

Object-oriented Matlab programming for deep learning

Neural Networks

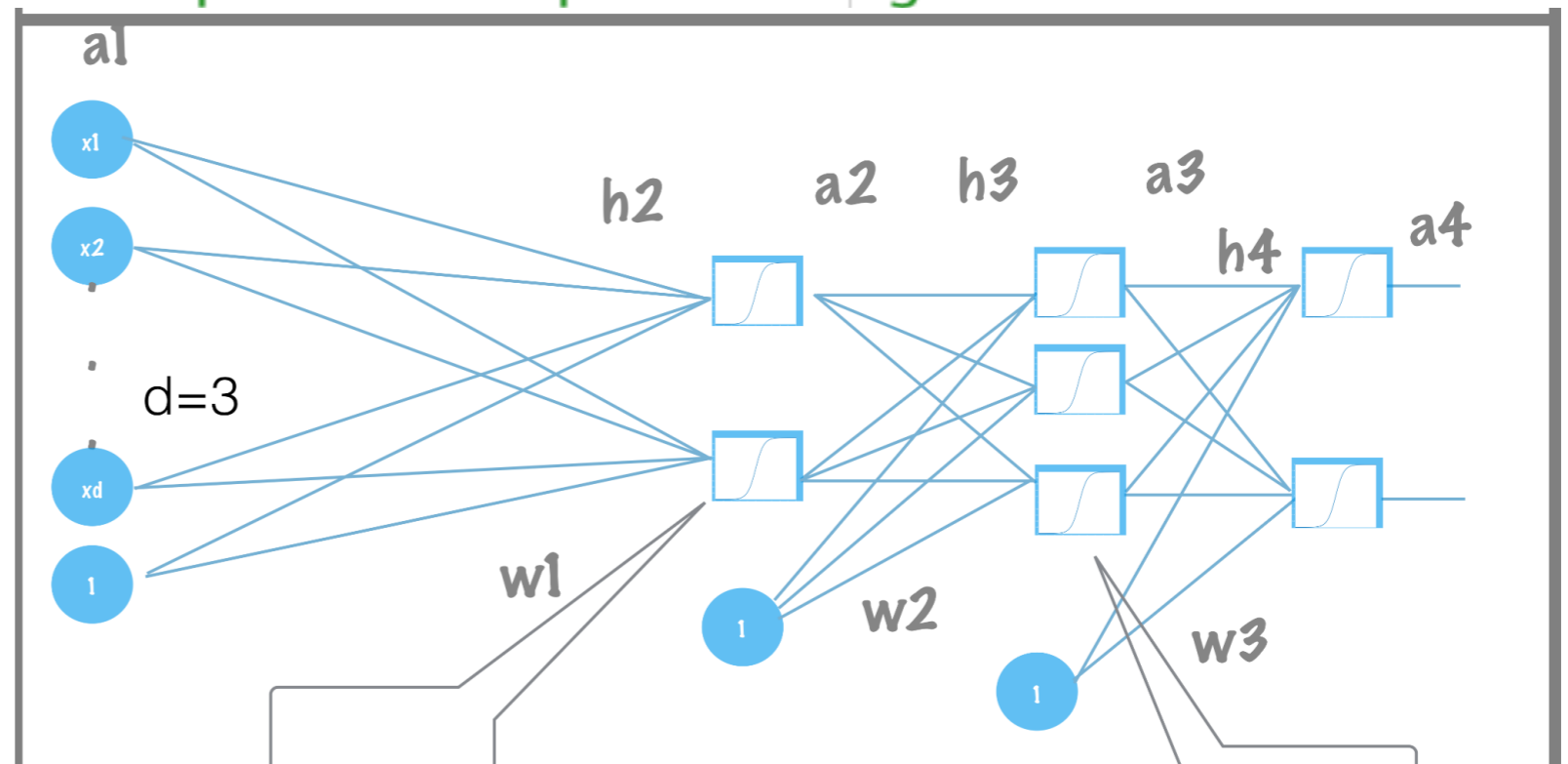
```
| classdef perceptrons  
| % Numerical Analysis of AM NDHU  
| % CopyRight Reserved  
| % Dr. Jiann-Ming Wu  
| % object-oriented programming
```

Neural networks

properties

layers; % number of layers in a network
w; % weight matrices n cells
nL; % linearity and nonlinearity of transformations of layers
a; % activation of input, hidden layers and output
u; % gradient of output with respect to activations
v; % gradient of output with respect to stimuli
gW; % gradient of output with respect to weight matrices

end



Methods

```
function obj=perceptrons(layers,w,nL)
```

```
function obj=ff(obj,x)
```

```
function draw(obj)
```

```
function obj=cal_uv(obj)
```

```
function obj=cal_gW(obj)
```

```
function err_g=gradient_check(obj,x)
```

```
function obj=perceptrons(layers,w,nL)
% This method initiates a neural network.
% w collects all weight matrices and represents them in cells.

% The length of w must be (layers - 1), where variable layers denotes the number
% all layers, including input, hidden and output layers.

% nL specifies nonlinearity of each hidden layer and output layer
% nL equals w in length
```

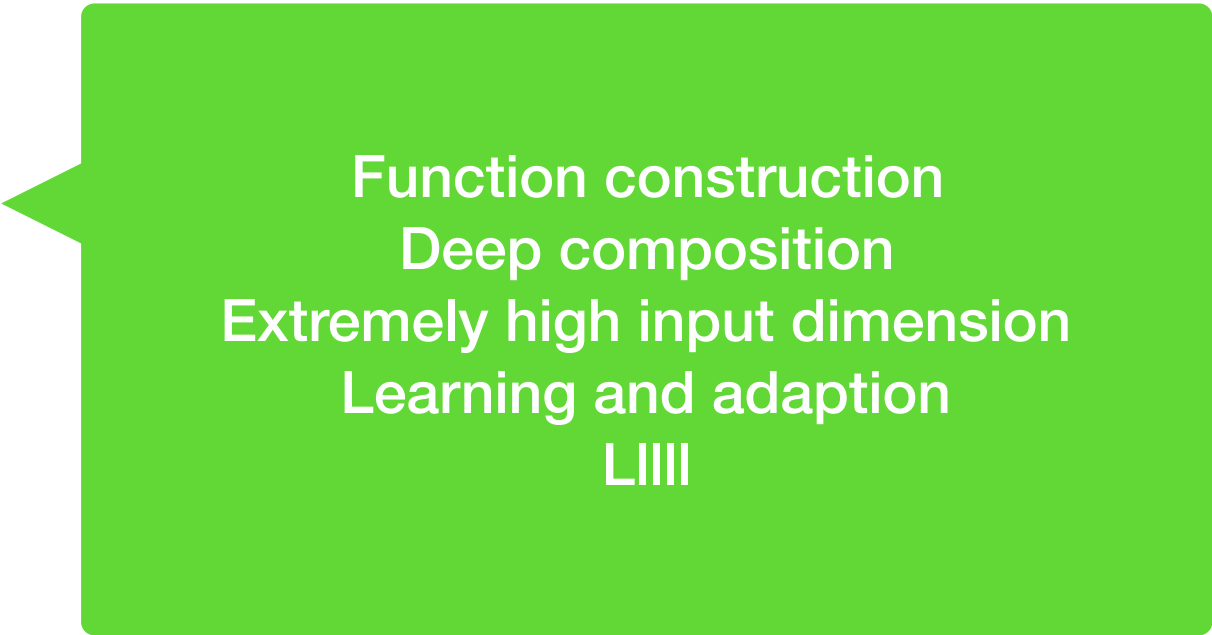
```
function obj=ff(obj,x)
```

```
% x is a matrix. Each row is an input pattern.
```

```
% This method translates x layer-by-layer forward to generate  
% activations.
```

```
% a{1} denotes input and a{end} denotes output
```

```
%
```



Function construction
Deep composition
Extremely high input dimension
Learning and adaption
LIII

```
function draw(obj)
% This method draws network functions by mesh
% It is asserted that dimension of input equals 2
% Activations will be reserved when existing
```

```

function draw(obj)
% This method draws network functions by mesh
% It is asserted that dimension of input equals 2
% Activations will be reserved when existing

[d(1) d(2)]=size(obj.w{1});
assert(d(1)==3,'exceed 2-dimensional inputs');
tag = 0;
if ~isempty(obj.a)
    ba=obj.a;
    tag = 1;
end
range=pi;
L=obj.layers;
x1=-range:0.1:range;
x2=x1;
M=size(obj.w{L-1},2);

for i=1:length(x1)

    obj=obj.ff([x1(i)*ones(length(x1),1) x2']);
    y=obj.a{L};
    for m=1:M
        C{m}(i,:)=y(:,m)';
    end
end
for m=1:M
    mesh(x1,x2,C{m}'); hold on
end
if tag==1
    obj.a=ba;
end
end
end

```



```
function obj=cal_uv(obj)
```

```
%
```

```
% calculate  $u\{n\}$  and  $v\{n\}$  for all  $n$ 
```

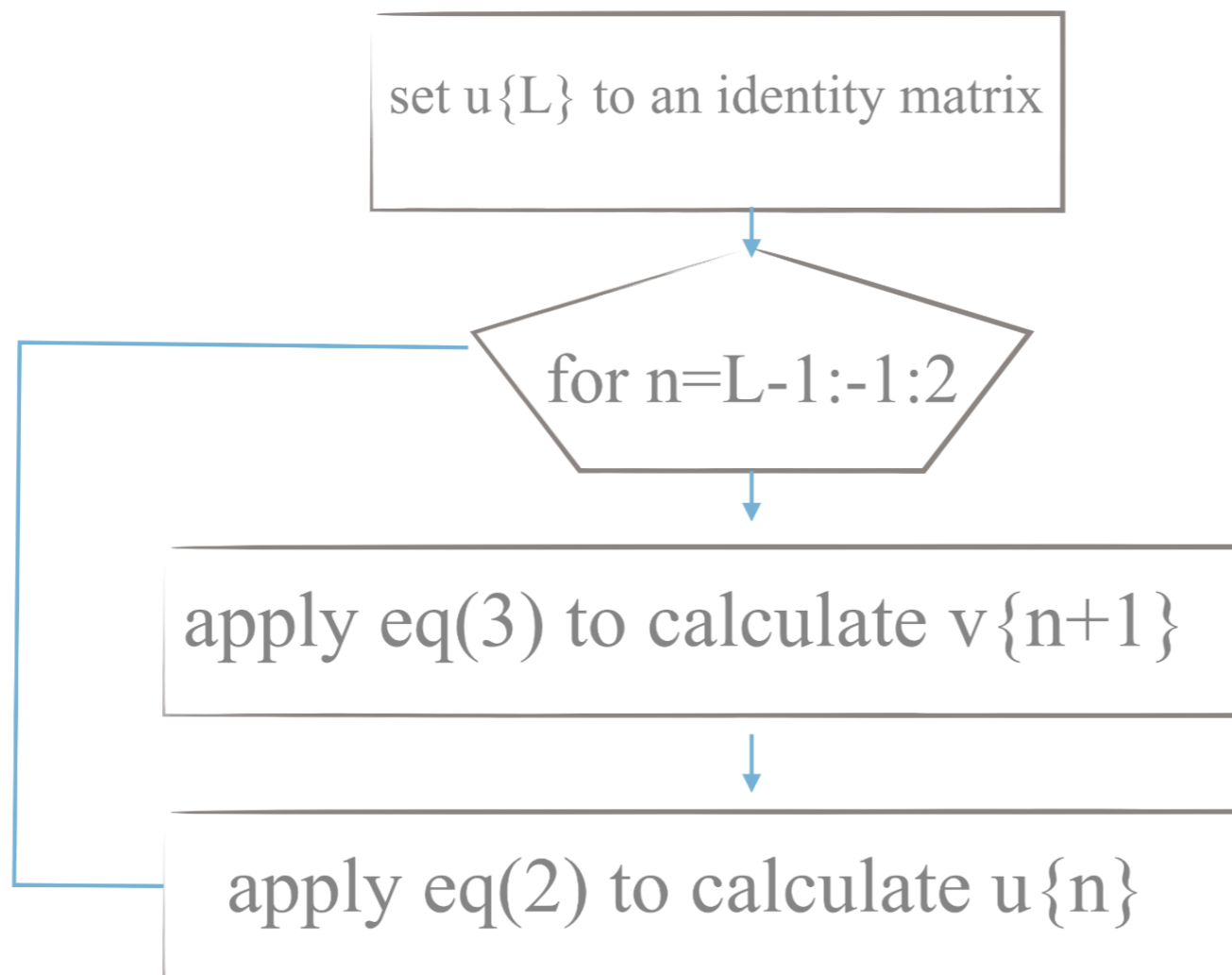
```
% according to flowchart 2 based on current activations
```

```
%  $a\{1\}$  could contain a batch of input data. This method
```

```
% realizes backpropagation. There are multiple output
```

```
% components.  $u$  and  $v$  are two-ary cells, where entries of cells correspond
```

```
% to output components and layers respectively
```



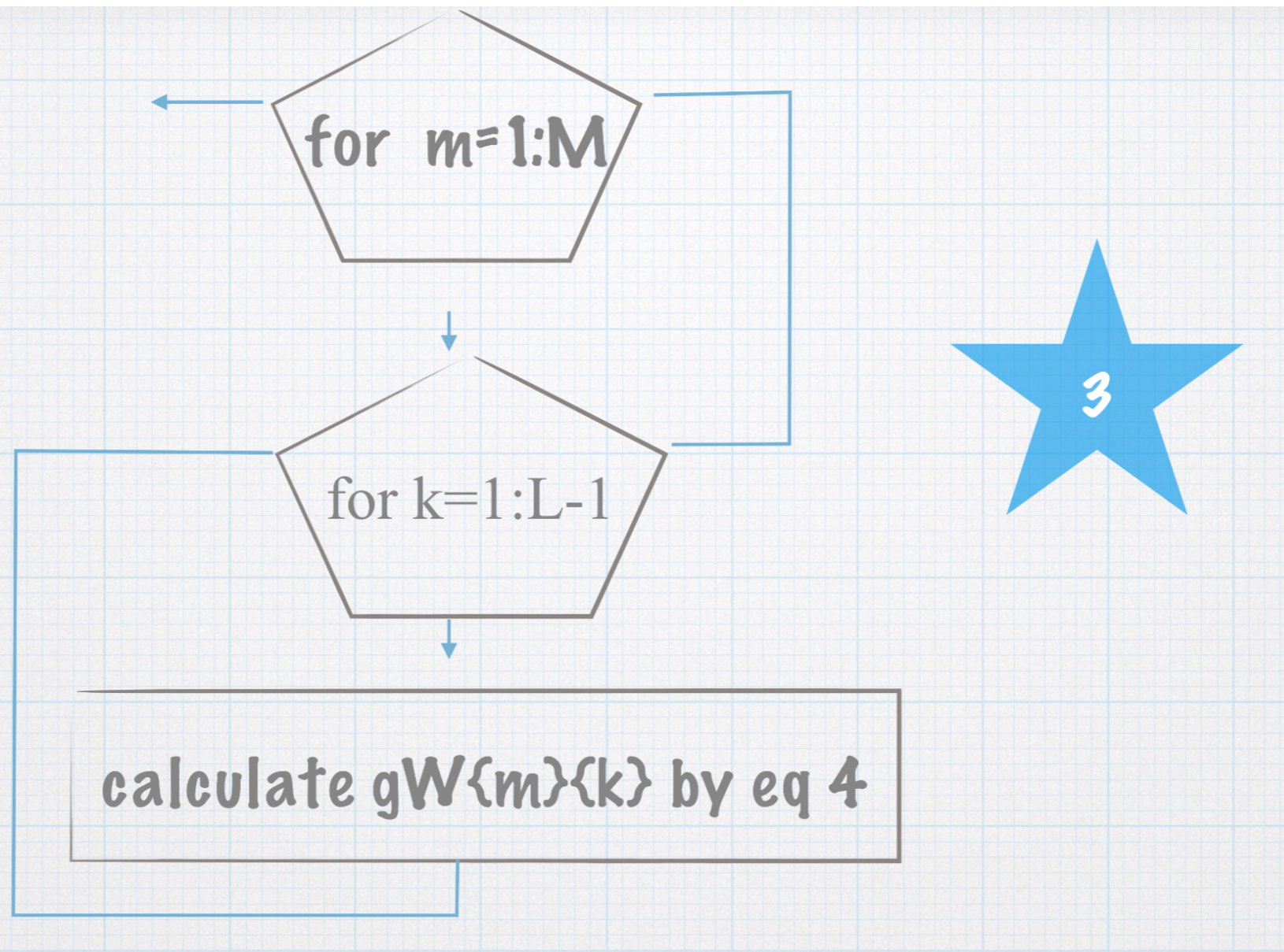
```
function obj=cal_gW(obj)
```

```
% This method calculates gradient of output with respect to w.
```

```
% It is asserted that properties a and v are provided.
```


```
% Here a{1} contains single data.
```

```
% flowchart 3
```



```
function err_g=gradient_check(obj,x)
    % Calculate gradient of output with respect to w by Richardson
    % Extrapolation by flow chart 4.
    % x contains single data
```



```
142     obj=obj.ff(x);
143     obj=obj.cal_uv();
144     obj=obj.cal_gW();
145     L=obj.layers;
146     M=size(obj.w{L-1},2);
147     z=0.01; err_g=0;
148     for m=1:M
149         for k=1:L-1
150             W_k=obj.w{k};
151             RE_gW = zeros(size(W_k));
152             for i=1:size(W_k,1)
153                 for j=1:size(W_k,2)
154                     
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163
164
165
166
167                 end
168             end
169             err_g=err_g+sum(sum(abs(obj.gW{m}{k}-RE_gW')));
170         end
171     end
```

```
% define a net of deep perceptrons
```

```
w{1}=[1 1 2;1 -1 -1]';nL{1}='tanh';
```

```
w{2}=[1 -1 1;-1 -1 -1; -2 1.5 0.5]';nL{2}='tanh';
```

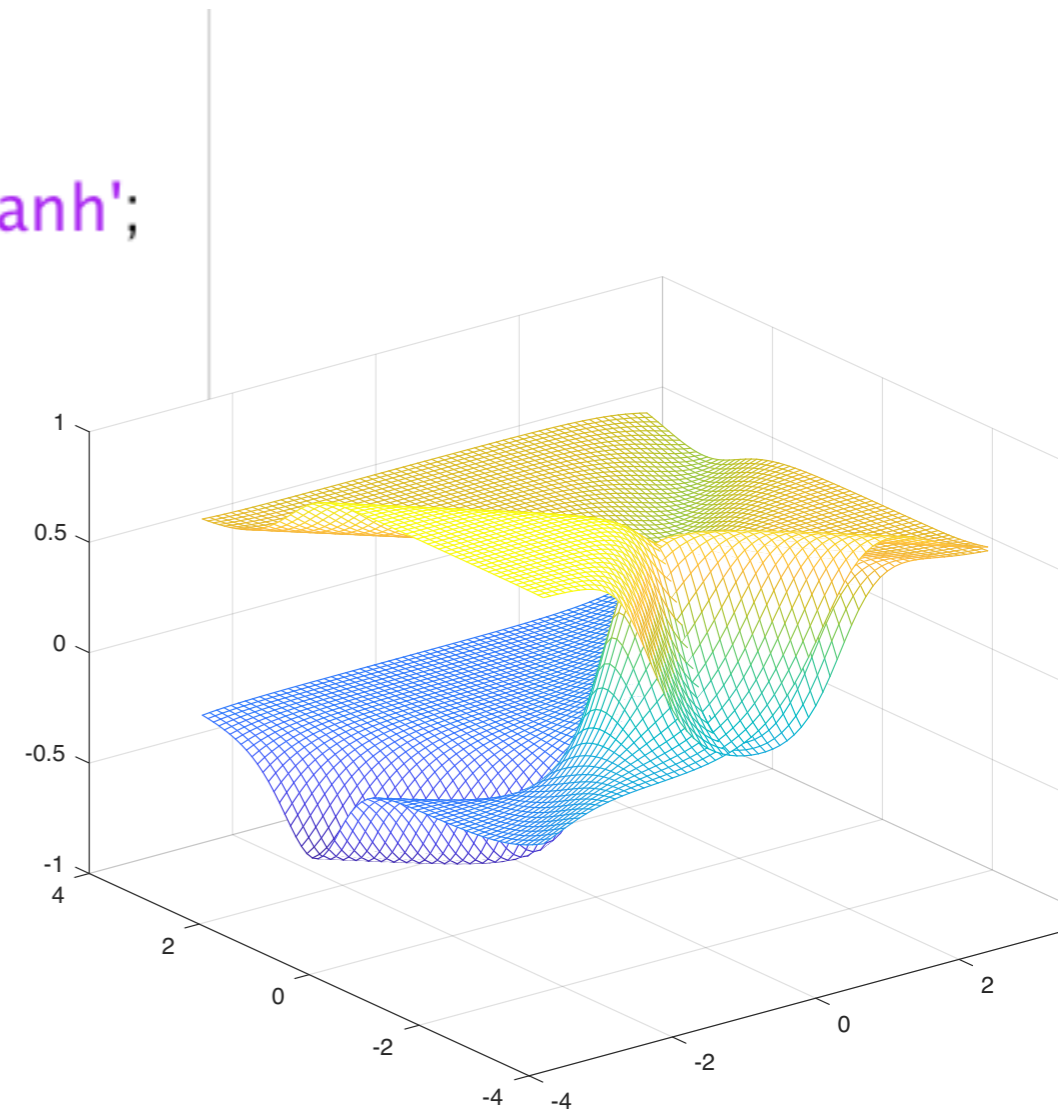
```
w{3}=[1 1 1/2 1;1 -1 1 -1]';nL{3}='tanh';
```

```
layers=4;
```

```
net=perceptrons(layers,w,nL);
```

```
% draw network functions if input dim is 2
```

```
net.draw();
```



```
x=rand(300,2)*10-5;  
net=net.ff(x);  
y=net.a{layers};  
plot3(x(:,1),x(:,2),y,'.');  
net=net.cal_uv(); % backpropagation
```

```
net=net.ff(x(10,:));  
net=net.cal_uv();  
net=net.cal_gW();
```

```
err=0;
for i=1:300
    err_g=net.gradient_check(x(i,:));
    err=err+err_g;
end
err/300
```