Assignment 5.2 - The Reuters Dataset

Loading the dataset

In [1]:
```
import numpy as np
from tensorflow.keras.datasets import reuters
```

In [2]:
```
# importing data from keras
(train_data, train_labels), (test_data, test_labels) = reuters.load_data
```

In [3]:
```
print(len(train_data))
print(len(test_data))
```

```
8982
2246
```

In [4]:
```
print(train_data[10])
```

```
[1, 245, 273, 207, 156, 53, 74, 160, 26, 14, 46, 296, 26, 39, 74, 2979, 355
4, 14, 46, 4689, 4329, 86, 61, 3499, 4795, 14, 61, 451, 4329, 17, 12]
```

Decoding newswires

In [5]:
```
# maps words to an integer index
word_index = reuters.get_word_index()

# maps integer indices to words
reverse_word_index = dict([(value,key) for (key, value) in word_index.ite

decoded_newswire = ' '.join([reverse_word_index.get(i - 3 , '?') for i in
decoded_newswire
```

Out[5]:
```
'? ? ? said as a result of its december acquisition of space co it expects
earnings per share in 1987 of 1 15 to 1 30 dlrs per share up from 70 cts in
1986 the company said pretax net should rise to nine to 10 mln dlrs from si
x mln dlrs in 1986 and rental operation revenues to 19 to 22 mln dlrs from
12 5 mln dlrs it said cash flow per share this year should be 2 50 to three
dlrs reuter 3'
```

Preparing the data

In [6]:
```
def vectorize_sequence(sequences, dimensions = 10000):
    results = np.zeros((len(sequences), dimensions))
    for i, sequences in enumerate(sequences):
        results[i, sequences] = 1
    return results
```

In [7]:
```
# Vectorize the training and testing datasets
x_train = vectorize_sequence(train_data)
x_test = vectorize_sequence(test_data)
```

In [8]:
```
def to_one_hot(labels, dimension=46):
    results = np.zeros((len(labels), dimension))
    for i, label in enumerate(labels):
        results[i, label] = 1
    return results
```

In [9]:
```
# Hot-encode the target attributes
y_train = to_one_hot(train_labels)
y_test = to_one_hot(test_labels)
```

Building the network

In [10]:
```
# Import keras libraries
from keras import models, layers, losses, metrics, optimizers
```

```
Using TensorFlow backend.
```

In [11]:
```
model = models.Sequential()
model.add(layers.Dense(64, activation='relu', input_shape=(10000,)))
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(46, activation='softmax'))
```

In [12]:
```
# compiling the model
model.compile(optimizer = 'rmsprop',
              loss = 'categorical_crossentropy',
              metrics = ['accuracy'])
```

Validating the model

In [13]:
```
x_val = x_train[:1000]
partial_x_train = x_train[1000:]

y_val = y_train[:1000]
partial_y_train = y_train[1000:]
```

In [14]:

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

```
Train on 7982 samples, validate on 1000 samples
Epoch 1/20
7982/7982 [==============================] - 2s 188us/step - loss: 2.5322 -
accuracy: 0.4955 - val_loss: 1.7208 - val_accuracy: 0.6120
Epoch 2/20
7982/7982 [==============================] - 1s 140us/step - loss: 1.4452 -
accuracy: 0.6879 - val_loss: 1.3459 - val_accuracy: 0.7060
Epoch 3/20
7982/7982 [==============================] - 1s 147us/step - loss: 1.0953 -
accuracy: 0.7651 - val_loss: 1.1708 - val_accuracy: 0.7430
Epoch 4/20
7982/7982 [==============================] - 1s 137us/step - loss: 0.8697 -
accuracy: 0.8165 - val_loss: 1.0793 - val_accuracy: 0.7590
Epoch 5/20
7982/7982 [==============================] - 1s 137us/step - loss: 0.7034 -
accuracy: 0.8472 - val_loss: 0.9844 - val_accuracy: 0.7810
Epoch 6/20
7982/7982 [==============================] - 1s 139us/step - loss: 0.5667 -
accuracy: 0.8802 - val_loss: 0.9411 - val_accuracy: 0.8040
Epoch 7/20
7982/7982 [==============================] - 1s 137us/step - loss: 0.4581 -
accuracy: 0.9048 - val_loss: 0.9083 - val_accuracy: 0.8020
Epoch 8/20
7982/7982 [==============================] - 1s 137us/step - loss: 0.3695 -
accuracy: 0.9231 - val_loss: 0.9363 - val_accuracy: 0.7890
Epoch 9/20
7982/7982 [==============================] - 1s 139us/step - loss: 0.3032 -
accuracy: 0.9315 - val_loss: 0.8917 - val_accuracy: 0.8090
Epoch 10/20
7982/7982 [==============================] - 1s 140us/step - loss: 0.2537 -
accuracy: 0.9414 - val_loss: 0.9071 - val_accuracy: 0.8110
Epoch 11/20
7982/7982 [==============================] - 1s 138us/step - loss: 0.2187 -
accuracy: 0.9471 - val_loss: 0.9177 - val_accuracy: 0.8130
Epoch 12/20
7982/7982 [==============================] - 1s 134us/step - loss: 0.1873 -
accuracy: 0.9508 - val_loss: 0.9027 - val_accuracy: 0.8130
Epoch 13/20
7982/7982 [==============================] - 1s 131us/step - loss: 0.1703 -
accuracy: 0.9521 - val_loss: 0.9333 - val_accuracy: 0.8110
Epoch 14/20
7982/7982 [==============================] - 1s 144us/step - loss: 0.1536 -
accuracy: 0.9554 - val_loss: 0.9717 - val_accuracy: 0.8050
Epoch 15/20
7982/7982 [==============================] - 1s 146us/step - loss: 0.1390 -
accuracy: 0.9560 - val_loss: 0.9725 - val_accuracy: 0.8150
Epoch 16/20
7982/7982 [==============================] - 1s 146us/step - loss: 0.1313 -
accuracy: 0.9560 - val_loss: 1.0276 - val_accuracy: 0.8060
Epoch 17/20
7982/7982 [==============================] - 1s 138us/step - loss: 0.1217 -
```

```
accuracy: 0.9579 - val_loss: 1.0340 - val_accuracy: 0.7970
Epoch 18/20
7982/7982 [==============================] - 1s 138us/step - loss: 0.1198 -
accuracy: 0.9582 - val_loss: 1.0553 - val_accuracy: 0.8060
Epoch 19/20
7982/7982 [==============================] - 1s 139us/step - loss: 0.1138 -
accuracy: 0.9597 - val_loss: 1.1103 - val_accuracy: 0.7970
Epoch 20/20
7982/7982 [==============================] - 1s 138us/step - loss: 0.1111 -
accuracy: 0.9593 - val_loss: 1.0778 - val_accuracy: 0.8020
```

Plotting the training and validation loss and accuracy

In [18]:

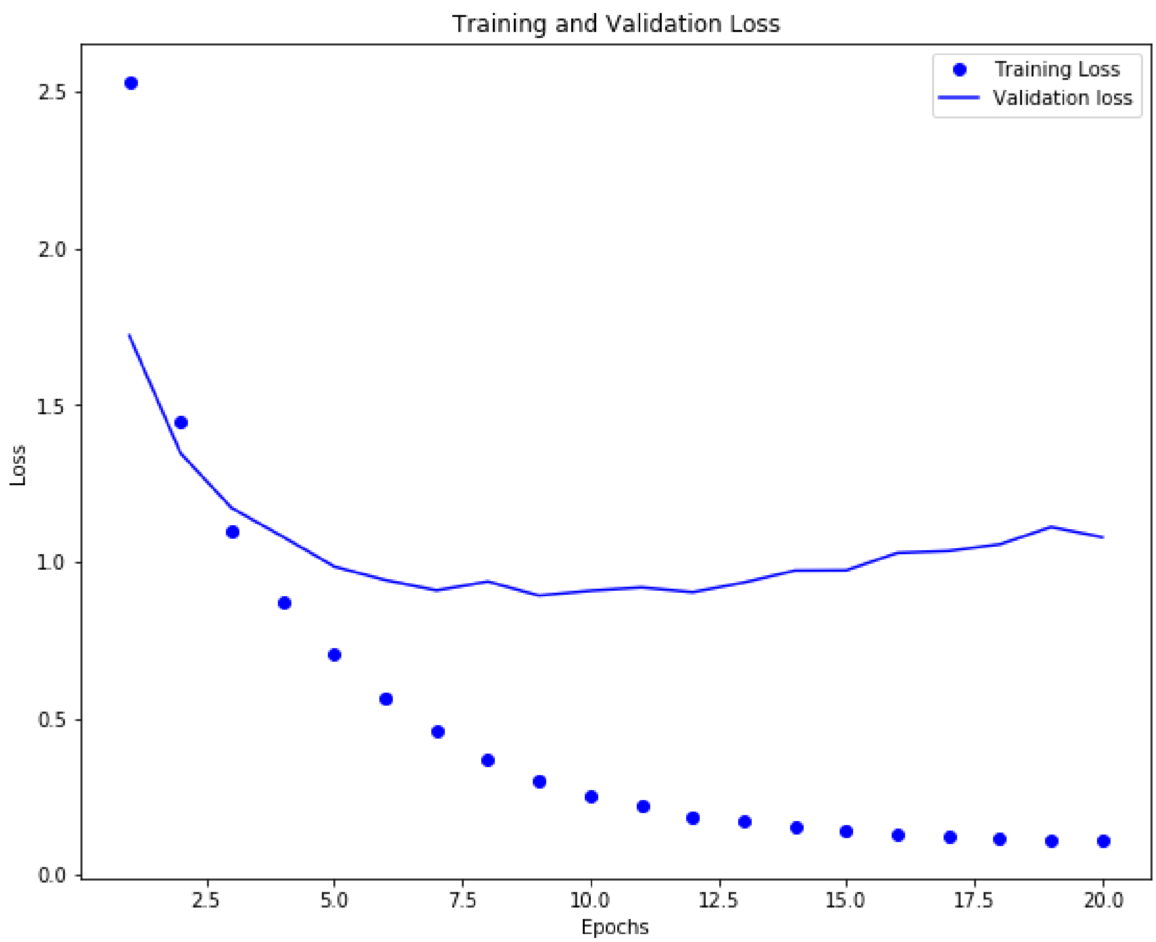
```
import matplotlib.pyplot as plt
```

In [19]:

```
history_dict = history.history
```

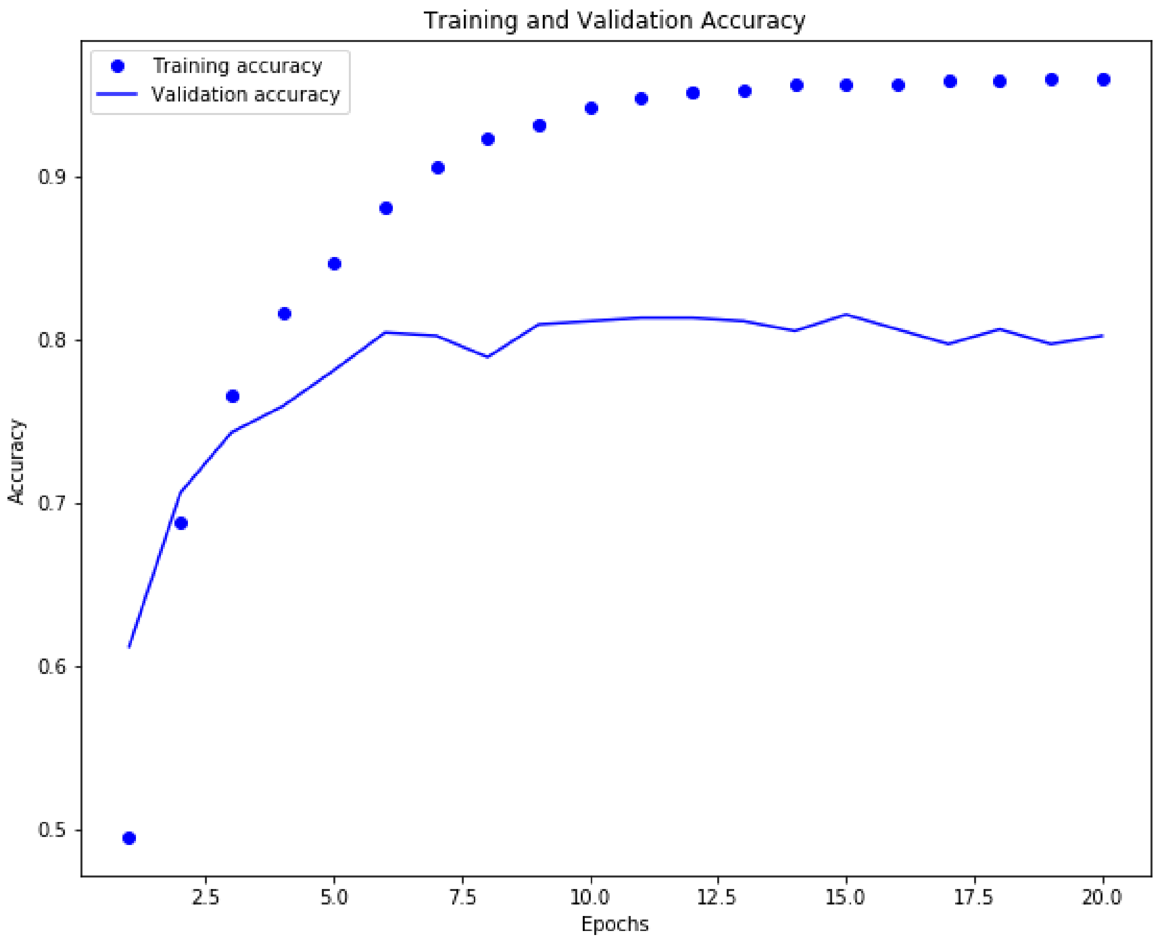
In [20]:

```
acc = history_dict['accuracy']
val_acc = history_dict['val_accuracy']

loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']

epochs = range(1,len(acc)+ 1)

plt.figure(figsize=(10,8))
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()
```



In [21]:

```
plt.figure(figsize=(10,8))
plt.plot(epochs, acc,  'bo', label = 'Training accuracy')
plt.plot(epochs, val_acc, 'b', label = 'Validation accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Retraining a model from scratch

In [22]:

```
model = models.Sequential()
model.add(layers.Dense(64, activation='relu', input_shape=(10000,)))
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(46, activation='softmax'))
```

In [23]:

```
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
model.fit(partial_x_train,
          partial_y_train,
          epochs=9,
          batch_size=512,
          validation_data=(x_val, y_val))
```

```
Train on 7982 samples, validate on 1000 samples
Epoch 1/9
7982/7982 [==============================] - 1s 160us/step - loss: 2.5398 -
accuracy: 0.5226 - val_loss: 1.6733 - val_accuracy: 0.6570
Epoch 2/9
7982/7982 [==============================] - 1s 130us/step - loss: 1.3712 -
accuracy: 0.7121 - val_loss: 1.2758 - val_accuracy: 0.7210
Epoch 3/9
7982/7982 [==============================] - 1s 135us/step - loss: 1.0136 -
accuracy: 0.7781 - val_loss: 1.1303 - val_accuracy: 0.7530
Epoch 4/9
7982/7982 [==============================] - 1s 136us/step - loss: 0.7976 -
accuracy: 0.8251 - val_loss: 1.0539 - val_accuracy: 0.7590
Epoch 5/9
7982/7982 [==============================] - 1s 141us/step - loss: 0.6393 -
accuracy: 0.8624 - val_loss: 0.9754 - val_accuracy: 0.7920
Epoch 6/9
7982/7982 [==============================] - 1s 137us/step - loss: 0.5124 -
accuracy: 0.8921 - val_loss: 0.9102 - val_accuracy: 0.8140
Epoch 7/9
7982/7982 [==============================] - 1s 137us/step - loss: 0.4124 -
accuracy: 0.9137 - val_loss: 0.8932 - val_accuracy: 0.8210
Epoch 8/9
7982/7982 [==============================] - 1s 138us/step - loss: 0.3355 -
accuracy: 0.9290 - val_loss: 0.8732 - val_accuracy: 0.8260
Epoch 9/9
7982/7982 [==============================] - 1s 139us/step - loss: 0.2782 -
accuracy: 0.9371 - val_loss: 0.9338 - val_accuracy: 0.8000
```

Out[23]:

```
<keras.callbacks.callbacks.History at 0x1daf322d908>
```

In [24]:

```
results = model.evaluate(x_test, y_test)
results
```

```
2246/2246 [==============================] - 0s 172us/step
```

Out[24]:

```
[1.02833829537525, 0.7756010890007019]
```

In [25]:
```
##random classification baseline
import copy
test_labels_copy = copy.copy(test_labels)
np.random.shuffle(test_labels_copy)
hits_array = np.array(test_labels) == np.array(test_labels_copy)
float(np.sum(hits_array)) / len(test_labels)
```

Out[25]: 0.182546749777382

Prediction on new data

In [26]:
```
predictions = model.predict(x_test)
predictions[0].shape
```

Out[26]: (46,)

In [27]:
```
np.sum(predictions[0])
```

Out[27]: 0.9999999

In [28]:
```
np.argmax(predictions[0])
```

Out[28]: 3

Different way to handle the labels and the loss

In [29]:
```
y_train2 = np.array(train_labels)
y_test2 = np.array(test_labels)

y_val2 = y_train2[:1000]
partial_y_train2 = y_train2[1000:]
```

In [30]:
```
model = models.Sequential()
model.add(layers.Dense(64, activation='relu', input_shape=(10000,)))
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(46, activation='softmax'))

model.compile(optimizer='rmsprop',
              loss='sparse_categorical_crossentropy',
              metrics=['acc'])
```

In [31]:

```
history = model.fit(partial_x_train,
                    partial_y_train2,
                    epochs=9,
                    batch_size=512,
                    validation_data=(x_val, y_val2), verbose = False)
results = model.evaluate(x_test, y_test2)
results
```

```
2246/2246 [==============================] - 0s 158us/step
```

Out[31]:

```
[0.952881737256411, 0.7876224517822266]
```

The importance of having sufficiently large intermediate layers

In [32]:

```
model = models.Sequential()
model.add(layers.Dense(64, activation='relu', input_shape=(10000,)))
model.add(layers.Dense(4, activation='relu'))
model.add(layers.Dense(46, activation='softmax'))

model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['acc'])

```

In [33]:

```
history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=128,
                    validation_data=(x_val, y_val),
                    verbose = False)

results = model.evaluate(x_test, y_test)
results
```

```
2246/2246 [==============================] - 0s 145us/step
```

Out[33]:

```
[1.9564781723973588, 0.6981300115585327]
```

In [ ]:

```

```