Deeper networks

Puteaux, Fall/Winter 2020-2021

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##                           ##
##   Deep Learning in Python  ##
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§1 Introduction to Deep Learning in Python
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§1.1 Basics of deep learning and neural networks
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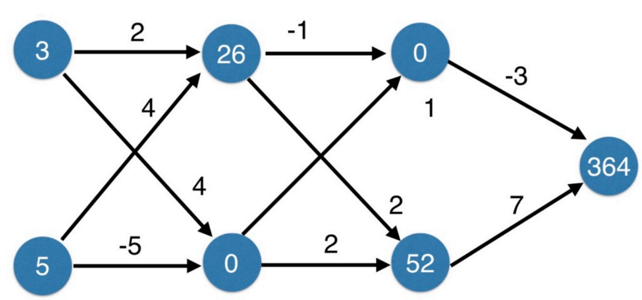
1 Deeper networks

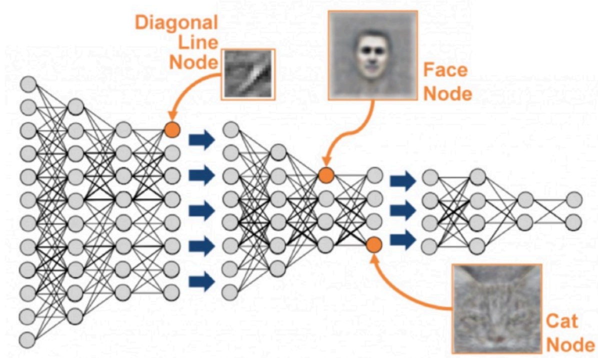
1.1 How do multiple hidden layers function?



Calculate with ReLU Activation Function

1.2 Why is deep learning also sometimes called representation learning?

- Deep networks internally build representations of patterns in the data; in this way, partially replace the need for feature engineering.
- Subsequent layers build increasingly sophisticated representations of raw data.

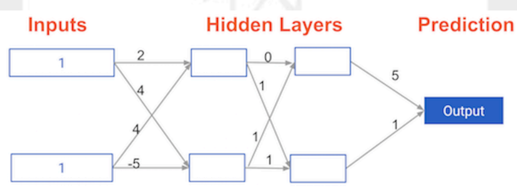


1.3 How does the deep learning process?

- The modeler doesn't need to specify the interactions.
- When training the model, the neural network gets weights that find the relevant patterns to make better predictions.

1.4 Practice question for the forward propagation in a deeper network:

- Ther is a model with two hidden layers. The values for an input data point are shown inside the input nodes. The weights are shown on the edges/lines. What prediction would this model make on this data point?
- Assume the activation function at each node is the *identity function*. That is, each node's output will be the same as its input. So the value of the bottom node in the first hidden layer is -1, and not 0, as it would be if the ReLU activation function was used.



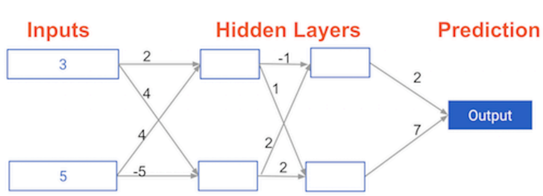
☒ 0.

☐ 7.

☐ 9.

1.5 Practice exercises for deeper networks:

▶ Diagram of the forward propagation:



▶ Package pre-loading:

[1]:
```
import numpy as np
```

▶ Data pre-loading:

[2]:
```
input_data = np.array([3, 5])

weights = {
    'node_0_0': np.array([2, 4]),
    'node_0_1': np.array([4, -5]),
    'node_1_0': np.array([-1, 2]),
    'node_1_1': np.array([1, 2]),
    'output': np.array([2, 7])
}
```

▶ Code pre-loading:

[3]:
```
def relu(input):
    output = max(0, input)
    return (output)
```

▶ Multi-layer neural networks practice:

[4]:
```
def predict_with_network(input_data):
    # Calculate node 0 in the first hidden layer
    node_0_0_input = (input_data * weights['node_0_0']).sum()
    node_0_0_output = relu(node_0_0_input)

    # Calculate node 1 in the first hidden layer
    node_0_1_input = (input_data * weights['node_0_1']).sum()
    node_0_1_output = relu(node_0_1_input)

    # Put node values into array: hidden_0_outputs
    hidden_0_outputs = np.array([node_0_0_output, node_0_1_output])

    # Calculate node 0 in the second hidden layer
    node_1_0_input = (hidden_0_outputs * weights['node_1_0']).sum()
    node_1_0_output = relu(node_1_0_input)

    # Calculate node 1 in the second hidden layer
    node_1_1_input = (hidden_0_outputs * weights['node_1_1']).sum()
    node_1_1_output = relu(node_1_1_input)

    # Put node values into array: hidden_1_outputs
    hidden_1_outputs = np.array([node_1_0_output, node_1_1_output])

    # Calculate model output: model_output
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```
    model_output = (hidden_1_outputs * weights['output']).sum()

    # Return model_output
    return (model_output)


output = predict_with_network(input_data)
print(output)
```

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1.6 Practice question for learned representations:

- How are the weights that determine the features/interactions in Neural Networks created?

  ☐ A user chooses them when creating the model.

  ☒ The model training process sets them to optimize predictive accuracy.

  ☐ The weights are random numbers.

1.7 Practice question for levels of representation:

- Which layers of a model capture more complex or “higher level” interactions?

  ☐ The first layers capture the most complex interactions.

  ☒ The last layers capture the most complex interactions.

  ☐ All layers capture interactions of similar complexity.