FALMOUTH
UNIVERSITY

COMP250 Artificial Intelligence
8: Neural networks

Neural networks

Artificial Neural Networks (ANNs)

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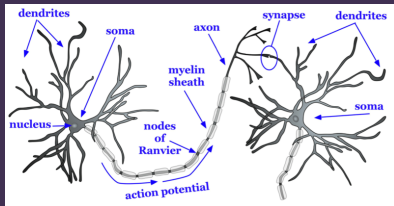- Idea has been around since the 1950s

Artificial Neural Networks (ANNs)

► **Inspired by** the structure of biological brains

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► Recent resurgence of interest: today's powerful CPUs and GPUs allow much larger ANNs to be used
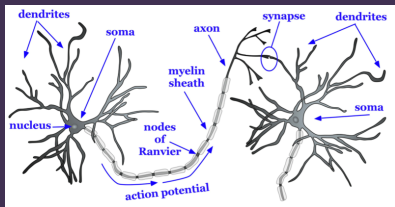
Real neurons
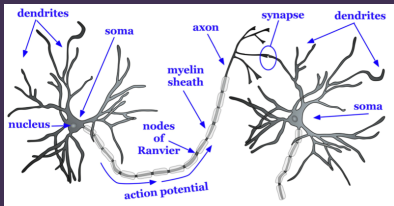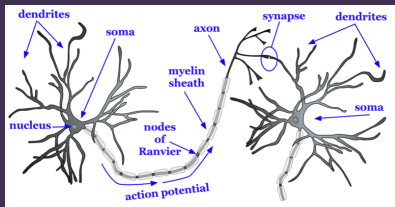
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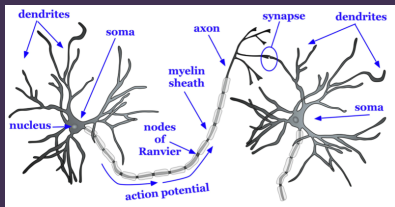► An **electrically excitable** cell

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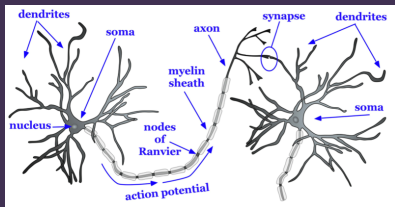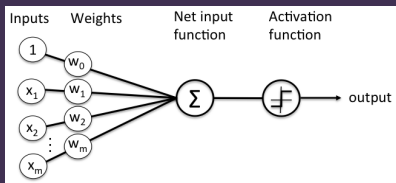

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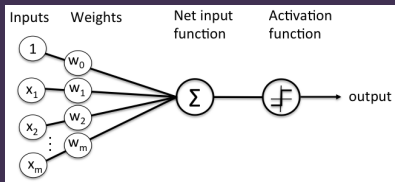- ▶ Human brain contains approximately **100 billion** neurons

An artificial neuron

An artificial neuron

► A **perceptron**

An artificial neuron
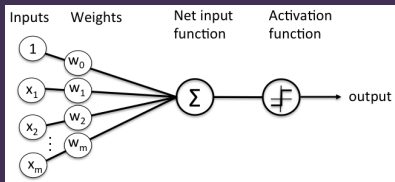
- A **perceptron**
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An artificial neuron

Inputs Weights Net input function Activation function

1 w_0
x_1 w_1
x_2 w_2
$\vdots$ w_m
x_m
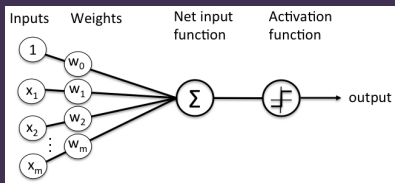
Σ → output

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

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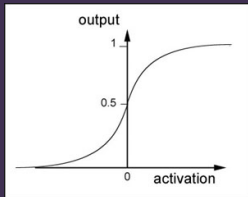
▶ More common: **sigmoid function**

An artificial neural network
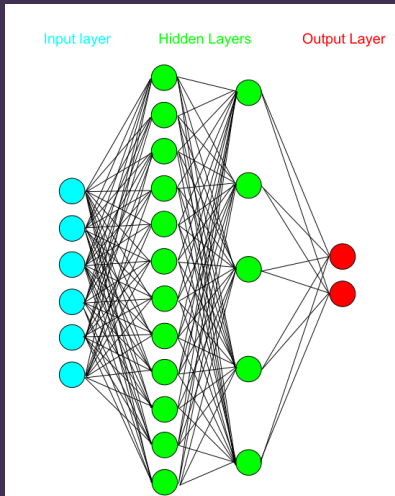
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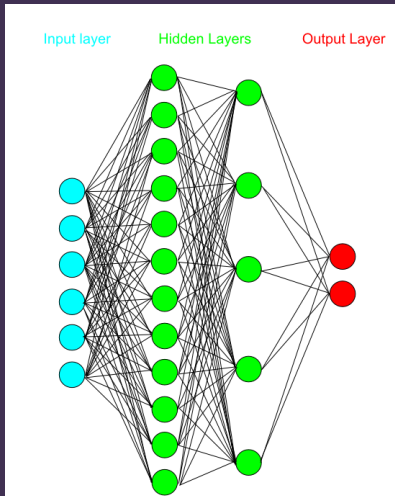
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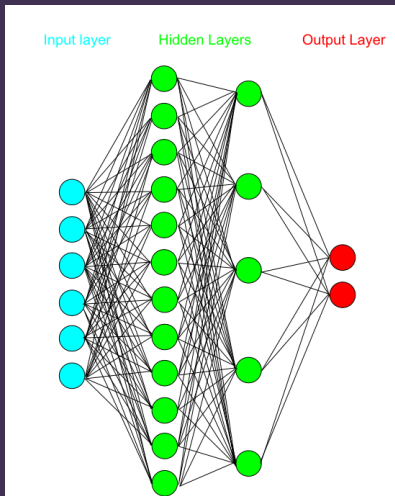
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An artificial neural network

Input layer   Hidden Layers   Output Layer

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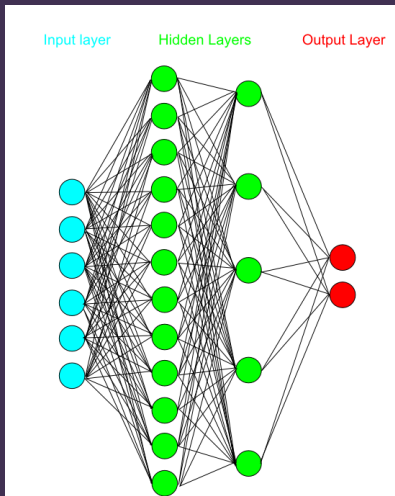
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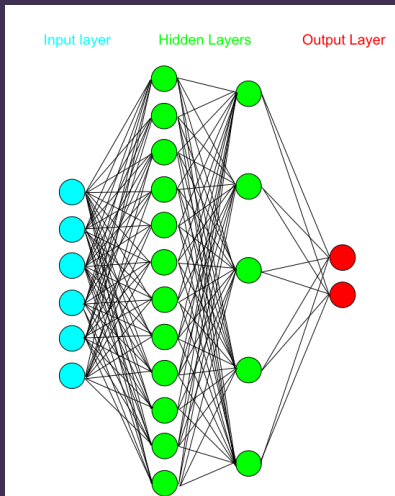- Each layer is an array of **perceptrons**
- Each perceptron's output is connected to **every** perceptron in the next layer

Image classification

Image classification

- Classic example: **handwritten digit recognition**

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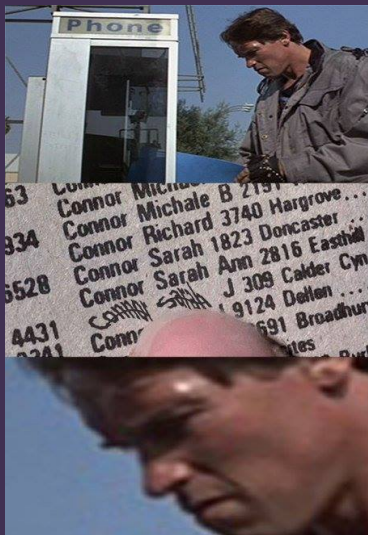
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  - ▶ Feed in **training data**
  - ▶ When the network happens to give the correct answer, **reinforce** the relevant weights
  - ▶ Repeat until a desired **accuracy** is obtained
- ▶ Note: this requires a large amount of training data that is **tagged**,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

Training

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- **Gradient descent**: it's an optimisation problem, so can apply hillclimbing

Overfitting

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Overfitting

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

Deep learning

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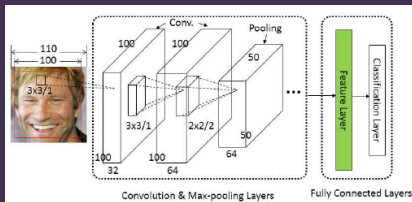► Basically, the use of large ANNs with **many layers**

Deep learning

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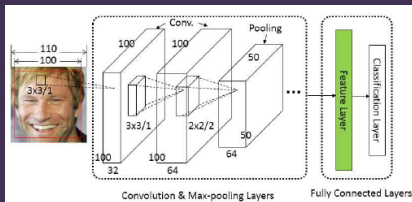
Deep learning

► Basically, the use of large ANNs with **many layers**
► Often uses **large training sets**
► Training often uses powerful **GPUs** — many times faster than training on the CPU

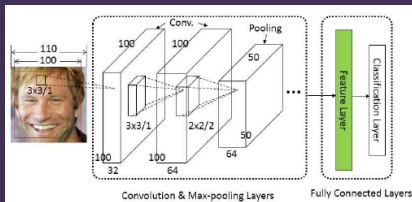# Convolutional Neural Networks (ConvNets)

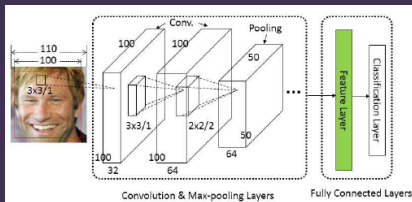# Convolutional Neural Networks (ConvNets)

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Convolutional Neural Networks (ConvNets)

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- There are also fully connected layers

Deep neural networks learn hierarchical feature representations

input layer   hidden layer 1   hidden layer 2   hidden layer 3   output layer
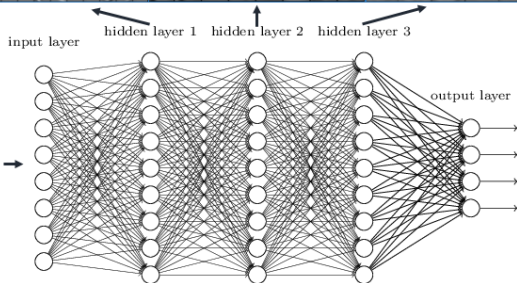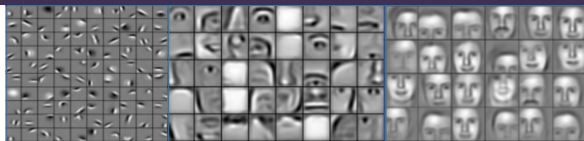
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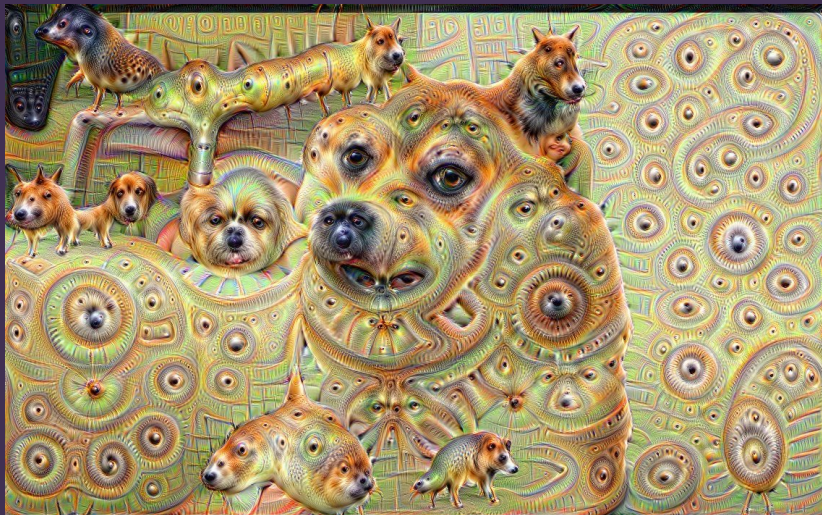
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Style transfer

Source image (**Style**)   Target image (**Content**)   Output (deepart)

A Neural Algorithm of Artistic Style [Gatys et al. 2015]

Generative Adversarial Networks (GANs)

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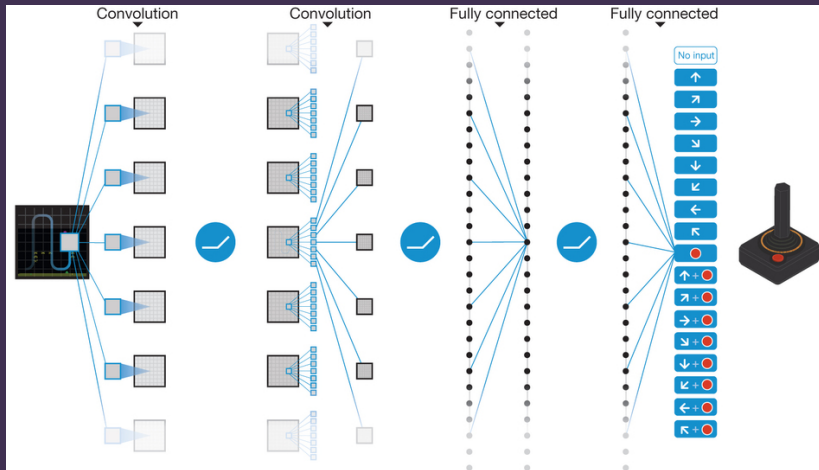 ► One to distinguish "real" from "fake"

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  - ► One to distinguish "real" from "fake"
- ► `http://research.nvidia.com/publication/2017-10_Progressive-Growing-of`

Learning to play Atari games (Mnih et al, 2015)

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- ► MCTS with ANNs for move pruning, simulation playouts and state evaluation

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► Defeated Lee Sedol, world Go champion

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► Stockfish is based on decades of research by expert chess players and AI programmers — AlphaZero started from no chess-specific knowledge whatsoever (other than the rules of the game)