```
1 from keras.datasets import imdb
2 %matplotlib inline
3 import numpy as np
4 import pandas as pd
5 from matplotlib import cm
6 import matplotlib.pyplot as plt
7 import seaborn as sns
8 import os
9 import time
1 from keras.preprocessing import sequence
2 from keras.models import Sequential
3 from keras.layers import Dense, Dropout, Activation
4 from keras.layers import Embedding
5 from keras.layers import Conv1D, GlobalMaxPooling1D
6 from keras.callbacks import EarlyStopping
7 from keras import models
1 (X_train, y_train), (X_test, y_test) = imdb.load_data()
2 X = np.concatenate((X_train, X_test), axis=0)
3 y = np.concatenate((y_train, y_test), axis=0)
   Downloading\ data\ from\ \underline{https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz}
   17464789/17464789 [===========] - 0s Ous/step
1 ##training data shape review
2 print("Training data: ")
3 print(X.shape)
4 print(y.shape)
5 print("Classes: ")
6 print(np.unique(y))
T→ Training data:
    (50000,)
    (50000,)
   Classes:
    [0 1]
1 print("Number of words: ")
2 print(len(np.unique(np.hstack(X))))
   Number of words:
   88585
1 print("Review length: ")
2 \text{ result} = [len(x) \text{ for } x \text{ in } X]
3 print("Mean %.2f words (%f)" % (np.mean(result), np.std(result)))
4 # plot review length
5 plt.boxplot(result)
6 plt.show()
   Review length:
   Mean 234.76 words (172.911495)
     2500
                                         0
                                         0
                                         0
     2000
                                         0 00000 000000
     1500
     1000
      500
        0
```

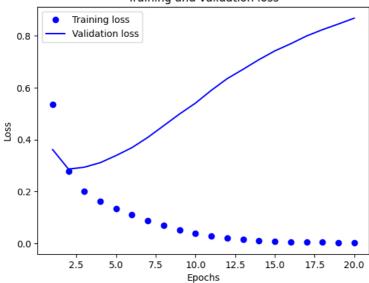
1 (train_data, train_labels), (test_data, test_labels) = imdb.load_data(num_words=5000)

```
1\ \mathsf{def}\ \mathsf{vectorize\_sequences}(\mathsf{sequences},\ \mathsf{dimension=5000})\colon
     # Create an all-zero matrix of shape (len(sequences), dimension)
3
     results = np.zeros((len(sequences), dimension))
4
     for i, sequence in enumerate(sequences):
5
          results[i, sequence] = 1. # set specific indices of results[i] to 1s
6
      return results
1 # Our vectorized training data
2 x_train = vectorize_sequences(train_data)
3 # Our vectorized test data
4 x_test = vectorize_sequences(test_data)
1 # Our vectorized labels one-hot encoder
2 y_train = np.asarray(train_labels).astype('float32')
3 y test = np.asarray(test_labels).astype('float32')
1 from keras import layers
2 from keras import models
3
4 model = models.Sequential()
5 model.add(layers.Dense(32, activation='relu', input_shape=(5000,)))
6 model.add(layers.Dense(32, activation='relu',))
7 model.add(layers.Dense(1, activation='sigmoid'))
1 #Set validation set aside
2
3 \times val = x_{train}[:10000]
4 partial_x_train = x_train[10000:]
6 y_val = y_train[:10000]
7 partial_y_train = y_train[10000:]
1 model.compile(optimizer='adam',
2
                loss='binary crossentropy',
3
                metrics=['acc'])
1 start_time_m1 = time.time()
2 history = model.fit(partial_x_train,
3
                      partial_y_train,
4
                      epochs=20,
5
                      batch size=512,
6
                      validation_data=(x_val, y_val))
7 total_time_m1 = time.time() - start_time_m1
   Epoch 1/20
   30/30 [===
                                  ======] - 3s 78ms/step - loss: 0.5351 - acc: 0.7623 - val_loss: 0.3614 - val_acc: 0.8574
   Epoch 2/20
   30/30 [===
                                             1s 34ms/step - loss: 0.2779 - acc: 0.8964 - val_loss: 0.2862 - val_acc: 0.8855
   Epoch 3/20
                                             1s 30ms/step - loss: 0.2011 - acc: 0.9265 - val_loss: 0.2935 - val_acc: 0.8833
   30/30 [===
   Epoch 4/20
   30/30 [===
                                           - 1s 33ms/step - loss: 0.1624 - acc: 0.9409 - val loss: 0.3109 - val acc: 0.8782
   Epoch 5/20
   30/30 [====
                                             1s 46ms/step - loss: 0.1350 - acc: 0.9536 - val_loss: 0.3385 - val_acc: 0.8736
   Epoch 6/20
                                           - 1s 47ms/step - loss: 0.1106 - acc: 0.9637 - val_loss: 0.3689 - val_acc: 0.8701
   30/30 [===
   Epoch 7/20
   30/30 [===
                                             1s 38ms/step - loss: 0.0885 - acc: 0.9737 - val_loss: 0.4085 - val_acc: 0.8654
   Epoch 8/20
   30/30 [==
                                            - 1s 33ms/step - loss: 0.0693 - acc: 0.9810 - val loss: 0.4534 - val acc: 0.8643
   Epoch 9/20
   30/30 [====
                                           - 1s 33ms/step - loss: 0.0520 - acc: 0.9876 - val_loss: 0.4986 - val_acc: 0.8616
   Epoch 10/20
   30/30 [==
                                           - 1s 33ms/step - loss: 0.0385 - acc: 0.9935 - val loss: 0.5402 - val acc: 0.8613
   Epoch 11/20
   30/30 [==:
                                             1s 34ms/step - loss: 0.0276 - acc: 0.9964 - val_loss: 0.5897 - val_acc: 0.8581
   Epoch 12/20
   30/30 [==
                                             1s 34ms/step - loss: 0.0200 - acc: 0.9986 - val_loss: 0.6346 - val_acc: 0.8564
   Epoch 13/20
   30/30 [===
                                             1s 30ms/step - loss: 0.0143 - acc: 0.9994 - val_loss: 0.6705 - val_acc: 0.8558
   Epoch 14/20
   30/30 [====
                                           - 1s 33ms/step - loss: 0.0103 - acc: 0.9998 - val_loss: 0.7077 - val_acc: 0.8572
   Epoch 15/20
   30/30 [===
                                           - 1s 33ms/step - loss: 0.0077 - acc: 0.9999 - val_loss: 0.7414 - val_acc: 0.8578
   Fnoch 16/20
                                             1s 30ms/step - loss: 0.0059 - acc: 0.9999 - val_loss: 0.7690 - val_acc: 0.8551
   30/30 [=====
   Epoch 17/20
   30/30 [====
                                    :=====] - 1s 33ms/step - loss: 0.0047 - acc: 1.0000 - val_loss: 0.7988 - val_acc: 0.8568
   Epoch 18/20
                                     =====] - 1s 46ms/step - loss: 0.0039 - acc: 1.0000 - val_loss: 0.8231 - val_acc: 0.8567
   30/30 [==
   Epoch 19/20
```

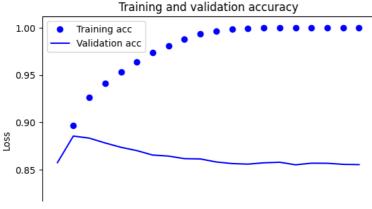
20 plt.show()

```
1 history_dict = history.history
 2 history_dict.keys()
    dict_keys(['loss', 'acc', 'val_loss', 'val_acc'])
 1 import matplotlib.pyplot as plt
 2 %matplotlib inline
 3
 4 acc = history.history['acc']
 5 val_acc = history.history['val_acc']
 6 loss = history.history['loss']
 7 val_loss = history.history['val_loss']
9 \text{ epochs} = \text{range}(1, \text{len(acc)} + 1)
10
11 # "bo" is for "blue dot"
12 plt.plot(epochs, loss, 'bo', label='Training loss')
13 # b is for "solid blue line"
14 plt.plot(epochs, val_loss, 'b', label='Validation loss')
15 plt.title('Training and validation loss')
16 plt.xlabel('Epochs')
17 plt.ylabel('Loss')
18 plt.legend()
19
```

Training and validation loss



```
1 plt.clf() # clear figure
2 acc_values = history_dict['acc']
3 val_acc_values = history_dict['val_acc']
4
5 plt.plot(epochs, acc, 'bo', label='Training acc')
6 plt.plot(epochs, val_acc, 'b', label='Validation acc')
7 plt.title('Training and validation accuracy')
8 plt.xlabel('Epochs')
9 plt.ylabel('Loss')
10 plt.legend()
11
12 plt.show()
```



1 model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 32)	160032
dense_1 (Dense)	(None, 32)	1056
dense_2 (Dense)	(None, 1)	33
=======================================		

Total params: 161,121 Trainable params: 161,121 Non-trainable params: 0

```
1 from sklearn.metrics import confusion_matrix, accuracy_score, auc
2 #predictions
3 pred = model.predict(x_test)
4 classes_x=np.argmax(pred,axis=1)
5
```

6 #accuracy

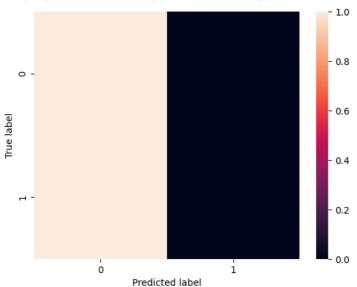
7 accuracy_score(y_test,classes_x)

```
782/782 [======] - 3s 3ms/step 0.5
```

```
1 #Confusion Matrix
2 conf_mat = confusion_matrix(y_test, classes_x)
3 print(conf_mat)
4
5 conf_mat_normalized = conf_mat.astype('float') / conf_mat.sum(axis=1)[:, np.newaxis]
6 sns.heatmap(conf_mat_normalized)
7 plt.ylabel('True label')
8 plt.xlabel('Predicted label')
```

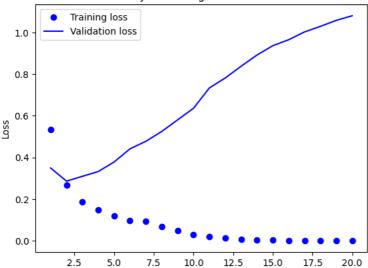
```
[[12500 0]
[12500 0]]
```

Text(0.5, 23.522222222222, 'Predicted label')

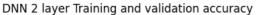


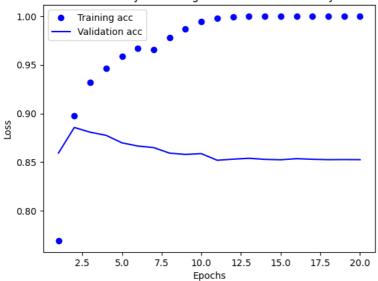
```
1 #Dense with Two Layer
 2 model2 = models.Sequential()
 3 model2.add(layers.Dense(32, activation='relu', input_shape=(5000,)))
 4 model2.add(layers.Dense(32, activation='relu'))
 5 model2.add(layers.Dense(32, activation='relu'))
 6 model2.add(layers.Dense(1, activation='sigmoid'))
 1 model2.compile(optimizer='adam',
 2
                 loss='binary_crossentropy',
 3
                 metrics=['acc'])
 1 start_time_m2 = time.time()
 2 history= model2.fit(partial x train,
                       partial_y_train,
 3
 4
                       epochs=20,
 5
                       batch_size=512,
 6
                       validation_data=(x_val, y_val))
 7 total_time_m2 = time.time() - start_time_m2
 9 print("The Dense Convolutional Neural Network 2 layers took %.4f seconds to train." % (total time m2))
    Epoch 1/20
                                  ======] - 3s 53ms/step - loss: 0.5337 - acc: 0.7692 - val loss: 0.3494 - val acc: 0.8593
    30/30 [===
    Epoch 2/20
    30/30 [===
                                    =====] - 1s 33ms/step - loss: 0.2657 - acc: 0.8977 - val_loss: 0.2862 - val_acc: 0.8856
    Epoch 3/20
    30/30 [====
                                              1s 33ms/step - loss: 0.1884 - acc: 0.9320 - val_loss: 0.3093 - val_acc: 0.8807
    Epoch 4/20
    30/30 [===
                                              1s 31ms/step - loss: 0.1493 - acc: 0.9462 - val loss: 0.3323 - val acc: 0.8775
    Epoch 5/20
                                              1s 33ms/step - loss: 0.1197 - acc: 0.9589 - val_loss: 0.3782 - val_acc: 0.8698
    30/30 [===
    Epoch 6/20
    30/30 [===
                                              1s 38ms/step - loss: 0.0973 - acc: 0.9667 - val_loss: 0.4412 - val_acc: 0.8665
    Epoch 7/20
    30/30 [===
                                              1s 49ms/step - loss: 0.0929 - acc: 0.9653 - val loss: 0.4773 - val acc: 0.8649
    Epoch 8/20
    30/30 [===
                                              1s 46ms/step - loss: 0.0677 - acc: 0.9779 - val_loss: 0.5246 - val_acc: 0.8592
    Epoch 9/20
    30/30 [=
                                              1s 33ms/step - loss: 0.0473 - acc: 0.9867 - val_loss: 0.5802 - val_acc: 0.8579
    Epoch 10/20
    30/30 [===
                                            - 1s 34ms/step - loss: 0.0309 - acc: 0.9946 - val loss: 0.6357 - val acc: 0.8587
    Epoch 11/20
    30/30 [====
                                            - 1s 30ms/step - loss: 0.0195 - acc: 0.9977 - val_loss: 0.7333 - val_acc: 0.8519
    Epoch 12/20
    30/30 [==:
                                              1s 34ms/step - loss: 0.0118 - acc: 0.9990 - val_loss: 0.7813 - val_acc: 0.8530
    Epoch 13/20
    30/30 [==
                                              1s 34ms/step - loss: 0.0066 - acc: 0.9998 - val_loss: 0.8375 - val_acc: 0.8539
    Epoch 14/20
    30/30 [==
                                              1s 30ms/step - loss: 0.0040 - acc: 1.0000 - val loss: 0.8915 - val acc: 0.8528
    Epoch 15/20
    30/30 [====
                                              1s 34ms/step - loss: 0.0027 - acc: 1.0000 - val_loss: 0.9363 - val_acc: 0.8524
    Epoch 16/20
    30/30 [====
                                            - 1s 30ms/step - loss: 0.0020 - acc: 1.0000 - val loss: 0.9649 - val acc: 0.8535
    Epoch 17/20
    30/30 [===
                                              1s 33ms/step - loss: 0.0015 - acc: 1.0000 - val_loss: 1.0025 - val_acc: 0.8529
    Epoch 18/20
    30/30 [===
                                            - 1s 44ms/step - loss: 0.0012 - acc: 1.0000 - val_loss: 1.0291 - val_acc: 0.8525
    Epoch 19/20
    30/30 [===
                                           - 2s 75ms/step - loss: 9.9880e-04 - acc: 1.0000 - val loss: 1.0578 - val acc: 0.8
    Epoch 20/20
                                    =====1 -
                                              1s 36ms/step - loss: 8.3502e-04 - acc: 1.0000 - val loss: 1.0800 - val acc: 0.8
    The Dense Convolutional Neural Network 2 layers took 24.6517 seconds to train.
 1 acc = history.history['acc']
 2 val_acc = history.history['val_acc']
 3 loss = history.history['loss']
 4 val loss = history.history['val loss']
 6 \text{ epochs} = \text{range}(1, \text{len(acc)} + 1)
8 # "bo" is for "blue dot"
 9 plt.plot(epochs, loss, 'bo', label='Training loss')
10 # b is for "solid blue line"
11 plt.plot(epochs, val_loss, 'b', label='Validation loss')
12 plt.title('DNN 2 layer Training and validation loss')
13 plt.xlabel('Epochs')
14 plt.ylabel('Loss')
15 plt.legend()
16
17 plt.show()
```

DNN 2 layer Training and validation loss



```
1 plt.clf() # clear figure
2 acc_values = history_dict['acc']
3 val_acc_values = history_dict['val_acc']
4
5 plt.plot(epochs, acc, 'bo', label='Training acc')
6 plt.plot(epochs, val_acc, 'b', label='Validation acc')
7 plt.title('DNN 2 layer Training and validation accuracy')
8 plt.xlabel('Epochs')
9 plt.ylabel('Loss')
10 plt.legend()
11
12 plt.show()
```





1 model2.summary()

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_3 (Dense)	(None, 32)	160032
dense_4 (Dense)	(None, 32)	1056
dense_5 (Dense)	(None, 32)	1056
dense_6 (Dense)	(None, 1)	33

Total params: 162,177

Trainable params: 162,177 Non-trainable params: 0 1

✓ 2s completed at 1:06 PM

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