Artificial Intelligence and Machine Learning

Barbara Caputo

Learning highly non-linear functions

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f: X → Y

- f might be non-linear function
- X (vector of) continuous and/or discrete vars
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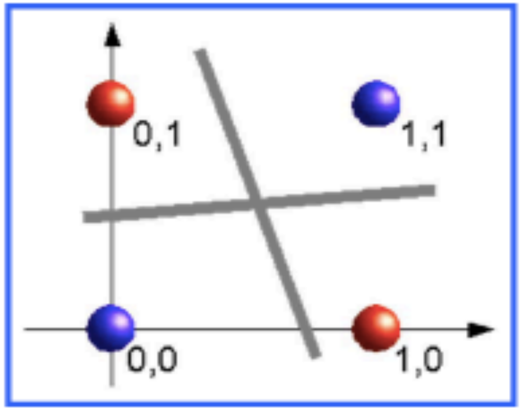
The XOR gate



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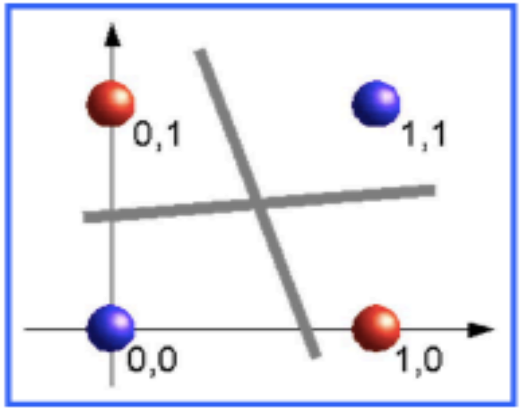
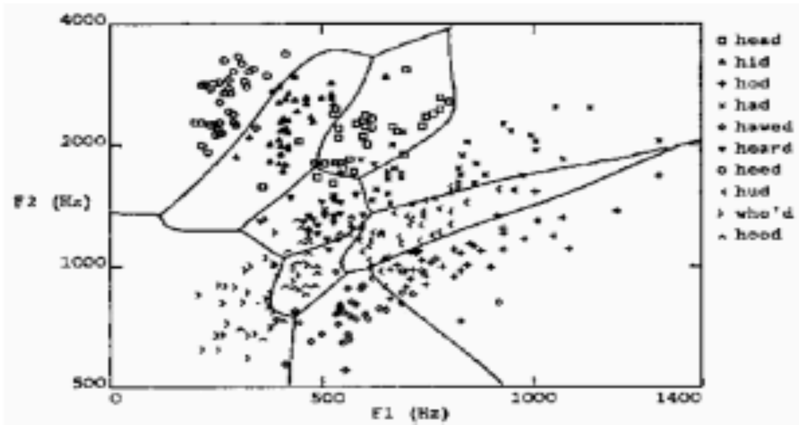
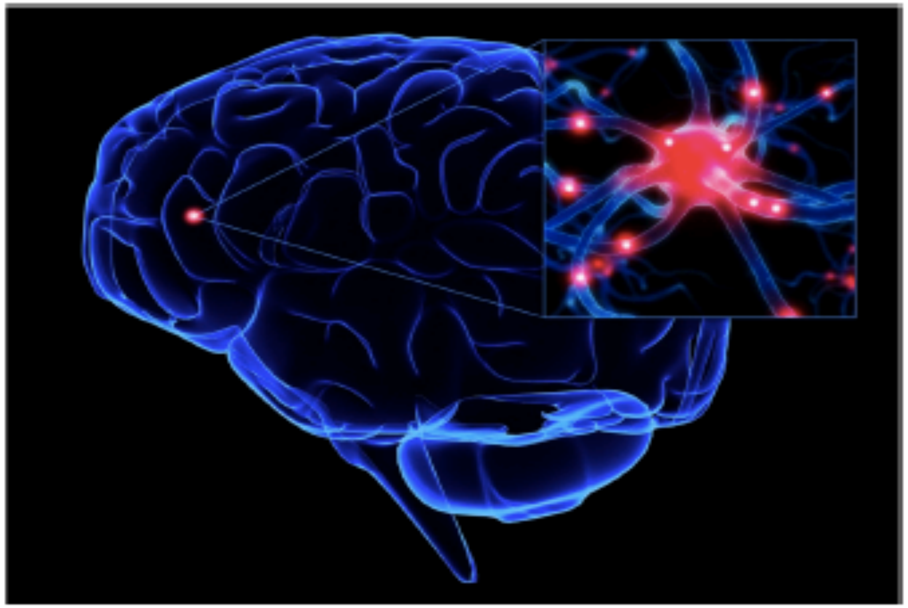


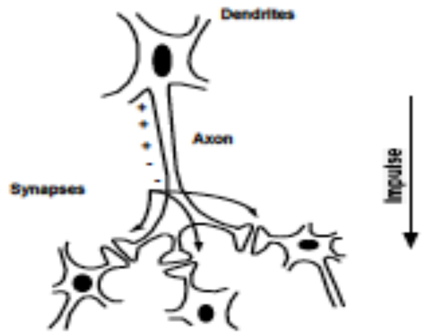
Speech recognition



Our brain is very good at this …



How a neuron works



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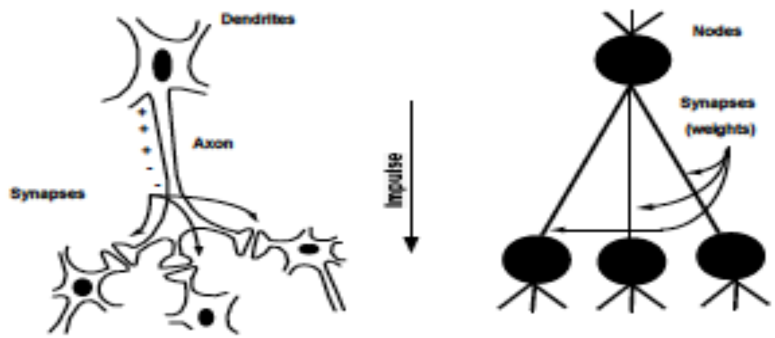

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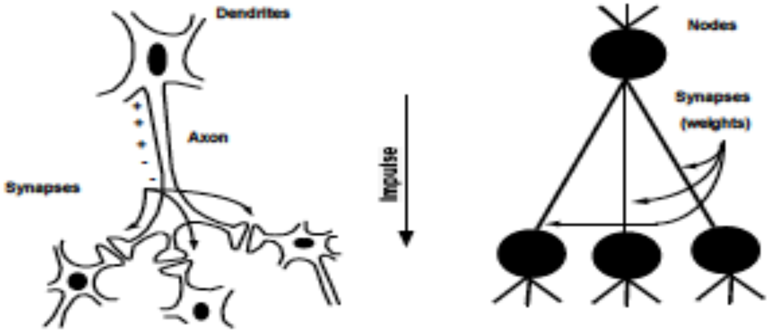
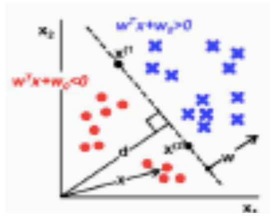


- Activation function:

$$X = \sum_{i=1}^{M} x_i w_i \qquad Y = \begin{cases} +1, & \text{if } X \geq \omega_0 \\ -1, & \text{if } X < \omega_0 \end{cases}$$



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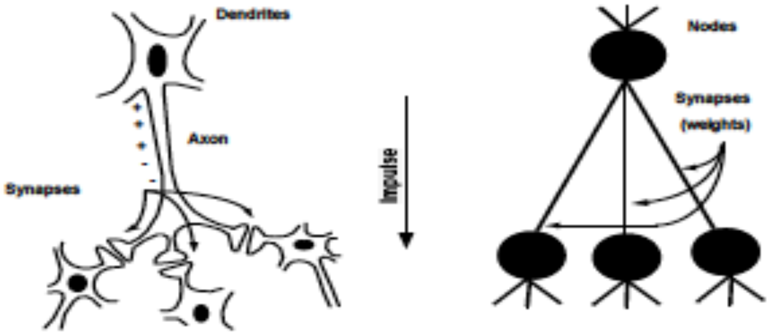

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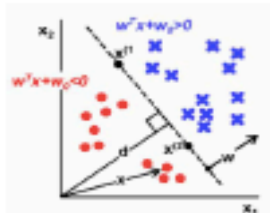
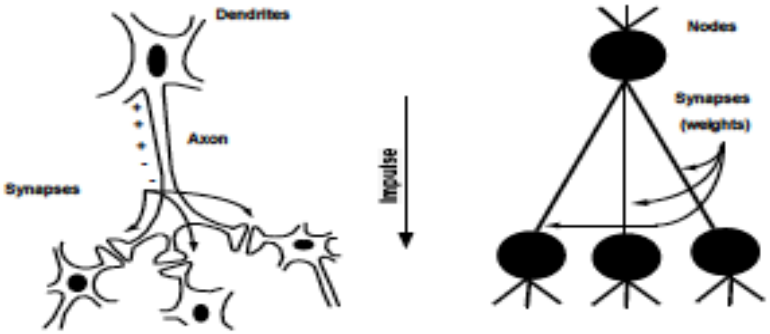


- An mathematical expression

$$p(y=1|x) = \frac{1}{1+\exp\left\{-\sum_{i=1}^{M} w_i x_i - \theta_0\right\}} = \frac{1}{1+e^{-w^T x}}$$

How a neuron works



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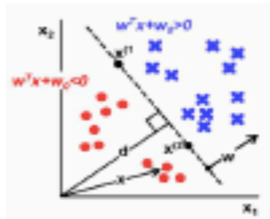

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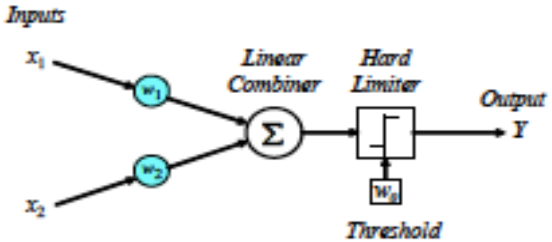
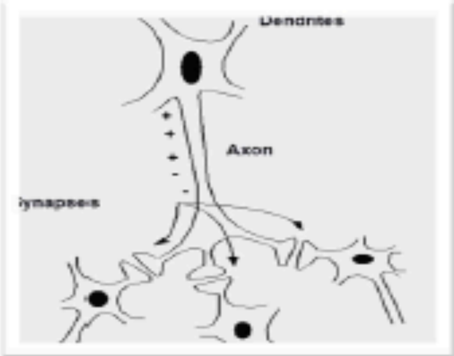


Perceptron and Neural Nets

- From biological neuron to artificial neuron (perceptron)



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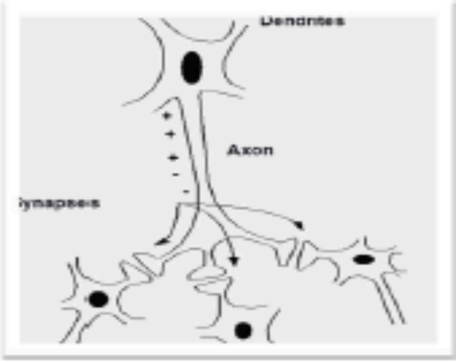

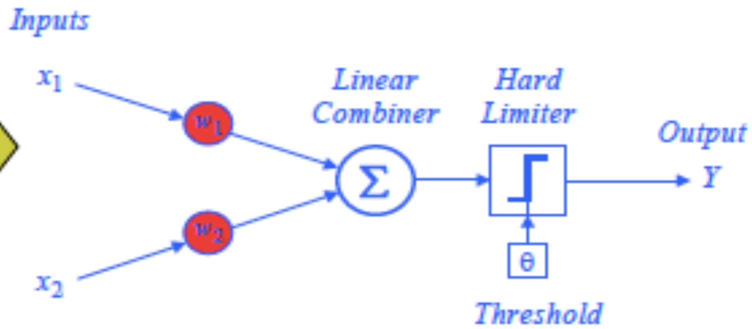

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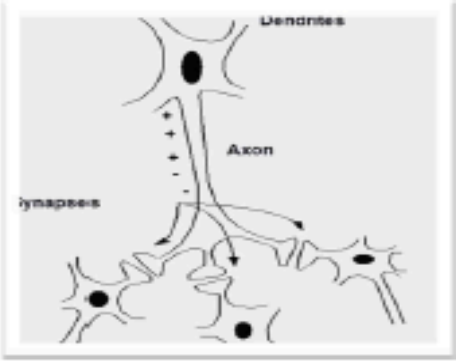

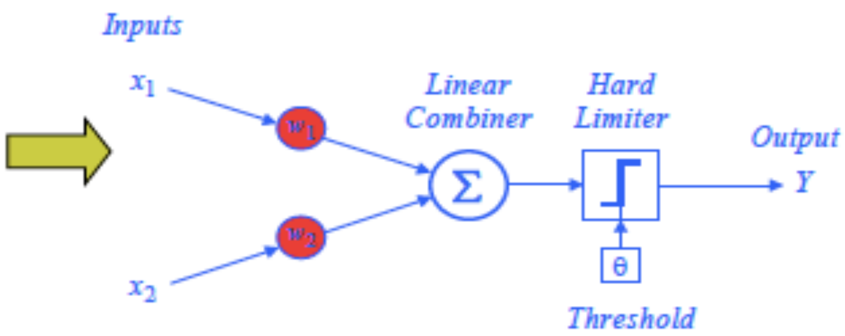

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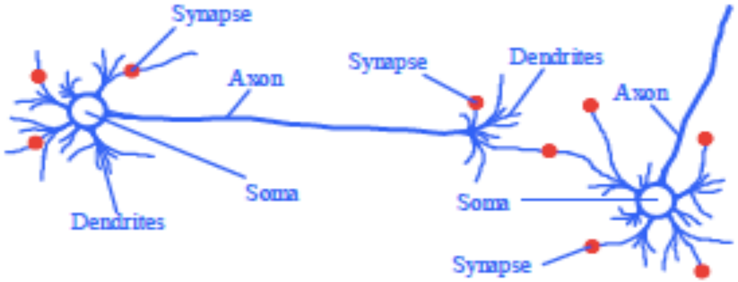

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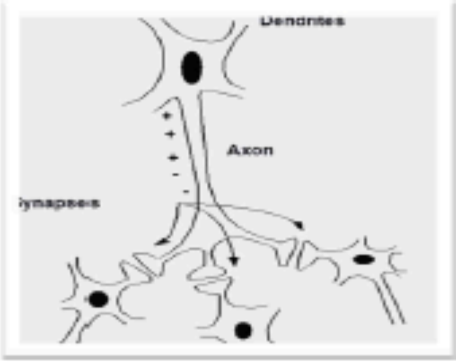

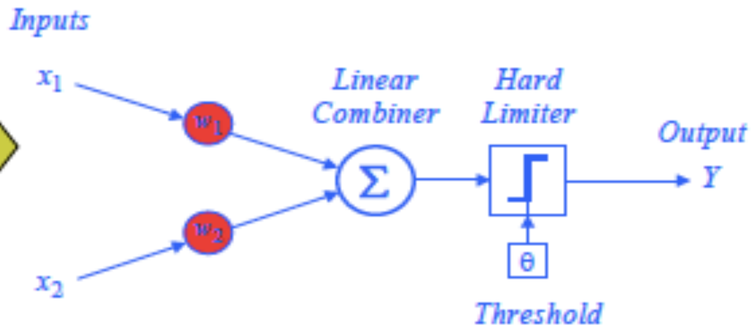

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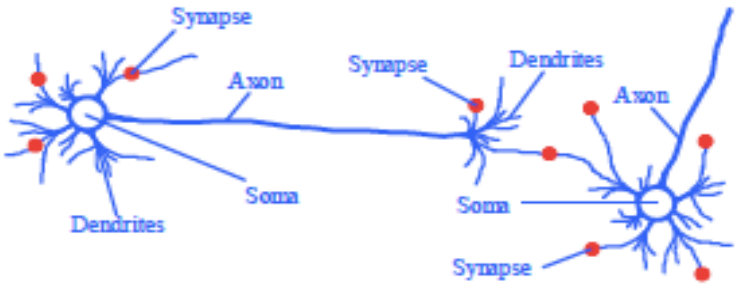

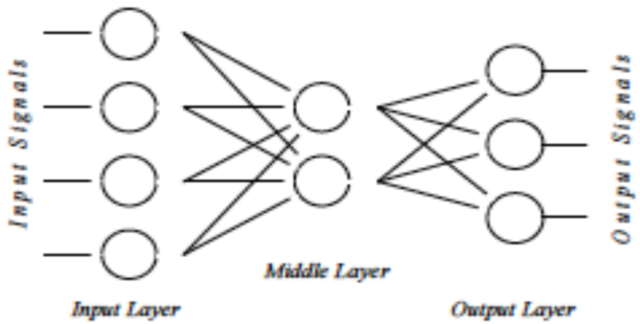

Jargon Pseudo-Correspondence

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- Dependent variable = output variable
- Coefficients = “weights”
- Estimates = “targets”

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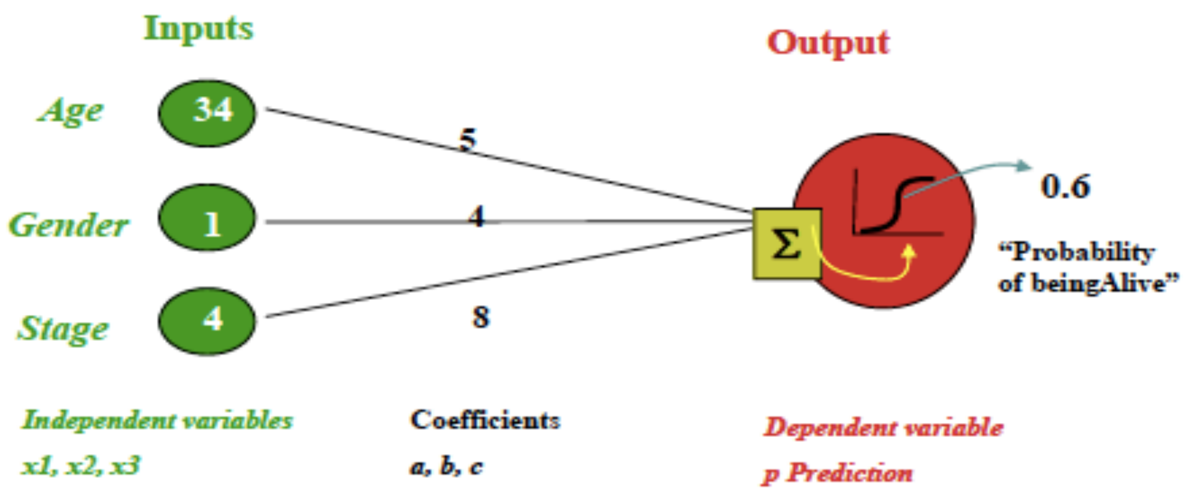
Logistic Regression Model (the sigmoid unit)



A perceptron learning algorithm

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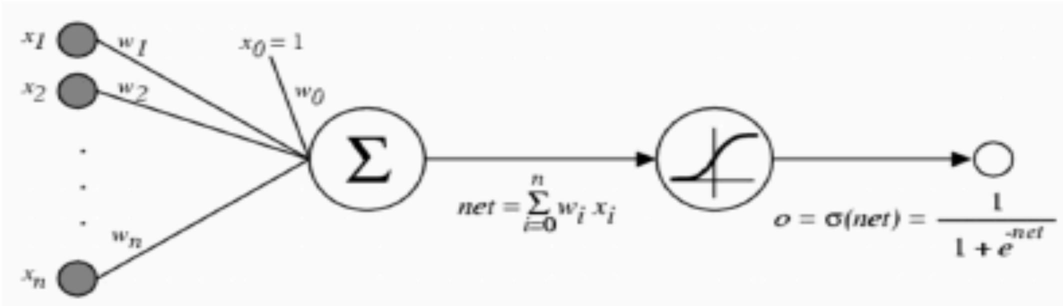

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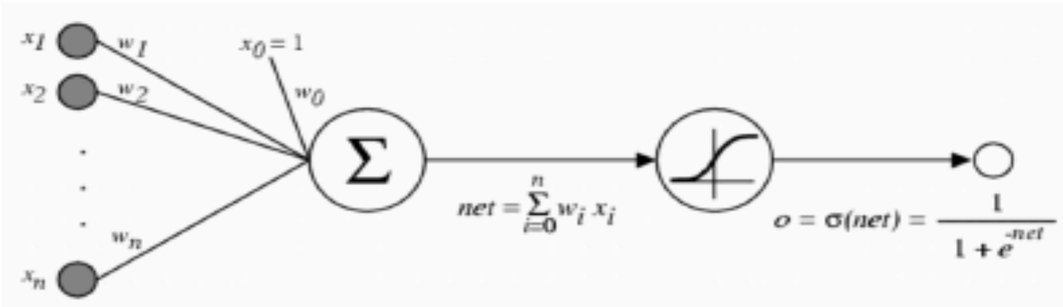

- Recall the nice property of sigmoid function $\frac{d\sigma}{dt} = \sigma(1-\sigma)$
- Consider regression problem f:X→Y , for scalar Y: $y = f(x) + \epsilon$

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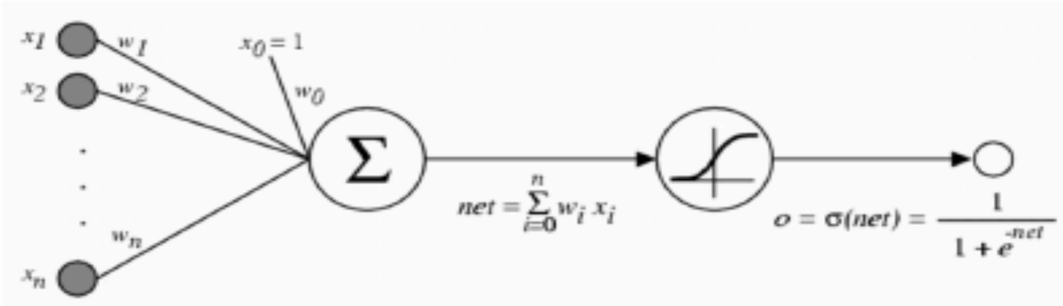

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$$\vec{w} = \arg\max_{\vec{w}} \ln \prod_i P(y_i | x_i; \vec{w})$$

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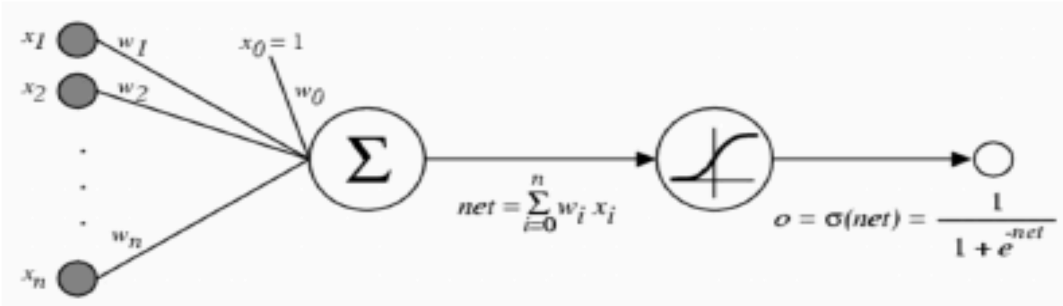

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- Here …

$$\vec{w} = \arg\min_{\vec{w}} \sum_i \frac{1}{2}(y_i - \hat{f}(x_i; \vec{w}))^2$$

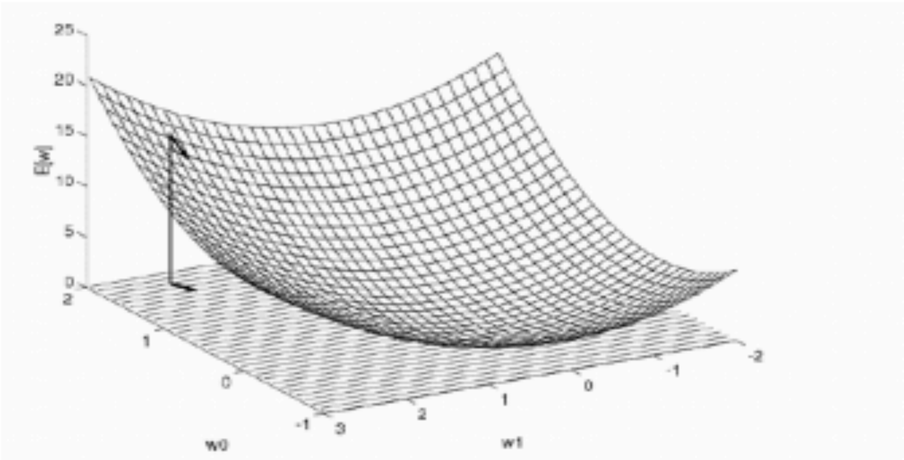
Gradient Descent

x_d = input

t_d = target output

o_d =observed unit output

w_i =weight i



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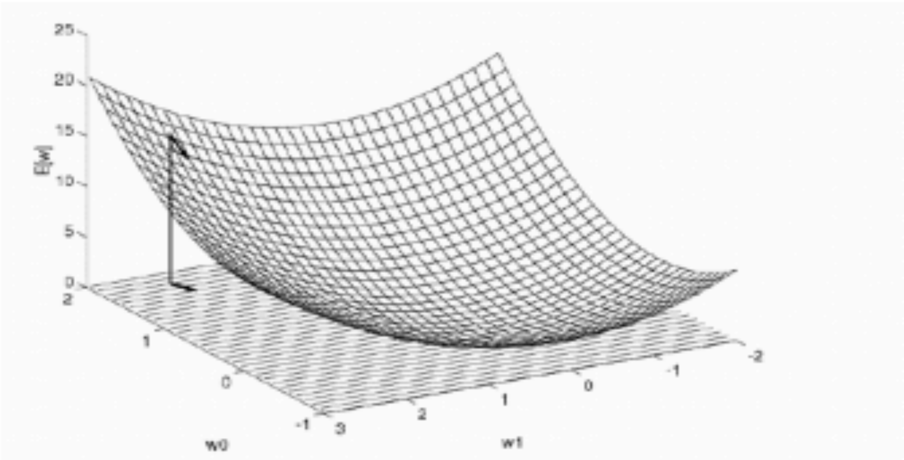

$$\frac{\partial E[\vec{w}]}{\partial w_j} = \frac{\partial}{\partial w_i}\frac{1}{2}\sum(t_d - o_d)^2$$
$$=$$

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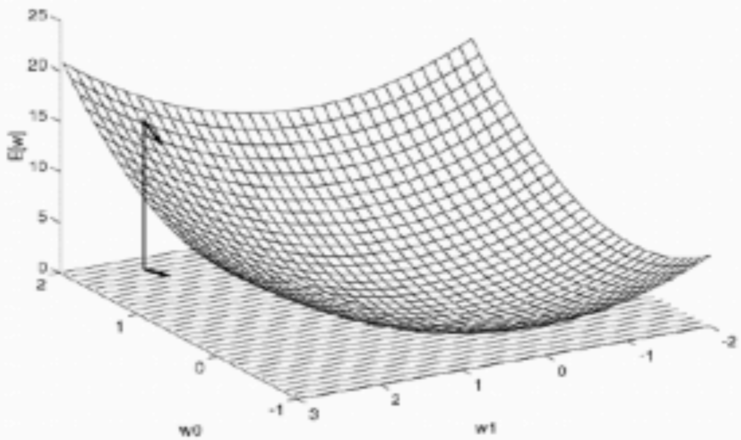

$$
\begin{aligned}
\frac{\partial E[\vec{w}]}{\partial w_j} &= \frac{\partial}{\partial w_i} \frac{1}{2} \sum (t_d - o_d)^2 \\
&=
\end{aligned}
$$

Gradient

$$\nabla E[\vec{w}] \equiv \left[\frac{\partial E}{\partial w_0}, \frac{\partial E}{\partial w_1}, \cdots \frac{\partial E}{\partial w_n}\right]$$

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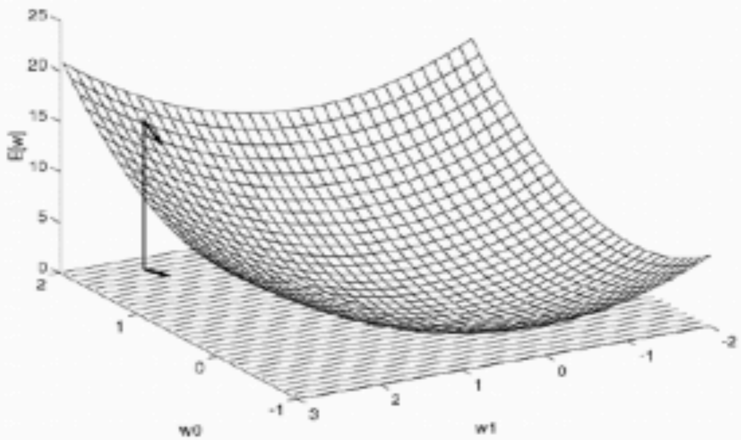

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Gradient

$$\nabla E[\vec{w}] \equiv \left[\frac{\partial E}{\partial w_0}, \frac{\partial E}{\partial w_1}, \cdots \frac{\partial E}{\partial w_n}\right]$$

Training rule:

$$\Delta\vec{w} = -\eta\nabla E[\vec{w}]$$

i.e.,

$$\Delta w_i = -\eta\frac{\partial E}{\partial w_i}$$

The perceptron learning rules

x_d = input

t_d = target output

o_d =observed unit output

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$$\frac{\partial E_D[\vec{w}])}{\partial w_j} = \frac{\partial}{\partial w_i}\frac{1}{2}\sum_d (t_d - o_d)^2$$

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$$\begin{aligned} \frac{\partial E_D[\vec{w}])}{\partial w_j} &= \frac{\partial}{\partial w_i}\frac{1}{2}\sum_d (t_d - o_d)^2 \\ &= \frac{1}{2}\sum_d 2(t_d - o_d)\frac{\partial}{\partial w_i}(t_d - o_d) \end{aligned}$$

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\frac{\partial E_D[\vec{w}])}{\partial w_j} &= \frac{\partial}{\partial w_i}\frac{1}{2}\sum_d (t_d - o_d)^2 \\
&= \frac{1}{2}\sum_d 2(t_d - o_d)\frac{\partial}{\partial w_i}(t_d - o_d) \\
&= \sum_d (t_d - o_d)(-\frac{\partial o_d}{\partial w_i})
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\end{aligned}
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Batch mode:

Do until converge:

1. compute gradient $\nabla E_D[w]$
2. $\vec{w} = \vec{w} - \eta \nabla E_D[\vec{w}]$

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\end{aligned}$$

Batch mode:

Do until converge:

1. compute gradient $\nabla E_D[w]$
2. $\vec{w} = \vec{w} - \eta \nabla E_D[\vec{w}]$

Incremental mode:

Do until converge:

- For each training example *d* in *D*
  1. compute gradient $\nabla E_d[w]$
  2. $\vec{w} = \vec{w} - \eta \nabla E_d[\vec{w}]$

  where

  $\nabla E_d[\vec{w}] = -(t_d - o_d)o_d(1 - o_d)\vec{x}_d$

MLE vs MAP

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MLE vs MAP

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Five mins break!

What decision surface does a perceptron define?

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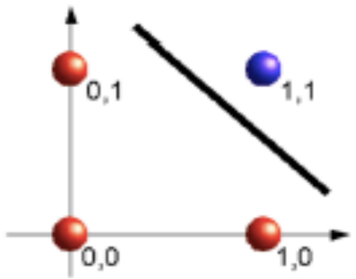

NAND

x	y	Z (color)
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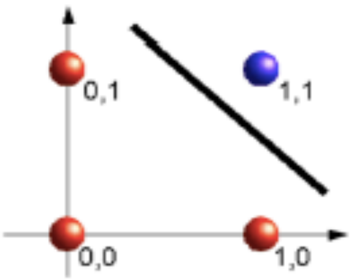

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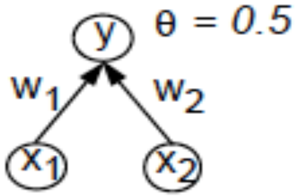
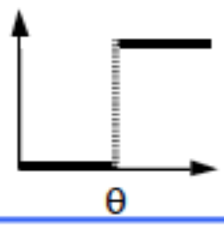


$$f(x_1 w_1 + x_2 w_2) = y$$
$$f(0w_1 + 0w_2) = 1$$
$$f(0w_1 + 1w_2) = 1$$
$$f(1w_1 + 0w_2) = 1$$
$$f(1w_1 + 1w_2) = 0$$



$$f(a) = \begin{cases} 1, & \text{for } a > \theta \\ 0, & \text{for } a \leq \theta \end{cases}$$

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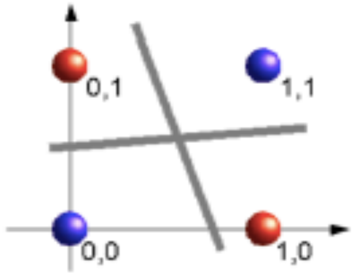

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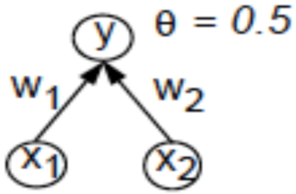
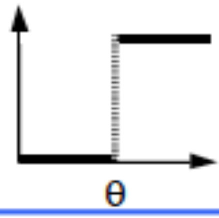
1	1	0



$$f(x_1 w_1 + x_2 w_2) = y$$

$$f(0w_1 + 0w_2) = 0$$
$$f(0w_1 + 1w_2) = 1$$
$$f(1w_1 + 0w_2) = 1$$
$$f(1w_1 + 1w_2) = 0$$

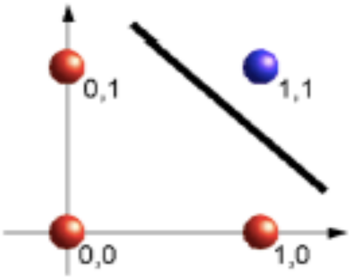


$$f(a) = \begin{cases} 1, \text{ for } a > \theta \\ 0, \text{ for } a \leq \theta \end{cases}$$

some possible values for w_1 and w_2

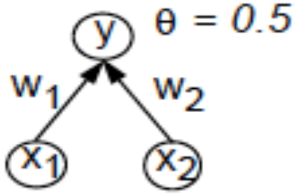
w_1	w_2

What decision surface does a perceptron define?



NAND

x	y	Z (color)
0	0	1
0	1	1
1	0	1
1	1	0



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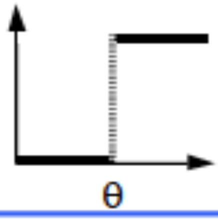
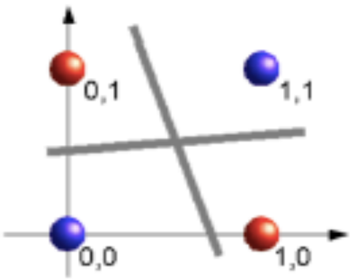


$$f(a) = \begin{cases} 1, \text{ for } a > \theta \\ 0, \text{ for } a \leq \theta \end{cases}$$

some possible values for w_1 and w_2

w_1	w_2
0.20	0.35
0.20	0.40
0.25	0.30
0.40	0.20

What decision surface does a perceptron define?



NAND

x	y	Z (color)
0	0	0
0	1	1
1	0	1
1	1	0

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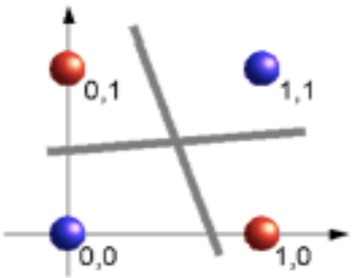
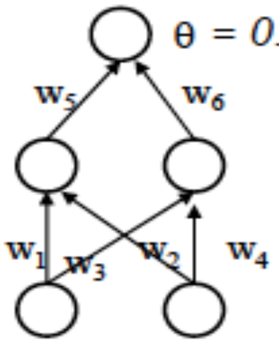
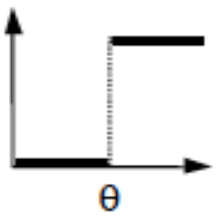


NAND

x	y	Z (color)
0	0	**0**
0	1	**1**
1	0	**1**
1	1	**0**

θ = *0.5 for all units*





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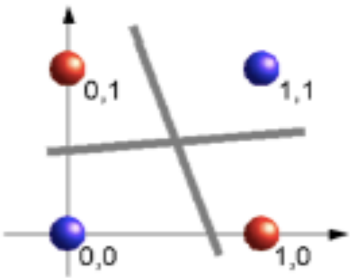
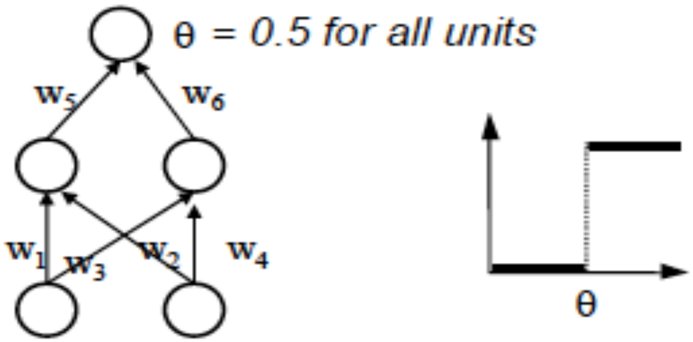


NAND

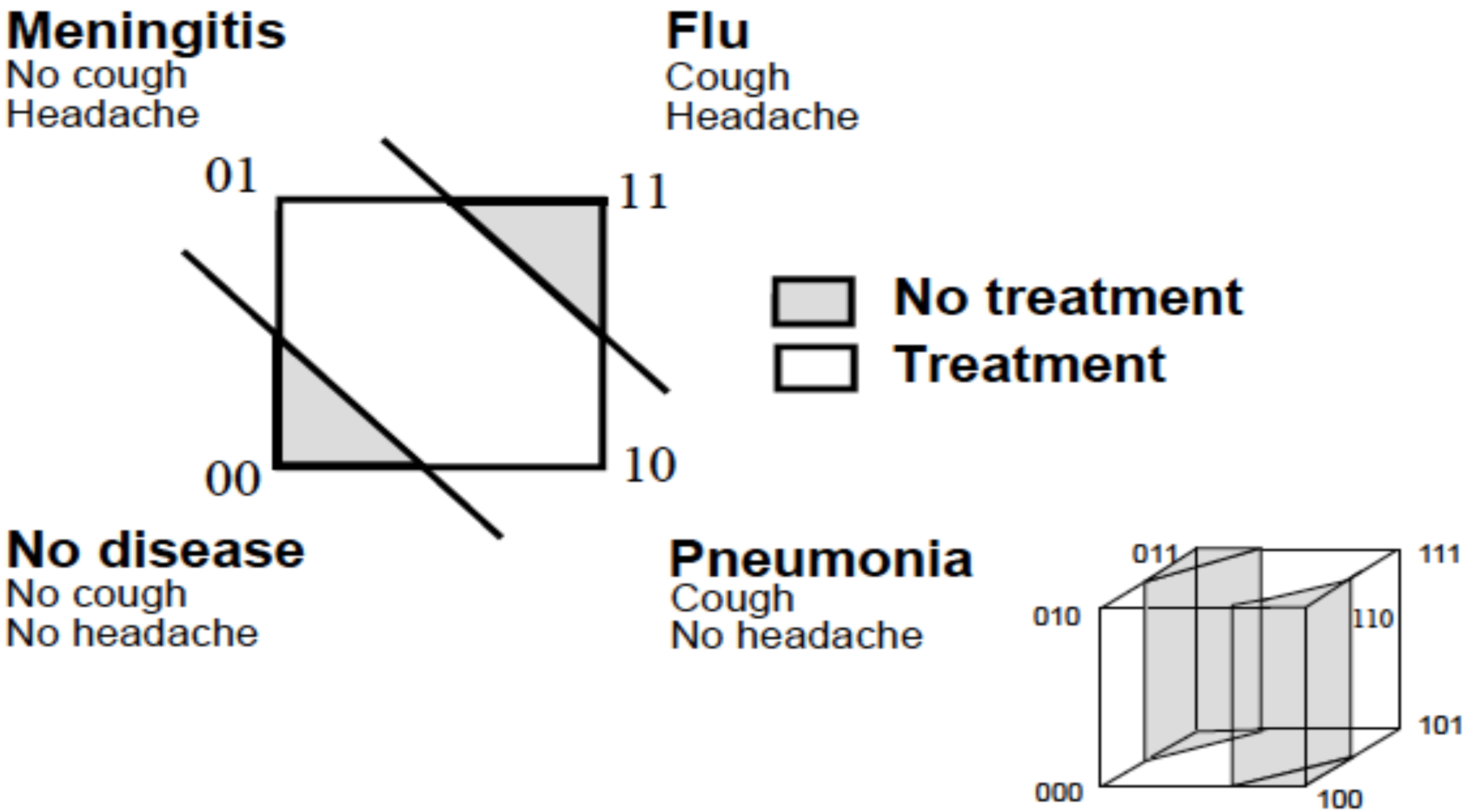
x	y	Z (color)
0	0	0
0	1	1
1	0	1
1	1	0



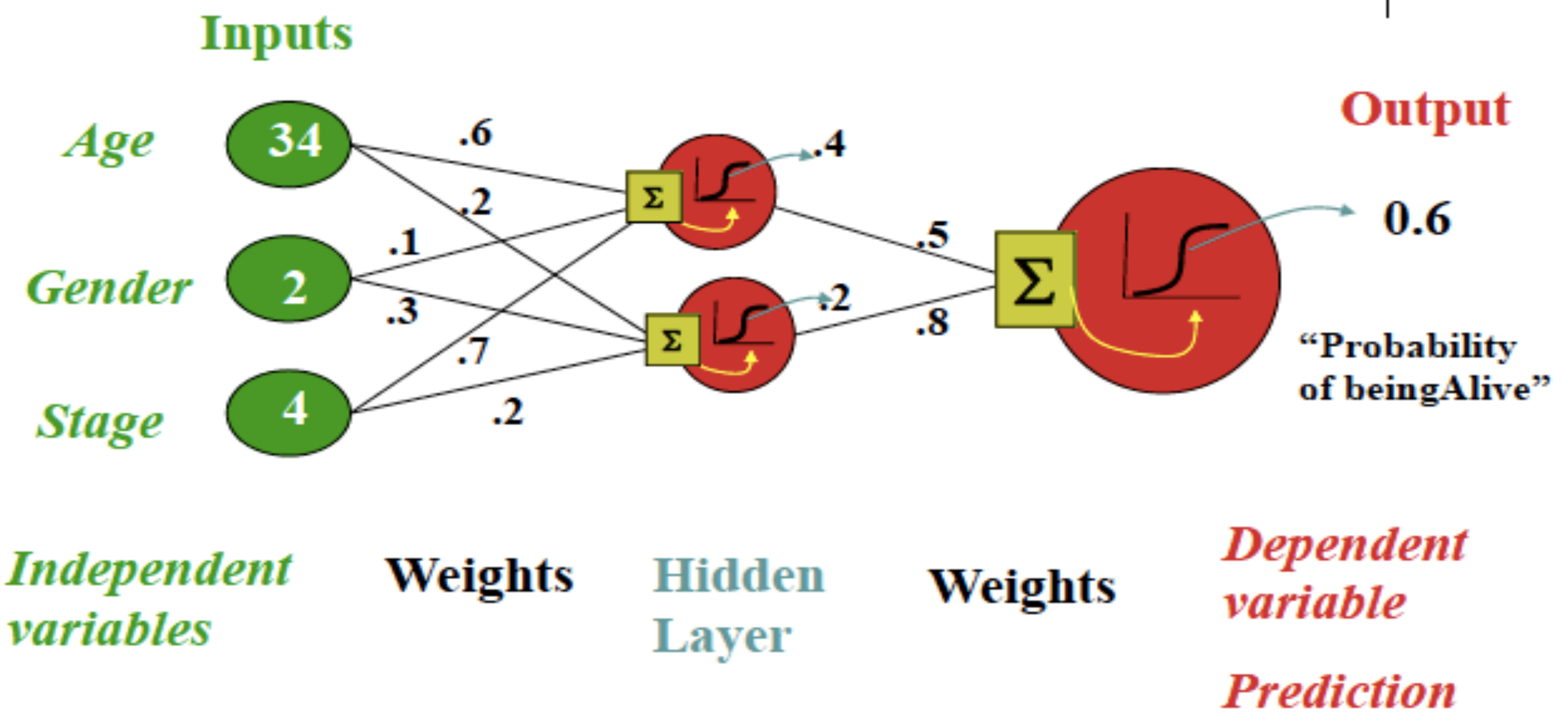
$$f(a) = \begin{cases} 1, \text{ for } a > \theta \\ 0, \text{ for } a \le \theta \end{cases}$$

a possible set of values for $(w_1, w_2, w_3, w_4, w_5, w_6)$:
(0.6,-0.6,-0.7,0.8,1,1)

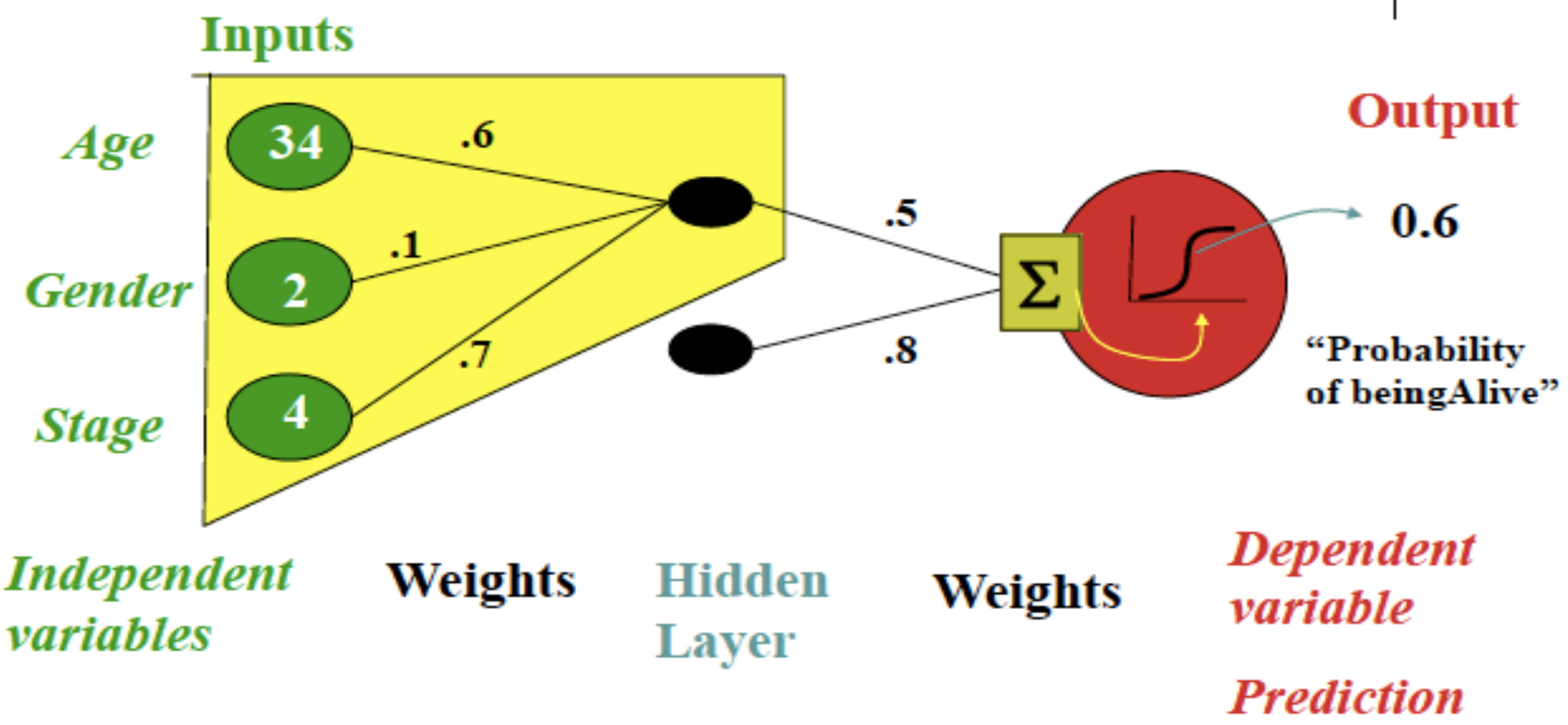
Non Linear Separation

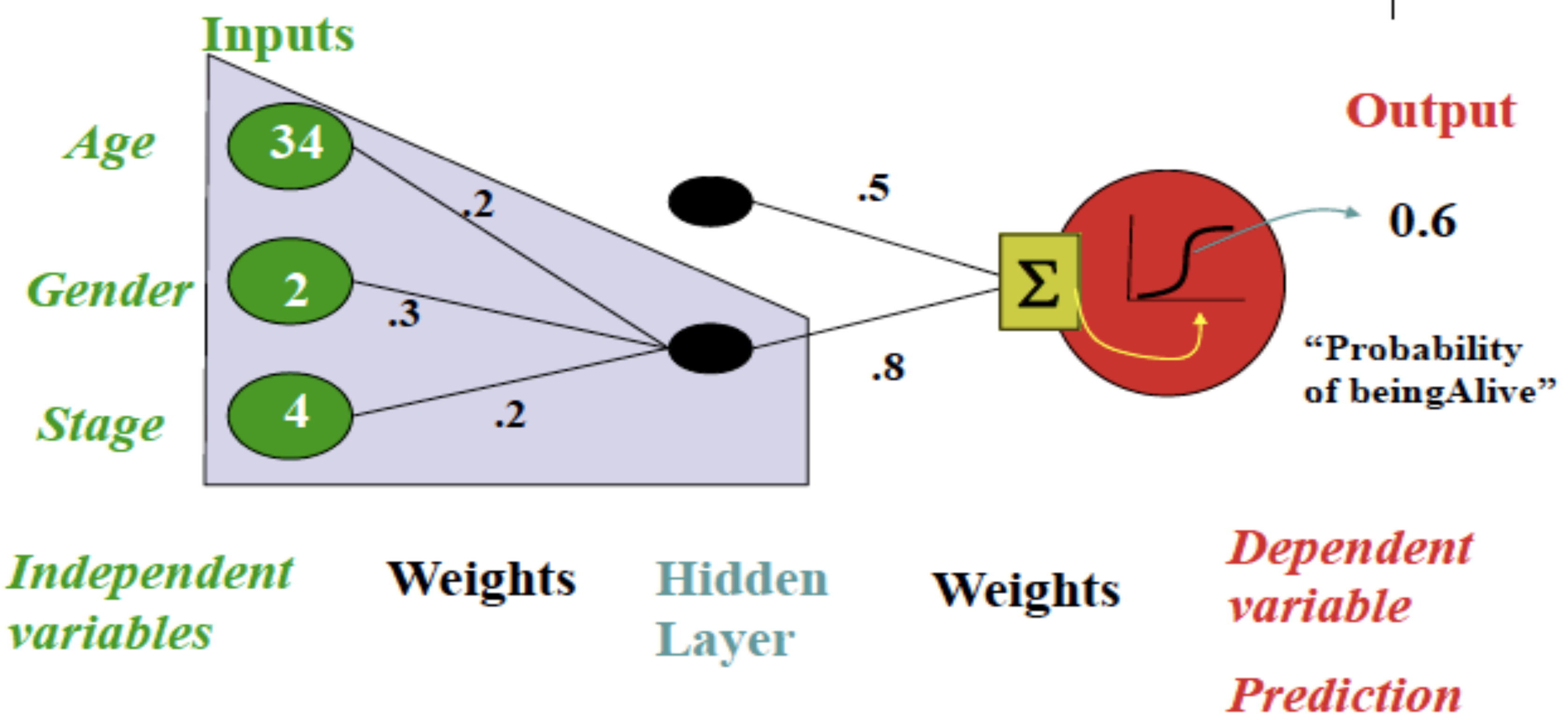


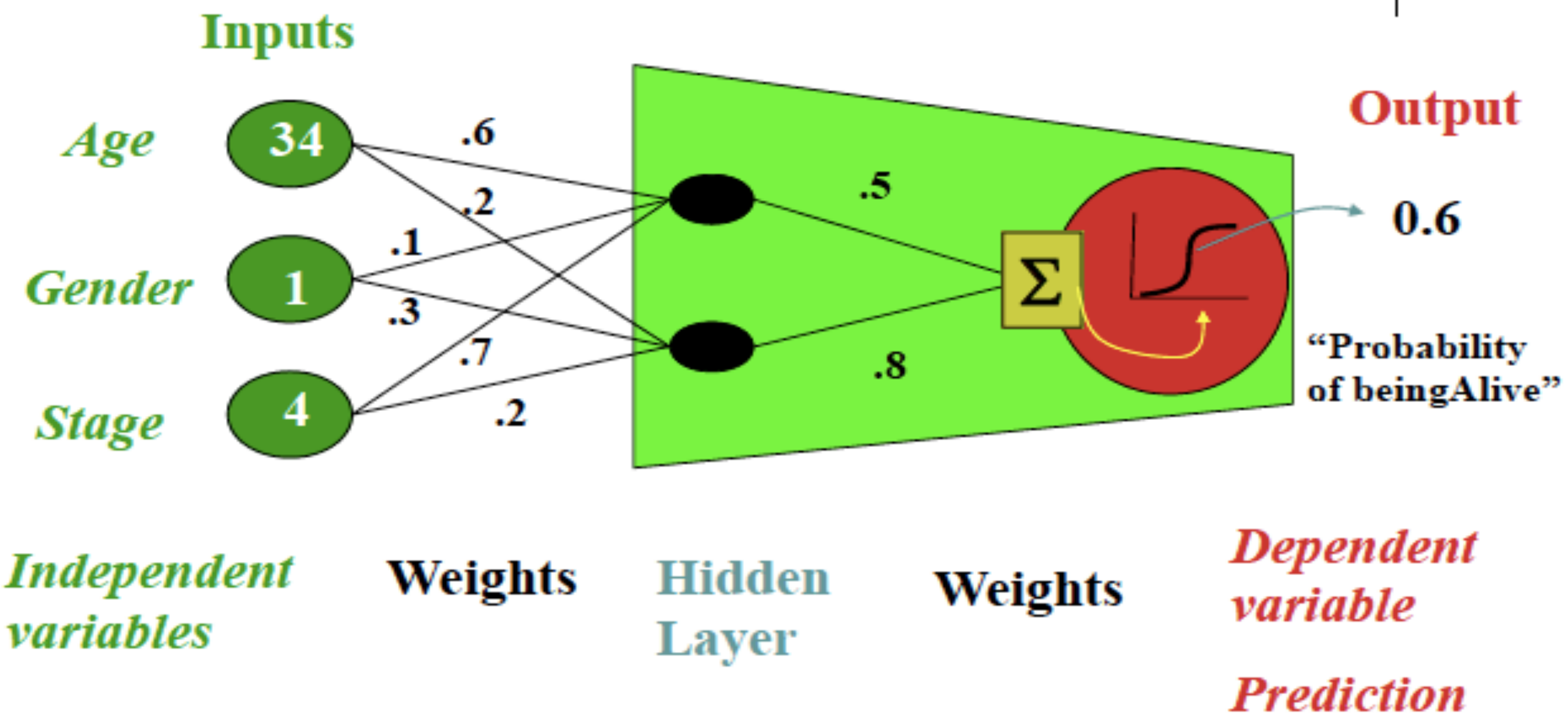
Neural Network Model



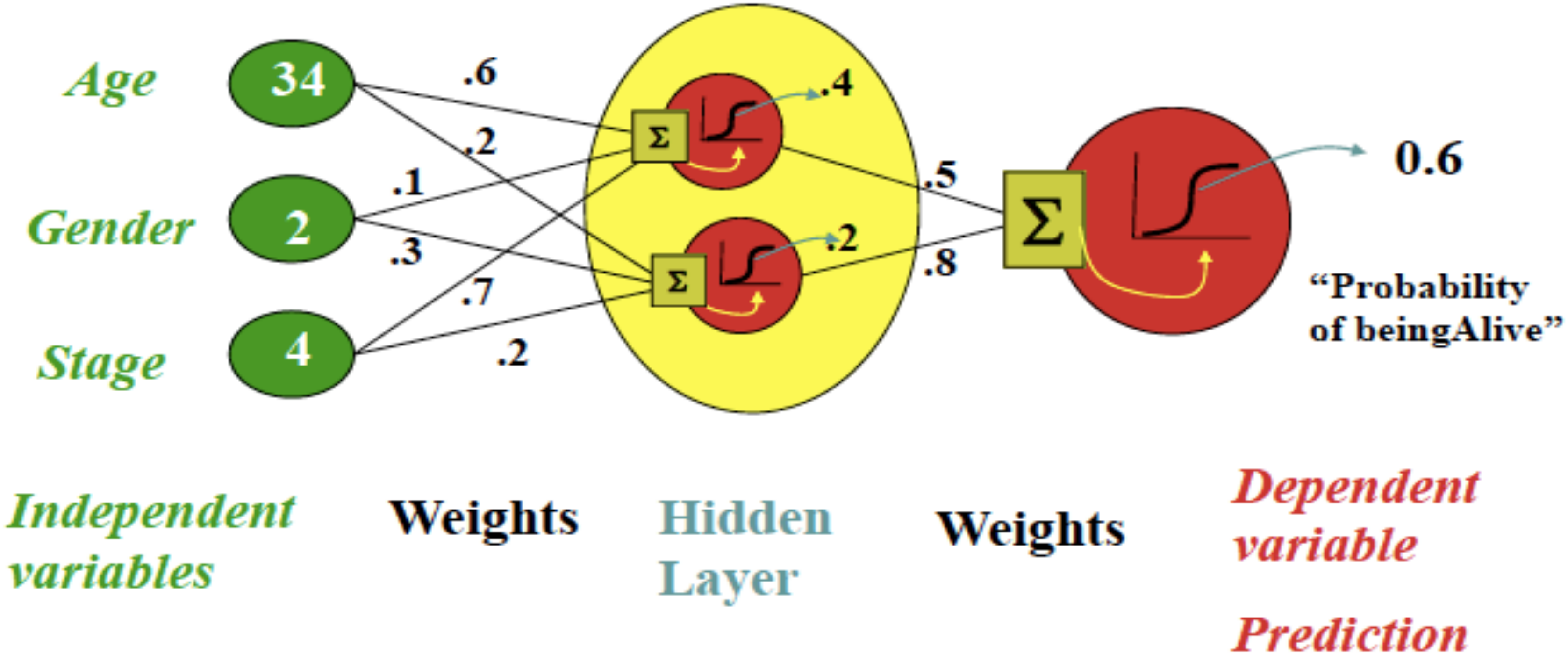
"Combined logistic models"




Inputs
Age
34
Gender
2
Stage
4
.2
.3
.2
.5
.8
Σ
Output
0.6
"Probability
of beingAlive"
Independent
variables
Weights
Hidden
Layer
Weights
Dependent
variable
Prediction

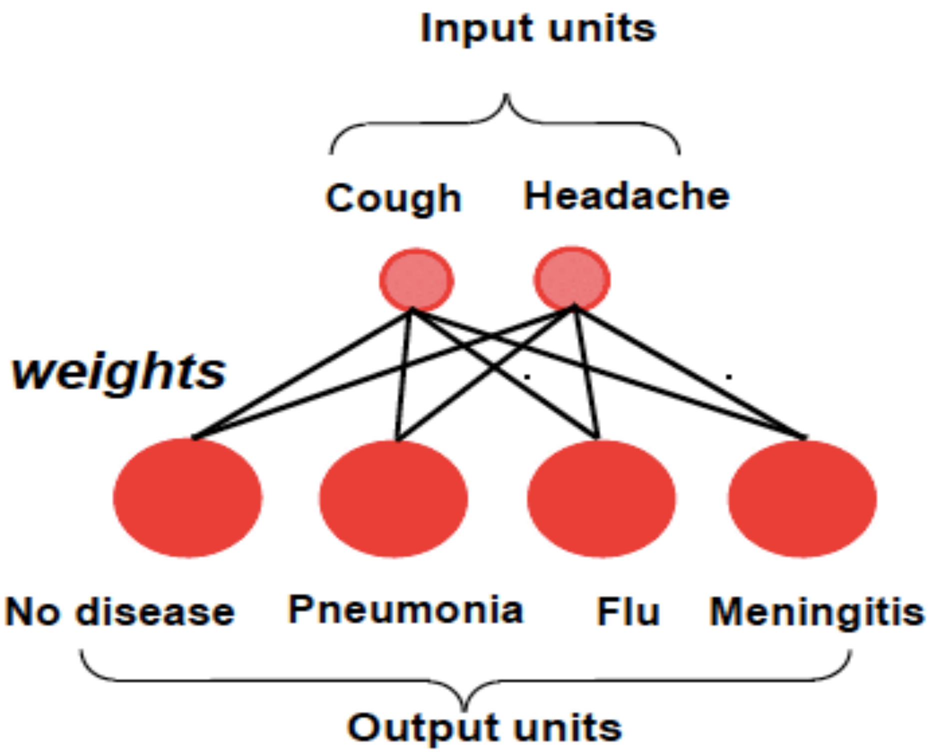

Inputs
Age
34
Gender
1
Stage
4
.6
.2
.1
.3
.7
.2
.5
.8
Σ
Output
0.6
"Probability of beingAlive"
Independent variables
Weights
Hidden Layer
Weights
Dependent variable
Prediction

Not really, no target for hidden units...



Recall perceptrons

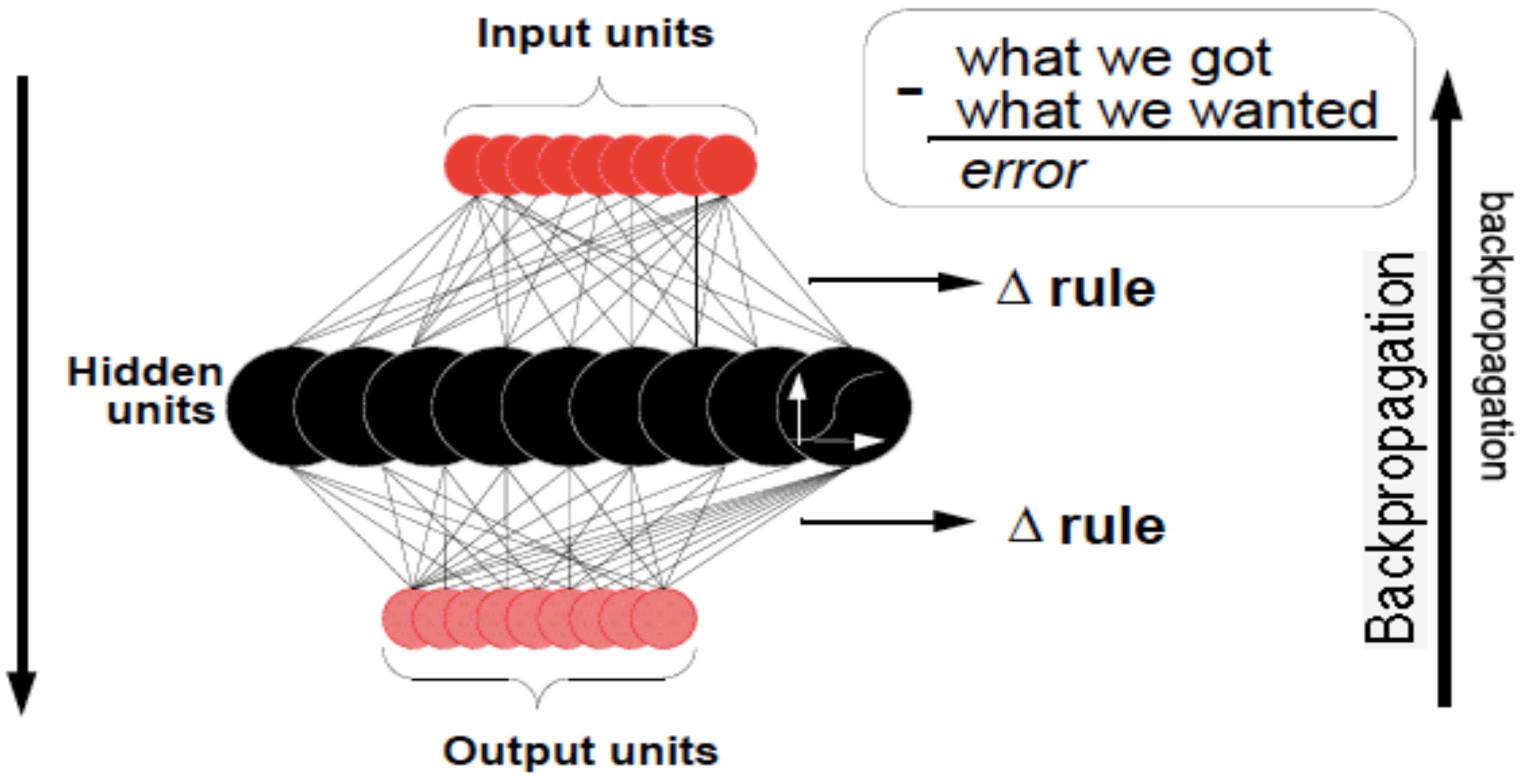
$$\vec{w} \leftarrow \vec{w} + \eta \sum_d (t_d - o_d) o_d (1 - o_d) \vec{x}_d$$



Δ rule
change weights to decrease the error

- what we got
what we wanted
error

Hidden Units and Backpropagation



Backpropagation Algorithm

x_d = input

t_d = target output

o_d =observed unit output

w_i =weight i

Backpropagation Algorithm

x_d = input
t_d = target output
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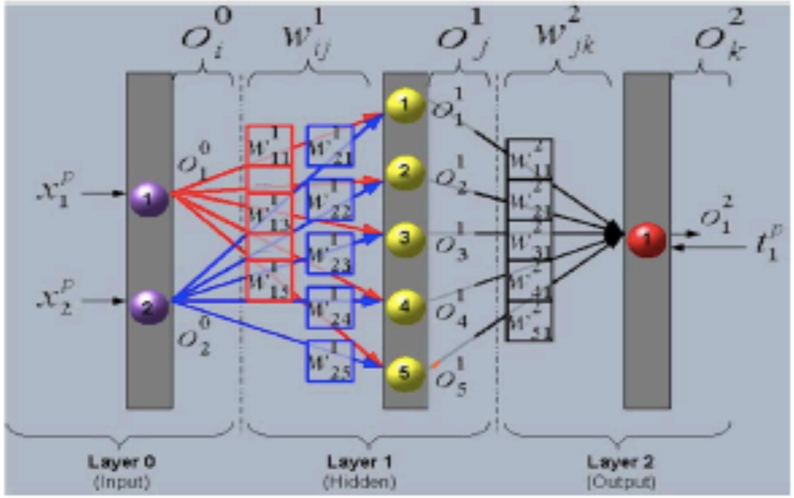
$$\vec{w} \leftarrow \vec{w} + \eta \sum_d (t_d - o_d) o_d (1 - o_d) \vec{x}_d$$

- Initialize all weights to small random numbers
  Until convergence, Do

  1. Input the training example to the network and compute the network outputs



Backpropagation Algorithm

x_d = input
t_d = target output
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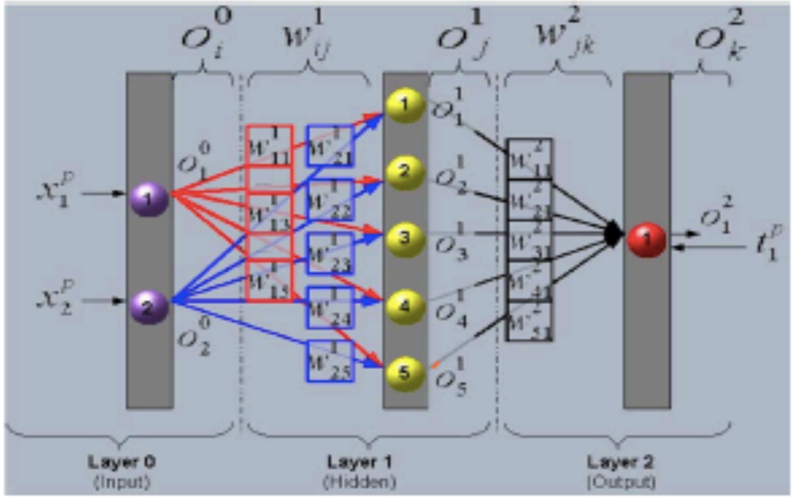
- Initialize all weights to small random numbers
  Until convergence, Do

  1. Input the training example to the network and compute the network outputs

  1. For each output unit k

$$\delta_k \leftarrow o_k^2(1 - o_k^2)(t - o_k^2)$$



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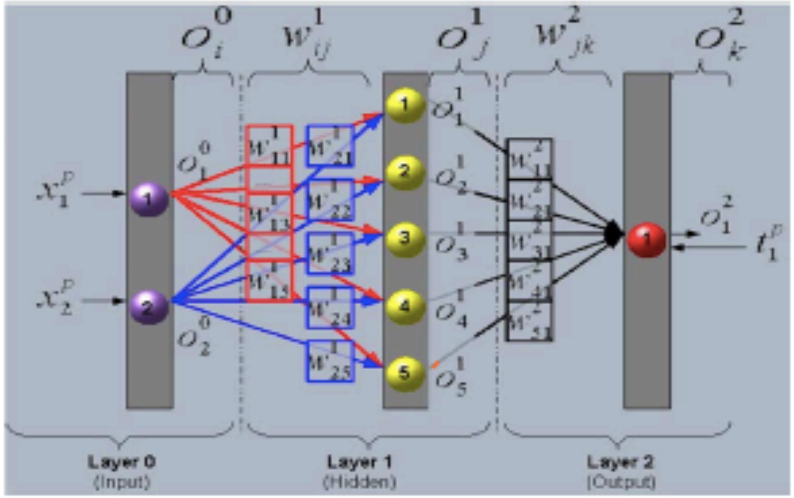


1. For each output unit k

$$\delta_k \leftarrow o_k^2(1 - o_k^2)(t - o_k^2)$$

2. For each hidden unit h

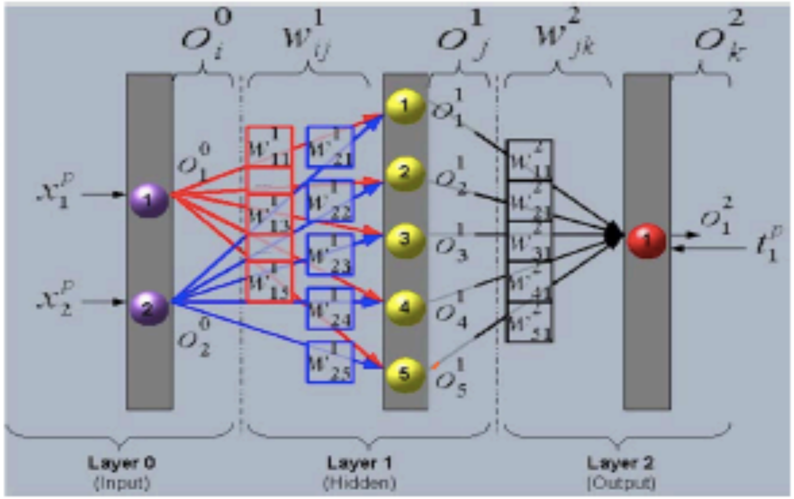
$$\delta_h \leftarrow o_h^1(1 - o_h^1) \sum_{k \in outputs} w_{h,k} \delta_k$$

Backpropagation Algorithm

x_d = input
t_d = target output
o_d =observed unit output
w_i =weight i

$$\vec{w} \leftarrow \vec{w} + \eta \sum_d (t_d - o_d) o_d (1 - o_d) \vec{x}_d$$

- Initialize all weights to small random numbers
  Until convergence, Do



1. Input the training example to the network and compute the network outputs

1. For each output unit k

$$\delta_k \leftarrow o_k^2(1 - o_k^2)(t - o_k^2)$$

2. For each hidden unit h

$$\delta_h \leftarrow o_h^1(1 - o_h^1) \sum_{k \in outputs} w_{h,k} \delta_k$$

3. Undate each network weight w_{ij}

$$w_{i,j} \leftarrow w_{i,j} + \Delta w_{i,j} \text{ where } \Delta w_{i,j} = \eta \delta_j x^j$$

More on Backpropatation

- It is doing gradient descent over entire network weight vector
- Easily generalized to arbitrary directed graphs
- Will find a local, not necessarily global error minimum
    - In practice, often works well (can run multiple times)

More on Backpropatation

- It is doing gradient descent over entire network weight vector
- Easily generalized to arbitrary directed graphs
- Will find a local, not necessarily global error minimum
  - In practice, often works well (can run multiple times)
- Often include weight *momentum* α

$$\Delta w_{i,j}(t) = \eta \delta_j x_{i,j} + \alpha \Delta w_{i,j}(t-1)$$

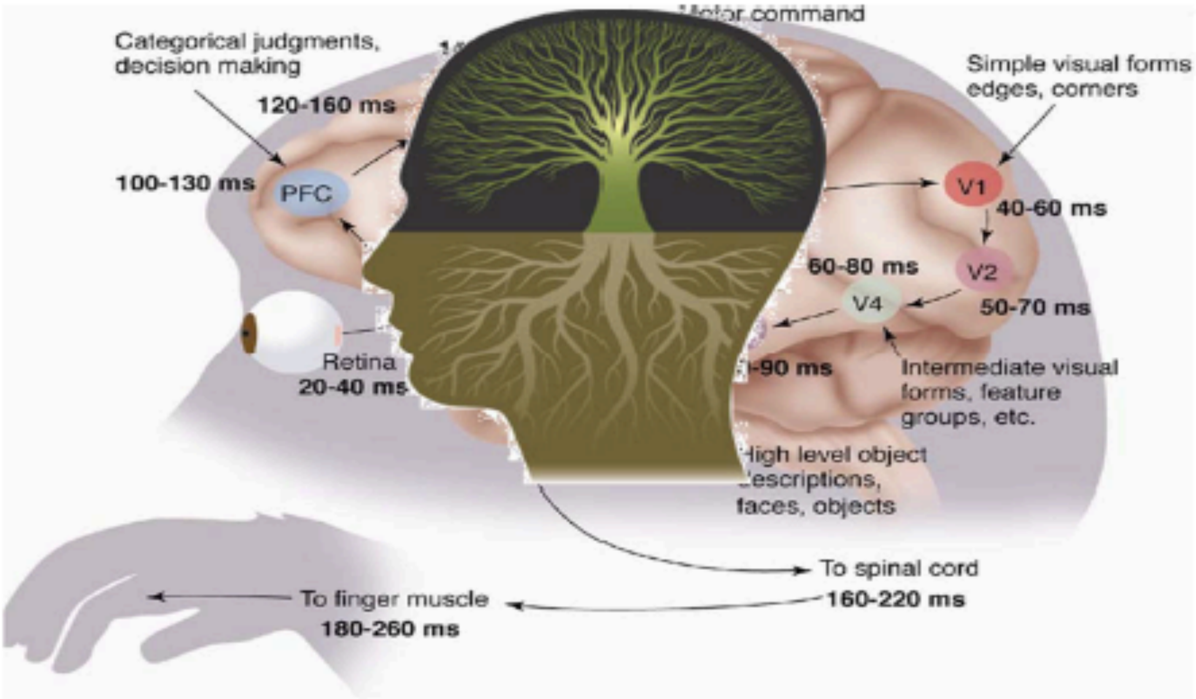
- Minimizes error over *training* examples
  - Will it generalize well to subsequent testing examples?
- Training can take thousands of iterations, → very slow!
- Using network after training is very fast

Artificial neural networks – what you should know

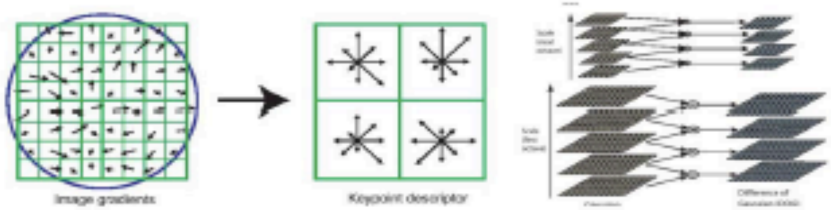
- Highly expressive non-linear functions
- Highly parallel network of logistic function units
- Minimizing sum of squared training errors
  - Gives MLE estimates of network weights if we assume zero mean Gaussian noise on output values
- Minimizing sum of sq errors plus weight squared (regularization)
  - MAP estimates assuming weight priors are zero mean Gaussian
- Gradient descent as training procedure
  - How to derive your own gradient descent procedure
- Discover useful representations at hidden units
- Local minima is greatest problem
- Overfitting, regularization, early stopping

Five mins break!

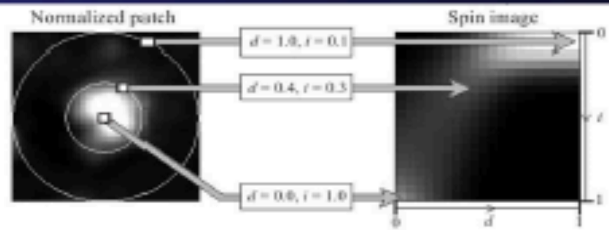
Modern ANN topics: "Deep" Learning



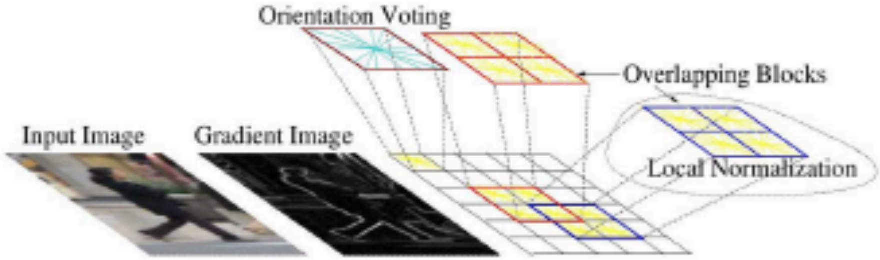
Computer vision features

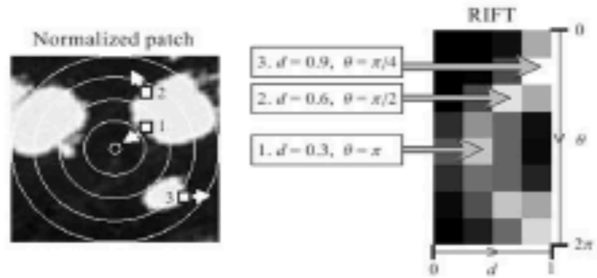


SIFT



Spin image





Drawbacks of feature engineering

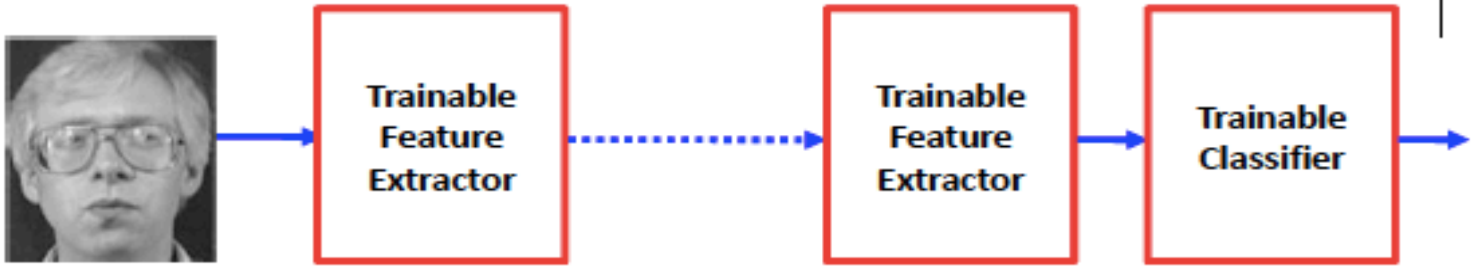
1. Needs expert knowledge
2. Time consuming hand-tuning

Textons

GLOH

... and Ng

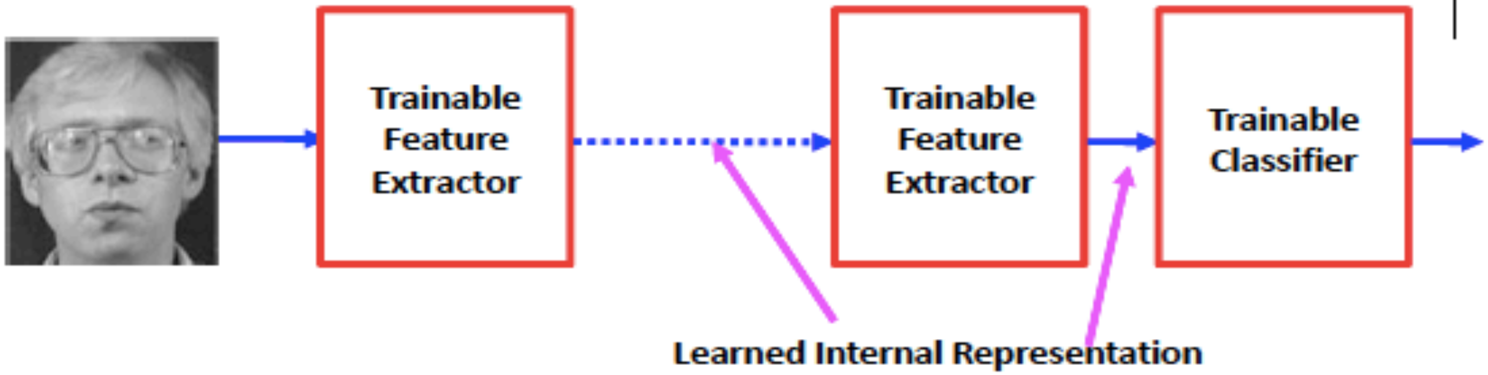
Using ANN to hierarchical representation



Good Representations are hierarchical

- In Language: hierarchy in syntax and semantics
  - Words->Parts of Speech->Sentences->Text
  - Objects,Actions,Attributes...-> Phrases -> Statements -> Stories
- In Vision: part-whole hierarchy
  - Pixels->Edges->Textons->Parts->Objects->Scenes

"Deep" learning: learning hierarchical representations



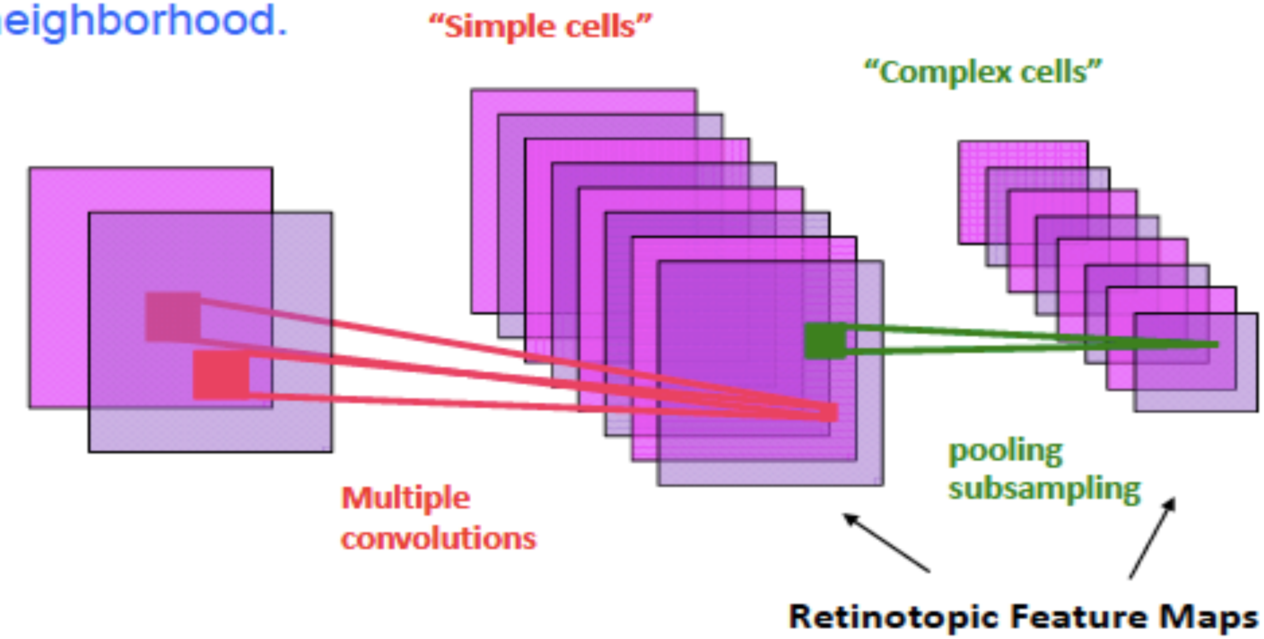
- Deep Learning: learning a hierarchy of internal representations
- From low-level features to mid-level invariant representations, to object identities
- Representations are increasingly invariant as we go up the layers
- using multiple stages gets around the specificity/invariance dilemma

"Deep" models

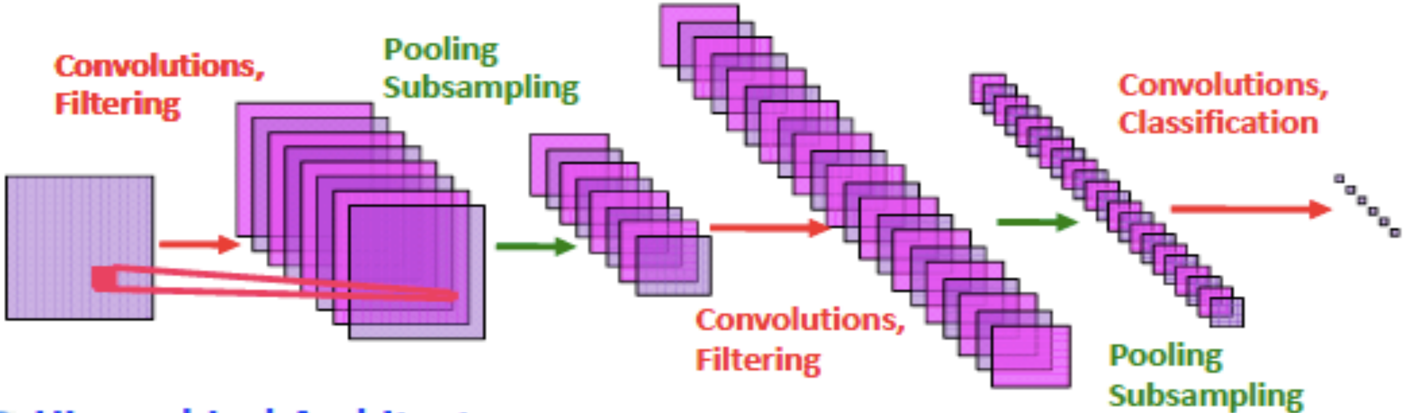
- Neural Networks: Feed-forward*
  - You have seen it
- Autoencoders (multilayer neural net with target output = input)
  - Probabilistic -- Directed: PCA, Sparse Coding
  - Probabilistic -- Undirected: MRFs and RBMs*
- Recursive Neural Networks*
- Convolutional Neural Nets

Filtering + NonLinearity + Pooling = 1 stage of a Convolutional Net

- [Hubel & Wiesel 1962]:
  - simple cells detect local features
  - complex cells "pool" the outputs of simple cells within a retinotopic neighborhood.

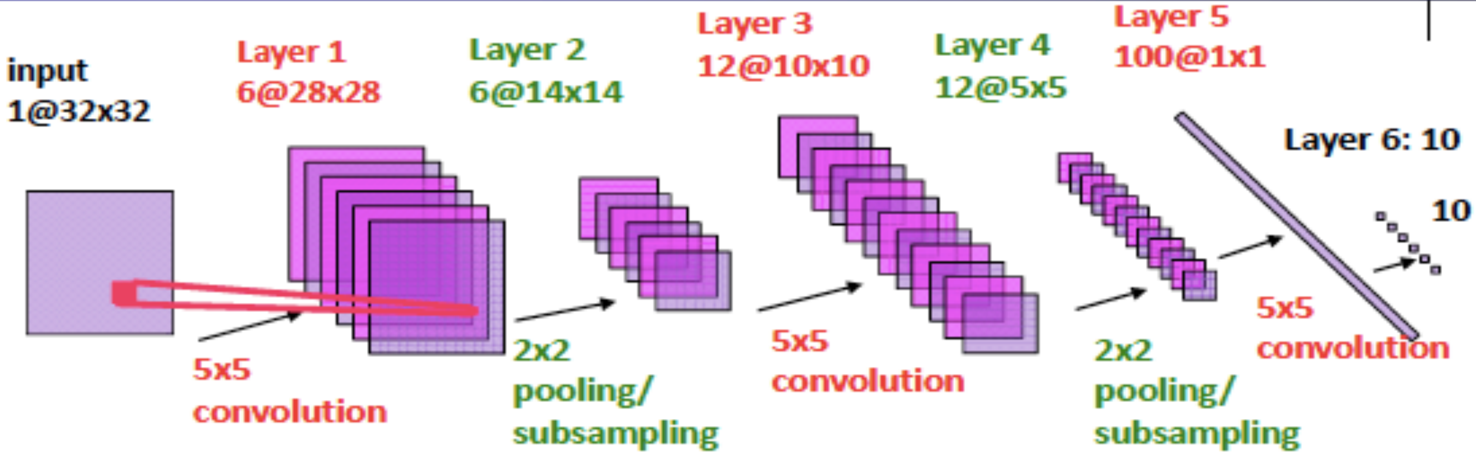


Convolutional Network: Multi-Stage Trainable Architecture



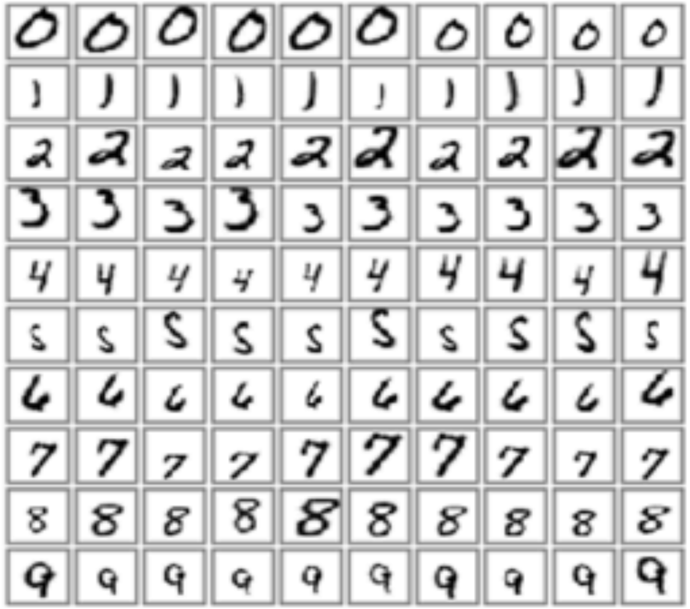
- **Hierarchical Architecture**
  - Representations are more global, more invariant, and more abstract as we go up the layers
- **Alternated Layers of Filtering and Spatial Pooling**
  - Filtering detects conjunctions of features
  - Pooling computes local disjunctions of features
- **Fully Trainable**
  - All the layers are trainable

Convolutional Net Architecture for Hand-writing recognition



- Convolutional net for handwriting recognition (400,000 synapses)
  - Convolutional layers (simple cells): all units in a feature plane share the same weights
  - Pooling/subsampling layers (complex cells): for invariance to small distortions.
  - Supervised gradient-descent learning using back-propagation
  - The entire network is trained end-to-end. All the layers are trained simultaneously.
  - [LeCun et al. Proc IEEE, 1998]

Application:
MNIST Handwritten Digit Dataset



Handwritten Digit Dataset MNIST: 60,000 training samples, 10,000 test samples

Results on MNIST Handwritten Digits

CLASSIFIER	DEFORMATION	PREPROCESSING	ERROR (%)	Reference
linear classifier (1-layer NN)		none	12.00	LeCun et al. 1998
linear classifier (1-layer NN)		deskewing	8.40	LeCun et al. 1998
pairwise linear classifier		deskewing	7.60	LeCun et al. 1998
K-nearest-neighbors, (L2)		none	3.09	Kenneth Wilder, U. Chicago
K-nearest-neighbors, (L2)		deskewing	2.40	LeCun et al. 1998
K-nearest-neighbors, (L2)		deskew, clean, blur	1.80	Kenneth Wilder, U. Chicago
K-NN L3, 2 pixel jitter		deskew, clean, blur	1.22	Kenneth Wilder, U. Chicago
K-NN, shape context matching		shape context feature	0.63	Belongie et al. IEEE PAMI 2002
40 PCA + quadratic classifier		none	3.30	LeCun et al. 1998
1000 RBF + linear classifier		none	3.60	LeCun et al. 1998
K-NN, Tangent Distance		subsamp 16x16 pixels	1.10	LeCun et al. 1998
SVM, Gaussian Kernel		none	1.40	
SVM deg 4 polynomial		deskewing	1.10	LeCun et al. 1998
Reduced Set SVM deg 5 poly		deskewing	1.00	LeCun et al. 1998
Virtual SVM deg-9 poly	Affine	none	0.80	LeCun et al. 1998
V-SVM, 2-pixel jittered		none	0.68	DeCoste and Scholkopf, MLJ2002
V-SVM, 2-pixel jittered		deskewing	0.56	DeCoste and Scholkopf, MLJ2002
2-layer NN, 300 HU, MSE		none	4.70	LeCun et al. 1998
2-layer NN, 300 HU, MSE,	Affine	none	3.60	LeCun et al. 1998
2-layer NN, 300 HU		deskewing	1.60	LeCun et al. 1998
3-layer NN, 500+ 150 HU		none	2.95	LeCun et al. 1998
3-layer NN, 500+ 150 HU	Affine	none	2.45	LeCun et al. 1998
3-layer NN, 500+ 300 HU, CE, reg		none	1.53	Hinton, unpublished, 2005
2-layer NN, 800 HU, CE		none	1.60	Simard et al., ICDAR 2003
2-layer NN, 800 HU, CE	Affine	none	1.10	Simard et al., ICDAR 2003
2-layer NN, 800 HU, MSE	Elastic	none	0.90	Simard et al., ICDAR 2003
2-layer NN, 800 HU, CE	Elastic	none	0.70	Simard et al., ICDAR 2003
Convolutional net LeNet-1		subsamp 16x16 pixels	1.70	LeCun et al. 1998
Convolutional net LeNet-4		none	1.10	LeCun et al. 1998
Convolutional net LeNet-5,		none	0.95	LeCun et al. 1998
Conv. net LeNet-5,	Affine	none	0.80	LeCun et al. 1998
Boosted LeNet-4	Affine	none	0.70	LeCun et al. 1998
Conv. net, CE	Affine	none	0.60	Simard et al., ICDAR 2003
Comv net, CE	Elastic	none	0.40	Simard et al., ICDAR 2003

Weaknesses & Criticisms

- Learning everything. Better to encode prior knowledge about structure of images.
- Not clear if an explicit global objective is indeed optimized, making theoretical analysis difficult
  - Many (arbitrary) approximations are introduced
  - Many different loss functions, gate functions, transformation functions are used
  - Many different implementation exist
- Comparison is based on the end empirical results on downstream task, not the actual direct task DNN is designed to compute, make verification and tuning of components of DNN very hard.

That’s all!