

# Evolutionary Computation

## COMP2002

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# Introduction

Today's topics:

- Optimisation
- Evolutionary computation
- Genetic algorithms

Session learning outcomes - by the end of today's lecture you will be able to:

- Recognise optimisation problems and describe their simple characteristics
- Interpret the steps of the genetic algorithms

Optimisation is a mathematical method to select the best element from a group of available alternatives.

In the selection process there may be some rules (criterion) which need to be followed.

There are two subfields in optimisation:

- discrete optimisation
- continuous optimisation

An optimization problem consists of maximizing or minimizing a real function by systematically choosing input values from within an allowed set and computing the value of the function.

# Travelling Salesperson Problem

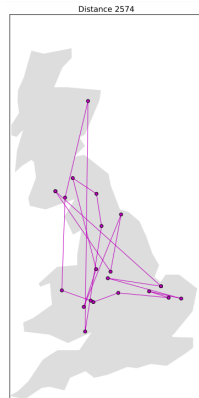
The task: a salesperson must visit cities A, B, C and D in one go – what is the most efficient route they should take?

The problem is fairly simple to solve for four cities – just enumerate each possible route and calculate its efficiency

What if there are 20 cities?

There are a total of  $N!$  possible routes

That is  $20 \times 19 \times 18 \times \dots \times 3 \times 2 \times 1 = 2,432,902,008,176,640,000$  routes



# Container Stowage Problem

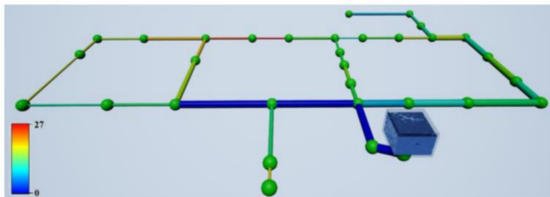


A modern large container ship can carry over 20,000 containers

How should the containers be loaded?

What problem constraints might exist?

# Water Distribution Network Design



M. B. Johns, D. J. Walker, E. Keedwell and D. Savić. "Interactive Visualisation of Water Distribution Network Optimisation". EPiC Series in Engineering (3):995-1003, 2018.

Design new WDNs or upgrade existing networks.

Optimisation of pressure, water quality, adherence to pressure constraints, robustness of the network. . .

# Solution Representation

## TwoLoop problem

Identify the optimal size for eight pipes (all pipes have equal length).

14 possible

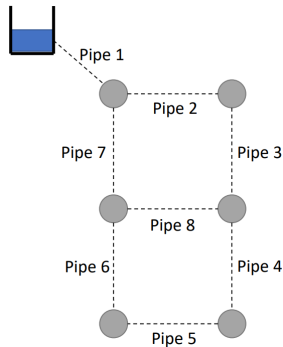
pipe diameters (1-24 inches) each with a known unit cost (\$/m) – lookup table

## Solution

Pipe #	1	2	3	4	5	6	7	8
$x =$	3	8	10	10	22	6	1	24

**Fitness function is sum of pipe costs**

$$y = f(x) = 8 + 23 + 32 + 32 + 300 + 16 + 2 + 550 = \$963/\text{m}$$



# Random Walk

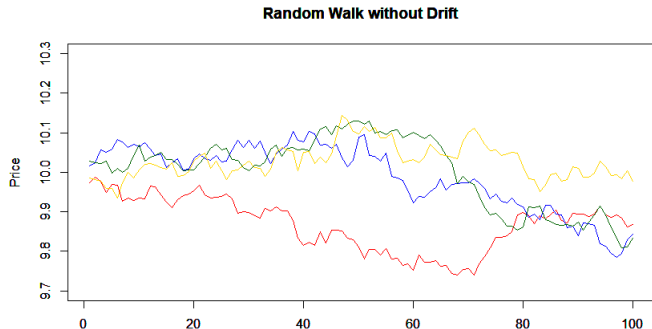
## Simplest optimisation algorithm – not intelligent

Generate a solution at random.

Then for a number of iterations, generate further random solutions.

Across the iterations keep track of the best solution found

Eventually the algorithm converges – but extremely slowly...





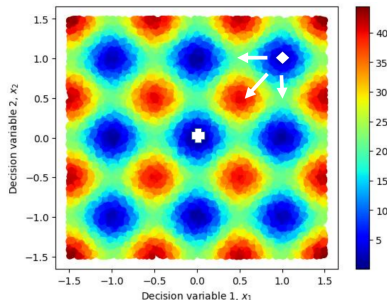
# Hill Climber

Generate a random solution  $x$ .

Perturb the solution – move it to a different part of the search space to produce a new solution.

If the new solution is better keep it – otherwise move back to the original solution.

The white diamond is in a local optima – reasonable quality but not the best and must get worse to get better by reaching the global optima

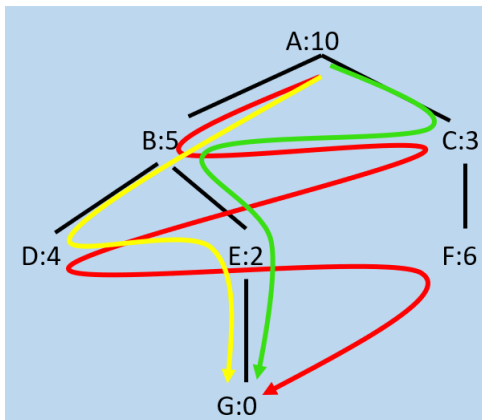


# Greedy Search

Expands the node with the best score.

The best node is removed from the list.

Method is dependant on the heuristic function.



# Pros And Cons Of Hill Climbers

- Hill Climbing is a simple and intuitive algorithm that is easy to understand and implement.
- It can be used in a wide variety of optimization problems.
- Hill Climbing is often very efficient in finding local optima.
- The algorithm can be easily modified and extended to include additional heuristics or constraints.

- Hill Climbing can get stuck in local optima, meaning that it may not find the global optimum of the problem.
- The algorithm is sensitive to the choice of initial solution, and a poor initial solution may result in a poor final solution.
- Hill Climbing does not explore the search space very thoroughly, which can limit its ability to find better solutions.
- It may be less effective than other optimization algorithms for certain types of problems.

# Genetic Algorithms

## Offspring generation

Crossover – combine genes from two or more parents

Mutation – randomly modify genes on a solution

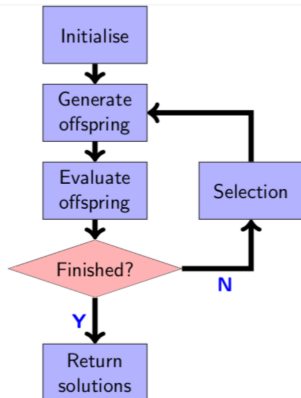
## Finished?

Fixed budget of function evaluations  
Online convergence detection

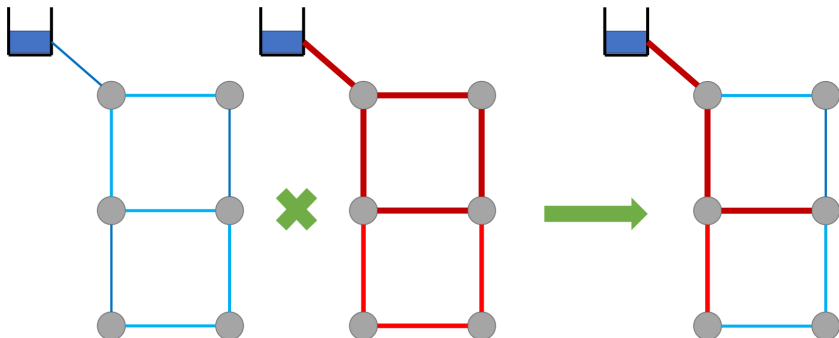
## Selection

Elitist

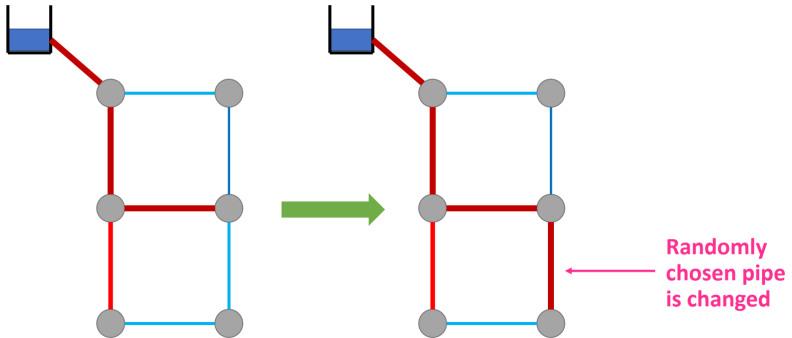
Rank, tournament selection. . .



# Crossover



# Mutation

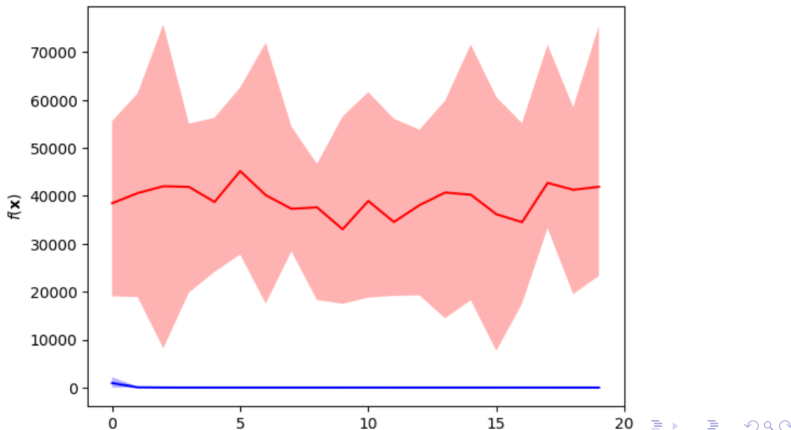


# TwoLoop With A GA

Optimise TwoLoop network

Use EpaNET to model hydraulics

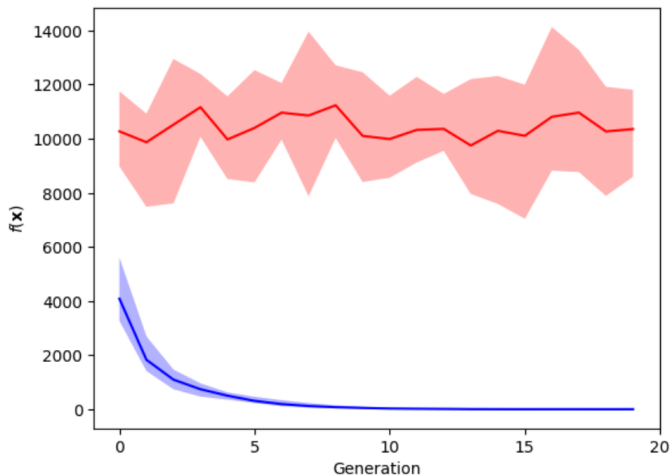
Minimise cost + constraint violations





# Hanoi With A GA

Same problem – different network

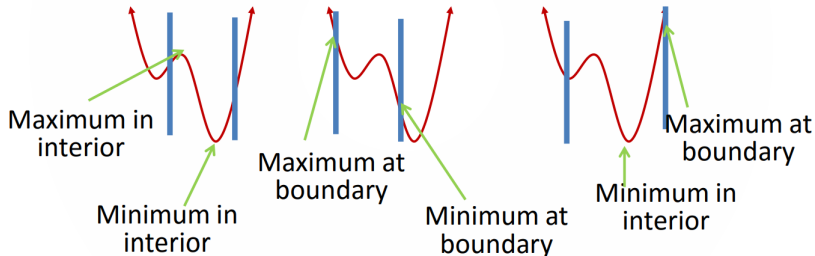


# Optimising With Constraints

So far we have not discussed the limits or boundaries for the functions being fed into the algorithms.

A constraint is a hard limit placed on the value of a variable, which prevents us from going forever in certain directions.

With nonlinear functions, the optimum values can either occur at the boundaries or between them.



# Examples Of Constraints

If you are attempting to maximize the objective function, typical constraints might involve time, money, and resources. The amounts of these things are limited, and these limits also place limits on the best possible value of the objective function.

If you are attempting to minimize, the constraints are more particular to the situation.

# Writing Constraints

This is going to involve algebra.

## Example

If a single apple costs 45p, then it follows that two cost 90, five apples cost £2.25.

In general,  $a$  apples cost  $45a$  or  $0.45a$ .

If you buy  $a$  apples at 45p and  $b$  blackberries at £2, then your total cost will be  $0.45a + 2b$ .

If you only have £10 to spend at the supermarket, then your total cost must be

$$0.45a + 2b \leq 10.$$

# Task - Writing Constraints

- 1 A batch of cookies requires 150g of flour, and a cake requires 200g. Write a constraint limiting the amount of cookies and cakes that can be made with 3kg of flour.
- 2 Box type 1 can hold 20 books and box type 2 can hold 12. Write a constraint for the number of boxes needed in order to box up 100 books.
- 3 If it takes you 4 minutes to bike a mile, 9 minutes to run a mile and 14 minutes to walk a mile, write a constraint that limits how many miles of each type of exercise you can get in a 45-minute lunch break.

# Timetabling – Optimising With Constraints

Constraints are rules within the problem formulation that cannot be broken.

	Mon 25 Feb	Tue 26 Feb	Wed 27 Feb	Thu 28 Feb	Fri 1 Mar
9:00			09:00 - 11:00 AINT202 (W) Practical /01 SMD 100 Al-Hafith, Neamah		
10:00					
11:00	11:00 - 13:00 AINT202 (W) Lecture ILB LT2 Ansel, Lauren	11:00 - 13:00 SOFT261 (W) Lecture PSQ Devonport LT Kalefounas, Vasileios		11:00 - 13:00 AINT202 (W) Practical /03 SMD 100 Al-Hafith, Neamah	11:00 - 13:00 SOFT261 (W) Practical /02 SMD 209 Kalefounas, Vasileios
12:00					
13:00					13:00 - 15:00 AINT202 (W) Practical /02 SMD 100 Al-Hafith, Neamah
14:00	14:00 - 16:00 SOFT261 (W) Practical /03 SMD 207 Kalefounas, Vasileios			14:00 - 16:00 SOFT261 (W) Practical /01 SMD 207 Kalefounas, Vasileios	
15:00					
16:00					

Example timetabling constraints:

- A student cannot be timetabled for two sessions at the same time.
- Two sessions cannot be placed in the same room at once.
- A session's allocated room must have capacity for the total number of students.

# Evolutionary Machine Learning

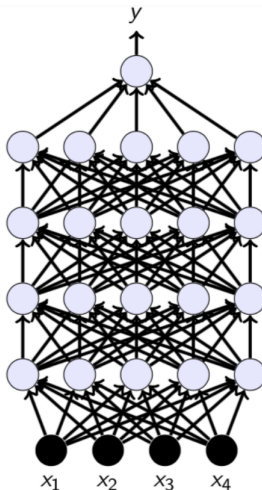
## Optimise the weights and structure of an ANN

What are the edge weights?

Which nodes and edges are needed?

What should their activation function be?

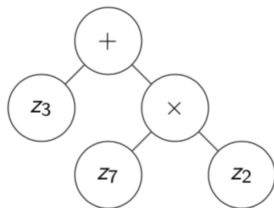
Fitness function is model accuracy



# Genetic Programming

Evolve symbolic expressions or executable code with desirable properties.

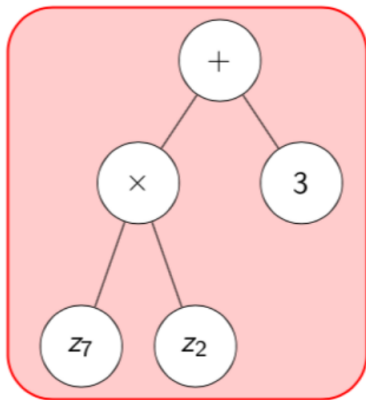
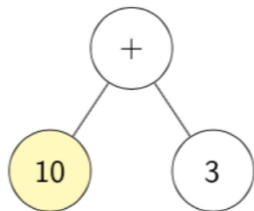
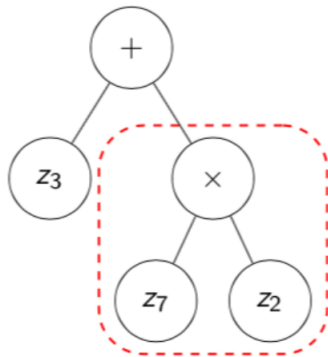
Wide range of applications – modelling, gameplay controllers, search-based software engineering... Solution is represented with a tree



Given model input vector  $z$ , model output is  $z_3 + (z_7 \times z_2)$



# Crossover In GP



# Expensive Optimisation

What if a function evaluation takes minutes, hours or even days?

## **Parallel evolution**

Execute (e.g.) each function evaluation on a different core.  
The whole EA can be run in parallel.

## **Surrogate modelling**

Build a model that simulates the function evaluation.  
The execution of the model will be much faster.  
Need data on which to base the model training.  
Still need to run the function evaluation at some point.

## **Evolutionary computation – nature-inspired optimisation**

- Problem formulation
- Genetic algorithms
- Genetic programming
- Expensive optimisation