This is a companion notebook for the book Deep Learning with Python, Second Edition. For readability, it only contains runnable code blocks and section titles, and omits everything else in the book: text paragraphs, figures, and pseudocode.

If you want to be able to follow what's going on, I recommend reading the notebook side by side with your copy of the book.

This notebook was generated for TensorFlow 2.6.

Getting started with neural networks: Classification and regression

Classifying movie reviews: A binary classification example

The IMDB dataset

Loading the IMDB dataset

#Importing an IMDB dataset from Keras. Here, we'll look at the 10000 words.

##Dividing the dataset into training and test sets.

```
from tensorflow.keras.datasets import imdb
(train_data, train_labels), (test_data, test_labels) = imdb.load_data(
    num_words=10000)
```

#Simply printing the first review from the training dataset.

```
train_data[0]
```

```
[1,
 14,
 22,
 16,
 43,
 530,
 973,
 1622,
 1385,
 65,
 458,
 4468,
 66,
 3941,
 4,
 173,
 36,
 256,
 5,
```

25,
100,
43,
838,
112,
50,
670,
2,
9,
35,
480,
284,
5,
150,
4,
172,
112,
167,
2,
336,
385,
39,
4,
172,
4536,
1111,
17,
546,
38,
13,
447,
4,
192,
50,
16,
6,
147,
2025,
19,
14,
22,
4,
1920,
4613,
469,
4,
22,
71,
87,
12,

16,
43,
530,
38,
76,
15,
13,
1247,
4,
22,
17,
515,
17,
12,
16,
626,
18,
2,
5,
62,
386,
12,
8,
316,
8,
106,
5,
4,
2223,
5244,
16,
480,
66,
3785,
33,
4,
130,
12,
16,
38,
619,
5,
25,
124,
51,
36,
135,
48,
25,
1415,

33,
6,
22,
12,
215,
28,
77,
52,
5,
14,
407,
16,
82,
2,
8,
4,
107,
117,
5952,
15,
256,
4,
2,
7,
3766,
5,
723,
36,
71,
43,
530,
476,
26,
400,
317,
46,
7,
4,
2,
1029,
13,
104,
88,
4,
381,
15,
297,
98,
32,
2071,

56,
26,
141,
6,
194,
7486,
18,
4,
226,
22,
21,
134,
476,
26,
480,
5,
144,
30,
5535,
18,
51,
36,
28,
224,
92,
25,
104,
4,
226,
65,
16,
38,
1334,
88,
12,
16,
283,
5,
16,
4472,
113,
103,
32,
15,
16,
5345,
19,
178,
32]

##checking the first review's label

```
train_labels[0]
```

```
1
```

```
max([max(sequence) for sequence in train_data])
```

```
9999
```

Decoding and displaying movie reviews in text

```
word_index = imdb.get_word_index()
reverse_word_index = dict(
    [(value, key) for (key, value) in word_index.items()])
decoded_review = " ".join(
    [reverse_word_index.get(i - 3, "?") for i in train_data[0]])
#As can be seen, the first review is positive, and the label is 1.
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb_word_index.json
1646592/1641221 [==============================] - 0s 0us/step
1654784/1641221 [==============================] - 0s 0us/step
```

Preparing the data

Encoding the integer sequences via multi-hot encoding

```
import numpy as np
def vectorize_sequences(sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        for j in sequence:
            results[i, j] = 1.
    return results
x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)
```

```
x_train[0]
```

```
array([0., 1., 1., ..., 0., 0., 0.])
```

```
y_train = np.asarray(train_labels).astype("float32")
y_test = np.asarray(test_labels).astype("float32")
```

Building your model

Model definition

```
from tensorflow import keras
from tensorflow.keras import layers
```

```
# #Here I am  using two hidden layers, each with 16 nodes, and only one node in the output layer for either +ve or -ve output. ReLu is used for hidden.
model = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
```

Compiling the model

##Adam is used as the optimizer, and binary crossentropy is used as the loss function.

```
model.compile(optimizer="adam",
              loss="binary_crossentropy",
              metrics=["accuracy"])
```

Validating your approach

Setting aside a validation set

```
x_val = x_train[:10000]
partial_x_train = x_train[10000:]
y_val = y_train[:10000]
partial_y_train = y_train[10000:]
```

Training your model

###we're training our model with 20 epochs and 512 batches.

```
history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/20
30/30 [==============================] - 2s 50ms/step - loss: 0.5796 - accuracy: 0.7176 - val_loss: 0.4524 - val_accuracy: 0.8536
Epoch 2/20
30/30 [==============================] - 1s 35ms/step - loss: 0.3484 - accuracy: 0.8947 - val_loss: 0.3253 - val_accuracy: 0.8826
Epoch 3/20
30/30 [==============================] - 1s 38ms/step - loss: 0.2318 - accuracy: 0.9276 - val_loss: 0.2794 - val_accuracy: 0.8882
Epoch 4/20
30/30 [==============================] - 1s 36ms/step - loss: 0.1633 - accuracy: 0.9485 - val_loss: 0.2807 - val_accuracy: 0.8881
Epoch 5/20
30/30 [==============================] - 1s 35ms/step - loss: 0.1228 - accuracy: 0.9661 - val_loss: 0.2958 - val_accuracy: 0.8835
Epoch 6/20
```

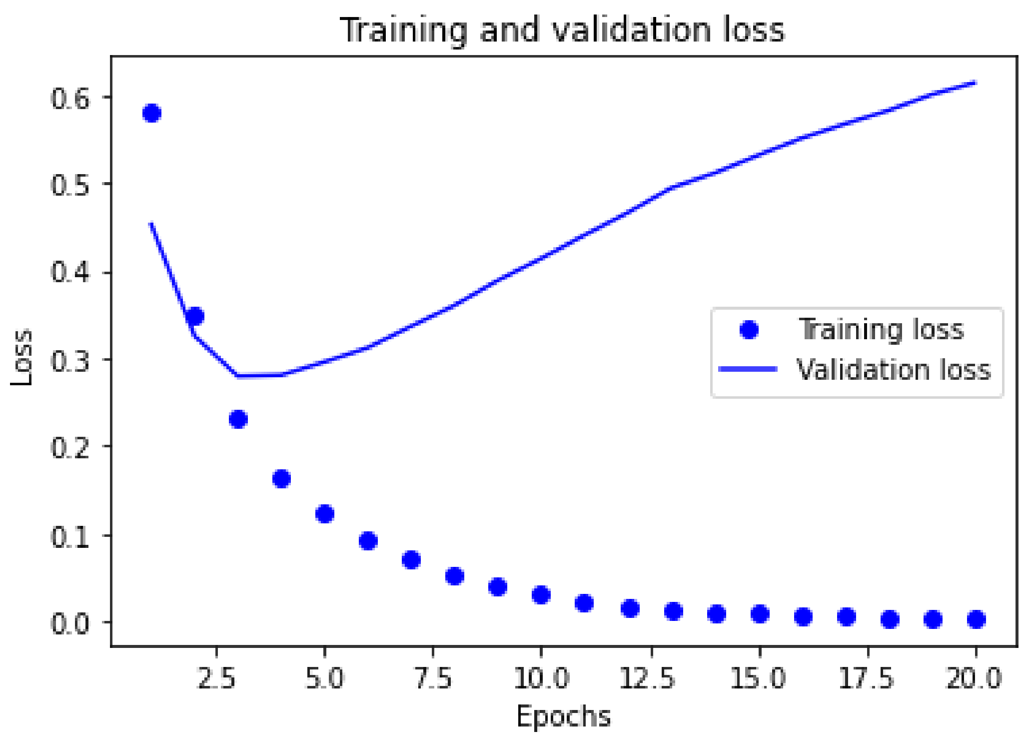
```
30/30 [==============================] - 1s 34ms/step - loss: 0.0937 -
accuracy: 0.9759 - val_loss: 0.3119 - val_accuracy: 0.8823
Epoch 7/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0704 -
accuracy: 0.9847 - val_loss: 0.3363 - val_accuracy: 0.8809
Epoch 8/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0533 -
accuracy: 0.9907 - val_loss: 0.3602 - val_accuracy: 0.8774
Epoch 9/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0399 -
accuracy: 0.9947 - val_loss: 0.3886 - val_accuracy: 0.8755
Epoch 10/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0298 -
accuracy: 0.9967 - val_loss: 0.4136 - val_accuracy: 0.8743
Epoch 11/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0225 -
accuracy: 0.9986 - val_loss: 0.4402 - val_accuracy: 0.8734
Epoch 12/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0172 -
accuracy: 0.9993 - val_loss: 0.4658 - val_accuracy: 0.8735
Epoch 13/20
30/30 [==============================] - 1s 38ms/step - loss: 0.0133 -
accuracy: 0.9997 - val_loss: 0.4940 - val_accuracy: 0.8711
Epoch 14/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0108 -
accuracy: 0.9997 - val_loss: 0.5109 - val_accuracy: 0.8707
Epoch 15/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0087 -
accuracy: 0.9999 - val_loss: 0.5311 - val_accuracy: 0.8699
Epoch 16/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0072 -
accuracy: 0.9999 - val_loss: 0.5505 - val_accuracy: 0.8690
Epoch 17/20
30/30 [==============================] - 1s 38ms/step - loss: 0.0060 -
accuracy: 0.9999 - val_loss: 0.5669 - val_accuracy: 0.8682
Epoch 18/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0051 -
accuracy: 0.9999 - val_loss: 0.5821 - val_accuracy: 0.8675
Epoch 19/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0044 -
accuracy: 0.9999 - val_loss: 0.6003 - val_accuracy: 0.8671
Epoch 20/20
30/30 [==============================] - 1s 44ms/step - loss: 0.0039 -
accuracy: 0.9999 - val_loss: 0.6141 - val_accuracy: 0.8670
```

```
history_dict = history.history
history_dict.keys()
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

Plotting the training and validation loss

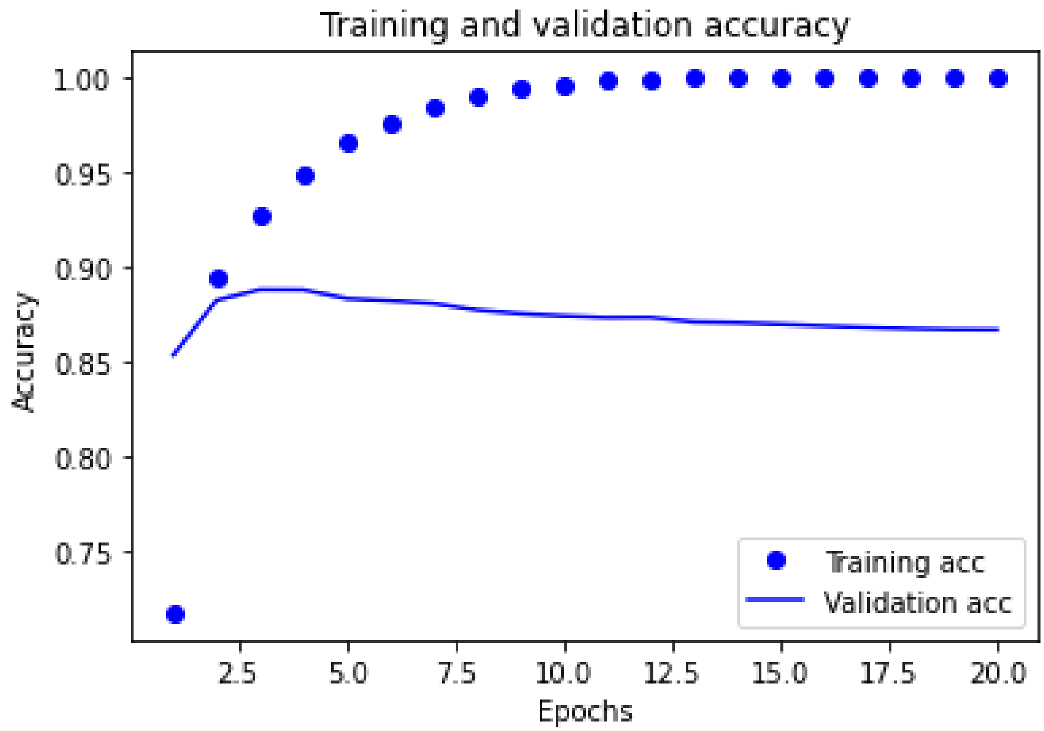
```
import matplotlib.pyplot as plt
history_dict = history.history
loss_values = history_dict["loss"]
val_loss_values = history_dict["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, "bo", label="Training loss")
plt.plot(epochs, val_loss_values, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



Validation loss and overfitting begin to increase after the third epoch. As a result, we must remodel using three or four epochs.

Plotting the training and validation accuracy

```
plt.clf()
acc = history_dict["accuracy"]
val_acc = history_dict["val_accuracy"]
plt.plot(epochs, acc, "bo", label="Training acc")
plt.plot(epochs, val_acc, "b", label="Validation acc")
plt.title("Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Validation accuracy starts to decline around the third epoch.

Retraining a model from scratch

```
model = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
#Here i am using three epochs to retrain the model here.
model.compile(optimizer="adam",
              loss="binary_crossentropy",
              metrics=["accuracy"])
model.fit(x_train, y_train, epochs=4, batch_size=512)
results = model.evaluate(x_test, y_test)
```

```
Epoch 1/4
49/49 [==============================] - 3s 33ms/step - loss: 0.4979 -
accuracy: 0.7956
Epoch 2/4
49/49 [==============================] - 1s 28ms/step - loss: 0.2574 -
accuracy: 0.9089
Epoch 3/4
49/49 [==============================] - 1s 28ms/step - loss: 0.1873 -
accuracy: 0.9348
Epoch 4/4
49/49 [==============================] - 1s 29ms/step - loss: 0.1515 -
accuracy: 0.9476
```

```
782/782 [==============================] - 2s 2ms/step - loss: 0.3027
- accuracy: 0.8815
```

```
results
```

```
[0.3026789724826813, 0.8814799785614014]
```

Building your model

1 using one or three hidden layers, and see how doing so

affects validation and test accuracy.

```
#I am creating a model with just 1 hidden layer and the ReLu
activation function.
model1_1 = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])

# I am using three hidden layers here, with ReLu activation function
and sigmoid for output layer.
model1_3 = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])

#Adam and binary crossentropy are used in both scenarios (3 and 1
layers)
model1_1.compile(optimizer="adam",
              loss="binary_crossentropy",
              metrics=["accuracy"])

model1_3.compile(optimizer="adam",
              loss="binary_crossentropy",
              metrics=["accuracy"])

# model fitting with 20 epochs and 512 batch size
history1_1 = model1_1.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/20
30/30 [==============================] - 2s 44ms/step - loss: 0.5550 -
accuracy: 0.7721 - val_loss: 0.4230 - val_accuracy: 0.8575
Epoch 2/20
30/30 [==============================] - 1s 35ms/step - loss: 0.3395 -
accuracy: 0.8928 - val_loss: 0.3305 - val_accuracy: 0.8800
```

```
Epoch 3/20
30/30 [==============================] - 1s 36ms/step - loss: 0.2556 -
accuracy: 0.9207 - val_loss: 0.2963 - val_accuracy: 0.8886
Epoch 4/20
30/30 [==============================] - 1s 37ms/step - loss: 0.2090 -
accuracy: 0.9379 - val_loss: 0.2829 - val_accuracy: 0.8912
Epoch 5/20
30/30 [==============================] - 1s 36ms/step - loss: 0.1771 -
accuracy: 0.9473 - val_loss: 0.2792 - val_accuracy: 0.8890
Epoch 6/20
30/30 [==============================] - 1s 37ms/step - loss: 0.1531 -
accuracy: 0.9567 - val_loss: 0.2777 - val_accuracy: 0.8898
Epoch 7/20
30/30 [==============================] - 1s 37ms/step - loss: 0.1334 -
accuracy: 0.9645 - val_loss: 0.2813 - val_accuracy: 0.8887
Epoch 8/20
30/30 [==============================] - 1s 36ms/step - loss: 0.1163 -
accuracy: 0.9704 - val_loss: 0.2859 - val_accuracy: 0.8858
Epoch 9/20
30/30 [==============================] - 1s 36ms/step - loss: 0.1028 -
accuracy: 0.9754 - val_loss: 0.2928 - val_accuracy: 0.8833
Epoch 10/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0913 -
accuracy: 0.9796 - val_loss: 0.3019 - val_accuracy: 0.8836
Epoch 11/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0810 -
accuracy: 0.9841 - val_loss: 0.3105 - val_accuracy: 0.8819
Epoch 12/20
30/30 [==============================] - 1s 38ms/step - loss: 0.0723 -
accuracy: 0.9866 - val_loss: 0.3207 - val_accuracy: 0.8813
Epoch 13/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0650 -
accuracy: 0.9890 - val_loss: 0.3329 - val_accuracy: 0.8814
Epoch 14/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0583 -
accuracy: 0.9912 - val_loss: 0.3420 - val_accuracy: 0.8802
Epoch 15/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0521 -
accuracy: 0.9931 - val_loss: 0.3524 - val_accuracy: 0.8802
Epoch 16/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0470 -
accuracy: 0.9939 - val_loss: 0.3632 - val_accuracy: 0.8785
Epoch 17/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0426 -
accuracy: 0.9953 - val_loss: 0.3752 - val_accuracy: 0.8779
Epoch 18/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0381 -
accuracy: 0.9967 - val_loss: 0.3865 - val_accuracy: 0.8761
Epoch 19/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0343 -
```

```
accuracy: 0.9973 - val_loss: 0.3972 - val_accuracy: 0.8749
Epoch 20/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0310 -
accuracy: 0.9977 - val_loss: 0.4088 - val_accuracy: 0.8744
```

```
history1_3 = model1_3.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/20
30/30 [==============================] - 2s 44ms/step - loss: 0.5949 -
accuracy: 0.6919 - val_loss: 0.4400 - val_accuracy: 0.8581
Epoch 2/20
30/30 [==============================] - 1s 36ms/step - loss: 0.3081 -
accuracy: 0.9013 - val_loss: 0.2897 - val_accuracy: 0.8863
Epoch 3/20
30/30 [==============================] - 1s 36ms/step - loss: 0.1828 -
accuracy: 0.9393 - val_loss: 0.2975 - val_accuracy: 0.8836
Epoch 4/20
30/30 [==============================] - 1s 36ms/step - loss: 0.1285 -
accuracy: 0.9601 - val_loss: 0.3090 - val_accuracy: 0.8838
Epoch 5/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0902 -
accuracy: 0.9733 - val_loss: 0.3323 - val_accuracy: 0.8817
Epoch 6/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0626 -
accuracy: 0.9861 - val_loss: 0.3785 - val_accuracy: 0.8791
Epoch 7/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0435 -
accuracy: 0.9923 - val_loss: 0.4120 - val_accuracy: 0.8758
Epoch 8/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0293 -
accuracy: 0.9959 - val_loss: 0.4520 - val_accuracy: 0.8750
Epoch 9/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0200 -
accuracy: 0.9983 - val_loss: 0.4930 - val_accuracy: 0.8737
Epoch 10/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0135 -
accuracy: 0.9991 - val_loss: 0.5300 - val_accuracy: 0.8710
Epoch 11/20
30/30 [==============================] - 1s 48ms/step - loss: 0.0096 -
accuracy: 0.9993 - val_loss: 0.5658 - val_accuracy: 0.8702
Epoch 12/20
30/30 [==============================] - 1s 46ms/step - loss: 0.0069 -
accuracy: 0.9995 - val_loss: 0.5957 - val_accuracy: 0.8687
Epoch 13/20
30/30 [==============================] - 1s 38ms/step - loss: 0.0050 -
accuracy: 0.9998 - val_loss: 0.6251 - val_accuracy: 0.8700
Epoch 14/20
```

```
30/30 [==============================] - 1s 38ms/step - loss: 0.0038 -
accuracy: 0.9999 - val_loss: 0.6513 - val_accuracy: 0.8682
Epoch 15/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0030 -
accuracy: 0.9999 - val_loss: 0.6784 - val_accuracy: 0.8674
Epoch 16/20
30/30 [==============================] - 1s 38ms/step - loss: 0.0024 -
accuracy: 1.0000 - val_loss: 0.6995 - val_accuracy: 0.8680
Epoch 17/20
30/30 [==============================] - 1s 38ms/step - loss: 0.0020 -
accuracy: 1.0000 - val_loss: 0.7212 - val_accuracy: 0.8674
Epoch 18/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0017 -
accuracy: 1.0000 - val_loss: 0.7402 - val_accuracy: 0.8667
Epoch 19/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0015 -
accuracy: 1.0000 - val_loss: 0.7577 - val_accuracy: 0.8663
Epoch 20/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0013 -
accuracy: 1.0000 - val_loss: 0.7751 - val_accuracy: 0.8666
```

plotting training vs validation loss

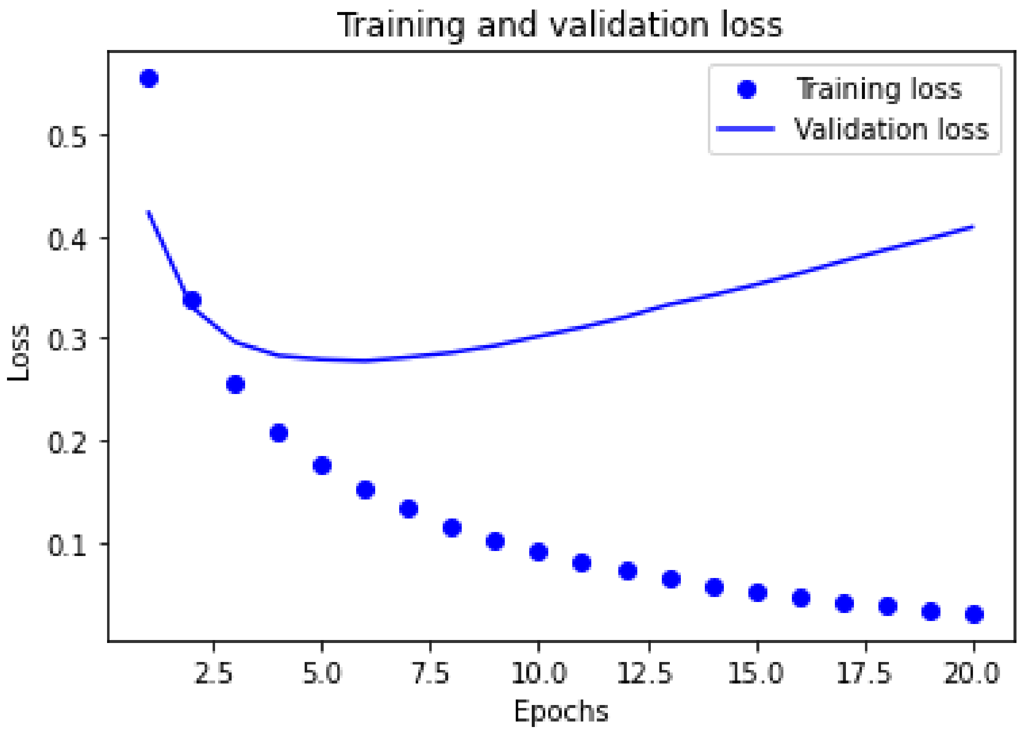
```
historyp1_1 = history1_1.history
historyp1_1.keys()
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

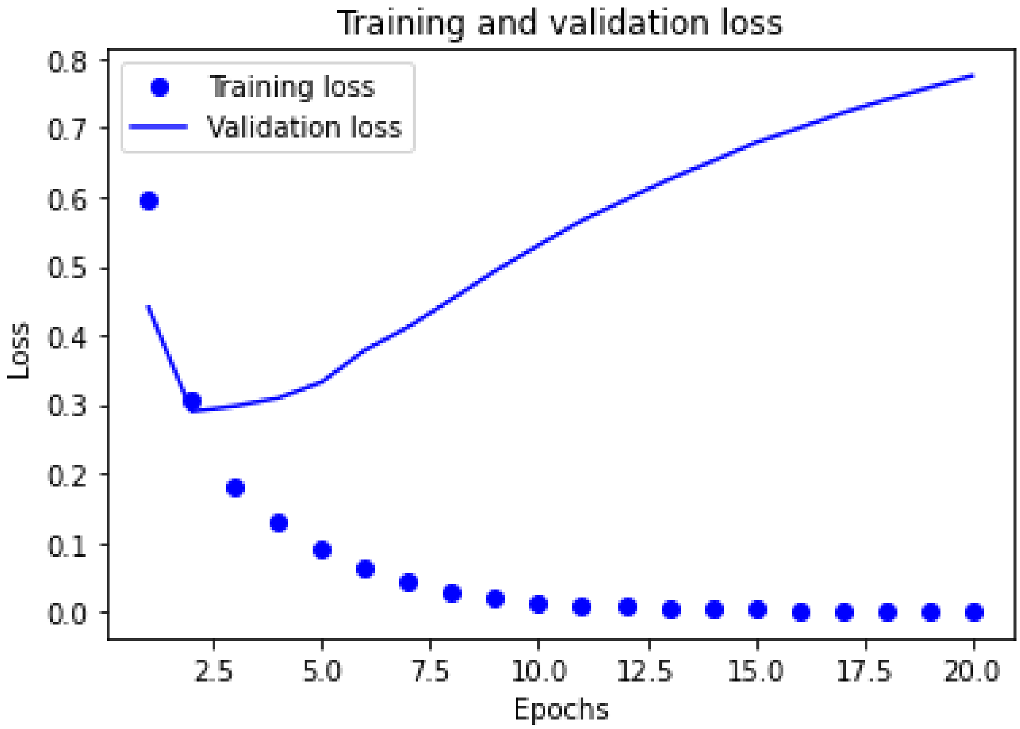
```
historyp1_3 = history1_1.history
historyp1_3.keys()
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

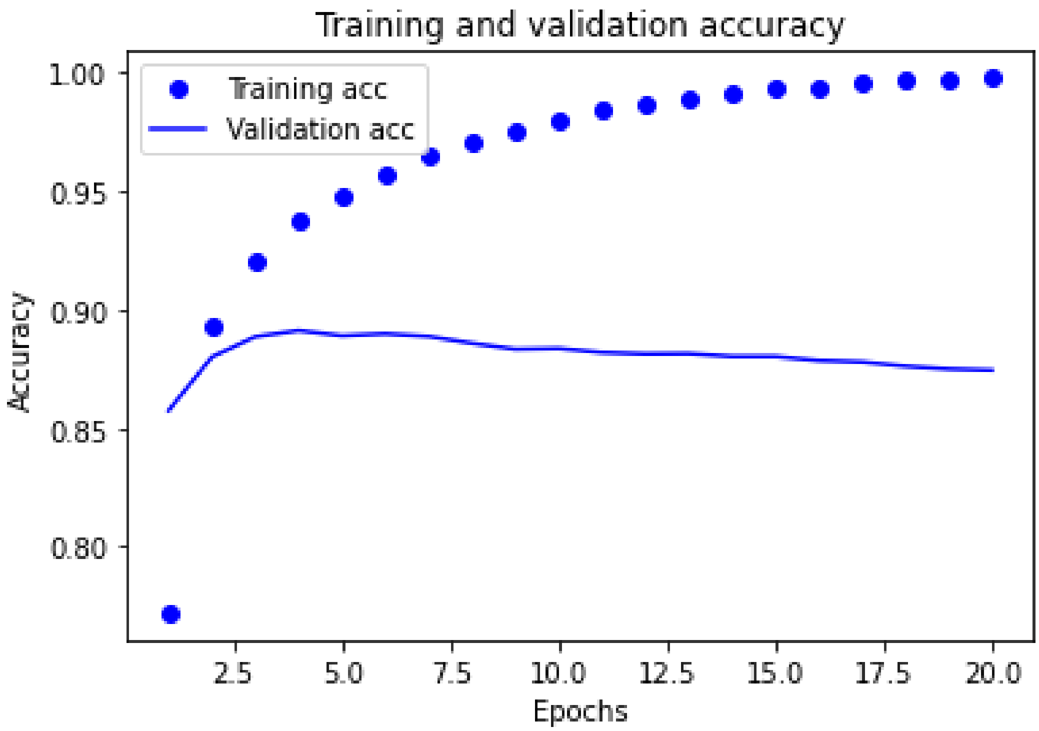
```
historyp1_1 = history1_1.history
loss_values1 = historyp1_1["loss"]
val_loss_values1 = historyp1_1["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values1, "bo", label="Training loss")
plt.plot(epochs, val_loss_values1, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



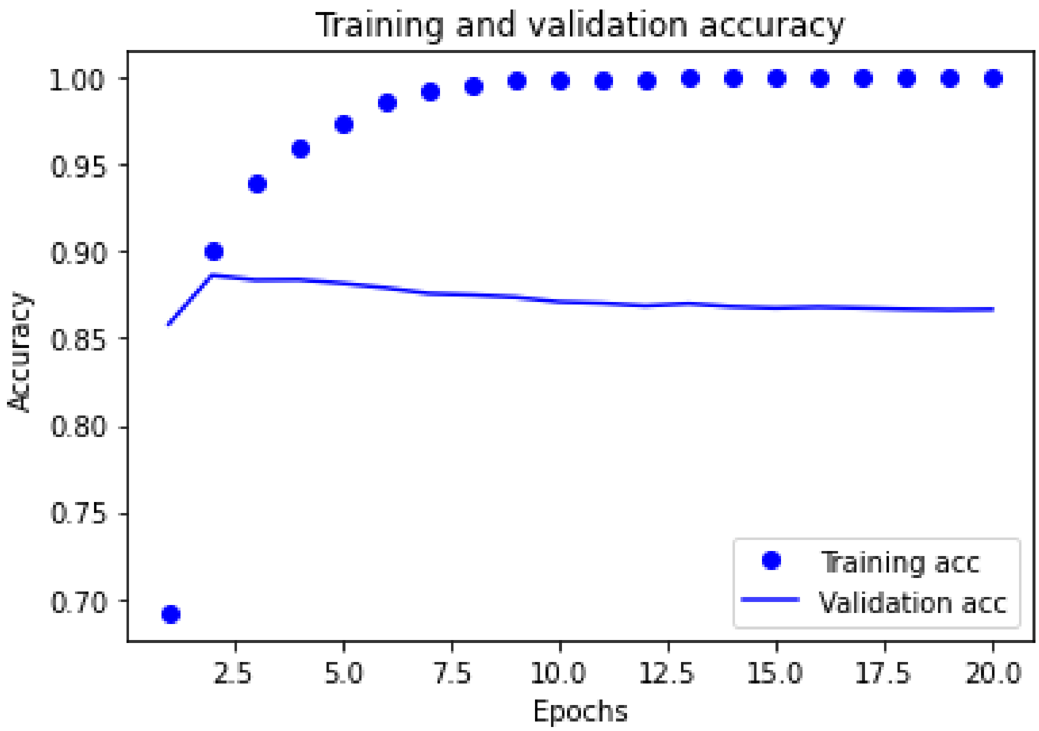

```
historyp1_3 = history1_3.history
loss_values3 = historyp1_3["loss"]
val_loss_values3 = historyp1_3["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values3, "bo", label="Training loss")
plt.plot(epochs, val_loss_values3, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```




```
plt.clf()
acc1 = historyp1_1["accuracy"]
val_acc1 = historyp1_1["val_accuracy"]
plt.plot(epochs, acc1, "bo", label="Training acc")
plt.plot(epochs, val_acc1, "b", label="Validation acc")
plt.title("Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```




```
plt.clf()
acc3 = historyp1_3["accuracy"]
val_acc3 = historyp1_3["val_accuracy"]
plt.plot(epochs, acc3, "bo", label="Training acc")
plt.plot(epochs, val_acc3, "b", label="Validation acc")
plt.title("Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



When only one hidden layer is used, validation accuracy begins to decline after the fourth epoch while training accuracy continues to rise. The training loss clearly shows a decreasing trend in the graph, whereas the validation loss initially decreased but increased after the fifth epoch, indicating overfitting. When using three hidden layers, accuracy increased for two epochs and then began to fluctuate. Adding more layers resulted in less accuracy.

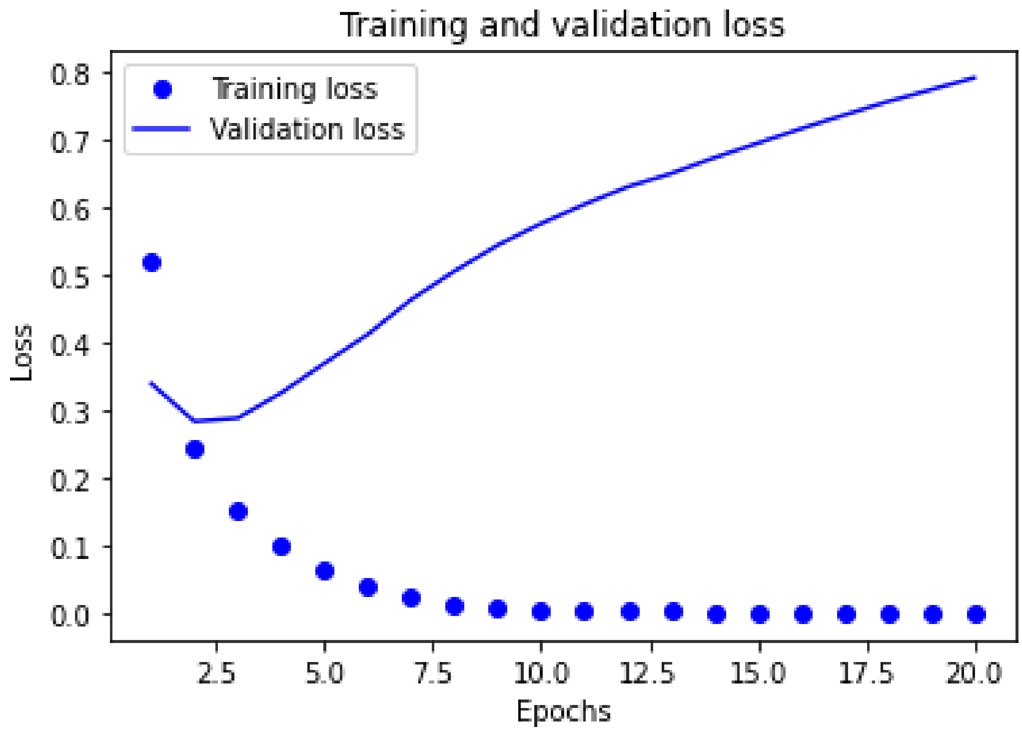
####2 For the hidden layers we are using nodes 32 units, 64 units

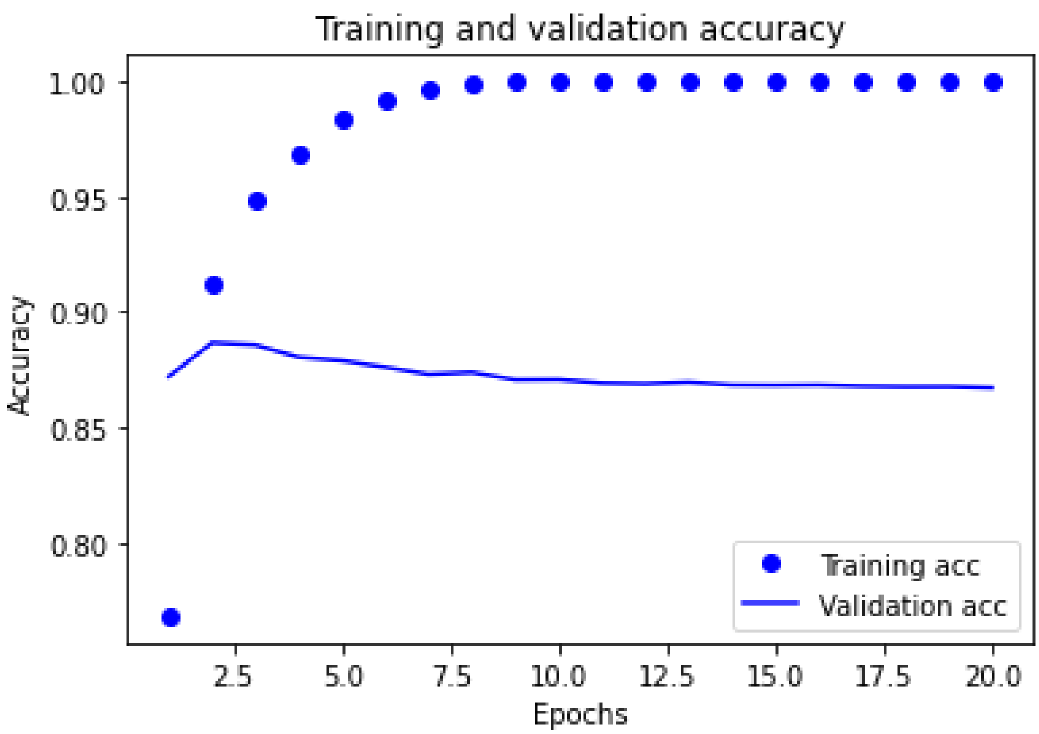
```
model2 = keras.Sequential([
    layers.Dense(32, activation="relu"),
    layers.Dense(64, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])

model2.compile(optimizer="adam",
              loss="binary_crossentropy",
              metrics=["accuracy"])

hist2 = model2.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))

Epoch 1/20
30/30 [==============================] - 2s 56ms/step - loss: 0.5203 -
accuracy: 0.7681 - val_loss: 0.3393 - val_accuracy: 0.8720
```

```
Epoch 2/20
30/30 [==============================] - 2s 73ms/step - loss: 0.2428 -
accuracy: 0.9117 - val_loss: 0.2833 - val_accuracy: 0.8866
Epoch 3/20
30/30 [==============================] - 2s 63ms/step - loss: 0.1513 -
accuracy: 0.9488 - val_loss: 0.2885 - val_accuracy: 0.8857
Epoch 4/20
30/30 [==============================] - 1s 46ms/step - loss: 0.1012 -
accuracy: 0.9691 - val_loss: 0.3255 - val_accuracy: 0.8804
Epoch 5/20
30/30 [==============================] - 1s 46ms/step - loss: 0.0655 -
accuracy: 0.9837 - val_loss: 0.3693 - val_accuracy: 0.8789
Epoch 6/20
30/30 [==============================] - 1s 48ms/step - loss: 0.0407 -
accuracy: 0.9921 - val_loss: 0.4121 - val_accuracy: 0.8761
Epoch 7/20
30/30 [==============================] - 1s 46ms/step - loss: 0.0233 -
accuracy: 0.9970 - val_loss: 0.4634 - val_accuracy: 0.8730
Epoch 8/20
30/30 [==============================] - 1s 46ms/step - loss: 0.0138 -
accuracy: 0.9995 - val_loss: 0.5055 - val_accuracy: 0.8738
Epoch 9/20
30/30 [==============================] - 1s 45ms/step - loss: 0.0085 -
accuracy: 0.9999 - val_loss: 0.5438 - val_accuracy: 0.8706
Epoch 10/20
30/30 [==============================] - 1s 46ms/step - loss: 0.0058 -
accuracy: 0.9999 - val_loss: 0.5758 - val_accuracy: 0.8707
Epoch 11/20
30/30 [==============================] - 1s 46ms/step - loss: 0.0041 -
accuracy: 0.9999 - val_loss: 0.6041 - val_accuracy: 0.8691
Epoch 12/20
30/30 [==============================] - 1s 45ms/step - loss: 0.0032 -
accuracy: 0.9999 - val_loss: 0.6301 - val_accuracy: 0.8688
Epoch 13/20
30/30 [==============================] - 1s 46ms/step - loss: 0.0025 -
accuracy: 0.9999 - val_loss: 0.6497 - val_accuracy: 0.8695
Epoch 14/20
30/30 [==============================] - 1s 46ms/step - loss: 0.0020 -
accuracy: 0.9999 - val_loss: 0.6729 - val_accuracy: 0.8683
Epoch 15/20
30/30 [==============================] - 1s 44ms/step - loss: 0.0016 -
accuracy: 0.9999 - val_loss: 0.6946 - val_accuracy: 0.8682
Epoch 16/20
30/30 [==============================] - 1s 45ms/step - loss: 0.0013 -
accuracy: 0.9999 - val_loss: 0.7159 - val_accuracy: 0.8683
Epoch 17/20
30/30 [==============================] - 1s 44ms/step - loss: 0.0010 -
accuracy: 0.9999 - val_loss: 0.7361 - val_accuracy: 0.8678
Epoch 18/20
30/30 [==============================] - 1s 44ms/step - loss: 8.5970e-
```

```
04 - accuracy: 0.9999 - val_loss: 0.7559 - val_accuracy: 0.8676
Epoch 19/20
30/30 [==============================] - 1s 44ms/step - loss: 6.8974e-
04 - accuracy: 1.0000 - val_loss: 0.7734 - val_accuracy: 0.8676
Epoch 20/20
30/30 [==============================] - 1s 44ms/step - loss: 5.7515e-
04 - accuracy: 1.0000 - val_loss: 0.7912 - val_accuracy: 0.8671
```

```
histp2 = hist2.history
loss_values = histp2["loss"]
val_loss_values = histp2["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, "bo", label="Training loss")
plt.plot(epochs, val_loss_values, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()

plt.clf()
acc = histp2["accuracy"]
val_acc = histp2["val_accuracy"]
plt.plot(epochs, acc, "bo", label="Training acc")
plt.plot(epochs, val_acc, "b", label="Validation acc")
plt.title("Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```





Trraining loss is studied less during the training phase, whereas validation loss is studied more from the third epoch. Validation accuracy increased after the third epoch and gradually decreased after that. Increasing the number of nodes in the network resulted in a decrease in accuracy.

#3 using the mse loss function instead of binary_crossentropy.

```
model3 = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
```

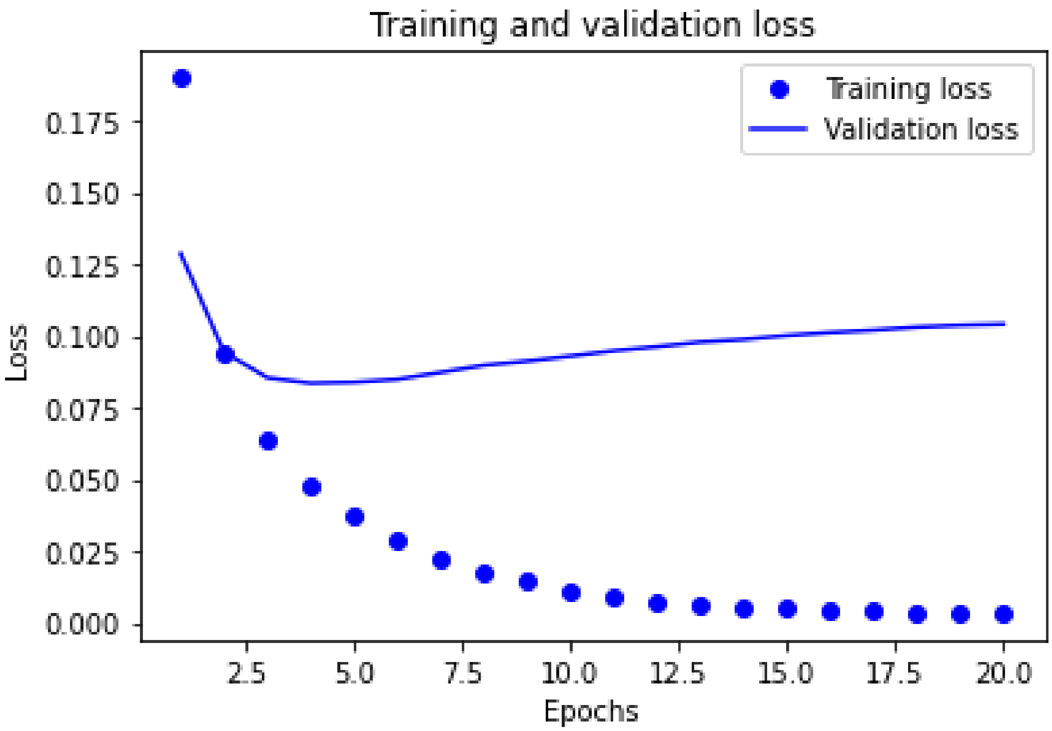
```
#So Here, I used the MSE loss function instead of the binary cross
entropy that he has previously used.
model3.compile(optimizer="adam",
              loss="mse",
              metrics=["accuracy"])
```

```
hist3 = model3.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

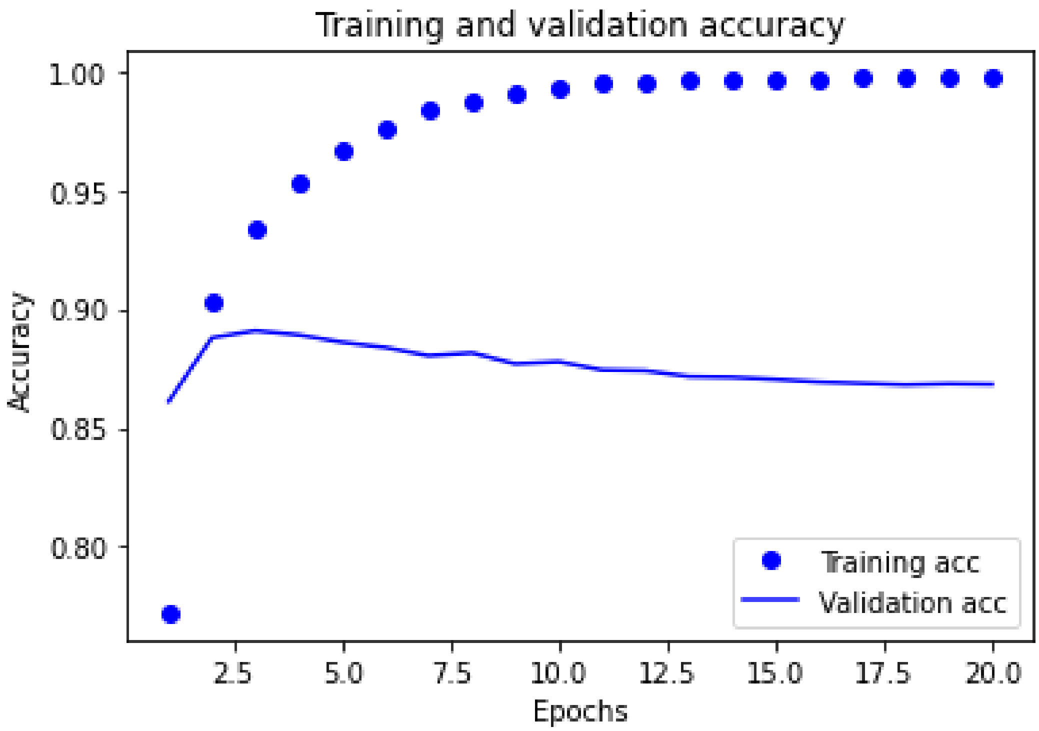
```
Epoch 1/20
30/30 [==============================] - 2s 54ms/step - loss: 0.1900 -
accuracy: 0.7722 - val_loss: 0.1287 - val_accuracy: 0.8611
Epoch 2/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0943 -
accuracy: 0.9025 - val_loss: 0.0943 - val_accuracy: 0.8879
Epoch 3/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0637 -
accuracy: 0.9342 - val_loss: 0.0854 - val_accuracy: 0.8909
Epoch 4/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0476 -
accuracy: 0.9530 - val_loss: 0.0835 - val_accuracy: 0.8891
Epoch 5/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0369 -
accuracy: 0.9665 - val_loss: 0.0838 - val_accuracy: 0.8860
Epoch 6/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0288 -
accuracy: 0.9757 - val_loss: 0.0849 - val_accuracy: 0.8838
Epoch 7/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0224 -
accuracy: 0.9833 - val_loss: 0.0873 - val_accuracy: 0.8803
Epoch 8/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0178 -
accuracy: 0.9876 - val_loss: 0.0897 - val_accuracy: 0.8815
Epoch 9/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0144 -
accuracy: 0.9910 - val_loss: 0.0912 - val_accuracy: 0.8769
Epoch 10/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0112 -
accuracy: 0.9931 - val_loss: 0.0929 - val_accuracy: 0.8778
Epoch 11/20
```

```
30/30 [==============================] - 1s 38ms/step - loss: 0.0088 -
accuracy: 0.9947 - val_loss: 0.0948 - val_accuracy: 0.8743
Epoch 12/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0072 -
accuracy: 0.9954 - val_loss: 0.0962 - val_accuracy: 0.8740
Epoch 13/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0061 -
accuracy: 0.9962 - val_loss: 0.0978 - val_accuracy: 0.8716
Epoch 14/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0054 -
accuracy: 0.9965 - val_loss: 0.0988 - val_accuracy: 0.8713
Epoch 15/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0048 -
accuracy: 0.9967 - val_loss: 0.1002 - val_accuracy: 0.8704
Epoch 16/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0043 -
accuracy: 0.9968 - val_loss: 0.1012 - val_accuracy: 0.8693
Epoch 17/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0040 -
accuracy: 0.9969 - val_loss: 0.1020 - val_accuracy: 0.8687
Epoch 18/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0038 -
accuracy: 0.9970 - val_loss: 0.1031 - val_accuracy: 0.8681
Epoch 19/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0036 -
accuracy: 0.9972 - val_loss: 0.1037 - val_accuracy: 0.8685
Epoch 20/20
30/30 [==============================] - 1s 38ms/step - loss: 0.0034 -
accuracy: 0.9972 - val_loss: 0.1041 - val_accuracy: 0.8683
```

```python
histp3 = hist3.history
loss_values = histp3["loss"]
val_loss_values = histp3["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, "bo", label="Training loss")
plt.plot(epochs, val_loss_values, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```




```
plt.clf()
acc = histp3["accuracy"]
val_acc = histp3["val_accuracy"]
plt.plot(epochs, acc, "bo", label="Training acc")
plt.plot(epochs, val_acc, "b", label="Validation acc")
plt.title("Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



When SME is used instead of binary crossentropy, accuracy is more stable. Training and validation loss showed a similar trend until two epochs, when there is a significant difference. Validation accuracy began to decline after the fourth epoch when MSE was used as the loss function.

#4 I am using tanh activation instead of relu.

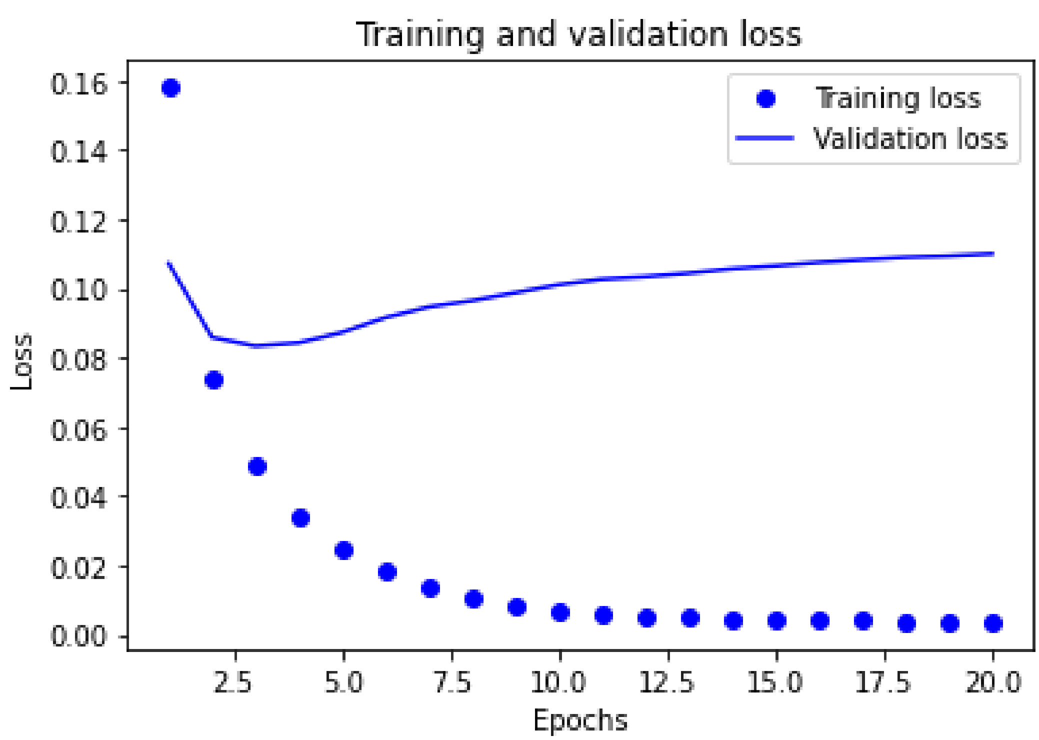
```
model4 = keras.Sequential([
    layers.Dense(16, activation="tanh"),
    layers.Dense(16, activation="tanh"),
    layers.Dense(1, activation="sigmoid")
])

model4.compile(optimizer="adam",
              loss="mse",
              metrics=["accuracy"])

hist4 = model4.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/20
30/30 [==============================] - 2s 45ms/step - loss: 0.1580 -
accuracy: 0.7921 - val_loss: 0.1071 - val_accuracy: 0.8664
Epoch 2/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0738 -
```

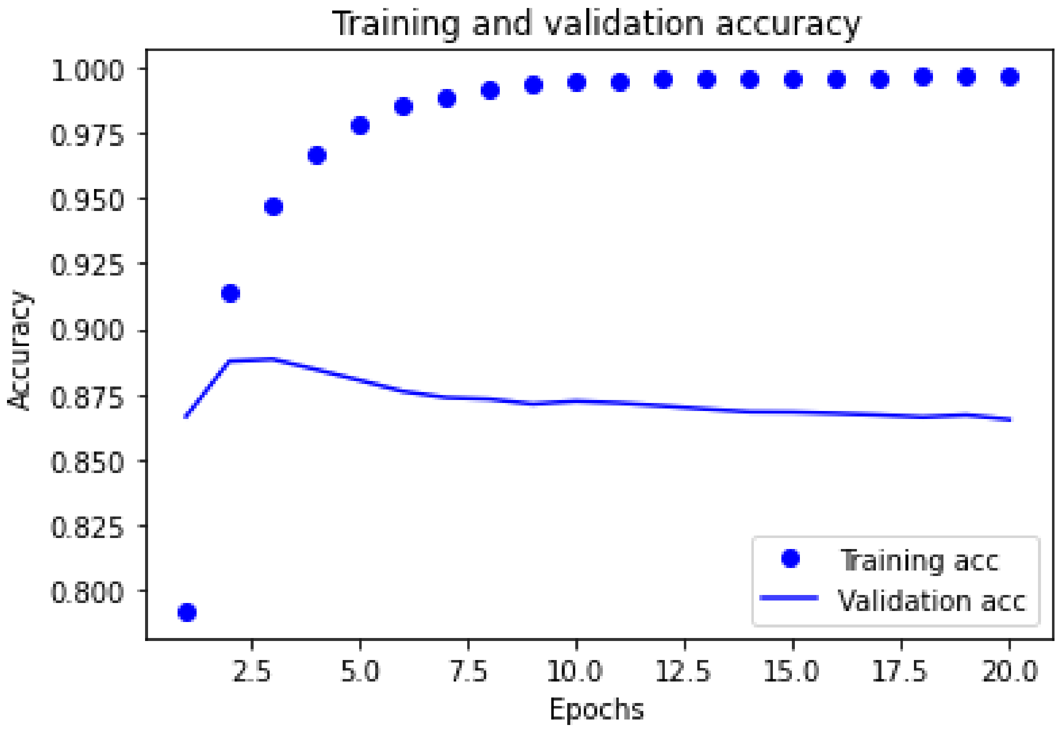
```
accuracy: 0.9142 - val_loss: 0.0858 - val_accuracy: 0.8876
Epoch 3/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0491 -
accuracy: 0.9473 - val_loss: 0.0833 - val_accuracy: 0.8884
Epoch 4/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0344 -
accuracy: 0.9671 - val_loss: 0.0842 - val_accuracy: 0.8844
Epoch 5/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0250 -
accuracy: 0.9782 - val_loss: 0.0873 - val_accuracy: 0.8803
Epoch 6/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0187 -
accuracy: 0.9853 - val_loss: 0.0915 - val_accuracy: 0.8761
Epoch 7/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0140 -
accuracy: 0.9891 - val_loss: 0.0946 - val_accuracy: 0.8737
Epoch 8/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0108 -
accuracy: 0.9921 - val_loss: 0.0964 - val_accuracy: 0.8731
Epoch 9/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0086 -
accuracy: 0.9937 - val_loss: 0.0987 - val_accuracy: 0.8712
Epoch 10/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0071 -
accuracy: 0.9948 - val_loss: 0.1010 - val_accuracy: 0.8723
Epoch 11/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0063 -
accuracy: 0.9951 - val_loss: 0.1026 - val_accuracy: 0.8716
Epoch 12/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0056 -
accuracy: 0.9956 - val_loss: 0.1033 - val_accuracy: 0.8705
Epoch 13/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0052 -
accuracy: 0.9957 - val_loss: 0.1043 - val_accuracy: 0.8693
Epoch 14/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0048 -
accuracy: 0.9959 - val_loss: 0.1056 - val_accuracy: 0.8682
Epoch 15/20
30/30 [==============================] - 1s 38ms/step - loss: 0.0045 -
accuracy: 0.9961 - val_loss: 0.1065 - val_accuracy: 0.8681
Epoch 16/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0043 -
accuracy: 0.9962 - val_loss: 0.1074 - val_accuracy: 0.8676
Epoch 17/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0041 -
accuracy: 0.9963 - val_loss: 0.1082 - val_accuracy: 0.8670
Epoch 18/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0039 -
accuracy: 0.9965 - val_loss: 0.1089 - val_accuracy: 0.8662
Epoch 19/20
```

```
30/30 [==============================] - 1s 37ms/step - loss: 0.0038 -
accuracy: 0.9965 - val_loss: 0.1093 - val_accuracy: 0.8670
Epoch 20/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0037 -
accuracy: 0.9966 - val_loss: 0.1099 - val_accuracy: 0.8653
```

```
histp4 = hist4.history
loss_values = histp4["loss"]
val_loss_values = histp4["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, "bo", label="Training loss")
plt.plot(epochs, val_loss_values, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()

plt.clf()
acc = histp4["accuracy"]
val_acc = histp4["val_accuracy"]
plt.plot(epochs, acc, "bo", label="Training acc")
plt.plot(epochs, val_acc, "b", label="Validation acc")
plt.title("Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
```



```
<matplotlib.legend.Legend at 0x7fc36dc7de50>
```



While training accuracy increased, validation accuracy increased until the second epoch and then declined. Validation loss increased more when ReLu was used than Tanh, and validation accuracy fluctuated more in ReLu than Tanh.

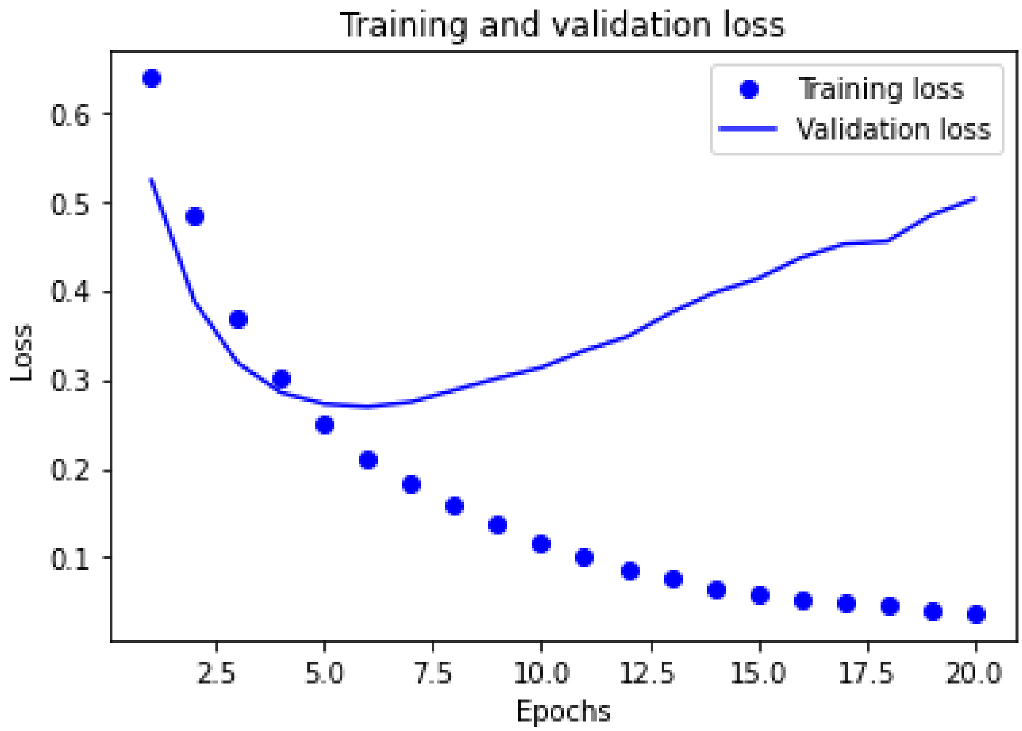
#5 In our network I am using Dropout Technique.

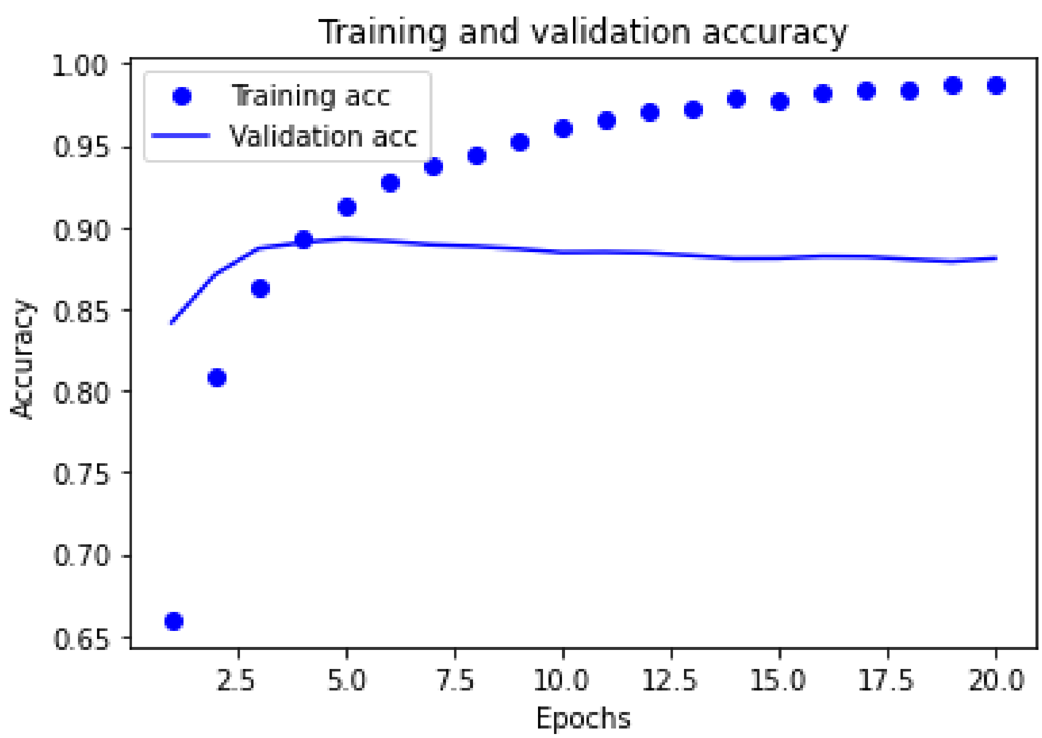
```
#I am using the dropout method with two hidden layers that have the
ReLu activation function.
from tensorflow import keras
from tensorflow.keras import layers
model5 = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dropout(0.5),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])

model5.compile(optimizer="adam",
              loss="binary_crossentropy",
              metrics=["accuracy"])

hist5 = model5.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/20
30/30 [==============================] - 2s 46ms/step - loss: 0.6380 -
accuracy: 0.6597 - val_loss: 0.5233 - val_accuracy: 0.8416
Epoch 2/20
30/30 [==============================] - 1s 37ms/step - loss: 0.4824 -
accuracy: 0.8091 - val_loss: 0.3869 - val_accuracy: 0.8708
Epoch 3/20
30/30 [==============================] - 1s 37ms/step - loss: 0.3696 -
accuracy: 0.8639 - val_loss: 0.3180 - val_accuracy: 0.8868
Epoch 4/20
30/30 [==============================] - 1s 37ms/step - loss: 0.3010 -
accuracy: 0.8924 - val_loss: 0.2849 - val_accuracy: 0.8904
Epoch 5/20
30/30 [==============================] - 1s 38ms/step - loss: 0.2504 -
accuracy: 0.9128 - val_loss: 0.2721 - val_accuracy: 0.8925
Epoch 6/20
30/30 [==============================] - 1s 37ms/step - loss: 0.2099 -
accuracy: 0.9283 - val_loss: 0.2690 - val_accuracy: 0.8911
Epoch 7/20
30/30 [==============================] - 1s 37ms/step - loss: 0.1825 -
accuracy: 0.9373 - val_loss: 0.2743 - val_accuracy: 0.8891
Epoch 8/20
30/30 [==============================] - 1s 36ms/step - loss: 0.1580 -
accuracy: 0.9447 - val_loss: 0.2878 - val_accuracy: 0.8881
Epoch 9/20
30/30 [==============================] - 1s 37ms/step - loss: 0.1379 -
accuracy: 0.9522 - val_loss: 0.3011 - val_accuracy: 0.8866
Epoch 10/20
30/30 [==============================] - 1s 37ms/step - loss: 0.1171 -
accuracy: 0.9603 - val_loss: 0.3130 - val_accuracy: 0.8844
Epoch 11/20
30/30 [==============================] - 1s 37ms/step - loss: 0.1002 -
accuracy: 0.9665 - val_loss: 0.3320 - val_accuracy: 0.8846
Epoch 12/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0872 -
accuracy: 0.9701 - val_loss: 0.3478 - val_accuracy: 0.8841
Epoch 13/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0762 -
accuracy: 0.9720 - val_loss: 0.3746 - val_accuracy: 0.8825
Epoch 14/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0642 -
accuracy: 0.9785 - val_loss: 0.3971 - val_accuracy: 0.8806
Epoch 15/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0596 -
accuracy: 0.9780 - val_loss: 0.4126 - val_accuracy: 0.8807
Epoch 16/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0525 -
accuracy: 0.9824 - val_loss: 0.4362 - val_accuracy: 0.8820
Epoch 17/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0492 -
```

```
accuracy: 0.9835 - val_loss: 0.4516 - val_accuracy: 0.8818
Epoch 18/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0469 -
accuracy: 0.9833 - val_loss: 0.4547 - val_accuracy: 0.8802
Epoch 19/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0403 -
accuracy: 0.9865 - val_loss: 0.4839 - val_accuracy: 0.8788
Epoch 20/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0379 -
accuracy: 0.9869 - val_loss: 0.5021 - val_accuracy: 0.8807
```

```
#Creating training vs. validation graphs Training vs. validation
accuracy and loss
import matplotlib.pyplot as plt
histp5 = hist5.history
loss_values = histp5["loss"]
val_loss_values = histp5["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, "bo", label="Training loss")
plt.plot(epochs, val_loss_values, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()

plt.clf()
acc = histp5["accuracy"]
val_acc = histp5["val_accuracy"]
plt.plot(epochs, acc, "bo", label="Training acc")
plt.plot(epochs, val_acc, "b", label="Validation acc")
plt.title("Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```





Training accuracy steadily increased, whereas validation accuracy increased until 8 epochs and then nearly decreased. Using the dropout technique, accuracy improved over many epochs, and the graph showed no significant change in validation accuracy.