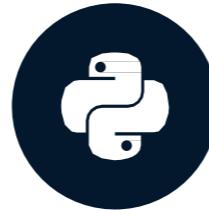


# What is Keras?

INTRODUCTION TO DEEP LEARNING WITH KERAS



# Theano vs Keras

```
import theano
import theano.tensor as T
from theano.ifelse import ifelse
import numpy as np
from random import random

# Define variables
x = T.matrix('x')
w1 = theano.shared(np.array([random(),random()]))
w2 = theano.shared(np.array([random(),random()]))
w3 = theano.shared(np.array([random(),random()]))

a2 = 1/(1+T.exp(-T.dot(x,w2)-b1))
x2 = T.stack([a1,a2],axis=1)
a3 = 1/(1+T.exp(-T.dot(x2,w3)-b2))

a_hat = T.vector('a_hat') #Actual output
cost = -(a_hat*T.log(a3) + (1-a_hat)*T.log(1-a3)).sum()
dw1,dw2,dw3,db1,db2 = T.grad(cost,[w1,w2,w3,b1,b2])

[w1, w1-learning_rate*dw1],
[w2, w2-learning_rate*dw2],
[w3, w3-learning_rate*dw3],
[b1, b1-learning_rate*db1],
[b2, b2-learning_rate*db2]

]

# You can (finally) train your model
cost = []
for iteration in range(30000):
    pred, cost_iter = train(inputs, outputs)
    cost.append(cost_iter)
```

```
from keras.layers import Dense
from keras.models import Sequential

# Define model and add layers
model = Sequential()
model.add(Dense(2,input_shape=(2,),activation='sigmoid'))
model.add(Dense(1,activation='sigmoid'))

model.compile(optimizer='adam',loss='categorical_crossentropy')

# Train model
model.fit(inputs,outputs)
```

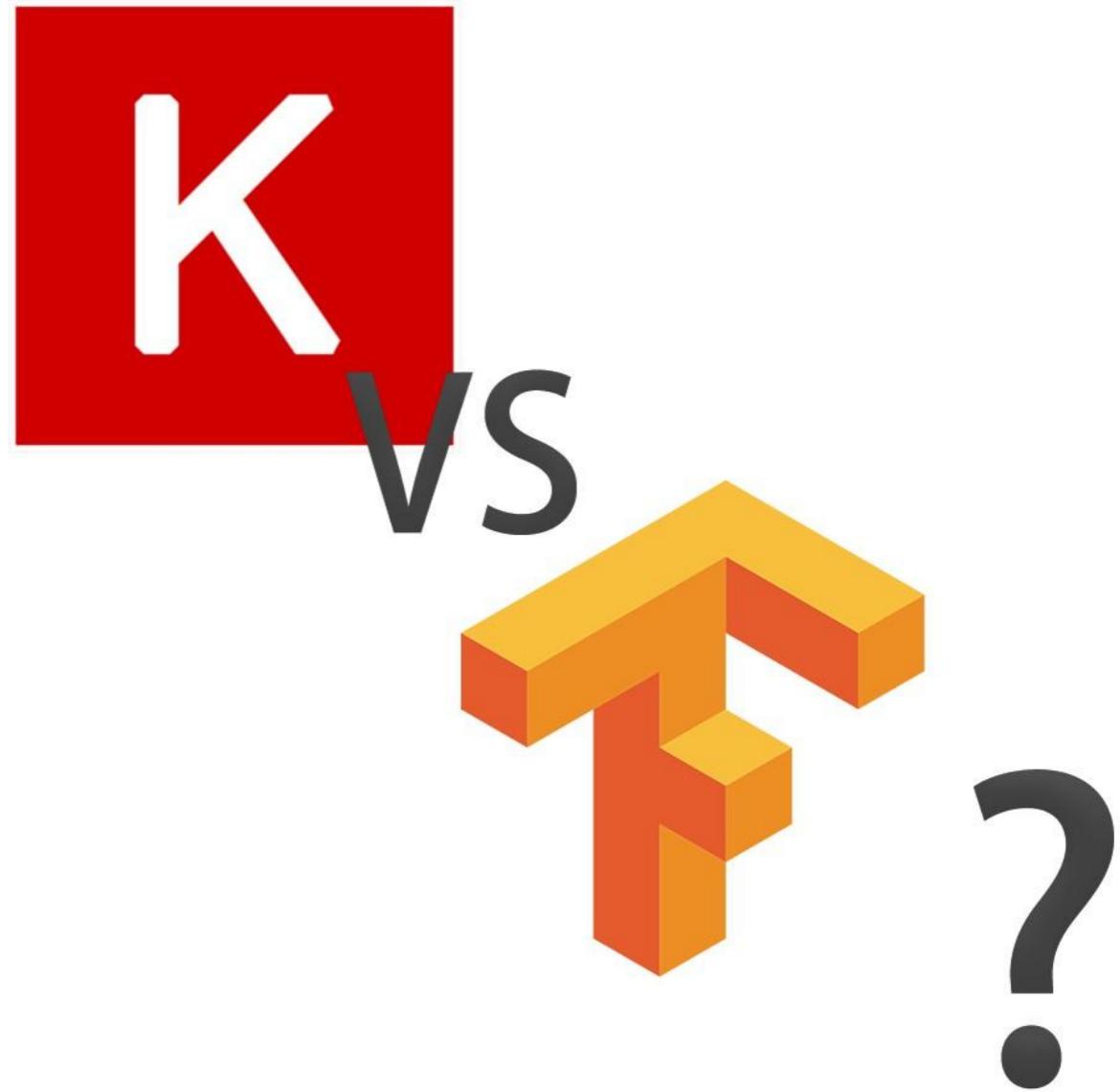
# Keras

- Deep Learning Framework
- Enables fast experimentation
- Runs on top of other frameworks
- Written by François Chollet



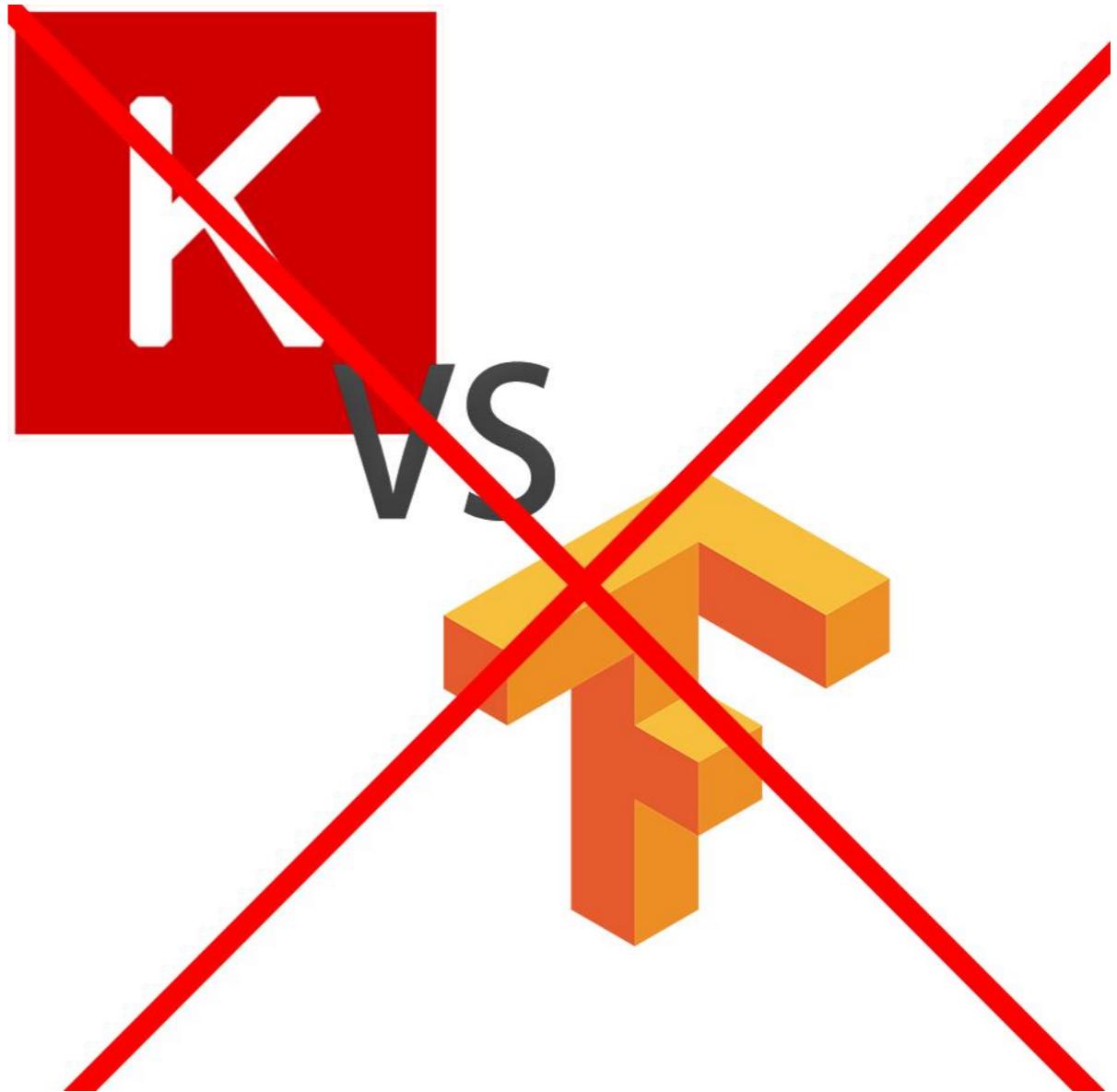
# Why use Keras?

- Fast industry-ready models
- For beginners and experts
- Less code
- Build any architecture
- Deploy models in multiple platforms

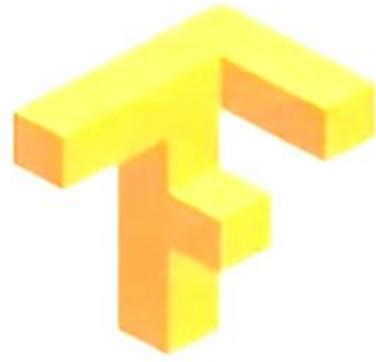


# Keras + TensorFlow

- TensorFlow's high level framework of choice
- Keras is complementary to TensorFlow
- You can use TensorFlow for low level features



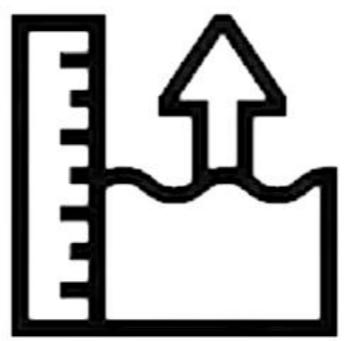
## 1. Level of API



High- and  
Low-Level  
API



High Level  
API



Low Level  
API



## 2. Speed



Very Fast,  
used for high  
performance



Slower than  
TensorFlow as it  
works on top of  
TensorFlow



Same speed  
as TensorFlow



### 3. Architecture



Has a complex architecture and is hard to use



Has a simpler architecture as abstraction is used to make it simple to use



Has a complex architecture



## 4. Datasets and Debugging



Used for very high-performance models. Debugging is hard



Used for smaller datasets. Debugging is easy and less frequent due to smaller models



Used for large datasets. Easier to debug than TensorFlow



## 5. Ease of Development



Hard to develop and write code



Easy to develop and is best for newbies



Easier to learn than TensorFlow

## 6. Ease of Deployment



Easy to deploy  
with 'TensorFlow  
Serving'



Keras

Model deployment  
can be done with  
TensorFlow serving  
or Flask



PyTorch

'Pytorch Mobile' makes  
deployment easy, but  
not as much as in  
TensorFlow



## Which framework should you use?



TensorFlow has implemented various levels of abstraction to make implementation easy. This also makes debugging easy



It is simple and easy, but not as fast as TensorFlow. It is more user-friendly than any other deep learning API



It is the preferred deep learning API for teachers but is not as widely used in production as TensorFlow. Faster, but lower GPU utilization

# Working principle of Keras

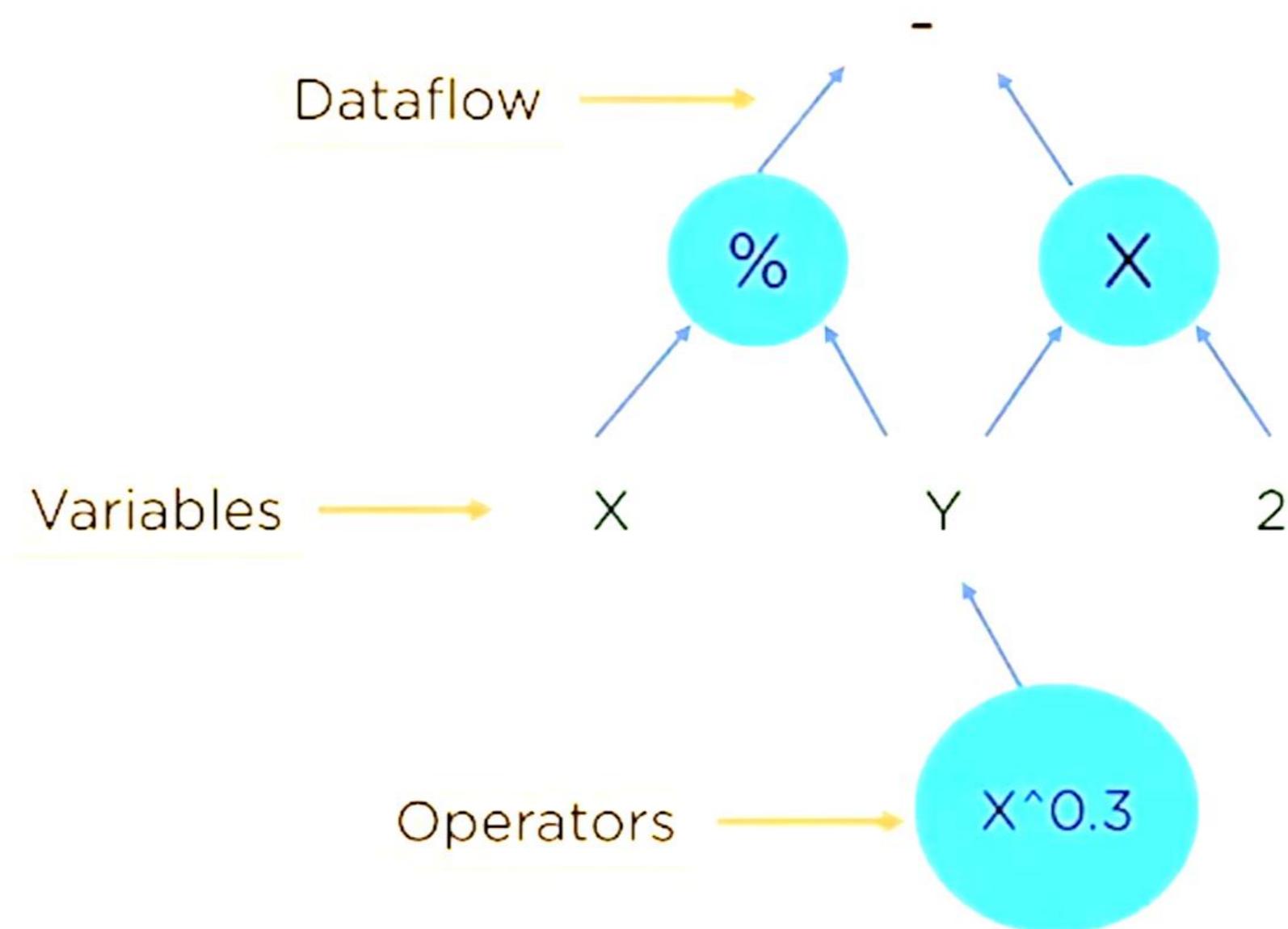
Keras uses computational graphs to express and evaluate mathematical expressions

1

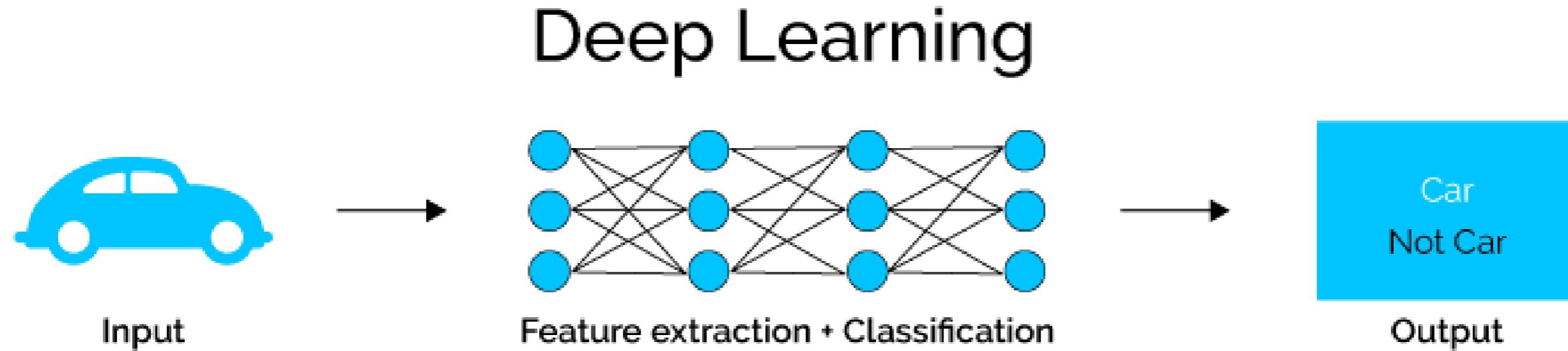
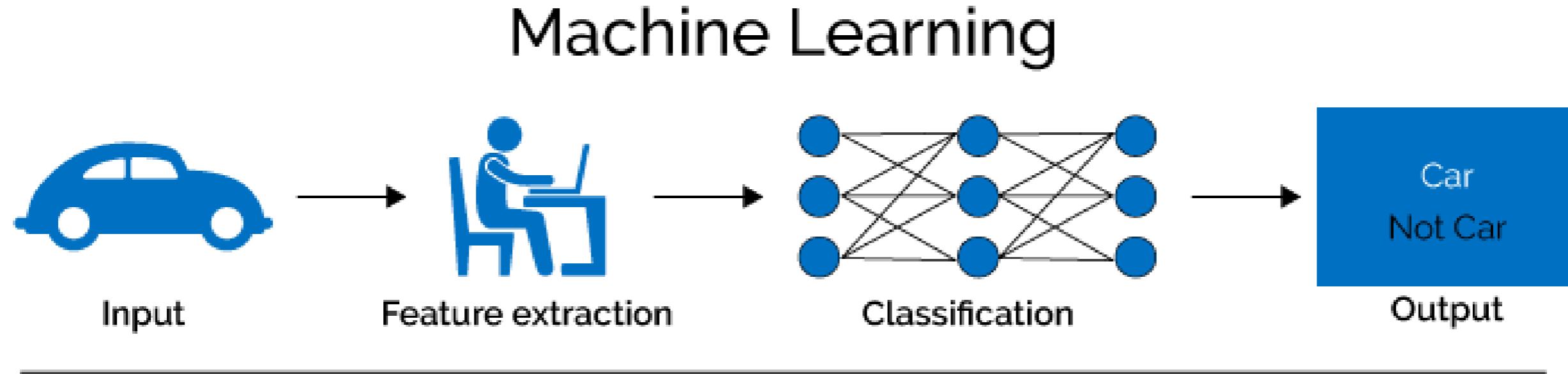
Expressing complex problems as combination of simple mathematical operators

2

Useful for calculating derivatives by using backpropagation

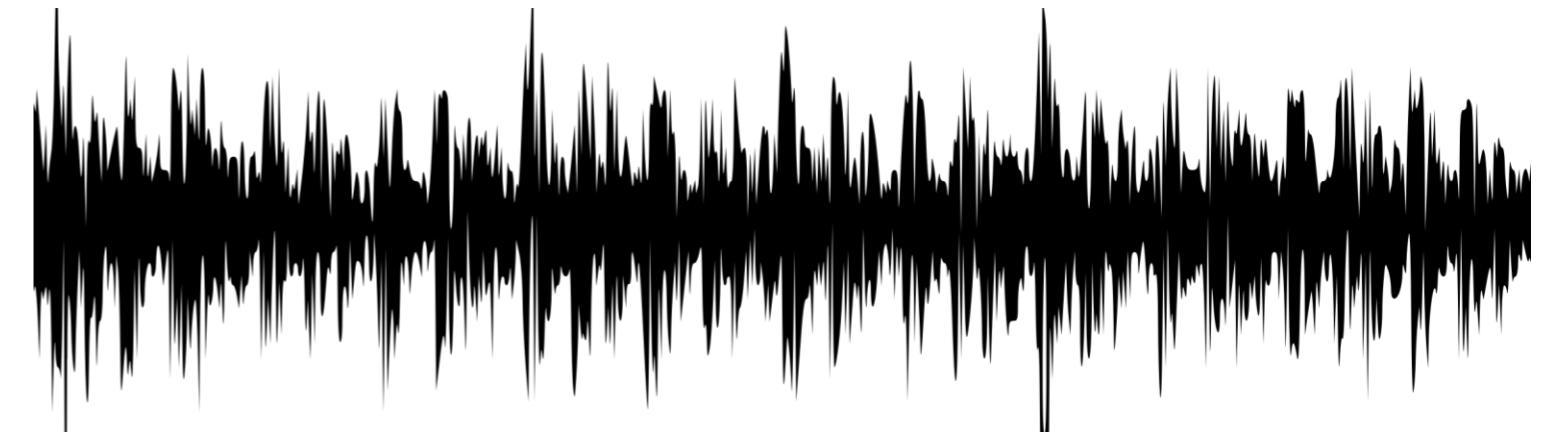
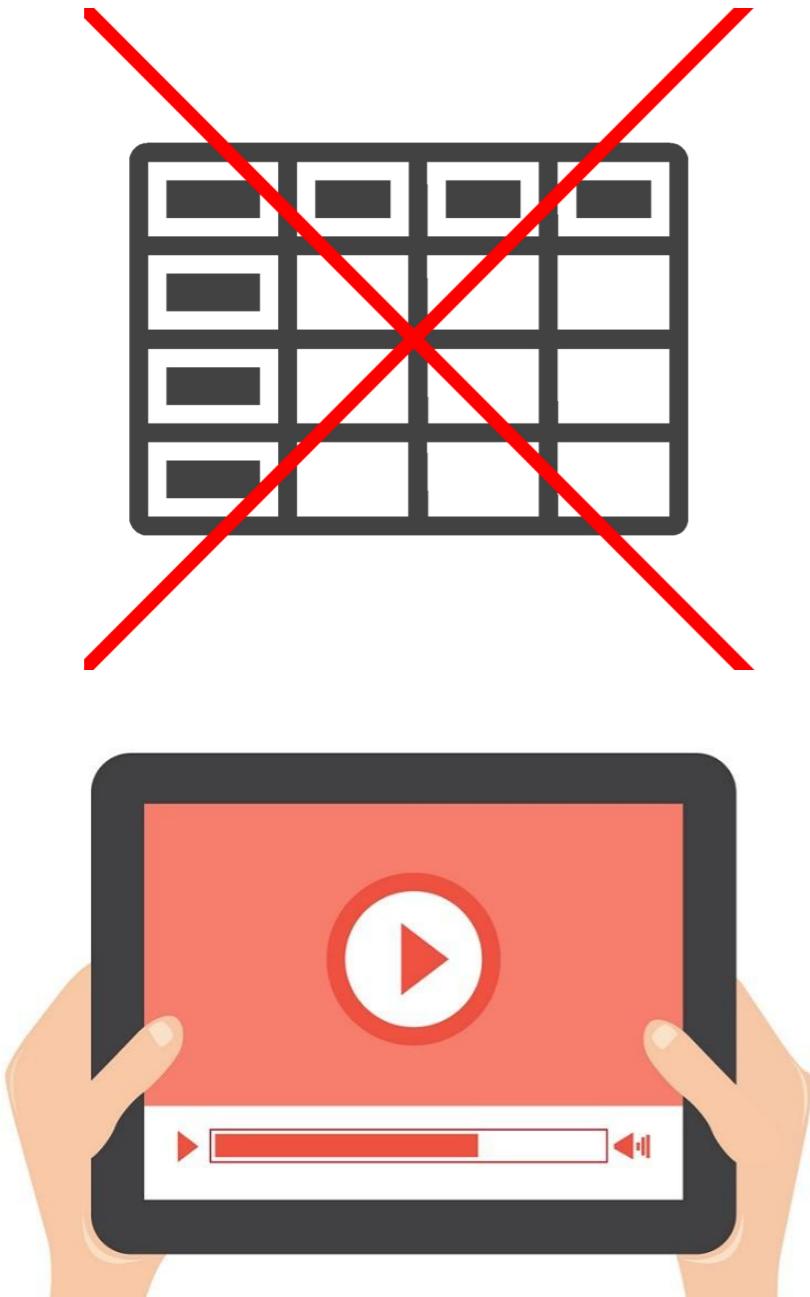


# Feature Engineering



<sup>1</sup> Towards Data Science

# Unstructured data

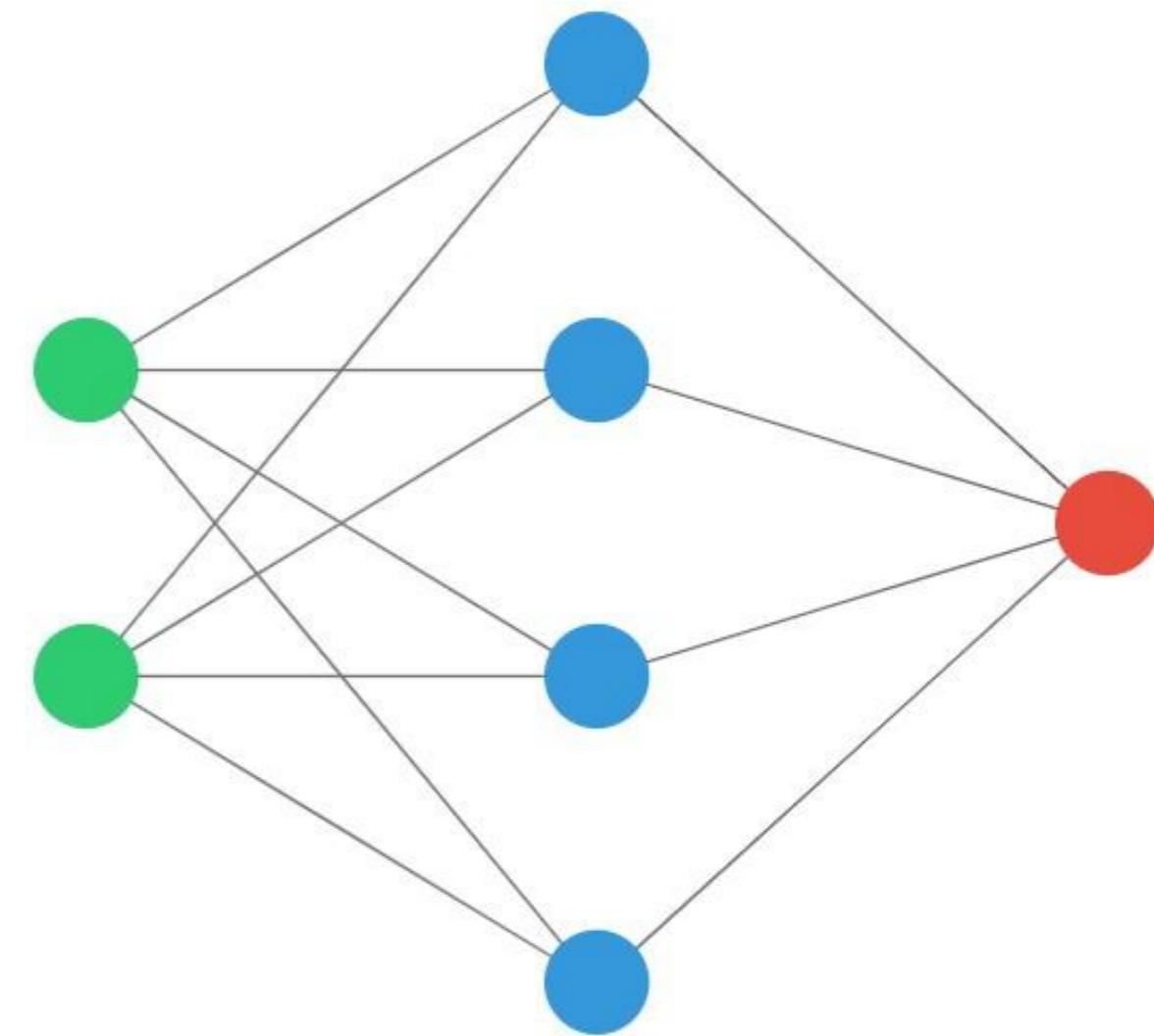


# So, when to use neural networks?

- Dealing with unstructured data
- Don't need easily interpretable results
- You can benefit from a known architecture

Example: Classify images of cats and dogs

- Images -> Unstructured data
- You don't care about why the network knows it's a cat or a dog
- You can benefit from convolutional neural networks

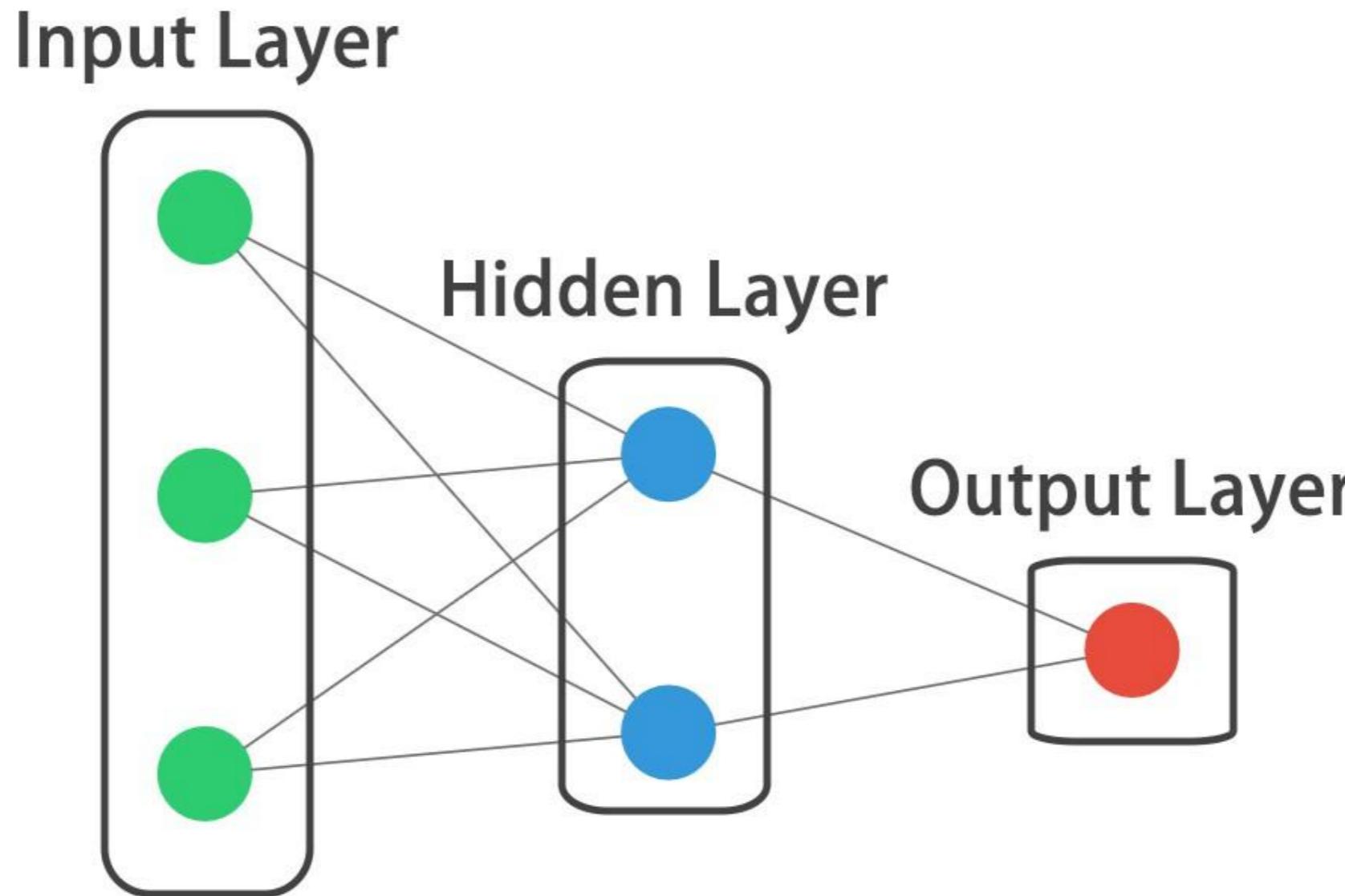


# Your first neural network

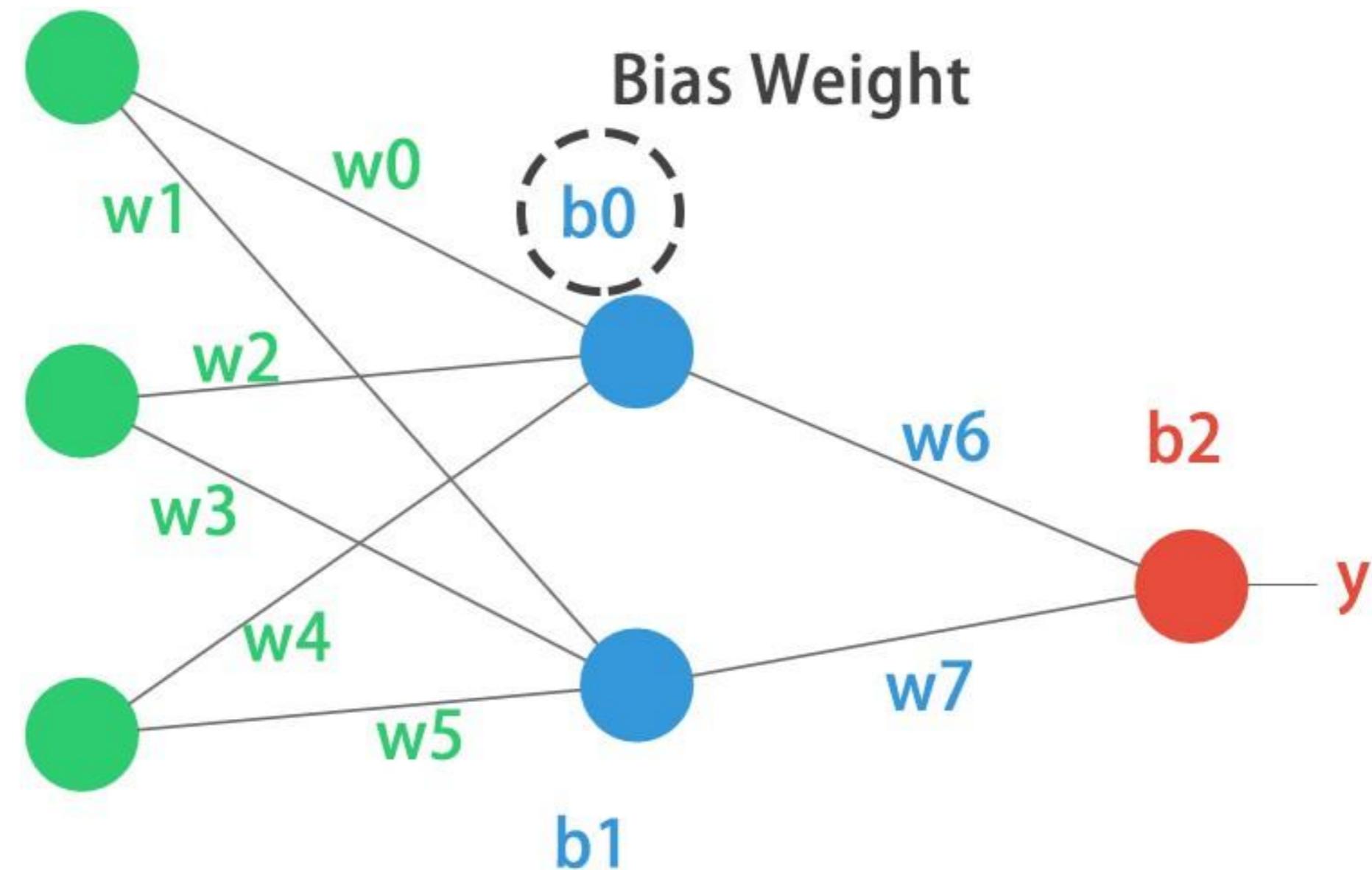
INTRODUCTION TO DEEP LEARNING WITH KERAS



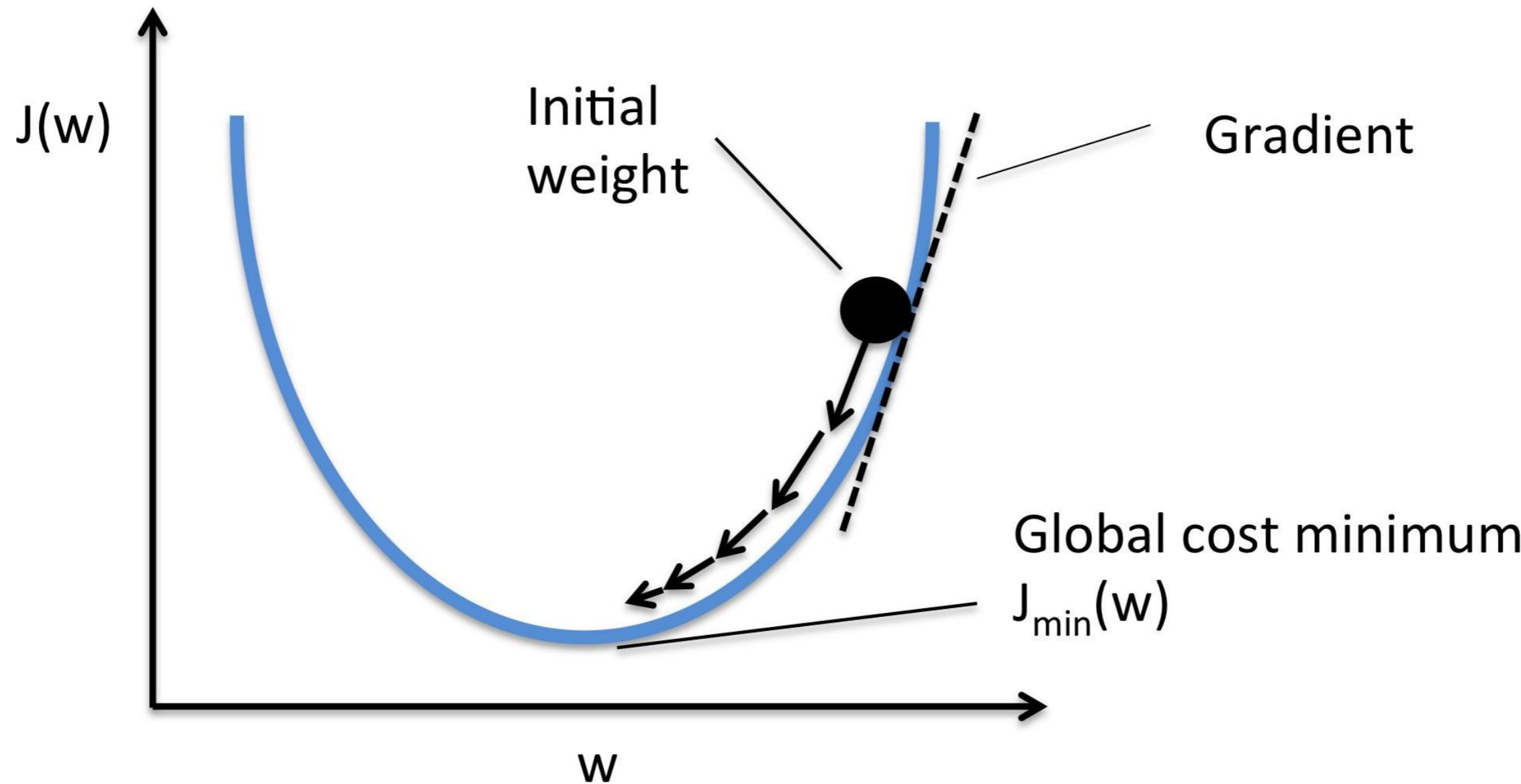
# A neural network?



# Parameters



# Gradient descent

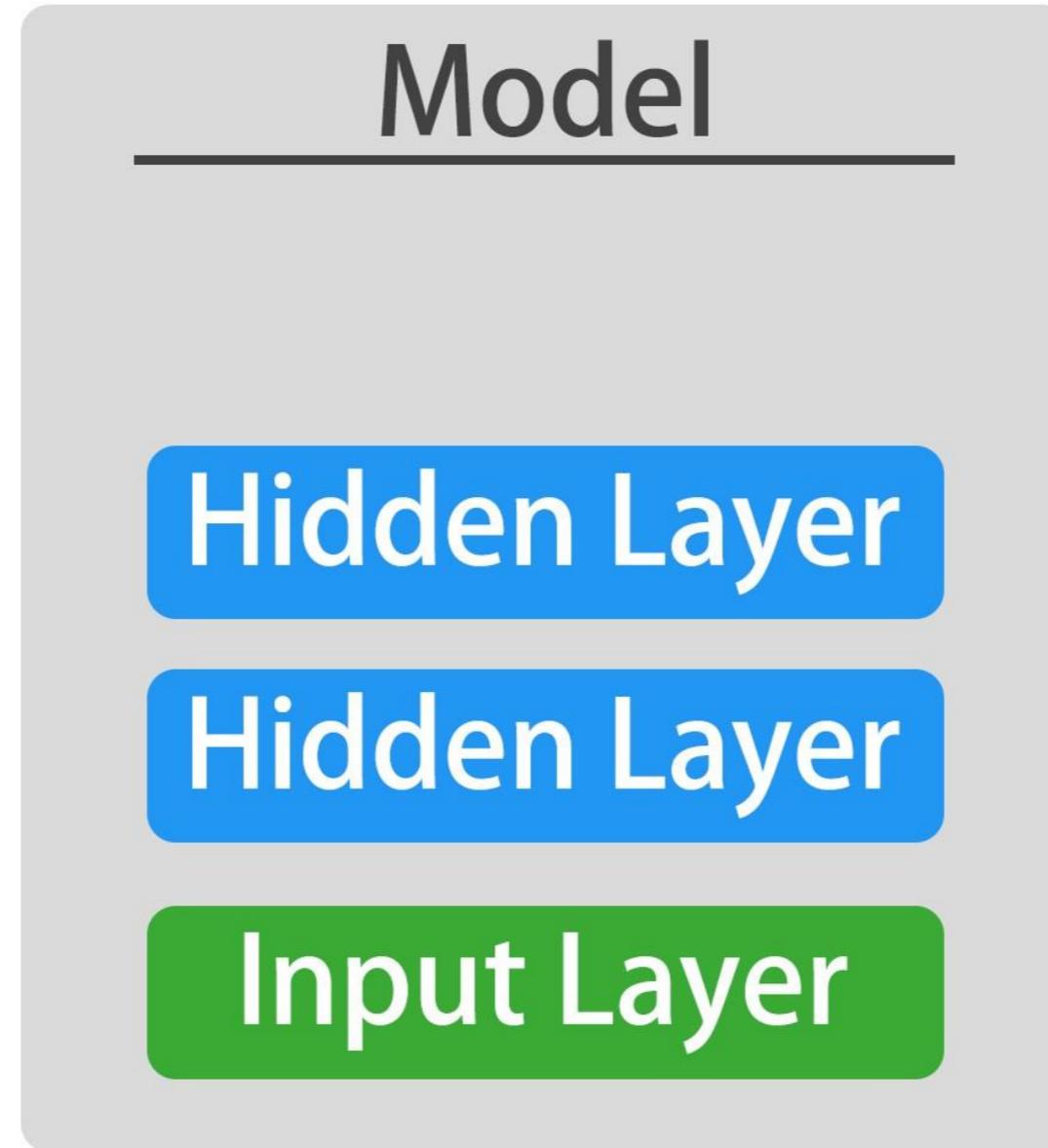


# The sequential API

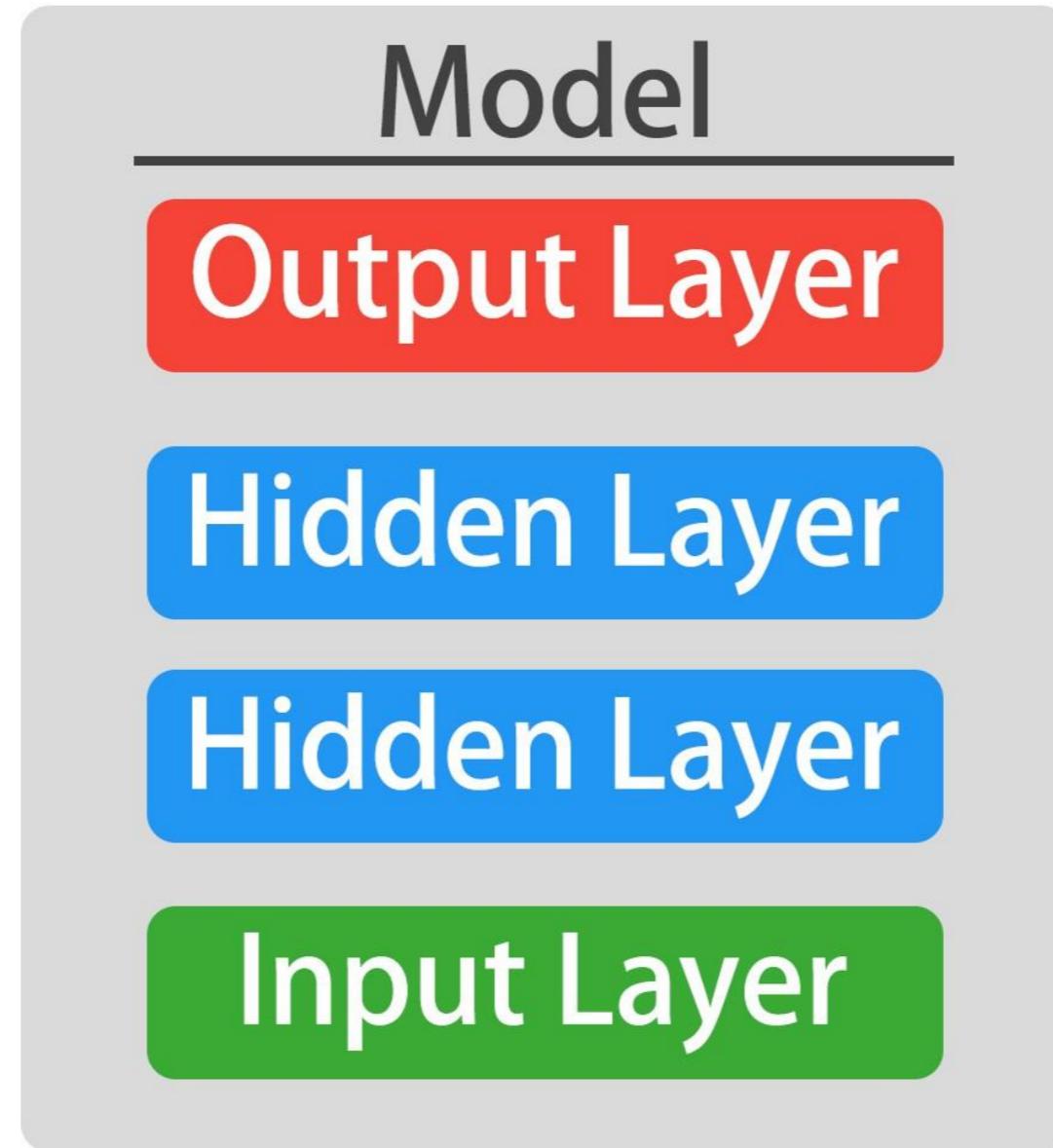
Model

Input Layer

# The sequential API

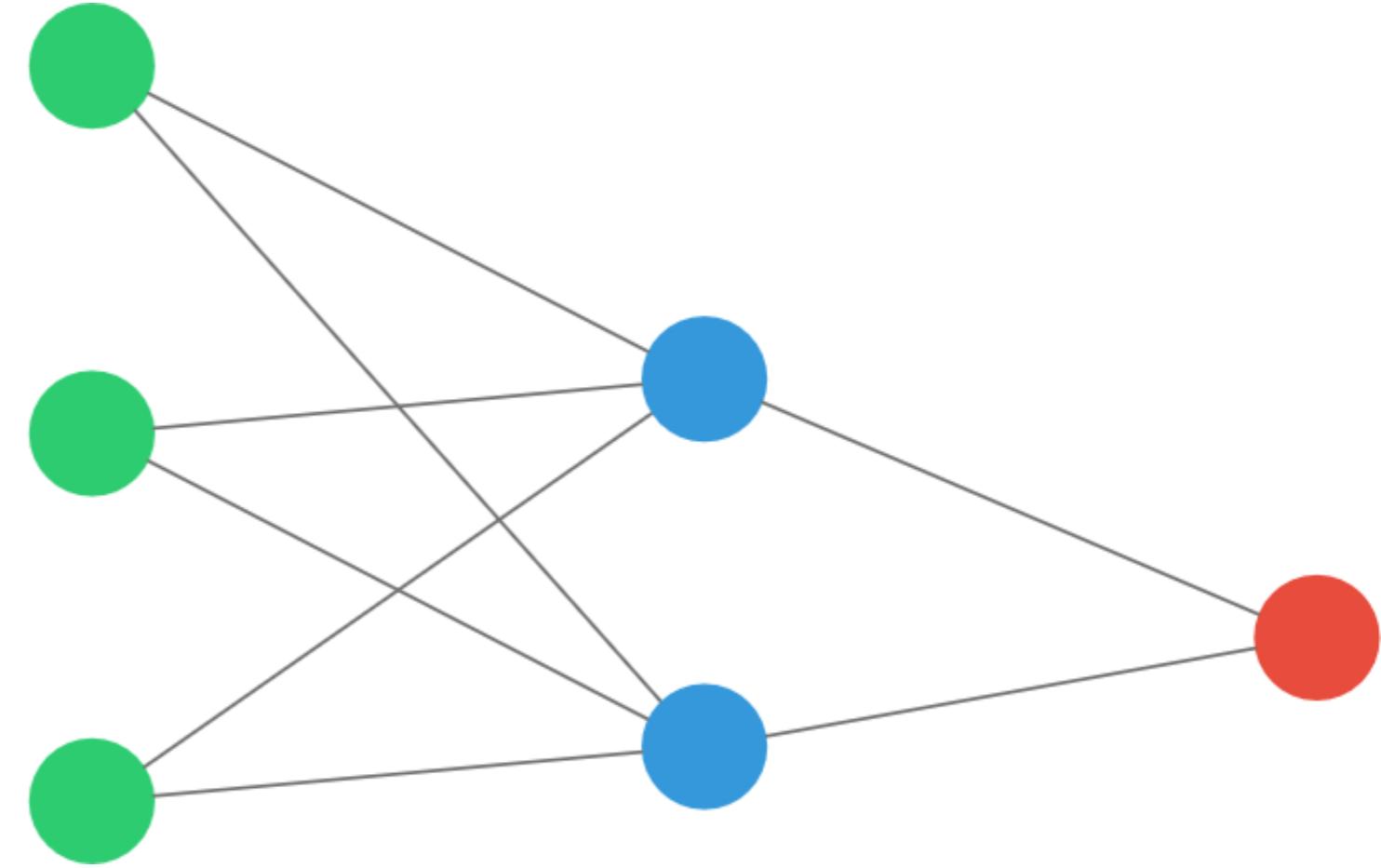


# The sequential API



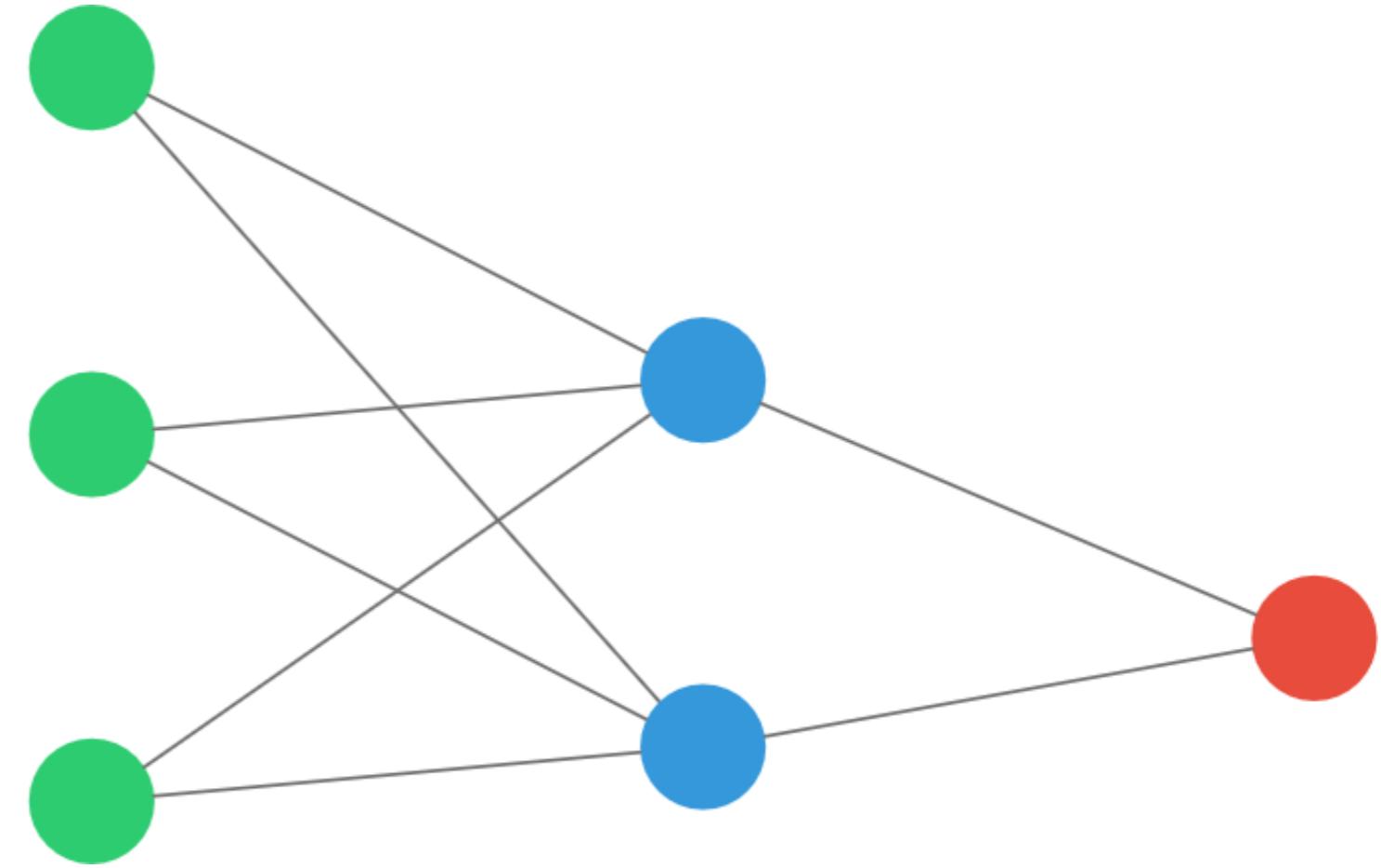
# Defining a neural network

```
from tensorflow.keras.models import Sequential  
from tensorflow.keras.layers import Dense  
  
# Create a new sequential model  
model = Sequential()  
  
# Add an input and dense layer  
model.add(Dense(2, input_shape=(3,)))  
  
# Add a final 1 neuron layer  
model.add(Dense(1))
```



# Adding activations

```
from tensorflow.keras.models import Sequential  
from tensorflow.keras.layers import Dense  
  
# Create a new sequential model  
model = Sequential()  
  
# Add an input and dense layer  
model.add(Dense(2, input_shape=(3,)))  
  
# Add a final 1 neuron layer  
model.add(Dense(1))
```



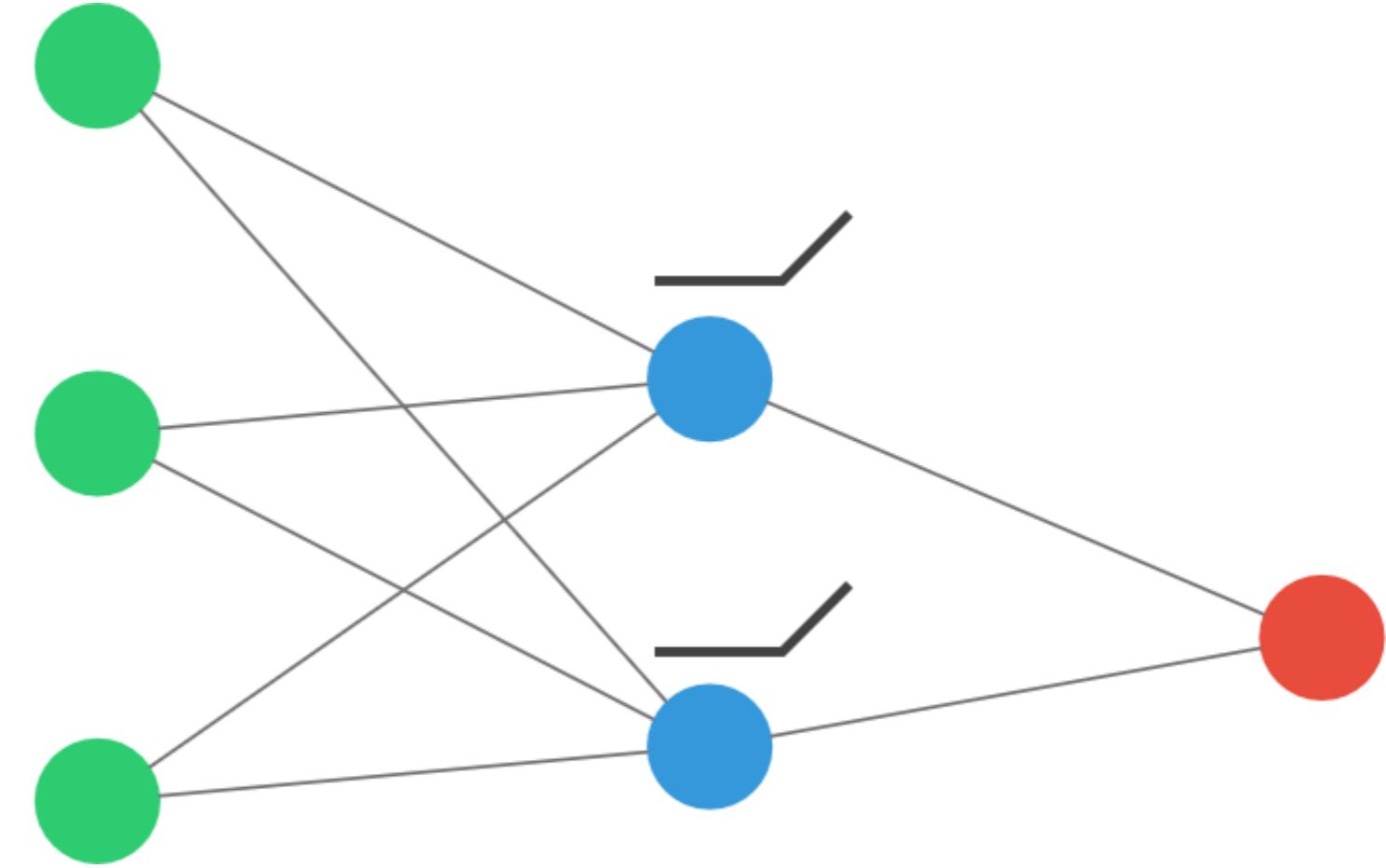
# Adding activations

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Create a new sequential model
model = Sequential()

# Add an input and dense layer
model.add(Dense(2, input_shape=(3,),
                activation="relu"))

# Add a final 1 neuron layer
model.add(Dense(1))
```

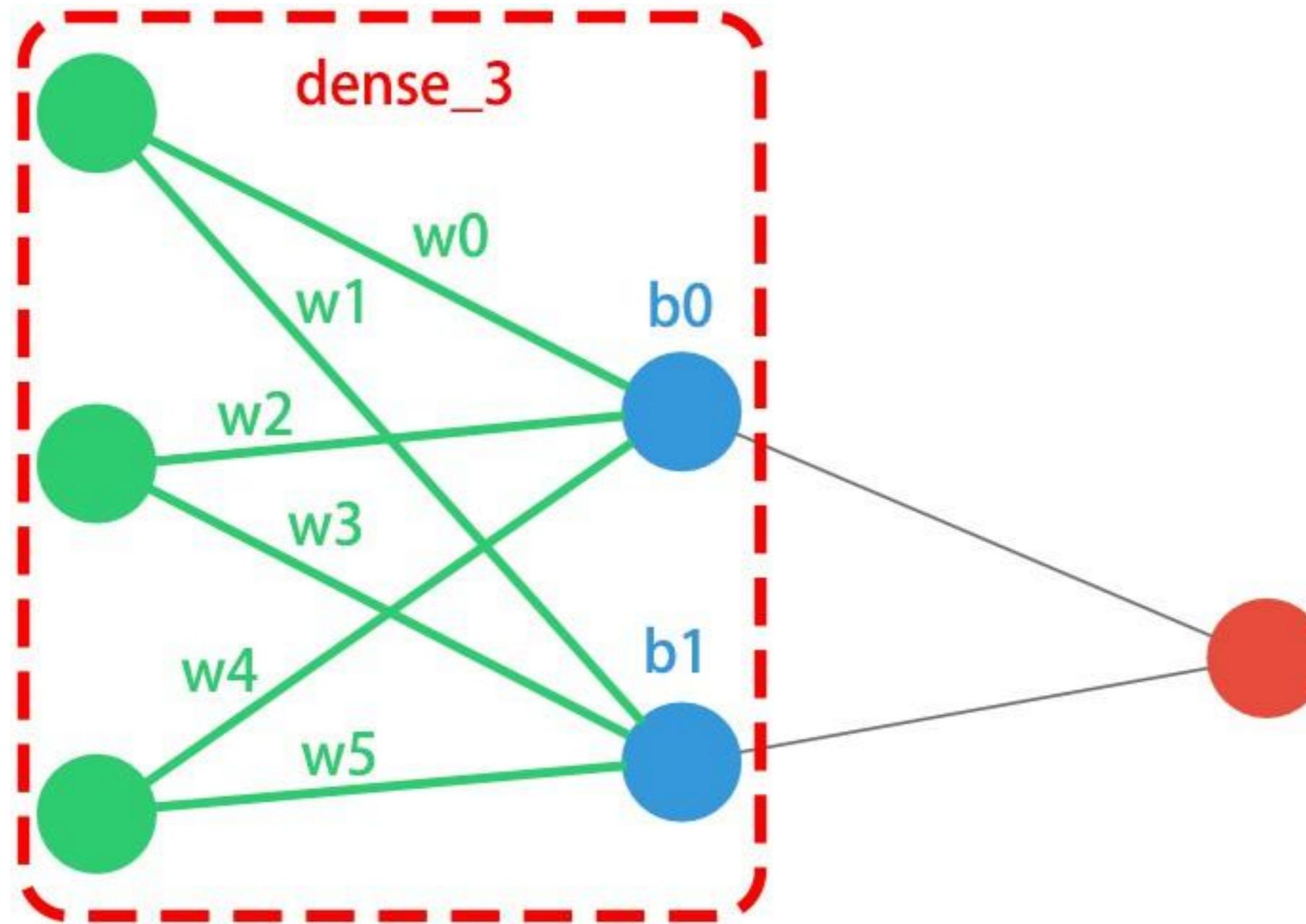


# Summarize your model!

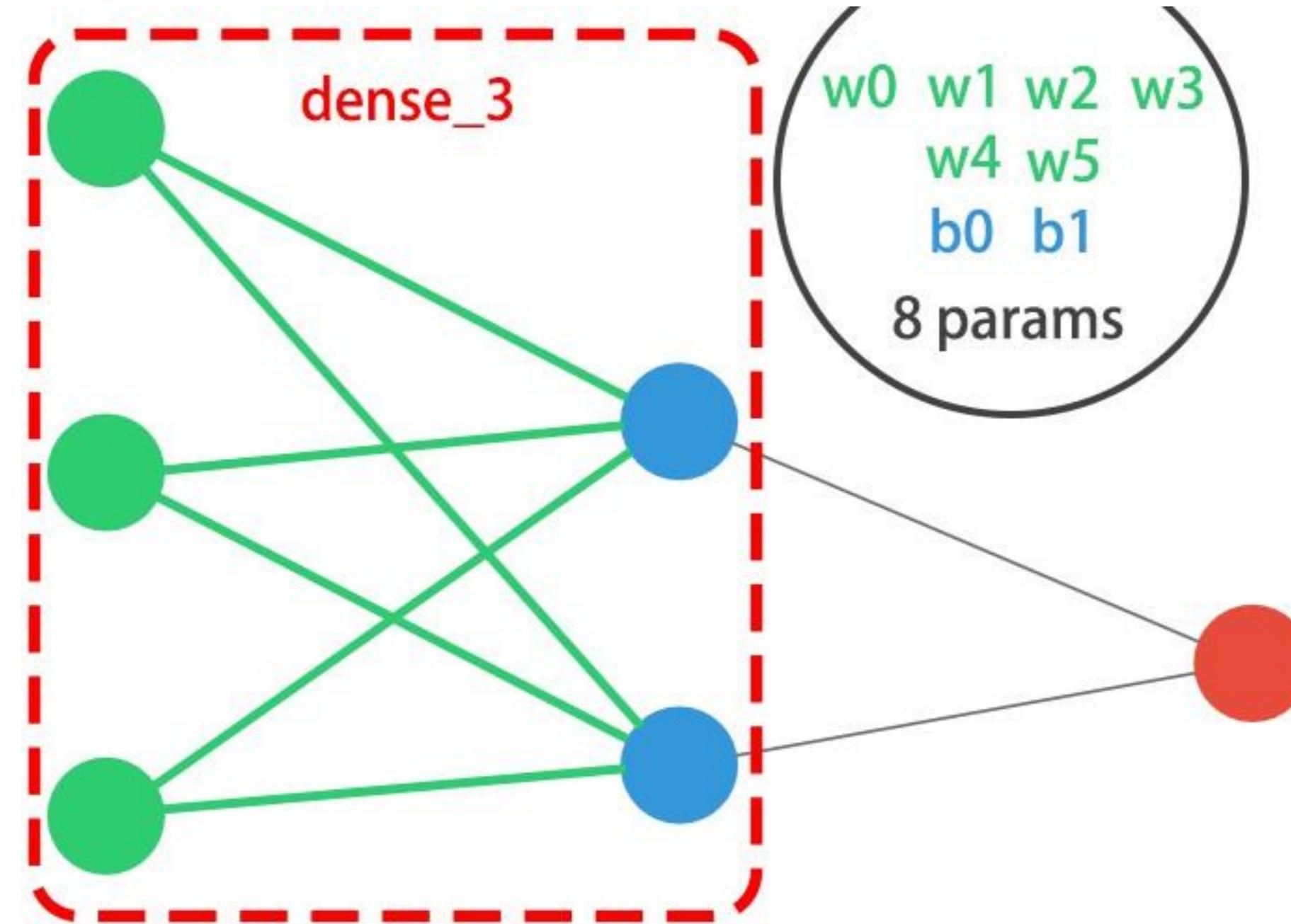
```
model.summary()
```

Layer (type)	Output Shape	Param #
<hr/>		
dense_3 (Dense)	(None, 2)	8
<hr/>		
dense_4 (Dense)	(None, 1)	3
<hr/>		
Total params:	11	
Trainable params:	11	
Non-trainable params:	0	

# Visualize parameters



# Visualize parameters



# Summarize your model!

```
model.summary()
```

Layer (type)	Output Shape	Param #
<hr/>		
dense_3 (Dense)	(None, 2)	--> 8 <--
<hr/>		
dense_4 (Dense)	(None, 1)	3
<hr/>		
Total params:	11	
Trainable params:	11	
Non-trainable params:	0	

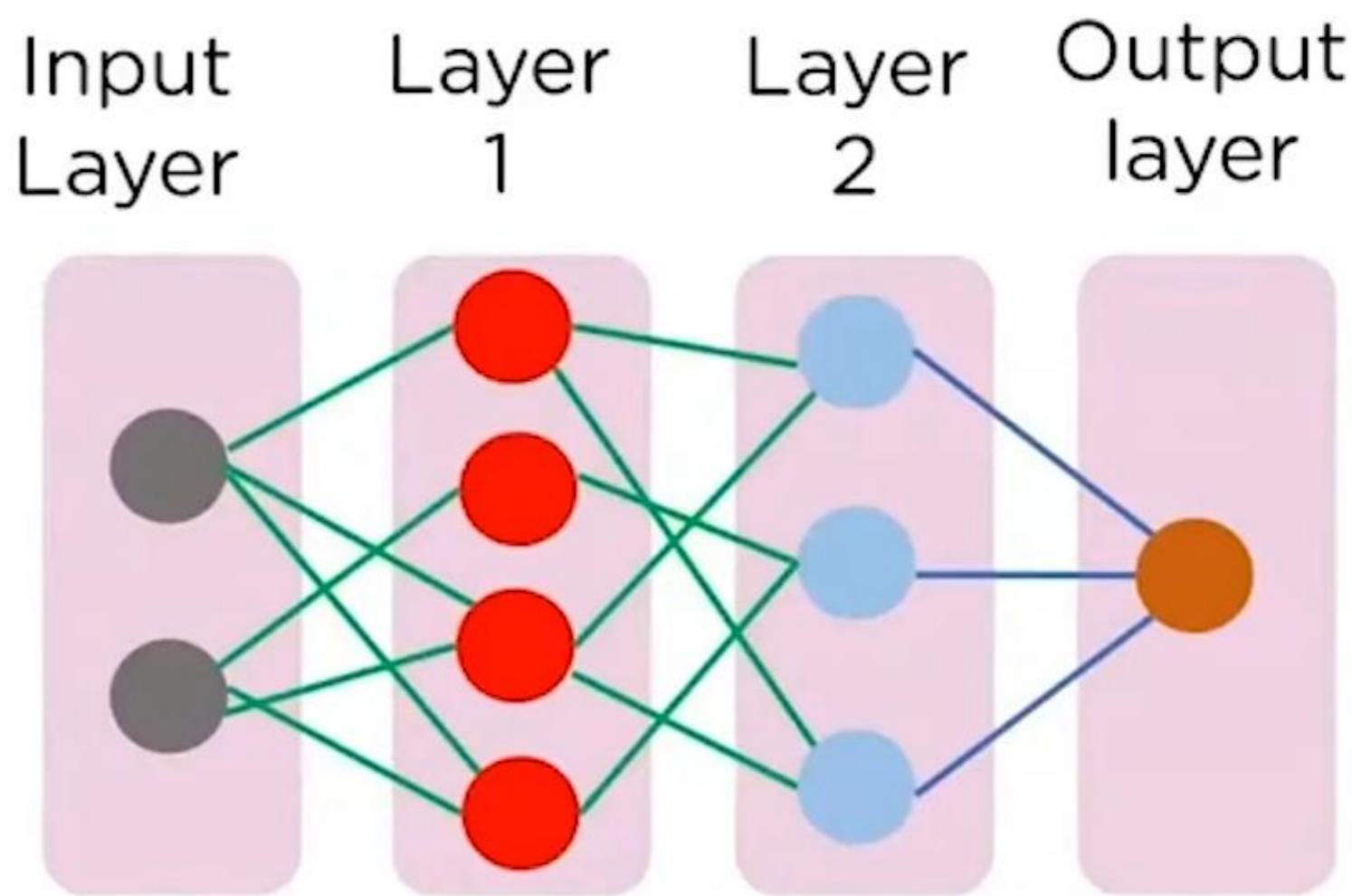
# Keras Model

1

## Sequential Model

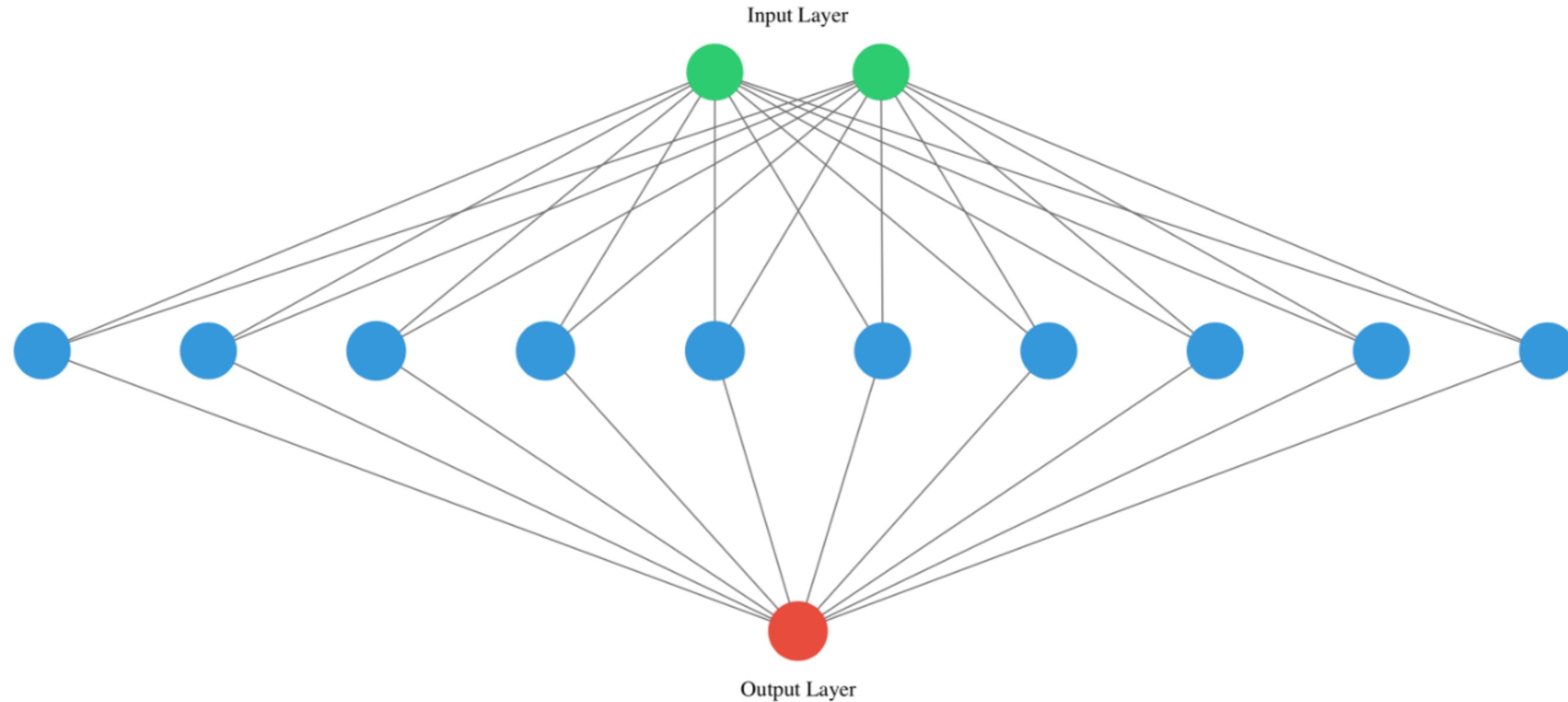
- ❑ Sequential Model is a linear stack of layers where the previous layer leads into the next layer
- ❑ Useful for simple classifier or decoder models

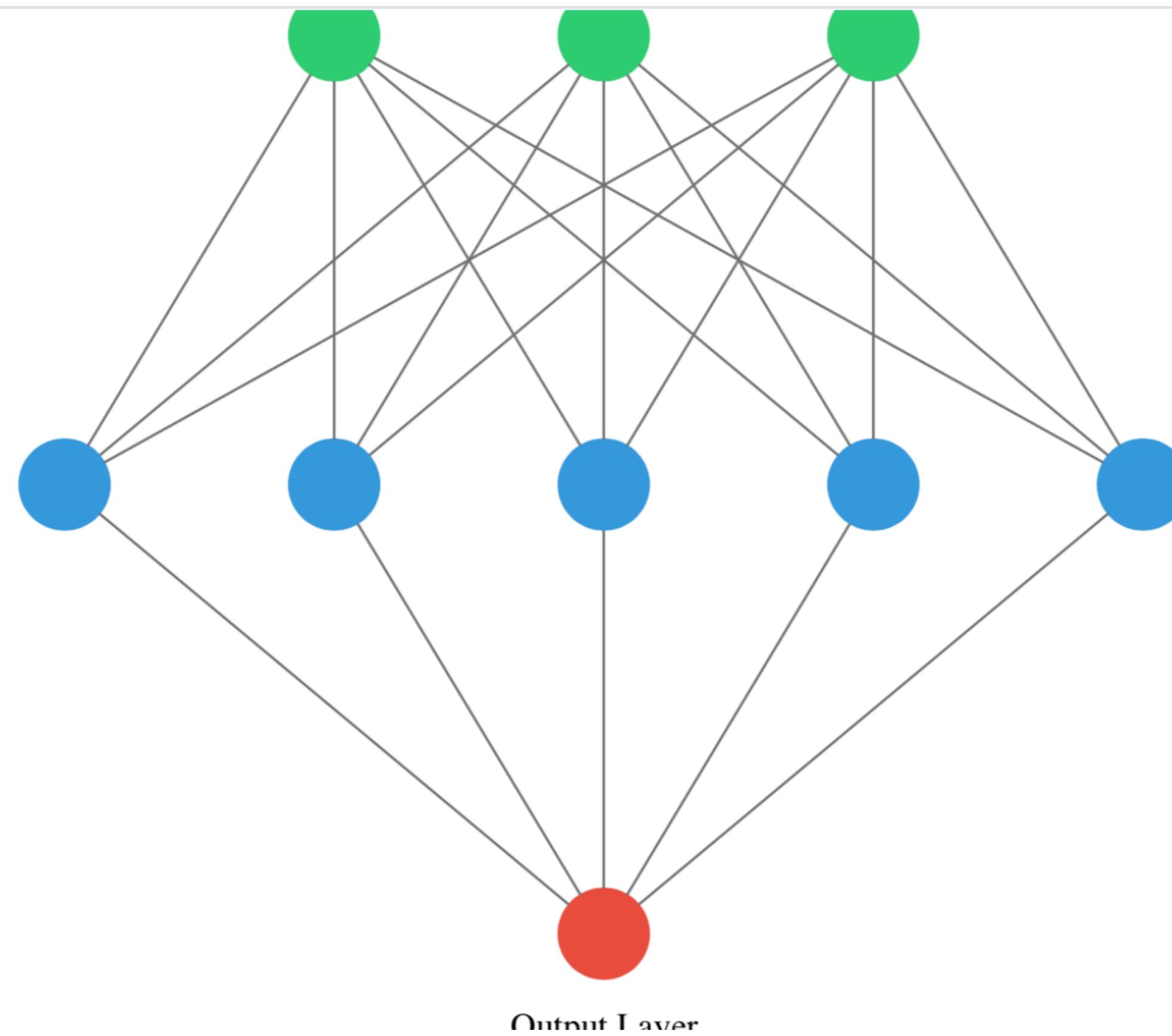
```
model = keras.Sequential([
    layers.Dense(1, activation="relu", name="layer1"),
    layers.Dense(2, activation="relu", name="layer2"),
    layers.Dense(3, name="layer3"), ])
# Call model on a test input x = tf.ones((3, 3)) y =
model(x)
```



# Let's code!

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## 2

### Functional Model

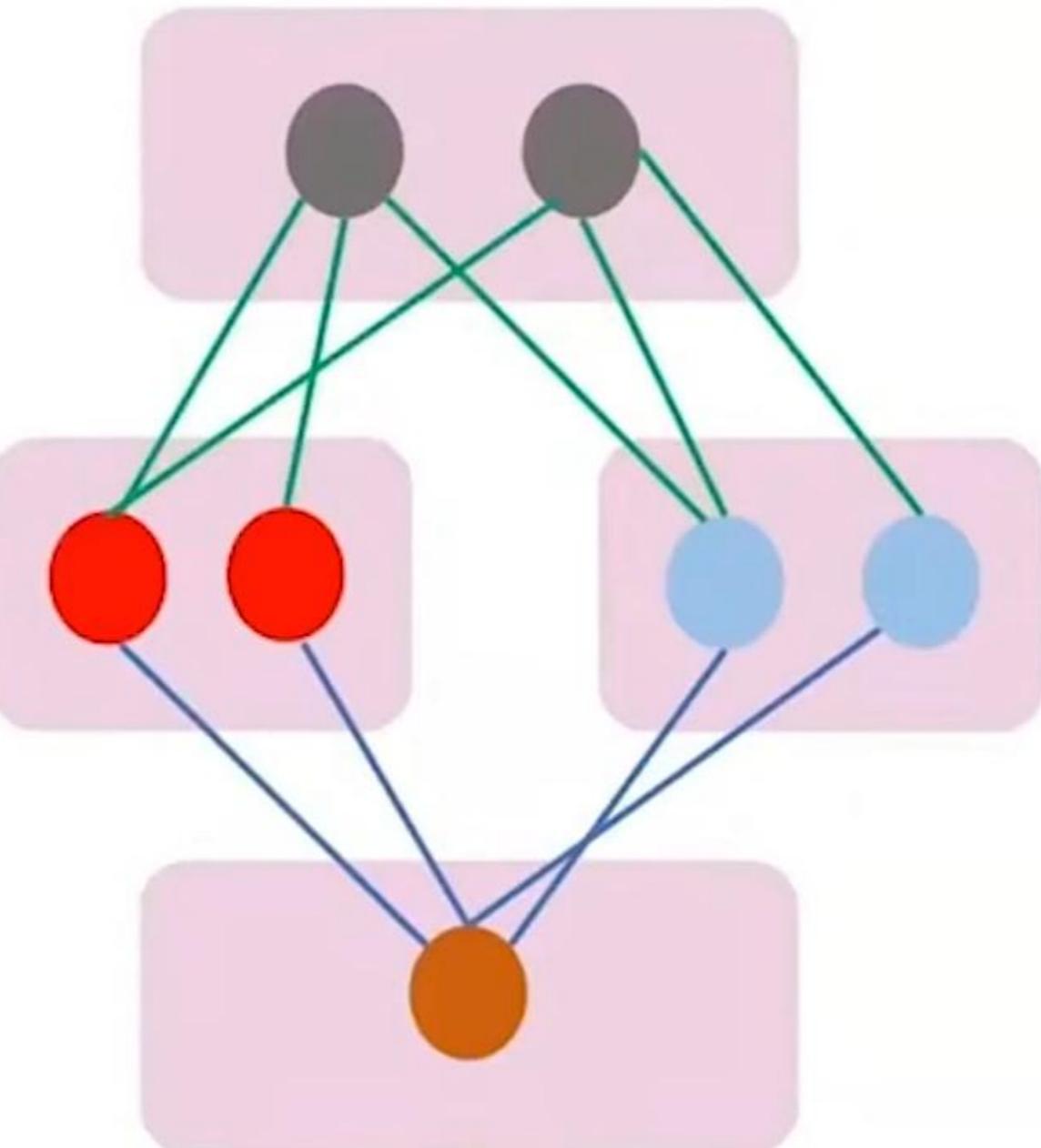
- ❑ Multi input and multi output model
- ❑ Complex model which forks into two or more branches

```
img_inputs = keras.Input(shape=(32, 32, 3))

dense = layers.Dense(64,
activation="relu") x = dense(inputs)

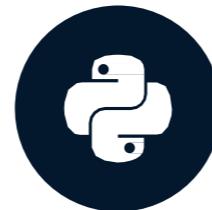
x = layers.Dense(64, activation="relu")
(x) outputs = layers.Dense(10)(x)

model = keras.Model(inputs=inputs,
outputs=outputs, name="mnist_model")
```



# Surviving a meteor strike

INTRODUCTION TO DEEP LEARNING WITH KERAS



# Recap

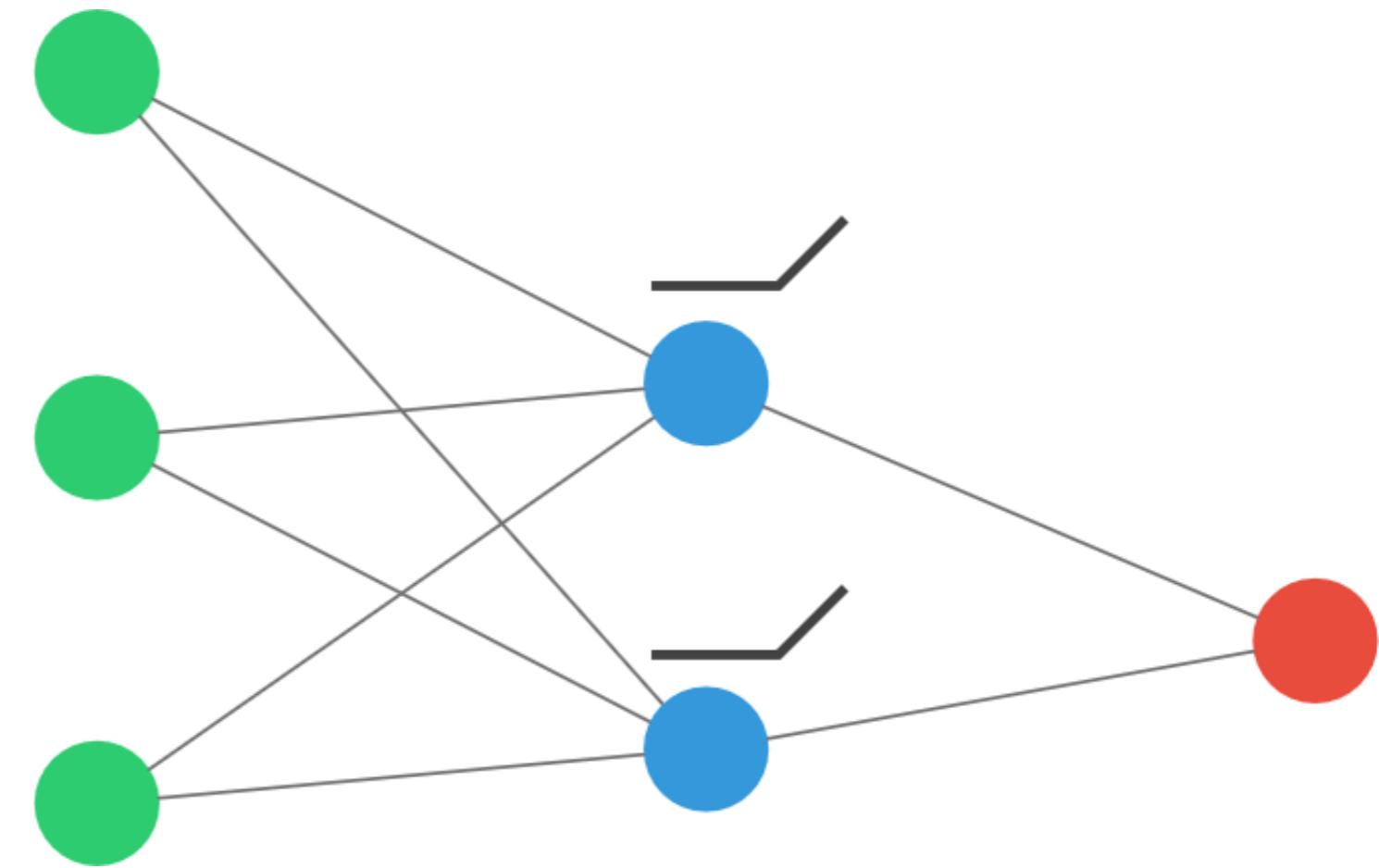
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Create a new sequential model
model = Sequential()

# Add an input and dense layer
model.add(Dense(2, input_shape=(3, ),
                activation="relu"))

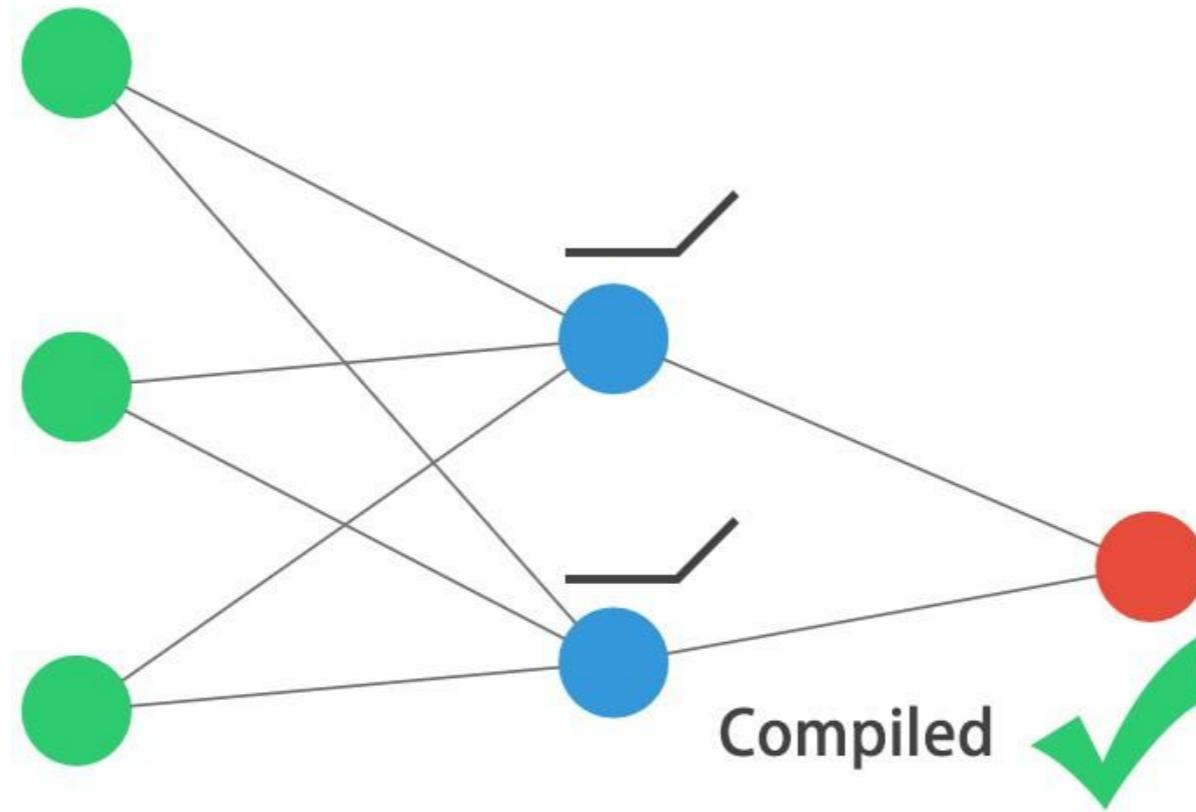
# Add a final 1 neuron layer
model.add(Dense(1))

<
```



# Compiling

```
# Compiling your previously built model  
model.compile(optimizer="adam", loss="mse")
```



# Training

```
# Train your model  
model.fit(X_train, y_train, epochs=5)
```

```
Epoch 1/5  
1000/1000 [=====] - 0s 242us/step - loss: 0.4090  
Epoch 2/5  
1000/1000 [=====] - 0s 34us/step - loss: 0.3602  
Epoch 3/5  
1000/1000 [=====] - 0s 37us/step - loss: 0.3223  
Epoch 4/5  
1000/1000 [=====] - 0s 34us/step - loss: 0.2958  
Epoch 5/5  
1000/1000 [=====] - 0s 33us/step - loss: 0.2795
```

# Predicting

```
# Predict on new data  
preds = model.predict(X_test)  
  
# Look at the predictions  
print(preds)
```

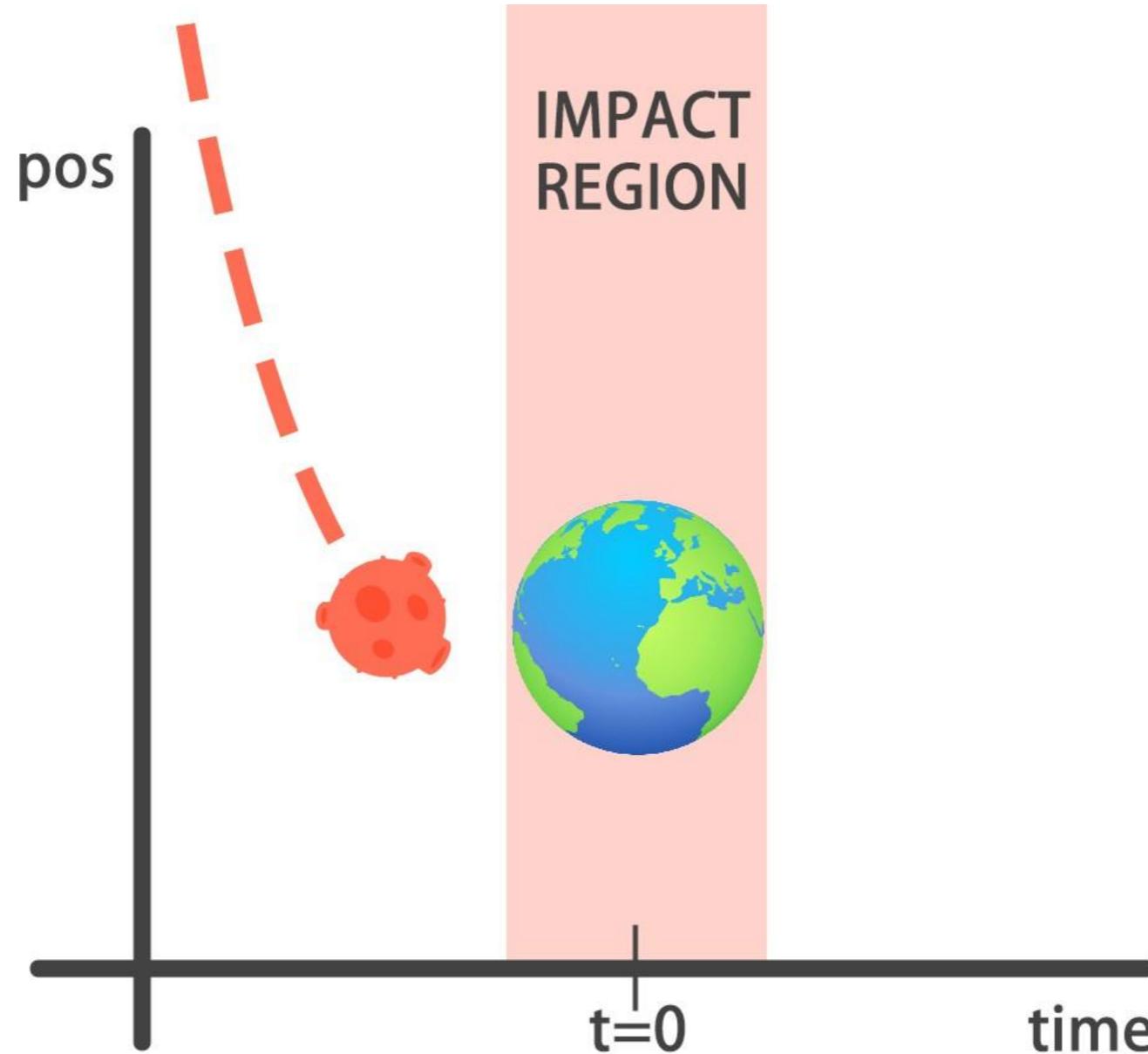
```
array([[0.6131608 ],  
       [0.5175948 ],  
       [0.60209155],  
       ...,  
       [0.55633    ],  
       [0.5305591 ],  
       [0.50682044]])
```

# Evaluating

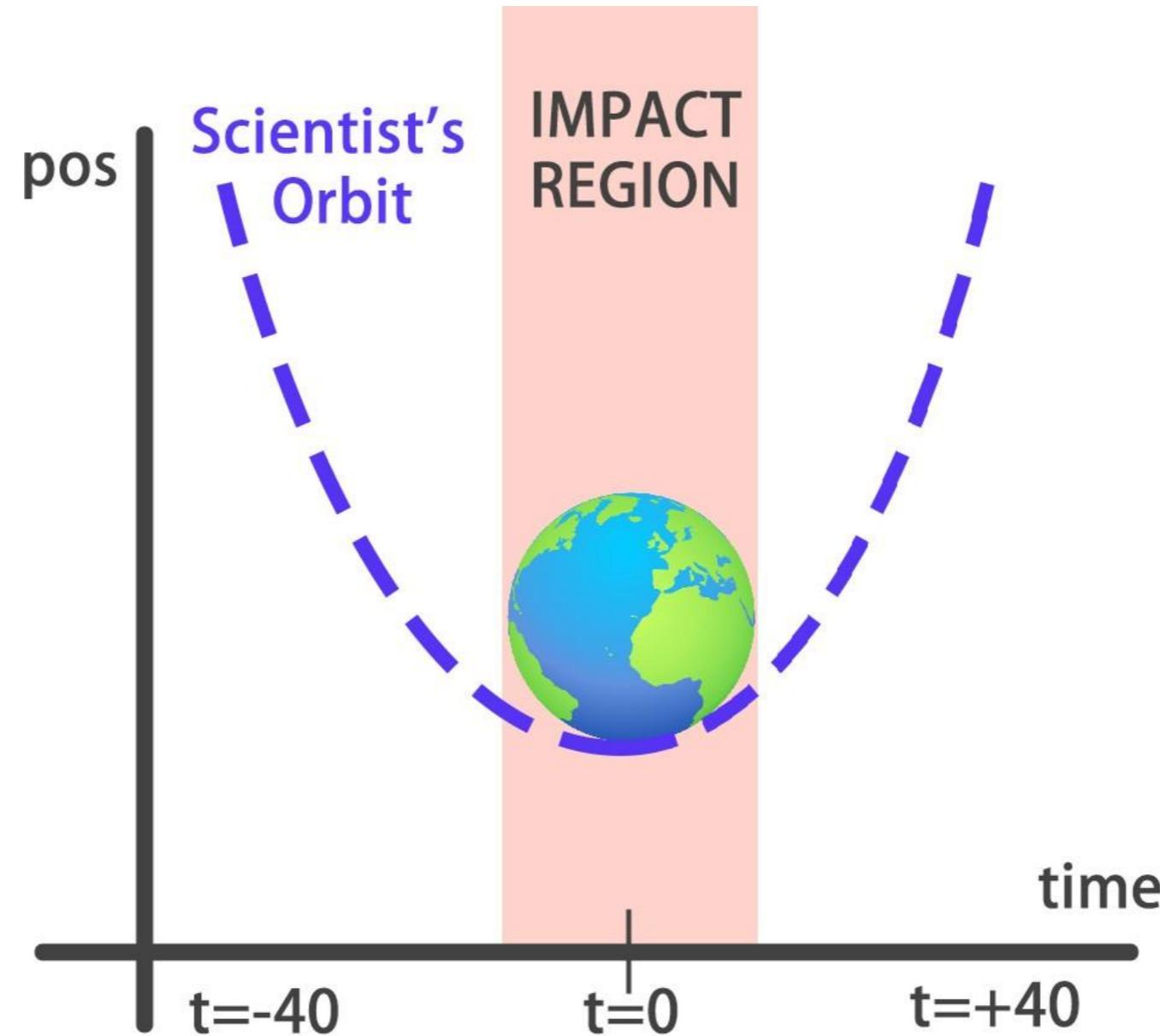
```
# Evaluate your results  
model.evaluate(X_test, y_test)
```

```
1000/1000 [=====] - 0s 53us/step  
0.25
```

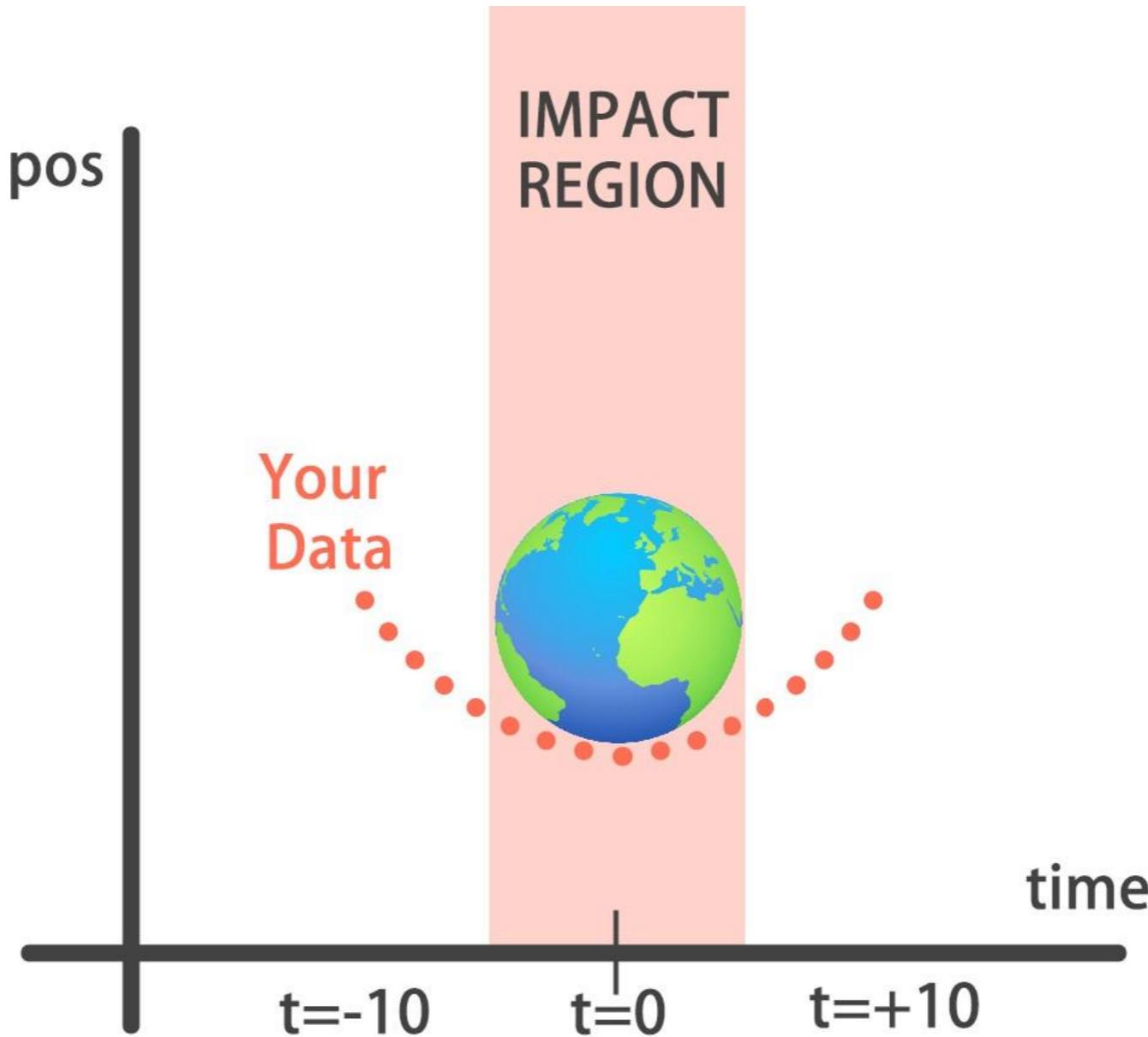
# The problem at hand



# Scientific prediction



# Your task



# Let's save the earth!

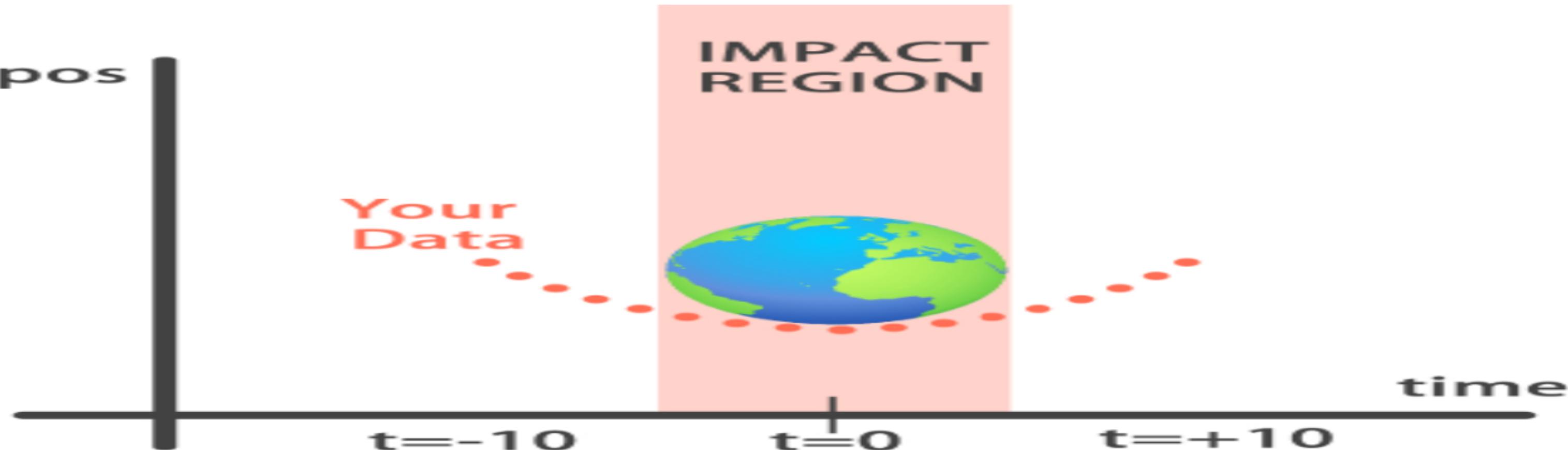
INTRODUCTION TO DEEP LEARNING WITH KERAS

## Specifying a model

You will build a simple regression model to predict the orbit of the meteor!

Your training data consist of measurements taken at time steps from -10 minutes before the Impact region to +10 minutes after. Each time step can be viewed as an X coordinate in our graph, which has an associated position Y for the meteor orbit at that time step.

*Note that you can view this problem as approximating a quadratic function via the use of neural networks.*



This data is stored in two numpy arrays: one called `time_steps`, what we call *features*, and another called `y_positions`, with the *labels*. Go on and build your model! It should be able to predict the y positions for the meteor orbit at future time steps.

Keras `Sequential` model and `Dense` layers are available for you to use.

```
1 # Instantiate a Sequential model
2 model = _____
3
4 # Add a Dense layer with 50 neurons and an input of 1 neuron
5 model.add(____(____, input_shape=(____,), activation='relu'))
6
7 # Add two Dense Layers with 50 neurons and relu activation
8 model.add(____(____, ____=____))
9 model._____
10
11 # End your model with a Dense layer and no activation
12 model._____
```

```
1 # Instantiate a Sequential model
2 model = Sequential()
3
4 # Add a Dense layer with 50 neurons and an input of 1 neuron
5 model.add(Dense(50, input_shape=(1,), activation='relu'))
6
7 # Add two Dense layers with 50 neurons and relu activation
8 model.add(Dense(50,activation='relu'))
9 model.add(Dense(50,activation='relu'))
10
11
12 # End your model with a Dense layer and no activation
13 model.add(Dense(1))
```

```
1 # Compile your model
2 model.compile(optimizer = 'adam', loss = 'mse')
3
4 print("Training started..., this can take a while:")
5
6 # Fit your model on your data for 30 epochs
7 model.fit(time_steps,y_positions, epochs = 30)
8
9 # Evaluate your model
10 print("Final loss value:",model.evaluate(time_steps,y_positions))
```

```
1 # Predict the twenty minutes orbit  
2 twenty_min_orbit = model.predict(np.arange(-10, 11))  
3  
4 # Plot the twenty minute orbit  
5 plot_orbit(twenty_min_orbit)
```

