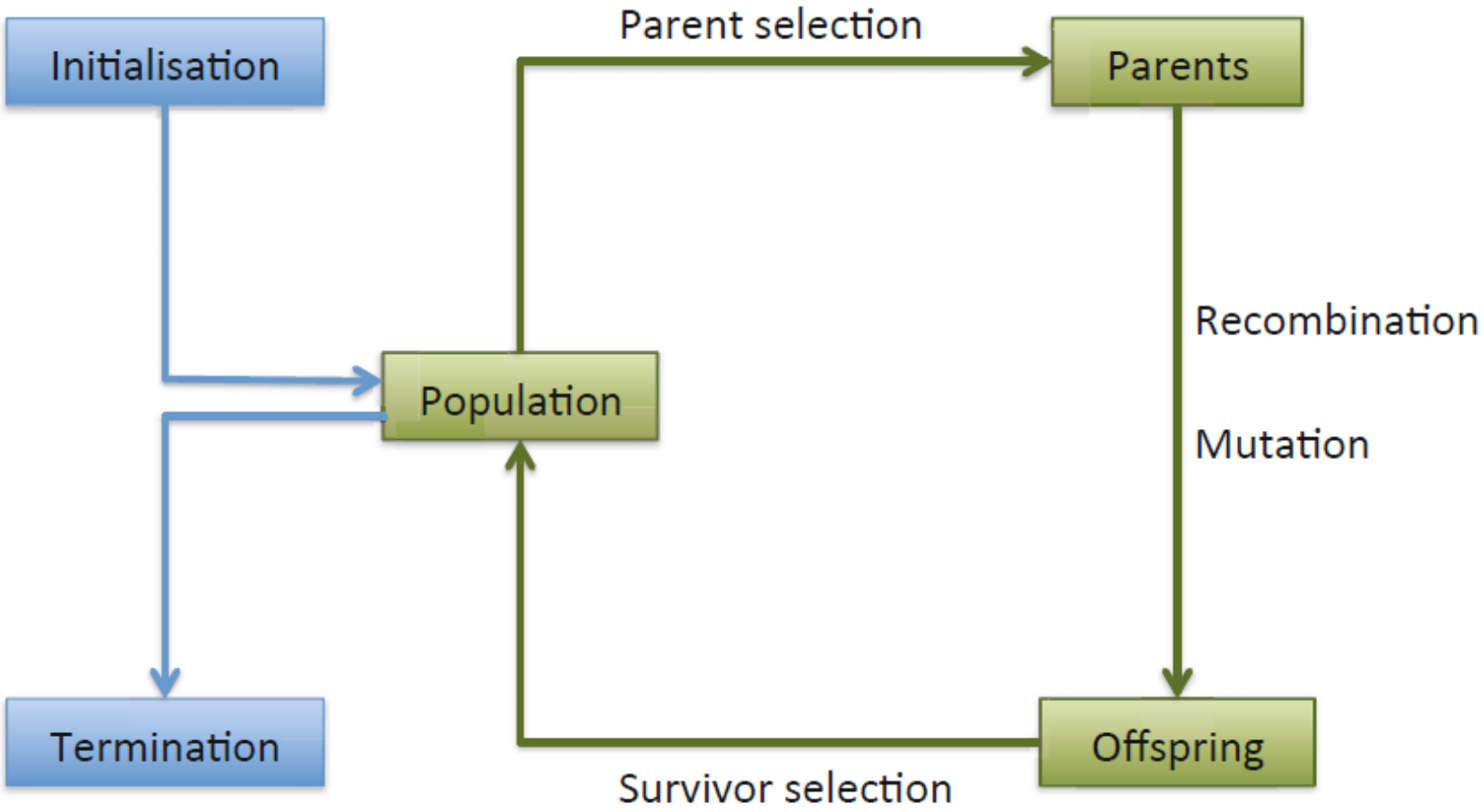

Eiben, A.E., Smith, J.E.: Introduction to Evolutionary Computing. Springer-Verlag, Berlin, Heidelberg (2015), Fig. 3.2

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  - The first population (usually populations are of fixed size) is filled with **randomly** generated individuals
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  - In some cases, initial population can contain existing solutions, or it can be filled with problem-specific heuristics
- **Evaluation** using a **fitness function**:
- **Parent selection**:
- **Recombination (crossover)**: merges information from parents into offspring thus creating diversity in population
- **Mutation**: (usually stochastically) acts on one genotype and delivers another
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- **Evaluation** using a **fitness function**:
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  - It assigns a single real-valued fitness to each phenotype
  - For example, if we want to minimize $f(x)$ we set just integers and we present each integer with binary code, then fitness of 10010 would be $18^2 = 324$
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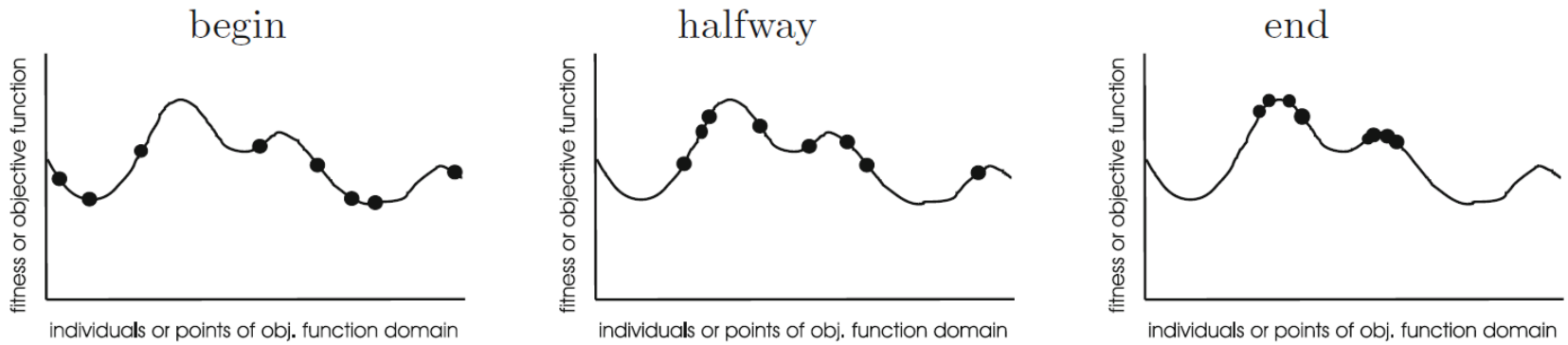
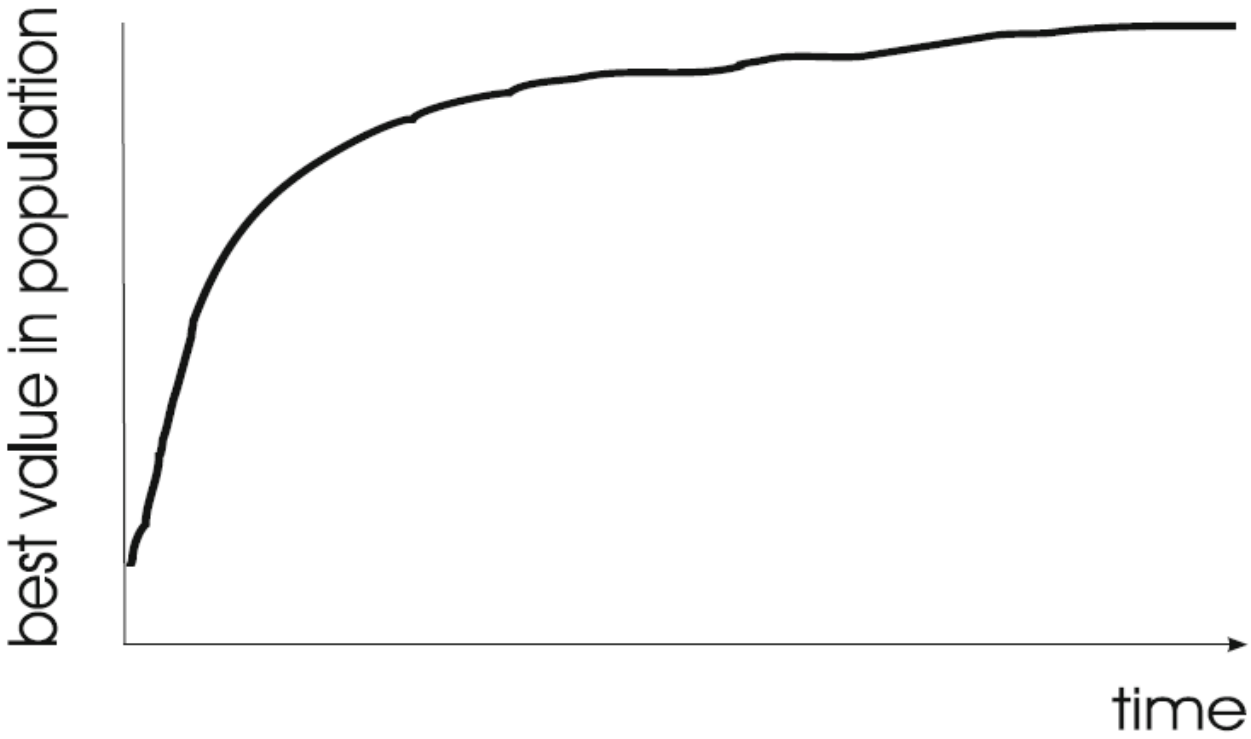


Eiben, A.E., Smith, J.E.: Introduction to Evolutionary Computing. Springer-Verlag, Berlin, Heidelberg (2015), Fig. 3.4

Anytime behavior of an EA



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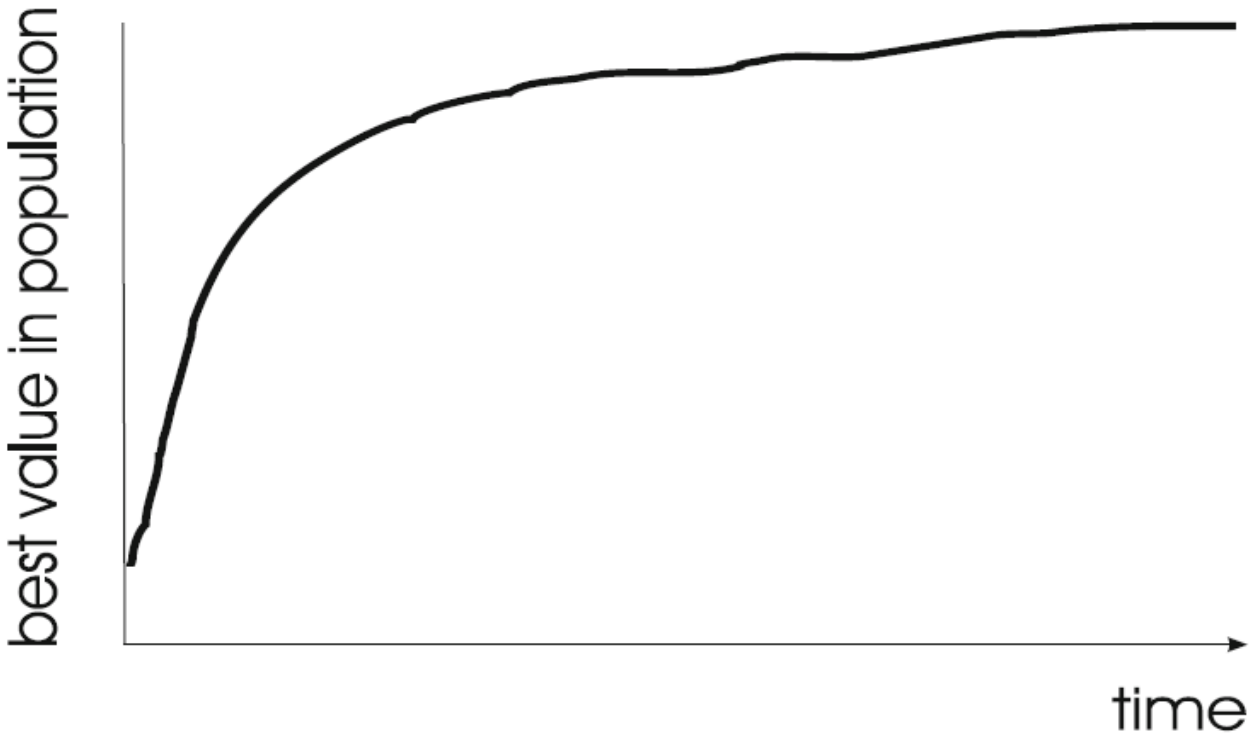

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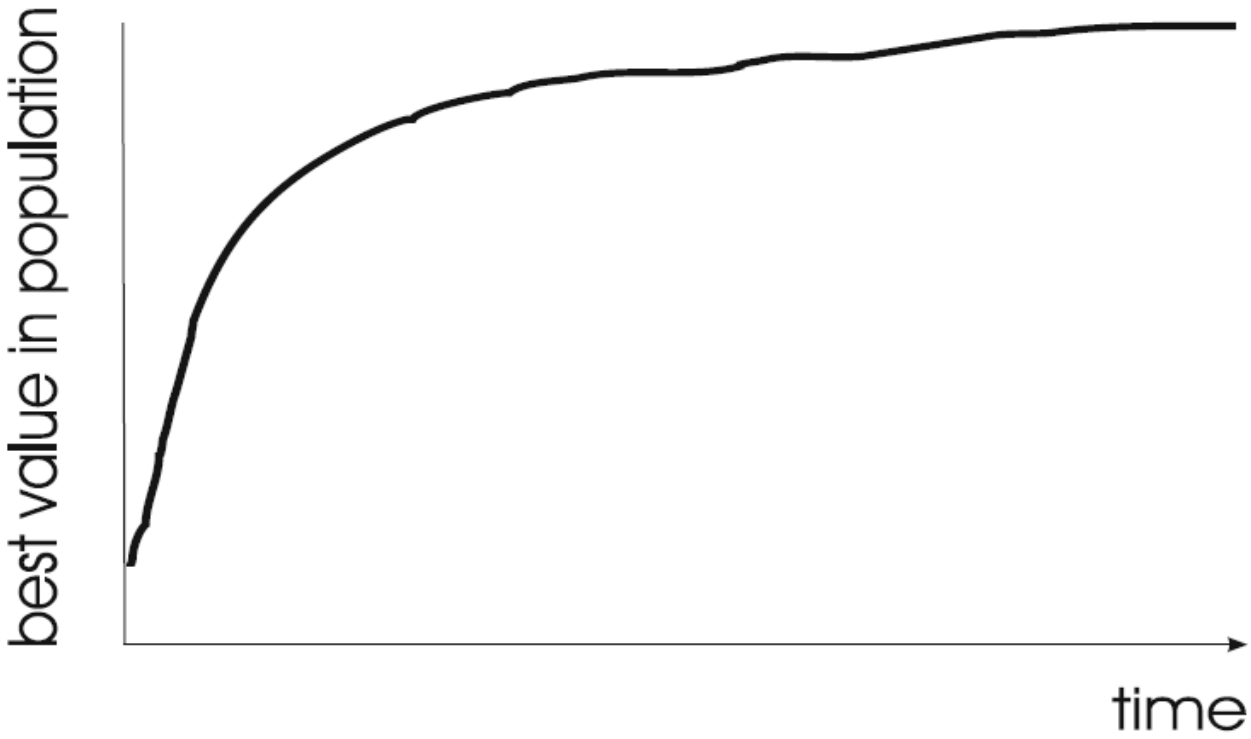

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Evolutionary Computing Can Generate New Solutions

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- The objective was to use an EA to design the geometry of the beam such that the vibrational noise does not travel through it
- Initially a flat two-dimensional beam was considered
- A genetic algorithm was used:

- Improvement was about 3 decades of performance (several thousands of percent!)
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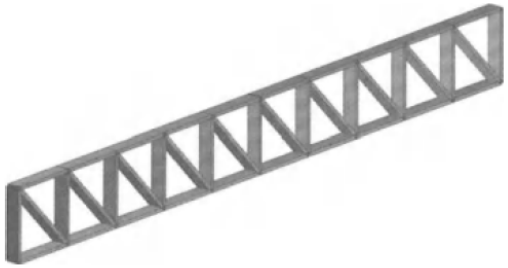

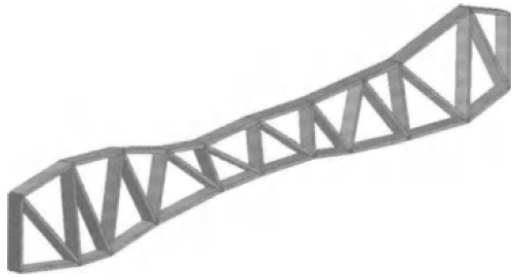

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- *Watch video*

Evolutionary Computing Can Generate New Solutions

Keane, A.: An Introduction to Evolutionary Computing in Design Search and Optimisation. In: Kallel, L., Naudts, B., Rogers, A. (eds.). Theoretical Aspects of Evolutionary Computing. Natural Computing Series. Springer, Berlin, Heidelberg (2001), Figs. 3–4

- Constructing a boom in space: they have severe vibration problems (no air to provide damping)
- The objective was to use an EA to design the geometry of the beam such that the vibrational noise does not travel through it
- Initially a flat two-dimensional beam was considered
- A genetic algorithm was used:
  - Population size of 300
  - Was run for 15 generations
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Evolutionary Algorithms Vs. Other Techniques

- Can work with a **coding** of a parameter set, not the parameters **themselves**
- Search from a **population of points**, not a single point
- Use **payoff** information, not derivatives or other auxiliary knowledge
- Use **stochastic** transition rules, not deterministic ones
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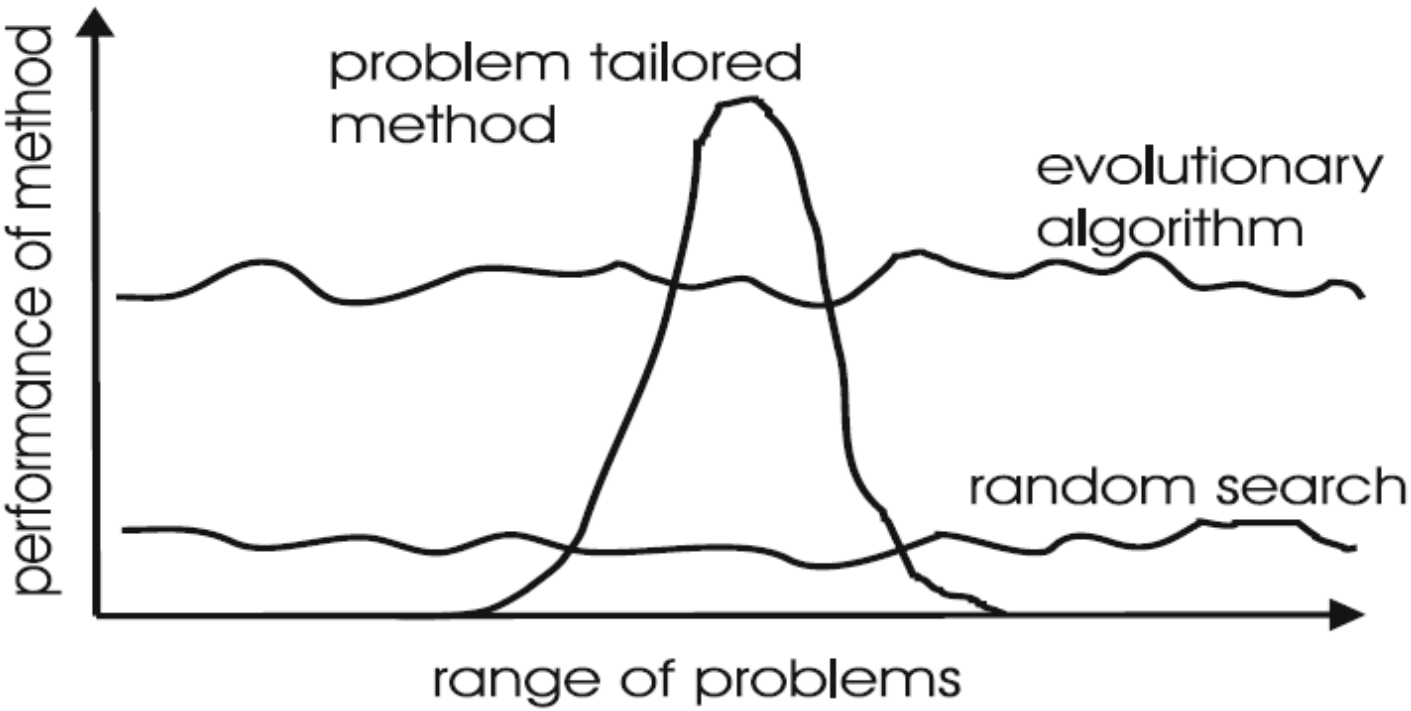

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- EAs are applicable to big search spaces, not unimodal, not smooth
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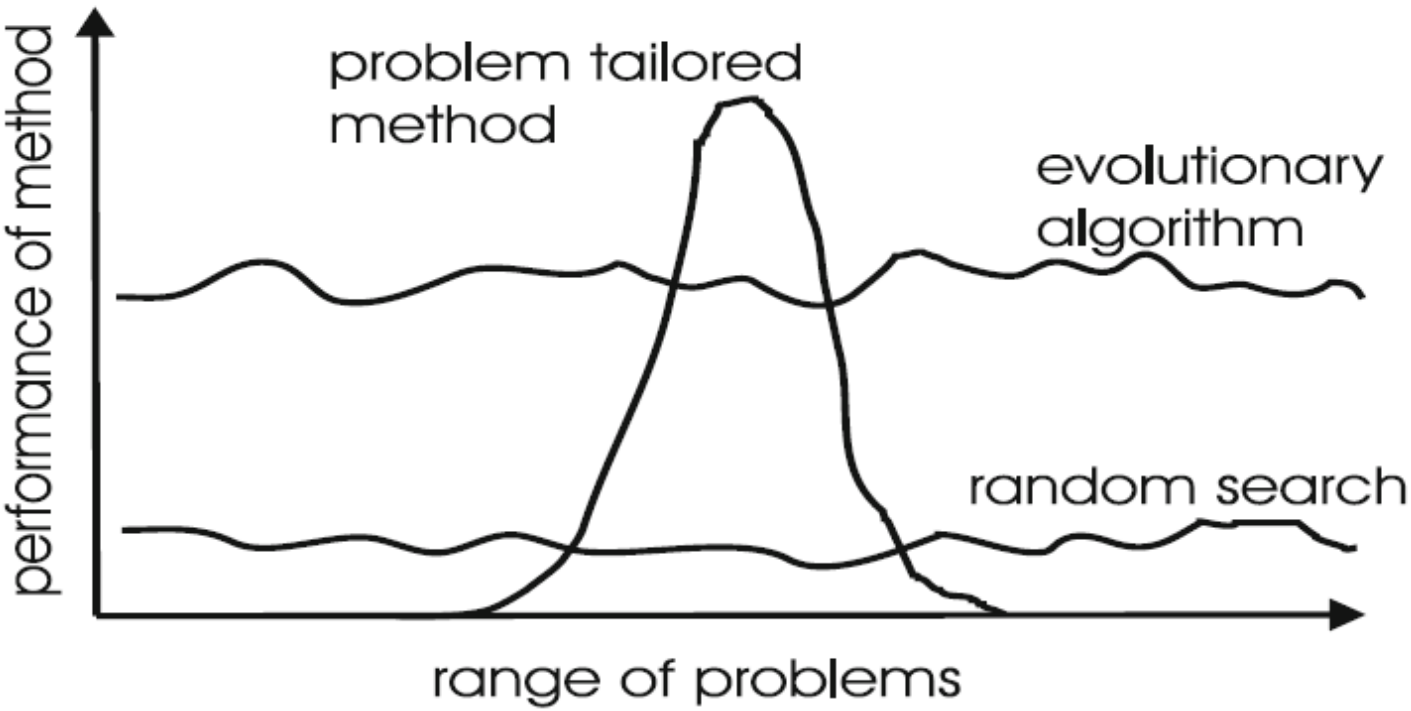

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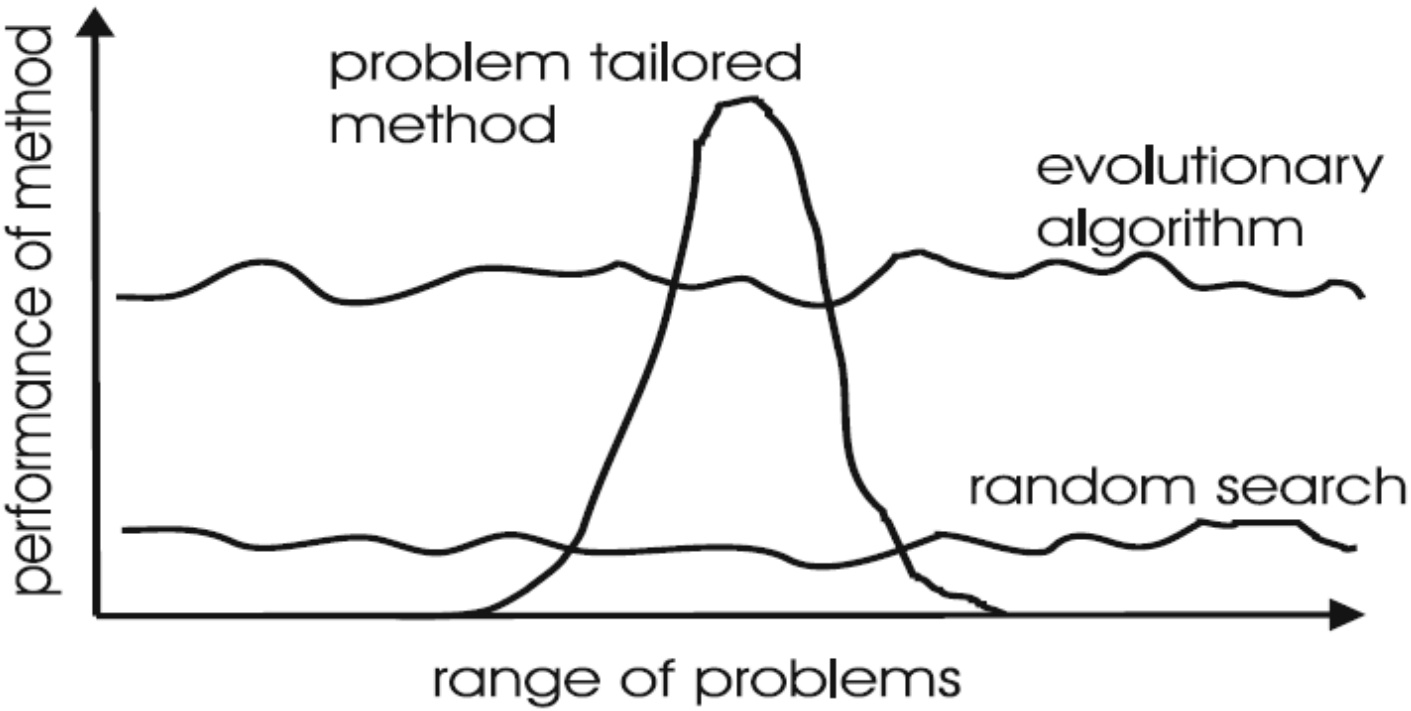

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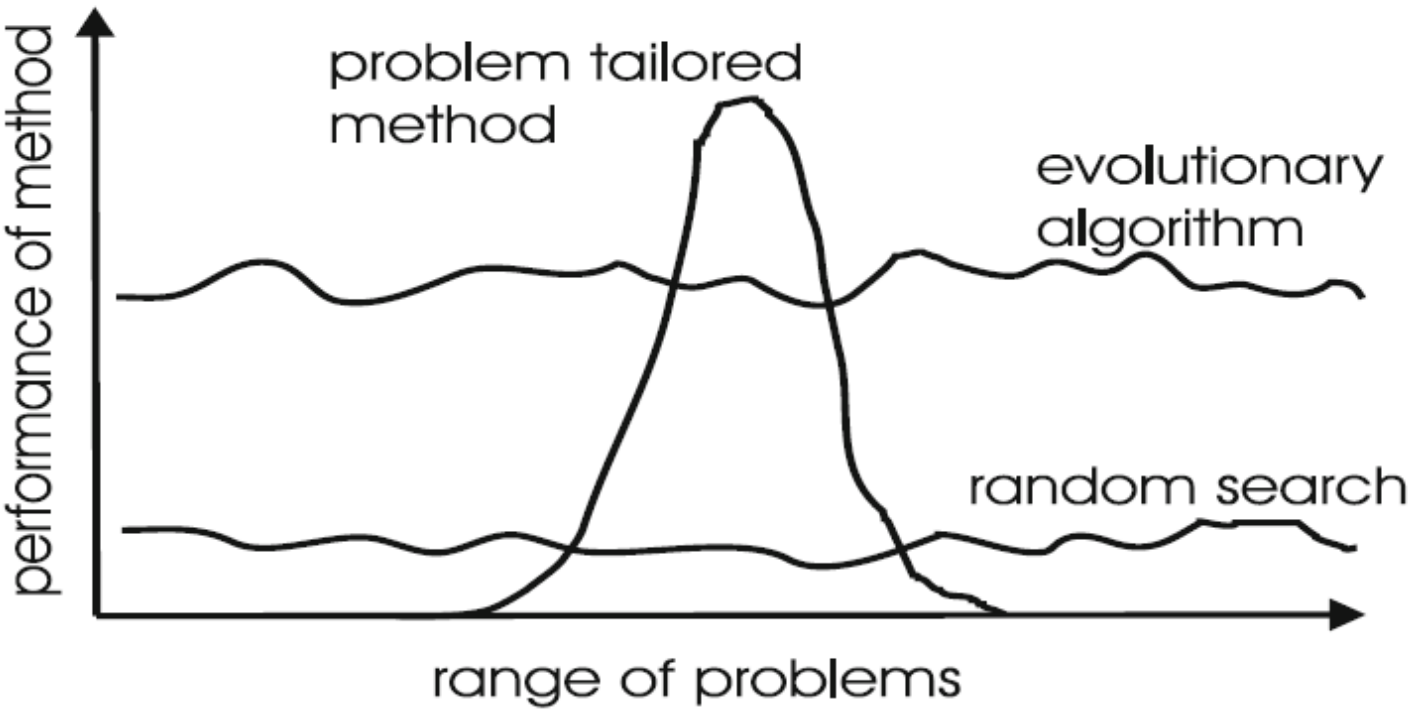

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Different Types of EAs

- Historically, different EAs have been associated with different representations
- Strings over a finite alphabet: **genetic algorithms** (Holland, 1975)
- Real-valued vectors: **evolution strategies** (Rechenberg, 1964)
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Further Reading

- Evolutionary Computing Books:
  - Eiben, A.E., Smith, J.E.: Introduction to Evolutionary Computing. Springer-Verlag, Berlin, Heidelberg (2015). Chapters 1–3
  - Goldberg, D.E.: Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley Professional (1989). Chapter 1
  - Baeck, T., Fogel, D.B., Michalewicz, Z.: Evolutionary Computation 1. Basic Algorithms and Operators. Taylor & Francis Group LLC (2000). Chapters 1–7
- Popular Science Books:
  - Dawkins, R.: The Selfish Gene. Oxford University Press, Oxford, New York (2006)
  - Dawkins, R.: The Blind Watchmaker. Longmans, London (1986)
  - Dennett, D.C.: Darwin's Dangerous Idea: Evolution and the Meanings of Life. Simon & Schuster (1996)

Outline

Writing an Evolutionary Algorithm

- To implement an evolutionary algorithm **for a specific problem**, it is necessary to make a number of choices:
  - Representation and fitness function
  - Type of crossover applicable to selected representation
  - Type of mutation applicable to selected representation
  - Population model
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Crossover in SGA

- **One-point (simple) crossover**:
  1. Choose a random integer in $[1; l-1]$
  2. Split the parents at this point
  3. Create children by exchanging the tails

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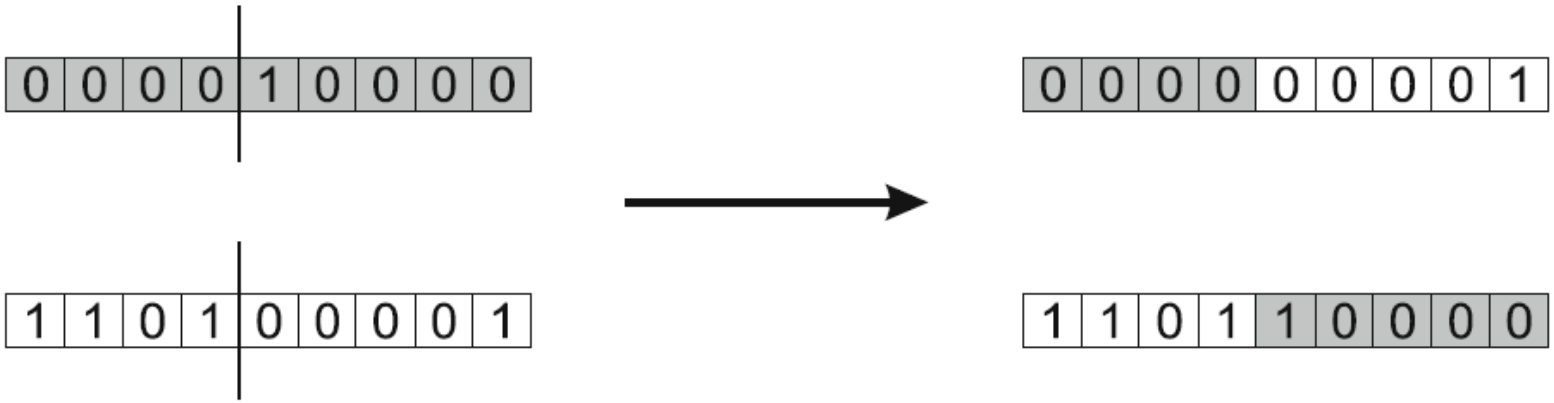

Eiben, A.E., Smith, J.E.: Introduction to Evolutionary Computing. Springer-Verlag, Berlin, Heidelberg (2015), Fig. 4.2

Mutation in SGA

- **Bit-flipping mutation**: flip each gene independently with a *small* probability p_m

Eiben, A.E., Smith, J.E.: Introduction to Evolutionary Computing. Springer-Verlag, Berlin, Heidelberg (2015), Fig. 4.1

Population Models in GA

- There are two basic population models in evolutionary algorithms
- The **generational model**:
  - In each generation, we begin with a population of size μ.
  - We select $\lambda = \mu$ parents.
  - We generate the offspring from this mating pool by means of mutation operators.
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- The **steady-state model**:
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Selection in SGA

- In SGA, we use **fitness proportionate selection**
- The probability that individual x_i, $i = 1, \ldots, \mu$, will be selected as a parent is given by

$$p_{x_i} = \frac{f(x_i)}{\sum_{j=1}^{\mu} f(x_j)}$$

- Here, $f(x_i)$ is the fitness of individual x_i
- All fitness values are assumed to be non-negative
- Implementation is done using a *Stochastic Universal Sampling* algorithm[2]:

2. Baker, J.E.: Reducing bias and inefficiency in the selection algorithm. In: Grefenstette, J.J. (ed.) Proceedings of the 2nd International Conference on Genetic Algorithms and Their Applications, pp. 14–21. Lawrence Erlbaum, Hillsdale, New Jersey (1987)

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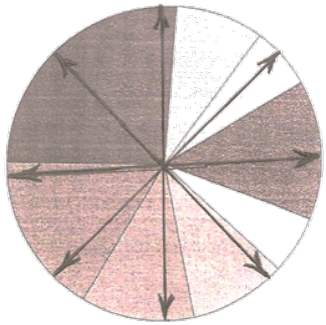

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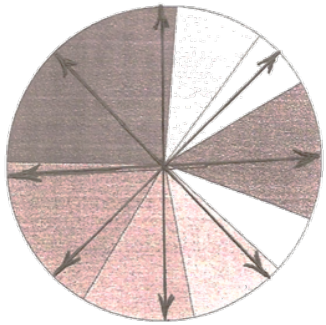

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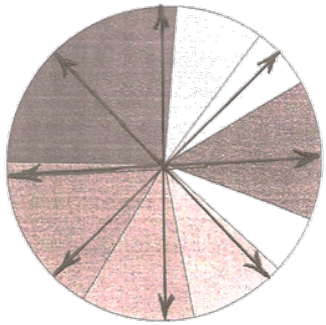

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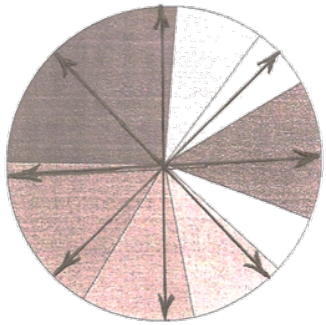

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Role of Selection, Crossover, and Mutation

- Individual strings in the population can be compared to **ideas**, and their substrings can be compared to **notions**[4]
- Then, Then, genetic algorithms exploit these ideas by:
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Computer Simulation of SGA

Simple Genetic Algorithm Jupyter Notebook, section 1

Premature Convergence

- What we see in the harder version of the problem is *premature convergence*
- There are two main reasons for why it occurs[5]
- At the beginning, it is common to have a few extraordinary individuals in a population of mediocre colleagues
- Such individuals quickly take over the population
- But later on in the run, the population *average* fitness may be close to the population *best* fitness
- And so average individuals and very good individuals get *nearly the same number of offspring*

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Fitness scaling

- To overcome these difficulties, **fitness scaling** is commonly used
- We will focus on *one* way of doing this called **linear fitness scaling**
- We apply linear transformation to fitness function $f(x)$ to get $g(x)$ as follows:

$$g(x) = af(x) + b$$

- Coefficients a and b have to satisfy the following constraints:

$$\frac{1}{\mu}\sum_{i=1}^{\mu} g(x_i) = \frac{1}{\mu}\sum_{i=1}^{\mu} f(x_i)$$

$$\max_{i=1,\ldots,\mu} g(x_i) = C_m \max_{i=1,\ldots,\mu} f(x_i)$$

- In practice, it is suggested[6] to use $C_m \in [1.2; 2.0]$
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$$\frac{1}{\mu}\sum_{i=1}^{\mu} g(x_i) = \frac{1}{\mu}\sum_{i=1}^{\mu} f(x_i)$$

$$\max_{i=1,\ldots,\mu} g(x_i) = C_m \max_{i=1,\ldots,\mu} f(x_i)$$

- In practice, it is suggested[6] to use $C_m \in [1.2; 2.0]$
- If, however, application of this formula leads to negative fitness values, the following two conditions need to be satisfied:

$$\frac{1}{\mu}\sum_{i=1}^{\mu} g(x_i) = \frac{1}{\mu}\sum_{i=1}^{\mu} f(x_i)$$

$$\min_{i=1,\ldots,\mu} g(x_i) = 0$$

6. Goldberg, D.E.: Genetic Algorithms in Search, Optimization, and Machine Learning. Addison Wesley Professional (1989)

Fitness scaling

- To overcome these difficulties, **fitness scaling** is commonly used
- We will focus on *one* way of doing this called **linear fitness scaling**
- We apply linear transformation to fitness function $f(x)$ to get $g(x)$ as follows:

$$g(x) = af(x) + b$$

- Coefficients a and b have to satisfy the following constraints:

$$\frac{1}{\mu}\sum_{i=1}^{\mu} g(x_i) = \frac{1}{\mu}\sum_{i=1}^{\mu} f(x_i)$$

$$\max_{i=1,\ldots,\mu} g(x_i) = C_m \max_{i=1,\ldots,\mu} f(x_i)$$

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Computer Simulation of SGA

Simple Genetic Algorithm Jupyter Notebook, section 2