Level 5: AI Game Programming

Lab 5

Simple multi-layer ANN and backpropagation

RECORD ALL THAT YOU DO IN YOUR LAB LOGBOOK (HARDCOPY 'OR' WORD FILE).

God Father of AI

Geoff Hinton

Backpropagation

Video

Training a 'simple' multilayer neural network to learn a simple task.

On some occasions, the learning strategy is for you to have some experience in figuring out what is going on in the lab, and then I'll reinforce it with a detailed explanation in the following lecture. It's more effective this way to 'train' your brain to master the subject.

Actually, this is similar to many training methods used for artificial neuron networks. The networks are incrementally adjusted until they can 'learn' the subject or task.

Therefore, if you do not quite understand the whole details in the lab, that's alright. You only need to 'try' it. This will prepare your brain for the detailed discussion in the following lecture. (For those with a strong background, you can treat it as an exercise to refresh your memory.)

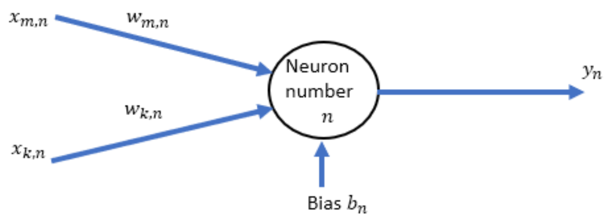
Note that training an ANN takes time; if you can't finish everything in the lab, you can carry on training and try in your own time or in the next lab.

Backpropagation

Consider the summary of the single-neuron training:

In summary:
find the ***error*** from the output of that neuron and use the error to (incrementally) adjust the weights of that ***particular*** neuron.

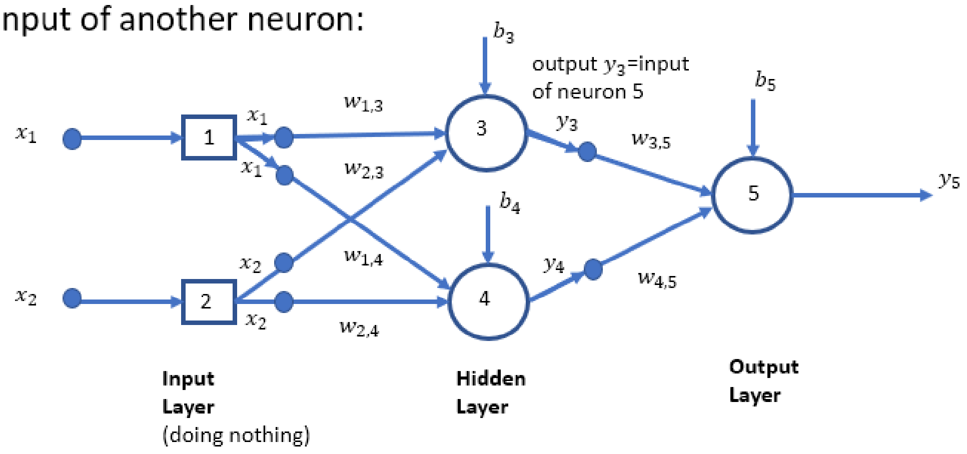
For a single neuron, it is straight forward.
We know the output of that neuron and it can be compared directly to the correct output to find the error.



At the end of the lecture on Monday, I asked:

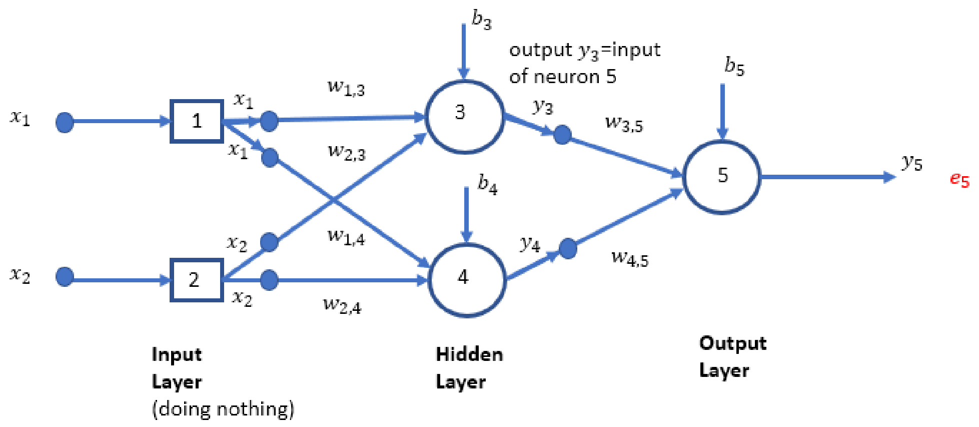
In multi-layer ANN, how could we find the error for 'each' neuron.. So that we could adjust the corresponding weights correctly?

- To make it easier to see how the output of one neuron is fed to the input of another neuron:



- The error can be can calculated by measuring the difference between the out put of the network (y_5) and the correct (desired) output, let's call it y_d. The error itself could be called e_5.
- This error can be used to adjust the weights of neuron 5 ($w_{3,5}$ and $w_{4,5}$) only.

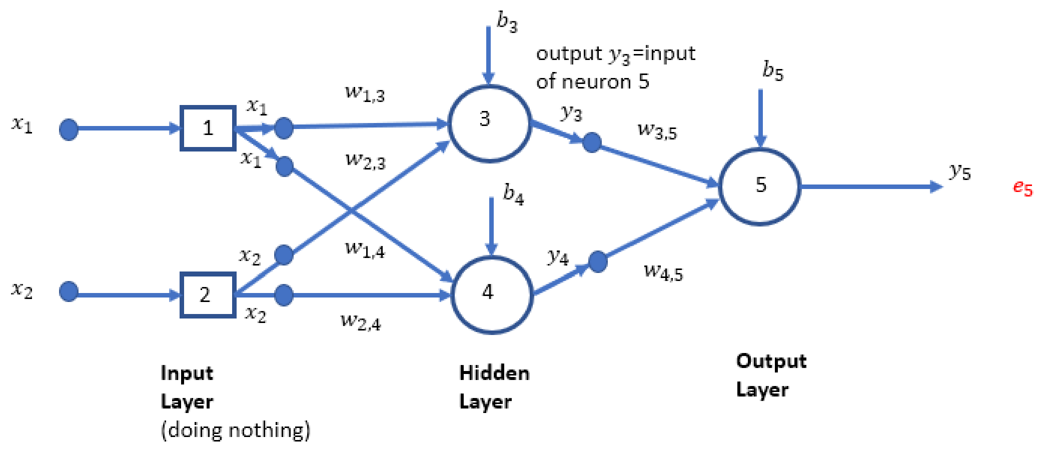
- What about the weights of neurons 3 and 4? What error values should be used?



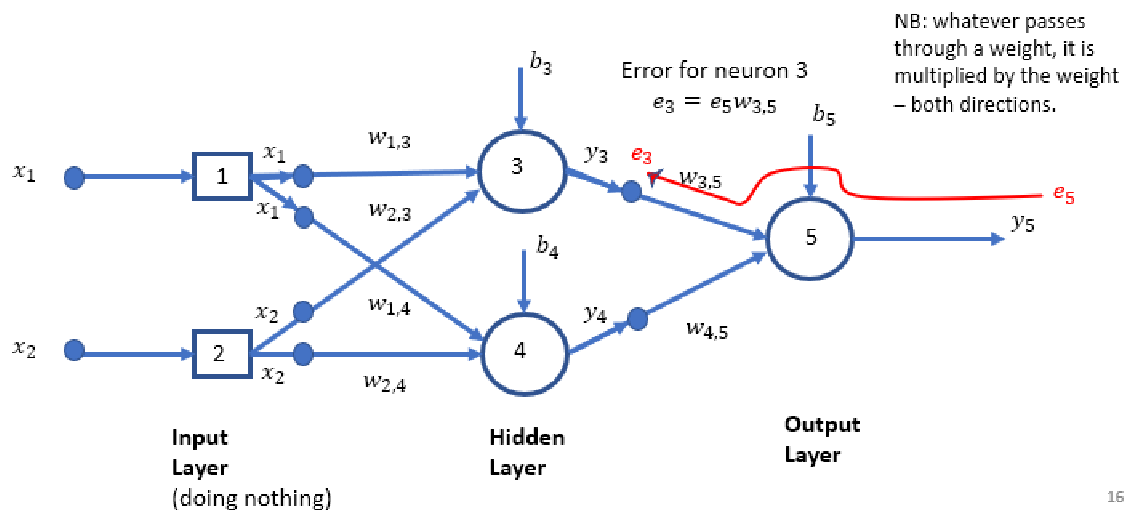
To solve the problem, we can propagate the error back to other neurons.

Backpropagation - fundamental

- *Propagate the error back* to the neurons in the hidden layer(s), so that it can be used to adjust the weights of those neurons.
- How?



The error is propagated back ***through the relevant weights*** to the relevant neurons.

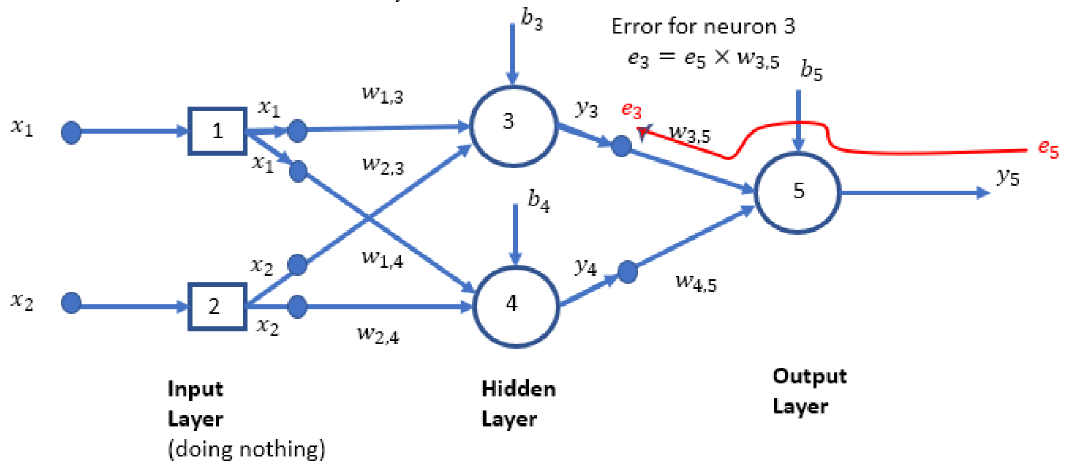


- Then the weights of neuron 3 can be adjusted by the same principle:

new weight = old weight + (learning rate x input x error)

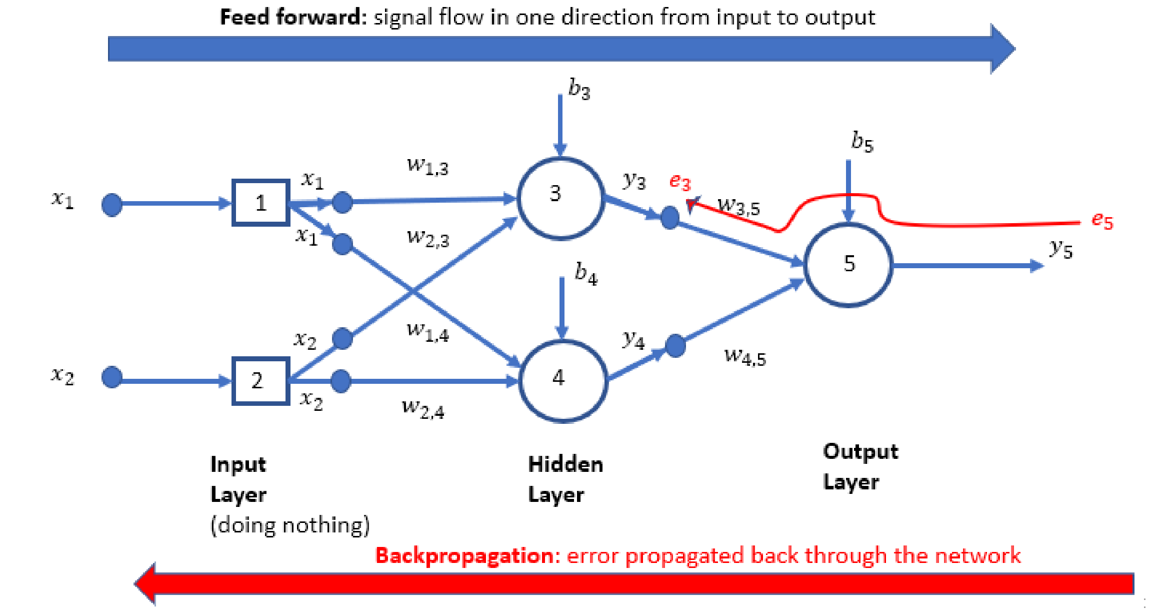
$$w'_{1,3} = w_{1,3} + \alpha x_1 e_3$$
$$w'_{2,3} = w_{2,3} + \alpha x_2 e_3$$

- Do the same for neuron 4, etc.



This is the most common type of neural networks where the data or signal flows forward and the error is propagated back to adjust the weights.

Feed forward ANN and backpropagation



Error and error gradient

In this lab, Sigmoid function will be used as the activation function and 'error gradient δ' will be used instead of 'error e' (difference between the current output and the correct output), see the figure below. Why? Please think about it, again to prepare you brain, before we discuss it in detail in the following lecture.

Hence from our example (now activation function is Sigmoid):

new weight = old weight + (learning rate x input x error gradient)

$$w'_{1,3} = w_{1,3} + \alpha x_1 e_3$$
$$w'_{2,3} = w_{2,3} + \alpha x_2 e_3$$

$$\Downarrow$$

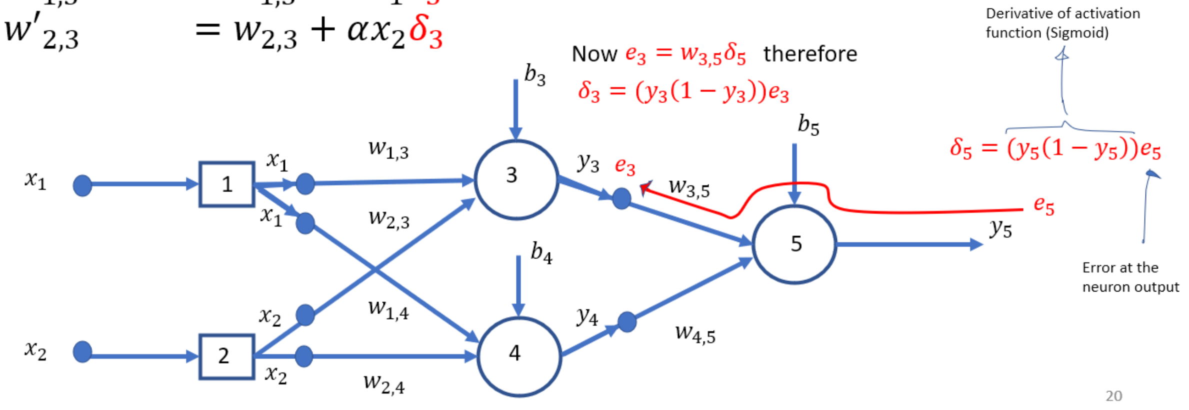
$$w'_{1,3} = w_{1,3} + \alpha x_1 \delta_3$$
$$w'_{2,3} = w_{2,3} + \alpha x_2 \delta_3$$

***Error gradient** = **derivative** of the activation function multiplied by the **error** at the neuron output*

Now $e_3 = w_{3,5}\delta_5$ therefore

$\delta_3 = (y_3(1 - y_3))e_3$

$\delta_5 = \underbrace{(y_5(1 - y_5))}_{}e_5$



TASK

Write Python code using Google Colab to implement the simple multilayer neural network above and the backpropagation training to make the network learn to handle a non-player character's decision making process in your game - that is, whether the creature will attack of flee, depending on the creature's power and enemy's power.

You may notice that the number of inputs and outputs in this example are still the same as those in our single-neuron case. This is because it's easier to manage and study. If this works, then you can easier the same method to more inputs, outputs and neurons.

(Note that for this type of decision, one neuron is not enough. If you wish, you could try it.)

INPUT		OUTPUT
Creature's power	Enemy's power	Creature's decision/action
Strong (1)	Strong (1)	Attack (0)
Weak (0)	Strong (1)	Flee (1)
Strong (1)	Weak (0)	Flee (1)
Weak (0)	Weak (0)	Attack (0)

- See an example pseudocode below; there are gaps you still need to fill. Then implement the code in Python using Google Colab.

- Pay attention to the epoch sum error used to measure if the training converts to the correct weights and biases.

- Check your results against the table. Does the training work?

Example pseudocode for this training

NB: This is an example of a very simple implementation. Once your code works, you can improve it to make it more effective and expandable to cope with more neurons, e.g. use functions and objects to represent each neuron, etc.

```
% AIGP Labs 5


Niteration = 1000000; % Number of iterations
                    %(by this number, you should have the result,
                    % otherwise, there may be something wrong in your code.

% Set initial weights and bias (normally, they are random numbers, but to
% make debugging easier, we begin with a fixed set of weights and biases
w(1,3) = 0.5; w(2,3) = 0.4;
w(1,4) = 0.9; w(2,4) = 1.0;
w(3,5) = -1.2; w(4,5) = 1.1;
Bias(3) = 0.8; Bias(4) = -0.1; Bias(5) = 0.3;

Alpha = 0.1; % Learning rate

%Prepare training data - inputs and correct outputs according to the
%decision table for the ANN to learn
```

```
x1(1) = 1; x2(1) = 1; Yd5(1) = 0; % Case 1
x1(2) = 0; x2(2) = 1; Yd5(2) = 1; % Case 2
x1(3) = 1; x2(3) = 0; Yd5(3) = 1; % Case 3
x1(4) = 0; x2(4) = 0; Yd5(4) = 0; % Case 4

p = 1; % iteration number

while p <= Niteration
    EpocSumError = 0; % Initiate the termination condition value

    % Begining of an Epoch
    for i = 1:4 % Case number
        p % print iteration number

        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % FEED FORWARD
        % Calculate output for neuron 3
        X(3) = x1(i)*w(1,3)+x2(i)*w(2,3)+Bias(3);
```

```
       % Activation Function - Sigmoid function (y = 1/(1+e^-X))
       % Note: exp(1) = e^1 = 2.7183 (Euler’s number)
      % (see the labsheet and lecture notes last week)
        y(3) = …..[You need to find out here how to calculate output y(3) of
neuron 3]

        % Calculate output for neuron 4
        X(4) = x1(i)*w(1,4)+x2(i)*w(2,4)+Bias(4);
        % Activation Function - Sigmoid function
        y(4) = …..[You need to find out here how to calculate output y(4) of
neuron 3]

        % Calculate output for neuron 5
        X(5) = y(3)*w(3,5)+y(4)*w(4,5)+Bias(5);
        % Activation Function - Sigmoid function
        y(5) = …..[You need to find out here how to calculate output y(5) of
neuron 3]


        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % BACK PROPAGATION
        % Back propagate the error and use the learning rule to update the
        % weights

        % Starting from neuron 5

        %.......................................................
        % COST FUNCTION
        % Calculate the cost (error) at the output of the network to propage back
        % through the network
        % Note that this one is the simplest cost (error) function (see the
        % lecture notes). It is used to update the weights in the case,
        % then use the new weights for the next case in the Epoch.

        % Later, you could try other cost function such as Quadratic cost
        % (see the lecture notes), but be aware, for Quadratic cost, you
        % first calculate the cost (error) from all cases in the Epoch, then use
        % that cost to propagate back and update the weights.
        e(5) = Yd5(i) - y(5);
        %..................................................................

        Delta(5) = y(5)*(1-y(5))*e(5);
        Wcurrent(3,5) = w(3,5); % safe the current value before updating it
        Wcurrent(4,5) = w(4,5); % safe the current value before updating it
        w(3,5) = w(3,5) + Alpha*y(3)*Delta(5);
        w(4,5) = w(4,5) + Alpha*y(4)*Delta(5);
        Bias(5) = Bias(5) + Alpha*(1)*Delta(5);

        % Neuron 3
        Delta(3) = y(3)*(1-y(3))*Delta(5)*Wcurrent(3,5);
        w(1,3) = w(1,3) + Alpha*x1(i)*Delta(3);
        w(2,3) = w(2,3) + Alpha*x2(i)*Delta(3);
        Bias(3) = Bias(3) + Alpha*(1)*Delta(3);

        % Neuron 4
        Delta(4) = y(4)*(1-y(4))*Delta(5)*Wcurrent(4,5);
        w(1,4) = w(1,4) + Alpha*x1(i)*Delta(4);
        w(2,4) = w(2,4) + Alpha*x2(i)*Delta(4);
        Bias(4) = Bias(4) + Alpha*(1)*Delta(4);

        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % Check the error for the whole epoch (all cases) to see if the set
        % of the weights and biases produce correct outputs for all cases
        % (Epoch).
        % Note that if you use Quadratic cost, then you can use the
        % Quadratic cost value as the condition, don't need to calculate
        % this part

        % Accumulating the sum of 'squared' errors in the Epoch
        % Recalculate the error at the end e(5) after updating all the
        % weights and biases
       % [Check what the code below means, why?]
         tX(3) = x1(i)*w(1,3)+x2(i)*w(2,3)+Bias(3);
         ty(3) = 1/( 1 + (exp(1))^(-(tX(3))));
         tX(4) = x1(i)*w(1,4)+x2(i)*w(2,4)+Bias(4);
         ty(4) = 1/( 1 + (exp(1))^(-(tX(4))));
         tX(5) = ty(3)*w(3,5)+ty(4)*w(4,5)+Bias(5);
         ty(5) = 1/( 1 + (exp(1))^(-(tX(5))));
         te(5) = Yd5(i) - ty(5);
         % Squared error
        EpocSumError =  EpocSumError + (te(5))^2; %[What is EpocSumError? What
does it do?]
        p = p+1;

    end % for i = 1:4

 % The training process is repeated until the sum of squared error in
    % The Epoch is acceptable, i.e. less than, for example, 0.001. We have to do
this because you won’t get the exact zero error
*** Put termination condition here ****
    EpocSumError
    if EpocSumError < 0.001 % Example
        break
    end


end % while p <= Niteration
```

When programming, it is a good practice to check carefully. For each step, check the results against the equations to ensure that the code is correct before running the whole thing for many iterations. This is a good way to practice implementing and debugging your code.

For example, in the first iteration, the values of the variables should be as follows. If your code produces results far from the values below, then you need to check for bugs:

First iteration p = 1
y(3) = 0.8455
y(4) = 0.8581
y(5) = 0.5571
e(5) = -0.5571
Delta(5) = -0.1375
w(3,5) = -1.2116
w(4,5) = 1.0882
Bias(5) = 0.2863
Delta(3) = 0.0215
w(1,3) = 0.5022
w(2,3) = 0.4022
Bias(3) = 0.8022
Delta(4) = -0.0184
w(1,4) = 0.8982
w(2,4) = 0.9982
Bias(4) = -0.1018
te(5) = -0.5483
EpocSumError = 0.3007

SOLUTIONS

The final weights and biases should be (approximately):

w(1,3) = 4.5742
w(1,4) = 6.6165
w(2,3) = 4.5669
w(2,4) = 6.5849
w(3,5) = -10.5474
w(4,5) = 9.7713

Bias(3) = -7.0188; Bias(4) = -2.9530; Bias(5) = -4.5013

Note that, from a multi-layer ANN, you won't get the clear, exact values for the desired outputs and exact zero errors. For example:

Inputs		Desired output	Actual output	Error	Sum of squared
x_1	x_2	y_d	y_5	e	errors
1	1	0	0.0155	−0.0155	0.0010
0	1	1	0.9849	0.0151	
1	0	1	0.9849	0.0151	
0	0	0	0.0175	−0.0175	