Importing the required libraries

```
import matplotlib
import matplotlib.pyplot as plt
import numpy as np
from keras import models
from keras import layers
```

Loading the IMDB dataset using tensorflow and keras

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

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.n
17465344/17464789 [==============================] - 0s 0us/step
17473536/17464789 [==============================] - 0s 0us/step
```

```
train_data[0]
```

```
 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]
```

```
train_labels[0]
```

```
1
```

Decoding reviews back to 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]])
```

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

We'll use One-hot Encoding to turn our lists into vectors of 0s and 1s in order to prepare our data. Every one of our sequences would be multiplied by 10,000, with 1 at all indexes linking all integers in the sequence. This vector will contain the element 0 for any indices that are not in integer sequence.

Each review will be represented by a 10,000-dimensional vector.

Vectorized the dataset

(len(sequences), dimension) and Sets specific indices of results[i] to 1s

```
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
```

Vectorizing Training and Test Dataset

```
x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)
y_train = np.asarray(train_labels).astype("float32")
y_test = np.asarray(test_labels).astype("float32")
```

Building Model

For our model, The relu activation function is used to zero negative values in two intermediate levels, each of which has 16 hidden layers. The output layer, which employs sigmoid activation, will be the third layer.

```
from tensorflow import keras
model = keras.Sequential([
layers.Dense(16, activation="relu"),
layers.Dense(16, activation="relu"),
layers.Dense(1, activation="sigmoid")
])
```

#DB-The vectors in our input dataset had to be transformed to encoder labels (0s and 1s). Note that Dense layers with relu activation operate well. HIDDEN LAYERS- A hidden layer is positioned between the algorithm's input and output in neural networks, and it applies weights to the inputs and directs them through an activation function as the output. In a nutshell, the hidden layers conduct nonlinear changes on the network's inputs.

Model definition

The following routines will be used in this case.

The loss function binary cross entropy is used for binary classification.(We can also use MSE) rmsprop is the optimizer that was employed. Accuracy is the yardstick by which performance is measured.

Binary cross entropy- Each of the projected probabilities is compared to the actual class output, which can be either 0 or 1. The score is then calculated, penalizing the probabilities depending on their deviation from the predicted value. This refers to how close or far the value is to the actual value.

The RMSprop optimizer limits oscillations in the vertical plane. As a result, we may boost our learning rate, allowing our algorithm to take greater horizontal steps and converge faster.

Model Compilation

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

Setting aside a validation set

As the model improves, we'll set aside some of our training data for validation of the model's correctness. Companies can use a validation set to track our model's development as it progresses through epochs during training on previously unseen data.

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

Model Training

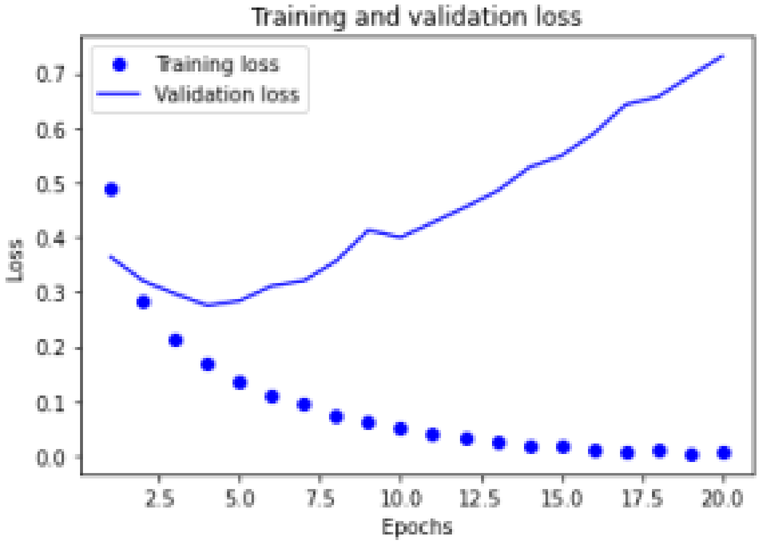
We are training the model with batch size 512 and epochs=20

```
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 46ms/step - loss: 0.4877 - accuracy: 0.7910
Epoch 2/20
30/30 [==============================] - 1s 33ms/step - loss: 0.2841 - accuracy: 0.9082
Epoch 3/20
30/30 [==============================] - 1s 33ms/step - loss: 0.2143 - accuracy: 0.9277
Epoch 4/20
30/30 [==============================] - 1s 33ms/step - loss: 0.1691 - accuracy: 0.9440
Epoch 5/20
30/30 [==============================] - 1s 34ms/step - loss: 0.1365 - accuracy: 0.9559
Epoch 6/20
30/30 [==============================] - 1s 33ms/step - loss: 0.1112 - accuracy: 0.9657
Epoch 7/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0949 - accuracy: 0.9706
Epoch 8/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0748 - accuracy: 0.9796
Epoch 9/20
30/30 [==============================] - 1s 32ms/step - loss: 0.0608 - accuracy: 0.9844
Epoch 10/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0499 - accuracy: 0.9882
Epoch 11/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0410 - accuracy: 0.9901
Epoch 12/20
30/30 [==============================] - 1s 34ms/step - loss: 0.0335 - accuracy: 0.9930
Epoch 13/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0265 - accuracy: 0.9945
Epoch 14/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0175 - accuracy: 0.9981
Epoch 15/20
30/30 [==============================] - 1s 34ms/step - loss: 0.0173 - accuracy: 0.9969
Epoch 16/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0125 - accuracy: 0.9987
Epoch 17/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0086 - accuracy: 0.9995
Epoch 18/20
30/30 [==============================] - 1s 34ms/step - loss: 0.0096 - accuracy: 0.9985
Epoch 19/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0041 - accuracy: 0.9999
Epoch 20/20
 30/30 [==============================] - 1s 32ms/step - loss: 0.0070 - accuracy: 0.9987
```

Plotting of Training and Validation Loss

```
history_dict = history.history
loss_values = history_dict["loss"]
3
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()
```

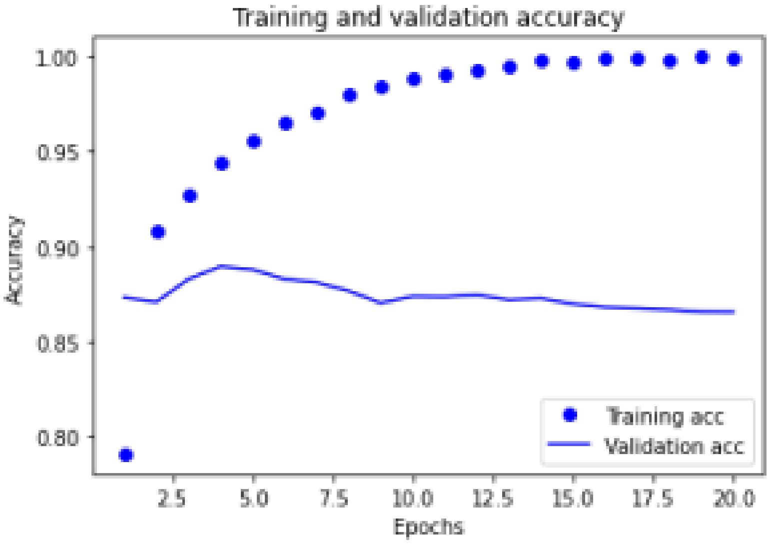


Validation loss started increasing from 3 epochs

Plotting 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()
```



#Summary for validation loss: 16 Nodes 2 layers(relu): Binary Cross Entropy When comparing the Validation loss in Binary Cross Entropy to the Training and Validation loss, I saw that the Validation loss in Binary Cross Entropy has dropped until a certain point and then dramatically increased.

When comparing the Validation accuracy in Binary Cross Entropy to the Training and Validation accuracy, I saw that the validation accuracy decreased and training accuracy increased.

Conclusion- It implies that while the model improves at classifying training data, it consistently produces worse predictions when it encounters new and unknown data, indicating that it is overfitting. After the fifth epoch, the model begins to resemble the training data too closely.

Retraining Model from begining

```
model = keras.Sequential([
layers.Dense(16, activation="relu"),
layers.Dense(16, activation="relu"),
layers.Dense(1, activation="sigmoid")
])
model.compile(optimizer="rmsprop",
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 [==============================] - 2s 26ms/step - loss: 0.4468 - accuracy: 0.8151
Epoch 2/4
49/49 [==============================] - 1s 26ms/step - loss: 0.2546 - accuracy: 0.9094
Epoch 3/4
49/49 [==============================] - 1s 27ms/step - loss: 0.1942 - accuracy: 0.9305
Epoch 4/4
49/49 [==============================] - 1s 26ms/step - loss: 0.1627 - accuracy: 0.9413
782/782 [==============================] - 3s 3ms/step - loss: 0.3160 - accuracy: 0.8759
```

Here we have used epocs=4 for training the data.

```
results
```

```
[0.31600797176361084, 0.8759199976921082]
```

ASSIGNMENT

1.You used two hidden layers. Try using one or three hidden layers, and see how doing so affects validation and test accuracy.

#model_1 is build with 3 layers of relu activation function and model_2 with 1 layers of relu activation function

```
model_1 = keras.Sequential([
layers.Dense(16, activation="relu"),
layers.Dense(16, activation="relu"),
layers.Dense(16, activation="relu"),
layers.Dense(1, activation="sigmoid")
])
model_2 = keras.Sequential([
layers.Dense(16, activation="relu"),
layers.Dense(1, activation="sigmoid")
])
```

#Using optimizer rmsprop and loss function binary crossentrophy for

calculating both the model [model_1(3layers), model_2(1layer)]

```
model_1.compile(optimizer="rmsprop",
```

```
loss="binary_crossentropy",
metrics=["accuracy"])
model_2.compile(optimizer="rmsprop",
loss="binary_crossentropy",
metrics=["accuracy"])
```

Model Training is done with epocs= 20

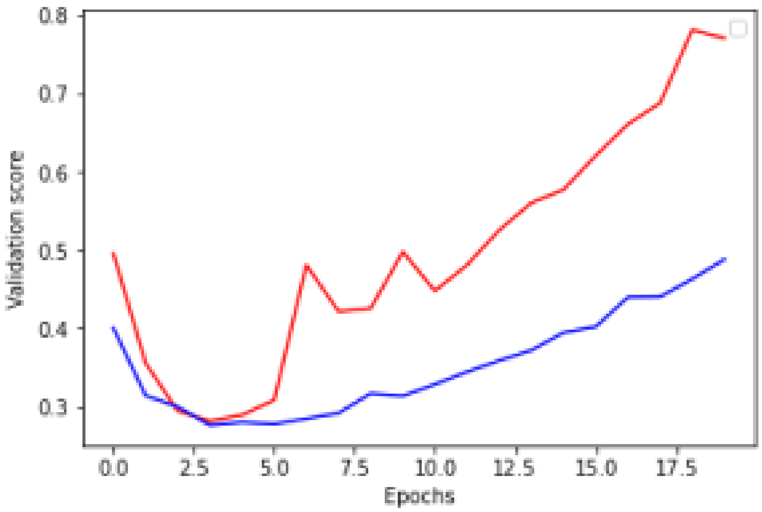
```
history_1 = model_1.fit(partial_x_train,
partial_y_train,
epochs=20,
batch_size=512,
validation_data=(x_val, y_val))
history_2 = model_2.fit(partial_x_train,
partial_y_train,
epochs=20,
batch_size=512,
validation_data=(x_val, y_val))

model 1 summary()
model_1.summary()
model_2.summary()
```

```
30/30 [ ] 1s 34ms/step loss: 0.1243 accuracy: 0.96 Epoch 8/20
30/30 [==============================] - 1s 40ms/step - loss: 0.1100 - accuracy: 0.96
Epoch 9/20
30/30 [==============================] - 2s 50ms/step - loss: 0.0955 - accuracy: 0.97
Epoch 10/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0850 - accuracy: 0.97
Epoch 11/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0744 - accuracy: 0.98
Epoch 12/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0662 - accuracy: 0.98
Epoch 13/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0585 - accuracy: 0.98
Epoch 14/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0521 - accuracy: 0.98
Epoch 15/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0453 - accuracy: 0.99
Epoch 16/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0397 - accuracy: 0.99
Epoch 17/20
30/30 [==============================] - 1s 34ms/step - loss: 0.0349 - accuracy: 0.99
Epoch 18/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0308 - accuracy: 0.99
Epoch 19/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0262 - accuracy: 0.99
Epoch 20/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0236 - accuracy: 0.99
Model: "sequential_2"
_________________________________________________________________
```

```
 Layer (type) Output Shape Param #
=================================================================
 dense_6 (Dense) (None, 16) 160016

 dense_7 (Dense) (None, 16) 272

 dense_8 (Dense) (None, 16) 272

 dense_9 (Dense) (None, 1) 17

=================================================================
Total params: 160,577
Trainable params: 160,577
Non-trainable params: 0
_________________________________________________________________
Model: "sequential_3"
_________________________________________________________________
 Layer (type) Output Shape Param #
=================================================================
 dense_10 (Dense) (None, 16) 160016

 dense_11 (Dense) (None, 1) 17

=================================================================
Total params: 160,033
      p ,
Trainable params: 160,033
Non-trainable params: 0
_________________________________________________________________
```

Plotting the training and validation loss

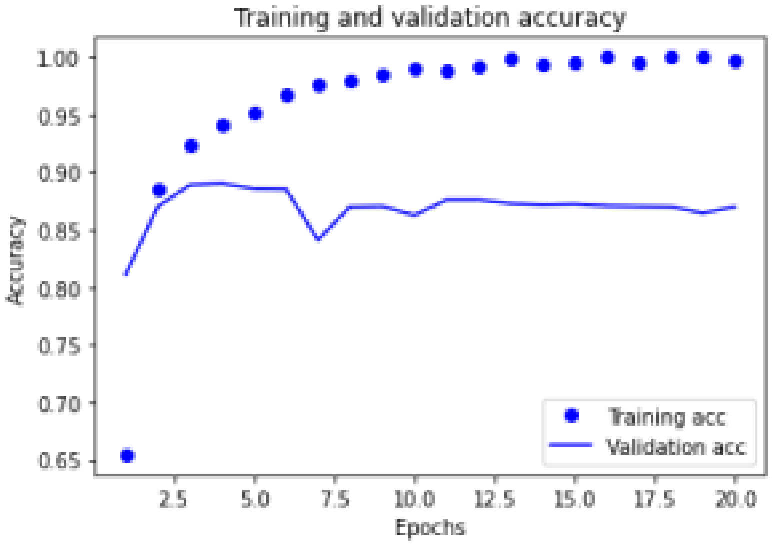
```
history_dict_1 = history_1.history
history_dict_2 = history_2.history
plt.plot(history_1.history['val_loss'], 'r', history_2.history['val_loss'], 'b')
plt.xlabel('Epochs')
plt.ylabel('Validation score')
plt.legend()
```



here the validation loss is at 5 epochs

Plotting Training and Validation accuracy

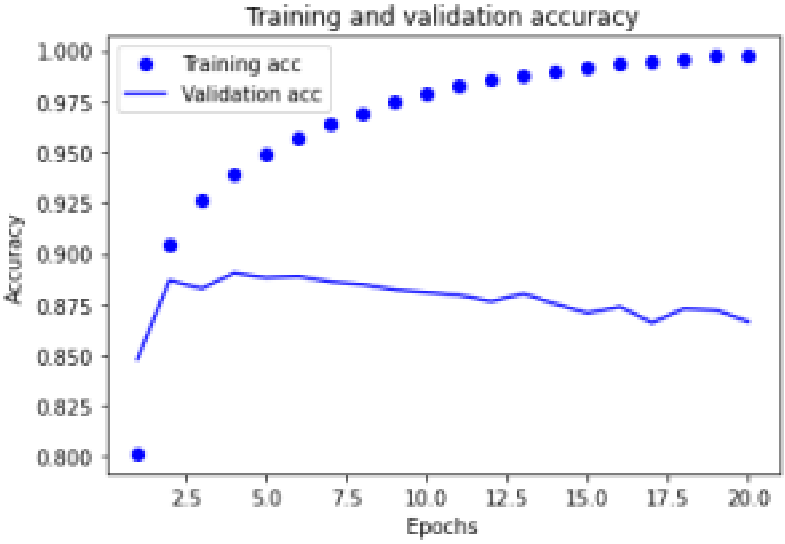
```
plt.clf()
acc = history_dict_1["accuracy"]
val_acc = history_dict_1["val_accuracy"]
plt.plot(epochs, acc, "bo", label="Training acc")
10
plt.plot(epochs, val_acc, "b", label="Validation acc")
plt.title("Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



here the validation accuracy is at 5 Epochs

plot_loss

```
 plt.clf()
acc = history_dict_2["accuracy"]
val_acc = history_dict_2["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()
```



Here, the maximum validation accuracy is observed at 5th epoch.

2. Try using layers with more hidden units or fewer hidden units: 32 units, 64 units, and so on.

```
model_3 = keras.Sequential([
layers.Dense(32, activation="relu"),
layers.Dense(64, activation="relu"),
layers.Dense(1, activation="sigmoid")
])
```

#We are using rmsprop and binary cross-entropy

```
model_3.compile(optimizer="rmsprop",
loss="binary_crossentropy",
metrics=["accuracy"])
```

#Here we have taken epochs= 20, and batch size=512 to fit the model

```
history_3 = model_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 54ms/step - loss: 0.5002 - accuracy: 0.7712
     Epoch 2/20
     30/30 [==============================] - 1s 42ms/step - loss: 0.2675 - accuracy: 0.9085
     Epoch 3/20
     30/30 [==============================] - 1s 44ms/step - loss: 0.1993 - accuracy: 0.9291
     Epoch 4/20
     30/30 [==============================] - 1s 43ms/step - loss: 0.1551 - accuracy: 0.9439
     Epoch 5/20
     30/30 [==============================] - 1s 42ms/step - loss: 0.1175 - accuracy: 0.9621
     Epoch 6/20
     30/30 [==============================] - 1s 42ms/step - loss: 0.0867 - accuracy: 0.9737
     Epoch 7/20
     30/30 [==============================] - 1s 43ms/step - loss: 0.0730 - accuracy: 0.9765
     Epoch 8/20
     30/30 [==============================] - 1s 41ms/step - loss: 0.0472 - accuracy: 0.9874
     Epoch 9/20
     30/30 [==============================] - 1s 42ms/step - loss: 0.0367 - accuracy: 0.9898
     Epoch 10/20
     30/30 [==============================] - 1s 42ms/step - loss: 0.0296 - accuracy: 0.9926
     Epoch 11/20
     30/30 [==============================] - 1s 43ms/step - loss: 0.0258 - accuracy: 0.9926
     Epoch 12/20
     30/30 [==============================] - 1s 43ms/step - loss: 0.0088 - accuracy: 0.9993
     Epoch 13/20
     30/30 [==============================] - 1s 42ms/step - loss: 0.0124 - accuracy: 0.9970
     Epoch 14/20
     30/30 [==============================] - 1s 42ms/step - loss: 0.0234 - accuracy: 0.9928
     Epoch 15/20
     30/30 [==============================] - 1s 42ms/step - loss: 0.0026 - accuracy: 0.9999
     Epoch 16/20
     30/30 [==============================] - 1s 42ms/step - loss: 0.0024 - accuracy: 0.9997
     Epoch 17/20
     30/30 [==============================] - 1s 42ms/step - loss: 0.0017 - accuracy: 1.0000
     Epoch 18/20
     30/30 [==============================] - 1s 41ms/step - loss: 0.0197 - accuracy: 0.9947
     Epoch 19/20
     30/30 [==============================] - 1s 43ms/step - loss: 4.8248e-04 - accuracy: 1.0
     Epoch 20/20
```

```
30/30 [==============================] - 1s 42ms/step - loss: 3.5065e-04 - accuracy: 1.0
```

```
model_3.summary()
```

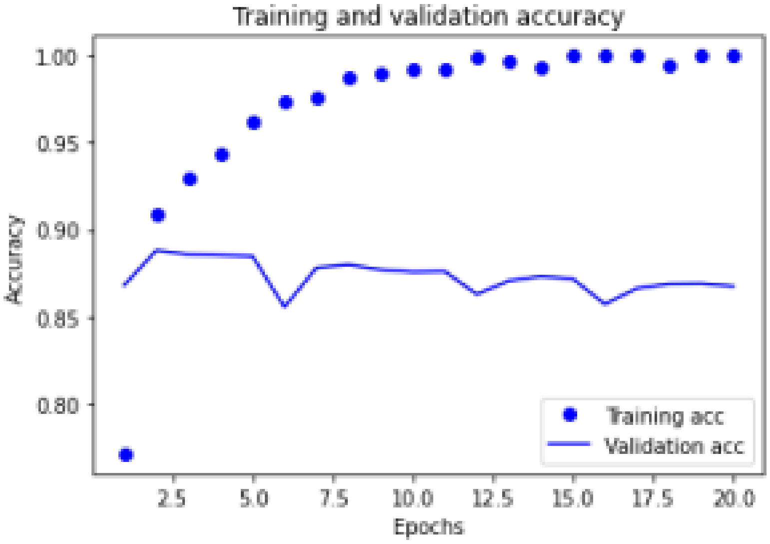
```
Model: "sequential_4"

 Layer (type) Output Shape Param #
=================================================================
 dense_12 (Dense) (None, 32) 320032

 dense_13 (Dense) (None, 64) 2112

 dense_14 (Dense) (None, 1) 65

=================================================================
Total params: 322,209
Trainable params: 322,209
Non-trainable params: 0
```

```
history_dict_3 = history_3.history
```

```
loss_values = history_dict_3["loss"]
val_loss_values = history_dict_3["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 = history_dict_3["accuracy"]
```

```
val_acc = history_dict_3["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()
```



The minimum validation loss is observed at 2.5th epoch and maximum validation accuracy is observed between 2.5th and 3rd epochs.

3.Try using the 'mse' loss function instead of 'binary_crossentropy’

```
model_4 = keras.Sequential([
layers.Dense(16, activation="relu"),
layers.Dense(16, activation="relu"),
layers.Dense(1, activation="sigmoid")
])
```

We are using rmsprop and mse

```
model_4.compile(optimizer="rmsprop",
loss="mse",
metrics=["accuracy"])
```

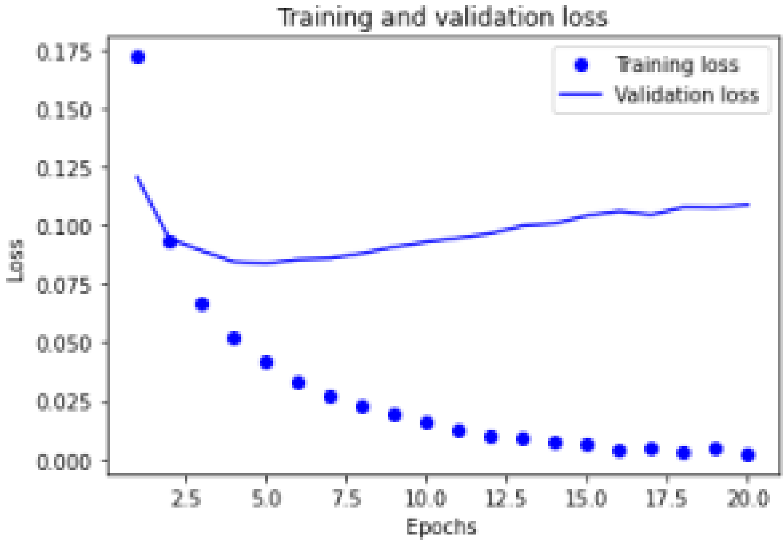
Training your model

```
history_4 = model_4.fit(partial_x_train,
partial_y_train,
epochs=20,
b t h i 512
batch_size=512,
validation_data=(x_val, y_val))
```

```
Epoch 1/20
30/30 [==============================] - 2s 50ms/step - loss: 0.1720 - accuracy: 0.7875
Epoch 2/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0931 - accuracy: 0.9063
Epoch 3/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0670 - accuracy: 0.9281
Epoch 4/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0517 - accuracy: 0.9457
Epoch 5/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0419 - accuracy: 0.9552
Epoch 6/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0336 - accuracy: 0.9657
Epoch 7/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0274 - accuracy: 0.9746
Epoch 8/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0228 - accuracy: 0.9793
Epoch 9/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0192 - accuracy: 0.9825
Epoch 10/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0159 - accuracy: 0.9868
Epoch 11/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0126 - accuracy: 0.9907
Epoch 12/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0099 - accuracy: 0.9929
Epoch 13/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0089 - accuracy: 0.9931
Epoch 14/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0075 - accuracy: 0.9940
Epoch 15/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0063 - accuracy: 0.9949
Epoch 16/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0042 - accuracy: 0.9970
Epoch 17/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0052 - accuracy: 0.9955
Epoch 18/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0031 - accuracy: 0.9975
Epoch 19/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0045 - accuracy: 0.9958
Epoch 20/20
 30/30 [==============================] - 1s 35ms/step - loss: 0.0024 - accuracy: 0.9979
```

```
history_dict_4 = history_4.history
loss_values = history_dict_4["loss"]
val_loss_values = history_dict_4["val_loss"]
```

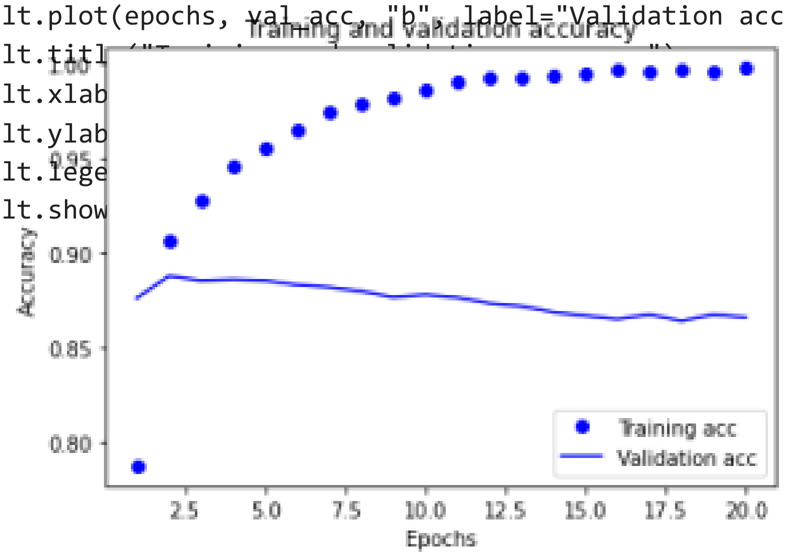
```
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, "bo", label="Training loss")
plt.plot(epochs, val_loss_values, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



Here, the minimum validation loss is observed in 3rd epoch

Plotting the training and validation accuracy

```
plt.clf()
acc = history_dict_4["accuracy"]
val_acc = history_dict_4["val_accuracy"]
plt.plot(epochs, acc, "bo", label="Training acc")
plt.plot(epochs, val_acc, "b", label="Validation acc")
plt.titl
plt.xlab
plt.ylab
plt.lege
plt.show
```



Here, the maximum accuracy is observed in 2nd and 3rd epochs.

4.Try using the tanh activation (an activation that was popular in the early days of neural networks) instead of 'relu'

```
model_5 = keras.Sequential([
layers.Dense(16, activation="tanh"),
layers.Dense(16, activation="tanh"),
layers.Dense(1, activation="sigmoid")
])
```

#here we are using rmsprop and mse

```
model_5.compile(optimizer="rmsprop",
loss="mse",
metrics=["accuracy"])
```

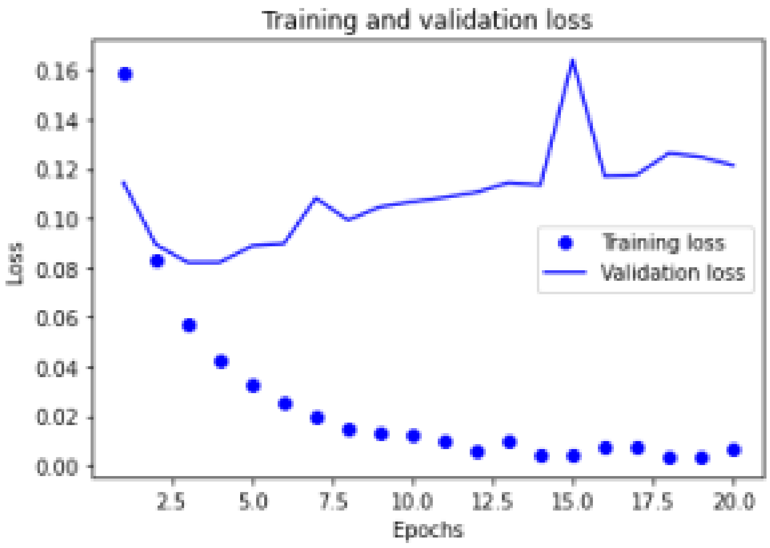
```
history_5 = model_5.fit(partial_x_train,
partial_y_train,
epochs=20,
batch_size=512,
validation_data=(x_val, y_val))
```

```
Epoch 1/20
30/30 [==============================] - 3s 54ms/step - loss: 0.1589 - accuracy: 0.8005
Epoch 2/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0827 - accuracy: 0.9083
Epoch 3/20
30/30 [==============================] - 1s 34ms/step - loss: 0.0569 - accuracy: 0.9349
Epoch 4/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0424 - accuracy: 0.9511
Epoch 5/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0326 - accuracy: 0.9635
Epoch 6/20
30/30 [==============================] - 1s 46ms/step - loss: 0.0258 - accuracy: 0.9717
Epoch 7/20
```

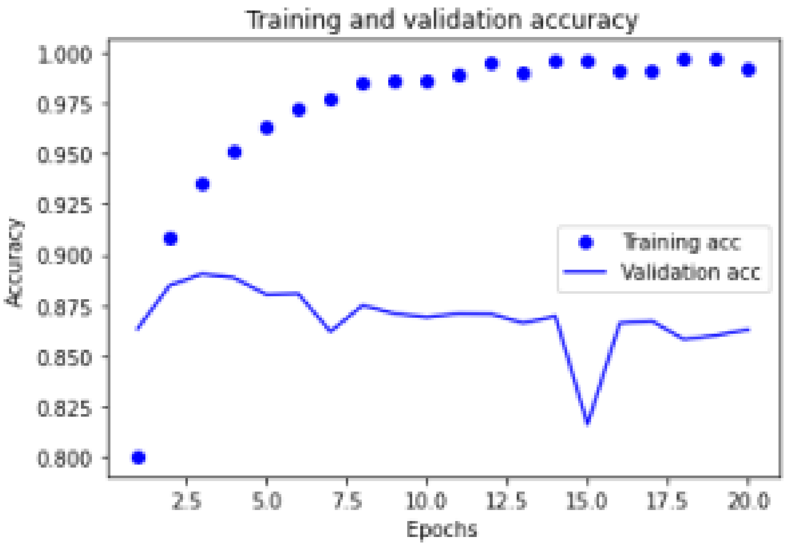
```
30/30 [==============================] - 2s 60ms/step - loss: 0.0200 - accuracy: 0.9772
Epoch 8/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0147 - accuracy: 0.9845
Epoch 9/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0130 - accuracy: 0.9863
Epoch 10/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0124 - accuracy: 0.9859
Epoch 11/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0101 - accuracy: 0.9887
Epoch 12/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0058 - accuracy: 0.9945
Epoch 13/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0097 - accuracy: 0.9894
Epoch 14/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0045 - accuracy: 0.9957
Epoch 15/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0044 - accuracy: 0.9957
Epoch 16/20
30/30 [==============================] - 1s 38ms/step - loss: 0.0078 - accuracy: 0.9907
Epoch 17/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0077 - accuracy: 0.9909
Epoch 18/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0037 - accuracy: 0.9964
Epoch 19/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0035 - accuracy: 0.9965
Epoch 20/20
 30/30 [==============================] - 1s 36ms/step - loss: 0.0069 - accuracy: 0.9919
```

```
history_dict_5 = history_5.history
loss_values = history_dict_5["loss"]
val_loss_values = history_dict_5["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()
```

Plotting the training and validation accuracy



```
plt.clf()
acc = history_dict_5["accuracy"]
val_acc = history_dict_5["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()
```



5.Use any technique we studied in class, and these include regularization,dropout, etc., to get your model to perform better on validation.

```
model_6 = keras.Sequential([
#layers.Dropout(0.2),
```

```
layers.Dense(20, activation="relu"),
layers.Dropout(0.2),
layers.Dense(15, activation="relu"),
layers.Dense(1, activation="sigmoid")
])
```

Model completion

```
model_6.compile(optimizer="rmsprop",
loss="binary_crossentropy",
metrics=["accuracy"])
history_6 = model_6.fit(partial_x_train,
partial_y_train,
epochs=20,
batch_size=512,
validation_data=(x_val, y_val))
```

```
Epoch 1/20
30/30 [==============================] - 3s 77ms/step - loss: 0.5114 - accuracy: 0.7702
Epoch 2/20
30/30 [==============================] - 1s 39ms/step - loss: 0.3204 - accuracy: 0.8874
Epoch 3/20
30/30 [==============================] - 1s 40ms/step - loss: 0.2396 - accuracy: 0.9173
Epoch 4/20
30/30 [==============================] - 1s 39ms/step - loss: 0.1930 - accuracy: 0.9324
Epoch 5/20
30/30 [==============================] - 1s 40ms/step - loss: 0.1575 - accuracy: 0.9451
Epoch 6/20
30/30 [==============================] - 1s 39ms/step - loss: 0.1321 - accuracy: 0.9575
Epoch 7/20
30/30 [==============================] - 1s 39ms/step - loss: 0.1077 - accuracy: 0.9656
Epoch 8/20
30/30 [==============================] - 1s 38ms/step - loss: 0.0908 - accuracy: 0.9699
Epoch 9/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0717 - accuracy: 0.9780
Epoch 10/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0614 - accuracy: 0.9828
Epoch 11/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0483 - accuracy: 0.9861
Epoch 12/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0389 - accuracy: 0.9900
Epoch 13/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0299 - accuracy: 0.9921
Epoch 14/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0265 - accuracy: 0.9931
Epoch 15/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0176 - accuracy: 0.9965
Epoch 16/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0152 - accuracy: 0.9969
Epoch 17/20
```

```
30/30 [==============================] - 1s 39ms/step - loss: 0.0125 - accuracy: 0.9974
Epoch 18/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0083 - accuracy: 0.9988
Epoch 19/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0101 - accuracy: 0.9977
Epoch 20/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0053 - accuracy: 0.9995
```

Compiling the model

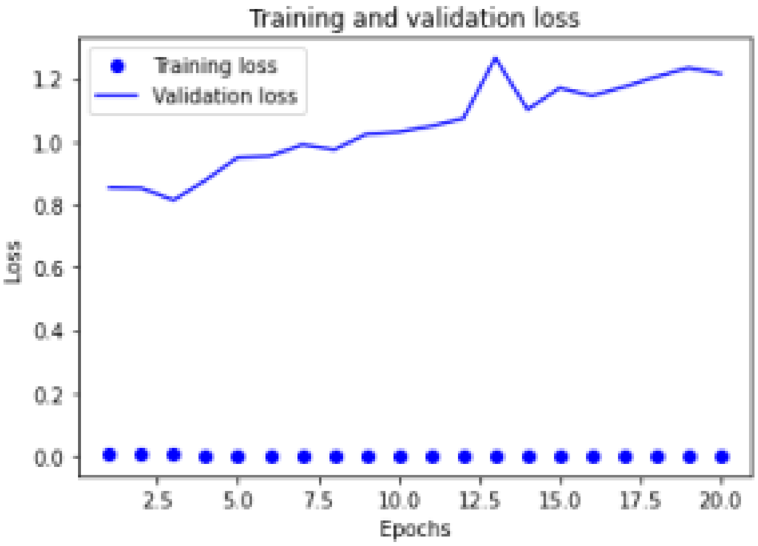
```
model_5.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
```

```
history_6 = model_6.fit(partial_x_train,
partial_y_train,
epochs=20,
batch_size=512,
validation_data=(x_val, y_val))
```

```
Epoch 1/20
30/30 [==============================] - 1s 46ms/step - loss: 0.0054 - accuracy: 0.9989
Epoch 2/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0060 - accuracy: 0.9986
Epoch 3/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0053 - accuracy: 0.9988
Epoch 4/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0029 - accuracy: 0.9994
Epoch 5/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0025 - accuracy: 0.9997
Epoch 6/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0031 - accuracy: 0.9993
Epoch 7/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0033 - accuracy: 0.9993
Epoch 8/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0033 - accuracy: 0.9995
Epoch 9/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0029 - accuracy: 0.9991
Epoch 10/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0038 - accuracy: 0.9994
Epoch 11/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0032 - accuracy: 0.9994
Epoch 12/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0019 - accuracy: 0.9997
Epoch 13/20
30/30 [==============================] - 1s 41ms/step - loss: 0.0021 - accuracy: 0.9995
Epoch 14/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0026 - accuracy: 0.9995
```

```
Epoch 15/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0015 - accuracy: 0.9997
Epoch 16/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0031 - accuracy: 0.9995
Epoch 17/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0014 - accuracy: 0.9998
Epoch 18/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0029 - accuracy: 0.9995
Epoch 19/20
30/30 [==============================] - 1s 40ms/step - loss: 0.0019 - accuracy: 0.9995
Epoch 20/20
 30/30 [==============================] - 1s 39ms/step - loss: 0.0031 - accuracy: 0.9993
```

```
history_dict_6 = history_6.history
loss_values = history_dict_6["loss"]
val_loss_values = history_dict_6["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()
```



Plotting the training and validation accuracy

```
plt.clf()
acc = history_dict_6["accuracy"]
val_acc = history_dict_6["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()
```