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Learning from nature

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Natural computation

- Using computers to model/simulate natural phenomena
  - to learn more about these phenomena
  - to learn new ways to solve computational problems
  - to learn how to build computational devices from biological material

Computers and humans

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What is learning?

- The ability to improve over time, based on experience
- Why?
  - Solutions to problems are not always programmable
- Examples
  - Handwritten character recognition
  - Adaptive control of production processes
  - Game programs that adjust parameters and/or strategies over time
  - Learning to walk by trial-and-error

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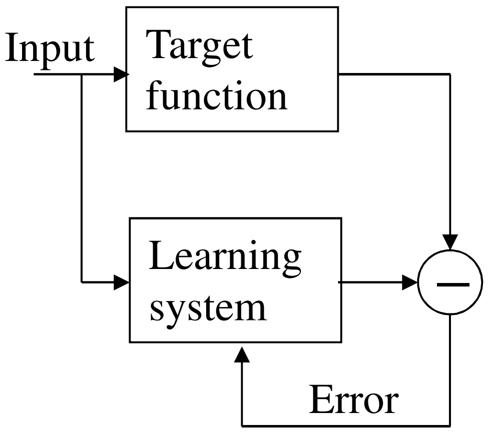
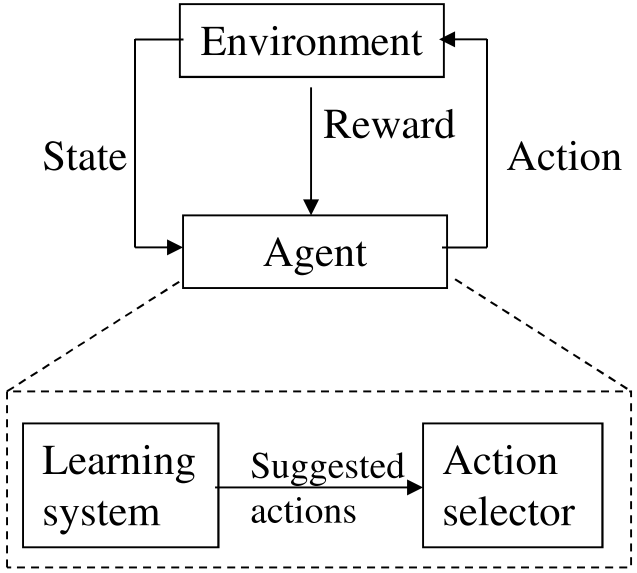
Three forms of learning

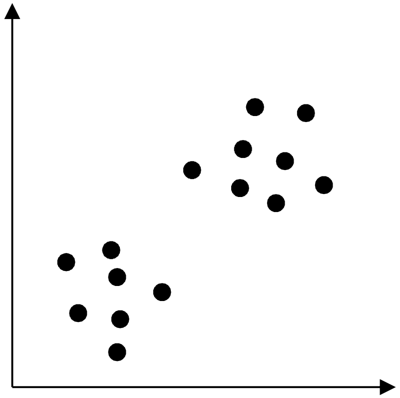
Supervised



Reinforcement



Unsupervised



Techniques (examples)

- Artificial neural networks (ANNs)
  - Inspired by biological nervous systems
  - E.g. Multilayer perceptrons, Self-Organizing Maps
- Reinforcement learning (RL)
  - Inspired by psychology, ethology and behaviourism
  - E.g. Menace, Q-Learning, TD(λ)
- Evolutionary Computing (EC)
  - Inspired by genetics, natural selection and evolution
  - E.g. Genetic algorithms, Genetic Programming
- Swarm intelligence
  - Inspired by social animals (bird flocks, ants, etc.)
  - E.g. Particle Swarm Optimization, Ant Colony Optimization, Cellular automata

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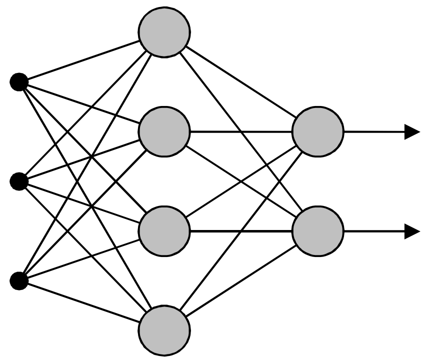
Artificial neural networks



- Begun in the 1940's
- Many simple processing elements (neurons), operating in parallel and communicating through weighted connections
- Based on very simple models of biological neurons and synaptic connections
- Used both for industrial applications and as a model to study biological systems

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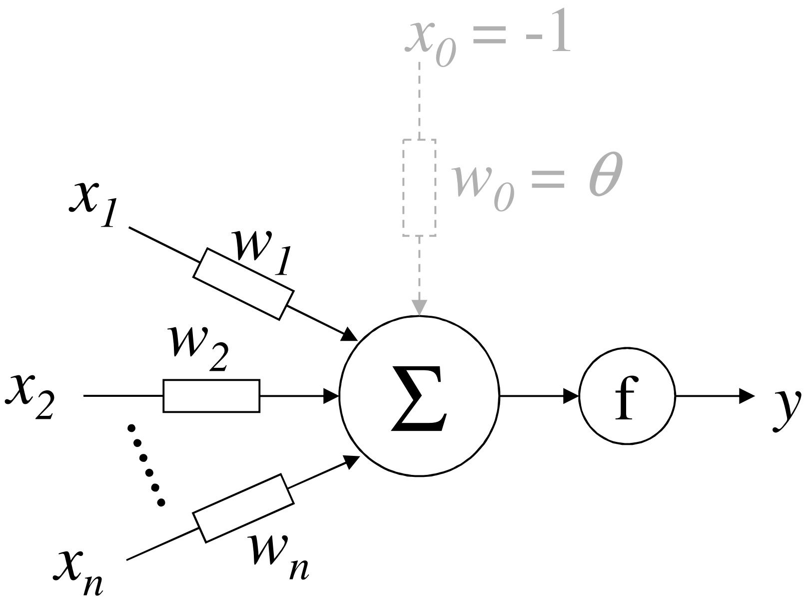
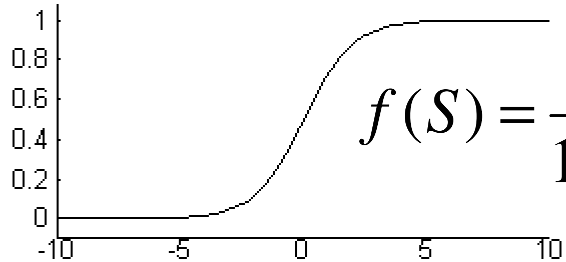
An artificial neuron



$$y = f(S)$$

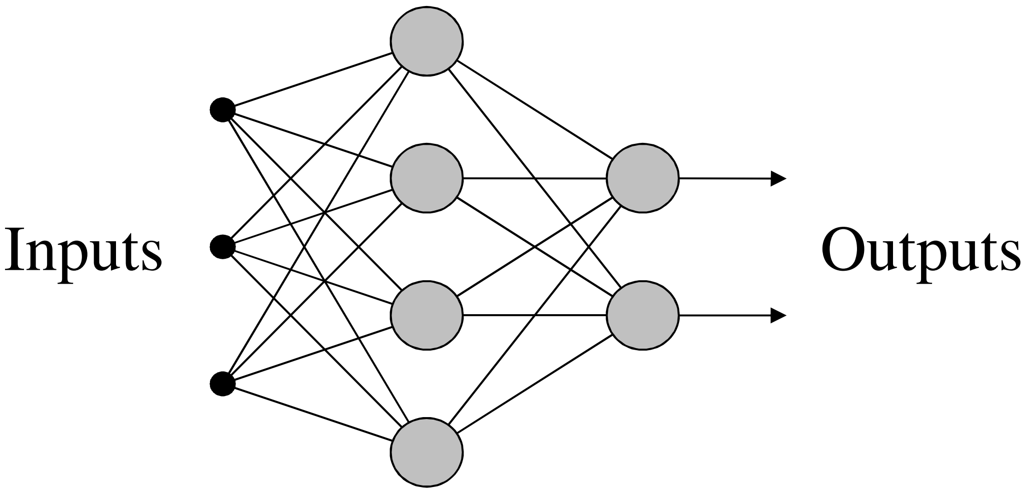
$$S = \sum_{i=1}^{n} w_i x_i - \theta = \sum_{i=0}^{n} w_i x_i$$

$f(S)$ = any non-linear, saturating function, e.g. a step function or a sigmoid:



$$f(S) = \frac{1}{1+e^{-S}}$$

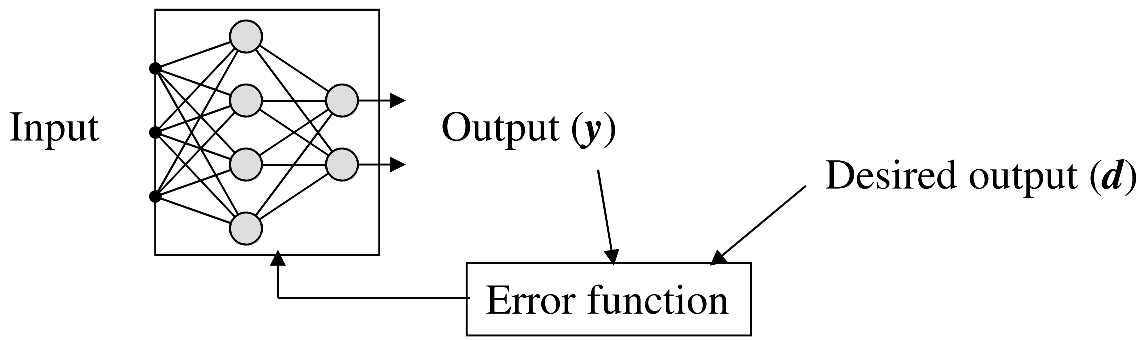
Multilayer perceptrons



Can approximate any function to any degree of accuracy, given a sufficiently rich internal structure (number of nodes and layers)

Most common training algorithm: *Back propagation*

Back propagation



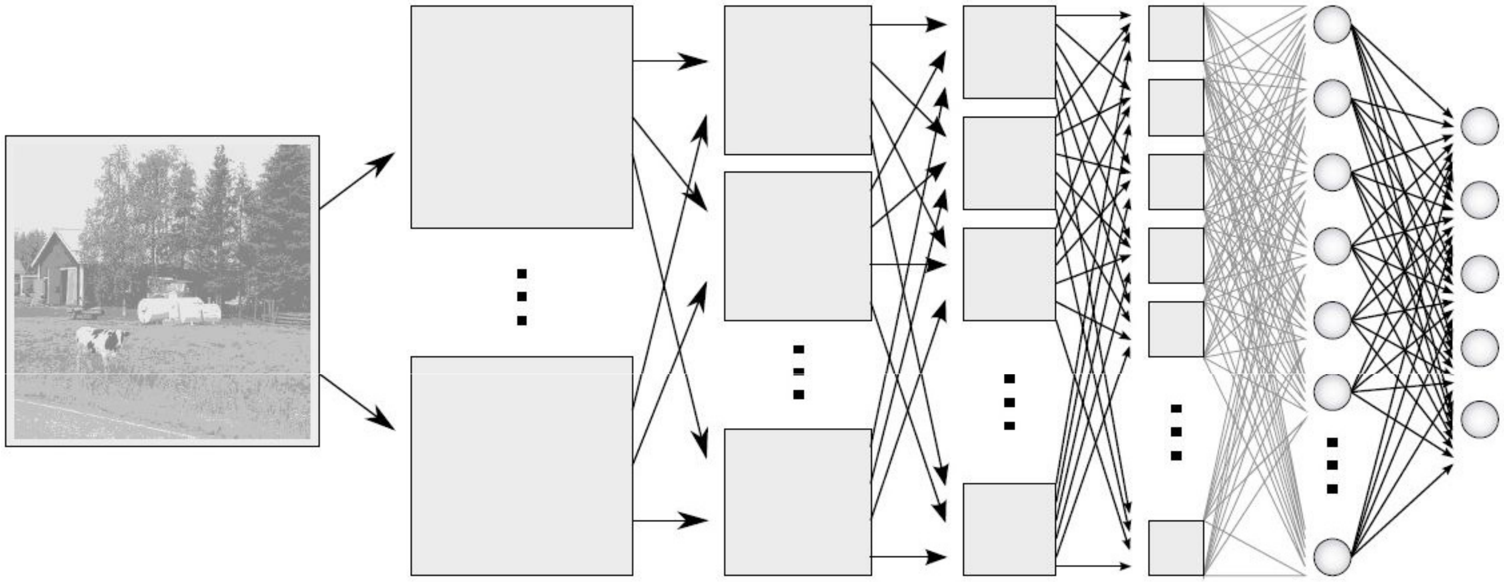
The contribution to the error E from a particular weight w_{ji} is $\frac{\partial E}{\partial w_{ji}}$

The weight should be moved in proportion to that contribution, but in the other direction:

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}}$$

⇨ Error function and activation function must both be differentiable.

Deep Learning



- A very deep multilayer structure (many layers)
- Back propagation ineffective for that many layers
- Layers instead trained separately

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Artificial neural networks …

- store information in the weights, not in the nodes
- are trained, by adjusting the weights, not programmed
- can generalize to previously unseen data
- are adaptive
- are concurrent
  - well suited for parallel simulation and/or hardware implementation
- are fault tolerant

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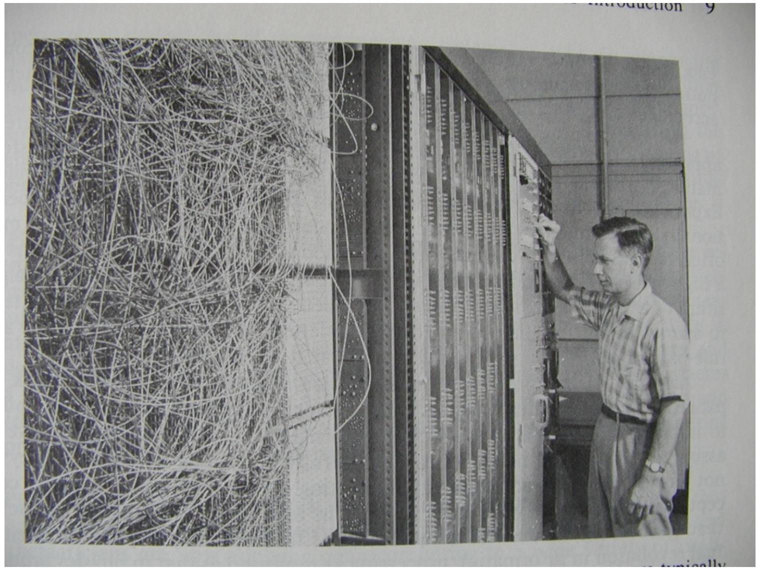
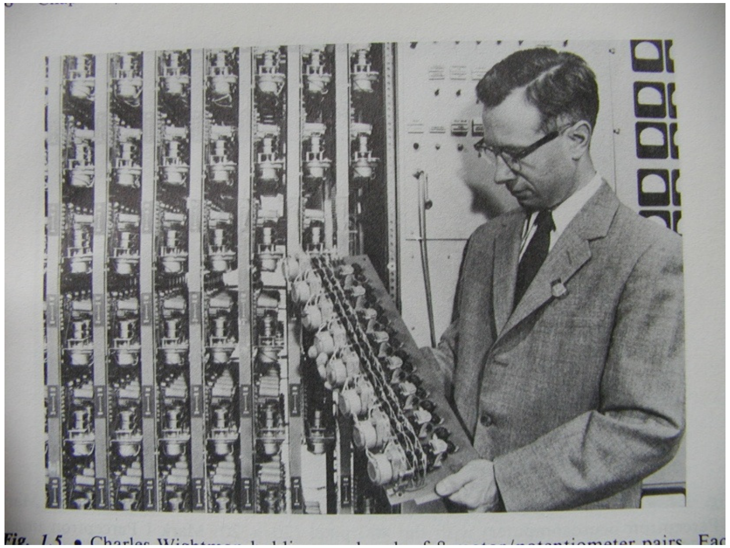
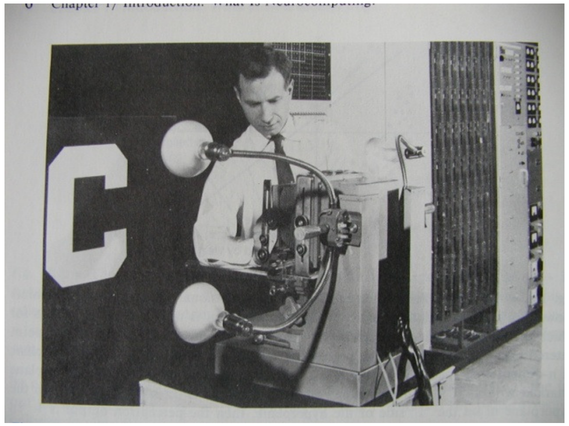
Early neurocomputers







Adam

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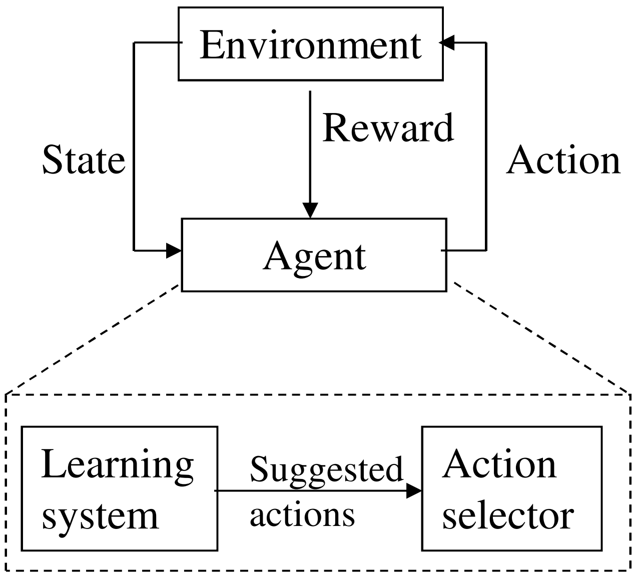
Reinforcement learning



- Reward: an evaluation of the environmental state (only indirectly an evaluation of the agent's actions)
- Goal: To make decisions (find actions) that maximise the long term reward received by the agent.
- The agent must be allowed to *explore*, i.e. sometimes do actions that at the time seem sub-optimal.
- Learning by trial-and-error

MENACE
(D. Michie 1961)

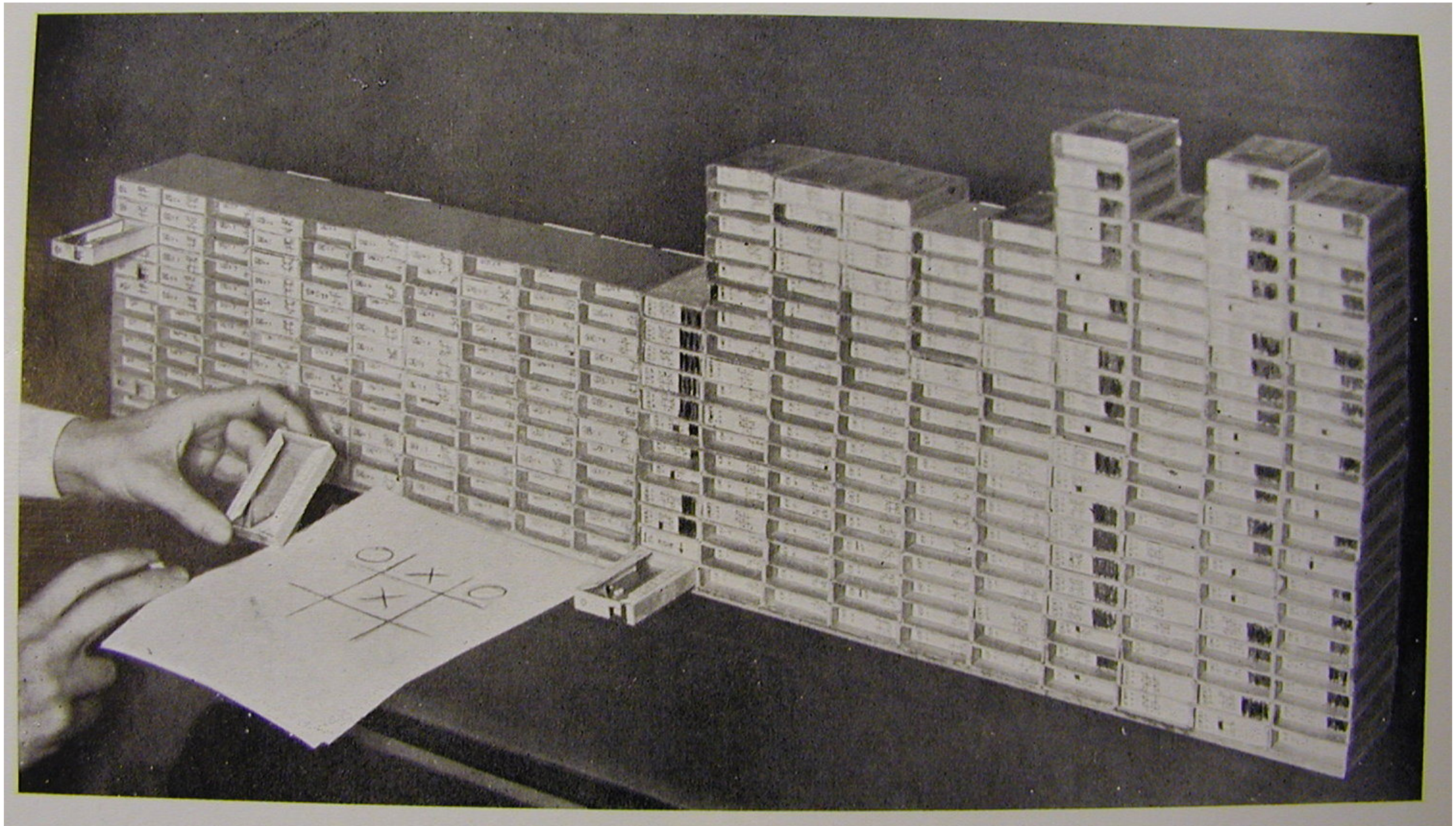


Plate 1. The original matchbox version of MENACE

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Typical RL problems

- Games
- Autonomous robots
- Control of unstable systems
  - Learning to ride a bicycle
  - Auto-pilot for helicopters
- Sequential optimization problems, for example:
  - Controlling the elevators in an office building
  - Resource allocation in computer networks

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Evolutionary computing

- Used for learning problems where the task is to maximize some measure of success (fitness)
- Essentially the same family of *problems* as in reinforcement learning, but the *methods* are different
- Methods inspired by genetics, natural selection and evolution
- However, the ”evolution” is controlled, so it’s more like breeding

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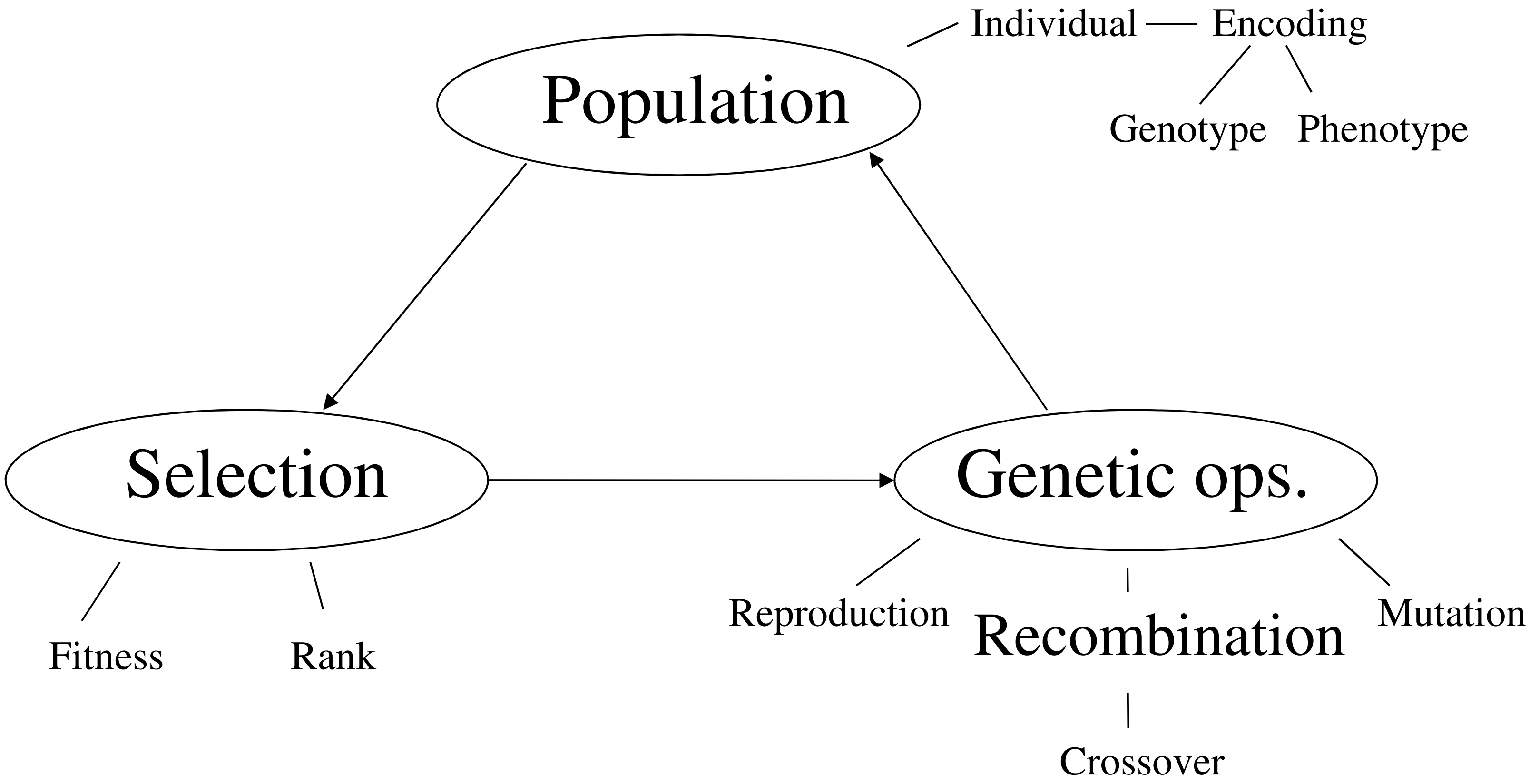
Evolutionary computing



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Genotypes

- A solution to the problem is encoded by the individual's *genotype* (*genome*, *artificial chromosome*)
  - In genetic algorithms, a string or parameter vector (e.g. bit string)
  - In genetic programming, a computer program
  - In evolutionary programming, a representation of a state machine
  - ...

Genetic Programming

- Usually operates on parse trees of computer programs
- E.g. the expression 5+3*4

In Lisp	As a tree
(+ 5 (* 3 4))	see tree below

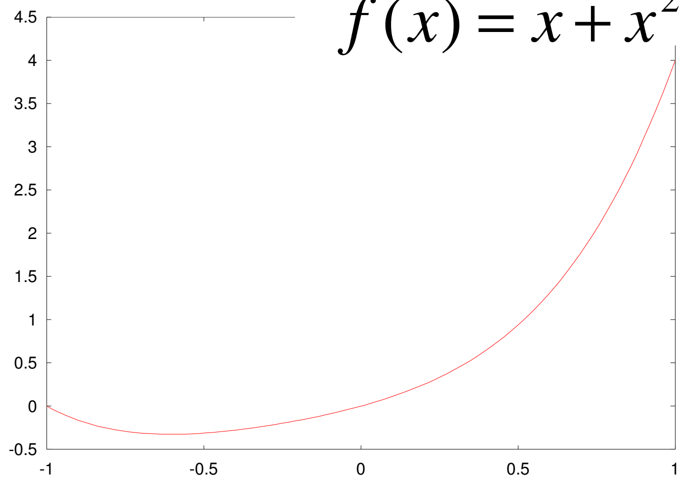
```
     +
    / \
   5   *
      / \
     3   4
```

- Crossover: Swap sub trees
- Works particularly well in Lisp!

GP example: function approximation

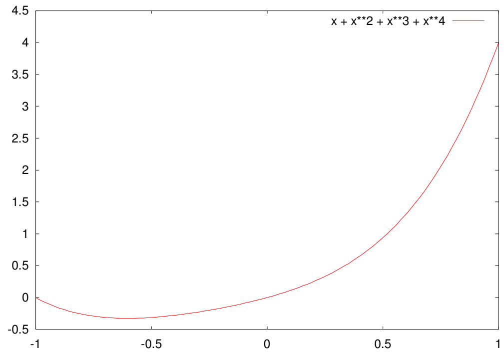
- Task: Given a training set, discover the function

$$f(x) = x + x^2 + x^3 + x^4, \text{ for } x \in [-1,1]$$



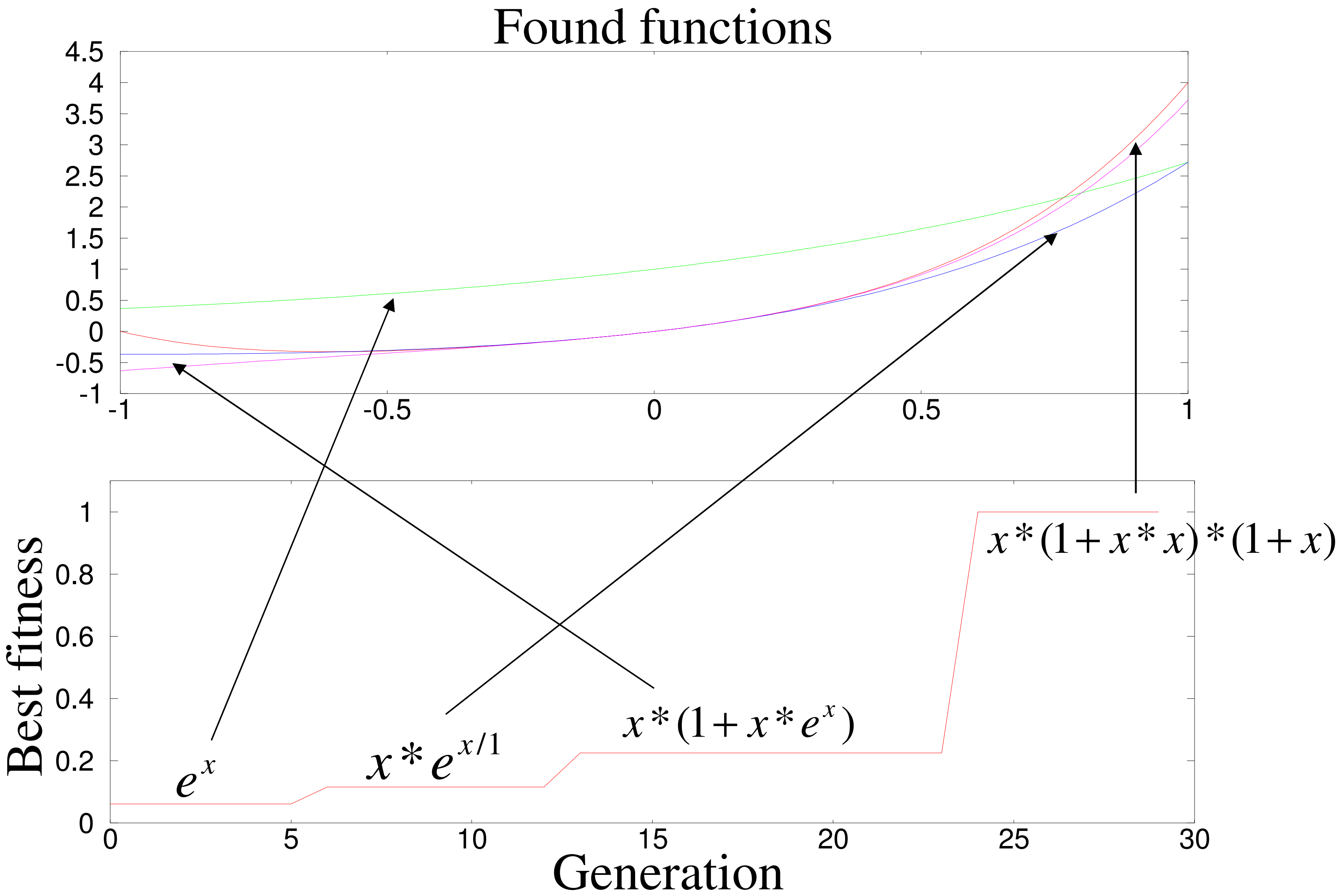
- A neural network would do a *numerical* approximation
- GP is *combinatorial* – it should be able to find the *exact* function (if given the necessary building blocks)

Implementation



- Create a population of random expressions, *y*(*x*), using the functions +, −, *, /, *sin*, *cos*, *exp* and *log*, and the terminals 1 and *x*
- Many lures (*exp* in particular)
- Fitness: 0 if illegal expression, else 1/(d+1), where d = |*f*(*x*) − *y*(*x*)|
- This way, fitness stays in [0,1])

Test run (100 individuals)



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Swarm Intelligence

- Bird flocks and fish schools move in a coordinated way, but there is no coordinator (leader)
  - So, what decides the behaviour of a leader-less flock?
- Ants and termites quickly find the shortest path between the nest and a food source
  - ... and solve many other advanced problems as well
    - keeping cattle, building (ventilated) housing, coordinated heavy transports, tactical warfare, cleaning house, etc.
  - A single ant is essentially a blind, memory-less, random walker!
- Distributed systems without central control
- Useful not only to simulate but also to solve optimization problems

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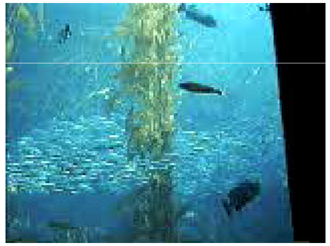
Bird flocks and fish schools

- Local interaction
- No leader
- Simple local rules – a weighted combination of several goals
  - match velocity of your neighbours
  - avoid collisions with your neighbours
  - avoid getting too far from your neighbours
    - or strive for centre of the flock (fish)



- To simulate an insect swarm, remove the match-velocity rule
- Sufficient to make very realistic simulations of fish schools and bird flocks
  - used in movies and computer graphics

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Stampede in ”Lion King”

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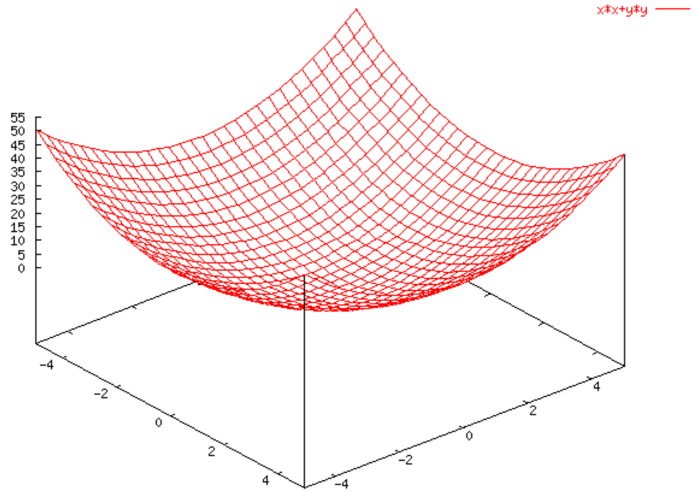
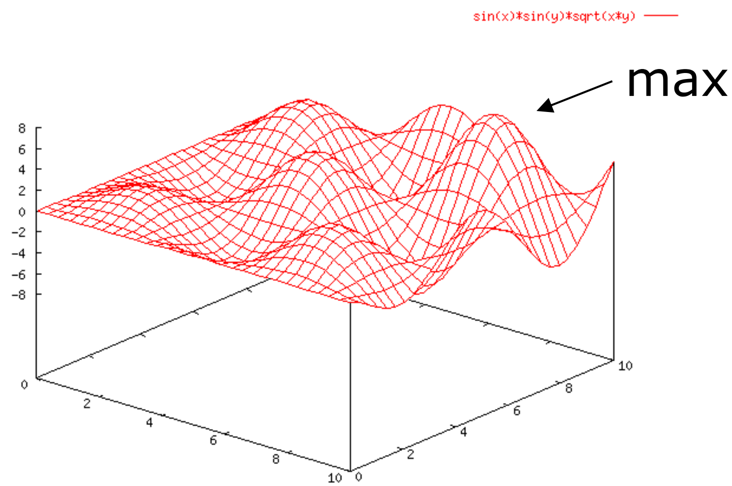
Particle Swarm Optimization

Lbest with $\varphi_1=1.8$, $\varphi_2=2.3$

- Nhood: the 2 immediate neighbours
- V_{max} = range/25



Bowl



Alpine 2D

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What about the ants?

- How do they find the shortest route?
  - They don’t (not the individual ants, that is)
  - The colony does!
- Ant colonies are much more intelligent than ants
  - Ant colonies adapt, ants don’t (much)
  - Ants have almost no memory and can not build cognitive maps. Ant colonies can (and do)
    - Mammals build cognitive maps in their brains
    - Ant colonies build them in their environment, through pheromone trails
- Ants are better thought of as cells in a greater organism – the colony
  - Also without leader – the queen is not a controller

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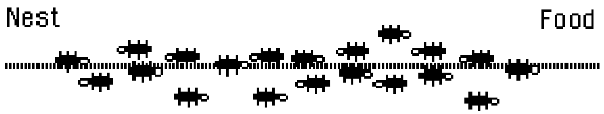
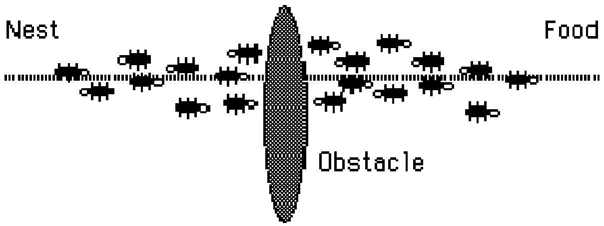
Ants find shortest paths

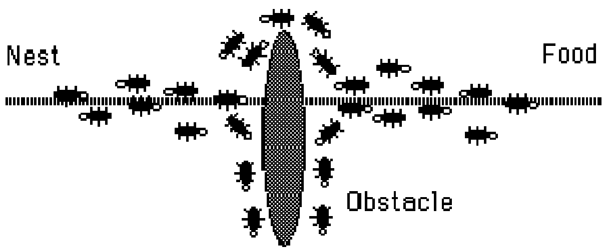


Ant path

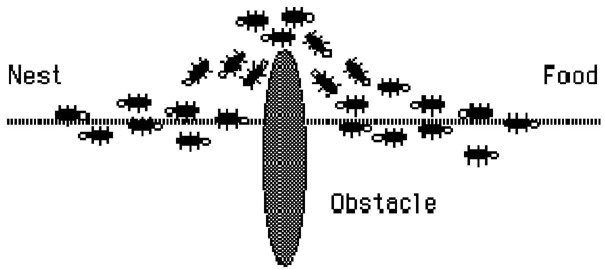


An obstacle appears

At first, the ants select at random



After a while, pheromones become more concentrated on the shortest route



Drawings by Marco Dorigo

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Stigmergy

Indirect communication and coordination, by local modification and sensing of the environment

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Ant Colony Optimization

- Family of combinatorial optimization algorithms, based on ant behaviour
- Common benchmark: the Travelling Salesman Problem (TSP)
- Common 'real' applications
  - Scheduling and
  - Network routing (AntNet)
- Members: ACS, Ant-Q, MMAS, AS_{rank}, ...
  - most of which are extensions to Dorigo's Ant System (AS)

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Cellular automata

- Massively parallel system of identical communicating state machines (cells)
- A cell's *state* (e.g. on/off) is a function of the states of it communicates with (its neighbours)
  - The neighbourhood is usually topological
- Used to model/animate fluids *(Find Nemo), gases*, bacterial growth, swaying grass (*Shreck?*), social interaction, epidemics, in ecological simulations etc.

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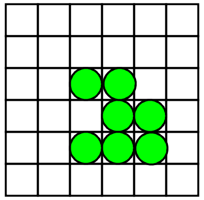
Conway's Game of Life

- World: a 2D grid. Each square represents a cell
- States: Living or dead
- Neighbourhood: The eight surrounding cells
- Initialize with a random number of living cells
- State transition rules:
  - A living cell with <2 living neighbours dies (loneliness)
  - A living cell with >3 living neighbours dies (overcrowded)
  - A dead cell with exactly 3 living neighbours comes alive
  - All other cells keep their current state



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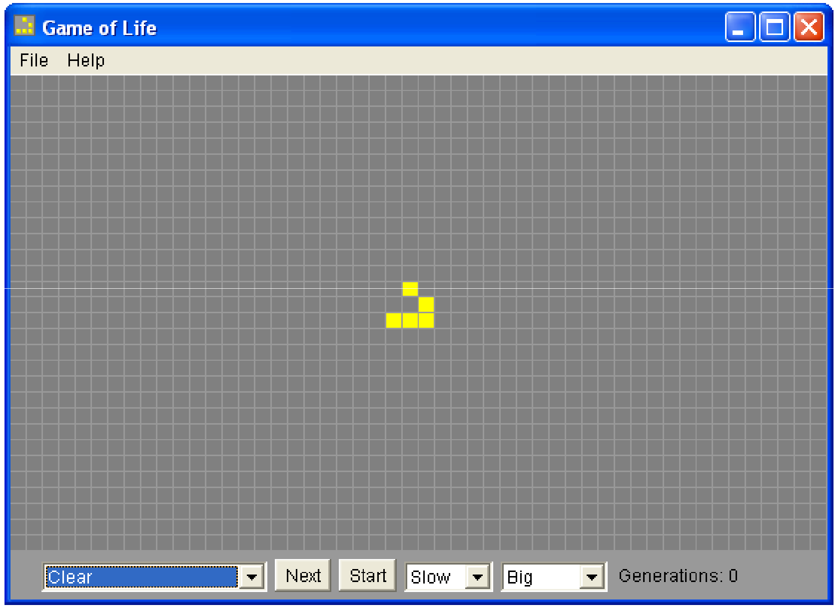
Life demo



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Machine Learning course

- Spring semester (10 credits)
- Natural computation algorithms
  - all the above, and more
  - emphasis on neural networks
- Flexible choice of end project

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