

Neural Networks

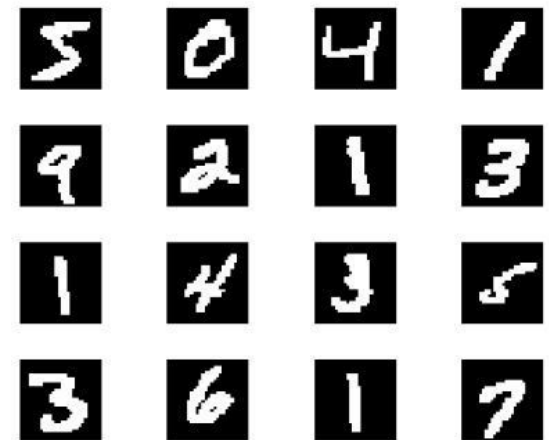
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Handwritten Digit Recognition



- Given a collection of handwritten digits and their corresponding labels, we'd like to be able to correctly classify handwritten digits
- A simple algorithmic technique can solve this problem with 95% accuracy
- State-of-the-art methods can achieve near 99% accuracy (you've probably seen these in action if you've deposited a check recently)



Digits from the MNIST data set

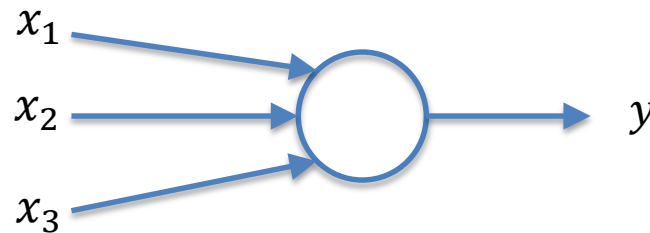
- The basis of neural networks was developed in the 1940s - 1960s
 - The idea was to build mathematical models that might “compute” in the same way that neurons in the brain do
 - As a result, neural networks are biologically inspired, though many of the algorithms developed for them are not biologically plausible
 - Perform surprisingly well for the handwritten digit recognition task (and many others)

- Neural networks consist of a collection of artificial neurons
- There are different types of neuron models that are commonly studied
 - The perceptron (one of the first studied)
 - The sigmoid neuron (one of the most common, but many more)
 - Rectified linear units
- A neural network is a directed graph consisting of a collection of neurons (the nodes), directed edges (each with an associated weight), and a collection of fixed binary inputs

The Perceptron

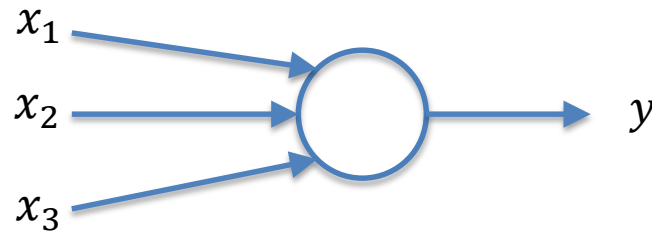


- A perceptron is an artificial neuron that takes a collection of binary inputs and produces a binary output
- The output of the perceptron is determined by summing up the weighted inputs and thresholding the result: if the weighted sum is larger than the threshold, the output is one (and zero otherwise)



$$y = \begin{cases} 1 & w_1x_1 + w_2x_2 + w_3x_3 > \textit{threshold} \\ 0 & \textit{otherwise} \end{cases}$$

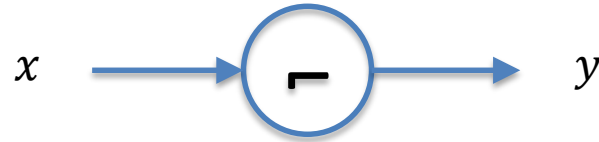
- Perceptrons are usually expressed in terms of a collection of input weights and a bias b (which is the negative threshold)



$$y = \begin{cases} 1 & w_1x_1 + w_2x_2 + w_3x_3 + b > 0 \\ 0 & \text{otherwise} \end{cases}$$

- A single node perceptron is just a linear classifier
- This is actually where the “perceptron algorithm” comes from

Perceptron for NOT

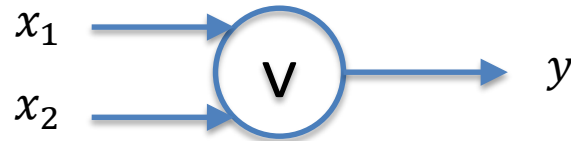


- Choose $w = -1$, threshold $= -.5$
- $$y = \begin{cases} 1 & -x > -.5 \\ 0 & -x \leq -.5 \end{cases}$$

Perceptron for OR



Perceptron for OR

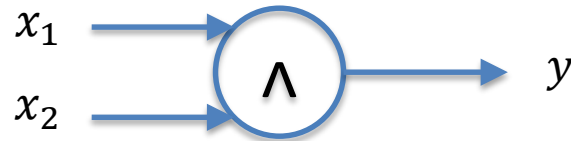


- Choose $w_1 = w_2 = 1$, threshold = 0
- $$y = \begin{cases} 1 & x_1 + x_2 > 0 \\ 0 & x_1 + x_2 \leq 0 \end{cases}$$

Perceptron for AND



Perceptron for AND



- Choose $w_1 = w_2 = 1$, threshold = 1.5
- $$y = \begin{cases} 1 & x_1 + x_2 > 1.5 \\ 0 & x_1 + x_2 \leq 1.5 \end{cases}$$

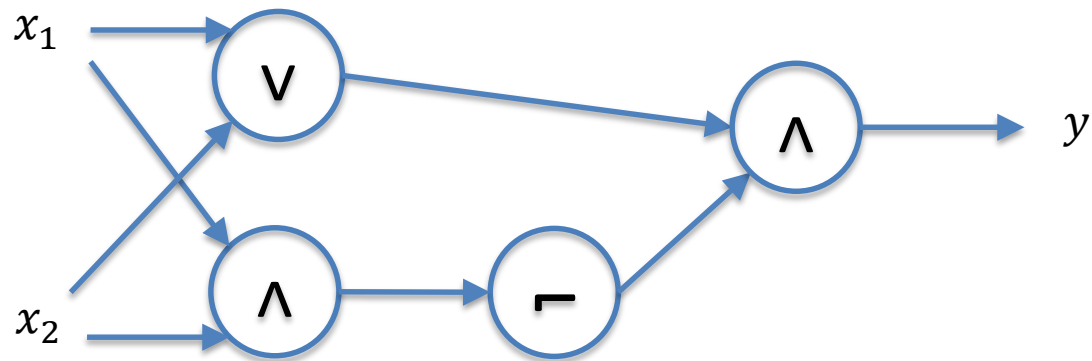
Perceptron for XOR



Perceptron for XOR

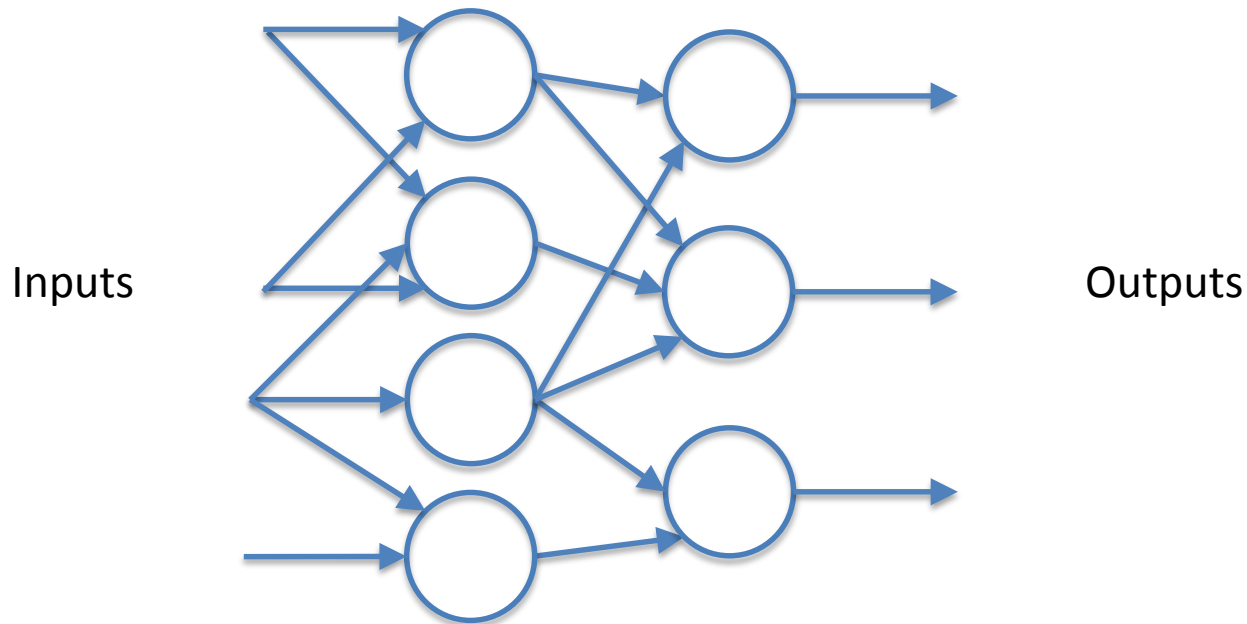


- Need more than one perceptron!



- Weights for incoming edges are chosen as before
- Networks of perceptrons can encode any circuit!

- Gluing a bunch of perceptrons together gives us a neural network
- In general, neural nets have a collection of binary inputs and a collection of binary outputs



Beyond Perceptrons

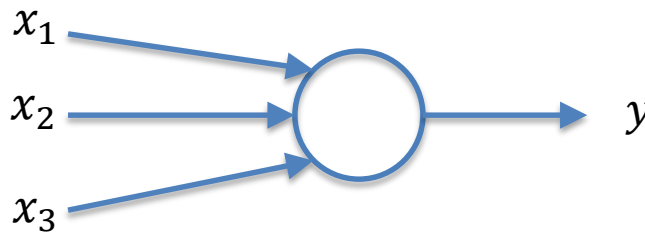


- Given a collection of input-output pairs, we'd like to learn the weights of the neural network so that we can correctly predict the output of an unseen input
 - We could try learning via gradient descent (e.g., by minimizing the Hamming loss)
 - This approach doesn't work so well: small changes in the weights can cause dramatic changes in the output
 - This is a consequence of the discontinuity of sharp thresholding (same problem we saw in SVMs)

The Sigmoid Neuron



- A sigmoid neuron is an artificial neuron that takes a collection of **inputs in the interval $[0,1]$ and produces an output in the interval $[0,1]$**
- The output is determined by summing up the weighted inputs plus the bias and applying the sigmoid function to the result



$$y = \sigma(w_1x_1 + w_2x_2 + w_3x_3 + b)$$

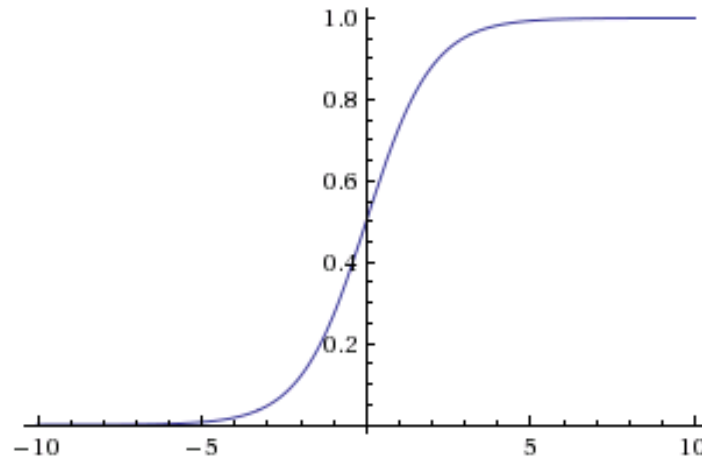
where σ is the **sigmoid function**

The Sigmoid Function



- The sigmoid function is a continuous function that approximates a step function

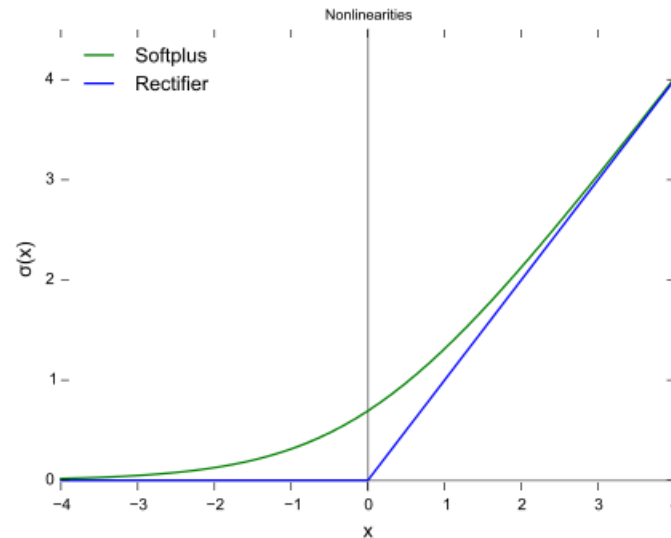
$$\sigma(z) = \frac{1}{1 + e^{-z}}$$



Rectified Linear Units



- The sigmoid neuron approximates a step function as a smooth function
- The relu is given by $\max(0, x)$ which can be approximated as a smooth continuous function $\ln(1 + e^x)$

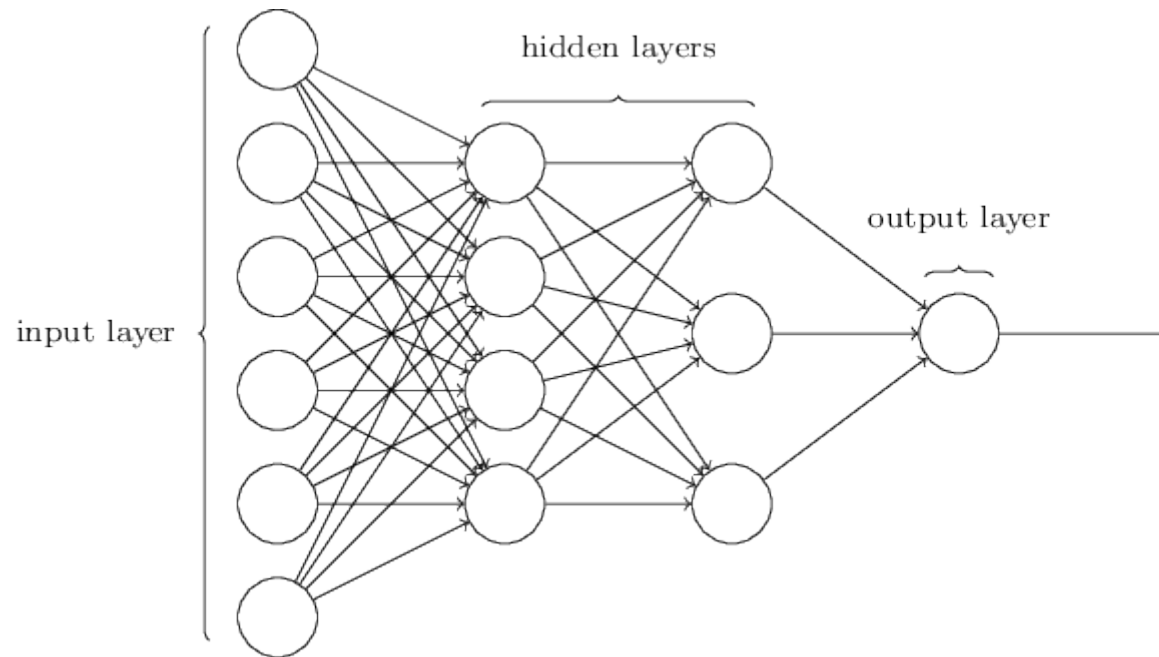


- The softmax function maps a vector of real numbers to a vector of probabilities as

$$\text{softmax}(z)_j = \frac{e^{z_j}}{\sum_k e^{z_k}}$$

- If there is a dominant value in z , then it will become one under the softmax
- Often used as the final layer of a neural network

Multilayer Neural Networks

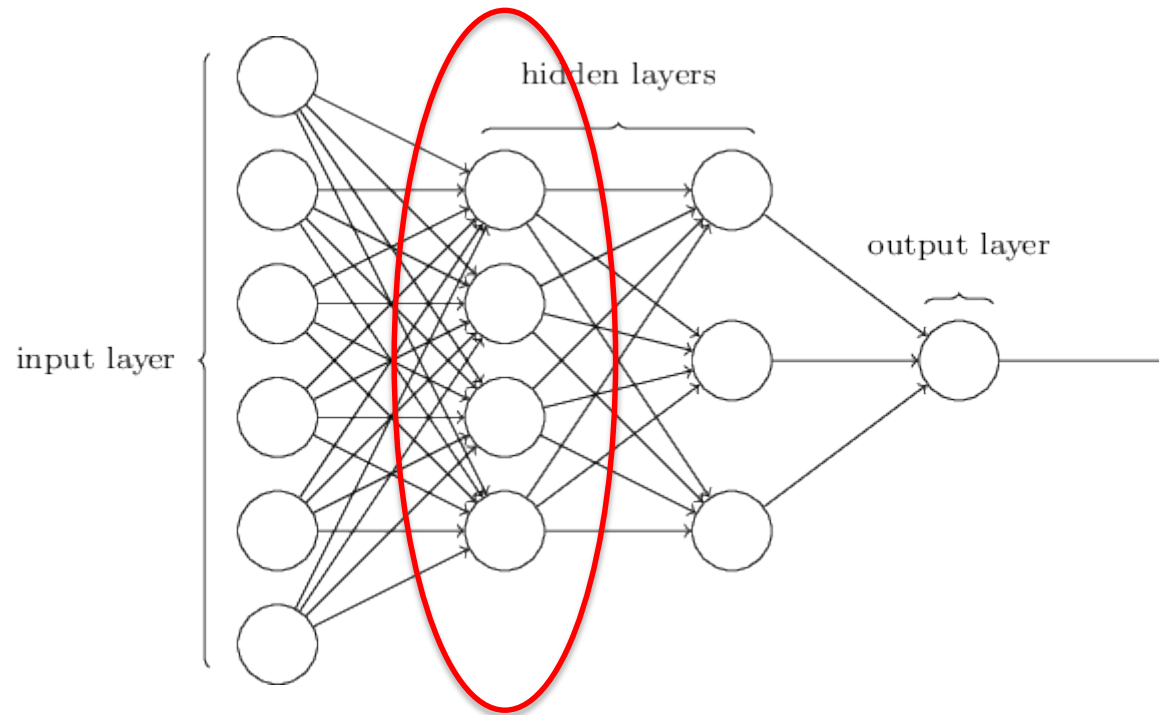


from Neural Networks and Deep Learning by Michael Nielson

Multilayer Neural Networks

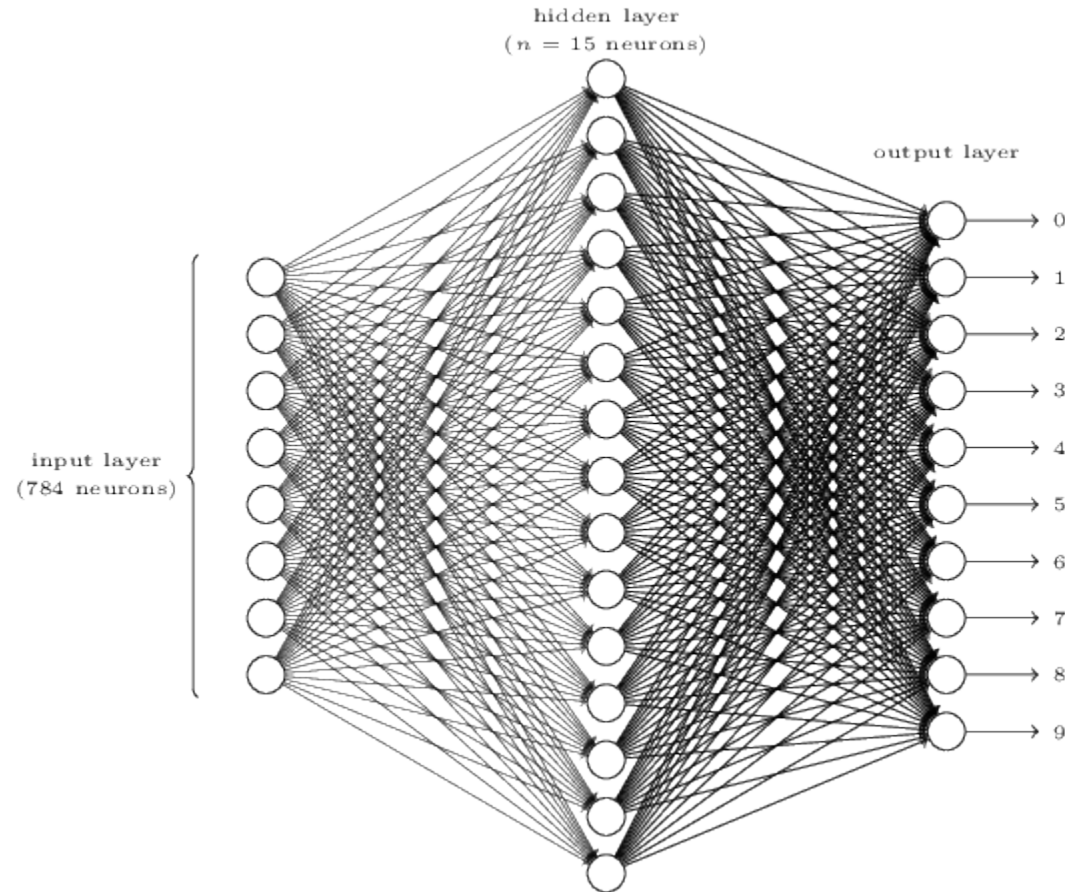


NO intralayer connections



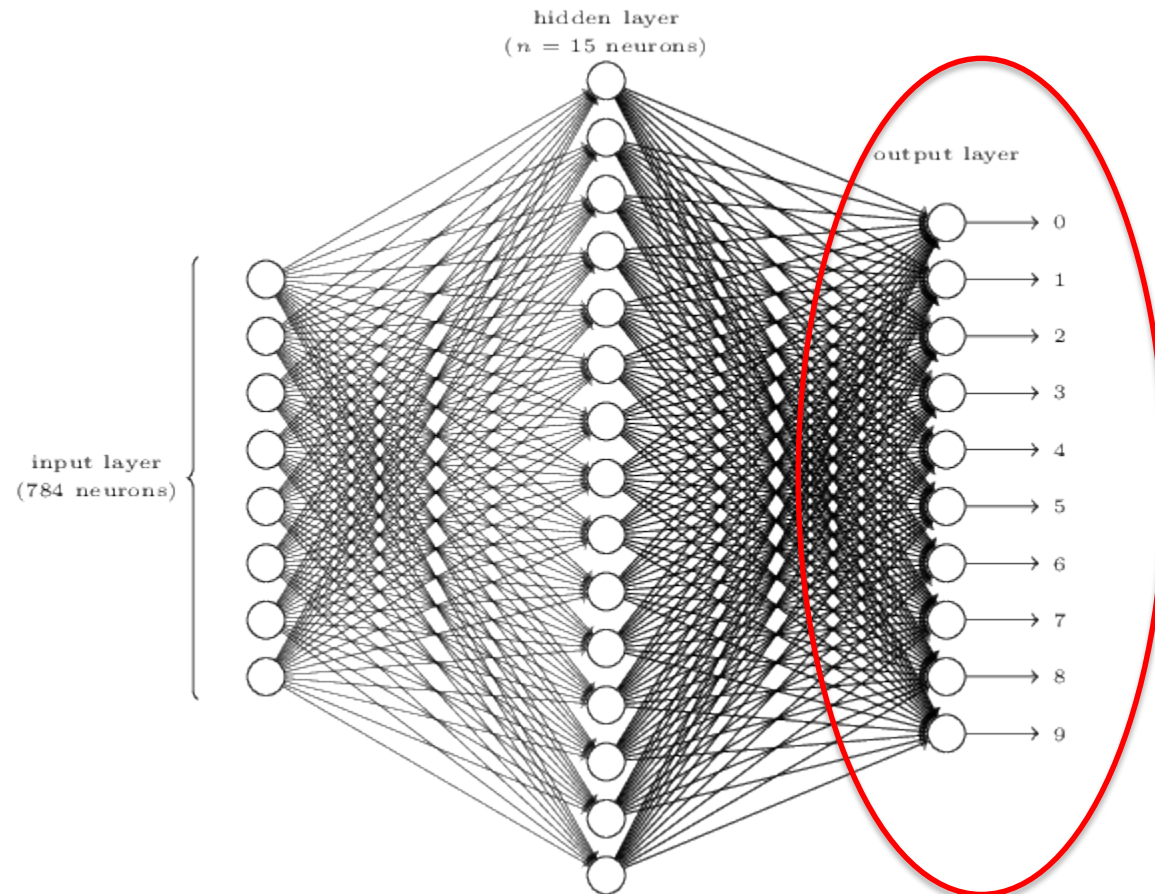
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Neural Network for Digit Classification



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Neural Network for Digit Classification



Why 10
instead of 4?

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- Boolean functions
 - Every Boolean function can be represented by a network with a single hidden layer consisting of possibly exponentially many hidden units
- Continuous functions
 - Every bounded continuous function can be approximated up to arbitrarily small error by a network with one hidden layer
 - Any function can be approximated to arbitrary accuracy with two hidden layers

- To do the learning, we first need to define a loss function to minimize

$$C(w, b) = \frac{1}{2M} \sum_m \|y^m - a(x^m, w, b)\|^2$$

- The training data consists of input output pairs $(x^1, y^1), \dots, (x^M, y^M)$
- $a(x^m, w, b)$ is the output of the neural network for the m^{th} sample
- w and b are the weights and biases

- The derivative of the loss function is calculated as follows

$$\frac{\partial \mathcal{C}(w, b)}{\partial w_k} = \frac{1}{M} \sum_m [y^m - a(x^m, w, b)] \frac{\partial a(x^m, w, b)}{\partial w_k}$$

- To compute the derivative of a , use the chain rule and the derivative of the sigmoid function

$$\frac{d\sigma(z)}{dz} = \sigma(z) \cdot (1 - \sigma(z))$$

- This gets complicated quickly with lots of layers of neurons

- To make the training more practical, stochastic gradient descent is used instead of standard gradient descent
- Recall, the idea of stochastic gradient descent is to approximate the gradient of a sum by sampling a few indices and averaging

$$\nabla_x \sum_{i=1}^n f_i(x) \approx \frac{1}{K} \sum_{k=1}^K \nabla_x f_{i^k}(x)$$

here, for example, each i^k is sampled uniformly at random from $\{1, \dots, n\}$

Computing the Gradient



- We'll compute the gradient for a single sample

$$C(w, b) = \frac{1}{2} \|y - a(x, w, b)\|^2$$

- Some definitions:
 - L is the number of layers
 - a_j^l is the output of the j^{th} neuron on the l^{th} layer
 - z_j^l is the weighted input of the j^{th} neuron on the l^{th} layer

$$z_j^l = \sum_k w_{jk}^l a_k^{l-1} + b_j^l$$

- δ_j^l is defined to be $\frac{\partial C}{\partial z_j^l}$

Computing the Gradient



For the output layer, we have the following partial derivative

$$\begin{aligned}\frac{\partial C}{\partial z_j^L} &= -(y_j - a_j^L) \frac{\partial a_j^L}{\partial z_j^L} \\ &= -(y_j - a_j^L) \frac{\partial \sigma(z_j^L)}{\partial z_j^L} \\ &= -(y_j - a_j^L) \sigma(z_j^L) (1 - \sigma(z_j^L)) \\ &= \delta_j^L\end{aligned}$$

- For simplicity, we will denote the vector of all such partials for each node in the l^{th} layer as δ^l

Computing the Gradient



For the $L - 1$ layer, we have the following partial derivative

$$\begin{aligned}\frac{\partial C}{\partial z_k^{L-1}} &= \sum_j (a_j^L - y_j) \frac{\partial a_j^L}{\partial z_k^{L-1}} \\&= \sum_j (a_j^L - y_j) \frac{\partial \sigma(z_j^L)}{\partial z_k^{L-1}} \\&= \sum_j (a_j^L - y_j) \sigma(z_j^L) (1 - \sigma(z_j^L)) \frac{\partial z_j^L}{\partial z_k^{L-1}} \\&= \sum_j (a_j^L - y_j) \sigma(z_j^L) (1 - \sigma(z_j^L)) \frac{\partial \sum_{k'} w_{jk'}^L a_{k'}^{L-1} + b_j^L}{\partial z_k^{L-1}} \\&= \sum_j (a_j^L - y_j) \sigma(z_j^L) (1 - \sigma(z_j^L)) \sigma(z_k^{L-1}) (1 - \sigma(z_k^{L-1})) w_{jk}^L \\&= \left((\delta^L)^T w_{*k}^L \right) \left(1 - \sigma(z_k^{L-1}) \right) \sigma(z_k^{L-1})\end{aligned}$$

Computing the Gradient



- We can think of w^l as a matrix
- This allows us to write

$$\delta^{L-1} = ((\delta^L)^T w^L)(1 - \sigma(z^{L-1}))\sigma(z^{L-1})$$

where $\sigma(z^{L-1})$ is the vector whose k^{th} component is $\sigma(z_k^{L-1})$

- Applying the same strategy, for $l < L$

$$\delta^l = ((\delta^{l+1})^T w^{l+1})(1 - \sigma(z^l))\sigma(z^l)$$

Computing the Gradient



- Now, for the partial derivatives that we care about

$$\frac{\partial C}{\partial b_j^l} = \frac{\partial C}{\partial z_j^l} \cdot \frac{\partial z_j^l}{\partial b_j^l} = \delta_j^l$$

$$\frac{\partial C}{\partial w_{jk}^l} = \frac{\partial C}{\partial z_j^l} \cdot \frac{\partial z_j^l}{\partial w_{jk}^l} = \delta_j^l a_k^{l-1}$$

- We can compute these derivatives one layer at a time!

Backpropagation: Putting it all together

- Compute the inputs/outputs for each layer by starting at the input layer and applying the sigmoid functions
- Compute δ^L for the output layer

$$\delta^L = -(y_j - a_j^L) \sigma(z_j^L) (1 - \sigma(z_j^L))$$

- Starting from $l = L - 1$ and working backwards, compute

$$\delta^l = \left((\delta^{l+1})^T w^{l+1} \right) \sigma(z^l) (1 - \sigma(z^l))$$

- Perform gradient descent

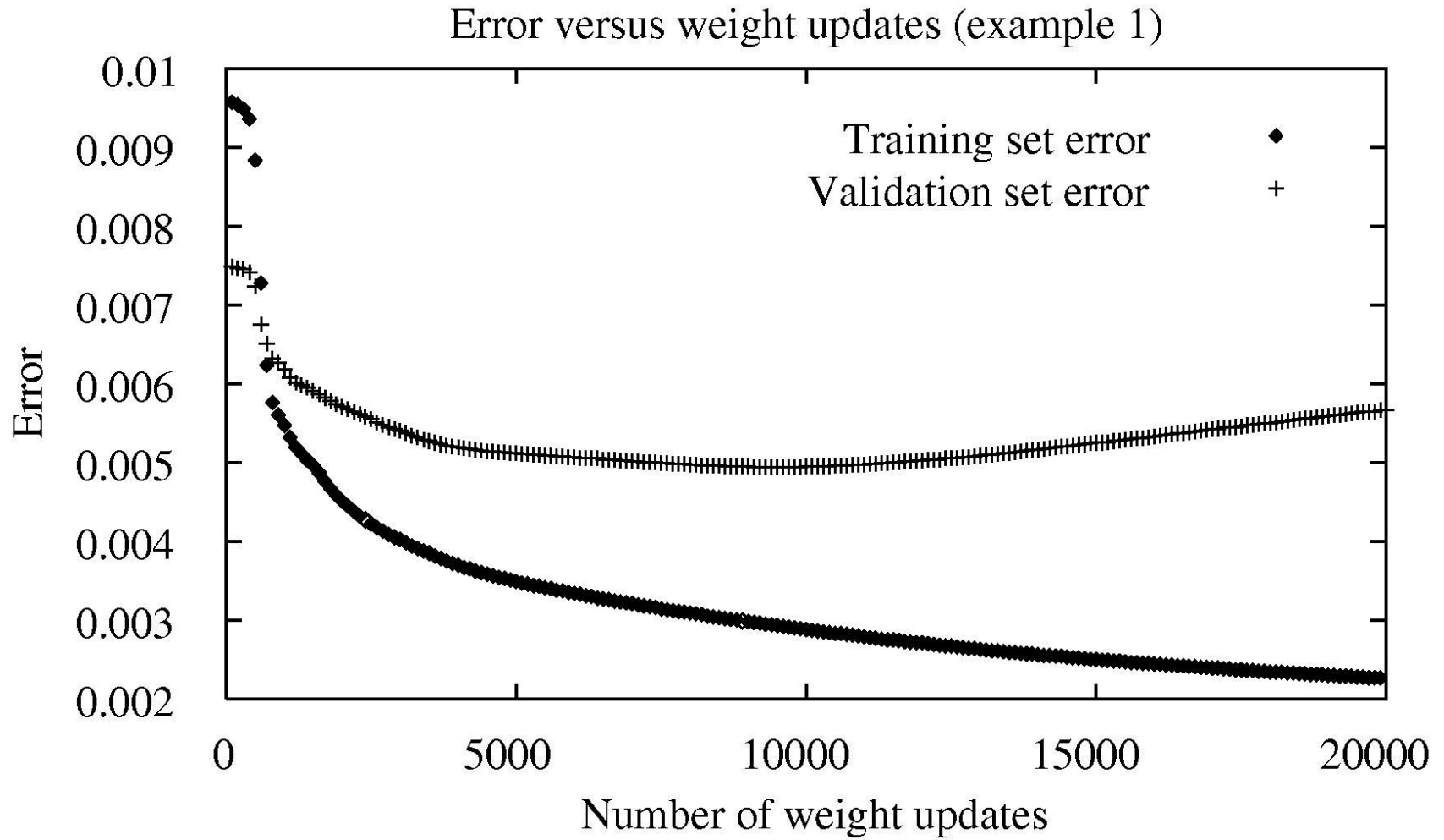
$$b_j^l = b_j^l - \gamma \cdot \delta_j^l$$

$$w_{jk}^l = w_{jk}^l - \gamma \cdot \delta_j^l a_k^{l-1}$$

- Backpropagation converges to a local minimum (loss is not convex in the weights and biases)
 - Like EM, can just run it several times with different initializations
 - Training can take a very long time (even with stochastic gradient descent)
 - Prediction after learning is fast
 - Sometimes include a **momentum** term α in the gradient update

$$w(t) = w(t - 1) - \gamma \cdot \nabla_w C(t - 1) + \alpha(-\gamma \cdot \nabla_w C(t - 2))$$

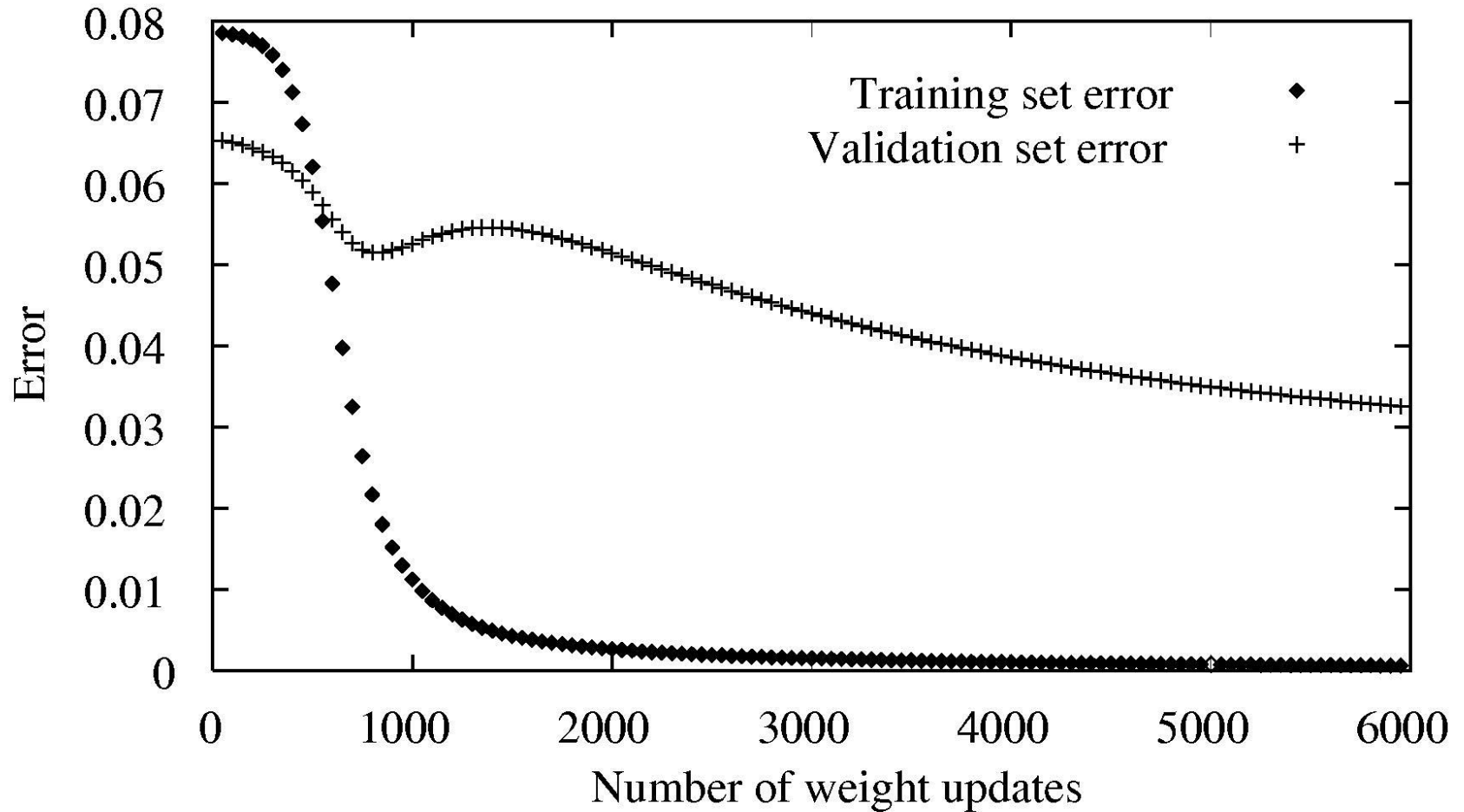
Overfitting



Overfitting



Error versus weight updates (example 2)



- Many ways to improve weight learning in NNs
 - Use a regularizer! (better generalization?)
 - Try other loss functions, e.g., the cross entropy
$$-y \log a(x, w, b) - (1 - y) \log(1 - a(x, w, b))$$
 - Initialize the weights of the network more cleverly
 - Random initializations are likely to be far from optimal
- The learning procedure can have numerical difficulties if there are a large number of layers

- Penalize learning large weights

$$C'(w,b) = \frac{1}{2M} \sum_m \|y^m - a(x^m, w, b)\|^2 + \frac{\lambda}{2} \|w\|_2^2$$

- Can still use the backpropagation algorithm in this setting
- ℓ_1 regularization can also be useful
- Regularization can help with convergence, λ should be chosen with a validation set

- A heuristic bagging-style approach applied to neural networks to counteract overfitting
 - Randomly remove a certain percentage of the neurons from the network and then train only on the remaining neurons
 - The networks are recombined using an approximate averaging technique (keeping around too many networks and doing proper bagging can be costly in practice)

- Early stopping
 - Stop the learning early in the hopes that this prevents overfitting
- Parameter tying
 - Assume some of the weights in the model are the same to reduce the dimensionality of the learning problem
 - Also a way to learn “simpler” models
 - Can lead to significant compression in neural networks (i.e., >90%)

- Convolutional neural networks
 - Instead of the output of every neuron at layer l being used as an input to every neuron at layer $l + 1$, the edges between layers are chosen more locally
 - Many tied weights and biases (i.e., convolution nets apply the same process to many different local chunks of neurons)
 - Often combined with pooling layers (i.e., layers that, say, half the number of neurons by replacing small regions of neurons with their maximum output)
 - Used extensively for image classification tasks