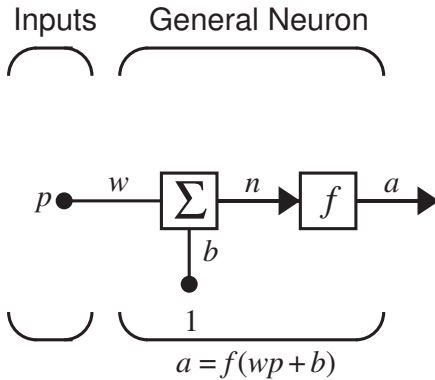


# Multilayer Networks

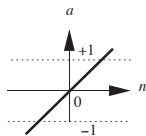
## Deep Learning



# Basic network building block (neuron)

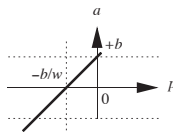


# Transfer (activation) functions (1)



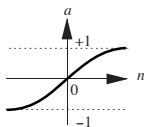
$$a = \text{purelin}(n)$$

Linear Function



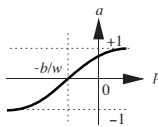
$$a = \text{purelin}(wp + b)$$

Single-Input *purelin* Neuron



$$a = \text{tansig}(n)$$

Tan-Sigmoid Function

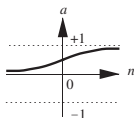


$$a = \text{tansig}(wp + b)$$

Single-Input *tansig* Neuron

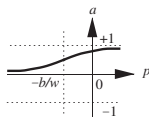


# Transfer (activation) functions (2)



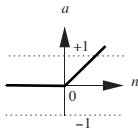
$$a = \text{logsig}(n)$$

Log-Sigmoid Transfer Function



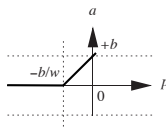
$$a = \text{logsig}(wp + b)$$

Single-Input *logsig* Neuron



$$a = \text{poslin}(n)$$

Positive Linear Function



$$a = \text{poslin}(wp + b)$$

Single-Input *poslin* Neuron



## Transfer (activation) functions (3)

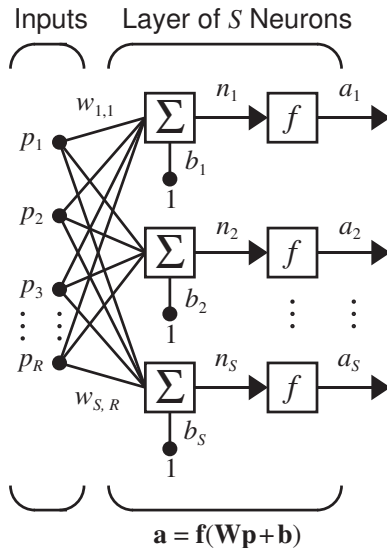
### Softmax

$$a_i = f_i(\mathbf{n}) = \frac{e^{n_i}}{\sum_{j=1}^S e^{n_j}}$$

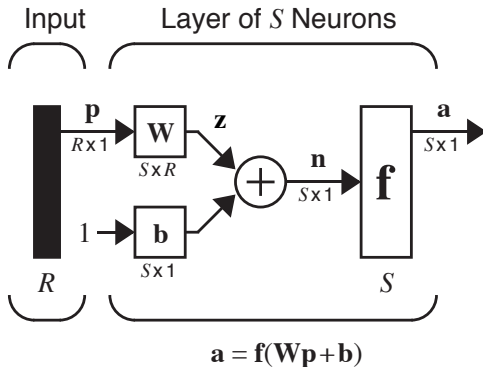
Used at the output layer of a pattern recognition network with multiple output neurons.



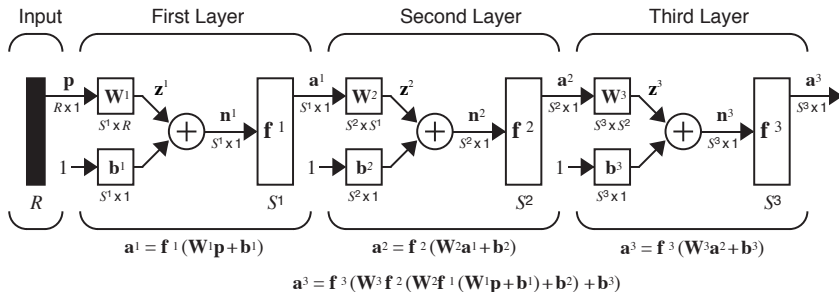
# Layer of neurons



# Matrix notation

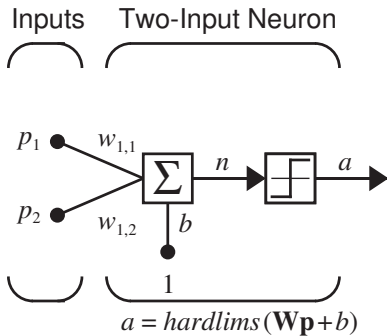


# Multiple layer network



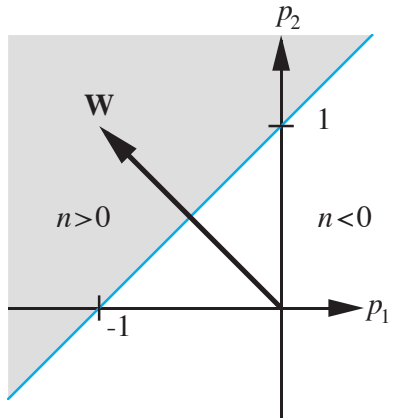


# Single layer network decision boundary

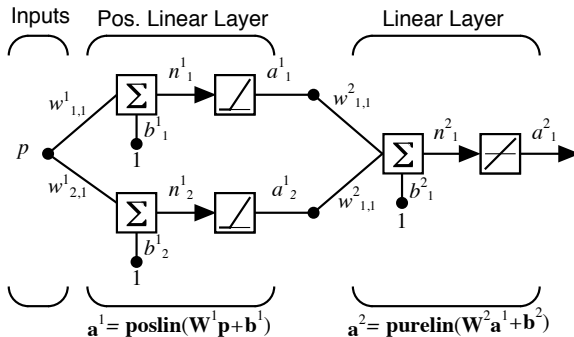


Decision boundary

$$n = \mathbf{W}\mathbf{p} + b == 0$$



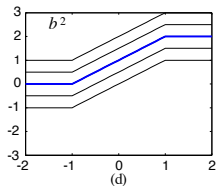
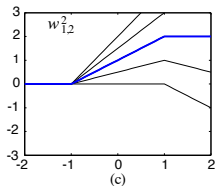
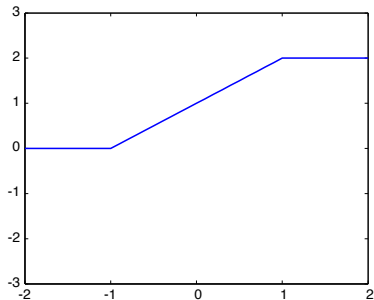
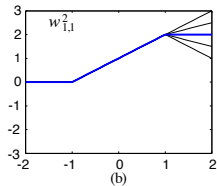
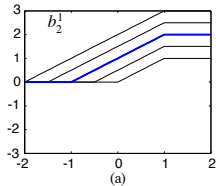
# Poslin network



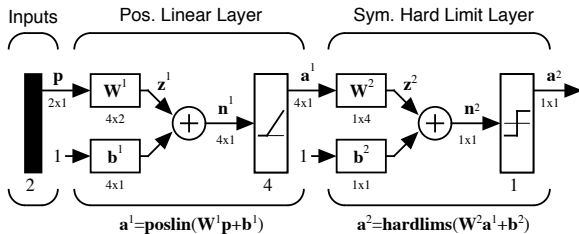
# Poslin network function

$$\mathbf{W}^1 = \begin{bmatrix} 1 & 1 \end{bmatrix}^T, \mathbf{b}^1 = \begin{bmatrix} -1 & 1 \end{bmatrix}^T$$

$$\mathbf{W}^2 = \begin{bmatrix} -1 & 1 \end{bmatrix}, \mathbf{b}^2 = [0]$$



## 2D poslin network

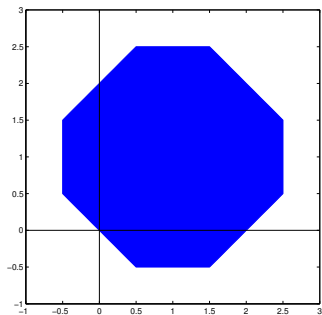
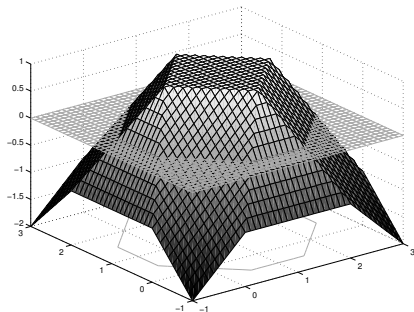


$$\mathbf{W}^1 = \begin{bmatrix} 1 & -1 & -1 & 1 \\ 1 & -1 & 1 & -1 \end{bmatrix}^T, \mathbf{b}^1 = [-1 \quad 3 \quad 1 \quad 1]^T$$

$$\mathbf{W}^2 = [-1 \quad -1 \quad -1 \quad -1], \mathbf{b}^2 = [5]$$



# 2D Poslin network surface and decision boundary



# Why do we need deep networks?

- Theoretically, two-layer networks (with sufficient hidden neurons) can approximate any practical function or decision region.
- In practice, deep networks have been able to solve problems that two-layer networks were not previously able to.
- The theoretical explanation of this is not complete.
- We will describe a couple of initial explanations.
- The idea is that deeper networks can produce more efficient realizations of some complex functions than two layer networks can.

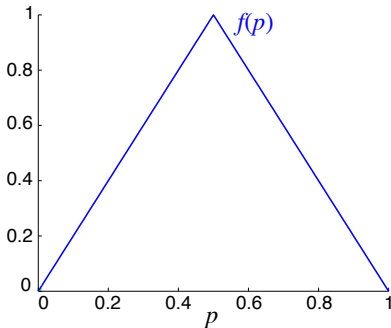


## Cascading layers (1)

- Consider again the earlier two-layer network, but change the weights.

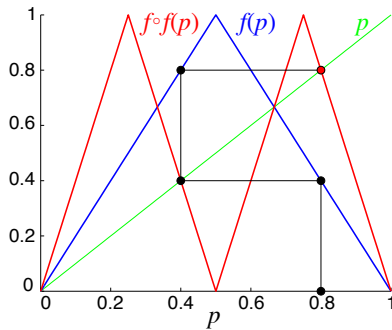
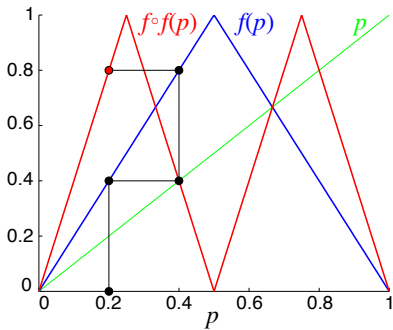
$$\mathbf{W}^1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \mathbf{b}^1 = \begin{bmatrix} 0 \\ -0.5 \end{bmatrix}, \mathbf{W}^2 = \begin{bmatrix} 2 & -4 \end{bmatrix}, \mathbf{b}^2 = \begin{bmatrix} 0 \end{bmatrix}$$

- We get the following function.



## Cascading layers (2)

- Now cascade the function with itself:  $f \circ f(p) = f(f(p))$ .
- We get the following function (in red).
- By adding a single layer we have doubled the complexity.





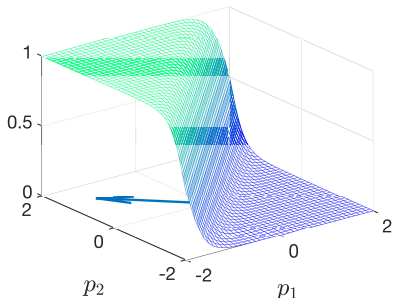
## Cascading layers (3)

- Each time we add a layer (a linear increase in the number of neurons), we double the number of neurons that would be required for a two layer network to implement the same function.
- Two-layer networks can create any function that can be created with a deep network.
- The number of neurons required in the two-layer network increase geometrically.
- The number of neurons increase linearly in the equivalent deep network.

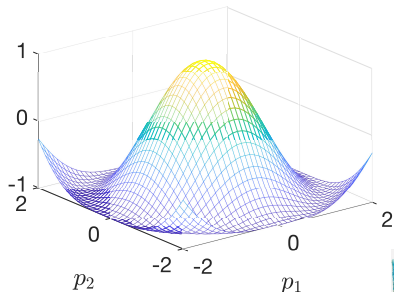


# Implementing radial functions

- A sigmoid neuron response does not change orthogonal to the weight direction, which creates a ridge function.
- It is difficult to approximate a radial function with a sum of ridges (two-layer network).
- With the addition of a third layer, a 2-4-2-1 network can easily make an accurate approximation.



Sigmoid Neuron Response



Radial Function

