An Introduction to Deep Learning With Python

[3.2] Classifying movie reviews a binary classification example

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pgs: 68 - 77

Loading the IMDB dataset

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

```
Using TensorFlow backend.
```

In [2]:
```
train_data[0:10000:10000]
```

Out[2]:
```
array([list([1, 14, 22, 16, 43, 530, 973, 1622, 1385, 65, 458, 4468, 66, 3941, 4, 173, 36, 256, 5,
25, 100, 43, 838, 112, 50, 670, 2, 9, 35, 480, 284, 5, 150, 4, 172, 112, 167, 2, 336, 385, 39, 4,
172, 4536, 1111, 17, 546, 38, 13, 447, 4, 192, 50, 16, 6, 147, 2025, 19, 14, 22, 4, 1920, 4613, 46
9, 4, 22, 71, 87, 12, 16, 43, 530, 38, 76, 15, 13, 1247, 4, 22, 17, 515, 17, 12, 16, 626, 18, 2,
5, 62, 386, 12, 8, 316, 8, 106, 5, 4, 2223, 5244, 16, 480, 66, 3785, 33, 4, 130, 12, 16, 38, 619,
5, 25, 124, 51, 36, 135, 48, 25, 1415, 33, 6, 22, 12, 215, 28, 77, 52, 5, 14, 407, 16, 82, 2, 8,
4, 107, 117, 5952, 15, 256, 4, 2, 7, 3766, 5, 723, 36, 71, 43, 530, 476, 26, 400, 317, 46, 7, 4,
2, 1029, 13, 104, 88, 4, 381, 15, 297, 98, 32, 2071, 56, 26, 141, 6, 194, 7486, 18, 4, 226, 22, 2
1, 134, 476, 26, 480, 5, 144, 30, 5535, 18, 51, 36, 28, 224, 92, 25, 104, 4, 226, 65, 16, 38, 133
4, 88, 12, 16, 283, 5, 16, 4472, 113, 103, 32, 15, 16, 5345, 19, 178, 32])],
      dtype=object)
```

In [3]:
```
train_labels[0]
```

Out[3]:
```
1
```

In [4]:
```
max([max(sequence) for sequence in train_data])
```

Out[4]:
```
9999
```

In [5]:
```
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]])
```

Preparing the data

Encoding the Integer sequences Into a binary matrix

In [6]:
```
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 [7]:
```
x_train[0]
```

Out[7]:
```
array([0., 1., 1., ..., 0., 0., 0.])
```

```
In [8]: y_train = np.asarray(train_labels).astype('float32')
        y_test = np.asarray(test_labels).astype('float32')
```

Building your model

The model definition

```
In [9]: from keras.models import Sequential
        from keras.layers import Dense

        model = Sequential()
        model.add(Dense(16, activation='relu', input_shape=(10000,)))
        model.add(Dense(16, activation='relu'))
        model.add(Dense(1, activation='sigmoid'))
        model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 16)                160016
_________________________________________________________________
dense_2 (Dense)              (None, 16)                272
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 17
=================================================================
Total params: 160,305
Trainable params: 160,305
Non-trainable params: 0
_________________________________________________________________
```

Compiling the model

```
In [10]: model.compile(optimizer = 'rmsprop',
                       loss = 'binary_crossentropy',
                       metrics = ['accuracy'])
```

Configuring the optimizer

```
In [11]: from keras import optimizers

         model.compile(optimizer = optimizers.RMSprop(lr=0.001),
                       loss = 'binary_crossentropy',
                       metrics = ['accuracy'])
```

Using custom losses and metrics

```
In [12]: from keras import losses
         from keras import metrics

         model.compile(optimizer = optimizers.RMSprop(lr=0.001),
                       loss = losses.binary_crossentropy,
                       metrics = [metrics.binary_accuracy])
```

Setting aside a validation set

```
In [13]: x_val = x_train[: 10000]
         partial_x_train = x_train[10000:]

         y_val = y_train[:10000]
         partial_y_train = y_train[10000:]
```

Training your model

In [14]:
```
model.compile(optimizer = 'rmsprop',
              loss = 'binary_crossentropy',
              metrics = ['acc'])

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

```
Train on 15000 samples, validate on 10000 samples
Epoch 1/20
15000/15000 [==============================] - 7s 484us/step - loss: 0.4976 - acc: 0.7953 - val_lo
ss: 0.3717 - val_acc: 0.8719
Epoch 2/20
15000/15000 [==============================] - 5s 360us/step - loss: 0.2958 - acc: 0.9045 - val_lo
ss: 0.2991 - val_acc: 0.8909
Epoch 3/20
15000/15000 [==============================] - 8s 541us/step - loss: 0.2160 - acc: 0.9285 - val_lo
ss: 0.3086 - val_acc: 0.8714
Epoch 4/20
15000/15000 [==============================] - 6s 384us/step - loss: 0.1741 - acc: 0.9431 - val_lo
ss: 0.2829 - val_acc: 0.8845
Epoch 5/20
15000/15000 [==============================] - 4s 268us/step - loss: 0.1414 - acc: 0.9542 - val_lo
ss: 0.2863 - val_acc: 0.8850
Epoch 6/20
15000/15000 [==============================] - 5s 340us/step - loss: 0.1143 - acc: 0.9653 - val_lo
ss: 0.3089 - val_acc: 0.8811
Epoch 7/20
15000/15000 [==============================] - 6s 391us/step - loss: 0.0971 - acc: 0.9711 - val_lo
ss: 0.3146 - val_acc: 0.8842
Epoch 8/20
15000/15000 [==============================] - 5s 302us/step - loss: 0.0803 - acc: 0.9765 - val_lo
ss: 0.3869 - val_acc: 0.8657
Epoch 9/20
15000/15000 [==============================] - 3s 232us/step - loss: 0.0659 - acc: 0.9820 - val_lo
ss: 0.3650 - val_acc: 0.8778
Epoch 10/20
15000/15000 [==============================] - 4s 234us/step - loss: 0.0554 - acc: 0.9850 - val_lo
ss: 0.3861 - val_acc: 0.8791
Epoch 11/20
15000/15000 [==============================] - 5s 347us/step - loss: 0.0455 - acc: 0.9884 - val_lo
ss: 0.4181 - val_acc: 0.8761
Epoch 12/20
15000/15000 [==============================] - 8s 559us/step - loss: 0.0387 - acc: 0.9911 - val_lo
ss: 0.4521 - val_acc: 0.8697
Epoch 13/20
15000/15000 [==============================] - 5s 334us/step - loss: 0.0298 - acc: 0.9937 - val_lo
ss: 0.4712 - val_acc: 0.8731
Epoch 14/20
15000/15000 [==============================] - 6s 390us/step - loss: 0.0244 - acc: 0.9949 - val_lo
ss: 0.5022 - val_acc: 0.8714
Epoch 15/20
15000/15000 [==============================] - 5s 346us/step - loss: 0.0186 - acc: 0.9974 - val_lo
ss: 0.5315 - val_acc: 0.8692
Epoch 16/20
15000/15000 [==============================] - 6s 427us/step - loss: 0.0156 - acc: 0.9981 - val_lo
ss: 0.5705 - val_acc: 0.8693
Epoch 17/20
15000/15000 [==============================] - 6s 370us/step - loss: 0.0151 - acc: 0.9975 - val_lo
ss: 0.6005 - val_acc: 0.8685
Epoch 18/20
15000/15000 [==============================] - 7s 465us/step - loss: 0.0099 - acc: 0.9987 - val_lo
ss: 0.6447 - val_acc: 0.8667
Epoch 19/20
15000/15000 [==============================] - 6s 376us/step - loss: 0.0060 - acc: 0.9999 - val_lo
ss: 0.7091 - val_acc: 0.8575
Epoch 20/20
15000/15000 [==============================] - 4s 243us/step - loss: 0.0082 - acc: 0.9986 - val_lo
ss: 0.6950 - val_acc: 0.8650
```

```
In [15]: history_dict = history.history
         history_dict.keys()
```

```
Out[15]: dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
```

Plotting the training and validation loss

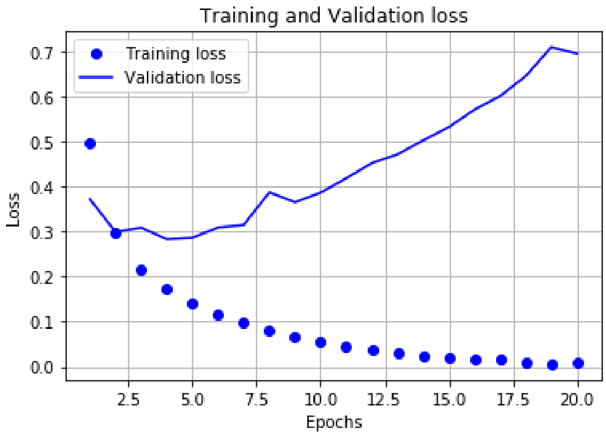
```
In [17]: import matplotlib.pyplot as plt

         loss_values = history_dict['loss']
         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.grid()

         plt.show()
```

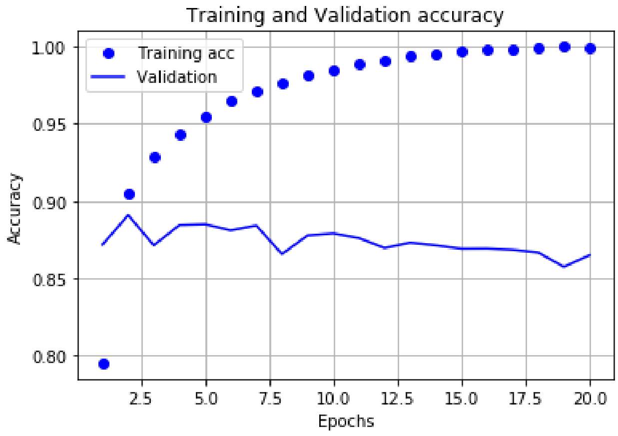


Plotting the training and validation accuracy

In [18]:
```
acc = history_dict['acc']
val_acc = history_dict['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()

plt.show()
```



Retraining a model from scratch

In [20]:
```
model = Sequential()
model.add(Dense(16, activation='relu', input_shape=(10000,)))
model.add(Dense(16, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

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

model.fit(x_train, y_train, epochs=4, batch_size=512)
```

```
Epoch 1/4
25000/25000 [==============================] - 7s 283us/step - loss: 0.4584 - acc: 0.8136
Epoch 2/4
25000/25000 [==============================] - 6s 221us/step - loss: 0.2630 - acc: 0.9093
Epoch 3/4
25000/25000 [==============================] - 4s 169us/step - loss: 0.2005 - acc: 0.9284
Epoch 4/4
25000/25000 [==============================] - 4s 172us/step - loss: 0.1685 - acc: 0.9389
```

Out[20]:
```
<keras.callbacks.History at 0x1db10695898>
```

In [21]:
```
results = model.evaluate(x_test, y_test)
print('Results [loss, acc] = ', results)
```

```
25000/25000 [==============================] - 8s 318us/step
Results [loss, acc] =  [0.2992388512086868, 0.88244]
```

Using a trained network to generate predictions on new data

In [22]:
```
model.predict(x_test)
```

Out[22]:
```
array([[0.2116582 ],
       [0.999501  ],
       [0.9304853 ],
       ...,
       [0.14387219],
       [0.1034008 ],
       [0.70603096]], dtype=float32)
```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