DL 2

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```
import numpy as np
from keras.datasets import imdb
from keras import models
from keras import layers
from keras import optimizers
from keras import losses
from keras import metrics


import matplotlib.pyplot as plt
%matplotlib inline
```

```
# Load the data, keeping only 10,000 of the most frequently occuring words
(train_data, train_labels), (test_data, test_labels) = imdb.load_data(num_words = 10000)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz
17464789/17464789 [==============================] - 0s 0us/step
```

```
train_data[: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, 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]),
       list([1, 194, 1153, 194, 8255, 78, 228, 5, 6, 1463, 4369, 5012, 134, 26, 4, 715, 8, 118, 1634, 14, 394, 20, 13, 119,
954, 189, 102, 5, 207, 110, 3103, 21, 14, 69, 188, 8, 30, 23, 7, 4, 249, 126, 93, 4, 114, 9, 2300, 1523, 5, 647, 4, 116, 9, 35,
8163, 4, 229, 9, 340, 1322, 4, 118, 9, 4, 130, 4901, 19, 4, 1002, 5, 89, 29, 952, 46, 37, 4, 455, 9, 45, 43, 38, 1543, 1905,
398, 4, 1649, 26, 6853, 5, 163, 11, 3215, 2, 4, 1153, 9, 194, 775, 7, 8255, 2, 349, 2637, 148, 605, 2, 8003, 15, 123, 125, 68,
2, 6853, 15, 349, 165, 4362, 98, 5, 4, 228, 9, 43, 2, 1157, 15, 299, 120, 5, 120, 174, 11, 220, 175, 136, 50, 9, 4373, 228,
8255, 5, 2, 656, 245, 2350, 5, 4, 9837, 131, 152, 491, 18, 2, 32, 7464, 1212, 14, 9, 6, 371, 78, 22, 625, 64, 1382, 9, 8, 168,
145, 23, 4, 1690, 15, 16, 4, 1355, 5, 28, 6, 52, 154, 462, 33, 89, 78, 285, 16, 145, 95])],
      dtype=object)
```

```
train_labels
```

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

```
# Check the first label
train_labels[0]
```

```
1
```

```
# Since we restricted ourselves to the top 10000 frequent words, no word index should exceed 10000
# we'll verify this below

# Here is a list of maximum indexes in every review --- we search the maximum index in this list of max indexes
print(type([max(sequence) for sequence in train_data]))

# Find the maximum of all max indexes
max([max(sequence) for sequence in train_data])
```

```
<class 'list'>
9999
```

```
# Let's quickly decode a review

# step 1: load the dictionary mappings from word to integer index
word_index = imdb.get_word_index()

# step 2: reverse word index to map integer indexes to their respective words
reverse_word_index = dict([(value, key) for (key, value) in word_index.items()])

# Step 3: decode the review, mapping integer indices to words
#
# indices are off by 3 because 0, 1, and 2 are reserverd 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
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets
1641221/1641221 [==============================] - 0s 0us/step
'? this film was just brilliant casting location scenery story direction everyon
e's really suited the part they played and you could just imagine being there ro
bert ? is an amazing actor and now the same being director ? father came from th
e 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 bril
liant so much that i bought the film as soon as it was released for ? and would
```

```
len(reverse_word_index)
```

```
88584
```

```
def vectorize_sequences(sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension))    # Creates an all zero matrix of shape (len(sequences),10K)
    for i,sequence in enumerate(sequences):
        results[i,sequence] = 1                        # Sets specific indices of results[i] to 1s
    return results

# Vectorize training Data
X_train = vectorize_sequences(train_data)

# Vectorize testing Data
X_test = vectorize_sequences(test_data)
```

```
X_train[0]
```

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

```
X_train.shape
```

```
(25000, 10000)
```

```
y_train = np.asarray(train_labels).astype('float32')
y_test  = np.asarray(test_labels).astype('float32')
```

```
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 = losses.binary_crossentropy,
    metrics = [metrics.binary_accuracy]
)
```

```
# Input for Validation
X_val = X_train[:10000]
partial_X_train = X_train[10000:]

# Labels for validation
y_val = y_train[:10000]
partial_y_train = y_train[10000:]
```

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

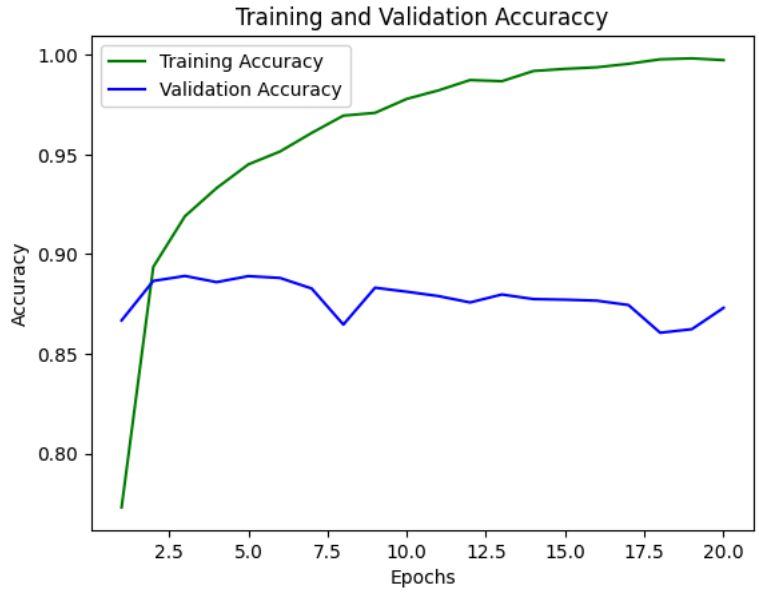
```
Epoch 1/20
30/30 [==============================] - 11s 331ms/step - loss: 0.5411 - binary_accuracy: 0.7730 - val_loss: 0.4159 - val_binary
Epoch 2/20
30/30 [==============================] - 3s 106ms/step - loss: 0.3425 - binary_accuracy: 0.8936 - val_loss: 0.3241 - val_binary_
Epoch 3/20
30/30 [==============================] - 2s 69ms/step - loss: 0.2561 - binary_accuracy: 0.9191 - val_loss: 0.2909 - val_binary_a
Epoch 4/20
30/30 [==============================] - 2s 84ms/step - loss: 0.2065 - binary_accuracy: 0.9332 - val_loss: 0.2853 - val_binary_a
Epoch 5/20
30/30 [==============================] - 1s 36ms/step - loss: 0.1726 - binary_accuracy: 0.9451 - val_loss: 0.2759 - val_binary_a
Epoch 6/20
30/30 [==============================] - 1s 38ms/step - loss: 0.1484 - binary_accuracy: 0.9515 - val_loss: 0.2850 - val_binary_a
Epoch 7/20
30/30 [==============================] - 1s 39ms/step - loss: 0.1272 - binary_accuracy: 0.9609 - val_loss: 0.3041 - val_binary_a
Epoch 8/20
30/30 [==============================] - 1s 45ms/step - loss: 0.1084 - binary_accuracy: 0.9695 - val_loss: 0.3543 - val_binary_a
Epoch 9/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0988 - binary_accuracy: 0.9709 - val_loss: 0.3162 - val_binary_a
Epoch 10/20
30/30 [==============================] - 1s 38ms/step - loss: 0.0833 - binary_accuracy: 0.9779 - val_loss: 0.3295 - val_binary_a
Epoch 11/20
30/30 [==============================] - 2s 60ms/step - loss: 0.0719 - binary_accuracy: 0.9822 - val_loss: 0.3579 - val_binary_a
Epoch 12/20
30/30 [==============================] - 1s 47ms/step - loss: 0.0599 - binary_accuracy: 0.9874 - val_loss: 0.3646 - val_binary_a
Epoch 13/20
30/30 [==============================] - 1s 32ms/step - loss: 0.0557 - binary_accuracy: 0.9868 - val_loss: 0.3862 - val_binary_a
Epoch 14/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0435 - binary_accuracy: 0.9919 - val_loss: 0.4171 - val_binary_a
Epoch 15/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0380 - binary_accuracy: 0.9930 - val_loss: 0.4315 - val_binary_a
Epoch 16/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0332 - binary_accuracy: 0.9938 - val_loss: 0.4511 - val_binary_a
Epoch 17/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0278 - binary_accuracy: 0.9955 - val_loss: 0.4626 - val_binary_a
Epoch 18/20
30/30 [==============================] - 1s 34ms/step - loss: 0.0221 - binary_accuracy: 0.9978 - val_loss: 0.5220 - val_binary_a
Epoch 19/20
30/30 [==============================] - 1s 32ms/step - loss: 0.0193 - binary_accuracy: 0.9983 - val_loss: 0.5301 - val_binary_a
Epoch 20/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0188 - binary_accuracy: 0.9974 - val_loss: 0.5322 - val_binary_a
```

```
history_dict = history.history
history_dict.keys()
```

```
dict_keys(['loss', 'binary_accuracy', 'val_loss', 'val_binary_accuracy'])
```

```
# Plotting losses
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']

epochs = range(1, len(loss_values) + 1)

plt.plot(epochs, loss_values, 'g', 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 Value')
plt.legend()

plt.show()
```


```
# Training and Validation Accuracy

acc_values = history_dict['binary_accuracy']
val_acc_values = history_dict['val_binary_accuracy']

epochs = range(1, len(loss_values) + 1)

plt.plot(epochs, acc_values, 'g', label="Training Accuracy")
plt.plot(epochs, val_acc_values, 'b', label="Validation Accuracy")

plt.title('Training and Validation Accuraccy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```




```
model.fit(
    partial_X_train,
    partial_y_train,
    epochs=3,
    batch_size=512,
    validation_data=(X_val, y_val)
)
```

```
Epoch 1/3
30/30 [==============================] - 2s 76ms/step - loss: 0.0117 - binary_accuracy: 0.9996 - val_loss: 0.5547 - val_binary_a
Epoch 2/3
30/30 [==============================] - 1s 38ms/step - loss: 0.0125 - binary_accuracy: 0.9987 - val_loss: 0.5754 - val_binary_a
```

```
Epoch 3/3
30/30 [==============================] - 1s 35ms/step - loss: 0.0141 - binary_accuracy: 0.9971 - val_loss: 0.5994 - val_binary_a
<keras.src.callbacks.History at 0x7df0f2a18d90>
```

```
# Making Predictions for testing data
np.set_printoptions(suppress=True)
result = model.predict(X_test)
```

```
782/782 [==============================] - 2s 2ms/step
```

```
result
```

```
array([[0.00944647],
       [1.        ],
       [0.92524046],
       ...,
       [0.00185398],
       [0.0067632 ],
       [0.91465694]], dtype=float32)
```

```
y_pred = np.zeros(len(result))
for i, score in enumerate(result):
    y_pred[i] = np.round(score)
```

```
mae = metrics.mean_absolute_error(y_pred, y_test)
mae
```