

Neural Networks

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Morning Objectives

This morning's objectives are:

- ▶ Know the best use cases for neural networks
- ▶ Know the benefits and drawbacks of using a neural network
- ▶ Build a simple neural network for binary classification
- ▶ Train a neural network using backpropagation

Background

Neural Networks were introduced in the 1950's as a model which mimics the human brain.

- ▶ Biological neurons “fire” at a certain voltage threshold
- ▶ An artificial neuron will be modeled by an activation function like sign, the sigmoid function, or tanh
- ▶ Otherwise, not a good analogy
 - ▶ Don’t think of neural networks as models for a brain

Why Neural Networks?

Pros:

- ▶ Works well with high dimensional data:
 - ▶ images
 - ▶ text
 - ▶ audio
- ▶ Can model *arbitrarily* complicated decision functions

Cons:

- ▶ Not interpretable
- ▶ Slow to train
- ▶ Easy to overfit
- ▶ Difficult to tune
 - ▶ Many parameters/choices when building the network

Example: Logistic Regression (1/3)

Recall logistic regression:

- ▶ Input \mathbf{x}
- ▶ Weights \mathbf{w}
- ▶ $\sigma(z) = \frac{1}{1+e^{-z}}$
- ▶ Classify \mathbf{x} as positive if $\sigma(\mathbf{w}^T \mathbf{x}) > 0.5$
- ▶ Think of σ as an *activation function* which *activates* if the input is larger than 0

Example: Logistic Regression (2/3)

Draw logistic regression schematically as

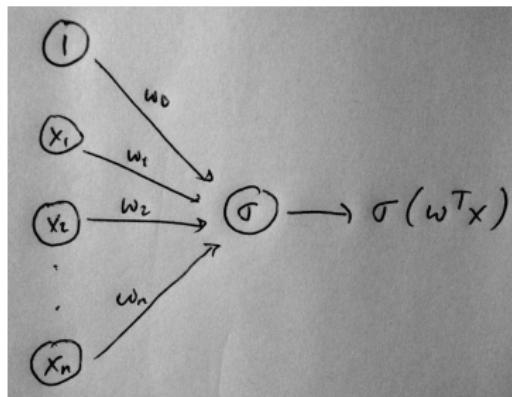


Figure 1:Logisitic Regression

Think of the diagram as having two *layers*

- ▶ Input layer: The nodes which hold the inputs $1, x_1, x_2, \dots, x_n$
- ▶ Output layer: The single node that holds the output value
- ▶ The weights w_0, w_1, \dots, w_n transition between the two layers

Example: Logistic Regression (3/3)

The hypothesis $h(\mathbf{x}; \mathbf{w}) = \sigma(\mathbf{w}^T \mathbf{x})$ only models linear decision functions.

- ▶ The decision boundary is the set of points where $\mathbf{w}^T \mathbf{x} = 0$, a hyperplane
- ▶ What about more complicated behavior?

Example: Neural Network with Multiple Layers (1/2)

Consider the following network with 4 layers:

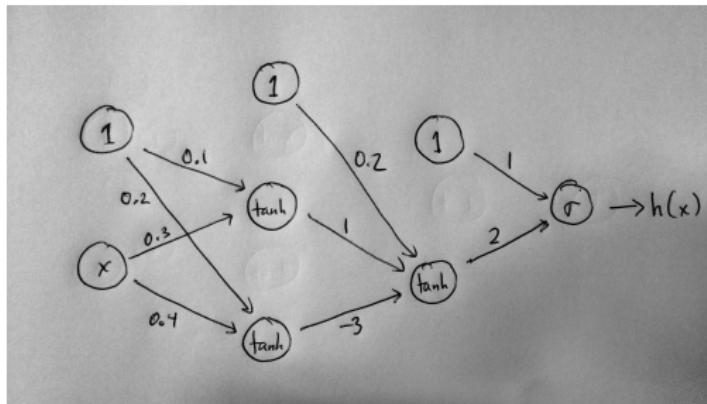


Figure 2:NN with Multiple Layers

- ▶ Input (layer 0): Contains the input value x and a bias term 1
- ▶ Two *hidden layers* (layers 1 and 2)
- ▶ Output (layer 3): Contains the output value (probability of positive classification)

Example: Neural Network with Multiple Layers (2/2)

Let's compute the output of the network for $x = 3$. We'll go layer by layer to keep things straight:

- ▶ Layer 1:
 - ▶ The first non-bias node is $\tanh((0.1)(1) + (0.3)(3)) = 0.76$
 - ▶ The second non-bias node is $\tanh((0.2)(1) + (0.4)(3)) = 0.89$
- ▶ Layer 2:
 - ▶ The non-bias node is
$$\tanh((0.2)(1) + (1)(0.76) + (-3)(0.89)) = -0.94$$
- ▶ Output:
 - ▶ The value of the output layer is $\sigma((1)(1) + (2)(-0.94)) = 0.29$

So $h(3) = 0.29$ for this example.

Check for Mastery

Compute the output of the this neural network for $x = 1$.

Why tanh?

The hyperbolic tangent function is commonly used as an *activation function* in hidden layers:

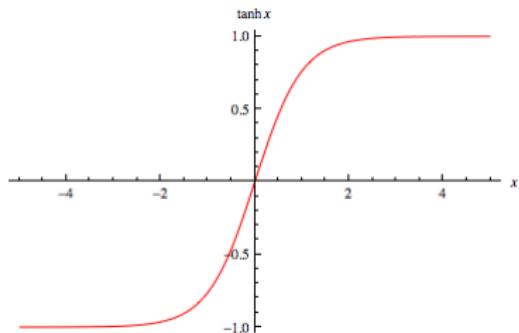


Figure 3:tanh

- ▶ Smooth (differentiable), unlike sign
- ▶ $\tanh(z) = 2\sigma(2z) - 1$
 - ▶ Same shape as the sigmoid function
 - ▶ Output values centered around 0
- ▶ $\tanh'(z) = 1 - \tanh^2(z)$

Check for Mastery

Why do you think the fact that the value of tanh being centered around 0 is important?

Let's Keep it Simple For Now

Since this is some heavy-duty stuff, let's keep things as simple as possible while still trying to grasp the general picture:

- ▶ Stick to networks for binary classification (a single output node)
- ▶ The output node will use the sigmoid activation function σ
- ▶ Hidden layers will use the tanh activation function
- ▶ θ will always represent an activation function (like sign, tanh, σ , or something else like a rectifier)

Notation (1/2)

We need a way to write down the network mathematically to do anything with it. As a warning, this can get quite messy:

- ▶ Layers are given by indices $0, 1, 2, \dots, L$ where 0 is the input layer, and L is the output layer
- ▶ For each layer ℓ :
 - ▶ $s^{(\ell)}$ is the $d^{(\ell)}$ -dimensional input vector
 - ▶ $x^{(\ell)}$ is the $d^{(\ell)} + 1$ -dimensional output vector
 - ▶ $W^{(\ell)}$ is the $d^{(\ell-1)} + 1 \times d^{(\ell)}$ matrix of input weights. $W_{ij}^{(\ell)}$ is the weight of the edge from the i -th node in layer $\ell - 1$ to the j -th node in ℓ

Notation (2/2)

If we zoom in to a single node in a single layer, the picture looks like:

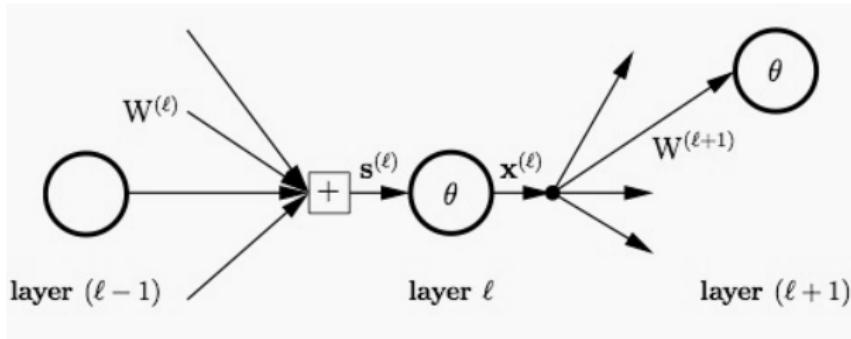


Figure 4: Artificial Neuron Schematic

Schematic

In general, neural networks look something like

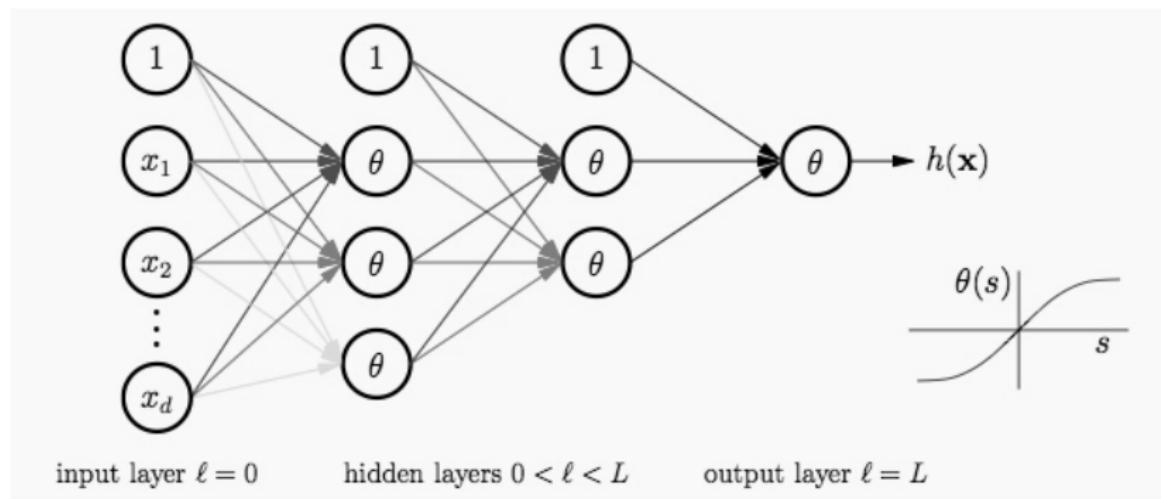


Figure 5: Neural Network

Example: Notation in Toy Network from Before (1/2)

Let's go back to our earlier example to clear up as much confusion as possible:

- ▶ $x^{(0)}$ is $\begin{bmatrix} 1 \\ 3 \end{bmatrix}$
- ▶ $W^{(1)} = \begin{bmatrix} 0.1 & 0.2 \\ 0.3 & 0.4 \end{bmatrix}$
- ▶ $s^{(1)}$ is the result of applying the weights on the edges between layer 0 and 1:

$$\begin{bmatrix} (0.1)(1) + (0.3)(3) \\ (0.2)(1) + (0.4)(3) \end{bmatrix} = \begin{bmatrix} 1 \\ 1.4 \end{bmatrix}$$

- ▶ $x^{(1)}$ is the output of layer 1 after applying tanh and adding a bias node:

$$\begin{bmatrix} 1 \\ \tanh(1) \\ \tanh(1.4) \end{bmatrix} = \begin{bmatrix} 1 \\ 0.76 \\ 0.89 \end{bmatrix}$$

Example: Notation in Toy Network from Before (2/2)

Continuing:

- ▶ $W^{(2)} = \begin{bmatrix} 0.2 \\ 1 \\ -3 \end{bmatrix}$
- ▶ $s^{(2)} = [(0.2)(1) + (1)(0.76) + (-3)(0.89)] = [-1.71]$
- ▶ $x^{(2)} = \begin{bmatrix} 1 \\ \tanh(-1.71) \end{bmatrix} = \begin{bmatrix} 1 \\ -0.94 \end{bmatrix}$
- ▶ $W^{(3)} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$
- ▶ $s^{(3)} = [(1)(1) + (2)(-0.94)] = [-0.88]$
- ▶ $x^{(3)} = [\sigma(-0.88)] = [0.29]$

Check for Mastery

What are $x^{(2)}$ and $s^{(2)}$ when $x = 1$?

Forward Propagation (1/2)

Studying the above example gives general formulae for computing the output of a neural network with fixed weights:

- ▶ $\mathbf{x}^{(\ell)} = \begin{bmatrix} 1 \\ \theta(\mathbf{s}^{(\ell)}) \end{bmatrix}$
- ▶ $\mathbf{s}^{(\ell)} = (\mathbf{W}^{(\ell)})^T \mathbf{x}^{(\ell-1)}$

So we get the chain:

$$\mathbf{x}^{(0)} \xrightarrow{\mathbf{W}^{(1)}} \mathbf{s}^{(1)} \xrightarrow{\theta} \mathbf{x}^{(1)} \xrightarrow{\mathbf{W}^{(2)}} \mathbf{s}^{(2)} \dots \rightarrow \mathbf{s}^{(L)} \xrightarrow{\theta} \mathbf{x}^{(L)} = h(\mathbf{x}^{(0)})$$

Forward Propagation (2/2)

This chain of transformations is called the *forward propagation* algorithm.

Check for Mastery

In terms of the number of nodes V and weights E , what is the algorithmic complexity of forward propagation (in Big-O notation)?

Backpropagation (1/4)

We now know how NNs with fixed weights make predictions. But how do we train a neural network?

- ▶ Training data $\{(\mathbf{x}_i, y_i)\}$
- ▶ Need to minimize some error function E on our training set over the weights $\mathbf{w} = (W^{(1)}, \dots, W^{(L)})$

- ▶ We'll use

$$E(\mathbf{w}) = \frac{1}{N} \sum_i (h(\mathbf{x}_i; \mathbf{w}) - y_i)^2$$

(mean squared error)

- ▶ This function can be *extremely* complicated to write algebraically
 - ▶ No closed form solution for minima

Check for Mastery

What tool/tools do we have available to find the minimum value?
Why don't we use sign as an activation function?

Backpropagation (2/4)

Train a neural network using a gradient descent algorithm called *backpropagation*:

- ▶ Recall the update step in gradient descent:

$$\mathbf{w}(t+1) = \mathbf{w}(t) - \eta \nabla E(\mathbf{w}(t))$$

- ▶ Our total error is a sum of the errors e_n on each input

$$E(\mathbf{w}) = \frac{1}{N} \sum e_i$$

- ▶ $e_i = (h(\mathbf{x}_i; \mathbf{w}) - y_i)^2$

- ▶ $\frac{\partial E}{\partial W^{(\ell)}} = \frac{1}{N} \sum \frac{\partial e_n}{\partial W^{(\ell)}}$

- ▶ Can consider one data point at a time and add the results to get the total gradient

Backpropagation (3/4)

Backpropagation uses the chain rule to compute the partial derivatives of layer ℓ in terms of layer $\ell + 1$.

- ▶ The *sensitivity vector* of layer ℓ is

$$\delta^{(l)} = \frac{\partial e}{\partial \mathbf{s}^{(\ell)}}$$

- ▶ Then we can compute

$$\frac{\partial e}{\partial W^{(\ell)}} = \mathbf{x}^{(l-1)} (\delta^{(\ell)})^T$$

- ▶ For j in $1, \dots, d^{(\ell)}$

$$\delta_j^{(\ell)} = \theta'(\mathbf{s}^{(\ell)})_j \times [W^{(\ell+1)} \delta^{(\ell+1)}]_j$$

Backpropagation (4/4)

- ▶ Can compute $\delta^{(\ell)}$ from $\delta^{(\ell+1)}$
- ▶ Must still compute $\delta^{(L)}$ to seed the process
 - ▶ Depends on the error function and the output activation function
 - ▶ In our case

$$\delta^{(L)} = 2(h(\mathbf{x}_i; \mathbf{w}) - y_i)h(\mathbf{x}_i; \mathbf{w})(1 - h(\mathbf{x}_i; \mathbf{w}))$$

- ▶ $W^{(\ell)} = W^{(\ell)} - \eta \frac{\partial E}{\partial W^{(\ell)}}$

Example: Backpropagation

Suppose our observation is $x = 2, y = 1$

- ▶ $\mathbf{x}^{(0)} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}; \mathbf{s}^{(1)} = \begin{bmatrix} 0.1 & 0.3 \\ 0.2 & 0.4 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \begin{bmatrix} 0.7 \\ 1 \end{bmatrix}; \mathbf{x}^{(1)} = \begin{bmatrix} 1 \\ 0.6 \\ 0.76 \end{bmatrix}$
- ▶ $\mathbf{s}^{(2)} = \begin{bmatrix} -1.48 \end{bmatrix}; \mathbf{x}^{(2)} = \begin{bmatrix} 1 \\ -0.90 \end{bmatrix}$
- ▶ $\mathbf{s}^{(3)} = \begin{bmatrix} -0.8 \end{bmatrix}; \mathbf{x}^{(3)} = \begin{bmatrix} 0.31 \end{bmatrix}$

Example: Backpropagation

Backpropagation gives:

- ▶ $\delta^{(3)} = 2(0.31 - 1)(0.31)(1 - 0.31) = -0.30;$
- $\delta^{(2)} = (1 - 0.9^2)(2)(-0.30) = -0.114; \delta^{(1)} = \begin{bmatrix} -0.072 \\ 0.144 \end{bmatrix}$

Now we can find the partial derivatives

- ▶ $\frac{\partial e}{\partial W^{(1)}} = \mathbf{x}^{(0)}(\delta^{(1)})^T = \begin{bmatrix} -0.072 & 0.144 \\ -0.144 & 0.288 \end{bmatrix};$
- $\frac{\partial e}{\partial W^{(2)}} = \mathbf{x}^{(1)}(\delta^{(2)})^T = \begin{bmatrix} -0.69 \\ -0.42 \\ -0.53 \end{bmatrix};$
- $\frac{\partial e}{\partial W^{(3)}} = \mathbf{x}^{(2)}(\delta^{(3)})^T = \begin{bmatrix} -1.85 \\ 1.67 \end{bmatrix}$

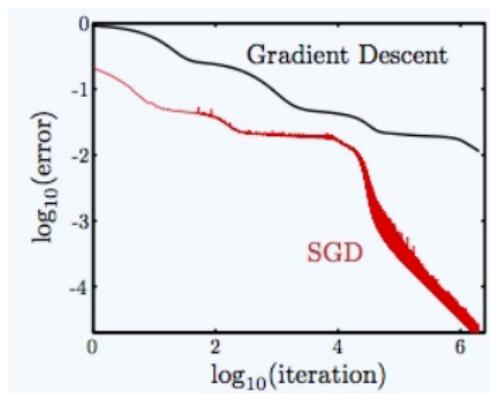
Stochastic Gradient Descent

Backpropagation finds the gradient at each observation, adds them up to find the total gradient

- ▶ $\nabla E(\mathbf{w}) = \frac{1}{N} \sum_i \nabla e_i(\mathbf{w})$
- ▶ $\mathbf{w}(t + 1) = \mathbf{w}(t) - \eta \nabla E(\mathbf{w}(t))$

Instead, update weights at each observation (or after a small batch of observations)

- ▶ $\mathbf{w}(t + 1) = \mathbf{w}(t) - \eta \nabla e_i(\mathbf{w}(t))$



Termination

The error function is generally an *extremely* non-convex function.

- ▶ Lots of local minima and flat spots
- ▶ Often best to terminate after a set number of iterations
- ▶ Also, can terminate when the gradient is small and the total error is small

Epochs

You'll often see the word *epoch*:

- ▶ An epoch is a single sweep through all your data
- ▶ If you have 100,000 observations, and a batch size of 100, each epoch consists of 1,000 gradient descent update steps

Afternoon Objectives

This afternoon we'll give a high-level overview of the ecosystem of neural networks:

- ▶ Understand how neural networks can be used for regression and multi-class classification by using different loss functions and output activations
- ▶ Explain the properties/pros/cons of different activation functions
- ▶ Explain some methods to avoid overfitting
- ▶ Learn about some more complicated versions of neural networks
- ▶ Use Keras to build neural networks in Python

Initialization (1/2)

1. What can go wrong if you set all the weights = 0 initially?
2. What happens if all the weights are initially very large?

Initialization (2/2)

Rule of thumb:

- ▶ Sample weights from $N(0, \sigma_w^2)$
- ▶ $\sigma_w^2 \max_i ||\mathbf{x}_i||^2 \ll 1$

Momentum

Helps push backpropagation out of local minima.

- ▶ Adds a fraction of the previous gradient in the new update step:

$$\mathbf{w}(t + 1) = \mathbf{w}(t) - \eta \nabla E(\mathbf{w}(t)) + m(\mathbf{w}(t) - \mathbf{w}(t - 1))$$

- ▶ $m = 0.9$ is standard
- ▶ Too high risks overshooting minimum
- ▶ Too low risks getting stuck in local minima

Regression and Multi-Class Classification

Neural Networks can also be used for regression and for data with multiple classes

- ▶ For regression, replace the output transformation with $\theta = id$ and use mean squared error
- ▶ For multiple classes:
 - ▶ The output layer will have multiple nodes, one for each class $1, 2, \dots, K$
 - ▶ The output activation function on the j -th component of the output layer is the *softmax* function

$$\frac{e^{\mathbf{s}_j^{(L)}}}{\sum_{i=1}^K e^{\mathbf{s}_i^{(L)}}}$$

- ▶ Minimize cross-entropy $\sum_i -y_i \log h(\mathbf{x}_i)$

Check for Mastery

Repeat the backpropagation example from the morning lecture, but for regression.

Activation Functions

There are many choices for activation functions in hidden layers.

Two popular choices are:

- ▶ tanh is similar to σ , and trains faster in most cases
 - ▶ Normalize your data!
- ▶ A *rectifier* or *hard max* function $\max\{0, x\}$ is also popular
 - ▶ An artificial neuron using this function is called a *rectified linear unit* (ReLU for short)
 - ▶ Gradient does not vanish as x gets large
 - ▶ 0 if $x < 0$, introduces sparsity into the network
 - ▶ Faster training
 - ▶ Doesn't require normalization of data

Check for Mastery

What's the derivative of a ReLU?

Overfitting

To avoid overfitting you can use:

- ▶ Regularization
 - ▶ Add an ℓ_2 -regularization term $\lambda \sum_{\ell,i,j} (w_{ij}^{(\ell)})^2$ to the error function
- ▶ Dropout
 - ▶ Randomly remove nodes from the network each time you run backpropagation

Fully Connected Neural Networks

This is the type of neural network you've already seen.

- ▶ Each layer is *fully connected* to the next
- ▶ No missing edges between nodes

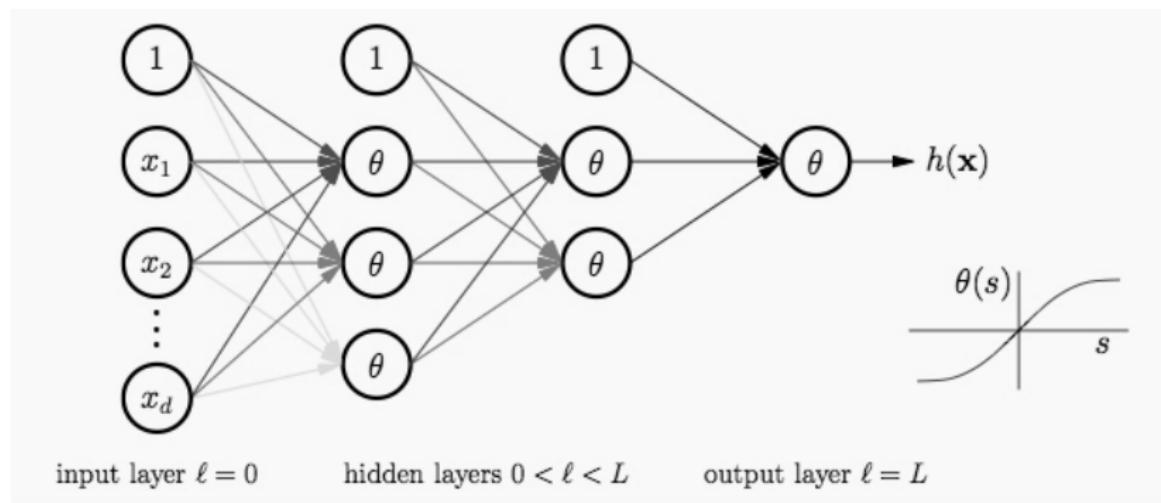


Figure 7:Fully Connected Neural Network

Deep Learning

Deep Learning is a buzz-phrase that just refers to NNs with more than 3 layers.

Convolutional Neural Networks

A type of NN modeled after the human eye.

- ▶ Not fully connected
- ▶ Used mainly for image classification
 - ▶ State of the art
- ▶ Employs *convolution layers*
 - ▶ Each node only “sees” a subset of the previous layer’s nodes
 - ▶ Applies *convolutions* (a sort of filter) to each sub-image to “look for” certain patterns or shapes (which are learned)

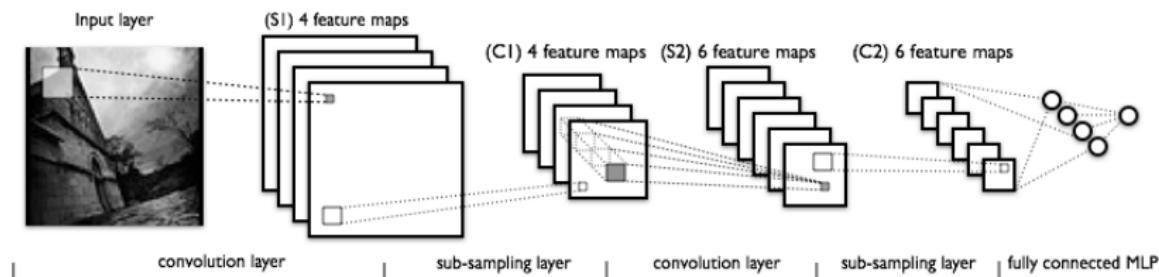


Figure 8: Convolution NN

References

Books

- ▶ Y. S. Abu-Mostafa, M. Magdon-Ismail, H.-T. Lin *Learning From Data: A Short Course*