Stoneburner, Kurt

- ## DSC 650 - Tensorflow Keras Binary Classifier Example

In [1]:

```python
import os
import sys
# //*** Imports and Load Data
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from tensorflow.keras.datasets import imdb
from tensorflow.keras import models
from tensorflow.keras import layers
from tensorflow.keras import optimizers


#//*** Use the whole window in the IPYNB editor
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>

#//*** Maximize columns and rows displayed by pandas
pd.set_option('display.max_rows', 100)
```

In [2]:

```python
from os import environ

environ["KERAS_BACKEND"] = "plaidml.keras.backend"

```

In [3]:

```python
#//*** Download Data and Load arrays
```

```
<__array_function__ internals>:5: VisibleDeprecationWarning: Creating
an ndarray from ragged nested sequences (which is a list-or-tuple of
lists-or-tuples-or ndarrays with different lengths or shapes) is depr
ecated. If you meant to do this, you must specify 'dtype=object' when
creating the ndarray.
C:\Users\stonk013\Anaconda3\envs\keras_env\lib\site-packages\tensorfl
ow\python\keras\datasets\imdb.py:159: VisibleDeprecationWarning: Crea
ting an ndarray from ragged nested sequences (which is a list-or-tupl
e of lists-or-tuples-or ndarrays with different lengths or shapes) is
deprecated. If you meant to do this, you must specify 'dtype=object'
when creating the ndarray.
  x_train, y_train = np.array(xs[:idx]), np.array(labels[:idx])
C:\Users\stonk013\Anaconda3\envs\keras_env\lib\site-packages\tensorfl
ow\python\keras\datasets\imdb.py:160: VisibleDeprecationWarning: Crea
ting an ndarray from ragged nested sequences (which is a list-or-tupl
e of lists-or-tuples-or ndarrays with different lengths or shapes) is
deprecated. If you meant to do this, you must specify 'dtype=object'
when creating the ndarray.
  x_test, y_test = np.array(xs[idx:]), np.array(labels[idx:])
```

In [ ]:

In [4]:

```

#//*** Word_index is dictionary mapping words to an integer index
word_index = imdb.get_word_index()

#//*** Maps indexes to words
reverse_word_index = dict(
    [(value, key) for (key, value) in word_index.items()])

#//*** Decodes the Review
decoded_review = ' '.join(
```

In [ ]:

You can't feed lists of integers into a neural network. You have to turn your lists intotensors. There are two ways to do that:

- Pad your lists so that they all have the same length, turn them into an integertensor of shape (samples,word_indices), and then use as the first layer inyour network a layer capable of handling such integer tensors (the Embeddinglayer, which we'll cover in detail later in the book).
- **(Example Below: vectorize_sequences)** One-hot encode your lists to turn them into vectors of 0s and 1s. This would mean, for instance, turning the sequence [3, 5] into a 10,000-dimensional vec-tor that would be all 0s except for indices 3 and 5, which would be 1s. Then you could use as the first layer in your network a Dense layer, capable of handling floating-point vector data.

In [5]:

```
#//*** Lists of integers must be converted into tensors.
def vectorize_sequences(sequences, dimension=10000):
    #//*** Builds zero filled matrix of shape dimension
    results = np.zeros((len(sequences), dimension))

    #//*** Assigns 1s to the specific integer for references.
    #//*** This is manual one-hot encoding
    for i, sequence in enumerate(sequences):

        for j in sequence:
            results[i, j] = 1.

    return results

#//*** Download Data and Load arrays
(train_data, train_labels), (test_data,test_labels) = imdb.load_da

#//*** Vectorize the Training and Test data
x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)

#//*** Vectorize the Training and Test Labels
```

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

Build the Network

The input data is vectors, and the labels are scalars (1s and 0s): this is the easiest setup you'll ever encounter. A type of network that performs well on such a problem is a simple stack of fully connected (Dense) layers with relu activations: *Dense(16,activation='relu')*.

The argument being passed to each Dense layer (16) is the number of hidden units of the layer. A hidden unit is a dimension in the representation space of the layer. Each such Dense layer with a relu activation implements the following chain of tensor operations:

output = relu(dot(W, input) + b)

Having 16 hidden units means the weight matrix W will have shape (input_dimension,16): the dot product with W will project the input data onto a 16-dimensional representation space (and then you'll add the bias vector b and apply the relu operation).

You can intuitively understand the dimensionality of your representation space as “how much freedom you're allowing the network to have when learning internal representations.” *Having more hidden units (a higher-dimensional representation space) allows your network to learn more-complex representations, but it makes the network more computationally expensive and may lead to learning unwanted patterns (patterns that will improve performance on the training data but not on the test data).*

There are two key architecture decisions to be made about such a stack of Dense layers:

- How many layers to use
- How many hidden units to choose for each layer

For the time being go with the following architecture choice:

- Two intermediate layers with 16 hidden units each
- A third layer that will output the scalar prediction regarding the sentiment ofthe current review

The intermediate layers will use *relu* as their activation function, and the final layer will use a sigmoid activation so as to output a probability (a score between 0 and 1, indicating how likely the sample is to have the target “1”: how likely the review is to be positive). A *relu* (rectified linear unit) is a function meant to zero out negative values, whereas a sigmoid “squashes” arbitrary values into the [0, 1] interval, outputting something that can be interpreted as a probability

In [6]:

```

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'))

#//*** Compile the Model



model.compile(
```

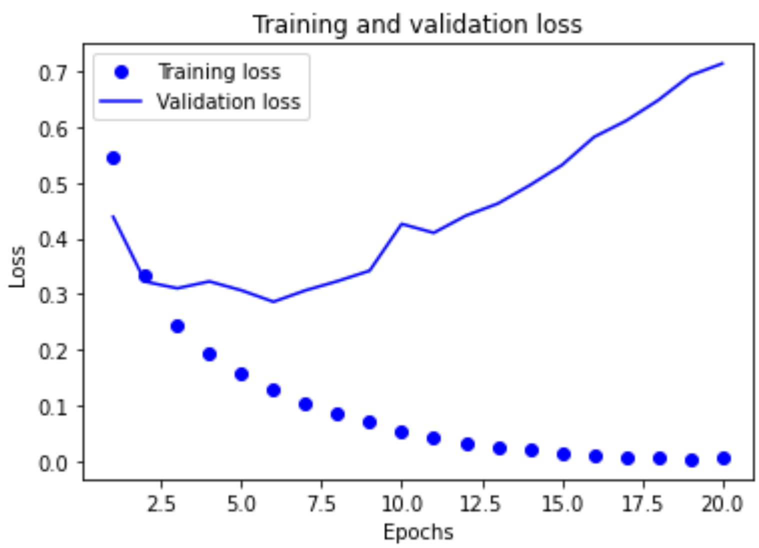
```python
    optimizer=optimizers.RMSprop(lr=0.001),
    loss='binary_crossentropy',
    metrics=['accuracy']
)

#//*** Configure the Optimizer
#model.compile(
#    optimizer=optimizers.RMSprop(lr=0.001),
#    loss=losses.binary_crossentropy,
#    metrics=[metrics.binary_accuracy]
#)


#//*** Use Custom Losses and Metrics
from tensorflow.keras import losses
from tensorflow.keras import metrics

#//*** Set Aside a Validation Set
x_val = x_train[:10000]
partial_x_train = x_train[10000:]

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

#//*** Train Model
model.compile(
    optimizer='rmsprop',
    loss='binary_crossentropy',
    metrics=['acc']
)

history = model.fit(
    partial_x_train,
    partial_y_train,
    epochs=20,
    batch_size=512,
```

```
Epoch 1/20
30/30 [==============================] - 1s 22ms/step - loss: 0.5176
- acc: 0.7755 - val_loss: 0.4462 - val_acc: 0.7928
Epoch 2/20
30/30 [==============================] - 0s 10ms/step - loss: 0.3044
- acc: 0.9021 - val_loss: 0.3056 - val_acc: 0.8882
Epoch 3/20
30/30 [==============================] - 0s 10ms/step - loss: 0.2242
- acc: 0.9257 - val_loss: 0.2771 - val_acc: 0.8926
Epoch 4/20
30/30 [==============================] - 0s 11ms/step - loss: 0.1767
- acc: 0.9417 - val_loss: 0.2825 - val_acc: 0.8852
Epoch 5/20
30/30 [==============================] - 0s 10ms/step - loss: 0.1452
- acc: 0.9531 - val_loss: 0.2785 - val_acc: 0.8908
Epoch 6/20
30/30 [==============================] - 0s 10ms/step - loss: 0.1202
- acc: 0.9635 - val_loss: 0.2968 - val_acc: 0.8861
Epoch 7/20
30/30 [==============================] - 0s 10ms/step - loss: 0.1008
```

```
- acc: 0.9705 - val_loss: 0.3074 - val_acc: 0.8827
Epoch 8/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0836
- acc: 0.9768 - val_loss: 0.3281 - val_acc: 0.8821
Epoch 9/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0714
- acc: 0.9789 - val_loss: 0.3535 - val_acc: 0.8776
Epoch 10/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0590
- acc: 0.9844 - val_loss: 0.3713 - val_acc: 0.8790
Epoch 11/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0482
- acc: 0.9883 - val_loss: 0.3954 - val_acc: 0.8757
Epoch 12/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0441
- acc: 0.9897 - val_loss: 0.4227 - val_acc: 0.8734
Epoch 13/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0341
- acc: 0.9930 - val_loss: 0.4499 - val_acc: 0.8718
Epoch 14/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0244
- acc: 0.9963 - val_loss: 0.5105 - val_acc: 0.8634
Epoch 15/20
30/30 [==============================] - 0s 11ms/step - loss: 0.0233
- acc: 0.9956 - val_loss: 0.5066 - val_acc: 0.8693
Epoch 16/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0155
- acc: 0.9984 - val_loss: 0.5628 - val_acc: 0.8631
Epoch 17/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0145
- acc: 0.9983 - val_loss: 0.5830 - val_acc: 0.8660
Epoch 18/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0138
- acc: 0.9971 - val_loss: 0.6116 - val_acc: 0.8660
Epoch 19/20
30/30 [==============================] - 0s 11ms/step - loss: 0.0064
- acc: 0.9996 - val_loss: 0.6432 - val_acc: 0.8650
Epoch 20/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0089
- acc: 0.9985 - val_loss: 0.6731 - val_acc: 0.8653
```

In [12]:

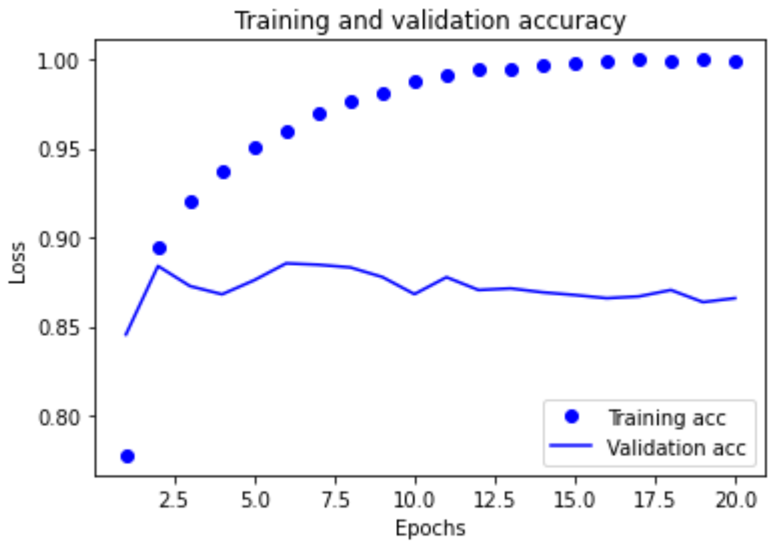
```
#//*** Plotting the training and validation loss
history_dict = history.history
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']
acc = history_dict['acc']
epochs = range(1, len(acc) + 1)
plt.plot(epochs, loss_values, 'bo', label='Training loss')
plt.plot(epochs, val_loss_values, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



In [ ]:

In [13]:

```
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()
```



In [14]:

```
#//*** retraining a model from scratch
#//*** Previous Results didn't go well. Book suggests Overfitting,
#//*** Accuracy and Validation values worked well.

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',metri
model.fit(x_train, y_train, epochs=20, batch_size=512)
results = model.evaluate(x_test, y_test)

```

```
Epoch 1/20
49/49 [==============================] - 3s 15ms/step - loss: 0.4363
- accuracy: 0.8263
Epoch 2/20
49/49 [==============================] - 1s 10ms/step - loss: 0.2505
- accuracy: 0.9109
Epoch 3/20
49/49 [==============================] - 1s 11ms/step - loss: 0.1930
- accuracy: 0.9325
Epoch 4/20
49/49 [==============================] - 1s 12ms/step - loss: 0.1635
- accuracy: 0.9431
Epoch 5/20
49/49 [==============================] - 0s 9ms/step - loss: 0.1384 -
accuracy: 0.9535
Epoch 6/20
49/49 [==============================] - 1s 11ms/step - loss: 0.1228
- accuracy: 0.9582 0s - loss: 0.1166 - ac
Epoch 7/20
49/49 [==============================] - 0s 9ms/step - loss: 0.1100 -
accuracy: 0.9635
Epoch 8/20
49/49 [==============================] - 0s 9ms/step - loss: 0.0953 -
accuracy: 0.9691
Epoch 9/20
49/49 [==============================] - 0s 9ms/step - loss: 0.0816 -
accuracy: 0.9749
Epoch 10/20
49/49 [==============================] - 0s 8ms/step - loss: 0.0747 -
accuracy: 0.9764
Epoch 11/20
49/49 [==============================] - 0s 8ms/step - loss: 0.0626 -
accuracy: 0.9814
Epoch 12/20
49/49 [==============================] - 0s 8ms/step - loss: 0.0569 -
accuracy: 0.9824
Epoch 13/20
49/49 [==============================] - 0s 9ms/step - loss: 0.0506 -
accuracy: 0.9847
Epoch 14/20
49/49 [==============================] - 1s 11ms/step - loss: 0.0391
- accuracy: 0.9899
Epoch 15/20
49/49 [==============================] - 0s 9ms/step - loss: 0.0352 -
accuracy: 0.9905
Epoch 16/20
49/49 [==============================] - 0s 9ms/step - loss: 0.0301 -
```

Out[14]:

```
[0.7695156931877136, 0.8503599762916565]
```

In [17]:

```python
def build_binary_output_model(**kwargs):
    #//*** Define the Model
    from tensorflow.keras import models
    from tensorflow.keras import layers
    from tensorflow.keras import optimizers


```

```
    #//****************************
    #//*** Set Default values
    #//****************************
    total_layers = 2
    hidden_units = 16
    first_activation = "relu"
    final_activation='sigmoid'
    optimizer='rmsprop'
    loss = 'mse'
    metrics=['accuracy']
    shape = (0,0)
    do_compile = True

    #//*** Apply Kwargs
    for key,value in kwargs.items():

        if key == 'layers':
            total_layers=value

        if key == 'hidden_units':
            hidden_units=value

        if key == 'loss':
            loss=value

        if key == 'first_activation':
            first_activation=value

        if key == 'final_activation':
            final_activation=value

        if key == 'optimizer':
            optimizer=value

        if key == 'metrics':
            metrics=value

        if key == 'shape':
            shape = value

        if key == 'compile':
            do_compile = value

    model = models.Sequential()


    #//*** Add First Layer
    model.add(layers.Dense(hidden_units, activation=first_activati


    #//*** Add Additional Layers if total_layers greater than 2
    for x in range(total_layers-2):

        #//*** These are basic layers with same number of hidden u
        model.add(layers.Dense(hidden_units, activation=first_acti

```

```


    #//*** Add Final Layer
    model.add(layers.Dense(1, activation=final_activation))

    #//*** Compile Model
    if do_compile:

        model.compile(optimizer=optimizer,loss=loss,metrics=metric

    return model

```

In [19]:

```
#//**************************
#//*** Book Supplied Settings
#//**************************
model_shape = (10000,)
layers = 3
hidden_units = 16
first_activation = "relu"
final_activation = "sigmoid"
optimizer = "rmsprop"
loss = 'binary_crossentropy'
model = build_binary_output_model(
    shape=model_shape,
    layers=layers,
    hidden_units = hidden_units,
    first_activation = first_activation,
    final_activation=final_activation,
    optimizer=optimizer,
    loss=loss,metrics=['accuracy']
)

model.fit(x_train, y_train, epochs=20, batch_size=512)
results = model.evaluate(x_test, y_test)

```

```
Epoch 1/20
49/49 [==============================] - 2s 23ms/step - loss: 0.4584
- accuracy: 0.8221
Epoch 2/20
49/49 [==============================] - 1s 11ms/step - loss: 0.2575
- accuracy: 0.9127
Epoch 3/20
49/49 [==============================] - 1s 12ms/step - loss: 0.2012
- accuracy: 0.9289
Epoch 4/20
49/49 [==============================] - 1s 12ms/step - loss: 0.1671
- accuracy: 0.9422
Epoch 5/20
49/49 [==============================] - 1s 11ms/step - loss: 0.1470
- accuracy: 0.9476
Epoch 6/20
49/49 [==============================] - 1s 11ms/step - loss: 0.1283
- accuracy: 0.9560
Epoch 7/20
49/49 [==============================] - 1s 11ms/step - loss: 0.1127
- accuracy: 0.9611
Epoch 8/20
49/49 [==============================] - 0s 10ms/step - loss: 0.1001
- accuracy: 0.9661
Epoch 9/20
49/49 [==============================] - 0s 10ms/step - loss: 0.0855
- accuracy: 0.9720
Epoch 10/20
49/49 [==============================] - 0s 9ms/step - loss: 0.0766 -
accuracy: 0.9756
Epoch 11/20
49/49 [==============================] - 0s 10ms/step - loss: 0.0677
- accuracy: 0.9780
Epoch 12/20
49/49 [==============================] - 0s 10ms/step - loss: 0.0588
- accuracy: 0.9821
Epoch 13/20
49/49 [==============================] - 0s 9ms/step - loss: 0.0517 -
accuracy: 0.9849
Epoch 14/20
49/49 [==============================] - 0s 8ms/step - loss: 0.0423 -
accuracy: 0.9883
```

Out[19]:
```
[0.8005822896957397, 0.8503599762916565]
```

Further experiments

The following experiments will help convince you that the architecture choices you've made are all fairly reasonable, although there's still room for improvement:

- You used two hidden layers. Try using one or three hidden layers, and see how doing so affects validation and test accuracy.
- Try using layers with more hidden units or fewer hidden units: 32 units, 64 units,and so on.
- Try using the mse loss function instead of binary_crossentropy.

- Try using the tanh activation (an activation that was popular in the early days ofneural networks) instead of relu.

In [20]:

```
#//***************************
#//*** Suggestion use One Hidden Layer
#//***************************
model_shape = (10000,)
layers = 2
hidden_units = 16
first_activation = "relu"
final_activation = "sigmoid"
optimizer = "rmsprop"
loss = 'binary_crossentropy'
model = build_binary_output_model(
    shape=model_shape,
    layers=layers,
    hidden_units = hidden_units,
    first_activation = first_activation,
    final_activation=final_activation,
    optimizer=optimizer,
    loss=loss,metrics=['accuracy']
)

model.fit(x_train, y_train, epochs=20, batch_size=512)
results = model.evaluate(x_test, y_test)

```

```
Epoch 1/20
49/49 [==============================] - 1s 16ms/step - loss: 0.4495
- accuracy: 0.8324
Epoch 2/20
49/49 [==============================] - 1s 16ms/step - loss: 0.2785
- accuracy: 0.9081
Epoch 3/20
49/49 [==============================] - 0s 8ms/step - loss: 0.2204 -
accuracy: 0.9239
Epoch 4/20
49/49 [==============================] - 0s 9ms/step - loss: 0.1874 -
accuracy: 0.9370
Epoch 5/20
49/49 [==============================] - 0s 10ms/step - loss: 0.1650
- accuracy: 0.9436
Epoch 6/20
49/49 [==============================] - 0s 9ms/step - loss: 0.1493 -
accuracy: 0.9503
Epoch 7/20
49/49 [==============================] - 1s 10ms/step - loss: 0.1349
- accuracy: 0.9552
Epoch 8/20
49/49 [==============================] - 0s 10ms/step - loss: 0.1243
- accuracy: 0.9589
Epoch 9/20
49/49 [==============================] - 1s 13ms/step - loss: 0.1146
- accuracy: 0.9626
Epoch 10/20
49/49 [==============================] - 0s 10ms/step - loss: 0.1049
- accuracy: 0.9666
Epoch 11/20
49/49 [==============================] - 0s 10ms/step - loss: 0.0973
- accuracy: 0.9700
```

Out[20]: [0.5385316610336304, 0.8536800146102905]

In [21]:

```
#//*****************************************
#//*** Suggestion: use Three Hidden Layers
#//*****************************************
model_shape = (10000,)
layers = 4
hidden_units = 16
first_activation = "relu"
final_activation = "sigmoid"
optimizer = "rmsprop"
loss = 'binary_crossentropy'
model = build_binary_output_model(
    shape=model_shape,
    layers=layers,
    hidden_units = hidden_units,
    first_activation = first_activation,
    final_activation=final_activation,
    optimizer=optimizer,
    loss=loss,metrics=['accuracy']
)

```

```
model.fit(x_train, y_train, epochs=20, batch_size=512)
results = model.evaluate(x_test, y_test)

```

```
Epoch 1/20
49/49 [==============================] - 5s 12ms/step - loss: 0.4572
- accuracy: 0.8080
Epoch 2/20
49/49 [==============================] - 1s 11ms/step - loss: 0.2557
- accuracy: 0.9085
Epoch 3/20
49/49 [==============================] - 0s 7ms/step - loss: 0.1973 -
accuracy: 0.9289
Epoch 4/20
49/49 [==============================] - 0s 8ms/step - loss: 0.1648 -
accuracy: 0.9420
Epoch 5/20
49/49 [==============================] - 0s 10ms/step - loss: 0.1415
- accuracy: 0.9494
Epoch 6/20
49/49 [==============================] - 0s 10ms/step - loss: 0.1246
- accuracy: 0.9551
Epoch 7/20
49/49 [==============================] - 0s 10ms/step - loss: 0.1048
- accuracy: 0.9638
Epoch 8/20
49/49 [==============================] - 0s 9ms/step - loss: 0.0933 -
accuracy: 0.9686
Epoch 9/20
49/49 [==============================] - 1s 10ms/step - loss: 0.0817
- accuracy: 0.9736 0s - loss: 0.0794 - accuracy: 0.
Epoch 10/20
49/49 [==============================] - 0s 8ms/step - loss: 0.0671 -
accuracy: 0.9793
Epoch 11/20
49/49 [==============================] - 1s 11ms/step - loss: 0.0574
- accuracy: 0.9816
Epoch 12/20
49/49 [==============================] - 1s 12ms/step - loss: 0.0459
- accuracy: 0.9872
Epoch 13/20
49/49 [==============================] - 0s 9ms/step - loss: 0.0402 -
accuracy: 0.9889
Epoch 14/20
49/49 [==============================] - 0s 8ms/step - loss: 0.0352 -
accuracy: 0.9893
Epoch 15/20
49/49 [==============================] - 0s 10ms/step - loss: 0.0277
- accuracy: 0.9921
Epoch 16/20
49/49 [==============================] - 1s 11ms/step - loss: 0.0219
- accuracy: 0.9941
Epoch 17/20
49/49 [==============================] - 0s 9ms/step - loss: 0.0162 -
accuracy: 0.9958
Epoch 18/20
49/49 [==============================] - 1s 12ms/step - loss: 0.0163
```

```
- accuracy: 0.9956
Epoch 19/20
49/49 [==============================] - 1s 12ms/step - loss: 0.0130
- accuracy: 0.9963
Epoch 20/20
49/49 [==============================] - 0s 9ms/step - loss: 0.0105 -
accuracy: 0.9970
782/782 [==============================] - 29s 38ms/step - loss: 0.88
51 - accuracy: 0.8500
```

Out[21]: [0.8851346969604492, 0.8499600291252136]

In [22]:

```
#//*************************************
#//*** Suggestion: use 32 Hidden Units
#//*************************************
model_shape = (10000,)
layers = 3
hidden_units = 32
first_activation = "relu"
final_activation = "sigmoid"
optimizer = "rmsprop"
loss = 'binary_crossentropy'
model = build_binary_output_model(
    shape=model_shape,
    layers=layers,
    hidden_units = hidden_units,
    first_activation = first_activation,
    final_activation=final_activation,
    optimizer=optimizer,
    loss=loss,metrics=['accuracy']
)

model.fit(x_train, y_train, epochs=20, batch_size=512)
results = model.evaluate(x_test, y_test)

```

```
Epoch 1/20
49/49 [==============================] - 1s 13ms/step - loss: 0.4266
- accuracy: 0.8257
Epoch 2/20
49/49 [==============================] - 1s 11ms/step - loss: 0.2386
- accuracy: 0.9136
Epoch 3/20
49/49 [==============================] - 1s 14ms/step - loss: 0.1878
- accuracy: 0.9325
Epoch 4/20
49/49 [==============================] - 1s 13ms/step - loss: 0.1589
- accuracy: 0.9416
Epoch 5/20
49/49 [==============================] - 1s 13ms/step - loss: 0.1383
- accuracy: 0.9494
Epoch 6/20
49/49 [==============================] - 1s 12ms/step - loss: 0.1209
- accuracy: 0.9580
Epoch 7/20
49/49 [==============================] - 1s 12ms/step - loss: 0.1022
- accuracy: 0.9631
Epoch 8/20
49/49 [==============================] - 1s 14ms/step - loss: 0.0927
- accuracy: 0.9674
Epoch 9/20
49/49 [==============================] - 1s 16ms/step - loss: 0.0812
- accuracy: 0.9720 0s - loss: 0.0737 - accuracy
Epoch 10/20
49/49 [==============================] - 1s 14ms/step - loss: 0.0681
- accuracy: 0.9779
Epoch 11/20
49/49 [==============================] - 1s 13ms/step - loss: 0.0606
- accuracy: 0.9811
Epoch 12/20
49/49 [==============================] - 1s 12ms/step - loss: 0.0499
- accuracy: 0.9839
Epoch 13/20
49/49 [==============================] - 1s 11ms/step - loss: 0.0393
- accuracy: 0.9883
Epoch 14/20
49/49 [==============================] - 1s 13ms/step - loss: 0.0352
- accuracy: 0.9893
```

Out[22]: [0.9207907319068909, 0.8514400124549866]

In [23]:

```
#//*****************************************
#//*** Suggestion: use 64 Hidden Units
#//*****************************************
model_shape = (10000,)
layers = 3
hidden_units = 64
first_activation = "relu"
final_activation = "sigmoid"
optimizer = "rmsprop"
loss = 'binary_crossentropy'
model = build_binary_output_model(
    shape=model_shape,
```

```
    layers=layers,
    hidden_units = hidden_units,
    first_activation = first_activation,
    final_activation=final_activation,
    optimizer=optimizer,
    loss=loss,metrics=['accuracy']
)

model.fit(x_train, y_train, epochs=5, batch_size=512)
results = model.evaluate(x_test, y_test)

```

```
Epoch 1/5
49/49 [==============================] - 1s 16ms/step - loss: 0.4240
- accuracy: 0.8107
Epoch 2/5
49/49 [==============================] - 1s 18ms/step - loss: 0.2395
- accuracy: 0.9076
Epoch 3/5
49/49 [==============================] - 1s 16ms/step - loss: 0.1847
- accuracy: 0.9298
Epoch 4/5
49/49 [==============================] - 1s 20ms/step - loss: 0.1458
- accuracy: 0.9434
Epoch 5/5
49/49 [==============================] - 1s 19ms/step - loss: 0.1128
- accuracy: 0.9589
782/782 [==============================] - 31s 40ms/step - loss: 0.36
07 - accuracy: 0.8748
```

Out[23]: [0.36067381501197815, 0.8748000264167786]

In [24]:

```
#//*****************************************
#//*** Suggestion: use tanh activation
#//*****************************************
model_shape = (10000,)
layers = 3
hidden_units = 16
first_activation = "tanh"
final_activation = "sigmoid"
optimizer = "rmsprop"
loss = 'binary_crossentropy'
model = build_binary_output_model(
    shape=model_shape,
    layers=layers,
    hidden_units = hidden_units,
    first_activation = first_activation,
    final_activation=final_activation,
    optimizer=optimizer,
    loss=loss,metrics=['accuracy']
)

model.fit(x_train, y_train, epochs=5, batch_size=512)
results = model.evaluate(x_test, y_test)

results
```

```
Epoch 1/5
49/49 [==============================] - 4s 11ms/step - loss: 0.4162
- accuracy: 0.8337
Epoch 2/5
49/49 [==============================] - 0s 10ms/step - loss: 0.2328
- accuracy: 0.9142
Epoch 3/5
49/49 [==============================] - 1s 11ms/step - loss: 0.1780
- accuracy: 0.9352
Epoch 4/5
49/49 [==============================] - 0s 9ms/step - loss: 0.1474 -
accuracy: 0.9478
Epoch 5/5
49/49 [==============================] - 0s 8ms/step - loss: 0.1265 -
accuracy: 0.9558
782/782 [==============================] - 29s 37ms/step - loss: 0.37
```

Out[24]: [0.3727782070636749, 0.867680013179779]

In [25]:

```
#//*********************************************
#//*** Suggestion: use MSE loss
#//*********************************************
model_shape = (10000,)
layers = 3
hidden_units = 16
first_activation = "relu"
final_activation = "sigmoid"
optimizer = "rmsprop"
loss = 'mse'
model = build_binary_output_model(
    shape=model_shape,
    layers=layers,
    hidden_units = hidden_units,
    first_activation = first_activation,
    final_activation=final_activation,
    optimizer=optimizer,
    loss=loss,metrics=['accuracy']
)

model.fit(x_train, y_train, epochs=5, batch_size=512)
results = model.evaluate(x_test, y_test)

```

```
Epoch 1/5
49/49 [==============================] - 1s 10ms/step - loss: 0.1479
- accuracy: 0.8266
Epoch 2/5
```

Out[25]: [0.0892355889081955, 0.8794400095939636]

In [ ]: