IE 345 - K “Introduction to Deep Learning: Fundamentals Concepts”

Resolution of the first example of the book Deep Learning with Python.

pg. 68 - 74

In [1]:

```
import keras
from keras.datasets import reuters
import numpy as np
```

```
Using TensorFlow backend.
```

In [2]:

```
(train_data, train_labels), (test_data, test_labels) = reuters.load_data(num_words=1000
0)
```

In [3]:

```
print(len(train_data), 'train sequences')
print(len(test_data), 'test sequences')
print('Train_data shape', train_data.shape)
print('Test_data shape', test_data.shape)
print('Train_labels shape', train_labels.shape)
print('Test_labels shape', test_labels.shape)
```

```
8982 train sequences
2246 test sequences
Train_data shape (8982,)
Test_data shape (2246,)
Train_labels shape (8982,)
Test_labels shape (2246,)
```

In [4]:

```
print(train_data[10])
```

```
[1, 245, 273, 207, 156, 53, 74, 160, 26, 14, 46, 296, 26, 39, 74, 2979, 35
54, 14, 46, 4689, 4329, 86, 61, 3499, 4795, 14, 61, 451, 4329, 17, 12]
```

In [5]:

```
word_index = reuters.get_word_index()
reverse_word_index = dict([(value,key) for(key,value) in word_index.items()])
decoder_newswire = ' '.join([reverse_word_index.get(i-3,'?') for i in train_data[0]])
print('Decoder newswire: ', decoder_newswire)
print('Train_labels 0: ', train_labels[0])
```

```
Decoder newswire:  ? ? ? said as a result of its december acquisition of s
pace co it expects earnings per share in 1987 of 1 15 to 1 30 dlrs per sha
re up from 70 cts in 1986 the company said pretax net should rise to nine
to 10 mln dlrs from six 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
Train_labels 0:  3
```

In [6]:

```
num_classes = np.max(train_labels) + 1
print(num_classes, 'classes')
```

```
46 classes
```

In [7]:

```
from keras.preprocessing.text import Tokenizer

tokenizer = Tokenizer(num_words=10000)
train_data=tokenizer.sequences_to_matrix(train_data, mode='binary')
test_data=tokenizer.sequences_to_matrix(test_data, mode='binary')
print('Train_data shape: ', train_data.shape)
print('Test_data shape: ', test_data.shape)
```

```
Train_data shape:  (8982, 10000)
Test_data shape:  (2246, 10000)
```

In [8]:

```
from keras.utils.np_utils import to_categorical

one_hot_train_labels = to_categorical(train_labels, num_classes)
one_hot_test_labels = to_categorical(test_labels, num_classes)
print('One hot train labels', one_hot_train_labels.shape)
print('One hot test labels', one_hot_test_labels.shape)
```

```
One hot train labels (8982, 46)
One hot test labels (2246, 46)
```

In [9]:

```
from keras import models, regularizers, layers

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.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_1 (Dense)              (None, 64)                640064    
_________________________________________________________________
dense_2 (Dense)              (None, 64)                4160      
_________________________________________________________________
dense_3 (Dense)              (None, 46)                2990      
=================================================================
Total params: 647,214
Trainable params: 647,214
Non-trainable params: 0
_________________________________________________________________
```

In [10]:

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

In [11]:

```
history = model.fit(train_data, one_hot_train_labels,
                    batch_size=512,
                    epochs=20,
                    verbose=1,
                    validation_split=0.1)
```

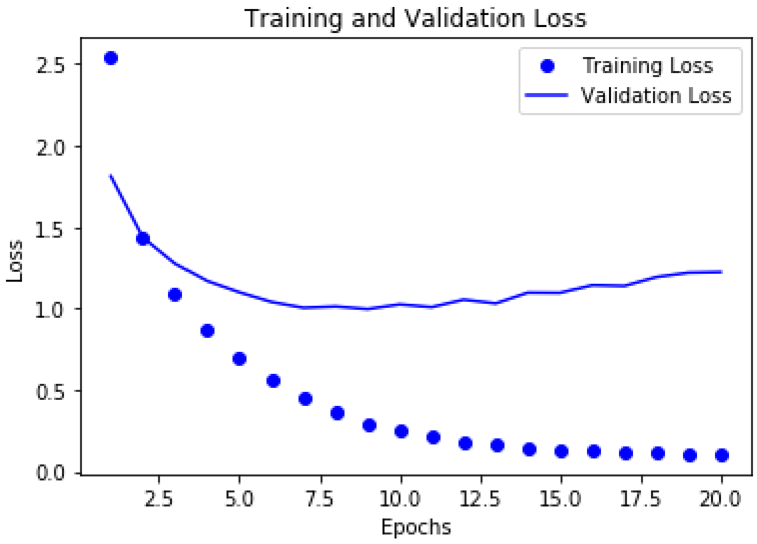
```
Train on 8083 samples, validate on 899 samples
Epoch 1/20
8083/8083 [==============================] - 3s 316us/step - loss: 2.5390
- acc: 0.4842 - val_loss: 1.8126 - val_acc: 0.6107
Epoch 2/20
8083/8083 [==============================] - 2s 241us/step - loss: 1.4388
- acc: 0.6879 - val_loss: 1.4359 - val_acc: 0.6841
Epoch 3/20
8083/8083 [==============================] - 2s 238us/step - loss: 1.0857
- acc: 0.7669 - val_loss: 1.2752 - val_acc: 0.7186
Epoch 4/20
8083/8083 [==============================] - 2s 239us/step - loss: 0.8621
- acc: 0.8170 - val_loss: 1.1681 - val_acc: 0.7486
Epoch 5/20
8083/8083 [==============================] - 2s 239us/step - loss: 0.6900
- acc: 0.8546 - val_loss: 1.0987 - val_acc: 0.7531
Epoch 6/20
8083/8083 [==============================] - 2s 239us/step - loss: 0.5571
- acc: 0.8831 - val_loss: 1.0395 - val_acc: 0.7820
Epoch 7/20
8083/8083 [==============================] - 2s 240us/step - loss: 0.4469
- acc: 0.9072 - val_loss: 1.0036 - val_acc: 0.7887
Epoch 8/20
8083/8083 [==============================] - 2s 238us/step - loss: 0.3584
- acc: 0.9228 - val_loss: 1.0118 - val_acc: 0.7831
Epoch 9/20
8083/8083 [==============================] - 2s 250us/step - loss: 0.2952
- acc: 0.9349 - val_loss: 0.9959 - val_acc: 0.7909
Epoch 10/20
8083/8083 [==============================] - 2s 239us/step - loss: 0.2483
- acc: 0.9425 - val_loss: 1.0245 - val_acc: 0.7920
Epoch 11/20
8083/8083 [==============================] - 2s 239us/step - loss: 0.2133
- acc: 0.9485 - val_loss: 1.0078 - val_acc: 0.8020
Epoch 12/20
8083/8083 [==============================] - 2s 239us/step - loss: 0.1803
- acc: 0.9520 - val_loss: 1.0536 - val_acc: 0.7831
Epoch 13/20
8083/8083 [==============================] - 2s 237us/step - loss: 0.1671
- acc: 0.9532 - val_loss: 1.0304 - val_acc: 0.7898
Epoch 14/20
8083/8083 [==============================] - 2s 236us/step - loss: 0.1476
- acc: 0.9550 - val_loss: 1.0966 - val_acc: 0.7898
Epoch 15/20
8083/8083 [==============================] - 2s 240us/step - loss: 0.1352
- acc: 0.9583 - val_loss: 1.0954 - val_acc: 0.7875
Epoch 16/20
8083/8083 [==============================] - 2s 237us/step - loss: 0.1308
- acc: 0.9562 - val_loss: 1.1426 - val_acc: 0.7786
Epoch 17/20
8083/8083 [==============================] - 2s 238us/step - loss: 0.1227
- acc: 0.9574 - val_loss: 1.1381 - val_acc: 0.7909
Epoch 18/20
8083/8083 [==============================] - 2s 237us/step - loss: 0.1154
- acc: 0.9589 - val_loss: 1.1927 - val_acc: 0.7864
Epoch 19/20
8083/8083 [==============================] - 2s 236us/step - loss: 0.1098
- acc: 0.9586 - val_loss: 1.2195 - val_acc: 0.7820
Epoch 20/20
8083/8083 [==============================] - 2s 236us/step - loss: 0.1062
- acc: 0.9587 - val_loss: 1.2234 - val_acc: 0.7709
```

In [15]:

```
import matplotlib.pyplot as plt

loss = history.history['loss']
val_loss = history.history['val_loss']

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

plt.plot(epochs, loss, 'bo', label = 'Training Loss')
plt.plot(epochs, val_loss, 'b', label = 'Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
```

Out[15]:

```
<matplotlib.legend.Legend at 0x1318d5a6358>
```

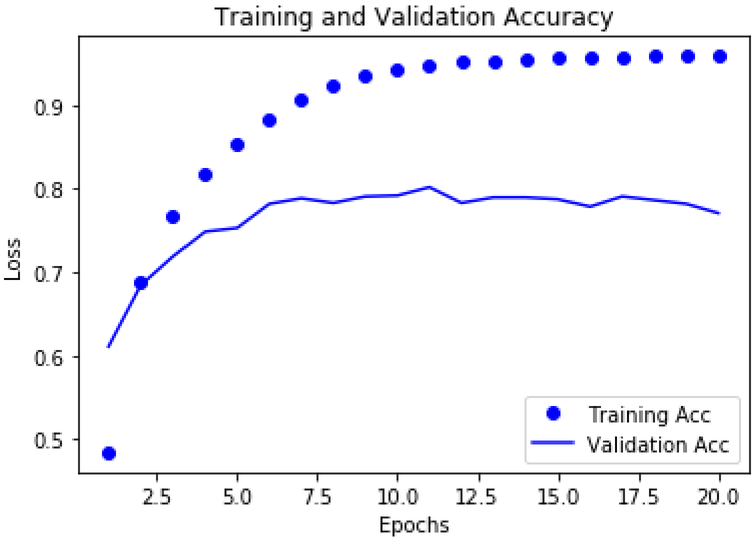


In [17]:

```
acc = history.history['acc']
val_acc = history.history['val_acc']

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('Loss')
plt.legend()
```

Out[17]:

```
<matplotlib.legend.Legend at 0x1318d66dd30>
```


Training and Validation Accuracy
Loss
Epochs
● Training Acc
— Validation Acc