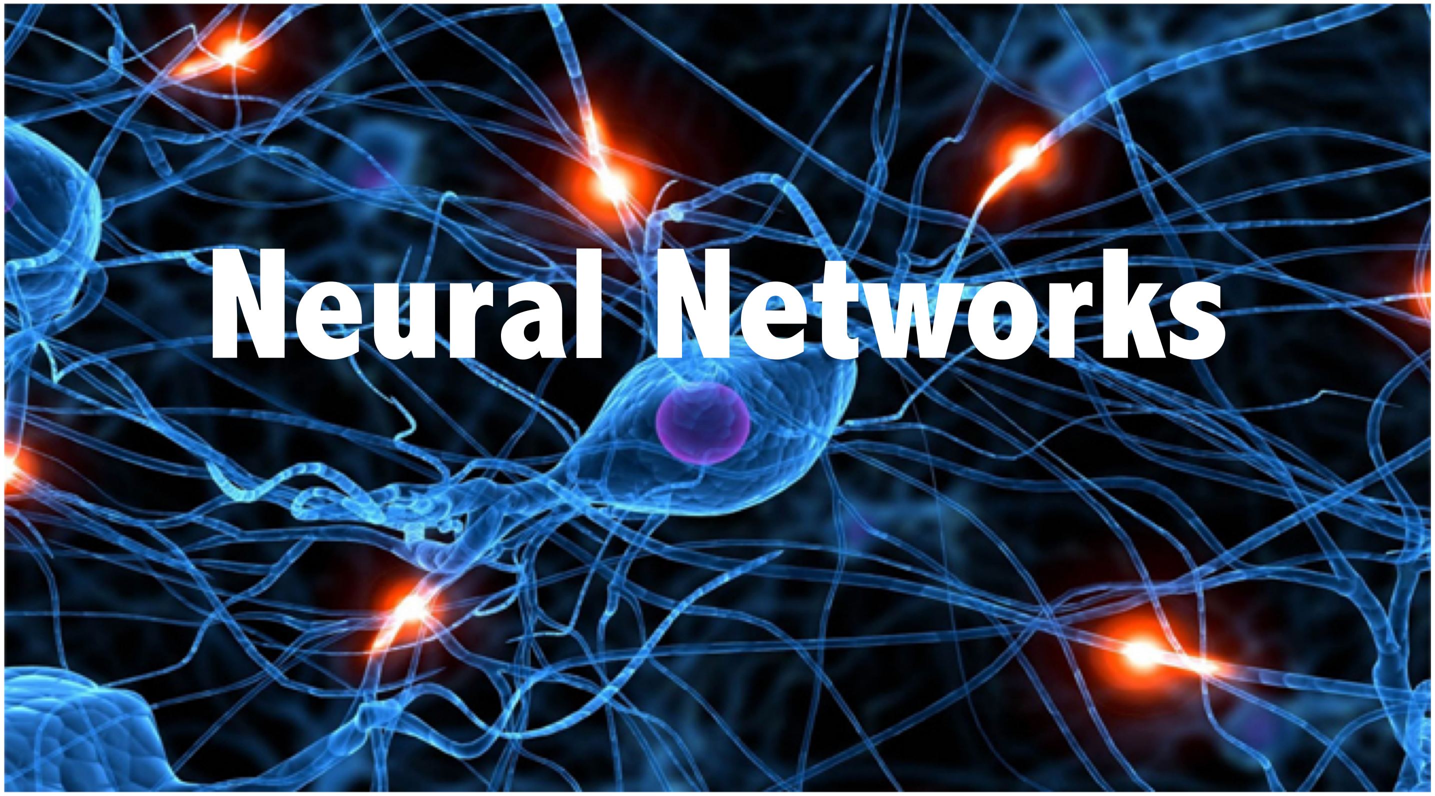
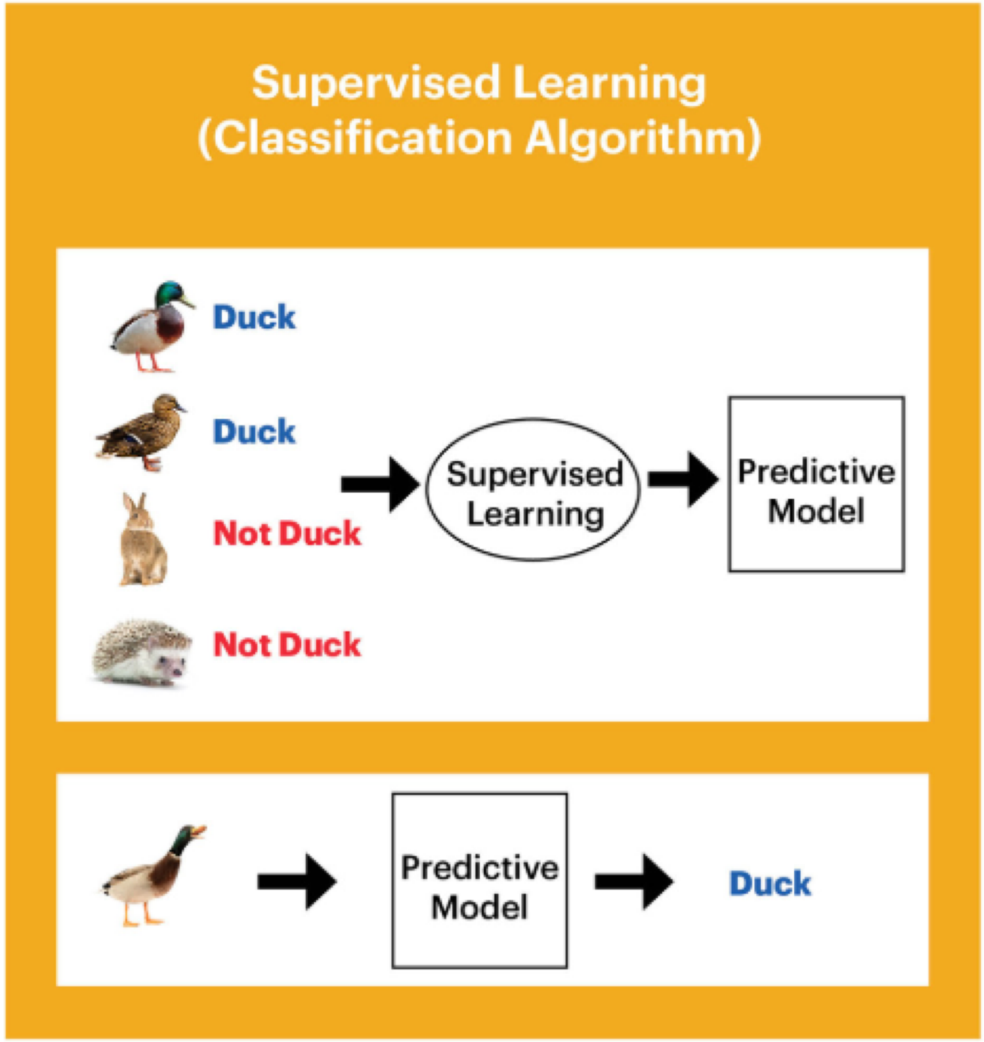

Neural Networks

Review: Machine learning concepts

- Three forms:
- Supervised learning
  - The agent is given some input-output pairs and it learns a function that maps the input to the output. The learning phase is often called training, and the
  - Example: training a naïve Bayes classifier.
- Unsupervised learning
  - The agent learns patterns in the input even though no explicit output or feedback is given.
  - Example: clustering
- Reinforcement learning
  - The agent is given feedback (rewards) during the steps of a task and the agent learns a function from states to predicted rewards.

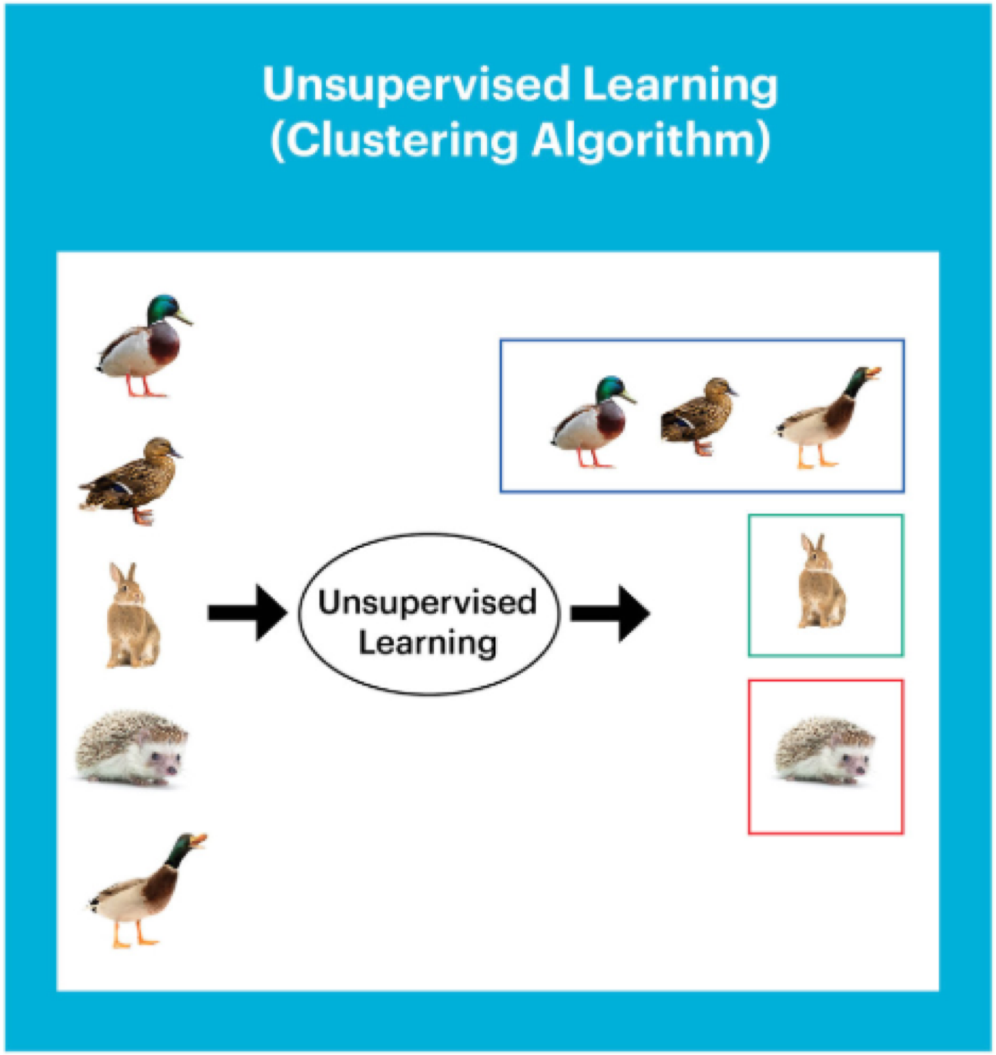
Supervised learning

- The agent is given some input-output pairs (*labeled* data) and it learns a function that maps the input to the output.
  - The input-output pairs given to the learning algorithm are called the *training set*.
  - The hope is that the function learned will do a good job at mapping previously-unseen inputs (inputs not in the training set) to outputs.
  - Sometimes, in order to evaluate how well a supervised learning algorithm performs, we hold back some of our input-output pairs and have a separate data set called the testing set that we use solely for evaluation, not for training.
- Most common algorithms are categorized as classification algorithms (output is categorical) or regression algorithms (output is numeric).


Supervised Learning
(Classification Algorithm)
Duck
Duck
Not Duck
Not Duck
Supervised Learning
Predictive Model
Predictive Model
Duck

Unsupervised learning

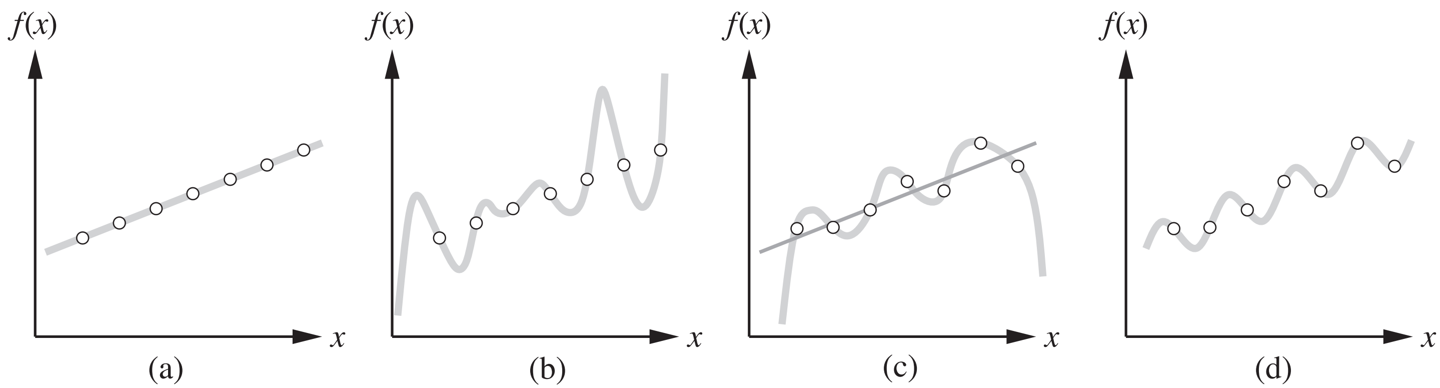
- The agent learns patterns in the input even though no explicit output or feedback is given.
- Training data is not labeled, so the goal is not to learn a function, but rather to find commonalities in the training set, and use those commonalities to draw inferences about new data.


Unsupervised Learning
(Clustering Algorithm)
Unsupervised
Learning

Supervised learning

- Given a ***training set*** of *N* example input-output pairs:
  - $(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)$
- Each y is generated by an unknown function $y = f(x)$.
- Goal: discover a function h that approximates the true function f.
- h is called a ***hypothesis***.
- Machine learning algorithms conduct searches for the "best" f.
- We can measure the accuracy of a hypothesis on a ***test set*** of examples that are distinct from the training set.
- A hypothesis ***generalizes well*** if it correctly predicts examples from the test set (even though it has never seen them before).

Supervised learning

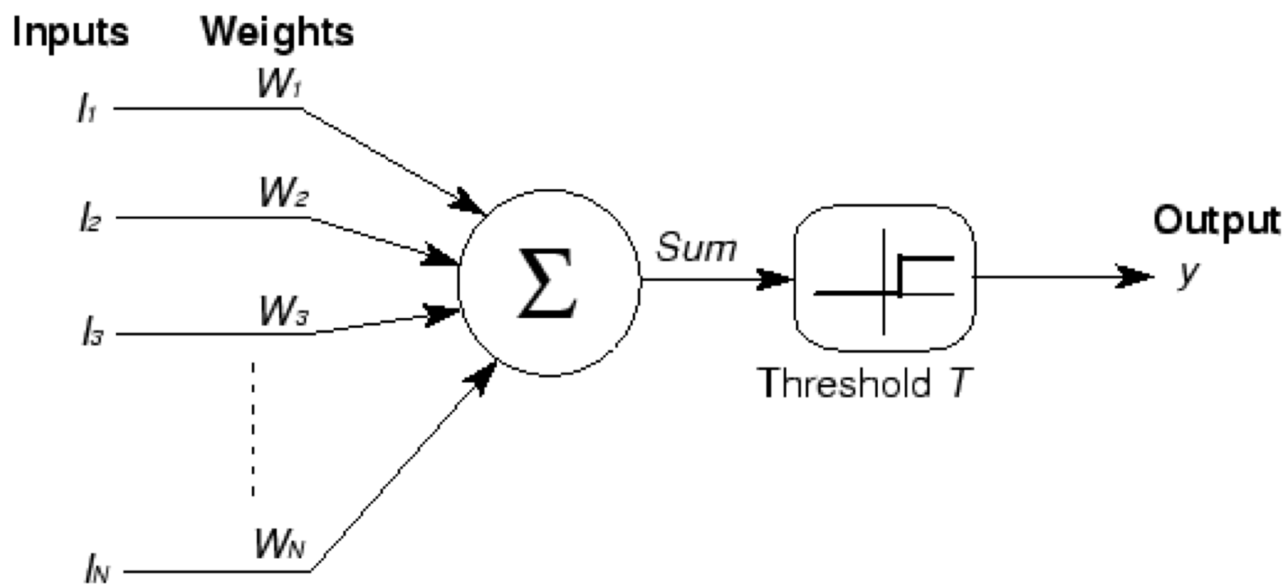


Supervised learning

- Poor generalization is sometimes caused by overfitting: our hypothesis has learned the training set very well, but it has poor accuracy on the test set.
  - Analogous to "memorizing" the training set.
- When the output y is one of a finite set of values (e.g., sunny/cloudy/rainy or true/false), the learning problem is called ***classification***.
- When the output is a number, the problem is called ***regression***.
  - Yes, linear regression is a machine learning algorithm!

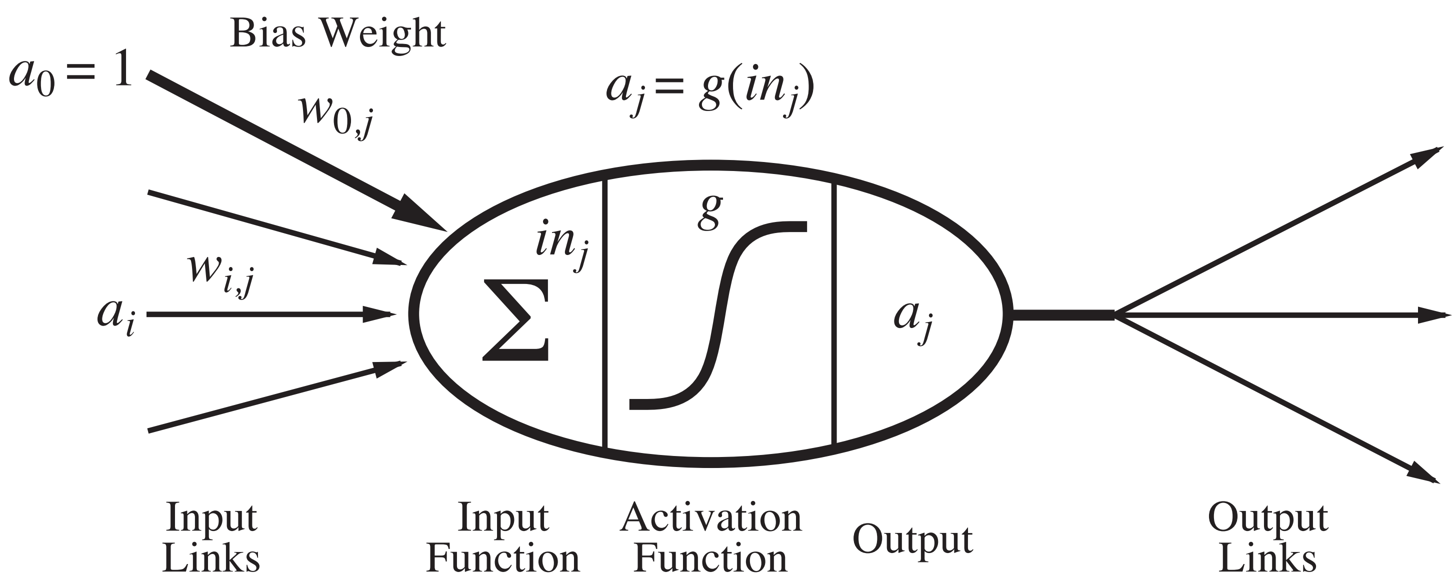
McCullough-Pitts neuron

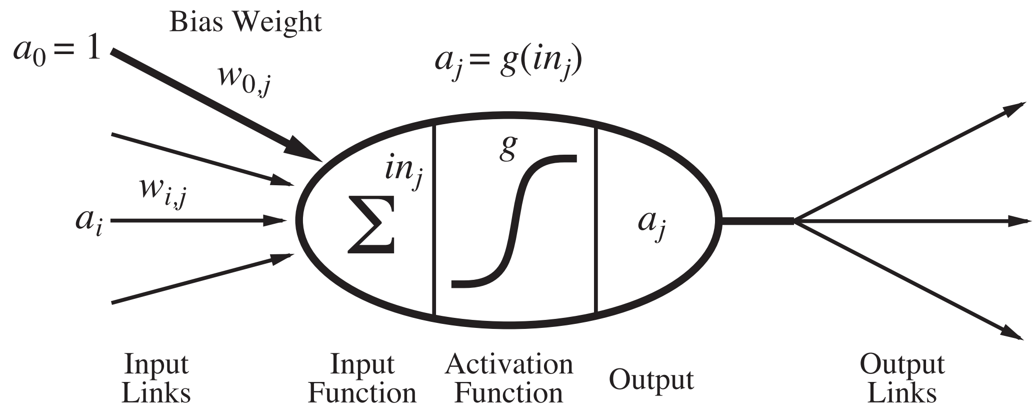
- 1943: Warren McCullough and Walter Pitts, two electrical engineers, develop the first model of an ***artificial neuron***, called threshold logical units.



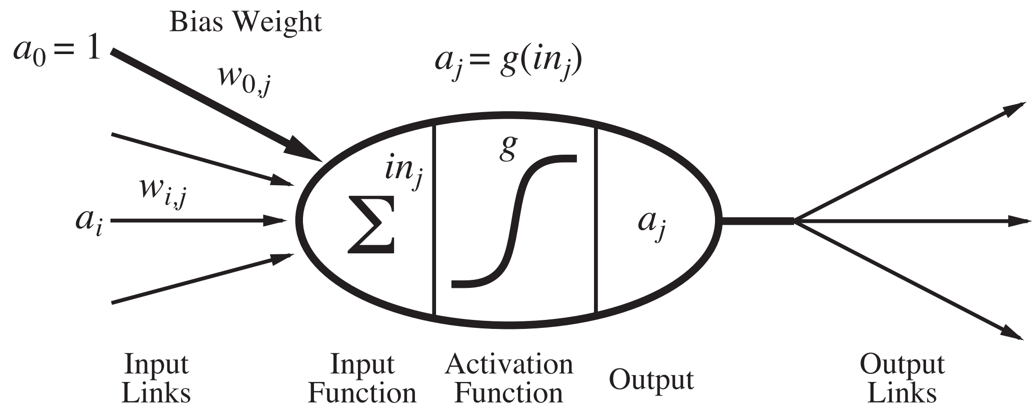
Perceptron

- 1958: Frank Rosenblatt refined the McCullough-Pitts neuron into the ***perceptron***.





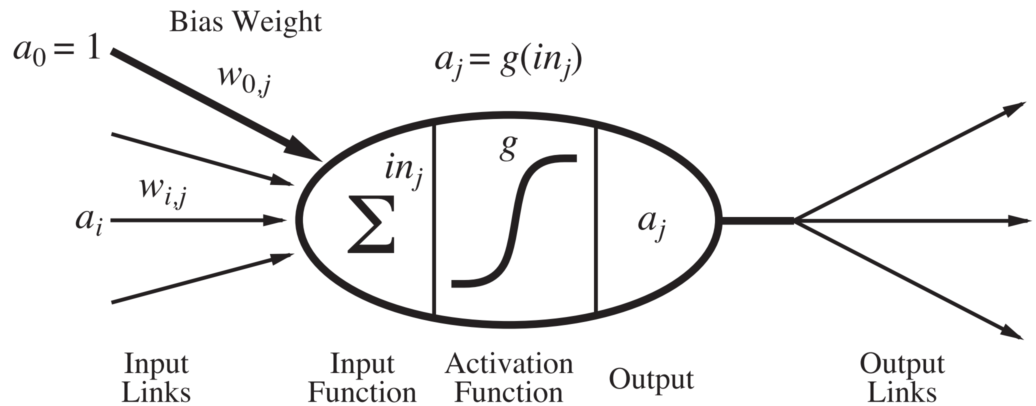
- NNs are composed of nodes or units connected by directed links (a graph structure).
- Each unit receives a collection of numeral inputs (a_0, a_1, ...) and produces a numeral output (a_j).
- A link from unit *i* to unit *j* has a weight w_{ij} associated with it.
- Each unit has a dummy input (a_0) that is always set to 1.



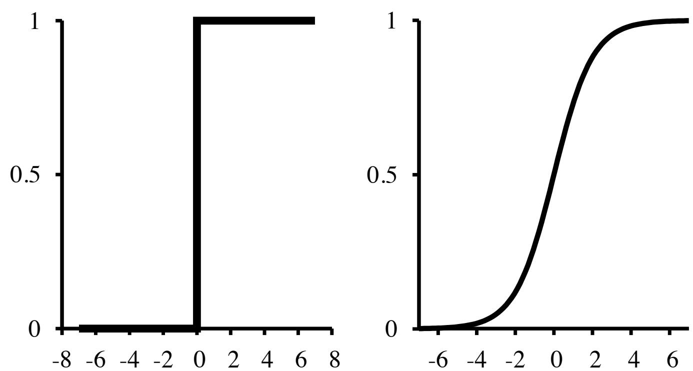
- Each unit j first computes a weighted sum of its inputs:

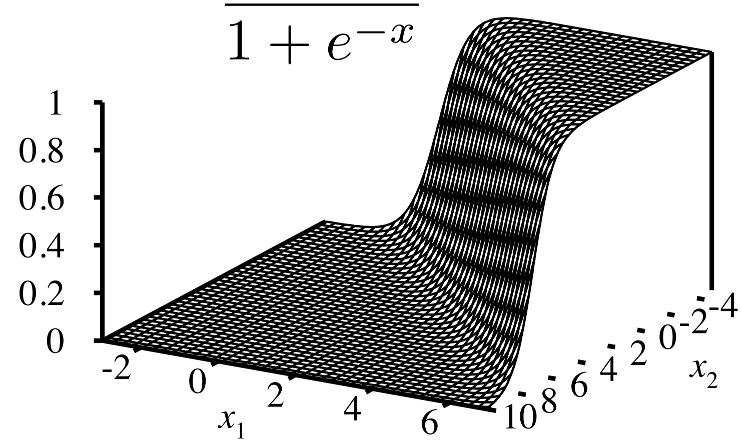
$$in_j = \sum_{i=0}^{n} w_{i,j} \cdot a_j$$

- Then it applies an activation function g to this sum to produce the output: $a_j = g(in_j)$



- The function g is typically either a hard threshold function or the logistic function: $\dfrac{1}{1+e^{-x}}$



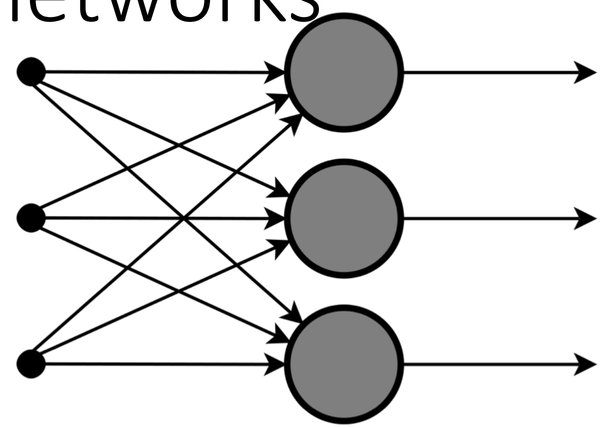


Neural networks

- Two basic types of networks.
  - Feed-forward: Links are only in one direction (DAG).
  - Recurrent: Allows outputs to feed back into inputs.
    - System may reach a steady state or may exhibit oscillations or chaotic behavior.
- Feed-forward networks are usually arranged in layers, where each layer only receives input from the previous layer.
  - Single layer – all inputs connected directly to outputs
  - Multi-layer - one or more ***hidden layers*** of units in between input and output.

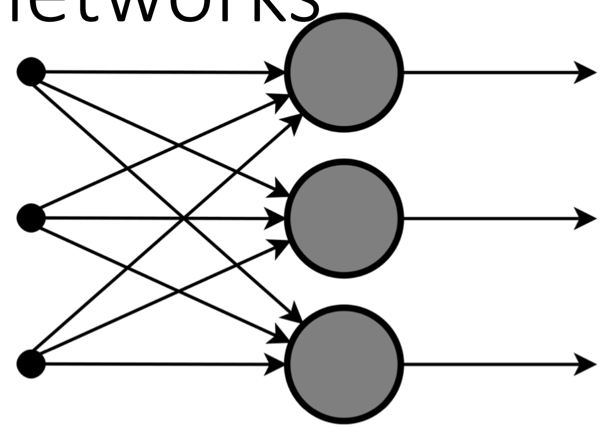
Single layer feed forward networks

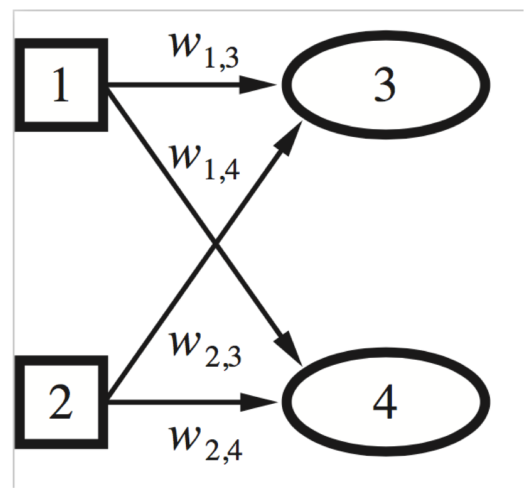
- One input layer (which is just the raw inputs).
- One output layer (of perceptron units).
- Example.



Single layer feed forward networks

- One input layer (which is just the raw inputs).
- One output layer (of perceptron units).
- Let's design a network to add two bits together.
- Needs two inputs (x_1, x_2), and two outputs (y_3, y_4).





Single layer feed forward networks

- There is an algorithm to change the weights of a single-layer network to make the network learn any function...
- Initialize starting weights randomly
- Do until you want to stop (*typically when accuracy is good enough or weights stop changing*):
  - for each training example (x, y):
    - use NN to get prediction of h(x)
    - if h(x) differs from y, update all weights:
    - w[i] = w[i] + (y – h(x)) * x[i]
  - compute accuracy over entire training data = (# predicted correctly)/(# of training examples)

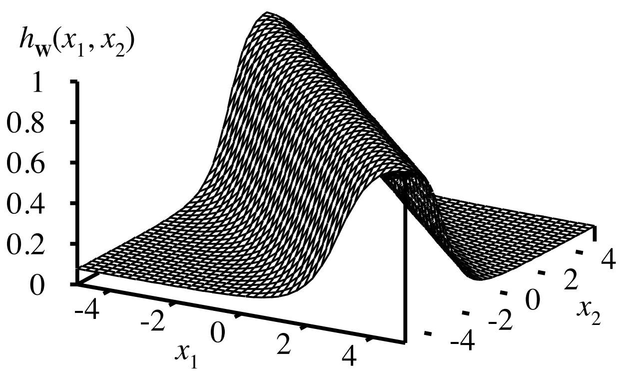
Single layer feed forward networks

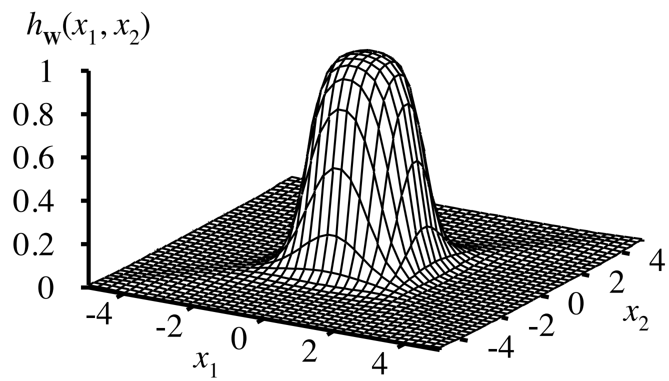
- There is an algorithm to change the weights of a single-layer network to make the network learn any function...
- as long as it is linearly-separable!

Multi-layer feed forward networks

- McCullough, Pitts, and Rosenblatt were all aware of the linear separability problem.
- If we add another layer of units between the input and output layers, we can learn any function!
- http://playground.tensorflow.org/

Multi-layer feed forward networks





Multi-layer feed forward networks

- Learning is done through the backpropagation algorithm (*backprop*).
- Derived through calculus (we will skip).

Review perceptron learning

- Initialize starting weights randomly
- Do until you want to stop (*typically when accuracy is good enough or weights stop changing*):
  - for each training example (x, y):
    - use NN to get prediction of h(x)
    - if h(x) differs from y, update all weights:
    - w[i] = w[i] + (y – h(x)) * x[i]
  - compute accuracy over entire training data = (# predicted correctly)/(# of training examples)

Review perceptron learning

- In the perceptron learning algorithm, where did the update equation come from?
- w[i] = w[i] + (y – h(x)) * x[i]
- Recall h(x) = w[0] * x[0] + w[1] * x[1] + ...
- If y = 1, but h(x) = 0, then h(x) is too small.
  - How do we increase h(x)?
  - Increase the weights w[0], w[1], ...
  - By how much?
  - Proportionally to their corresponding input x[i] value.

repeat
    for each weight $w_{i,j}$ in *network* **do**
        $w_{i,j} \leftarrow$ a small random number
    for each example $(\mathbf{x}, \mathbf{y})$ **in** *examples* **do**
        / * *Propagate the inputs forward to compute the outputs* * /
        for each node i in the input layer **do**
            $a_i \leftarrow x_i$
        for $\ell = 2$ **to** L **do**
            for each node j in layer ℓ **do**
                $in_j \leftarrow \sum_i w_{i,j}\, a_i$
                $a_j \leftarrow g(in_j)$
        / * *Propagate deltas backward from output layer to input layer* * /
        for each node j in the output layer **do**
            $\Delta[j] \leftarrow g'(in_j) \times (y_j - a_j)$
        for $\ell = L - 1$ **to** 1 **do**
            for each node i in layer ℓ **do**
                $\Delta[i] \leftarrow g'(in_i) \sum_j w_{i,j}\, \Delta[j]$
        / * *Update every weight in network using deltas* * /
        for each weight $w_{i,j}$ in *network* **do**
            $w_{i,j} \leftarrow w_{i,j} + \alpha \times a_i \times \Delta[j]$
until some stopping criterion is satisfied
return *network*

Backprop highlights

repeat
    for each weight $w_{i,j}$ in *network* **do**
        $w_{i,j} \leftarrow$ a small random number
    for each example $(\mathbf{x}, \mathbf{y})$ **in** *examples* **do**
        /* *Propagate the inputs forward to compute the outputs* */
        for each node i in the input layer **do**
            $a_i \leftarrow x_i$
        for $\ell = 2$ **to** L **do**
            for each node j in layer ℓ **do**
                $in_j \leftarrow \sum_i w_{i,j}\, a_i$
                $a_j \leftarrow g(in_j)$

Backprop highlights

/ Propagate deltas backward from output layer to input layer */*

for each node j in the output layer **do**

  $\Delta[j] \leftarrow g'(in_j) \times (y_j - a_j)$

for $\ell = L - 1$ **to** 1 **do**

  for each node i in layer ℓ **do**

    $\Delta[i] \leftarrow g'(in_i) \sum_j w_{i,j} \Delta[j]$

/ Update every weight in network using deltas */*

for each weight $w_{i,j}$ in *network* **do**

  $w_{i,j} \leftarrow w_{i,j} + \alpha \times a_i \times \Delta[j]$

Compare

- w[i] = w[i] + (y – h(x)) * x[i]

$$\Delta[j] \leftarrow g'(in_j) \times (y_j - a_j)$$

$$\Delta[i] \leftarrow g'(in_i) \sum_j w_{i,j} \Delta[j]$$

$$w_{i,j} \leftarrow w_{i,j} + \alpha \times a_i \times \Delta[j]$$

History

- 1943 – McCullough-Pitts neuron (can't be trained)
- 1958 – Rosenblatt's perceptron (can be trained)
- 1969 – Minsky and Papert publish *Perceptrons*, which explains the limits of single-layer NNs.
    - Ushers in first "AI Winter"
- 1982 – Backprop algorithm for NNs is published.
    - Was known in the 60s! AI Winter eliminated a lot of AI funding and people were discouraged from working on AI projects.
- 1980s – NNs rise again!
- 1989 – NNs are "universal approximators."

History

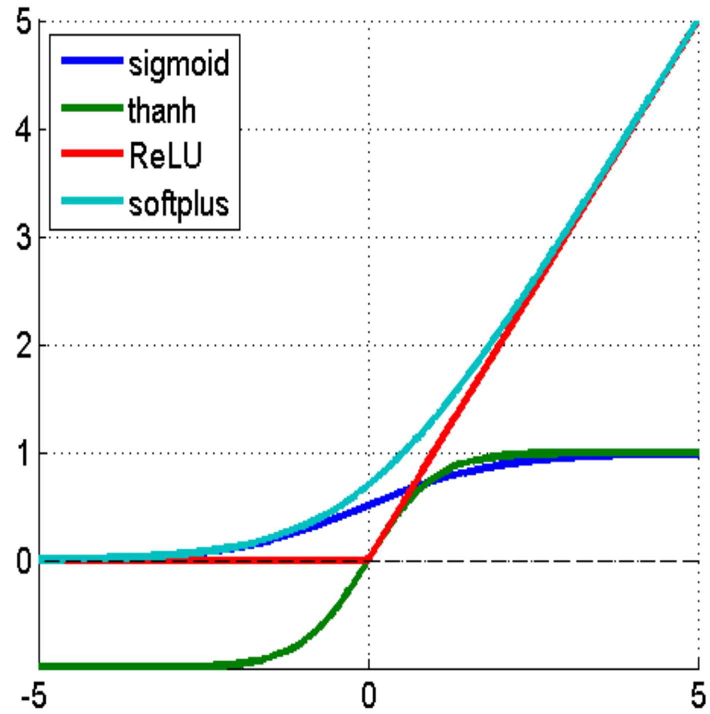
- 1989 – Convolutional NN used to do handwritten digit recognition for ZIP codes. (Yann LeCun)
- 1990s – NNs start to be seen as "painfully slow." Takes a long time to train them. At the same time, people start making more and more modifications to make NNs predict things better – adding more layers, making them recurrent etc.
- Mid 90s – 2nd AI Winter occurs when everything breaks down and the community loses faith in NNs (too slow, too hard to train with backprop, don't work well, nobody understands them anyway).
  - Move to other models, especially probabilistic.

History

- Winter continues through early 2000s, though some people continue working on NNs.
- 2006 paper: "A fast learning algorithm for deep belief nets"
  - Key idea – don't initialize weights randomly. Start off with a round of unsupervised learning to find reasonable initial values for the weights, then finish with regular supervised learning.
- 2nd key idea – pure computational power of GPUs.
  - Massively parallel! 70x faster than training on CPUs.
- 3rd key idea – huge data sets.

History

- 2010 – Turns out the activation function used makes a huge difference on training time and performance.



Lessons

- Our labeled datasets were thousands of times too small.
- Our computers were millions of times too slow.
- We initialized the weights in a stupid way.
- We used the wrong type of non-linearity.