COMP250: Artificial Intelligence

10: Deep learning

Neural networks

Artificial Neural Networks (ANNs)

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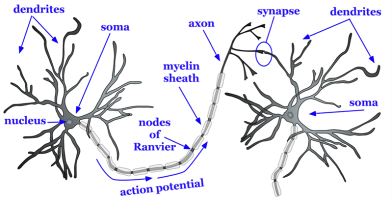
- Idea has been around since the 1950s
- Recent resurgence of interest: today's powerful CPUs and GPUs allow much larger ANNs to be used

Real neurons



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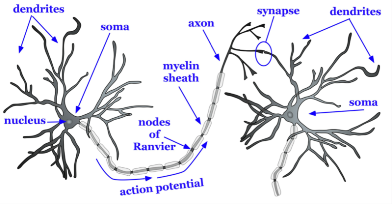

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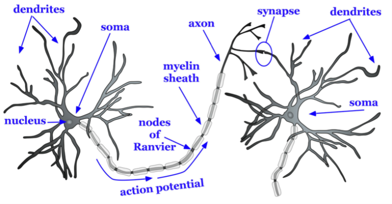

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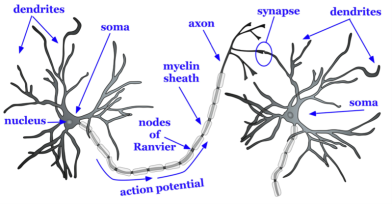

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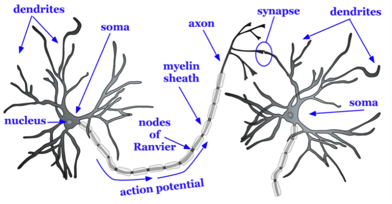

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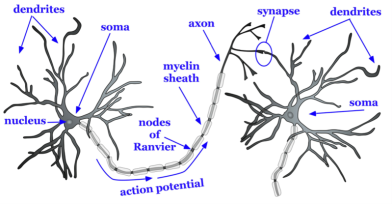

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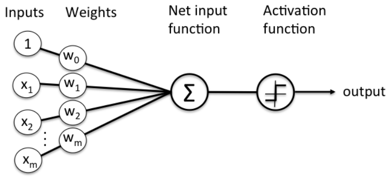
- Human brain contains approximately **100 billion** neurons

An artificial neuron



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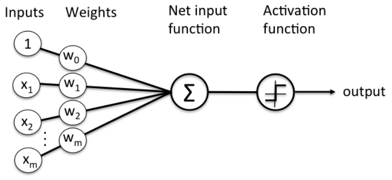

- A **perceptron**

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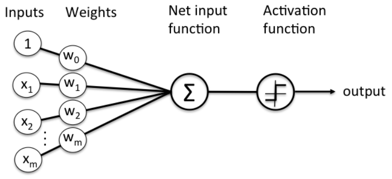

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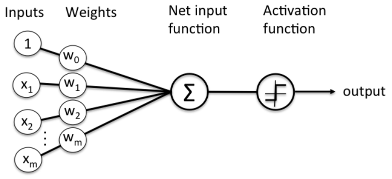

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- Each input has a **weight** w_i between -1 and $+1$

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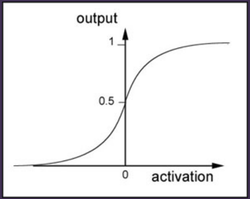
- More common: **sigmoid function**



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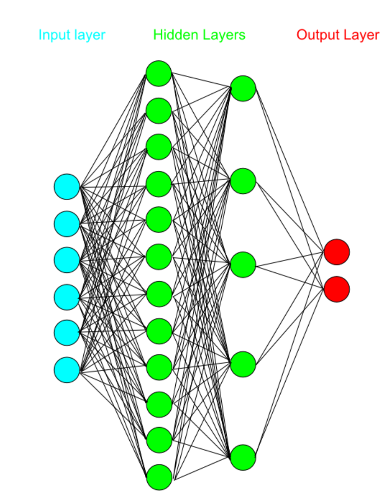

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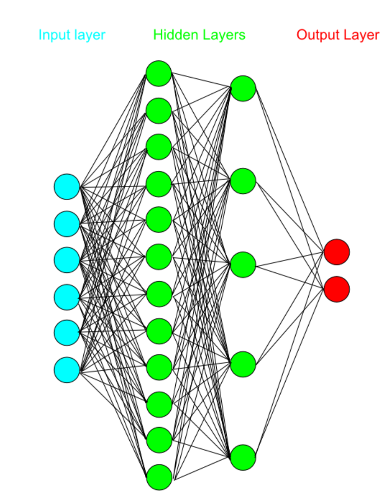

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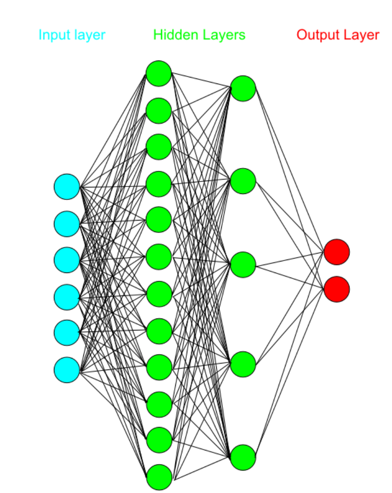

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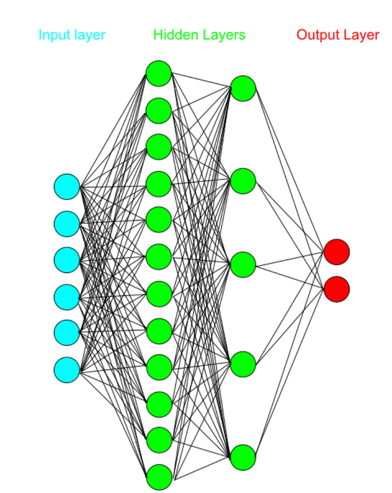

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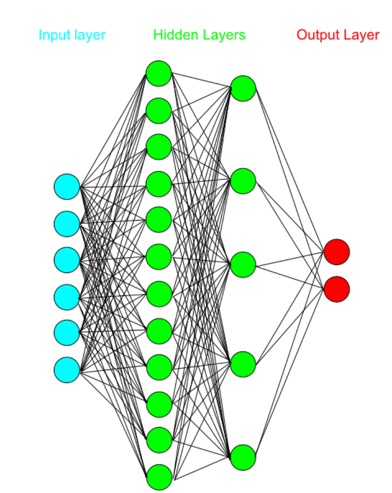

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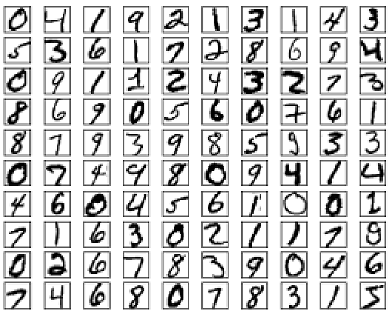
- Each perceptron's output is connected to **every** perceptron in the next layer

Image classification



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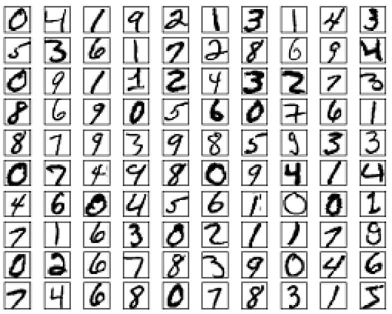

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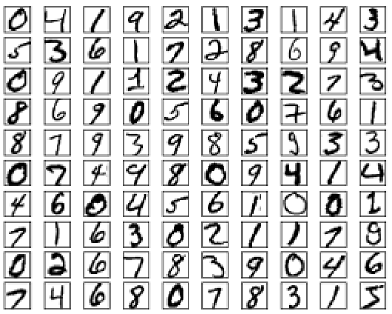

- Classic example: **handwritten digit recognition**
- Given a **raster image**, which of the digits 0 to 9 does it represent?

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

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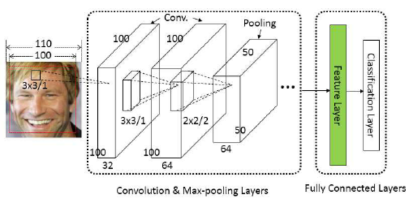
- Often uses **large training sets**
- Training often uses powerful **GPUs** — many times faster than training on the CPU

Convolutional Neural Networks (ConvNets)



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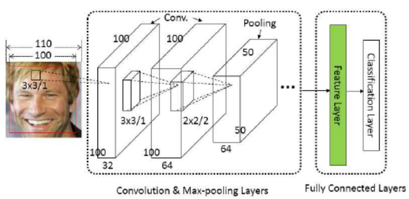

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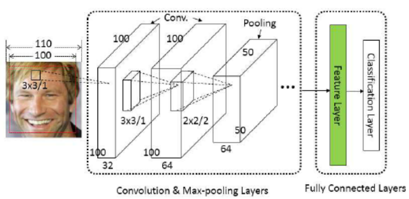

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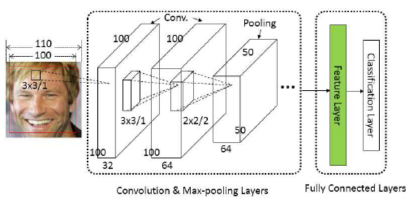

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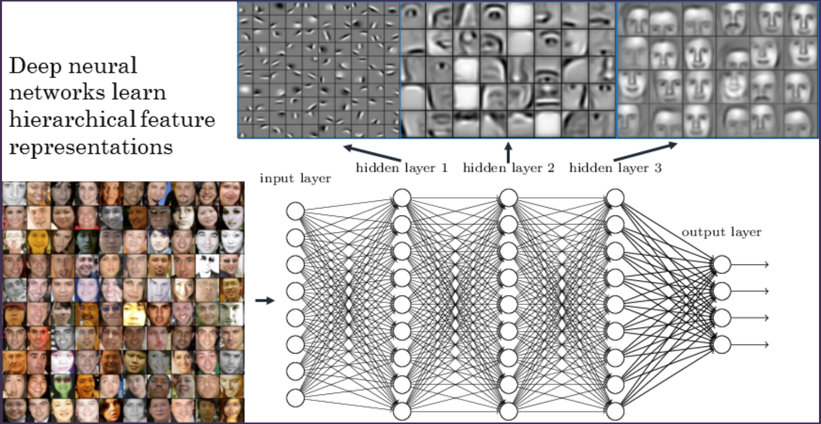
- There are also fully connected layers


Deep neural
networks learn
hierarchical feature
representations
input layer
hidden layer 1
hidden layer 2
hidden layer 3
output layer

DeepDream

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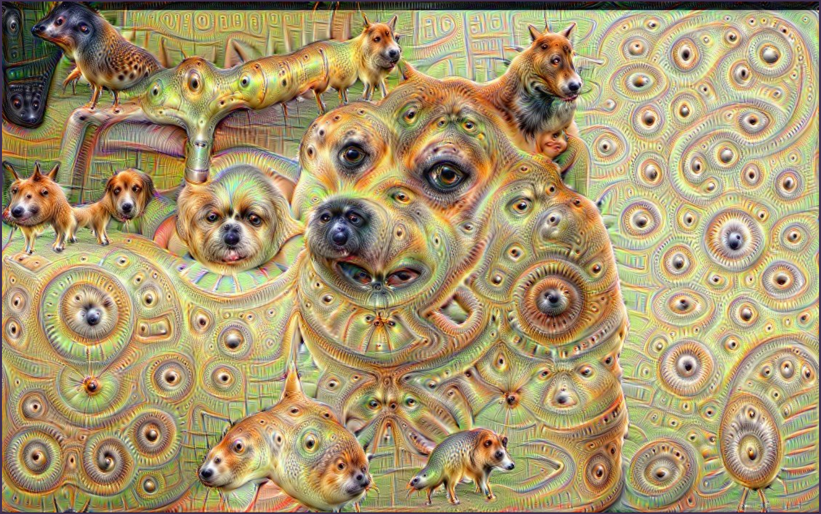

Style transfer

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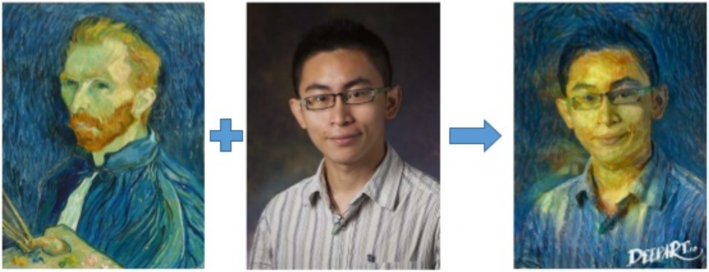
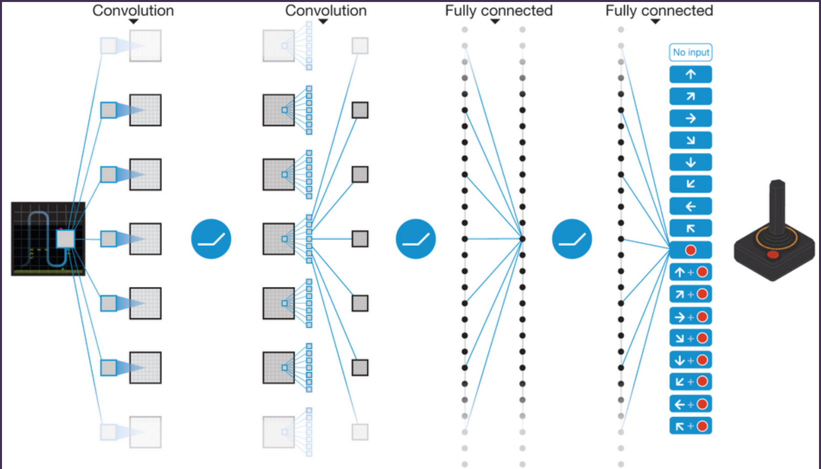


Source image (**Style**) | Target image (**Content**) | Output (deepart)

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

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



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Deep learning for PCG

https://www.youtube.com/watch?v=3wcpLwvBTYo