An Introduction to Deep Learning With Python

[3.3] Classifying newswire: a multiclass classification example

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pgs: 78 - 84

The Reuters dataset

In [1]:
```
from keras.datasets import reuters
(train_data, train_labels),(test_data, test_labels) = reuters.load_data(num_words = 10000)
```

```
Using TensorFlow backend.
```

In [2]:
```
len(train_data)
```

Out[2]: 8982

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

Out[3]: 2246

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

```
[1, 245, 273, 207, 156, 53, 74, 160, 26, 14, 46, 296, 26, 39, 74, 2979, 3554, 14, 46, 4689, 4329,
86, 61, 3499, 4795, 14, 61, 451, 4329, 17, 12]
```

Decoding newswire back to text

In [5]:
```
word_index = reuters.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]])
```

In [6]:
```
train_labels[10]
```

Out[6]: 3

Preparing the data

In [7]:
```
import numpy as np

def vectorize_sequences(sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        results[i, sequence] = 1.
    return results

x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(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

one_hot_train_labels = to_one_hot(train_labels)
one_hot_test_labels = to_one_hot(test_labels)
```

In [9]:
```
from keras.utils.np_utils import to_categorical

one_hot_train_labels = to_categorical(train_labels)
one_hot_test_labels = to_categorical(test_labels)
```

Building your network

In [10]:
```
from keras import models
from keras import 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
_________________________________________________________________
```

Compiling the model

In [11]:
```
model.compile(optimizer = 'rmsprop',
              loss = 'categorical_crossentropy',
              metrics = ['accuracy'])
```

Validating your approach

In [12]:
```
x_val = x_train[:1000]
partial_x_train = x_train[1000:]

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

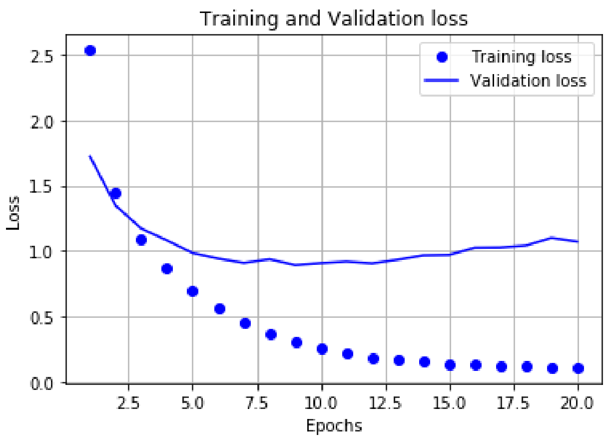
Training the model

In [13]:
```
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 [==============================] - 5s 650us/step - loss: 2.5322 - acc: 0.4955 - val_los
s: 1.7206 - val_acc: 0.6120
Epoch 2/20
7982/7982 [==============================] - 4s 457us/step - loss: 1.4451 - acc: 0.6875 - val_los
s: 1.3453 - val_acc: 0.7060
Epoch 3/20
7982/7982 [==============================] - 6s 796us/step - loss: 1.0950 - acc: 0.7653 - val_los
s: 1.1710 - val_acc: 0.7430
Epoch 4/20
7982/7982 [==============================] - 7s 826us/step - loss: 0.8691 - acc: 0.8156 - val_los
s: 1.0803 - val_acc: 0.7580
Epoch 5/20
7982/7982 [==============================] - 6s 733us/step - loss: 0.7028 - acc: 0.8474 - val_los
s: 0.9843 - val_acc: 0.7820
Epoch 6/20
7982/7982 [==============================] - 5s 616us/step - loss: 0.5662 - acc: 0.8796 - val_los
s: 0.9419 - val_acc: 0.8030
Epoch 7/20
7982/7982 [==============================] - 5s 660us/step - loss: 0.4579 - acc: 0.9044 - val_los
s: 0.9087 - val_acc: 0.8000
Epoch 8/20
7982/7982 [==============================] - 5s 650us/step - loss: 0.3693 - acc: 0.9233 - val_los
s: 0.9369 - val_acc: 0.7900
Epoch 9/20
7982/7982 [==============================] - 6s 690us/step - loss: 0.3032 - acc: 0.9308 - val_los
s: 0.8917 - val_acc: 0.8080
Epoch 10/20
7982/7982 [==============================] - 5s 575us/step - loss: 0.2541 - acc: 0.9415 - val_los
s: 0.9069 - val_acc: 0.8110
Epoch 11/20
7982/7982 [==============================] - 4s 464us/step - loss: 0.2187 - acc: 0.9469 - val_los
s: 0.9190 - val_acc: 0.8120
Epoch 12/20
7982/7982 [==============================] - 4s 465us/step - loss: 0.1876 - acc: 0.9510 - val_los
s: 0.9051 - val_acc: 0.8130
Epoch 13/20
7982/7982 [==============================] - 4s 467us/step - loss: 0.1705 - acc: 0.9524 - val_los
s: 0.9334 - val_acc: 0.8090
Epoch 14/20
7982/7982 [==============================] - 5s 594us/step - loss: 0.1538 - acc: 0.9551 - val_los
s: 0.9663 - val_acc: 0.8060
Epoch 15/20
7982/7982 [==============================] - 4s 522us/step - loss: 0.1390 - acc: 0.9560 - val_los
s: 0.9695 - val_acc: 0.8150
Epoch 16/20
7982/7982 [==============================] - 4s 484us/step - loss: 0.1316 - acc: 0.9562 - val_los
s: 1.0243 - val_acc: 0.8050
Epoch 17/20
7982/7982 [==============================] - 4s 468us/step - loss: 0.1217 - acc: 0.9582 - val_los
s: 1.0260 - val_acc: 0.7970
Epoch 18/20
7982/7982 [==============================] - 4s 509us/step - loss: 0.1199 - acc: 0.9577 - val_los
s: 1.0413 - val_acc: 0.8080
Epoch 19/20
7982/7982 [==============================] - 4s 449us/step - loss: 0.1139 - acc: 0.9598 - val_los
s: 1.0997 - val_acc: 0.7990
Epoch 20/20
7982/7982 [==============================] - 4s 480us/step - loss: 0.1111 - acc: 0.9593 - val_los
s: 1.0713 - val_acc: 0.8020
```

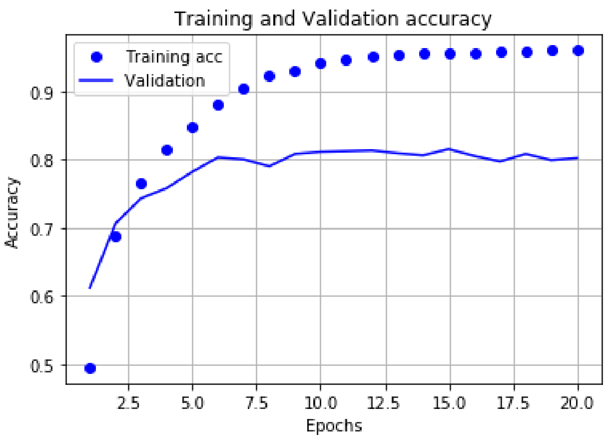
Plotting the training and validation loss

```
In [27]: 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()
plt.grid()
```



Plotting the training and validation accuracy

```
In [15]: 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 ')
plt.title('Training and Validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid()
```



Retraining a model from scratch

In [16]:
```
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='binary_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 [==============================] - 5s 589us/step - loss: 0.0735 - acc: 0.9803 - val_los
s: 0.0503 - val_acc: 0.9857
Epoch 2/9
7982/7982 [==============================] - 3s 426us/step - loss: 0.0417 - acc: 0.9887 - val_los
s: 0.0391 - val_acc: 0.9898
Epoch 3/9
7982/7982 [==============================] - 4s 442us/step - loss: 0.0320 - acc: 0.9914 - val_los
s: 0.0355 - val_acc: 0.9902
Epoch 4/9
7982/7982 [==============================] - 3s 424us/step - loss: 0.0261 - acc: 0.9928 - val_los
s: 0.0341 - val_acc: 0.9907
Epoch 5/9
7982/7982 [==============================] - 4s 460us/step - loss: 0.0218 - acc: 0.9939 - val_los
s: 0.0322 - val_acc: 0.9912
Epoch 6/9
7982/7982 [==============================] - 4s 466us/step - loss: 0.0181 - acc: 0.9947 - val_los
s: 0.0305 - val_acc: 0.9919
Epoch 7/9
7982/7982 [==============================] - 4s 464us/step - loss: 0.0152 - acc: 0.9954 - val_los
s: 0.0300 - val_acc: 0.9920
Epoch 8/9
7982/7982 [==============================] - 4s 460us/step - loss: 0.0128 - acc: 0.9961 - val_los
s: 0.0297 - val_acc: 0.9922
Epoch 9/9
7982/7982 [==============================] - 4s 478us/step - loss: 0.0108 - acc: 0.9965 - val_los
s: 0.0317 - val_acc: 0.9916
```

Out[16]:
```
<keras.callbacks.History at 0x1dc4b32bcc0>
```

In [17]:
```
results = model.evaluate(x_test, one_hot_test_labels)
print('Results [loss, acc] = ', results)
```

```
2246/2246 [==============================] - 1s 632us/step
Results [loss, acc] =  [0.03402860169419198, 0.990843640409828]
```

In [18]:
```
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[18]:
```
0.182546749777382
```

Generating predictions on new data

In [19]:
```
predictions = model.predict(x_test)
```

In [20]:
```
predictions[0].shape
```

Out[20]:
```
(46,)
```

In [21]:
```
np.sum(predictions[0])
```

Out[21]:
```
0.99999976
```

In [22]:
```
np.argmax(predictions[0])
```

Out[22]: 3

A different way to handle the labels and the loss

In [23]:
```
y_train = np.array(train_labels)
y_test = np.array(test_labels)
```

In [24]:
```
model.compile(optimizer='rmsprop',
              loss='sparse_categorical_crossentropy',
              metrics=['acc'])
```

The importance of having sufficiently large intermediate layers

In [25]:
```
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='binary_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 [==============================] - 5s 619us/step - loss: 0.0918 - acc: 0.9783 - val_los
s: 0.0828 - val_acc: 0.9783
Epoch 2/9
7982/7982 [==============================] - 3s 417us/step - loss: 0.0764 - acc: 0.9785 - val_los
s: 0.0705 - val_acc: 0.9790
Epoch 3/9
7982/7982 [==============================] - 4s 473us/step - loss: 0.0641 - acc: 0.9808 - val_los
s: 0.0607 - val_acc: 0.9822
Epoch 4/9
7982/7982 [==============================] - 4s 476us/step - loss: 0.0549 - acc: 0.9841 - val_los
s: 0.0538 - val_acc: 0.9846
Epoch 5/9
7982/7982 [==============================] - 3s 418us/step - loss: 0.0481 - acc: 0.9874 - val_los
s: 0.0490 - val_acc: 0.9878
Epoch 6/9
7982/7982 [==============================] - 3s 415us/step - loss: 0.0433 - acc: 0.9896 - val_los
s: 0.0462 - val_acc: 0.9891
Epoch 7/9
7982/7982 [==============================] - 4s 471us/step - loss: 0.0400 - acc: 0.9902 - val_los
s: 0.0443 - val_acc: 0.9892
Epoch 8/9
7982/7982 [==============================] - 4s 518us/step - loss: 0.0374 - acc: 0.9906 - val_los
s: 0.0431 - val_acc: 0.9892
Epoch 9/9
7982/7982 [==============================] - 4s 455us/step - loss: 0.0350 - acc: 0.9909 - val_los
s: 0.0417 - val_acc: 0.9895
```

Out[25]: <keras.callbacks.History at 0x1dc0b118710>

In [26]:
```
results = model.evaluate(x_test, one_hot_test_labels)
print('Results [loss, acc] = ', results)
```

```
2246/2246 [==============================] - 2s 800us/step
Results [loss, acc] =  [0.043604926223587165, 0.9893046785759693]
```

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