Homework 3 - Chapter 4

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This is the initail copy of code from Chapter 4

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

In [2]:
```
max([max(sequence) for sequence in train_data])
```

Out[2]: 9999

In [3]:
```
word_index = imdb.get_word_index()
reverse_word_index = dict(
    [(value, key) for (key, value) in word_index.items()])
decoded_review = " ".join(
    [reverse_word_index.get(i - 3, "?") for i in train_data[2]])
```

In [4]:
```
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 corresponds to the data
x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)
print(x_train.shape)
```

```
(25000, 10000)
```

In [5]:
```
# y corresponds to the labells
y_train = np.asarray(train_labels).astype("float32")
y_test = np.asarray(test_labels).astype("float32")
print(y_train.shape)
```

```
(25000,)
```

1) Change the model to use one hidden (aka "representation") layer, and see how this affects validation and test accuracy. Show this by plotting them (on the same plot, like in the book). Repeat this for three hidden layers. Comment on any differences you find, as well as what you'd expect.

Part 1 - One Layer Model

In [6]:

```
from tensorflow import keras
from tensorflow.keras import layers

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

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

x_val = x_train[:10000]
partial_x_train = x_train[10000:]
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))

history_dict_onelayer = history.history
history_dict_onelayer.keys()
```

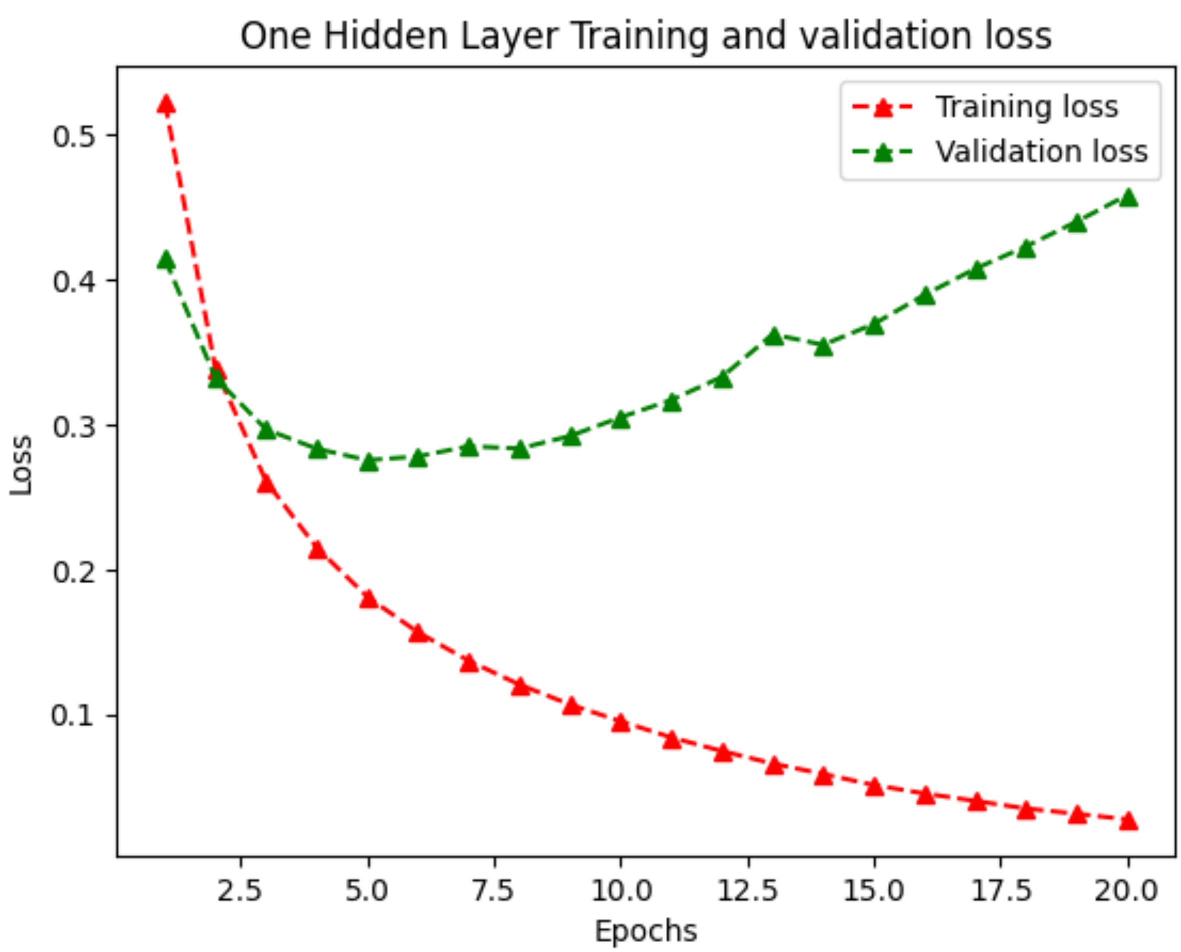
```
Epoch 1/20
30/30 [==============================] - 6s 153ms/step - loss: 0.5228 - acc
uracy: 0.7941 - val_loss: 0.4145 - val_accuracy: 0.8629
Epoch 2/20
30/30 [==============================] - 1s 38ms/step - loss: 0.3386 - accu
racy: 0.8995 - val_loss: 0.3321 - val_accuracy: 0.8803
Epoch 3/20
30/30 [==============================] - 1s 26ms/step - loss: 0.2608 - accu
racy: 0.9191 - val_loss: 0.2967 - val_accuracy: 0.8883
Epoch 4/20
30/30 [==============================] - 1s 24ms/step - loss: 0.2150 - accu
racy: 0.9321 - val_loss: 0.2834 - val_accuracy: 0.8881
Epoch 5/20
30/30 [==============================] - 1s 27ms/step - loss: 0.1811 - accu
```

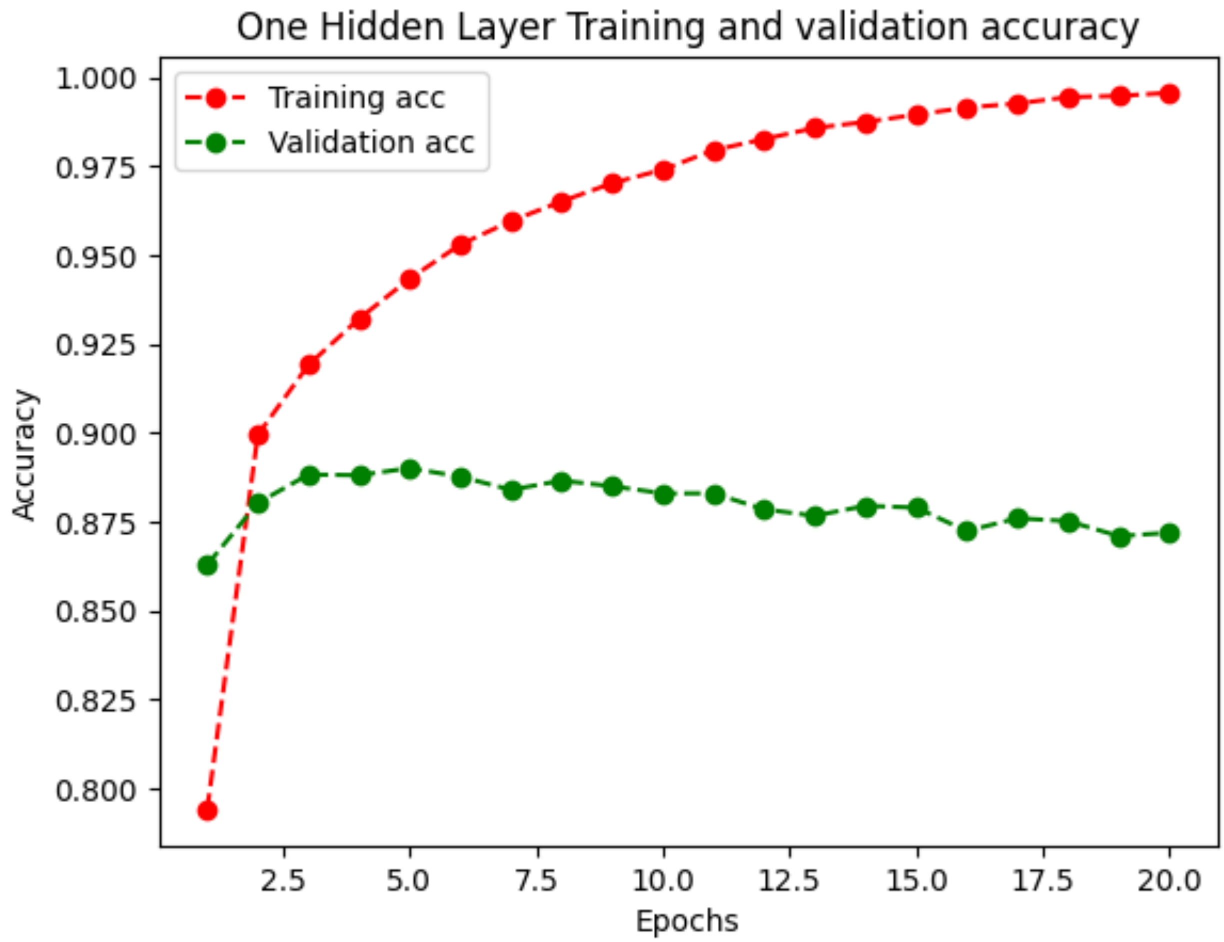
```
racy: 0.9434 - val_loss: 0.2755 - val_accuracy: 0.8901
Epoch 6/20
30/30 [==============================] - 1s 29ms/step - loss: 0.1566 - accu
racy: 0.9530 - val_loss: 0.2781 - val_accuracy: 0.8877
Epoch 7/20
30/30 [==============================] - 1s 32ms/step - loss: 0.1370 - accu
racy: 0.9596 - val_loss: 0.2851 - val_accuracy: 0.8840
Epoch 8/20
30/30 [==============================] - 1s 35ms/step - loss: 0.1206 - accu
racy: 0.9651 - val_loss: 0.2835 - val_accuracy: 0.8866
Epoch 9/20
30/30 [==============================] - 1s 30ms/step - loss: 0.1068 - accu
racy: 0.9703 - val_loss: 0.2921 - val_accuracy: 0.8850
Epoch 10/20
30/30 [==============================] - 1s 28ms/step - loss: 0.0952 - accu
racy: 0.9741 - val_loss: 0.3051 - val_accuracy: 0.8830
Epoch 11/20
30/30 [==============================] - 1s 27ms/step - loss: 0.0841 - accu
racy: 0.9795 - val_loss: 0.3170 - val_accuracy: 0.8830
Epoch 12/20
30/30 [==============================] - 1s 29ms/step - loss: 0.0747 - accu
racy: 0.9827 - val_loss: 0.3330 - val_accuracy: 0.8785
Epoch 13/20
30/30 [==============================] - 1s 29ms/step - loss: 0.0661 - accu
racy: 0.9858 - val_loss: 0.3623 - val_accuracy: 0.8767
Epoch 14/20
30/30 [==============================] - 1s 25ms/step - loss: 0.0589 - accu
racy: 0.9875 - val_loss: 0.3551 - val_accuracy: 0.8795
Epoch 15/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0512 - accu
racy: 0.9895 - val_loss: 0.3695 - val_accuracy: 0.8790
Epoch 16/20
30/30 [==============================] - 1s 23ms/step - loss: 0.0454 - accu
racy: 0.9915 - val_loss: 0.3896 - val_accuracy: 0.8724
Epoch 17/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0403 - accu
racy: 0.9927 - val_loss: 0.4076 - val_accuracy: 0.8760
Epoch 18/20
30/30 [==============================] - 1s 25ms/step - loss: 0.0350 - accu
racy: 0.9945 - val_loss: 0.4230 - val_accuracy: 0.8752
Epoch 19/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0314 - accu
racy: 0.9948 - val_loss: 0.4401 - val_accuracy: 0.8710
Epoch 20/20
30/30 [==============================] - 1s 23ms/step - loss: 0.0276 - accu
racy: 0.9957 - val_loss: 0.4584 - val_accuracy: 0.8719
```

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

Results of Model with One Layer

In [7]:
```
import matplotlib.pyplot as plt

# Training Loss vs Validatin Loss
loss_values = history_dict_onelayer["loss"]
val_loss_values = history_dict_onelayer["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, label="Training loss", color = 'red', linestyl
plt.plot(epochs, val_loss_values, label="Validation loss", color = 'green',
plt.title("One Hidden Layer Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
plt.clf()

# Training Accuracy vs. Validation Accuracy
acc = history_dict_onelayer["accuracy"]
val_acc = history_dict_onelayer["val_accuracy"]
plt.plot(epochs, acc, label="Training acc", color='red', linestyle='--', mar
plt.plot(epochs, val_acc, label="Validation acc", color='green', linestyle='
plt.title("One Hidden Layer Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```





Part 2 - 3 Layer Model

In [8]:
```
model = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])

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

history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))

history_dict_threelayers = history.history
history_dict_threelayers.keys()
```

```
Epoch 1/20
30/30 [==============================] - 4s 58ms/step - loss: 0.5367 - accu
racy: 0.7705 - val_loss: 0.3985 - val_accuracy: 0.8614
Epoch 2/20
```

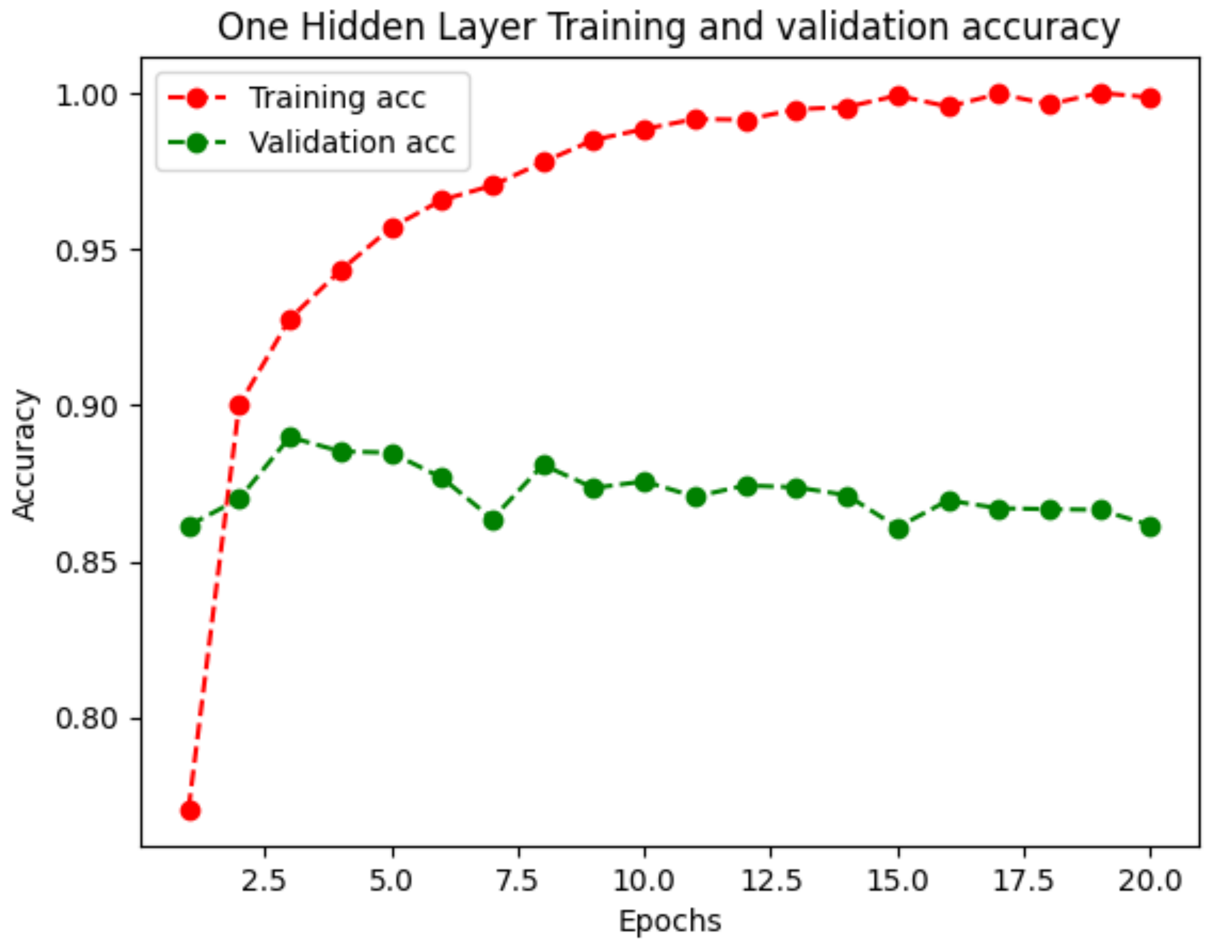
```
30/30 [==============================] - 1s 30ms/step - loss: 0.3120 - accu
racy: 0.9000 - val_loss: 0.3268 - val_accuracy: 0.8700
Epoch 3/20
30/30 [==============================] - 1s 34ms/step - loss: 0.2210 - accu
racy: 0.9277 - val_loss: 0.2784 - val_accuracy: 0.8898
Epoch 4/20
30/30 [==============================] - 1s 28ms/step - loss: 0.1713 - accu
racy: 0.9431 - val_loss: 0.2884 - val_accuracy: 0.8852
Epoch 5/20
30/30 [==============================] - 1s 24ms/step - loss: 0.1357 - accu
racy: 0.9568 - val_loss: 0.3007 - val_accuracy: 0.8848
Epoch 6/20
30/30 [==============================] - 1s 23ms/step - loss: 0.1105 - accu
racy: 0.9657 - val_loss: 0.3252 - val_accuracy: 0.8768
Epoch 7/20
30/30 [==============================] - 1s 25ms/step - loss: 0.0928 - accu
racy: 0.9703 - val_loss: 0.4247 - val_accuracy: 0.8636
Epoch 8/20
30/30 [==============================] - 1s 32ms/step - loss: 0.0770 - accu
racy: 0.9778 - val_loss: 0.3520 - val_accuracy: 0.8809
Epoch 9/20
30/30 [==============================] - 2s 57ms/step - loss: 0.0565 - accu
racy: 0.9849 - val_loss: 0.3877 - val_accuracy: 0.8735
Epoch 10/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0457 - accu
racy: 0.9884 - val_loss: 0.4302 - val_accuracy: 0.8756
Epoch 11/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0352 - accu
racy: 0.9916 - val_loss: 0.4565 - val_accuracy: 0.8707
Epoch 12/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0313 - accu
racy: 0.9914 - val_loss: 0.4842 - val_accuracy: 0.8743
Epoch 13/20
30/30 [==============================] - 1s 31ms/step - loss: 0.0228 - accu
racy: 0.9947 - val_loss: 0.5177 - val_accuracy: 0.8737
Epoch 14/20
30/30 [==============================] - 1s 32ms/step - loss: 0.0180 - accu
racy: 0.9955 - val_loss: 0.5566 - val_accuracy: 0.8712
Epoch 15/20
30/30 [==============================] - 1s 30ms/step - loss: 0.0083 - accu
racy: 0.9991 - val_loss: 0.6149 - val_accuracy: 0.8609
Epoch 16/20
30/30 [==============================] - 1s 25ms/step - loss: 0.0168 - accu
racy: 0.9956 - val_loss: 0.6381 - val_accuracy: 0.8695
Epoch 17/20
30/30 [==============================] - 1s 25ms/step - loss: 0.0041 - accu
racy: 0.9997 - val_loss: 0.6736 - val_accuracy: 0.8670
Epoch 18/20
30/30 [==============================] - 1s 24ms/step - loss: 0.0136 - accu
racy: 0.9963 - val_loss: 0.7203 - val_accuracy: 0.8667
Epoch 19/20
30/30 [==============================] - 1s 26ms/step - loss: 0.0020 - accu
racy: 1.0000 - val_loss: 0.7403 - val_accuracy: 0.8665
```

```
Epoch 20/20
30/30 [==============================] - 1s 25ms/step - loss: 0.0048 - accu
racy: 0.9985 - val_loss: 0.8746 - val_accuracy: 0.8615
```

Out[8]:
```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

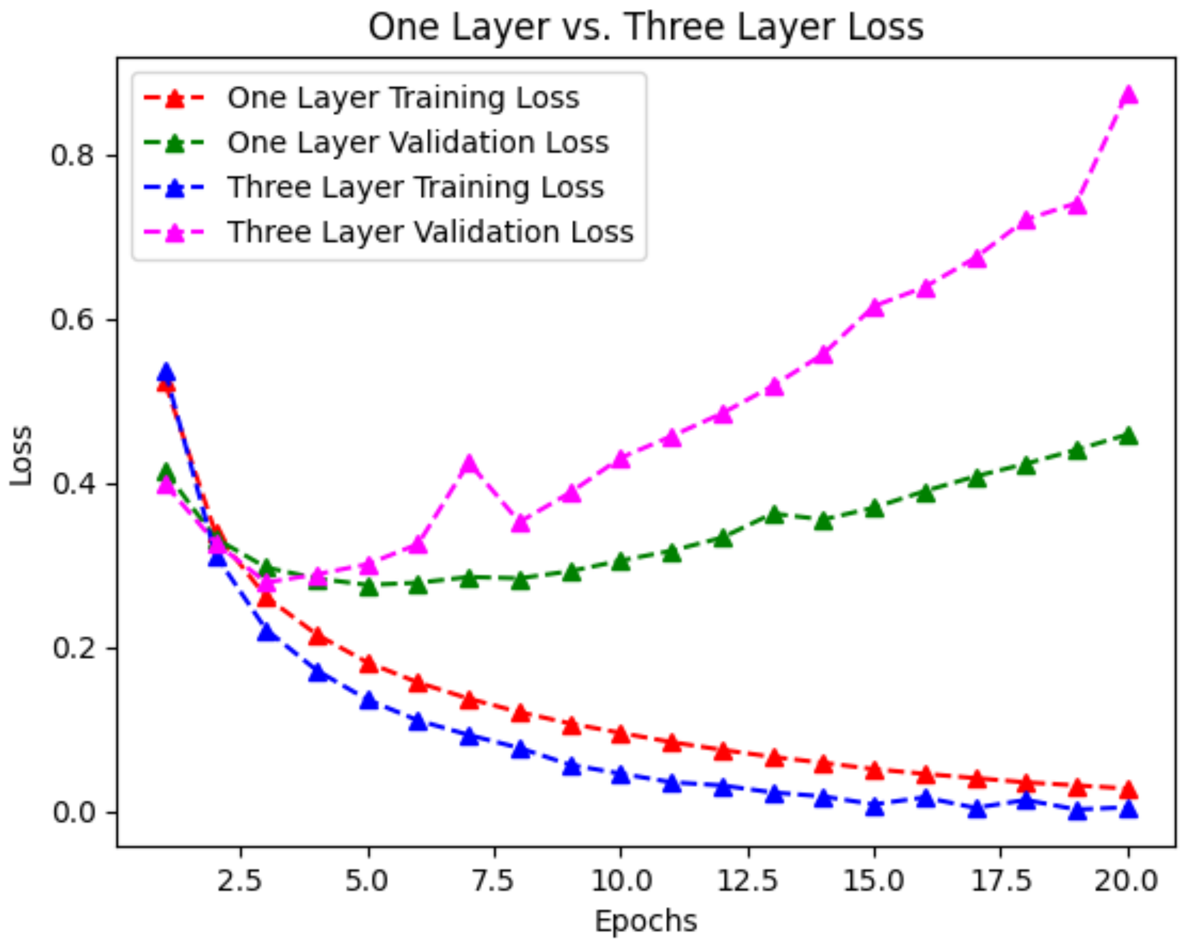
In [9]:
```python
import matplotlib.pyplot as plt

# Training Loss vs Validatin Loss
loss_values = history_dict_threelayers["loss"]
val_loss_values = history_dict_threelayers["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, label="Training loss", color = 'red', linestyl
plt.plot(epochs, val_loss_values, label="Validation loss", color = 'green',
plt.title("One Hidden Layer Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
plt.clf()

# Training Accuracy vs. Validation Accuracy
acc = history_dict_threelayers["accuracy"]
val_acc = history_dict_threelayers["val_accuracy"]
plt.plot(epochs, acc, label="Training acc", color='red', linestyle='--', mar
plt.plot(epochs, val_acc, label="Validation acc", color='green', linestyle='
plt.title("One Hidden Layer Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```


One Hidden Layer Training and validation loss
Training loss
Validation loss
Loss
0.0
0.2
0.4
0.6
0.8
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Epochs

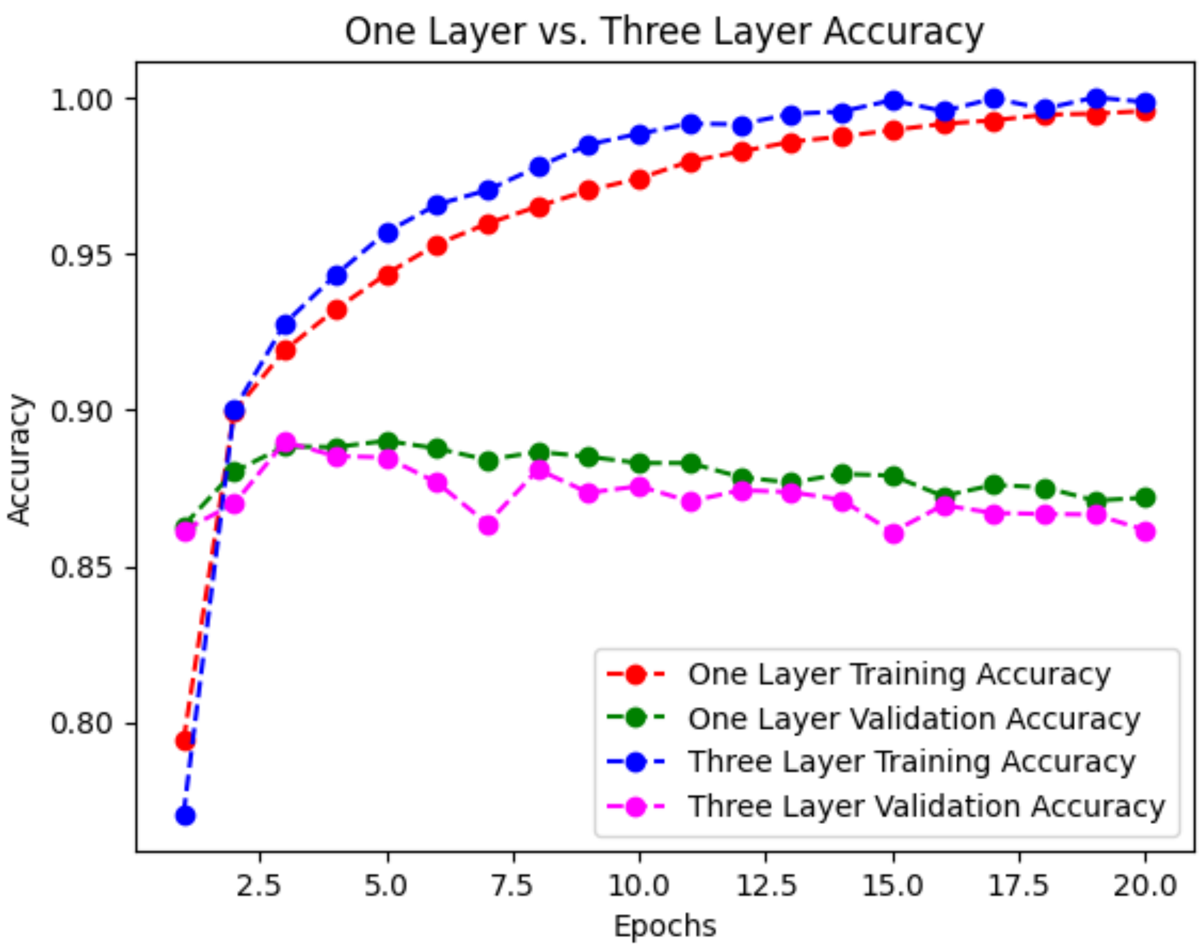


One Layer vs 3 Layer

In [10]:
```
loss_values = [
    history_dict_onelayer['loss'],
    history_dict_onelayer['val_loss'],
    history_dict_threelayers['loss'],
    history_dict_threelayers['val_loss']
]

acc_values = [
    history_dict_onelayer['accuracy'],
    history_dict_onelayer['val_accuracy'],
    history_dict_threelayers['accuracy'],
    history_dict_threelayers['val_accuracy']
]

loss_labels = ['One Layer ', 'Three Layer ', 'Training Loss', 'Validation Lo
accuracy_labels = ['One Layer ', 'Three Layer ', 'Training Accuracy', 'Valid
colors = ['red', 'green', 'blue', 'magenta']

for idx, x in enumerate(loss_values):
    plt.plot(epochs, x, label=loss_labels[int(idx/2)] + loss_labels[idx%2 +
             color=colors[idx], linestyle='--', marker = '^')

plt.title("One Layer vs. Three Layer Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
plt.clf()

for idx, x in enumerate(acc_values):
    plt.plot(epochs, x, label=accuracy_labels[int(idx/2)] + accuracy_labels[
             color=colors[idx], linestyle='--', marker = 'o')

plt.title("One Layer vs. Three Layer Accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
plt.clf()
```



One Layer vs. Three Layer Loss
One Layer Training Loss
One Layer Validation Loss
Three Layer Training Loss
Three Layer Validation Loss
Loss
0.0
0.2
0.4
0.6
0.8
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Epochs




```
<Figure size 640x480 with 0 Axes>
```

The best validation accuracy achieved was 88.98

by the 3 layer model. The best validation accuracy by the one layer model was 88.99

On comparing the loss and accuracies of the one layer and three layer side by side, we can see that the validation accuracy changes for the worse after the 4th epoch. Conversely, the accuracy and loss corresponding to the training set steadily increases past the 4th epoch - this implies that the model is overfitting itself to the training data - and from this we can infer that the best model is achieved soon after the 4th epoch of training.

Another key feature to note is that both models have relatively similar loss and accuracy on the Validation Set uptill the 4th epoch, but the Three Layer model exhibits a higher training accuracy and lower loss than the one layer model; thereby telling us that the Three Layer Model performs slightly better.

2) Try changing the number of nodes in the hidden layers to 100. See how this affects validation and test accuracy. Show this by plotting them (on the same plot, like in the book).**

Part 1 - 1 Layer, 100 Nodes

In [11]:
```
# Model Generation
model = keras.Sequential([
    layers.Dense(100, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])

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

history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))

history_dict_onelayer = history.history
history_dict_onelayer.keys()
```

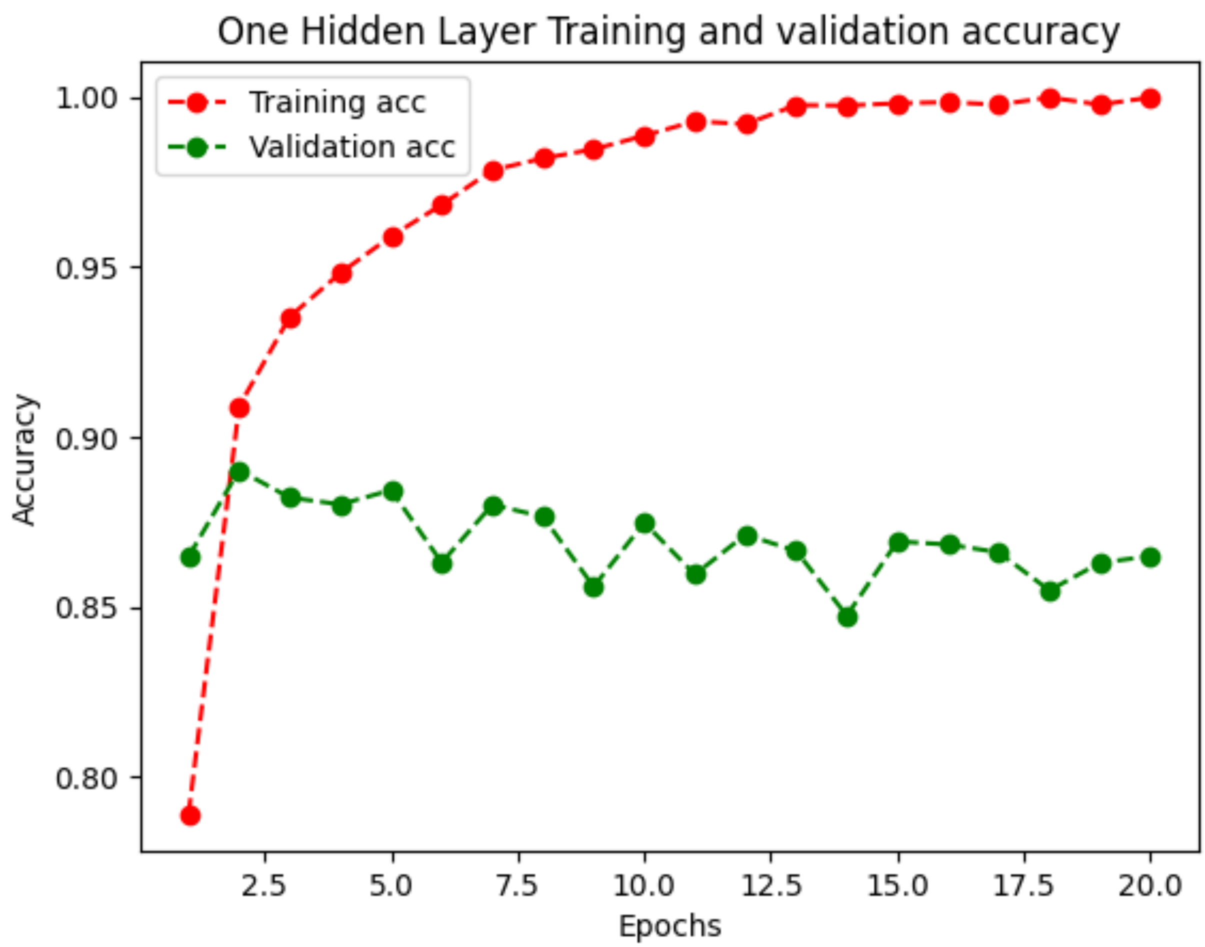
```
Epoch 1/20
30/30 [==============================] - 4s 100ms/step - loss: 0.4662 - acc
uracy: 0.7889 - val_loss: 0.3418 - val_accuracy: 0.8647
Epoch 2/20
30/30 [==============================] - 2s 78ms/step - loss: 0.2543 - accu
racy: 0.9090 - val_loss: 0.2804 - val_accuracy: 0.8902
Epoch 3/20
30/30 [==============================] - 2s 59ms/step - loss: 0.1864 - accu
racy: 0.9353 - val_loss: 0.2940 - val_accuracy: 0.8821
Epoch 4/20
30/30 [==============================] - 2s 52ms/step - loss: 0.1518 - accu
racy: 0.9482 - val_loss: 0.3046 - val_accuracy: 0.8801
Epoch 5/20
30/30 [==============================] - 2s 55ms/step - loss: 0.1234 - accu
racy: 0.9590 - val_loss: 0.2998 - val_accuracy: 0.8843
Epoch 6/20
30/30 [==============================] - 2s 54ms/step - loss: 0.0995 - accu
racy: 0.9683 - val_loss: 0.3891 - val_accuracy: 0.8630
Epoch 7/20
30/30 [==============================] - 2s 54ms/step - loss: 0.0797 - accu
racy: 0.9785 - val_loss: 0.3419 - val_accuracy: 0.8800
Epoch 8/20
30/30 [==============================] - 2s 57ms/step - loss: 0.0668 - accu
racy: 0.9819 - val_loss: 0.3758 - val_accuracy: 0.8765
```

```
Epoch 9/20
30/30 [==============================] - 1s 50ms/step - loss: 0.0540 - accu
racy: 0.9846 - val_loss: 0.4650 - val_accuracy: 0.8559
Epoch 10/20
30/30 [==============================] - 2s 55ms/step - loss: 0.0452 - accu
racy: 0.9886 - val_loss: 0.4081 - val_accuracy: 0.8747
Epoch 11/20
30/30 [==============================] - 2s 53ms/step - loss: 0.0339 - accu
racy: 0.9929 - val_loss: 0.5188 - val_accuracy: 0.8595
Epoch 12/20
30/30 [==============================] - 2s 55ms/step - loss: 0.0350 - accu
racy: 0.9920 - val_loss: 0.4684 - val_accuracy: 0.8712
Epoch 13/20
30/30 [==============================] - 2s 55ms/step - loss: 0.0195 - accu
racy: 0.9976 - val_loss: 0.5065 - val_accuracy: 0.8664
Epoch 14/20
30/30 [==============================] - 2s 53ms/step - loss: 0.0180 - accu
racy: 0.9975 - val_loss: 0.6879 - val_accuracy: 0.8474
Epoch 15/20
30/30 [==============================] - 2s 55ms/step - loss: 0.0148 - accu
racy: 0.9981 - val_loss: 0.5580 - val_accuracy: 0.8692
Epoch 16/20
30/30 [==============================] - 1s 50ms/step - loss: 0.0133 - accu
racy: 0.9985 - val_loss: 0.5927 - val_accuracy: 0.8683
Epoch 17/20
30/30 [==============================] - 2s 55ms/step - loss: 0.0127 - accu
racy: 0.9977 - val_loss: 0.6254 - val_accuracy: 0.8660
Epoch 18/20
30/30 [==============================] - 2s 56ms/step - loss: 0.0052 - accu
racy: 0.9999 - val_loss: 0.7158 - val_accuracy: 0.8548
Epoch 19/20
30/30 [==============================] - 2s 56ms/step - loss: 0.0105 - accu
racy: 0.9977 - val_loss: 0.6848 - val_accuracy: 0.8629
Epoch 20/20
30/30 [==============================] - 2s 62ms/step - loss: 0.0031 - accu
racy: 0.9999 - val_loss: 0.7149 - val_accuracy: 0.8649
```

```
Out[11]: dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

In [12]:

```
# Training Loss vs Validatin Loss
loss_values = history_dict_onelayer["loss"]
val_loss_values = history_dict_onelayer["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, label="Training loss", color = 'red', linestyl
plt.plot(epochs, val_loss_values, label="Validation loss", color = 'green',
plt.title("One Hidden Layer Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
plt.clf()

# Training Accuracy vs. Validation Accuracy
acc = history_dict_onelayer["accuracy"]
val_acc = history_dict_onelayer["val_accuracy"]
plt.plot(epochs, acc, label="Training acc", color='red', linestyle='--', mar
plt.plot(epochs, val_acc, label="Validation acc", color='green', linestyle='
plt.title("One Hidden Layer Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Part 2 - Three Layers, 100 Nodes each

In [13]:
```
model = keras.Sequential([
    layers.Dense(100, activation="relu"),
    layers.Dense(100, activation="relu"),
    layers.Dense(100, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])

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

history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))

history_dict_threelayers = history.history
history_dict_threelayers.keys()
```

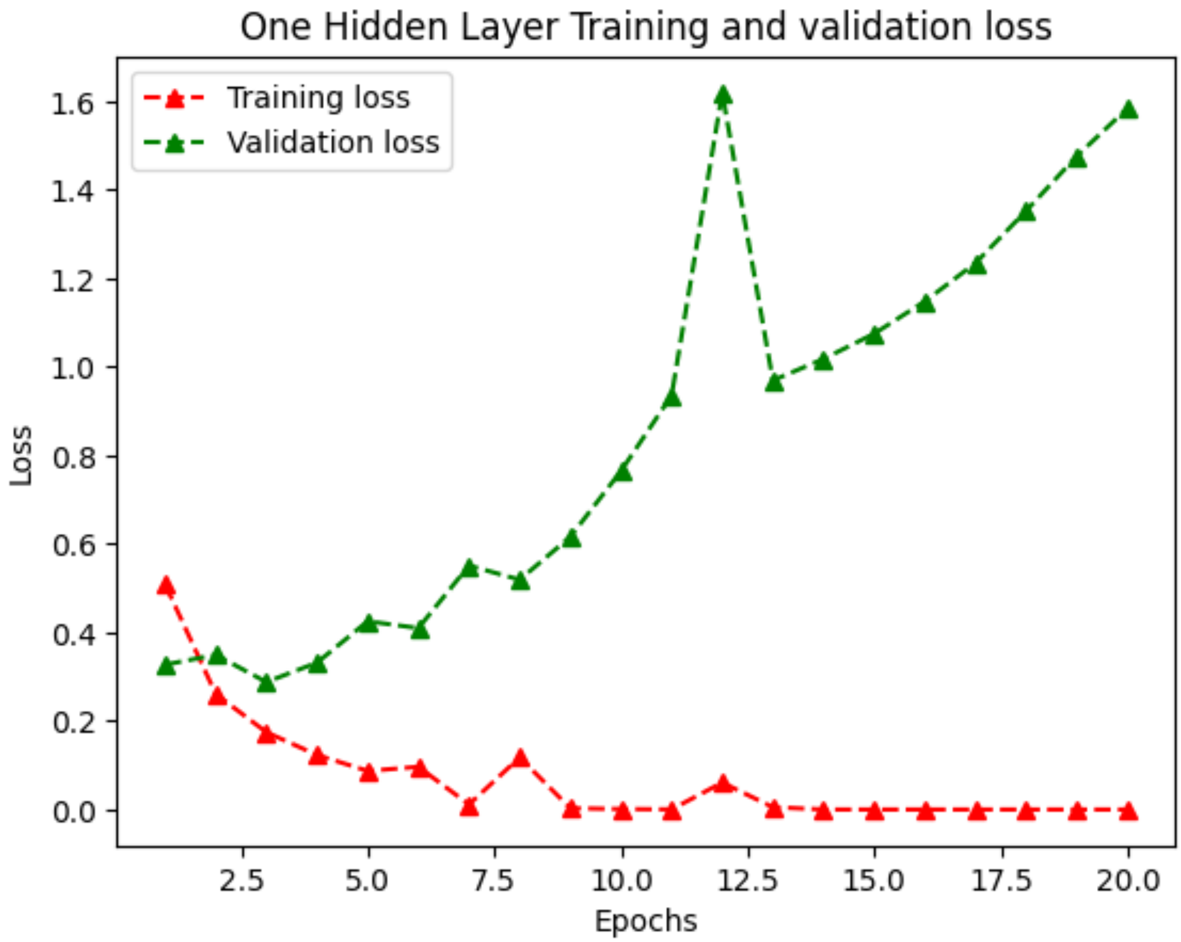
```
Epoch 1/20
30/30 [==============================] - 4s 94ms/step - loss: 0.5087 - accu
racy: 0.7556 - val_loss: 0.3272 - val_accuracy: 0.8741
```

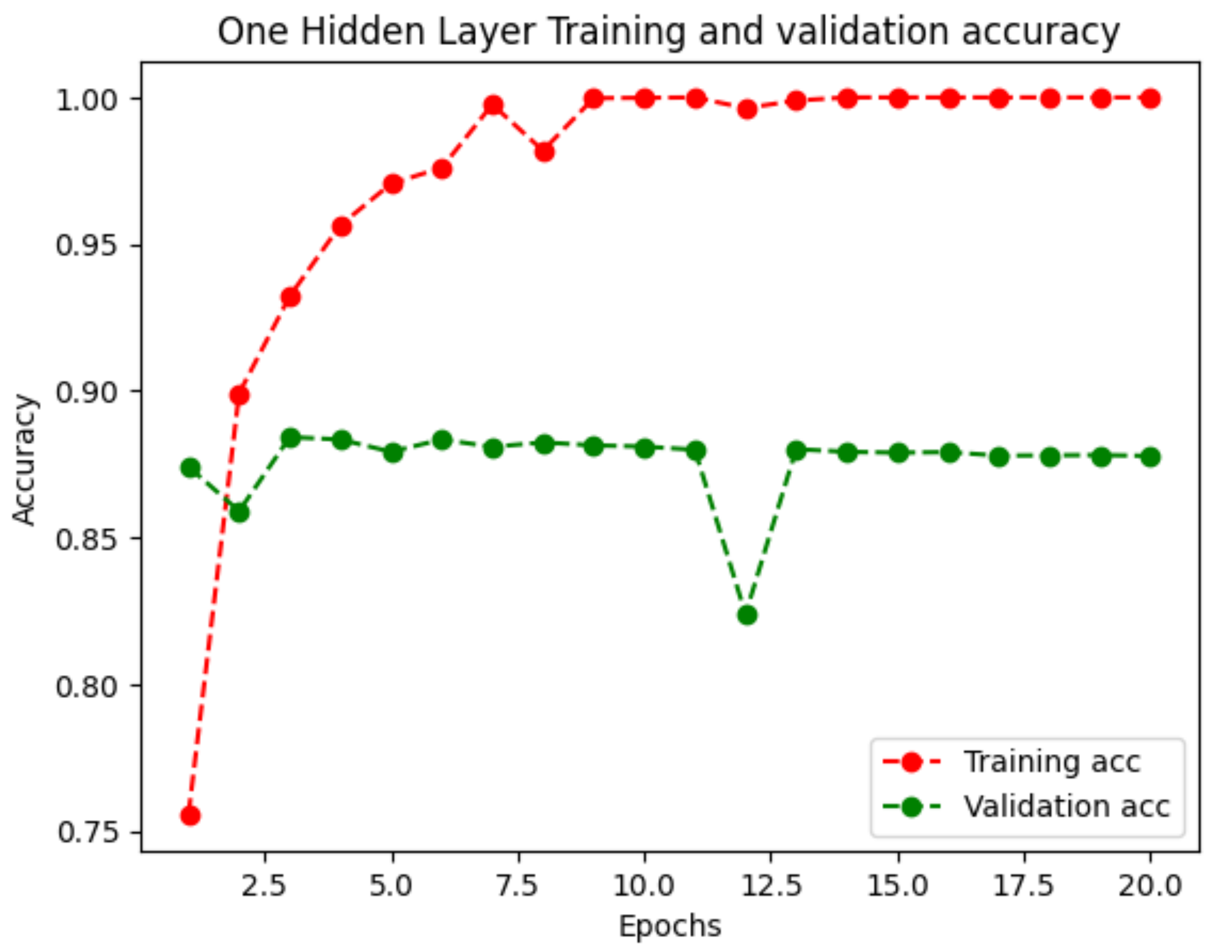
```
Epoch 2/20
30/30 [==============================] - 2s 78ms/step - loss: 0.2609 - accu
racy: 0.8992 - val_loss: 0.3495 - val_accuracy: 0.8590
Epoch 3/20
30/30 [==============================] - 2s 60ms/step - loss: 0.1746 - accu
racy: 0.9323 - val_loss: 0.2879 - val_accuracy: 0.8842
Epoch 4/20
30/30 [==============================] - 2s 51ms/step - loss: 0.1232 - accu
racy: 0.9565 - val_loss: 0.3320 - val_accuracy: 0.8834
Epoch 5/20
30/30 [==============================] - 2s 54ms/step - loss: 0.0872 - accu
racy: 0.9706 - val_loss: 0.4254 - val_accuracy: 0.8792
Epoch 6/20
30/30 [==============================] - 2s 54ms/step - loss: 0.0964 - accu
racy: 0.9760 - val_loss: 0.4099 - val_accuracy: 0.8834
Epoch 7/20
30/30 [==============================] - 2s 51ms/step - loss: 0.0115 - accu
racy: 0.9976 - val_loss: 0.5513 - val_accuracy: 0.8809
Epoch 8/20
30/30 [==============================] - 2s 54ms/step - loss: 0.1177 - accu
racy: 0.9819 - val_loss: 0.5193 - val_accuracy: 0.8824
Epoch 9/20
30/30 [==============================] - 2s 52ms/step - loss: 0.0029 - accu
racy: 0.9997 - val_loss: 0.6162 - val_accuracy: 0.8814
Epoch 10/20
30/30 [==============================] - 2s 61ms/step - loss: 0.0010 - accu
racy: 0.9999 - val_loss: 0.7648 - val_accuracy: 0.8810
Epoch 11/20
30/30 [==============================] - 1s 50ms/step - loss: 2.4093e-04 -
accuracy: 1.0000 - val_loss: 0.9356 - val_accuracy: 0.8799
Epoch 12/20
30/30 [==============================] - 1s 50ms/step - loss: 0.0608 - accu
racy: 0.9963 - val_loss: 1.6195 - val_accuracy: 0.8239
Epoch 13/20
30/30 [==============================] - 2s 55ms/step - loss: 0.0053 - accu
racy: 0.9989 - val_loss: 0.9696 - val_accuracy: 0.8801
Epoch 14/20
30/30 [==============================] - 2s 51ms/step - loss: 3.0510e-05 -
accuracy: 1.0000 - val_loss: 1.0182 - val_accuracy: 0.8792
Epoch 15/20
30/30 [==============================] - 2s 55ms/step - loss: 1.9752e-05 -
accuracy: 1.0000 - val_loss: 1.0752 - val_accuracy: 0.8789
Epoch 16/20
30/30 [==============================] - 1s 50ms/step - loss: 1.1328e-05 -
accuracy: 1.0000 - val_loss: 1.1483 - val_accuracy: 0.8791
Epoch 17/20
30/30 [==============================] - 2s 58ms/step - loss: 5.1798e-06 -
accuracy: 1.0000 - val_loss: 1.2348 - val_accuracy: 0.8779
Epoch 18/20
30/30 [==============================] - 2s 60ms/step - loss: 1.8011e-06 -
accuracy: 1.0000 - val_loss: 1.3528 - val_accuracy: 0.8780
Epoch 19/20
30/30 [==============================] - 2s 50ms/step - loss: 5.0501e-07 -
```

```
accuracy: 1.0000 - val_loss: 1.4765 - val_accuracy: 0.8781
Epoch 20/20
30/30 [==============================] - 2s 54ms/step - loss: 1.3725e-07 -
accuracy: 1.0000 - val_loss: 1.5845 - val_accuracy: 0.8778
```

Out[13]:
```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

In [14]:
```
# Training Loss vs Validatin Loss
loss_values = history_dict_threelayers["loss"]
val_loss_values = history_dict_threelayers["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, label="Training loss", color = 'red', linestyl
plt.plot(epochs, val_loss_values, label="Validation loss", color = 'green',
plt.title("One Hidden Layer Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
plt.clf()

# Training Accuracy vs. Validation Accuracy
acc = history_dict_threelayers["accuracy"]
val_acc = history_dict_threelayers["val_accuracy"]
plt.plot(epochs, acc, label="Training acc", color='red', linestyle='--', mar
plt.plot(epochs, val_acc, label="Validation acc", color='green', linestyle='
plt.title("One Hidden Layer Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```

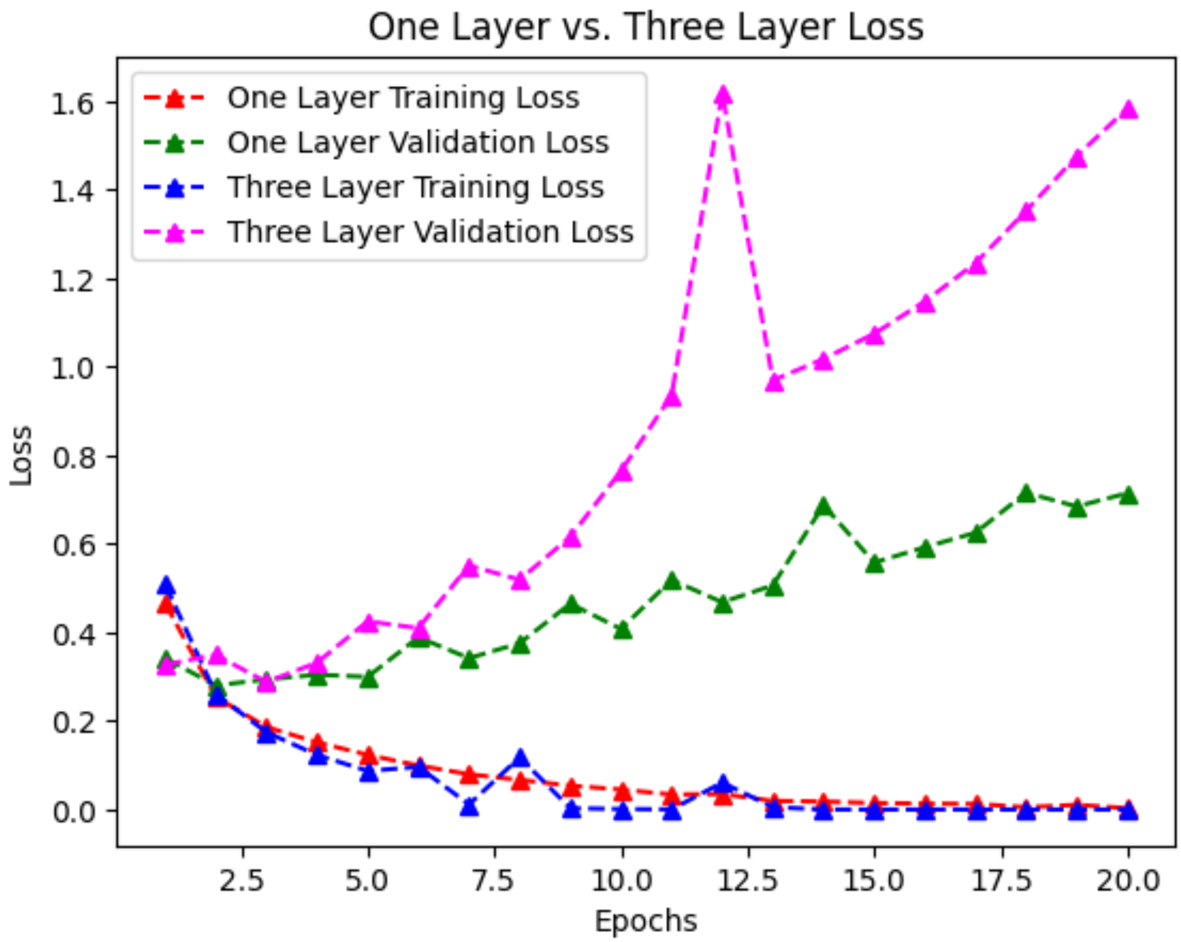

One Hidden Layer Training and validation loss
Training loss
Validation loss
Loss
Epochs
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

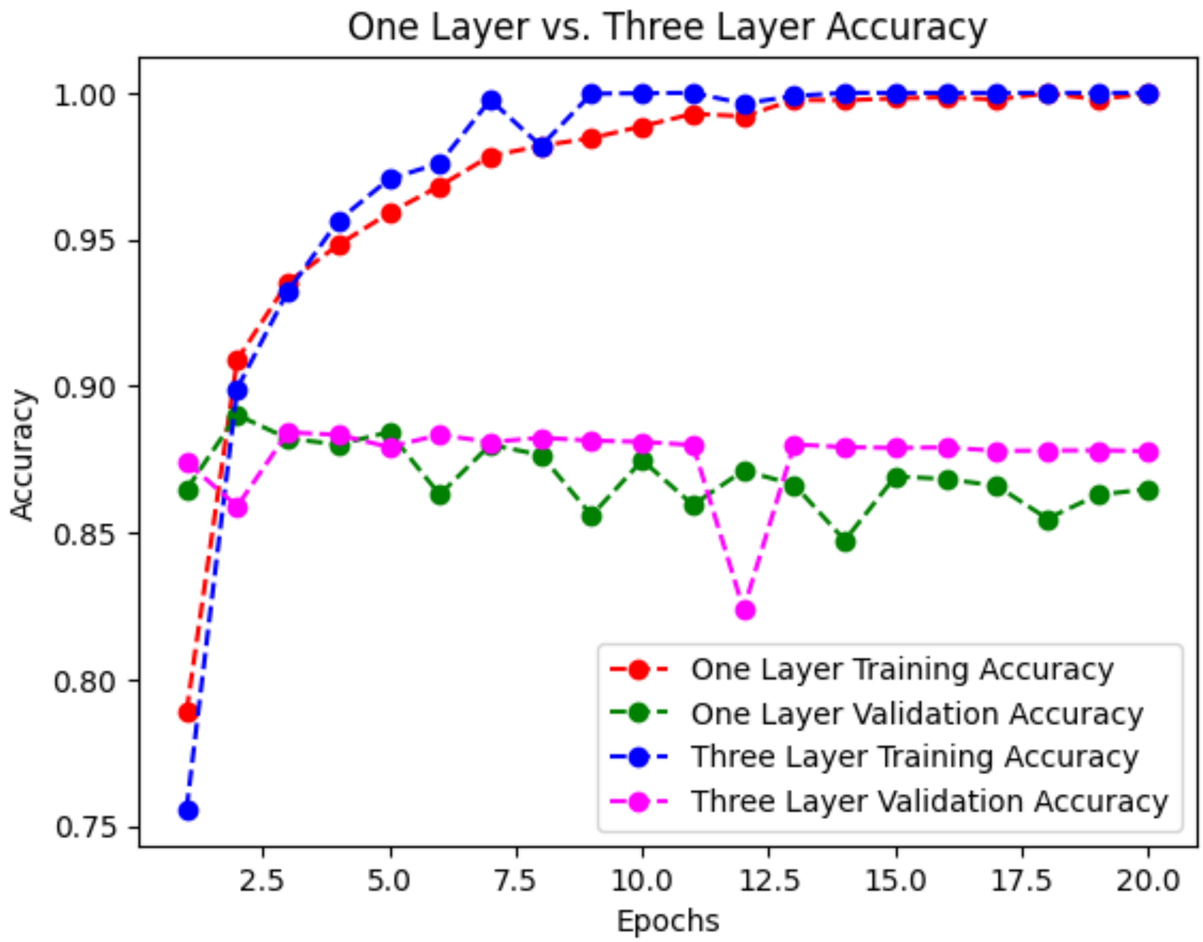


Results from Part 1 and Part 2 Plotted Against each other

In [15]:

```
loss_values = [
    history_dict_onelayer['loss'],
    history_dict_onelayer['val_loss'],
    history_dict_threelayers['loss'],
    history_dict_threelayers['val_loss']
]

acc_values = [
    history_dict_onelayer['accuracy'],
    history_dict_onelayer['val_accuracy'],
    history_dict_threelayers['accuracy'],
    history_dict_threelayers['val_accuracy']
]

loss_labels = ['One Layer ', 'Three Layer ', 'Training Loss', 'Validation Lo
accuracy_labels = ['One Layer ', 'Three Layer ', 'Training Accuracy', 'Valid
colors = ['red', 'green', 'blue', 'magenta']

for idx, x in enumerate(loss_values):
    plt.plot(epochs, x, label=loss_labels[int(idx/2)] + loss_labels[idx%2 +
             color=colors[idx], linestyle='--', marker = '^')

plt.title("One Layer vs. Three Layer Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
plt.clf()

for idx, x in enumerate(acc_values):
    plt.plot(epochs, x, label=accuracy_labels[int(idx/2)] + accuracy_labels[
             color=colors[idx], linestyle='--', marker = 'o')

plt.title("One Layer vs. Three Layer Accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
plt.clf()
```


One Layer vs. Three Layer Loss
One Layer Training Loss
One Layer Validation Loss
Three Layer Training Loss
Three Layer Validation Loss
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Loss
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Epochs




```
<Figure size 640x480 with 0 Axes>
```

One of the biggest differences between the 100 node and the 16 node architecture is 100 node architecture plateuas at a much higher validation accuracy while maintaining a similar high training accurracy and corresponding low losses.

Other than that, the differences between both the Three Layer Model and the One Layer model both running the 100 node architecture, the Three Layer Model plateaus at a much higher validation accuracy and correspodingly lower loss.

3) Evaluate the test accuracy of the model before any training has taken place. Compare this to the accuracy post-training, and comment on whether or not this is what you'd expect.

Question attempted with 3 layer model with 100 node architecture as from previous tests, this gave the best results.

Pretraining results

In [16]:
```
pretraining_model = keras.Sequential([
    layers.Dense(100, activation="relu"),
    layers.Dense(100, activation="relu"),
    layers.Dense(100, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
pretraining_model.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
pretraining_model.evaluate(x_test, y_test)
```

```
782/782 [==============================] - 4s 5ms/step - loss: 0.6938 - acc
uracy: 0.4966
```

Out[16]:
```
[0.6938191652297974, 0.4966000020503998]
```

In [17]:
```
posttraining_model = keras.Sequential([
    layers.Dense(100, activation="relu"),
    layers.Dense(100, activation="relu"),
    layers.Dense(100, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
posttraining_model.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
posttraining_model.fit(x_train, y_train, epochs = 4, batch_size=512, validat
```

```
Epoch 1/4
49/49 [==============================] - 14s 261ms/step - loss: 0.4371 - ac
curacy: 0.8038 - val_loss: 0.3197 - val_accuracy: 0.8698
Epoch 2/4
49/49 [==============================] - 3s 64ms/step - loss: 0.2379 - accu
racy: 0.9075 - val_loss: 0.2920 - val_accuracy: 0.8815
Epoch 3/4
49/49 [==============================] - 3s 67ms/step - loss: 0.1694 - accu
racy: 0.9350 - val_loss: 0.5071 - val_accuracy: 0.8044
Epoch 4/4
49/49 [==============================] - 3s 65ms/step - loss: 0.1207 - accu
racy: 0.9535 - val_loss: 0.3135 - val_accuracy: 0.8796
```

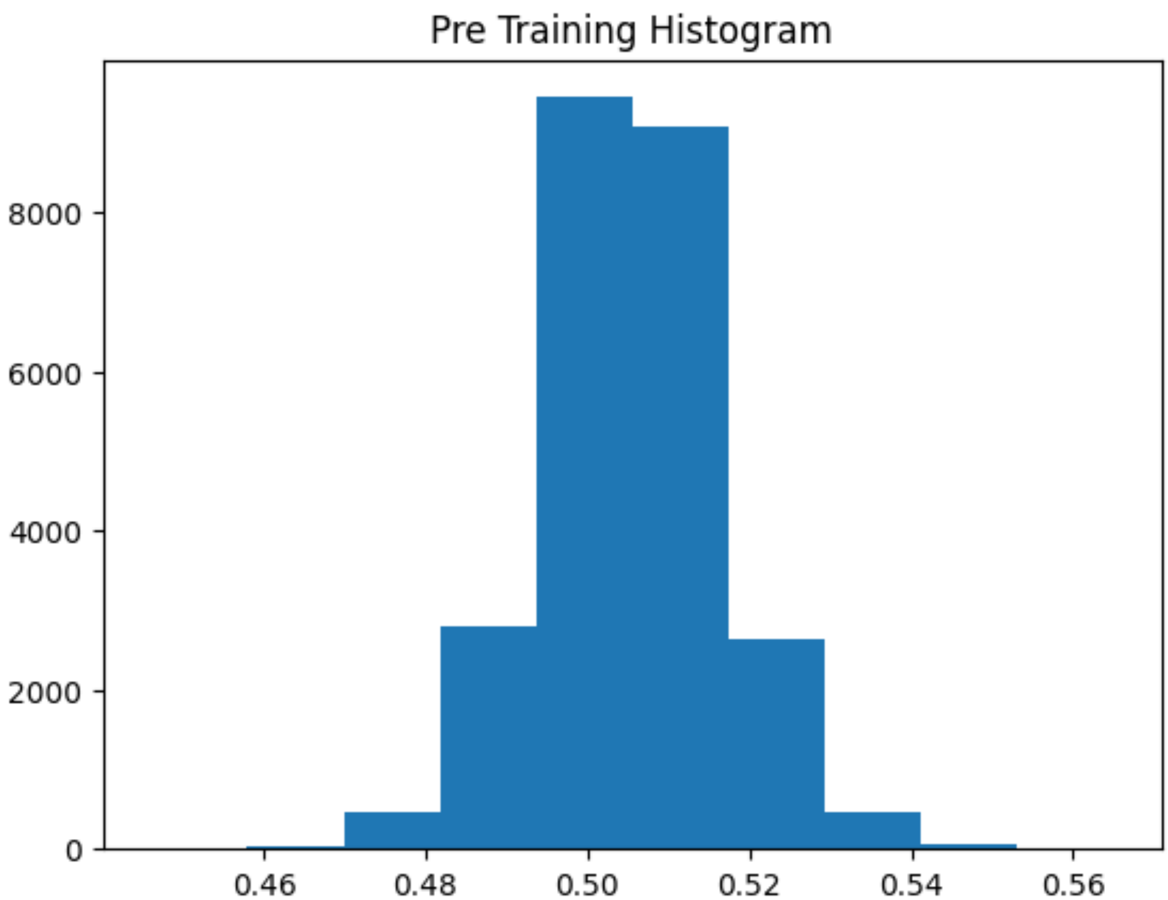
Out[17]:
```
<keras.callbacks.History at 0x17a0a89db80>
```

The results kind of represent what I expected. The untrained model achieved a accuracy of 50% which is higher than expected but hopefully the histogram of ouputs provides more insight into this. The trained model achieved a much higher accuracy with an accuracy of 87.5% after 4 epochs of training.

4) Generate a histogram of the output probabilities. Explain what this represents. (use 10 bins)

In [18]:
```
pre_prediction = pretraining_model.predict(x_test)
plt.hist(pre_prediction, bins=10)
plt.gca().set(title='Pre Training Histogram');
```

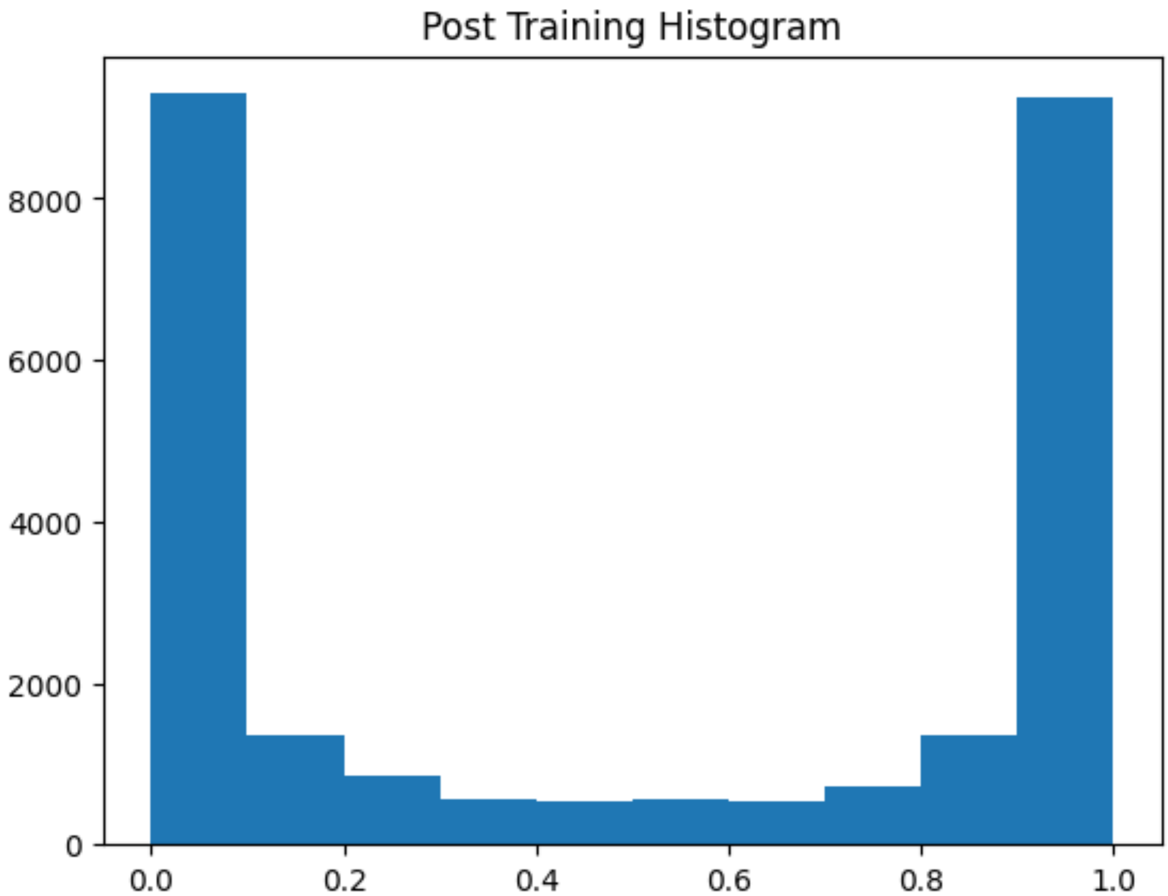
```
782/782 [==============================] - 4s 3ms/step
```



Post Training Results

In [19]:
```
post_prediction = posttraining_model.predict(x_test)
plt.hist(post_prediction, bins=10)
plt.gca().set(title='Post Training Histogram');
```

```
782/782 [==============================] - 2s 3ms/step
```



The histogram did provide more insight. In the untrained model, the results are centered roughly around 0.5, in whihc values below 0.5 were rounded to 0 and values above, to 1. This loosely explains why the results had around a 50% accuracy.

After the model was trained, it provided more concrete predictions as to whether it was a 1 or 0.

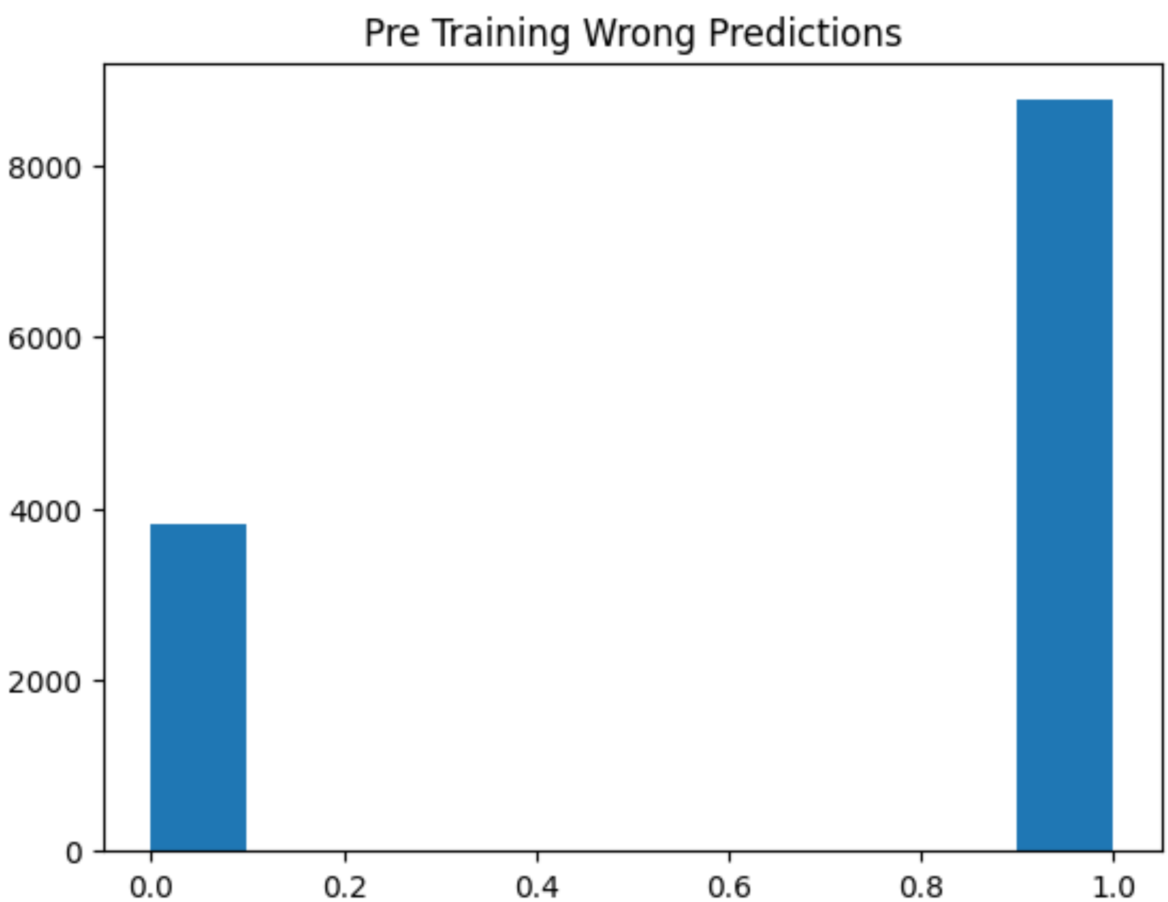
5) Find all the predictions where the model got the answer wrong. Generate a histogram of the corresponding output probabilities. Explain what this represents, and comment on whether or not it looks like you'd expect. (Use 10 bins)

In [20]:

```
pre_prediction_falses = np.round(pre_prediction)[:, 0]
pre_prediction_falses = pre_prediction_falses[pre_prediction_falses != y_tes
num_untrained_falses = len(pre_prediction_falses)
plt.hist(pre_prediction_falses, bins=10)
plt.gca().set(title='Pre Training Wrong Predictions')
```

Out[20]:

```
[Text(0.5, 1.0, 'Pre Training Wrong Predictions')]
```

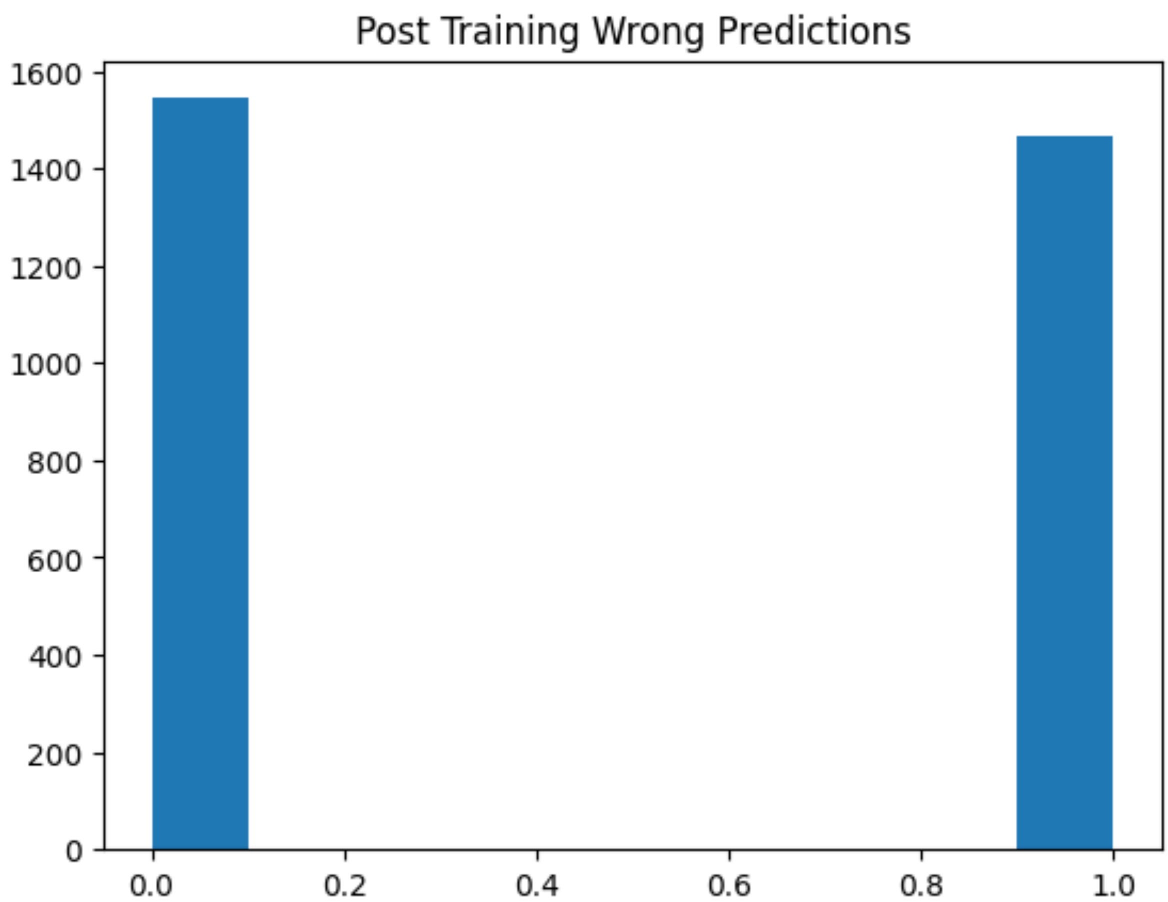


The pre training model predicted around 12500 results wrong - 12000 of them were predicted to be 1s but were acutally 0s and around 500 were 0s when they should have been 1s. This matches our expectations of a 50% accuracy as 12500 is 50% of the original dataset. Moreover we noticed the pre-training histogram was skewed to the right, which means that more values were predicted to be ones and correspondingly a larger number were false predictions.

In [23]:
```
post_prediction_falses = np.round(post_prediction)[:, 0]
post_prediction_falses = post_prediction_falses[post_prediction_falses != y_
num_trained_falses = len(post_prediction_falses)
print(len(post_prediction_falses))
plt.hist(post_prediction_falses, bins=10)
plt.gca().set(title='Post Training Wrong Predictions')
```

```
3010
```

Out[23]:
```
[Text(0.5, 1.0, 'Post Training Wrong Predictions')]
```



The Trained Model predicted a total of 3010 values wrong (around 1550 were predicted to be 0s instead of 1s and around 1.5k were predicted to be 1s instead of 0s). 3010 wrong values results in an error rate of 12.04% which corresponds to a accuracy of 87.86% which matches with our results from the sections before. No unexpected behaviour was seen here.

6) Divide the answers from the second histogram by the answers from the first histogram. Explain what this represents.

Dividing the number of errors by the total number of samples (second_hist/first_hist) gives us the error rate.

In [22]:
```
error_rate_untrained = num_untrained_falses/len(pre_prediction)
print("The untrained model's error rate was {}".format(error_rate_untrained)

error_rate_trained = num_trained_falses/len(post_prediction)
print("The trained model's error rate was {}".format(error_rate_trained))
```

```
The untrained model's error rate was 0.5034
The trained model's error rate was 0.1204
```

7) Try to improve the model performance. The team with the highest score will receive 50 extra points on the assignment.

In [31]:
```
model = keras.Sequential([
    layers.Dropout(0.2),
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dropout(0.2),
    layers.Dense(1, activation="sigmoid")
])

model.compile(optimizer="Adam",
              loss="binary_crossentropy",
              metrics=["accuracy"])

history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=10,
                    batch_size=2000,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/10
8/8 [==============================] - 8s 454ms/step - loss: 0.6831 - accur
acy: 0.5941 - val_loss: 0.6478 - val_accuracy: 0.7404
Epoch 2/10
8/8 [==============================] - 3s 367ms/step - loss: 0.6055 - accur
acy: 0.7486 - val_loss: 0.5460 - val_accuracy: 0.8227
Epoch 3/10
8/8 [==============================] - 3s 330ms/step - loss: 0.5049 - accur
acy: 0.8067 - val_loss: 0.4502 - val_accuracy: 0.8553
Epoch 4/10
8/8 [==============================] - 3s 328ms/step - loss: 0.4150 - accur
acy: 0.8509 - val_loss: 0.3820 - val_accuracy: 0.8699
Epoch 5/10
8/8 [==============================] - 3s 338ms/step - loss: 0.3491 - accur
acy: 0.8743 - val_loss: 0.3349 - val_accuracy: 0.8786
Epoch 6/10
8/8 [==============================] - 3s 321ms/step - loss: 0.3021 - accur
acy: 0.8924 - val_loss: 0.3057 - val_accuracy: 0.8846
Epoch 7/10
8/8 [==============================] - 3s 328ms/step - loss: 0.2653 - accur
acy: 0.9037 - val_loss: 0.2900 - val_accuracy: 0.8899
Epoch 8/10
8/8 [==============================] - 3s 339ms/step - loss: 0.2357 - accur
acy: 0.9182 - val_loss: 0.2816 - val_accuracy: 0.8908
Epoch 9/10
8/8 [==============================] - 3s 339ms/step - loss: 0.2186 - accur
acy: 0.9213 - val_loss: 0.2783 - val_accuracy: 0.8912
Epoch 10/10
8/8 [==============================] - 3s 313ms/step - loss: 0.2001 - accur
acy: 0.9277 - val_loss: 0.2790 - val_accuracy: 0.8895
```

The highest accuracy we achieved was 89.12 using this model. We used dropout layers which utilizes a mask to ignore the inputs from certain nodes during training. This thereby kind of reduces overfitting

```
In [ ]:
```