Deep Learning: Feedforward Neural Nets and Convolutional Neural Nets

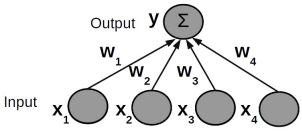
Piyush Rai

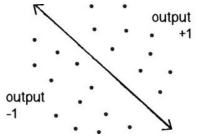
Machine Learning (CS771A)

Nov 2, 2016

A Prelude: Linear Models

- Linear models are nice and simple





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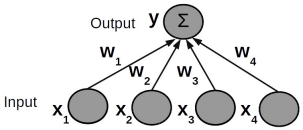

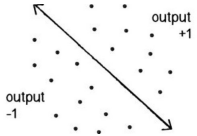

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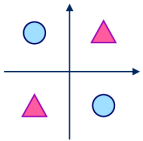
- But linear models have limitations: Can't learn nonlinear functions



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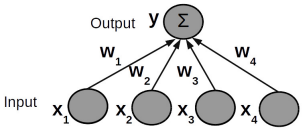

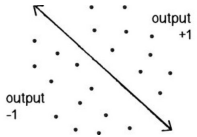

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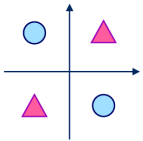
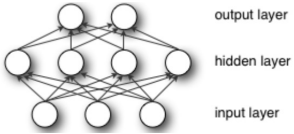


- Before kernel methods (e.g., SVMs) were invented, people thought about this a lot and tried to come up with ways to address this

Multi-layer Perceptron

- Composed of several Perceptron-like units arranged in multiple layers



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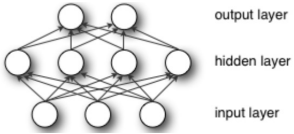

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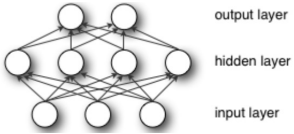

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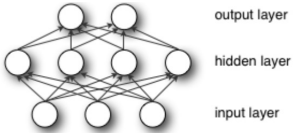

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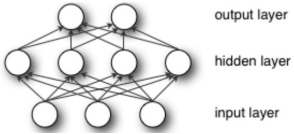

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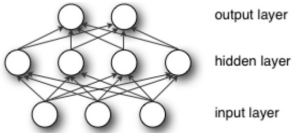

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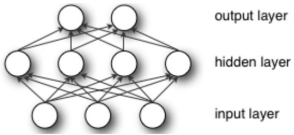

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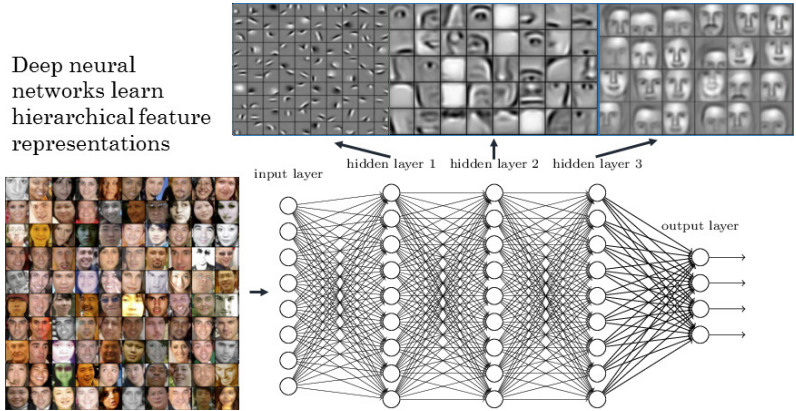
- Universal Function Approximator (Hornik, 1991): A one hidden layer FFNN with sufficiently large number of hidden nodes can approximate any function
  - Caveat: This results is only in terms of theoretical feasibility. Learning the model can be very difficult in practice (e.g., due to optimization difficulties)

What do Hidden Layers Learn?

- Hidden layers can automatically extract features from data



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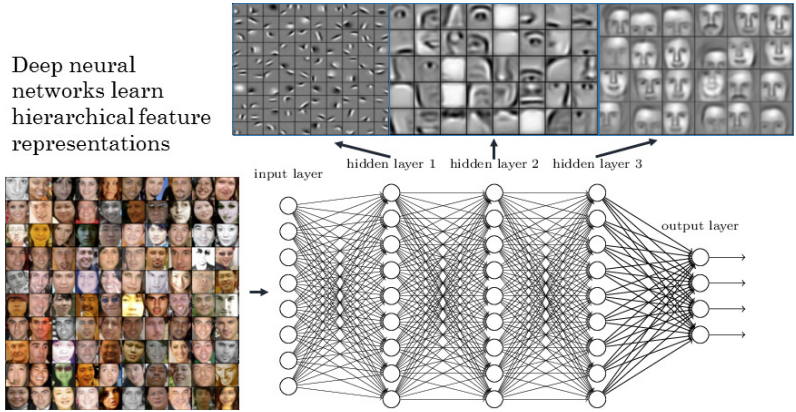
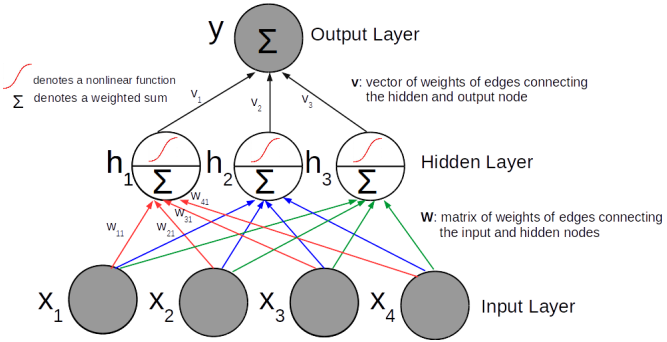


- The bottom-most hidden layer captures very low level features (e.g., edges). Subsequent hidden layers learn progressively more high-level features (e.g., parts of objects) that are composed of previous layer's features

A Simple Feedforward Neural Net

- Below: FFNN with 4 inputs, one hidden layer with 3 nodes, and 1 output



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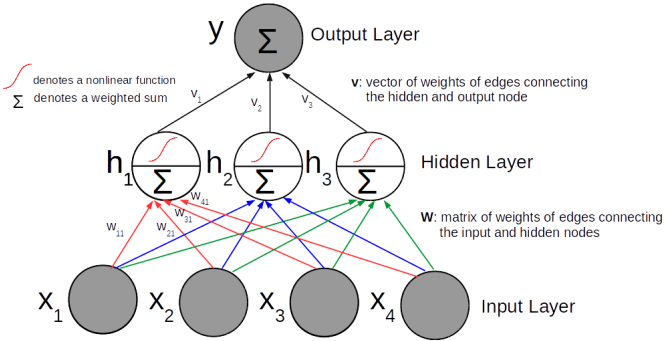

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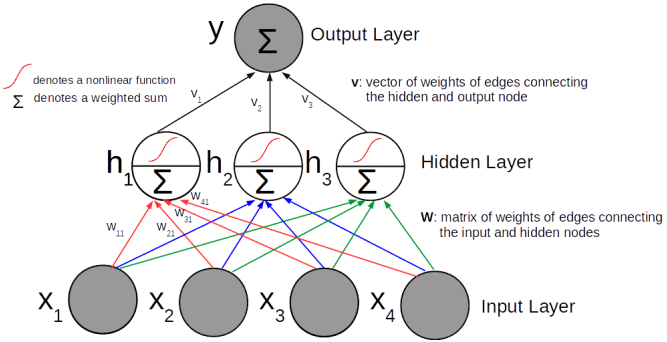

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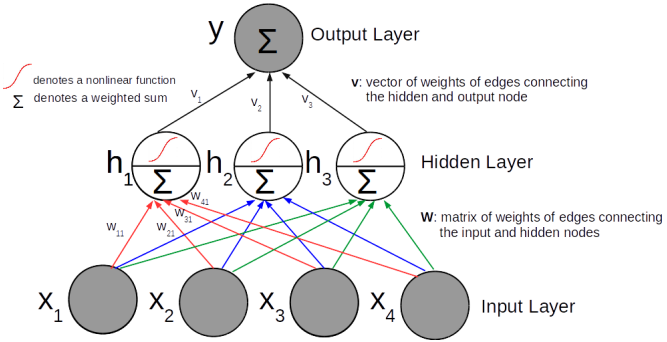

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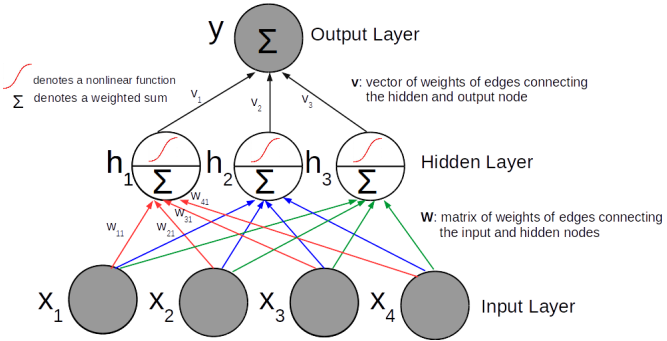

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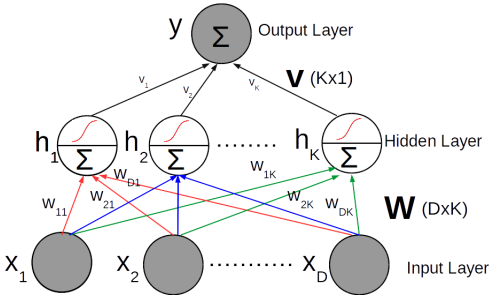
- Output y is a weighted comb. of the preceding layer's hidden nodes (followed by another transform if y isn't real valued, e.g., binary/multiclass label)

Feedforward Neural Net



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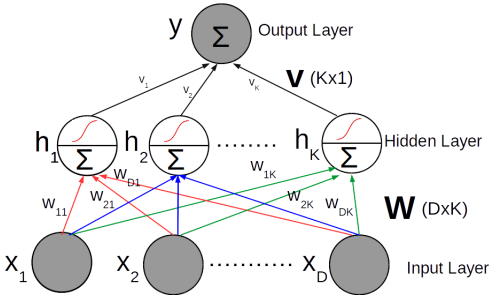

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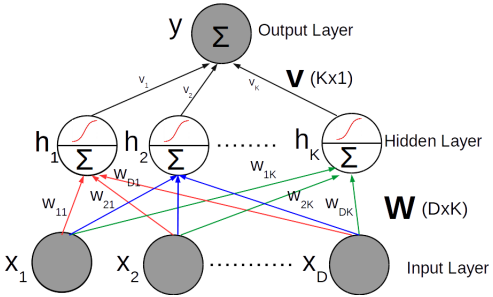

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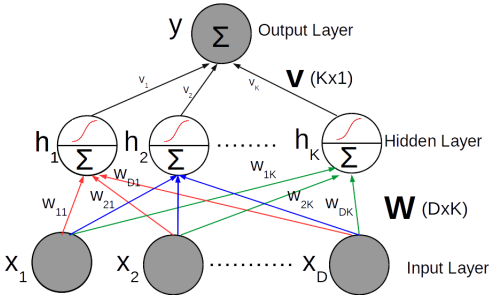

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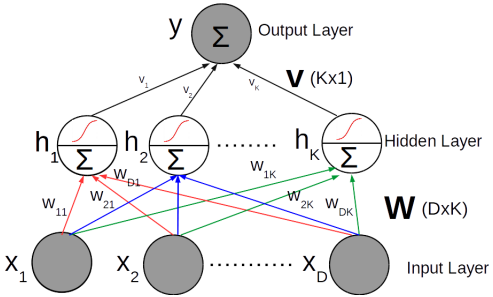

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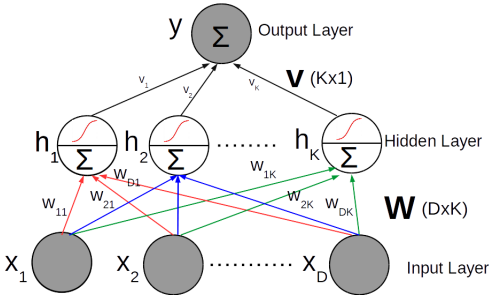

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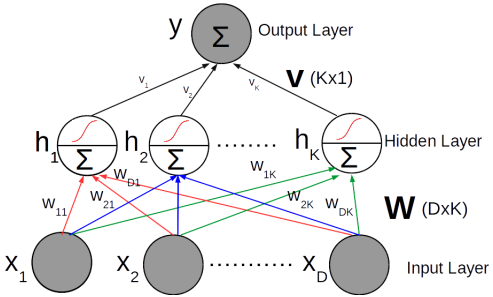

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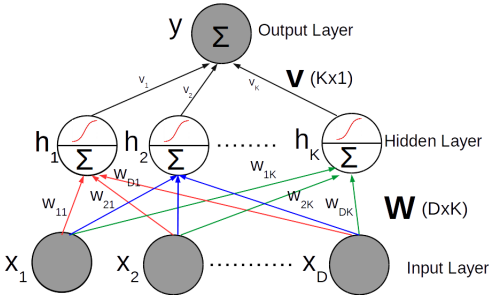

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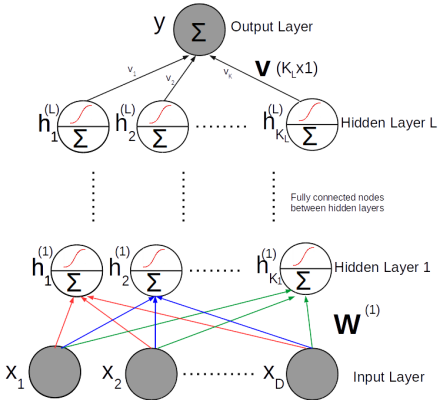
- Each hidden node's value is computed as: $h_k = f(\boldsymbol{w}_k^\top \boldsymbol{x}) = f(\sum_{d=1}^{D} w_{dk} x_d)$

(Deeper) Feedforward Neural Net

- Feedforward neural net with L hidden layers $\boldsymbol{h}^{(1)}, \boldsymbol{h}^{(2)}, \ldots, \boldsymbol{h}^{(L)}$ where

$$\boldsymbol{h}^{(1)} = f(\mathbf{W}^{(1)\top}\boldsymbol{x}) \quad \text{and} \quad \boldsymbol{h}^{(\ell)} = f(\mathbf{W}^{(\ell)\top}\boldsymbol{h}^{(\ell-1)}), \ell \geq 2$$



- Note: The hidden layer ℓ contains K_ℓ hidden nodes, $\mathbf{W}^{(1)}$ is of size $D \times K_1$, $\mathbf{W}^{(\ell)}$ for $\ell \geq 2$ is of size $K_\ell \times K_{\ell+1}$, $\boldsymbol{v}$ is of size $K_L \times 1$

Nonlinear Activation Functions

- Some popular choices for the nonlinear activation function f
  - Sigmoid: $f(x) = \sigma(x) = \frac{1}{1+\exp(-x)}$ (range between 0-1)
  - tanh: $f(x) = 2\sigma(2x) - 1$ (range between -1 and $+1$)
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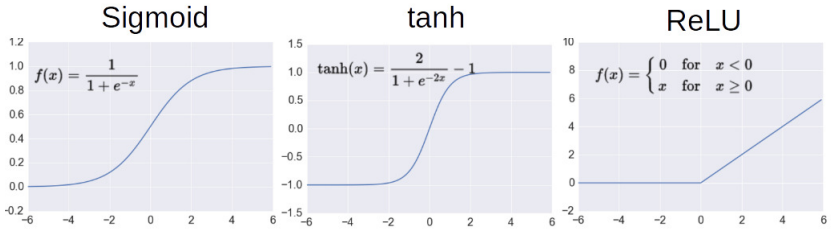

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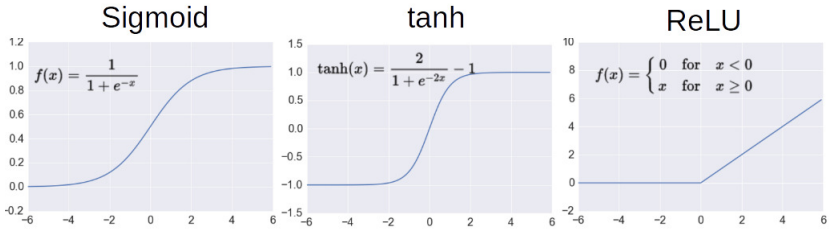

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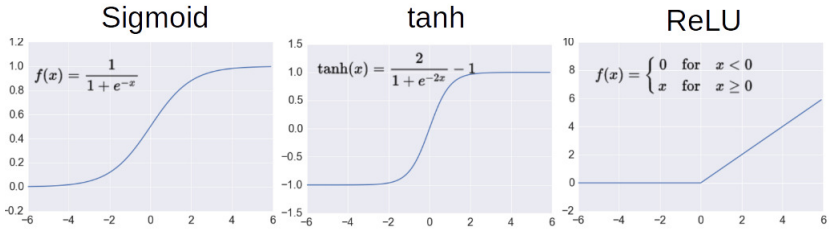

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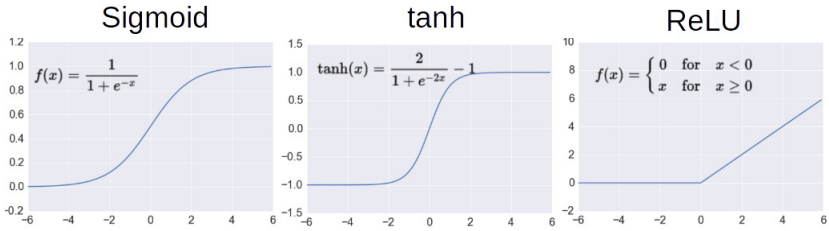

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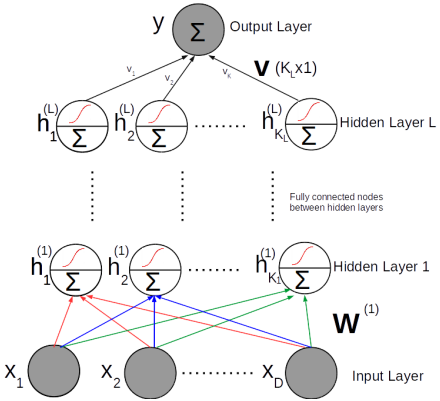
- ReLU is currently the most popular (also cheap to compute)

Learning Feedforward Neural Nets

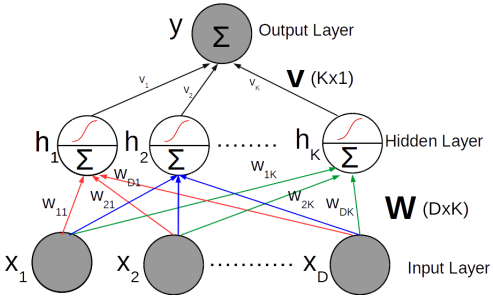
- Want to learn the parameters by minimizing some loss function



- Backpropagation (gradient descent + chain rule for derivatives) is commonly used to do this efficiently

Learning Feedforward Neural Nets

- Consider the feedforward neural net with one hidden layer



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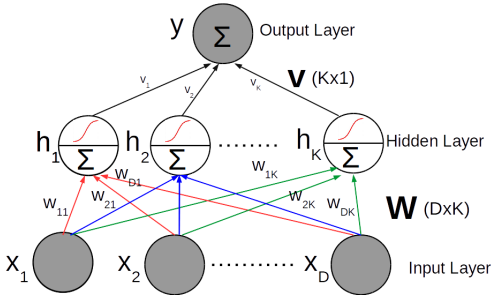

- Recall that $\boldsymbol{h} = [h_1 \ h_2 \ \ldots \ h_K] = f(\mathbf{W}^\top \boldsymbol{x})$
- Assuming a regression problem, the optimization problem would be

$$\min_{\mathbf{W},\boldsymbol{v}} \frac{1}{2} \sum_{n=1}^{N} \left(y_n - \boldsymbol{v}^\top f(\mathbf{W}^\top \boldsymbol{x}_n)\right)^2 = \min_{\mathbf{W},\boldsymbol{v}} \frac{1}{2} \sum_{n=1}^{N} \left(y_n - \sum_{k=1}^{K} v_k f(\boldsymbol{w}_k^\top \boldsymbol{x}_n)\right)^2$$

where $\boldsymbol{w}_k$ is the k-th column of the $D \times K$ matrix $\mathbf{W}$

Learning Feedforward Neural Nets

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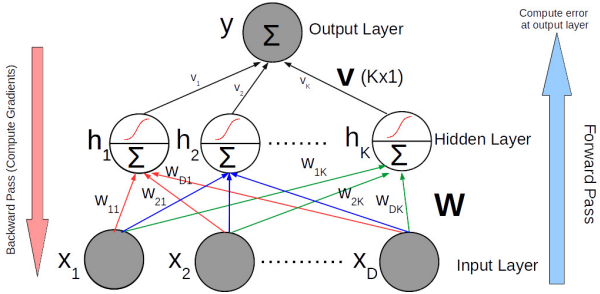
- These calculations can be done efficiently using backpropagation

Backpropagation

- Basically consists of a forward pass and a backward pass



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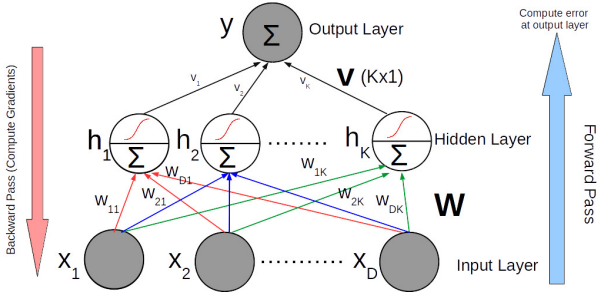

- Forward pass computes the errors $\boldsymbol{e}_n$ using the current parameters
- Backward pass computes the gradients and updates the parameters, starting from the parameters at the top layer and then moving backwards
- Also good at reusing previous computations (updates of parameters at any layer depends on parameters at the layer above)

Kernel Methods vs Deep Neural Nets

- Recall the prediction rule for a kernel method (e.g., kernel SVM)

$$y = \sum_{n=1}^{N} \alpha_n k(\boldsymbol{x}_n, \boldsymbol{x})$$

- This is analogous to a single hidden layer NN with fixed/pre-defined hidden nodes $\{k(\boldsymbol{x}_n, \boldsymbol{x})\}_{n=1}^{N}$ and output layer weights $\{\alpha_n\}_{n=1}^{N}$
- The prediction rule for a deep neural network

$$y = \sum_{k=1}^{K} v_k h_k$$

- In this case, the h_k's are learned from data (possibly after multiple layers of nonlinear transformations)
- Both kernel methods and deep NNs be seen as using nonlinear basis functions for making predictions. Kernel methods use fixed basis functions (defined by the kernel) whereas NN learns the basis functions adaptively from data

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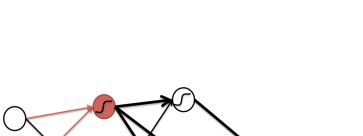
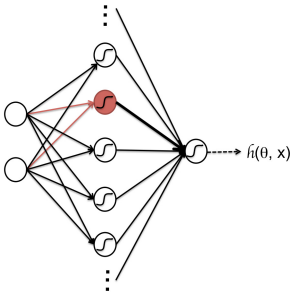


Deep Network



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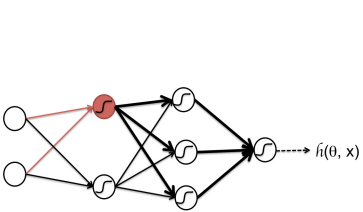

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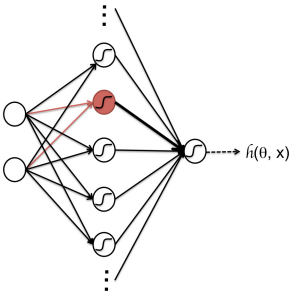

Shallow Network

Learning Certain functions may require a huge number of units in a shallow model

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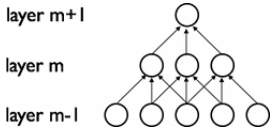

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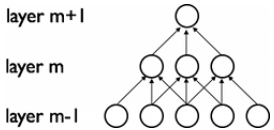
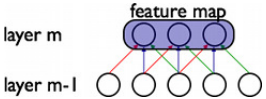
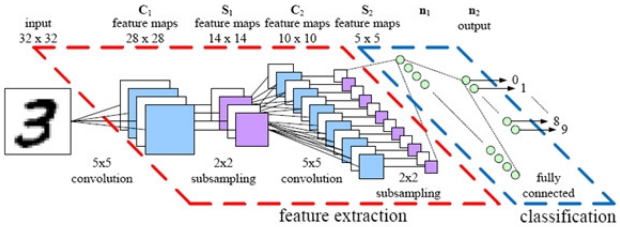


- Shared weights (like a "global" filter). Helps capture the local properties of the signal (useful for data such as images or time-series)



Convolutional Neural Network (CNN)

- Uses a sequence of 2 operations, convolution and pooling (subsampling), applied repeatedly on the input data



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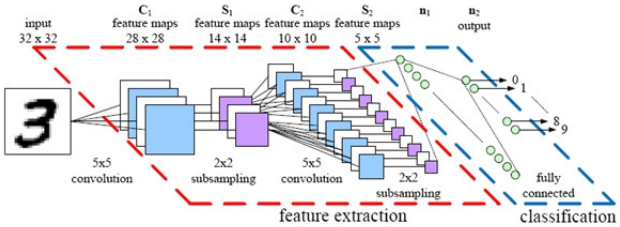

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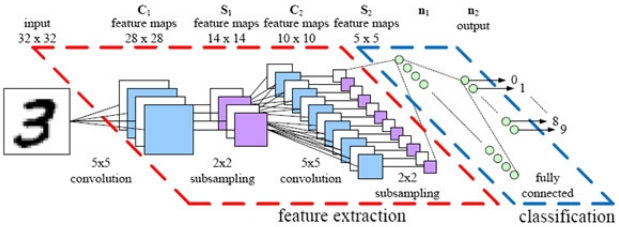

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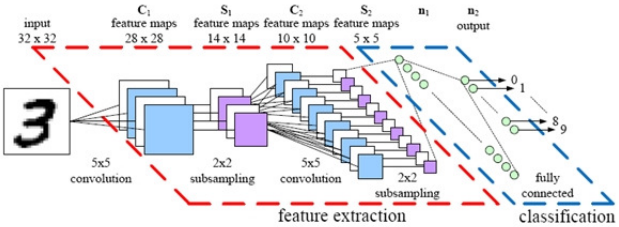

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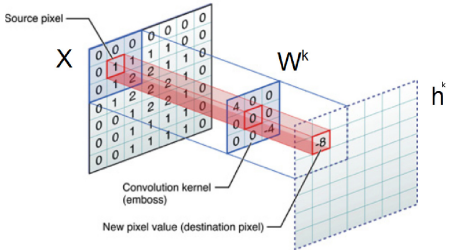
- Note: A nonlinearity is also introduced after the convolution layer

Convolution

- An operation that captures local (e.g., spatial) properties of a signal



- Mathematically, the operation is defined as

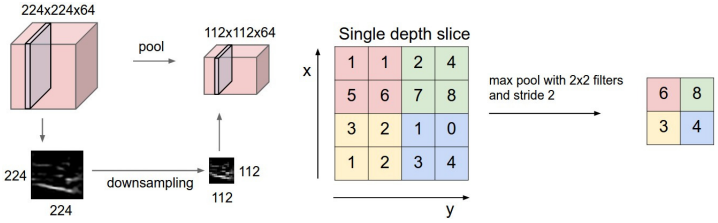
$$h_{ij}^k = f((W^k * \mathbf{X})_{ij} + b_k)$$

where W^k is a filter, $*$ is the convolution operator, and f is a nonlinearity

- Usually a number of filters $\{W^k\}_{k=1}^K$ are applied (each will produce a separate "feature map"). These filters have to be learned
- Size of these filters have to be specified

Pooling/Subsampling

This operation is used to reduce the size of the representation



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- Deep learning models can also be probabilistic and generative, e.g., deep belief networks (we did not consider these here)