

Data Mining and Machine Learning

Assignment Project Exam Help Introduction to Artificial Neural Networks

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Objectives

- Introduce Artificial Neural Networks (ANNs)
- Feed-forward ANNs – **Multi-Layer Perceptrons** (MLPs) **Assignment Project Exam Help**
- Basic MLP calculations **<https://powcoder.com>**
- Geometric interpretation of MLPs **Add WeChat powcoder**



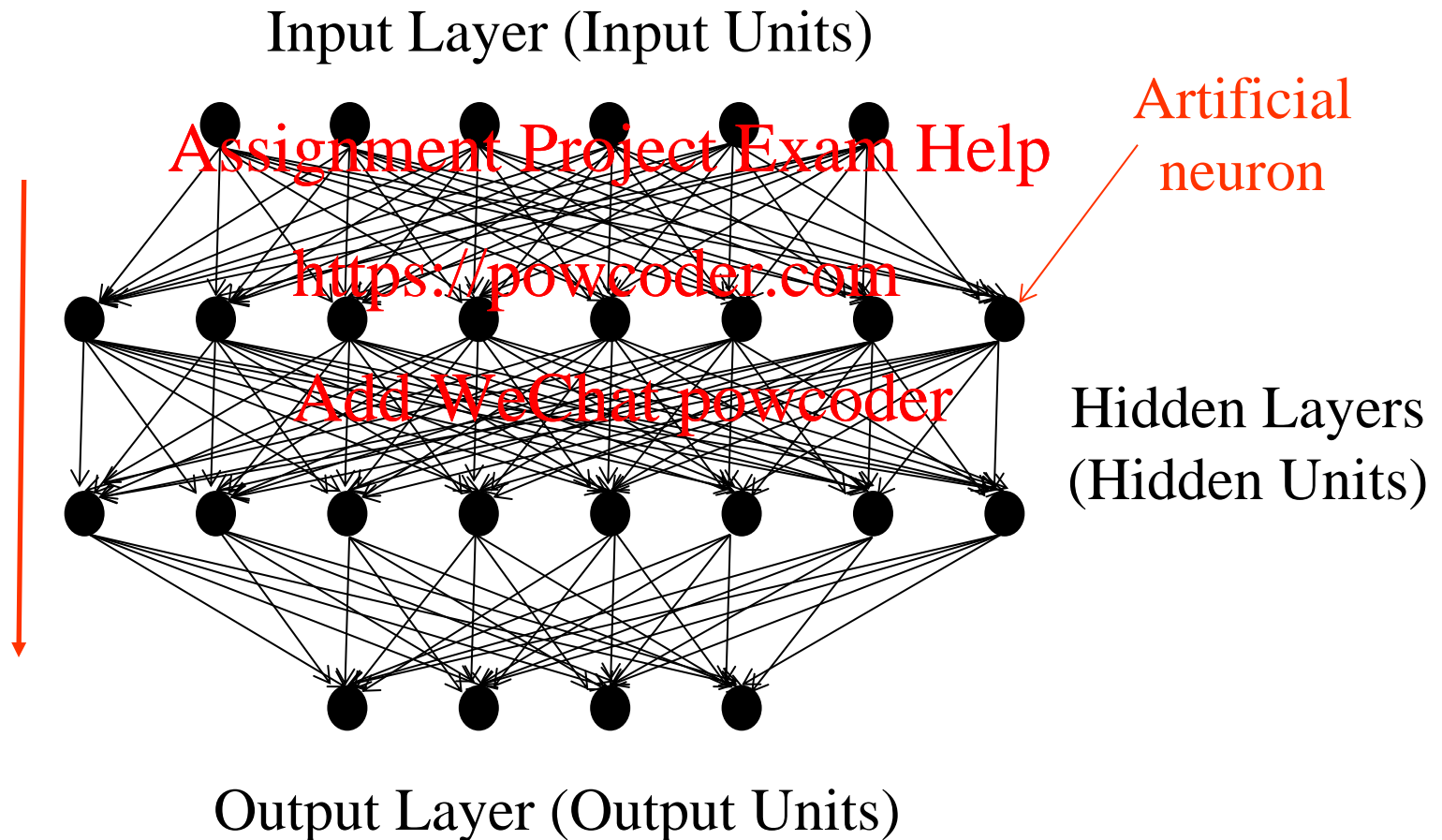
Artificial Neural Networks

- (Artificial) Neural Networks (NNs) offer another approach to data analysis
- Popularised in 1980s, resurgence in 2000s
- “Machine learning” (or most recently “AI”) often synonymous with the use of NNs
- Inspiration for the basic elements of a NN (artificial neuron) comes from biology, but analogy stops there
- ANNs are just a computational device for processing patterns – not “artificial brains”

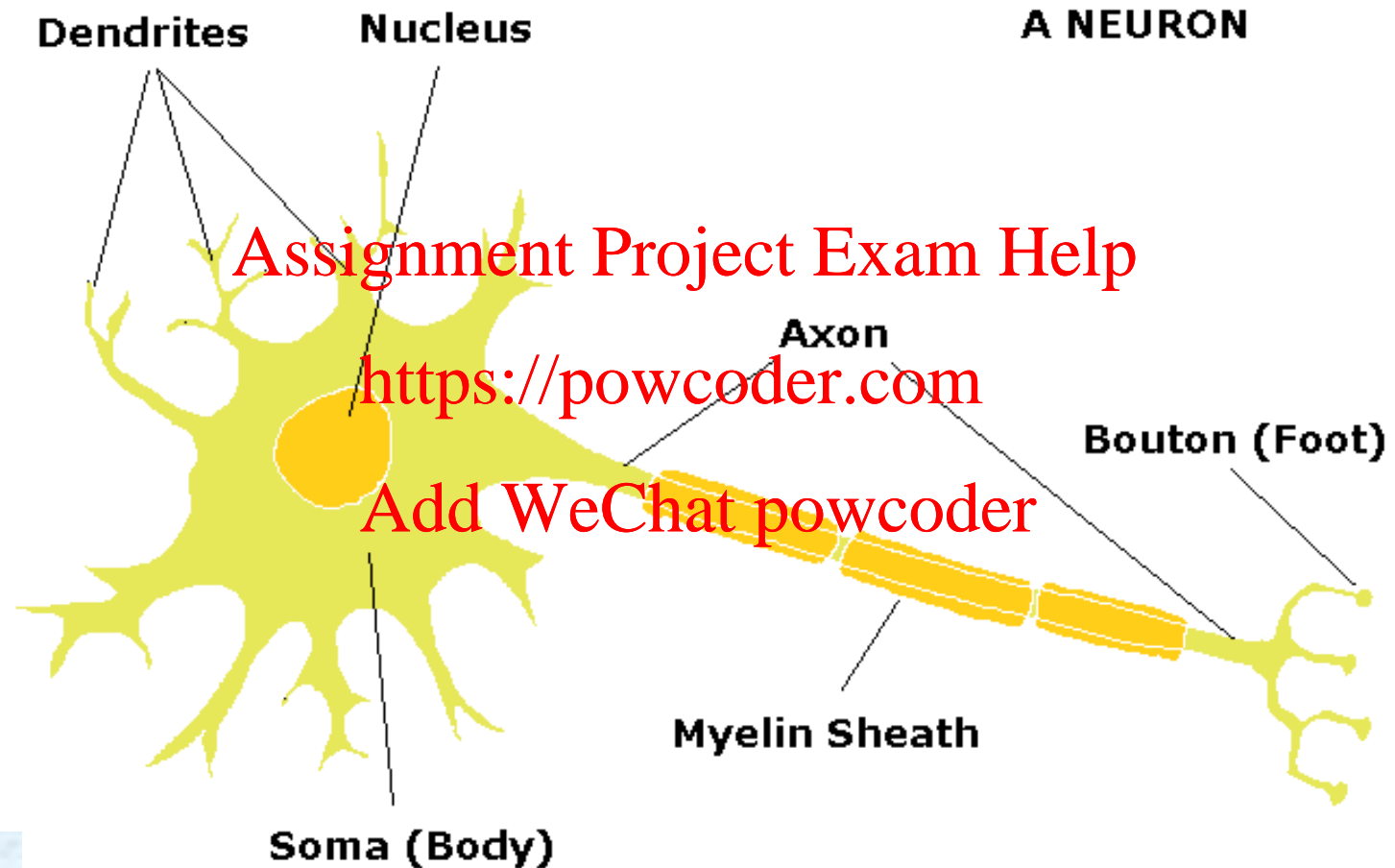


Feed-forward Neural Networks

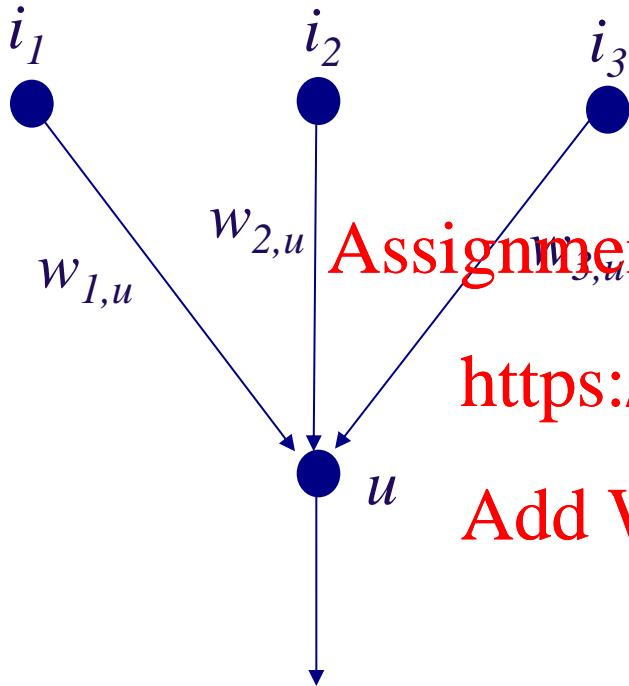
Multi-Layer Perceptron - Feed-Forward Neural Network



A simple model of a neuron



A Simple Artificial Neuron



- Basic idea –

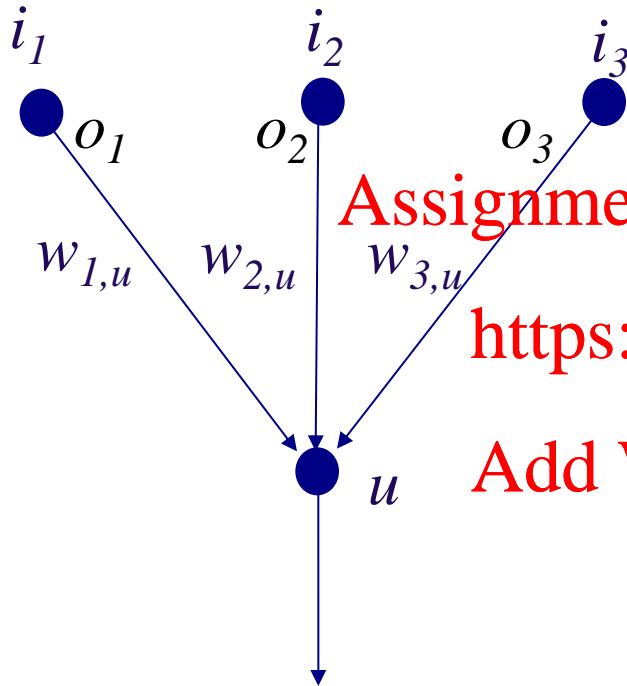
- if the input i_u to unit u is big enough, the neurone ‘fires’

- Otherwise nothing happens

- How do we calculate the input to u ?



Artificial Neurone (2)



- Suppose the inputs to units 1, 2 and 3 are i_1 , i_2 and i_3 and these are also the outputs o_1 , o_2 and o_3

- Then the input to u is:

$$i_u = o_1 w_{1,u} + o_2 w_{2,u} + o_3 w_{3,u}$$

- In general, for an artificial neuron u that receives input from N units, the input to unit u is:

$$i_u = \sum_{n=1}^N o_n w_{n,u}$$



The sigmoid activation function

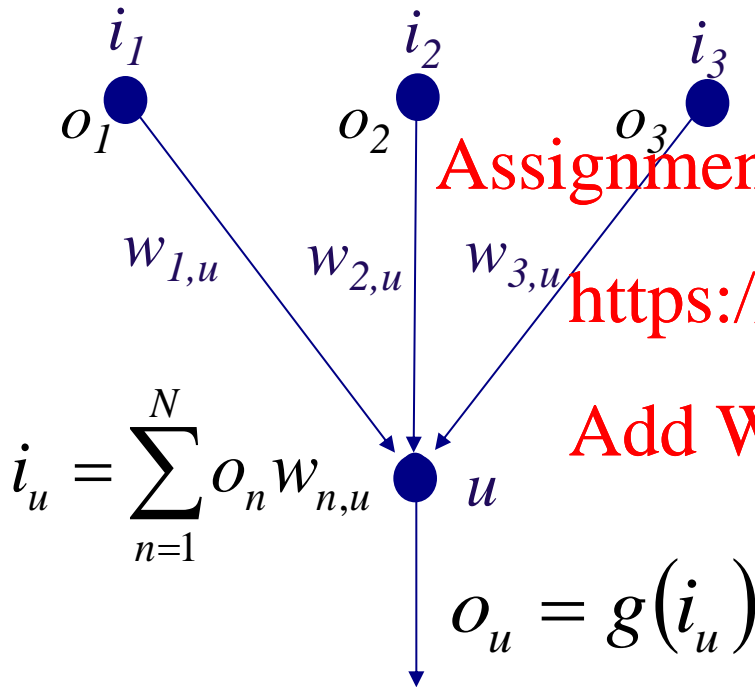
- The activation function defines the output of a neuron - whether the neuron should “fire”

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A typical activation function is the sigmoid function g :

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$$g(x) = \frac{1}{1 + e^{-kx}}$$



- The output of u is then:

$$o_u = g(i_u)$$



Activation functions

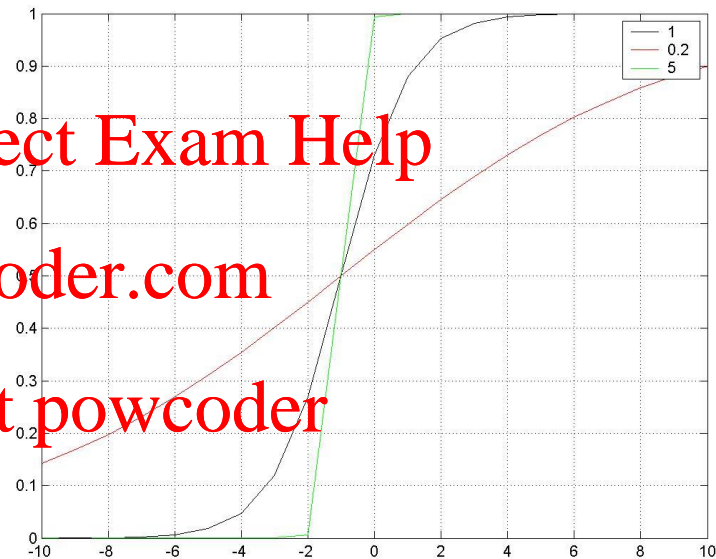
- Linear activation function
(output equals input):

$$g(x) = x$$

- Sigmoid activation function:

$$g(x) = \frac{1}{1 + e^{-kx}}$$

- The sigmoid is a ‘soft’ threshold function

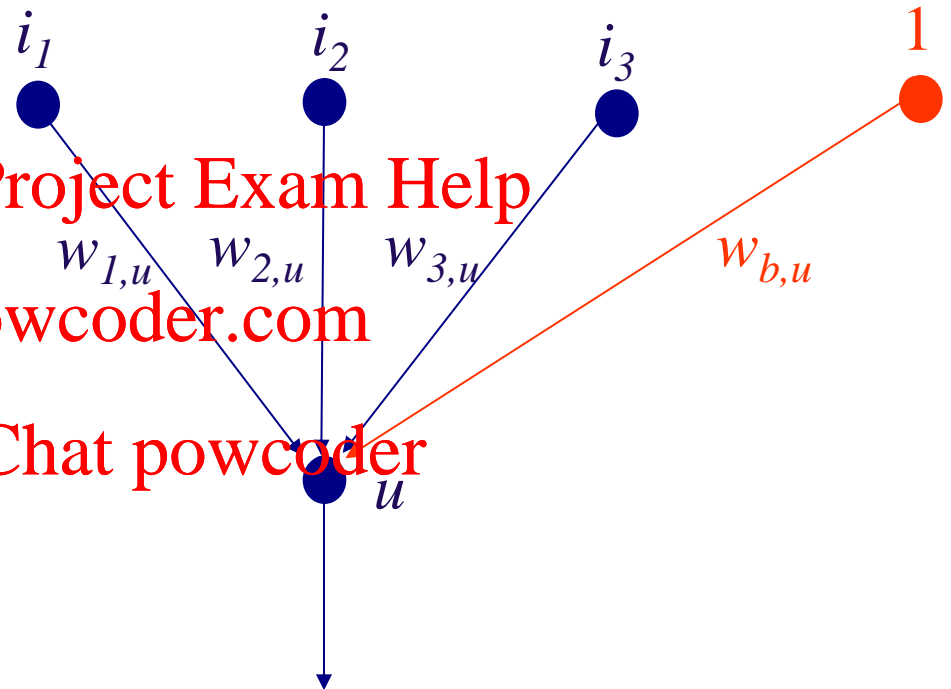


Sigmoid activation function



The 'bias'

- As described, the neuron will 'fire' only if its input is greater than 0
- We can change the value of the point of firing by introducing a bias
- This is an additional input unit whose input is fixed at 1



How the bias works...

- According to the sigmoid activation function, the artificial neuron u ‘fires’ if the input to u is greater than or equal to 0

- i.e: $i_u = o_1 w_{1,u} + o_2 w_{2,u} + o_3 w_{3,u} + w_{b,u} \geq 0$

- But this happens only if

$$i_1 w_{1,u} + i_2 w_{2,u} + i_3 w_{3,u} \geq -w_{b,u}$$

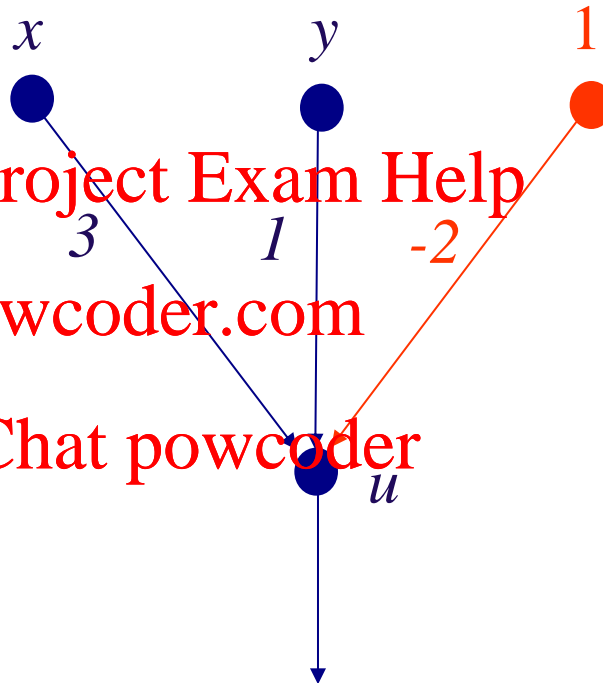


Example (2D)

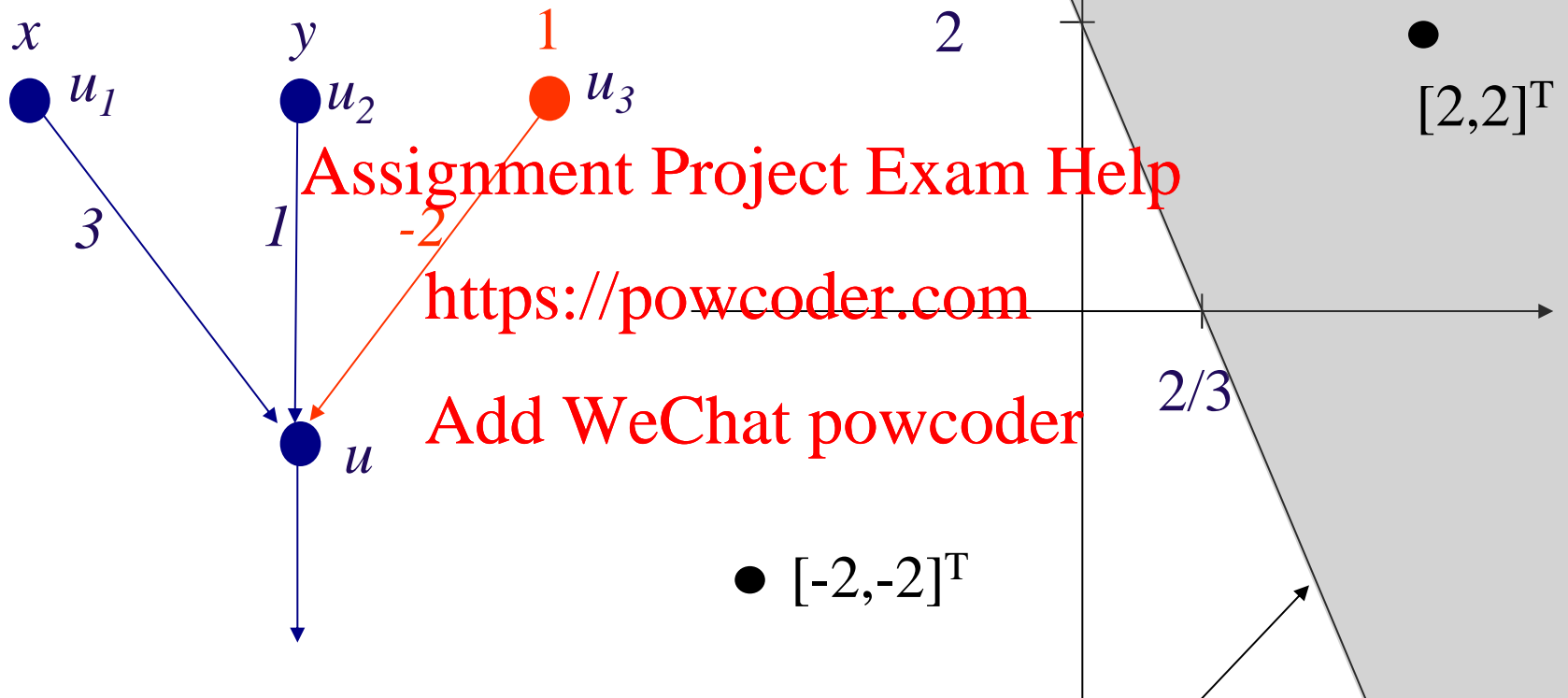
- Suppose u has a sigmoid activation function. Then, for these values of weight, u will 'fire' if:

$$i_u = 3x + y - 2 \geq 0$$

$$\text{i.e. } y \geq -3x + 2$$



Example (continued)



A single artificial neuron
defines a linear decision
boundary

$$y = -3x + 2$$

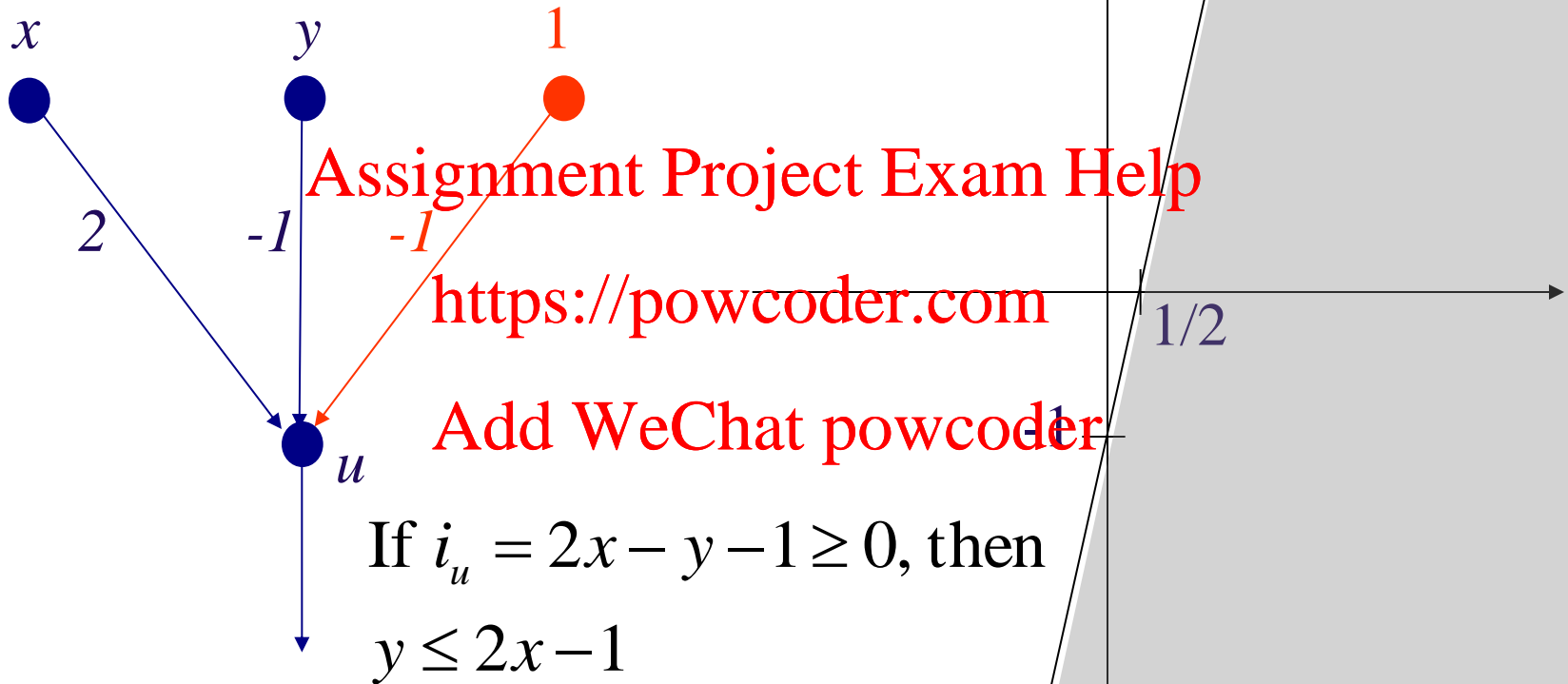


Example (continued)

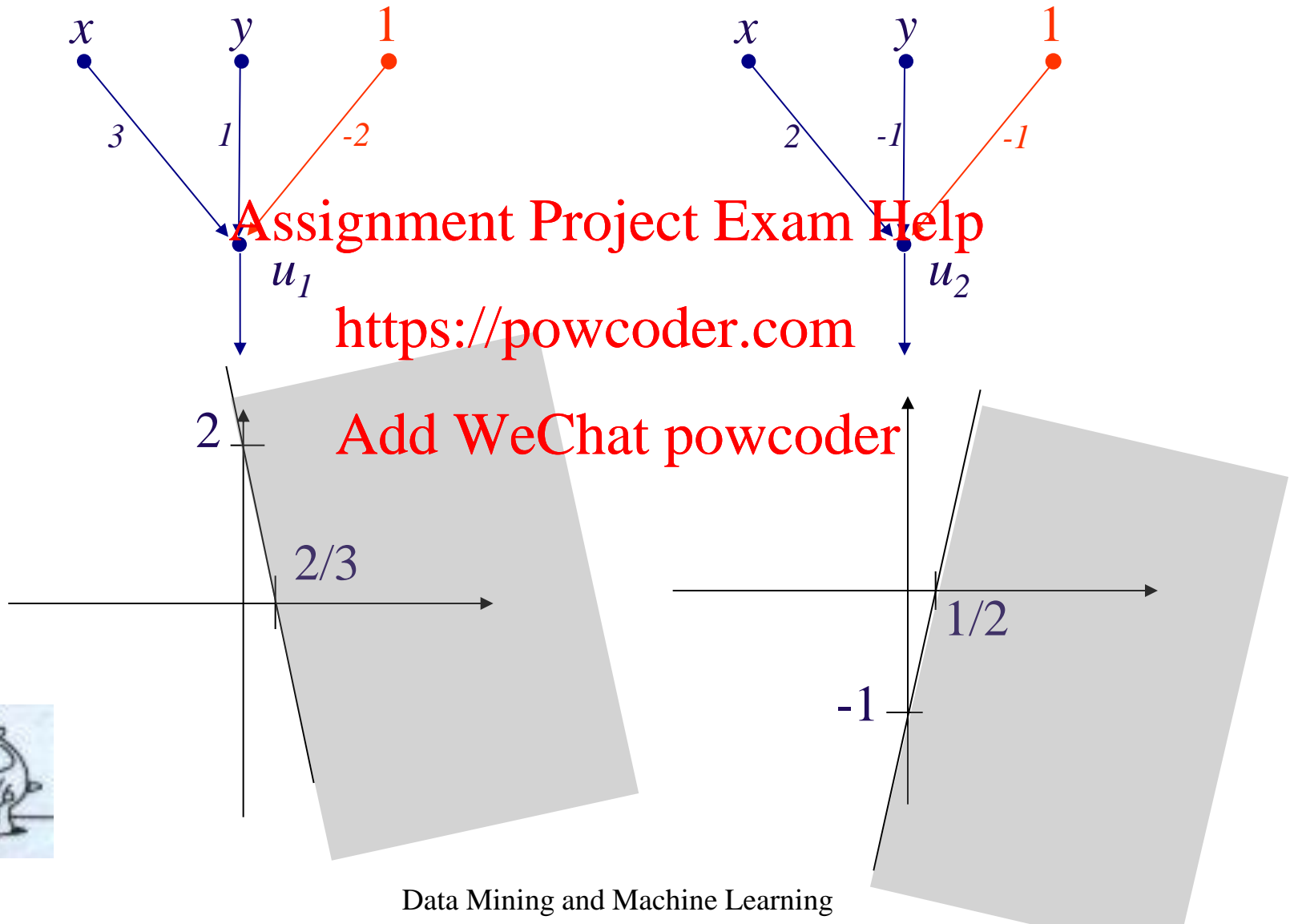
- Assume
 - Linear activation functions for units u_1 , u_2 and u_3
 - Sigmoid activation function for u
- Case1: input to u_1 is 2 and input to u_2 is 2, then:
 - Input i_u to u is $2 \times 3 + 2 \times 1 + 1 \times (-2) = 6$
 - Hence output o_u from u is $g(6) = 0.998$
- Case 2: input to u_1 is -2 and input to u_2 is -2, then:
 - Input i_u to u is $-2 \times 3 + -2 \times 1 + 1 \times (-2) = -10$
 - Hence output o_u from u is $g(-10) = 4.54 \times 10^{-5} \approx 0$



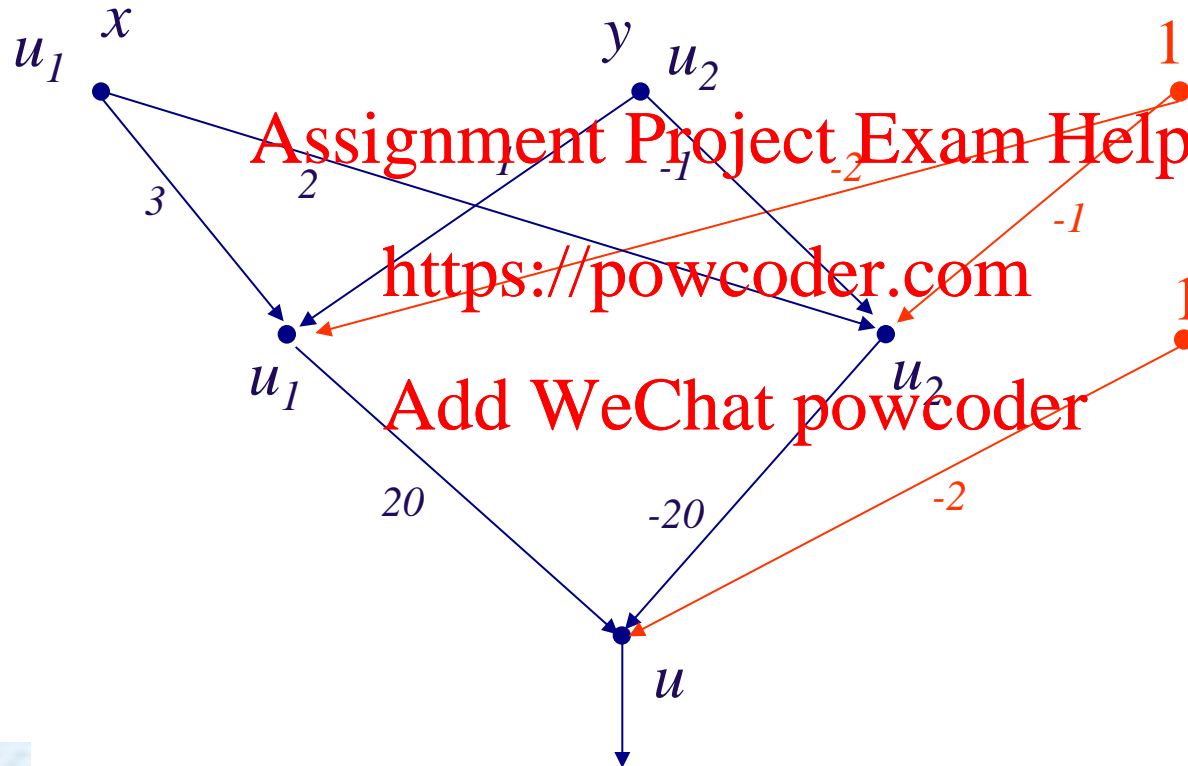
Example 2



Combining 2 Artificial Neurons

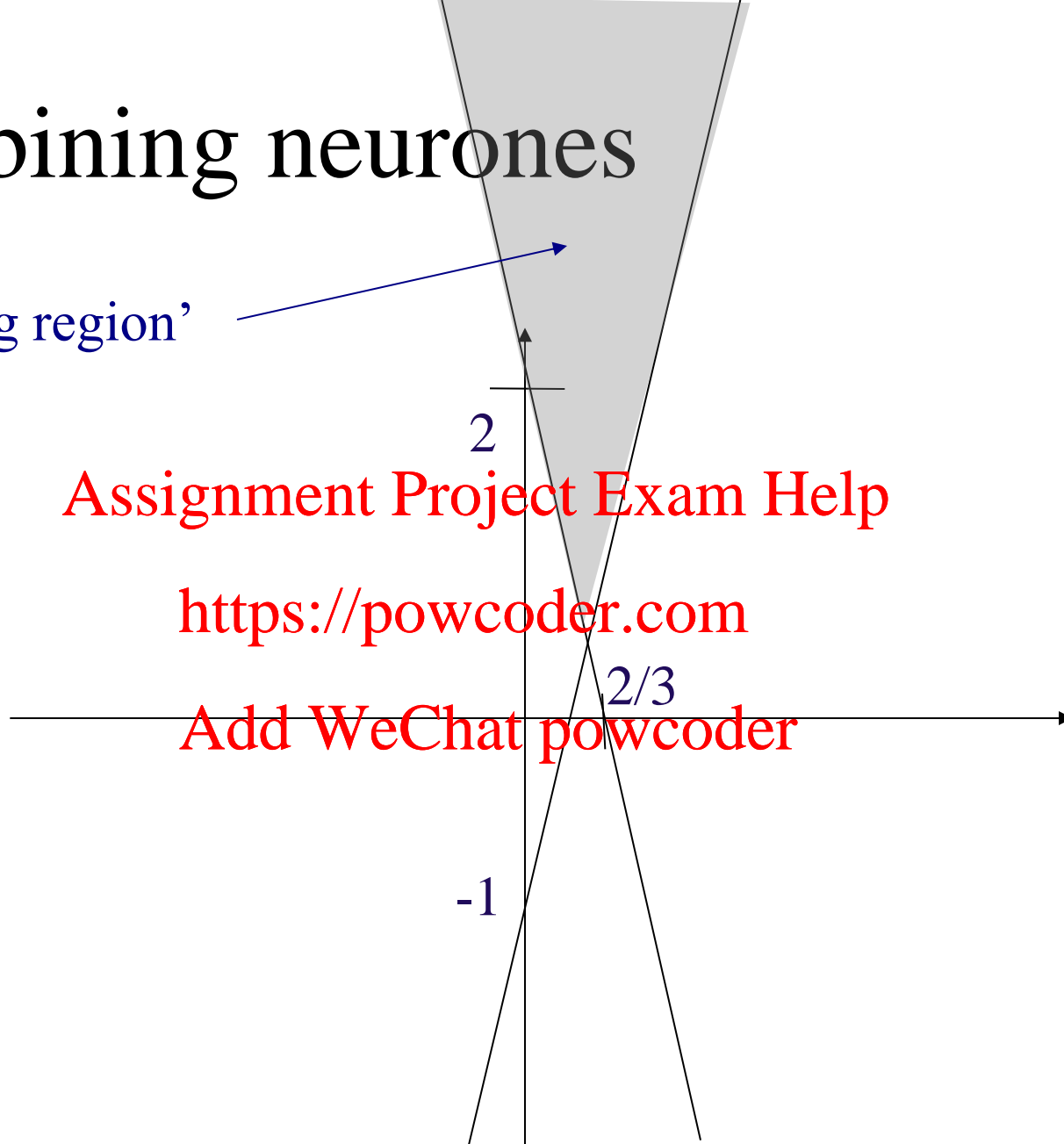


Combining neurons – artificial neural networks



Combining neurones

‘firing region’



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Combining neurons

- Input to u_1 is $3x + y - 2$
- Input to u_2 is $2x - y - 1$
- When $x = 3, y = 0$
 - Input i_{u1} to u_1 is 7, input i_{u2} to u_2 is 5
 - Output o_{u1} from u_1 is 1, output o_{u2} from u_2 is 0.993
 - Input i_u to u is $1 \times 20 + 0.993 \times (-20) - 2 = -1.88$
 - Output o_u from u is $g(-1.88) = 0.13$



Outputs

i_1	i_2	o_u
3	0	0.13
0.5	2	1.00
0.5	-2	0.00
-1	0	0.06

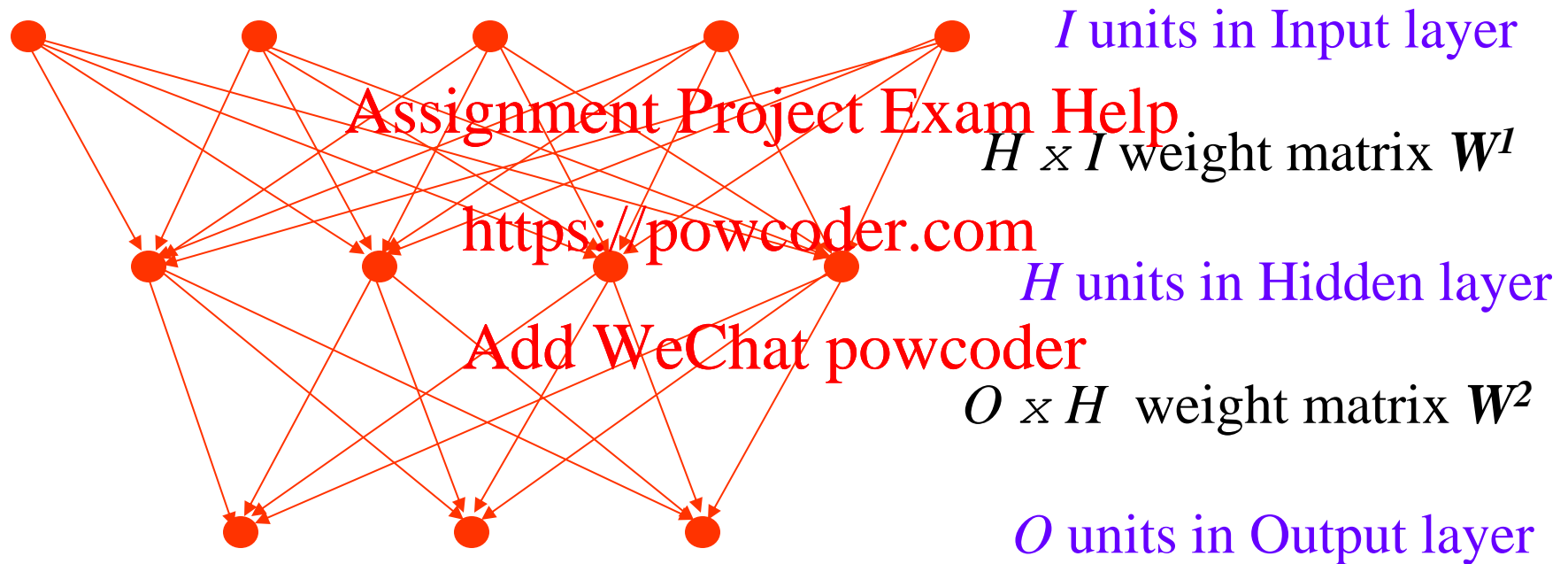
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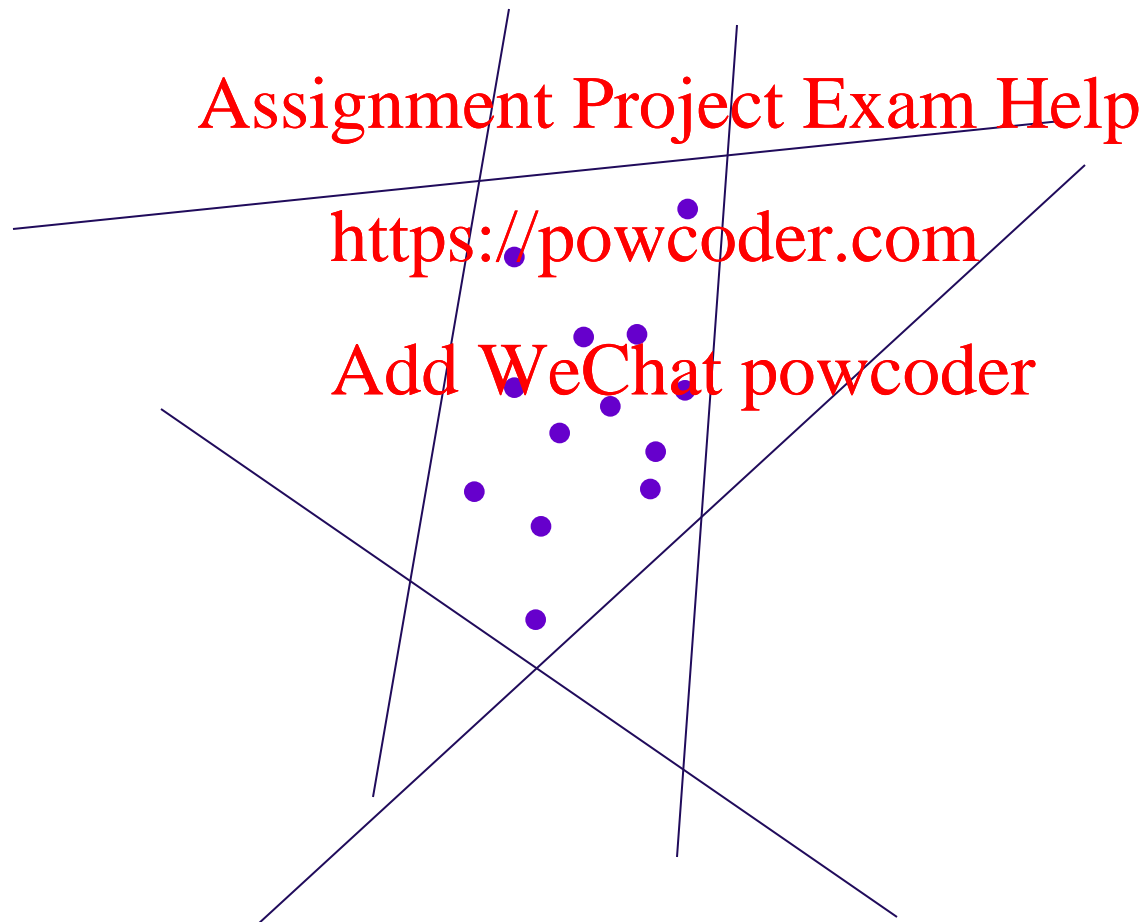


Single hidden layer Multi-Layer Perceptron (MLP)

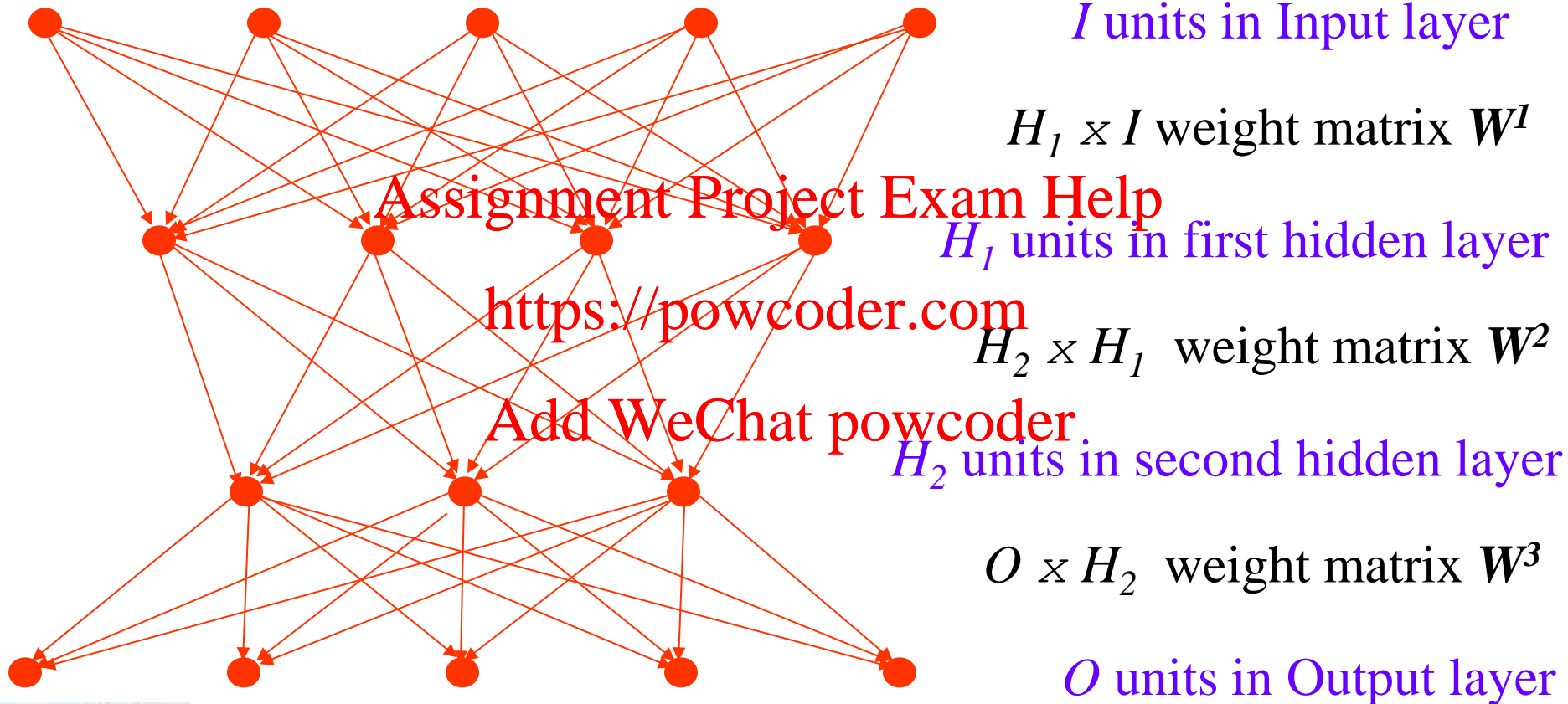


Single hidden layer MLP

- Can characterize arbitrary convex regions
- Defines the region using linear decision boundaries



Two hidden layer MLP



Two hidden layer MLP

- An MLP with two hidden layers can characterize arbitrary shapes
- First hidden layer characterises convex regions
- Second hidden layer combines these convex regions
- In theory, there is no advantage in having more than two hidden layers
- In practice multiple hidden layer “deep” neural networks give best performance (e.g. Speech recognition)

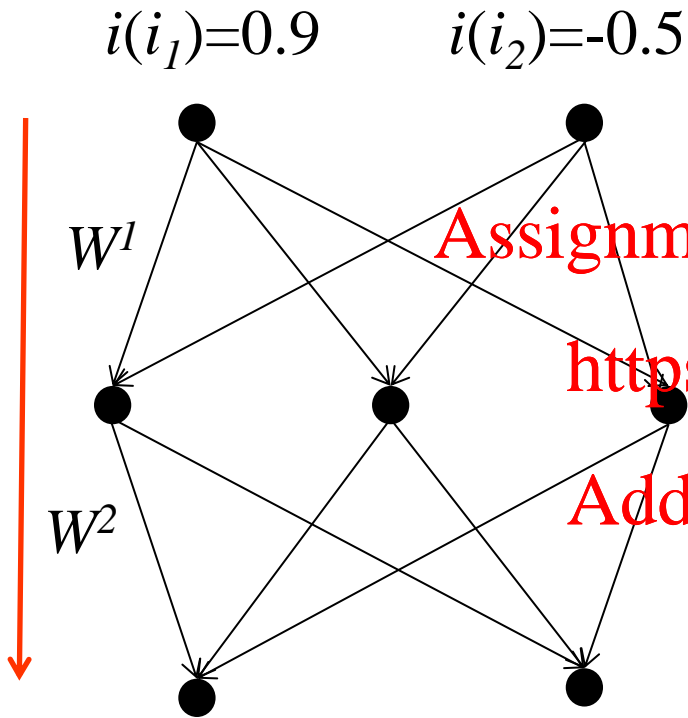


Formal definition: MLP with a single hidden layer

- A single hidden layer MLP consists of:
 1. A set of I input units, and for each input unit i an activation function g_i (typically linear)
 2. A set of H hidden units, and for each hidden unit h an activation function g_h (typically sigmoid)
 3. A set of O output units, and for each output unit o an activation function g_o
 4. An $H \times I$ weight matrix W^1 , which maps the outputs of the input units to the inputs of the hidden units
 5. An $O \times H$ weight matrix W^2 , which maps the outputs of the hidden units to the inputs of the output units



Example



- 2 unit input layer, linear activation ($I = 2$)
- Single 3 unit hidden layer, sigmoid activation ($H = 3$)
- 2 unit output layer, linear activation ($O = 2$)
- A 3×2 weight matrix W^1 between input and hidden layer
- A 2×3 weight matrix W^2 between hidden and output layer



Example continued

$$W^1 = \begin{bmatrix} 2.6 & -1.7 \\ 0.2 & 1.0 \\ -4.0 & 2.5 \end{bmatrix}, W^2 = \begin{bmatrix} 1.0 & -0.5 & 1.0 \\ 0.5 & 0.6 & -1.0 \end{bmatrix}$$

$$\text{Input} = \begin{bmatrix} 0.9 \\ -0.5 \end{bmatrix}$$

$$\text{Output from first layer} = \begin{bmatrix} 0.9 \\ -0.5 \end{bmatrix} \text{ (linear activation)}$$



Example (continued)

Inputs to hidden layer:

$$i(h_1) = w_{11}^1 o_1 + w_{12}^1 o_2 = 2.6 \times 0.9 + (-1.7) \times (-0.5) = 2.34 + 0.85 = 3.19,$$

$$i(h_2) = w_{21}^1 o_1 + w_{22}^1 o_2 = 0.2 \times 0.9 + 1.0 \times (-0.5) = 0.18 - 0.5 = -0.32,$$

$$i(h_3) = w_{31}^1 o_1 + w_{32}^1 o_2 = (-4.0) \times 0.9 + 2.5 \times (-0.5) = -3.6 - 1.25 = -4.85$$

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In matrix notation:

$$i(h) = W^1 o$$

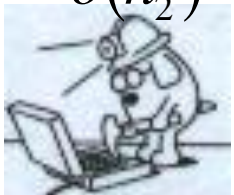
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Outputs from hidden layer.

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$$o(h_1) = \frac{1}{1 + e^{-3.19}} = 0.96,$$

$$o(h_2) = \frac{1}{1 + e^{0.32}} = 0.42, o(h_3) = \frac{1}{1 + e^{4.85}} = 0.008.$$



Example (continued)

Inputs to the output layer:

$$i(o_1) = w_{11}^2 \times o(h_1) + w_{12}^2 \times o(h_2) + w_{13}^2 \times o(h_3)$$

$$i(o_1) = 1 \times 0.96 + (-0.5) \times 0.42 + 1 \times 0.008 = 0.96 - 0.21 + 0.008 = 0.758.$$

$$i(o_2) = w_{21}^2 \times o(h_1) + w_{22}^2 \times o(h_2) + w_{23}^2 \times o(h_3)$$

$$i(o_2) = 0.5 \times 0.96 + 0.1 \times 0.42 + 1 \times 0.008 = 0.48 + 0.042 + 0.008 = 0.53.$$

In matrix notation:

$$i(o) = W^2 o(h)$$

Linear output unit activation:

$$o(o_1) = 0.758, o(o_2) = 0.742.$$



Summary

- Introduction to neural networks
- Definition of an ‘artificial neurone’
- Activation functions – linear and sigmoid
- Linear boundary defined by a single neurone
- Convex region defined by a one-level MLP
- Two-level MLPs
- Forward propagation in an MLP (calculation)

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