

Introduction to deep learning

INTRODUCTION TO DEEP LEARNING IN PYTHON



Dan Becker

Data Scientist and contributor to Keras
and TensorFlow libraries

Imagine you work for a bank

- You need to predict how many transactions each customer will make next year

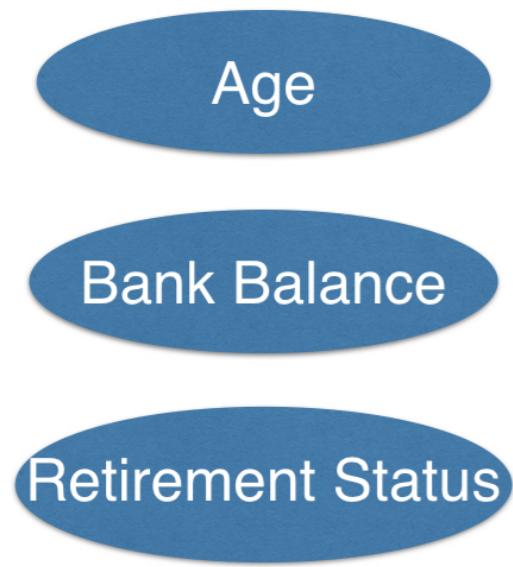
Example as seen by linear regression



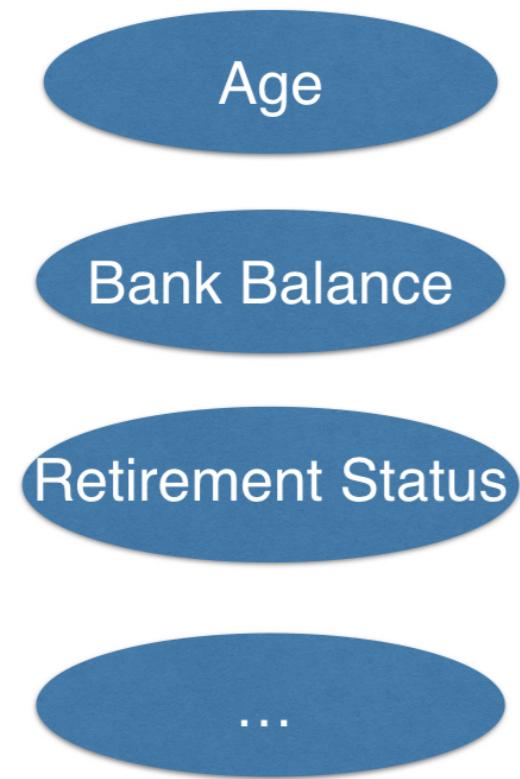
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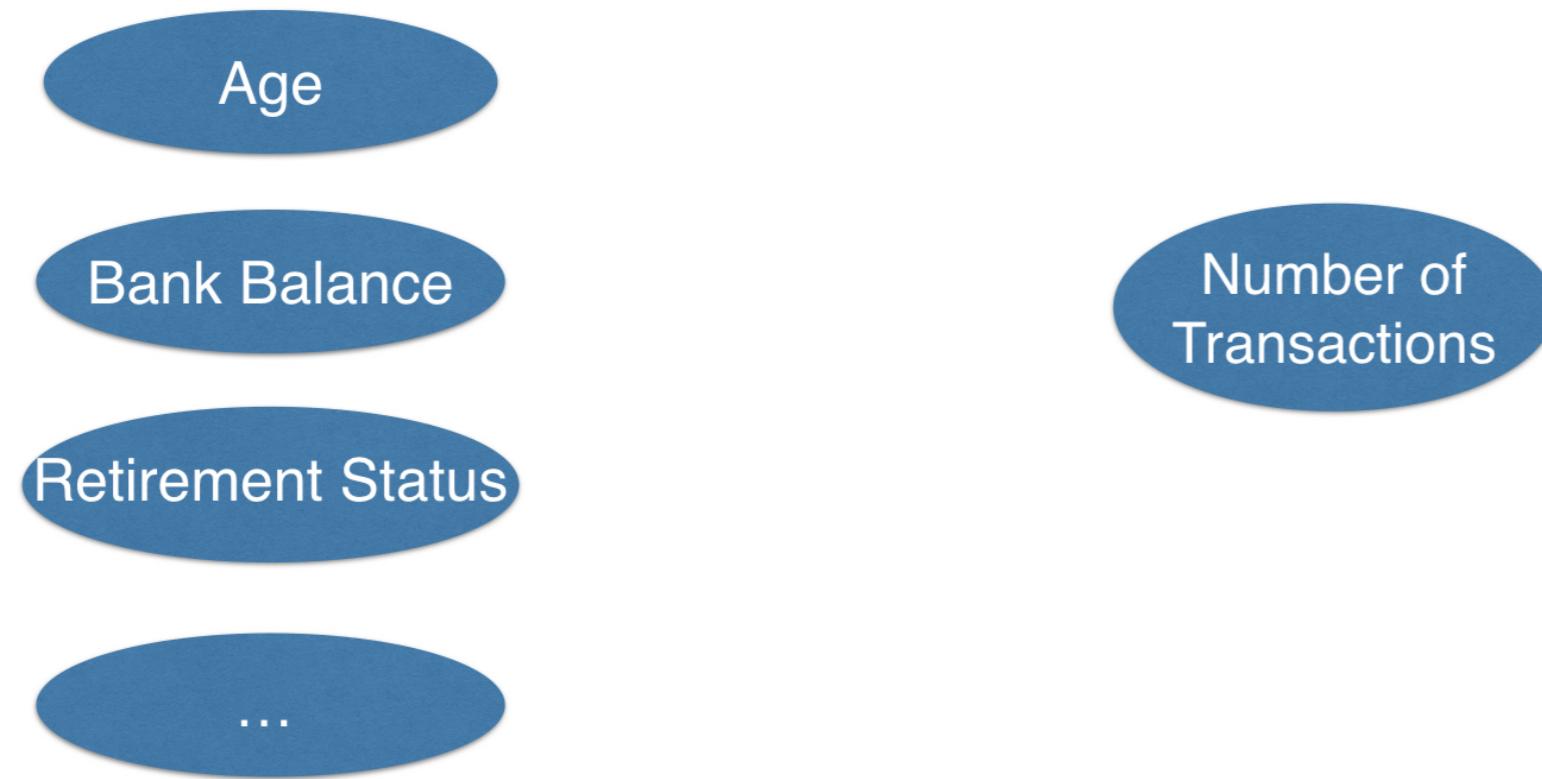
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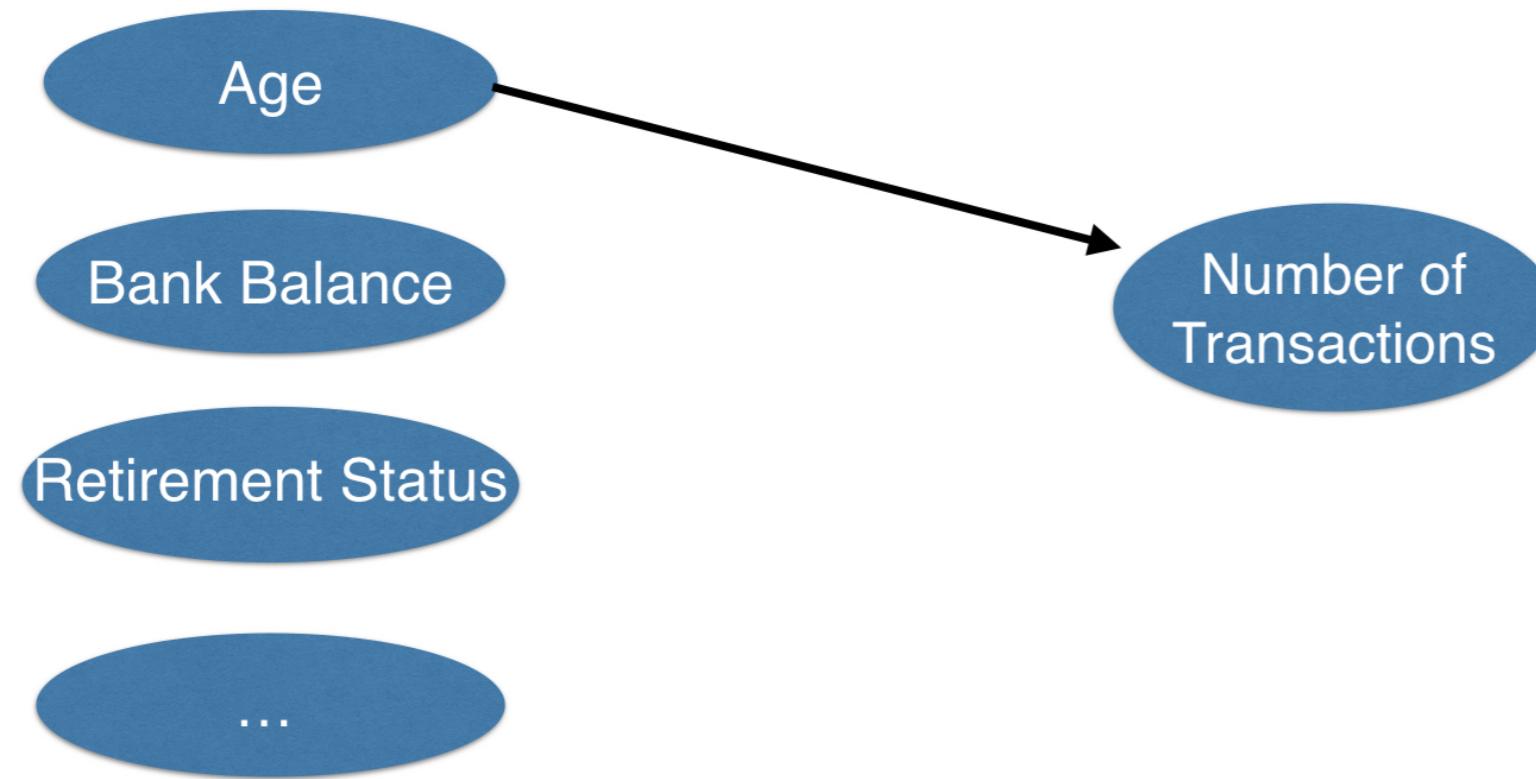
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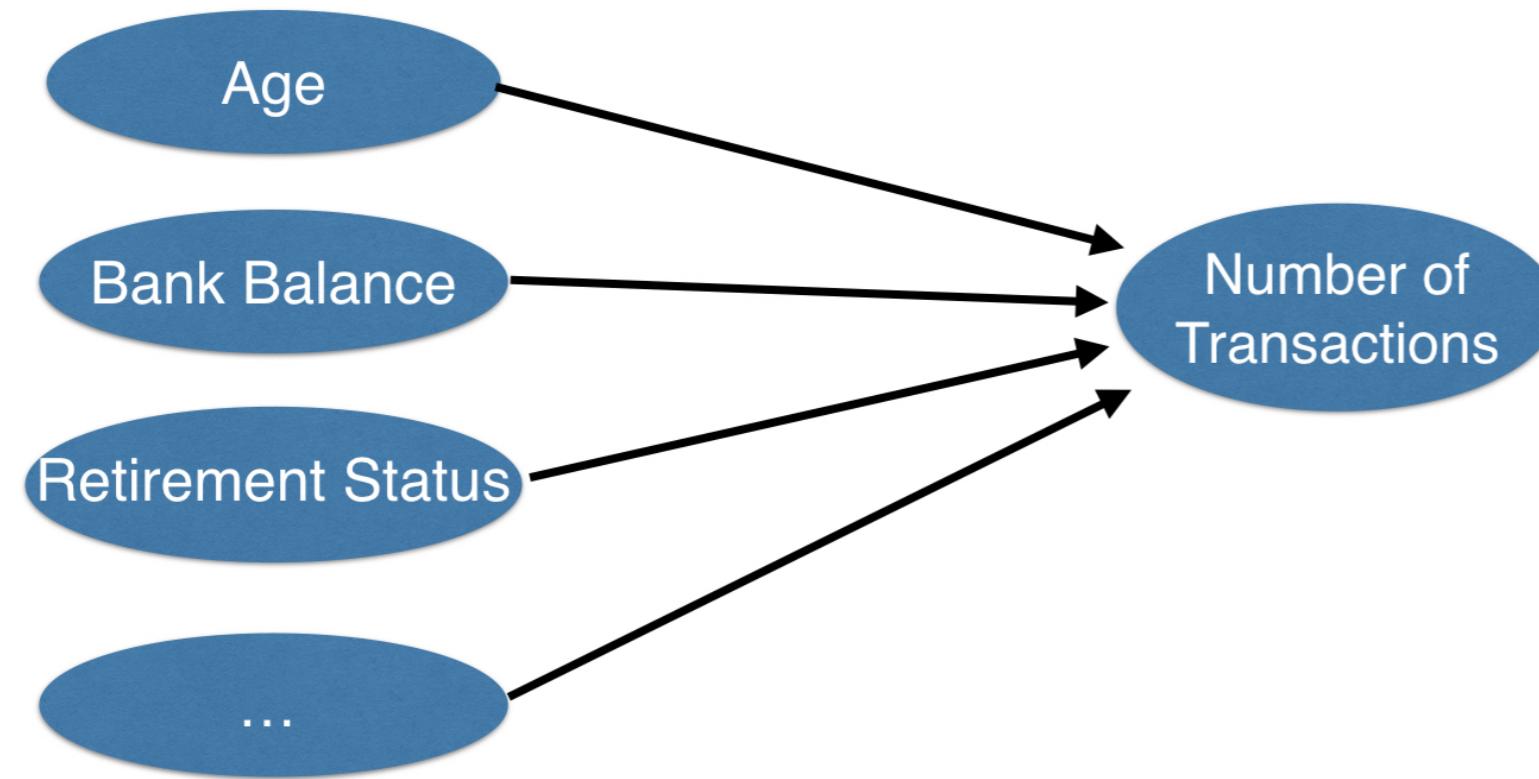
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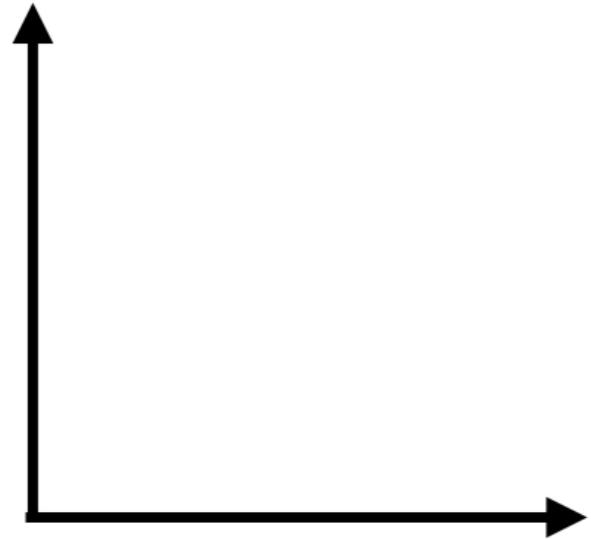
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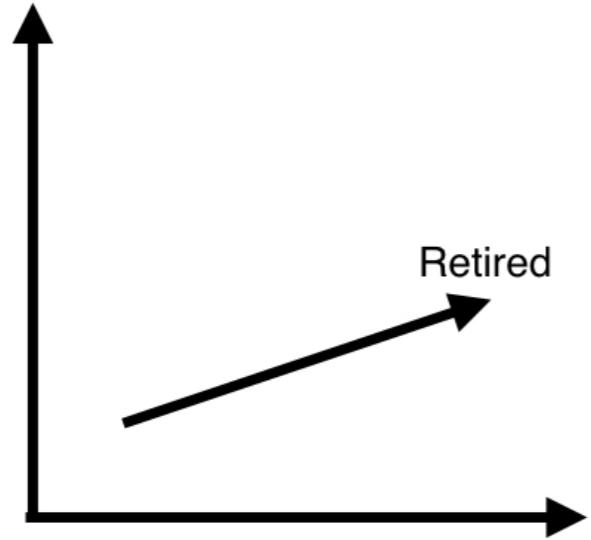
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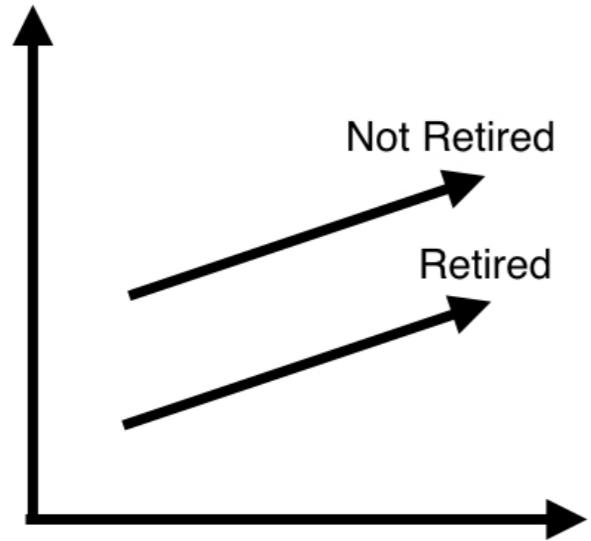
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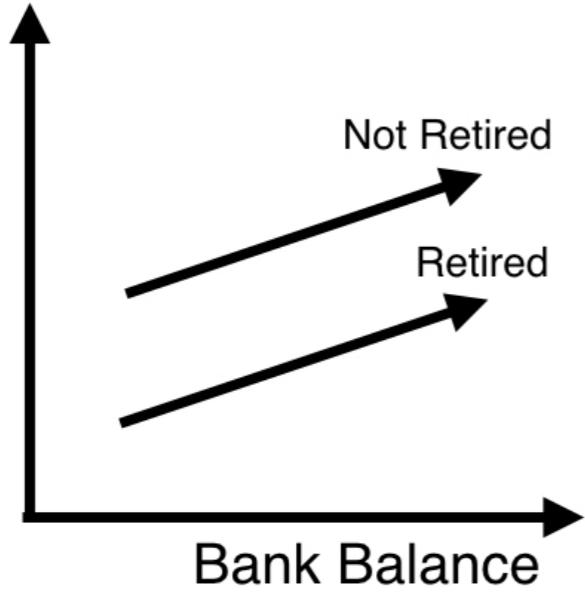
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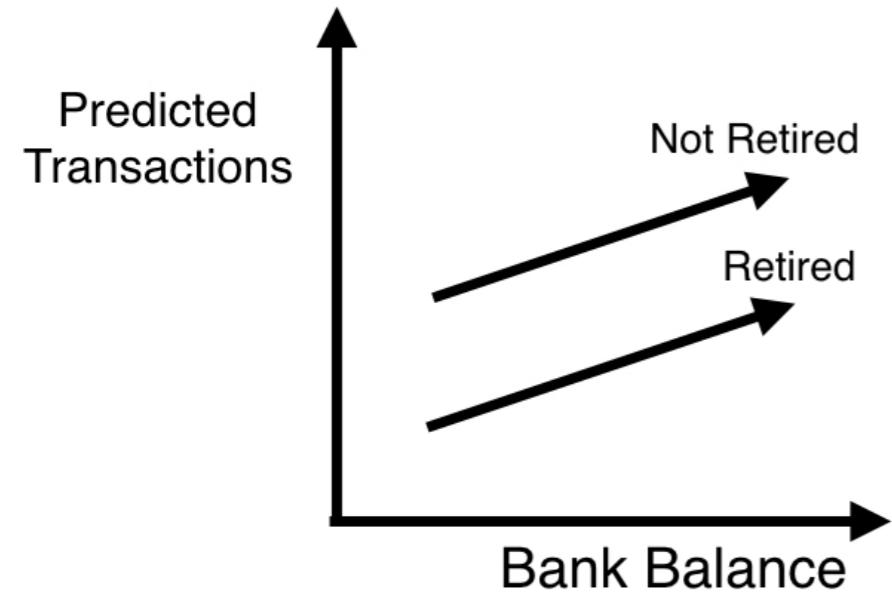
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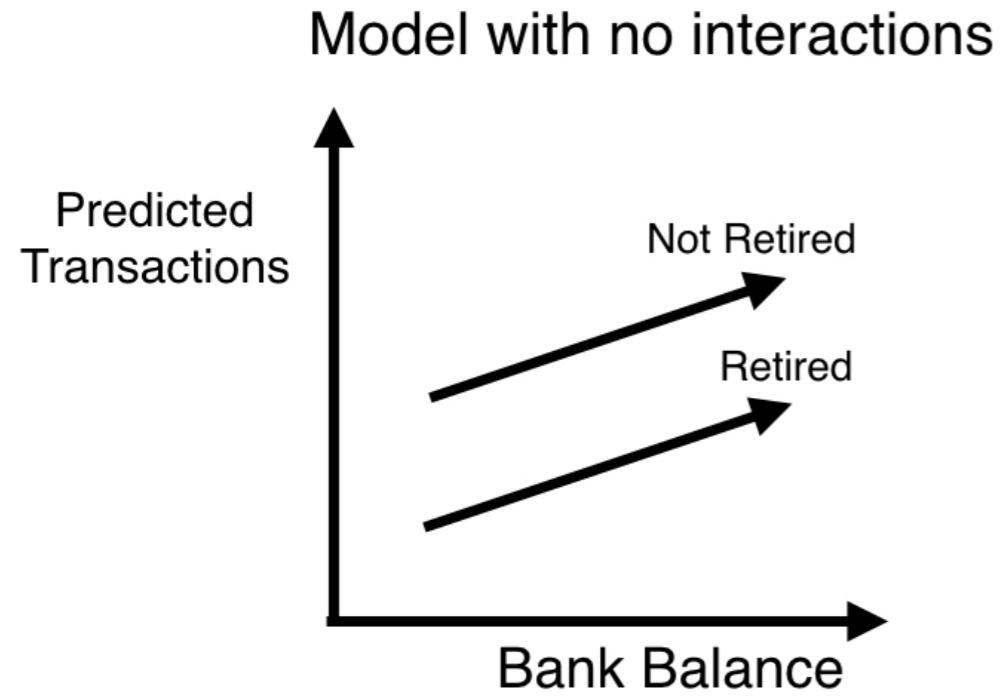
Example as seen by linear regression



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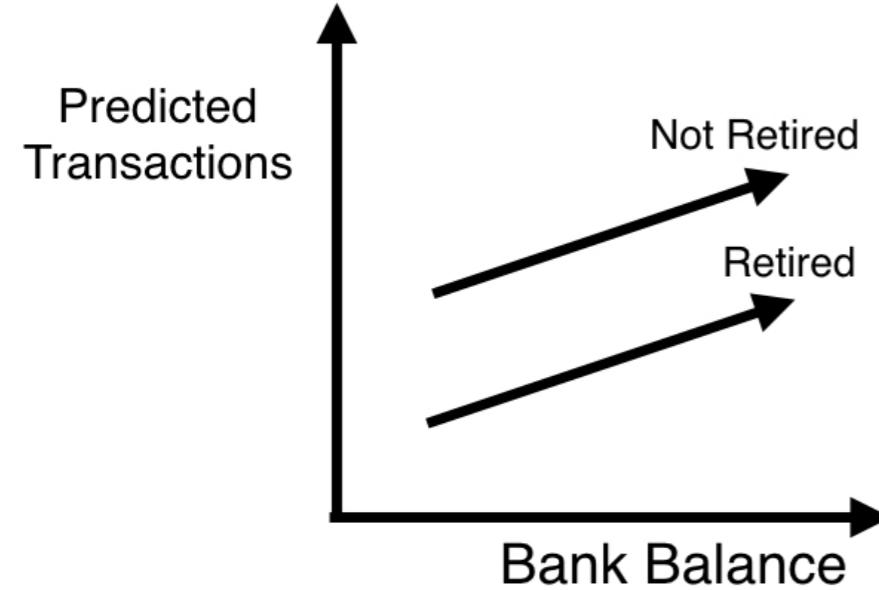


Example as seen by linear regression

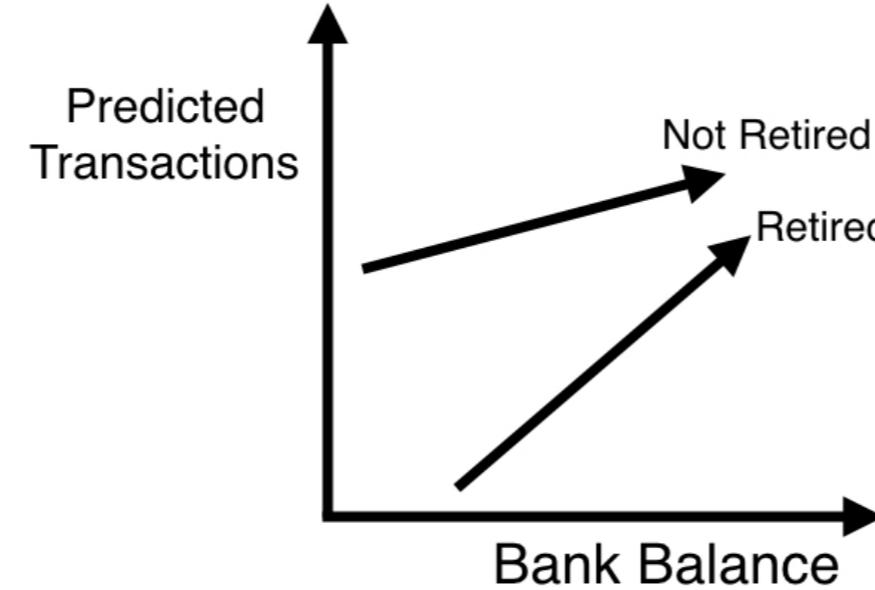


Example as seen by linear regression

Model with no interactions



Model with interactions



Interactions

- Neural networks account for interactions really well
- Deep learning uses especially powerful neural networks
 - Text
 - Images
 - Videos
 - Audio
 - Source code

Course structure

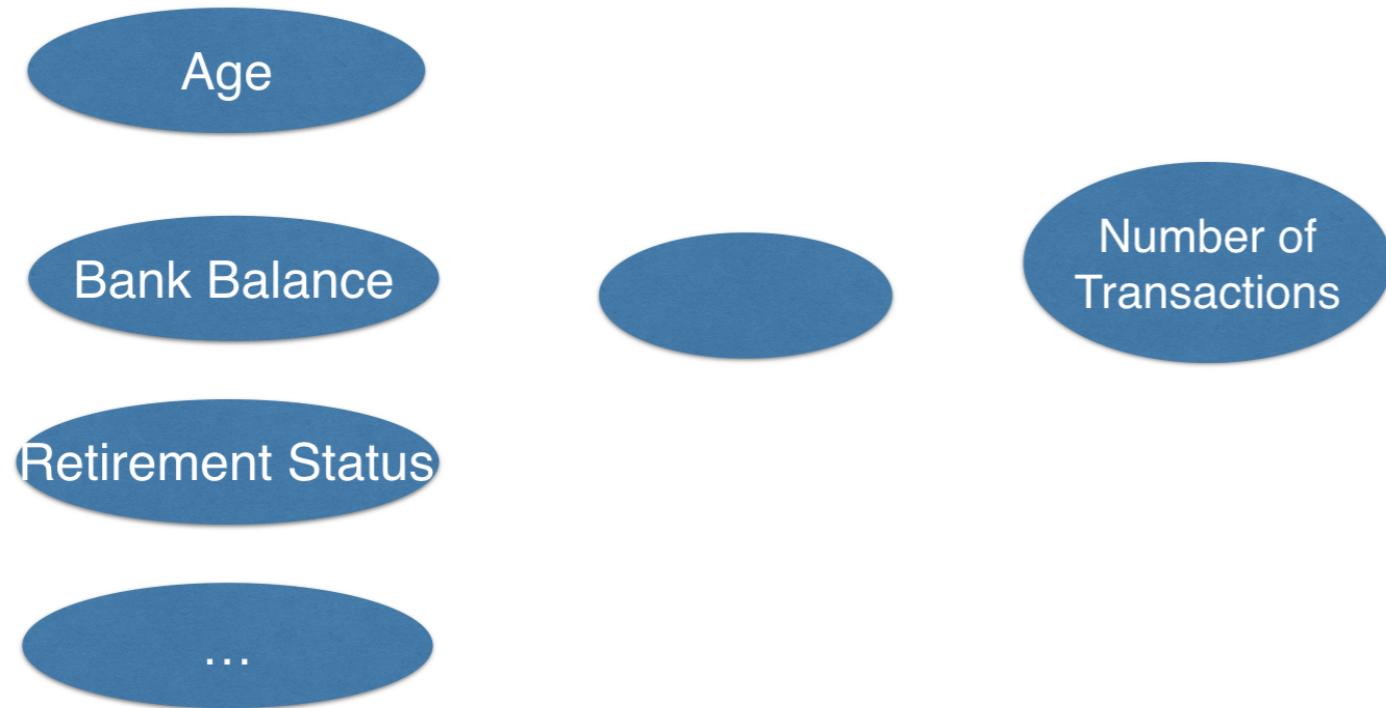
- First two chapters focus on conceptual knowledge
 - Debug and tune deep learning models on conventional prediction problems
 - Lay the foundation for progressing towards modern applications
- This will pay off in the third and fourth chapters

Build and tune deep learning models using keras

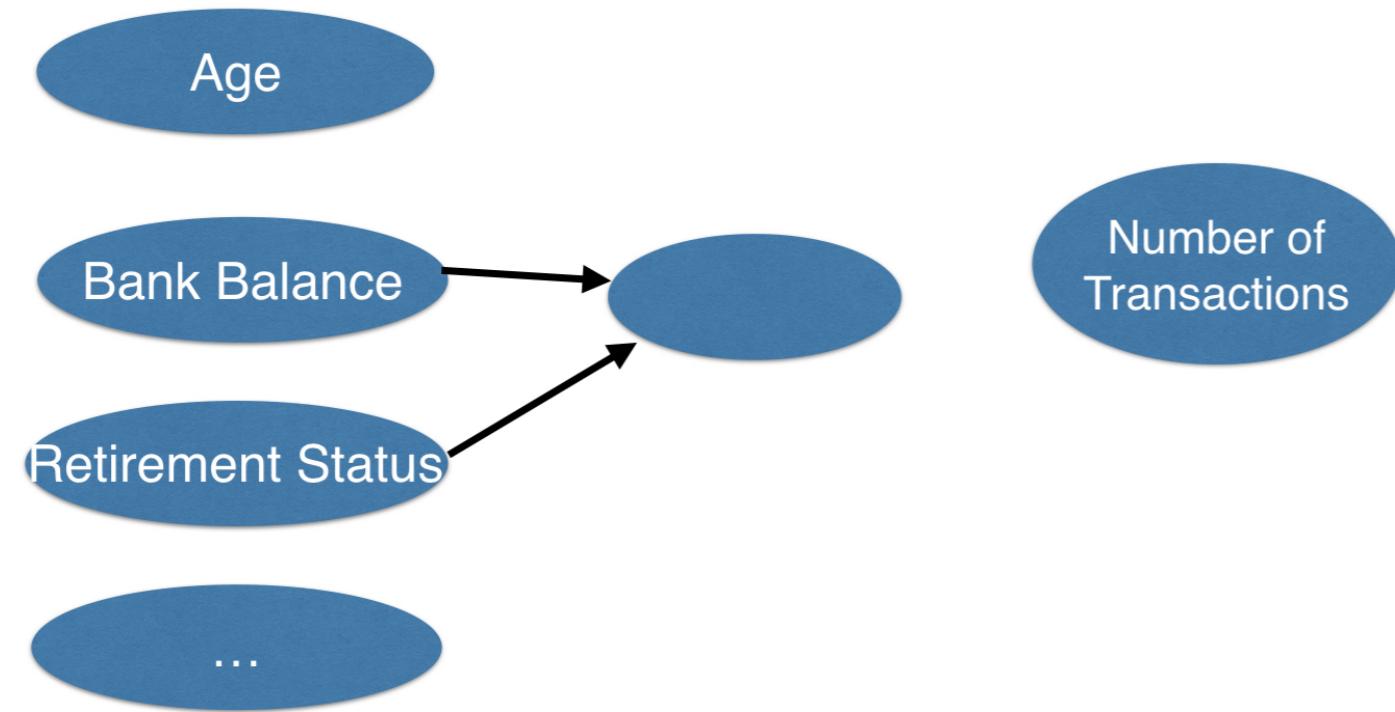
```
import numpy as np
from keras.layers import Dense
from keras.models import Sequential
predictors = np.loadtxt('predictors_data.csv', delimiter=',')
n_cols = predictors.shape[1]
model = Sequential()

model.add(Dense(100, activation='relu', input_shape = (n_cols,)))
model.add(Dense(100, activation='relu'))
model.add(Dense(1))
```

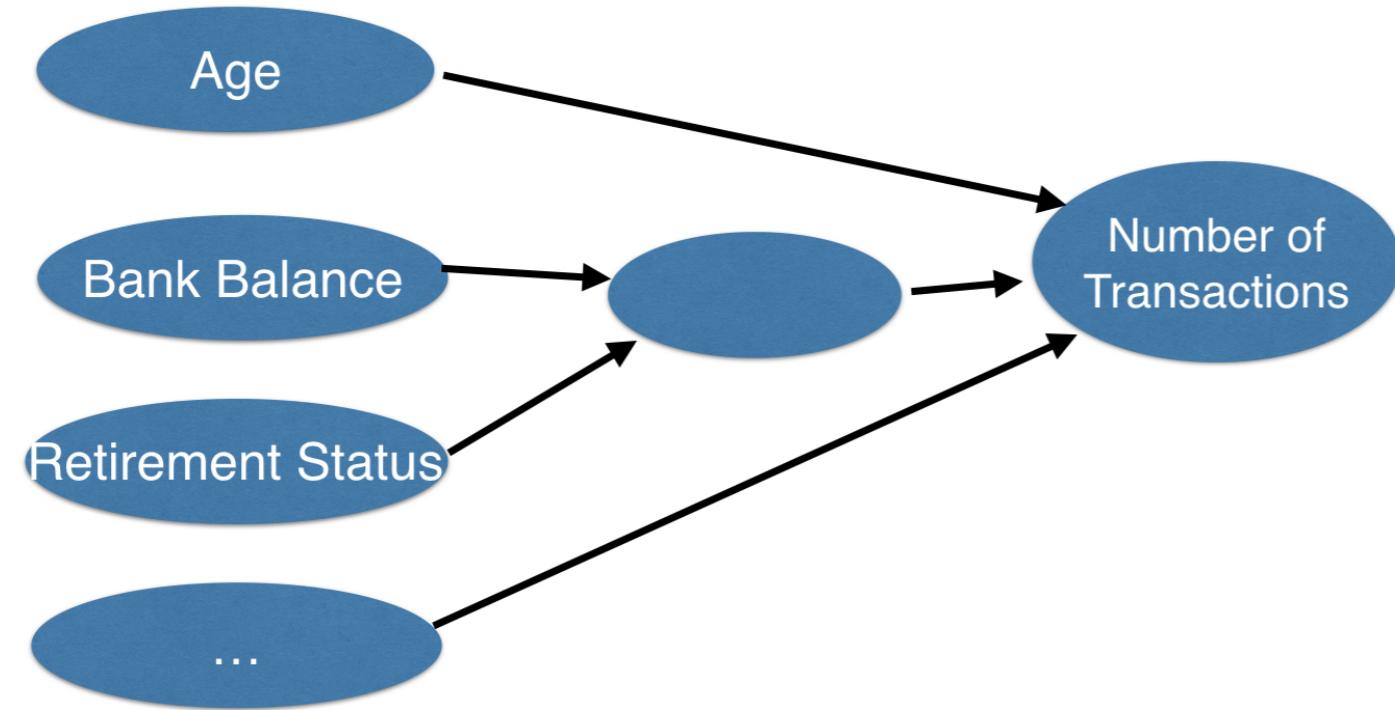
Deep learning models capture interactions



Deep learning models capture interactions



Deep learning models capture interactions



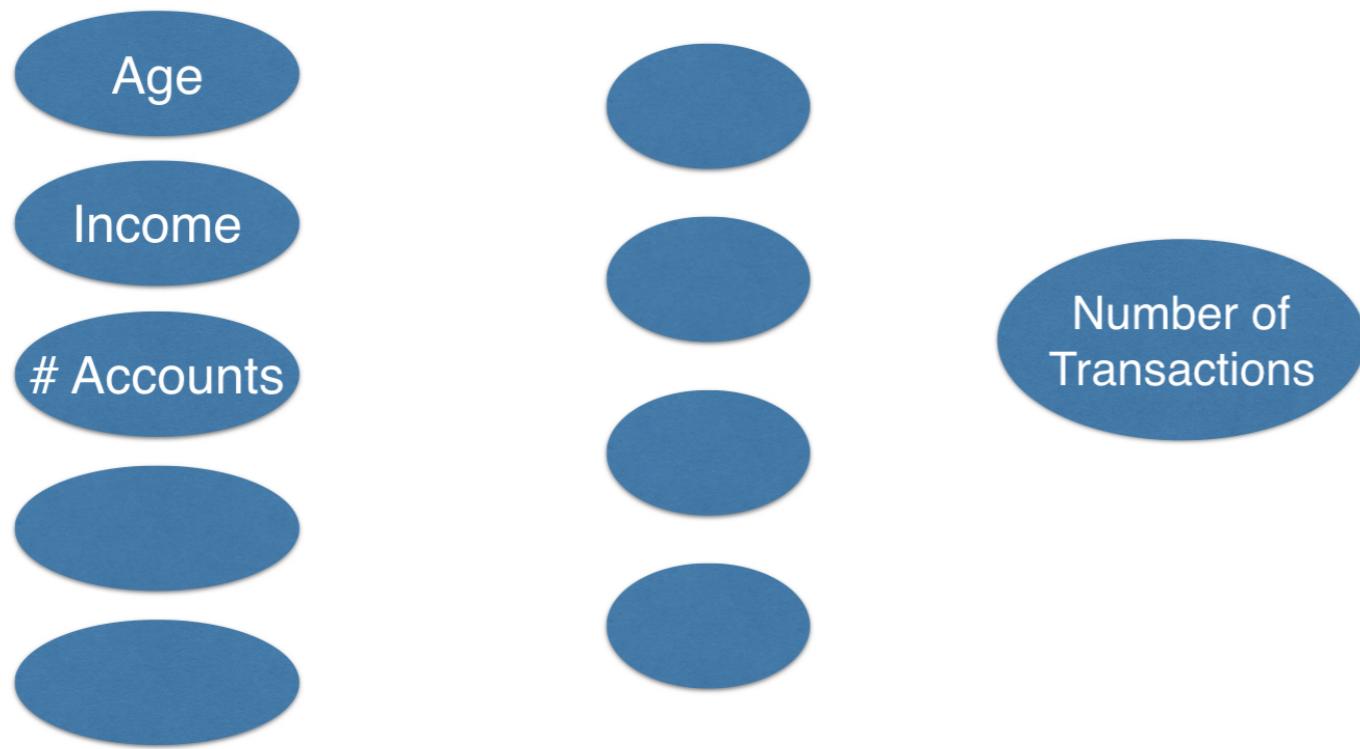
Interactions in neural network



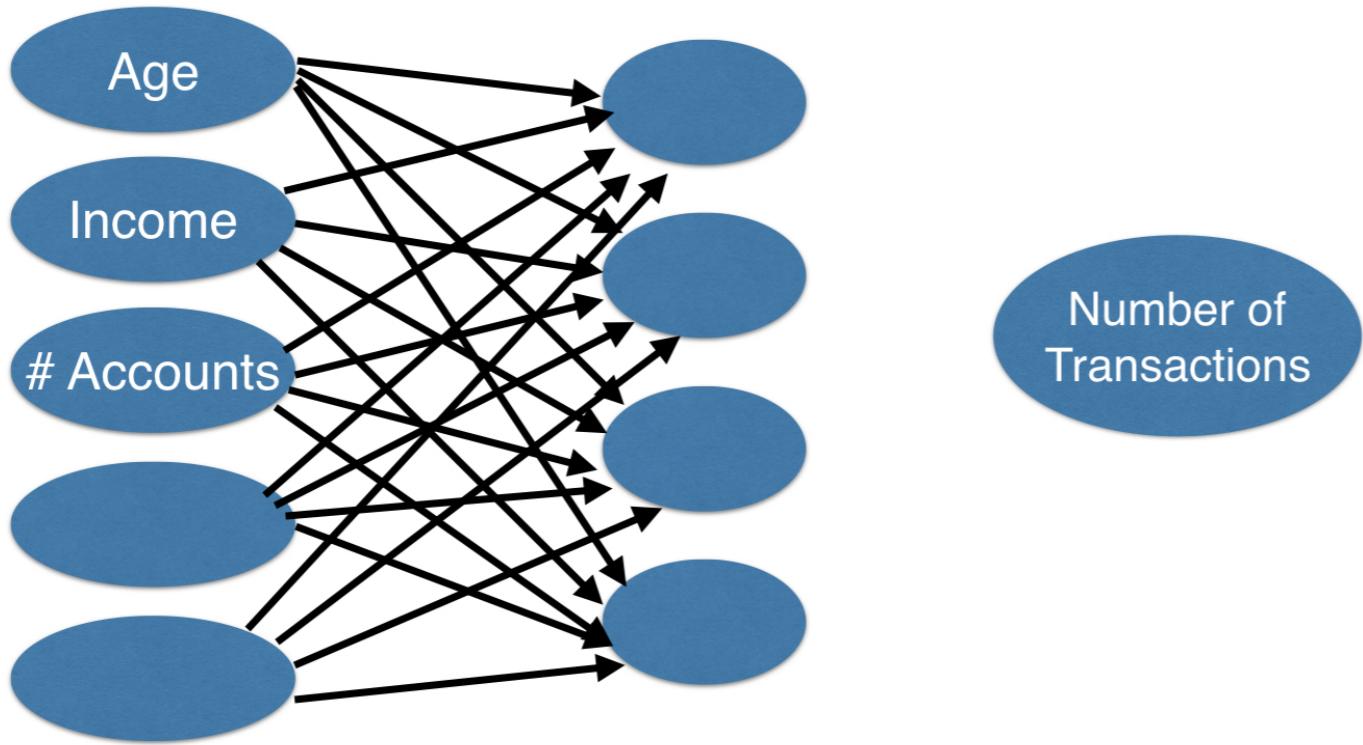
Interactions in neural network



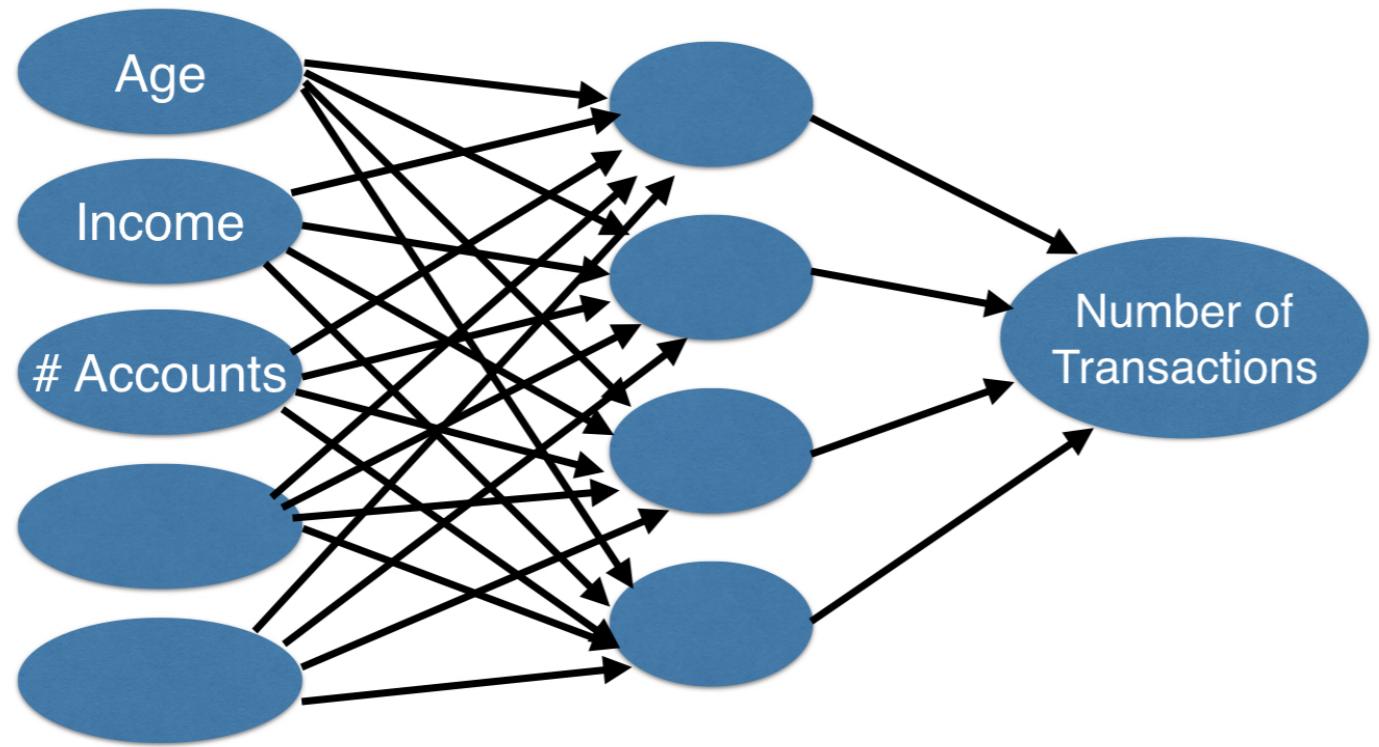
Interactions in neural network



Interactions in neural network



Interactions in neural network

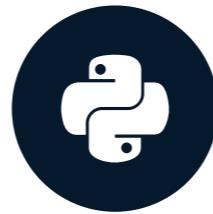


Let's practice!

INTRODUCTION TO DEEP LEARNING IN PYTHON

Forward propagation

INTRODUCTION TO DEEP LEARNING IN PYTHON



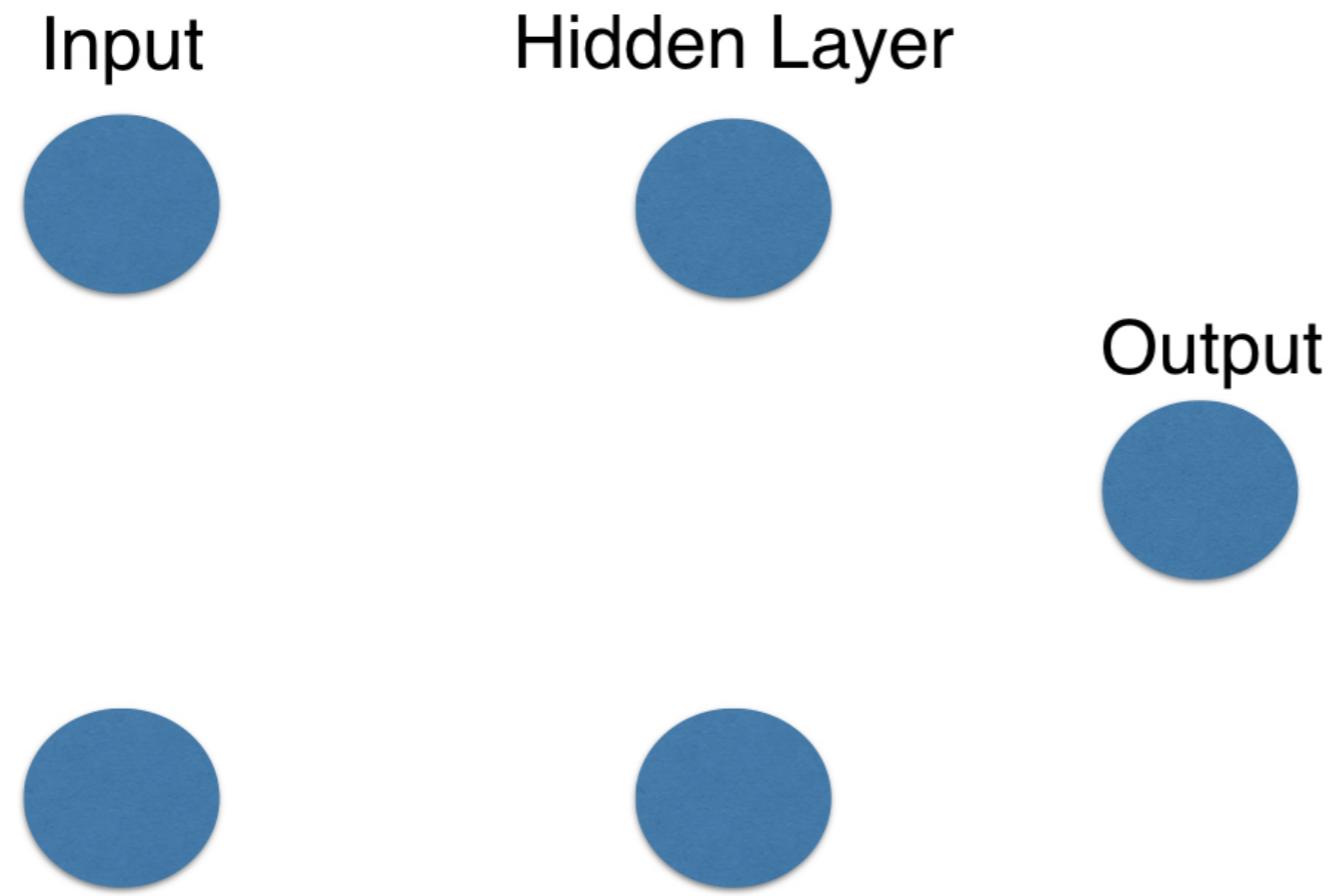
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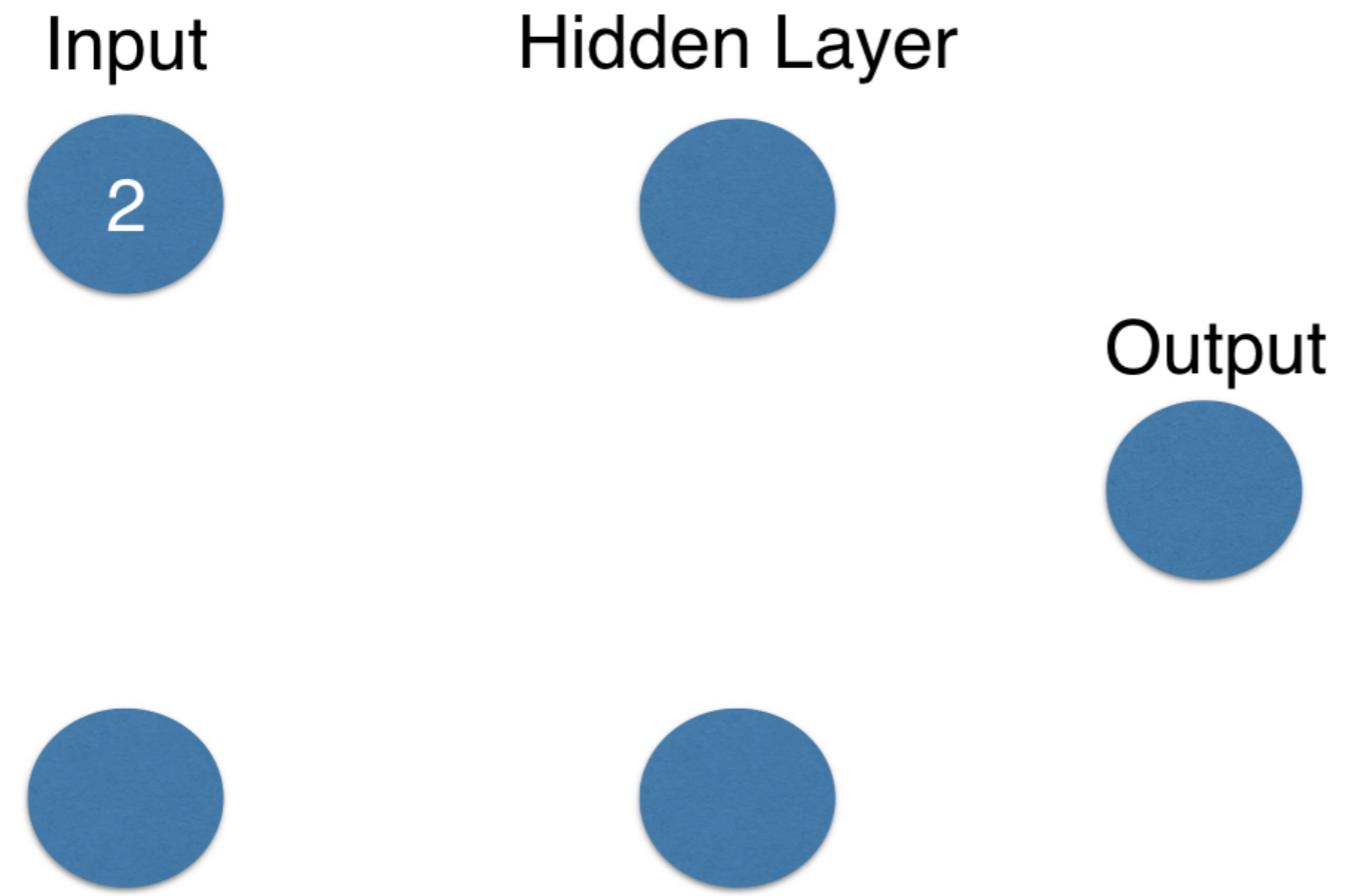
Bank transactions example

- Make predictions based on:
 - Number of children
 - Number of existing accounts

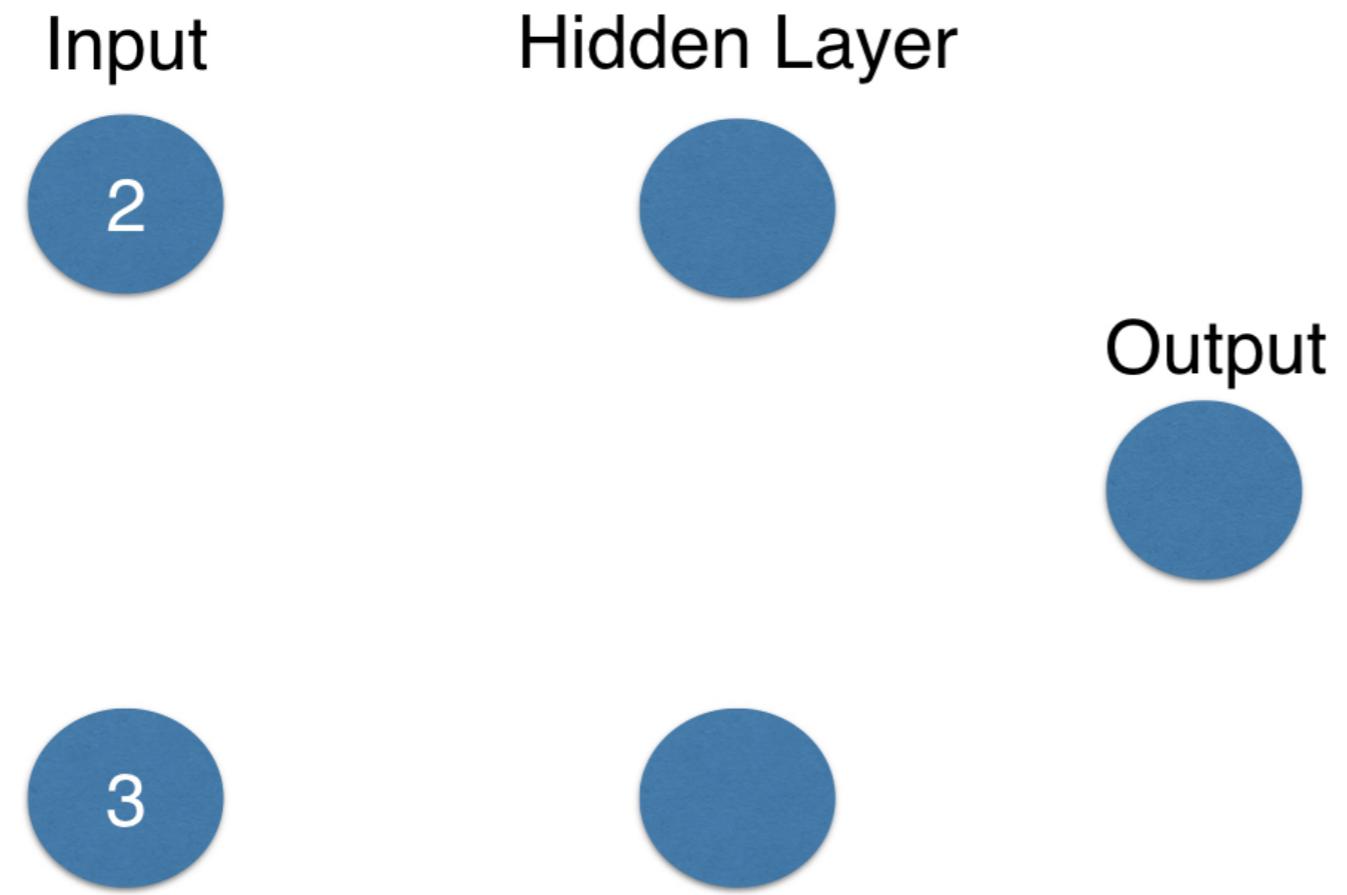
Forward propagation



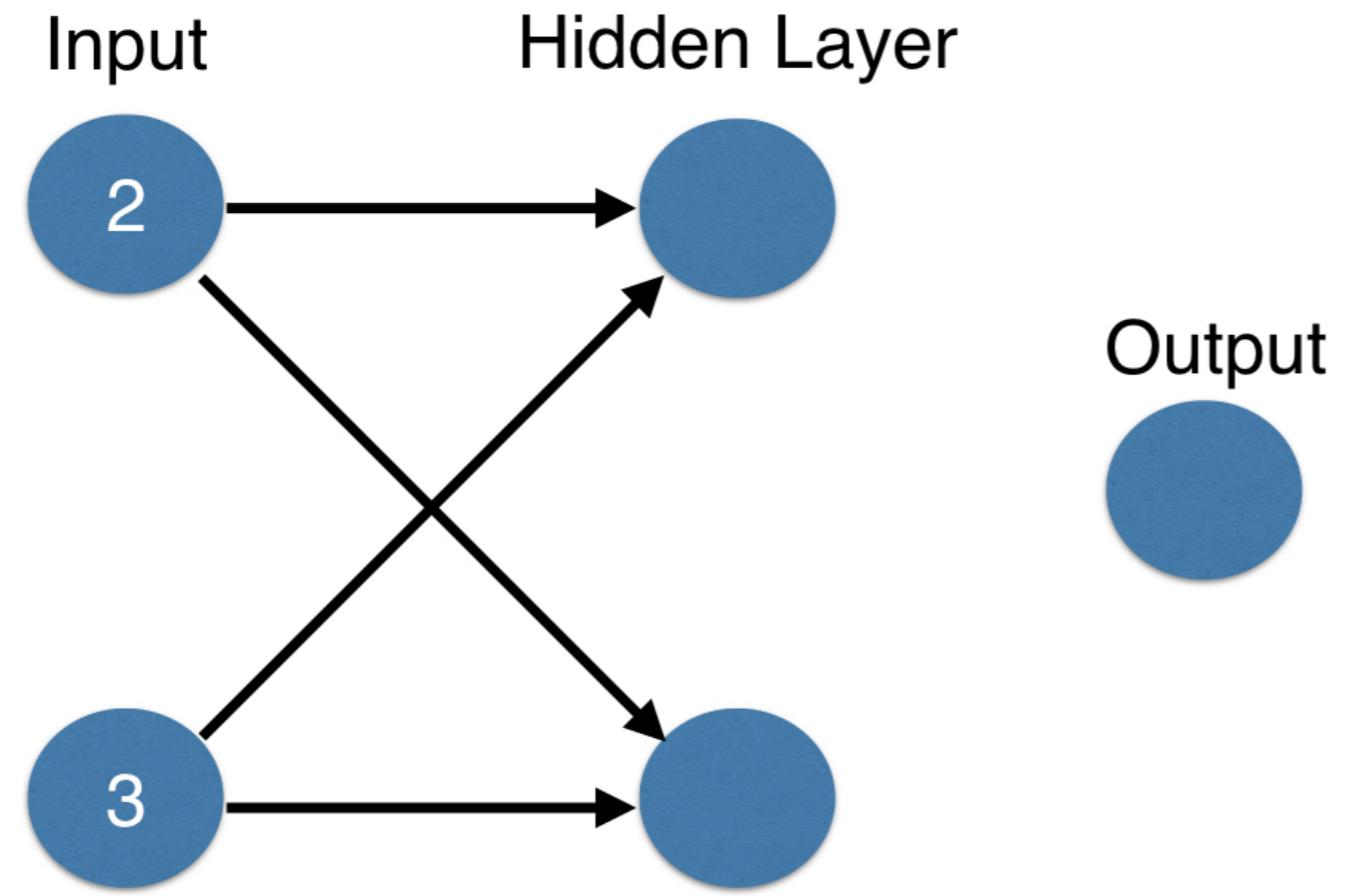
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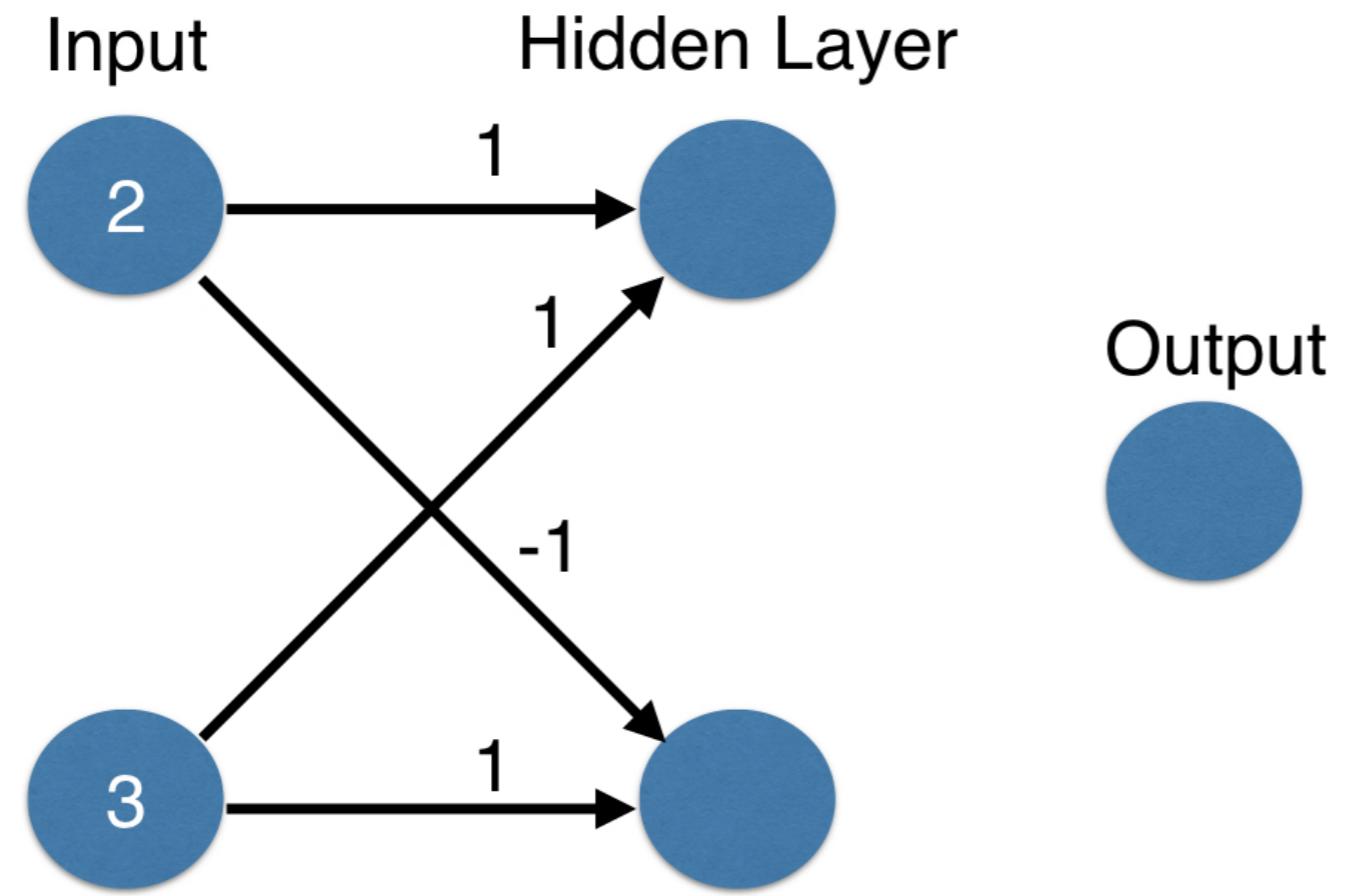
Forward propagation



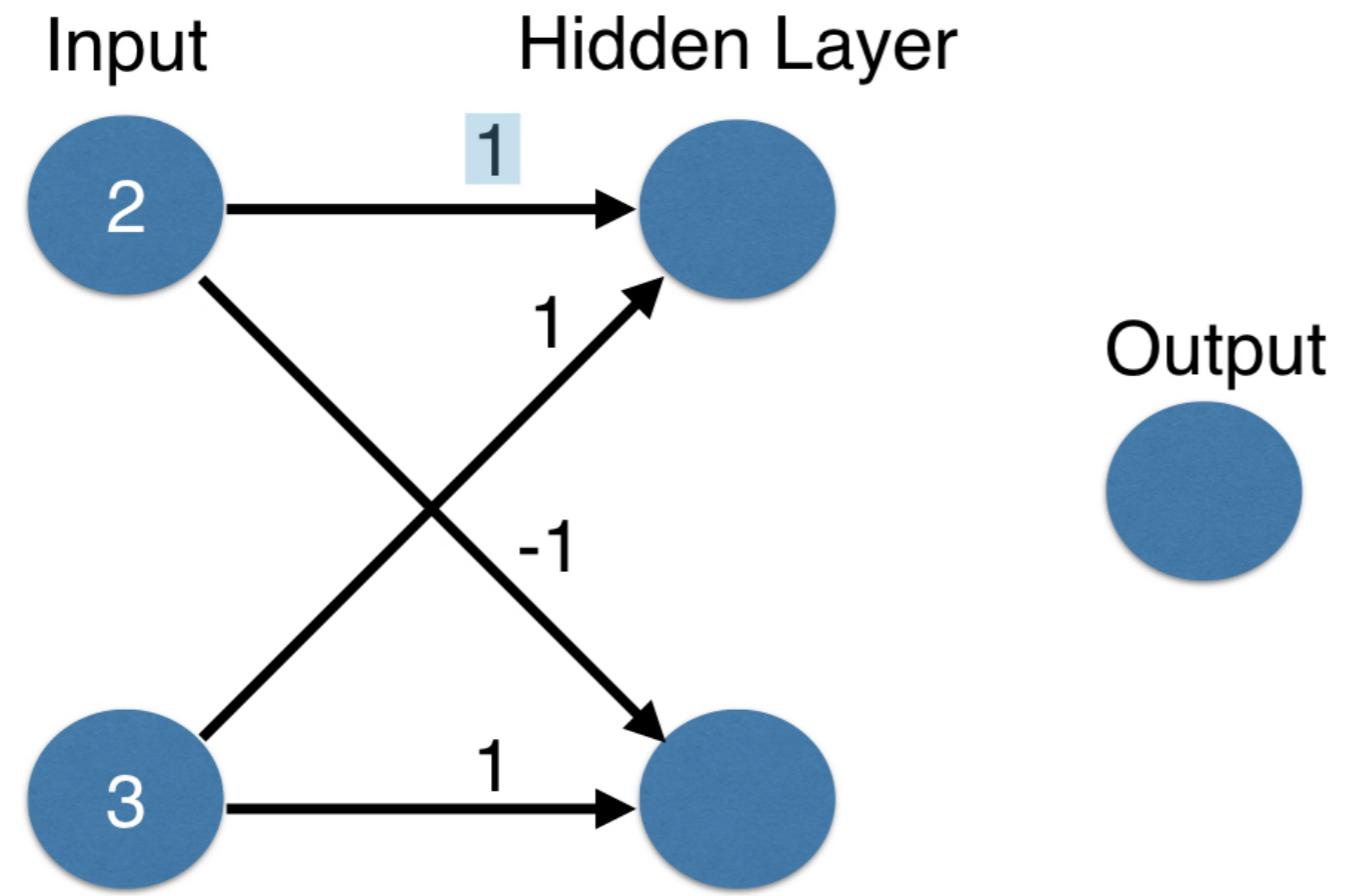
Forward propagation



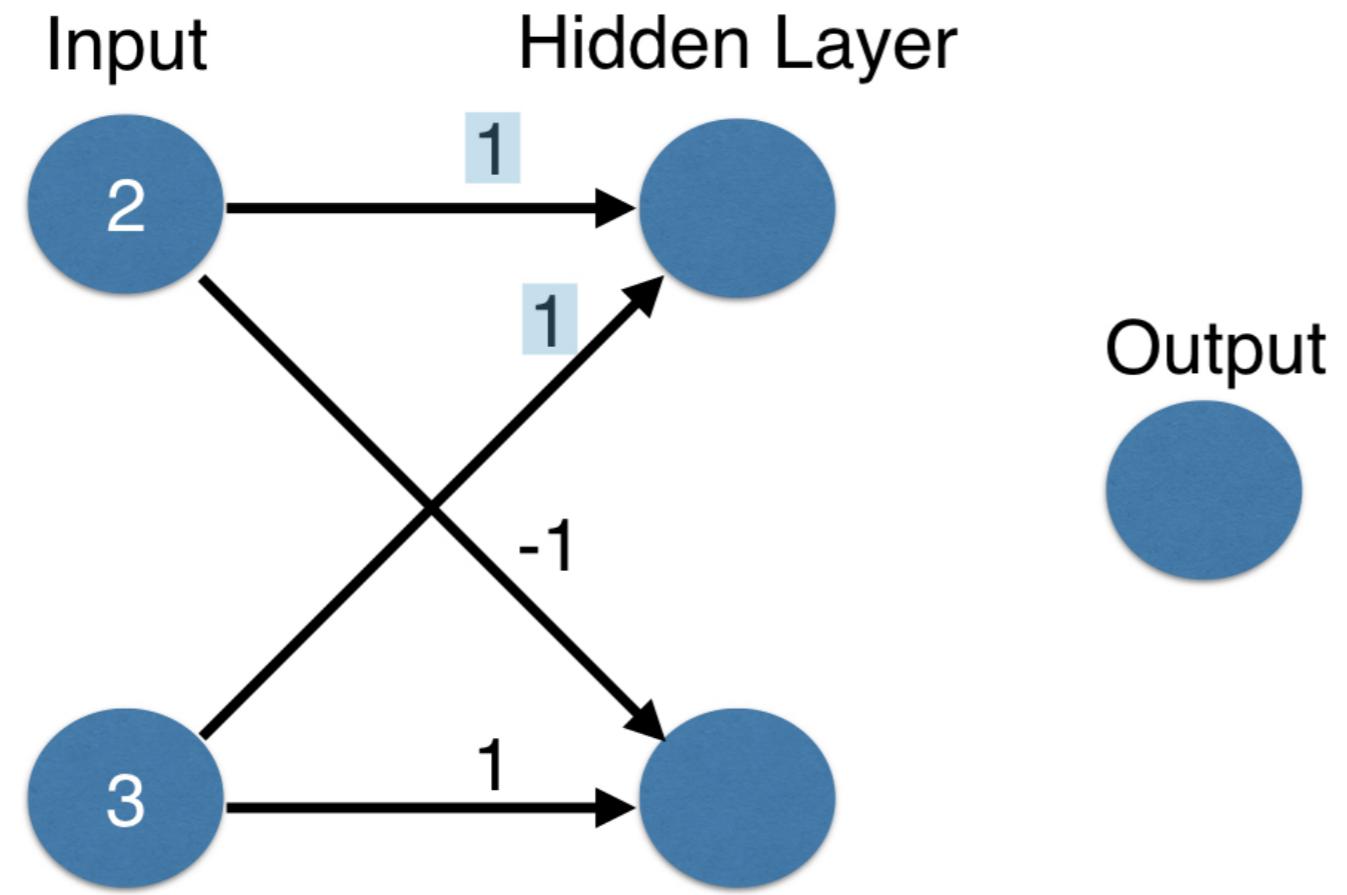
Forward propagation



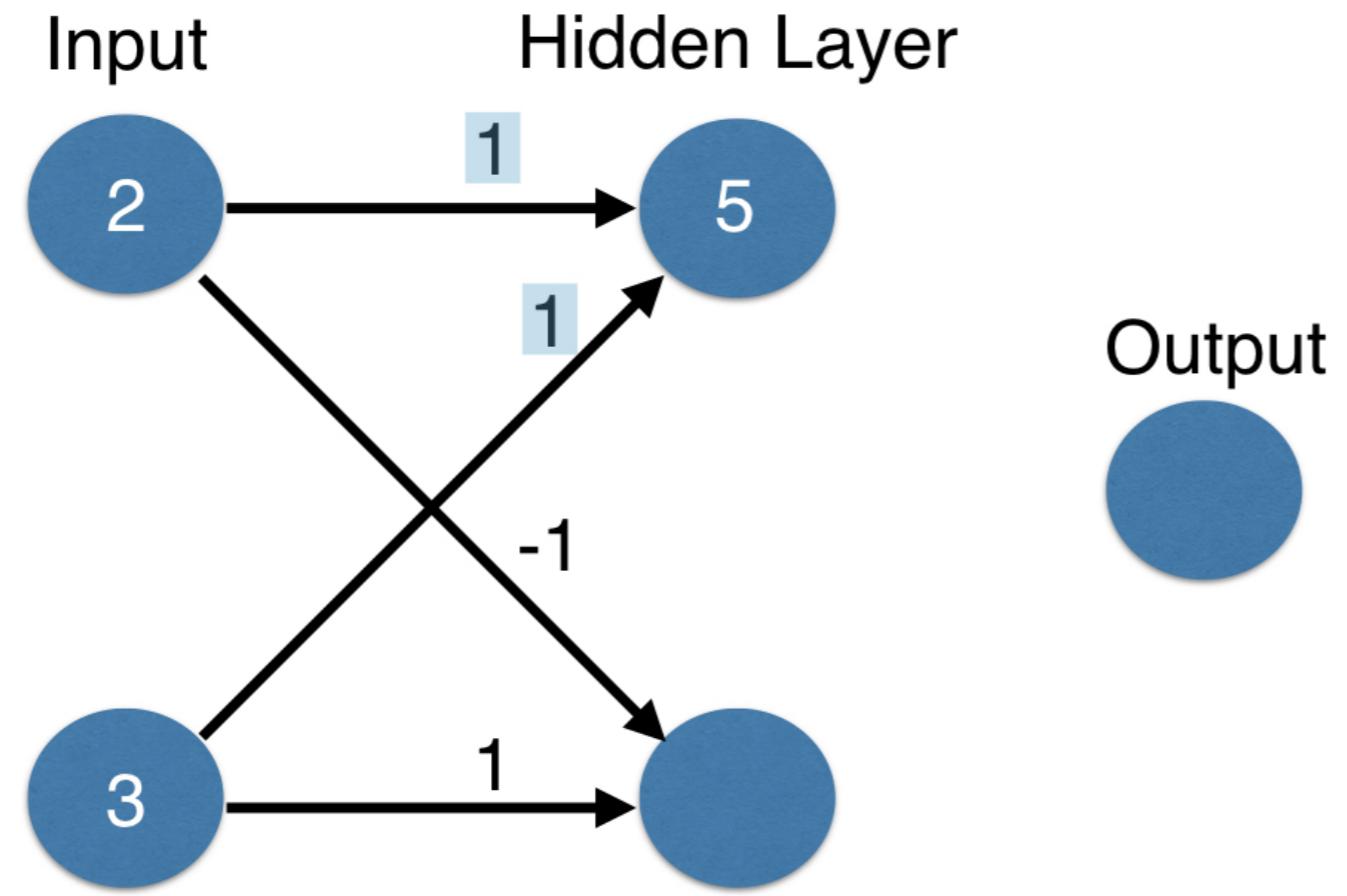
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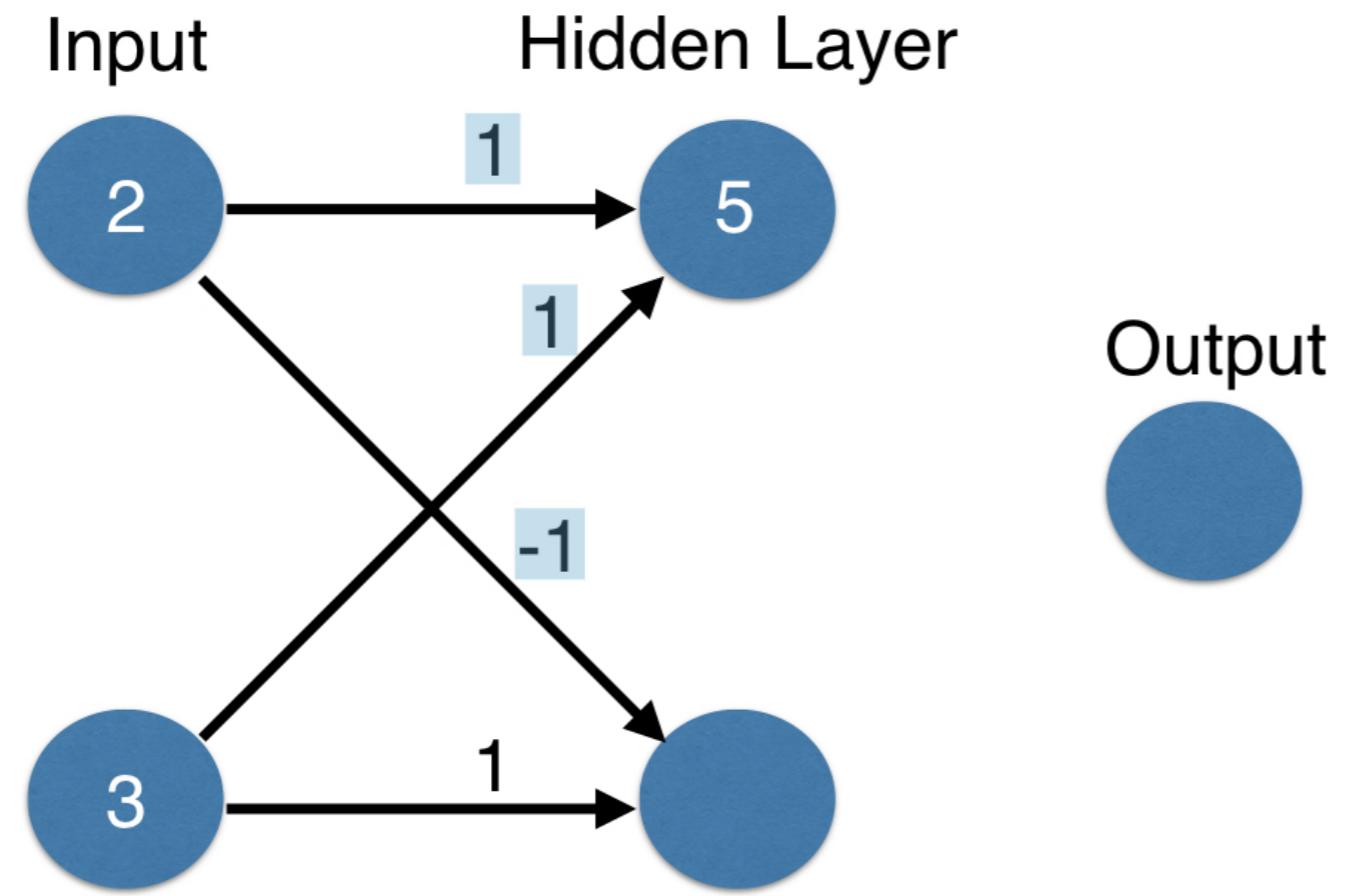
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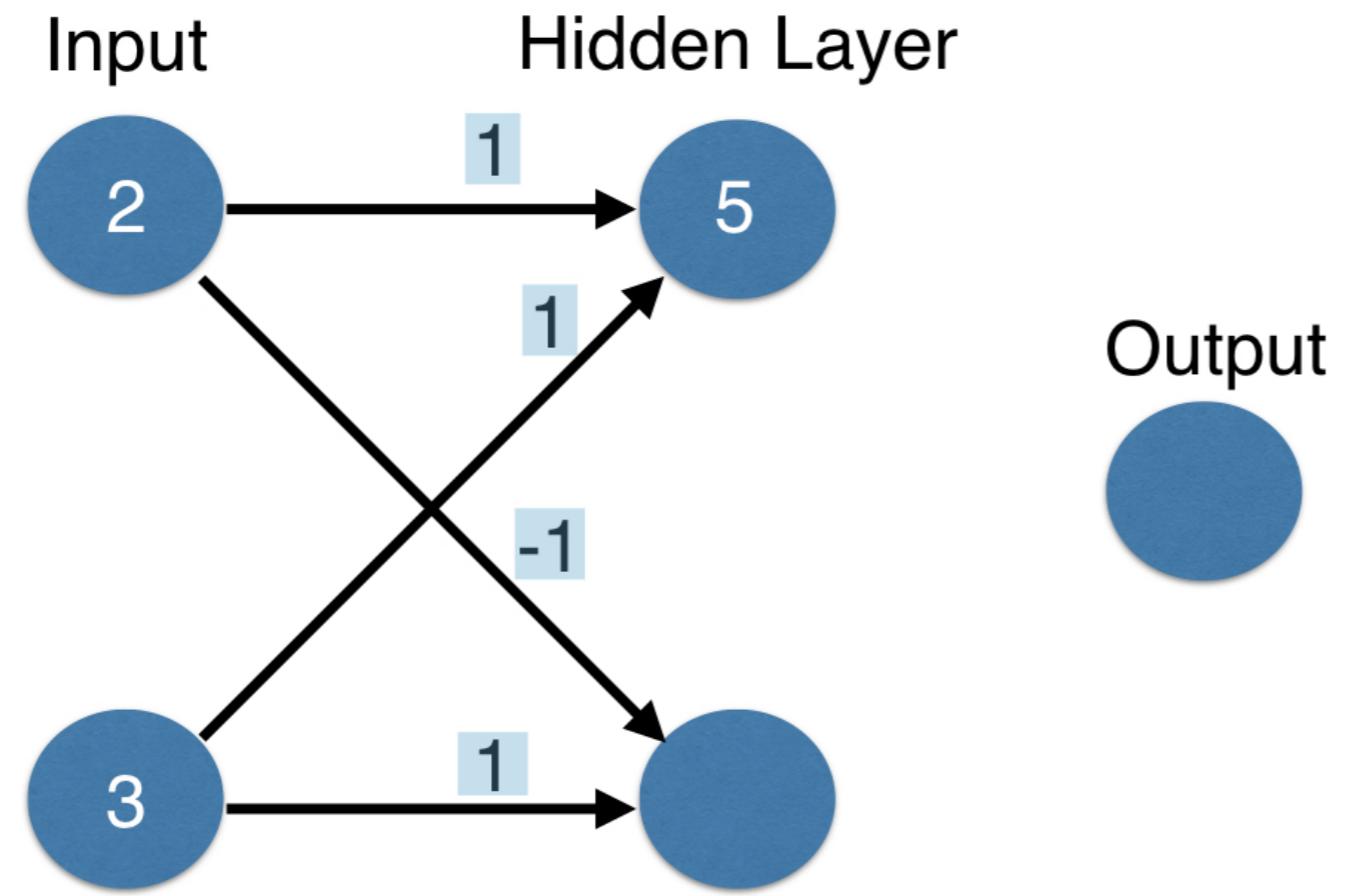
Forward propagation



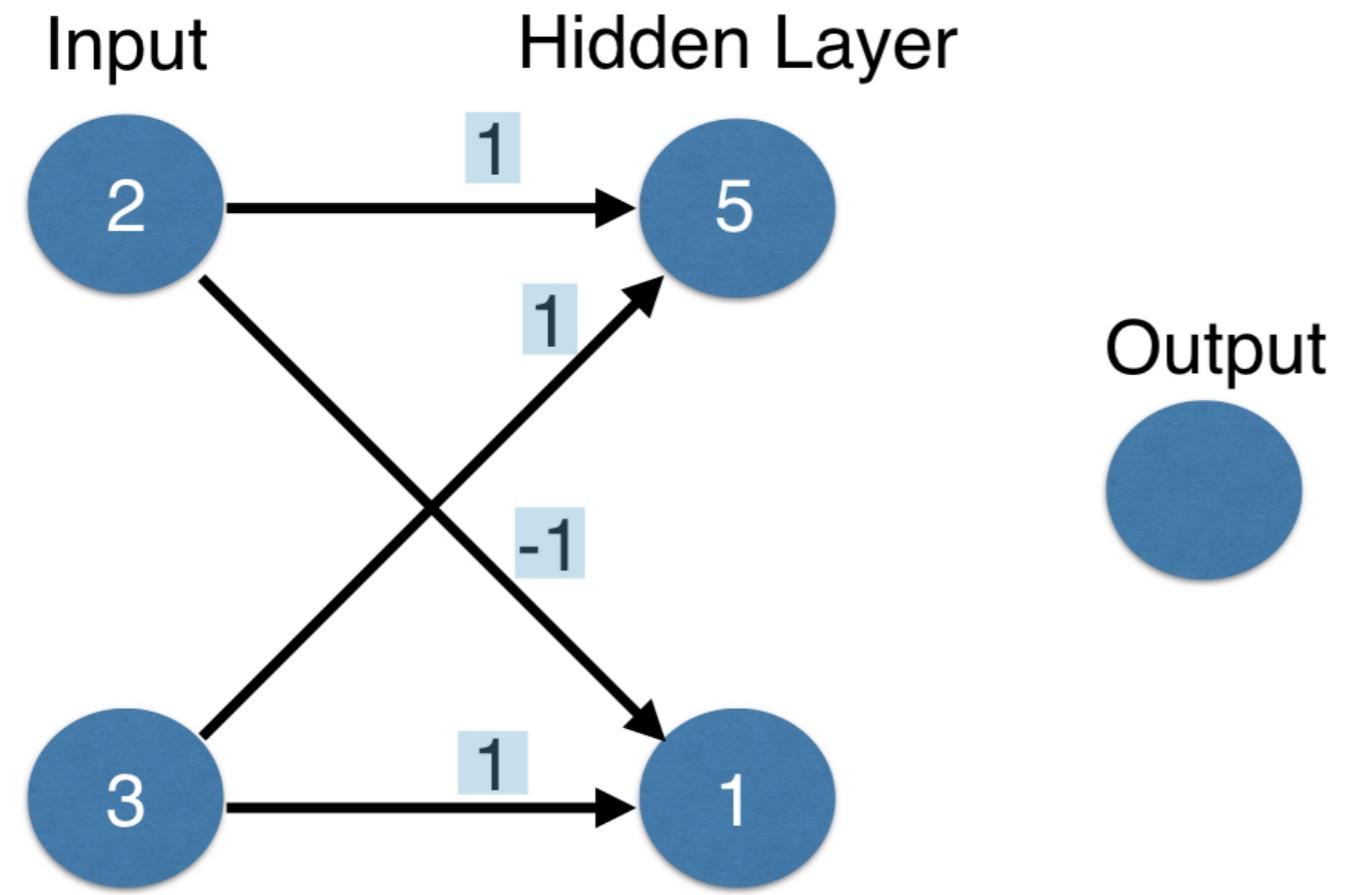
Forward propagation



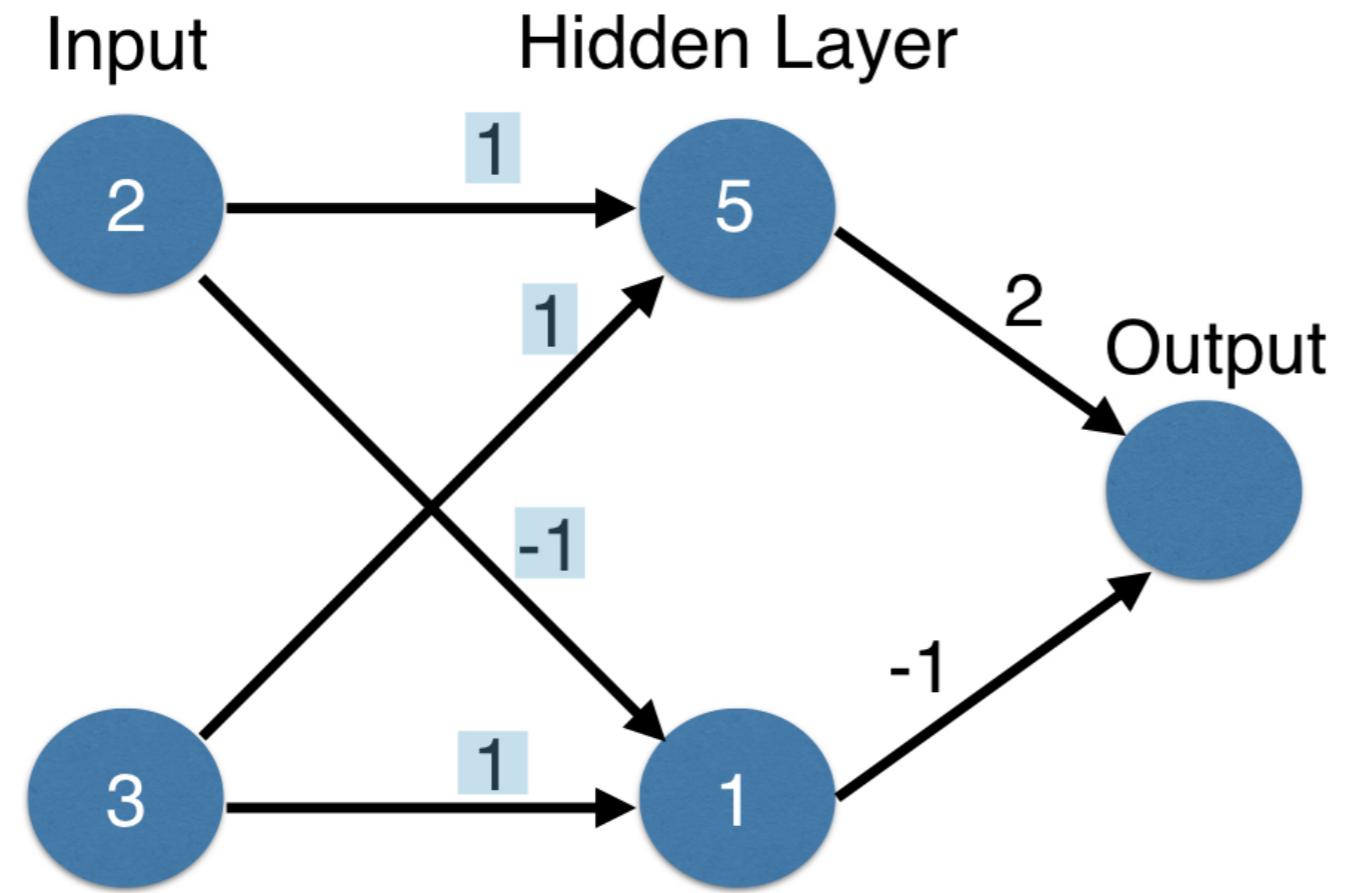
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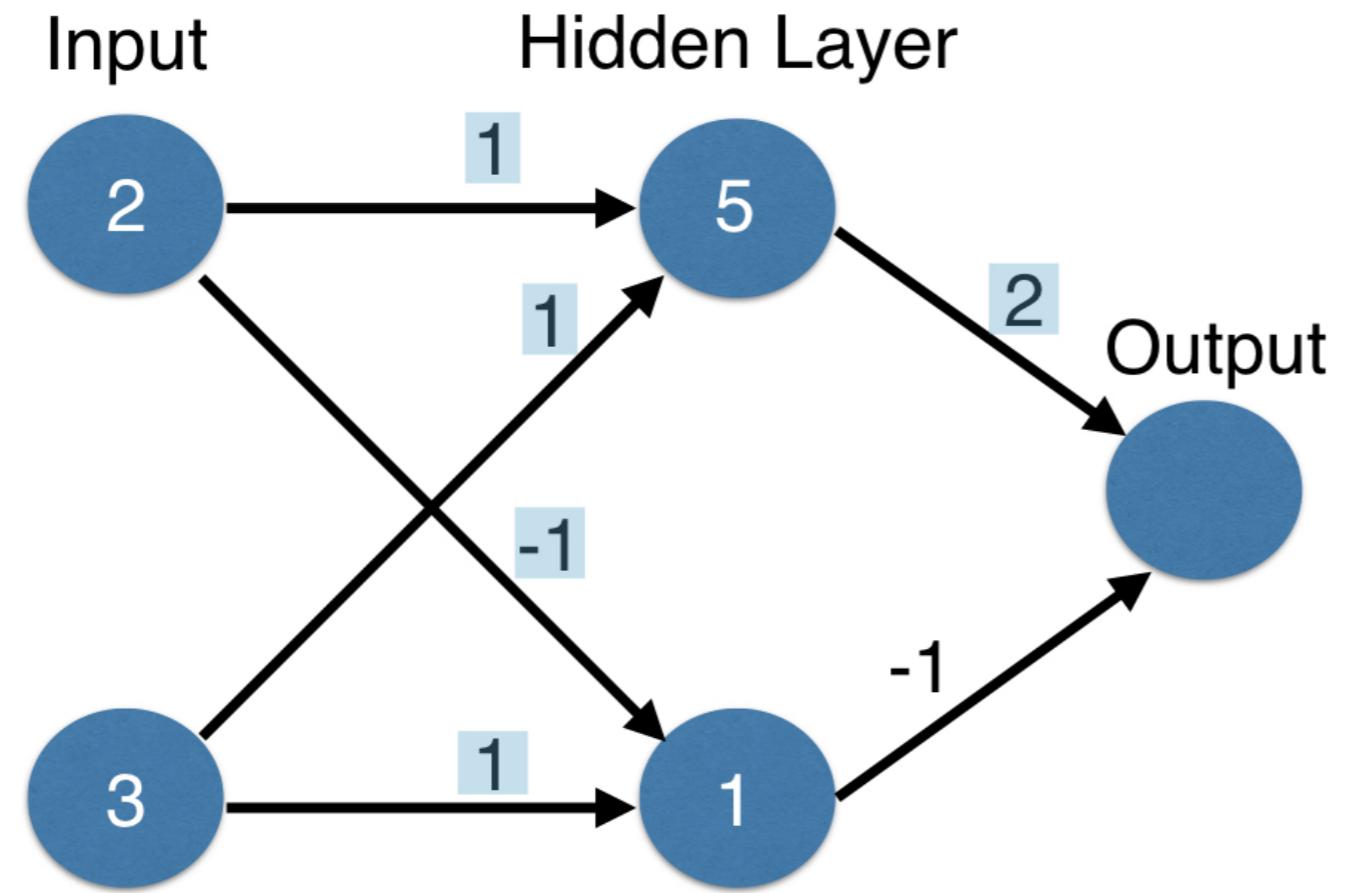
Forward propagation



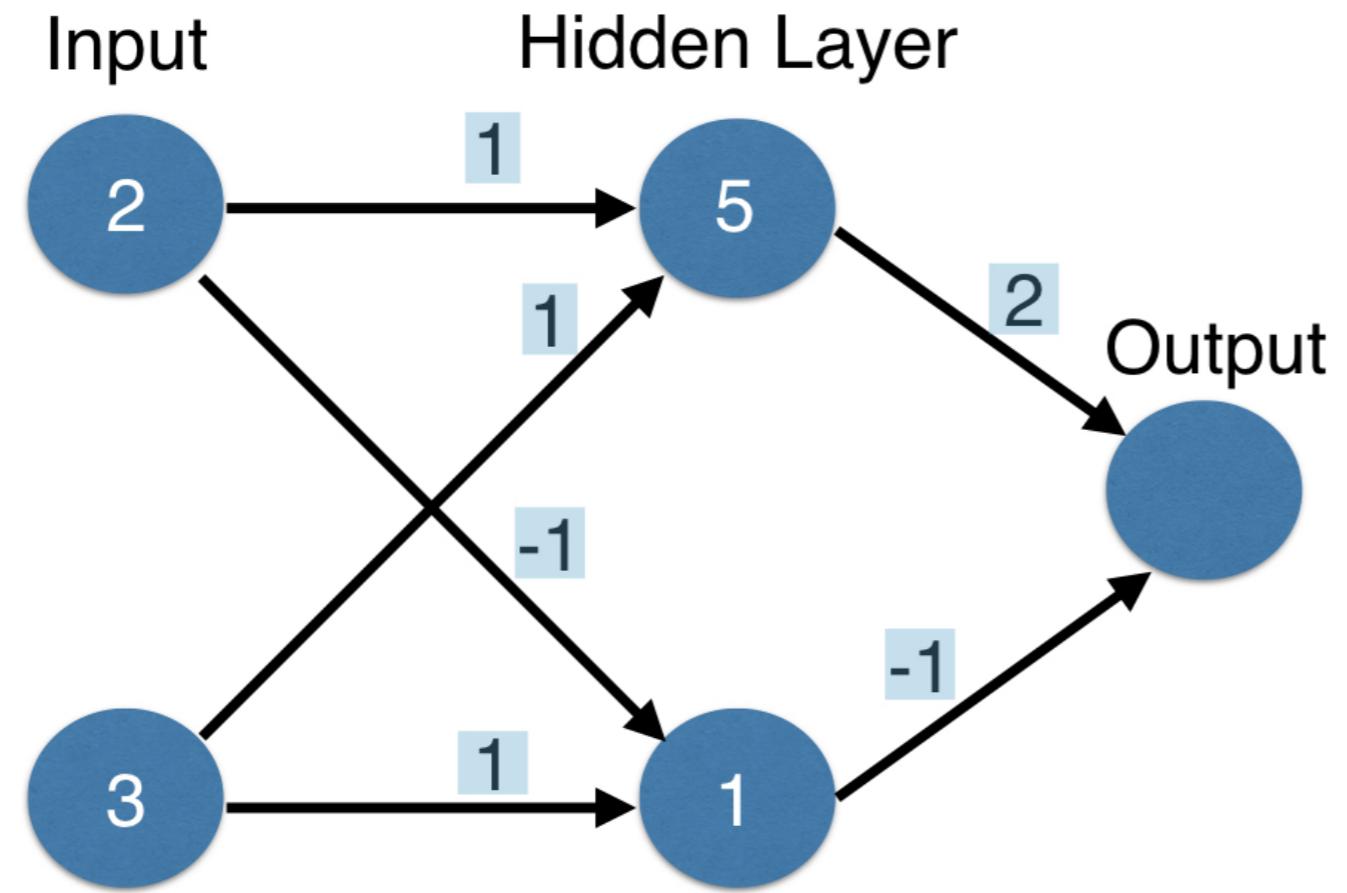
Forward propagation



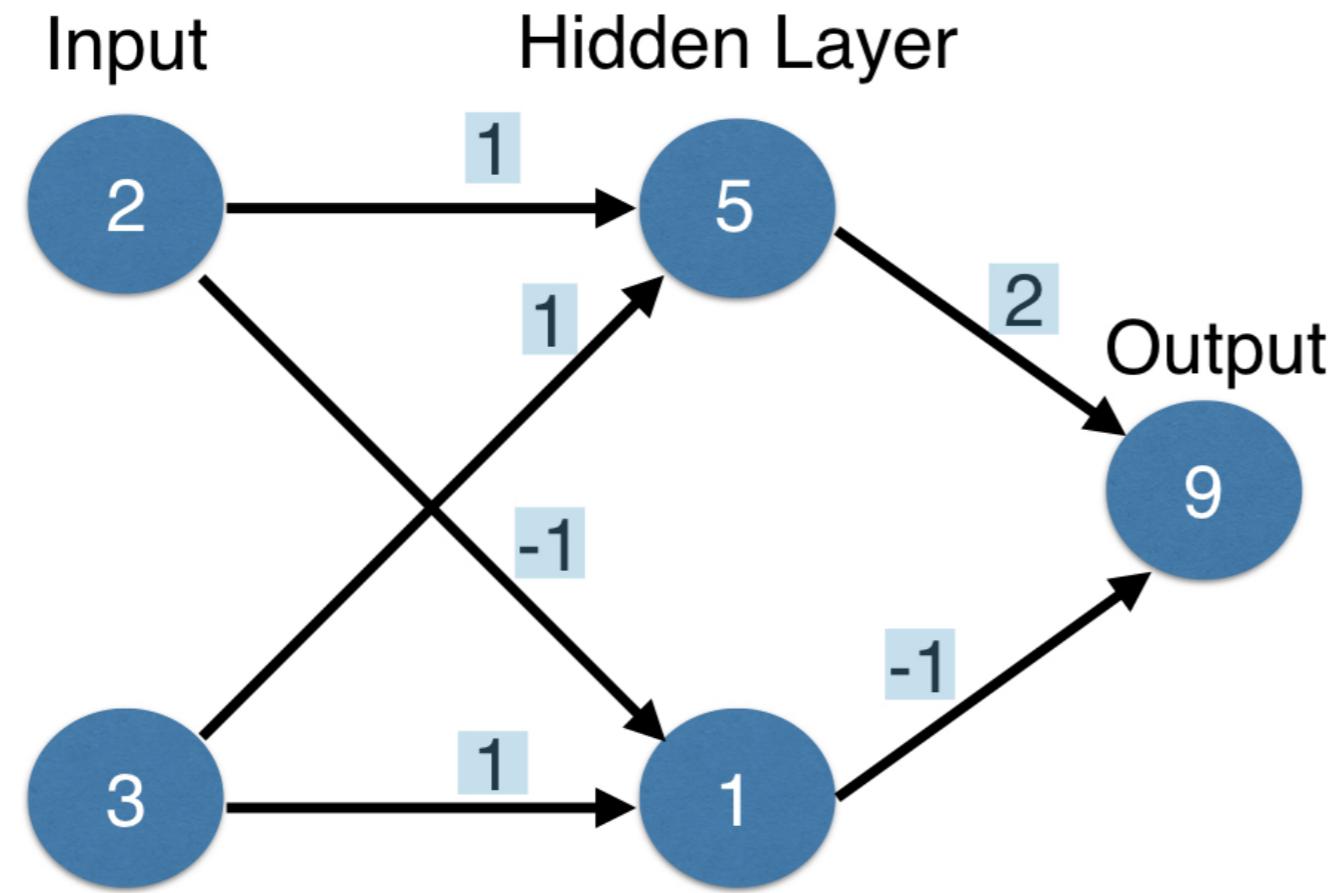
Forward propagation



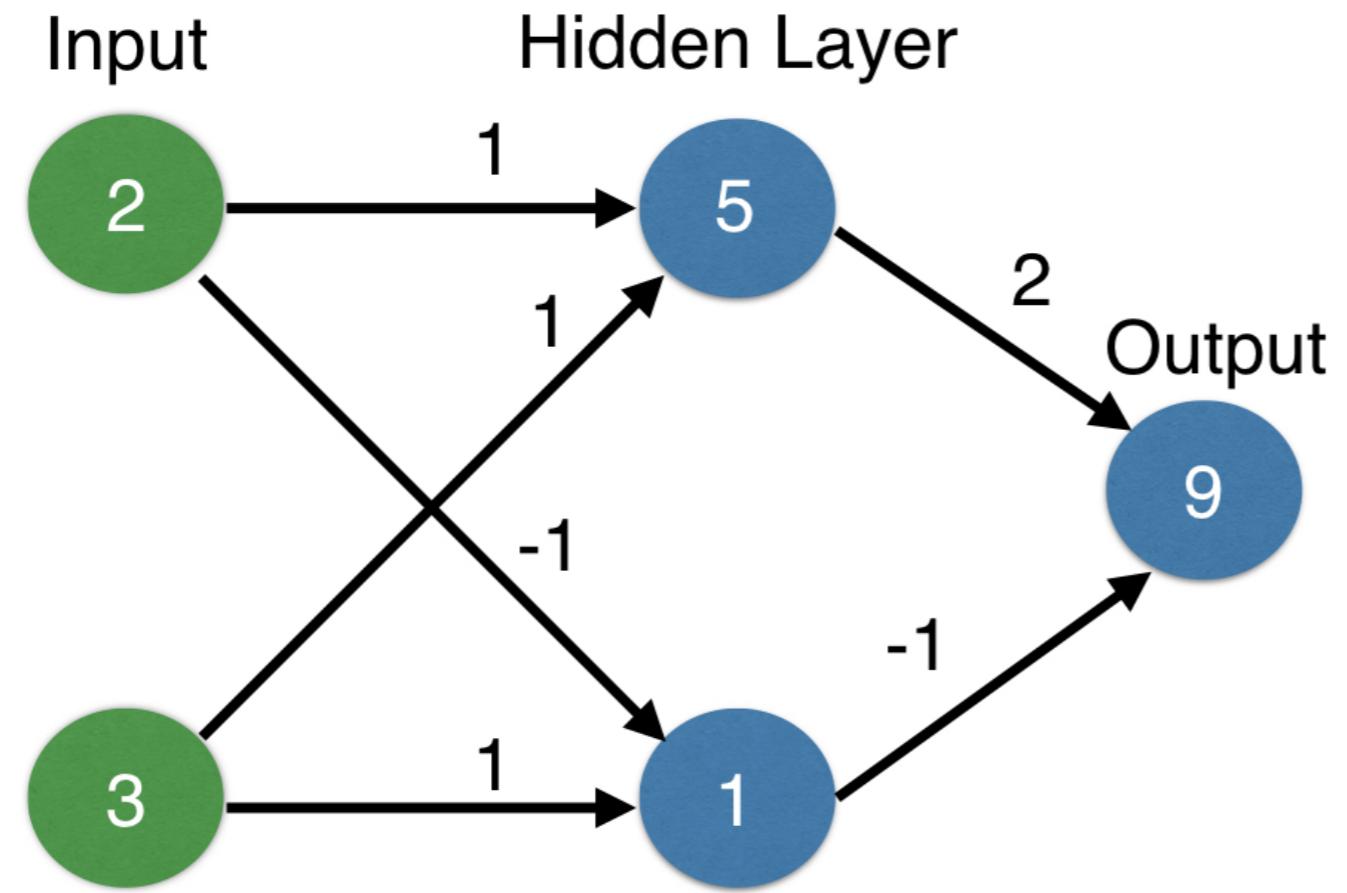
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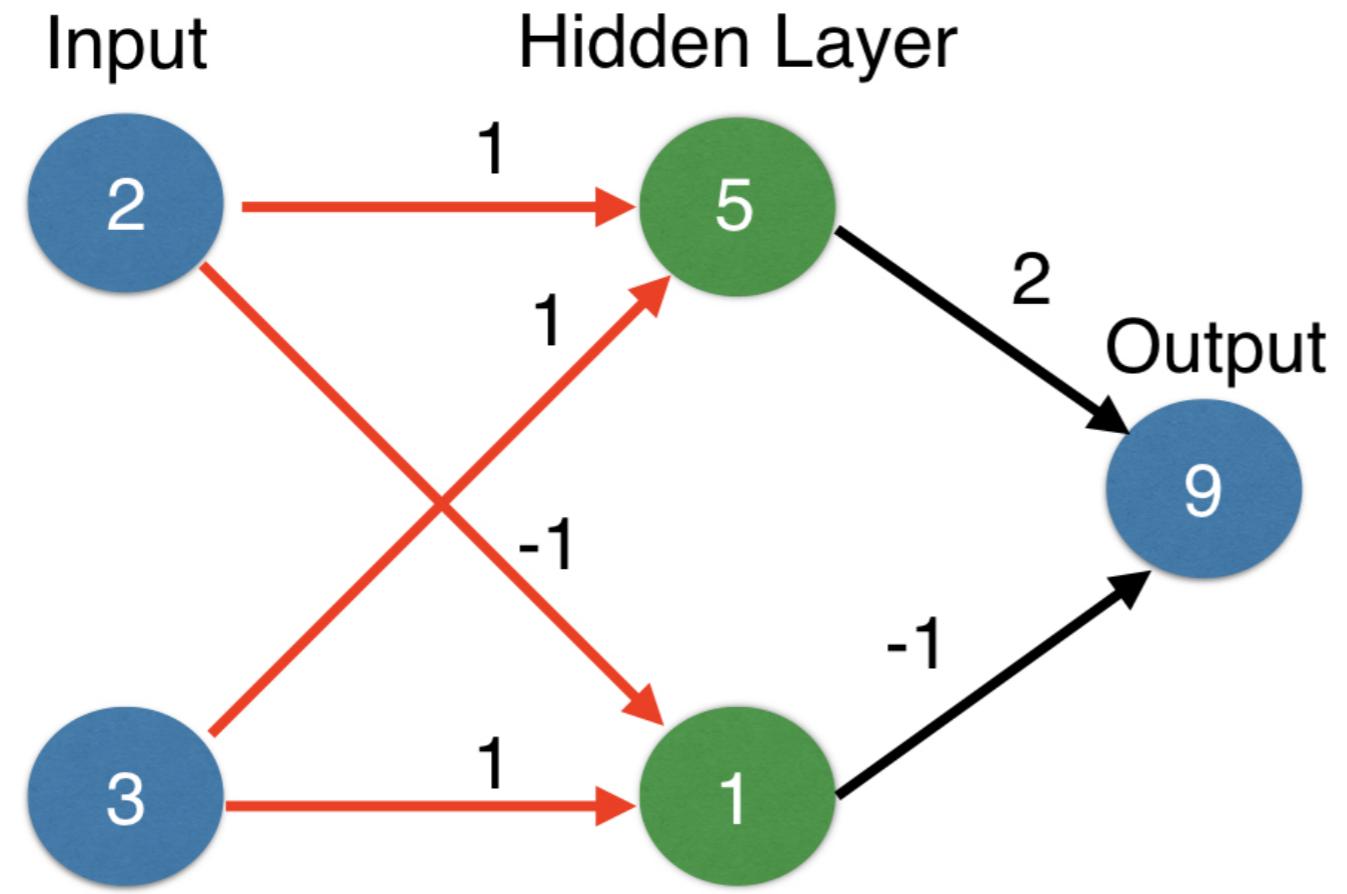
Forward propagation



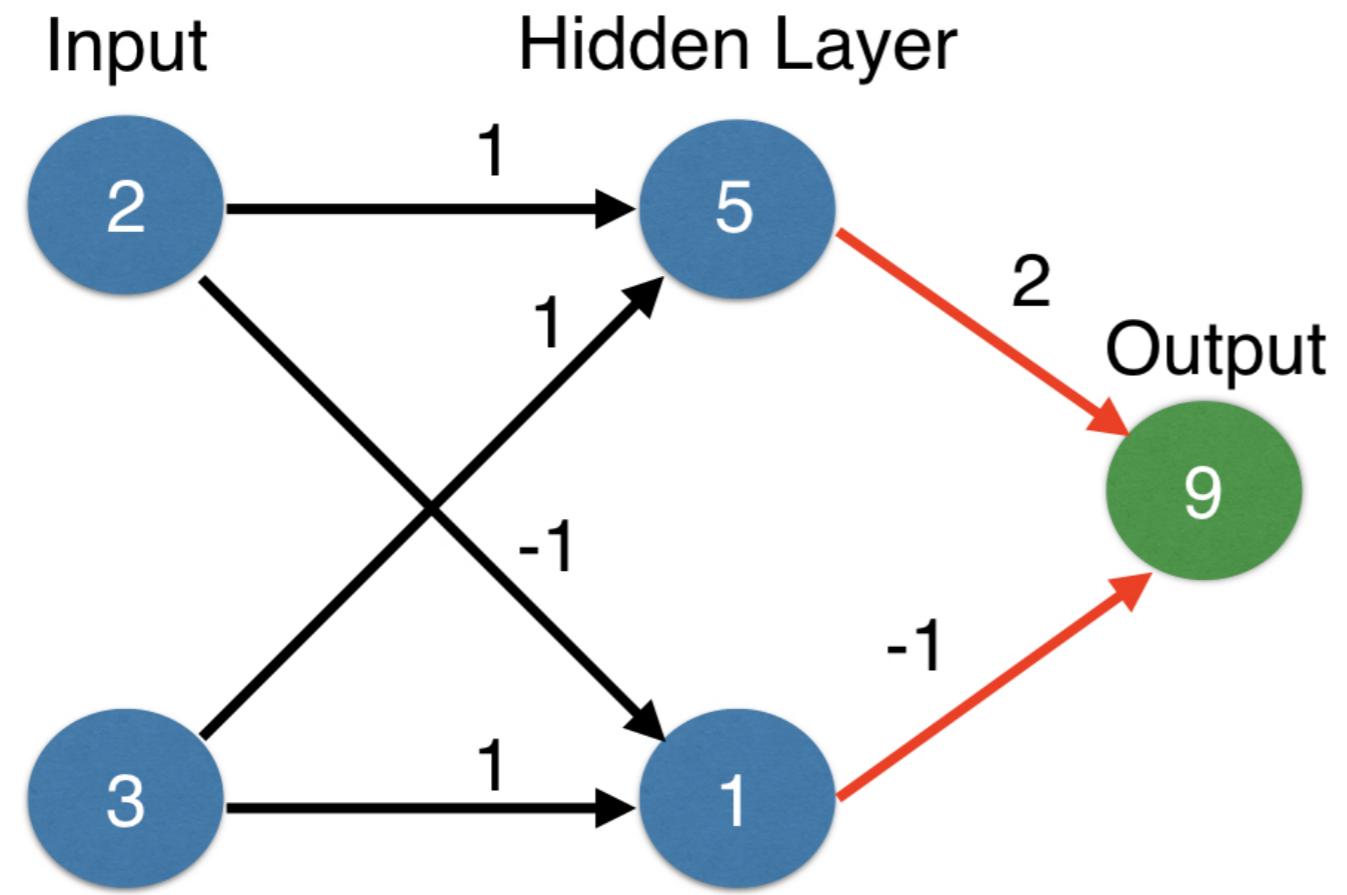
Forward propagation



Forward propagation



Forward propagation



Forward propagation

- Multiply - add process
- Dot product
- Forward propagation for one data point at a time
- Output is the prediction for that data point

Forward propagation code

```
import numpy as np

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

weights = {'node_0': np.array([1, 1]),
           'node_1': np.array([-1, 1]),
           'output': np.array([2, -1])}

node_0_value = (input_data * weights['node_0']).sum()
node_1_value = (input_data * weights['node_1']).sum()
```

Forward propagation code

```
hidden_layer_values = np.array([node_0_value, node_1_value])  
print(hidden_layer_values)
```

```
[5, 1]
```

```
output = (hidden_layer_values * weights['output']).sum()  
print(output)
```

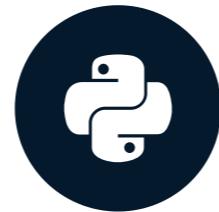
```
9
```

Let's practice!

INTRODUCTION TO DEEP LEARNING IN PYTHON

Activation functions

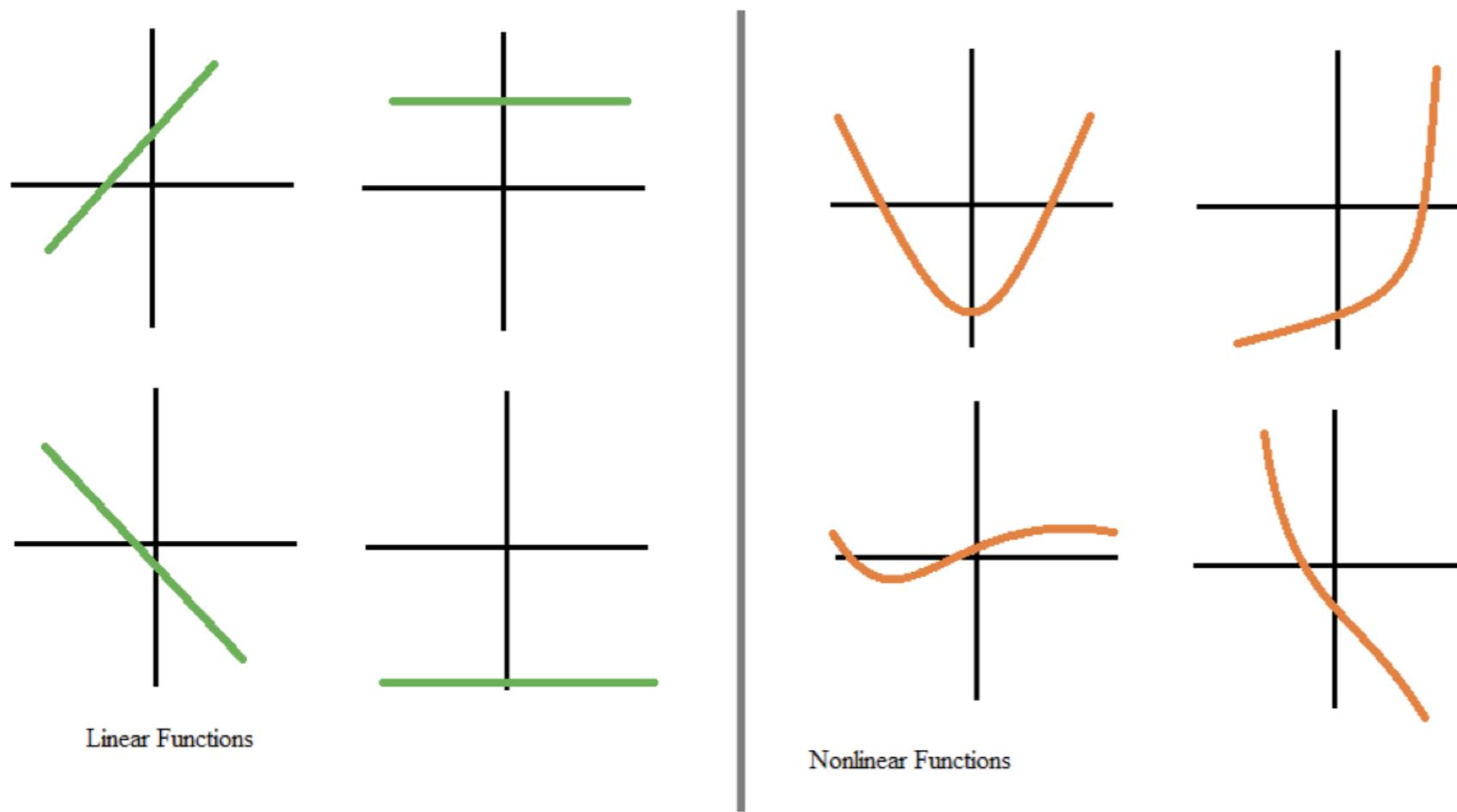
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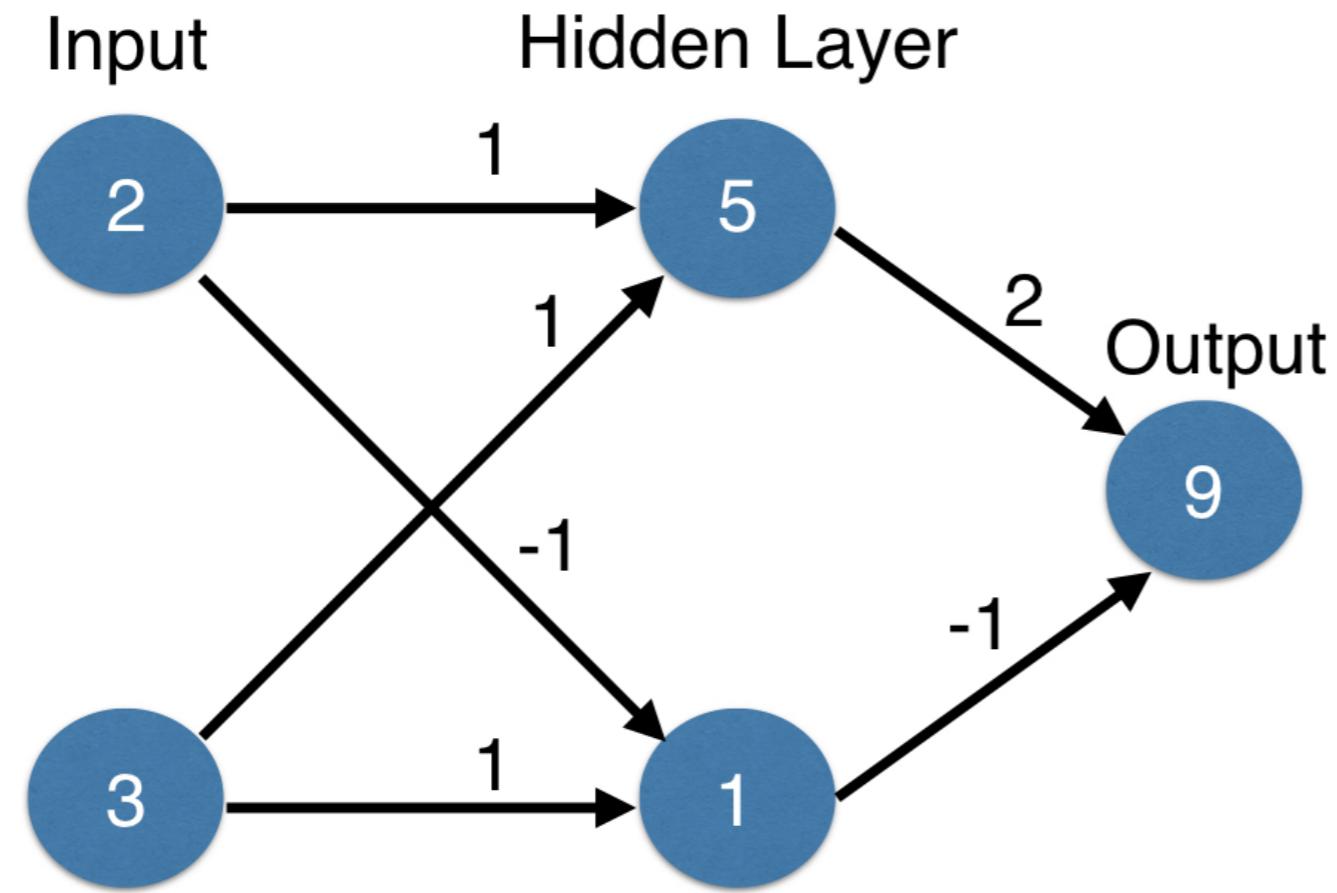
Linear vs Nonlinear Functions



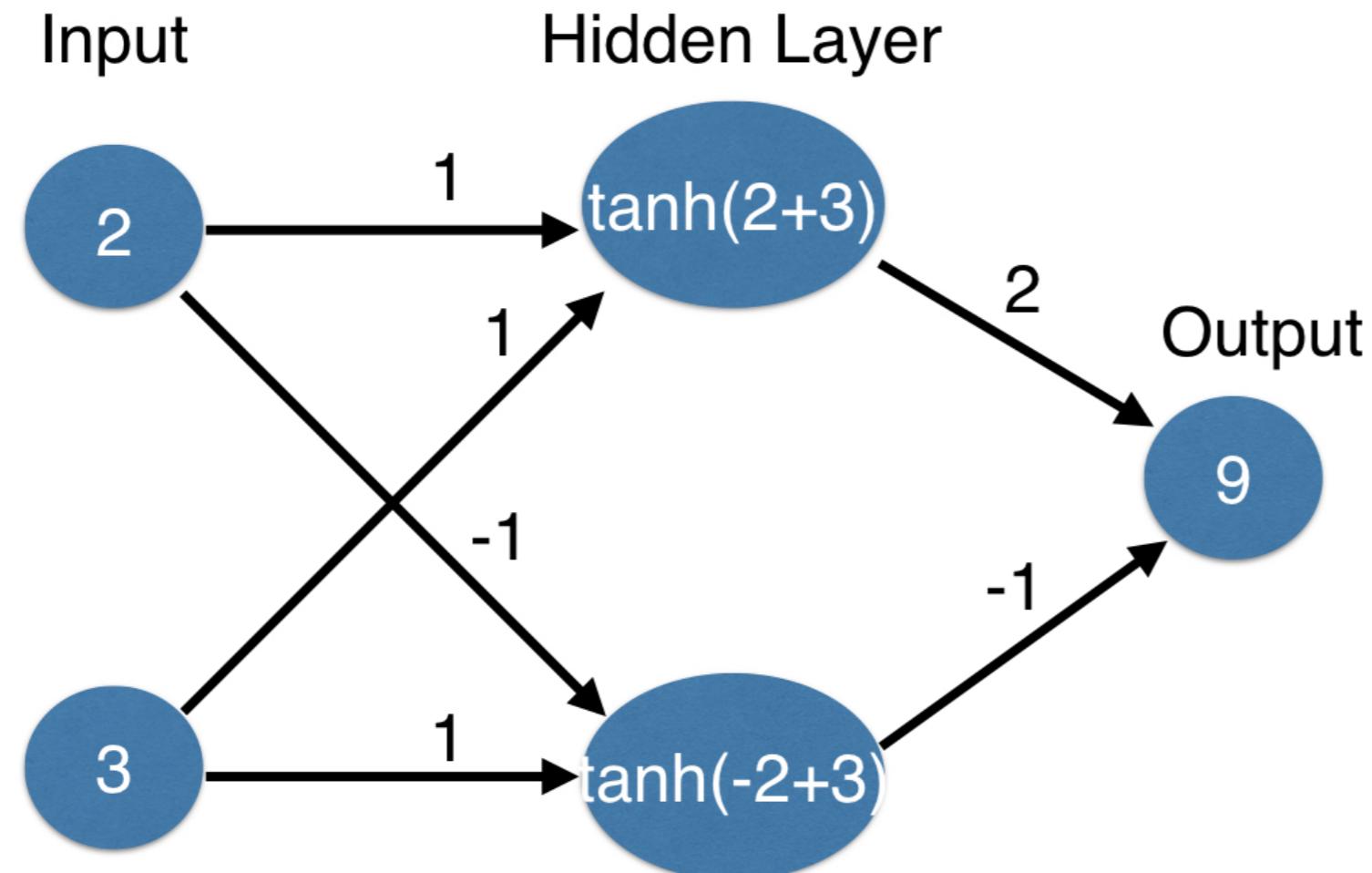
Activation functions

- Applied to node inputs to produce node output

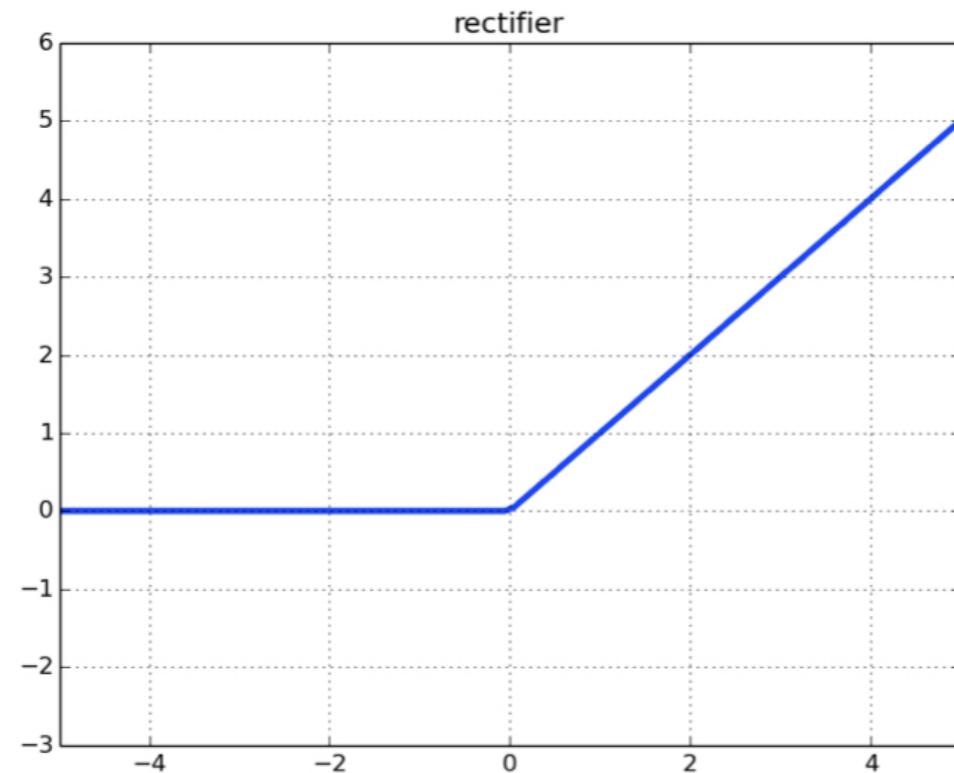
Improving our neural network



Activation functions



ReLU (Rectified Linear Activation)



$$RELU(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases}$$

Activation functions

```
import numpy as np  
input_data = np.array([-1, 2])  
weights = {'node_0': np.array([3, 3]),  
           'node_1': np.array([1, 5]),  
           'output': np.array([2, -1])}  
node_0_input = (input_data * weights['node_0']).sum()  
node_0_output = np.tanh(node_0_input)  
node_1_input = (input_data * weights['node_1']).sum()  
node_1_output = np.tanh(node_1_input)  
hidden_layer_outputs = np.array([node_0_output, node_1_output])  
output = (hidden_layer_outputs * weights['output']).sum()
```

```
print(output)
```

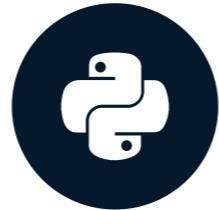
```
1.2382242525694254
```

Let's practice!

INTRODUCTION TO DEEP LEARNING IN PYTHON

Deeper networks

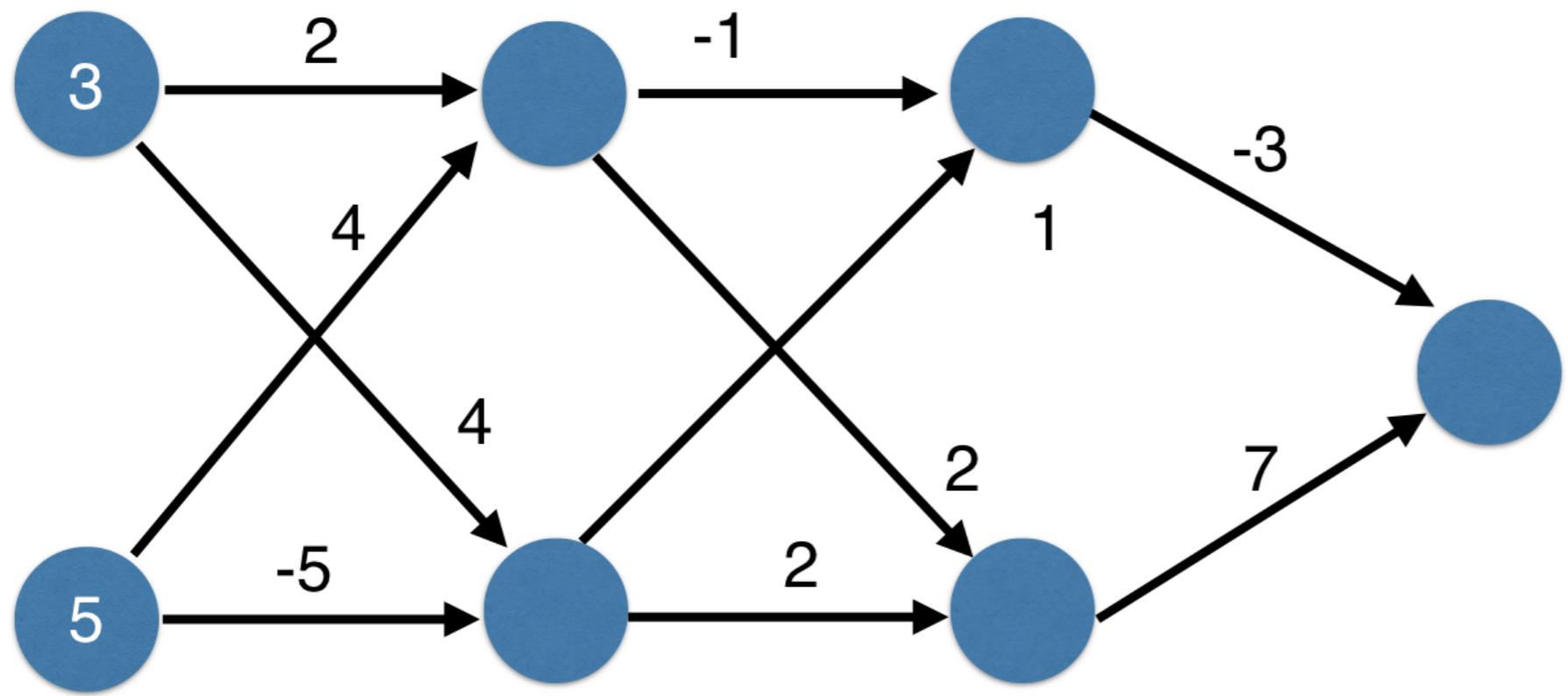
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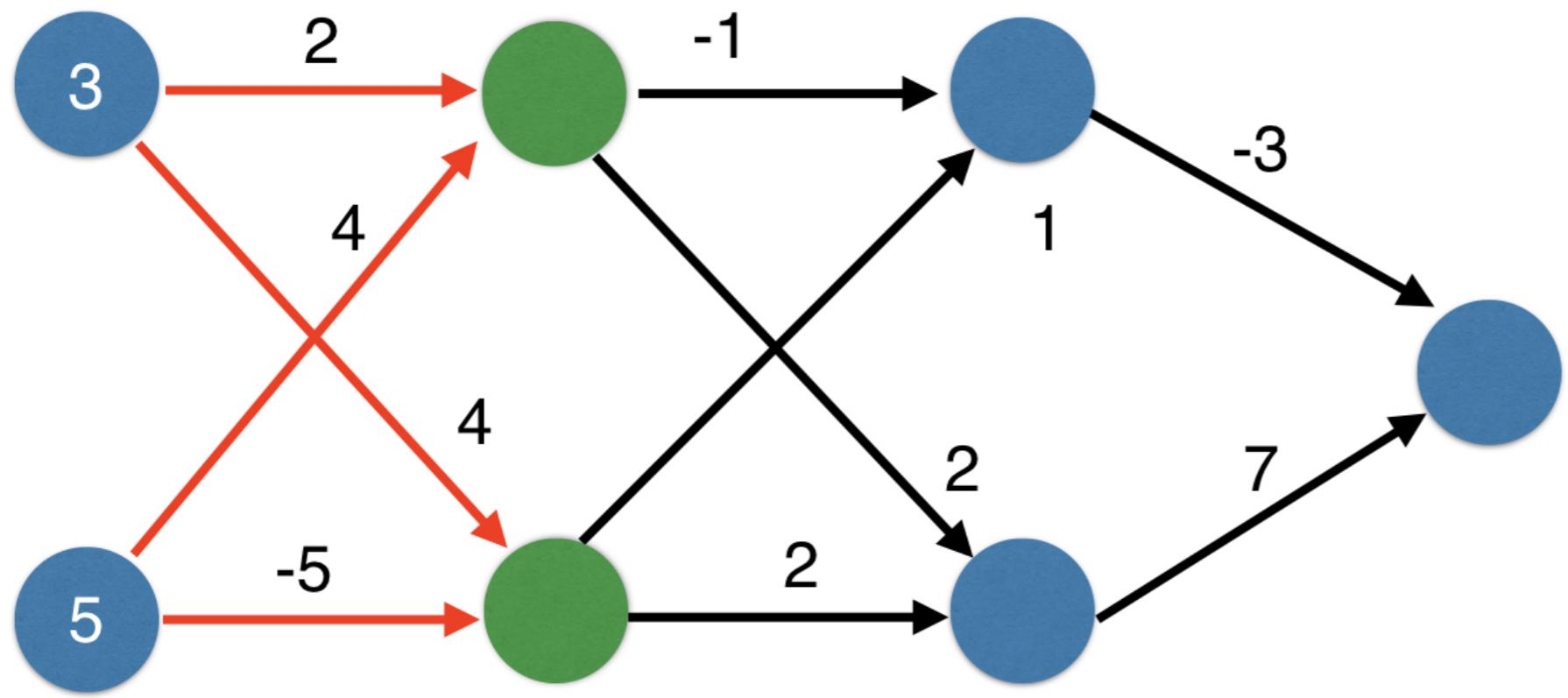
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Multiple hidden layers



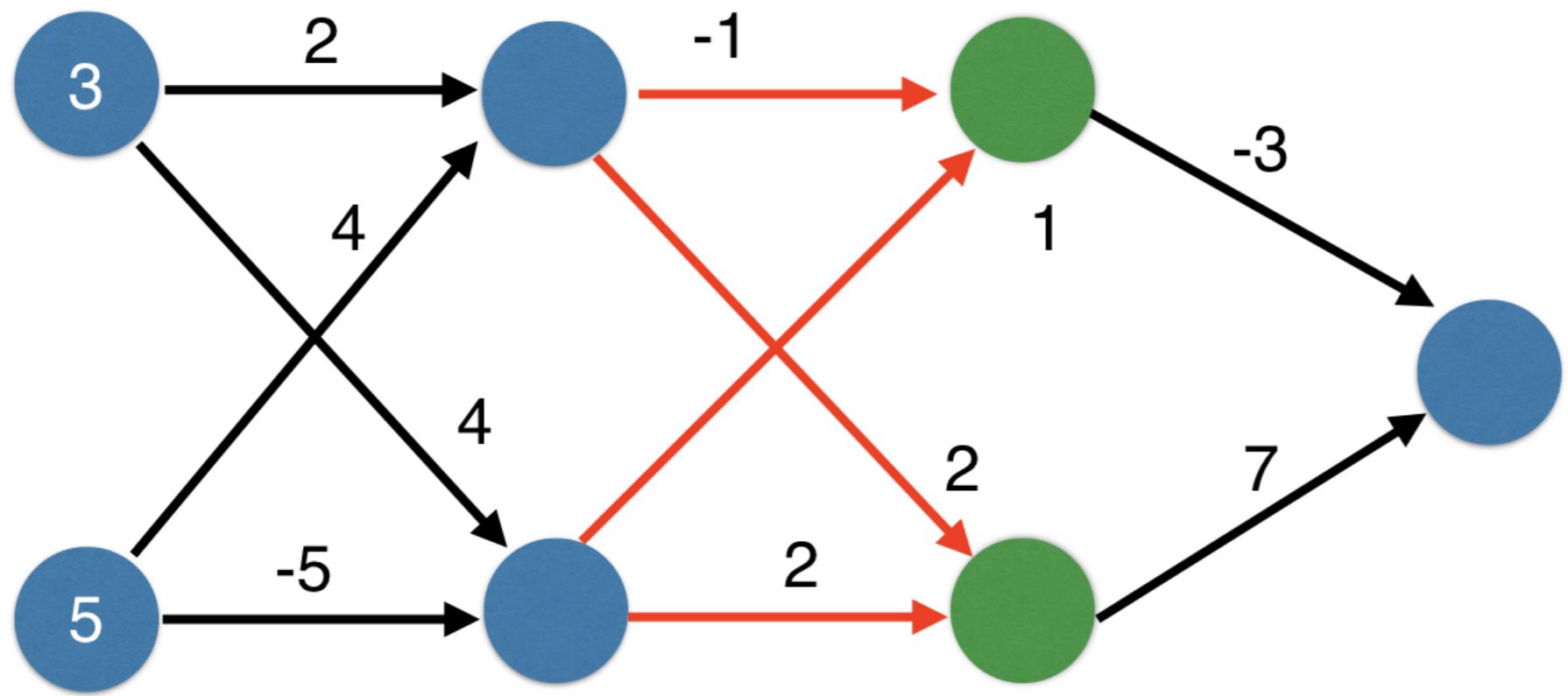
Calculate with ReLU Activation Function

Multiple hidden layers



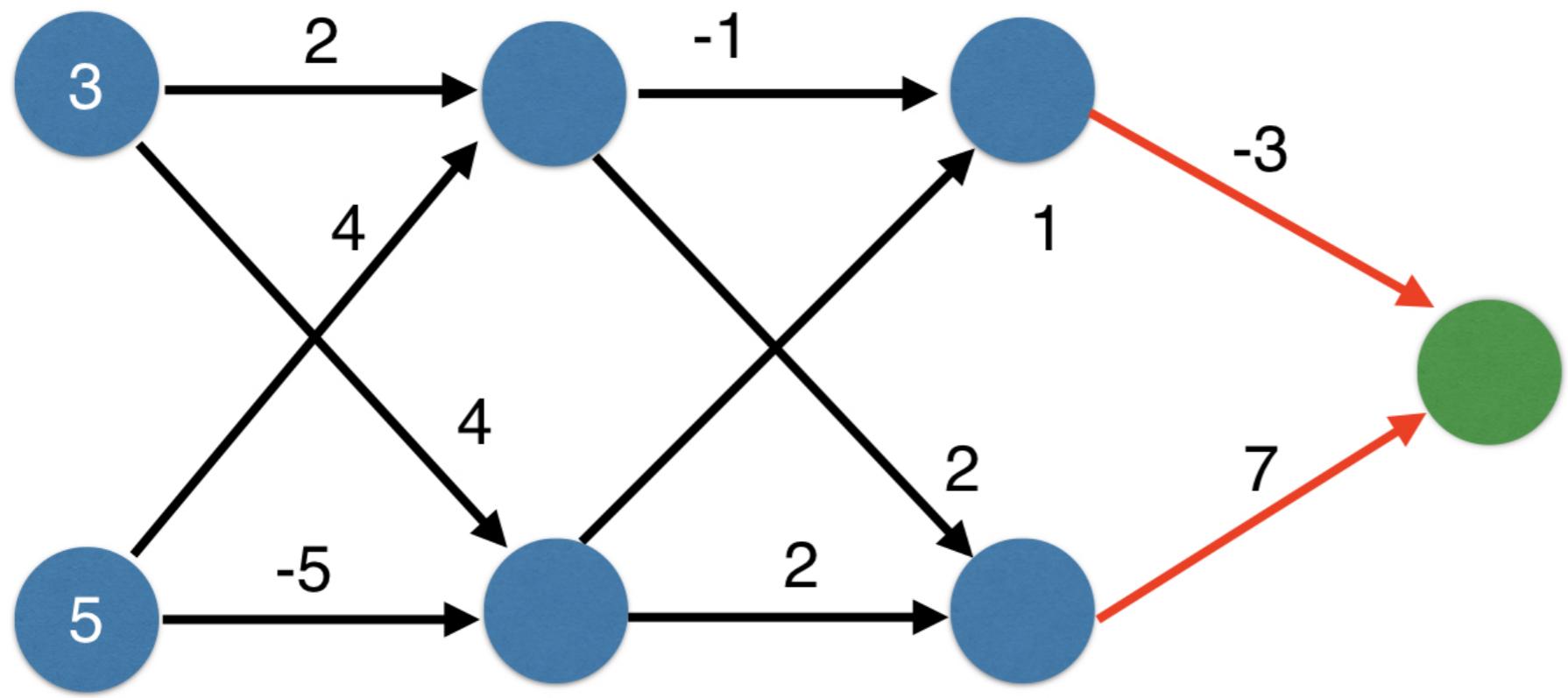
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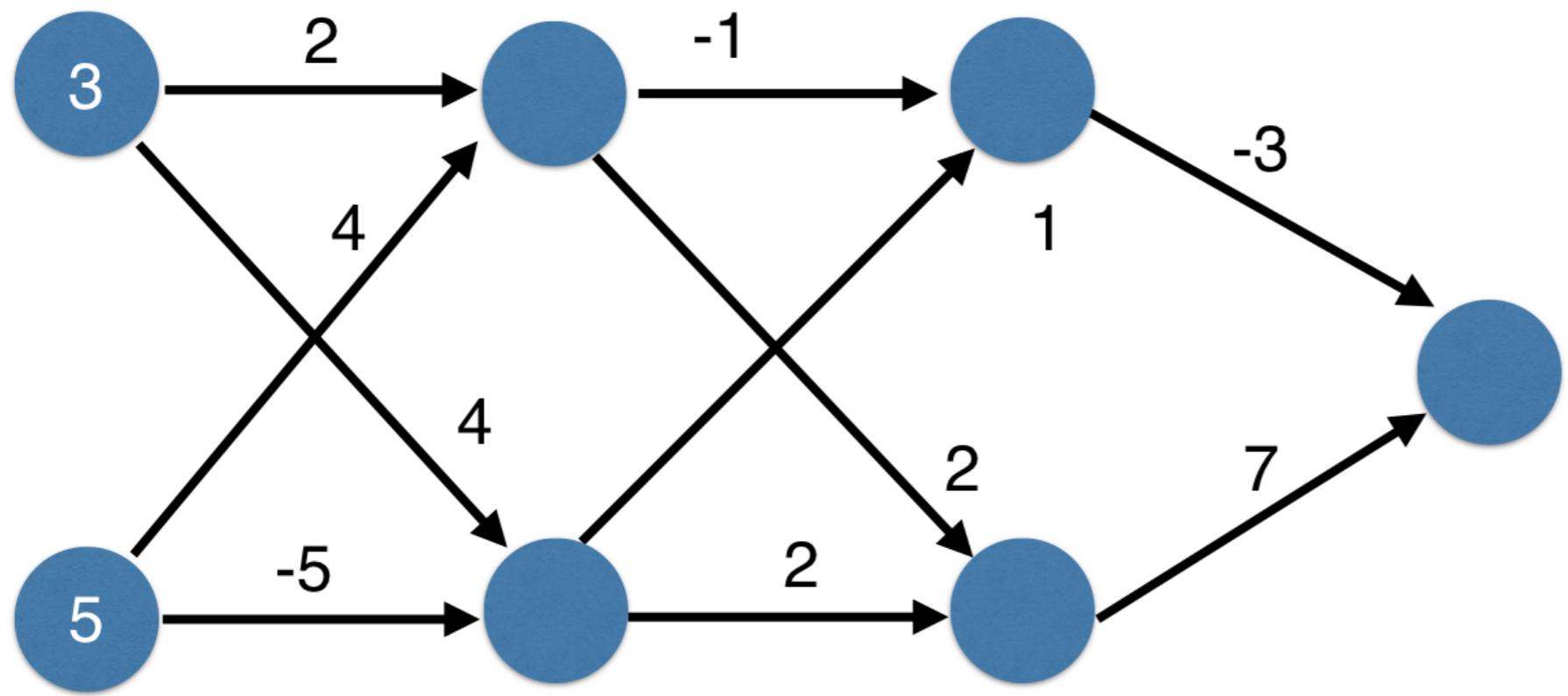
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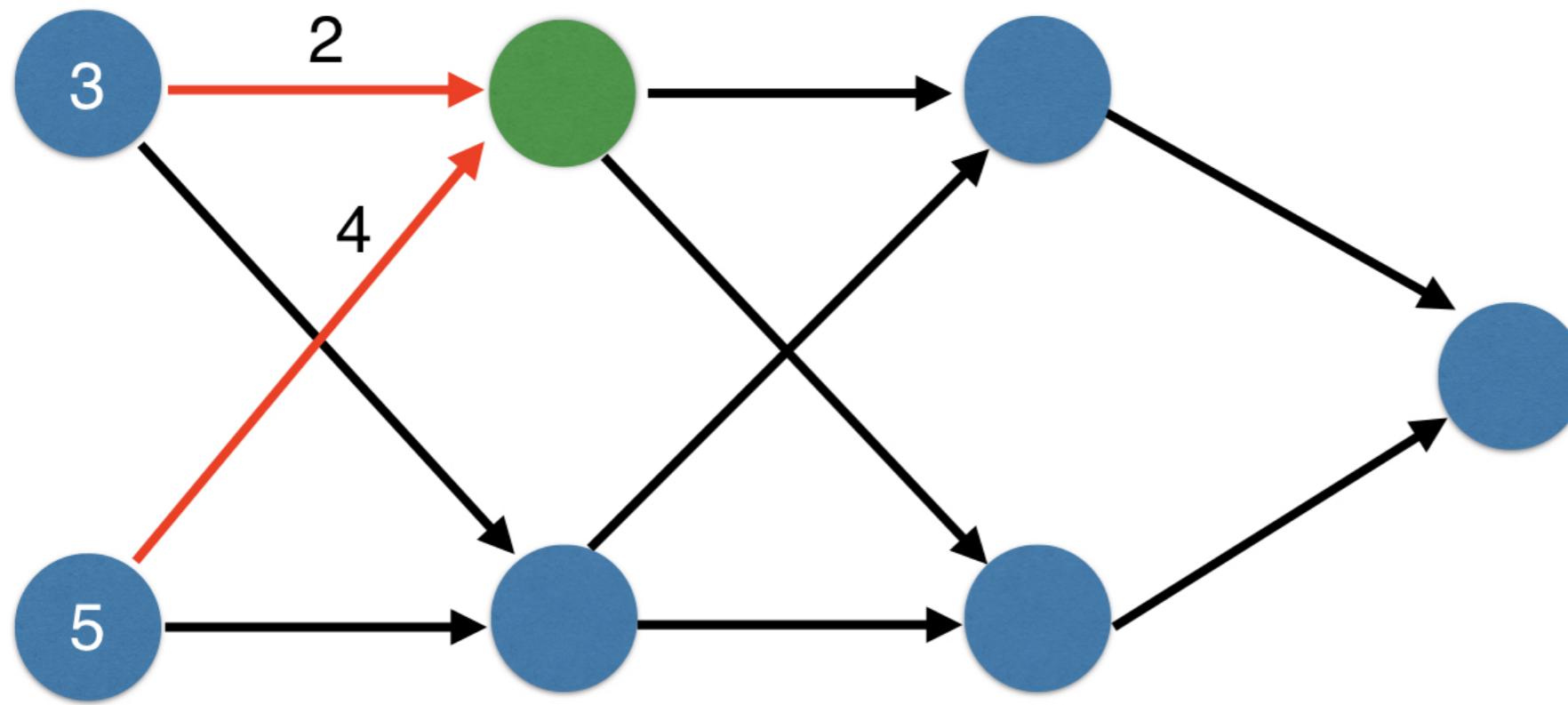
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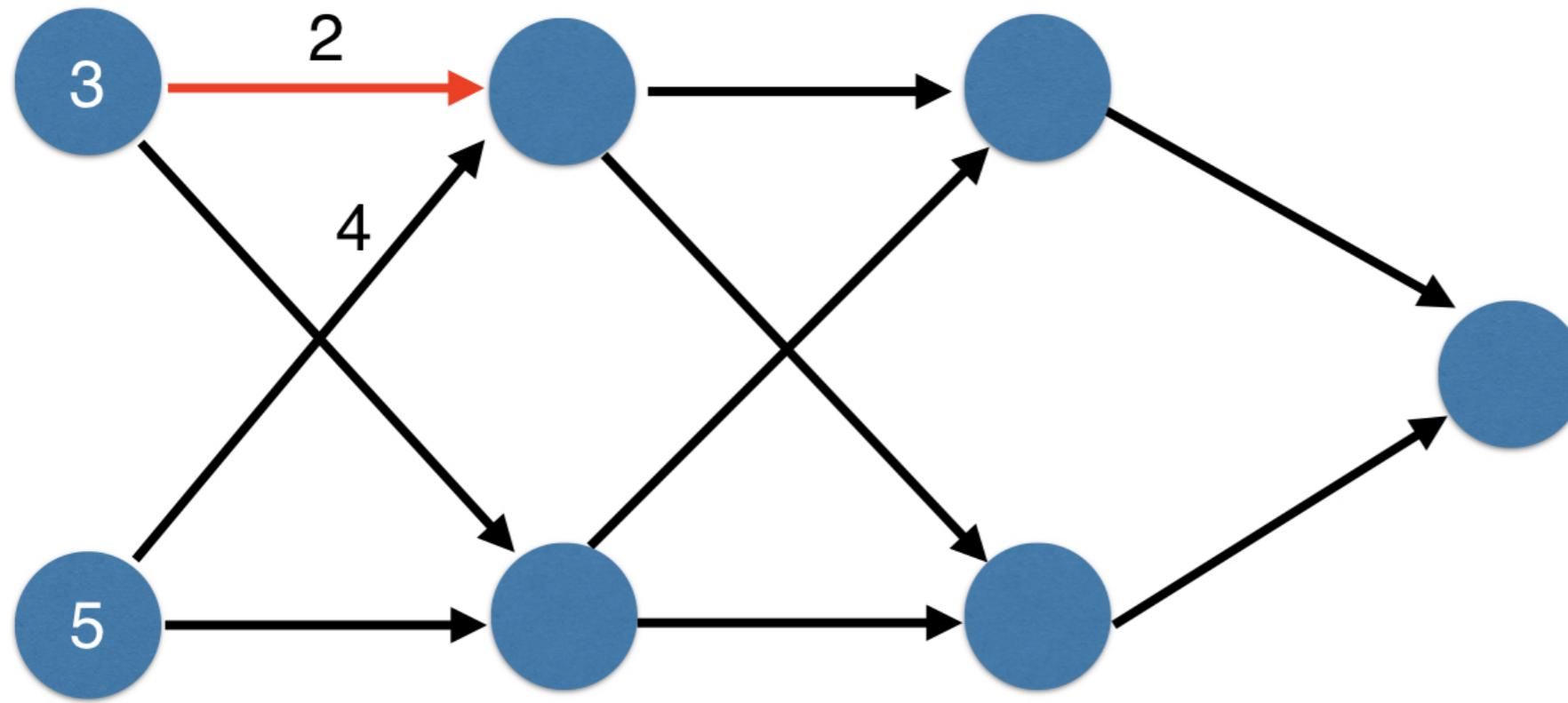
Calculate with ReLU Activation Function

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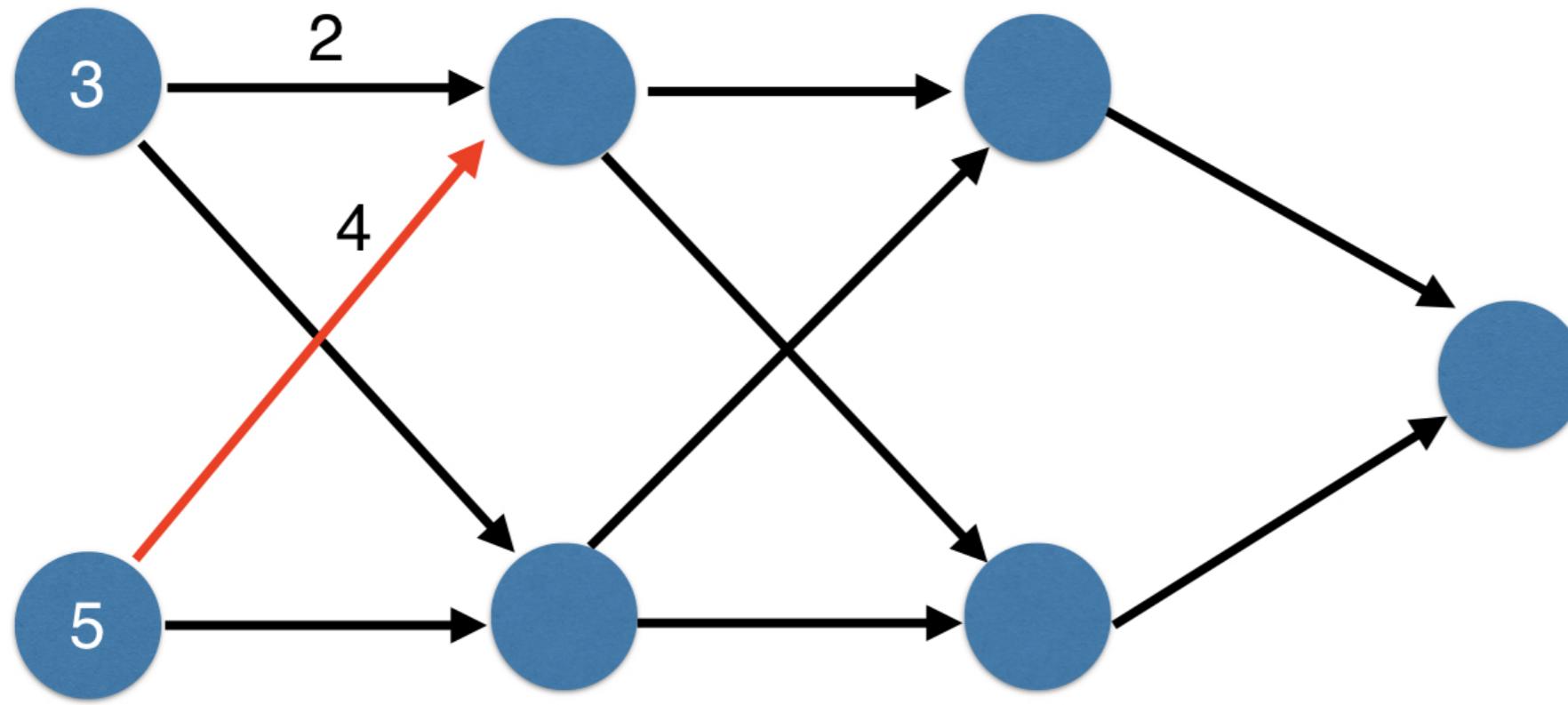
Calculate with ReLU Activation Function

Multiple hidden layers



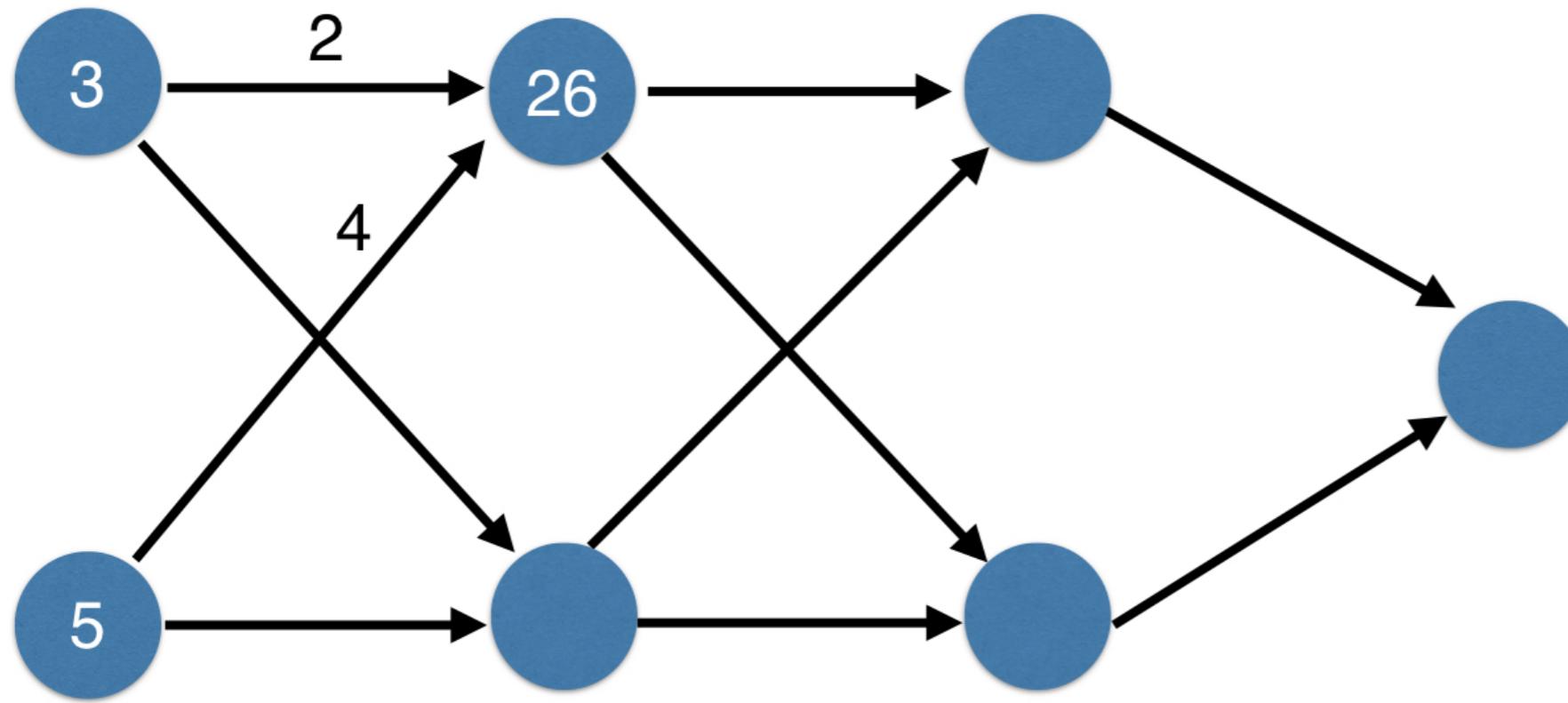
Calculate with ReLU Activation Function

Multiple hidden layers



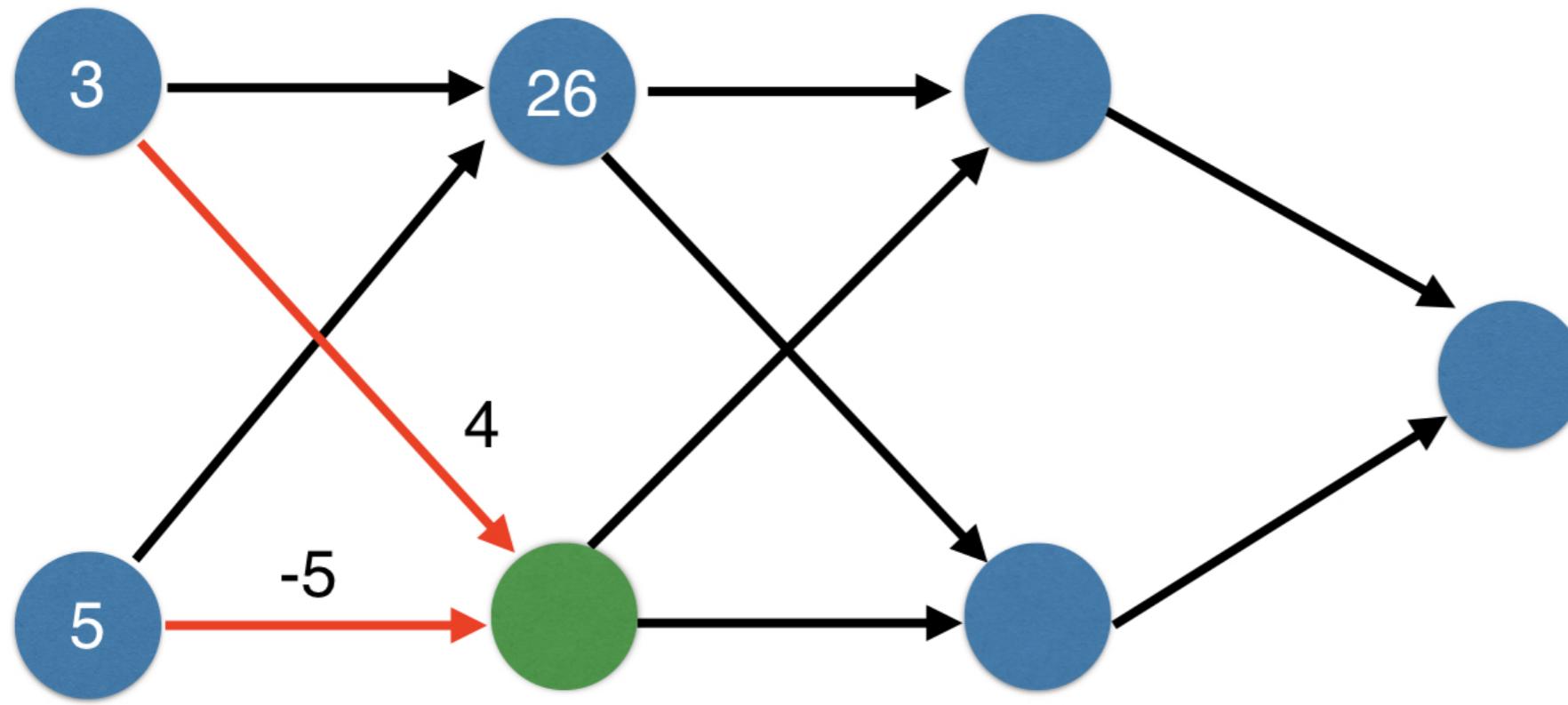
Calculate with ReLU Activation Function

Multiple hidden layers



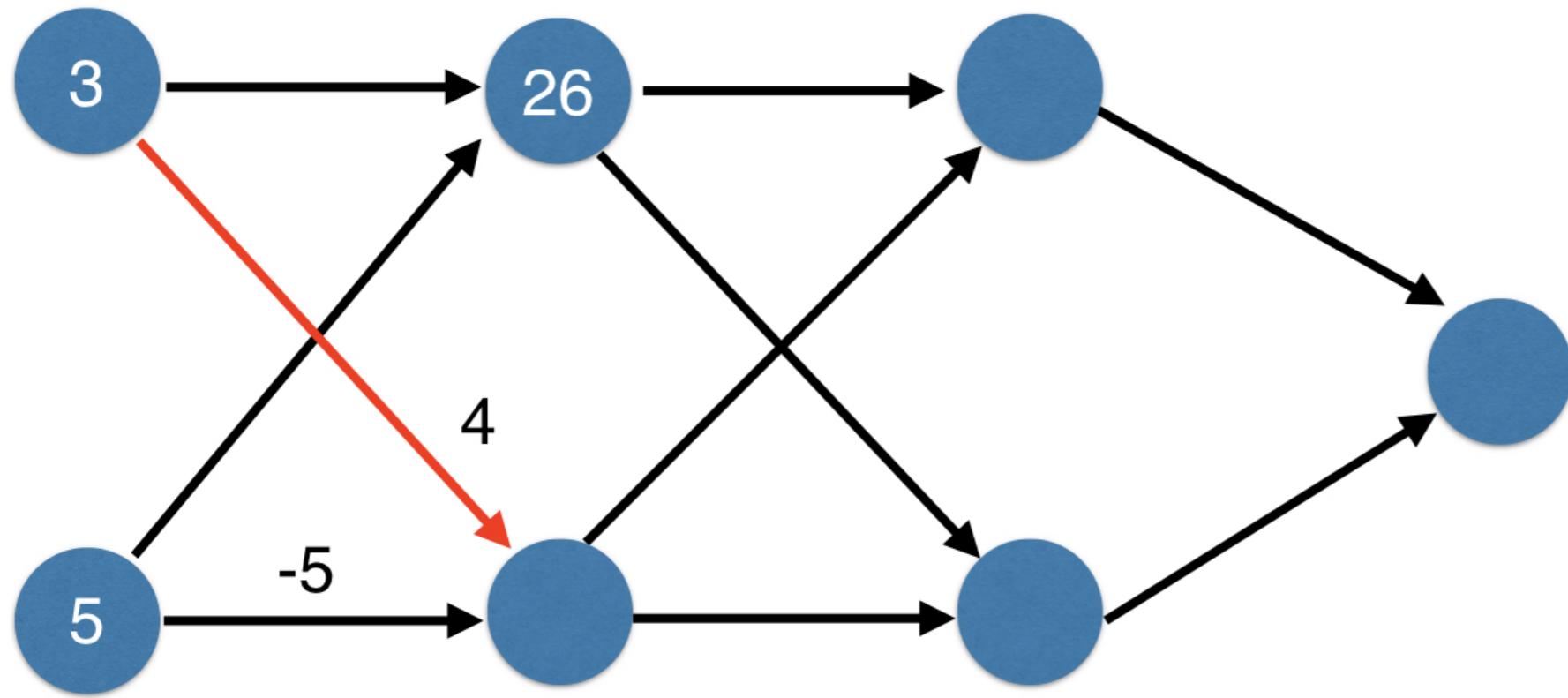
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Multiple hidden layers



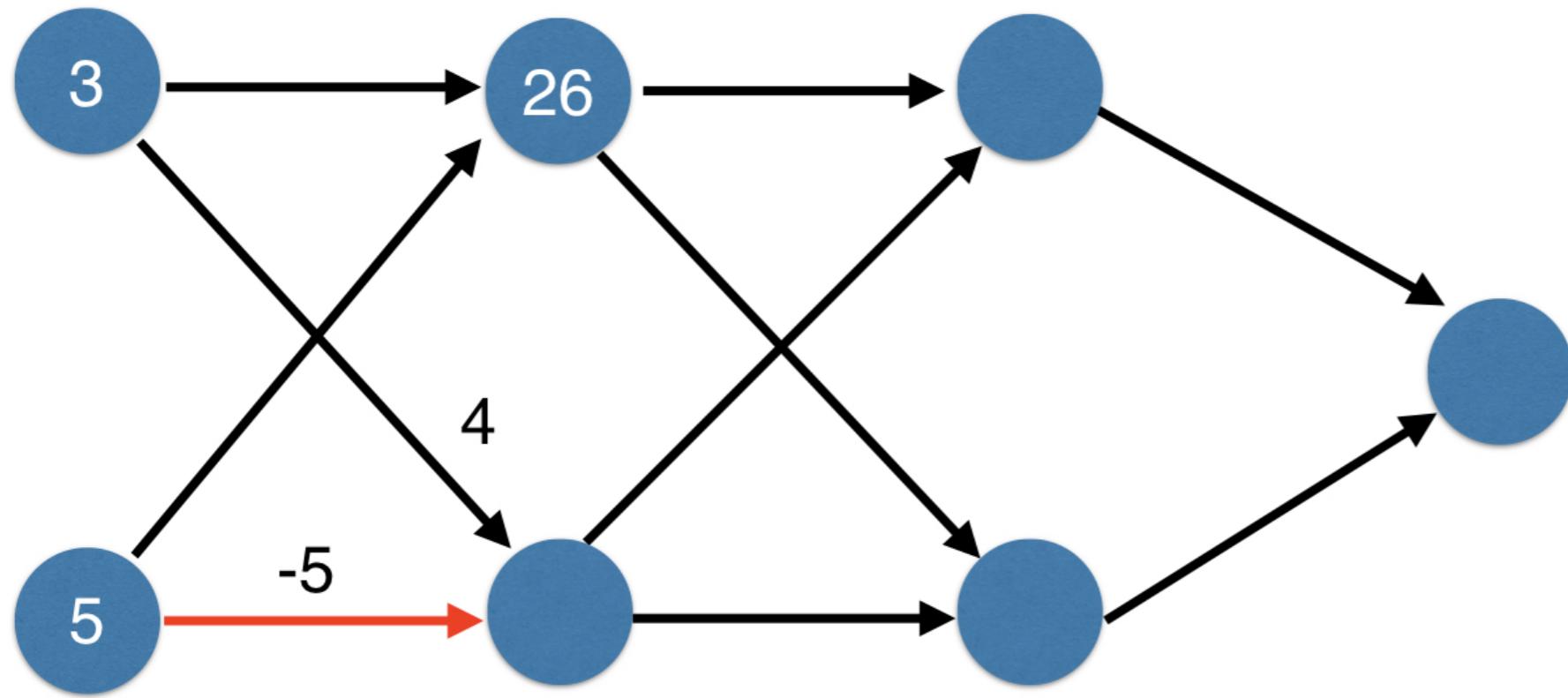
Calculate with ReLU Activation Function

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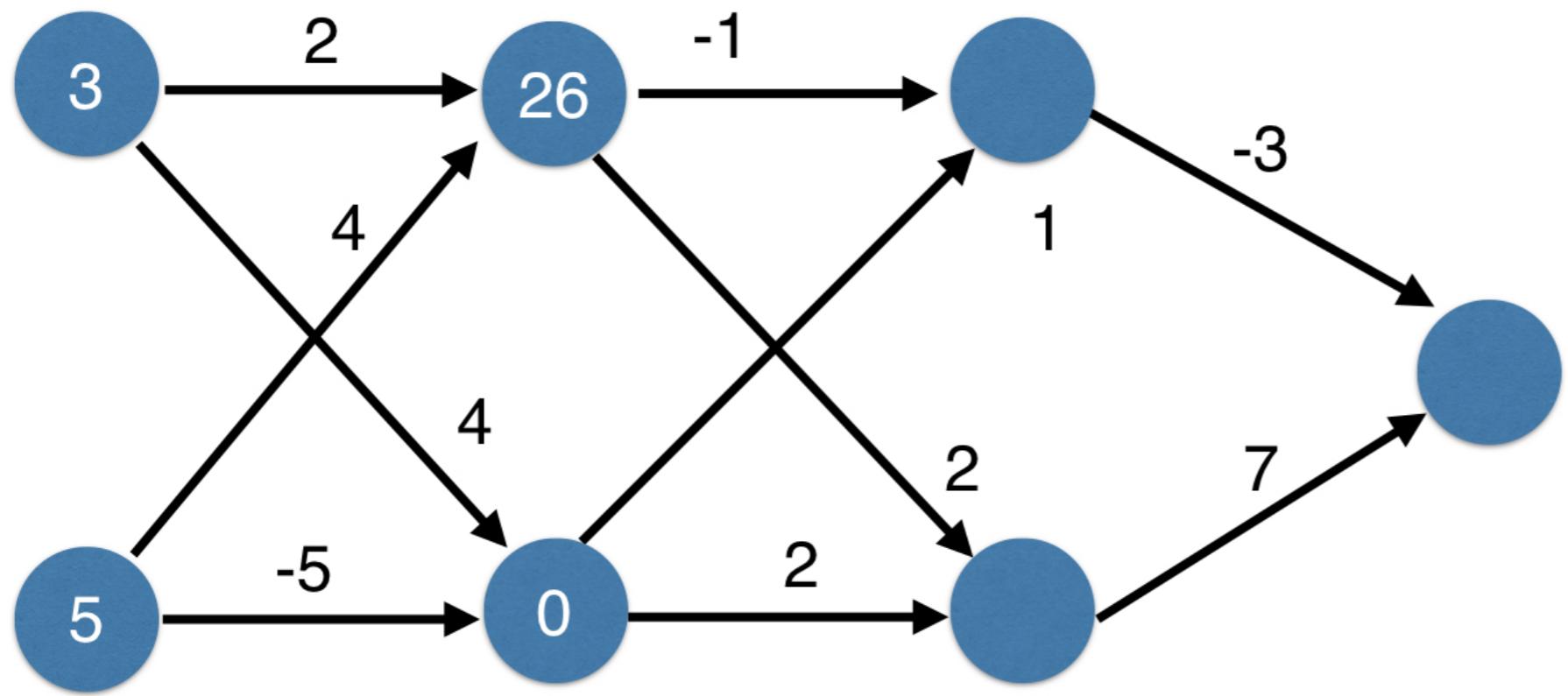
Calculate with ReLU Activation Function

Multiple hidden layers



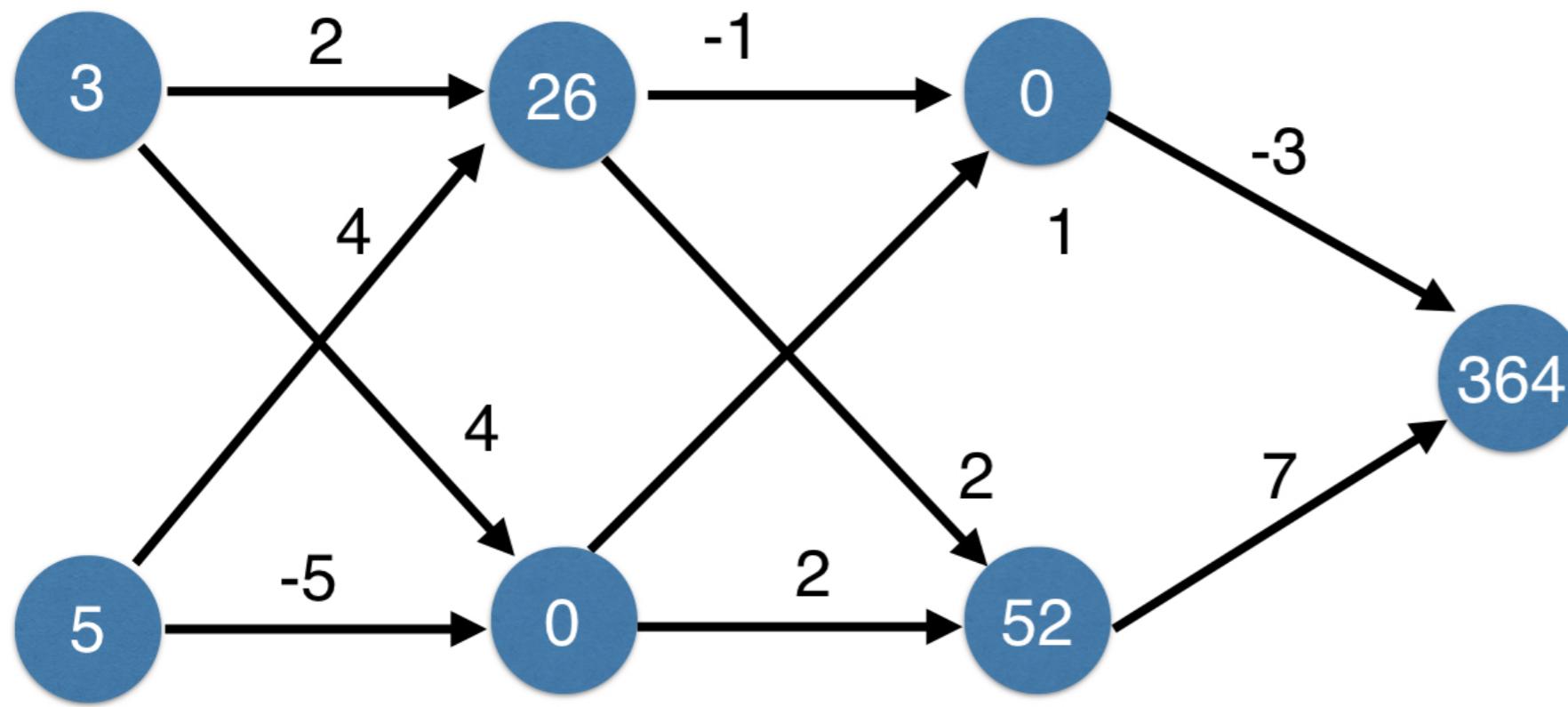
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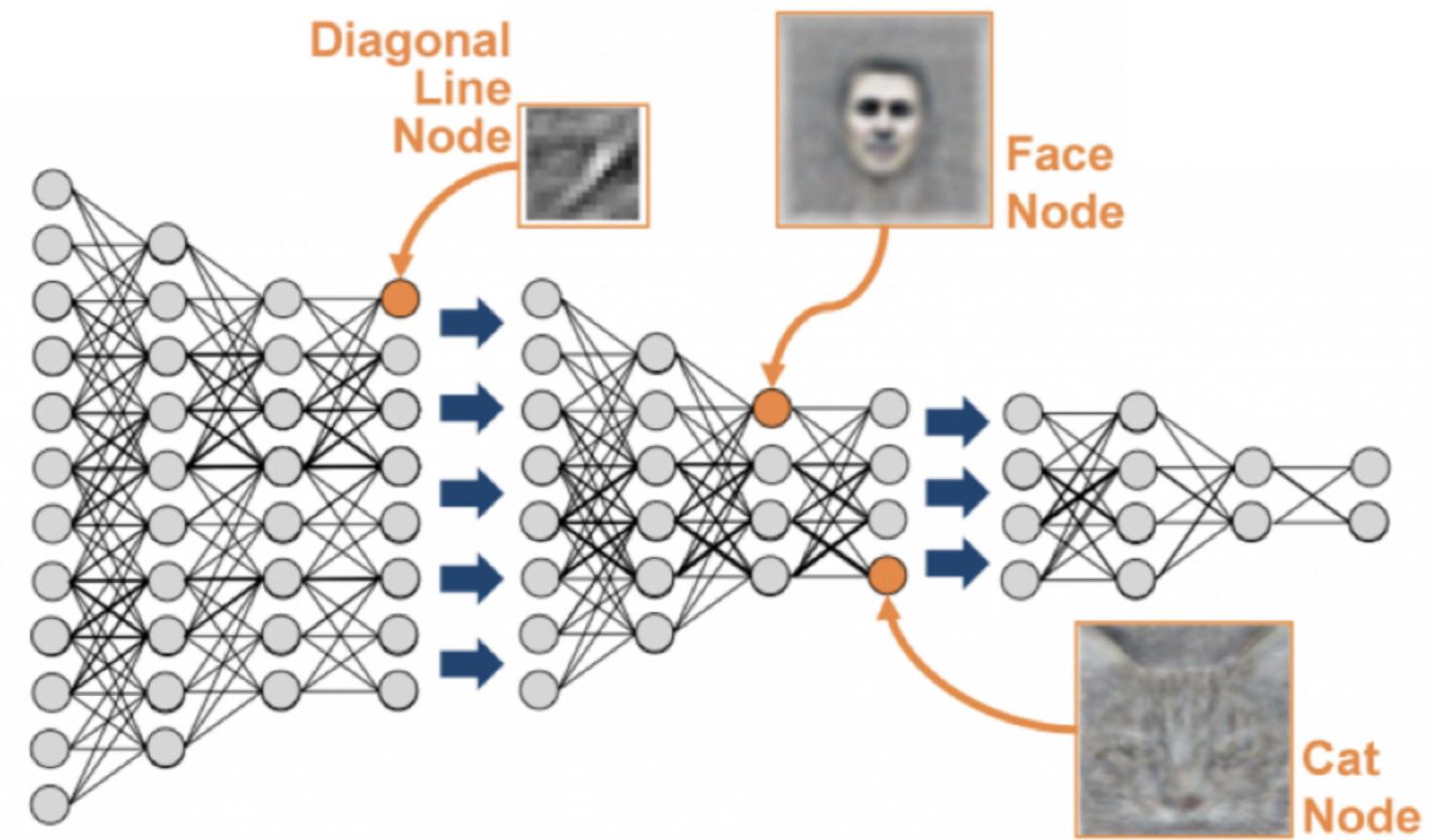


Calculate with ReLU Activation Function

Representation learning

- Deep networks internally build representations of patterns in the data
- Partially replace the need for feature engineering
- Subsequent layers build increasingly sophisticated representations of raw data

Representation learning



Deep learning

- Modeler doesn't need to specify the interactions
- When you train the model, the neural network gets weights that find the relevant patterns to make better predictions

Let's practice!

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