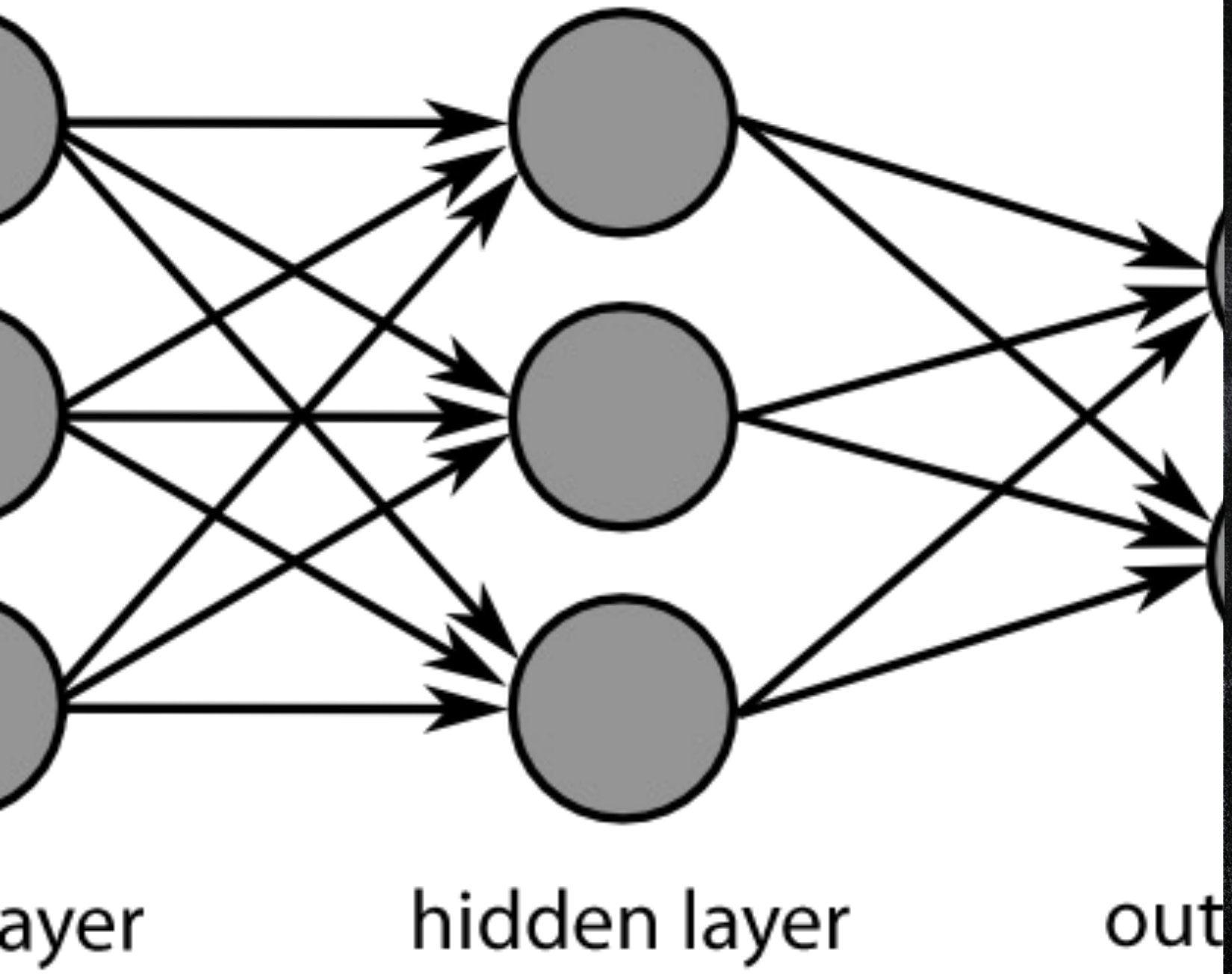
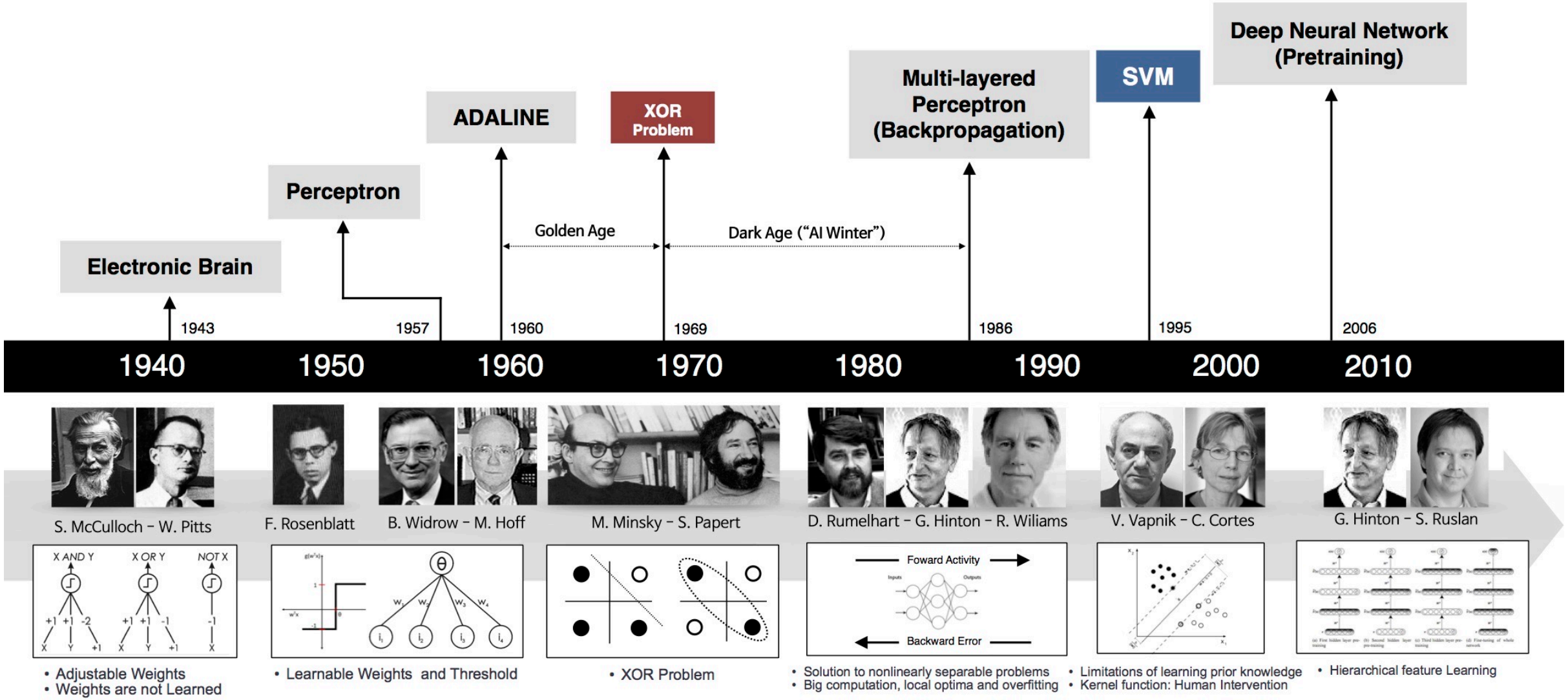


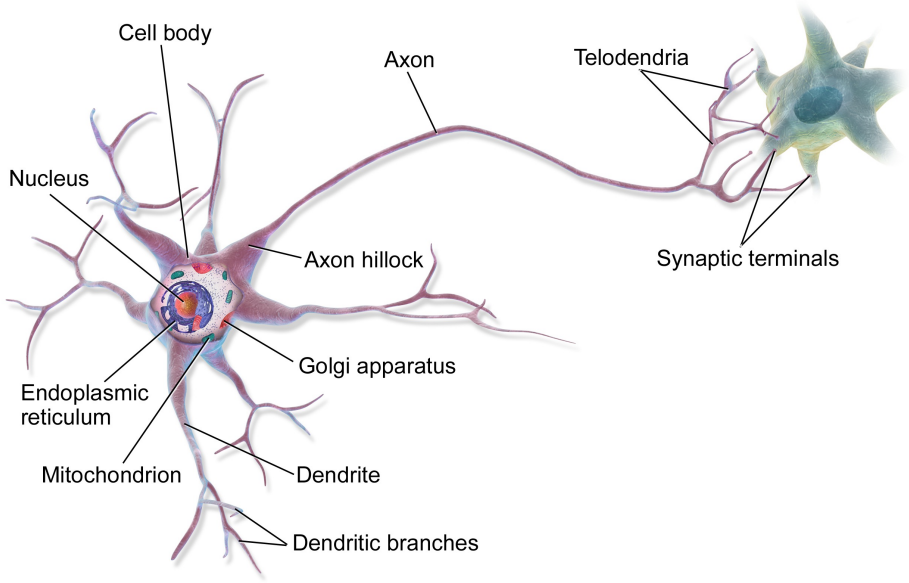
Redes Neuronales

TC3006C


Deep Neural Network (Pretraining)
SVM
Multi-layered Perceptron (Backpropagation)
XOR Problem
ADALINE
Perceptron
Electronic Brain
Golden Age
Dark Age ("AI Winter")
1943
1957
1960
1969
1986
1995
2006
1940
1950
1960
1970
1980
1990
2000
2010
S. McCulloch - W. Pitts
F. Rosenblatt
B. Widrow - M. Hoff
M. Minsky - S. Papert
D. Rumelhart - G. Hinton - R. Wiliams
V. Vapnik - C. Cortes
G. Hinton - S. Ruslan
X AND Y
X OR Y
NOT X
Foward Activity
Backward Error
• Adjustable Weights
• Weights are not Learned
• Learnable Weights and Threshold
• XOR Problem
• Solution to nonlinearly separable problems
• Big computation, local optima and overfitting
• Limitations of learning prior knowledge
• Kernel function: Human Intervention
• Hierarchical feature Learning

Introduction

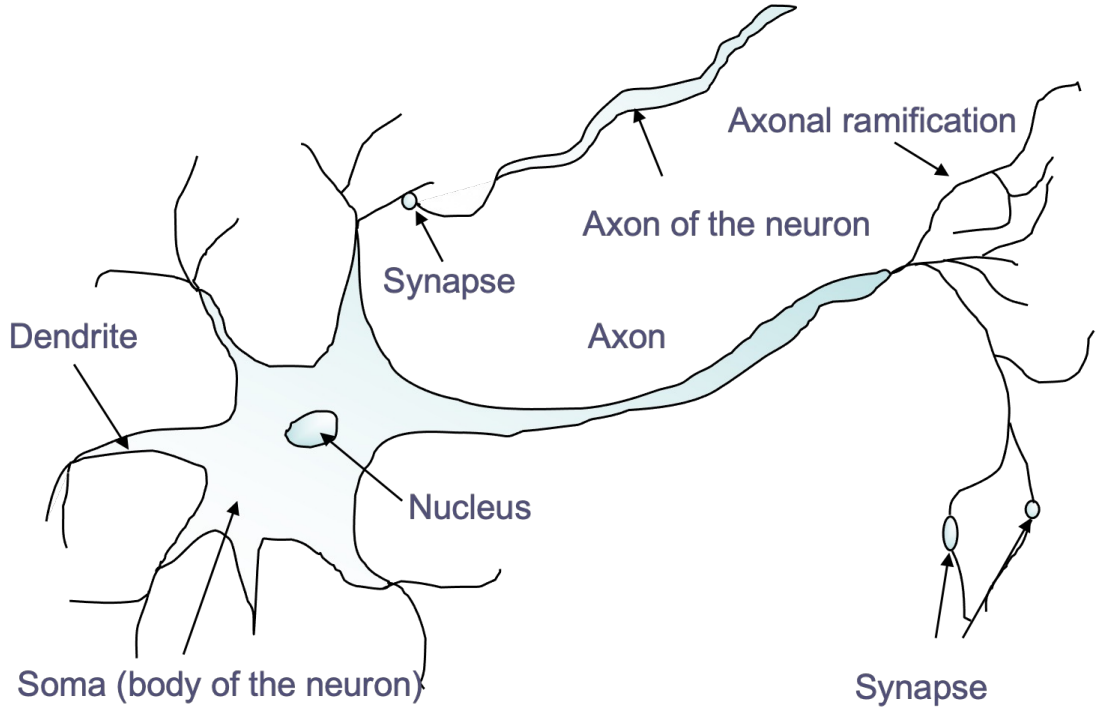
- General, robust, and practical method for learning
  - Real values
  - Discrete values
  - Vector values



- Inspired by biological learning systems
  - Very complex webs of interconnected neurons.
  - Human brain
    - Network 10^{11} neurons
    - Each connected on average to 10^{4} neurons.
    - Neuron switching times 10^{-3} seconds (very slow compared to computers)
    - 10^{-1} second to recognize a familiar face (very fast compared to computers)
      - Sequence of neuron firings cannot be more than a few hundreds due to switching speed.

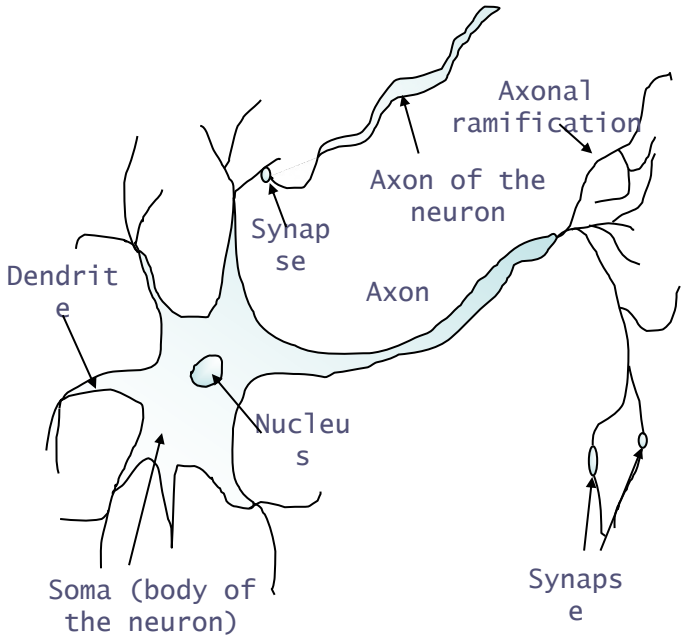
Electrochemical processing

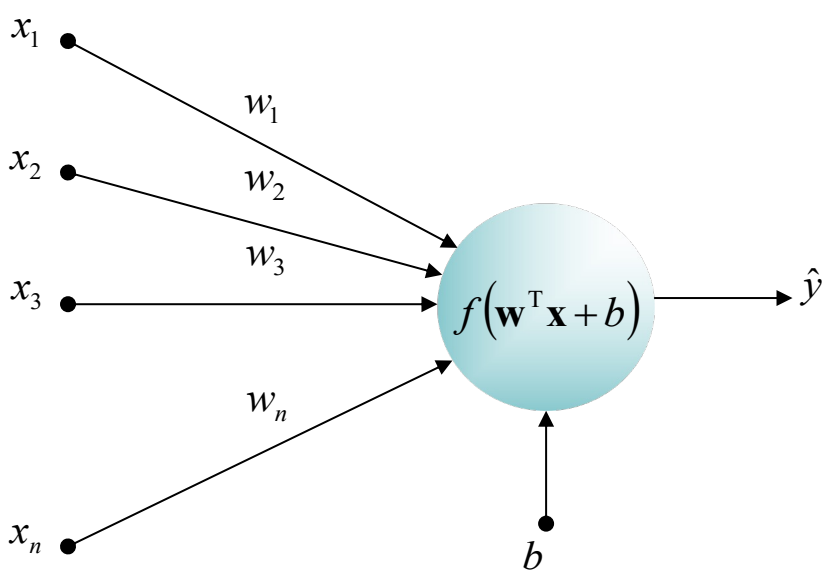
- Electrochemical process 70-100mV, more negative inside the cell.
- Connections generate a difference in electrical potential. This difference jumpstarts the neuron.
- It is really hard to make a computer program based on the functioning of biological neuronal networks. Actually, its functioning is not completely known.
- Sebastian Seung: I am my connectome (http://www.youtube.com/watch?v=HA7GwKXfJB0&feature=colike)
- Brain wiring a no-brainer? Scans reveal astonishingly simple 3D grid structure
  - http://medicalxpress.com/news/2012-03-brain-wiring-no-brainer-scans-reveal.html
  - Video: http://www.youtube.com/watch?v=_oTEhFAAARE



Formal (artificial) neuron

- Parallel signals arrive
- Dendrites are weights: *w*
- Synapses: Pondered sum
- threshold: activating function





Entry | Weights | Sum and Activating function | Exit

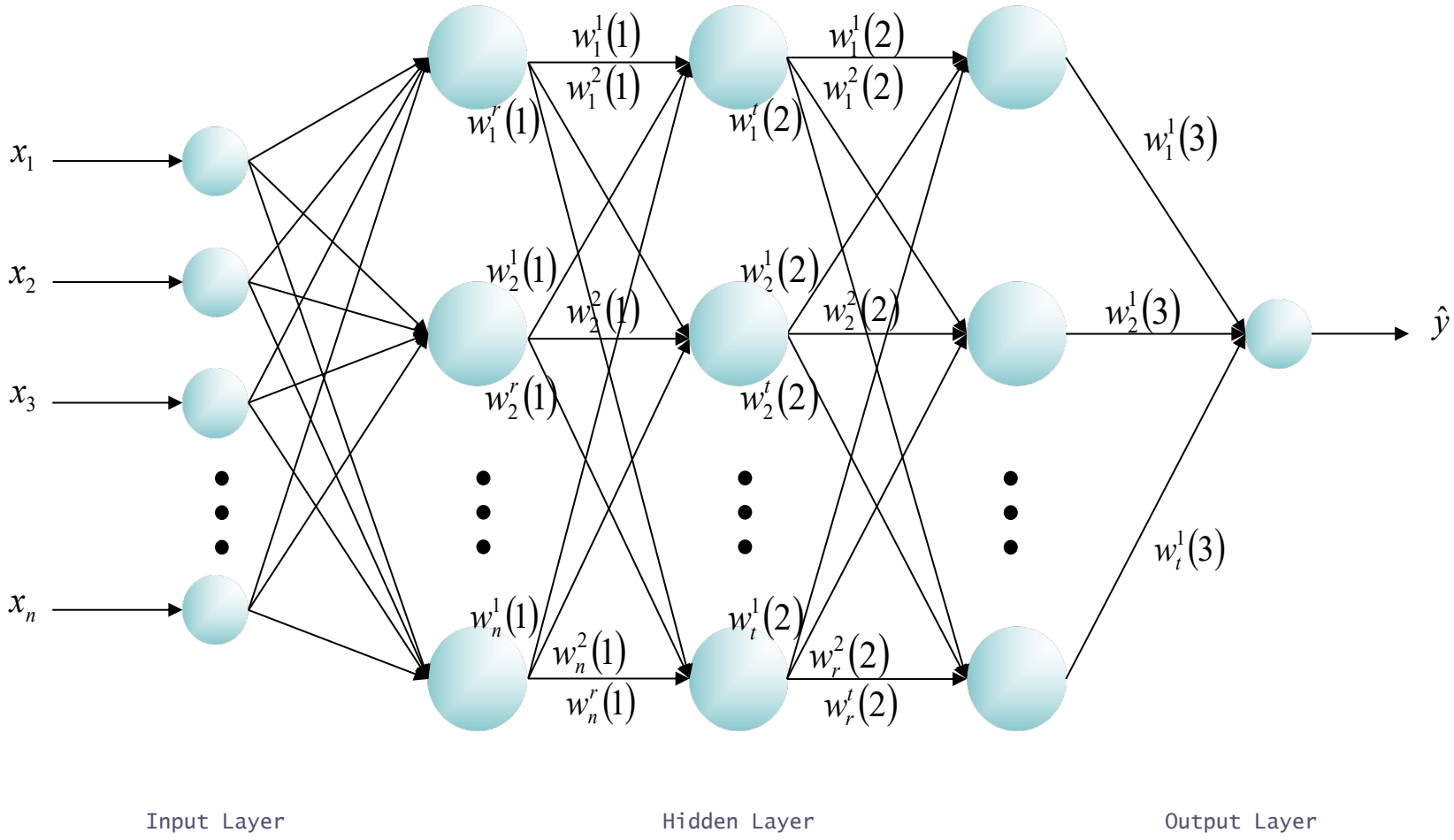
Dendrites | **Sinapsis threshold** | **Axon**

Neurocomputing: Studies neurocomputing in RNA

1943

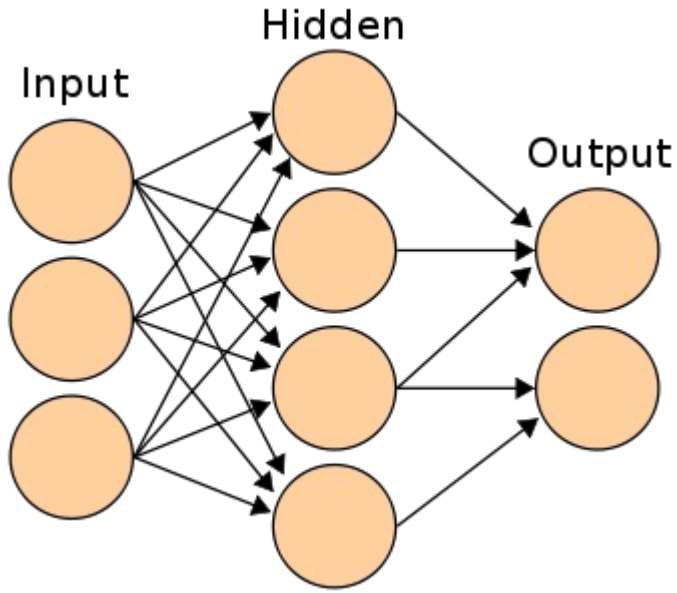
Elements of a Neuronal Network

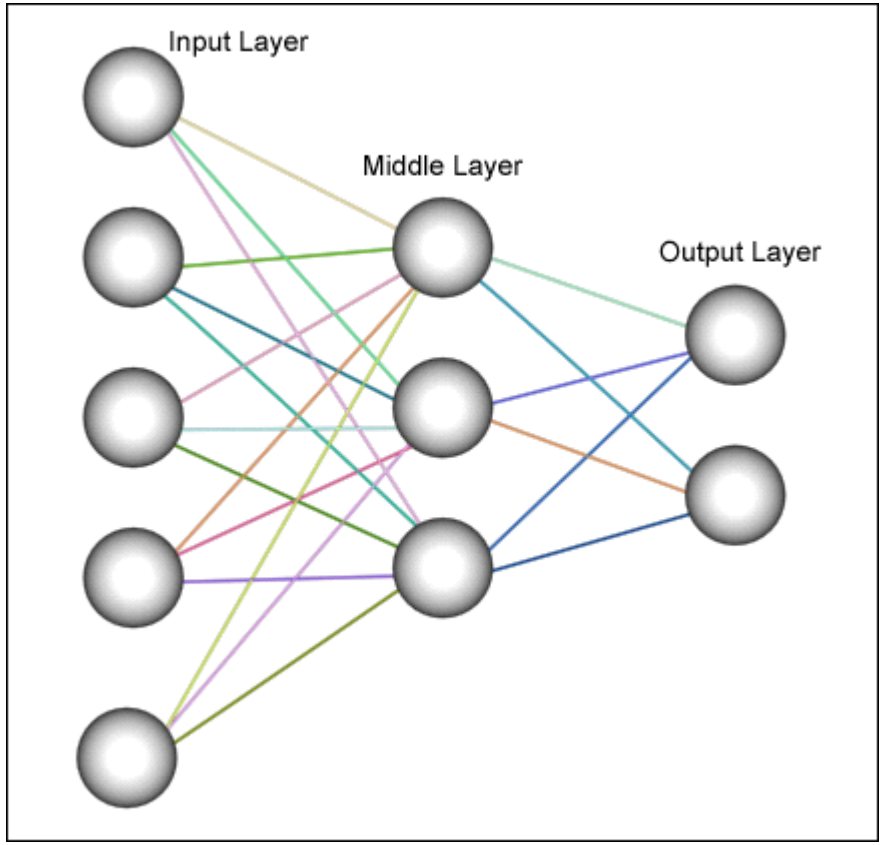
- Network architecture
- Processing units
  - Activation State
  - Activating Function
- Learning Algorithm
- Patterns or Individuals
- Generalization



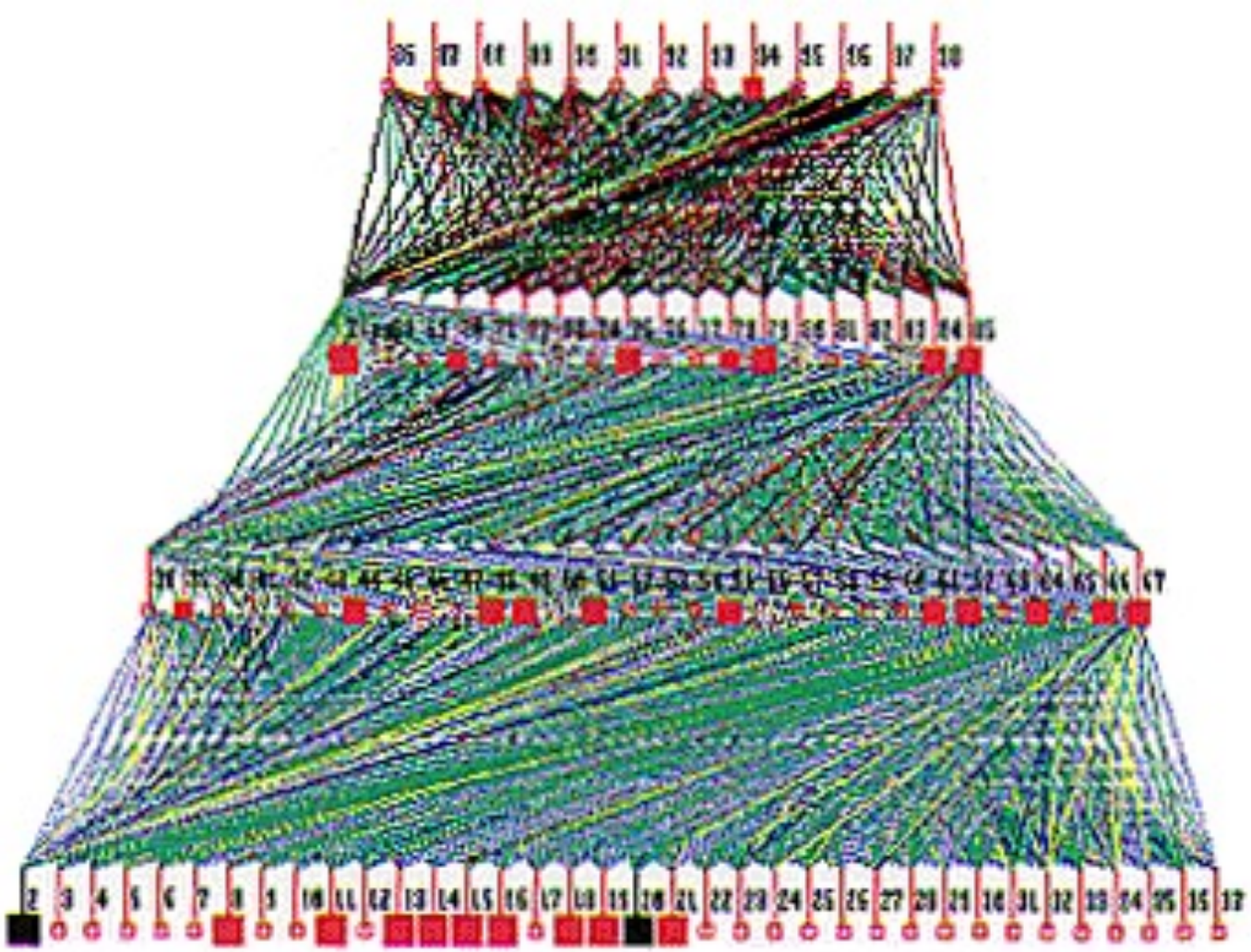
Examples of neuronal networks

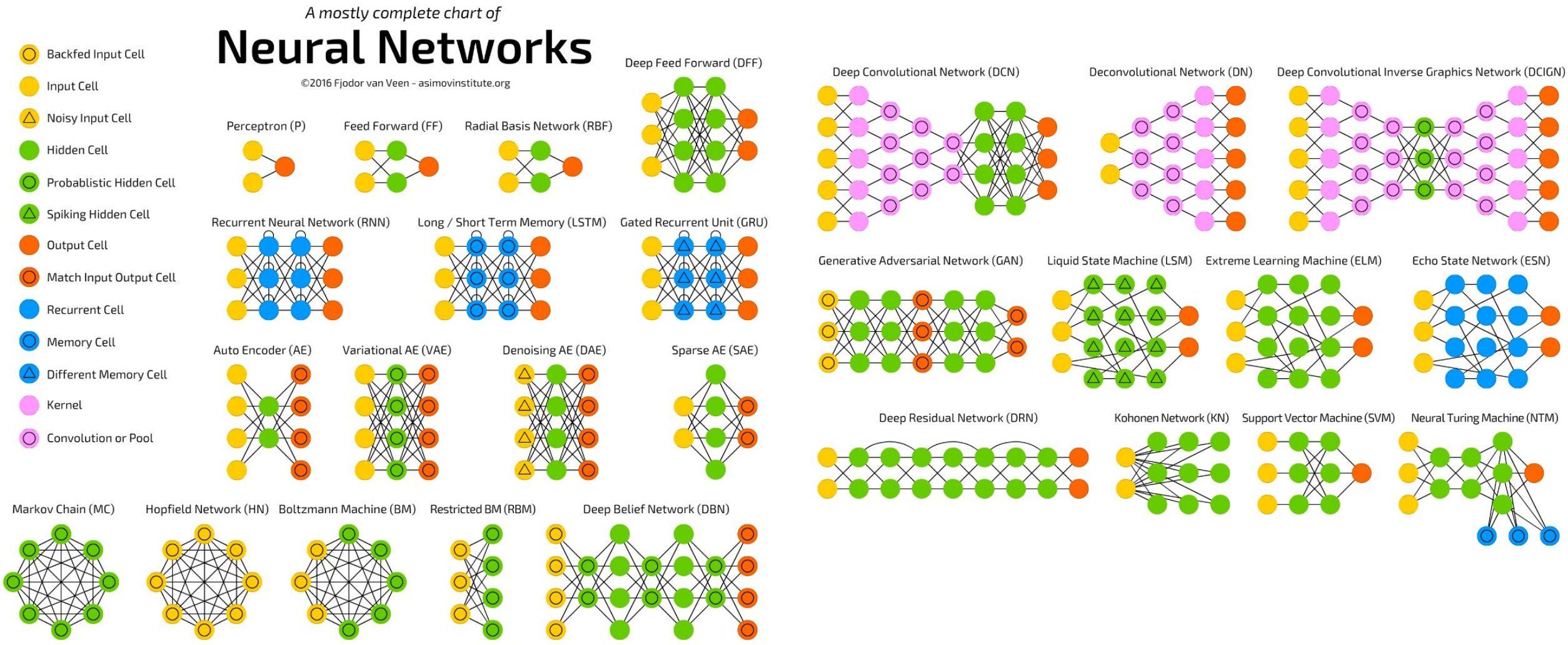
Architectures





Example of a neuronal network for missiles





http://www.asimovinstitute.org/neural-network-zoo/

Training or learning

- Training phase is the interactive **actualization of the weights** in each processing unit.
- Traditional optimization methods: Newton, Square Minimal, Gradient Descents,...
- To each interaction, a learning pattern is presented in the network.
- Each cell calculates its exit and the weights are modified.

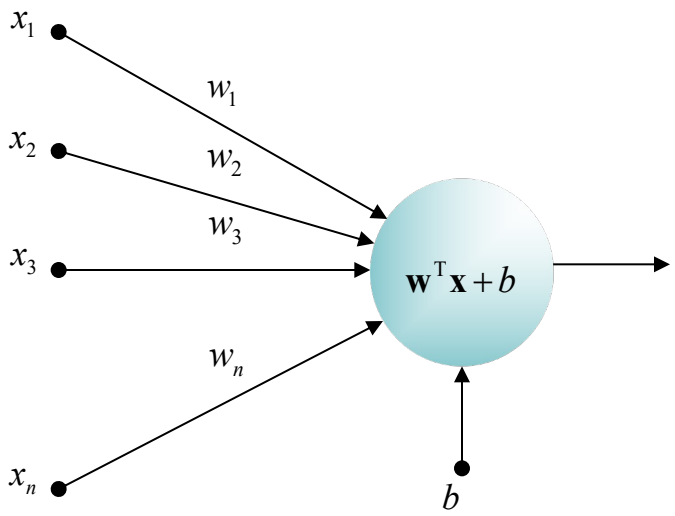
Appropriate problems for ANN learning

- Artificial neural networks are suitable for noisy and complex sensor data.

- Characteristics:
  - Instances are represented by many attribute-value pairs.
  - Target function output may be discrete-valued, real-valued, or vector of several real or discrete valued attributes.
  - Training examples may contain errors.
  - Long training times are acceptable.
  - Fast evaluation of learned target function may be required.
  - Ability of humans to understand learned target function is not important.

Linear Separation

- Formula given decision border



$$\sum w_i x_i + b = 0$$

- "*If all patterns are well classified, with an hyperplane, we say it is a linearly separable problem*". Minsky y Papert [1988]

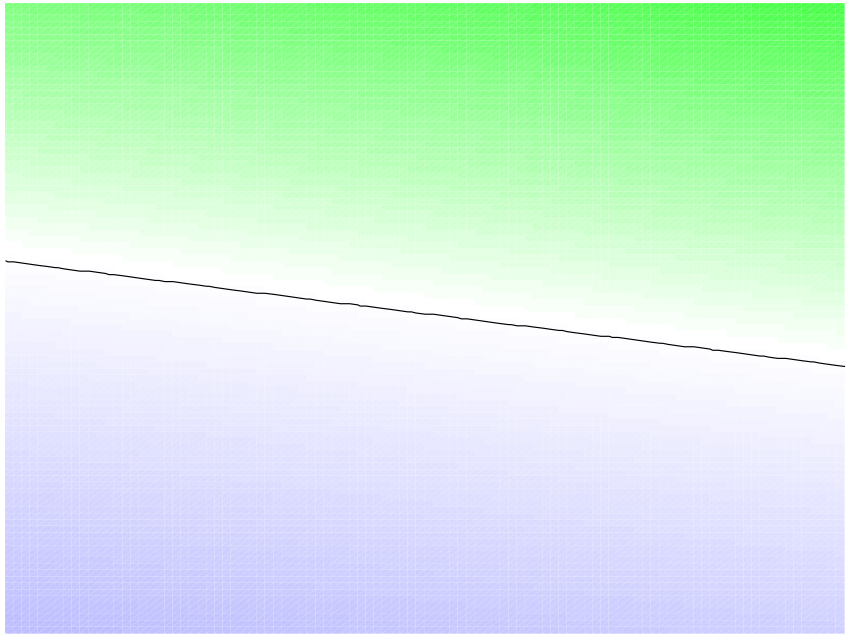
- **One neuron can only separate LS problems**

Linear Separation

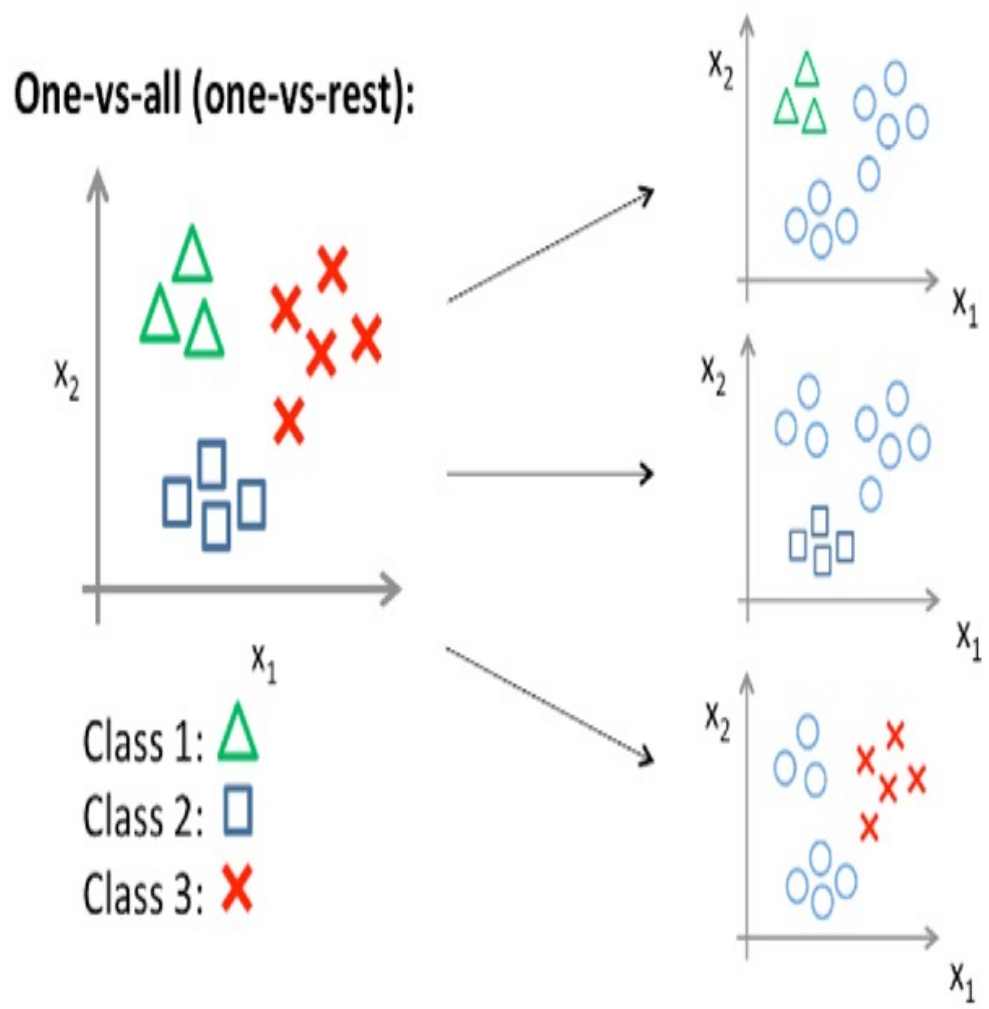
- The regions that are separated, are called separation regions (or decision regions).
- Only one neuron for classification, we can only make linearly separable regions.

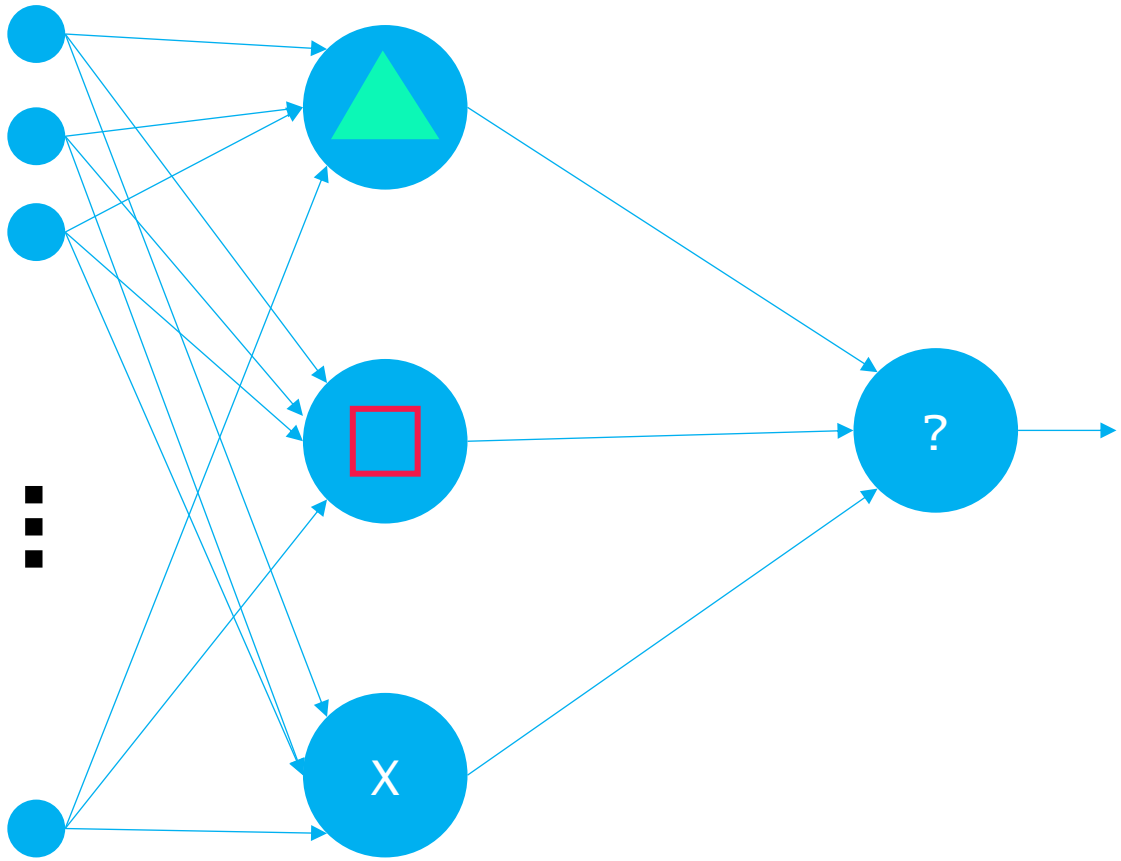
$$x_1 w_1 + x_2 w_2 + b = 0$$

$$x_2 = -\frac{w_1}{w_2} x_1 - \frac{b}{w_2}, w_2 \neq 0.$$



Multi-class classification





McCulloch - Pitts Model

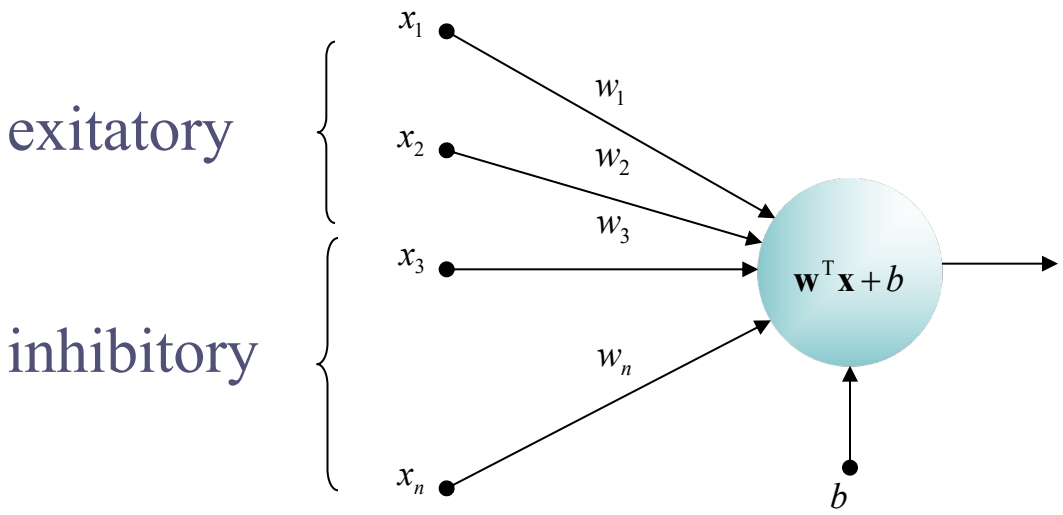
Artificial Neural Networks

2022FJ juresti@tec.mx

McCulloch – Pitts, NMcCP Characteristics.

- 1943
- Binary Activation.
- Neurons connected through weights.
- Connection is excitatory, positive weight
- Connection is inhibitory, negative weight
- Neuron turns on if pondered sum is higher than the threshold.

McCulloch – Pitts, NMcCP Characteristics.



$$a = \sum w_i x_i + \sum w_i x_i - b$$

$$f(a) = \begin{cases} 1 \ldots if \ldots a \geq 0 \\ 0 \ldots if \ldots a < 0 \end{cases}$$

McCulloch – Pitts, Algorithm

- There is not a learning algorithm, properly said.
- Weights (*w*) and threshold (*b*) are set at the same time.
- Parameterization through visual analysis.
- Executes logical functions.

McCulloch – Pitts, AND Example

X1	X2	w	AND
0	0	I	0
0	I	I	0
I	0	I	0
I	I	I	I

$$\sum w_i x_i - b \geq 0 \qquad 1$$

$$\sum w_i x_i - b < 0 \qquad 0$$

- Objective: find w_1, w_2 and b in order for the function to ensure compliance

$$w_1=1,\ w_2=1,\ b=2$$

McCulloch – Pitts, OR Example

X1	X2	w	OR
0	0	I	0
0	I	I	I
I	0	I	I
I	I	I	I

$$\sum w_i x_i - b \geq 0 \qquad 1$$

$$\sum w_i x_i - b < 0 \qquad 0$$

Objetive: find w_1, w_2 and b in order for the function to ensure compliance

$$w_1=1,\ w_2=1,\ b=1$$

McCulloch – Pitts, XOR Example

X1	X2	I	XOR
0	0	I	0
0	I	I	I
I	0	I	I
I	I	I	0

$$\sum w_i x_i - b \geq 0 \qquad 1$$

$$\sum w_i x_i - b < 0 \qquad 0$$

Objetive: find w_1, w_2 and b in order for the function to ensure compliance

McCulloch-Pitts Applications

- Once we know how to decompose a logic function in the *sum of products* or *products of* sums, it is possible to implement any type of function as a 3-layer neuronal network.

$$f = \overline{x_1} x_2 x_3 + x_1 x_2 \overline{x_3}, \ldots$$

- Advantages: speed
- Distributed calculus

Hebb Learning

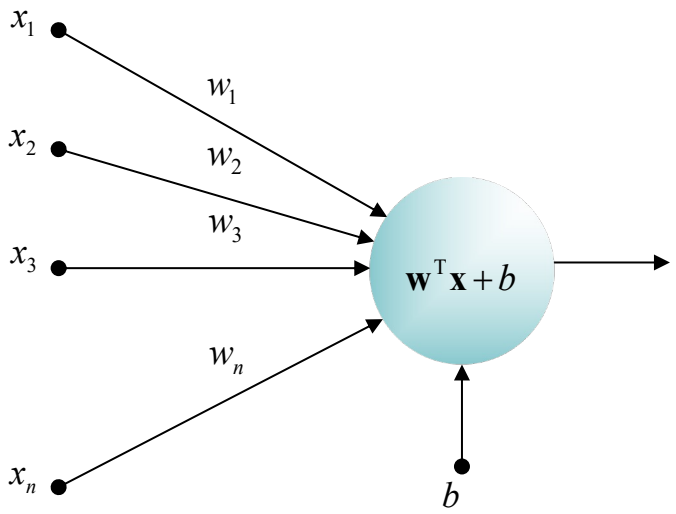
Artificial Neural Networks

2022FJ juresti@tec.mx

Hebb Learning, Characteristics

- First known learning algorithm (1949)
- Learning, modification Δw of the weights
  - Modification if two neurons are interconnected and on at the same time
  - Algorithm says nothing about neurons turned off.
- Hebb modified, more robust if they are taken on or off.
- Used for other types of learning algorithms.
- Bipolar inputs and outputs.
  - Inputs and outputs in: 1, -1.

Hebb Learning, Learning Algorithm



$$\sum w_i x_i - b = 0$$

$$w_i(new) = w_i(old) + \Delta w_i$$

$$\Delta w_i = x_i y_i$$

- Initialization, $w_i = 0$, $i = 0,\ldots,n$
- For every l elements of the database.

$$w_i(new) = w_i(old) + \Delta w_i$$

$$\Delta w_i = x_i y_i$$

$$\sum w_i x_i + b \geq 0 \qquad 1$$

$$\sum w_i x_i + b < 0 \qquad 0$$

Hebb Learning, Examples of Learning AND 1, -1

			Δb			b		
x1	x2	y	Δw0	Δw1	Δw2	w0	w1	w2
						0	0	0
-1	-1	-1	-1	1	1	-1	1	1
-1	1	-1	-1	1	-1	-2	2	0
1	-1	-1	-1	-1	1	-3	1	1
1	1	1	1	1	1	-2	2	2

Hebb Learning, Examples of Learning AND 1, -1

$$2x_1 + 2x_2 - 2 = 0$$

All the elements suffer modifications,

Hebb Learning, Examples of Learning, OR 1,-1

			Δb			b		
x1	x2	y	Δw0	Δw1	Δw2	w0	w1	w2
						0	0	0
-1	-1	-1	-1	1	1	-1	1	1
-1	1	1	1	-1	1	0	0	2
1	-1	1	1	1	-1	1	1	1
1	1	1	1	1	1	2	2	2

Hebb Learning, Examples of Learning, AND, output -1

			Δb			b		
x1	x2	y	Δw0	Δw1	Δw2	w0	w1	w2
						0	0	0
0	0	-1	-1	0	0	0	0	-1
0	1	-1	-1	0	-1	0	-1	-2
1	0	-1	-1	-1	0	-1	-1	-3
1	1	1	1	1	1	0	0	-2

Classical error: mixing 0, -1 y 1

Hebb Learning, Examples of Learning AND Output -1

$$-2x_2 = 0$$

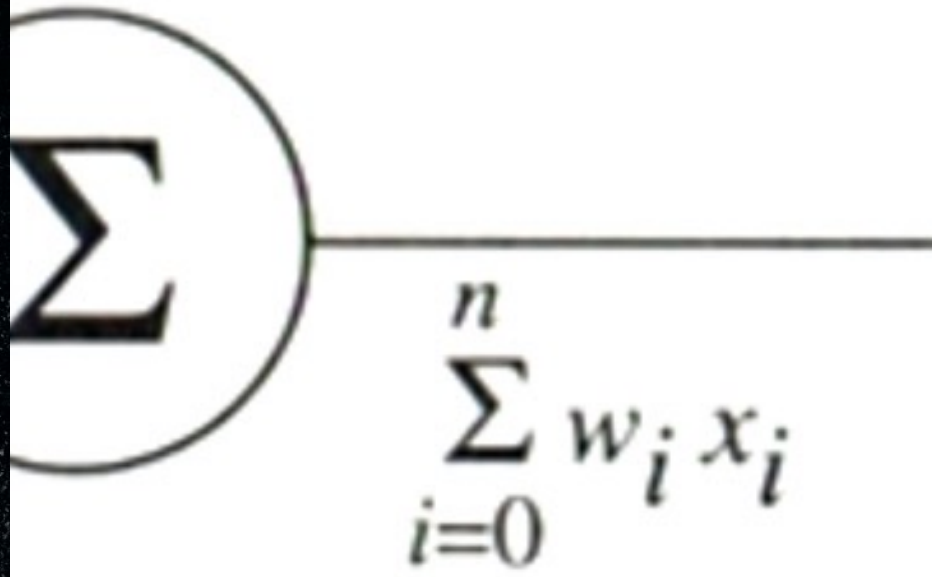
Inputs and error modification play a very important role.

Hebb Learning

- First learning algorithm that follows a defined pattern
- Quite sensitive to the types of inputs and outputs: binary or bipolar.
- The algorithm does not consider non-linearly separable problems.
- Relatively easy problems

Perceptron

Redes Neuronales

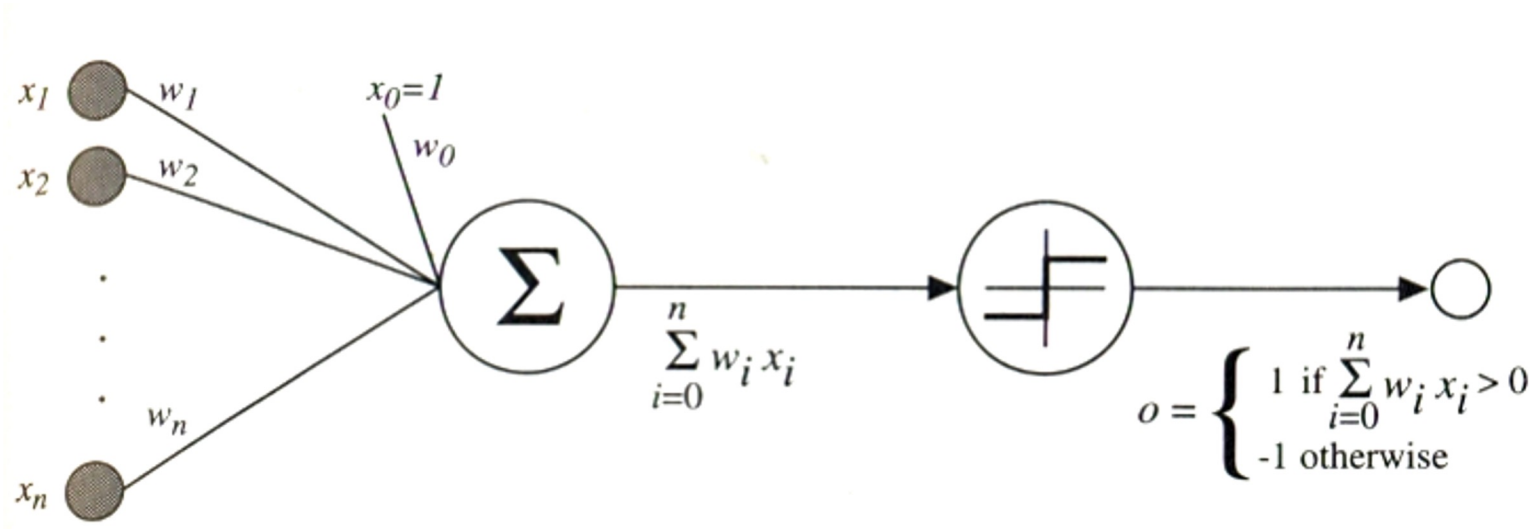


Perceptron

Characteristics

- Perceptron : Rossemblat ,1962
- Is guaranteed under certain characteristics, the learning algorithm converges to the optimal solution to the problem.
- The perceptrons were developed for vision.
- Inspired by the retina of a fly, which had a captor, a unit of processing and output.
- Inversely performing, about the number of observations.
- Perceptron convergence theorem:
  - For one unit(neuron) and 2 different classes, if the problem, is linearly separable, learning will be completed in a finite number of iterations.

Perceptron



- Input: vector of real-values.
- Calculates a linear combination of these inputs
- Output:
  - 1 if the result is greater than some threshold
  - -1 otherwise
- Equation: $$o(x_1,\ldots,x_n) = \begin{cases} 1 & if \quad w_0 + w_1 x_1 + w_2 x_2 + \cdots + w_n x_n > 0 \\ -1 & otherwise \end{cases}$$

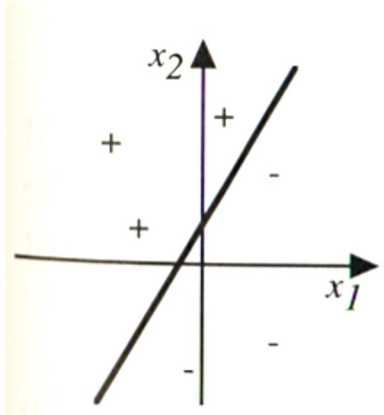
Perceptron …

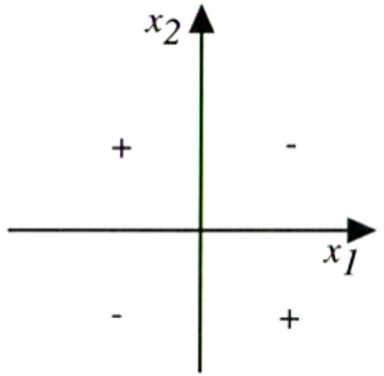
- w_0 is usually negative (- w_0) as it is a **threshold** that must be surpassed to in order for the perceptron to output 1.
- If we add an additional constant $X_0 = 1$ then we can write: $\sum_{i=0}^{n} w_i x_i > 0$
- Or in vector form: $\vec{w} \cdot \vec{x} > 0$
- So the perceptron function can be written: $o(\vec{x}) = \text{sgn}\left(\vec{w} \cdot \vec{x}\right)$
- where: $\text{sgn}(y) = \begin{cases} 1 & if \quad y > 0 \\ -1 & otherwise \end{cases}$
- So the space of candidate hypothesis considered in perceptron learning are the set of weights:

$$H = \left\{ \vec{w} \middle| \vec{w} \in \Re^{(n+1)} \right\}$$

Representational power of perceptrons

- Represents hyperplane decision surfaces in n-dimensional spaces.
  - 1 for instances on one side of the hyperplane.
  - -1 for instances on the other side.





- Called *linearly separable* sets of examples.

Representational …

Boolean function

- A single perceptron can be used to represent many boolean functions.
  - Usually 1 if TRUE and -1 if FALSE.
  - All primitive booleans functions: AND, OR, NAND, NOR.
  - Very easy if all input weights all set to the same value (e.g. 1) and setting the threshold w_0 accordingly.
- **Every** boolean function can be represented by some network of interconnected units **based on** primitive boolean functions
  - SOP or POS (two levels deep).
- An input to a boolean function can be negated by **changing the sign** of the corresponding input weight.

Perceptron training rule

Perceptron training rule …

1. Begin with random weights.

2. Apply iteratively the perceptron to each training example (Forward Propagation)
   1. Modify perceptron weights whenever it misclassifies an example.

   2. Use the ***perceptron training rule***: $w_i \leftarrow w_i + \Delta w_i$

      where: $\Delta w_i = \eta(t - o)x_i$

      - t is the target output for current training example
      - o is the output generated by the perceptron
      - η is the learning rate – moderates degree to which weights change
        - usually a small value (0.1) and sometimes is made to decay as iterations increase.

3. Repeat step 2 until perceptron classifies all training examples correctly.

Perceptron training rule …

- Converges toward successful weight values within a finite number of applications of the perceptron training rule.

- Provided:
  - Training examples are linearly separable.
  - A sufficiently small learning rate is used (Minsky and Papert, 1969).

Gradient descent and Delta rule

Gradient descent and Delta rule

- Converges toward a best-fit approximation to the target function when training examples are not linearly separable.

- Uses the ***gradient descent*** to search the hypothesis space of possible weight vectors.

- This rule is the basis of the **Backpropagation** algorithm
  - Can learn networks with many interconnected units.
  - Gradient descent can also serve as the basis for linear algorithms that learn continuously parameterized hypothesis.

Gradient descent and Delta rule …

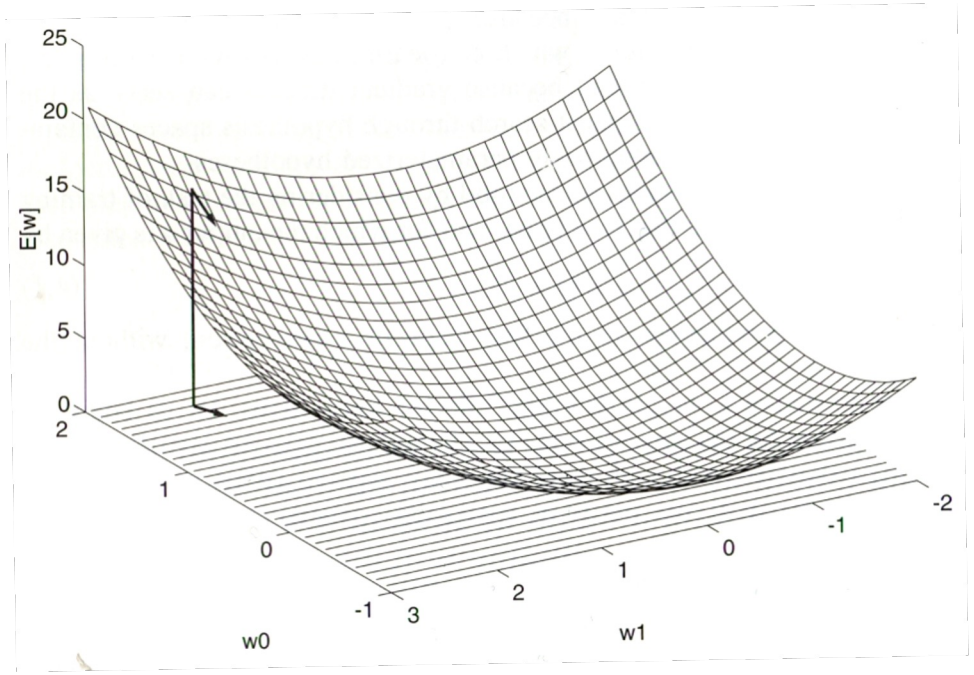
- Unthresholded perceptron $o(\vec{x}) = \vec{w} \cdot \vec{x}$

  - Linear unit: correspond to the first stage of perceptron without the threshold.

- Training error
  - Of a hypothesis relative to the training examples

$$E(w) \equiv \frac{1}{2} \sum_{d \in D} (t_d - o_d)^2$$

  - D: set of training examples
  - t_d: target output
  - o_d: linear unit output



Gradient descent and Delta rule …

- Gradient descent search determines a weight vector that minimizes *E* by:
  1. Starting with an arbitrary initial weight vector.
  2. Repeatedly modifying it in small steps.
  3. At each step, the weight vector is altered in the direction that produces the steepest descent along the error surface.
  4. Process continues until the global minimum error is found.

Gradient descent and Delta rule …

- Gradient of *E* with respect to $\vec{w}$ is: $\nabla E(\vec{w})$
  - Vector that specifies the direction that produces the *steepest increase* in *E*.
- Training rule for *gradient descent* is: $\vec{w} \leftarrow \vec{w} + \Delta \vec{w}$

  where: $\Delta \vec{w} = -\eta \nabla E(\vec{w})$
- For the component form it can be rewritten as:

$$w_i \leftarrow w_i + \Delta w_i$$

  - where:

$$\Delta w_i = \eta \sum_{d \in D} (t_d - o_d) x_{id}$$

Gradient descent and Delta rule …

Gradient-Descent (training_examples, η)

Each training example is a pair of the form $\langle \vec{x}, t \rangle$, where $\vec{x}$ is the vector of input values, and *t* is the target output value, η is the learning rate.

1. Initialize each w_i to some small random value.
2. Until the termination condition is met, Do
   1. Initialize each Δw_i to zero.
   2. For each $\langle \vec{x}, t \rangle$ in training_examples, Do
      1. Input the instance $\vec{x}$ to the unit and compute the output *o* *(Forward Propagation)*
      2. For each linear unit weight w_i, Do

$$\Delta wi \leftarrow \Delta wi + \eta(t - o)x_i$$

   3. For each linear unit weight w_i, Do

$$w_i \leftarrow w_i + \Delta w_i$$

Gradient descent and Delta rule …

- Advantages
  - Search strategy for large or infinite hypothesis space.
    - Hypothesis space contains continuously parameterized hypothesis (like weights in a linear unit)
    - Error can be differentiated with respect to these hypothesis parameters.

- Disadvantages
  - Converging to a local minimum can be quite slow – thousand of descent steps.
  - No guarantee of finding the global minimum with multiple local minima in the error surface

Class Exercise

- Using and AND or an OR
- Perform a Feed Forward Propagation by hand

Gradient descent and Delta rule …

- Stochastic gradient descent (incremental gradient descent)
  - Alternative to alleviate disadvantages of gradient descent.
  - Instead of updating weights after summing over *all* training examples, weights are updated after *each* training example is presented.
  - **Delta rule** (LMS rule, Adaline rule, Widrow-Hoff rule):

$$\Delta wi \leftarrow \eta(t-o)x_i$$

  - So, the error is defined over each individual training example:

$$E_d(\vec{w}) = \frac{1}{2}(t_d - o_d)^2$$

Gradient descent and Delta rule …

Stochastic-Gradient-Descent (training_examples, η)

Each training example is a pair of the form $\langle \vec{x}, t \rangle$, where $\vec{x}$ is the vector of input values, and t is the target output value, η is the learning rate.

1. Initialize each w_i to some small random value.
2. Until the termination condition is met, Do
   1. Initialize each Δw_i to zero.
   2. For each $\langle \vec{x}, t \rangle$ in training_examples, Do
      1. Input the instance $\vec{x}$ to the unit and compute the output o. *(Forward Propagation)*
      2. For each linear unit weight w_i, Do

$$wi \leftarrow wi + \eta(t - o)x_i$$

Class Program

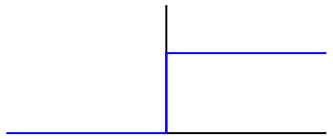
- Program a function for a **Feed Forward Propagation** of a Stochastic Gradient-Descent Perceptron

- feedForwardNN.py

Activation Functions

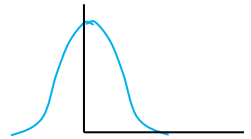
- Binary

$$f(s,b)=\begin{Bmatrix}1 & si & s\geq b\\ 0 & si & s<b\end{Bmatrix}$$



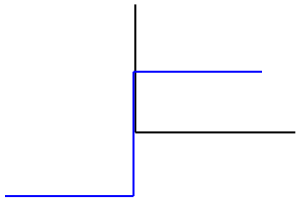
- Radial

$$f(s,\mu)=e^{-\frac{1}{2}\frac{(s-\mu)^2}{\sigma^2}}$$



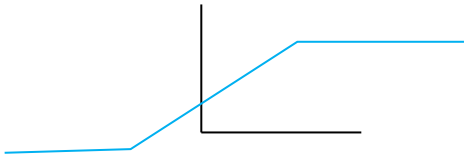
- Sign

$$f(s,b)=\begin{Bmatrix}1 & si & s\geq b\\ -1 & si & s<b\end{Bmatrix}$$



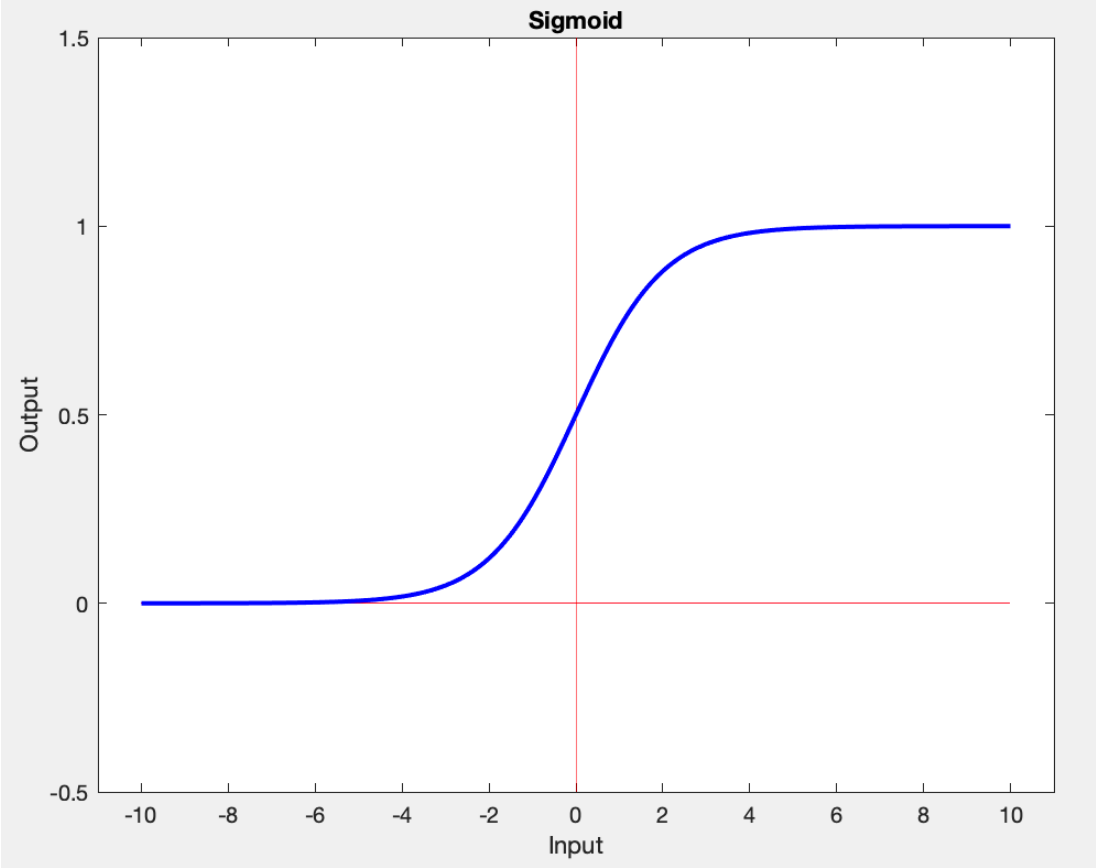
- Linear with threshold

$$f(s,b)=\begin{Bmatrix}1 & si & s>b\\ \frac{s-a}{b-a} & si & a\leq s\leq b\\ 0 & si & s<a\end{Bmatrix}$$

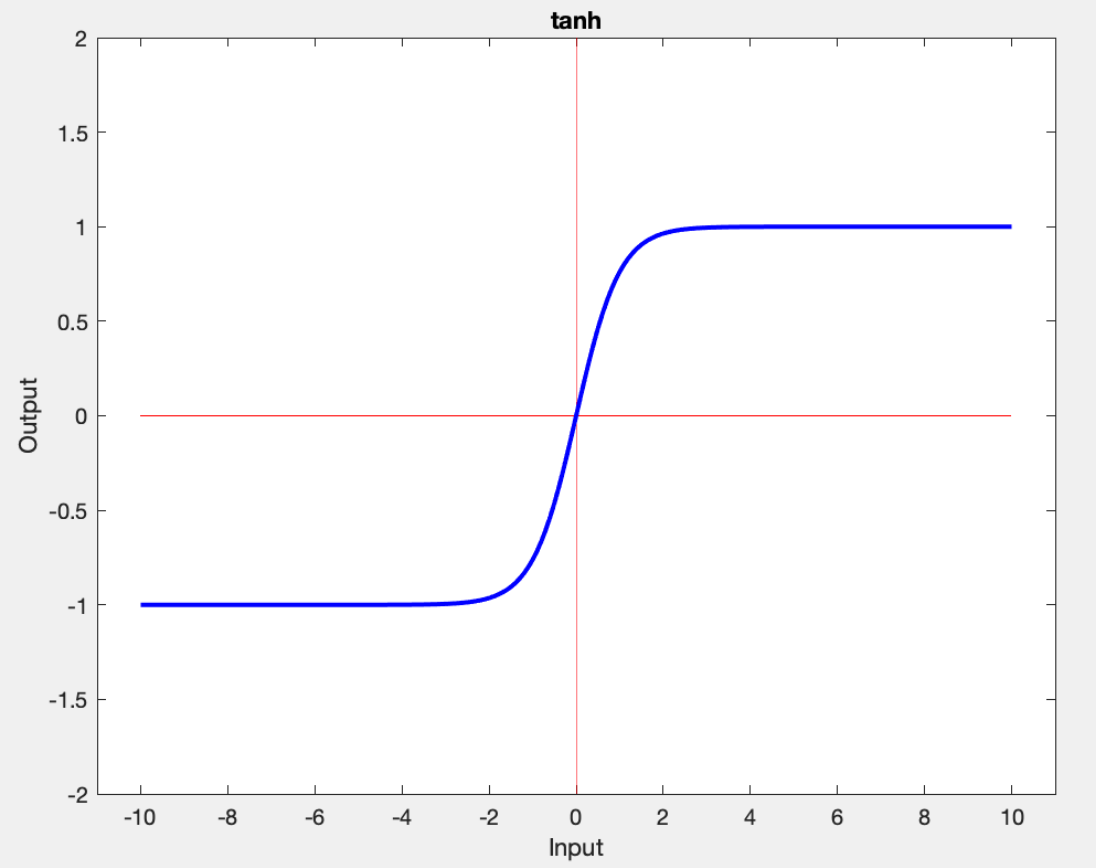


Activation Functions…

Sigmoid

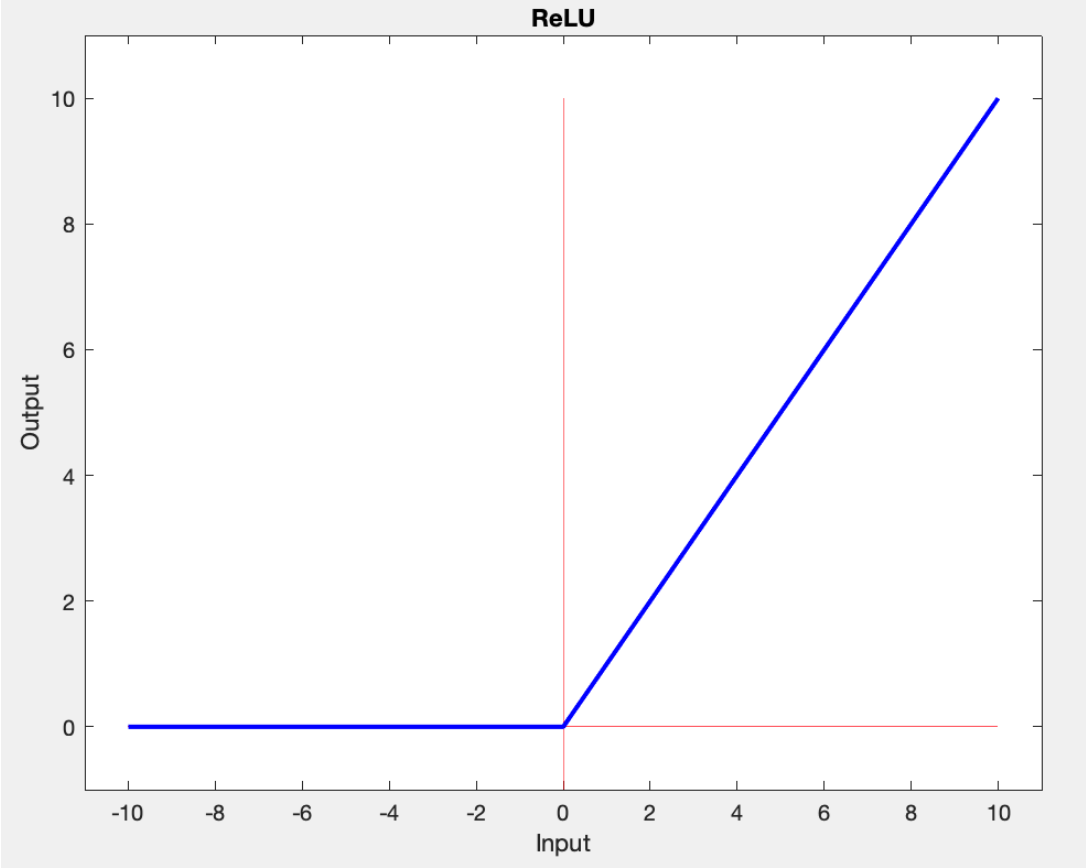


Hyperbolic tangent (tanh)

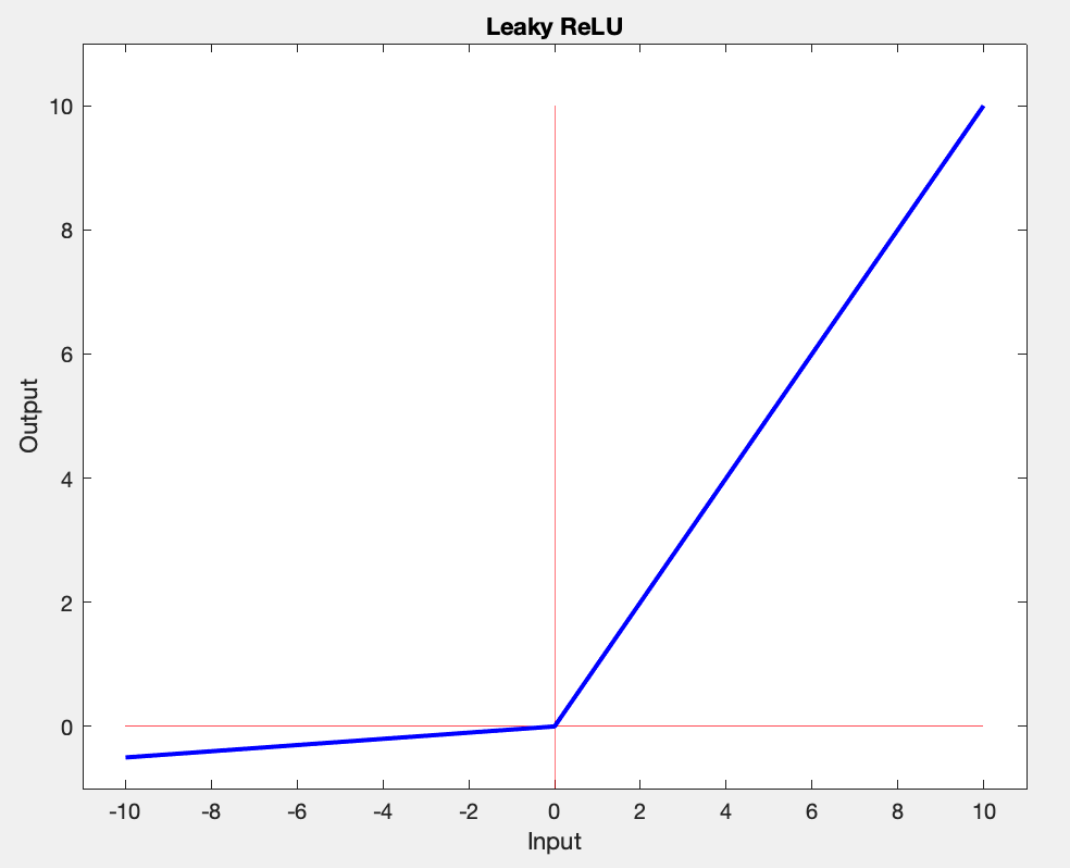


Activation Functions…

ReLU (Rectified linear unit)



Leaky ReLU



Softmax Activation

Definition

- Calculates the relative probabilities of its inputs

$$softmax(x_i) = \frac{\exp(x_i)}{\sum_n \exp(x_j)}$$

- The sum of all probabilities must be 1

- It returns a vector with all the probabilities

Example

X = [2.33, -1.46, 0.56]

softmax(2.33) = 0.8383

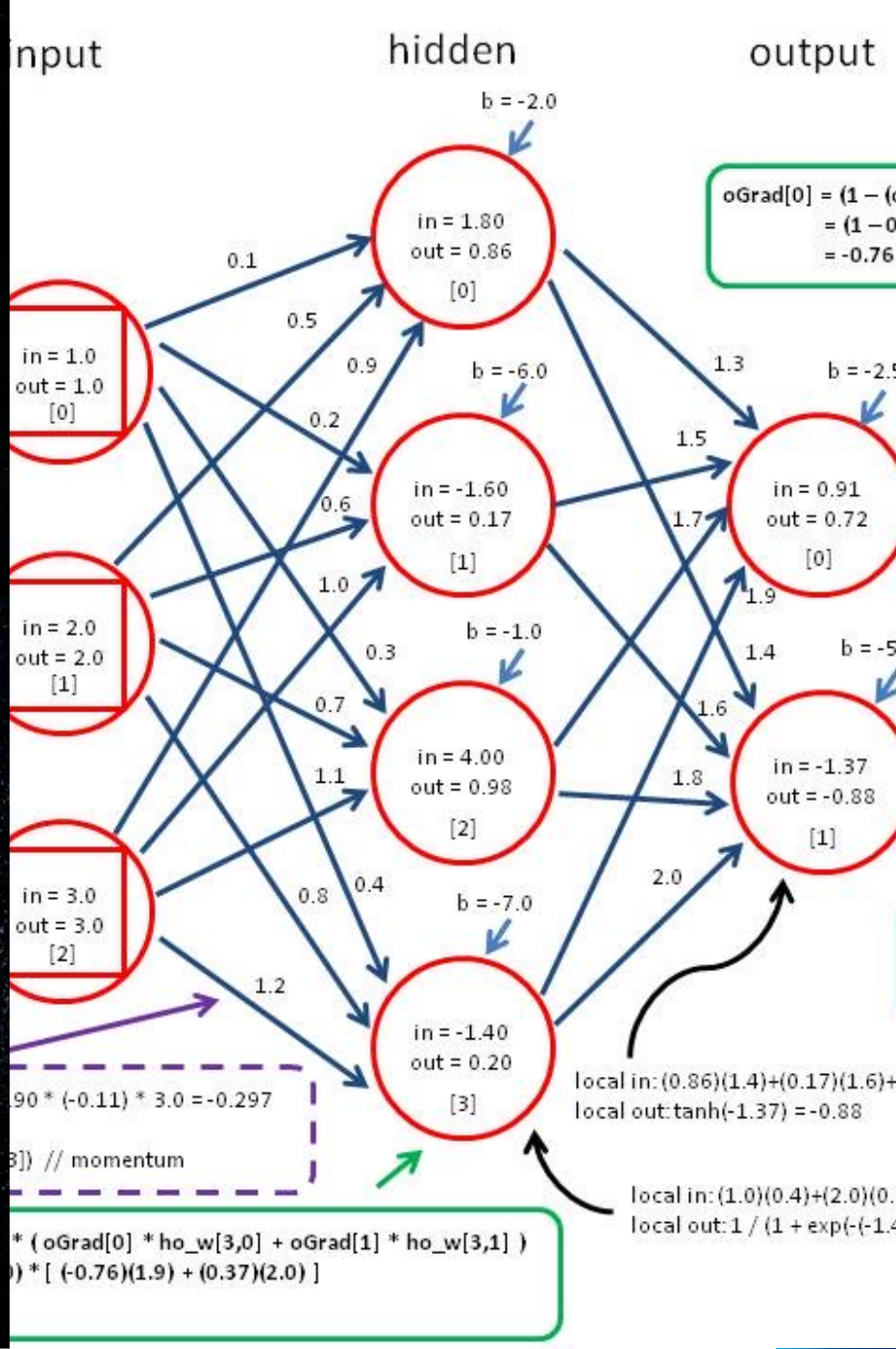
softmax(-1.46) = 0.0189

softmax(0.56) = 0.1428

softmax(X) = [0.8383, 0.0189, 0.1428]

Backpropagation

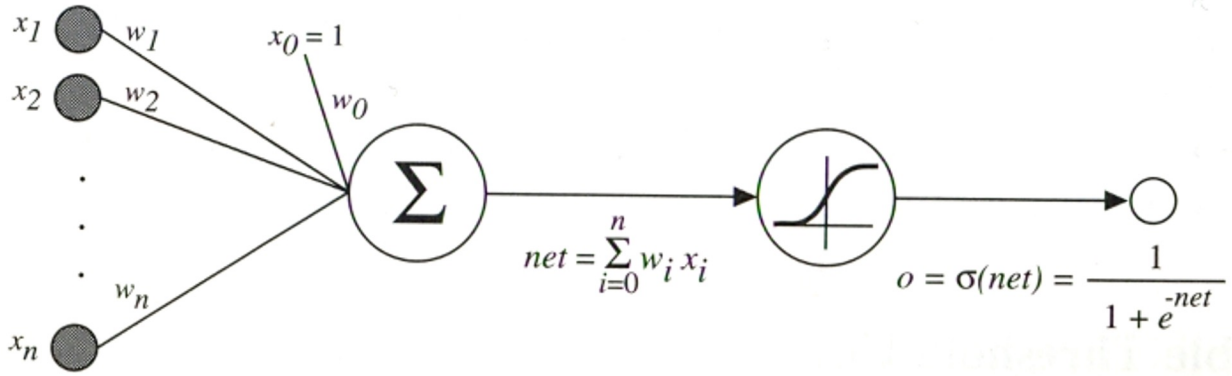
Multilayer networks



Backpropagation Algorithm

- The backpropagation algorithm was originally introduced in the 1970s.
- Its importance wasn't fully appreciated until a famous 1986 paper by David Rumelhart, Geoffrey Hinton, and Ronald Williams (“Learning representations by back-propagating errors”, Nature, 9 October).
- Today, the backpropagation algorithm is the workhorse of learning in neural networks.

The sigmoid threshold unit



- Basis for constructing multilayer networks
  - Linear units produce linear functions even with multilayer networks.
  - Sigmoid units are capable of representing nonlinear functions.
    - Provides a smooth differentiable threshold function.
      - It is has a very simple derivative.
    - Output is between 0.0 and 1.0 (a continuous function of its input).

$$o = \sigma(\vec{w} \cdot \vec{x})$$

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

Backpropagation algorithm

- Learns the weights of a multilayer network.
- Employs gradient descent to minimize squared error between network's output and target.
- Error *E* is redefined as: $$E(\vec{w}) = \frac{1}{2} \sum_{d \in D} \sum_{k \in outputs} (t_{kd} - o_{kd})^2$$
- Hypothesis space is defined over all possible values of weight values for all units in the network.

Backpropagation(training_examples, η ,n_{in}, n_{out}, n_{hidden}) – stochastic version

Each training example is a pair of the form $\langle \vec{x}, \vec{t} \rangle$, where $\vec{x}$ is the vector of network input values, and $\vec{t}$ is the vector of target network values.

n_{in} is the number of network inputs, n_{hidden} the number of units in the hidden layer, and n_{out} the number of output units.

The input from unit *i* into unit *j* is denoted x_{ji}, and the weight from unit *i* to unit *j* is denoted w_{ji}.

- Create a feed-forward network with n_{in} inputs, n_{hidden} units, and n_{out} units.
- Initialize all network weights to small random numbers (e.g. -0.5 to 0.5).
- Until the termination condition is met, Do
  - For each $\langle \vec{x}, \vec{t} \rangle$ in training_examples, Do
    - Propagate the input forward through the network:
      1. Input the instance $\vec{x}$ to the network and compute the output o_u of every unit *u* in the network.
    - Propagate the errors backward through the network:
      2. For each network output unit *k*, calculate its error term $\delta_k \leftarrow o_k(1-o_k)(t_k-o_k)$
      3. For each hidden unit *h*, calculate its error term $\delta_h \leftarrow o_h(1-o_h)\sum_{k \in outputs} w_{kh}\delta_k$
      4. Update each network weight w_{ji} $w_{ji} \leftarrow w_{ji} + \Delta w_{ji}$

where $\Delta w_{ji} = \eta \delta_j x_{ji}$

Backpropagation algorithm …

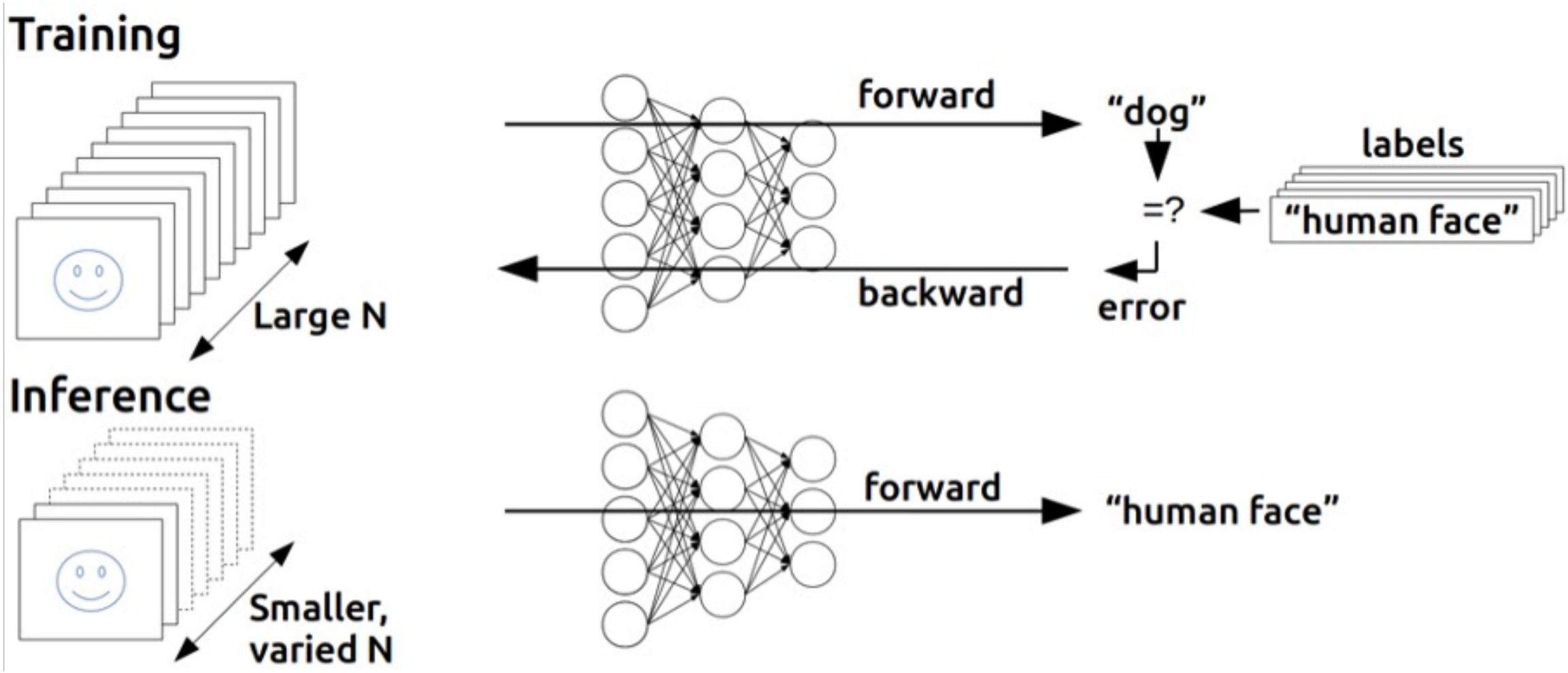
- The true gradient of *E* (non-stochastic) can be obtained by performing $\sum_{d \in D} \delta_j x_{ji}$ before updating weight values.

- Number of iterations can be thousands of times.

- Termination conditions:
  - Fixed number of iterations.
  - Error on training examples falls below a threshold.
  - Error on a validation set of examples meets a criterion.

  - Important:
    - Too few iterations can fail to reduce error sufficiently.
    - Too many iterations can lead to overfitting training data.

Backpropagation algorithm …



Backpropagation algorithm …

Convergence and local minima

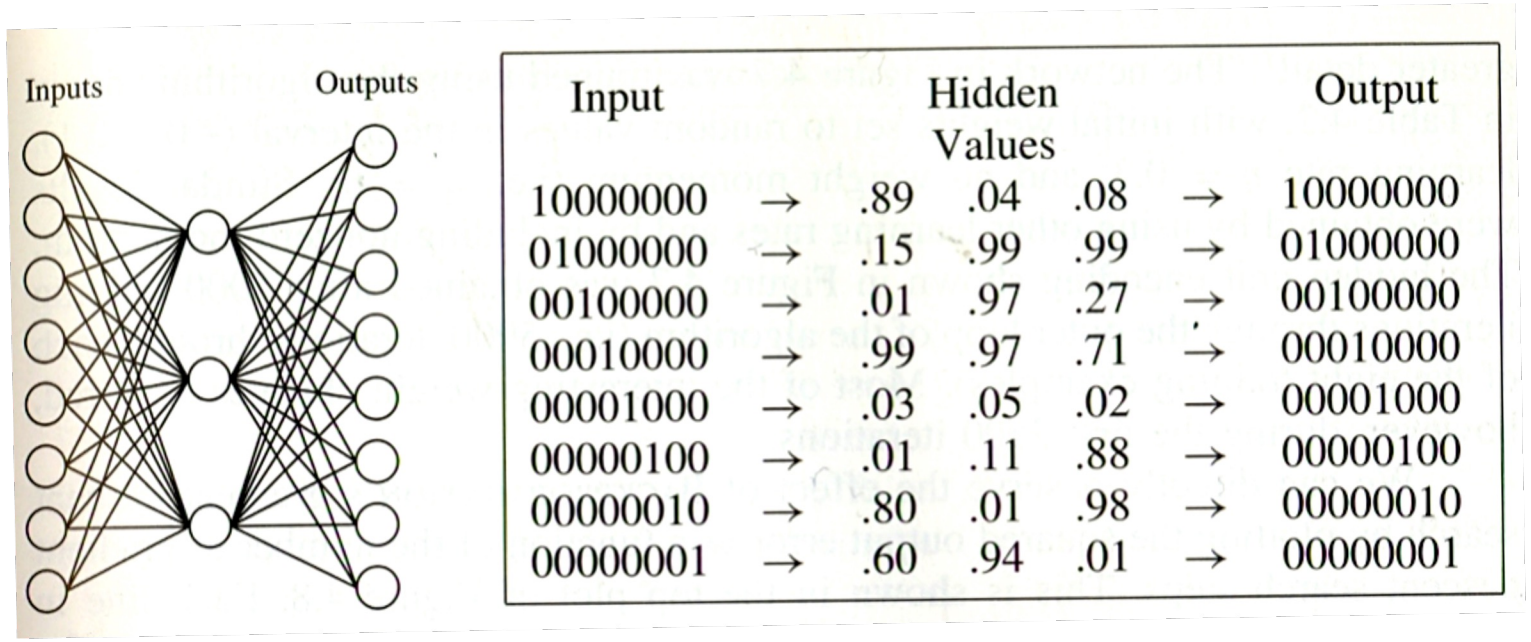
- Backpropagation over multilayer networks is only guaranteed to **converge toward some local minima**.
  - Error surface in multilayer networks can contain many local minima.
  - Backpropagation is in practice **highly effective**.
    - If a local minima is found in one weight the most probable is that this is not a local minima for other weights, allowing backpropagation to get out of the local minima.
- Gradient descent over complex error surfaces is poorly understood.
- Common heuristics to avoid local minima are:
  - Use momentum for weight update.
  - Use stochastic gradient descent.
  - Train multiple networks using the same data but different random weights.
    - Select network with best performance.
    - Form a “committee” of networks to decide on output.

Backpropagation algorithm …

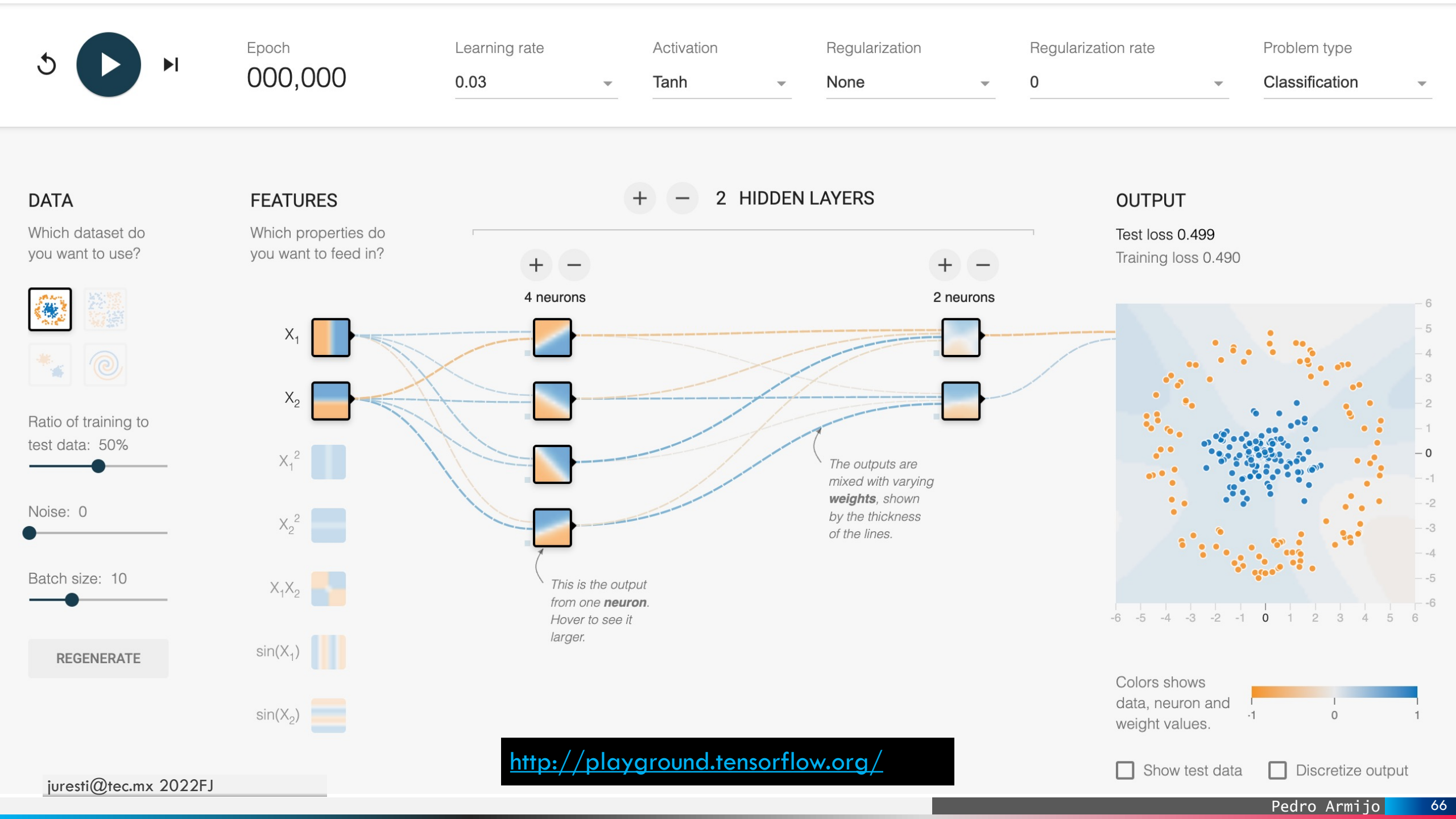
- Representational power
  - Boolean functions
    - Generate an input unit that is active only when an specific value is input to the network (AND).
    - Implement an output unit as an OR.
  - Continous functions
    - Every bounded continuous function can be approximated with an arbitrarily small error by a network of two (2) layers (Cybenko, 1989).
      - Sigmoid units at hidden layer.
      - Linear units at output layer.
  - Arbitrary functions
    - Any function can be approximated to arbitrary accuracy by a network of three (3) layers (Cybenko, 1988).
      - Output layer uses linear units.
      - Hidden layers use sigmoid units.

Backpropagation algorithm …

- Hidden layers
  - Backpropagation has the ability of *discovering* useful intermediate representations at the hidden units.
  - Weight-tuning procedure is *free to set weights* that define whatever hidden unit representation is most effective at minimizing *E*.



Input		Hidden Values				Output
10000000	→	.89	.04	.08	→	10000000
01000000	→	.15	.99	.99	→	01000000
00100000	→	.01	.97	.27	→	00100000
00010000	→	.99	.97	.71	→	00010000
00001000	→	.03	.05	.02	→	00001000
00000100	→	.01	.11	.88	→	00000100
00000010	→	.80	.01	.98	→	00000010
00000001	→	.60	.94	.01	→	00000001


Epoch
000,000
Learning rate
0.03
Activation
Tanh
Regularization
None
Regularization rate
0
Problem type
Classification
DATA
Which dataset do you want to use?
Ratio of training to test data: 50%
Noise: 0
Batch size: 10
REGENERATE
FEATURES
Which properties do you want to feed in?
X_1
X_2
X_1^2
X_2^2
X_1X_2
$\sin(X_1)$
$\sin(X_2)$
2 HIDDEN LAYERS
4 neurons
2 neurons
The outputs are mixed with varying weights, shown by the thickness of the lines.
This is the output from one neuron. Hover to see it larger.
OUTPUT
Test loss 0.499
Training loss 0.490
Colors shows data, neuron and weight values.
-1
0
1
Show test data
Discretize output
http://playground.tensorflow.org/

Backpropagation Programs

From scratch

- https://www.geeksforgeeks.org/implementation-of-neural-network-from-scratch-using-numpy/
  - Simplified version
  - Ignores bias in neurons

Using library (framework)

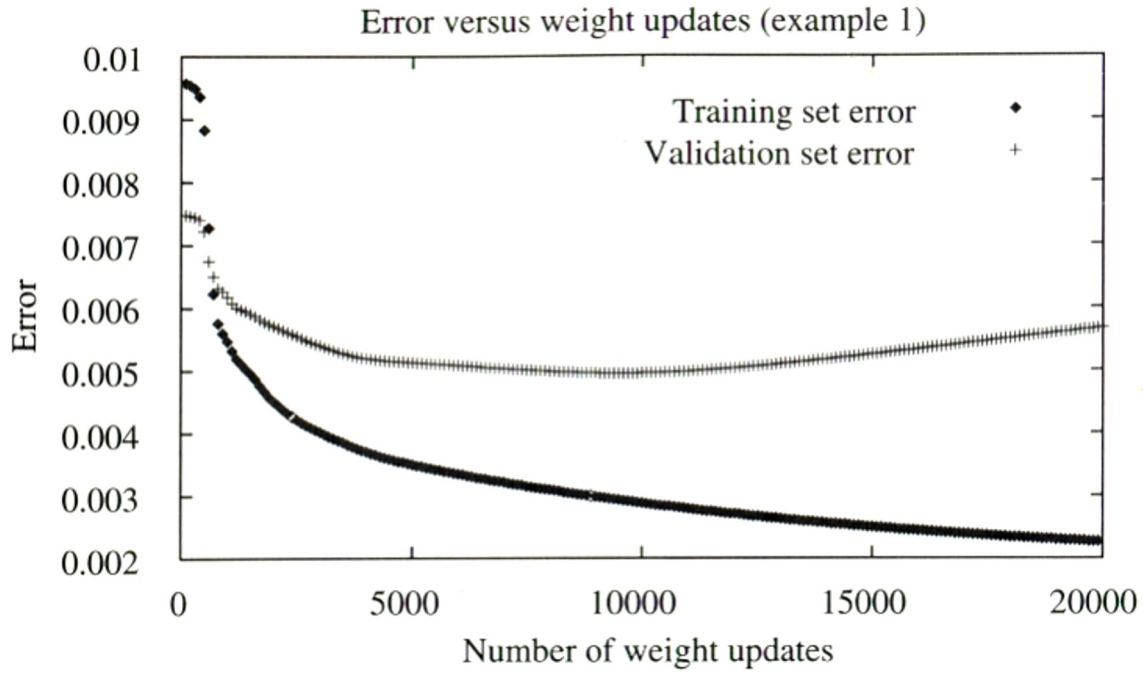
- MNIST Fashion example using Keras
  - Check Github

Diagnostics for Neural Networks

juresti@tec.mx 2022FJ

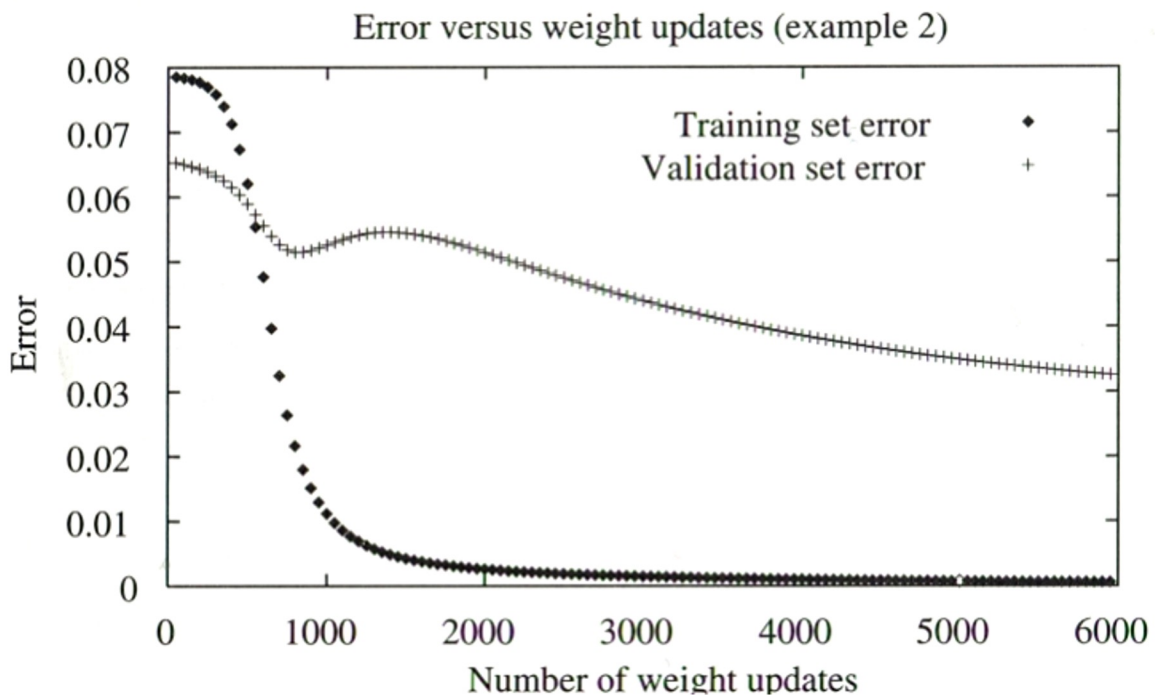
Generalization, overfitting and stopping criterion

- Stopping the weight update cycle until the error *E* is below a threshold is not a good solution.
- Backpropagation is susceptible to overfitting.
- Overfitting occurs when the algorithm starts learning very specific details of training data, i.e. noise.

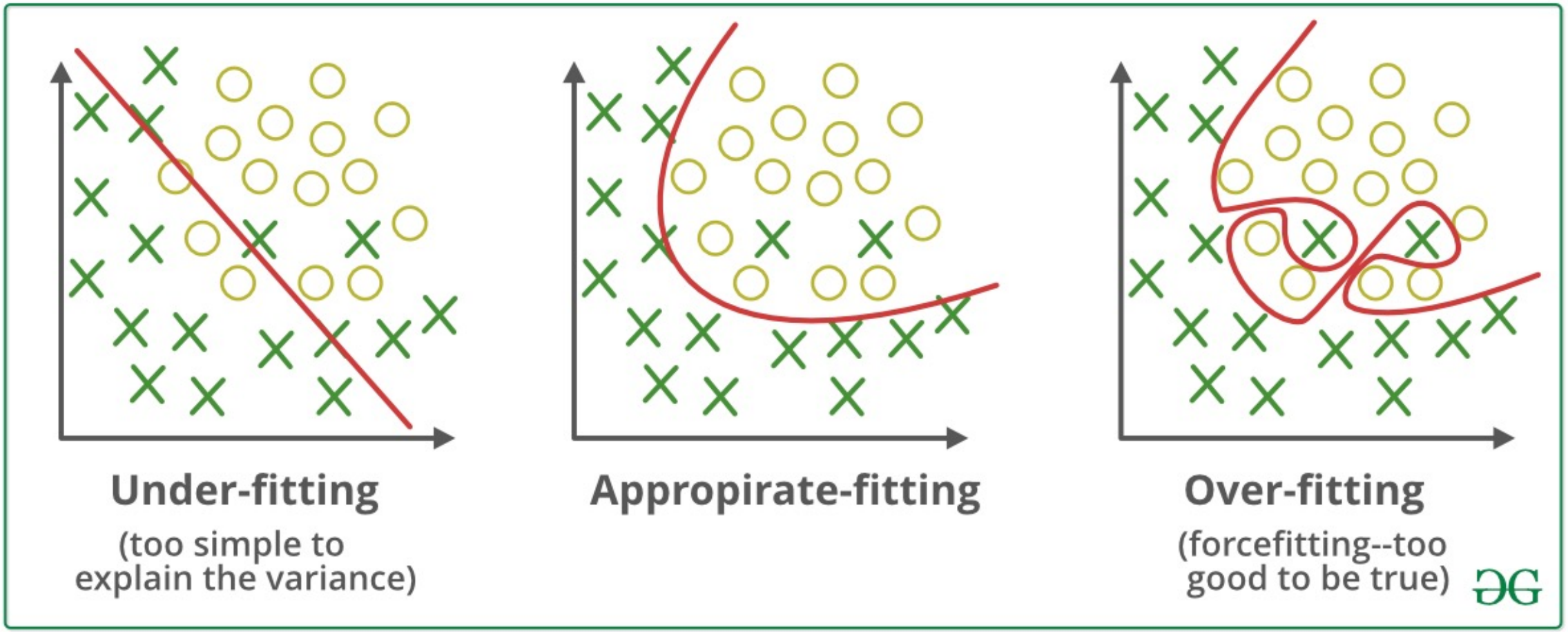


Generalization, overfitting and stopping criterion…

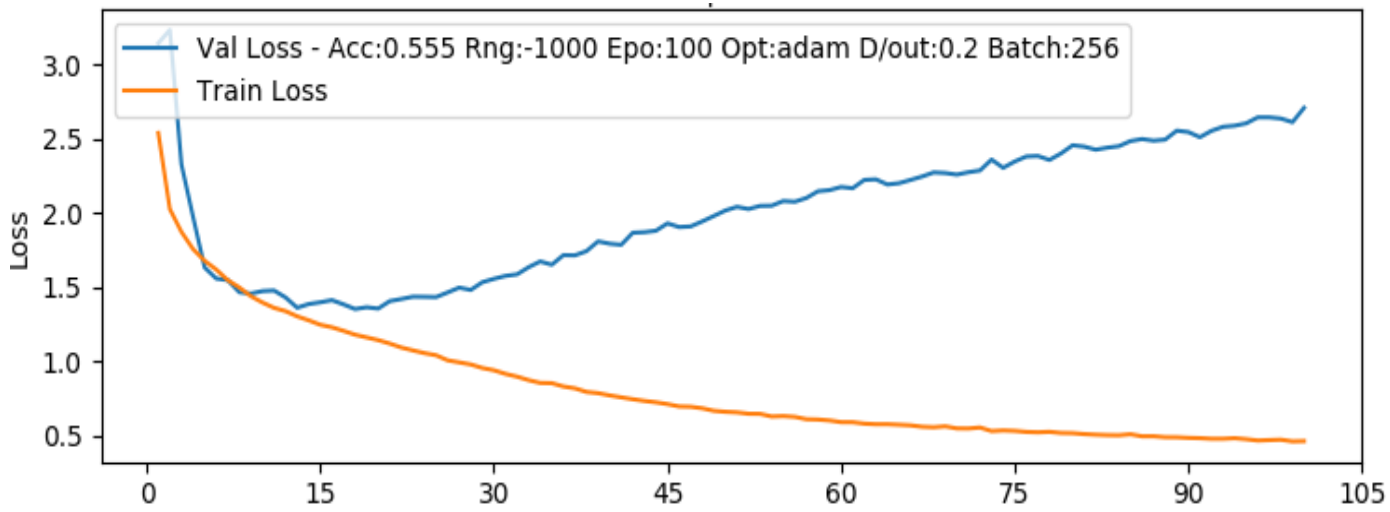
- Solutions:
  - Weight decay – decrease each weight by some small factor during each iteration.
  - Set of validation data
    - One of the most successful.
    - Algorithm monitors error with respect to validation set.
    - Uses training set to update weights.
    - Should use the number of iterations that produces the lowest error over the validation set.
      - Store a set of weights for training and another with the best-performing weights so far.
      - When the trained weights reach a significantly higher error over the validation set than the stored weights, training is terminated.

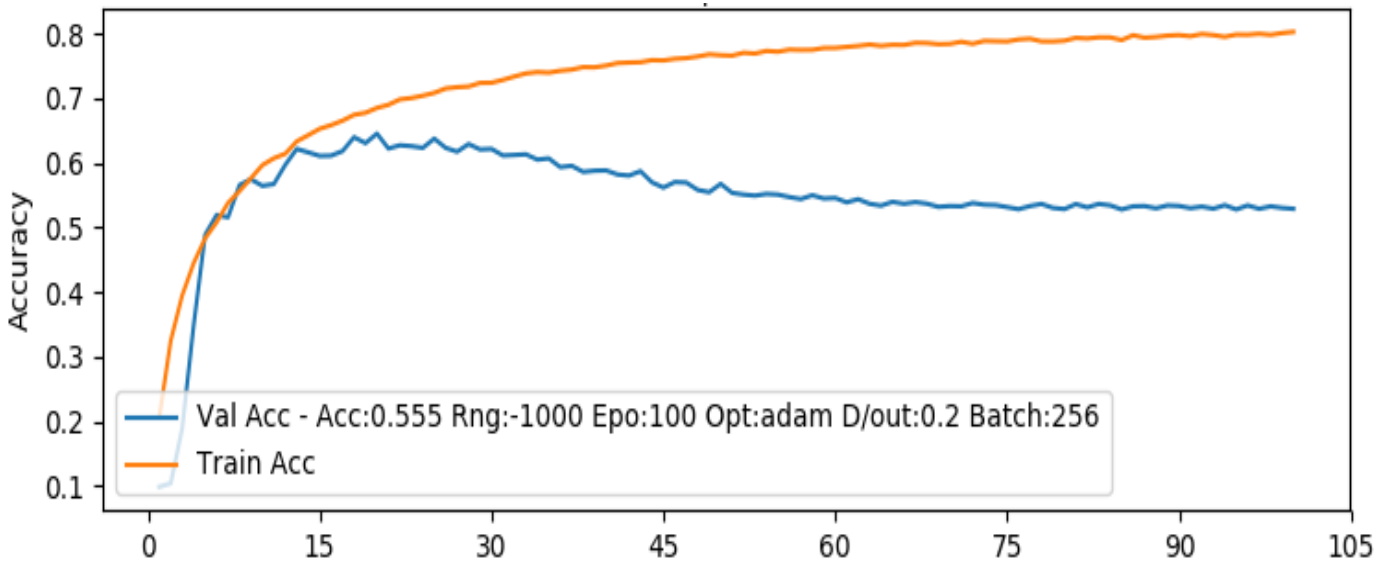


Generalization, overfitting and stopping criterion…

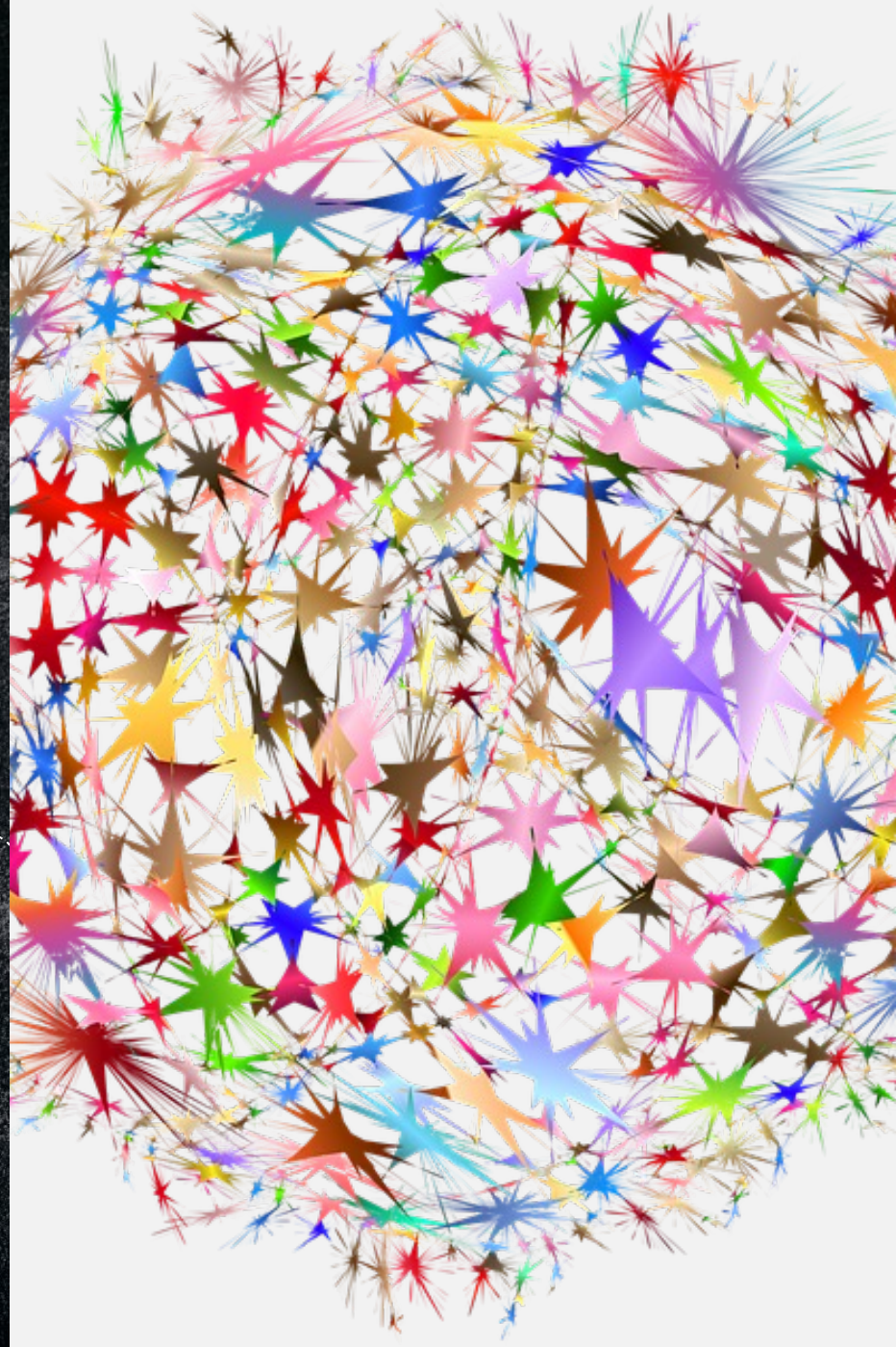


Generalization, overfitting and stopping criterion…





Regularization



Regularization

L1 and L2 Regularization

- Used for the weights of neural networks
- Help to avoid overfitting
- Penalize or restrict the weights
- Reduces the generalization error
- Pays less attention to less relevant input variables

- Large weights
  - Make network unstable
  - Small changes in input may lead to large changes in output
  - Usually, a sign of overfitting
  - Normally due to long training time
  - Generates complex models

- Small weights
  - Generate simple models
  - Allow models to focus learning
  - Considered regular or less specialized (more room for learning)

L1 Regularization

$$E = \frac{1}{2} * \sum (t_k - o_k)^2 + \lambda * \sum |w_i|$$

squared error

L1 weight penalty

- Encourages weights to be 0.0
- Usually has many sparse weights (weights with more 0.0 values)
- Lambda varies between 0.0 and 1.0 (Penalty)
  - Controls amount of bias in model
  - 0.0 (low bias and high variance)
  - 1.0 (high bias and low variance)
- Strong penalty implies underfitting
- Low penalty implies overfitting

L2 Regularization

Also called Weight Decay in NN or "*shrinkage*" in statistics

$$E = \frac{1}{2} * \sum (t_k - o_k)^2 + \frac{\lambda}{2} * \sum {w_i}^2$$

plain error weight penalty

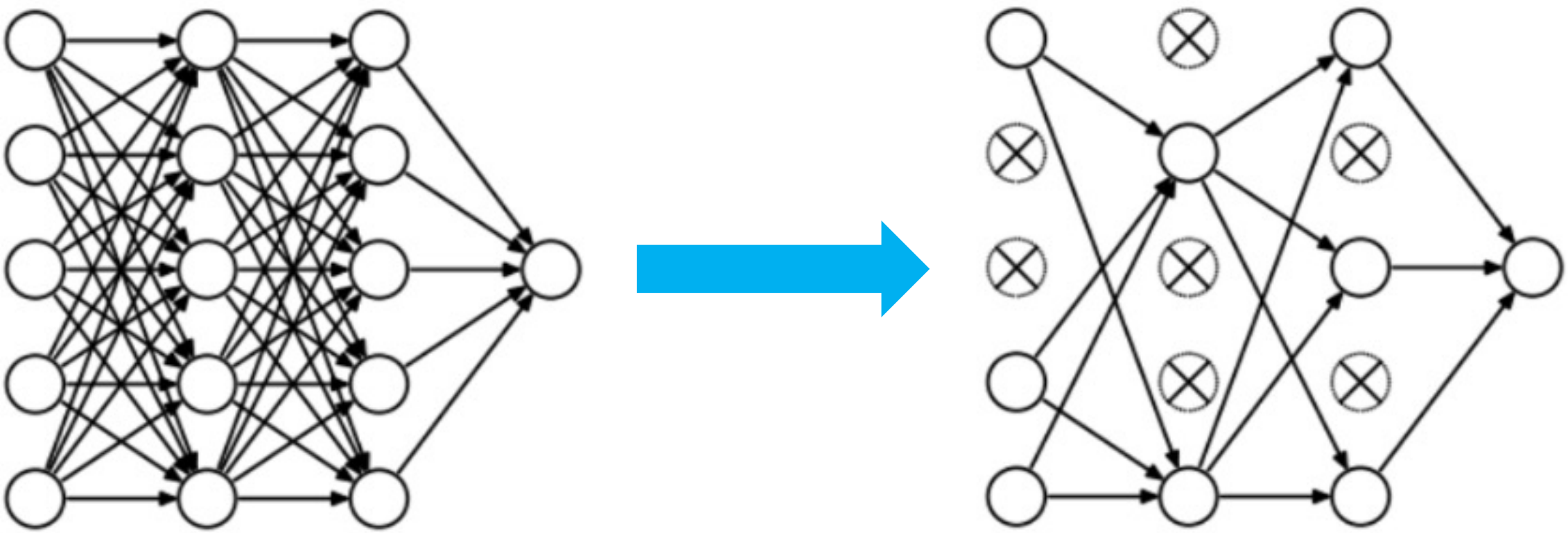
- Most used
- Penalizes larger weights severely
- Has few sparse weights
- Called Ridge Regression in when used in Linear and Logistic regressions

Tips

L1 and L2 Regularization

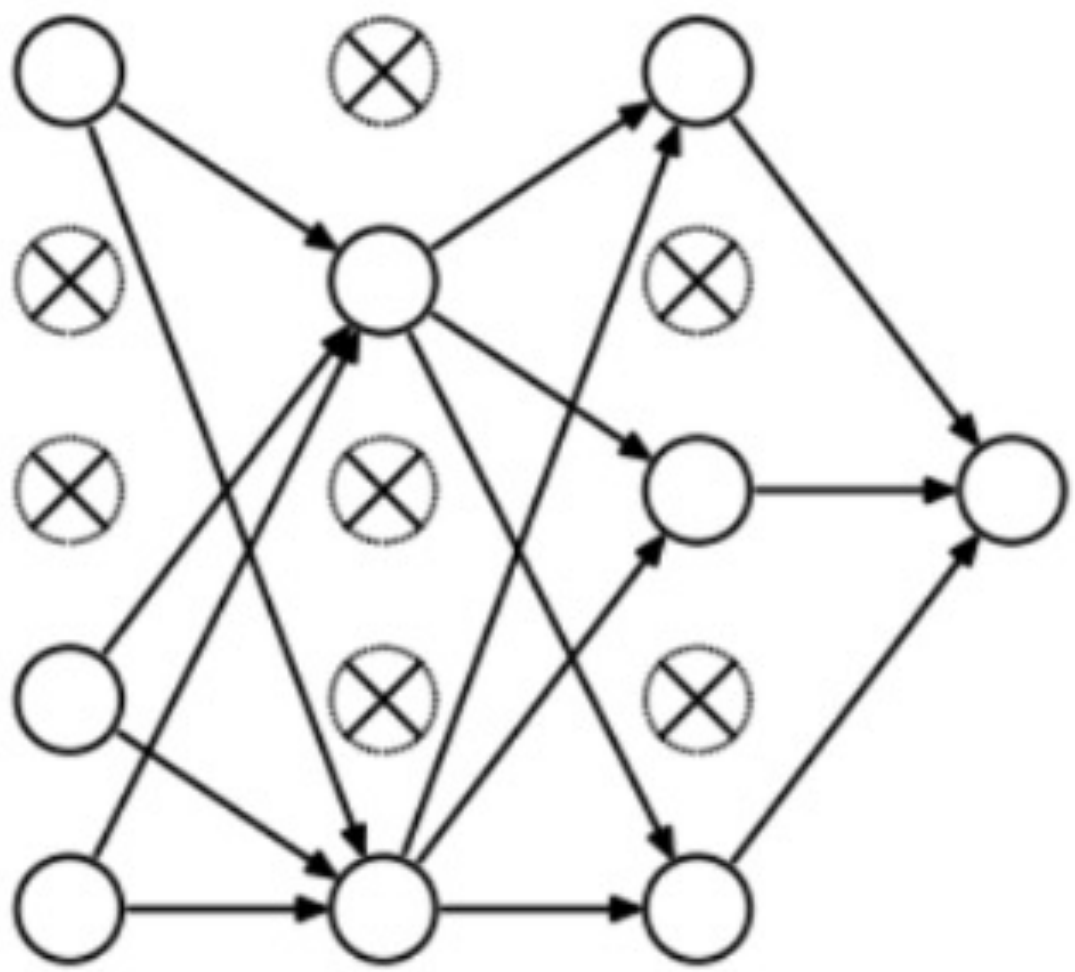
- Scale input data
- Work best with larger networks as this networks are prone to overfitting
- Log scaling works well when tunning
- Use L1 + L2 together

Dropout

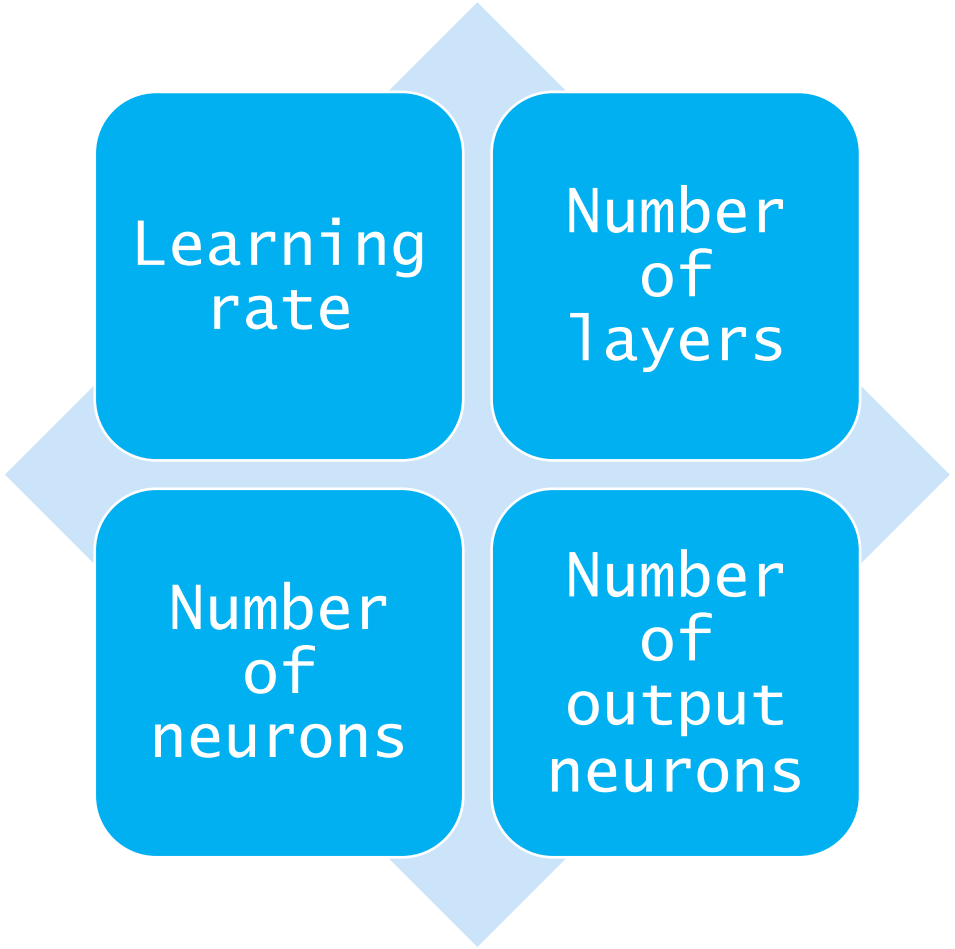


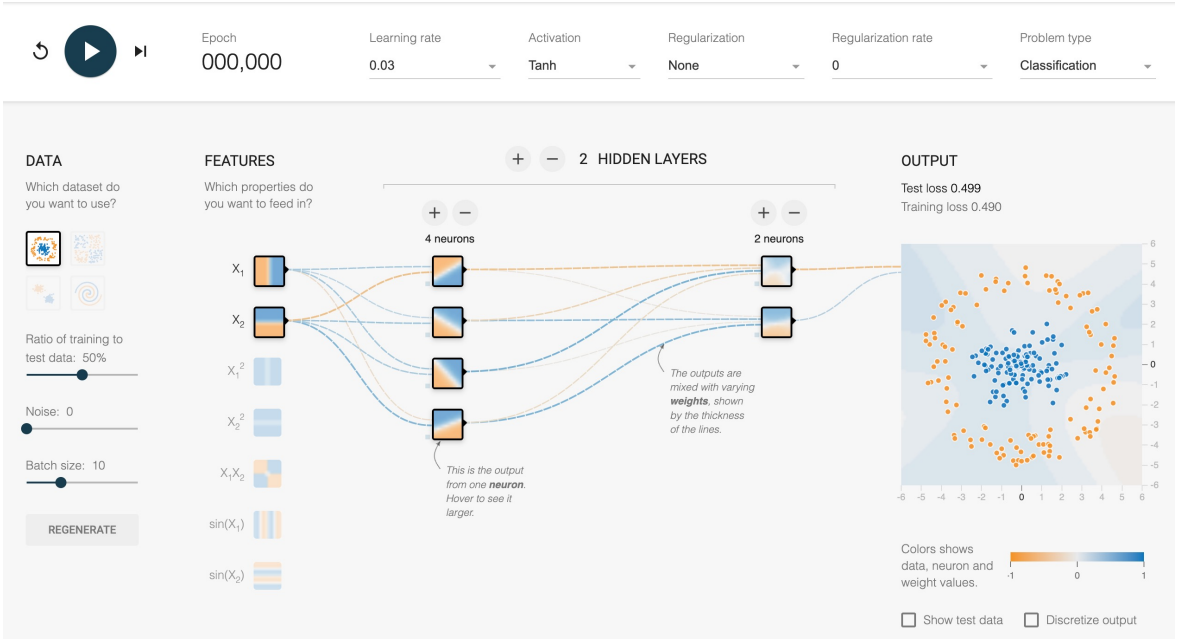
Dropout…

- The most common regularization technique in Deep Learning
- Dropout values are between 0.0 and 1.0
  - Probability of dropping neuron
- Introduces randomness
- Reduces overfitting
- Produces very good results
- Can be applied to hidden and input layers



Neural Network Hyper-Parameters





http://playground.tensorflow.org/

References

- Russell, S. & Norvig, P. (2010). *Artificial Intelligence: A Modern Approach*. Third Edition. Prentice Hall.

- Mitchell, T. (1997). Machine Learning. McGraw-Hill.

- Creator of the presentation design: Pedro Armijo. MS Office theme.