Assignment1_yli130

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1 Assignment 1: Neural Networks

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1.0.1 The IMDB dataset

Loading the IMDB dataset

[1]:
```
from tensorflow.keras.datasets import imdb
(train_data, train_labels), (test_data, test_labels) = imdb.load_data(
    num_words=10000)
```

[2]:
```
import matplotlib.pyplot as plt # for figure plot
```

[3]:
```
len(train_data)  # comments in training data set
```

[3]: 25000

[4]:
```
len(train_data[1]) # check the length of first comment in training data
```

[4]: 189

[5]:
```
max_len = max([len(i) for i in train_data]) #check max length in each list in␣
↪the training data
max_len
```

[5]: 2494

[6]:
```
max([max(sequence) for sequence in train_data])  # check the maxmium number in␣
↪the list
```

[6]: 9999

1.0.2 Preparing the data

Encoding the integer sequences via multi-hot encoding

[3]:
```python
import numpy as np
def vectorize_sequences(sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        for j in sequence:
            results[i, j] = 1.
    return results
x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)
```

[8]:
```python
x_train[1] # result for the multi-hot encoding for index 1
```

[8]:
```
array([0., 1., 1., …, 0., 0., 0.])
```

[9]:
```python
x_train.shape, x_test.shape  # show both train_test data set shape
```

[9]:
```
((25000, 10000), (25000, 10000))
```

[10]:
```python
len(x_train[0])  # check the length for the first sample in training data set
```

[10]:
```
10000
```

[4]:
```python
y_train = np.asarray(train_labels).astype("float32")  # convert both train &␣
↪test lables into floats
y_test = np.asarray(test_labels).astype("float32")
```

[12]:
```python
type(x_train), type(y_train) #check data format in training data set
```

[12]:
```
(numpy.ndarray, numpy.ndarray)
```

[13]:
```python
y_train.shape, y_test.shape  # check train and test label shape
```

[13]:
```
((25000,), (25000,))
```

1.0.3 Original model

Build the model

[5]:
```python
# Model definition
from tensorflow import keras
from tensorflow.keras import layers

model = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
```

```python
# Compile the model
model.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])

# Settingt the validation set
x_val = x_train[:10000]              # validation for the first 10000 data in␣
↪training set
partial_x_train = x_train[10000:]       # trainig data for the rest of data␣
↪which is 25000-10000=15000
y_val = y_train[:10000]
partial_y_train = y_train[10000:]

# Train the model
history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,     # run the model for 20 epoch and each epoch␣
↪for 512 batch
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/20
30/30 [==============================] - 2s 41ms/step - loss: 0.5497 - accuracy:
0.7778 - val_loss: 0.4259 - val_accuracy: 0.8672
Epoch 2/20
30/30 [==============================] - 1s 24ms/step - loss: 0.3458 - accuracy:
0.8992 - val_loss: 0.3439 - val_accuracy: 0.8668
Epoch 3/20
30/30 [==============================] - 1s 22ms/step - loss: 0.2524 - accuracy:
0.9224 - val_loss: 0.2913 - val_accuracy: 0.8895
Epoch 4/20
30/30 [==============================] - 1s 24ms/step - loss: 0.1966 - accuracy:
0.9373 - val_loss: 0.2869 - val_accuracy: 0.8855
Epoch 5/20
30/30 [==============================] - 1s 24ms/step - loss: 0.1635 - accuracy:
0.9473 - val_loss: 0.2824 - val_accuracy: 0.8880
Epoch 6/20
30/30 [==============================] - 1s 24ms/step - loss: 0.1344 - accuracy:
0.9595 - val_loss: 0.2829 - val_accuracy: 0.8862
Epoch 7/20
30/30 [==============================] - 1s 21ms/step - loss: 0.1156 - accuracy:
0.9658 - val_loss: 0.2958 - val_accuracy: 0.8837
Epoch 8/20
30/30 [==============================] - 1s 22ms/step - loss: 0.0944 - accuracy:
0.9740 - val_loss: 0.3133 - val_accuracy: 0.8818
Epoch 9/20
30/30 [==============================] - 1s 22ms/step - loss: 0.0794 - accuracy:
```

```
0.9789 - val_loss: 0.3397 - val_accuracy: 0.8780
Epoch 10/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0659 - accuracy:
0.9829 - val_loss: 0.3759 - val_accuracy: 0.8761
Epoch 11/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0564 - accuracy:
0.9859 - val_loss: 0.3818 - val_accuracy: 0.8774
Epoch 12/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0459 - accuracy:
0.9901 - val_loss: 0.4082 - val_accuracy: 0.8747
Epoch 13/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0375 - accuracy:
0.9919 - val_loss: 0.4532 - val_accuracy: 0.8691
Epoch 14/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0313 - accuracy:
0.9941 - val_loss: 0.4610 - val_accuracy: 0.8729
Epoch 15/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0251 - accuracy:
0.9956 - val_loss: 0.4997 - val_accuracy: 0.8704
Epoch 16/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0199 - accuracy:
0.9971 - val_loss: 0.5239 - val_accuracy: 0.8699
Epoch 17/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0149 - accuracy:
0.9985 - val_loss: 0.5921 - val_accuracy: 0.8632
Epoch 18/20
30/30 [==============================] - 1s 20ms/step - loss: 0.0148 - accuracy:
0.9974 - val_loss: 0.5924 - val_accuracy: 0.8678
Epoch 19/20
30/30 [==============================] - 1s 18ms/step - loss: 0.0103 - accuracy:
0.9989 - val_loss: 0.6206 - val_accuracy: 0.8677
Epoch 20/20
30/30 [==============================] - 1s 18ms/step - loss: 0.0066 - accuracy:
0.9997 - val_loss: 0.6738 - val_accuracy: 0.8637
```

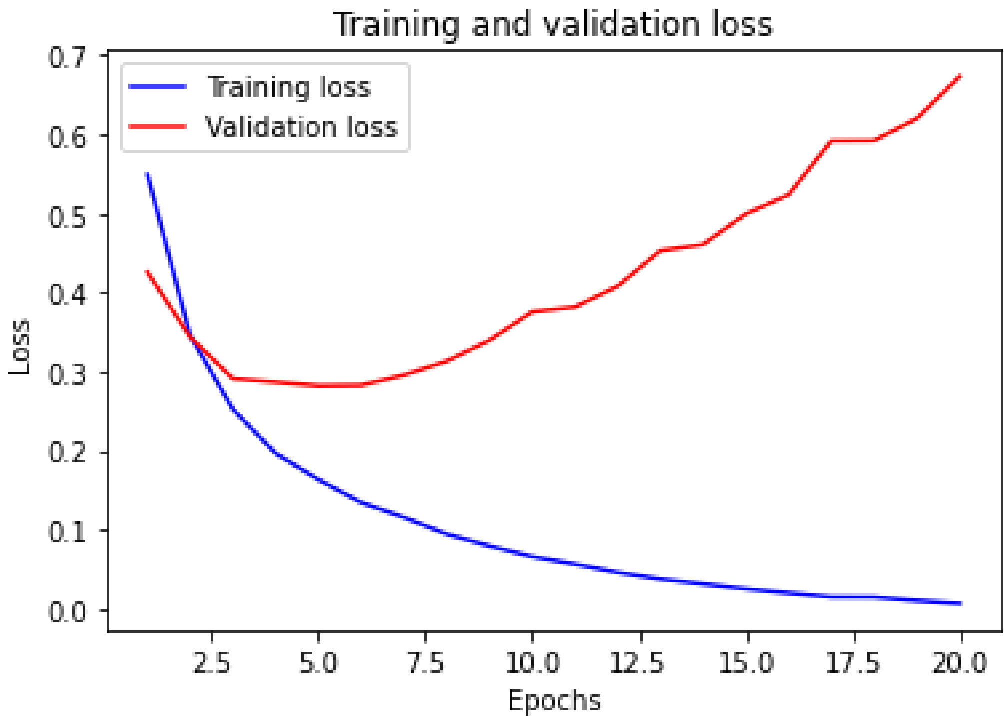
[6]:
```
history_dict = history.history
history_dict.keys()  # show key names in the dictionary
```

[6]:
```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

Plotting the training and validation loss

[7]:
```
history_dict = history.history
loss_values = history_dict["loss"]
val_loss_values = history_dict["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, "b", label="Training loss")
plt.plot(epochs, val_loss_values, "r", label="Validation loss")
```

```
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



From the loss pattern in training & validation, the validation loss **starts to increase** around 4 epochs, the **original model choose the 4 epochs** to retrain the model using the testing data.

Retraining a model from scratch

[17]:
```
model = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    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)  # change to 4 epochs
results = model.evaluate(x_test, y_test)
```

```
Epoch 1/4
49/49 [==============================] - 2s 21ms/step - loss: 0.4621 - accuracy:
```

```
0.8190
Epoch 2/4
49/49 [==============================] - 1s 17ms/step - loss: 0.2676 - accuracy:
0.9075
Epoch 3/4
49/49 [==============================] - 1s 14ms/step - loss: 0.2040 - accuracy:
0.9261
Epoch 4/4
49/49 [==============================] - 1s 13ms/step - loss: 0.1698 - accuracy:
0.9404
782/782 [==============================] - 1s 573us/step - loss: 0.2900 -
accuracy: 0.8840
```

[21]:
```
results
```

[21]:
```
[0.29001015424728394, 0.8840000033378601]
```

The original model **test data prediction** result: **loss: 0.2926, accuracy: 0.8840**.

1.1 Question 1: Change to three hidden layers

[18]:
```
# Build the model with 3 layers
model_3_layers = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])

# Compile the model
model_3_layers.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])

# Train the model
history_3_layers = model_3_layers.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,     # run the model for 20 epoch and each epoch␣
 ↪for 512 batch
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

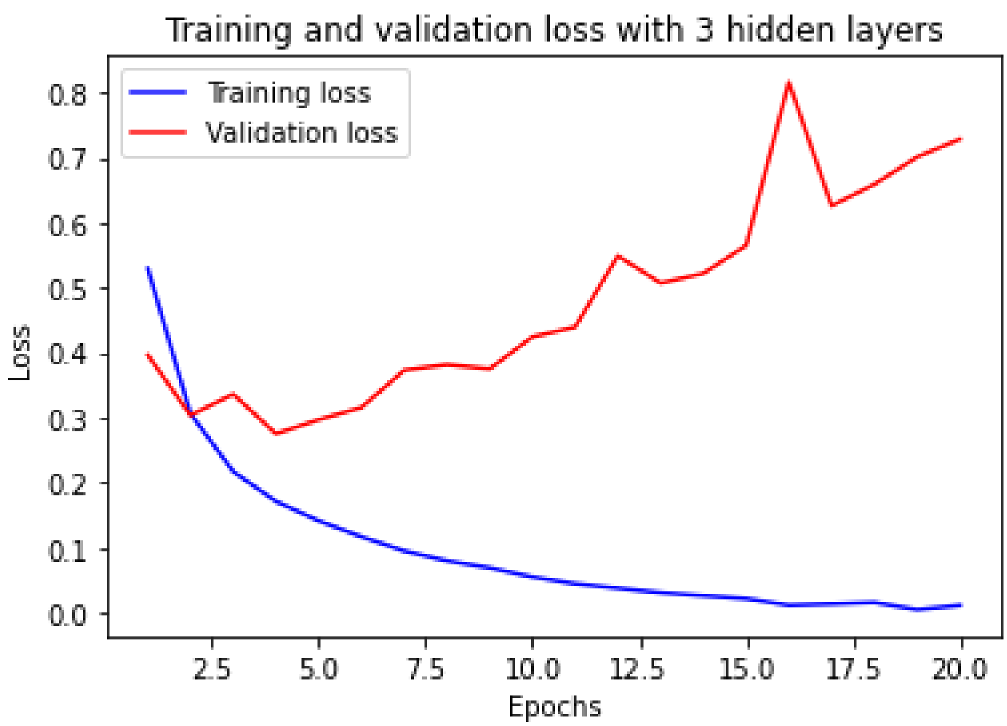
```
Epoch 1/20
30/30 [==============================] - 2s 35ms/step - loss: 0.5298 - accuracy:
0.7732 - val_loss: 0.3966 - val_accuracy: 0.8613
Epoch 2/20
30/30 [==============================] - 1s 23ms/step - loss: 0.3064 - accuracy:
0.9027 - val_loss: 0.3038 - val_accuracy: 0.8858
```

```
Epoch 3/20
30/30 [==============================] - 1s 21ms/step - loss: 0.2173 - accuracy:
0.9287 - val_loss: 0.3364 - val_accuracy: 0.8625
Epoch 4/20
30/30 [==============================] - 1s 21ms/step - loss: 0.1714 - accuracy:
0.9434 - val_loss: 0.2753 - val_accuracy: 0.8910
Epoch 5/20
30/30 [==============================] - 1s 23ms/step - loss: 0.1416 - accuracy:
0.9526 - val_loss: 0.2970 - val_accuracy: 0.8845
Epoch 6/20
30/30 [==============================] - 1s 21ms/step - loss: 0.1171 - accuracy:
0.9625 - val_loss: 0.3157 - val_accuracy: 0.8821
Epoch 7/20
30/30 [==============================] - 1s 23ms/step - loss: 0.0951 - accuracy:
0.9706 - val_loss: 0.3732 - val_accuracy: 0.8660
Epoch 8/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0800 - accuracy:
0.9759 - val_loss: 0.3818 - val_accuracy: 0.8668
Epoch 9/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0692 - accuracy:
0.9797 - val_loss: 0.3752 - val_accuracy: 0.8744
Epoch 10/20
30/30 [==============================] - 1s 27ms/step - loss: 0.0552 - accuracy:
0.9839 - val_loss: 0.4244 - val_accuracy: 0.8738
Epoch 11/20
30/30 [==============================] - 1s 31ms/step - loss: 0.0447 - accuracy:
0.9881 - val_loss: 0.4395 - val_accuracy: 0.8667
Epoch 12/20
30/30 [==============================] - 1s 28ms/step - loss: 0.0379 - accuracy:
0.9903 - val_loss: 0.5489 - val_accuracy: 0.8503
Epoch 13/20
30/30 [==============================] - 1s 30ms/step - loss: 0.0310 - accuracy:
0.9923 - val_loss: 0.5070 - val_accuracy: 0.8730
Epoch 14/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0263 - accuracy:
0.9936 - val_loss: 0.5220 - val_accuracy: 0.8703
Epoch 15/20
30/30 [==============================] - 1s 25ms/step - loss: 0.0219 - accuracy:
0.9945 - val_loss: 0.5650 - val_accuracy: 0.8695
Epoch 16/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0118 - accuracy:
0.9987 - val_loss: 0.8162 - val_accuracy: 0.8320
Epoch 17/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0137 - accuracy:
0.9971 - val_loss: 0.6260 - val_accuracy: 0.8630
Epoch 18/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0160 - accuracy:
0.9956 - val_loss: 0.6589 - val_accuracy: 0.8660
```

```
Epoch 19/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0049 - accuracy:
0.9998 - val_loss: 0.7011 - val_accuracy: 0.8653
Epoch 20/20
30/30 [==============================] - 1s 20ms/step - loss: 0.0116 - accuracy:
0.9970 - val_loss: 0.7284 - val_accuracy: 0.8638
```

Train & Validation loss

[19]:
```
history_dict_3layers = history_3_layers.history
loss_values = history_dict_3layers["loss"]
val_loss_values = history_dict_3layers["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, "b", label="Training loss")
plt.plot(epochs, val_loss_values, "r", label="Validation loss")
plt.title("Training and validation loss with 3 hidden layers")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



The 3 hiddel layer model still need to **choose 4 epochs** to run the test data.

Test accuracy

[20]:
```
model_3_layers = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
model_3_layers.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
model_3_layers.fit(x_train, y_train, epochs=4, batch_size=512)  # change to 4␣
↪epochs
results_3_layers = model_3_layers.evaluate(x_test, y_test)
```

```
Epoch 1/4
49/49 [==============================] - 2s 19ms/step - loss: 0.4586 - accuracy:
0.8158 0s - loss: 0.5132 - accuracy
Epoch 2/4
49/49 [==============================] - 1s 15ms/step - loss: 0.2501 - accuracy:
0.9092
Epoch 3/4
49/49 [==============================] - 1s 13ms/step - loss: 0.1936 - accuracy:
0.9316
Epoch 4/4
49/49 [==============================] - 1s 14ms/step - loss: 0.1618 - accuracy:
0.9426
782/782 [==============================] - 1s 615us/step - loss: 0.3106 -
accuracy: 0.8806
```

[22]:
```
results_3_layers
```

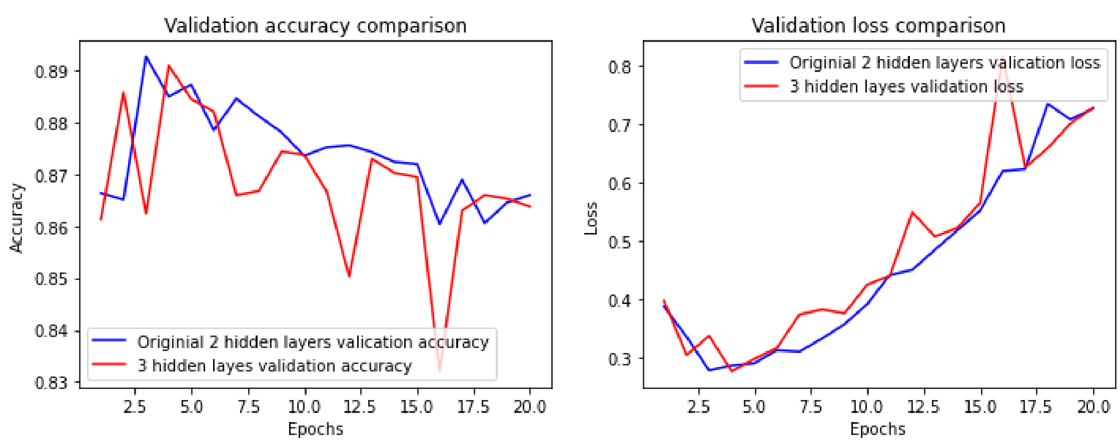
[22]:
```
[0.31061962246894836, 0.8805999755859375]
```

The 3 hidden layers model test data prediction result: **loss: 0.3108, accuracy: 0.8805**.

Validation accuracy & loss comparison

[23]:
```
#plt.rcParams['figure.dpi'] = 300
history_dict_3layer = history_3_layers.history
val_acc_3_layers = history_dict_3layer['val_accuracy']
val_acc = history_dict['val_accuracy']

val_loss_3_layers = history_dict_3layer['val_loss']
val_loss = history_dict['val_loss']

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

plt.figure(figsize=(10,4)) # set the figure size
```

```
plt.subplot(1, 2, 1)  # row, column, index
plt.plot(epochs, val_acc, "b", label="Originial 2 hidden layers valication accuracy")
plt.plot(epochs, val_acc_3_layers, "r", label="3 hidden layes validation accuracy")
plt.title("Validation accuracy comparison")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(epochs, val_loss, "b", label="Originial 2 hidden layers valication loss")
plt.plot(epochs, val_loss_3_layers, "r", label="3 hidden layes validation loss")
plt.title("Validation loss comparison")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()

plt.tight_layout() # minimize the overlap of the two figures
plt.show()
```



1.1.1 Summary for Question 1:

Similarly, 4 epoch is also appropriate for the 3 hidden layers to **minimize the loss function as well as avoid overfit**. Validation accuracy in both models(2&3 hidden layers) are **close to each other**. As for the 4 epoch, 3 hidden layers **accuracy is even lower** than the original 2 hidden layers

Model with 3 hidden layers test accuracy is 0.8805, while the original model with 2 hidden layers test accuracy is 0.0.8840. Increasing the number of hidden layers from 2 to 3 even **lower the test accuracy**.

1.2 Question 2: 32 units with 2 hidden layers

[8]:
```
# Build the model with 32units and 2 layers
model_32units = keras.Sequential([
    layers.Dense(32, activation="relu"),
    layers.Dense(32, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])

# Compile the model
model_32units.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])

# Train the model
history_32units = model_32units.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,     # run the model for 20 epochs and each epoch␣
 ↪for 512 batch
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

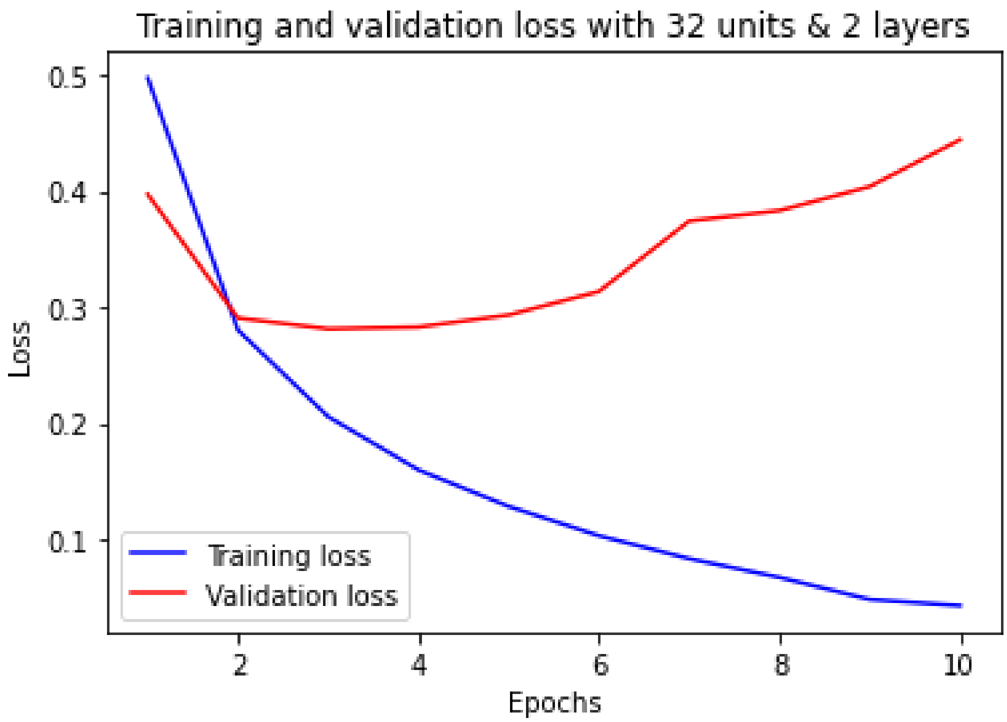
```
Epoch 1/20
30/30 [==============================] - 3s 42ms/step - loss: 0.4974 - accuracy:
0.7850 - val_loss: 0.3971 - val_accuracy: 0.8410
Epoch 2/20
30/30 [==============================] - 1s 28ms/step - loss: 0.2802 - accuracy:
0.9047 - val_loss: 0.2906 - val_accuracy: 0.8891
Epoch 3/20
30/30 [==============================] - 1s 25ms/step - loss: 0.2055 - accuracy:
0.9273 - val_loss: 0.2813 - val_accuracy: 0.8880
Epoch 4/20
30/30 [==============================] - 1s 27ms/step - loss: 0.1597 - accuracy:
0.9462 - val_loss: 0.2829 - val_accuracy: 0.8889
Epoch 5/20
30/30 [==============================] - 1s 27ms/step - loss: 0.1283 - accuracy:
0.9569 - val_loss: 0.2932 - val_accuracy: 0.8859
Epoch 6/20
30/30 [==============================] - 1s 28ms/step - loss: 0.1030 - accuracy:
0.9672 - val_loss: 0.3135 - val_accuracy: 0.8852
Epoch 7/20
30/30 [==============================] - 1s 34ms/step - loss: 0.0832 - accuracy:
0.9737 - val_loss: 0.3742 - val_accuracy: 0.8754
Epoch 8/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0671 - accuracy:
0.9798 - val_loss: 0.3831 - val_accuracy: 0.8781
Epoch 9/20
30/30 [==============================] - 1s 25ms/step - loss: 0.0480 - accuracy:
```

```
0.9883 - val_loss: 0.4038 - val_accuracy: 0.8741
Epoch 10/20
30/30 [==============================] - 1s 25ms/step - loss: 0.0427 - accuracy:
0.9879 - val_loss: 0.4442 - val_accuracy: 0.8750
Epoch 11/20
30/30 [==============================] - 1s 25ms/step - loss: 0.0280 - accuracy:
0.9943 - val_loss: 0.6271 - val_accuracy: 0.8494
Epoch 12/20
30/30 [==============================] - 1s 25ms/step - loss: 0.0289 - accuracy:
0.9913 - val_loss: 0.4948 - val_accuracy: 0.8737
Epoch 13/20
30/30 [==============================] - 1s 27ms/step - loss: 0.0165 - accuracy:
0.9970 - val_loss: 0.6834 - val_accuracy: 0.8439
Epoch 14/20
30/30 [==============================] - 1s 25ms/step - loss: 0.0097 - accuracy:
0.9993 - val_loss: 0.5662 - val_accuracy: 0.8711
Epoch 15/20
30/30 [==============================] - 1s 27ms/step - loss: 0.0165 - accuracy:
0.9948 - val_loss: 0.6008 - val_accuracy: 0.8702
Epoch 16/20
30/30 [==============================] - 1s 27ms/step - loss: 0.0044 - accuracy:
0.9998 - val_loss: 0.6510 - val_accuracy: 0.8647
Epoch 17/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0099 - accuracy:
0.9972 - val_loss: 0.6760 - val_accuracy: 0.8664
Epoch 18/20
30/30 [==============================] - 1s 31ms/step - loss: 0.0023 - accuracy:
0.9999 - val_loss: 0.7145 - val_accuracy: 0.8664
Epoch 19/20
30/30 [==============================] - 1s 28ms/step - loss: 0.0091 - accuracy:
0.9967 - val_loss: 0.7447 - val_accuracy: 0.8657
Epoch 20/20
30/30 [==============================] - 1s 28ms/step - loss: 0.0012 - accuracy:
0.9999 - val_loss: 0.7755 - val_accuracy: 0.8656
```

Train & Validation loss

[9]:
```python
history_dict_32units = history_32units.history

loss_values = history_dict_32units['loss'][:10]  # select 10 epoch could be␣
 ↪easier to detect the suitable epoch.
val_loss_values = history_dict_32units['val_loss'][:10]

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

plt.plot(epochs, loss_values, "b", label="Training loss")
plt.plot(epochs, val_loss_values, "r", label="Validation loss")
plt.title("Training and validation loss with 32 units & 2 layers")
```

```
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



For the 32 units with 2 layers, I choose **3 epochs** to run the test data.

Test accuracy

[10]:
```
model_32units = keras.Sequential([
    layers.Dense(32, activation="relu"),
    layers.Dense(32, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
model_32units.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
model_32units.fit(x_train, y_train, epochs=3, batch_size=512)  # change to 3␣
 ↪epochs
results_32units = model_32units.evaluate(x_test, y_test)
```

```
Epoch 1/3
49/49 [==============================] - 2s 25ms/step - loss: 0.4352 - accuracy:
0.8206
```

```
Epoch 2/3
49/49 [==============================] - 1s 17ms/step - loss: 0.2392 - accuracy:
0.9138
Epoch 3/3
49/49 [==============================] - 1s 17ms/step - loss: 0.1929 - accuracy:
0.9289
782/782 [==============================] - 1s 706us/step - loss: 0.2894 -
accuracy: 0.8851
```

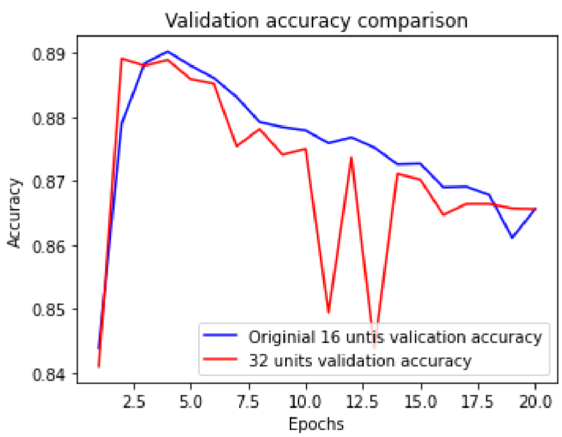
[11]:
```
results_32units
```

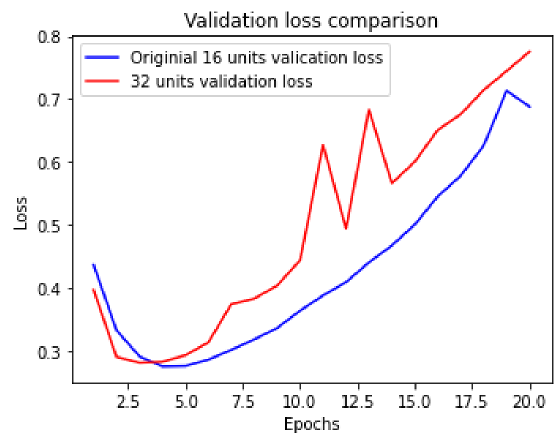
[11]: [0.2894221544265747, 0.8850799798965454]

The 32 units with 2 layers model test data prediction result: **loss: 0.2894, accuracy: 0.8850.**

Validation accuracy & loss comparison

[12]:
```
val_acc_32units = history_dict_32units['val_accuracy']
val_acc = history_dict['val_accuracy']

val_loss_32units = history_dict_32units['val_loss']
val_loss = history_dict['val_loss']

epochs = range(1, len(val_acc_32units)+1)

plt.figure(figsize=(10,4)) # set the figure size

plt.subplot(1, 2, 1)  # row, column, index
plt.plot(epochs, val_acc, "b", label="Originial 16 untis valication accuracy")
plt.plot(epochs, val_acc_32units, "r", label="32 units validation accuracy")
plt.title("Validation accuracy comparison")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(epochs, val_loss, "b", label="Originial 16 units valication loss")
plt.plot(epochs, val_loss_32units, "r", label="32 units validation loss")
plt.title("Validation loss comparison")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()

plt.tight_layout() # minimize the overlap of the two figures
plt.show()
```





1.2.1 Summary for Question 2:

3 epoch is appropriate for the 32 units with 2 layers to **minimize the loss function as well as avoid overfit**. **Validation accuracy in 32 units is lower** than the original model, and from the validatio loss, **32units begins overfit ealier** than the original 16units model.

Model with **32 units test accuracy is 0.8850**, while the original model with **16 units test accuracy is 0.8840**. Changing the number of units from 16 to 32 **increase the test accuracy.**

1.3 Question 3: Using MSE loss function

[13]:
```
# Build the model with 16units and 2 layers
model_mse = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])

# Compile the model
model_mse.compile(optimizer="rmsprop",
              loss="MSE",
              metrics=["accuracy"])

# Train the model
history_mse = model_mse.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,     # run the model for 20 epochs and each epoch␣
 ↪for 512 batch
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

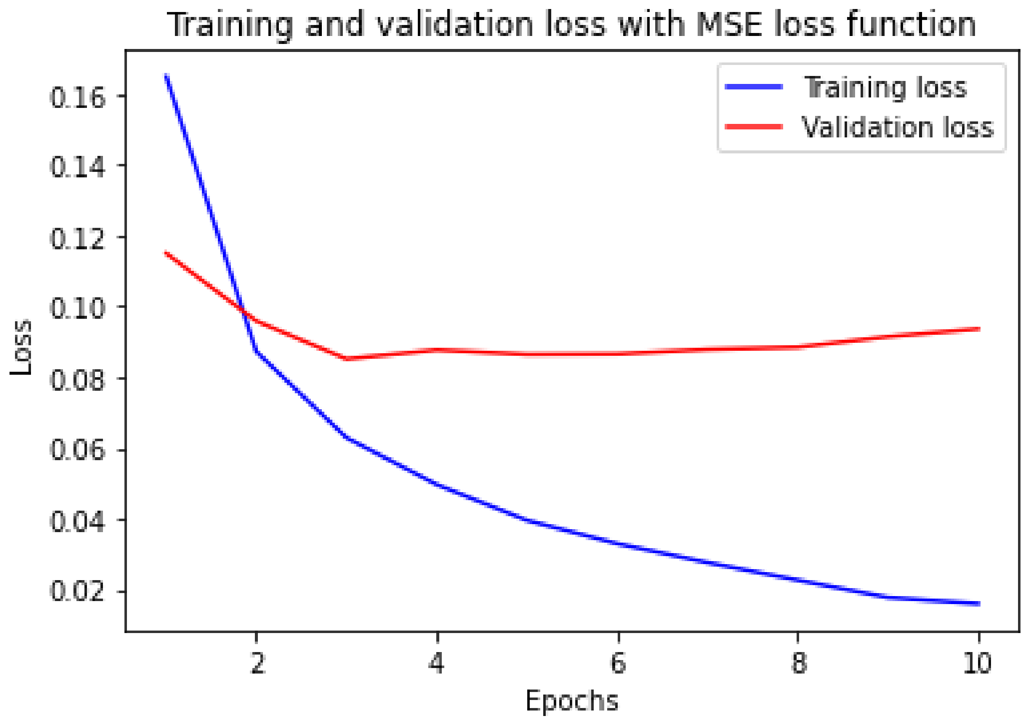
```
Epoch 1/20
30/30 [==============================] - 2s 38ms/step - loss: 0.1650 - accuracy:
```

```
0.7911 - val_loss: 0.1150 - val_accuracy: 0.8745
Epoch 2/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0873 - accuracy:
0.9063 - val_loss: 0.0959 - val_accuracy: 0.8818
Epoch 3/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0629 - accuracy:
0.9313 - val_loss: 0.0852 - val_accuracy: 0.8878
Epoch 4/20
30/30 [==============================] - 1s 28ms/step - loss: 0.0497 - accuracy:
0.9457 - val_loss: 0.0877 - val_accuracy: 0.8824
Epoch 5/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0396 - accuracy:
0.9599 - val_loss: 0.0865 - val_accuracy: 0.8816
Epoch 6/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0330 - accuracy:
0.9679 - val_loss: 0.0866 - val_accuracy: 0.8817
Epoch 7/20
30/30 [==============================] - 1s 25ms/step - loss: 0.0276 - accuracy:
0.9729 - val_loss: 0.0879 - val_accuracy: 0.8818
Epoch 8/20
30/30 [==============================] - 1s 23ms/step - loss: 0.0227 - accuracy:
0.9791 - val_loss: 0.0885 - val_accuracy: 0.8793
Epoch 9/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0177 - accuracy:
0.9846 - val_loss: 0.0915 - val_accuracy: 0.8785
Epoch 10/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0160 - accuracy:
0.9863 - val_loss: 0.0937 - val_accuracy: 0.8752
Epoch 11/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0130 - accuracy:
0.9894 - val_loss: 0.0958 - val_accuracy: 0.8736
Epoch 12/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0105 - accuracy:
0.9918 - val_loss: 0.0996 - val_accuracy: 0.8695
Epoch 13/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0093 - accuracy:
0.9922 - val_loss: 0.1002 - val_accuracy: 0.8718
Epoch 14/20
30/30 [==============================] - 1s 23ms/step - loss: 0.0077 - accuracy:
0.9949 - val_loss: 0.1030 - val_accuracy: 0.8678
Epoch 15/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0067 - accuracy:
0.9943 - val_loss: 0.1039 - val_accuracy: 0.8702
Epoch 16/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0050 - accuracy:
0.9967 - val_loss: 0.1053 - val_accuracy: 0.8674
Epoch 17/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0060 - accuracy:
```

```
0.9948 - val_loss: 0.1075 - val_accuracy: 0.8670
Epoch 18/20
30/30 [==============================] - 1s 20ms/step - loss: 0.0033 - accuracy:
0.9975 - val_loss: 0.1091 - val_accuracy: 0.8651
Epoch 19/20
30/30 [==============================] - 1s 17ms/step - loss: 0.0054 - accuracy:
0.9947 - val_loss: 0.1096 - val_accuracy: 0.8652
Epoch 20/20
30/30 [==============================] - 1s 20ms/step - loss: 0.0027 - accuracy:
0.9976 - val_loss: 0.1115 - val_accuracy: 0.8627
```

Train & Validation loss

[14]:
```
history_dict_mse = history_mse.history

loss_values = history_dict_mse['loss'][:10]  # select 10 epoch could be easier␣
↪to detect the suitable epoch.
val_loss_values = history_dict_mse['val_loss'][:10]

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

plt.plot(epochs, loss_values, "b", label="Training loss")
plt.plot(epochs, val_loss_values, "r", label="Validation loss")
plt.title("Training and validation loss with MSE loss function")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



The MSE loss function model still need to choose **4 epochs** to run the test data. But we **cannot tell any increase from the validation loss** curve.

Test accuracy

[15]:
```
model_mse = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
model_mse.compile(optimizer="rmsprop",
              loss="MSE",
              metrics=["accuracy"])
model_mse.fit(x_train, y_train, epochs=4, batch_size=512)  # change to 3 epochs
results_mse = model_mse.evaluate(x_test, y_test)
```

```
Epoch 1/4
49/49 [==============================] - 2s 17ms/step - loss: 0.1477 - accuracy:
0.8126
Epoch 2/4
49/49 [==============================] - 1s 19ms/step - loss: 0.0777 - accuracy:
0.9104
Epoch 3/4
49/49 [==============================] - 1s 15ms/step - loss: 0.0586 - accuracy:
0.9310
```

```
Epoch 4/4
49/49 [==============================] - 1s 13ms/step - loss: 0.0472 - accuracy:
0.9456
782/782 [==============================] - 1s 679us/step - loss: 0.0889 -
accuracy: 0.8804
```

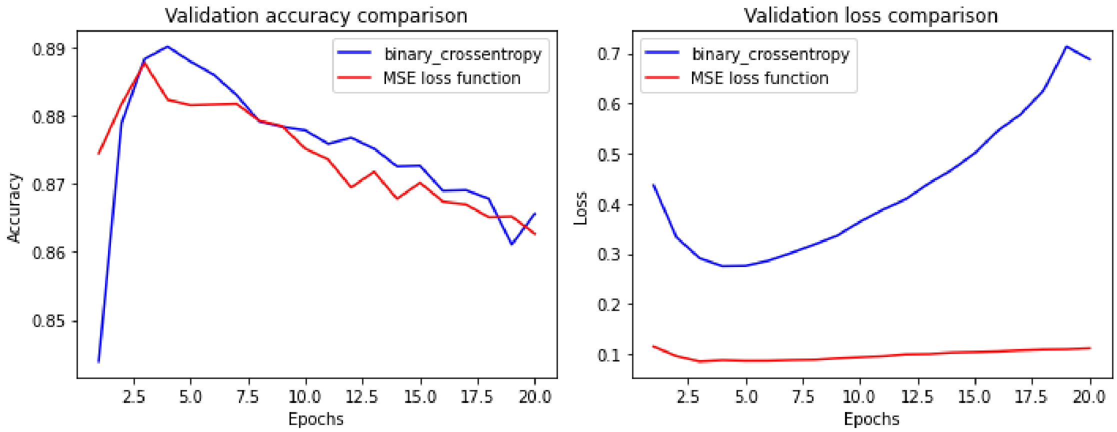
[16]:
```python
results_mse
```

[16]:
```
[0.08892610669136047, 0.8804000020027161]
```

The MSE loss function model test data prediction result: **loss: 0.089, accuracy: 0.8804**.

Validation accuracy & loss comparison

[17]:
```python
val_acc_mse = history_dict_mse['val_accuracy']
val_acc = history_dict['val_accuracy']

val_loss_mse = history_dict_mse['val_loss']
val_loss = history_dict['val_loss']

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

plt.figure(figsize=(10,4)) # set the figure size

plt.subplot(1, 2, 1)  # row, column, index
plt.plot(epochs, val_acc, "b", label="binary_crossentropy")
plt.plot(epochs, val_acc_mse, "r", label="MSE loss function")
plt.title("Validation accuracy comparison")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(epochs, val_loss, "b", label="binary_crossentropy")
plt.plot(epochs, val_loss_mse, "r", label="MSE loss function")
plt.title("Validation loss comparison")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()

plt.tight_layout() # minimize the overlap of the two figures
plt.show()
```



1.3.1 Summary for Question 3:

Although the **loss function MSE doesnot change much in test data loss and accuracy as well as validation data accuracy**, the validation loss figure shows that the **MSE loss doesnot change with the epochs increasing**. MSE loss function **should not be used** in this condition.

Distinguish binary_crossentropy & MSE Loss function **binary_crossentropy** is a loss function that is often used for **binary classification** problems, where the output is a probability distribution over a set of classes.Cross entropy loss function penalizes the neural network for assigning low probabilities to the correct class and high probabilities to the wrong classes.
MSE, **mean squared error**, is often used for **regression** problems, where the output is a continuous value or a vector of values. MSE penalizes the neural network for deviating from the true output by squaring the difference between them.

1.4 Question 4: Using tanh activation

[8]:
```
# Build the model with 16 units and 2 layers
model_tanh = keras.Sequential([
    layers.Dense(16, activation="tanh"),
    layers.Dense(16, activation="tanh"),
    layers.Dense(1, activation="sigmoid")
])

# Compile the model
model_tanh.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])

# Train the model
history_tanh = model_tanh.fit(partial_x_train,
                    partial_y_train,
```

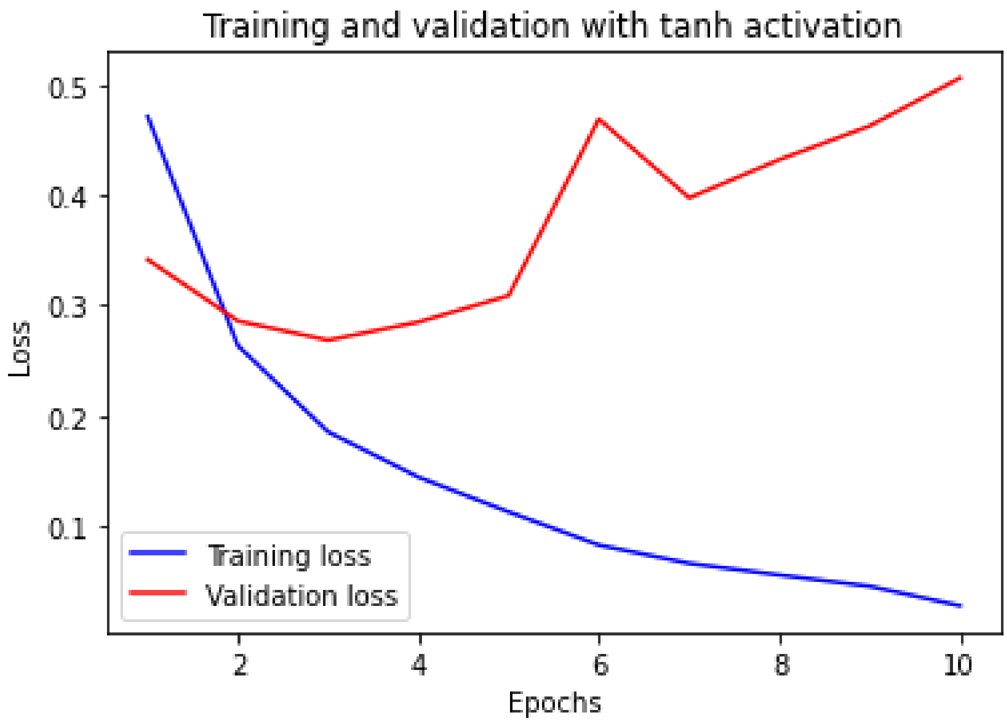
```
                    epochs=10,     # run the model for 10 epochs and each epoch␣
↪for 512 batch
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/10
30/30 [==============================] - 2s 35ms/step - loss: 0.4712 - accuracy:
0.7972 - val_loss: 0.3415 - val_accuracy: 0.8754
Epoch 2/10
30/30 [==============================] - 1s 21ms/step - loss: 0.2634 - accuracy:
0.9083 - val_loss: 0.2859 - val_accuracy: 0.8854
Epoch 3/10
30/30 [==============================] - 1s 24ms/step - loss: 0.1854 - accuracy:
0.9377 - val_loss: 0.2685 - val_accuracy: 0.8904
Epoch 4/10
30/30 [==============================] - 1s 21ms/step - loss: 0.1444 - accuracy:
0.9485 - val_loss: 0.2849 - val_accuracy: 0.8872
Epoch 5/10
30/30 [==============================] - 1s 21ms/step - loss: 0.1129 - accuracy:
0.9617 - val_loss: 0.3089 - val_accuracy: 0.8836
Epoch 6/10
30/30 [==============================] - 1s 21ms/step - loss: 0.0828 - accuracy:
0.9735 - val_loss: 0.4691 - val_accuracy: 0.8535
Epoch 7/10
30/30 [==============================] - 1s 21ms/step - loss: 0.0661 - accuracy:
0.9786 - val_loss: 0.3976 - val_accuracy: 0.8730
Epoch 8/10
30/30 [==============================] - 1s 20ms/step - loss: 0.0556 - accuracy:
0.9829 - val_loss: 0.4322 - val_accuracy: 0.8731
Epoch 9/10
30/30 [==============================] - 1s 27ms/step - loss: 0.0454 - accuracy:
0.9861 - val_loss: 0.4628 - val_accuracy: 0.8730
Epoch 10/10
30/30 [==============================] - 1s 24ms/step - loss: 0.0278 - accuracy:
0.9929 - val_loss: 0.5062 - val_accuracy: 0.8697
```

Train & validation loss

[9]:
```
history_dict_tanh = history_tanh.history

loss_values = history_dict_tanh['loss'][:10]  # select 10 epoch could be easier␣
↪to detect the suitable epoch.
val_loss_values = history_dict_tanh['val_loss'][:10]

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

plt.plot(epochs, loss_values, "b", label="Training loss")
plt.plot(epochs, val_loss_values, "r", label="Validation loss")
```

```
plt.title("Training and validation with tanh activation")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



For the tanh activation model with 16 units and 2 layers, I choose **3 epochs** to run the test data.

Test accuracy

[10]:
```
model_tanh = keras.Sequential([
    layers.Dense(16, activation="tanh"),
    layers.Dense(16, activation="tanh"),
    layers.Dense(1, activation="sigmoid")
])
model_tanh.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
model_tanh.fit(x_train, y_train, epochs=3, batch_size=512)  # change to 3 epochs
results_tanh = model_tanh.evaluate(x_test, y_test)
```

```
Epoch 1/3
49/49 [==============================] - 2s 21ms/step - loss: 0.4226 - accuracy:
0.8226
```

```
Epoch 2/3
49/49 [==============================] - 1s 14ms/step - loss: 0.2289 - accuracy:
0.9153
Epoch 3/3
49/49 [==============================] - 1s 13ms/step - loss: 0.1800 - accuracy:
0.9323 0s - loss: 0.1789 - accuracy - ETA: 0s - loss: 0.1813 - accuracy: 0.93
782/782 [==============================] - 1s 620us/step - loss: 0.3003 -
accuracy: 0.8820
```

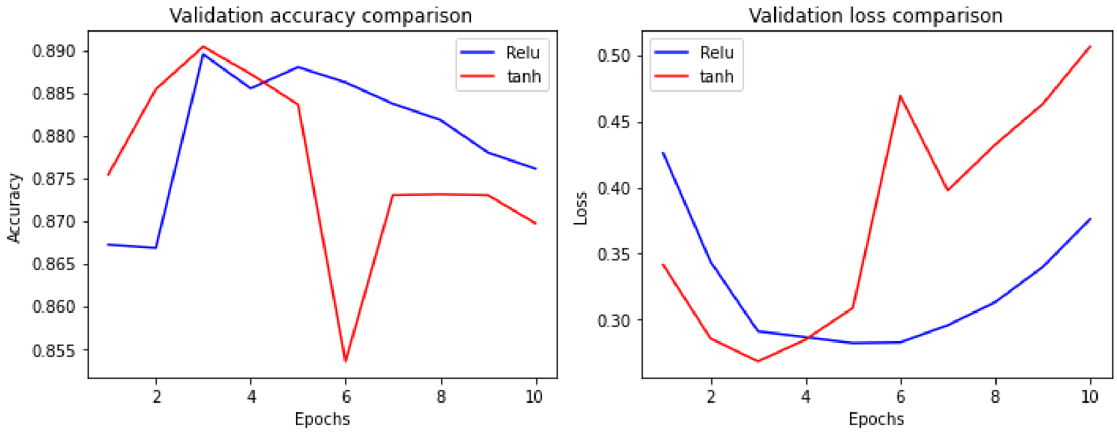
[11]:
```
results_tanh
```

[11]:
```
[0.3002675473690033, 0.8819599747657776]
```

The tanh activation model test data prediction result: **loss: 0.30626, accuracy: 0.8820.**

Validation accuracy & loss comparison

[13]:
```
val_acc_tanh = history_dict_tanh['val_accuracy']
val_acc = history_dict['val_accuracy'][:10]

val_loss_tanh = history_dict_tanh['val_loss']
val_loss = history_dict['val_loss'][:10]

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

plt.figure(figsize=(10,4)) # set the figure size

plt.subplot(1, 2, 1)  # row, column, index
plt.plot(epochs, val_acc, "b", label="Relu")
plt.plot(epochs, val_acc_tanh, "r", label="tanh")
plt.title("Validation accuracy comparison")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(epochs, val_loss, "b", label="Relu")
plt.plot(epochs, val_loss_tanh, "r", label="tanh")
plt.title("Validation loss comparison")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()

plt.tight_layout() # minimize the overlap of the two figures
plt.show()
```



1.4.1 Summary for Question 4:

The validation accuracy **doesnot change too much** comparing the 2 activation. As for the validation loss, **tanh activation become overfit earlier than Relu.**

Tanh activation model test accuracy is **lower than** the original Relu model.

ReLu and Tanh activation Relu, Rectified linear unit, **output the input for positive values, and 0 otherwise**.
Relu is the best and most advanced activation function in deep learning right now because it removes the **vanishing gradient problem** and also computationally less expensive compared to the other activation function like sigmoid and tanh.

1.5 Question 5_1: Using regularization to improve model

[14]:
```
from tensorflow.keras import regularizers
```

[15]:
```
# Build the model with regularization
model_regu = keras.Sequential([
    layers.Dense(16, kernel_regularizer=regularizers.l2(0.002),␣
 ↪activation="relu"), # use L2 regularization
    layers.Dense(16, kernel_regularizer=regularizers.l2(0.002),␣
 ↪activation="relu"),
    layers.Dense(1, activation="sigmoid")
])

# Compile the model
model_regu.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])

# Train the model
```

```
history_regu = model_regu.fit(partial_x_train,
                    partial_y_train,
                    epochs=10,     # run the model for 20 epochs and each epoch␣
 ↪for 512 batch
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/10
30/30 [==============================] - 2s 38ms/step - loss: 0.6240 - accuracy:
0.7784 - val_loss: 0.4972 - val_accuracy: 0.8612
Epoch 2/10
30/30 [==============================] - 1s 24ms/step - loss: 0.4267 - accuracy:
0.8882 - val_loss: 0.4089 - val_accuracy: 0.8779
Epoch 3/10
30/30 [==============================] - 1s 24ms/step - loss: 0.3500 - accuracy:
0.9099 - val_loss: 0.3747 - val_accuracy: 0.8870
Epoch 4/10
30/30 [==============================] - 1s 21ms/step - loss: 0.3145 - accuracy:
0.9195 - val_loss: 0.3635 - val_accuracy: 0.8875
Epoch 5/10
30/30 [==============================] - 1s 25ms/step - loss: 0.2926 - accuracy:
0.9257 - val_loss: 0.3605 - val_accuracy: 0.8875
Epoch 6/10
30/30 [==============================] - 1s 28ms/step - loss: 0.2791 - accuracy:
0.9310 - val_loss: 0.3617 - val_accuracy: 0.8843
Epoch 7/10
30/30 [==============================] - 1s 27ms/step - loss: 0.2704 - accuracy:
0.9336 - val_loss: 0.3663 - val_accuracy: 0.8821
Epoch 8/10
30/30 [==============================] - 1s 24ms/step - loss: 0.2613 - accuracy:
0.9367 - val_loss: 0.3662 - val_accuracy: 0.8850
Epoch 9/10
30/30 [==============================] - 1s 21ms/step - loss: 0.2525 - accuracy:
0.9403 - val_loss: 0.3829 - val_accuracy: 0.8774
Epoch 10/10
30/30 [==============================] - 1s 20ms/step - loss: 0.2485 - accuracy:
0.9436 - val_loss: 0.3822 - val_accuracy: 0.8764
```

[16]:

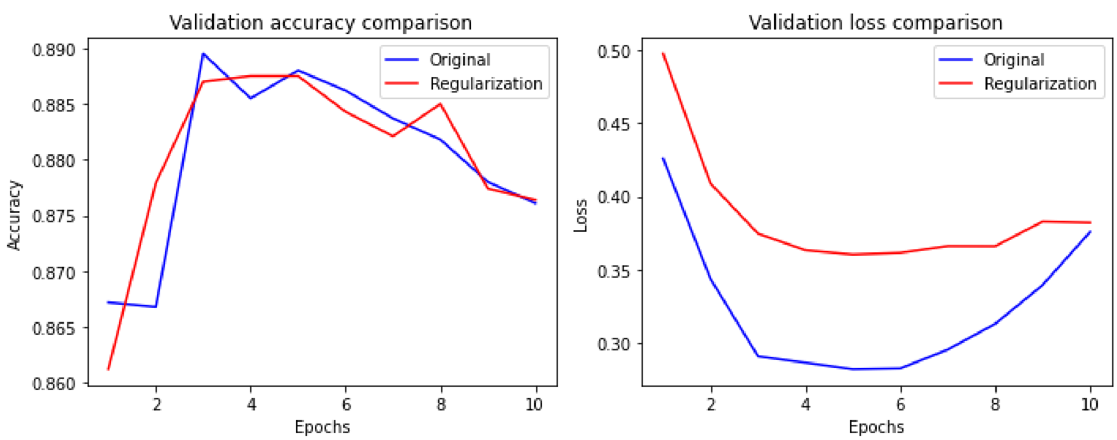
```
history_dict_regu = history_regu.history
```

Comparing the validation accuracy & loss

[17]:

```
val_acc_regu = history_dict_regu['val_accuracy']
val_acc = history_dict['val_accuracy'][:10]

val_loss_regu = history_dict_regu['val_loss']
val_loss = history_dict['val_loss'][:10]
```

```
epochs = range(1, len(val_acc_regu)+1)

plt.figure(figsize=(10,4)) # set the figure size

plt.subplot(1, 2, 1)  # row, column, index
plt.plot(epochs, val_acc, "b", label="Original")
plt.plot(epochs, val_acc_regu, "r", label="Regularization")
plt.title("Validation accuracy comparison")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(epochs, val_loss, "b", label="Original")
plt.plot(epochs, val_loss_regu, "r", label="Regularization")
plt.title("Validation loss comparison")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()

plt.tight_layout() # minimize the overlap of the two figures
plt.show()
```



Using the regularization **doesnot increase the validation accuracy or decrease the loss**, if we zoom in the figure, the validation loss is **even increase** after regularization.

1.6 Question 5_2: Using dropout to improve model

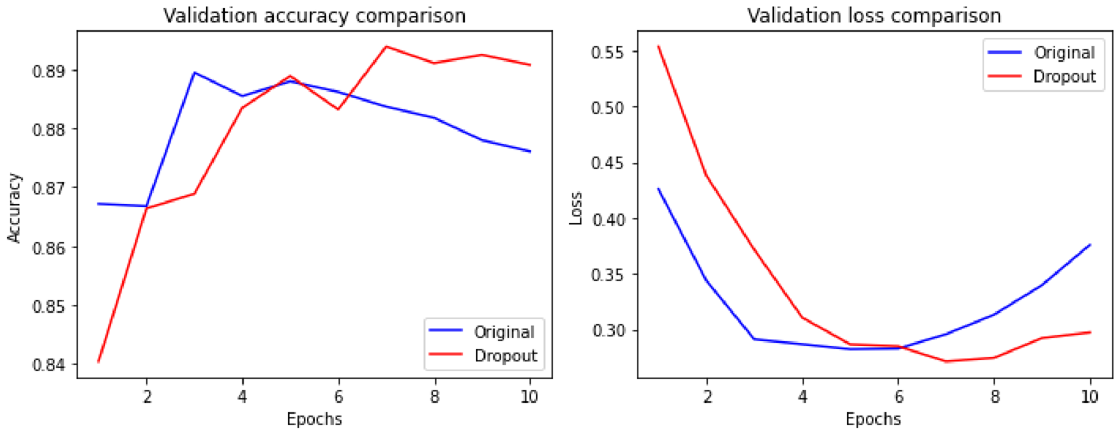
[18]:
```
# Build the model with dropout
model_drop = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dropout(0.5),
    layers.Dense(16, activation="relu"),
    layers.Dropout(0.5),
    layers.Dense(1, activation="sigmoid")
])

# Compile the model
model_drop.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])

# Train the model
history_drop = model_drop.fit(partial_x_train,
                    partial_y_train,
                    epochs=10,     # run the model for 20 epochs and each epoch␣
 ↪for 512 batch
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/10
30/30 [==============================] - 2s 35ms/step - loss: 0.6375 - accuracy:
0.6392 - val_loss: 0.5536 - val_accuracy: 0.8404
Epoch 2/10
30/30 [==============================] - 1s 23ms/step - loss: 0.5255 - accuracy:
0.7679 - val_loss: 0.4380 - val_accuracy: 0.8664
Epoch 3/10
30/30 [==============================] - 1s 21ms/step - loss: 0.4454 - accuracy:
0.8154 - val_loss: 0.3716 - val_accuracy: 0.8689
Epoch 4/10
30/30 [==============================] - 1s 24ms/step - loss: 0.3739 - accuracy:
0.8543 - val_loss: 0.3108 - val_accuracy: 0.8835
Epoch 5/10
30/30 [==============================] - 1s 21ms/step - loss: 0.3233 - accuracy:
0.8778 - val_loss: 0.2867 - val_accuracy: 0.8889
Epoch 6/10
30/30 [==============================] - 1s 24ms/step - loss: 0.2844 - accuracy:
0.8997 - val_loss: 0.2851 - val_accuracy: 0.8832
Epoch 7/10
30/30 [==============================] - 1s 21ms/step - loss: 0.2488 - accuracy:
0.9135 - val_loss: 0.2714 - val_accuracy: 0.8939
Epoch 8/10
30/30 [==============================] - 1s 23ms/step - loss: 0.2274 - accuracy:
0.9217 - val_loss: 0.2746 - val_accuracy: 0.8911
```

```
Epoch 9/10
30/30 [==============================] - 1s 24ms/step - loss: 0.1985 - accuracy:
0.9375 - val_loss: 0.2923 - val_accuracy: 0.8925
Epoch 10/10
30/30 [==============================] - 1s 24ms/step - loss: 0.1810 - accuracy:
0.9422 - val_loss: 0.2974 - val_accuracy: 0.8908
```

Validation accuracy & loss

[19]:
```python
history_dict_drop = history_drop.history

val_acc_drop = history_dict_drop['val_accuracy']
val_acc = history_dict['val_accuracy'][:10]

val_loss_drop = history_dict_drop['val_loss']
val_loss = history_dict['val_loss'][:10]

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

plt.figure(figsize=(10,4)) # set the figure size

plt.subplot(1, 2, 1)  # row, column, index
plt.plot(epochs, val_acc, "b", label="Original")
plt.plot(epochs, val_acc_drop, "r", label="Dropout")
plt.title("Validation accuracy comparison")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(epochs, val_loss, "b", label="Original")
plt.plot(epochs, val_loss_drop, "r", label="Dropout")
plt.title("Validation loss comparison")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()

plt.tight_layout() # minimize the overlap of the two figures
plt.show()
```



Adding the dropout can slightly increase the validation accuracy and slightly lower the validation loss as well as becoming overfit in a larger epoch number.

1.6.1 Summary for Question 5:

In the current model, using **dropout method is more appropriate** to increase the validation accuracy and avoid overfit.

Using the regularization **doesnot increase the validation accuracy or decrease the loss**, if we zoom in the figure, the validation loss is **even increase** after regularization.
Dropout could be a more efficient method to lower the validation loss and increase the validation accuracy than regularization from the figure above based on this model.

1.7 Summary for this assignment:

This assignment helps us to learn the deep learning practical programming. I played with the several different model which changing the parameters in the model.
We can change **the number of hidden layers**, **each layers number of units**, **type of loss function**, **type of activation function** and add **regularization & dropout**(not make the model **too complex** which could **cause the overfit** happens) strategies to adjust the model.
All the **hyperparameters** changing in this practice has one goal: make the **model has better performance on the unseen test data set**.