# Madhukar\_Ayachit\_5.1

## April 26, 2022

## 0.1 Assignment 5.1

```
[1]: # Import libraries
     from tensorflow import keras
     from tensorflow.keras.datasets import mnist
     from tensorflow.keras.models import Sequential
     from tensorflow.keras.layers import Dense, Dropout
     from tensorflow.keras.optimizers import RMSprop
[2]: import keras
     keras.__version__
[2]: '2.4.3'
[3]: # Load the dataset
     from keras.datasets import imdb
     (train_data, train_labels), (test_data, test_labels) = imdb.
      →load_data(num_words=10000)
[4]: train_data[0]
[4]: [1,
      14,
      22,
      16,
      43,
      530,
      973,
      1622,
      1385,
      65,
      458,
      4468,
      66,
      3941,
      4,
      173,
      36,
```

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,

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,

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,

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,

```
283,
5,
16,
4472,
113,
103,
32,
15,
16,
5345,
19,
178,
32]
```

### [6]: train labels[0]

#### [6]: 1

[7]: #Since we restricted ourselves to the top 10,000 most frequent words, no word\_\_\_\_

→ index will exceed 10,000:

max([max(sequence) for sequence in train\_data])

[7]: 9999

```
[9]: # word_index is a dictionary mapping words to an integer index
word_index = imdb.get_word_index()
# We reverse it, mapping integer indices to words
reverse_word_index = dict([(value, key) for (key, value) in word_index.items()])
# We decode the review; note that our indices were offset by 3
# because 0, 1 and 2 are reserved indices for "padding", "start of
→ sequence", and "unknown".
decoded_review = ' '.join([reverse_word_index.get(i - 3, '?') for i in
→ train_data[0]])
decoded_review
```

[9]: "? 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"

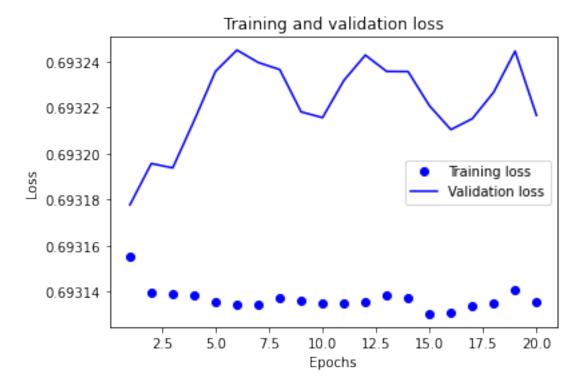
```
[13]: import numpy as np
     def vectorize_sequences(sequences, dimension=10000):
     # Create an all-zero matrix of shape (len(sequences), dimension)
         results = np.zeros((len(sequences), dimension))
         for i, sequence in enumerate(sequences):
             results[i, sequence] = 1 # set specific indices of results[i] to 1s
             return results
     # Our vectorized training data
     x_train = vectorize_sequences(train_data) # Our vectorized test data
     x_test = vectorize_sequences(test_data)
[14]: # Print sample
     x_train[0]
[14]: array([0., 1., 1., ..., 0., 0., 0.])
[15]: # vectorized labels
     y_train = np.asarray(train_labels).astype('float32')
     y_test = np.asarray(test_labels).astype('float32')
[17]: #The Keras implementation
     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'))
[30]: model.
      [31]: from keras import optimizers
     model.compile(optimizer=optimizers.RMSprop(lr=0.001),__
      →loss='binary_crossentropy',metrics=['accuracy'])
     from keras import losses
     from keras import metrics
     model.compile(optimizer=optimizers.RMSprop(lr=0.001), loss=losses.
      ⇒binary_crossentropy, metrics=[metrics.binary_accuracy])
```

```
[32]: x_val = x_train[:10000]
    partial_x_train = x_train[10000:]
    y_val = y_train[:10000]
    partial_y_train = y_train[10000:]
[33]: history = model.
    →fit(partial_x_train,partial_y_train,epochs=20,batch_size=512,validation_data=(x_val,_
    \rightarrowy_val))
   Epoch 1/20
   binary_accuracy: 0.4983 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
   Epoch 2/20
   binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
   Epoch 3/20
   30/30 [============ ] - 1s 27ms/step - loss: 0.6931 -
   binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
   Epoch 4/20
   30/30 [============= ] - 1s 30ms/step - loss: 0.6931 -
   binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
   Epoch 5/20
   30/30 [============= ] - 1s 29ms/step - loss: 0.6931 -
   binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
   Epoch 6/20
   binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
   Epoch 7/20
   30/30 [============ ] - 1s 28ms/step - loss: 0.6931 -
   binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
   Epoch 8/20
   binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
   Epoch 9/20
   binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
   Epoch 10/20
   binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
   Epoch 11/20
   binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
   Epoch 12/20
   binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
   Epoch 13/20
```

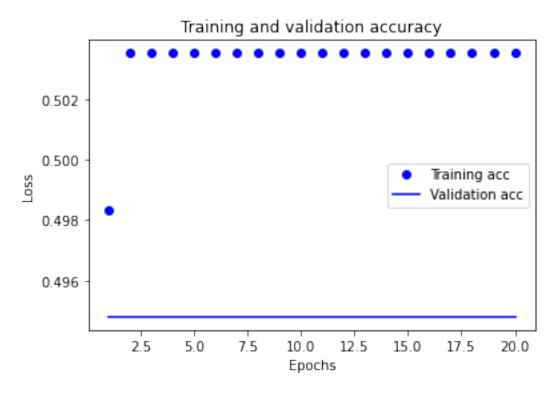
```
binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
    Epoch 14/20
    binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
    Epoch 15/20
    30/30 [============ ] - 1s 30ms/step - loss: 0.6931 -
    binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
    Epoch 16/20
    30/30 [============= ] - 1s 27ms/step - loss: 0.6931 -
    binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
    Epoch 17/20
    binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
    Epoch 18/20
    30/30 [============ ] - 1s 28ms/step - loss: 0.6931 -
    binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
    Epoch 19/20
    binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
    Epoch 20/20
    30/30 [============ ] - 1s 26ms/step - loss: 0.6931 -
    binary_accuracy: 0.5035 - val_loss: 0.6932 - val_binary_accuracy: 0.4948
[34]: history dict = history.history
     history_dict.keys()
     \#dict_keys(['loss', 'val_loss', 'binary_accuracy', 'val_binary_accuracy'])_{\sqcup}
     →#history_dict = history.history
     print(history dict)
    {'loss': [0.69315505027771, 0.6931398510932922, 0.6931390762329102,
    0.6931386590003967, 0.6931353807449341, 0.6931343674659729, 0.6931347846984863,
    0.6931373476982117, 0.6931362748146057, 0.6931352019309998, 0.6931352615356445,
    0.6931353807449341, 0.6931385397911072, 0.6931371688842773, 0.6931304931640625,
    0.6931309700012207, 0.6931340098381042, 0.6931349039077759, 0.6931409239768982,
    0.6931357979774475], 'binary_accuracy': [0.49833333349227905, 0.5035333037376404,
    0.5035333037376404, 0.5035333037376404, 0.5035333037376404, 0.5035333037376404,
    0.5035333037376404, 0.5035333037376404, 0.5035333037376404, 0.5035333037376404,
    0.5035333037376404, 0.5035333037376404, 0.5035333037376404, 0.5035333037376404,
    0.5035333037376404, 0.5035333037376404, 0.5035333037376404, 0.5035333037376404,
    0.5035333037376404, 0.5035333037376404], 'val loss': [0.6931777596473694,
    0.6931957006454468, 0.693193793296814, 0.6932142972946167, 0.6932356953620911,
    0.6932449340820312, 0.6932395100593567, 0.6932364702224731, 0.6932181119918823,
    0.6932156085968018, 0.6932317614555359, 0.6932427287101746, 0.6932356357574463,
    0.6932355761528015, 0.6932207345962524, 0.6932104229927063, 0.6932151317596436,
    0.6932266354560852, 0.693244457244873, 0.6932166218757629,
     'val_binary_accuracy': [0.49480000138282776, 0.49480000138282776,
    0.49480000138282776, 0.49480000138282776, 0.49480000138282776,
    0.49480000138282776, 0.49480000138282776, 0.49480000138282776,
```

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0.49480000138282776, 0.49480000138282776, 0.49480000138282776, 0.49480000138282776, 0.49480000138282776, 0.49480000138282776, 0.49480000138282776, 0.49480000138282776, 0.49480000138282776, 0.49480000138282776, 0.49480000138282776]}
```

```
[35]: import matplotlib.pyplot as plt
      acc = history.history['binary_accuracy']
      val_acc = history.history['val_binary_accuracy']
      #acc = history.history['acc']
      #val_acc = history.history['val_acc']
      loss = history.history['loss']
      val_loss = history.history['val_loss']
      epochs = range(1, len(acc) + 1)
      # "bo" is for "blue dot"
      plt.plot(epochs, loss, 'bo', label='Training loss')
      # b is for "solid blue line"
      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()
```



```
[36]: plt.clf() # clear figure
    #acc_values = history_dict['acc']
    #val_acc_values = history_dict['val_acc']
    acc = history.history['binary_accuracy']
    val_acc = history.history['val_binary_accuracy']
    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()
```



```
[37]: 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

```
0.5000
  Epoch 2/4
  0.4989
  Epoch 3/4
  0.4987
  Epoch 4/4
  49/49 [======
            0.4983
  782/782 [=========== ] - 2s 2ms/step - loss: 0.6932 -
  accuracy: 0.5000
[38]: results
[38]: [0.6931527256965637, 0.5]
[39]: model.predict(x_test)
[39]: array([[0.56660044],
      [0.50014085],
      [0.50014085],
      [0.50014085],
      [0.50014085],
      [0.50014085]], dtype=float32)
[]:
```