ANN with TensorFlow: Theory and Practice

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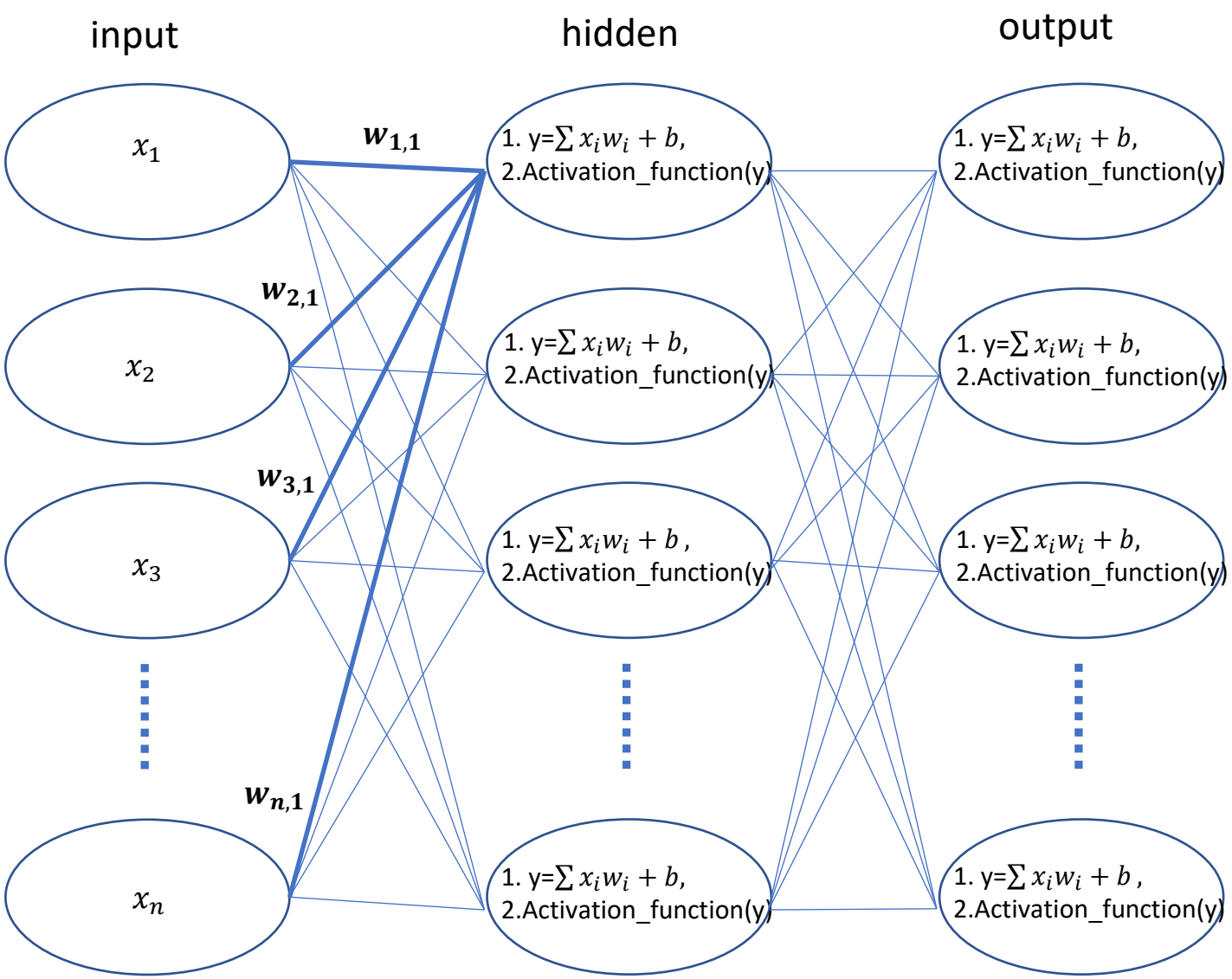
2nd lecture

- Networks and Neurons
- Gradient descent
- Code: Custom_model



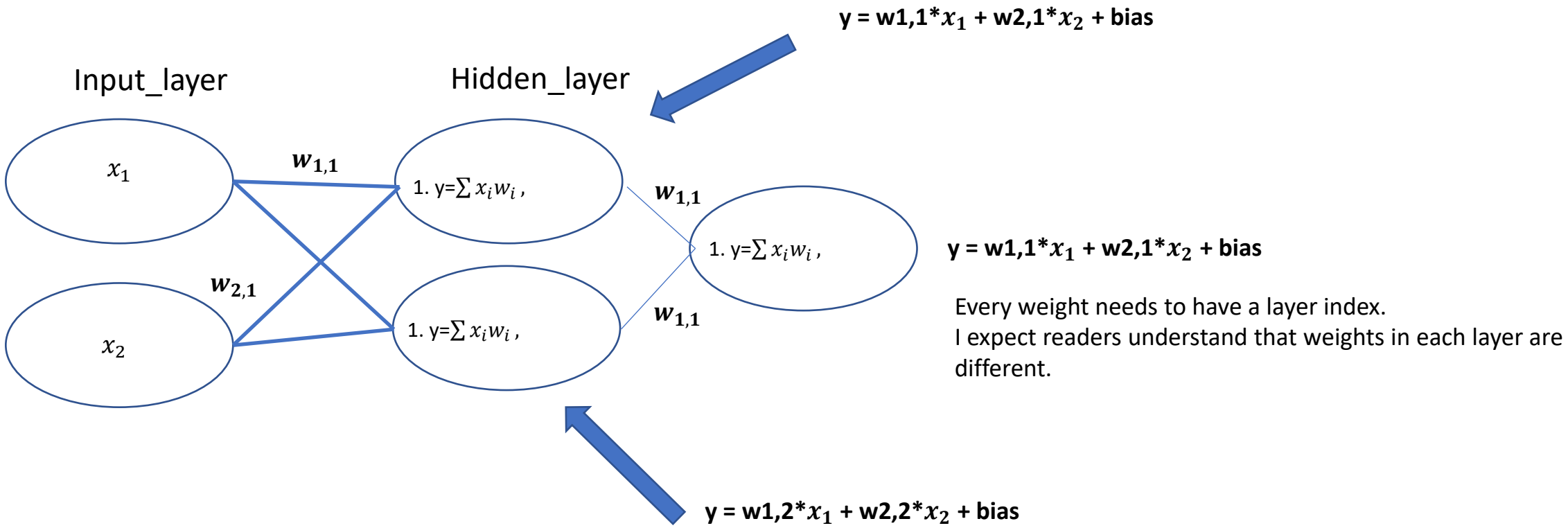

```
model = keras.Sequential()
Model.add(layers.Dense(n)
Model.add(layers.Dense(n, activation='relu'))
Model.add(layers.Dense(n, activation='relu'))
.
.
.
Model.add(layers.Dense(n, activation='relu'))
```

Activation function

- RelU
- Sigmoid
- Hyperbolic tangent
- Leaky ReLU
- Softmax

We will make a neural network has two inputs, one output, and
One hidden layer
We do not use an activation function in this example.

```
input_layer = keras.Input(shape=(2,))
hidden_layer = keras.layers.Dense(2)(input_layer)
output_layer = keras.layers.Dense(1)(hidden_layer)
```



Every weight needs to have a layer index.
I expect readers understand that weights in each layer are different.

Update weights

- Training is the updating of weights.
- To update weights, Gradient descent is used.
- **Gradient descent** is the same way to solve a regression problem in the last lecture.
- I will explain **gradient descent** with an example and code.
- Learning methods
  - Hebbian Learning (Hebbian Rule)
  - Perceptron Rule
  - **Gradient Descent** (Delta Rule, **Least Mean Square**)
  - Back propagation

data

x	y	z
1	1	7
2	2	12
2	2	12
3	3	17
4	4	22
5	5	27
6	21	77
7	1	19
1	2	10
1	3	13
2	4	18
3	5	23
4	6	28
5	7	33
6	2	20
7	1	19
1	2	10
2	3	15
3	4	20

We will make a neural network that will find the z value with the given x, y.

This is an example.
The equation (“z=x*2+y*3+2”) makes the data.
We can easily verify if our neural network is learning well.

Although this is a simple example, we can easily extend it to solve many regression problems with various inputs.
I did not use scaling of the data set for beginner’s understanding.
However, in practice, we need to use scaling of the data set.

Code (https://github.com/jhrrlee/mlcode.git) for the custom model is written for low-level handling of losses tracked by the model from a reference to the TensorFlow doc (https://www.tensorflow.org/guide/keras/writing_a_training_loop_from_scratch).

Handling low-level is better for studying and seeing operations during learning.

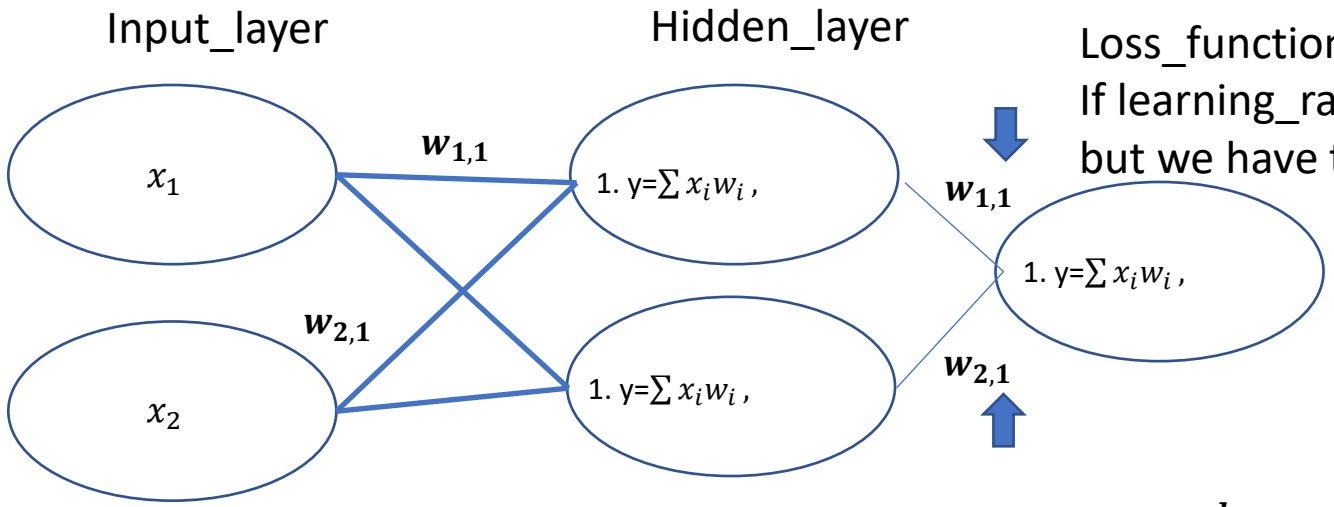
We consider gradient descent with Least Mean Squre using Mean Squre Error $\mathrm{E}(\hat{Y}_i - Y_i)^2 = \frac{1}{n}\sum(\hat{Y}_i - Y_i)^2$

We learned this in the last lecture.

Learning sequence:

1. Get loss value
2. Partial derivative to update weights (weights between the input layer and hidden layer can be calculated by chain rule

We can use any loss function other than MSE; it is just for convenience to use mathematical theory. However, mathematically, it is impossible to calculate the minimum error since the result is experimental result ($\hat{y}_i$).
This is an important point that we may find some better ways in experiments.
We can try



$$\boldsymbol{w_{1,1}} = \boldsymbol{w_{1,1}} + learning\_rate * \frac{\partial f(x_1,x_2)}{\partial x_1},\ f(x_1,x_2) =$$ Loss_function,

If learning_rate has large value then learning _speed will be fast, but we have to consider diffusion.

$\hat{y}_i = \boldsymbol{w_{1,1}} * \boldsymbol{x_1} + \boldsymbol{w_{2,1}} * \boldsymbol{x_2} + \textbf{bias}$

Loss_function = $\frac{1}{2m}\sum(\hat{y}_i - z_i)^2$: z_i in data set

$$\boldsymbol{w_{2,1}} = \boldsymbol{w_{2,1}} + learning\_rate * \frac{\partial f(x_1,x_2)}{\partial x_2}$$

$\frac{1}{2}$ in $\frac{1}{2m}$ is because of convenience of calculation of derivative?
BTW, it will not be important because it depends on $learninrate$ again in $learning\_rate * \frac{\partial f(x_1,x_2)}{\partial x_1}$

Reference:

Logistic regression (https://en.wikipedia.org/wiki/Logistic_regression)

Least mean square (https://en.wikipedia.org/wiki/Least_mean_squares_filter)

- Next, we will learn from code (https://github.com/jhrrlee/mlcode.git)