Assignment 5

April 16, 2023

Gabriel Avinaz

Week 5

4/16/23

0.0.1 Assignment 5.1

Section 3.4

[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, 469, 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, 21, 134, 476, 26, 480, 5, 144, 30, 5535, 18, 51, 36, 28, 224, 92, 25, 104, 4, 226, 65, 16, 38, 1334, 88, 12, 16, 283, 5, 16, 4472, 113, 103, 32, 15, 16, 5345, 19, 178, 32]

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

[]: 9999

```
[]: 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]])
decoded_review
```

[]: "? this film was just brilliant casting location scenery story direction everyone's really suited the part they played and you could just imagine being there robert? is an amazing actor and now the same being director? father came from the same scottish island as myself so i loved the fact there was a real connection with this film the witty remarks throughout the film were great it was just brilliant so much that i bought the film as soon as it was released for? and would recommend it to everyone to watch and the fly fishing was amazing really cried at the end it was so sad and you know what they say if you cry at a film it must have been good and this definitely was also? to the two little boy's that played the? of norman and paul they were just brilliant children are often left out of the? list i think because the stars that play them all grown up are such a big profile for the whole film but these children are amazing and should be praised for what they have done don't you think the whole story was so lovely because it was true and was someone's life after all that was shared with us all"

```
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)

x_train[0]
```

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

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

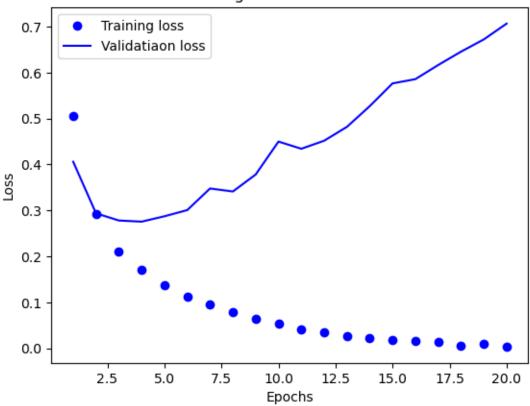
```
[]: from keras import optimizers
   model.compile(optimizer=optimizers.RMSprop(learning_rate=0.001),_
    →loss='binary_crossentropy', metrics=['accuracy'])
[]: from keras import losses, metrics
   model.compile(optimizer=optimizers.RMSprop(learning_rate=0.001), loss=losses.
    ⇒binary_crossentropy, metrics=[metrics.binary_accuracy])
[]: x_val = x_train[:10000]
   partial_x_train = x_train[10000:]
   y_val = y_train[:10000]
   partial_y_train = y_train[10000:]
[]: model.compile(optimizer=optimizers.RMSprop(learning rate=0.001),
   →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
  0.7801 - val_loss: 0.4060 - val_acc: 0.8346
  Epoch 2/20
  0.9004 - val_loss: 0.2938 - val_acc: 0.8898
  Epoch 3/20
  0.9312 - val_loss: 0.2782 - val_acc: 0.8903
  Epoch 4/20
  0.9435 - val_loss: 0.2757 - val_acc: 0.8907
  Epoch 5/20
  0.9559 - val_loss: 0.2874 - val_acc: 0.8853
  Epoch 6/20
  0.9660 - val_loss: 0.3008 - val_acc: 0.8836
  Epoch 7/20
  0.9721 - val_loss: 0.3478 - val_acc: 0.8774
  Epoch 8/20
  0.9782 - val_loss: 0.3413 - val_acc: 0.8811
  Epoch 9/20
```

```
Epoch 10/20
  0.9867 - val_loss: 0.4498 - val_acc: 0.8604
  Epoch 11/20
  0.9903 - val_loss: 0.4342 - val_acc: 0.8742
  Epoch 12/20
  0.9924 - val_loss: 0.4516 - val_acc: 0.8723
  Epoch 13/20
  0.9954 - val_loss: 0.4818 - val_acc: 0.8723
  Epoch 14/20
  30/30 [============= ] - Os 8ms/step - loss: 0.0223 - acc:
  0.9957 - val_loss: 0.5269 - val_acc: 0.8684
  Epoch 15/20
  0.9971 - val_loss: 0.5763 - val_acc: 0.8624
  Epoch 16/20
  0.9970 - val_loss: 0.5856 - val_acc: 0.8664
  Epoch 17/20
  0.9971 - val_loss: 0.6163 - val_acc: 0.8656
  Epoch 18/20
  0.9996 - val_loss: 0.6453 - val_acc: 0.8666
  Epoch 19/20
  0.9973 - val_loss: 0.6720 - val_acc: 0.8641
  Epoch 20/20
  0.9999 - val_loss: 0.7064 - val_acc: 0.8635
[]: history_dict = history.history
  history_dict.keys()
[]: dict_keys(['loss', 'acc', 'val_loss', 'val_acc'])
[]: 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")
```

0.9821 - val_loss: 0.3782 - val_acc: 0.8748

```
plt.plot(epochs,val_loss_values, 'b', label="Validatiaon loss")
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()

plt.show()
```

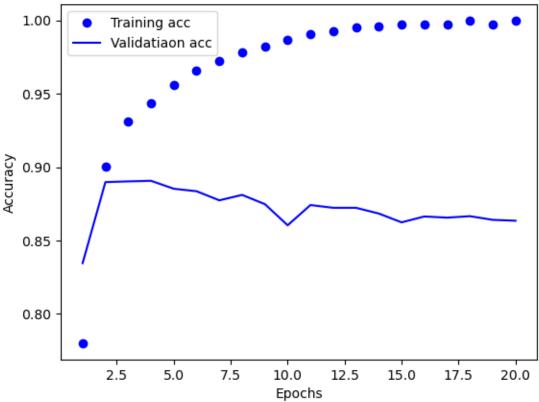


```
plt.clf()
    acc = history_dict['acc']
    val_acc = history_dict['val_acc']

plt.plot(epochs, acc, 'bo', label="Training acc")
    plt.plot(epochs, val_acc, 'b', label="Validatiaon acc")
    plt.title("Training and validation accuracy")
    plt.xlabel("Epochs")
    plt.ylabel("Accuracy")
    plt.legend()
```

plt.show()





```
[]: 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=optimizers.RMSprop(learning_rate=0.001), __
      →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
                           ========] - 1s 4ms/step - loss: 0.4761 - accuracy:
    49/49 [=====
    0.8186
    Epoch 2/4
                         =========] - Os 5ms/step - loss: 0.2718 - accuracy:
    49/49 [=======
    0.9066
    Epoch 3/4
```

```
0.9255
   Epoch 4/4
   0.9408
   accuracy: 0.8820
[]: results
[]: [0.2972390949726105, 0.8819599747657776]
[]: model.predict(x_test)
   782/782 [========== ] - 23s 29ms/step
[]: array([[0.14347336],
          [0.9999418],
          [0.831859],
          [0.10431504],
          [0.06340731],
          [0.41998455]], dtype=float32)
[]: model_1 = models.Sequential()
    model_1.add(layers.Dense(16, activation='relu', input_shape=(10000,)))
    model_1.add(layers.Dense(1, activation='sigmoid'))
    model_1.compile(optimizer=optimizers.RMSprop(learning_rate=0.001),_
     ⇔loss='binary_crossentropy', metrics=['acc'])
    history_1 = model_1.fit(partial_x_train, partial_y_train, epochs=20,_
     ⇒batch_size=512, validation_data=(x_val, y_val))
    model_2 = models.Sequential()
    model_2.add(layers.Dense(16, activation='relu', input_shape=(10000,)))
    model_2.add(layers.Dense(16,activation='relu'))
    model_2.add(layers.Dense(1, activation='sigmoid'))
    model_2.compile(optimizer=optimizers.RMSprop(learning_rate=0.001),_
     ⇔loss='binary_crossentropy', metrics=['acc'])
    history_2 = model_2.fit(partial_x_train, partial_y_train, epochs=20,__
     ⇒batch_size=512, validation_data=(x_val, y_val))
    model_3 = models.Sequential()
    model_3.add(layers.Dense(16, activation='relu', input_shape=(10000,)))
    model_3.add(layers.Dense(16,activation='relu'))
```

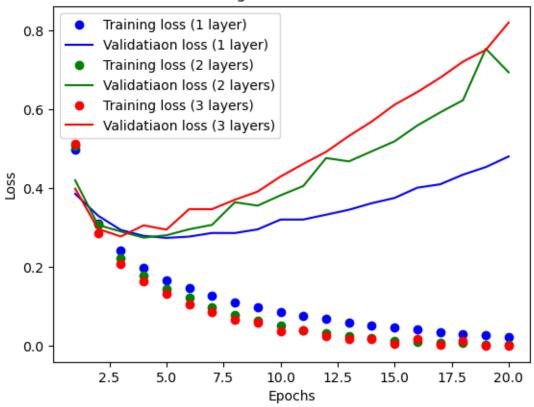
```
model_3.add(layers.Dense(16,activation='relu'))
model_3.add(layers.Dense(1, activation='sigmoid'))
model_3.compile(optimizer=optimizers.RMSprop(learning_rate=0.001),_
 ⇔loss='binary_crossentropy', metrics=['acc'])
history_3 = model_3.fit(partial_x_train, partial_y_train, epochs=20,_
 ⇒batch_size=512, validation_data=(x_val, y_val))
history_dict_1 = history_1.history
history_dict_2 = history_2.history
history_dict_3 = history_3.history
Epoch 1/20
30/30 [============= ] - 1s 23ms/step - loss: 0.4982 - acc:
0.7992 - val_loss: 0.3863 - val_acc: 0.8670
Epoch 2/20
0.9046 - val_loss: 0.3310 - val_acc: 0.8749
Epoch 3/20
0.9259 - val_loss: 0.2946 - val_acc: 0.8863
Epoch 4/20
0.9387 - val_loss: 0.2797 - val_acc: 0.8884
Epoch 5/20
30/30 [=============== ] - Os 10ms/step - loss: 0.1677 - acc:
0.9507 - val_loss: 0.2744 - val_acc: 0.8907
Epoch 6/20
0.9571 - val_loss: 0.2778 - val_acc: 0.8879
Epoch 7/20
0.9637 - val_loss: 0.2870 - val_acc: 0.8850
Epoch 8/20
0.9695 - val_loss: 0.2868 - val_acc: 0.8862
Epoch 9/20
0.9739 - val_loss: 0.2961 - val_acc: 0.8855
Epoch 10/20
0.9779 - val_loss: 0.3209 - val_acc: 0.8784
Epoch 11/20
30/30 [============== ] - Os 10ms/step - loss: 0.0779 - acc:
0.9812 - val_loss: 0.3211 - val_acc: 0.8834
```

```
Epoch 12/20
0.9840 - val_loss: 0.3333 - val_acc: 0.8800
Epoch 13/20
0.9873 - val_loss: 0.3458 - val_acc: 0.8806
Epoch 14/20
0.9898 - val_loss: 0.3624 - val_acc: 0.8772
Epoch 15/20
0.9906 - val_loss: 0.3758 - val_acc: 0.8775
Epoch 16/20
0.9923 - val_loss: 0.4018 - val_acc: 0.8776
Epoch 17/20
0.9941 - val_loss: 0.4104 - val_acc: 0.8755
Epoch 18/20
0.9955 - val_loss: 0.4348 - val_acc: 0.8759
Epoch 19/20
0.9963 - val_loss: 0.4541 - val_acc: 0.8682
Epoch 20/20
0.9974 - val_loss: 0.4809 - val_acc: 0.8660
Epoch 1/20
0.7899 - val_loss: 0.4205 - val_acc: 0.8364
Epoch 2/20
0.9053 - val_loss: 0.3073 - val_acc: 0.8865
Epoch 3/20
0.9297 - val_loss: 0.2907 - val_acc: 0.8836
Epoch 4/20
30/30 [================= ] - Os 12ms/step - loss: 0.1794 - acc:
0.9413 - val_loss: 0.2752 - val_acc: 0.8899
Epoch 5/20
0.9541 - val_loss: 0.2812 - val_acc: 0.8854
0.9620 - val_loss: 0.2964 - val_acc: 0.8858
Epoch 7/20
30/30 [=============== ] - Os 10ms/step - loss: 0.0980 - acc:
0.9723 - val_loss: 0.3076 - val_acc: 0.8833
```

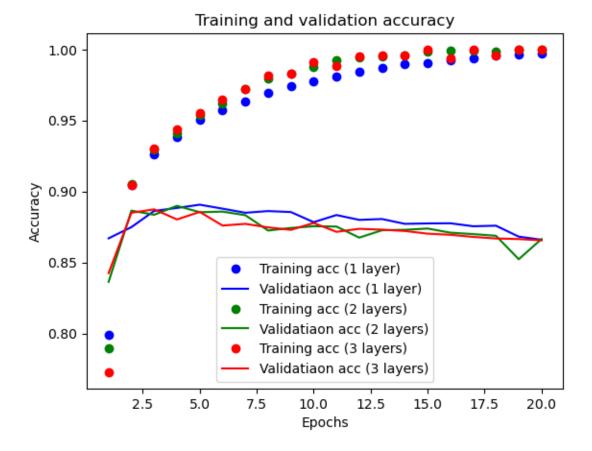
```
Epoch 8/20
0.9797 - val_loss: 0.3648 - val_acc: 0.8725
Epoch 9/20
0.9833 - val_loss: 0.3563 - val_acc: 0.8743
Epoch 10/20
30/30 [================= ] - Os 10ms/step - loss: 0.0536 - acc:
0.9874 - val_loss: 0.3824 - val_acc: 0.8755
Epoch 11/20
0.9925 - val_loss: 0.4060 - val_acc: 0.8753
Epoch 12/20
0.9942 - val_loss: 0.4770 - val_acc: 0.8675
Epoch 13/20
0.9951 - val_loss: 0.4685 - val_acc: 0.8727
Epoch 14/20
0.9960 - val_loss: 0.4941 - val_acc: 0.8730
Epoch 15/20
0.9985 - val_loss: 0.5193 - val_acc: 0.8739
Epoch 16/20
0.9994 - val_loss: 0.5596 - val_acc: 0.8710
Epoch 17/20
30/30 [============== ] - Os 10ms/step - loss: 0.0094 - acc:
0.9990 - val_loss: 0.5927 - val_acc: 0.8700
Epoch 18/20
0.9984 - val_loss: 0.6236 - val_acc: 0.8688
Epoch 19/20
0.9999 - val_loss: 0.7541 - val_acc: 0.8523
Epoch 20/20
0.9998 - val_loss: 0.6944 - val_acc: 0.8665
Epoch 1/20
0.7727 - val_loss: 0.3995 - val_acc: 0.8425
0.9047 - val_loss: 0.2972 - val_acc: 0.8850
Epoch 3/20
0.9299 - val_loss: 0.2782 - val_acc: 0.8874
```

```
Epoch 4/20
30/30 [============= ] - Os 8ms/step - loss: 0.1639 - acc:
0.9435 - val_loss: 0.3063 - val_acc: 0.8803
Epoch 5/20
0.9549 - val_loss: 0.2955 - val_acc: 0.8856
Epoch 6/20
0.9647 - val_loss: 0.3476 - val_acc: 0.8760
Epoch 7/20
0.9721 - val_loss: 0.3473 - val_acc: 0.8772
Epoch 8/20
0.9817 - val_loss: 0.3713 - val_acc: 0.8747
Epoch 9/20
0.9827 - val_loss: 0.3919 - val_acc: 0.8730
Epoch 10/20
30/30 [============== ] - Os 10ms/step - loss: 0.0379 - acc:
0.9913 - val_loss: 0.4301 - val_acc: 0.8778
Epoch 11/20
0.9884 - val_loss: 0.4622 - val_acc: 0.8716
Epoch 12/20
0.9949 - val_loss: 0.4927 - val_acc: 0.8737
Epoch 13/20
0.9961 - val_loss: 0.5330 - val_acc: 0.8731
Epoch 14/20
0.9957 - val_loss: 0.5695 - val_acc: 0.8722
Epoch 15/20
0.9996 - val_loss: 0.6122 - val_acc: 0.8703
Epoch 16/20
0.9937 - val_loss: 0.6443 - val_acc: 0.8695
Epoch 17/20
0.9998 - val_loss: 0.6806 - val_acc: 0.8680
Epoch 18/20
30/30 [============= ] - Os 9ms/step - loss: 0.0135 - acc:
0.9959 - val_loss: 0.7214 - val_acc: 0.8669
Epoch 19/20
0.9999 - val_loss: 0.7512 - val_acc: 0.8665
```

```
Epoch 20/20
    0.9999 - val_loss: 0.8203 - val_acc: 0.8656
[]: loss_values_1 = history_dict_1['loss']
    val_loss_values_1 = history_dict_1['val_loss']
    loss_values_2 = history_dict_2['loss']
    val_loss_values_2 = history_dict_2['val_loss']
    loss values 3 = history dict 3['loss']
    val_loss_values_3 = history_dict_3['val_loss']
    epochs = range(1, len(loss_values_1) + 1)
    plt.plot(epochs,loss_values_1, 'bo', label="Training loss (1 layer)")
    plt.plot(epochs,val_loss_values_1, 'b', label="Validatiaon loss (1 layer)")
    plt.plot(epochs,loss_values_2, 'go', label="Training loss (2 layers)")
    plt.plot(epochs,val_loss_values_2, 'g', label="Validatiaon loss (2 layers)")
    plt.plot(epochs,loss_values_3, 'ro', label="Training loss (3 layers)")
    plt.plot(epochs,val_loss_values_3, 'r', label="Validatiaon loss (3 layers)")
    plt.title("Training and validation loss")
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()
```



```
[]: plt.clf()
     acc_1 = history_dict_1['acc']
     val_acc_1 = history_dict_1['val_acc']
     acc_2 = history_dict_2['acc']
     val_acc_2 = history_dict_2['val_acc']
     acc_3 = history_dict_3['acc']
     val_acc_3 = history_dict_3['val_acc']
     plt.plot(epochs, acc_1, 'bo', label="Training acc (1 layer)")
     plt.plot(epochs, val_acc_1, 'b', label="Validatiaon acc (1 layer)")
     plt.plot(epochs, acc_2, 'go', label="Training acc (2 layers)")
     plt.plot(epochs, val_acc_2, 'g', label="Validatiaon acc (2 layers)")
     plt.plot(epochs, acc_3, 'ro', label="Training acc (3 layers)")
     plt.plot(epochs, val_acc_3, 'r', label="Validatiaon acc (3 layers)")
     plt.title("Training and validation accuracy")
     plt.xlabel("Epochs")
     plt.ylabel("Accuracy")
     plt.legend()
```



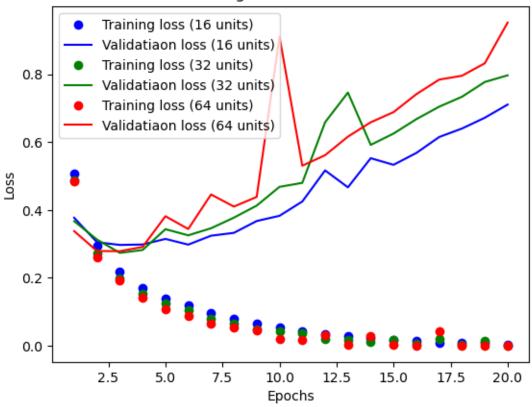
```
model_32.compile(optimizer=optimizers.RMSprop(learning_rate=0.001),_
 ⇔loss='binary_crossentropy', metrics=['acc'])
history_32 = model_32.fit(partial_x_train, partial_y_train, epochs=20,_
 ⇒batch_size=512, validation_data=(x_val, y_val))
model_64 = models.Sequential()
model_64.add(layers.Dense(64, activation='relu', input_shape=(10000,)))
model_64.add(layers.Dense(64,activation='relu'))
model_64.add(layers.Dense(1, activation='sigmoid'))
model 64.compile(optimizer=optimizers.RMSprop(learning rate=0.001),
 ⇔loss='binary_crossentropy', metrics=['acc'])
history_64 = model_64.fit(partial_x_train, partial_y_train, epochs=20,_
 ⇒batch_size=512, validation_data=(x_val, y_val))
history_dict_16 = history_16.history
history_dict_32 = history_32.history
history_dict_64 = history_64.history
Epoch 1/20
30/30 [=============== ] - 1s 23ms/step - loss: 0.5080 - acc:
0.7830 - val_loss: 0.3770 - val_acc: 0.8749
Epoch 2/20
0.9065 - val_loss: 0.3050 - val_acc: 0.8842
Epoch 3/20
0.9287 - val_loss: 0.2970 - val_acc: 0.8820
Epoch 4/20
0.9469 - val loss: 0.2983 - val acc: 0.8816
Epoch 5/20
30/30 [=============== ] - Os 11ms/step - loss: 0.1398 - acc:
0.9544 - val_loss: 0.3147 - val_acc: 0.8768
0.9631 - val_loss: 0.2979 - val_acc: 0.8867
Epoch 7/20
0.9721 - val_loss: 0.3242 - val_acc: 0.8800
Epoch 8/20
0.9772 - val_loss: 0.3326 - val_acc: 0.8812
Epoch 9/20
```

```
0.9830 - val_loss: 0.3675 - val_acc: 0.8797
Epoch 10/20
0.9861 - val_loss: 0.3829 - val_acc: 0.8758
Epoch 11/20
30/30 [============== ] - Os 10ms/step - loss: 0.0427 - acc:
0.9906 - val_loss: 0.4250 - val_acc: 0.8745
Epoch 12/20
30/30 [=============== ] - Os 14ms/step - loss: 0.0340 - acc:
0.9923 - val_loss: 0.5166 - val_acc: 0.8568
Epoch 13/20
30/30 [============= ] - Os 9ms/step - loss: 0.0297 - acc:
0.9943 - val_loss: 0.4668 - val_acc: 0.8736
Epoch 14/20
0.9957 - val_loss: 0.5526 - val_acc: 0.8604
Epoch 15/20
0.9982 - val_loss: 0.5332 - val_acc: 0.8719
Epoch 16/20
0.9972 - val_loss: 0.5681 - val_acc: 0.8694
Epoch 17/20
0.9995 - val_loss: 0.6150 - val_acc: 0.8642
Epoch 18/20
0.9991 - val_loss: 0.6401 - val_acc: 0.8671
Epoch 19/20
30/30 [=============== ] - Os 12ms/step - loss: 0.0080 - acc:
0.9986 - val_loss: 0.6718 - val_acc: 0.8668
Epoch 20/20
0.9999 - val_loss: 0.7107 - val_acc: 0.8648
Epoch 1/20
0.7860 - val_loss: 0.3670 - val_acc: 0.8567
Epoch 2/20
0.9062 - val_loss: 0.3129 - val_acc: 0.8723
Epoch 3/20
30/30 [============== ] - Os 13ms/step - loss: 0.1982 - acc:
0.9309 - val_loss: 0.2736 - val_acc: 0.8914
Epoch 4/20
30/30 [=============== ] - Os 10ms/step - loss: 0.1526 - acc:
0.9485 - val_loss: 0.2822 - val_acc: 0.8884
Epoch 5/20
```

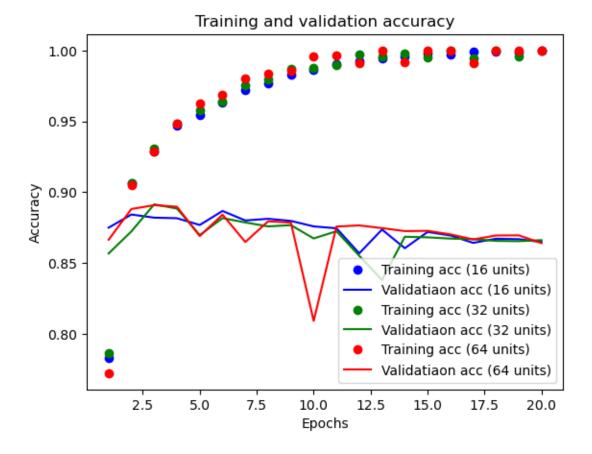
```
30/30 [=============== ] - Os 11ms/step - loss: 0.1250 - acc:
0.9576 - val_loss: 0.3434 - val_acc: 0.8697
Epoch 6/20
0.9643 - val_loss: 0.3254 - val_acc: 0.8817
Epoch 7/20
30/30 [============== ] - Os 10ms/step - loss: 0.0783 - acc:
0.9758 - val_loss: 0.3462 - val_acc: 0.8786
Epoch 8/20
30/30 [=============== ] - Os 11ms/step - loss: 0.0641 - acc:
0.9794 - val_loss: 0.3774 - val_acc: 0.8758
Epoch 9/20
30/30 [============== ] - Os 13ms/step - loss: 0.0477 - acc:
0.9871 - val_loss: 0.4129 - val_acc: 0.8767
Epoch 10/20
30/30 [============== ] - Os 10ms/step - loss: 0.0423 - acc:
0.9877 - val_loss: 0.4682 - val_acc: 0.8673
Epoch 11/20
30/30 [=============== ] - Os 10ms/step - loss: 0.0367 - acc:
0.9895 - val_loss: 0.4800 - val_acc: 0.8724
Epoch 12/20
0.9971 - val_loss: 0.6586 - val_acc: 0.8551
Epoch 13/20
30/30 [============== ] - Os 10ms/step - loss: 0.0181 - acc:
0.9962 - val_loss: 0.7460 - val_acc: 0.8380
Epoch 14/20
0.9981 - val_loss: 0.5919 - val_acc: 0.8685
Epoch 15/20
30/30 [=============== ] - Os 14ms/step - loss: 0.0183 - acc:
0.9951 - val_loss: 0.6253 - val_acc: 0.8681
Epoch 16/20
0.9999 - val_loss: 0.6677 - val_acc: 0.8672
Epoch 17/20
30/30 [================== ] - Os 13ms/step - loss: 0.0191 - acc:
0.9948 - val_loss: 0.7044 - val_acc: 0.8668
Epoch 18/20
0.9999 - val_loss: 0.7337 - val_acc: 0.8656
Epoch 19/20
30/30 [============== ] - Os 13ms/step - loss: 0.0154 - acc:
0.9958 - val_loss: 0.7772 - val_acc: 0.8654
Epoch 20/20
30/30 [=============== ] - Os 12ms/step - loss: 0.0014 - acc:
0.9999 - val_loss: 0.7969 - val_acc: 0.8661
Epoch 1/20
```

```
0.7721 - val_loss: 0.3378 - val_acc: 0.8664
Epoch 2/20
0.9047 - val_loss: 0.2791 - val_acc: 0.8881
Epoch 3/20
0.9287 - val_loss: 0.2786 - val_acc: 0.8908
Epoch 4/20
30/30 [=============== ] - Os 15ms/step - loss: 0.1425 - acc:
0.9481 - val_loss: 0.2912 - val_acc: 0.8897
Epoch 5/20
0.9627 - val_loss: 0.3817 - val_acc: 0.8690
Epoch 6/20
30/30 [=============== ] - Os 12ms/step - loss: 0.0886 - acc:
0.9689 - val_loss: 0.3439 - val_acc: 0.8841
Epoch 7/20
30/30 [=============== ] - Os 12ms/step - loss: 0.0657 - acc:
0.9801 - val_loss: 0.4458 - val_acc: 0.8648
Epoch 8/20
0.9835 - val_loss: 0.4101 - val_acc: 0.8794
Epoch 9/20
30/30 [============== ] - Os 14ms/step - loss: 0.0452 - acc:
0.9857 - val_loss: 0.4385 - val_acc: 0.8785
Epoch 10/20
0.9961 - val_loss: 0.9109 - val_acc: 0.8091
Epoch 11/20
30/30 [============== ] - Os 12ms/step - loss: 0.0168 - acc:
0.9963 - val_loss: 0.5305 - val_acc: 0.8757
Epoch 12/20
0.9910 - val loss: 0.5615 - val acc: 0.8765
Epoch 13/20
0.9999 - val_loss: 0.6162 - val_acc: 0.8746
Epoch 14/20
0.9917 - val_loss: 0.6585 - val_acc: 0.8725
Epoch 15/20
30/30 [============= ] - Os 13ms/step - loss: 0.0016 - acc:
0.9999 - val_loss: 0.6884 - val_acc: 0.8727
Epoch 16/20
30/30 [============== ] - Os 13ms/step - loss: 0.0011 - acc:
0.9999 - val_loss: 0.7414 - val_acc: 0.8702
Epoch 17/20
```

```
30/30 [============== ] - Os 15ms/step - loss: 0.0413 - acc:
   0.9914 - val_loss: 0.7842 - val_acc: 0.8666
   Epoch 18/20
   1.0000 - val_loss: 0.7956 - val_acc: 0.8694
   Epoch 19/20
   1.0000 - val_loss: 0.8324 - val_acc: 0.8695
   Epoch 20/20
   1.0000 - val_loss: 0.9522 - val_acc: 0.8640
[]: loss values 16 = history dict 16['loss']
    val_loss_values_16 = history_dict_16['val_loss']
    loss_values_32 = history_dict_32['loss']
    val_loss_values_32 = history_dict_32['val_loss']
    loss_values_64 = history_dict_64['loss']
    val_loss_values_64 = history_dict_64['val_loss']
    epochs = range(1, len(loss_values_64) + 1)
    plt.plot(epochs,loss_values_16, 'bo', label="Training loss (16 units)")
    plt.plot(epochs,val_loss_values_16, 'b', label="Validatiaon loss (16 units)")
    plt.plot(epochs,loss values 32, 'go', label="Training loss (32 units)")
    plt.plot(epochs,val_loss_values_32, 'g', label="Validatiaon loss (32 units)")
    plt.plot(epochs,loss_values_64, 'ro', label="Training loss (64 units)")
    plt.plot(epochs,val_loss_values_64, 'r', label="Validatiaon loss (64 units)")
    plt.title("Training and validation loss")
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()
```



```
[]: plt.clf()
     acc_16 = history_dict_16['acc']
     val_acc_16 = history_dict_16['val_acc']
     acc_32 = history_dict_32['acc']
     val_acc_32 = history_dict_32['val_acc']
     acc_64 = history_dict_64['acc']
     val_acc_64 = history_dict_64['val_acc']
     plt.plot(epochs, acc_16, 'bo', label="Training acc (16 units)")
     plt.plot(epochs, val_acc_16, 'b', label="Validatiaon acc (16 units)")
     plt.plot(epochs, acc_32, 'go', label="Training acc (32 units)")
     plt.plot(epochs, val_acc_32, 'g', label="Validatiaon acc (32 units)")
     plt.plot(epochs, acc_64, 'ro', label="Training acc (64 units)")
     plt.plot(epochs, val_acc_64, 'r', label="Validatiaon acc (64 units)")
     plt.title("Training and validation accuracy")
     plt.xlabel("Epochs")
     plt.ylabel("Accuracy")
     plt.legend()
```



```
model_mse.compile(optimizer=optimizers.RMSprop(learning_rate=0.001),__
 ⇒loss='mse', metrics=['acc'])
history_mse = model_mse.fit(partial_x_train, partial_y_train, epochs=20,_
 ⇒batch size=512, validation data=(x val, y val))
history_dict_mse = history_mse.history
Epoch 1/20
30/30 [============== ] - 1s 28ms/step - loss: 0.5380 - acc:
0.7799 - val_loss: 0.4071 - val_acc: 0.8757
Epoch 2/20
0.9006 - val_loss: 0.3109 - val_acc: 0.8905
Epoch 3/20
30/30 [============= ] - Os 10ms/step - loss: 0.2335 - acc:
0.9253 - val_loss: 0.2797 - val_acc: 0.8911
Epoch 4/20
30/30 [=============== ] - Os 11ms/step - loss: 0.1841 - acc:
0.9409 - val_loss: 0.3197 - val_acc: 0.8700
Epoch 5/20
0.9515 - val_loss: 0.2958 - val_acc: 0.8812
Epoch 6/20
0.9635 - val_loss: 0.2926 - val_acc: 0.8858
Epoch 7/20
0.9693 - val_loss: 0.3045 - val_acc: 0.8844
Epoch 8/20
0.9767 - val_loss: 0.3236 - val_acc: 0.8821
Epoch 9/20
0.9827 - val_loss: 0.3435 - val_acc: 0.8784
Epoch 10/20
0.9864 - val_loss: 0.3838 - val_acc: 0.8727
Epoch 11/20
30/30 [============== ] - Os 10ms/step - loss: 0.0439 - acc:
0.9899 - val_loss: 0.4362 - val_acc: 0.8690
Epoch 12/20
0.9918 - val_loss: 0.4247 - val_acc: 0.8744
Epoch 13/20
```

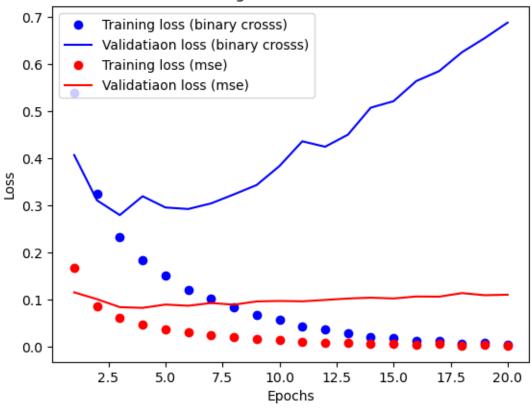
```
0.9941 - val_loss: 0.4503 - val_acc: 0.8742
Epoch 14/20
0.9968 - val_loss: 0.5075 - val_acc: 0.8663
Epoch 15/20
0.9969 - val_loss: 0.5214 - val_acc: 0.8711
Epoch 16/20
0.9989 - val_loss: 0.5642 - val_acc: 0.8682
Epoch 17/20
30/30 [============== ] - Os 10ms/step - loss: 0.0120 - acc:
0.9982 - val_loss: 0.5852 - val_acc: 0.8696
Epoch 18/20
30/30 [============= ] - Os 10ms/step - loss: 0.0063 - acc:
0.9997 - val_loss: 0.6252 - val_acc: 0.8680
Epoch 19/20
0.9985 - val_loss: 0.6553 - val_acc: 0.8677
Epoch 20/20
0.9991 - val_loss: 0.6881 - val_acc: 0.8659
Epoch 1/20
0.7774 - val_loss: 0.1157 - val_acc: 0.8703
Epoch 2/20
0.9052 - val_loss: 0.1013 - val_acc: 0.8668
0.9342 - val_loss: 0.0843 - val_acc: 0.8894
Epoch 4/20
0.9481 - val_loss: 0.0828 - val_acc: 0.8863
Epoch 5/20
0.9607 - val loss: 0.0899 - val acc: 0.8794
Epoch 6/20
30/30 [=============== ] - Os 10ms/step - loss: 0.0316 - acc:
0.9693 - val_loss: 0.0873 - val_acc: 0.8834
Epoch 7/20
0.9750 - val_loss: 0.0931 - val_acc: 0.8731
Epoch 8/20
0.9799 - val_loss: 0.0895 - val_acc: 0.8793
Epoch 9/20
30/30 [============= ] - Os 10ms/step - loss: 0.0168 - acc:
```

```
Epoch 10/20
  30/30 [============= ] - Os 12ms/step - loss: 0.0142 - acc:
  0.9884 - val_loss: 0.0975 - val_acc: 0.8722
  Epoch 11/20
  0.9906 - val_loss: 0.0967 - val_acc: 0.8741
  Epoch 12/20
  30/30 [============== ] - Os 10ms/step - loss: 0.0094 - acc:
  0.9929 - val_loss: 0.0996 - val_acc: 0.8753
  Epoch 13/20
  0.9931 - val_loss: 0.1027 - val_acc: 0.8726
  Epoch 14/20
  0.9939 - val_loss: 0.1045 - val_acc: 0.8690
  Epoch 15/20
  0.9948 - val_loss: 0.1028 - val_acc: 0.8711
  Epoch 16/20
  0.9971 - val_loss: 0.1070 - val_acc: 0.8679
  Epoch 17/20
  0.9941 - val_loss: 0.1066 - val_acc: 0.8674
  Epoch 18/20
  0.9973 - val_loss: 0.1141 - val_acc: 0.8609
  Epoch 19/20
  0.9958 - val_loss: 0.1096 - val_acc: 0.8652
  Epoch 20/20
  0.9976 - val_loss: 0.1108 - val_acc: 0.8649
[]: loss_values_bin = history_dict_bin['loss']
   val_loss_values_bin = history_dict_bin['val_loss']
   loss_values_mse = history_dict_mse['loss']
   val_loss_values_mse = history_dict_mse['val_loss']
   epochs = range(1, len(loss_values) + 1)
   plt.plot(epochs, loss_values_bin, 'bo', label="Training loss (binary crosss)")
   plt.plot(epochs, val_loss_values_bin, 'b', label="Validatiaon loss (binary ∪
   ⇔crosss)")
   plt.plot(epochs, loss_values_mse, 'ro', label="Training loss (mse)")
```

0.9863 - val_loss: 0.0965 - val_acc: 0.8732

```
plt.plot(epochs, val_loss_values_mse, 'r', label="Validatiaon loss (mse)")
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()

plt.show()
```



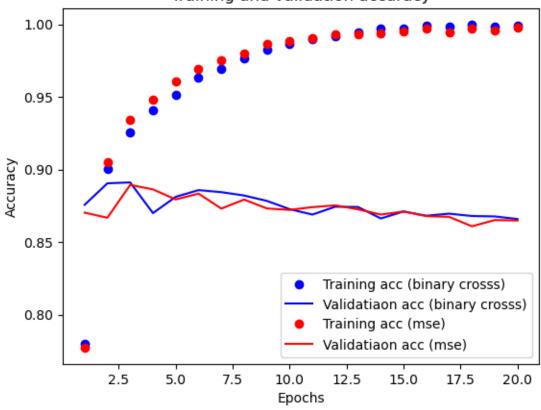
```
[]: plt.clf()
    acc_bin = history_dict_bin['acc']
    val_acc_bin = history_dict_bin['val_acc']
    acc_mse = history_dict_mse['acc']
    val_acc_mse = history_dict_mse['val_acc']

plt.plot(epochs, acc_bin, 'bo', label="Training acc (binary crosss)")
    plt.plot(epochs, val_acc_bin, 'b', label="Validatiaon acc (binary crosss)")
    plt.plot(epochs, acc_mse, 'ro', label="Training acc (mse)")
    plt.plot(epochs, val_acc_mse, 'r', label="Validatiaon acc (mse)")
    plt.title("Training and validation accuracy")
```

```
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()

plt.show()
```

Training and validation accuracy

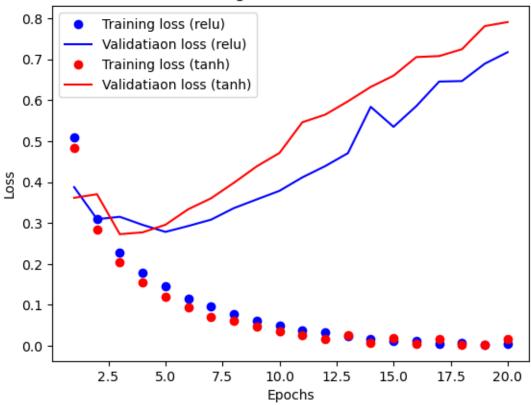


```
model_tanh = models.Sequential()
model_tanh.add(layers.Dense(16, activation='tanh', input_shape=(10000,)))
model_tanh.add(layers.Dense(16,activation='tanh'))
model_tanh.add(layers.Dense(1, activation='sigmoid'))
model_tanh.compile(optimizer=optimizers.RMSprop(learning_rate=0.001),_
 ⇔loss='binary_crossentropy', metrics=['acc'])
history_tanh = model_tanh.fit(partial_x_train, partial_y_train, epochs=20,__
 ⇒batch_size=512, validation_data=(x_val, y_val))
history_dict_tanh = history_tanh.history
Epoch 1/20
30/30 [============== ] - 1s 20ms/step - loss: 0.5102 - acc:
0.7929 - val_loss: 0.3876 - val_acc: 0.8711
Epoch 2/20
0.9021 - val_loss: 0.3095 - val_acc: 0.8888
Epoch 3/20
0.9295 - val_loss: 0.3152 - val_acc: 0.8727
Epoch 4/20
0.9441 - val_loss: 0.2955 - val_acc: 0.8804
Epoch 5/20
0.9549 - val_loss: 0.2784 - val_acc: 0.8876
Epoch 6/20
30/30 [============= ] - Os 8ms/step - loss: 0.1150 - acc:
0.9647 - val_loss: 0.2928 - val_acc: 0.8849
Epoch 7/20
30/30 [============= ] - Os 9ms/step - loss: 0.0968 - acc:
0.9702 - val_loss: 0.3082 - val_acc: 0.8830
0.9789 - val_loss: 0.3364 - val_acc: 0.8781
Epoch 9/20
30/30 [============== ] - Os 10ms/step - loss: 0.0608 - acc:
0.9844 - val_loss: 0.3577 - val_acc: 0.8774
Epoch 10/20
0.9876 - val_loss: 0.3787 - val_acc: 0.8786
Epoch 11/20
30/30 [============ ] - Os 9ms/step - loss: 0.0375 - acc:
0.9925 - val_loss: 0.4115 - val_acc: 0.8751
Epoch 12/20
```

```
0.9930 - val_loss: 0.4389 - val_acc: 0.8760
Epoch 13/20
0.9959 - val_loss: 0.4708 - val_acc: 0.8748
Epoch 14/20
0.9980 - val_loss: 0.5839 - val_acc: 0.8562
Epoch 15/20
0.9988 - val_loss: 0.5350 - val_acc: 0.8725
Epoch 16/20
0.9982 - val_loss: 0.5857 - val_acc: 0.8694
Epoch 17/20
0.9997 - val_loss: 0.6456 - val_acc: 0.8630
Epoch 18/20
0.9991 - val_loss: 0.6469 - val_acc: 0.8702
Epoch 19/20
0.9999 - val_loss: 0.6892 - val_acc: 0.8696
Epoch 20/20
0.9991 - val_loss: 0.7173 - val_acc: 0.8667
Epoch 1/20
0.8022 - val_loss: 0.3616 - val_acc: 0.8775
Epoch 2/20
0.9068 - val_loss: 0.3704 - val_acc: 0.8385
Epoch 3/20
0.9315 - val_loss: 0.2727 - val_acc: 0.8883
Epoch 4/20
0.9497 - val_loss: 0.2772 - val_acc: 0.8871
Epoch 5/20
0.9619 - val_loss: 0.2958 - val_acc: 0.8861
Epoch 6/20
30/30 [============== ] - Os 10ms/step - loss: 0.0947 - acc:
0.9723 - val_loss: 0.3337 - val_acc: 0.8801
Epoch 7/20
0.9784 - val_loss: 0.3604 - val_acc: 0.8774
Epoch 8/20
```

```
0.9819 - val_loss: 0.3983 - val_acc: 0.8768
  Epoch 9/20
  0.9877 - val_loss: 0.4384 - val_acc: 0.8726
  Epoch 10/20
  0.9917 - val_loss: 0.4712 - val_acc: 0.8727
  Epoch 11/20
  0.9938 - val_loss: 0.5461 - val_acc: 0.8588
  Epoch 12/20
  0.9969 - val_loss: 0.5647 - val_acc: 0.8674
  Epoch 13/20
  30/30 [=============== ] - Os 10ms/step - loss: 0.0258 - acc:
  0.9928 - val_loss: 0.5973 - val_acc: 0.8671
  Epoch 14/20
  0.9991 - val_loss: 0.6325 - val_acc: 0.8652
  Epoch 15/20
  0.9941 - val_loss: 0.6600 - val_acc: 0.8656
  Epoch 16/20
  0.9995 - val_loss: 0.7055 - val_acc: 0.8601
  Epoch 17/20
  0.9954 - val_loss: 0.7079 - val_acc: 0.8641
  Epoch 18/20
  0.9997 - val_loss: 0.7247 - val_acc: 0.8635
  Epoch 19/20
  0.9997 - val loss: 0.7812 - val acc: 0.8601
  Epoch 20/20
  0.9953 - val_loss: 0.7910 - val_acc: 0.8601
[]: loss_values_relu = history_dict_relu['loss']
  val_loss_values_relu = history_dict_relu['val_loss']
  loss_values_tanh = history_dict_tanh['loss']
  val_loss_values_tanh = history_dict_tanh['val_loss']
  epochs = range(1, len(loss_values) + 1)
```

```
plt.plot(epochs, loss_values_relu, 'bo', label="Training loss (relu)")
plt.plot(epochs, val_loss_values_relu, 'b', label="Validatiaon loss (relu)")
plt.plot(epochs, loss_values_tanh, 'ro', label="Training loss (tanh)")
plt.plot(epochs, val_loss_values_tanh, 'r', label="Validatiaon loss (tanh)")
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
```



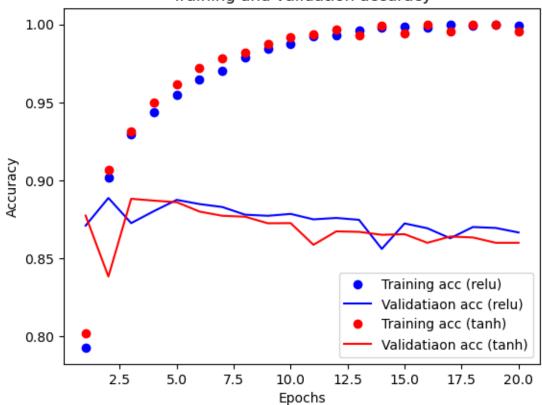
```
[]: plt.clf()

acc_relu = history_dict_relu['acc']
val_acc_relu = history_dict_relu['val_acc']
acc_tanh = history_dict_tanh['acc']
val_acc_tanh = history_dict_tanh['val_acc']

plt.plot(epochs, acc_relu, 'bo', label="Training acc (relu)")
plt.plot(epochs, val_acc_relu, 'b', label="Validatiaon acc (relu)")
```

```
plt.plot(epochs, acc_tanh, 'ro', label="Training acc (tanh)")
plt.plot(epochs, val_acc_tanh, 'r', label="Validatiaon acc (tanh)")
plt.title("Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```





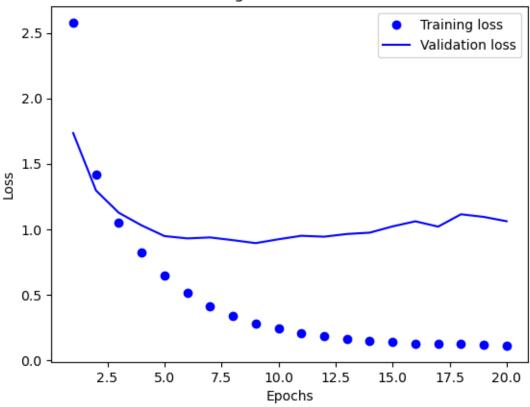
0.0.2 Assignment 5.2

Section 3.5

```
[]: 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]
[]: word_index = reuters.get_word_index()
     reverse_word_index = dict([(value, key) for (key, value) in word_index.items()])
     decoded_newswire = ' '.join([reverse_word_index.get(i - 3, '?') for i in_
      →train_data[0]])
     train_labels[10]
[]: 3
[]: x_train = vectorize_sequences(train_data)
     x_test = vectorize_sequences(test_data)
     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)
[]: from keras.utils.np_utils import to_categorical
     one_hot_train_labels = to_categorical(train_labels)
     one_hot_test_labels = to_categorical(test_labels)
[]: 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='categorical_crossentropy',
      →metrics=['acc'])
[]: 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:]
```

```
0.5279 - val_loss: 1.7344 - val_acc: 0.6430
Epoch 2/20
0.7096 - val_loss: 1.2960 - val_acc: 0.7150
Epoch 3/20
0.7829 - val_loss: 1.1259 - val_acc: 0.7650
Epoch 4/20
0.8326 - val_loss: 1.0295 - val_acc: 0.7830
Epoch 5/20
0.8637 - val_loss: 0.9482 - val_acc: 0.8000
Epoch 6/20
0.8928 - val_loss: 0.9303 - val_acc: 0.7930
Epoch 7/20
0.9143 - val_loss: 0.9377 - val_acc: 0.7900
Epoch 8/20
16/16 [=============== ] - Os 13ms/step - loss: 0.3388 - acc:
0.9290 - val_loss: 0.9169 - val_acc: 0.8040
Epoch 9/20
0.9371 - val_loss: 0.8940 - val_acc: 0.8110
Epoch 10/20
0.9461 - val_loss: 0.9237 - val_acc: 0.8160
Epoch 11/20
0.9486 - val_loss: 0.9503 - val_acc: 0.8020
Epoch 12/20
0.9546 - val_loss: 0.9434 - val_acc: 0.8070
Epoch 13/20
0.9540 - val_loss: 0.9639 - val_acc: 0.8080
Epoch 14/20
16/16 [=============== ] - Os 10ms/step - loss: 0.1509 - acc:
0.9535 - val_loss: 0.9740 - val_acc: 0.8050
Epoch 15/20
```

```
0.9570 - val_loss: 1.0218 - val_acc: 0.8030
   Epoch 16/20
   16/16 [============== ] - Os 10ms/step - loss: 0.1291 - acc:
   0.9575 - val_loss: 1.0607 - val_acc: 0.8040
   Epoch 17/20
   16/16 [=============== ] - Os 11ms/step - loss: 0.1229 - acc:
   0.9560 - val_loss: 1.0201 - val_acc: 0.8110
   Epoch 18/20
   16/16 [============== ] - Os 10ms/step - loss: 0.1229 - acc:
   0.9580 - val_loss: 1.1142 - val_acc: 0.8020
   Epoch 19/20
   0.9572 - val_loss: 1.0941 - val_acc: 0.8060
   Epoch 20/20
   0.9592 - val_loss: 1.0612 - val_acc: 0.8050
[]: 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.show()
```

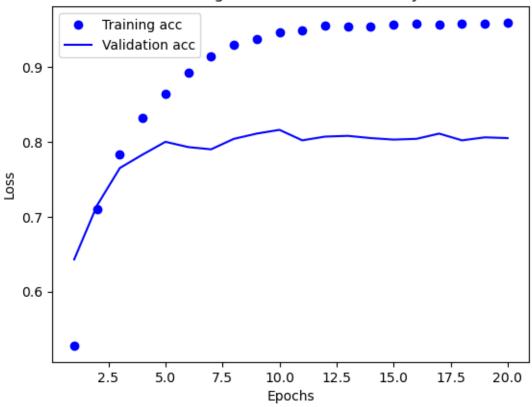


```
[]: plt.clf()
    acc = history.history['acc']
    val_acc = history.history['val_acc']

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()

plt.show()
```

Training and validation accuracy



```
0.7752 - val_loss: 1.1179 - val_acc: 0.7540
   Epoch 4/8
   16/16 [=============== ] - Os 10ms/step - loss: 0.8190 - acc:
   0.8257 - val_loss: 1.0161 - val_acc: 0.7860
   Epoch 5/8
   0.8604 - val_loss: 0.9635 - val_acc: 0.7900
   Epoch 6/8
   16/16 [============== ] - Os 10ms/step - loss: 0.5201 - acc:
   0.8931 - val_loss: 0.9542 - val_acc: 0.7830
   Epoch 7/8
   0.9108 - val_loss: 0.9073 - val_acc: 0.8080
   Epoch 8/8
   16/16 [============= ] - Os 9ms/step - loss: 0.3408 - acc:
   0.9271 - val_loss: 0.9281 - val_acc: 0.8070
   0.7827
[]: [0.9946668148040771, 0.7827248573303223]
[]: import copy
   test_labels_copy = copy.copy(test_labels)
   np.random.shuffle(test_labels_copy)
   float(np.sum(np.array(test_labels) == np.array(test_labels_copy))) /__
     →len(test_labels)
[]: 0.18165627782724844
[]: predictions = model.predict(x_test)
   predictions[0].shape
   71/71 [========] - 2s 33ms/step
[]: (46,)
[]: np.sum(predictions[0])
[]: 1.0000001
[]: np.argmax(predictions[0])
[]: 3
[]: y_train = np.array(train_labels)
   y_test = np.array(test_labels)
```

```
model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy', __
 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', u
 →metrics=['accuracy'])
model.fit(partial_x_train, partial_y_train, epochs=20, batch_size=128,_
 ⇔validation_data=(x_val, y_val))
Epoch 1/20
0.3760 - val_loss: 2.0033 - val_accuracy: 0.5820
Epoch 2/20
0.6255 - val_loss: 1.4635 - val_accuracy: 0.6400
Epoch 3/20
0.6740 - val_loss: 1.3605 - val_accuracy: 0.6580
Epoch 4/20
63/63 [============= ] - Os 5ms/step - loss: 1.1184 - accuracy:
0.7170 - val_loss: 1.3060 - val_accuracy: 0.6850
Epoch 5/20
0.7423 - val_loss: 1.2793 - val_accuracy: 0.6940
Epoch 6/20
0.7662 - val_loss: 1.2910 - val_accuracy: 0.7020
Epoch 7/20
0.7849 - val_loss: 1.2974 - val_accuracy: 0.6990
0.8001 - val_loss: 1.3531 - val_accuracy: 0.7020
Epoch 9/20
0.8107 - val_loss: 1.3574 - val_accuracy: 0.7080
Epoch 10/20
0.8259 - val_loss: 1.3887 - val_accuracy: 0.7070
Epoch 11/20
0.8428 - val_loss: 1.4368 - val_accuracy: 0.7140
Epoch 12/20
```

```
0.8545 - val_loss: 1.4797 - val_accuracy: 0.7110
  Epoch 13/20
  0.8593 - val_loss: 1.5517 - val_accuracy: 0.7050
  Epoch 14/20
  0.8644 - val_loss: 1.6403 - val_accuracy: 0.7050
  Epoch 15/20
  0.8715 - val_loss: 1.6493 - val_accuracy: 0.7030
  Epoch 16/20
  0.8756 - val_loss: 1.7236 - val_accuracy: 0.7040
  Epoch 17/20
  0.8801 - val_loss: 1.7677 - val_accuracy: 0.7030
  Epoch 18/20
  0.8811 - val_loss: 1.8639 - val_accuracy: 0.7010
  Epoch 19/20
  0.8889 - val_loss: 1.9237 - val_accuracy: 0.7030
  Epoch 20/20
  0.8871 - val_loss: 1.9612 - val_accuracy: 0.7010
[]: <keras.callbacks.History at 0x236a2b1ac10>
[]: model_32 = models.Sequential()
   model 32.add(layers.Dense(32, activation='relu', input shape=(10000,)))
   model_32.add(layers.Dense(32, activation='relu'))
   model_32.add(layers.Dense(46, activation='softmax'))
   model_32.compile(optimizer='rmsprop', loss='categorical_crossentropy', __
    →metrics=['acc'])
   history_32 = model_32.fit(partial_x_train, partial_y_train, epochs=20,_
   ⇒batch_size=512, validation_data=(x_val, y_val))
   model_64 = models.Sequential()
   model_64.add(layers.Dense(64, activation='relu', input_shape=(10000,)))
   model_64.add(layers.Dense(64, activation='relu'))
   model_64.add(layers.Dense(46, activation='softmax'))
   model_64.compile(optimizer='rmsprop', loss='categorical_crossentropy', u
    →metrics=['acc'])
```

```
history_64 = model_64.fit(partial_x_train, partial_y_train, epochs=20,_
 ⇒batch_size=512, validation_data=(x_val, y_val))
model 128 = models.Sequential()
model_128.add(layers.Dense(128, activation='relu', input_shape=(10000,)))
model 128.add(layers.Dense(128, activation='relu'))
model_128.add(layers.Dense(46, activation='softmax'))
model_128.compile(optimizer='rmsprop', loss='categorical_crossentropy', u
 →metrics=['acc'])
history_128 = model_128.fit(partial_x_train, partial_y_train, epochs=20,_u
 ⇒batch size=512, validation data=(x val, y val))
Epoch 1/20
0.4996 - val_loss: 2.2671 - val_acc: 0.6080
Epoch 2/20
0.6689 - val_loss: 1.6634 - val_acc: 0.6600
Epoch 3/20
0.7093 - val_loss: 1.3851 - val_acc: 0.6980
Epoch 4/20
0.7464 - val_loss: 1.2350 - val_acc: 0.7240
Epoch 5/20
0.7871 - val_loss: 1.1529 - val_acc: 0.7430
Epoch 6/20
0.8151 - val_loss: 1.0762 - val_acc: 0.7660
Epoch 7/20
0.8405 - val_loss: 1.0372 - val_acc: 0.7680
0.8626 - val_loss: 0.9975 - val_acc: 0.7810
Epoch 9/20
0.8835 - val_loss: 0.9610 - val_acc: 0.8010
Epoch 10/20
0.8954 - val_loss: 0.9560 - val_acc: 0.7950
Epoch 11/20
16/16 [============ ] - Os 7ms/step - loss: 0.4098 - acc:
0.9085 - val_loss: 0.9387 - val_acc: 0.8020
Epoch 12/20
```

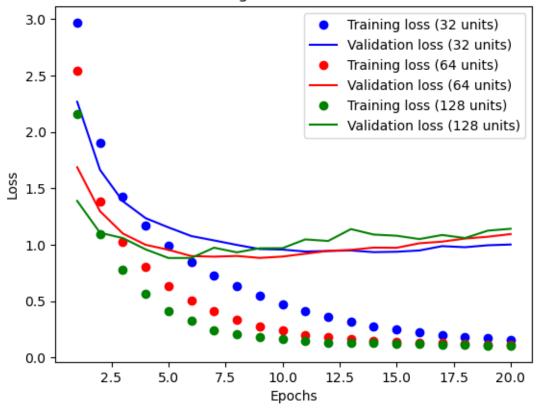
```
0.9194 - val_loss: 0.9439 - val_acc: 0.8020
Epoch 13/20
0.9270 - val_loss: 0.9482 - val_acc: 0.8090
Epoch 14/20
0.9364 - val_loss: 0.9334 - val_acc: 0.8090
Epoch 15/20
0.9405 - val_loss: 0.9369 - val_acc: 0.8150
Epoch 16/20
0.9460 - val_loss: 0.9482 - val_acc: 0.8120
Epoch 17/20
0.9491 - val_loss: 0.9868 - val_acc: 0.7970
Epoch 18/20
0.9506 - val_loss: 0.9772 - val_acc: 0.8070
Epoch 19/20
0.9538 - val_loss: 0.9945 - val_acc: 0.8060
Epoch 20/20
0.9549 - val_loss: 1.0011 - val_acc: 0.8010
Epoch 1/20
0.5296 - val_loss: 1.6864 - val_acc: 0.6350
Epoch 2/20
16/16 [=============== ] - Os 10ms/step - loss: 1.3850 - acc:
0.7097 - val_loss: 1.2965 - val_acc: 0.7040
Epoch 3/20
0.7809 - val loss: 1.0988 - val acc: 0.7790
Epoch 4/20
0.8327 - val_loss: 0.9985 - val_acc: 0.8010
Epoch 5/20
0.8690 - val_loss: 0.9543 - val_acc: 0.7970
Epoch 6/20
16/16 [=============== ] - Os 11ms/step - loss: 0.5084 - acc:
0.8948 - val_loss: 0.8985 - val_acc: 0.8120
Epoch 7/20
0.9123 - val_loss: 0.8933 - val_acc: 0.8080
Epoch 8/20
```

```
0.9282 - val_loss: 0.8995 - val_acc: 0.8010
Epoch 9/20
0.9406 - val_loss: 0.8821 - val_acc: 0.8180
Epoch 10/20
0.9440 - val_loss: 0.8942 - val_acc: 0.8130
Epoch 11/20
0.9498 - val_loss: 0.9194 - val_acc: 0.8200
Epoch 12/20
0.9516 - val_loss: 0.9446 - val_acc: 0.8120
Epoch 13/20
16/16 [=============== ] - Os 10ms/step - loss: 0.1663 - acc:
0.9519 - val_loss: 0.9536 - val_acc: 0.8190
Epoch 14/20
0.9557 - val_loss: 0.9736 - val_acc: 0.8130
Epoch 15/20
0.9560 - val_loss: 0.9720 - val_acc: 0.8020
Epoch 16/20
0.9579 - val_loss: 1.0120 - val_acc: 0.8060
Epoch 17/20
0.9583 - val_loss: 1.0266 - val_acc: 0.8040
Epoch 18/20
0.9568 - val_loss: 1.0537 - val_acc: 0.7990
Epoch 19/20
0.9575 - val loss: 1.0701 - val acc: 0.8040
Epoch 20/20
0.9580 - val_loss: 1.0935 - val_acc: 0.7990
Epoch 1/20
0.5660 - val_loss: 1.3875 - val_acc: 0.7030
Epoch 2/20
16/16 [============== ] - Os 14ms/step - loss: 1.0943 - acc:
0.7615 - val_loss: 1.1057 - val_acc: 0.7590
Epoch 3/20
0.8338 - val_loss: 1.0581 - val_acc: 0.7620
Epoch 4/20
```

```
0.8820 - val_loss: 0.9580 - val_acc: 0.7850
Epoch 5/20
0.9143 - val_loss: 0.8815 - val_acc: 0.8190
Epoch 6/20
0.9300 - val_loss: 0.8816 - val_acc: 0.8170
Epoch 7/20
0.9432 - val_loss: 0.9728 - val_acc: 0.8120
Epoch 8/20
0.9485 - val_loss: 0.9316 - val_acc: 0.8190
0.9536 - val_loss: 0.9679 - val_acc: 0.8080
Epoch 10/20
16/16 [=============== ] - Os 13ms/step - loss: 0.1604 - acc:
0.9548 - val_loss: 0.9689 - val_acc: 0.8100
Epoch 11/20
0.9558 - val_loss: 1.0462 - val_acc: 0.8090
Epoch 12/20
16/16 [=============== ] - Os 14ms/step - loss: 0.1322 - acc:
0.9564 - val_loss: 1.0324 - val_acc: 0.8100
Epoch 13/20
0.9551 - val_loss: 1.1380 - val_acc: 0.7930
Epoch 14/20
0.9562 - val_loss: 1.0893 - val_acc: 0.8020
Epoch 15/20
0.9569 - val loss: 1.0791 - val acc: 0.8030
Epoch 16/20
0.9579 - val_loss: 1.0494 - val_acc: 0.8130
Epoch 17/20
0.9573 - val_loss: 1.0856 - val_acc: 0.8090
Epoch 18/20
16/16 [=============== ] - Os 17ms/step - loss: 0.1109 - acc:
0.9580 - val_loss: 1.0585 - val_acc: 0.8080
Epoch 19/20
0.9590 - val_loss: 1.1239 - val_acc: 0.8070
Epoch 20/20
```

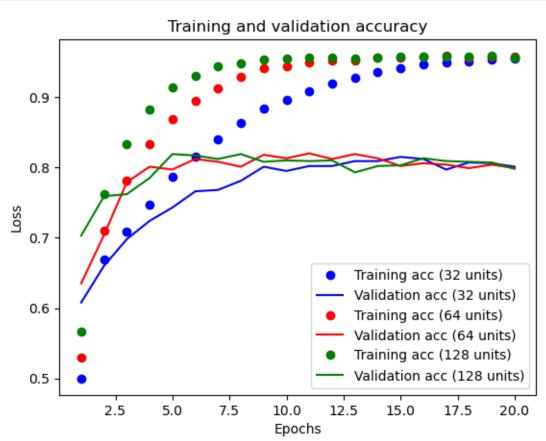
```
[]: loss_32 = history_32.history['loss']
     val_loss_32 = history_32.history['val_loss']
     loss_64 = history_64.history['loss']
     val_loss_64 = history_64.history['val_loss']
     loss_128 = history_128.history['loss']
     val_loss_128 = history_128.history['val_loss']
     epochs = range(1, len(loss_32) + 1)
     plt.plot(epochs, loss_32, 'bo', label='Training loss (32 units)')
     plt.plot(epochs, val_loss_32, 'b', label='Validation loss (32 units)')
     plt.plot(epochs, loss_64, 'ro', label='Training loss (64 units)')
    plt.plot(epochs, val_loss_64, 'r', label='Validation loss (64 units)')
     plt.plot(epochs, loss_128, 'go', label='Training loss (128 units)')
    plt.plot(epochs, val_loss_128, 'g', label='Validation loss (128 units)')
     plt.title('Training and validation loss')
     plt.xlabel('Epochs')
     plt.ylabel('Loss')
     plt.legend()
     plt.show()
```

Training and validation loss



```
[]: plt.clf()
     acc_32 = history_32.history['acc']
     val_acc_32 = history_32.history['val_acc']
     acc_64 = history_64.history['acc']
     val_acc_64 = history_64.history['val_acc']
     acc_128 = history_128.history['acc']
     val_acc_128 = history_128.history['val_acc']
     plt.plot(epochs, acc_32, 'bo', label='Training acc (32 units)')
     plt.plot(epochs, val_acc_32, 'b', label='Validation acc (32 units)')
     plt.plot(epochs, acc_64, 'ro', label='Training acc (64 units)')
     plt.plot(epochs, val_acc_64, 'r', label='Validation acc (64 units)')
    plt.plot(epochs, acc_128, 'go', label='Training acc (128 units)')
     plt.plot(epochs, val_acc_128, 'g', label='Validation acc (128 units)')
     plt.title('Training and validation accuracy')
     plt.xlabel('Epochs')
     plt.ylabel('Loss')
```

```
plt.legend()
plt.show()
```



```
model_2.compile(optimizer='rmsprop', loss='categorical_crossentropy', __

→metrics=['acc'])
history_2 = model_2.fit(partial_x_train, partial_y_train, epochs=20,__
 ⇒batch_size=512, validation_data=(x_val, y_val))
model_3 = models.Sequential()
model_3.add(layers.Dense(32, activation='relu', input_shape=(10000,)))
model_3.add(layers.Dense(32, activation='relu'))
model_3.add(layers.Dense(32, activation='relu'))
model_3.add(layers.Dense(46, activation='softmax'))
model_3.compile(optimizer='rmsprop', loss='categorical_crossentropy', __
→metrics=['acc'])
history_3 = model_3.fit(partial_x_train, partial_y_train, epochs=20,_u
 ⇒batch_size=512, validation_data=(x_val, y_val))
Epoch 1/20
0.5055 - val_loss: 2.7193 - val_acc: 0.6290
Epoch 2/20
0.6721 - val_loss: 1.9871 - val_acc: 0.6830
Epoch 3/20
0.7187 - val_loss: 1.5624 - val_acc: 0.7140
Epoch 4/20
0.7625 - val_loss: 1.3153 - val_acc: 0.7380
Epoch 5/20
0.7912 - val_loss: 1.1691 - val_acc: 0.7550
Epoch 6/20
0.8197 - val_loss: 1.0735 - val_acc: 0.7840
Epoch 7/20
0.8454 - val_loss: 1.0082 - val_acc: 0.7910
Epoch 8/20
0.8677 - val_loss: 0.9616 - val_acc: 0.7950
Epoch 9/20
0.8851 - val_loss: 0.9242 - val_acc: 0.8070
Epoch 10/20
0.8999 - val_loss: 0.8993 - val_acc: 0.8150
```

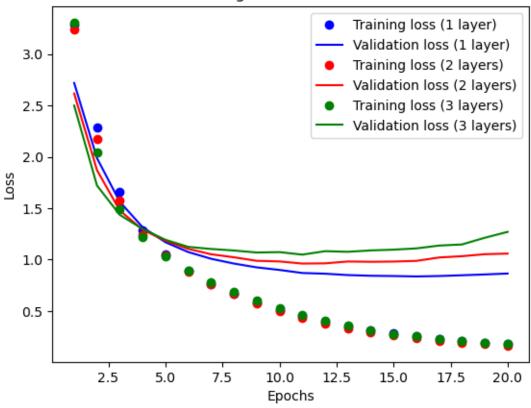
```
Epoch 11/20
0.9110 - val_loss: 0.8697 - val_acc: 0.8180
Epoch 12/20
0.9217 - val_loss: 0.8627 - val_acc: 0.8160
Epoch 13/20
0.9287 - val_loss: 0.8493 - val_acc: 0.8200
Epoch 14/20
0.9335 - val_loss: 0.8427 - val_acc: 0.8210
Epoch 15/20
0.9409 - val_loss: 0.8401 - val_acc: 0.8170
Epoch 16/20
0.9435 - val_loss: 0.8358 - val_acc: 0.8160
Epoch 17/20
0.9478 - val_loss: 0.8402 - val_acc: 0.8170
Epoch 18/20
16/16 [================== ] - Os 13ms/step - loss: 0.2108 - acc:
0.9504 - val_loss: 0.8475 - val_acc: 0.8160
Epoch 19/20
16/16 [============= ] - Os 8ms/step - loss: 0.1928 - acc:
0.9514 - val_loss: 0.8555 - val_acc: 0.8210
Epoch 20/20
0.9519 - val_loss: 0.8644 - val_acc: 0.8200
Epoch 1/20
0.3924 - val_loss: 2.6162 - val_acc: 0.5940
Epoch 2/20
0.6538 - val_loss: 1.8704 - val_acc: 0.6500
Epoch 3/20
0.7073 - val_loss: 1.4773 - val_acc: 0.6920
Epoch 4/20
0.7479 - val_loss: 1.2914 - val_acc: 0.7150
0.7811 - val_loss: 1.1826 - val_acc: 0.7460
Epoch 6/20
0.8122 - val_loss: 1.1047 - val_acc: 0.7640
```

```
Epoch 7/20
0.8383 - val_loss: 1.0519 - val_acc: 0.7760
Epoch 8/20
0.8594 - val_loss: 1.0225 - val_acc: 0.7860
Epoch 9/20
0.8804 - val_loss: 0.9883 - val_acc: 0.8000
Epoch 10/20
0.8975 - val_loss: 0.9822 - val_acc: 0.8040
Epoch 11/20
0.9122 - val_loss: 0.9614 - val_acc: 0.8020
Epoch 12/20
0.9206 - val_loss: 0.9635 - val_acc: 0.8110
Epoch 13/20
0.9278 - val_loss: 0.9817 - val_acc: 0.8070
Epoch 14/20
0.9340 - val_loss: 0.9786 - val_acc: 0.8110
Epoch 15/20
0.9386 - val_loss: 0.9812 - val_acc: 0.8090
Epoch 16/20
16/16 [============= ] - Os 8ms/step - loss: 0.2323 - acc:
0.9465 - val_loss: 0.9875 - val_acc: 0.8190
Epoch 17/20
0.9481 - val_loss: 1.0207 - val_acc: 0.8040
Epoch 18/20
0.9514 - val_loss: 1.0329 - val_acc: 0.8060
Epoch 19/20
0.9519 - val_loss: 1.0524 - val_acc: 0.8050
Epoch 20/20
0.9541 - val_loss: 1.0587 - val_acc: 0.8070
0.4042 - val_loss: 2.4995 - val_acc: 0.5410
Epoch 2/20
0.5864 - val_loss: 1.7209 - val_acc: 0.6170
```

```
Epoch 3/20
0.6642 - val_loss: 1.4352 - val_acc: 0.6730
Epoch 4/20
0.7225 - val_loss: 1.2986 - val_acc: 0.6940
Epoch 5/20
0.7656 - val_loss: 1.1926 - val_acc: 0.7320
Epoch 6/20
0.8036 - val_loss: 1.1240 - val_acc: 0.7540
Epoch 7/20
0.8271 - val_loss: 1.1035 - val_acc: 0.7570
Epoch 8/20
0.8449 - val_loss: 1.0886 - val_acc: 0.7620
Epoch 9/20
0.8589 - val_loss: 1.0689 - val_acc: 0.7600
Epoch 10/20
0.8760 - val_loss: 1.0727 - val_acc: 0.7730
Epoch 11/20
0.8871 - val_loss: 1.0483 - val_acc: 0.7780
Epoch 12/20
0.9038 - val_loss: 1.0820 - val_acc: 0.7650
Epoch 13/20
0.9164 - val_loss: 1.0760 - val_acc: 0.7730
Epoch 14/20
0.9262 - val_loss: 1.0894 - val_acc: 0.7690
Epoch 15/20
0.9336 - val_loss: 1.0968 - val_acc: 0.7830
Epoch 16/20
0.9415 - val_loss: 1.1090 - val_acc: 0.7820
Epoch 17/20
0.9424 - val_loss: 1.1367 - val_acc: 0.7850
Epoch 18/20
0.9485 - val_loss: 1.1473 - val_acc: 0.7770
```

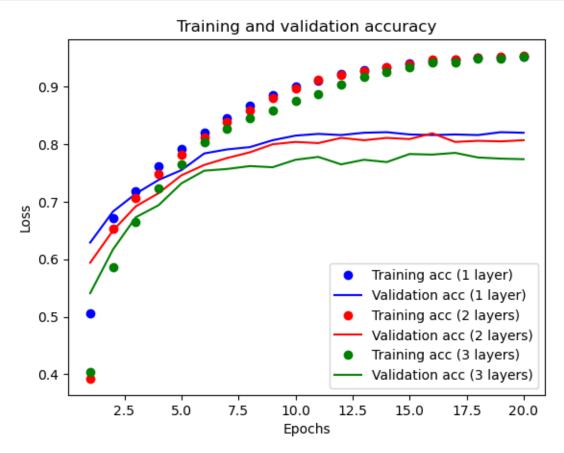
```
Epoch 19/20
   0.9493 - val_loss: 1.2125 - val_acc: 0.7750
   Epoch 20/20
   0.9523 - val_loss: 1.2699 - val_acc: 0.7740
[]: loss_1 = history_1.history['loss']
    val_loss_1 = history_1.history['val_loss']
    loss 2 = history 2.history['loss']
    val_loss_2 = history_2.history['val_loss']
    loss_3 = history_3.history['loss']
    val_loss_3 = history_3.history['val_loss']
    epochs = range(1, len(loss_32) + 1)
    plt.plot(epochs, loss_1, 'bo', label='Training loss (1 layer)')
    plt.plot(epochs, val_loss_1, 'b', label='Validation loss (1 layer)')
    plt.plot(epochs, loss_2, 'ro', label='Training loss (2 layers)')
    plt.plot(epochs, val_loss_2, 'r', label='Validation loss (2 layers)')
    plt.plot(epochs, loss_3, 'go', label='Training loss (3 layers)')
    plt.plot(epochs, val_loss_3, 'g', label='Validation loss (3 layers)')
    plt.title('Training and validation loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()
    plt.show()
```

Training and validation loss



```
[]: plt.clf()
     acc_1 = history_1.history['acc']
     val_acc_1 = history_1.history['val_acc']
     acc_2 = history_2.history['acc']
     val_acc_2 = history_2.history['val_acc']
     acc_3 = history_3.history['acc']
     val_acc_3 = history_3.history['val_acc']
     plt.plot(epochs, acc_1, 'bo', label='Training acc (1 layer)')
     plt.plot(epochs, val_acc_1, 'b', label='Validation acc (1 layer)')
     plt.plot(epochs, acc_2, 'ro', label='Training acc (2 layers)')
     plt.plot(epochs, val_acc_2, 'r', label='Validation acc (2 layers)')
     plt.plot(epochs, acc_3, 'go', label='Training acc (3 layers)')
     plt.plot(epochs, val_acc_3, 'g', label='Validation acc (3 layers)')
     plt.title('Training and validation accuracy')
     plt.xlabel('Epochs')
     plt.ylabel('Loss')
```

```
plt.legend()
plt.show()
```



0.0.3 Assignment 5.3

Section 3.6

```
22.2 16.7 12.7 15.6 18.4 21. 30.1 15.1 18.7 9.6 31.5 24.8 19.1 22.
     14.5 11. 32. 29.4 20.3 24.4 14.6 19.5 14.1 14.3 15.6 10.5 6.3 19.3
     19.3 13.4 36.4 17.8 13.5 16.5 8.3 14.3 16. 13.4 28.6 43.5 20.2 22.
     23. 20.7 12.5 48.5 14.6 13.4 23.7 50. 21.7 39.8 38.7 22.2 34.9 22.5
     31.1 28.7 46. 41.7 21. 26.6 15. 24.4 13.3 21.2 11.7 21.7 19.4 50.
     22.8 19.7 24.7 36.2 14.2 18.9 18.3 20.6 24.6 18.2 8.7 44.
     21.2 37. 30.7 22.9 20. 19.3 31.7 32. 23.1 18.8 10.9 50.
     14.4 19.8 13.8 19.6 23.9 24.5 25. 19.9 17.2 24.6 13.5 26.6 21.4 11.9
     22.6 19.6 8.5 23.7 23.1 22.4 20.5 23.6 18.4 35.2 23.1 27.9 20.6 23.7
     28. 13.6 27.1 23.6 20.6 18.2 21.7 17.1 8.4 25.3 13.8 22.2 18.4 20.7
     31.6 30.5 20.3 8.8 19.2 19.4 23.1 23. 14.8 48.8 22.6 33.4 21.1 13.6
     32.2 13.1 23.4 18.9 23.9 11.8 23.3 22.8 19.6 16.7 13.4 22.2 20.4 21.8
     26.4 14.9 24.1 23.8 12.3 29.1 21. 19.5 23.3 23.8 17.8 11.5 21.7 19.9
     25. 33.4 28.5 21.4 24.3 27.5 33.1 16.2 23.3 48.3 22.9 22.8 13.1 12.7
     22.6 15. 15.3 10.5 24. 18.5 21.7 19.5 33.2 23.2 5. 19.1 12.7 22.3
     10.2 13.9 16.3 17. 20.1 29.9 17.2 37.3 45.4 17.8 23.2 29.
     17.4 34.6 20.1 25. 15.6 24.8 28.2 21.2 21.4 23.8 31. 26.2 17.4 37.9
               8.3 23.9 8.4 13.8 7.2 11.7 17.1 21.6 50. 16.1 20.4 20.6
     21.4 20.6 36.5 8.5 24.8 10.8 21.9 17.3 18.9 36.2 14.9 18.2 33.3 21.8
     19.7 31.6 24.8 19.4 22.8 7.5 44.8 16.8 18.7 50. 50. 19.5 20.1 50.
     17.2 20.8 19.3 41.3 20.4 20.5 13.8 16.5 23.9 20.6 31.5 23.3 16.8 14.
     33.8 36.1 12.8 18.3 18.7 19.1 29. 30.1 50. 50. 22. 11.9 37.6 50.
     22.7 20.8 23.5 27.9 50. 19.3 23.9 22.6 15.2 21.7 19.2 43.8 20.3 33.2
     19.9 22.5 32.7 22. 17.1 19. 15. 16.1 25.1 23.7 28.7 37.2 22.6 16.4
         29.8 22.1 17.4 18.1 30.3 17.5 24.7 12.6 26.5 28.7 13.3 10.4 24.4
         20. 17.8 7. 11.8 24.4 13.8 19.4 25.2 19.4 19.4 29.1]
[]: mean = train_data.mean(axis=0)
    train_data -= mean
    std = train_data.std(axis=0)
    train_data /= std
    test_data -= mean
    test_data /= std
[]: def build_model():
        model = models.Sequential()
        model.add(layers.Dense(64, activation='relu', input_shape=(train_data.
      ⇔shape[1],)))
        model.add(layers.Dense(64, activation='relu'))
        model.add(layers.Dense(1))
        model.compile(optimizer='rmsprop', loss='mse', metrics=['mae'])
        return model
[ ]: k = 4
    num_val_samples = len(train_data) // k
```

16.6 17.5 22.3 16.1 14.9 23.1 34.9 25. 13.9 13.1 20.4 20. 15.2 24.7

```
num_epochs = 100
    all_scores = []
[]: for i in range(k):
        print('processing fold #', i)
        val_data = train_data[i * num_val_samples: (i + 1) * num_val_samples]
        val_targets = train_targets[i * num_val_samples: (i + 1) * num_val_samples]
        partial_train_data = np.concatenate([train_data[:i * num_val_samples],__
     partial_train_targets = np.concatenate([train_targets[:i *_
      num_val_samples], train_targets[(i + 1) * num_val_samples:]], axis=0)
        model = build_model()
        model.fit(partial_train_data, partial_train_targets, epochs=num_epochs,_u
     ⇒batch size=1, verbose=0)
        val_mse, val_mae = model.evaluate(val_data, val_targets, verbose=0)
        all_scores.append(val_mae)
    processing fold # 0
    processing fold # 1
    processing fold # 2
    processing fold # 3
[]: all_scores
[]: [2.108128309249878, 2.6189517974853516, 2.4960572719573975, 2.7731285095214844]
[]: np.mean(all scores)
[]: 2.499066472053528
[]: num_epochs = 500
    all_mae_histories = []
    for i in range(k):
        print('processing fold #', i)
        val_data = train_data[i * num_val_samples: (i + 1) * num_val_samples]
        val_targets = train_targets[i * num_val_samples: (i + 1) * num_val_samples]
        partial_train_data = np.concatenate([train_data[:i * num_val_samples],__
     partial_train_targets = np.concatenate([train_targets[:i *_
     _num_val_samples], train_targets[(i + 1) * num_val_samples:]], axis=0)
        model = build_model()
```

```
history = model.fit(partial_train_data, partial_train_targets,__
validation_data=(val_data, val_targets), epochs=num_epochs, batch_size=1,__
verbose=0)

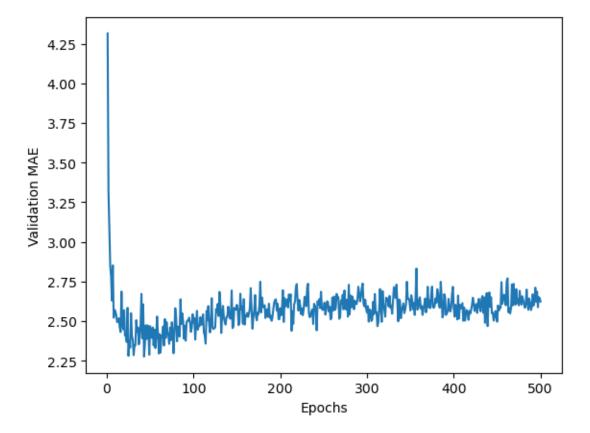
mae_history = history.history['val_mae']

all_mae_histories.append(mae_history)

average_mae_history = [np.mean([x[i] for x in all_mae_histories]) for i in__
range(num_epochs)]
```

```
processing fold # 0
processing fold # 1
processing fold # 2
processing fold # 3

[]: plt.plot(range(1, len(average_mae_history) + 1), average_mae_history)
plt.xlabel('Epochs')
plt.ylabel('Validation MAE')
plt.show()
```

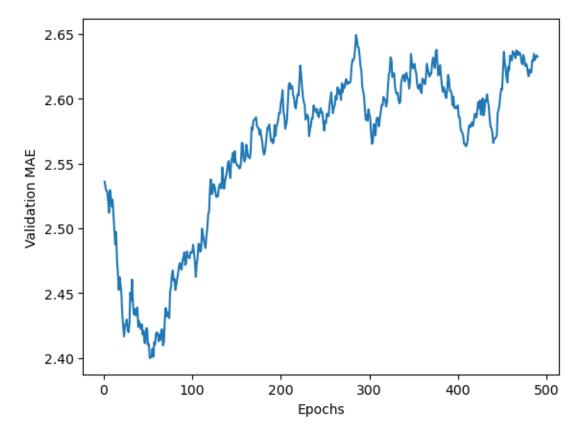


```
[]: def smooth_curve(points, factor=0.9):
    smoothed_points = []
```

```
for point in points:
    if smoothed_points:
        previous = smoothed_points[-1]
        smoothed_points.append(previous * factor + point * (1 - factor))
    else:
        smoothed_points.append(point)
    return smoothed_points

smooth_mae_history = smooth_curve(average_mae_history[10:])

plt.plot(range(1, len(smooth_mae_history) + 1), smooth_mae_history)
plt.xlabel('Epochs')
plt.ylabel('Validation MAE')
plt.show()
```



```
[]: model = build_model()
model.fit(train_data, train_targets, epochs=80, batch_size=16, verbose=0)

test_mae_score, test_mae_score = model.evaluate(test_data, test_targets)
test_mae_score
```

[]: 2.5546085834503174