COMP9321:
Data services engineering

Week 10: Introduction to Deep Learning

Term 3, 2019

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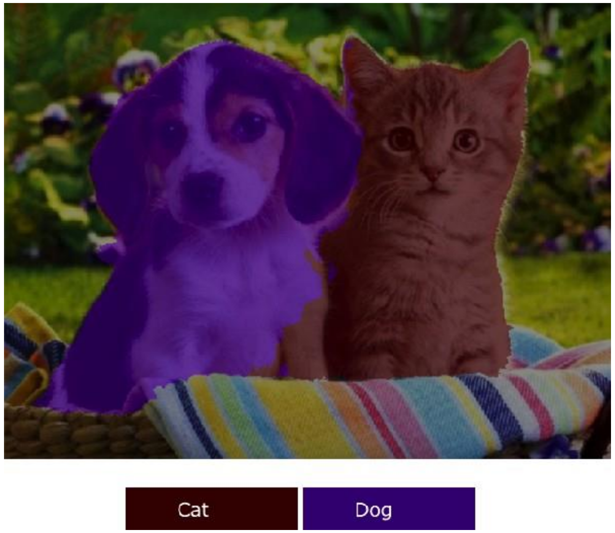
Deep Learning

AT&T
2:51 PM
What can I help you with?


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.
- 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

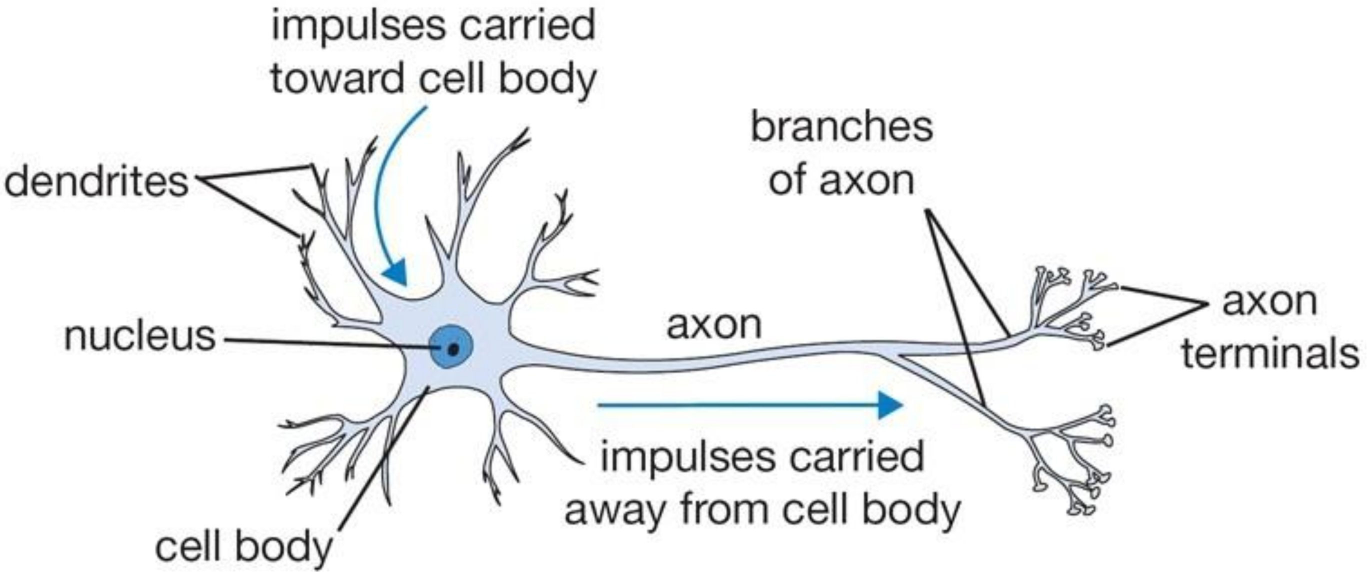

impulses carried toward cell body
dendrites
branches of axon
nucleus
axon
axon terminals
impulses carried away from cell body
cell body

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

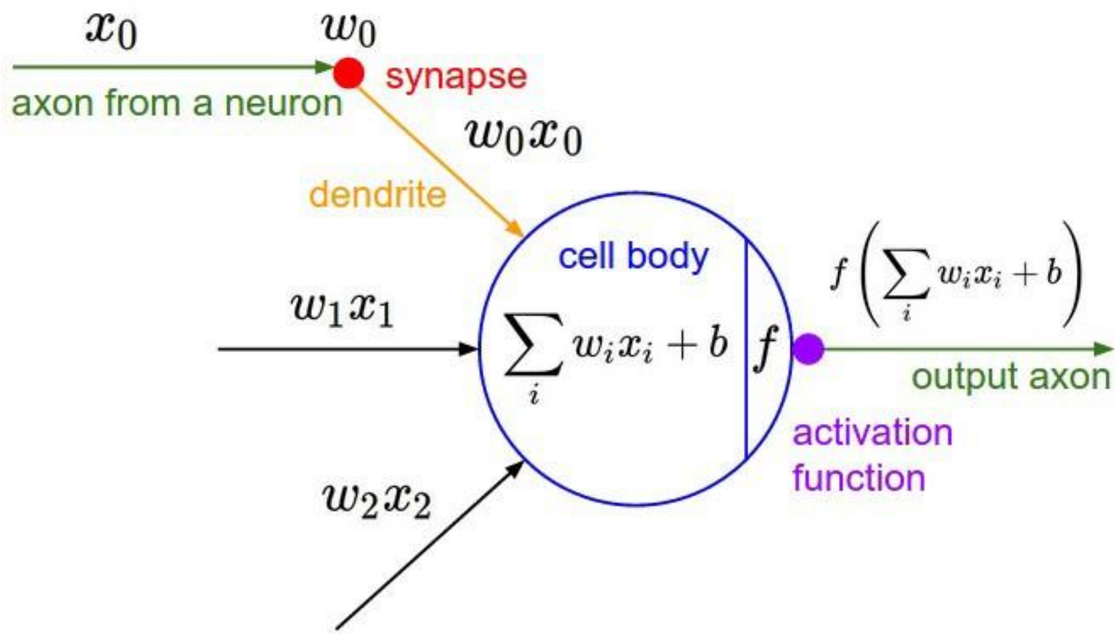


Figure : A mathematical model of the neuron in a neural network

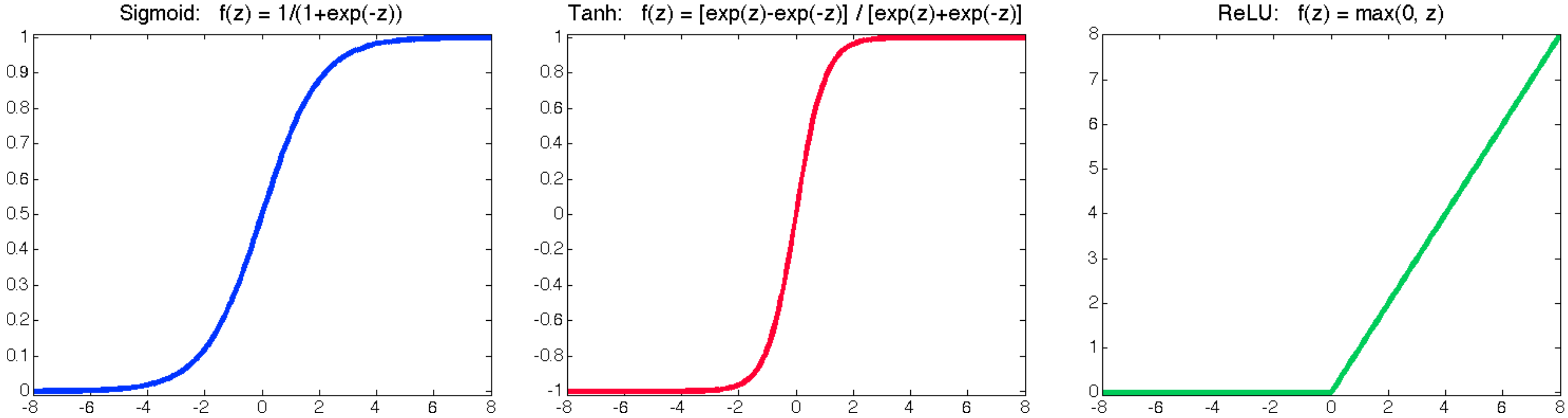
[Pic credit: http://cs231n.github.io/neural-networks-1/]

Most commonly used activation functions:

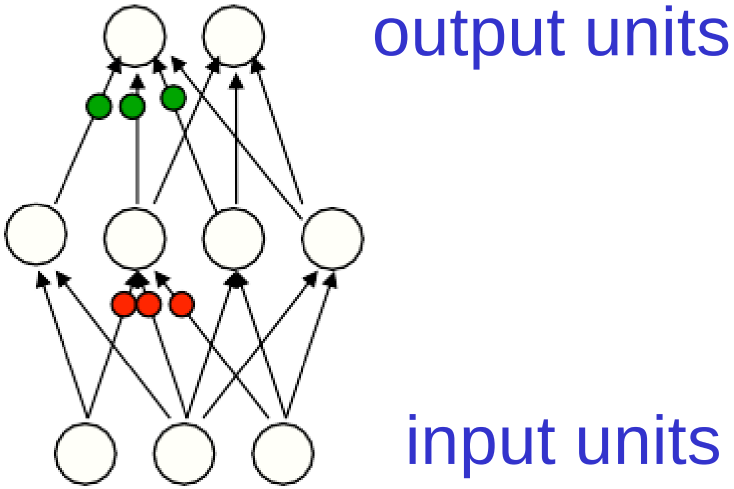
Sigmoid: $\sigma(z) = \frac{1}{1+\exp(-z)}$

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:



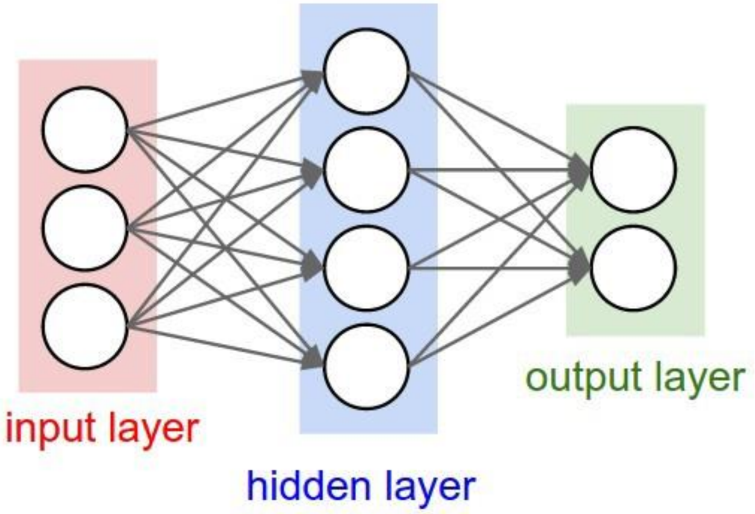


Figure : Two different visualizations of a 2-layer neural network. In this example: 3 input units, 4 hidden units and 2 output units

Naming conventions; a 2-layer neural network:

- One layer of hidden units
- One output layer
  - (we do not count the inputs as a layer)

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

Zemel, Urtasun, Fidler (UofT)

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

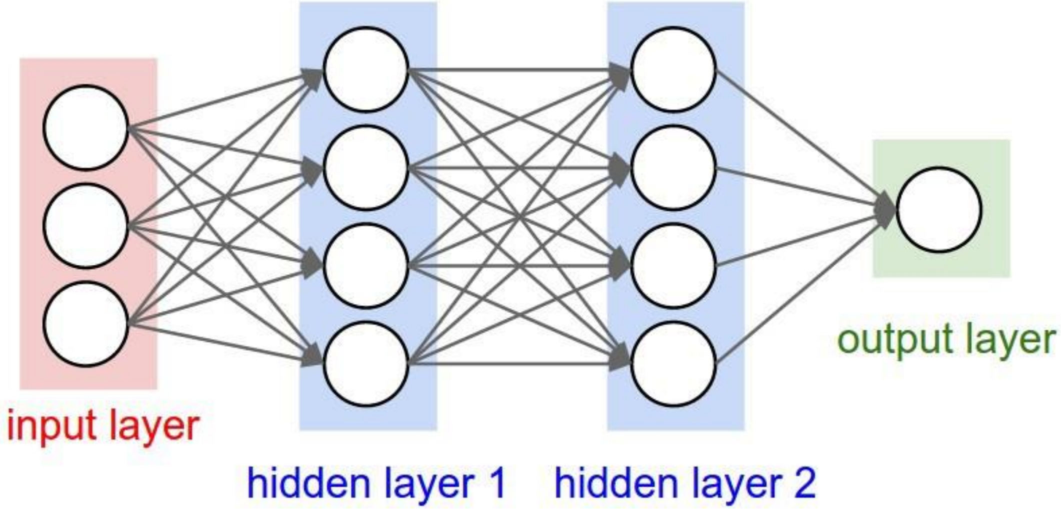


Figure : A 3-layer neural net with 3 input units, 4 hidden units in the first and second hidden layer and 1 output unit

Naming conventions; a N-layer neural network:

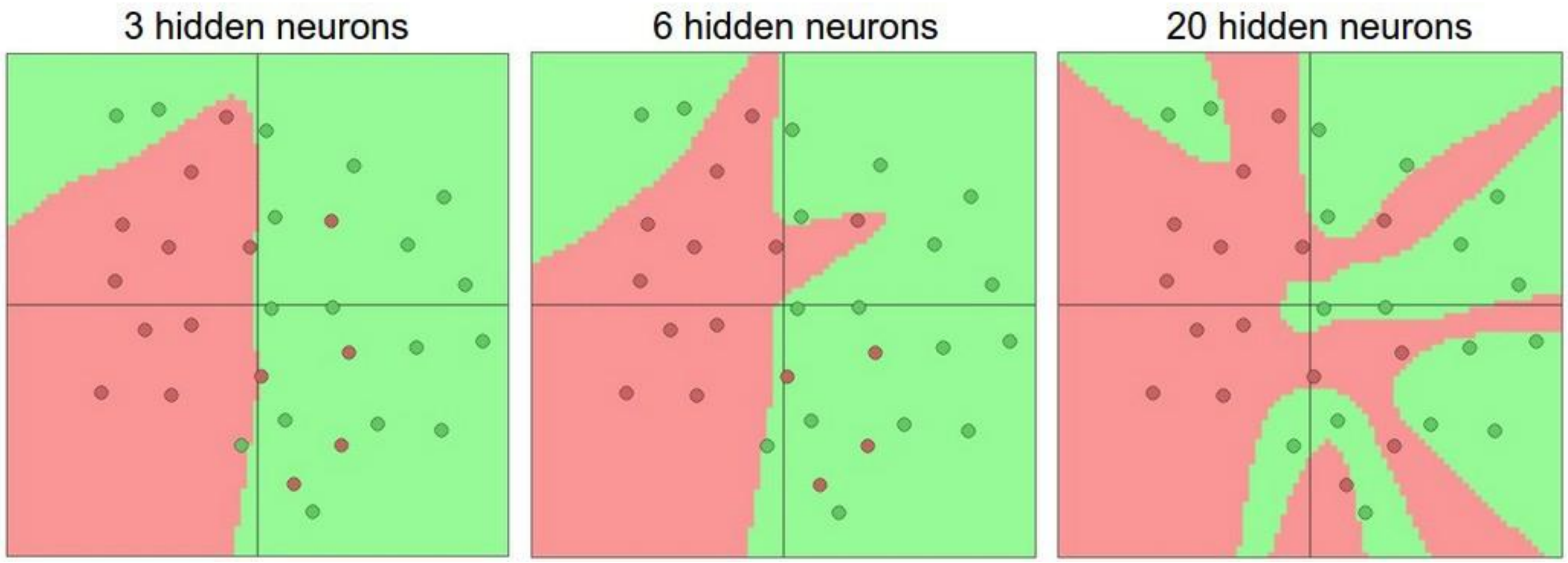
$N - 1$ layers of hidden units

One output layer

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

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

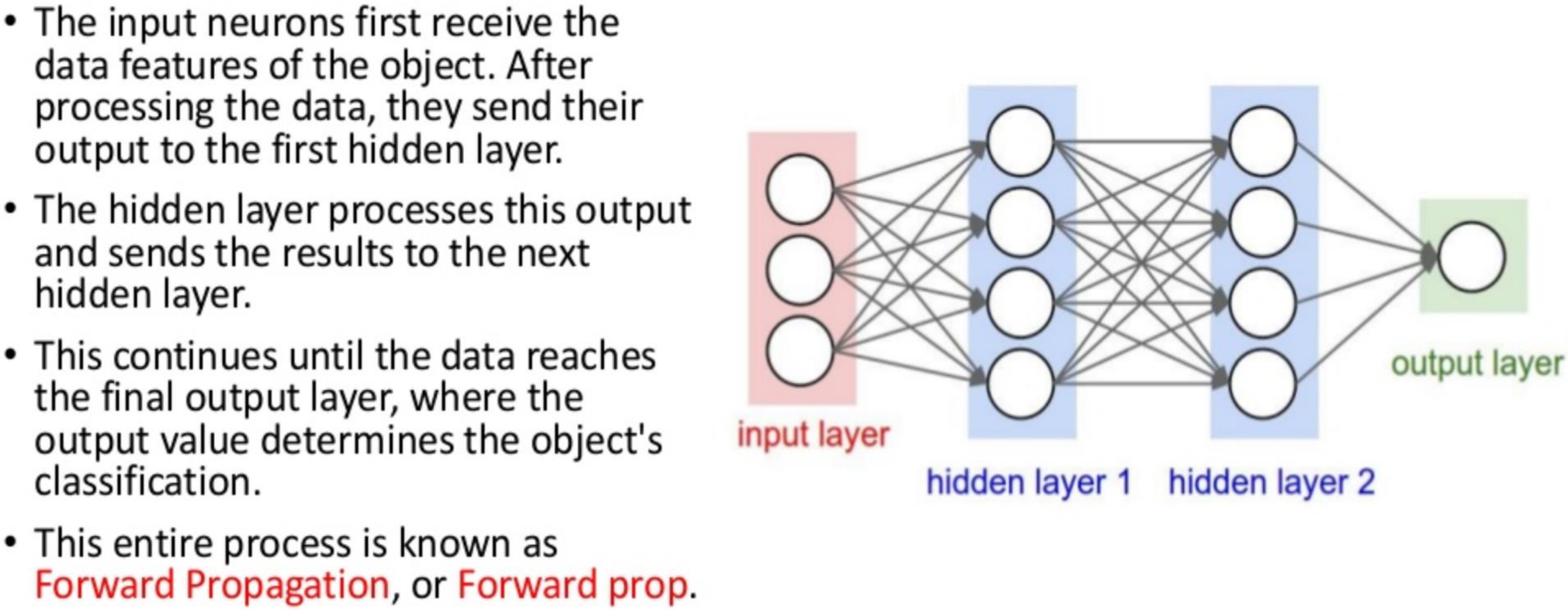


The capacity of the network increases with more hidden units and more hidden layers

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

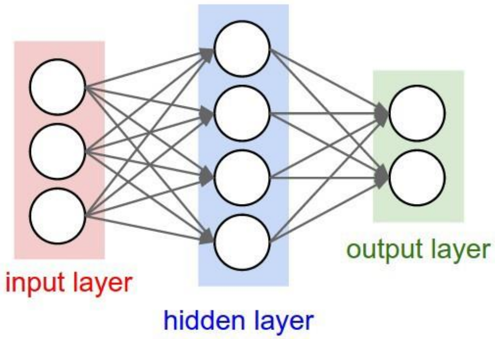
[http://cs231n.github.io/neural-networks-1/]

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.

Forward Pass (Forward Propagation)



Output of the network can be written as:

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

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

(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:

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

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

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

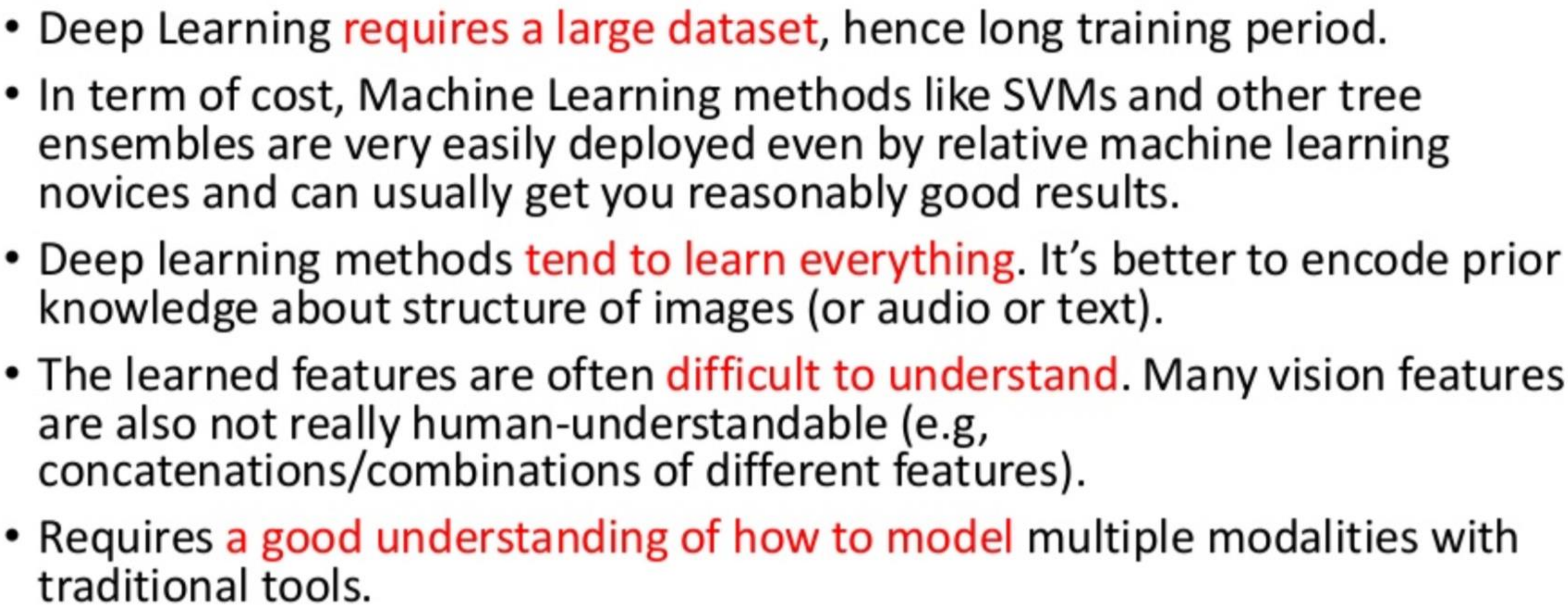
$$\mathbf{w}^{t+1} = \mathbf{w}^t - \eta \frac{\partial E}{\partial \mathbf{w}^t}$$

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.

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

Q&A