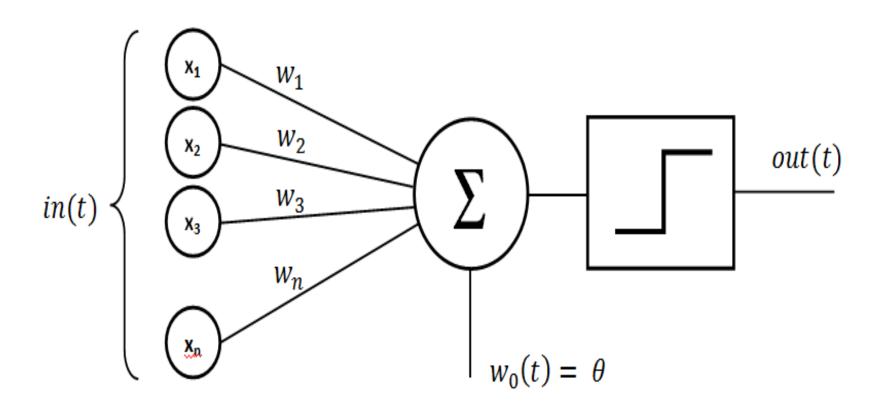


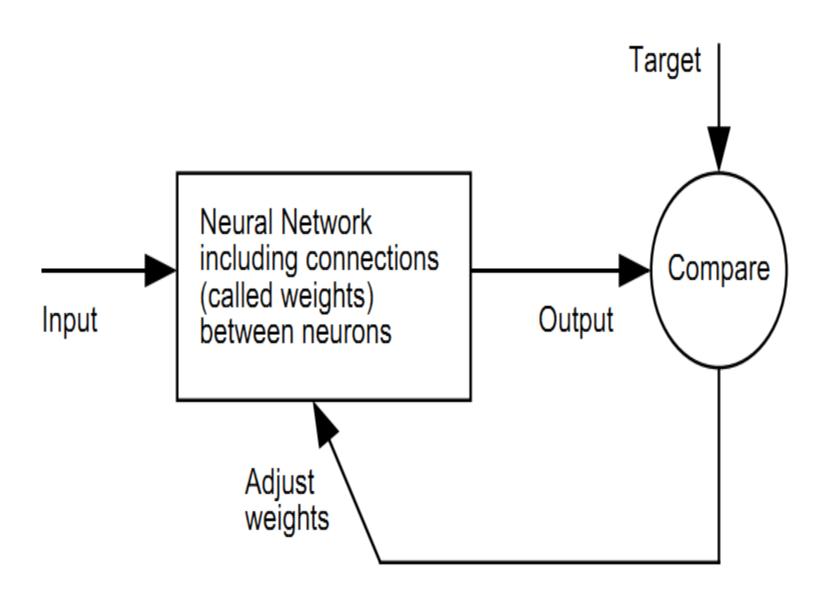
#### **Chandan Verma**

**Corporate Trainer(Machine Learning, AI, Cloud Computing, IOT)** 

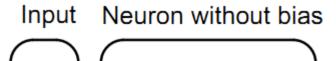
www.facebook.com/verma.chandan.070

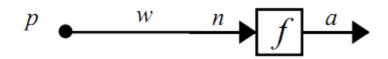
# Perceptrons



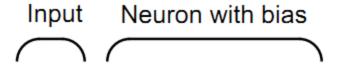


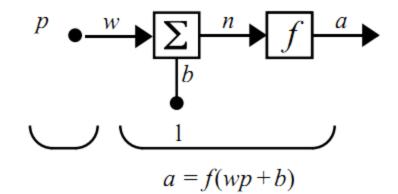
# Simple Neuron



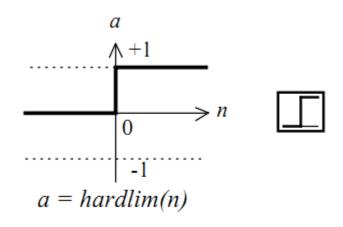


$$a = f(wp)$$

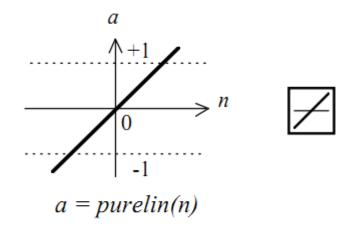




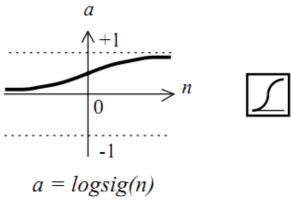
#### **Transfer Functions**



Hard-Limit Transfer Function

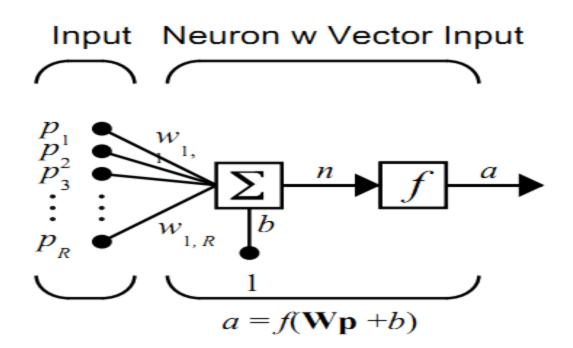


Linear Transfer Function



Log-Sigmoid Transfer Function

# Perceptrons



$$n = W*p + b$$

#### hardlim

hardlim is a neural transfer function. Transfer functions calculate a layer's output from its net input.

```
>> x= -5:0.1:5;
>> y=hardlim(x);
>> plot(x,y)
```

# tansig

Transfer functions calculate a layer's output from its net input.

each element of N in is squashed from the interval [-inf inf] to the interval [-1 1] with an "S-shaped" function.

# Example

```
p=[1;-1];
w=[2 0];
b=1;
n=w*p+b;
a=hardlim(n);
disp(a)
```

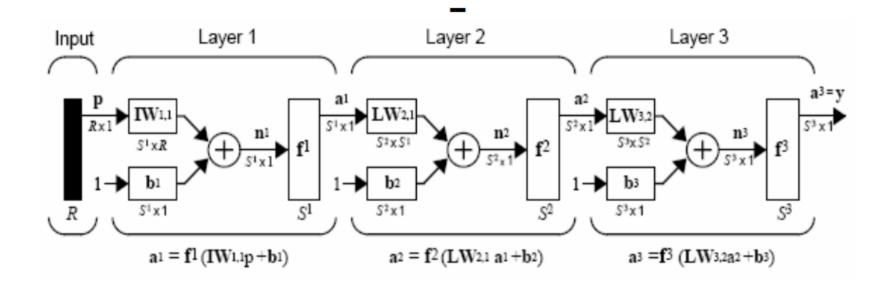
```
p=[1;-1];
w=[2 0];
b=1;
n=w*p+b;
a=tansig(n);
disp(a)
```

## Multiple Layer of Neuron

```
Input Vector 2 Column
p = [1;-1]
Laybe1:Node=3
w1=[2\ 0;1\ 2;1\ 3];
b1=[1;2;3];
Layer2: node=2
w2=[2 0 1;1 2 1];
b2 = [0;0]
Layer3:node=1
w3=[2\ 0];
b3 = [1]
```

## Output

outputnet= tansig(w3\*(tansig(w2\*(tansig(w1\*p+b1)) +b2)) +b3); disp(outputnet)



# Creating a Linear Neuron (newlin)

net = newlin(P,S,ID,LR)

P input vectors.

S - Number of elements in the output vector.

ID - Input delay vector, default = [0].

LR - Learning rate, default = 0.01;

```
net=newlin([-1 1;-1 1],1);
w=net.IW\{1,1\}
b=net.b\{1\}
net.IW\{1,1\}=[2,3];
w = net.IW\{1,1\}
net.b{1}=[-4];
```

## newp-Create a perceptron

Perceptrons are used to solve simple (i.e. linearly separable) classification problems.

- PR Rx2 matrix of min and max values for R input elements.
- S Number of neurons.
- TF Transfer function, default = 'hardlim'.
- LF Learning function, default = 'learnp'.

#### Train a neural network

[NET,TR] = train(NET,X,T)

takes a network NET, input data Xand target data T and returns the network after training it, and a training record TR.

```
net = newp([0 1;0 1],1);
p=[0\ 0\ 1\ 1;0\ 1\ 0\ 1];
t=[0\ 0\ 0\ 1];
net.IW\{1\}=[1,1];
net.b{1}=1;
net.trainParam.nettepochs=2;
net=train(net,p,t);
a=sim(net,p);
disp(a)
```

## perceptron

perceptron(hardlimitTF,perceptronLF)

Perceptrons are simple single-layer binary classifiers, which divide the input space with a linear decision boundary.

Suppose you have the following classification problem and would like to solve it with a single vector input, two-element perceptron network.

$$\begin{cases}
\mathbf{p}_1 = \begin{bmatrix} 2 \\ 2 \end{bmatrix}, t_1 = 0 \\
\end{cases} \begin{cases}
\mathbf{p}_2 = \begin{bmatrix} 1 \\ -2 \end{bmatrix}, t_2 = 1 \\
\end{cases} \begin{cases}
\mathbf{p}_3 = \begin{bmatrix} -2 \\ 2 \end{bmatrix}, t_3 = 0 \\
\end{cases} \begin{cases}
\mathbf{p}_4 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}, t_4 = 1 \\
\end{cases}$$

$$\mathbf{W}(0) = \begin{bmatrix} 0 & 0 \end{bmatrix} \quad b(0) = 0$$

Start by calculating the perceptron's output a for the first input vector  $\mathbf{p}_1$ , using the initial weights and bias.

 $\alpha = hardlim(W(0)p1 + b(0))$ 

 $= hardlim([0\ 0][2\ 2]'+0)$ 

=hardlim(0)=1

The output a does not equal the target value  $t_1$ , so use the perceptron rule to find the incremental changes to the weights and biases based on the error.

$$e=t1-\alpha=0-1=-1$$
  
 $\Delta \mathbf{W}=e\mathbf{p}T1=(-1)[2\ 2]=[-2\ -2]$   
 $\Delta b=e=(-1)=-1$ 

new weights and bias using the perceptron update rules.

$$Wnew=Wold+epT$$
  
=[0 0]+[-2 -2]=[-2 -2]=W(1)  
 $bnew=bold+e=$   
0+(-1)=-1= $b$ (1)

next input vector,  $\mathbf{p}_2$ . The output is calculated below.

$$\alpha = hardlim(\mathbf{W}(1)\mathbf{p}2 + b(1))$$

$$=$$
 hardlim([-2 -2][1 -2] -1)

$$=$$
hardlim(1)=1

On this occasion, the target is 1, so the error is zero. Thus there are no changes in weights or bias, so  $\mathbf{W}(2) = \mathbf{W}(1) = [-2 - 2]$  and b(2) = b(1) = -1.

```
>> net=perceptron;
>> p=[2;2];
>> t=[0];
>> net.trainParam.epochs=1;
>> net=train(net,p,t);
>> w=net.IW\{1,1\}
>> b = net.b\{1\}
>> net=perceptron;
>> net.trainParam.epochs=1;
>> p = [[2;2] [1;-2] [-2;2] [-1;1]];
>> t = [0 \ 1 \ 0 \ 1];
>> net = train(net,p,t);
>>  w = net.iw{1,1}, b = net.b{1}
```

>> **o**=**net**(**p**)

# **Increasing Epochs**

```
>> net.trainParam.epochs = 1000;

>> net = train(net,p,t);

>> w = net.iw{1,1}, b = net.b{1}

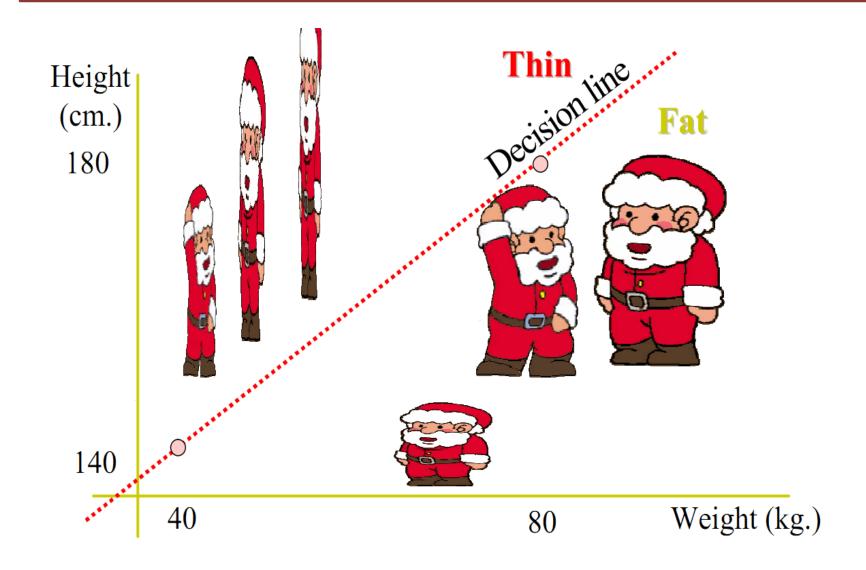
>> a = net(p)

>> a-t
```

# logical-OR

```
x = [0 0 1 1; 0 1 0 1];
t = [0 1 1 1];
net = perceptron;
net = train(net,x,t);
view(net)
y = net(x)
```

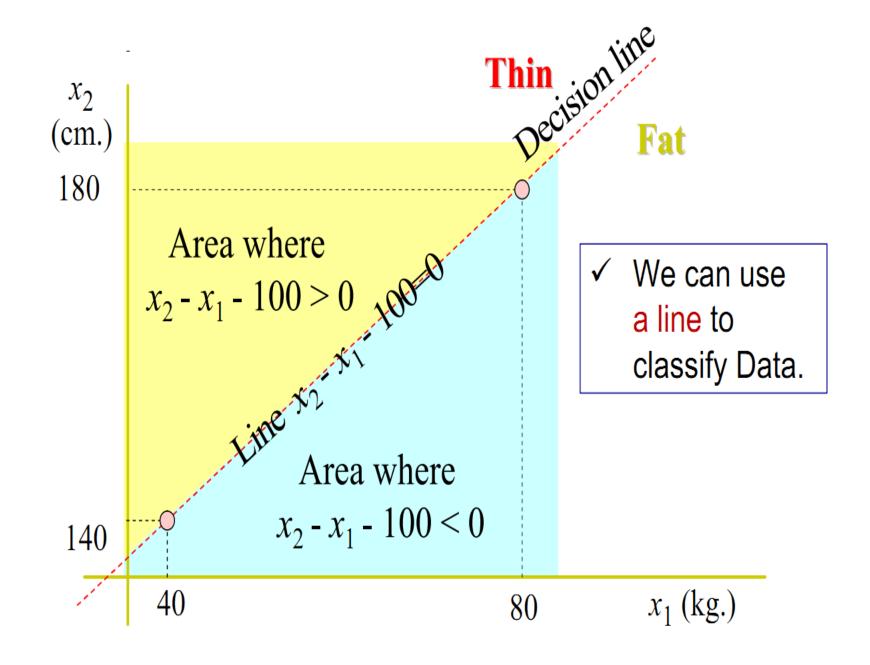
# How can we classify fat and thin boys



#### use a mathematical function

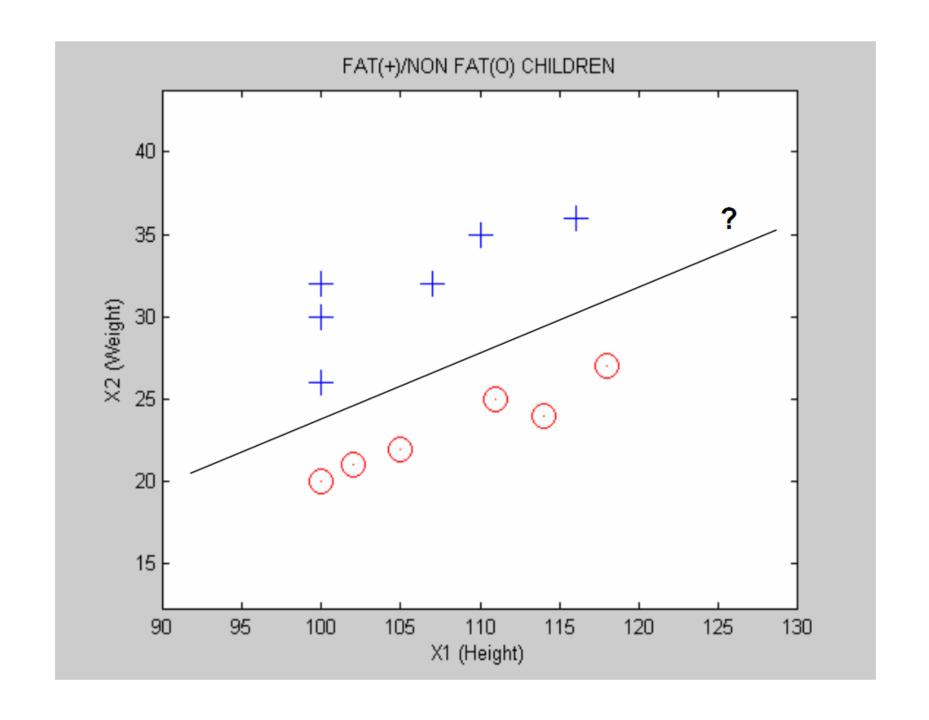
$$y = \begin{cases} 1 \text{ (thin)} & \text{if } x_2 - x_1 - 100 \ge 0 \\ 0 \text{ (fat)} & \text{if } x_2 - x_1 - 100 < 0 \end{cases}$$

$$y = g(w_1x_1 + w_2x_2 - \mu)$$
$$= g(-x_1 + x_2 - 100)$$



# **Training Samples**

No.	Height (Cm.)	Weight (Kg.)	Fat/Not Fat (+1/-1)
1.	100	20	-1
2.	100	26	+1
3.	100	30	+1
4.	100	32	+1
5.	102	21	-1
6.	105	22	-1
7.	107	<b>32</b>	+1
8.	110	35	+1
9.	111	25	-1
10.	114	24	-1
11.	116	36	+1
12.	118	27	-1



```
net = newp([90 \ 130; \ 10 \ 50], 1);
P = [100 20; 100 26; 100 30; 100 32; 102 21; 105 22; 107
32; 110 35; 111 25;114 24; 116 36; 118 27]';
T = [0; 1; 1; 1; 0; 0; 1; 1; 0; 0; 1; 0]';
net.trainParam.epochs = 40;
net = train(net, P, T);
plotpv(P,T);
plotpc(net.IW{1},net.b{1});
```

```
NP = [120 32]';
hold on;
plot(NP(1),NP(2),'*r');
Y = sim(net,NP)
```

# Classification of linearly separable data with a perceptron

- 1. Define input and output data
- 2. Create and train perceptron
- 3.Plot decision boundary

plotpv

Plot perceptron input/target vectors

## Define input and output data

```
close all,clear all,clc
N=20;
offset=5;
x=[randn(2,N) randn(2,N)+offset];
y=[zeros(1,N) ones(1,N)];
```

```
figure(1) plotpv(x,y)
```

# Plotting input/output

Plotpv

plotpv Plot perceptron input/target vectors.

```
x = [0\ 0\ 1\ 1; 0\ 1\ 0\ 1];

t = [0\ 0\ 0\ 1];

plotpv(x,t)
```

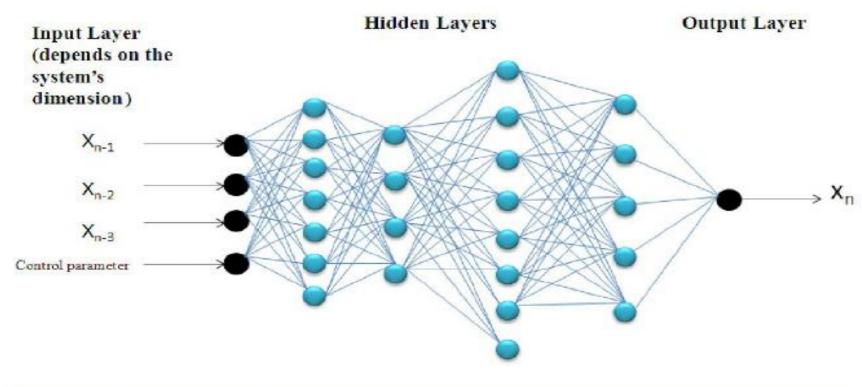
## Create and train perceptron

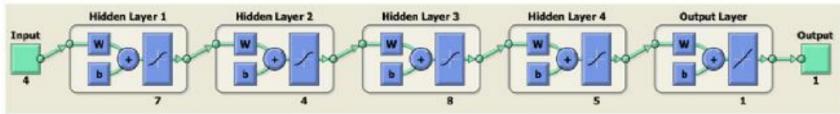
```
net =perceptron;
net=train(net,x,y);
view(net)
```

```
figure(1)
plotpc(net.IW{1},net.b{1});
```

Plot decision boundary
Plot a classification line on a perceptron vector plot.
plotpc(W,B)

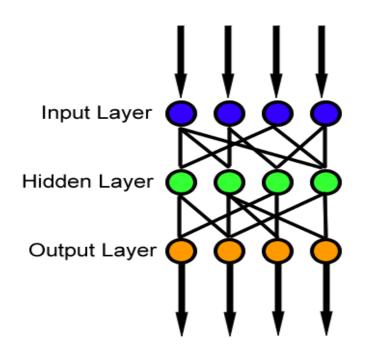
#### feedforwardnet





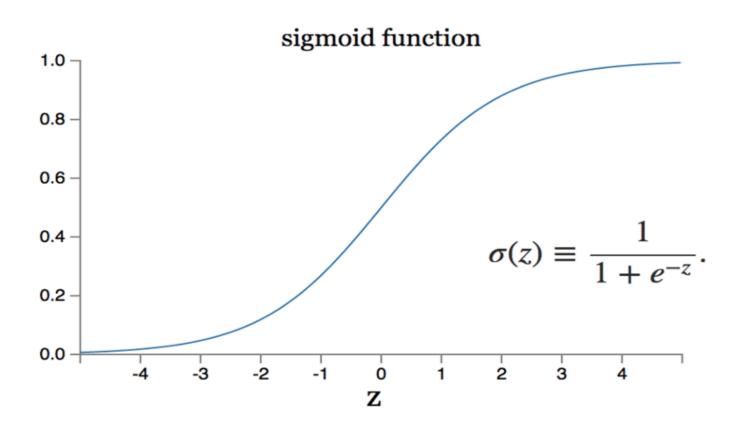
The feedforward neural network is the first and simplest type of artificial neural network.

In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network



$$C(w,b) \equiv \frac{1}{2n} \sum_{x} ||y(x) - a||^2.$$

# sigmoid function.



#### feedforwardnet

feedforwardnet(hiddenSizes,trainFcn)

```
[x,t] = simplefit_dataset;
net = feedforwardnet(10);
net = train(net,x,t);
view(net)
y = net(x);
perf = perform(net,y,t)
```

## Working With Iris Data

https://archive.ics.uci.edu/ml/datasets/iris



## Iris Data Set

Download: Data Folder, Data Set Description

Abstract: Famous database; from Fisher, 1936

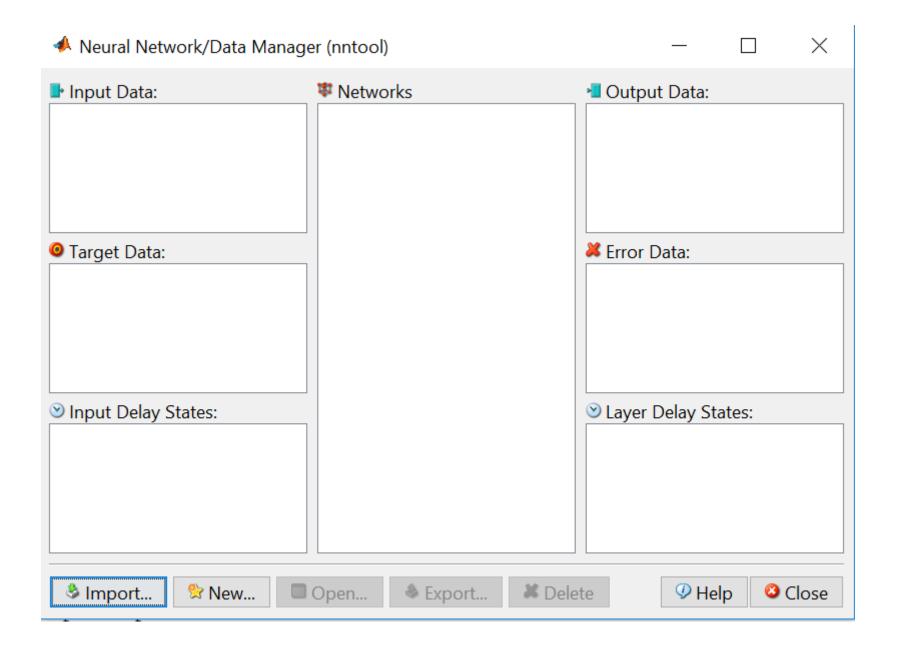


Data Set Characteristics:	Multivariate	Number of Instances:	150	Area:	Life
Attribute Characteristics:	Real	Number of Attributes:	4	Date Donated	1988-07-01
Associated Tasks:	Classification	Missing Values?	No	Number of Web Hits:	1817398

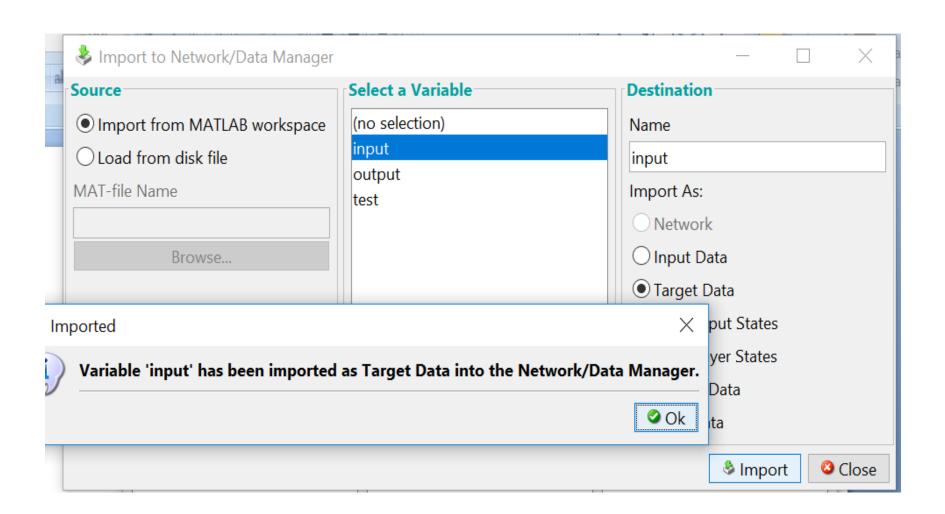
1	SEPAL LENGTH	SEPAL WIDTH	PETAL LENGTH	PETAL WIDTH	FLOWER
2	5.1	3.5	1.4	0.2	Iris-setosa
3	4.9	3	1.4	0.2	Iris-setosa
4	4.7	3.2	1.3	0.2	Iris-setosa
5	4.6	3.1	1.5	0.2	Iris-setosa
6	5	3.6	1.4	0.2	Iris-setosa
7	5.4	3.9	1.7	0.4	Iris-setosa
8	4.6	3.4	1.4	0.3	Iris-setosa
9	5	3.4	1.5	0.2	Iris-setosa
10	4.4	2.9	1.4	0.2	Iris-setosa
11	4.9	3.1	1.5	0.1	Iris-setosa
12	5.4	3.7	1.5	0.2	Iris-setosa
13	4.8	3.4	1.6	0.2	Iris-setosa
14	4.8	3	1.4	0.1	Iris-setosa
15	4.3	3	1.1	0.1	Iris-setosa
16	5.8	4	1.2	0.2	Iris-setosa
17	5.7	4.4	1.5	0.4	Iris-setosa
18	5.4	3.9	1.3	0.4	Iris-setosa
19	5.1	3.5	1.4	0.3	Iris-setosa

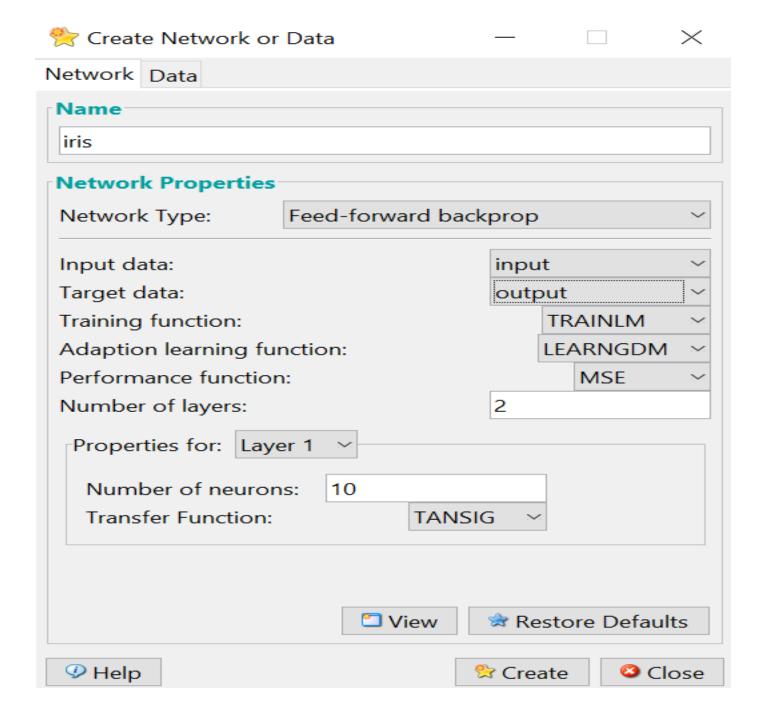
## **Data Collection**

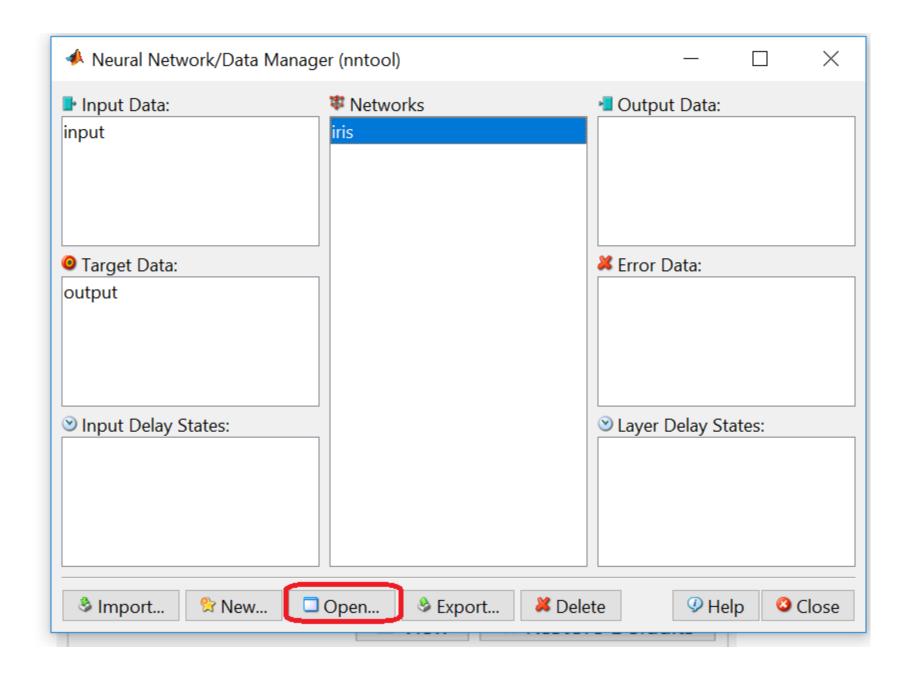
```
>> input=[]
>> output=[]
>> test=[]
>> input=input';
>> output=output';
>> test=test';
```

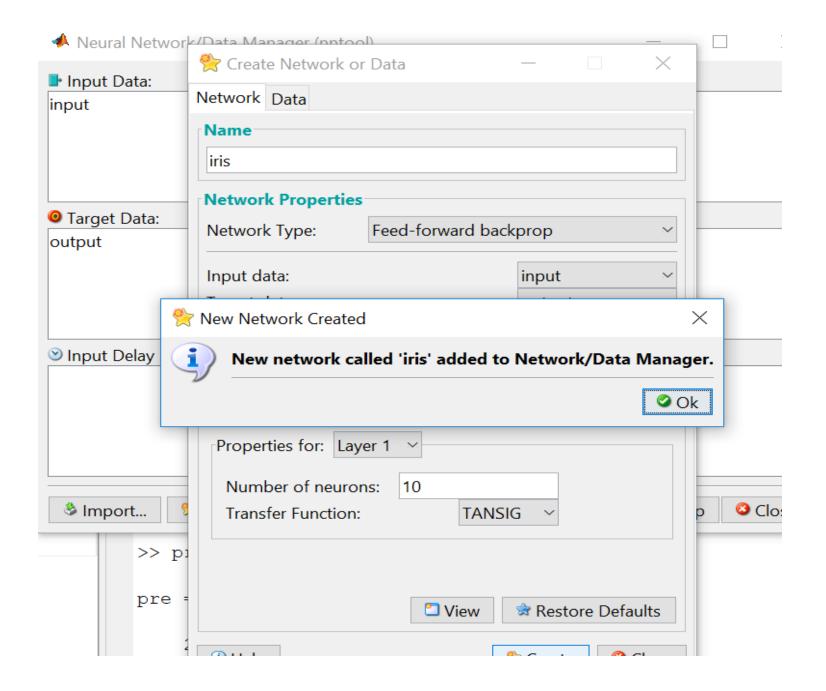


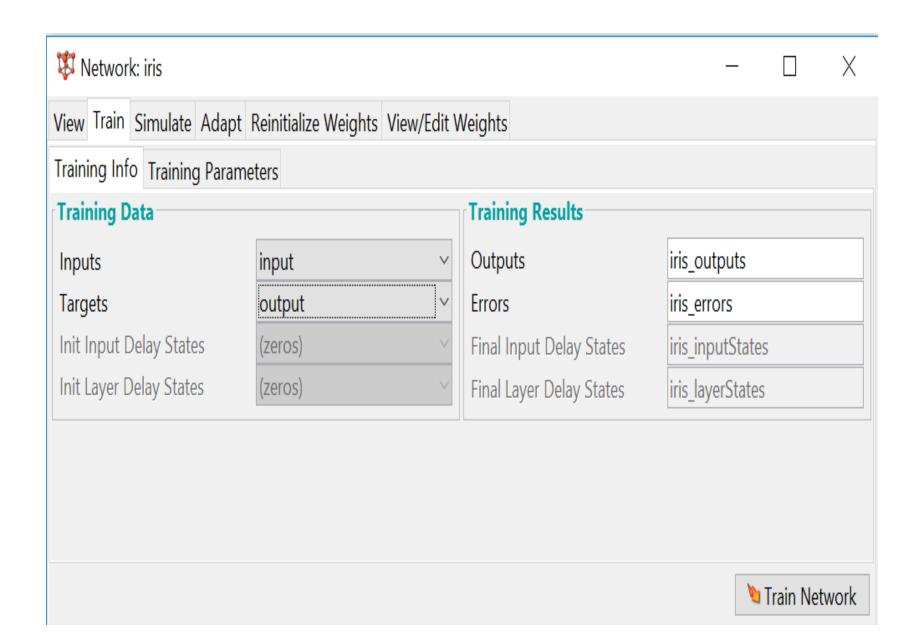
Source	Select a Variable	Destination	
Import from MATLAB workspace	(no selection)	Name	
O Load from disk file	input		
MAT-file Name	output	Import As:	
		Network	
Browse		Input Data	
		○ Target Data	
		O Initial Input States	
		O Initial Layer States	
		Output Data	
		○ Error Data	

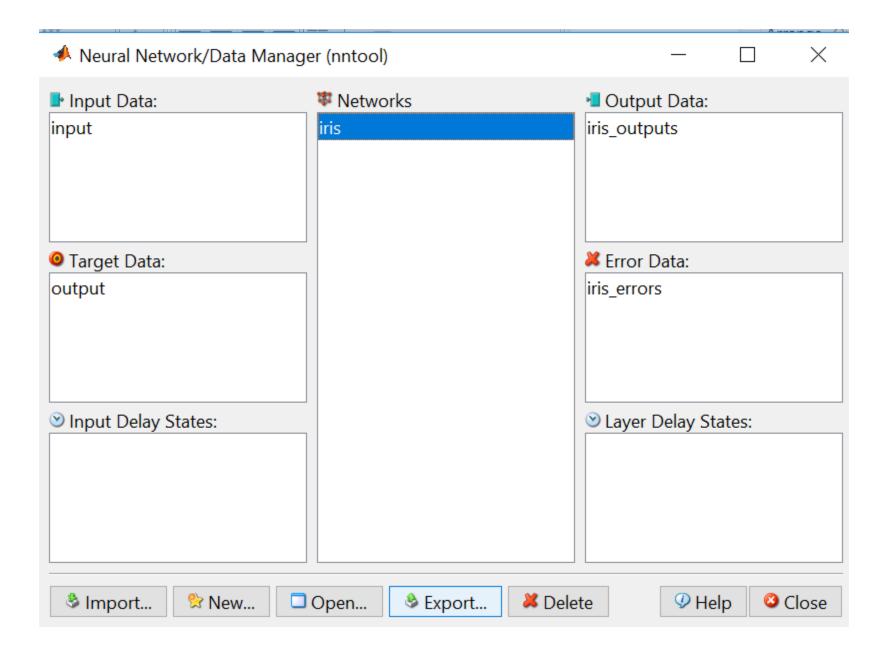


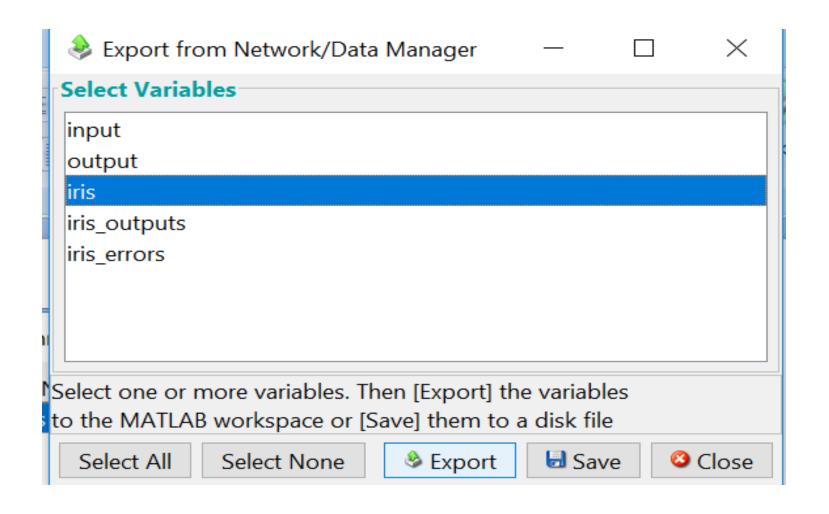












>> pre=sim(iris,test)