

3.4 Classifying movie reviews:

a binary classification example

```
In [2]: from keras.datasets import imdb
        (train_data, train_labels), (test_data, test_labels) = imdb.load_data(
            num_words=10000)

<_array_function__ internals>:5: VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tup
les-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray
/Users/astrid/opt/anaconda3/lib/python3.8/site-packages/keras/datasets/imdb.py:155: VisibleDeprecationWarning: Creating an ndarray from ragged nested s
equences (which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must sp
ecify 'dtype=object' when creating the ndarray
  x_train, y_train = np.array(xs[:idx]), np.array(labels[:idx])
/Users/astrid/opt/anaconda3/lib/python3.8/site-packages/keras/datasets/imdb.py:156: VisibleDeprecationWarning: Creating an ndarray from ragged nested s
equences (which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must sp
ecify 'dtype=object' when creating the ndarray
  x_test, y_test = np.array(xs[idx:]), np.array(labels[idx:])

In [3]: 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]])

In [4]: 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 [5]: y_train = np.asarray(train_labels).astype('float32')
        y_test = np.asarray(test_labels).astype('float32')

In [6]: from keras import models
        from keras import layers
        model = models.Sequential()
        model.add(layers.Dense(16, activation='relu', input_shape=(10000,)))
        model.add(layers.Dense(16, activation='relu'))
        model.add(layers.Dense(1, activation='sigmoid'))

In [7]: model.compile(optimizer='rmsprop',
                    loss='binary_crossentropy',
                    metrics=['accuracy'])

In [11]: #from keras import optimizers
         #from tensorflow.keras import optimizers
         from tensorflow import keras
         from keras import optimizers

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

In [17]: from keras import losses
         from keras import metrics

        model.compile(optimizer="rmsprop",
                    loss=losses.binary_crossentropy,
                    metrics=[metrics.binary_accuracy])

In [18]: x_val = x_train[:10000]
        partial_x_train = x_train[10000:]
        y_val = y_train[:10000]
        partial_y_train = y_train[10000:]

In [19]: 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))

Epoch 1/20
30/30 [=====] - 14s 49ms/step - loss: 0.6045 - acc: 0.6903 - val_loss: 0.3998 - val_acc: 0.8629
Epoch 2/20
30/30 [=====] - 0s 12ms/step - loss: 0.3357 - acc: 0.9022 - val_loss: 0.3096 - val_acc: 0.8826
Epoch 3/20
30/30 [=====] - 0s 12ms/step - loss: 0.2252 - acc: 0.9323 - val_loss: 0.2935 - val_acc: 0.8837
Epoch 4/20
30/30 [=====] - 0s 12ms/step - loss: 0.1768 - acc: 0.9420 - val_loss: 0.3082 - val_acc: 0.8747
Epoch 5/20
30/30 [=====] - 0s 12ms/step - loss: 0.1437 - acc: 0.9572 - val_loss: 0.2820 - val_acc: 0.8866
Epoch 6/20
30/30 [=====] - 0s 12ms/step - loss: 0.1201 - acc: 0.9649 - val_loss: 0.2933 - val_acc: 0.8870
Epoch 7/20
30/30 [=====] - 0s 12ms/step - loss: 0.0971 - acc: 0.9726 - val_loss: 0.3470 - val_acc: 0.8770
Epoch 8/20
30/30 [=====] - 0s 12ms/step - loss: 0.0874 - acc: 0.9758 - val_loss: 0.3304 - val_acc: 0.8790
Epoch 9/20
30/30 [=====] - 0s 12ms/step - loss: 0.0670 - acc: 0.9820 - val_loss: 0.3780 - val_acc: 0.8779
Epoch 10/20
30/30 [=====] - 0s 12ms/step - loss: 0.0522 - acc: 0.9893 - val_loss: 0.3808 - val_acc: 0.8743
Epoch 11/20
30/30 [=====] - 0s 12ms/step - loss: 0.0452 - acc: 0.9906 - val_loss: 0.4100 - val_acc: 0.8728
Epoch 12/20
30/30 [=====] - 0s 12ms/step - loss: 0.0399 - acc: 0.9912 - val_loss: 0.4510 - val_acc: 0.8675
Epoch 13/20
30/30 [=====] - 0s 12ms/step - loss: 0.0309 - acc: 0.9940 - val_loss: 0.4773 - val_acc: 0.8731
Epoch 14/20
30/30 [=====] - 0s 12ms/step - loss: 0.0234 - acc: 0.9965 - val_loss: 0.5227 - val_acc: 0.8694
Epoch 15/20
30/30 [=====] - 0s 12ms/step - loss: 0.0185 - acc: 0.9976 - val_loss: 0.5273 - val_acc: 0.8678
Epoch 16/20
30/30 [=====] - 0s 12ms/step - loss: 0.0146 - acc: 0.9985 - val_loss: 0.5687 - val_acc: 0.8684
Epoch 17/20
30/30 [=====] - 0s 13ms/step - loss: 0.0102 - acc: 0.9995 - val_loss: 0.5961 - val_acc: 0.8680
Epoch 18/20
30/30 [=====] - 0s 13ms/step - loss: 0.0115 - acc: 0.9980 - val_loss: 0.6345 - val_acc: 0.8625
Epoch 19/20
30/30 [=====] - 0s 12ms/step - loss: 0.0066 - acc: 0.9997 - val_loss: 0.6700 - val_acc: 0.8646
Epoch 20/20
30/30 [=====] - 0s 13ms/step - loss: 0.0049 - acc: 0.9997 - val_loss: 0.7010 - val_acc: 0.8632

In [27]: history_dict = history.history

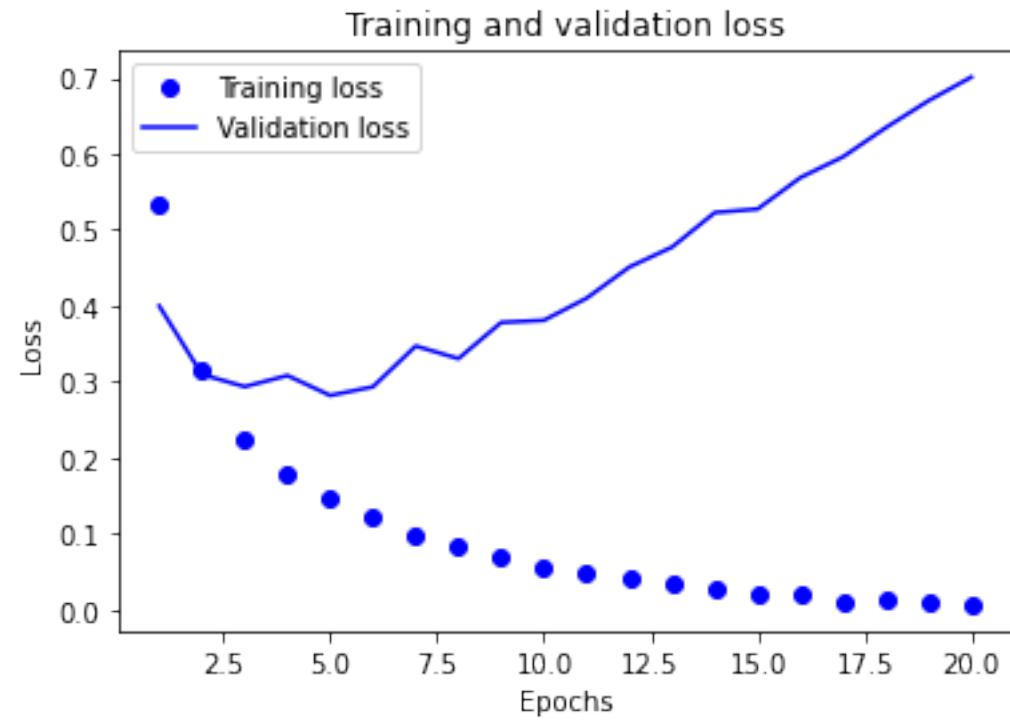
In [28]: history_dict.keys()

Out[28]: dict_keys(['loss', 'acc', 'val_loss', 'val_acc'])

In [30]: import matplotlib.pyplot as plt

        history_dict = history.history
        loss_values = history_dict['loss']
        val_loss_values = history_dict['val_loss']
        acc = history_dict['acc']
        epochs = range(1, len(acc) + 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.show()

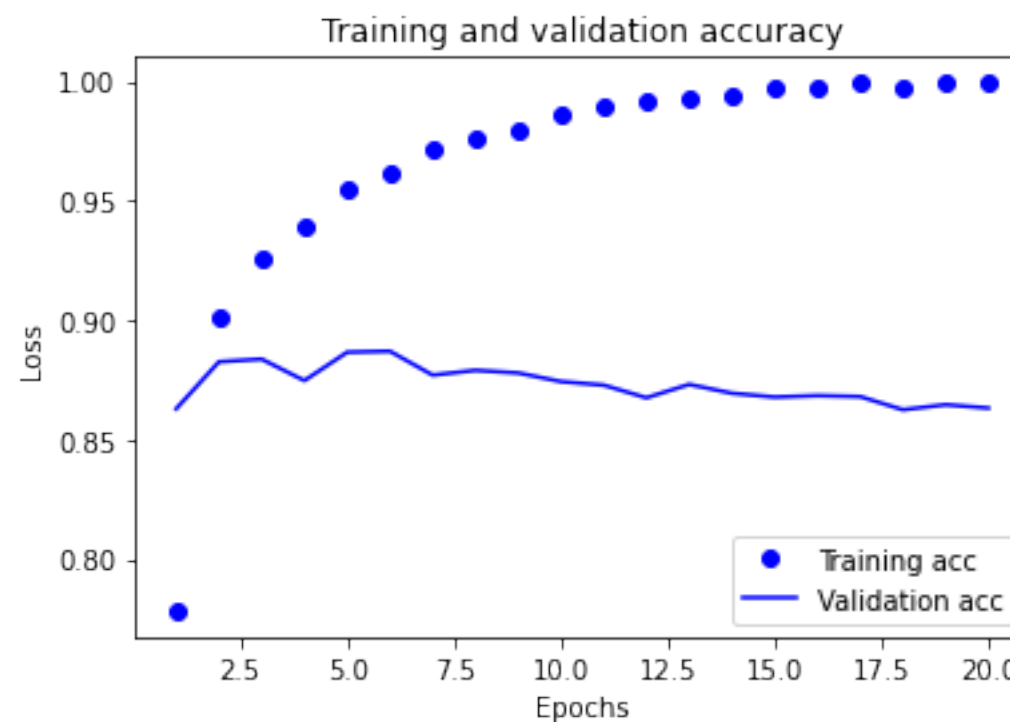
Training and validation loss


In [33]: plt.clf()

        acc_values = history_dict['acc']
        val_acc_values = history_dict['val_acc']

        plt.plot(epochs, acc_values, 'bo', label='Training acc')
        plt.plot(epochs, val_acc_values, 'b', label='Validation acc')
        plt.title('Training and validation accuracy')
        plt.xlabel('Epochs')
        plt.ylabel('Loss')
        plt.legend()

        plt.show()

Training and validation accuracy


In [34]: model = models.Sequential()
        model.add(layers.Dense(16, activation='relu', input_shape=(10000,)))
        model.add(layers.Dense(16, activation='relu'))
        model.add(layers.Dense(1, activation='sigmoid'))
        model.compile(optimizer='rmsprop',
                    loss='binary_crossentropy',
                    metrics=['accuracy'])
        model.fit(x_train, y_train, epochs=4, batch_size=512)
        results = model.evaluate(x_test, y_test)

Epoch 1/4
49/49 [=====] - 1s 8ms/step - loss: 0.5301 - accuracy: 0.7508
Epoch 2/4
49/49 [=====] - 0s 8ms/step - loss: 0.2604 - accuracy: 0.9114
Epoch 3/4
49/49 [=====] - 0s 8ms/step - loss: 0.2021 - accuracy: 0.9281
Epoch 4/4
49/49 [=====] - 0s 8ms/step - loss: 0.1613 - accuracy: 0.9454
782/782 [=====] - 1s 1ms/step - loss: 0.3024 - accuracy: 0.8803

In [ ]:
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