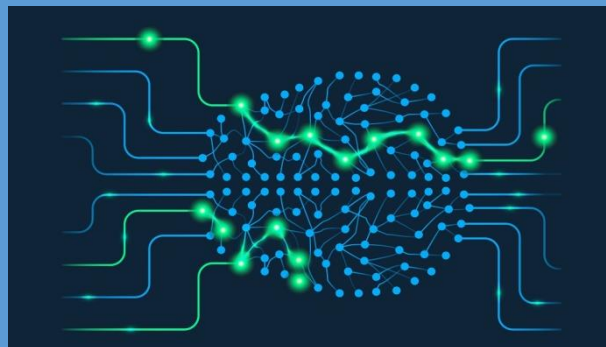


# EMS702P Statistical Thinking and Applied Machine Learning

## Week 8.2 – Neural Networks

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## **Neural Networks**

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Edition:

v1.1

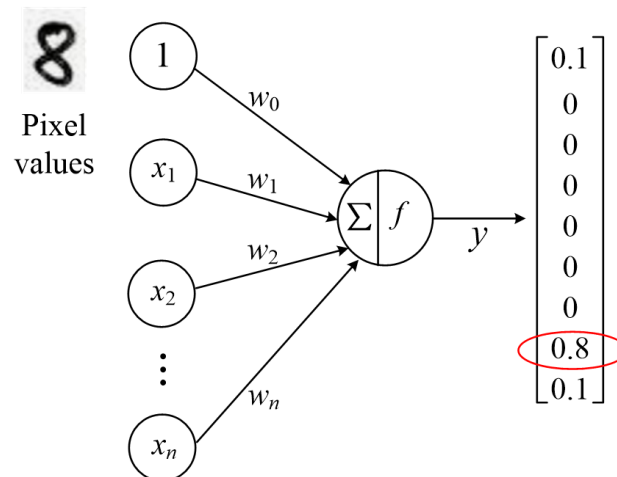
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# 1 Multi-Layer perceptron

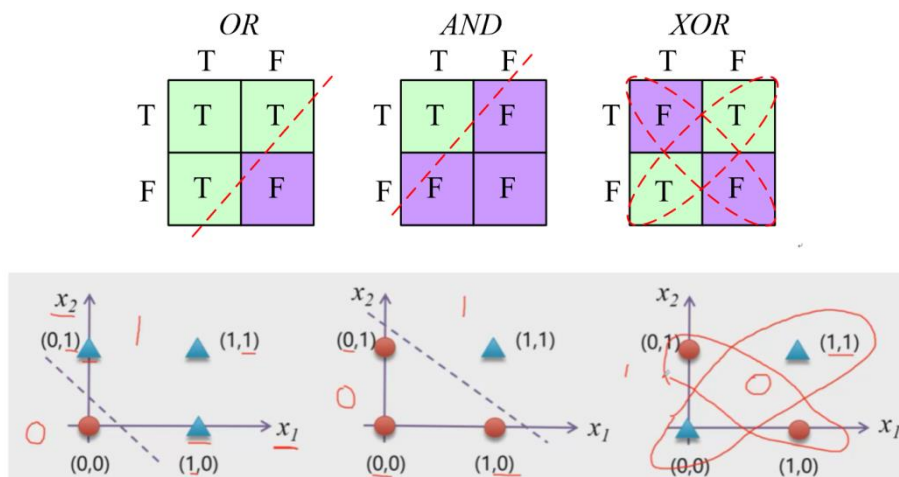
## 1.1 Multi-layer perceptron mechanism

We have learned perceptron, which can be used to separate two classes of data. Why don't we stop here?



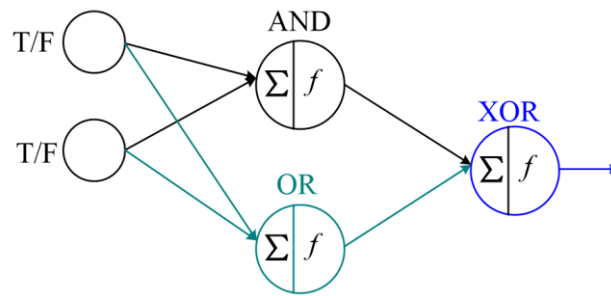
We mentioned that a perceptron can only resolve **Linearly Separable** problems. It cannot solve the eXclusive OR (XOR) problem.

**XOR:** False if two inputs are the same, otherwise True.

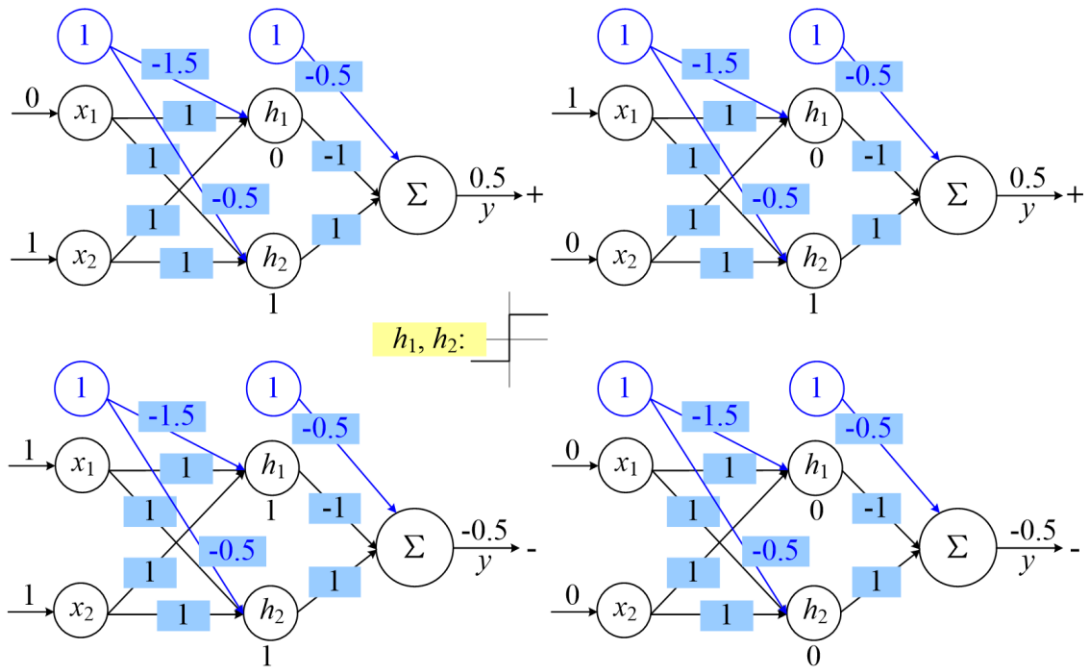


XOR problem is not linearly separable. The problem can be resolved by using multiple perceptrons, which is known as the Multi-Layer Perceptron.

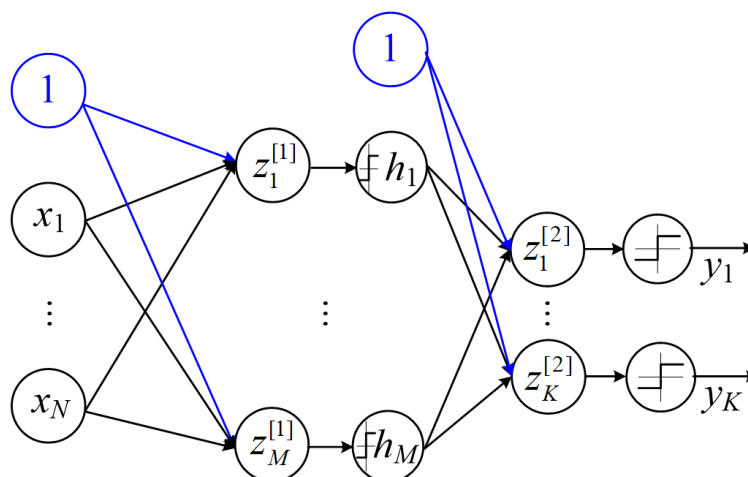
Considering one perceptron solve AND problem, and another solve OR problem. An additional perceptron for their output can be used to solve XOR problem.



For example:



A general structure of the Multi-Layer Perceptron is shown below



where

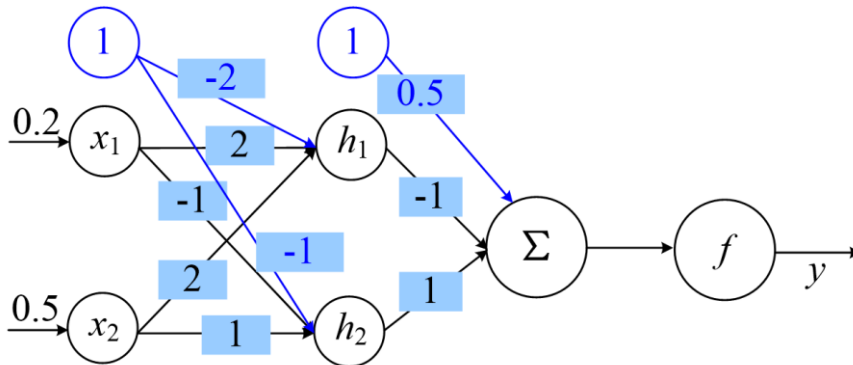
$$\begin{cases} z_m^{[1]} = w_{0,m}^{[1]} + w_{1,m}^{[1]}x_1 + \dots + w_{N,m}^{[1]}x_N = w_{0,m}^{[1]} + \sum_{n=1}^N w_{n,m}^{[1]}x_n, m=1,\dots,M \\ h_m = f(z_m^{[1]}) \\ z_k^{[2]} = w_{0,k}^{[2]} + w_{1,k}^{[2]}h_1 + \dots + w_{M,k}^{[2]}h_M = w_{0,k}^{[2]} + \sum_{m=1}^M w_{m,k}^{[2]}h_m, k=1,\dots,K \\ y_k = f(z_k^{[2]}) \end{cases}$$

with

- $w_{nm}^{[1]}$  representing the weights of the first connections from the  $n$ th node of the input layer to the  $m$ th node of the middle layer, while
- $w_{mk}^{[2]}$  representing the weights of the second connections from the  $m$ th node of the middle layer to the  $k$ th node of the output layer.
- $f(.)$  is a step function

### Quiz 1.1:

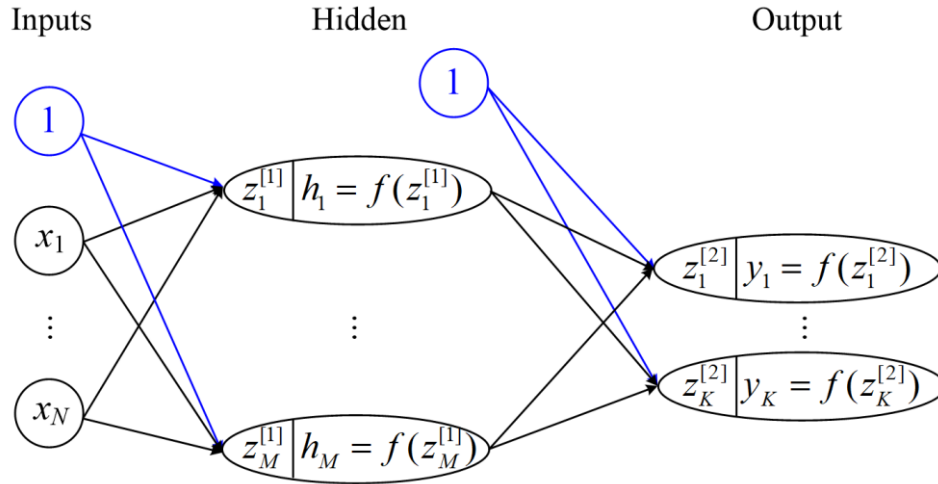
Calculate the output of the multiple layer perceptron:



## 2 Fully connected feed-forward artificial neural network

### 2.1 Structure of the feed-forward artificial neural network

In a Multi-Layer Perceptron each layer's outputs are activated by an activation function. The new network is a typical structure of neural network.



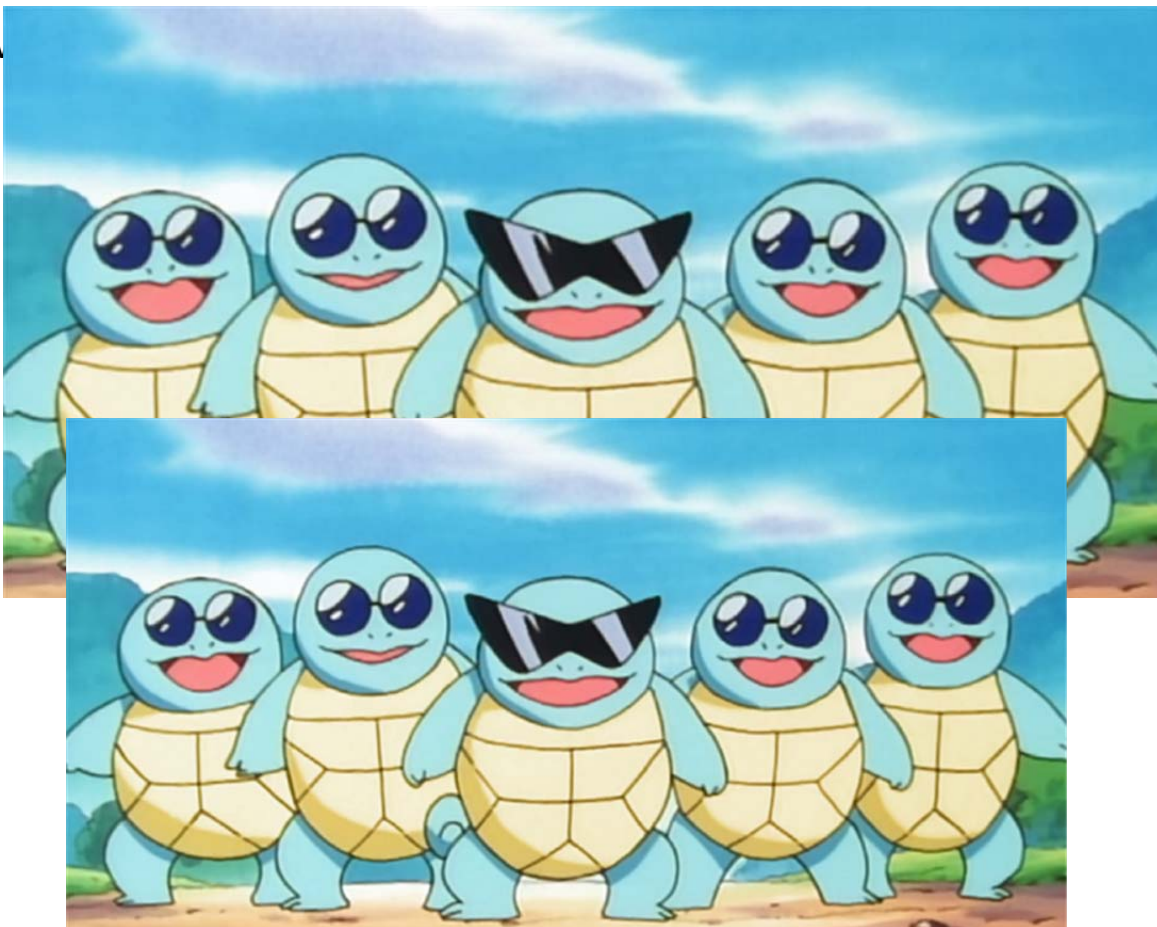
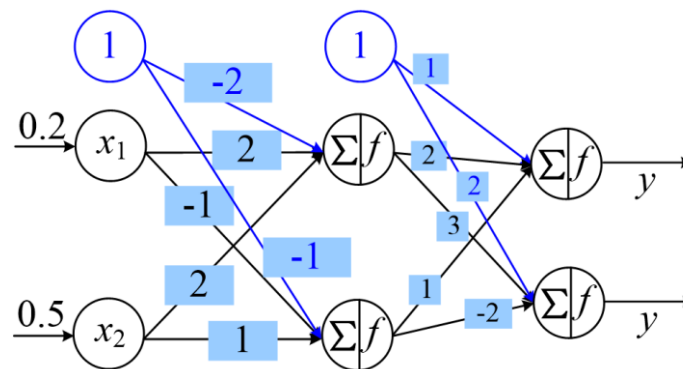
In a neural network, the first layer is the **input layer**, the middle layer is the **hidden layer**, and the final layer is the **output layer**. The network in the plot may be described as a **2-layer network**, because it is the number of layers of adaptive weights that is important for determining the network properties.

$$\begin{cases} \begin{cases} z_m^{[1]} = w_{0,m}^{[1]} + w_{1,m}^{[1]}x_1 + \dots + w_{N,m}^{[1]}x_N = w_{0,m}^{[1]} + \sum_{n=1}^N w_{n,m}^{[1]}x_n, m = 1, \dots, M \\ h_m = f(z_m^{[1]}) \end{cases} \\ \begin{cases} z_k^{[2]} = w_{0,k}^{[2]} + w_{1,k}^{[2]}h_1 + \dots + w_{M,k}^{[2]}h_M = w_{0,k}^{[2]} + \sum_{m=1}^M w_{m,k}^{[2]}h_m, k = 1, \dots, K \\ y_k = f(z_k^{[2]}) \end{cases} \end{cases}$$

where  $f(\cdot)$  is an activation function

It can be seen that a Multi-Layer Perceptron is a special case of the neural network.

**Quiz 2.1:** the activation functions are Sigmoid functions. Calculate the outputs:

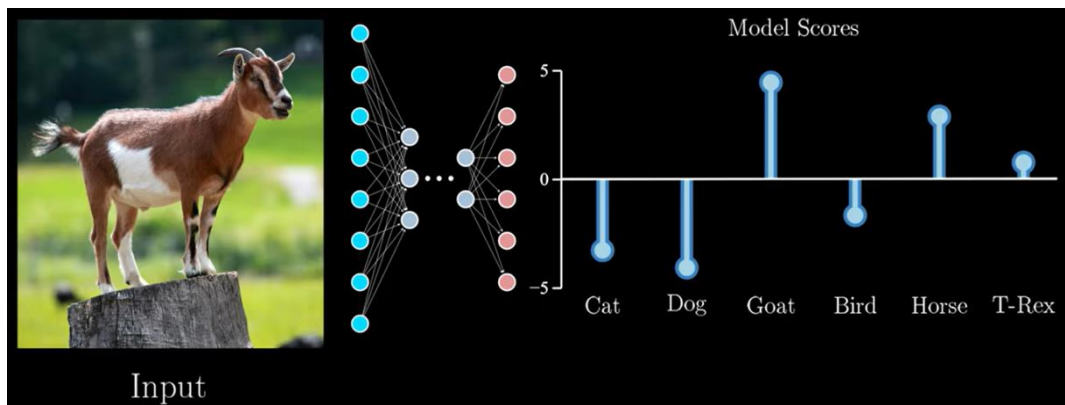
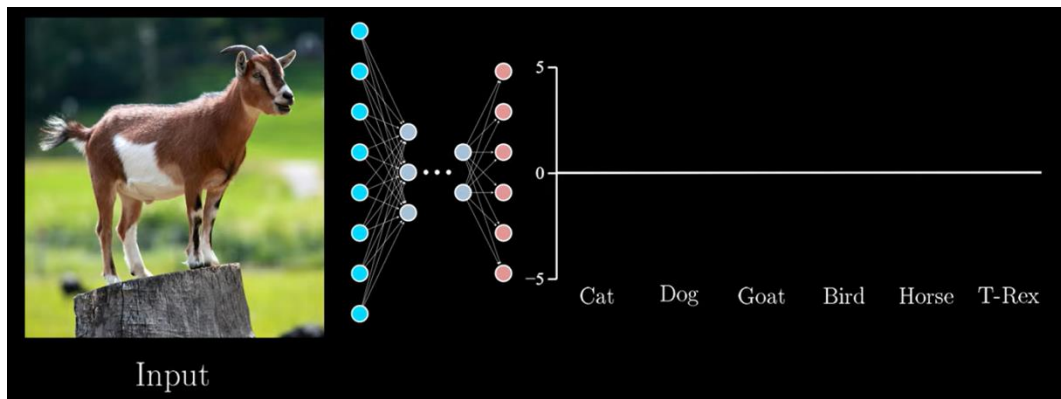


## 2.2 Neural network based classification and regression

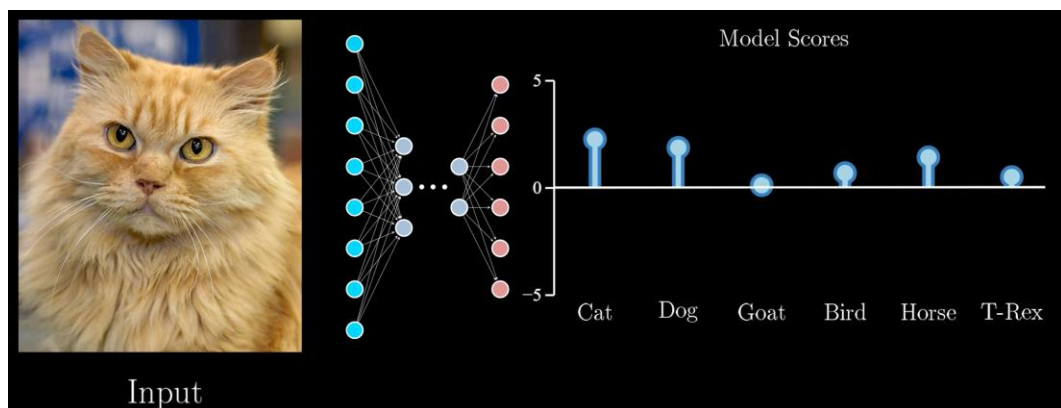
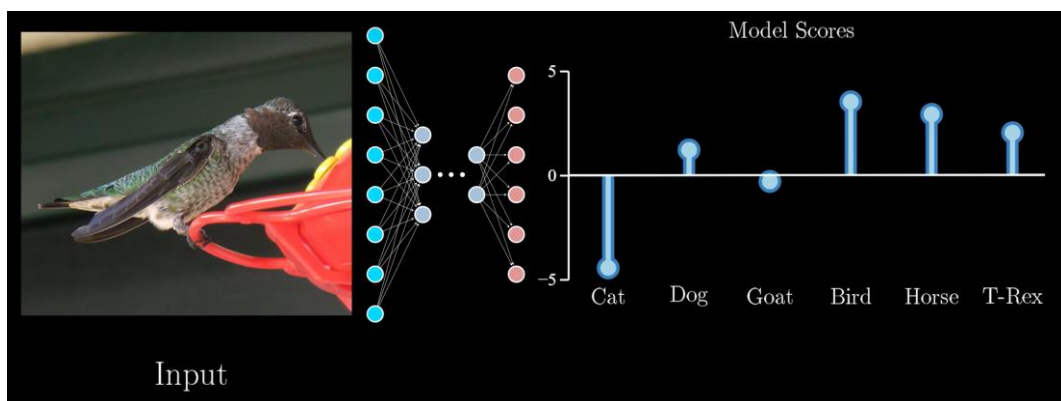
### (1) Classification

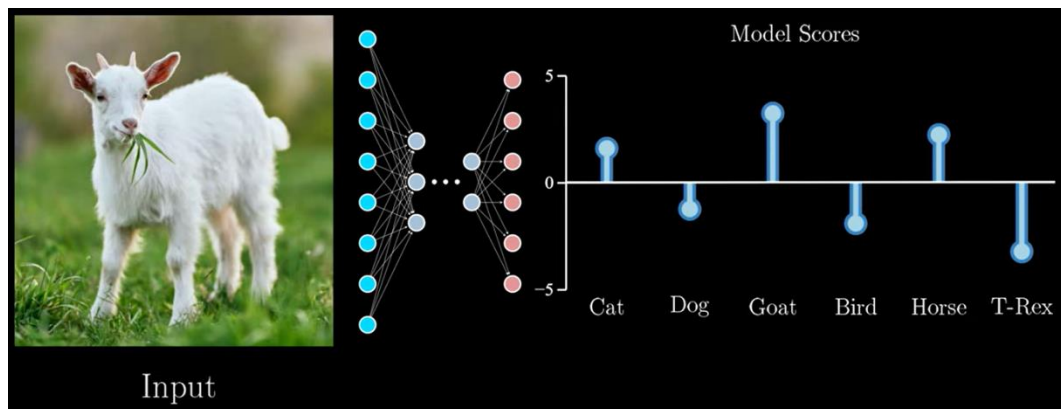
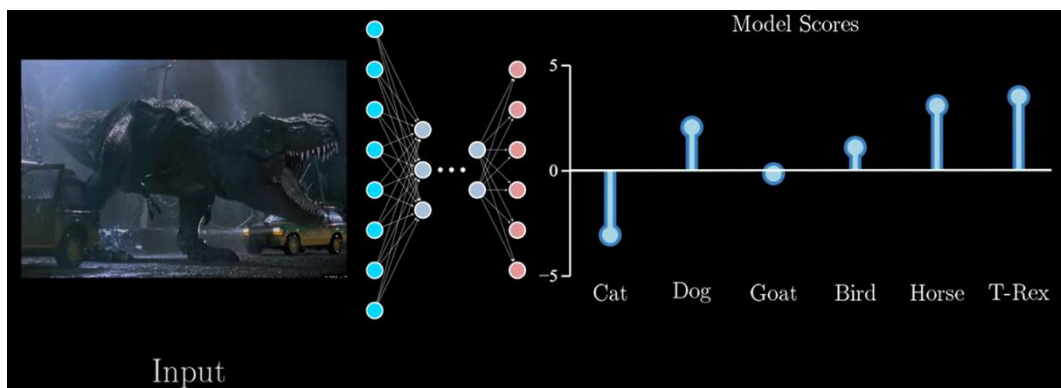
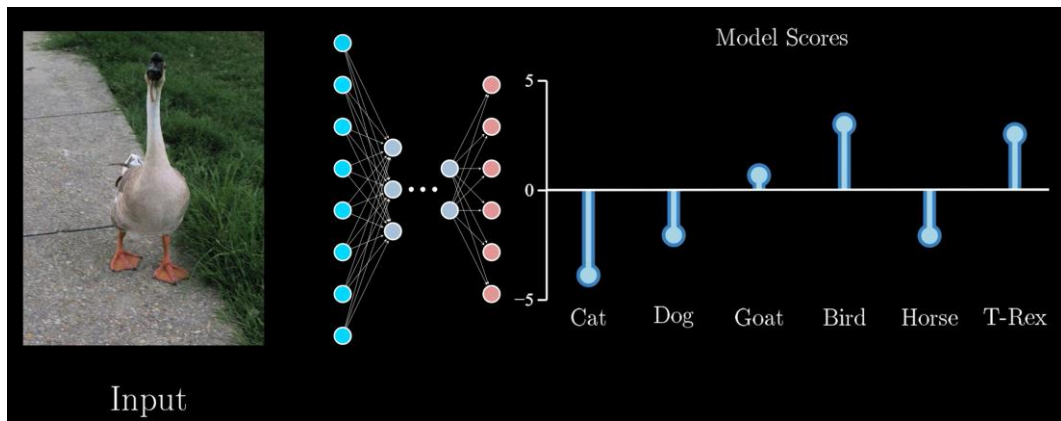
As we have learned in the linear classification, multiple linear functions can also be used to solve a K-class classification problem based on one-vs-the rest approach. However, many classification problems are not **linearly separable**. Neural network provide a nonlinear classifier to solve this problem as illustrated in the Multi-Layer Perceptron.





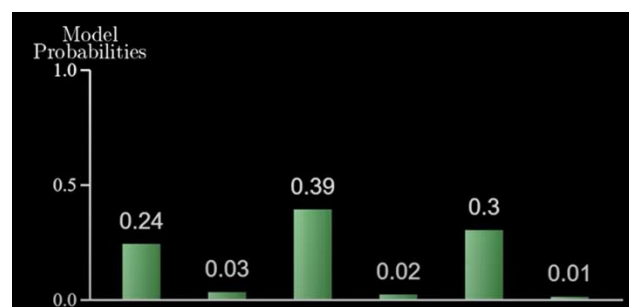
For different inputs:

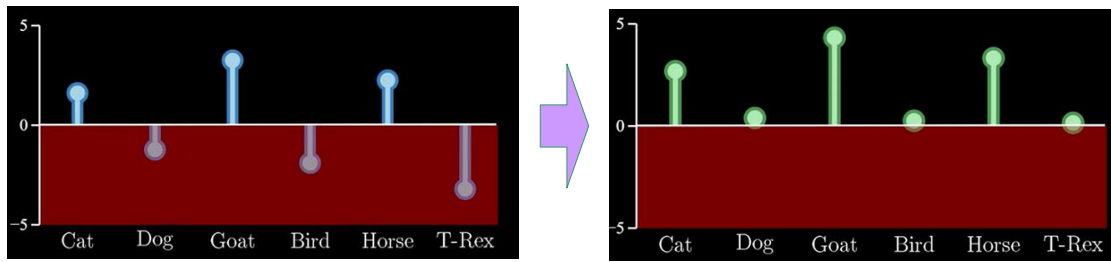




This is **incomplete**. Very often, these scores need to be mapped to **probabilities**.

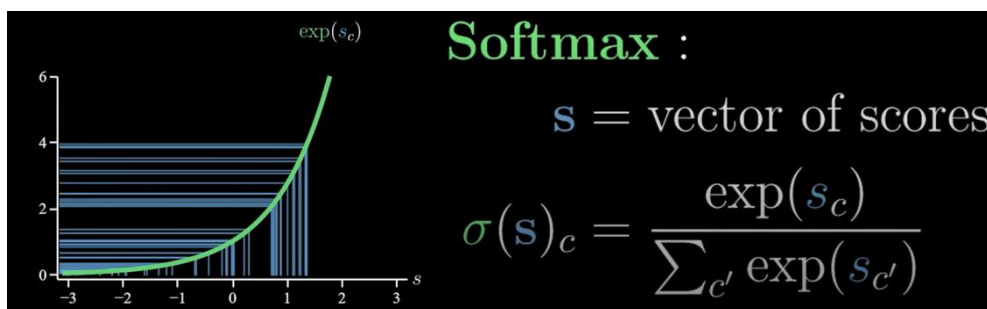
- Sum of the probabilities is 1.
- The mapping function is differentiable.





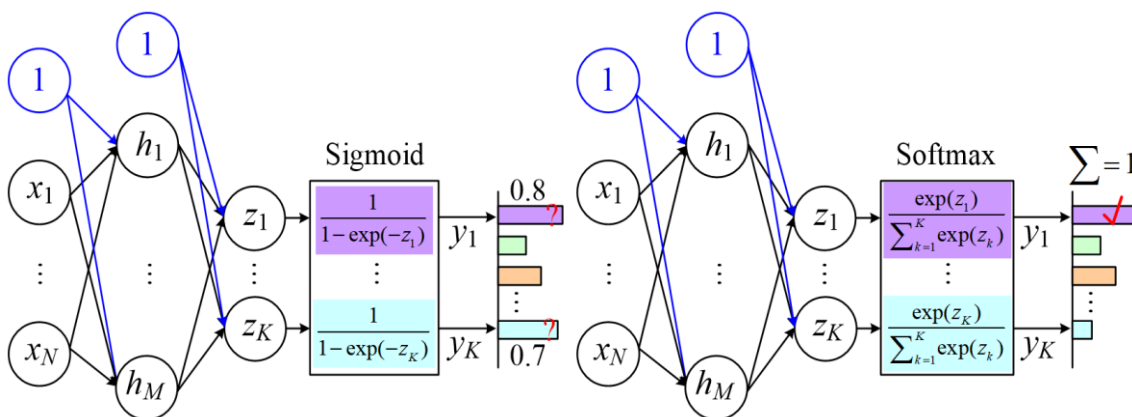
In the neural network based classification, the activation functions of the output layer are often defined as a Softmax functions:

$$f(z_k) = \frac{\exp(z_k)}{\sum_{k=1}^K \exp(z_k)}$$

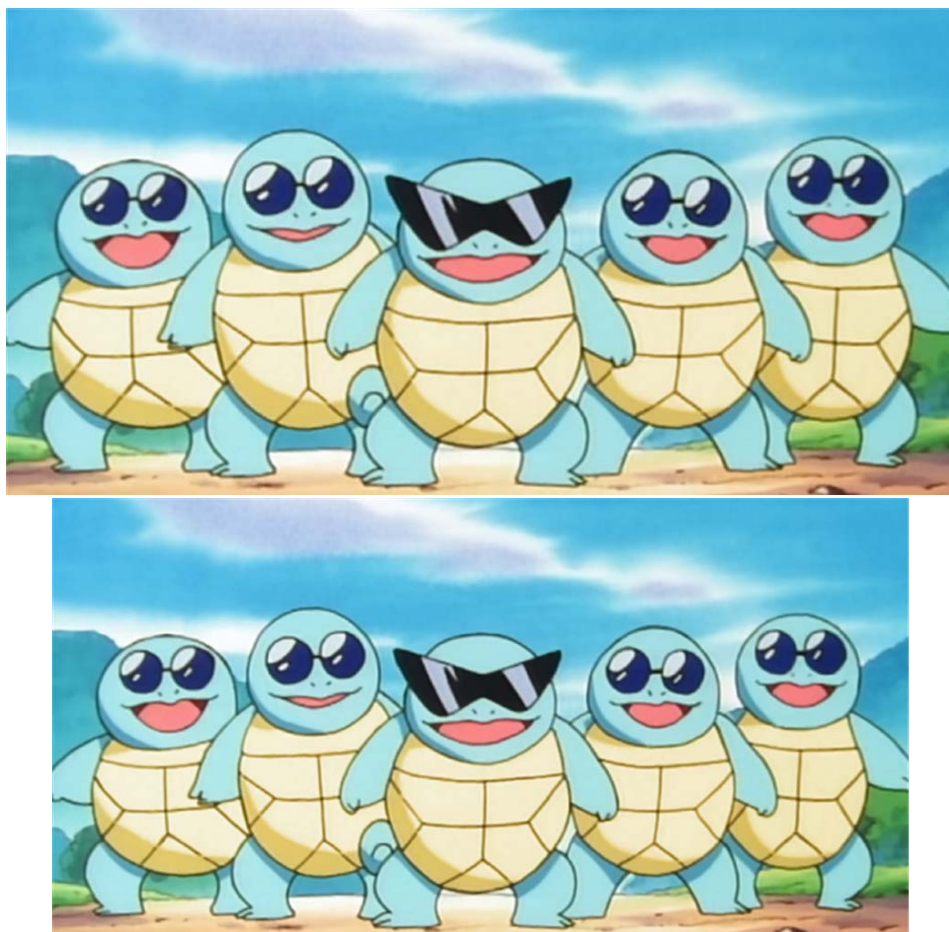
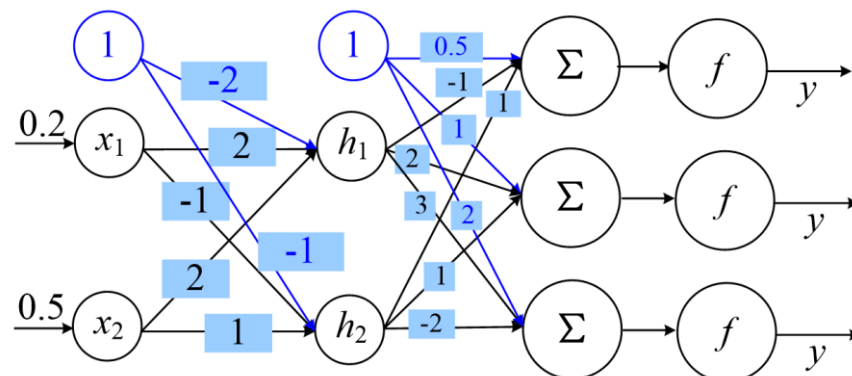


Compared with simply using a Sigmoid function, Softmax function can provide a single classification result for each input set. Therefore, Softmax function is often used to solve multi-class classification problems (i.e. cat/dog), while Sigmoid function is often used to solve multi-label classification problems (i.e. 4 legs/tail/fur) [4].

For a 2-class classification problem, the Softmax function is the same as the Sigmoid function. A Softmax function has the value from 0 to 1, representing the probability of each class from all classes.



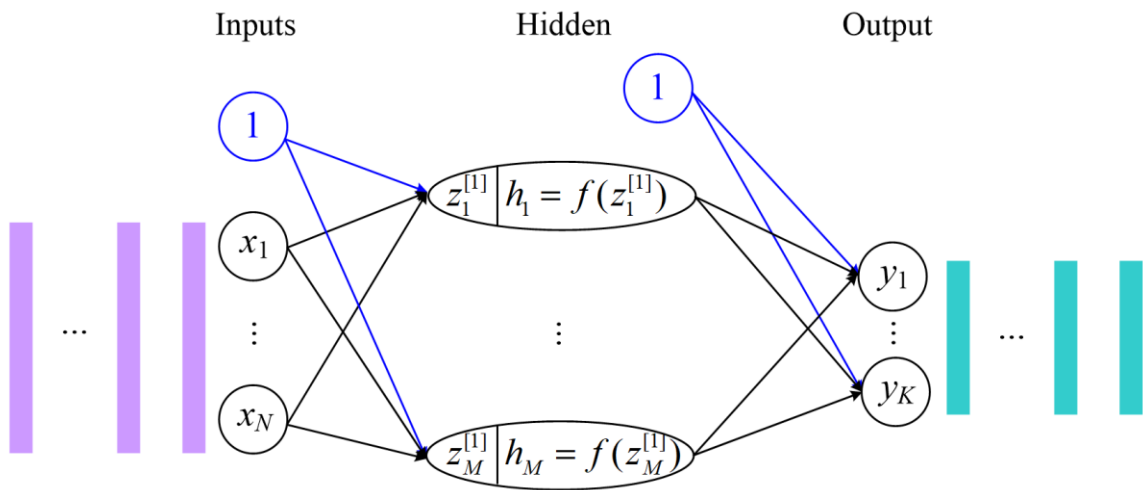
**Quiz 2.2:**  $f$  is the softmax function, the activation function are step functions. Calculate the outputs:



## (2) Regression

The introduction of neural networks is often based on classification problems. How to use a neural network to solve regression problems?

From the aspect of network structures, neural network for regression doesn't use activation function in the output layer.



Python: FFNN\_221.py

FFNN\_Sine\_181.py