

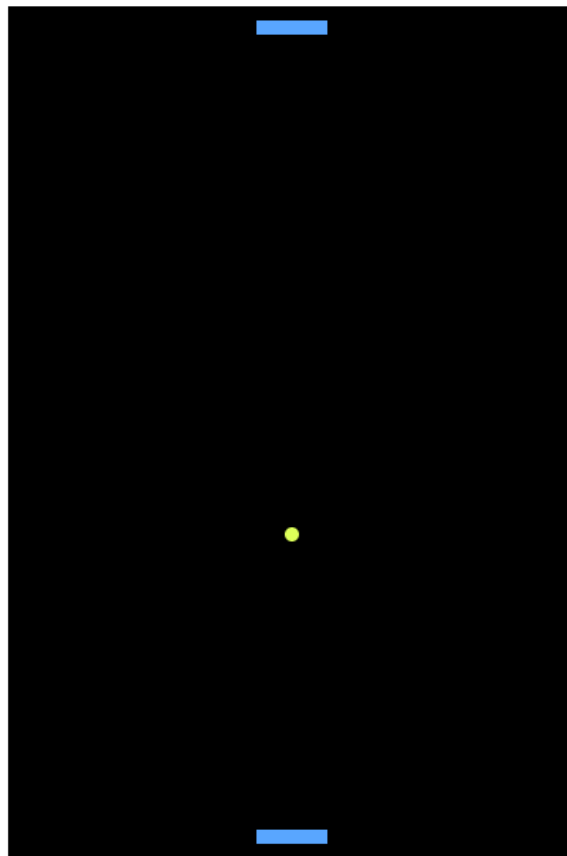
物聯網實務

11_30

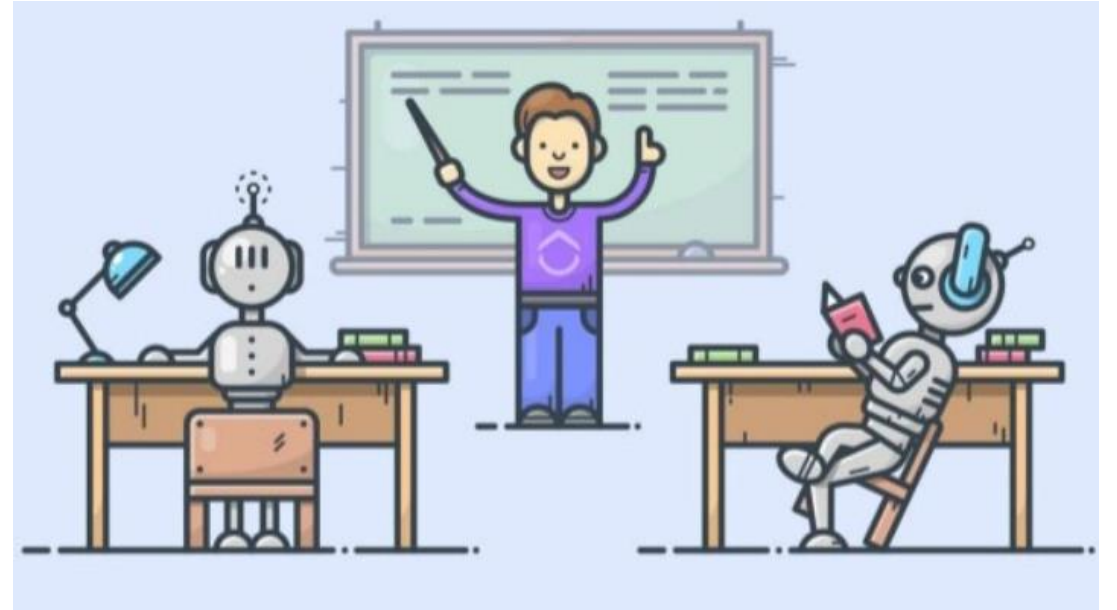
廖裕評

AI game

Yu-Ping Liao Ping Pong Game



Teaching AI to Understand Our World



<https://www.slideshare.net/sakhaglobal/unsupervised-learning-teaching-ai-to-understand-our-world>

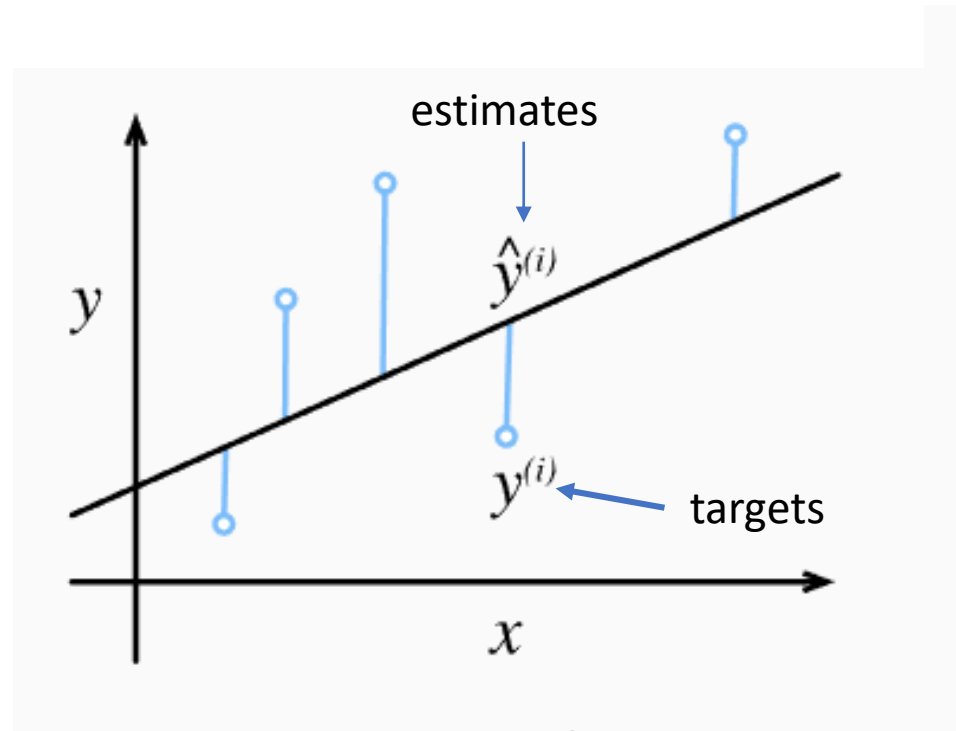
Regression

- *Regression* refers to a set of methods for **modeling the relationship** between one or more independent **variables** and a dependent variable.
- *Prediction*: predicting prices (of homes, stocks, etc.), predicting length of stay (for patients in the hospital), demand forecasting (for retail sales)



<http://davidgildeh.com/2013/09/16/the-future-of-enterprise-machine-learning/>

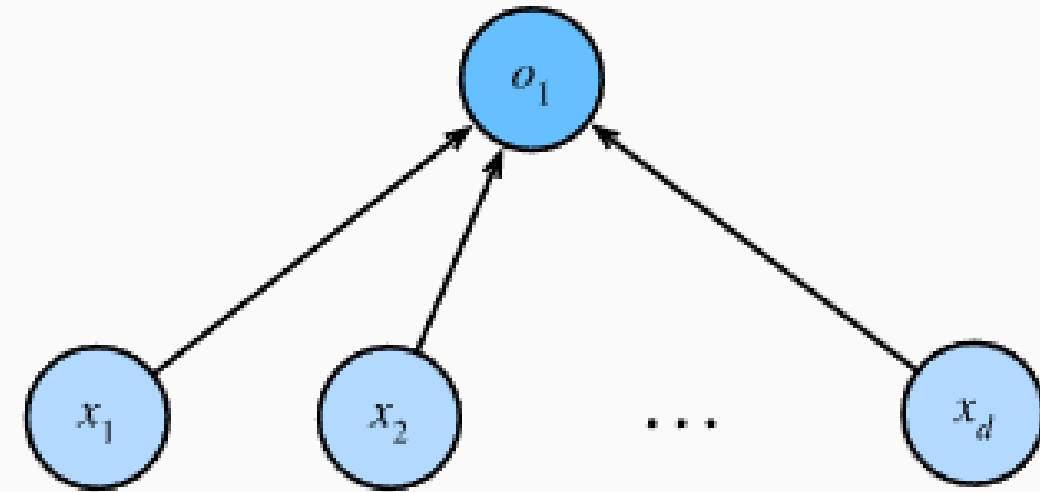
Linear regression



$$y = wx + b$$

Output layer

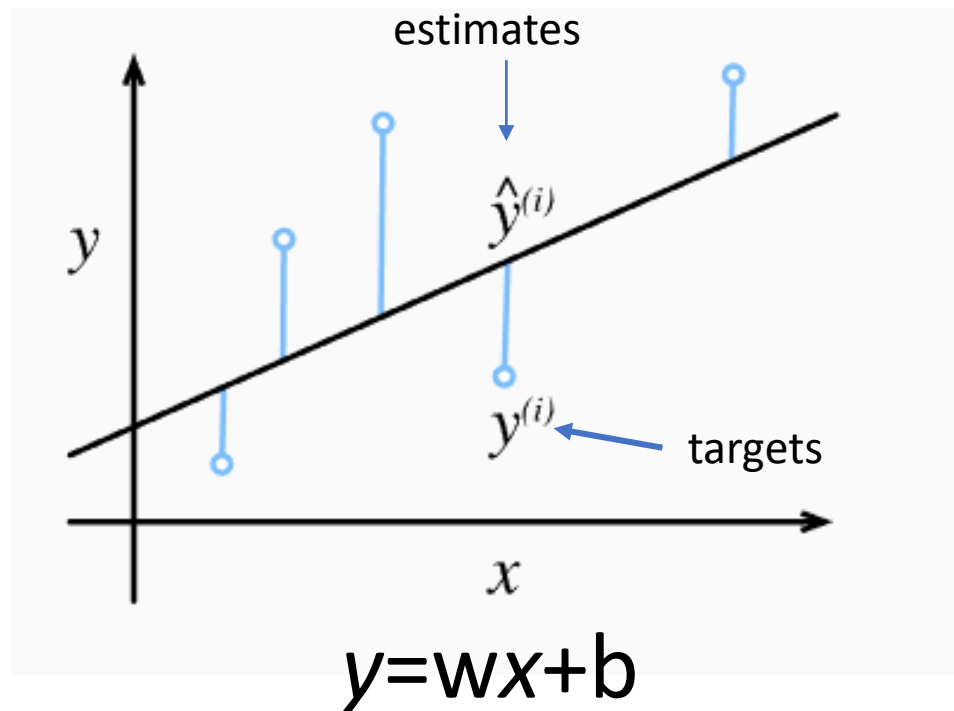
Input layer



$$\hat{y} = w_1 x_1 + \dots + w_d x_d + b$$

single-layer neural network

Loss Function



squared error

$$l^{(i)}(\mathbf{w}, b) = \frac{1}{2} \left(\hat{y}^{(i)} - y^{(i)} \right)^2.$$

the losses on the training set

$$L(\mathbf{w}, b) = \frac{1}{n} \sum_{i=1}^n l^{(i)}(\mathbf{w}, b)$$

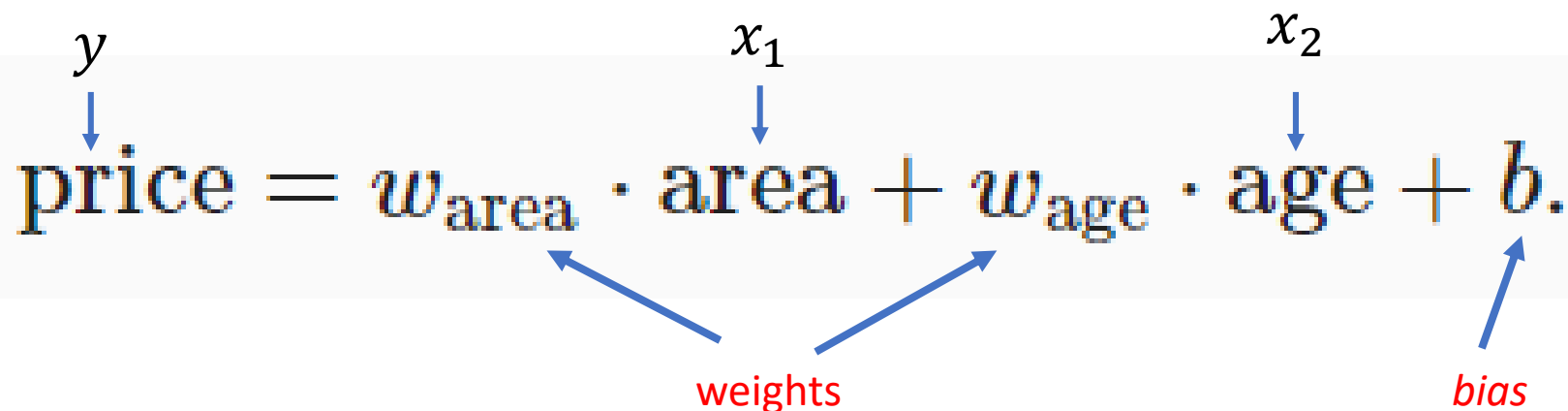
training the model

$$\mathbf{w}^*, b^* = \operatorname{argmin}_{\mathbf{w}, b} L(\mathbf{w}, b).$$

our prediction for an example i is $\hat{y}^{(i)}$ and the corresponding true label is $y^{(i)}$

Regression

- Typically, we will use n to denote the number of examples in our dataset. We index the data examples by i , denoting each input as $x^{(i)} = [x_1^{(i)}, x_2^{(i)}]^T$ and the corresponding label as $y^{(i)}$.



The diagram shows the equation $\text{price} = w_{\text{area}} \cdot \text{area} + w_{\text{age}} \cdot \text{age} + b$. Annotations include: a blue arrow from y to price ; a blue arrow from x_1 to area ; a blue arrow from x_2 to age ; a red arrow from the word weights to w_{area} and w_{age} ; and a red arrow from the word bias to b .

$$\text{price} = w_{\text{area}} \cdot \text{area} + w_{\text{age}} \cdot \text{age} + b.$$

$$y^{(i)} = w_{\text{area}} \cdot x_1^{(i)} + w_{\text{age}} \cdot x_2^{(i)} + b$$

$$y^{(i)} = w_1 \cdot x_1^{(i)} + w_2 \cdot x_2^{(i)} + b$$

Regression

- When our inputs consist of d features, we express our **prediction** \hat{y} (in general the “hat” symbol denotes estimates) as

$$\hat{y} = w_1 x_1 + \dots + w_d x_d + b.$$

$$\hat{y} = \mathbf{w}^\top \mathbf{x} + b.$$

a vector $\mathbf{w} \in \mathbb{R}^d$

a vector $\mathbf{x} \in \mathbb{R}^d$

$$\hat{y} = [w_1 \quad w_2 \quad \dots \quad w_d] \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_d \end{bmatrix}$$

$$\mathbf{x} = [x_1 \quad x_2 \quad \dots \quad x_d]^\top = \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_d \end{bmatrix}$$

$$\mathbf{w} = [w_1 \quad w_2 \quad \dots \quad w_d]^\top = \begin{bmatrix} w_1 \\ w_2 \\ \dots \\ w_d \end{bmatrix}$$

$$\mathbf{w}^\top = [w_1 \quad w_2 \quad \dots \quad w_d]$$

Regression

$$\hat{\mathbf{y}} \in \mathbb{R}^n \quad \mathbf{X} \in \mathbb{R}^{n \times d}.$$

$$\hat{\mathbf{y}} = \mathbf{X}\mathbf{w} + b,$$

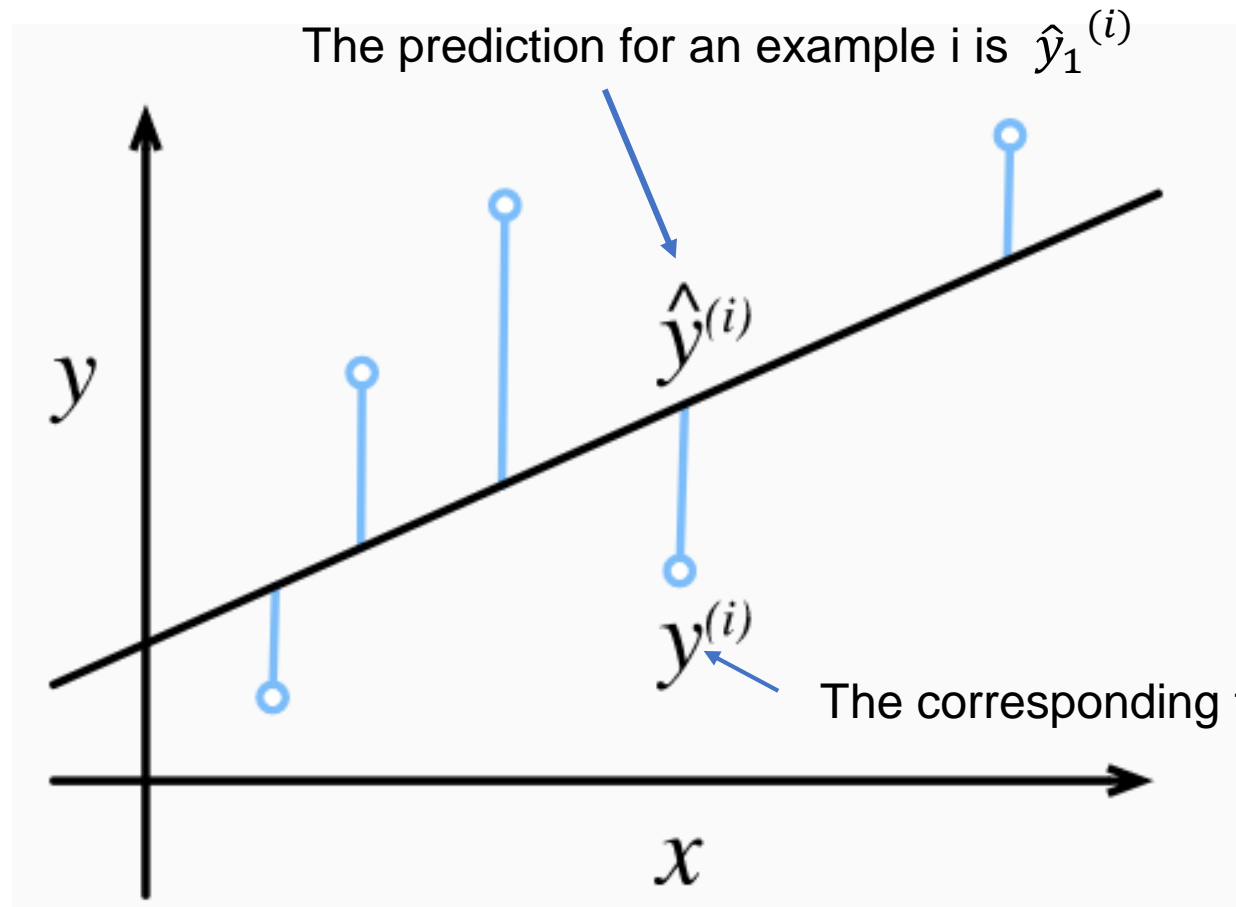
$$x^{(i)} = [x_1^{(i)}, x_2^{(i)}, \dots, x_d^{(i)}]^T = \begin{bmatrix} x_1^{(i)} \\ x_2^{(i)} \\ \dots \\ x_d^{(i)} \end{bmatrix}$$

$$X = \begin{bmatrix} x_1^{(1)} & x_2^{(1)} & \dots & x_d^{(1)} \\ x_1^{(2)} & x_2^{(2)} & \dots & x_d^{(2)} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{(n)} & x_2^{(n)} & \dots & x_d^{(n)} \end{bmatrix}$$

$$\mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \\ \dots \\ w_d \end{bmatrix}$$

$$\begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \vdots \\ \hat{y}_n \end{bmatrix} = \begin{bmatrix} x_1^{(1)} & x_2^{(1)} & \dots & x_d^{(1)} \\ x_1^{(2)} & x_2^{(2)} & \dots & x_d^{(2)} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{(n)} & x_2^{(n)} & \dots & x_d^{(n)} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_d \end{bmatrix} + b$$

Loss Function



The loss function for an example i is:

$$l^{(i)}(\mathbf{w}, b) = \frac{1}{2} \left(\hat{y}^{(i)} - y^{(i)} \right)^2.$$

Fig. 3.1.1 Fit data with a linear model. [¶](#)

average loss

$$L(\mathbf{w}, b) = \frac{1}{n} \sum_{i=1}^n l^{(i)}(\mathbf{w}, b) = \frac{1}{n} \sum_{i=1}^n \frac{1}{2} \left(\mathbf{w}^\top \mathbf{x}^{(i)} + b - y^{(i)} \right)^2. \quad (3.1.6)$$

When training the model, we want to find parameters (\mathbf{w}^*, b^*) that minimize the total loss across all training examples:

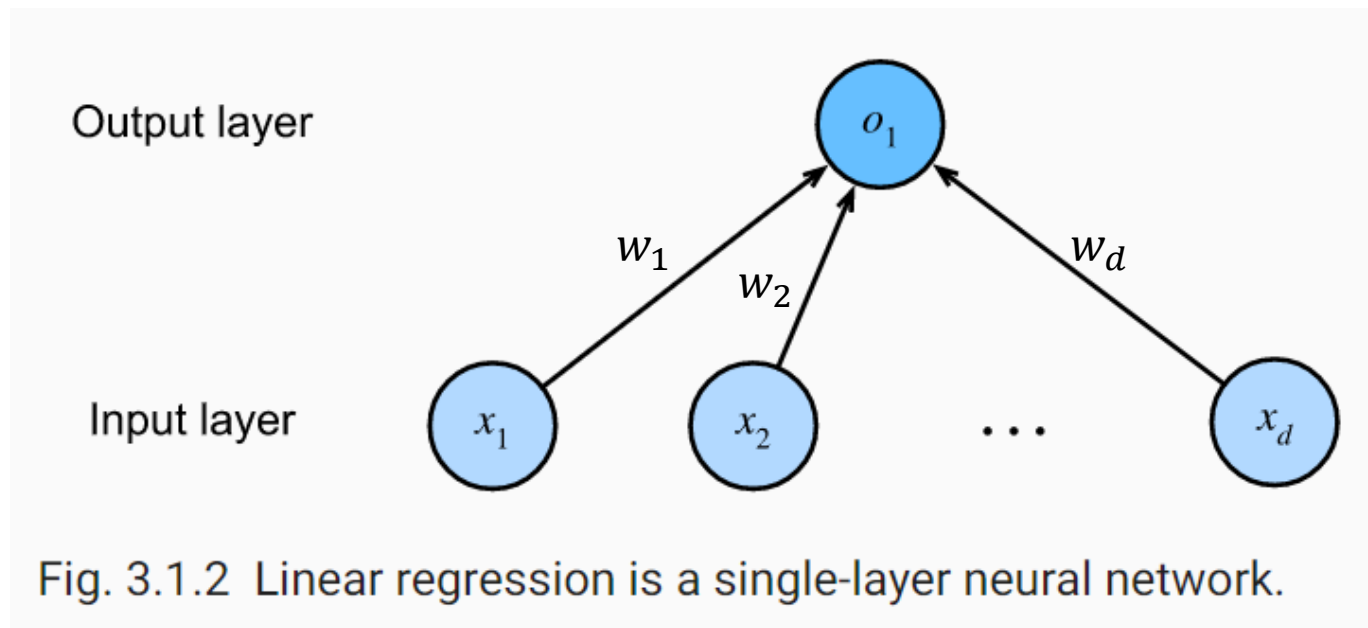
$$\mathbf{w}^*, b^* = \operatorname{argmin}_{\mathbf{w}, b} L(\mathbf{w}, b). \quad (3.1.7)$$

Making Predictions with the Learned Model

- Given the learned linear regression model $\hat{w}^T x + \hat{b}$, we can now estimate **the price of a new house** (not contained in the training data)
- given its area x_1 and age x_2 . **Estimating targets** given features is commonly called *prediction* or *inference*.

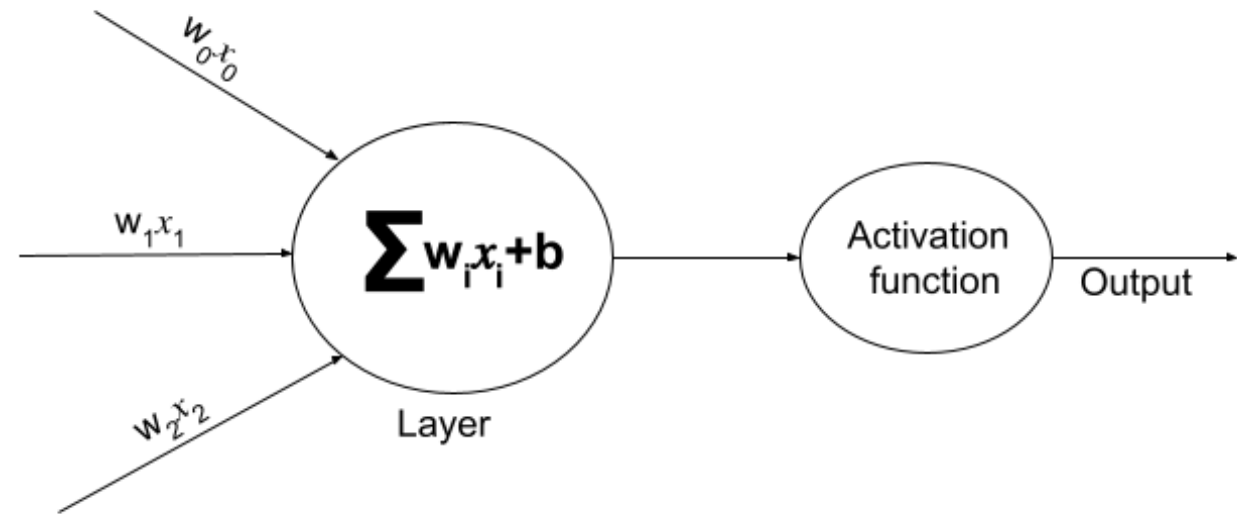
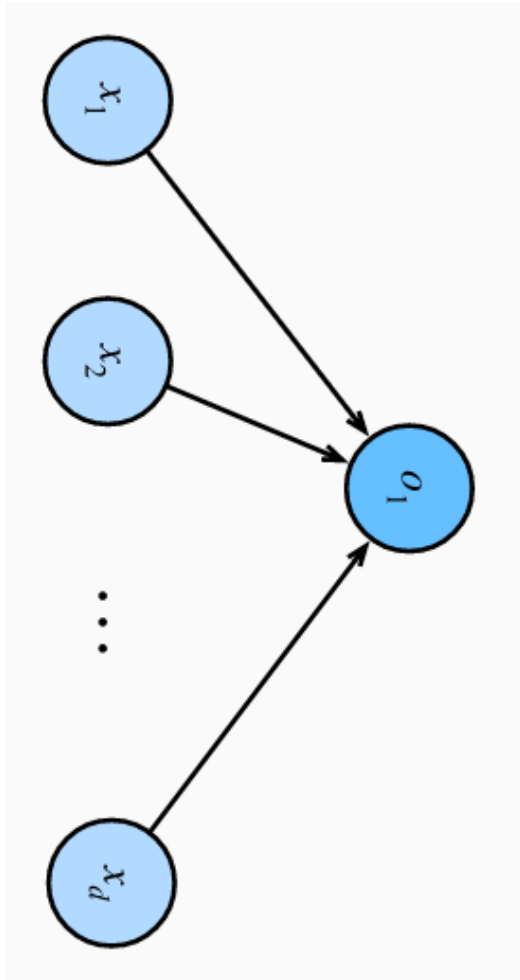
From Linear Regression to Deep Networks

- Neural Network Diagram



Since for linear regression, every input is connected to every output (in this case there is only one output), we can regard this transformation (the output layer in [Fig. 3.1.2](#)) as a *fully-connected layer* or *dense layer*.

Activation function

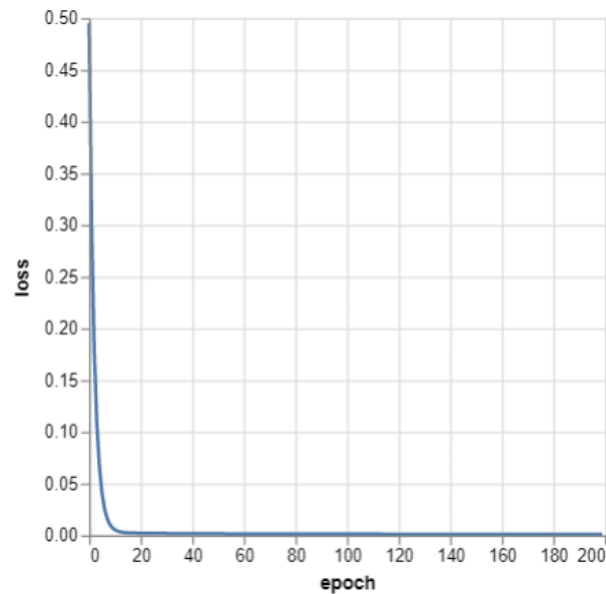
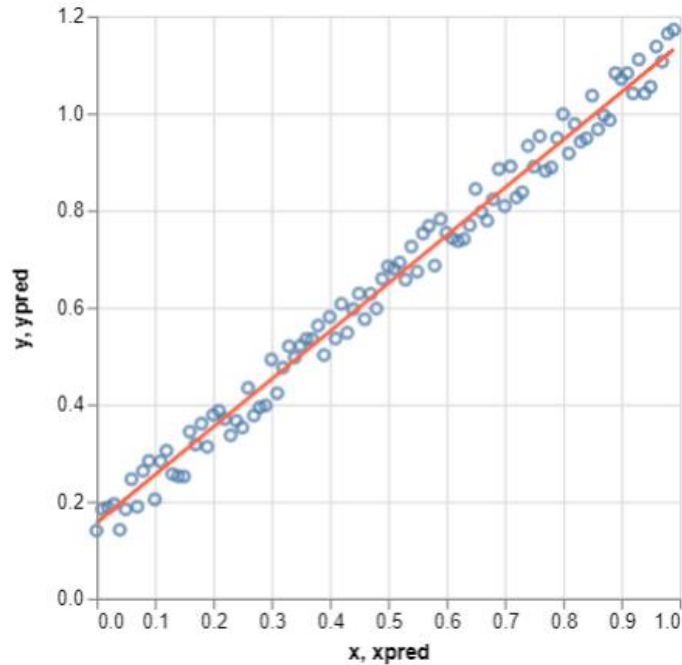


<https://androidkt.com/advantages-relu-tanh-sigmoid-activation-function-deep-neural-networks/>

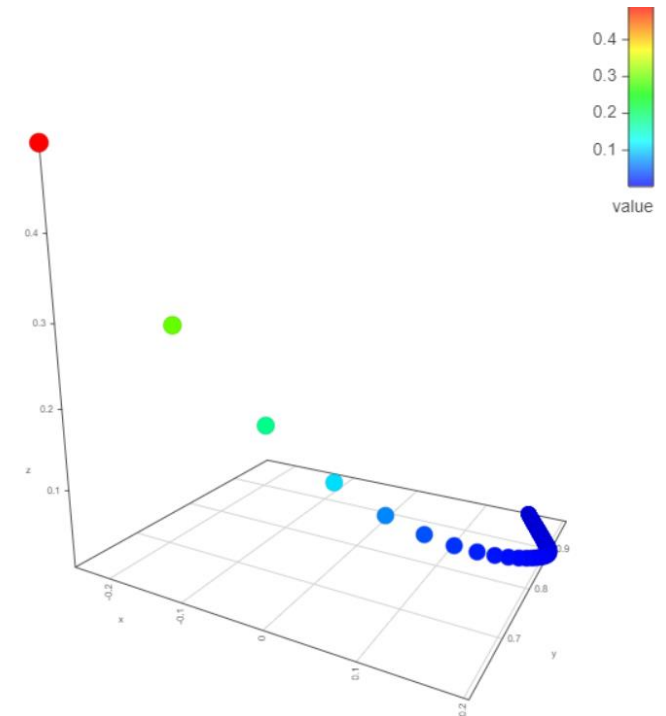
Exercise 11-1

- ex1130_1.html (copy from ex1130_1.txt)

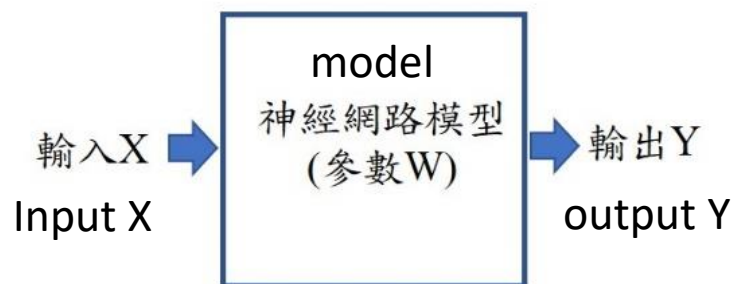
Linear Regression



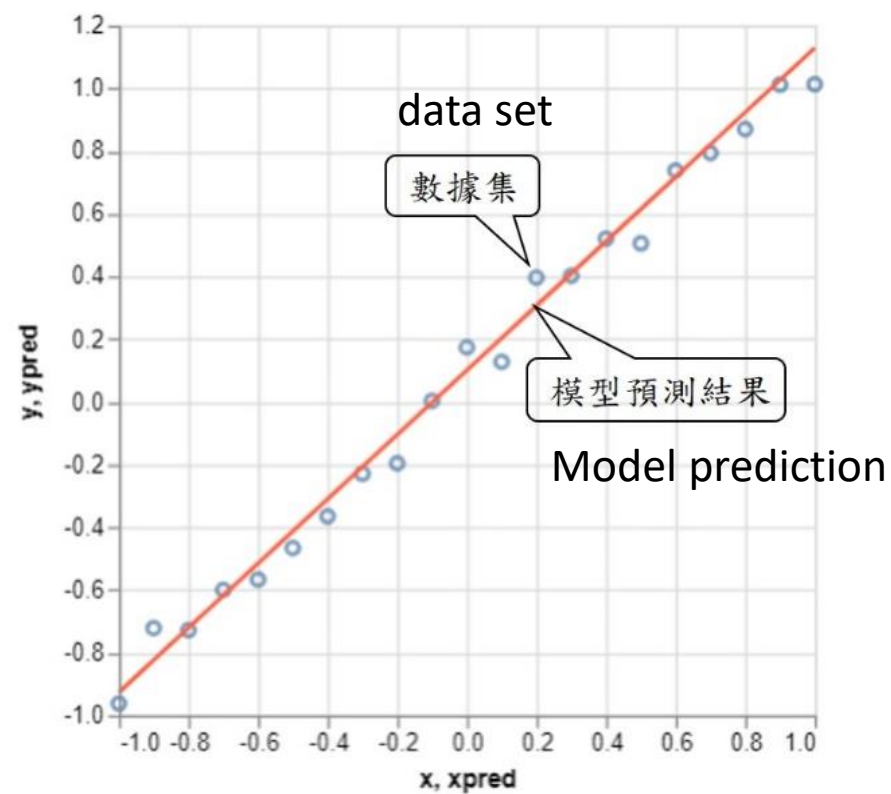
[Save as SVG](#)[Save as PNG](#)[View Source](#)[Open in Vega Editor](#)



Linear Regression



Linear Regression

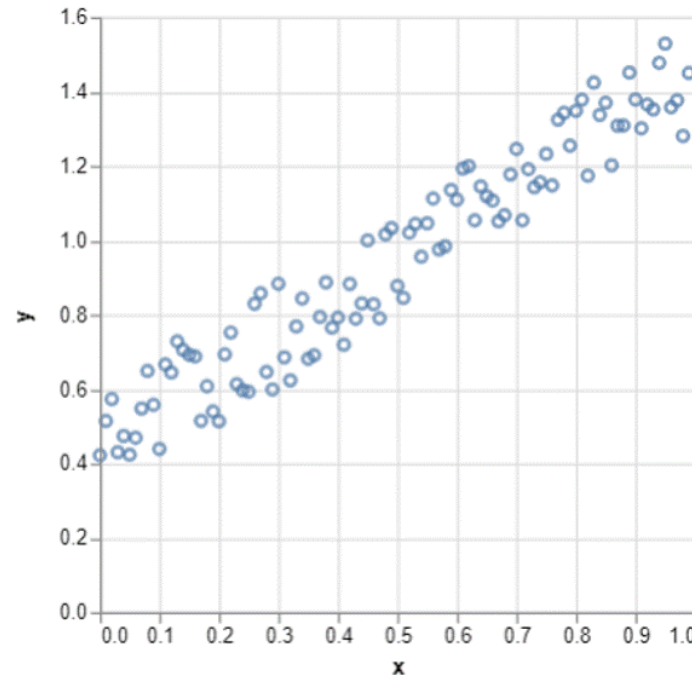


Data set

`coeffs = [1, 0.1];`

```
let y= coeffs[0] * x + coeffs[1]*(1+Math.random()) ;
```

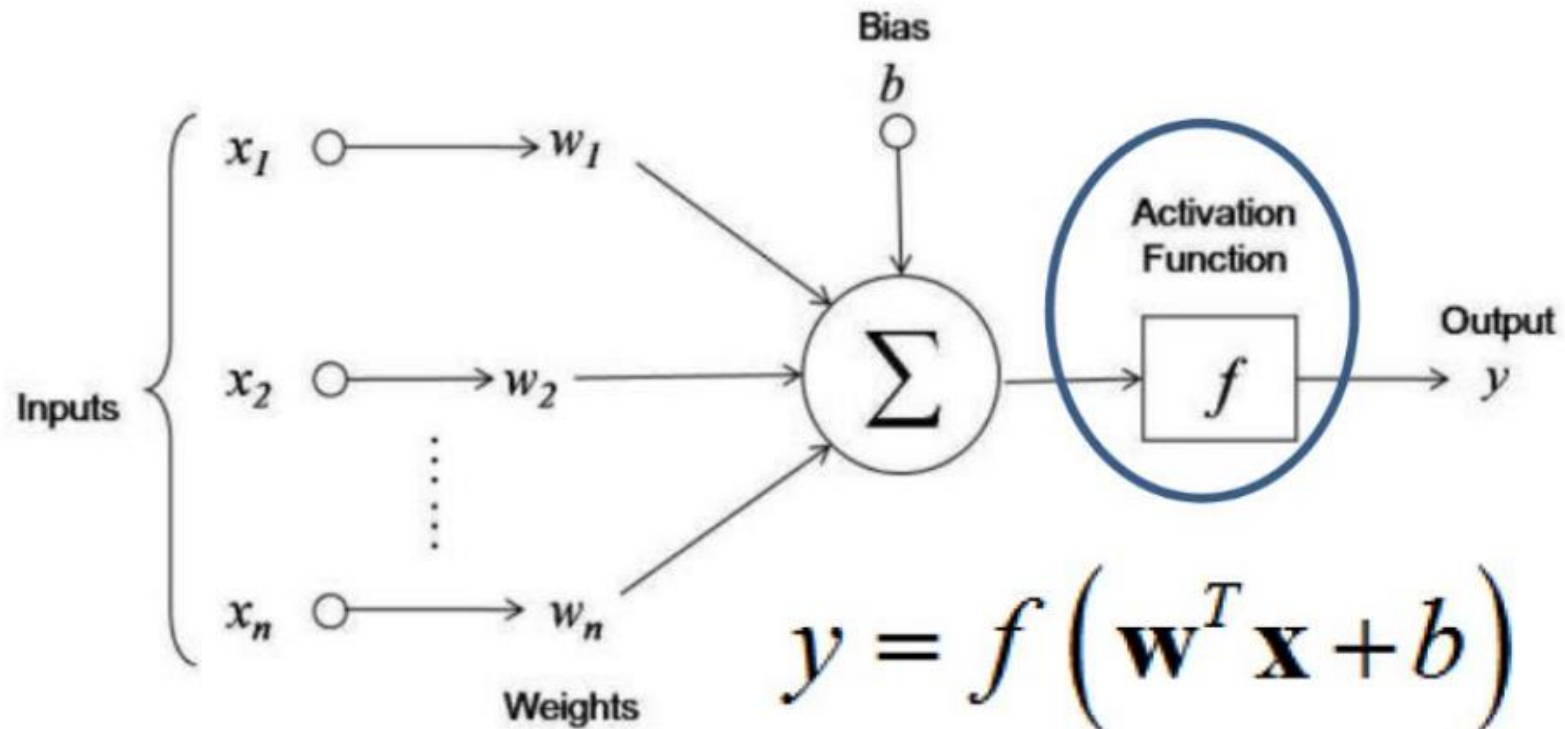
Linear Regression



[Save as SVG](#)[Save as PNG](#)[View Source](#)[Open in Vega Editor](#)

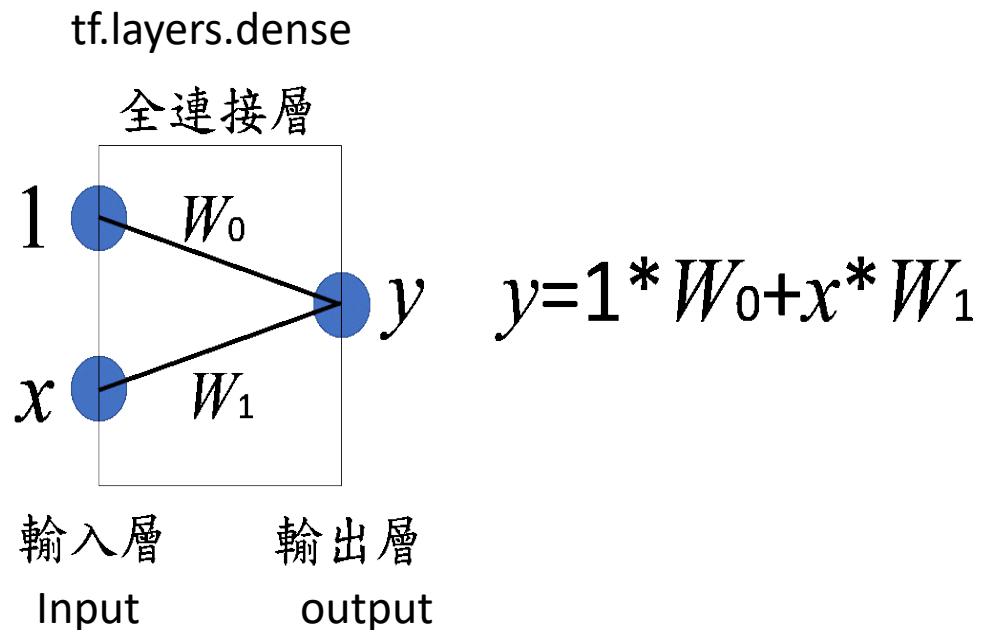
Tensorflow.js

tf.layers.dense

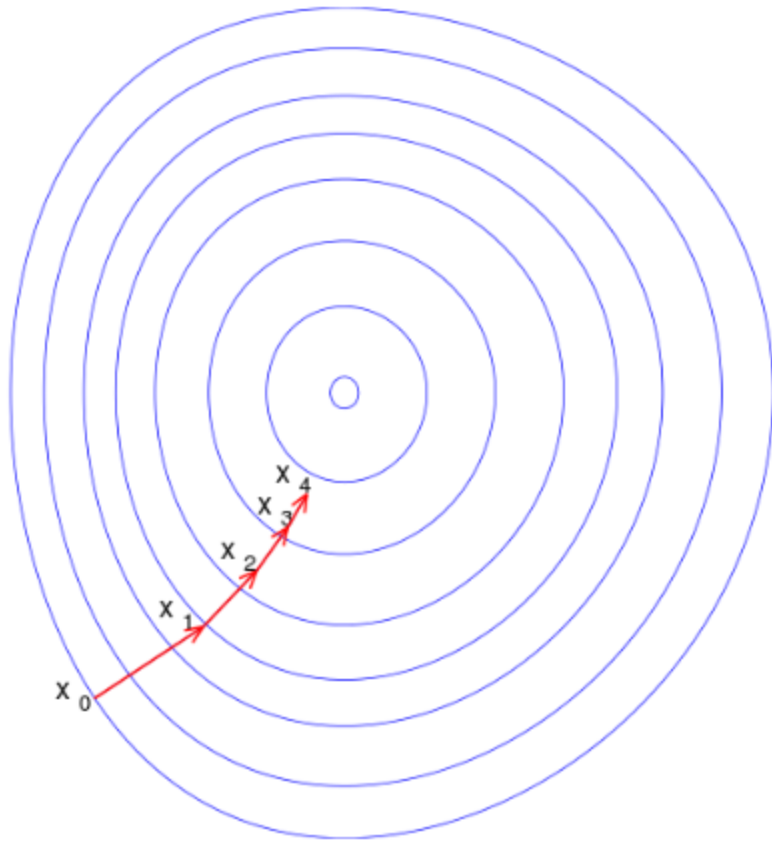


model

```
model = tf.sequential();  
  
model.add(tf.layers.dense({units: 1, inputShape: [2],  
    useBias: false}));
```



Optimization algorithms



Gradient descent

https://en.wikipedia.org/wiki/Gradient_descent

- Gradient method

B

- Biconjugate gradient method
- Biconjugate gradient stabilized method

C

- Conjugate gradient method
- Contour currents
- Coordinate descent

D

- Derivation of the conjugate gradient method

F

- *Gradient flow*
- Frank–Wolfe algorithm

G

- Gradient descent

L

- Landweber iteration

M

- Mirror descent

N

- Nonlinear conjugate gradient method

P

- Proximal gradient method

R

- Random coordinate descent

S

- Stochastic gradient descent
- Stochastic gradient Langevin dynamics
- Stochastic variance reduction

https://en.wikipedia.org/wiki/Category:Gradient_methods

最佳化的演算法

- 梯度下降（gradient descent, GD）法，梯度下降法是一個一階找最佳解的一種方法，是希望用梯度下降法找到損失函數的最小值，如3-6圖的某模型參數座標點對應到曲面上梯度的方向是走向最大的方向，所以在梯度下降法中是往梯度的反方向走，變化模型參數往讓損失函數最小值方向移動，如式子(9)所示。

-

$$\bullet \quad W(t+1) = W(t) - \gamma \nabla(f) \quad (9)$$

其中 f 為損失函數， $\nabla(f)$ 為函數 f 的梯度， γ 為學習率(learning rate)， $W(t)$ 為在某時間點模型參數座標值， $W(t+1)$ 為調整後的模型參數座標。

Loss function

- 均方誤差(**mean-square error, MSE**)函數，是各測量值誤差的平方和取平均值，以有 n 個量測值 y_i 與模型計算出的結果 y_i^p 之均方誤差表示如**(8)**所示:

-

$$\bullet \text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - y_i^p)^2 \quad (8)$$

- 其中 $y_i^p = 1 * W_0 + x_i * W_1$ ， x_i 為第 i 筆測試資料的 x 值，根據第 i 筆測試資料的 x 值帶入 W_0 與 W_1 計算出的 y 值就是 y_i^p

Setting Optimization algorithm & loss function

```
43 const learningRate = 0.01;  
44 const sgd = tf.train.sgd(learningRate);  
45 // 'meanSquaredError'  
46 model.compile({optimizer: sgd, loss: 'meanSquaredError'});  
47
```

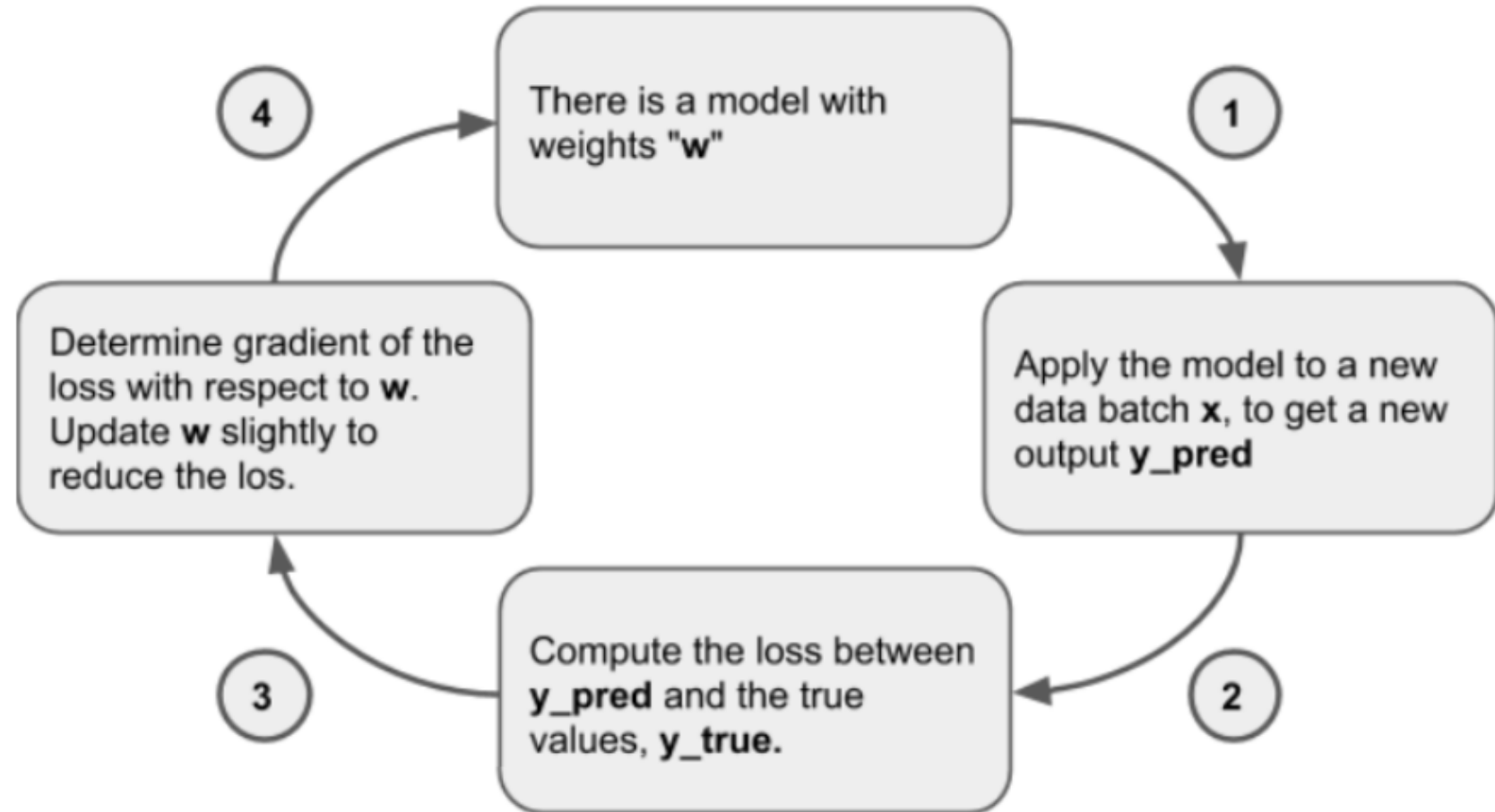
Optimization algorithm



loss function



Training process



Training

```
const batchSize = 10;
const epochs = 200;
await model.fit( xtensor,ytensor, {
  batchSize: batchSize,
  epochs: epochs,
  callbacks: {
    onEpochEnd: async (epoch, log) => { console.log(epoch),
      console.log(log.loss); Prediction(x);
      plotloss("#vis2", log.loss, epoch);
      var W= Array.from(model.trainableWeights[0].read().dataSync());
      var style = log.loss;
      data3d.add({x:W[0],y:W[1],z:log.loss,style:style});
      drawVisualizationdot("vis3",data3d);
    }
  }
});
```

Prediction

```
const xtensor = tf.tensor2d(xArrayData, [nVx.length, 2]);  
  
xtensor.print();  
  
const predictOut = await model.predict(xtensor);  
  
Ysfinal = predictOut.dataSync();  
console.log('Ysfinal =', Ysfinal);  
  
predictOut.dispose();  
xtensor.dispose();  
plotData2("#vis1", xyData[0], xyData[1], xyData[0], Ysfinal);
```

Plot

- `function drawVisualizationdot(containerid,datadot) {

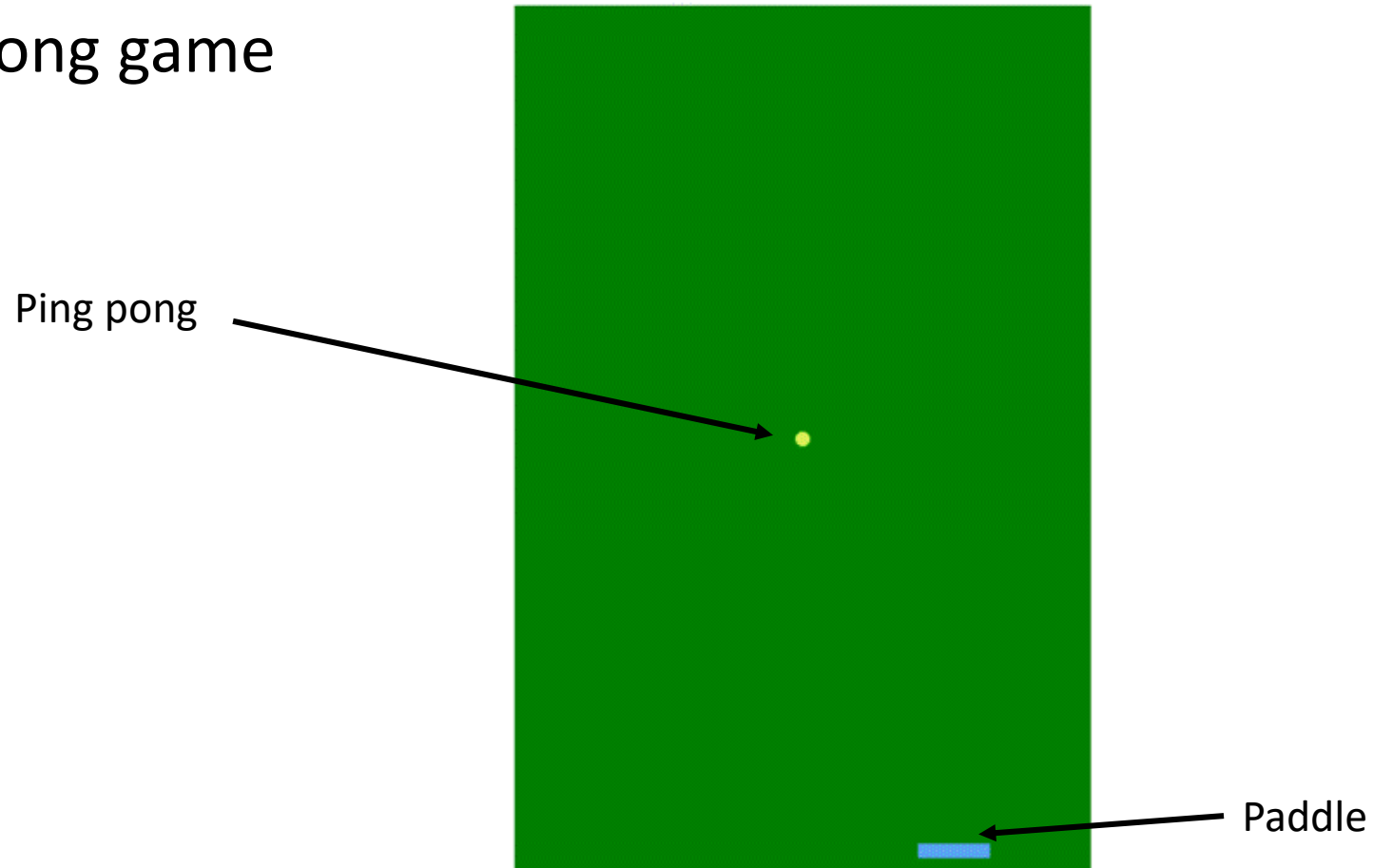
}`
- `function plotloss(container, loss, epoch) {

}`
- `function plotData2(container, xs, ys, xspreds, yspreds) {

}`

Exercise 11-2

- ex1130_2.html (copy from ex1130_2.txt)
- Ping pong game



網頁內容

Console視窗

Ping Pong Game

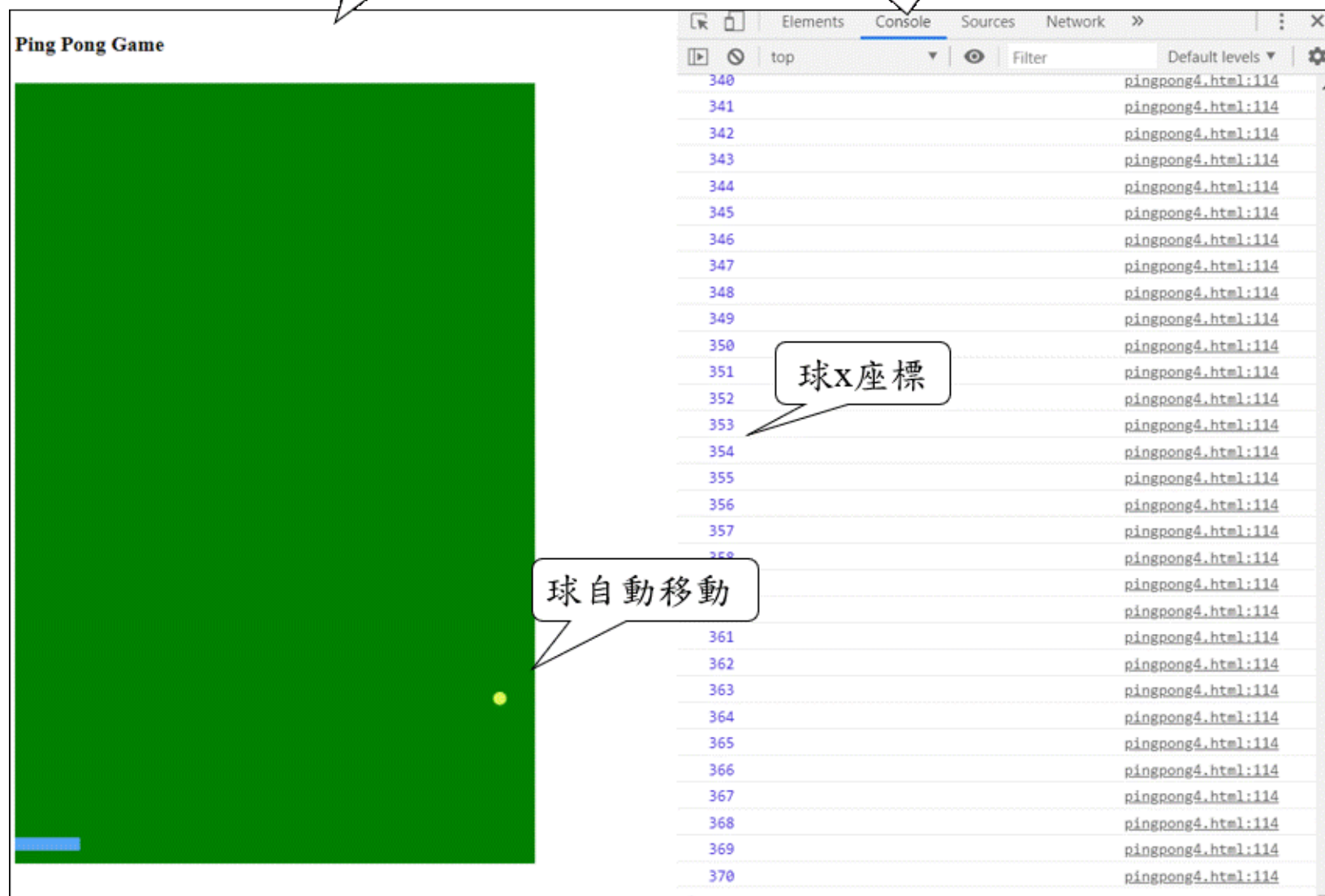
球拍移動

按鍵代碼

keysDown内容

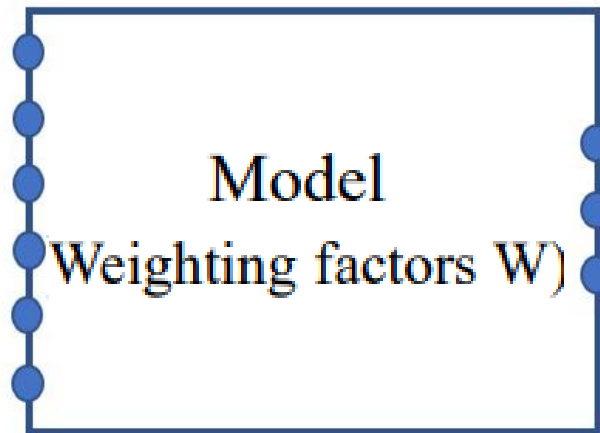
網頁內容

Console視窗



Model

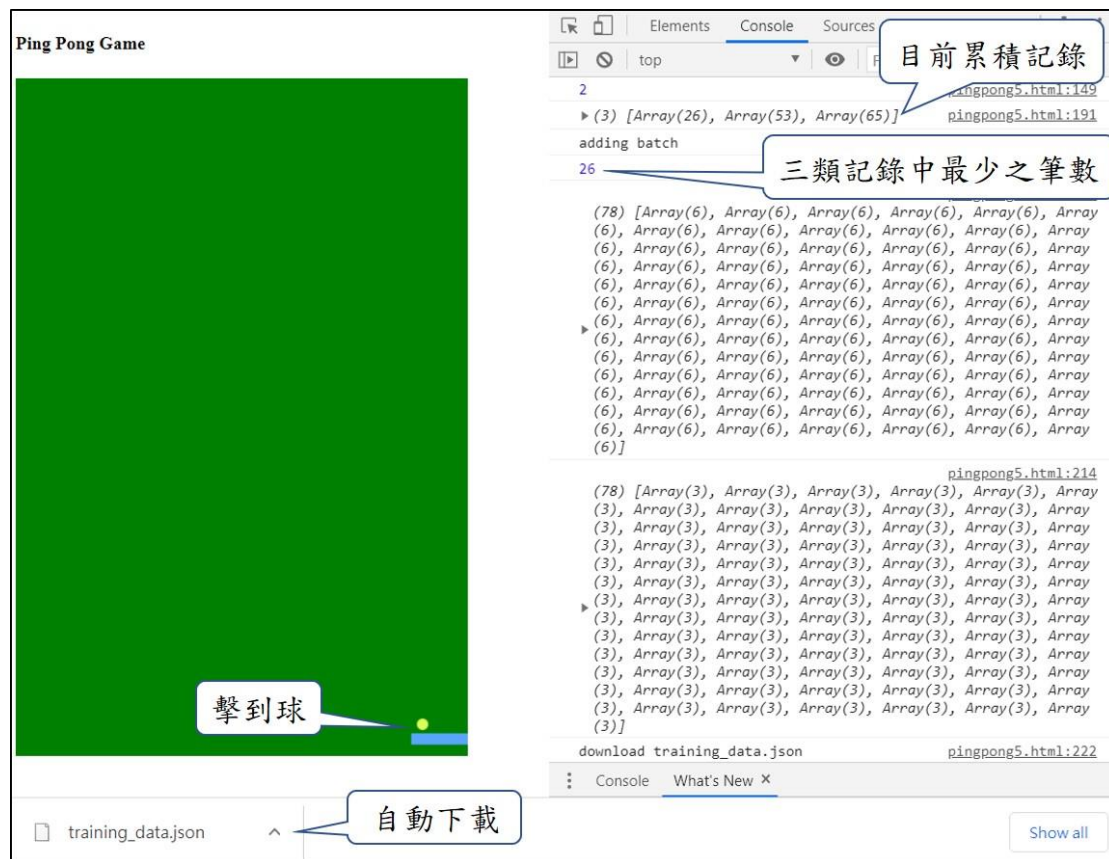
Ball x
Ball y
previous ball x
previous ball y
previous player paddle x
previous computer paddle x



Paddle moves left
Paddle does nothing
Paddle moves right

Exercise 11-3

- ex1130_3.html (copy from ex1130_3.txt)
- Record playing data



[illegible]

```
1 console.log(len);
```

```
2 var data_xx=[];
```

```
3 var data_yy=[];
```

```
4  
5 if (len > 10){
```

```
6   for(i = 0; i < 3; i++){
```

```
7     data_xx.push(...training_data[i].slice(0, len));
```

```
8     // trims training data to 'len' length
```

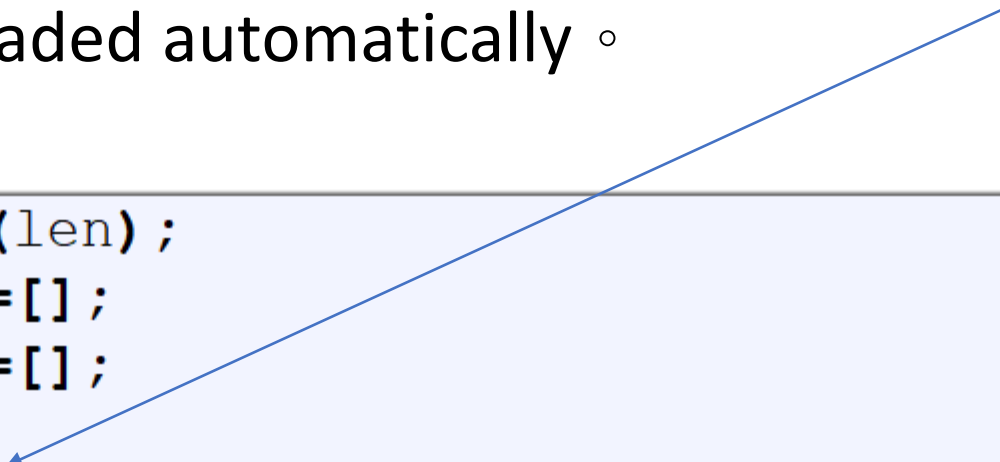
```
9     data_yy.push(...Array(len).fill([i==0?1:0, i==1?1:0  
10    , i==2?1:0])); // creates 'len' number records  
11    of embedding data
```

Blob

```
var a = document.createElement("a");  
// var a = document.getElementById("a");  
var file = new Blob([JSON.stringify({xs: data_xx, ys  
: data_yy})]), {type: 'application/json'});  
a.href = URL.createObjectURL(file);  
a.download = 'training_data.json';  
a.click();  
console.log('download training_data.json');  
//印出文字'download training_data.json'
```

Exercise 11-4

- change code: when the length of the record is larger than 3000, the json file will be downloaded automatically ◦



```
1 console.log(len);
2 var data_xx=[];
3 var data_yy=[];
4
5 if (len > 10){
6     for(i = 0; i < 3; i++){
7         data_xx.push(...training_data[i].slice(0, len));
8         // trims training data to 'len' length
9
10        data_yy.push(...Array(len).fill([i==0?1:0, i==1?1:0
11        , i==2?1:0])); // creates 'len' number records
```

Classification Problem

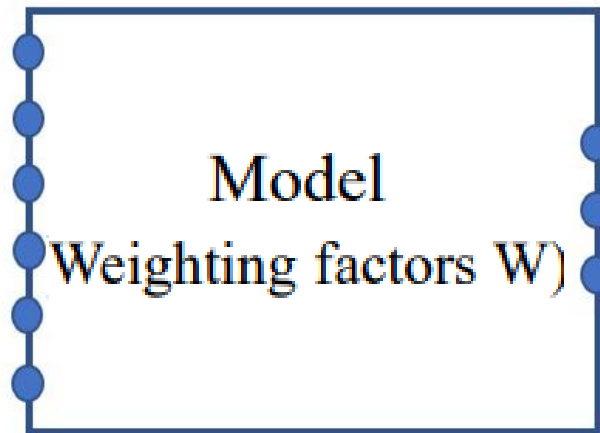
- $y \in \{\text{dog, cat, chicken}\} \Rightarrow y \in \{1, 2, 3\} \Rightarrow y \in \{(1, 0, 0), (0, 1, 0), (0, 0, 1)\}$
- In our case, a label y would be a three-dimensional vector, with $(1, 0, 0)$ corresponding to “cat”, $(0, 1, 0)$ to “chicken”, and $(0, 0, 1)$ to “dog”:
- $y \in \{\text{baby, toddler, adolescent, young adult, geriatric}\} \Rightarrow y \in \{1, 2, \dots, ?\} \Rightarrow y \in \{????\}$

Classification

Classification	Label
Paddle move left	[1,0,0]
Paddle does nothing	[0,1,0]
Paddle move right	[0,0,1]

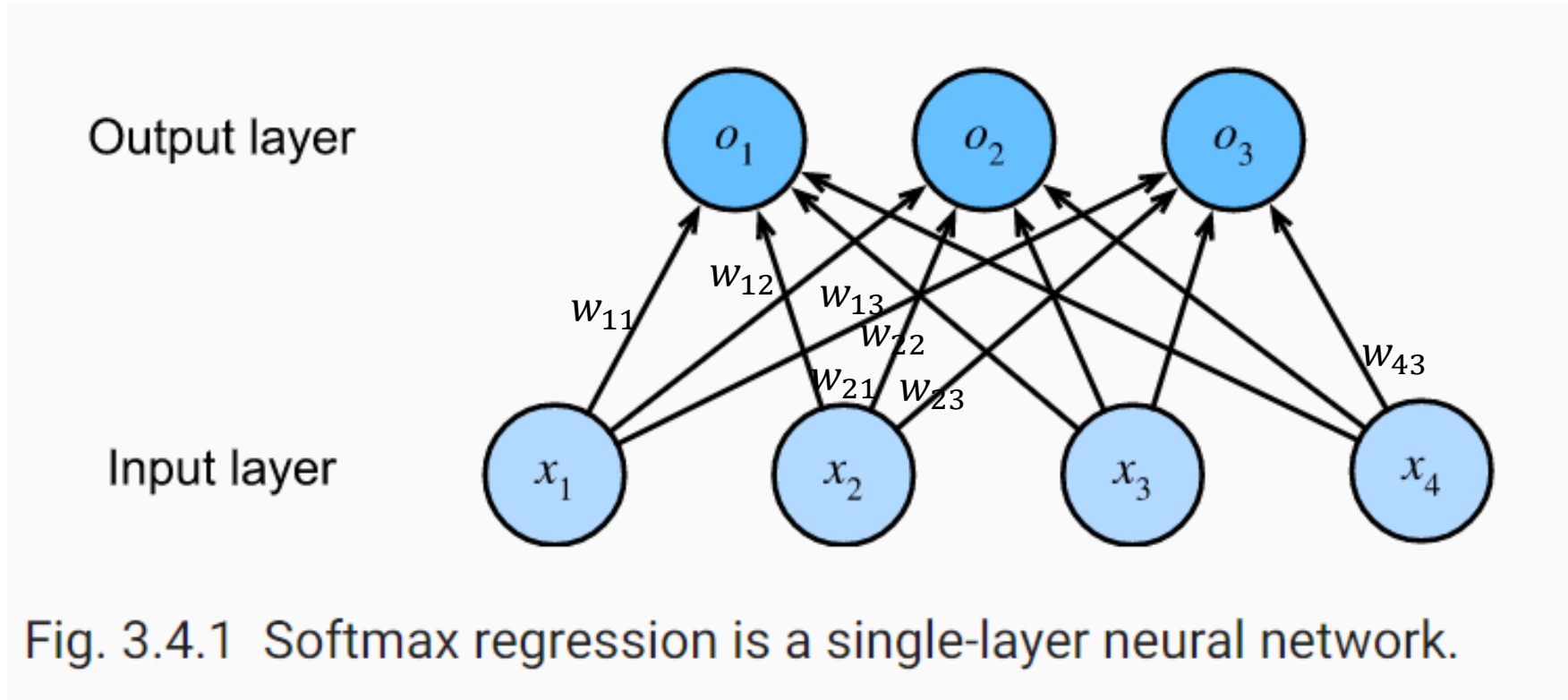
Model

Ball x
Ball y
previous ball x
previous ball y
previous player paddle x
previous computer paddle x



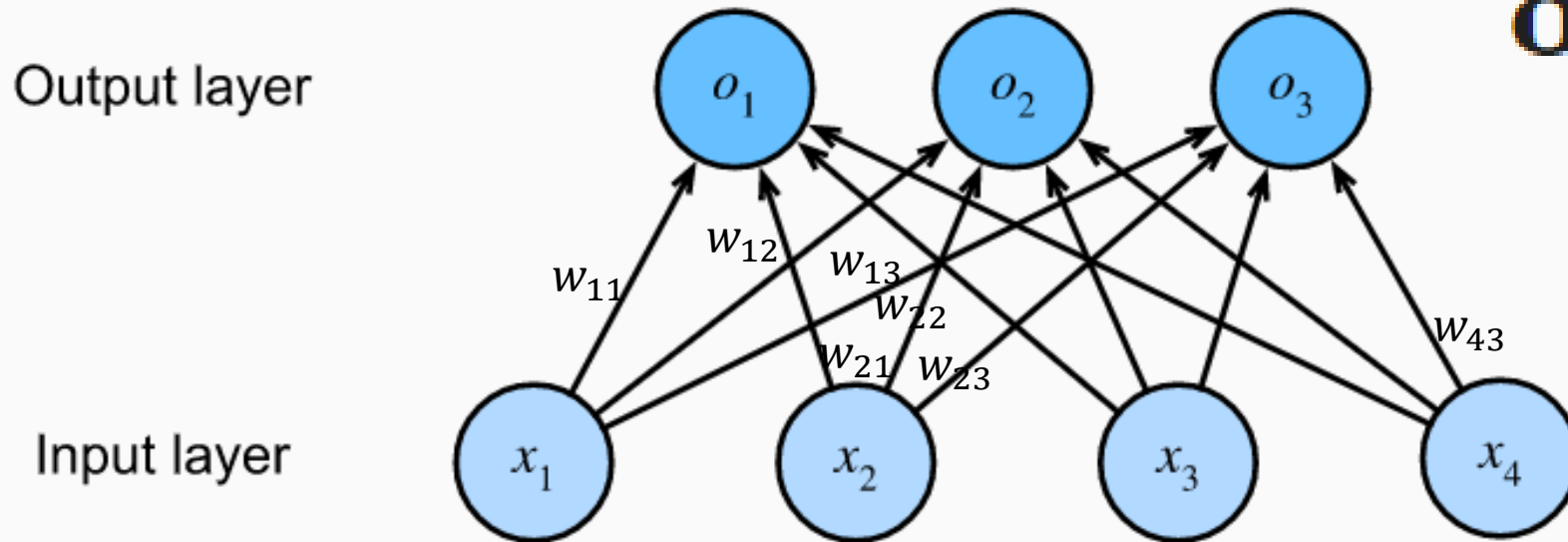
Paddle moves left
Paddle does nothing
Paddle moves right

Network Architecture



$$\mathbf{o} = \mathbf{W}\mathbf{x} + \mathbf{b},$$

Network Architecture



$$\mathbf{o} = \mathbf{W}\mathbf{x} + \mathbf{b},$$

Fig. 3.4.1 Softmax regression is a single-layer neural network.

$$\begin{aligned} o_1 &= x_1 w_{11} + x_2 w_{12} + x_3 w_{13} + x_4 w_{14} + b_1, \\ o_2 &= x_1 w_{21} + x_2 w_{22} + x_3 w_{23} + x_4 w_{24} + b_2, \\ o_3 &= x_1 w_{31} + x_2 w_{32} + x_3 w_{33} + x_4 w_{34} + b_3. \end{aligned}$$

$$\begin{aligned} o_1 &= w_{11}x_1 + w_{12}x_2 + w_{13}x_3 + w_{14}x_4 + b_1 \\ o_2 &= ? \\ o_3 &= ? \end{aligned}$$

Softmax Operation

$$\hat{\mathbf{y}} = \text{softmax}(\mathbf{o}) \quad \text{where} \quad \hat{y}_j = \frac{\exp(o_j)}{\sum_k \exp(o_k)}. \quad (3.4.3)$$

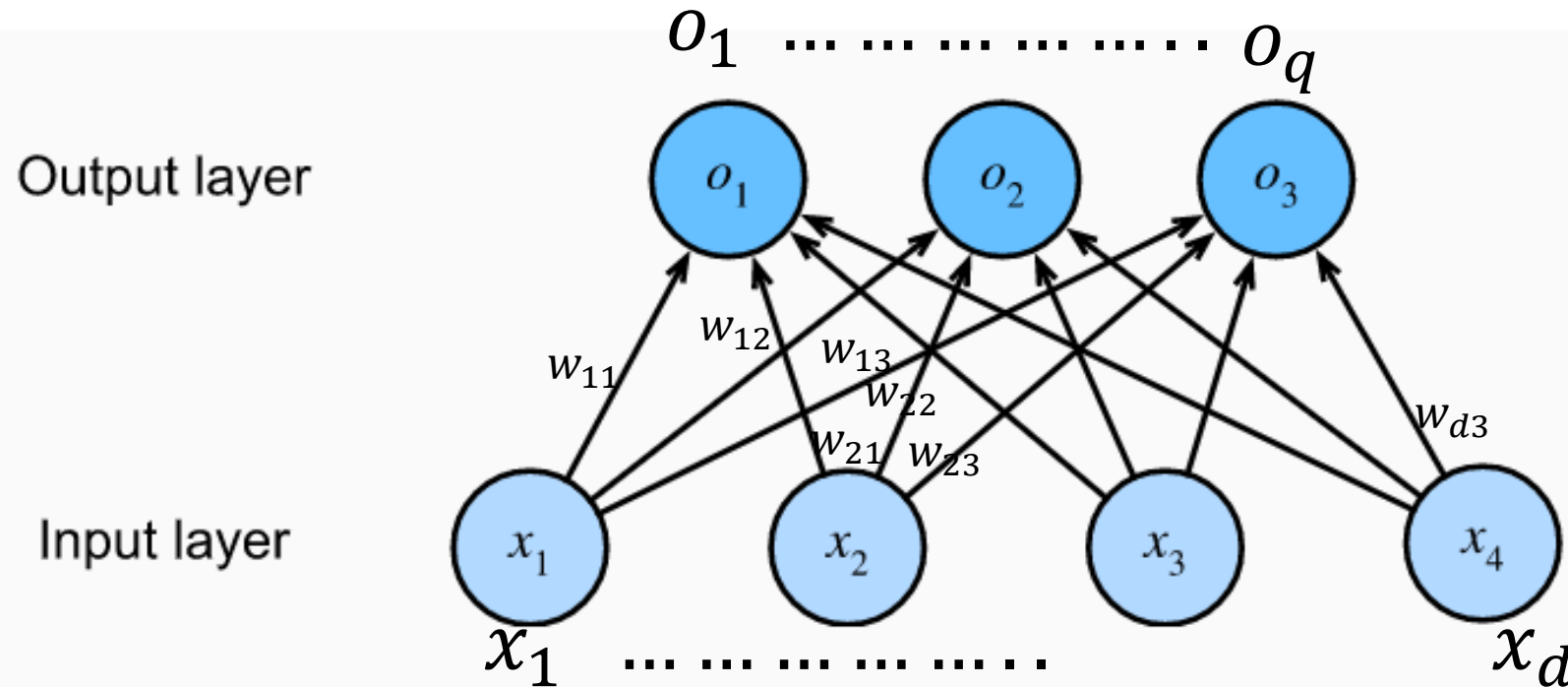
It is easy to see $\hat{y}_1 + \hat{y}_2 + \hat{y}_3 = 1$ with $0 \leq \hat{y}_j \leq 1$ for all j . Thus, $\hat{\mathbf{y}}$ is a proper probability distribution whose element values can be interpreted accordingly.

we can still pick out the most likely class by

$$\underset{j}{\operatorname{argmax}} \hat{y}_j = \underset{j}{\operatorname{argmax}} o_j. \quad (3.4.4)$$

Although softmax is a nonlinear function, the outputs of softmax regression are still *determined* by an affine transformation of input features; thus, softmax regression is a linear model.

Vectorization for Minibatches



$$\mathbf{X} \in \mathbb{R}^{n \times d}.$$

$$\mathbf{W} \in \mathbb{R}^{d \times q}$$

$$\mathbf{O} = \mathbf{XW} + \mathbf{b},$$

$$\hat{\mathbf{Y}} = \text{softmax}(\mathbf{O}).$$

Fig. 3.4.1 Softmax regression is a single-layer neural network.

Multilayer Perceptrons

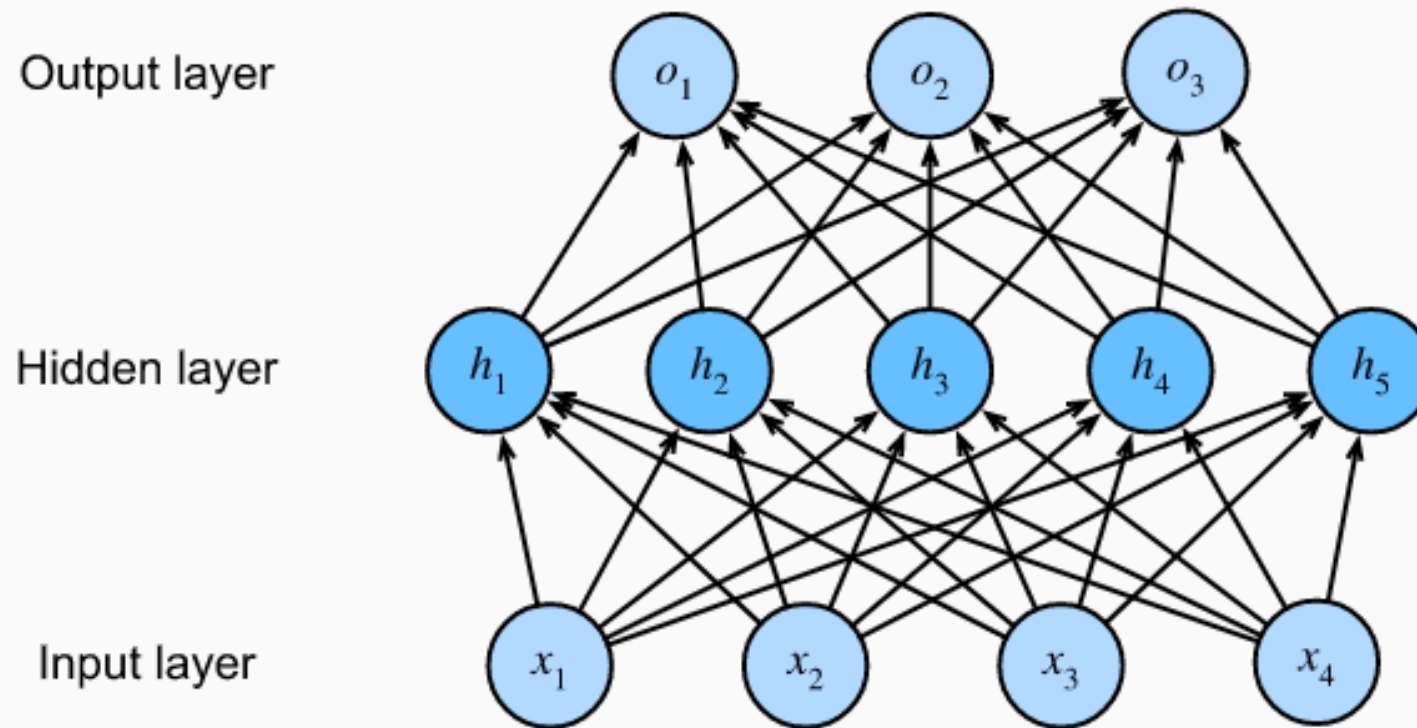


Fig. 4.1.1 An MLP with a hidden layer of 5 hidden units.

Multilayer Perceptrons

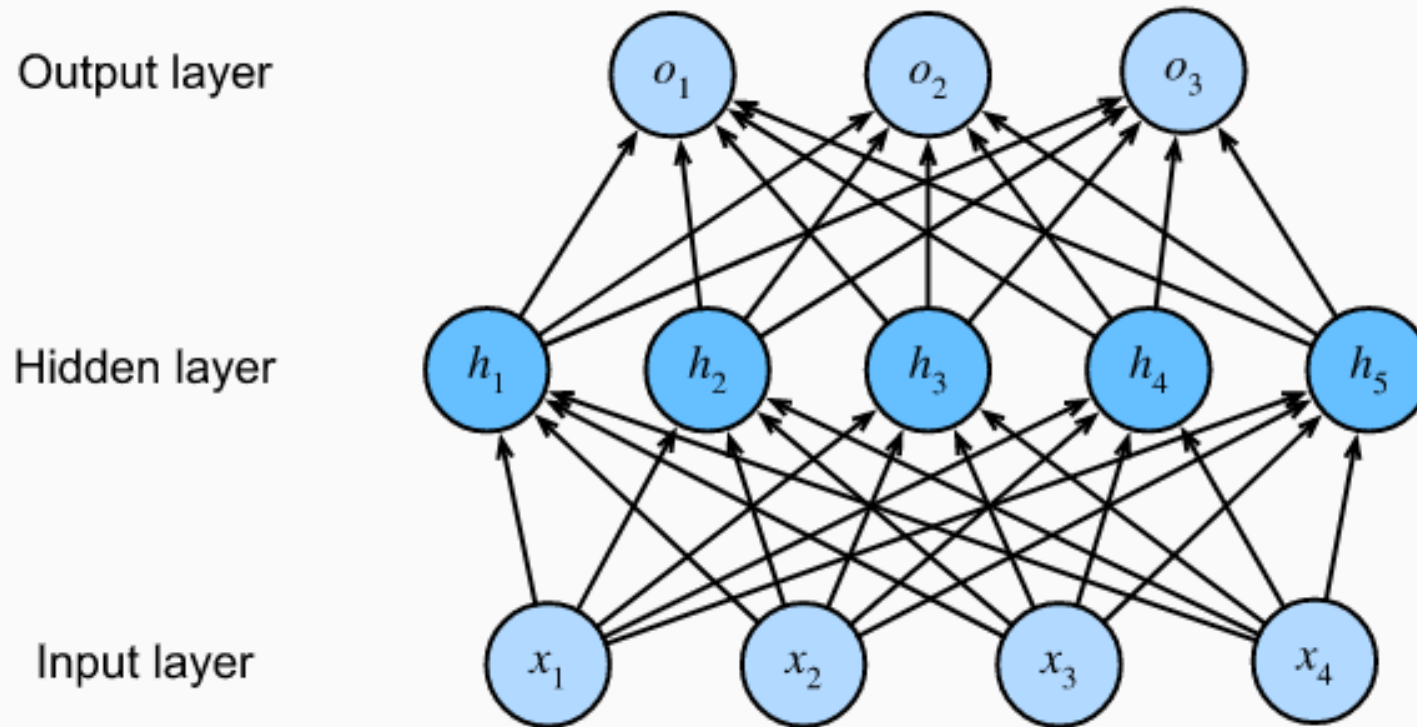
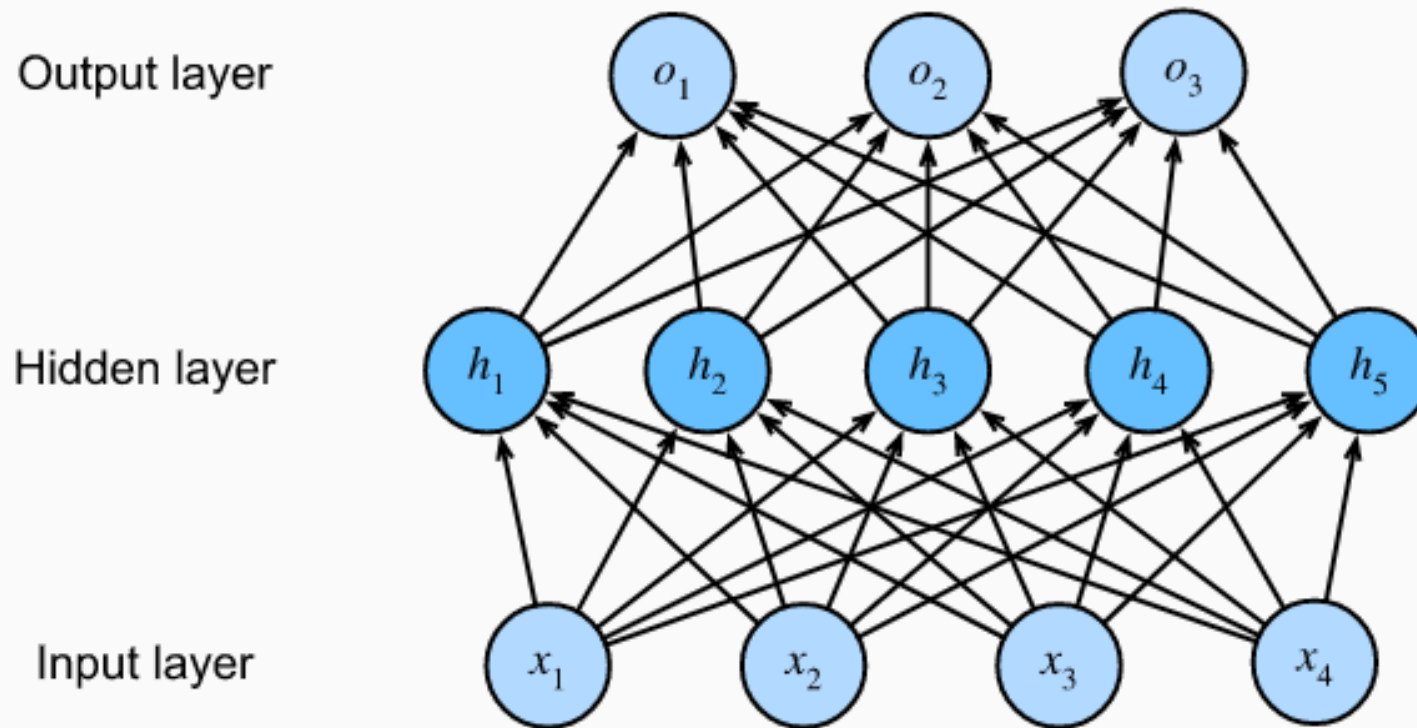


Fig. 4.1.1 An MLP with a hidden layer of 5 hidden units.

$$\mathbf{H} = \mathbf{XW}^{(1)} + \mathbf{b}^{(1)},$$

Multilayer Perceptrons

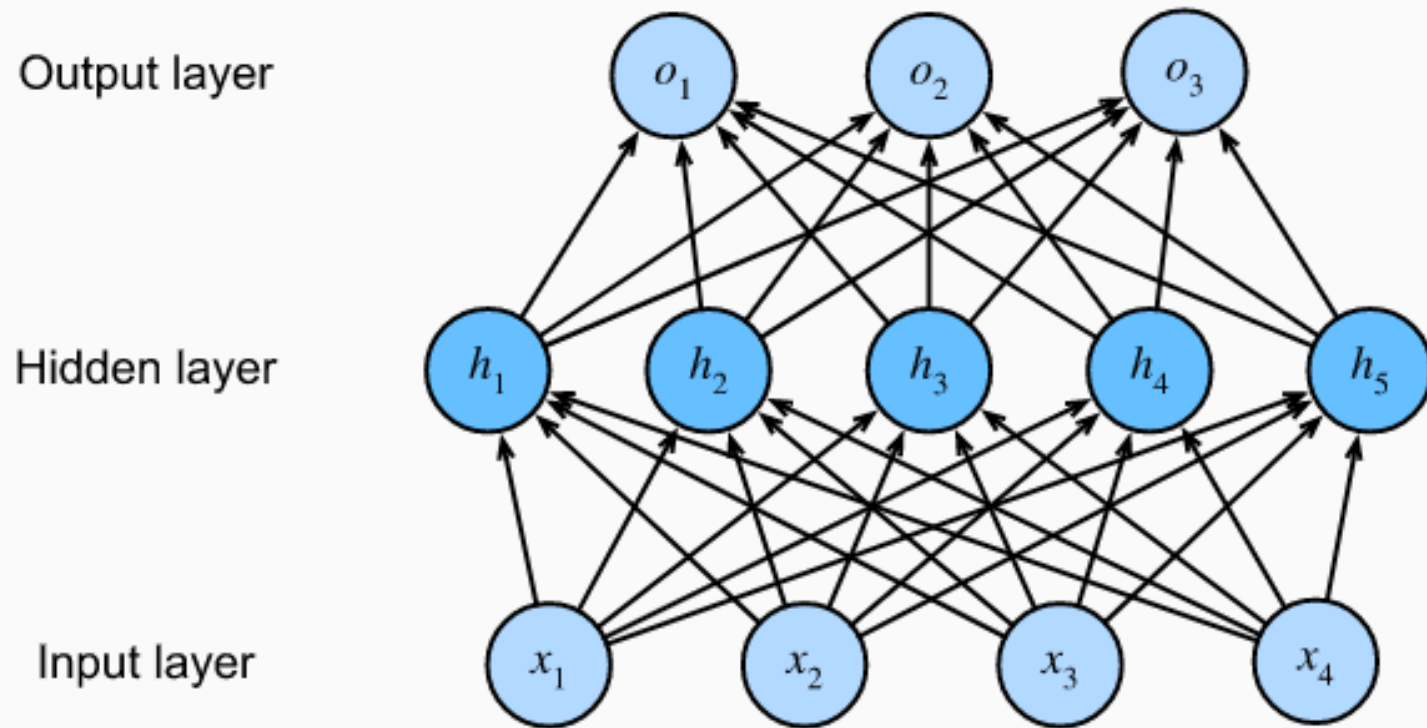


$$\mathbf{O} = \mathbf{H}\mathbf{W}^{(2)} + \mathbf{b}^{(2)}.$$

$$\mathbf{H} = \mathbf{X}\mathbf{W}^{(1)} + \mathbf{b}^{(1)},$$

Fig. 4.1.1 An MLP with a hidden layer of 5 hidden units.

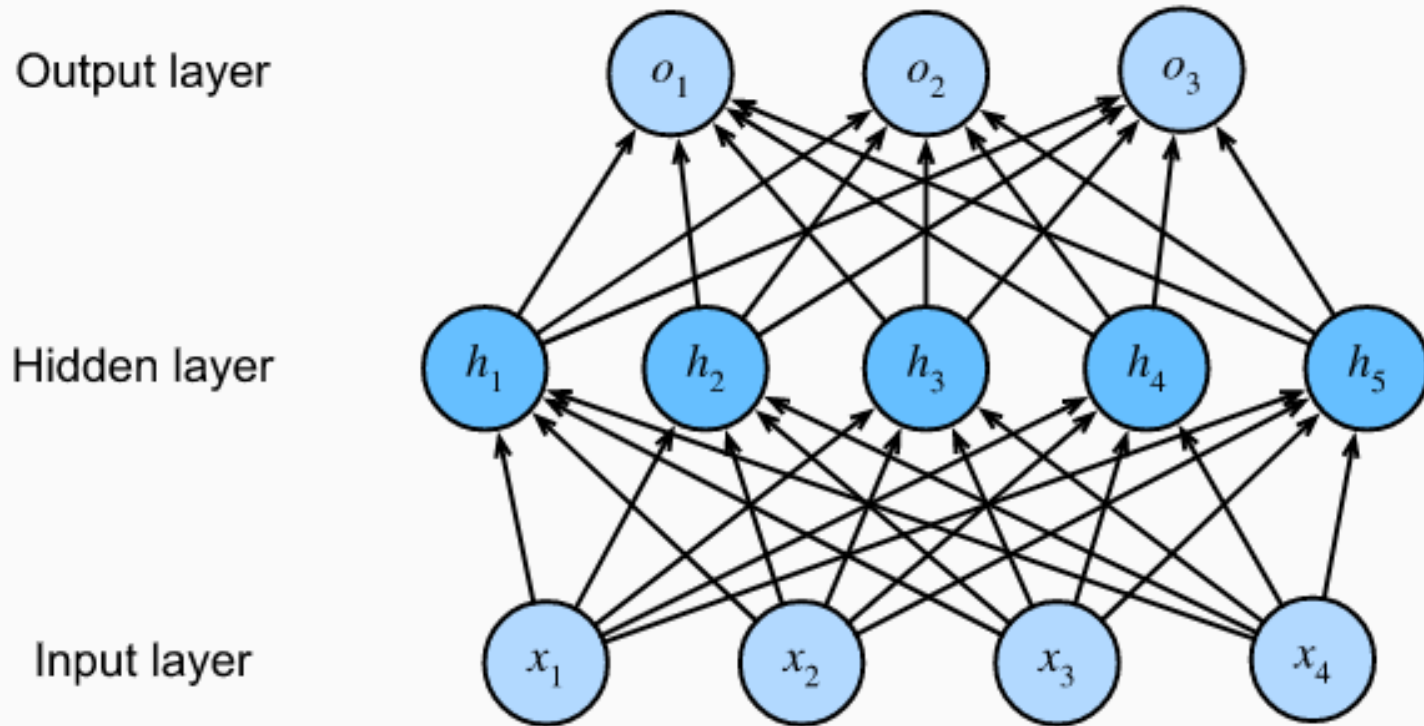
From Linear to Nonlinear



$$\mathbf{H} = \sigma(\mathbf{X}\mathbf{W}^{(1)} + \mathbf{b}^{(1)}),$$

Fig. 4.1.1 An MLP with a hidden layer of 5 hidden units.

From Linear to Nonlinear



$$\mathbf{O} = \mathbf{H}\mathbf{W}^{(2)} + \mathbf{b}^{(2)}.$$

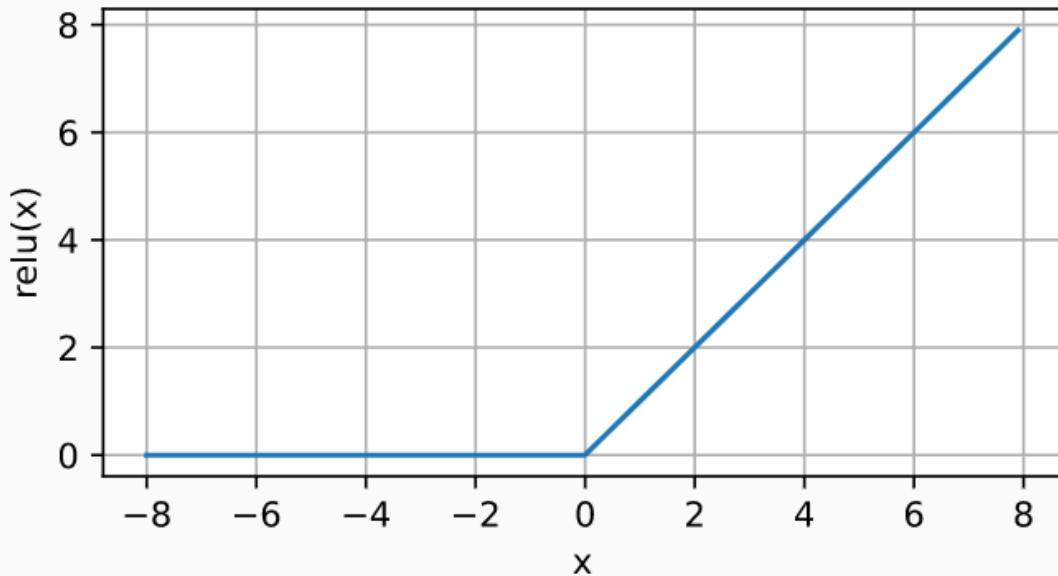
$$\mathbf{H} = \sigma(\mathbf{X}\mathbf{W}^{(1)} + \mathbf{b}^{(1)}),$$

↑
Activation Functions

Fig. 4.1.1 An MLP with a hidden layer of 5 hidden units.

Activation Functions

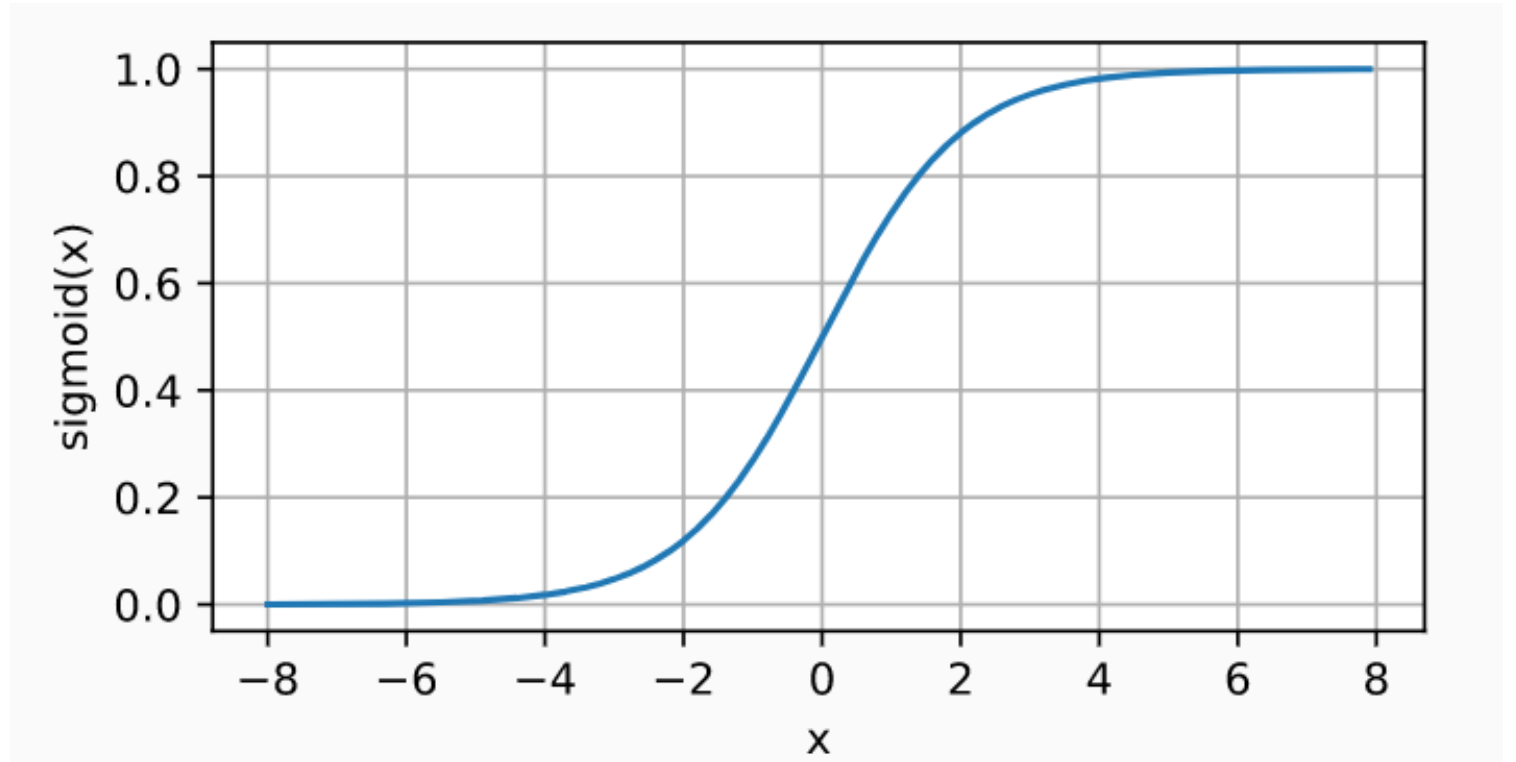
- ReLU Function



$$\text{ReLU}(x) = \max(x, 0).$$

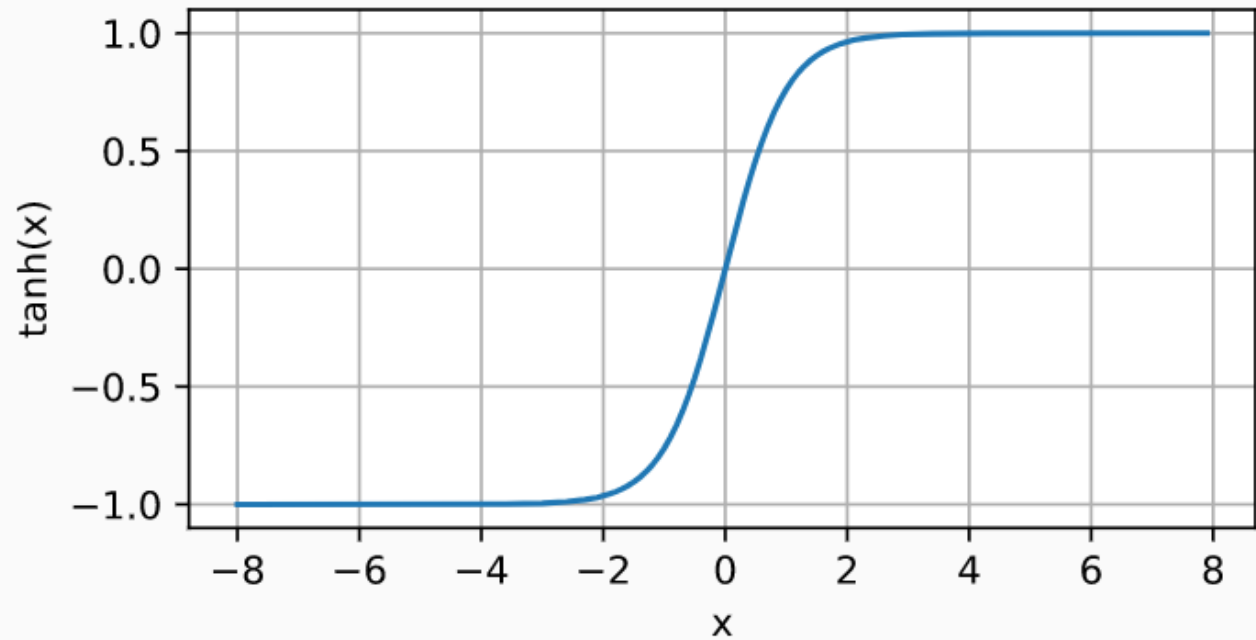
Sigmoid Function

$$\text{sigmoid}(x) = \frac{1}{1 + \exp(-x)}.$$



Tanh Function

$$\tanh(x) = \frac{1 - \exp(-2x)}{1 + \exp(-2x)}.$$



```
// Initializes a sequential model
const model = tf.sequential();
// The line below needs curly braced inputs (note the syntax similarity with TF K
// We are using 10 units and ReLU activation. The input shape is a 28 by 28 monoc
model.add(tf.layers.dense({units:64,inputShape:[28,28,1],activation:'relu'}));
// This line compiles the model quite similar to model.compile in TensorFlow, wit
model.compile({
  optimizer:'adam',
  loss:'categoricalCrossentropy'
});
// This line fits the model on the dataset, which is currently stored in a tensor
await model.fit(xs,ys,{
  epochs: 100,
  callbacks: { // The line below may look scary, but all it does it prints the lo
    onEpochEnd: async(epoch,logs) =>{
      console.log("Epoch :" + epoch + " Loss:" + logs.loss);
    }
  }
});
// Done!
```

Initializes a sequential model



Add layers



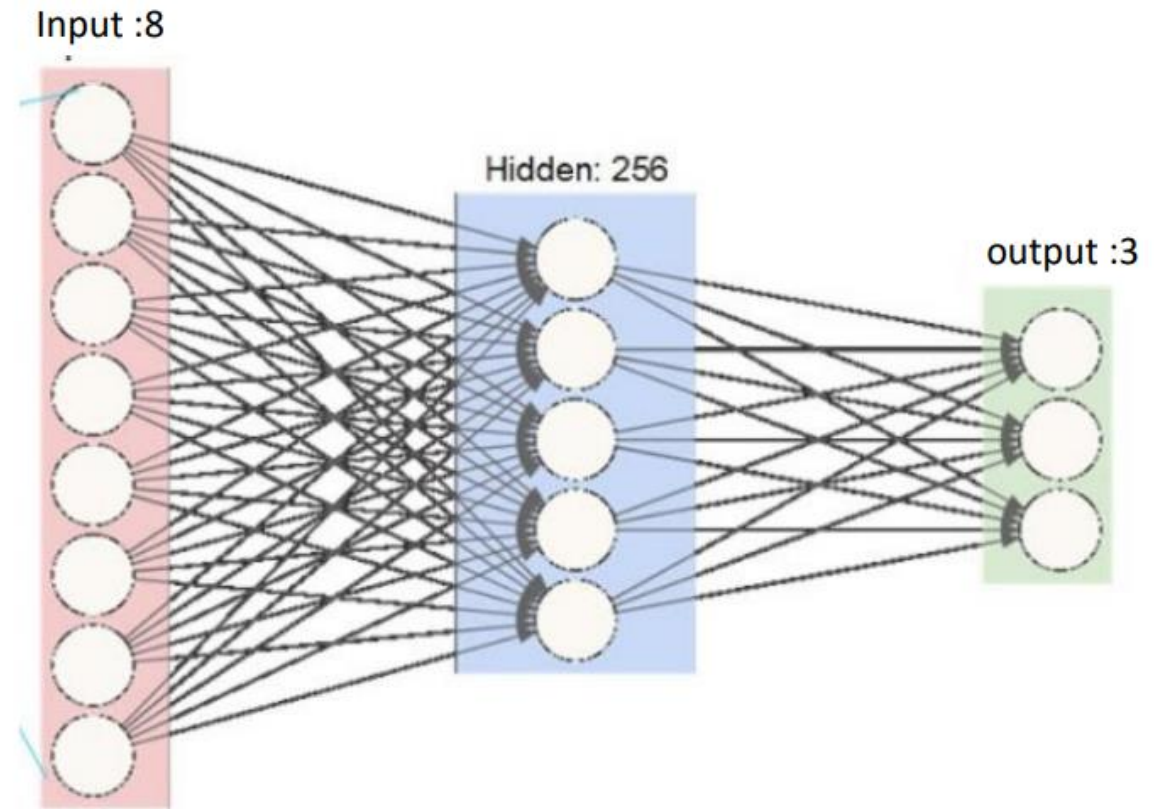
Compile



fit

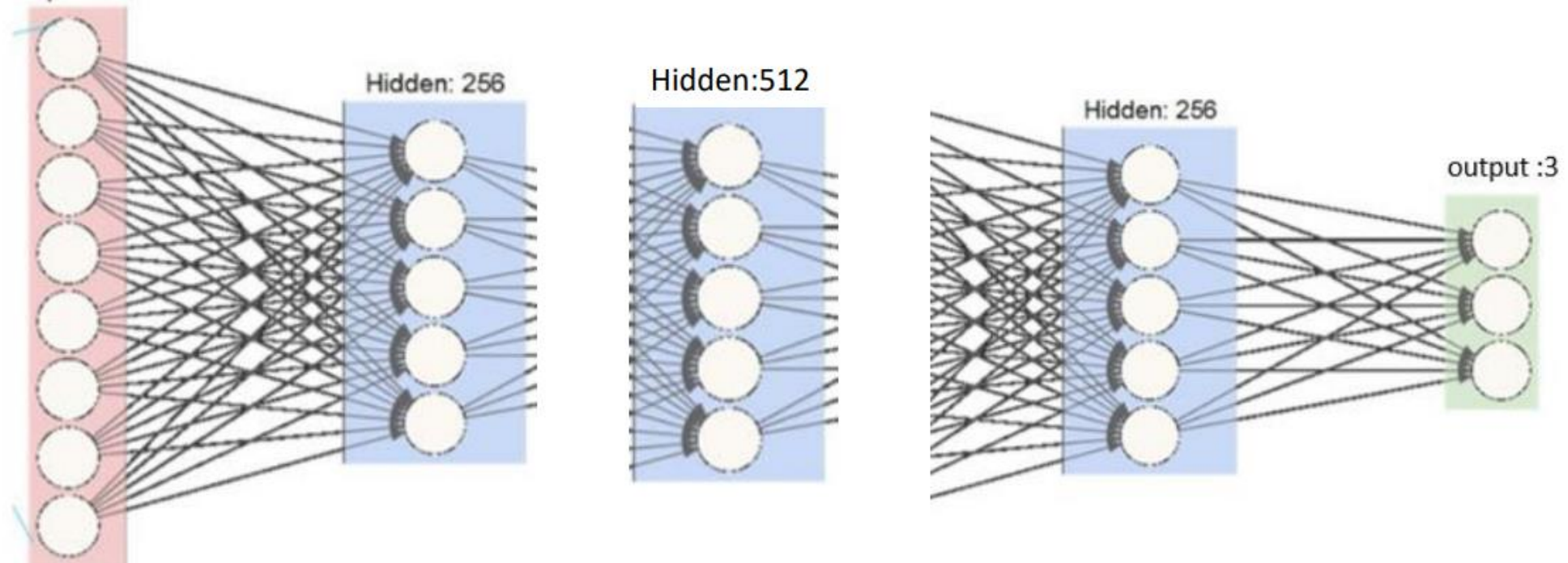
model

```
const model = tf.sequential();  
model.add(tf.layers.dense({units: 256, inputShape: [8]}));  
model.add(tf.layers.dense({units: 3, inputShape: [256]}));  
//returns a 1x3
```



```
// initial model definition
const model = tf.sequential();
model.add(tf.layers.dense({units: 256, inputShape: [8]})); //input is a 1x8
model.add(tf.layers.dense({units: 512, inputShape: [256]}));
model.add(tf.layers.dense({units: 256, inputShape: [512]}));
model.add(tf.layers.dense({units: 3, inputShape: [256]})); //returns a 1x3
```

Input :8



Exercise 11-5

- ex1130_5.html (copy from ex1130_5.txt)
- Train model

model

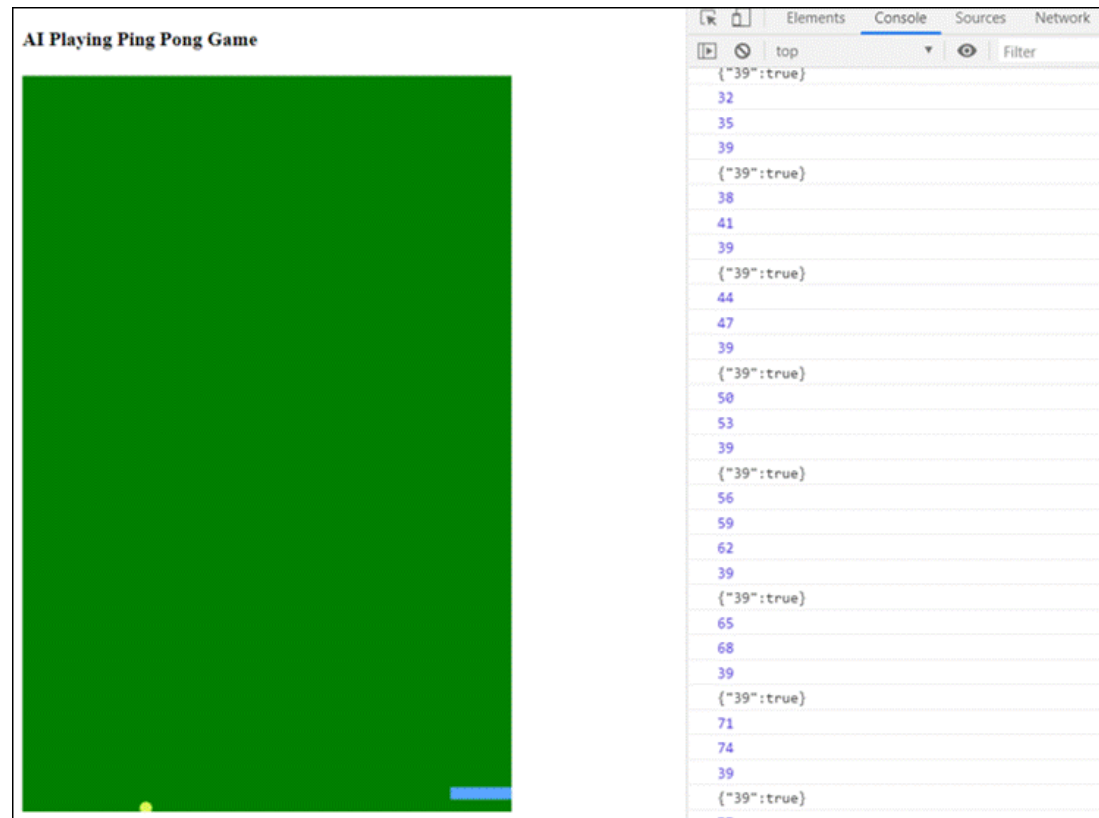
```
model = tf.sequential();  
model.add(tf.layers.dense({units: 64, activation: 'relu',  
inputShape: [6]})); //input is a 1x8  
model.add(tf.layers.dropout(0.5));  
model.add(tf.layers.dense({units: 64, activation: 'relu'}));  
model.add(tf.layers.dropout(0.5));  
model.add(tf.layers.dense({units: 3, activation: 'softmax'}));
```


Setting Optimization algorithm & loss function

```
// set optimiser and compile model
const learningRate = 0.001;
const optimizer = tf.train.adam(learningRate);
model.compile({loss: 'categoricalCrossentropy', optimizer:
optimizer, metrics: ['accuracy']});
console.log( 'compile finished');
```

Exercise 11-6

- ex1130_6.html (copy from ex1130_6.txt)
- AI play ping pong game



Model summary

Layer (type)	Output shape	Param #

dense_Dense1 (Dense)	[null,64]	448

dropout_Dropout1 (Dropout)	[null,64]	0

dense_Dense2 (Dense)	[null,64]	4160

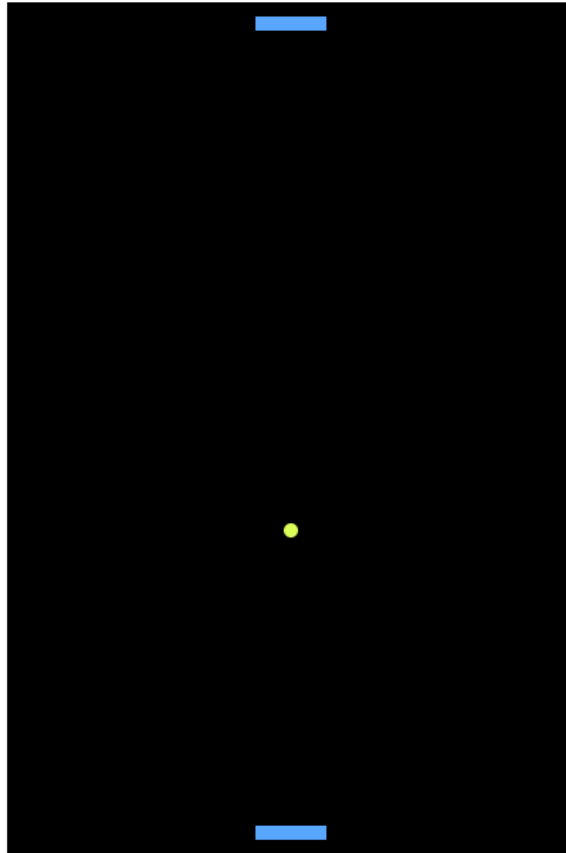
dropout_Dropout2 (Dropout)	[null,64]	0

dense_Dense3 (Dense)	[null,3]	195

Total params: 4803		
Trainable params: 4803		
Non-trainable params: 0		

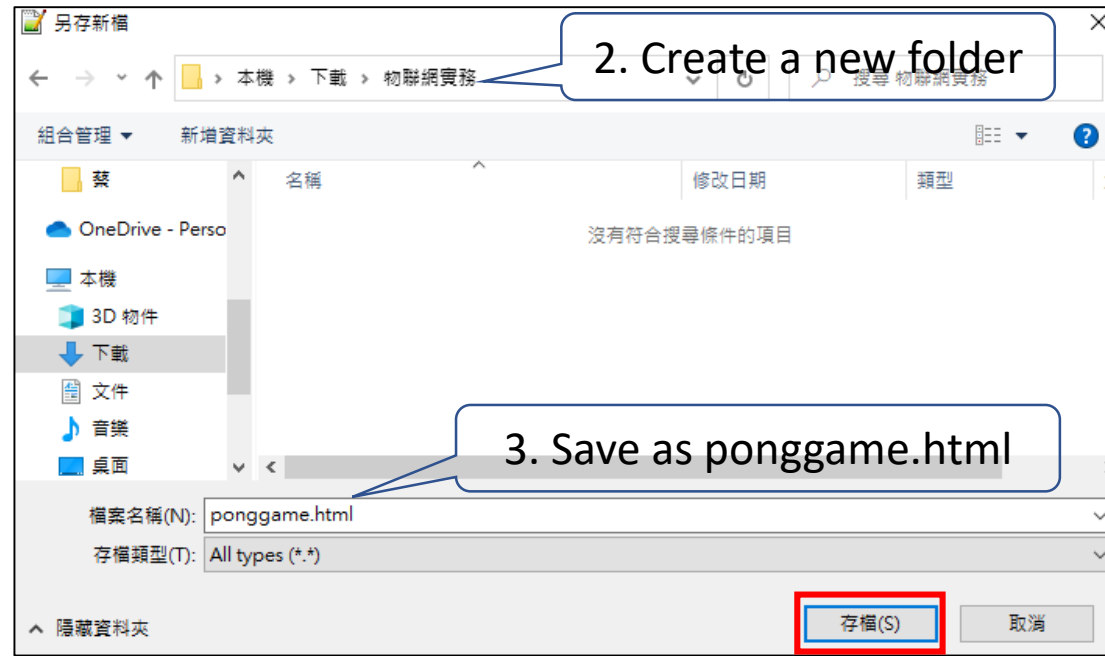
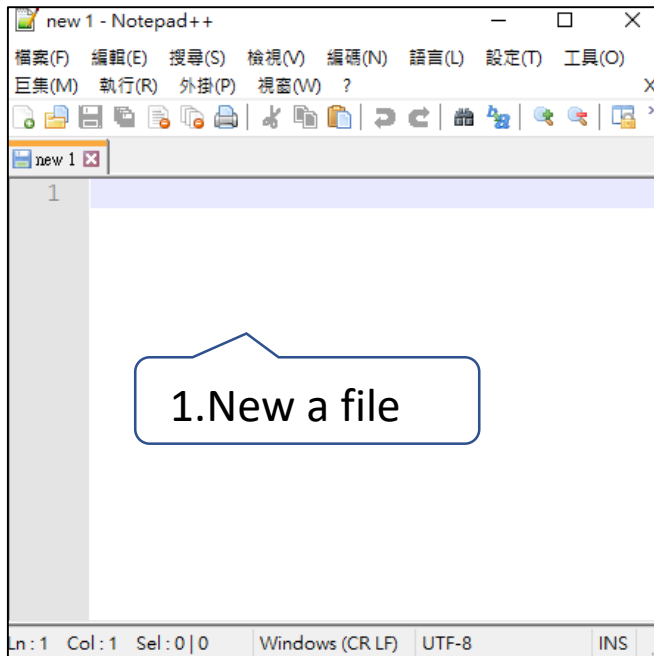
Pong Game AI using TensorFlow JS

Yu-Ping Liao Ping Pong Game



Exercise 11-7

- **Pong Clone In JavaScript**
- • we will have just a simple HTML file that is: "ponggame.html"

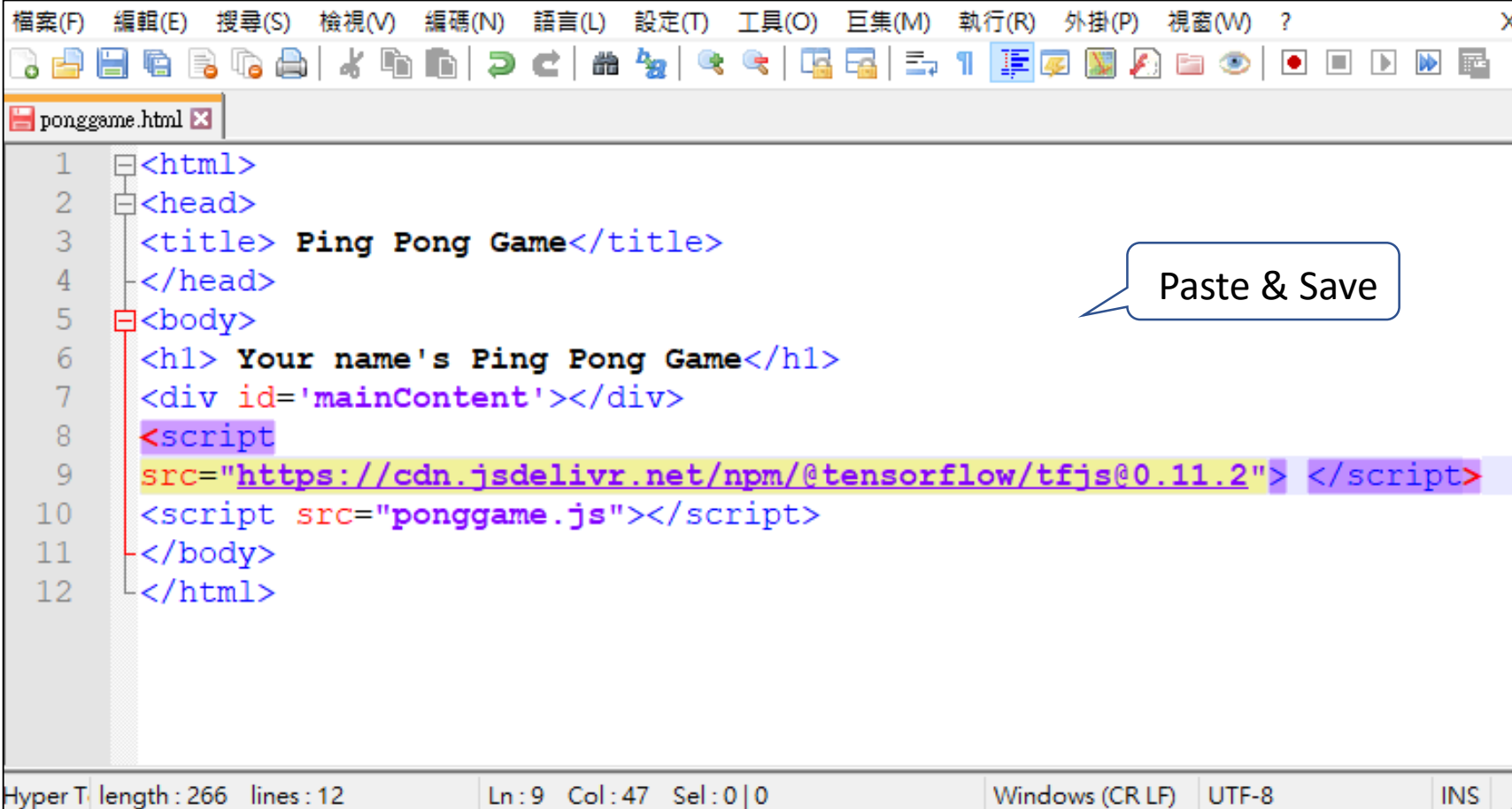


ponggame.html

```
<html>
<head>
<title> Ping Pong Game</title>
</head>
<body>
<h1> Your name's Ping Pong Game</h1>
<div id='mainContent'></div>
<script src="https://cdn.jsdelivr.net/npm/@tensorflow/tfjs@0.11.2"> </script>
<script src="ponggame.js"></script>
</body>
</html>
```

A yellow speech bubble button with a black border and the word "Copy" inside.

ponggame.html

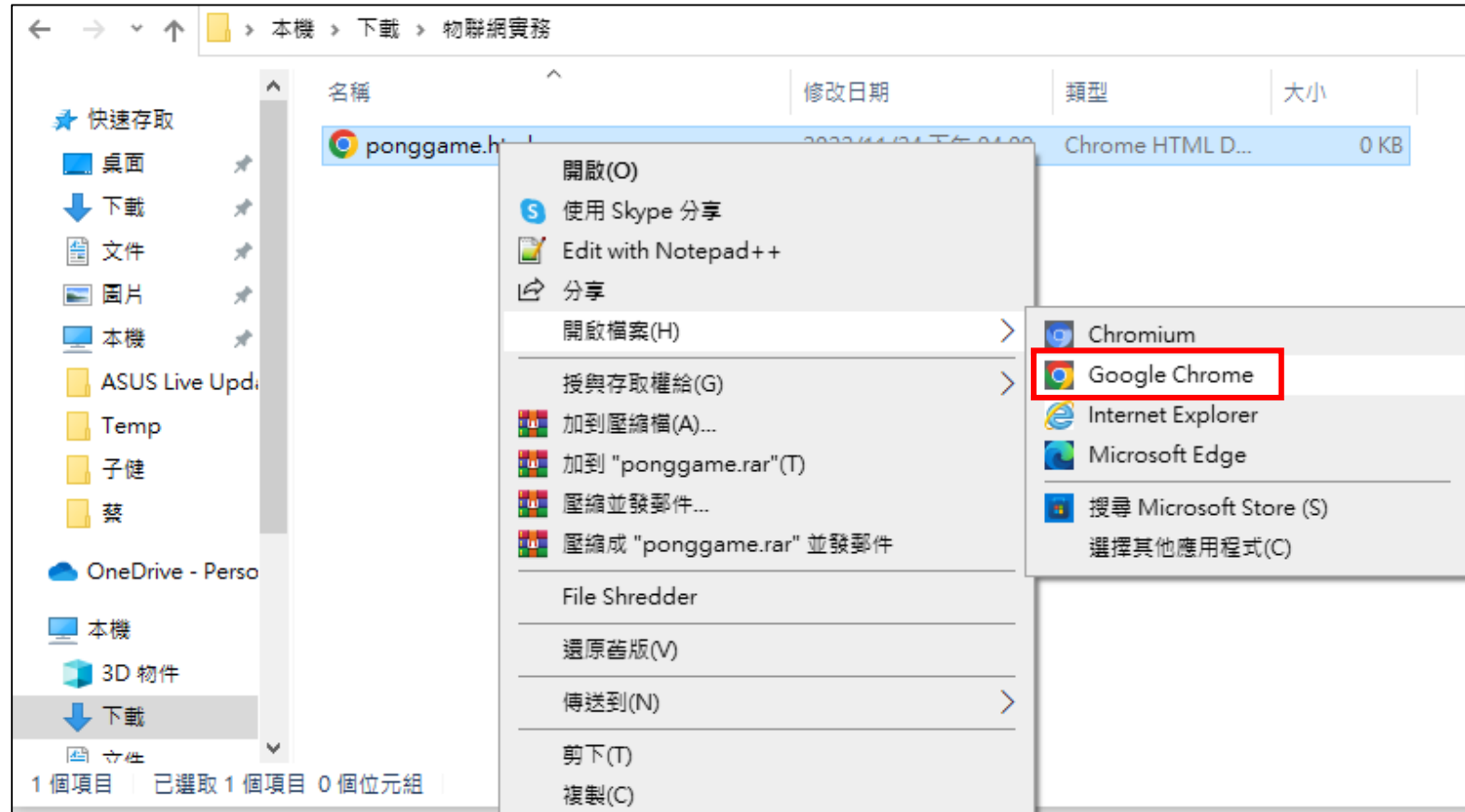


```
1 <html>
2 <head>
3   <title> Ping Pong Game</title>
4 </head>
5 <body>
6   <h1> Your name's Ping Pong Game</h1>
7   <div id='mainContent'></div>
8   <script
9     src="https://cdn.jsdelivr.net/npm/@tensorflow/tfjs@0.11.2"> </script>
10  <script src="ponggame.js"></script>
11 </body>
12 </html>
```

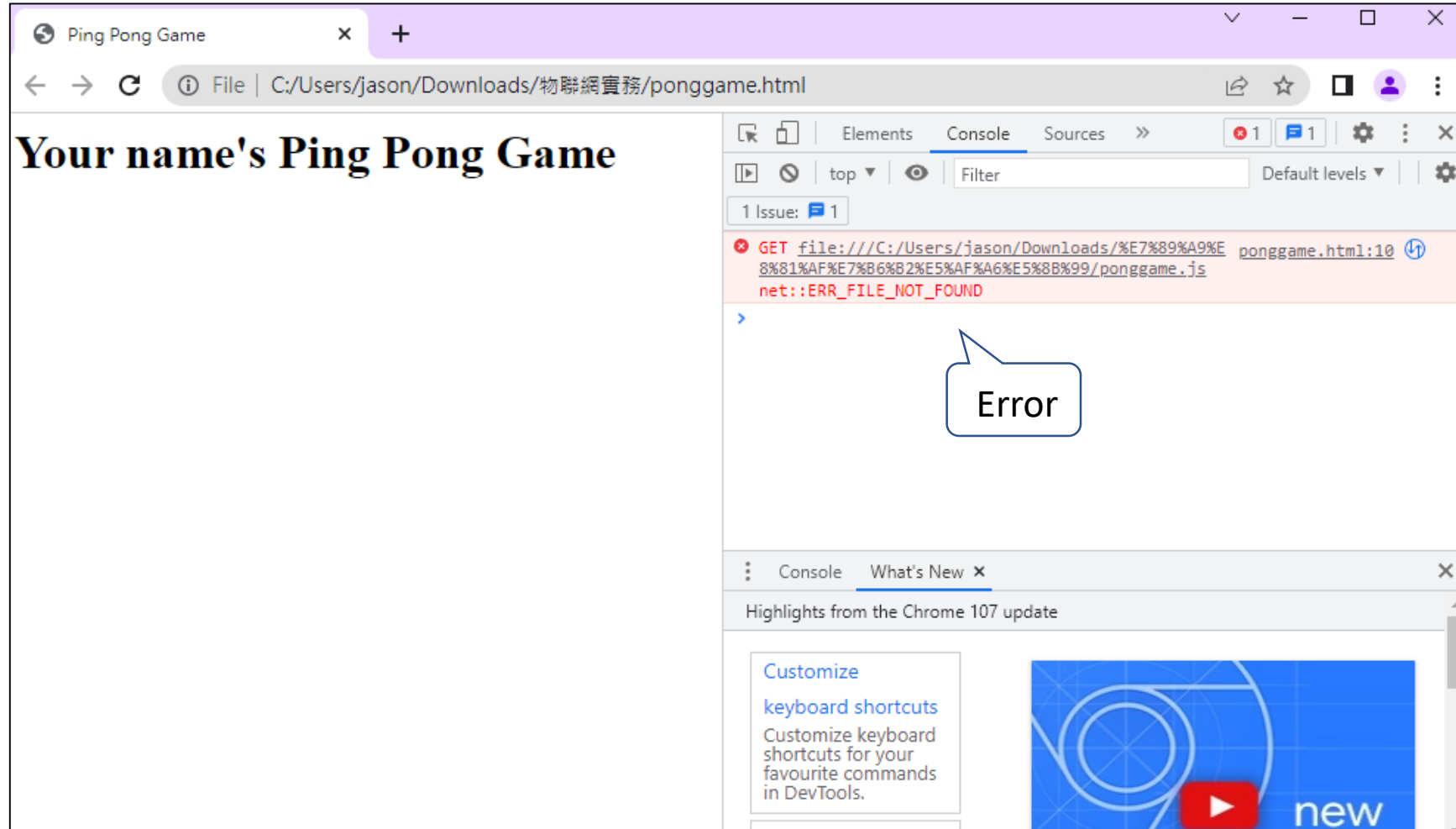
Paste & Save

Hyper T | length : 266 | lines : 12 | Ln : 9 | Col : 47 | Sel : 0 | 0 | Windows (CR LF) | UTF-8 | INS

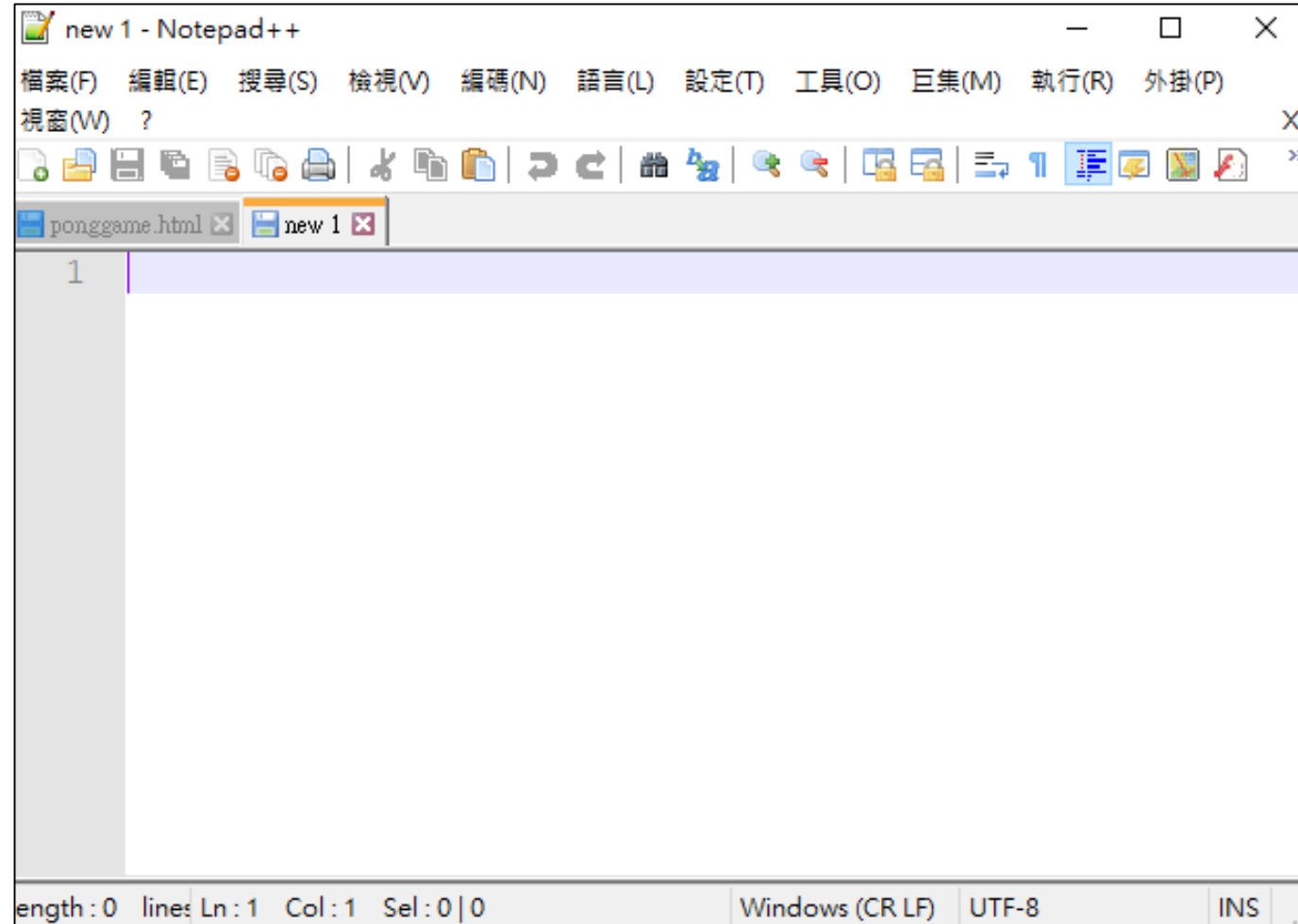
Open ponggame.html with Google Chrome



Ctrl+Shift+I

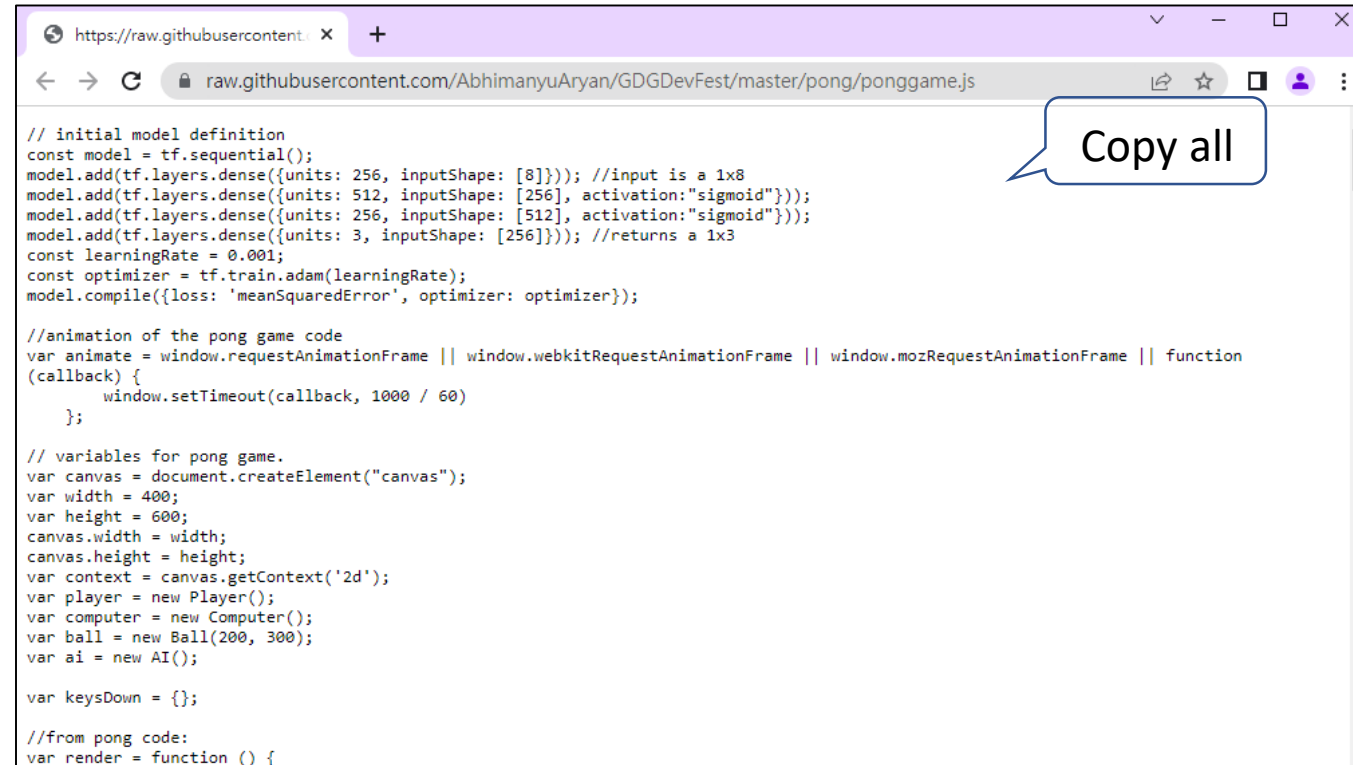


New a file



Copy

- <https://raw.githubusercontent.com/AbhimanyuAryan/GDGDDevFest/master/pong/ponggame.js>



```
// initial model definition
const model = tf.sequential();
model.add(tf.layers.dense({units: 256, inputShape: [8]})); //input is a 1x8
model.add(tf.layers.dense({units: 512, inputShape: [256], activation:"sigmoid"}));
model.add(tf.layers.dense({units: 256, inputShape: [512], activation:"sigmoid"}));
model.add(tf.layers.dense({units: 3, inputShape: [256]})); //returns a 1x3
const learningRate = 0.001;
const optimizer = tf.train.adam(learningRate);
model.compile({loss: 'meanSquaredError', optimizer: optimizer});

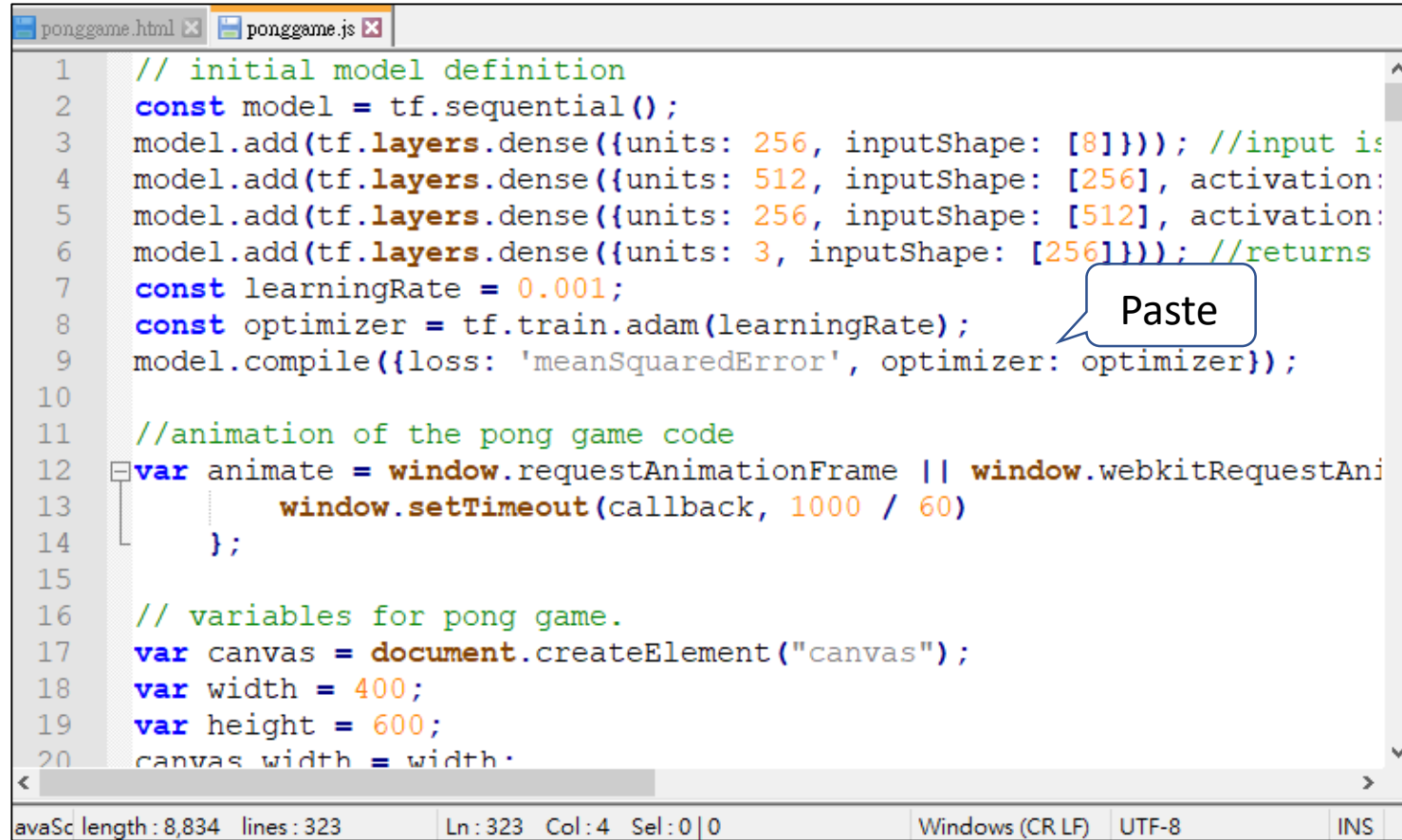
//animation of the pong game code
var animate = window.requestAnimationFrame || window.webkitRequestAnimationFrame || window.mozRequestAnimationFrame || function
(callback) {
  window.setTimeout(callback, 1000 / 60)
};

// variables for pong game.
var canvas = document.createElement("canvas");
var width = 400;
var height = 600;
canvas.width = width;
canvas.height = height;
var context = canvas.getContext('2d');
var player = new Player();
var computer = new Computer();
var ball = new Ball(200, 300);
var ai = new AI();

var keysDown = {};

//from pong code:
var render = function () {
```

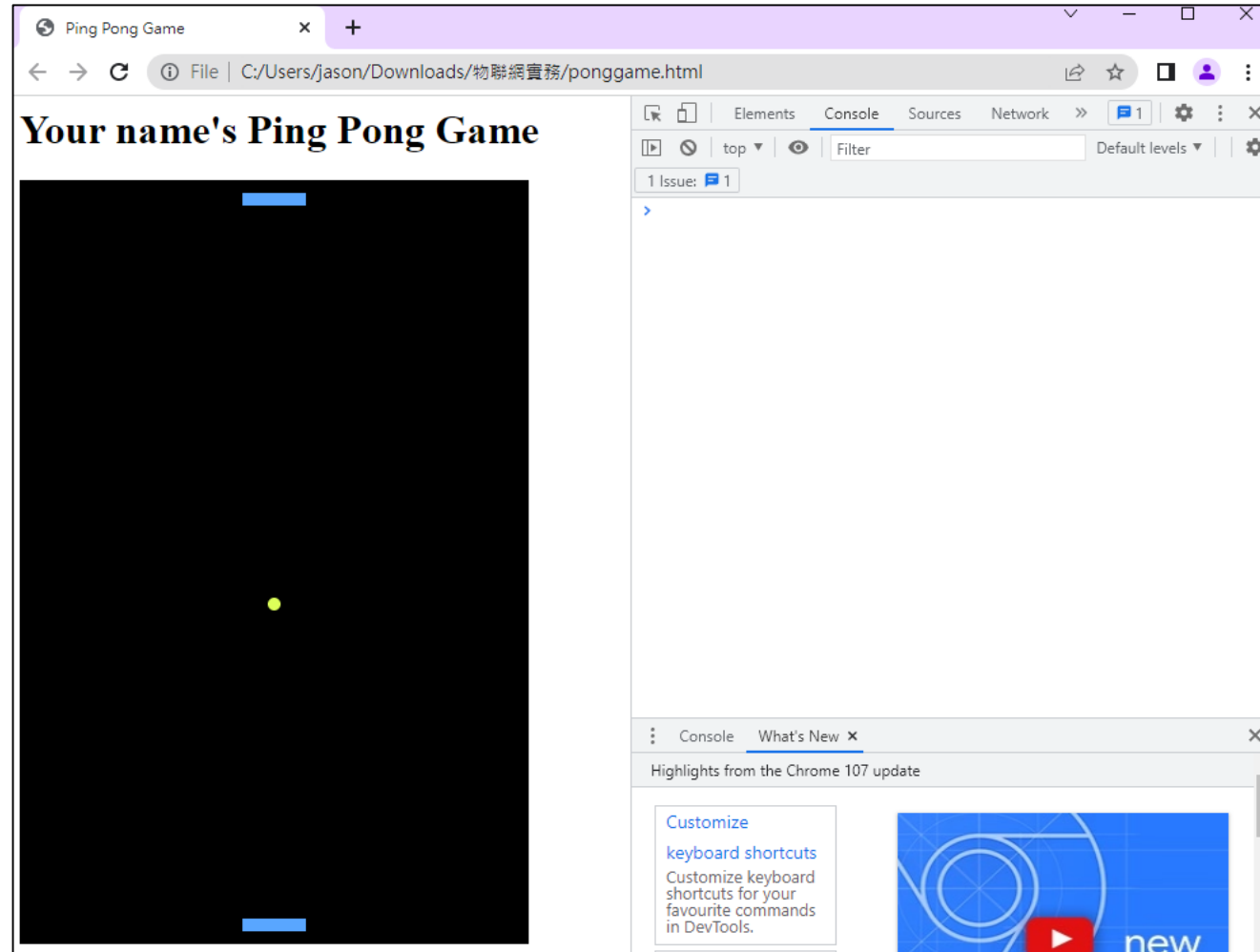
Save As ponggame.js



```
1 // initial model definition
2 const model = tf.sequential();
3 model.add(tf.layers.dense({units: 256, inputShape: [8]})); //input is
4 model.add(tf.layers.dense({units: 512, inputShape: [256], activation:
5 model.add(tf.layers.dense({units: 256, inputShape: [512], activation:
6 model.add(tf.layers.dense({units: 3, inputShape: [256]})); //returns
7 const learningRate = 0.001;
8 const optimizer = tf.train.adam(learningRate);
9 model.compile({loss: 'meanSquaredError', optimizer: optimizer});
10
11 //animation of the pong game code
12 var animate = window.requestAnimationFrame || window.webkitRequestAni
13     window.setTimeout(callback, 1000 / 60)
14     };
15
16 // variables for pong game.
17 var canvas = document.createElement("canvas");
18 var width = 400;
19 var height = 600;
20 canvas width = width.
```

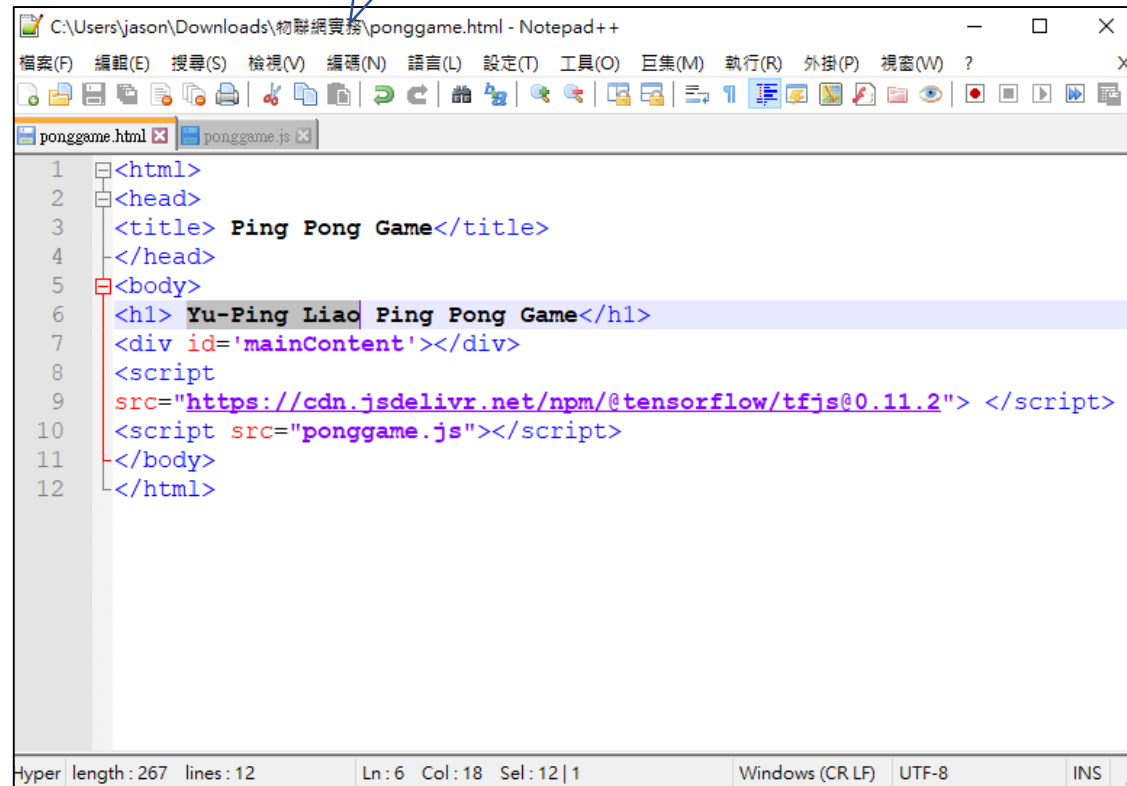
avaSc length: 8,834 lines: 323 Ln: 323 Col: 4 Sel: 0 | 0 Windows (CR LF) UTF-8 INS

Reload ponggame.html (F5)

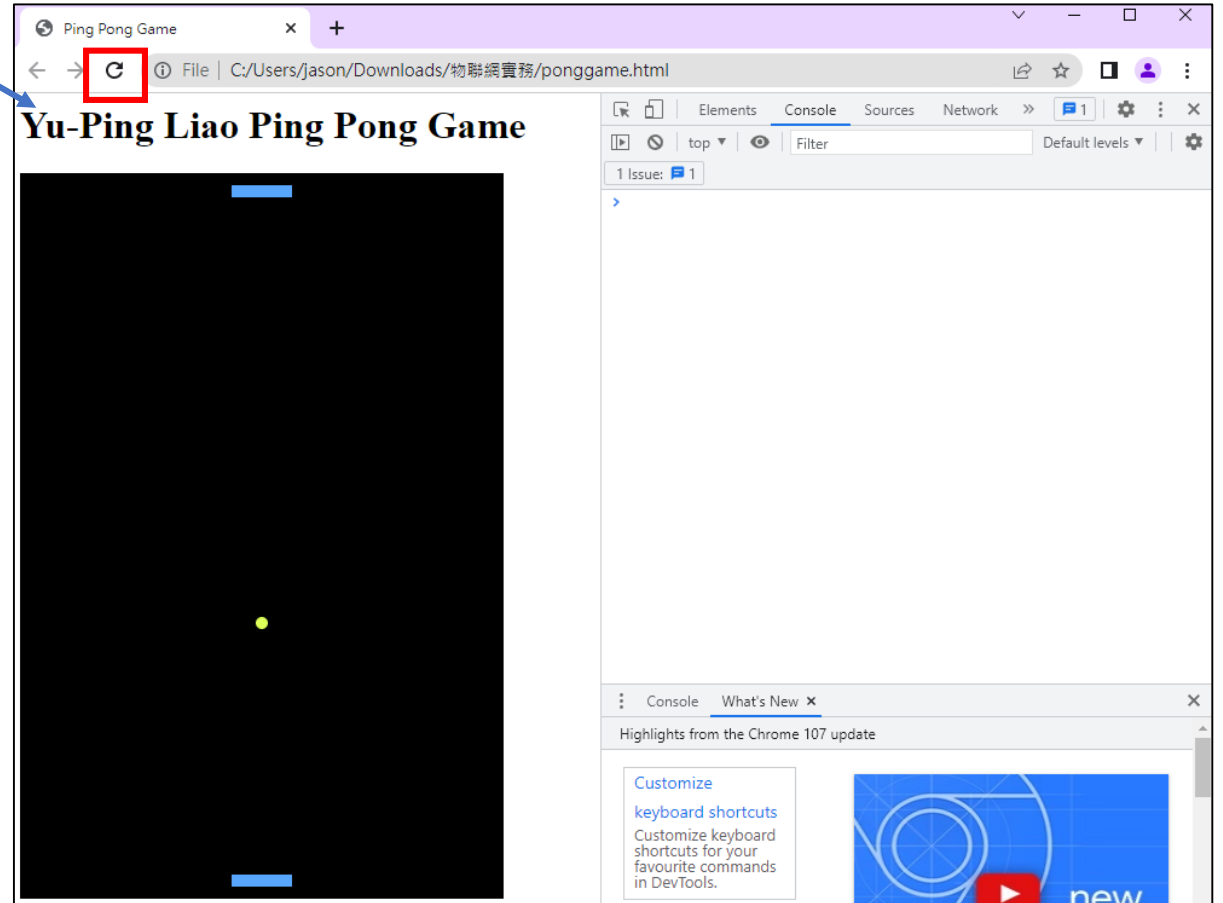


Edit name

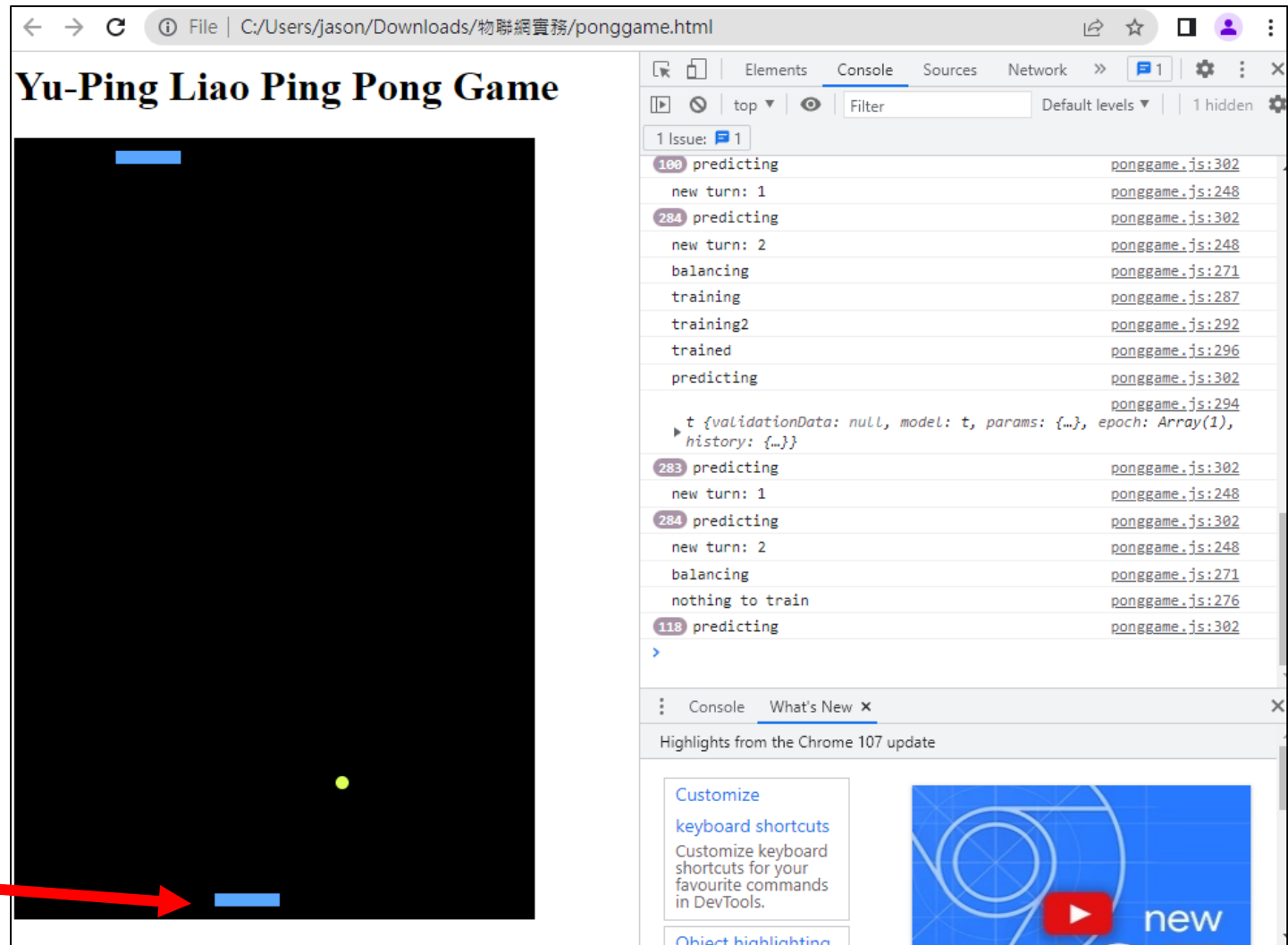
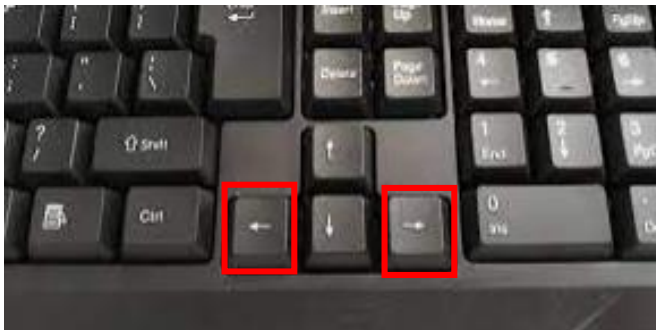
Ponggame.html



```
1 <html>
2 <head>
3   <title> Ping Pong Game</title>
4 </head>
5 <body>
6   <h1> Yu-Ping Liao Ping Pong Game</h1>
7   <div id='mainContent'></div>
8   <script
9     src="https://cdn.jsdelivr.net/npm/@tensorflow/tfjs@0.11.2"> </script>
10  <script src="ponggame.js"></script>
11 </body>
12 </html>
```



Play with AI



Model

1. Player paddle x
2. Computer paddle x
3. Ball x
4. Ball y
5. previous ball x
6. previous ball y
7. previous player paddle x
8. previous computer paddle x

