Introduction to Artificial Intelligence

COMP307/AIML420

Evolutionary Computation 1:
Evolutionary Computation and Learning

Dr Andrew Lensen

Andrew.Lensen@vuw.ac.nz

Outline

- Why evolutionary computation (EC) and learning?
- What is EC?
- EC Techniques
- Key characteristics and design questions
- Genetic algorithms: representation, selection and genetic operators
- Overview of other evolutionary algorithms

Why Do We Need Evolutionary Computation?

- We have discussed several methods and algorithms in ML
- But they have limitations:
  - Local optima
  - Unreasonable assumptions
  - Needs to predefine/fix the structure/model of the solution, and only learns the parameters/coefficients
  - Many parameters to learn (high-dimensional optimisation)
- Evolutionary Computation (EC) is one technique that can avoid some of the problems

Evolutionary Computation and Learning

- In computer science, **evolutionary computation** is a family of “*nature inspired*” AI algorithms for global optimisation.

- In technical terminology, they are a family of population-based trial-and-error problem solvers with a metaheuristic or stochastic optimisation character.

- **Evolutionary Learning** is the use of evolutionary computation methods for tackling machine learning tasks

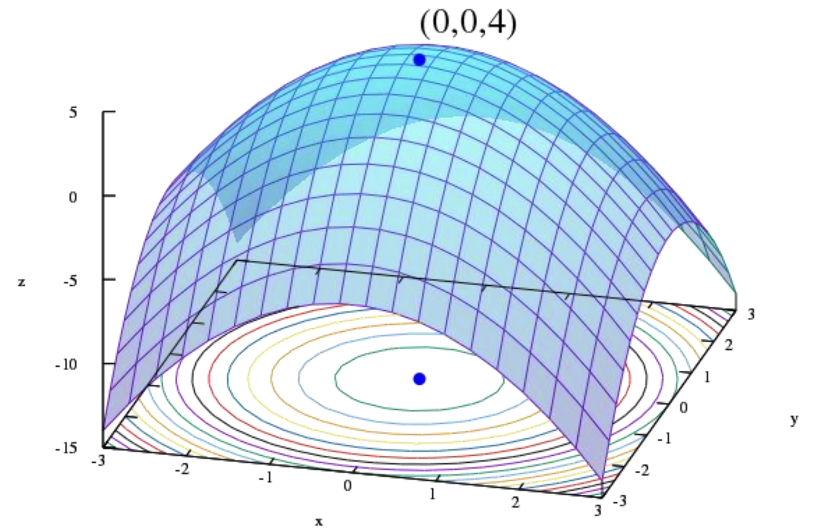
- *(Shameless) Source: https://en.wikipedia.org/wiki/Evolutionary_computation*

What is Optimisation?

- In an optimization problem, we are trying to find the best values of the variables that gives the optimal value of the function that we are optimising.

- E.g. minimise fuel use of courier deliveries.

- Decision variable(s)
- Objective function(s)
- Constraint(s)
- …



Examples

- In machine learning
  - Optimise the weights of a neural network
  - Optimise the architecture (#layers, #nodes) of a neural network
  - Optimise the distance measure for k-NN classifier
  - Optimise the distance measure for clustering methods
  - Feature selection (select a subset of important features to use)

- Other domains
  - Design the shape of a racing car/plane wings
  - **Schedule** lecture rooms (timetabling)
  - **Schedule** jobs in cloud network
  - **Schedule** trucks for delivery

Evolutionary Computation: Origin Story

- In the 1950s, long before computers were widely used, the idea to use *Darwinian* principles for automatic problem solving was first suggested.

- Three different interpretations of this idea were developed independently:
  - Evolutionary programming: Lawrence Fogel (USA)
  - Evolutionary strategies: Ingo Rechenberg (Germany)
  - Genetic algorithms: John Holland (USA)

- These areas developed separately for over 15 or 20 years

- Since the early 1990s, they have been seen as different representatives of one technology: evolutionary computation

EC Techniques

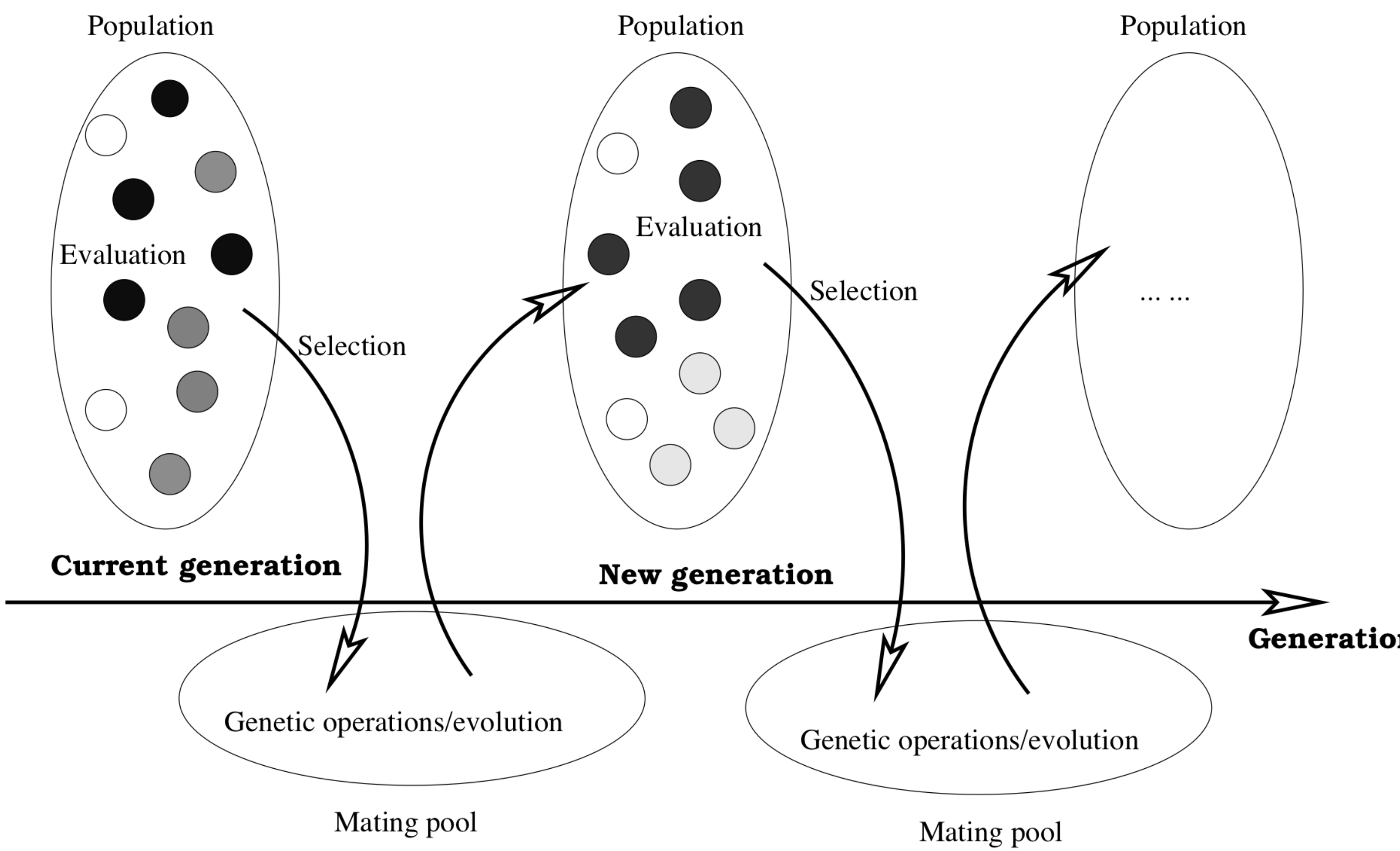
- Evolutionary algorithms (EAs)
  - Genetic algorithms (the biggest branch)
  - Evolutionary programming
  - Evolutionary strategies
  - Genetic Programming (Koza, 1990s, fast growing area)

- Swarm intelligence (SI)
  - Ant colony optimisation
  - Particle swarm optimisation (PSO)
  - Artificial immune systems

- Other techniques
  - Differential evolution
  - Estimation of distribution algorithms
  - …

Evolutionary Algorithms

- Search for the best individual by evolving a *population* with reproduction (e.g. crossover, mutation)



Key Characteristics

- One (or more) populations of *individuals*
- Dynamically changing populations due to the birth and death of individuals (through crossover, mutation, …)
- A *fitness function* which reflects the ability of an individual to survive and reproduce ("survival of the fittest")
- Variational inheritance: offspring closely resemble their parents, but are not identical

- Final solution (individual): the one with the best *fitness*
- Fitness could be accuracy, cost, error, …

Evolutionary Search

- Search space of **candidate solutions**
  - Not space of partial solutions
  - Modify whole solutions rather than extending partial solutions

- Genetic beam search
  - Keep track of a set of good solutions
  - Not all candidate solutions, unlike best first or A$*$
  - Not only the best candidates, unlike in hill climbing or gradient descent

- *Combine* good candidates to construct new candidates
  - Can modify candidates in isolation (mutation)
  - Or different candidates can *interact* in evolution (crossover)

Key Design Questions

- Representation
  - How can we represent individuals (solutions)?
- Evaluation
  - How can we evaluate individuals (fitness function)?
  - A fitter individual should have a better objective value (e.g. smaller error)
- Selection
  - How to select individuals into the mating pool (selection scheme)?
  - Fitter individuals should be more likely to survive/reproduce
  - Selection pressure
- Genetic Operators
  - How to generate new individuals (crossover, mutation operators)?
  - Children inherit strong parts of parents
  - Maintain diversity (jump out of local optima)
- Other parameters
  - population size, mating pool size, stopping criteria, …

Individual Representation

- Problem dependent

- Binary string (e.g. feature selection)

1	0	0	1	1

0	0	0	1	1

- Continuous vector (e.g. ANN weight optimisation)

-0.73	0.10	0.35	-0.06	0.23

-0.13	0.10	0.35	-0.06	-0.29

- Permutation (e.g. traveling salesman problem)

1	3	5	2	4

1	3	5	4	2

- Variable length (e.g. symbolic regression)

Fitness Evaluation

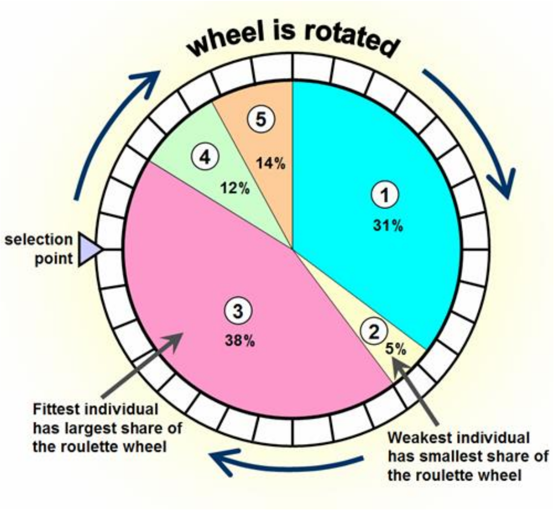
- **Fitness function**: reflect the quality of individuals
  - Must correspond to optimality property
  - Must be computable
  - Smoothness:
    - Small changes to candidate -> small changes to quality/fitness
    - Large changes to candidate -> large changes?

- Depending on the problem, the fitness function could be:
  - the larger, the better --- maximisation
  - the smaller, the better --- minimisation

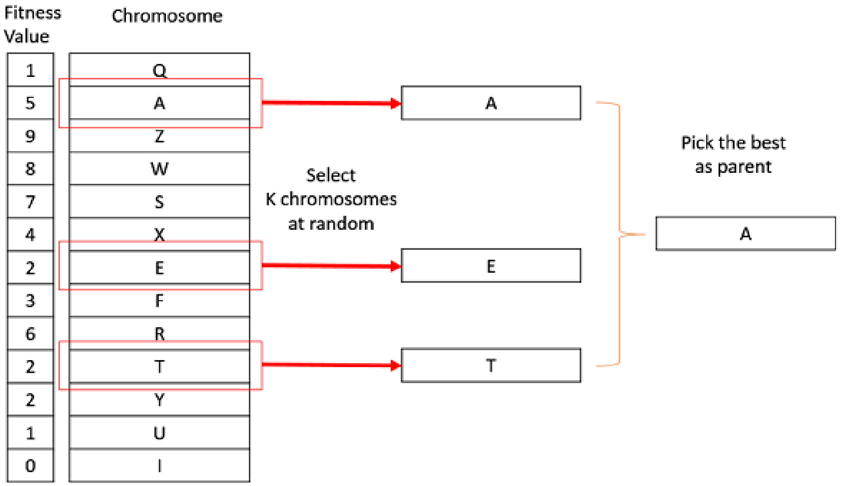
Selection

- Uniform selection
  – Each individual has the same chance to be selected

- Roulette wheel selection
  – The probability of being selected is proportional to the fitness
  – Assume fitness is maximised



- K-tournament selection



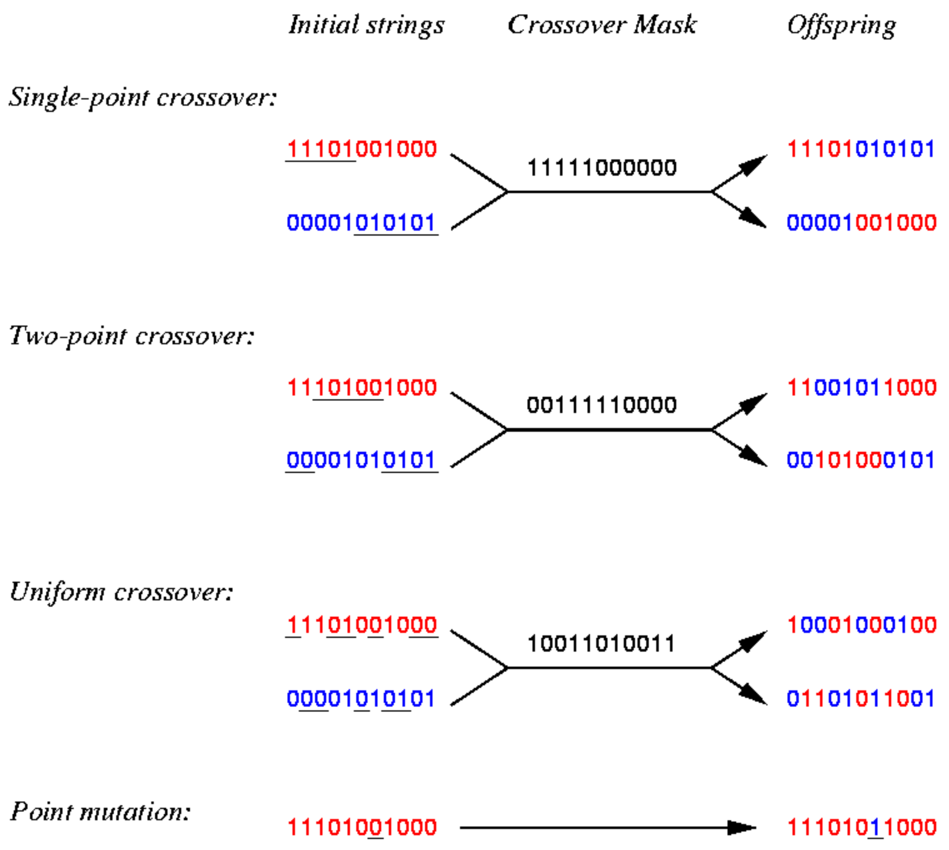
- Truncate selection
  – Select the best k individuals

Genetic Operators

- Depends on the problem – individual representation
  - Swap a bit of a binary vector
  - Resample an element of a continuous vector
  - Shuffle a part of a sequence
  - …
- A representative: Genetic Algorithms

Genetic Algorithm

- Representation: binary string
- An individual is also called a chromosome



- Other representations as well: continuous vector, permutation, …

A Basic Genetic Algorithm

- Randomly initialise a population of chromosomes

- **Repeat until** stopping criteria are met:
  - Construct an empty new population
  - **Repeat until** the new population is full:
    - Select **two** parents from the population by roulette wheel selection
    - Apply crossover to the two parents to generate two children
    - Each child has a probability (mutation rate) to undergo mutation
    - Put the two children into the new population
  - **End Repeat**
  - Move to the new population (new generation)
- **End Repeat**

- Output the best individual from the final population

A Simple GA Example

- **OneMax Problem**
  - Target to (11111…1)
  - More zeros means worse: far away from the target
  - Simple “benchmark” problem!

- Representation: bit string
- Fitness function: $1 + \sum_i x_i$ (the larger the better)
- Crossover: single-point crossover
- Mutation: point mutation

- ***Assume our algorithm does not know the problem or fitness function!***

A Simple GA Example

- 10 bits (Optimal fitness = 11)
- population size = 20
- mutation rate = 0.25 (25%)
- Run for 10 generations

```
At generation 0 average fitness is 6.0, best fitness is 9
At generation 1 average fitness is 6.65, best fitness is 10
At generation 2 average fitness is 6.8, best fitness is 11
At generation 3 average fitness is 6.9, best fitness is 9
At generation 4 average fitness is 6.45, best fitness is 9
At generation 5 average fitness is 6.95, best fitness is 9
At generation 6 average fitness is 7.3, best fitness is 11
At generation 7 average fitness is 6.65, best fitness is 10
At generation 8 average fitness is 6.25, best fitness is 8
At generation 9 average fitness is 6.6, best fitness is 8
```

Other Techniques

- Particle swarm optimization (PSO):
  - http://en.wikipedia.org/wiki/Particle swarm optimization
- Learning Classifier Systems:
  - http://en.wikipedia.org/wiki/Learning classifier system
- Ant colony optimization:
  - http://en.wikipedia.org/wiki/Ant colony optimization
- Differential evolution:
  - http://en.wikipedia.org/wiki/Differential evolution
- Other useful links:
  - http://en.wikipedia.org/wiki/Genetic Algorithm
  - http://en.wikipedia.org/wiki/Evolution strategies
  - http://en.wikipedia.org/wiki/Evolutionary programming

- (Wikipedia comes from a CS background!!)

Summary

- Evolutionary computing overview
- Main idea and process
- Representations of candidate solutions
- Selection and genetic operators
- Genetic algorithms
- Other EC algorithms and techniques

- Next lecture: Genetic programming (GP)