COMP250 Artificial Intelligence

10: Evolutionary Algorithms

Optimisation

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- **Higher** scores are **better**
- We are exploring a **fitness landscape**

Running example

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- Want to generate a map where there is a path from start to goal, and that path is as long as possible
- Fitness measure:

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

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- Repeat

Local optima

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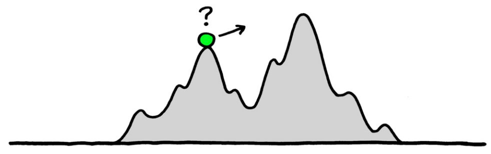

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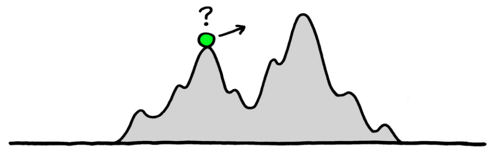

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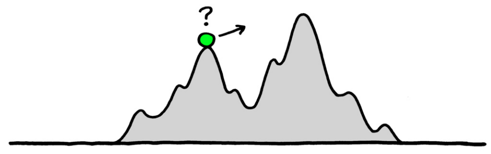

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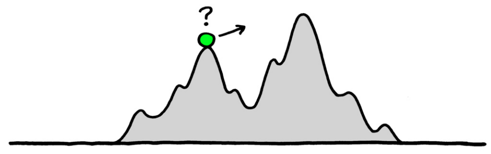

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- This may be much worse than the **global optimum**
- Have to let the solution get worse before it gets better — hillclimbing doesn't allow this

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  - This probability decreases as search progresses

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Evolutionary algorithms

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- Generation 0: choose N solutions at random
- Generation $i + 1$: choose N new solutions based on the **fittest** individuals from generation i

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  - Randomly choose t individuals
  - Select the fittest out of those t

Mutation

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- Add the changed individual to the new population

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Elitism

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

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- **Linear combination**:

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

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

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

Genetic programming

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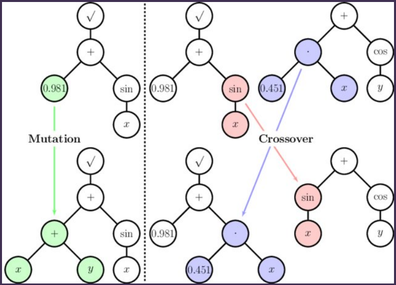

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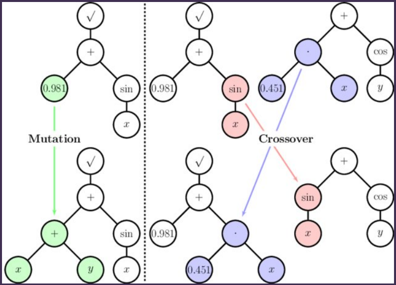

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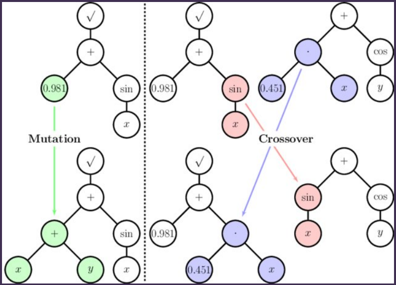

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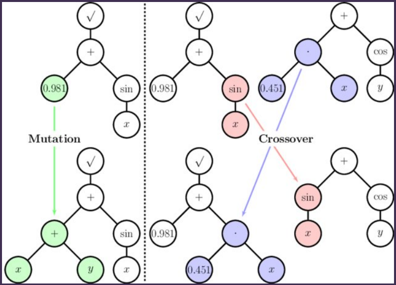

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- Other approaches exist e.g. template-based

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Neural networks

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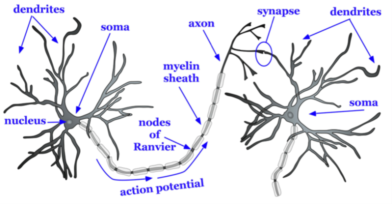
- Idea has been around since the 1950s
- Recent resurgence of interest: today's powerful CPUs and GPUs allow much larger ANNs to be used

Real neurons



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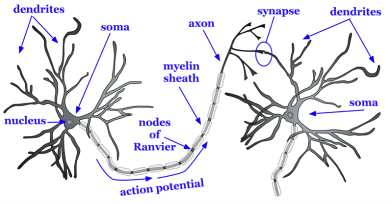

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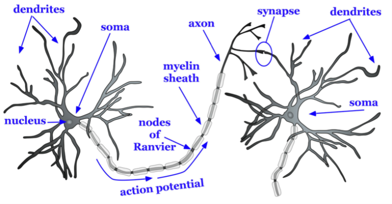

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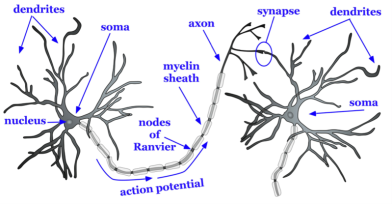

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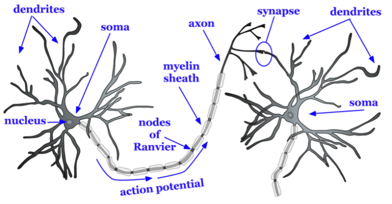

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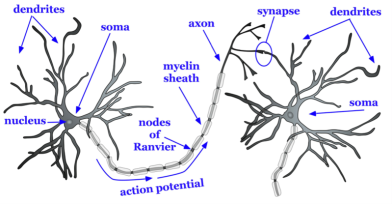

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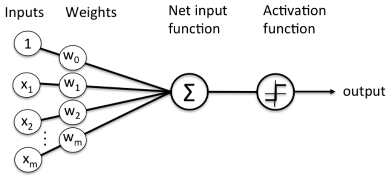
- Human brain contains approximately **100 billion** neurons

An artificial neuron



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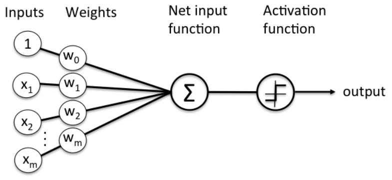

- A **perceptron**

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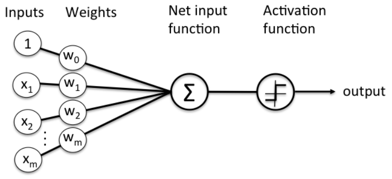

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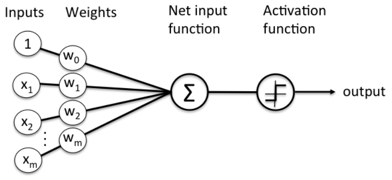

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- Each input has a **weight** w_i between -1 and $+1$

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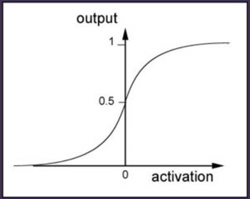
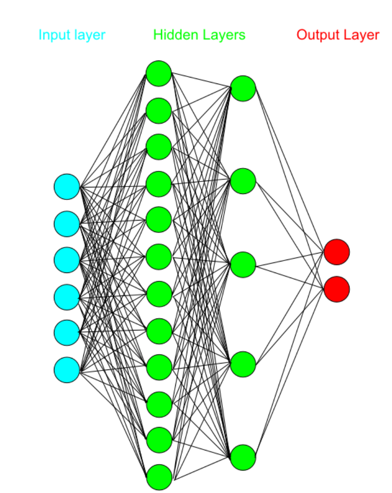
- More common: **sigmoid function**



An artificial neural network



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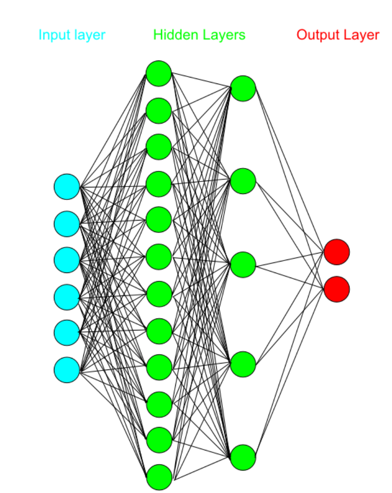

- A **multilayer perceptron (MLP)**

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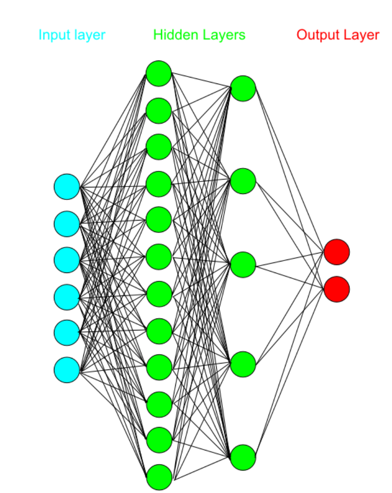

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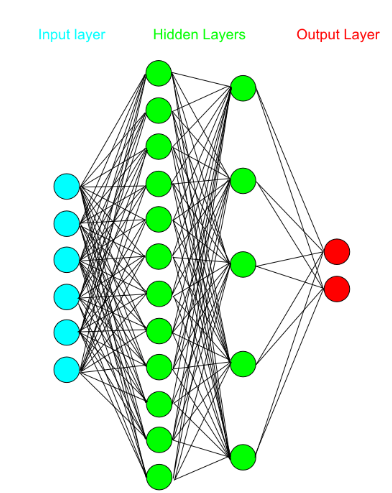

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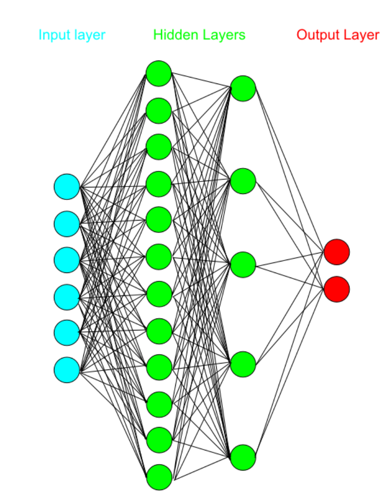

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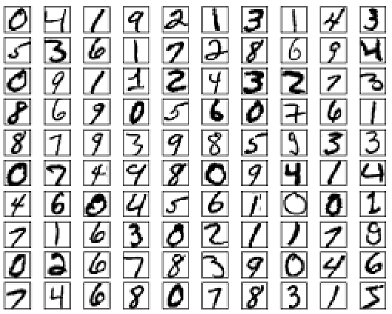
Image classification



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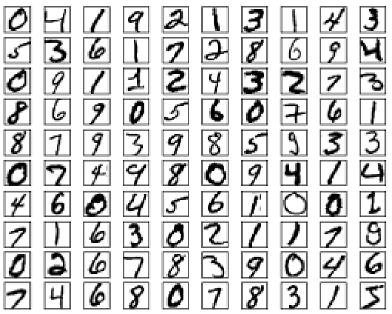

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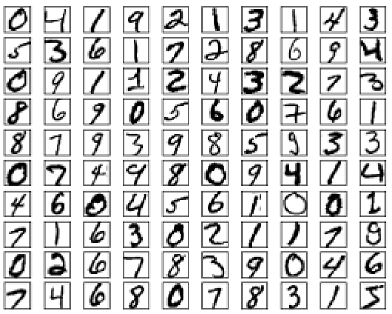

- Classic example: **handwritten digit recognition**
- Given a **raster image**, which of the digits 0 to 9 does it represent?

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

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- Note: this requires a large amount of training data that is **tagged**, i.e. for which we already know the correct answer

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- **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

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

Next time

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- Deep learning

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- Currently state-of-the-art in AI

Workshop — more MicroRTS