Evolutionar
y
Computing
The Inspiration from Biology

- **Darwinian Evolution**
- Given an environment that can host only a **limited number of individuals**, and the basic instinct of individuals to **reproduce, selection** becomes inevitable if the population size is not to grow exponentially.
- **Natural selection** favors those individuals that compete for the given resources most effectively, in other words,

those that are adapted or fit to the environmental conditions best.

- This phenomenon is also known as **survival of the fittest**.

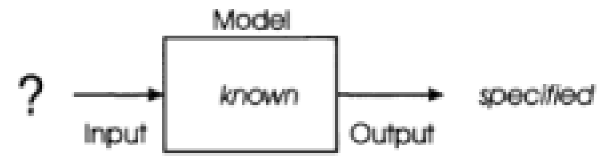
Evolutionary Computing: Why?

- Developing **automated problem solvers** (that is, algorithms) is one of the central themes of mathematics and computer science.

• Nature's solutions has always been a source of inspiration, copying "**natural problem solvers**" • The most powerful natural problem solver, there

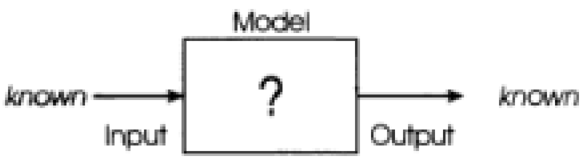
are two rather straight forward candidates: – **The human brain**-neurocomputing
– **The evolutionary process**-evolutionary computing

Evolutionary Computing: Why? 1.

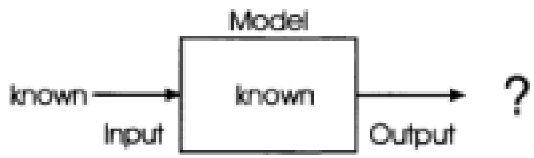
Optimization problems 

2.

Modeling or system identification problem



3. Simulation problem

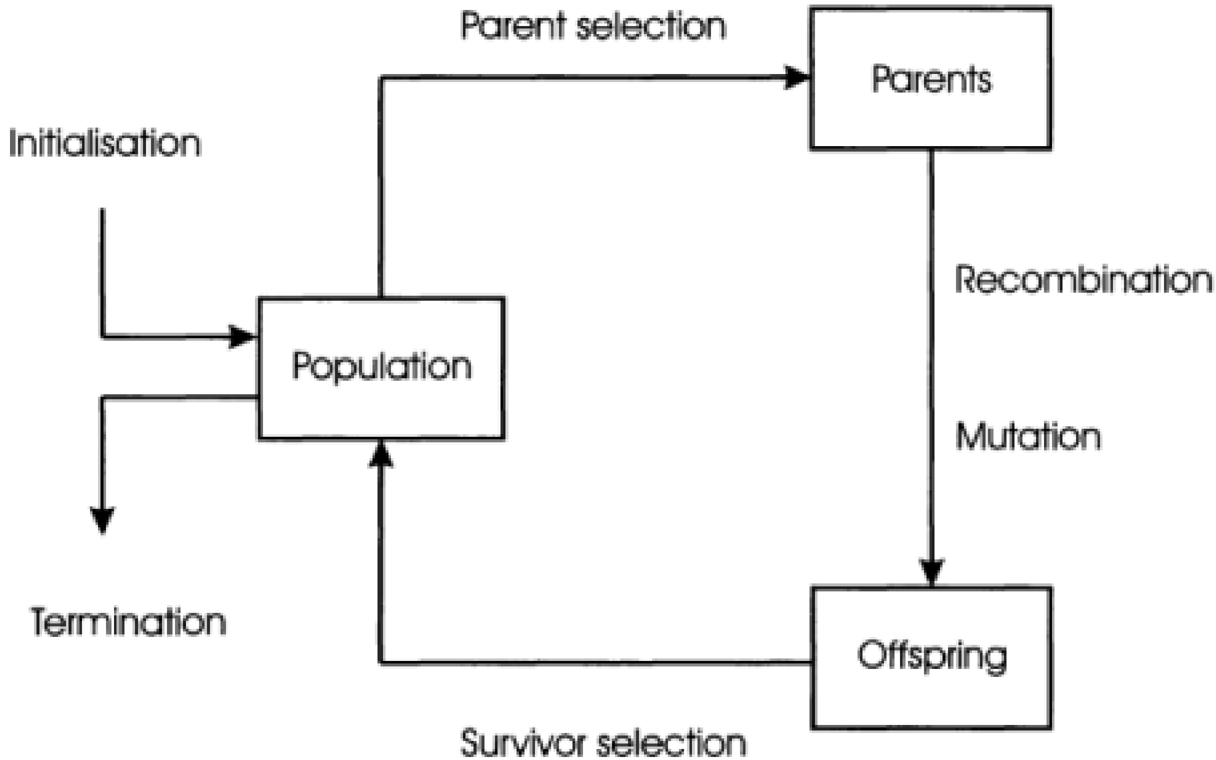


What is an Evolutionary Algorithm?

- There are many different variants of evolutionary algorithms. The common underlying idea behind all these techniques is the same:

1. Given a **population of individuals**
2. The environmental pressure causes **natural selection (survival of the fittest)**, which causes a rise in the fitness of the population.

What is an Evolutionary Algorithm?



What is an Evolutionary Algorithm?

```
BEGIN
  INITIALISE population with random candidate solutions;
  EVALUATE each candidate;
  REPEAT UNTIL ( TERMINATION CONDITION is satisfied ) DO
    1 SELECT parents;
    2 RECOMBINE pairs of parents;
    3 MUTATE the resulting offspring;
    4 EVALUATE new candidates;
    5 SELECT individuals for the next generation;
  OD
END
```

Properties of Evolutionary Algorithm

- EAs are **population based**, i.e., they process a whole collection of candidate solutions simultaneously.

- EAs mostly use **recombination** to mix information of more candidate solutions into a new one.

- EAs are **stochastic**.
  - Having a random probability distribution or pattern that may be analyzed statistically but **may not be predicted precisely**.

Components of Evolutionary Algorithms

1. Representation (definition of individuals)

2. Evaluation function (or fitness function)

3. Population

4. Parent selection mechanism

5. Variation operators, recombination and mutation

6. Survivor selection mechanism (replacement)

Representation (Definition of Individuals)

- The first step in defining an EA is to link the "real world" to the "EA world“.

- **Phenotypes** - Objects forming possible solutions within the original problem context.
- **Genotypes** - Objects encoding, that is, the individuals within the EA.

- **Representation**
  - Specifying a **mapping** from the phenotypes onto a set of genotypes that are said to represent these phenotypes.
  - In case of set of integers, **18** would be seen as a phenotype, and **10010** as a genotype.

Evaluation Function (Fitness Function)

- It is a **function or procedure** that assigns a **quality measure** to genotypes.

- To **maximize square(*x*)** fitness of the genotype **10010** could be defined as the square of its corresponding phenotype: **Square(18)=324**.
- Also called **objective function.**

Population

- The role of the population is to hold (the representation of) **possible solutions**.
- A population is a **multiset** of genotypes.
- Defining a population can be as simple as specifying how many individuals are in it, that is, setting the **population**

size.

- **Best individual** of the given population is chosen to seed the **next generation**, or the **worst individual** of the given population is chosen to be **replaced by a new one**.
- The **diversity** of a population is a **measure of the number of different solutions** present.

Parent Selection Mechanism

- The role of **parent selection or mating selection is to distinguish among** individuals based on their quality, in particular, to allow the better individuals to become parents of the next generation.
- An individual is a **parent if it has been selected** to undergo variation in order to create offspring. •

High-quality individuals get a **higher chance** to become parents than those with low quality. • Nevertheless, low-quality individuals are often given a small, but positive chance; otherwise the whole search could become too greedy and **get stuck in a local optimum**.

Variation Operators

- The role of **variation operators is to create new individuals from old ones**.

- **Mutation**

- **Recombination**

Mutation

- A **unary variation** operator is commonly called mutation.
- It is applied to **one genotype and delivers a (slightly) modified mutant**, the child or offspring of it.

Recombination

- A **binary variation** operator is called recombination or crossover.

- As the names indicate, such an **operator merges information from two parent genotypes into one** or two offspring genotypes.

Survivor Selection Mechanism (Replacement)

- The role of survivor selection or environmental selection is to **distinguish among individuals based on their quality**.
- **Survivor selection** is also often called **replacement or replacement strategy**.

Initialization

- Initialization is kept simple in most EA applications: The first population is seeded by **randomly generated** individuals.
- In principle, problem specific heuristics can be used in this step aiming at an **initial population with higher fitness**.

Termination Condition

- If the problem has a **known optimal fitness level**, probably coming from a known optimum of the given objective function, then reaching this level (perhaps only with a given precision **E > 0**) should be used as stopping condition.

- The **maximally allowed CPU time elapses**. • The **total number of fitness evaluations reaches a given limit**.
- For a given period of time (i.e, **for a number of generations or fitness evaluations**), the fitness improvement remains under a threshold value.
- The population **diversity drops under a given threshold**.

The Eight-Queens Problem

- Our candidate solutions are complete, rather than partial, board configurations where **all eight queens are placed**. • The quality q(p) of any phenotype can be simply quantified by the **number of checking queen pairs**.
- **q(p) = 0**, indicates a good solution.

- As for mutation we can use an operator that **selects two positions in a given chromosome randomly** and **swaps the values** standing on those positions.

The Eight-Queens Problem

- we select two parents delivering two children and the new population of size n will contain the best n of the resulting **n + 2** individuals.
- **Parent selection** will be done by choosing five individuals randomly from the population and taking the best two as parents that undergo crossover.

1. Select a random position, the crossover point, $i \in \{1, \ldots, 7\}$
2. Cut both parents in two segments after this position
3. Copy the first segment of parent 1 into child 1 and the first segment of parent 2 into child 2
4. Scan parent 2 from left to right and fill the second segment of child 1 with values from parent 2, skipping those that are already contained in it
5. Do the same for parent 1 and child 2

Fig. 2.3. "Cut-and-crossfill" crossover

The Eight-Queens Problem

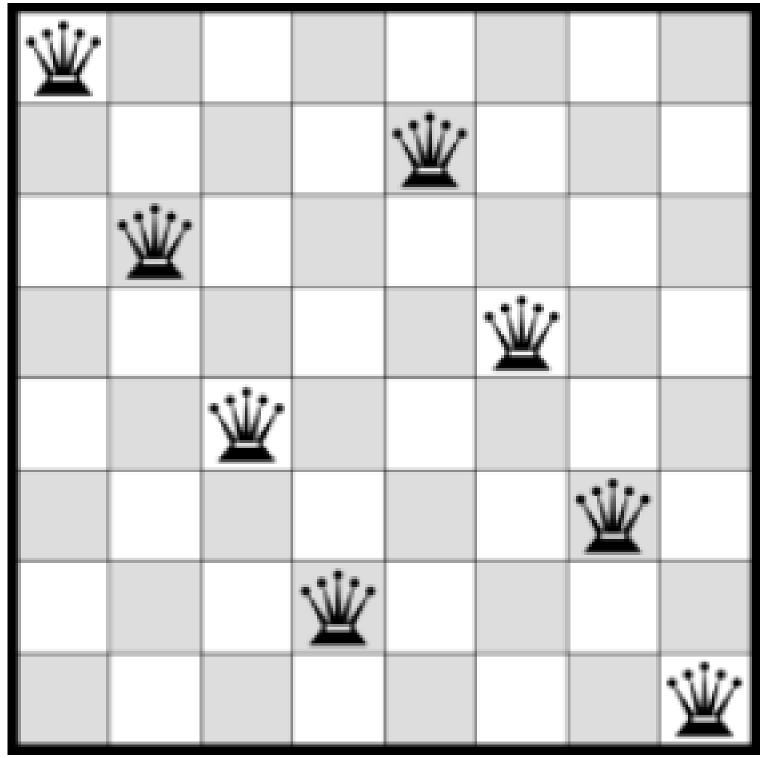
• The strategy we will use merges the population and offspring, then ranks them according to fitness, and **deletes the worst two**.

• Terminate the search if we find a **solution** or **10,000 fitness** evaluations have elapsed.

Representation	Permutations
Recombination	"Cut-and-crossfill" crossover
Recombination probability	100%
Mutation	Swap
Mutation probability	80%
Parent selection	Best 2 out of random 5
Survival selection	Replace worst
Population size	100
Number of Offspring	2
Initialisation	Random
Termination condition	Solution or 10,000 fitness evaluation

The Eight-Queens

Problem



0-1 Knapsack

Let us consider that the capacity of the knapsack **W = 60** and the list of provided items are shown in the following table.

Profit (pi)	**280**	**100**	**120**	**50**
Weight(wi)	**40**	**10**	**20**	**10**
Ratio (pi/wi)	**7**	**10**	**6**	**5**

0-1 Knapsack

After sorting, the items are as shown in the following table.

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The total weight of the selected items is **10 + 40 + 10= 60**
And the total profit is **100 + 280 + 50= 380 + 50 = 430**

The Knapsack Problem

Representation	Binary strings of length n
Recombination	One point crossover
Recombination probability	70%
Mutation	Each value inverted with independent probability p_m
Mutation probability p_m	$1/n$
Parent selection	Best out of random 2
Survival selection	Generational
Population size	500
Number of offspring	500
Initialisation	Random
Termination condition	No improvement in last 25 generations

Thank you