

COMP250 Artificial Intelligence

10: Evolutionary Algorithms

Optimisation

Optimisation

- ▶ Define a **fitness function** $f(x)$
- ▶ $f(x)$ **evaluates** a piece of content x , assigning it a **numerical score**
- ▶ **Higher** scores are **better**
- ▶ We are exploring a **fitness landscape**

Running example

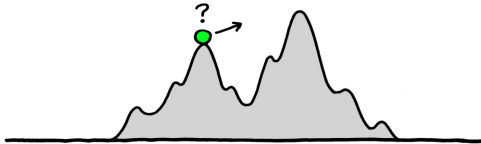
- ▶ `https://github.com/Falmouth-Games-Academy/comp250-workshop-10`
- ▶ Want to generate a map where there is a path from start to goal, and that path is as long as possible
- ▶ Fitness measure:

$$f(x) = \begin{cases} \text{path length} & \text{if a path exists} \\ 0 & \text{otherwise} \end{cases}$$

Hillclimbing (a.k.a. gradient ascent)

- ▶ Start with an element x
- ▶ Create an element x' by making a **small change** to x
 - ▶ May choose the small change at random
 - ▶ Or may try every possible change
- ▶ If $f(x') > f(x)$, set $x = x'$
- ▶ Otherwise, throw x' away and keep x as it is
- ▶ Repeat

Local optima



- ▶ Hillclimbing tends to get stuck at a **local optimum**
- ▶ This may be much worse than the **global optimum**
- ▶ Have to let the solution get worse before it gets better
— hillclimbing doesn't allow this

Escaping the local optimum

- ▶ Shotgun search (a.k.a. random restart)
 - ▶ Do several runs of hillclimbing from different starting positions
- ▶ Simulated annealing
 - ▶ Probability of allowing the search to keep a worse solution
 - ▶ This probability decreases as search progresses

Evolutionary algorithms

Evolutionary algorithms (EAs)

- ▶ Optimisation technique inspired by **biological evolution**
- ▶ We have a **population** of N solutions
- ▶ Generation 0: choose N solutions at random
- ▶ Generation $i + 1$: choose N new solutions based on the **fittest** individuals from generation i

Selecting the fittest

- ▶ **All** individuals should have a **chance** of being selected
- ▶ But **fitter** individuals should be selected **more often**
- ▶ Simple method: **tournament selection**
 - ▶ Randomly choose t individuals
 - ▶ Select the fittest out of those t

Mutation

- ▶ Select an individual
- ▶ Make a small change to it
- ▶ Add the changed individual to the new population

Crossover

- ▶ Select two individuals
- ▶ Combine them somehow (take “half” of one and “half” of the other)
- ▶ Add the resulting individual to the new population

Elitism

- Take the top $x\%$ of generation i , and pass it straight through to generation $i + 1$

Not just for PCG

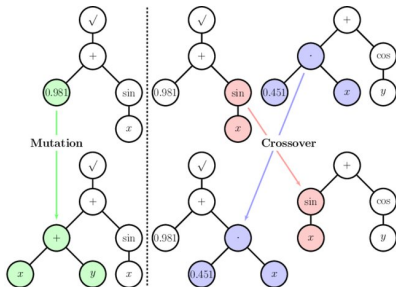
- ▶ Common use for optimisation: **parameter tuning**
- ▶ Suppose we have several simple heuristic evaluation functions h_1, h_2, \dots, h_n which we want to combine into a single heuristic
- ▶ **Linear combination:**

$$w_1 h_1 + w_2 h_2 + \dots + w_n h_n$$

where w_1, w_2, \dots, w_n are constants: **weights**

- ▶ What value to choose for the weights? This is an optimisation problem!

Genetic programming



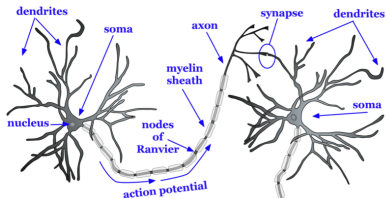
- Evolutionary algorithms for generating **code**
- Typically uses a **tree-based** representation of code
- Other approaches exist e.g. template-based

Neural networks

Artificial Neural Networks (ANNs)

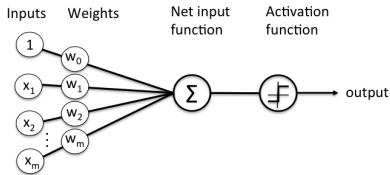
- ▶ **Inspired by** the structure of biological brains
- ▶ Idea has been around since the 1950s
- ▶ Recent resurgence of interest: today's powerful CPUs and GPUs allow much larger ANNs to be used

Real neurons



- ▶ An **electrically excitable** cell
 - ▶ Neurons are **connected together**
 - ▶ Connections can be **excitatory** or **inhibitory**
-
- ▶ If enough excitatory signals are received, the neuron **fires** — sends an electrical signal to the connected neurons
 - ▶ Human brain contains approximately **100 billion** neurons

An artificial neuron



- A **perceptron**
- Inputs x_1, \dots, x_m are outputs from **other perceptrons**
- Each input has a **weight** w_i between -1 and $+1$

Perceptron activation

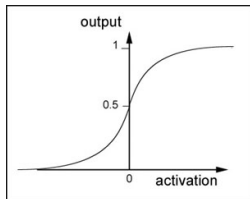
- ▶ The perceptron calculates a **weighted sum**

$$w_0 + w_1x_1 + \cdots + w_mx_m$$

- ▶ This goes through an **activation function**
- ▶ Simplest: **step function**

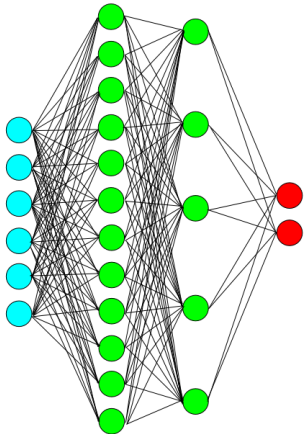
$$\text{output} = \begin{cases} 1 & \text{if sum} \geq \text{threshold} \\ 0 & \text{if sum} < \text{threshold} \end{cases}$$

- ▶ More common: **sigmoid function**



An artificial neural network

Input layer Hidden Layers Output Layer

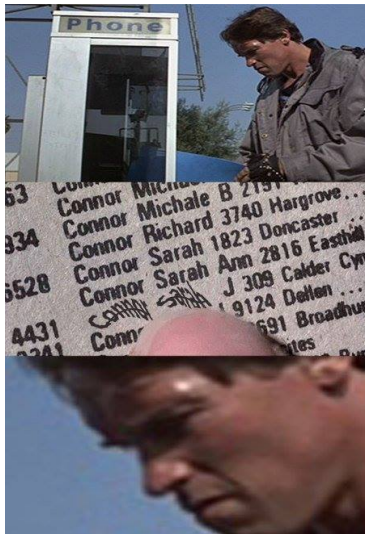


- ▶ A **multilayer perceptron (MLP)**
- ▶ Consists of an **input layer**, several **hidden layers** and an **output layer**
- ▶ Each layer is an array of **perceptrons**
- ▶ Each perceptron's output is connected to **every** perceptron in the next layer

Image classification



- ▶ Classic example:
handwritten digit recognition
- ▶ Given a **raster image**, which of the digits 0 to 9 does it represent?



<https://twitter.com/NaughtThought/status/846262063827730432>

MLPs for image classification

- ▶ **Input:** pixels of the image, reduced down to 1 bit per pixel (i.e. black or white)
 - ▶ Input layer: 1 perceptron per pixel
- ▶ **Output:** 10 bits corresponding to digits 0 to 9, of which exactly one should be set
 - ▶ Output layer: 10 perceptrons
- ▶ **Hidden layers:** ???
 - ▶ Parameters to tune
- ▶ **Weights:** ???

How to set the weights?

- ▶ We need to **train** the network
- ▶ Idea:
 - ▶ Feed in **training data**
 - ▶ When the network happens to give the correct answer, **reinforce** the relevant weights
 - ▶ Repeat until a desired **accuracy** is obtained
- ▶ Note: this requires a large amount of training data that is **tagged**, i.e. for which we already know the correct answer

Stochastic gradient descent

- ▶ **Gradient descent**: opposite of **gradient ascent** a.k.a. **hillclimbing**
- ▶ Want to minimise the **error** over the training data
- ▶ **Stochastic**: perform several training **epochs**
- ▶ Each epoch uses a randomly sampled **subset** of the training data
- ▶ This reduces computation time, and helps to escape local optima

ANN example

<http://playground.tensorflow.org>

Overfitting

- ▶ ANN learns **patterns** in the training data
- ▶ Insufficient training data might result in the network learning “patterns” that are actually random anomalies

Next time

- ▶ Deep learning
- ▶ Basically, large and computationally intensive neural networks
- ▶ Currently state-of-the-art in AI