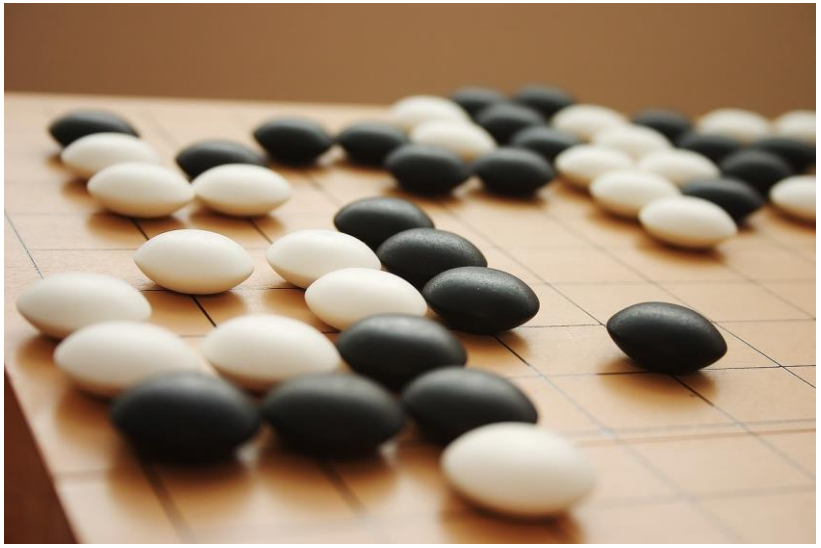
COMP9321:
Data services engineering

Week 10: Introduction to Deep Learning

Term 1, 2020

By Mortada Al-Banna, CSE UNSW


Deep Learning



Cat Dog

Why Deep Learning

- Deal very well with unstructured Data
- More Data = Better Learning
- More Accurate in some cases
- Extensive feature engineering is not required

When to use Deep Learning

- Deep Learning outperform other techniques if the *data size is large*. But with small data size, traditional Machine Learning algorithms are preferable.
- Deep Learning techniques need to have *high end infrastructure* to train in reasonable time.
- When there is *lack of domain understanding for feature introspection*, Deep Learning techniques outshines others as you have to worry less about feature engineering.

反省

- Deep Learning really shines when it comes to *complex problems such as image classification, natural language processing, and speech recognition*.

Many machine learning methods inspired by biology, e.g., the (human) brain

Our brain has $\sim 10^{11}$ neurons, each of which communicates (is connected) to $\sim 10^{4}$ other neurons

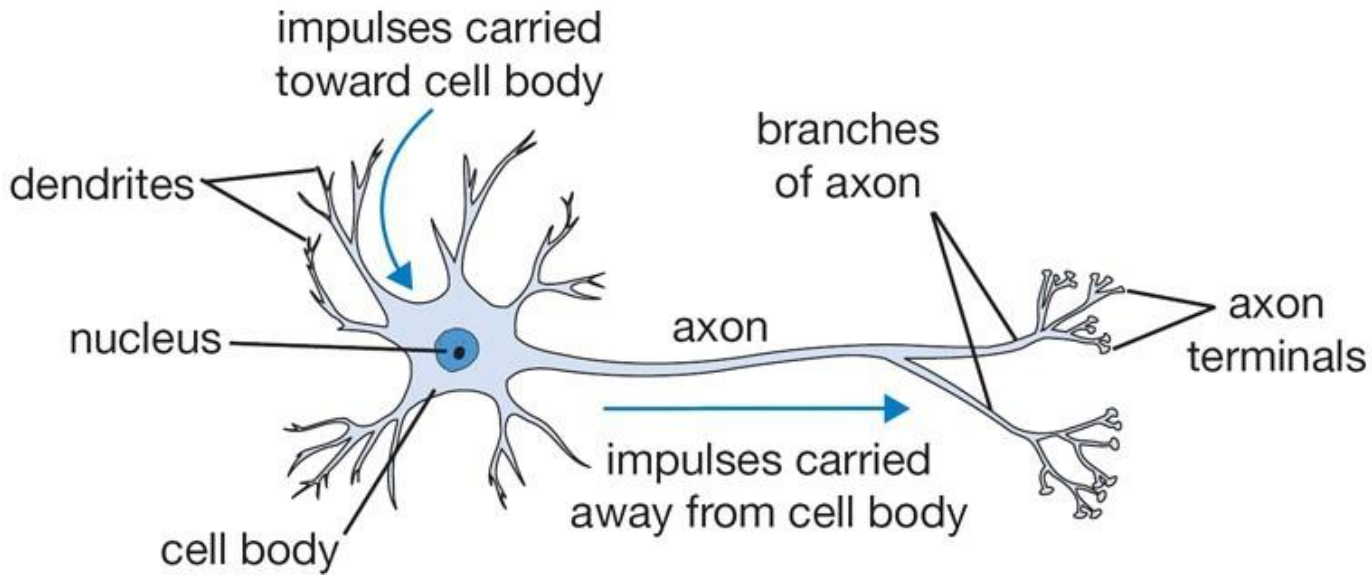


Figure : The basic computational unit of the brain: Neuron

[Pic credit: http://cs231n.github.io/neural-networks-1/]

Neural networks define functions of the inputs (hidden features), computed by neurons

Artificial neurons are called units

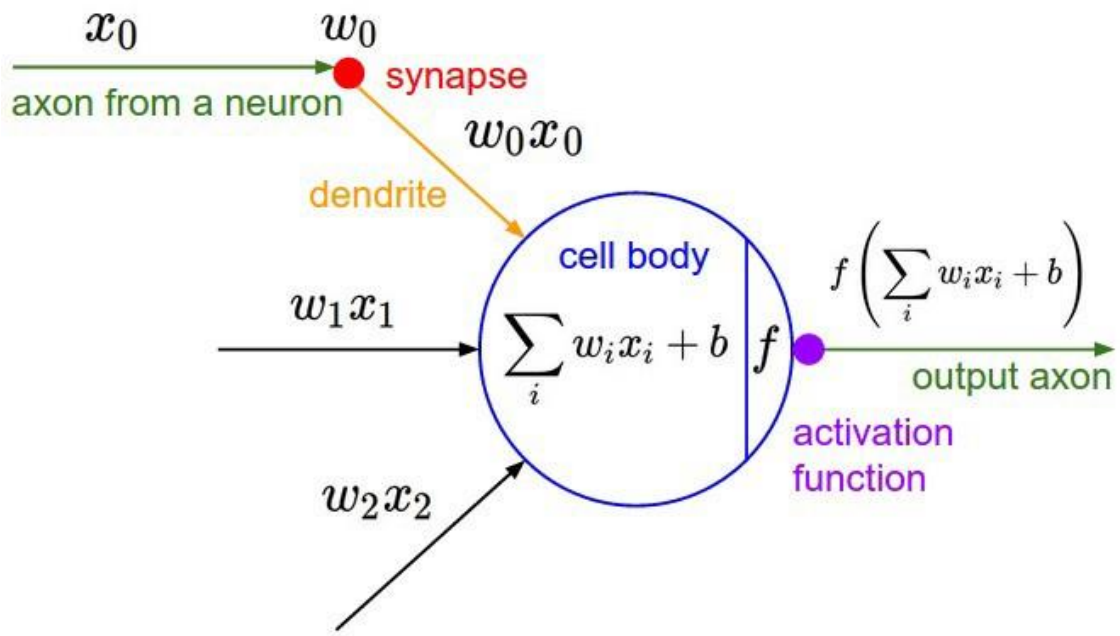


Figure : A mathematical model of the neuron in a neural network

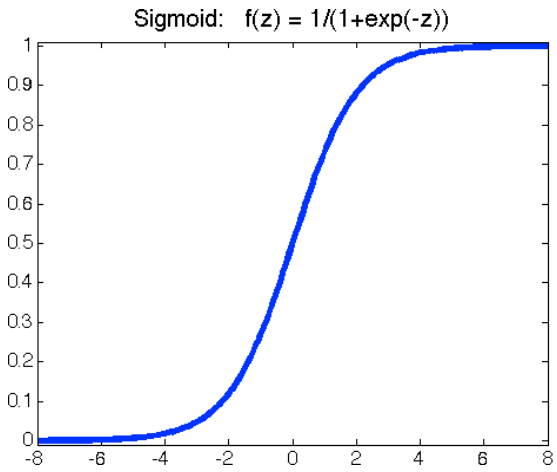
[Pic credit: http://cs231n.github.io/neural-networks-1/]

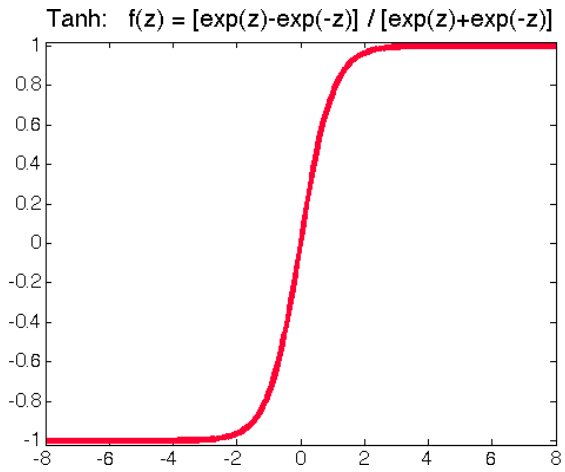
Most commonly used activation functions:

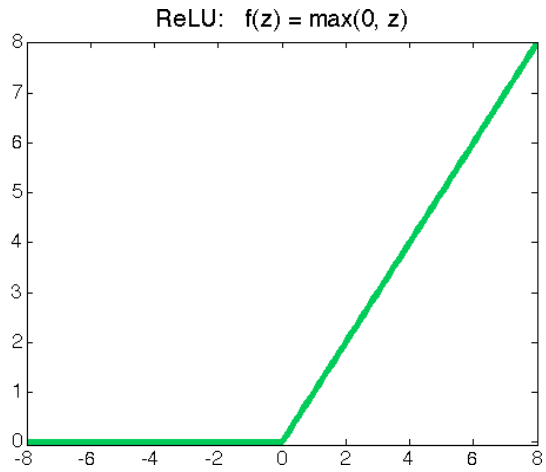
Sigmoid: $\sigma(z) = \frac{1}{1+\exp(-z)}$

Tanh: $\tanh(z) = \frac{\exp(z)-\exp(-z)}{\exp(z)+\exp(-z)}$

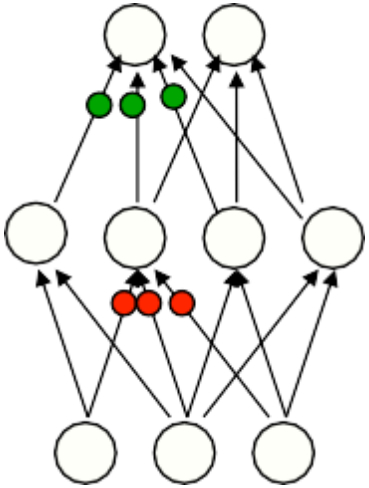
ReLU (Rectified Linear Unit): $\mathrm{ReLU}(z) = \max(0, z)$







Network with one layer of four hidden units:



output units

input units

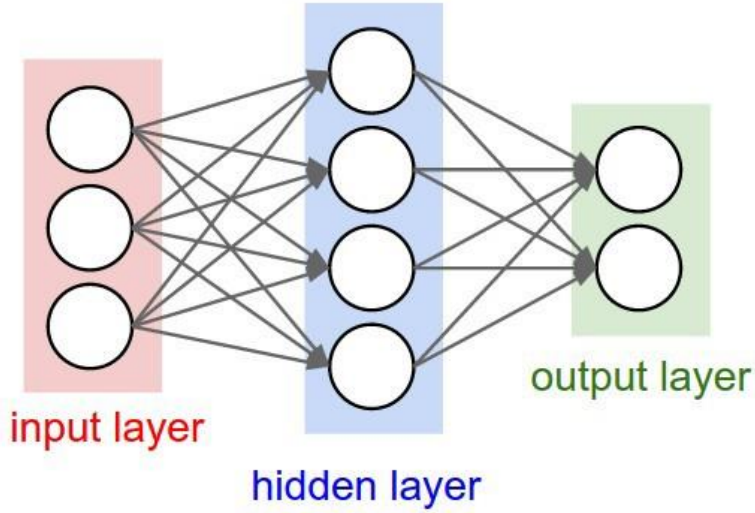


Figure : Two different visualizations of a 2-layer neural network. In this example: 3 input units, 4 hidden units and 2 output units

Naming conventions; a 2-layer neural network:

One layer of hidden units

One output layer

(we do not count the inputs as a layer)

Going deeper: a 3-layer neural network with two layers of hidden units

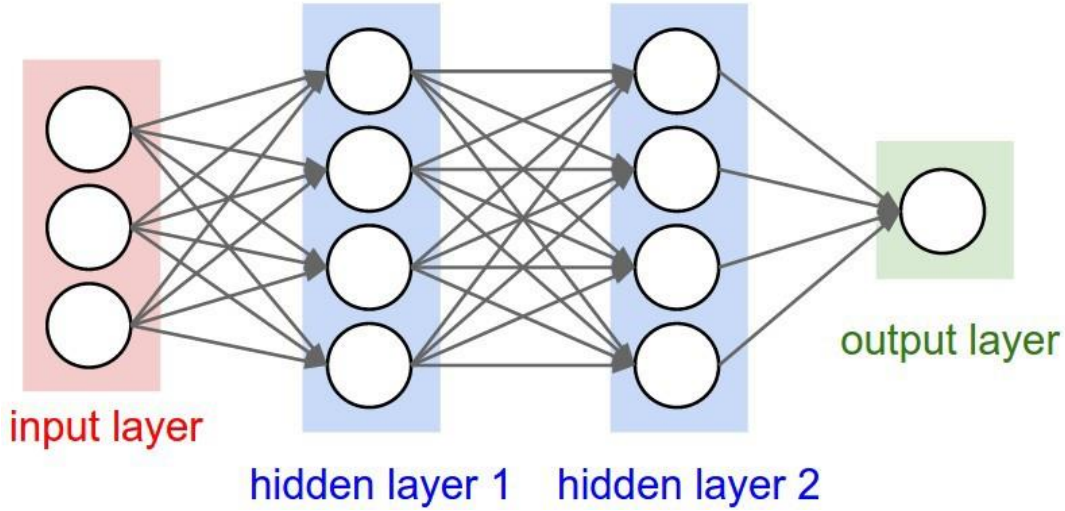


Figure : A 3-layer neural net with 3 input units, 4 hidden units in the first and second hidden layer and 1 output unit

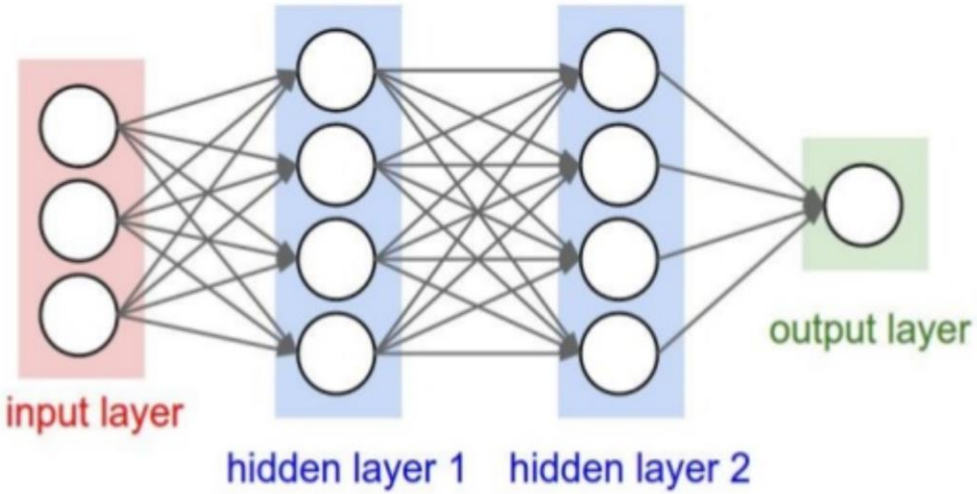
Naming conventions; a N-layer neural network:

- $N-1$ layers of hidden units
- One output layer

[http://cs231n.github.io/neural-networks-1/]

Forward Pass (Forward Propagation)

- The input neurons first receive the data features of the object. After processing the data, they send their output to the first hidden layer.
- The hidden layer processes this output and sends the results to the next hidden layer.
- This continues until the data reaches the final output layer, where the output value determines the object's classification.
- This entire process is known as Forward Propagation, or Forward prop.



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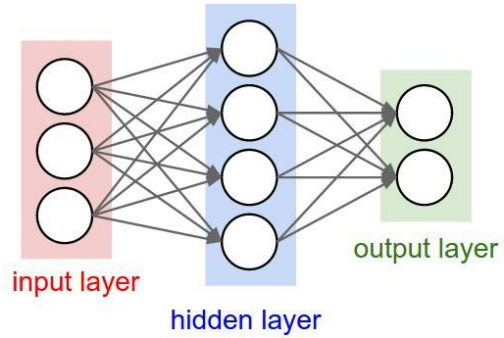


Output of the network can be written as:

$$h_j(\mathbf{x}) = f\left(v_{j0} + \sum_{i=1}^{D} x_i v_{ji}\right)$$

$$o_k(\mathbf{x}) = g\left(w_{k0} + \sum_{j=1}^{J} h_j(\mathbf{x}) w_{kj}\right)$$

(j indexing hidden units, k indexing the output units, D number of inputs)

Activation functions f , g : sigmoid/logistic, tanh, or rectified linear (ReLU)

$$\sigma(z) = \frac{1}{1+\exp(-z)}, \quad \tanh(z) = \frac{\exp(z)-\exp(-z)}{\exp(z)+\exp(-z)}, \quad \mathrm{ReLU}(z) = \max(0, z)$$

Backward Pass (Back-propagation)

- Back-propagation: an efficient method for computing gradients needed to perform gradient-based optimization of the weights in a multi-layer network

Training neural nets:

Loop until convergence:

- for each example n
  1. Given input $\mathbf{x}^{(n)}$, propagate activity forward ($\mathbf{x}^{(n)} \rightarrow \mathbf{h}^{(n)} \rightarrow o^{(n)}$) (**forward pass**)
  2. Propagate gradients backward (**backward pass**)
  3. Update each weight (via gradient descent)

What are we propagating Backward?

- Find weights:

$$\mathbf{w}^* = \underset{\mathbf{w}}{\operatorname{argmin}} \sum_{n=1}^{N} \operatorname{loss}(\mathbf{o}^{(n)}, \mathbf{t}^{(n)})$$

  where $\mathbf{o} = f(\mathbf{x}; \mathbf{w})$ is the output of a neural network

- Define a loss function, eg:
  - Squared loss: $\sum_k \frac{1}{2}(o_k^{(n)} - t_k^{(n)})^2$
  - Cross-entropy loss: $-\sum_k t_k^{(n)} \log o_k^{(n)}$

- Gradient descent:

$$\mathbf{w}^{t+1} = \mathbf{w}^t - \eta \frac{\partial E}{\partial \mathbf{w}^t}$$

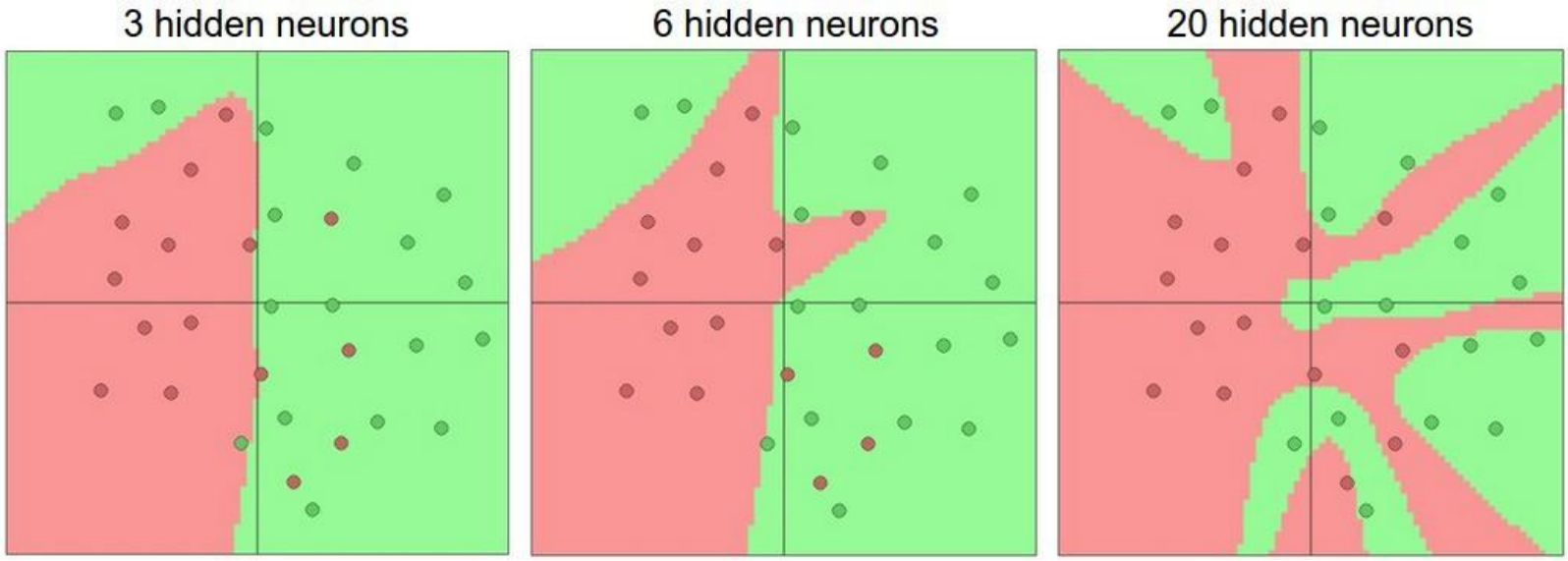
  where η is the learning rate (and E is error/loss)

Some Types of Deep Neural Networks

- **Feedforward Networks (FFN):** Best for when we have an idea of the output
- **Recurrent Neural Network (RNN):** Best for time series Data
- **Convolutional Neural Network (CNN):** Best of Image, text, voice recognition.

Neural network with at **least one hidden layer** is a universal approximator (can represent any function).

Proof in: Approximation by Superpositions of Sigmoidal Function, Cybenko, paper



The capacity of the network increases with more hidden units and more hidden layers

Why go deeper? Read e.g.,: Do Deep Nets Really Need to be Deep? Jimmy Ba, Rich Caruana, Paper: paper]

[http://cs231n.github.io/neural-networks-1/]

How to Determine Number of Layers and Number of Neurons in Each Layer?

- Based on the data, draw an expected decision boundary to separate the classes.
- Express the decision boundary as a set of lines. Note that the combination of such lines must yield to the decision boundary.
- The number of selected lines represents the number of hidden neurons in the first hidden layer.
- To connect the lines created by the previous layer, a new hidden layer is added. Note that a new hidden layer is added each time you need to create connections among the lines in the previous hidden layer.
- The number of hidden neurons in each new hidden layer equals the number of connections to be made.

https://towardsdatascience.com/beginners-ask-how-many-hidden-layers-neurons-to-use-in-artificial-neural-networks-51466afa0d3e

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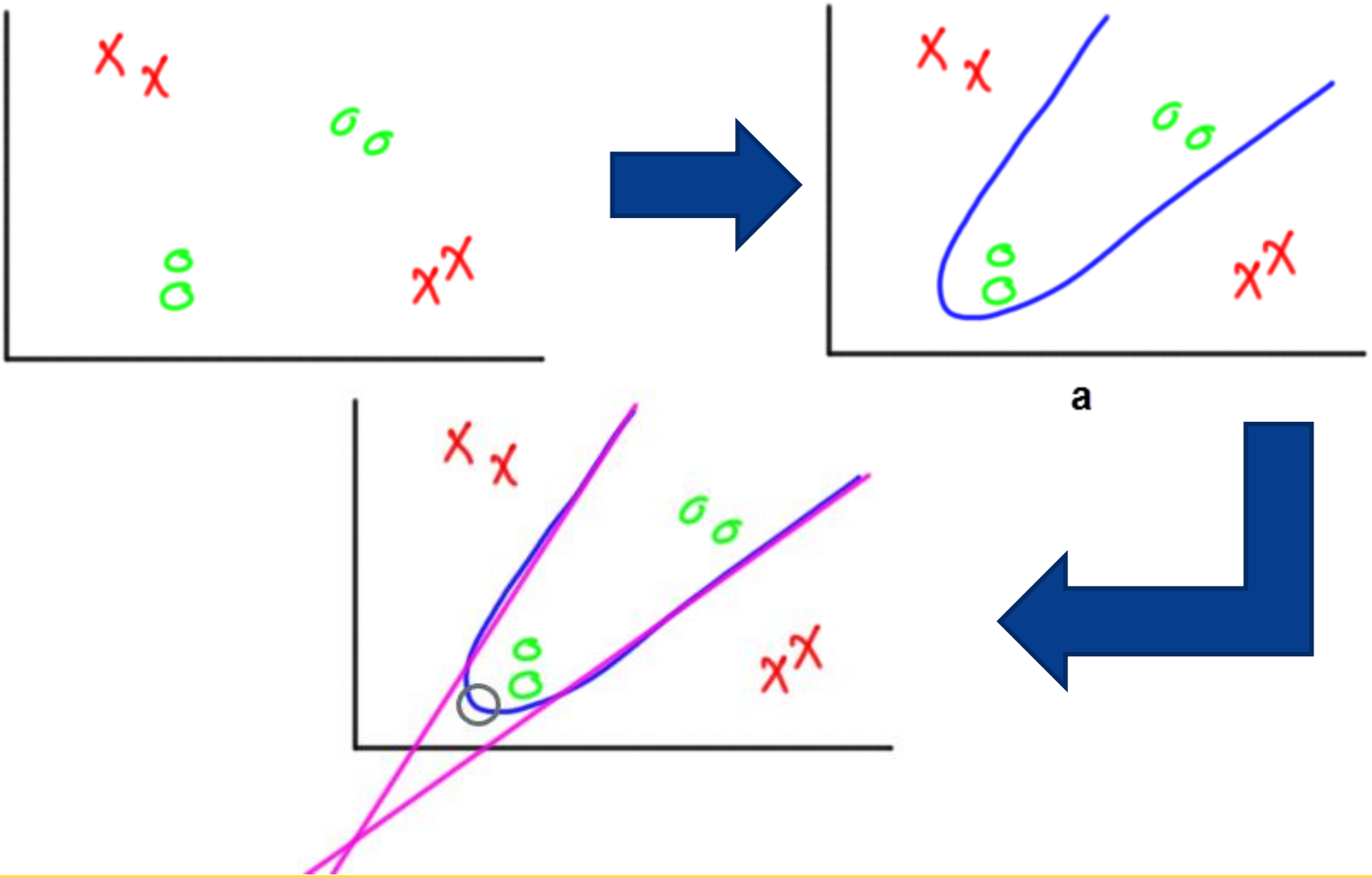

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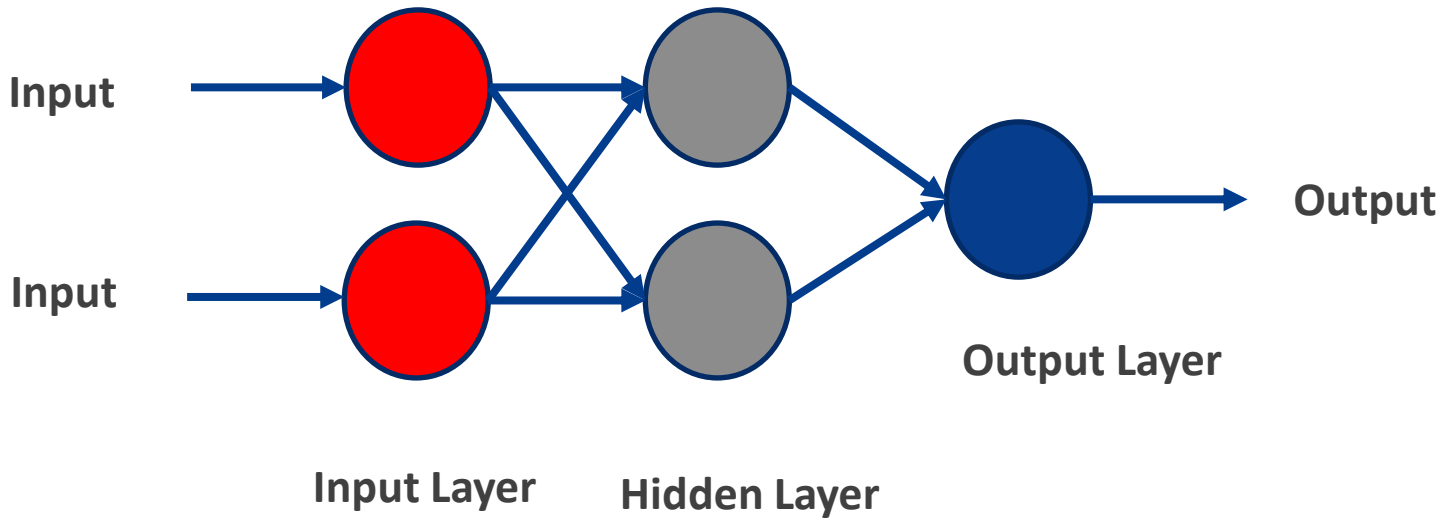

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Deep Neural Networks Weaknesses

- Deep Learning requires a large dataset, hence long training period.
- In term of cost, Machine Learning methods like SVMs and other tree ensembles are very easily deployed even by relative machine learning novices and can usually get you reasonably good results.
- Deep learning methods tend to learn everything. It's better to encode prior knowledge about structure of images (or audio or text).
- The learned features are often difficult to understand. Many vision features are also not really human-understandable (e.g, concatenations/combinations of different features).
- Requires a good understanding of how to model multiple modalities with traditional tools.

Useful Tools

- TensorFlow
- PyTorch
- Apache MXNet
- Caffe

Useful Resources

- https://towardsdatascience.com/introducing-deep-learning-and-neural-networks-deep-learning-for-rookies-1-bd68f9cf5883
- https://www.edureka.co/blog/backpropagation/
- https://towardsdatascience.com/multi-layer-neural-networks-with-sigmoid-function-deep-learning-for-rookies-2-bf464f09eb7f
- https://machinelearningmastery.com/how-to-configure-the-number-of-layers-and-nodes-in-a-neural-network/
- https://medium.com/datadriveninvestor/thats-not-enough-we-have-to-go-deeper-24dd16d85828

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