Assignment 5.1

July 7, 2021

1 3.4 Classifying movie reviews

1.1 3.4.1 The IMDB Dataset

[1]:
```
from tensorflow.keras.datasets import imdb
```

[2]:
```
# Importing the data to training and testing sets
(train_data, train_labels), (test_data, test_labels) = imdb.
↪load_data(num_words=10000)
```

```
<__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 deprecated. If you meant to do
this, you must specify 'dtype=object' when creating the ndarray
C:\Users\hotal\AppData\Roaming\Python\Python38\site-
packages\tensorflow\python\keras\datasets\imdb.py:159:
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 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\hotal\AppData\Roaming\Python\Python38\site-
packages\tensorflow\python\keras\datasets\imdb.py:160:
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 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:])
```

[3]:
```
# Training data consists of vectors pointing to words in the word index.
train_data[0][:5]
```

[3]:
```
[1, 14, 22, 16, 43]
```

[4]:
```
# Two possible classifications
# Negative and Positive
set(train_labels)
```

[4]:
```
{0, 1}
```

```
[5]: # Verifying the vocabulary limit set to 10,000
max([max(sequence) for sequence in train_data])
```

```
[5]: 9999
```

```
[6]: # Getting the word dictionary from the dataset
word_index = imdb.get_word_index()

# Reversing the dictionary for easier indexing
reverse_word_index = dict([(value,key) for (key, value) in word_index.items()])

# Building a review using the training array and the reversed dictionary
decoded_review = ' '.join([reverse_word_index.get(i - 3 , '?') for i in␣
↪train_data[8728]])

# Printing the review
print(decoded_review)
```

```
? it was just a terrible movie no one should waste their time go see something
else this movie is without a doubt one of the worst movies i have ever seen in
my life if you want to see a good movie don't see made men
```

1.2 3.4.2 Preparing the data

```
[7]: import numpy as np

# Convert the training arrays into a 2D array with the columns representing the␣
↪words used.
def vectorize_sequence(sequences, dimensions = 10000):
    """
    Return a 2D array with the columns representing the word usage of each␣
↪entry.
    Parameters
    ----------
    sequences : array_like
        Array representing the word usage in each entry
    dimensions : data-type, optional
        Number of columns in the 2D array
    """

    results = np.zeros((len(sequences), dimensions))
    for i, sequences in enumerate(sequences):
        results[i, sequences] = 1
    return results
```

```
[8]: # Vectorize the training and testing datasets
X_train = vectorize_sequence(train_data)
```

```
X_test = vectorize_sequence(test_data)
```

[9]:
```
# Verify the target attributes are numeric and in array format
y_train = np.asarray(train_labels).astype('float32')
y_test = np.asarray(test_labels).astype('float32')
```

1.3 3.4.3 Building your network

[10]:
```
# Import keras libraries
from keras import models, layers, losses, metrics, optimizers
```

[11]:
```
# Creating a neural net with shape (1000,16,16,1)
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'))
```

[12]:
```
model.compile(optimizer='rmsprop',
              loss = 'binary_crossentropy',
              metrics = ['accuracy'])
```

[13]:
```
model.compile(optimizer = optimizers.RMSprop(lr = 0.001),
             loss = losses.binary_crossentropy,
             metrics = [metrics.binary_accuracy])
```

1.4 3.4.4 Validating your approach

[14]:
```
# Splitting the data into validation sets
X_val = X_train[:10000]
partial_X_train = X_train[10000:]

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

[15]:
```
model.compile(optimizer='rmsprop',
              loss = 'binary_crossentropy',
              metrics = ['acc'])
```

[16]:
```
# Training the neural network
history = model.fit(partial_X_train,
                  partial_y_train,
                  epochs = 20,
                  batch_size = 512,
                  validation_data = (X_val, y_val))
```

```
Epoch 1/20
30/30 [==============================] - 3s 66ms/step - loss: 0.5796 - acc:
0.7081 - val_loss: 0.3859 - val_acc: 0.8609
```

```
Epoch 2/20
30/30 [==============================] - 1s 21ms/step - loss: 0.3149 - acc:
0.9025 - val_loss: 0.3153 - val_acc: 0.8744
Epoch 3/20
30/30 [==============================] - 1s 21ms/step - loss: 0.2250 - acc:
0.9296 - val_loss: 0.2931 - val_acc: 0.8840
Epoch 4/20
30/30 [==============================] - 1s 21ms/step - loss: 0.1697 - acc:
0.9490 - val_loss: 0.2747 - val_acc: 0.8909
Epoch 5/20
30/30 [==============================] - 1s 21ms/step - loss: 0.1372 - acc:
0.9585 - val_loss: 0.2903 - val_acc: 0.8870
Epoch 6/20
30/30 [==============================] - 1s 21ms/step - loss: 0.1053 - acc:
0.9718 - val_loss: 0.3118 - val_acc: 0.8804
Epoch 7/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0864 - acc:
0.9768 - val_loss: 0.3176 - val_acc: 0.8821
Epoch 8/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0713 - acc:
0.9822 - val_loss: 0.3445 - val_acc: 0.8787
Epoch 9/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0564 - acc:
0.9861 - val_loss: 0.3928 - val_acc: 0.8712
Epoch 10/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0462 - acc:
0.9898 - val_loss: 0.4160 - val_acc: 0.8688
Epoch 11/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0358 - acc:
0.9936 - val_loss: 0.4385 - val_acc: 0.8742
Epoch 12/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0279 - acc:
0.9954 - val_loss: 0.4575 - val_acc: 0.8771
Epoch 13/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0237 - acc:
0.9964 - val_loss: 0.4978 - val_acc: 0.8674
Epoch 14/20
30/30 [==============================] - 1s 22ms/step - loss: 0.0154 - acc:
0.9985 - val_loss: 0.6105 - val_acc: 0.8522
Epoch 15/20
30/30 [==============================] - 1s 22ms/step - loss: 0.0142 - acc:
0.9986 - val_loss: 0.6009 - val_acc: 0.8610
Epoch 16/20
30/30 [==============================] - 1s 23ms/step - loss: 0.0101 - acc:
0.9996 - val_loss: 0.6830 - val_acc: 0.8487
Epoch 17/20
30/30 [==============================] - 1s 22ms/step - loss: 0.0090 - acc:
0.9991 - val_loss: 0.6193 - val_acc: 0.8682
```

```
Epoch 18/20
30/30 [==============================] - 1s 22ms/step - loss: 0.0053 - acc:
0.9997 - val_loss: 0.6493 - val_acc: 0.8673
Epoch 19/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0041 - acc:
0.9995 - val_loss: 0.6772 - val_acc: 0.8670
Epoch 20/20
30/30 [==============================] - 1s 20ms/step - loss: 0.0047 - acc:
0.9994 - val_loss: 0.7089 - val_acc: 0.8680
```

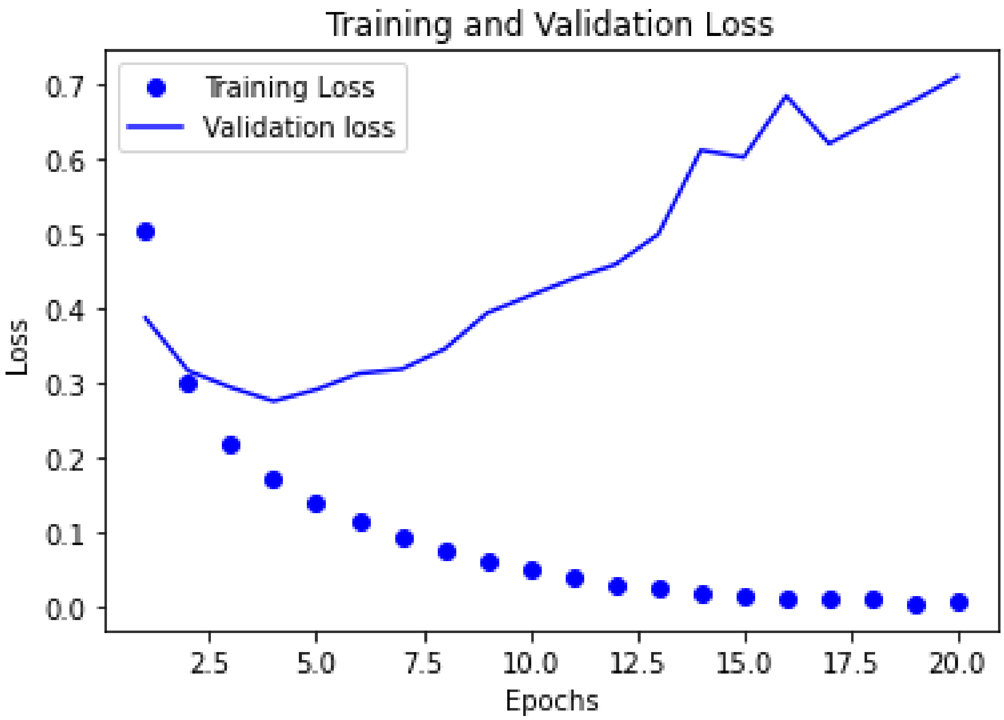
[17]:
```
history_dict = history.history
history_dict.keys()
```

[17]:
```
dict_keys(['loss', 'acc', 'val_loss', 'val_acc'])
```

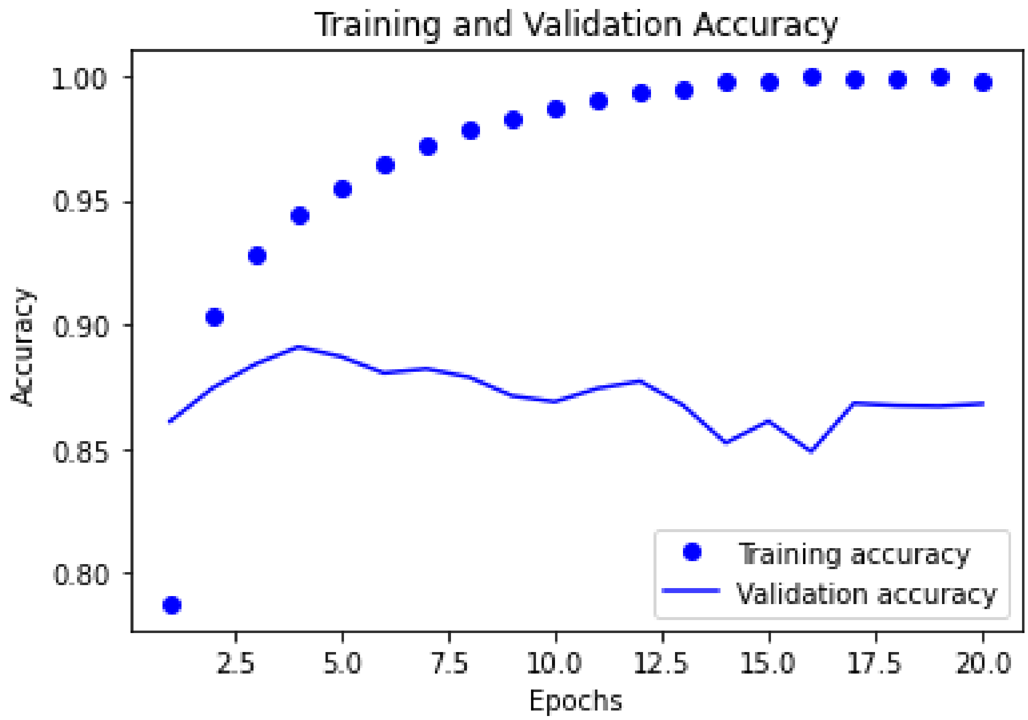
[18]:
```
import matplotlib.pyplot as plt
```

[19]:
```
history_dict = history.history
acc = history_dict['acc']
val_acc = history_dict['val_acc']

loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']

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

[20]:
```
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()
```



[21]:
```
plt.plot(epochs, acc,  'bo', label = 'Training accuracy')
plt.plot(epochs, val_acc, 'b', label = 'Validation accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



[22]:
```
model = models.Sequential()
model.add(layers.Dense(16, activation = 'relu', input_shape = (10000,)))
model.add(layers.Dense(16, activation = 'relu'))
model.add(layers.Dense(1, activation = 'sigmoid'))

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

model.fit(partial_X_train,
          partial_y_train,
          epochs = 4,
          batch_size = 512)

results = model.evaluate(X_test, y_test)
results
```

```
Epoch 1/4
30/30 [==============================] - 1s 14ms/step - loss: 0.5916 - accuracy:
0.6956
Epoch 2/4
30/30 [==============================] - 0s 13ms/step - loss: 0.3190 - accuracy:
0.9001
Epoch 3/4
```

```
30/30 [==============================] - 0s 13ms/step - loss: 0.2268 - accuracy:
0.9267
Epoch 4/4
30/30 [==============================] - 0s 12ms/step - loss: 0.1751 - accuracy:
0.9462
782/782 [==============================] - 1s 2ms/step - loss: 0.2921 -
accuracy: 0.8835
```

[22]:
```
[0.292120099067688, 0.8835200071334839]
```

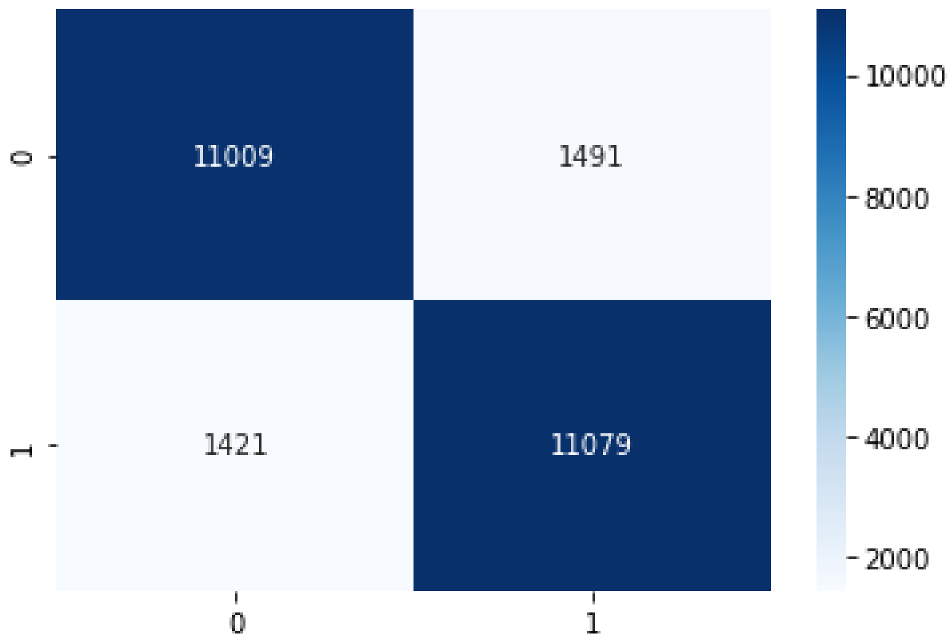
1.5 3.4.5 Using a trained neural network to generate predictions on new data

[23]:
```python
model.predict(X_test)
```

[23]:
```
array([[0.25748008],
       [0.9994006 ],
       [0.9178364 ],
       …,
       [0.10280168],
       [0.12940067],
       [0.5308584 ]], dtype=float32)
```

[24]:
```python
import sklearn.metrics as metrics
from seaborn import heatmap

confusion_matrix = metrics.confusion_matrix(y_true=y_test, y_pred=np.
 ↪round(model.predict(X_test)))
heatmap(confusion_matrix, annot = True, cmap='Blues', fmt='g')
```

[24]:
```
<AxesSubplot:>
```



1.6 3.4.6 Further Experiments

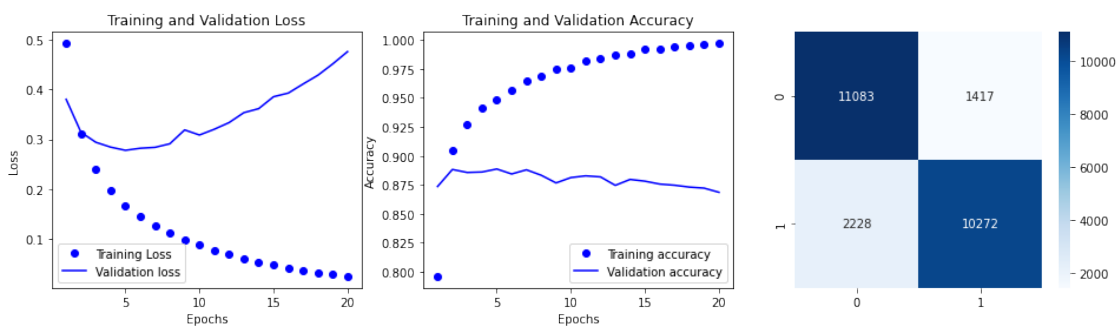
You used two hidden layers. Try using one or three hidden layers, and see how doing so affects validation and test accuracy

1.6.1 One Hidden Layer

[25]:
```
# Creating a neural net with shape (1000,16,1)
model = models.Sequential()
model.add(layers.Dense(16, activation = 'relu', input_shape = (10000,)))
model.add(layers.Dense(1, activation = 'sigmoid'))

model.compile(optimizer='rmsprop',
              loss = 'binary_crossentropy',
              metrics = ['acc'])

# Training the neural network
history = model.fit(partial_X_train,
                  partial_y_train,
                  epochs = 20,
                  batch_size = 512,
                  validation_data = (X_val, y_val), verbose = False)

results = model.evaluate(X_test, y_test)
print(results)
```

```python
history_dict = history.history

acc = history_dict['acc']
val_acc = history_dict['val_acc']
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']
epochs = range(1,len(acc) + 1)

# Plotting metrics
fig, [ax1, ax2, ax3] = plt.subplots(1,3, figsize=(16,4))

ax1.plot(epochs, loss_values,  'bo', label = 'Training Loss')
ax1.plot(epochs, val_loss_values, 'b', label = 'Validation loss')
ax1.set_title('Training and Validation Loss')
ax1.set_xlabel("Epochs")
ax1.set_ylabel("Loss")
ax1.legend()

ax2.plot(epochs, acc,  'bo', label = 'Training accuracy')
ax2.plot(epochs, val_acc, 'b', label = 'Validation accuracy')
ax2.set_title('Training and Validation Accuracy')
ax2.set_xlabel("Epochs")
ax2.set_ylabel("Accuracy")
ax2.legend()

confusion_matrix = metrics.confusion_matrix(y_true=y_test, y_pred=np.
 ↪round(model.predict(X_test)))
heatmap(confusion_matrix, annot = True, cmap='Blues', fmt='g', ax = ax3);
```

```
782/782 [==============================] - 1s 2ms/step - loss: 0.5227 - acc:
0.8542
[0.5226899981498718, 0.854200005531311]
```

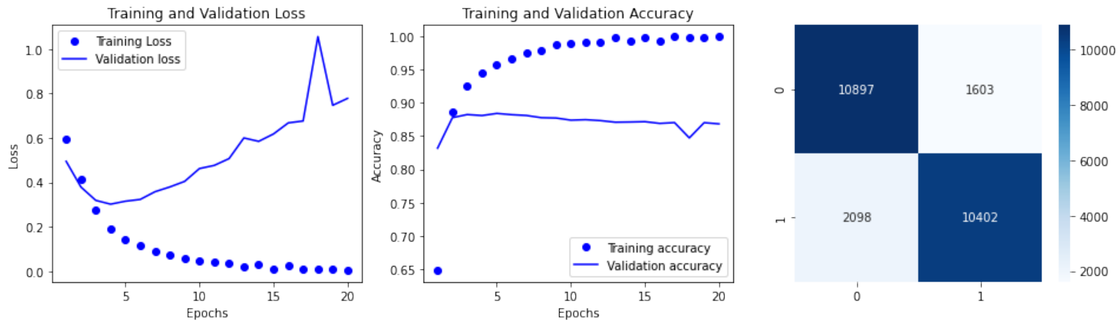


1.6.2 Three Hidden Layers

[26]:
```
# Creating a neural net with shape (1000,16,16,16,1)
model = models.Sequential()
model.add(layers.Dense(16, activation = 'relu', input_shape = (10000,)))
model.add(layers.Dense(16, activation = 'relu'))
model.add(layers.Dense(16, activation = 'relu'))
model.add(layers.Dense(1, activation = 'sigmoid'))

model.compile(optimizer='rmsprop',
              loss = 'binary_crossentropy',
              metrics = ['acc'])

# Training the neural network
history = model.fit(partial_X_train,
                  partial_y_train,
                  epochs = 20,
                  batch_size = 512,
                  validation_data = (X_val, y_val), verbose = False)
results = model.evaluate(X_test, y_test)
print(results)

history_dict = history.history

acc = history_dict['acc']
val_acc = history_dict['val_acc']
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']
epochs = range(1,len(acc) + 1)

# Plotting metrics
fig, [ax1, ax2, ax3] = plt.subplots(1,3, figsize=(16,4))

ax1.plot(epochs, loss_values,  'bo', label = 'Training Loss')
ax1.plot(epochs, val_loss_values, 'b', label = 'Validation loss')
ax1.set_title('Training and Validation Loss')
ax1.set_xlabel("Epochs")
ax1.set_ylabel("Loss")
ax1.legend()

ax2.plot(epochs, acc,  'bo', label = 'Training accuracy')
ax2.plot(epochs, val_acc, 'b', label = 'Validation accuracy')
ax2.set_title('Training and Validation Accuracy')
ax2.set_xlabel("Epochs")
ax2.set_ylabel("Accuracy")
ax2.legend()
```

```
confusion_matrix = metrics.confusion_matrix(y_true=y_test, y_pred=np.
 ↪round(model.predict(X_test)))
heatmap(confusion_matrix, annot = True, cmap='Blues', fmt='g', ax = ax3);
```

```
782/782 [==============================] - 1s 2ms/step - loss: 0.8454 - acc:
0.8520
[0.8454091548919678, 0.8519600033760071]
```



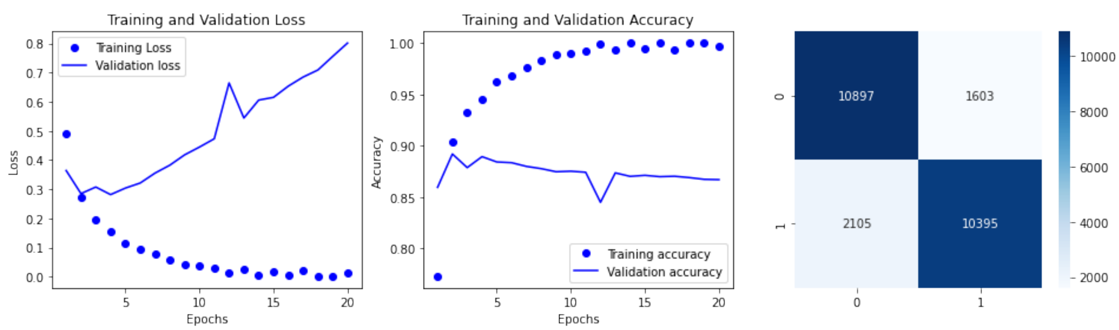
Try using layers with more hidden units or fewer hidden units: 32 units, 64 units, and so on.

1.6.3 32 Hidden Units

[27]:
```
# Creating a neural net with shape (1000,32,32,1)
model = models.Sequential()
model.add(layers.Dense(32, activation = 'relu', input_shape = (10000,)))
model.add(layers.Dense(32, activation = 'relu'))
model.add(layers.Dense(1, activation = 'sigmoid'))

model.compile(optimizer='rmsprop',
              loss = 'binary_crossentropy',
              metrics = ['acc'])

# Training the neural network
history = model.fit(partial_X_train,
                    partial_y_train,
                    epochs = 20,
                    batch_size = 512,
                    validation_data = (X_val, y_val), verbose = False)

results = model.evaluate(X_test, y_test)
print(results)

history_dict = history.history

acc = history_dict['acc']
val_acc = history_dict['val_acc']
```

```
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']
epochs = range(1,len(acc) + 1)

# Plotting metrics
fig, [ax1, ax2, ax3] = plt.subplots(1,3, figsize=(16,4))

ax1.plot(epochs, loss_values,  'bo', label = 'Training Loss')
ax1.plot(epochs, val_loss_values, 'b', label = 'Validation loss')
ax1.set_title('Training and Validation Loss')
ax1.set_xlabel("Epochs")
ax1.set_ylabel("Loss")
ax1.legend()

ax2.plot(epochs, acc,  'bo', label = 'Training accuracy')
ax2.plot(epochs, val_acc, 'b', label = 'Validation accuracy')
ax2.set_title('Training and Validation Accuracy')
ax2.set_xlabel("Epochs")
ax2.set_ylabel("Accuracy")
ax2.legend()

confusion_matrix = metrics.confusion_matrix(y_true=y_test, y_pred=np.
↪round(model.predict(X_test)))
heatmap(confusion_matrix, annot = True, cmap='Blues', fmt='g', ax = ax3);
```

```
782/782 [==============================] - 1s 2ms/step - loss: 0.8922 - acc:
0.8517
[0.892244815826416, 0.8516799807548523]
```

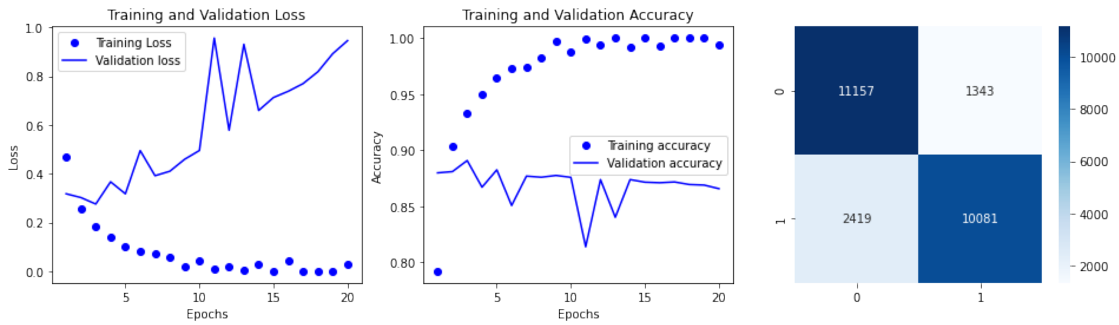


1.6.4 64 Hidden Units

[28]:
```
# Creating a neural net with shape (1000,64,64,1)
model = models.Sequential()
model.add(layers.Dense(64, activation = 'relu', input_shape = (10000,)))
model.add(layers.Dense(64, activation = 'relu'))
```

```python
model.add(layers.Dense(1, activation = 'sigmoid'))

model.compile(optimizer='rmsprop',
              loss = 'binary_crossentropy',
              metrics = ['acc'])

# Training the neural network
history = model.fit(partial_X_train,
                  partial_y_train,
                  epochs = 20,
                  batch_size = 512,
                  validation_data = (X_val, y_val), verbose = False)

results = model.evaluate(X_test, y_test)
print(results)

history_dict = history.history

acc = history_dict['acc']
val_acc = history_dict['val_acc']
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']
epochs = range(1,len(acc) + 1)

# Plotting metrics
fig, [ax1, ax2, ax3] = plt.subplots(1,3, figsize=(16,4))

ax1.plot(epochs, loss_values,  'bo', label = 'Training Loss')
ax1.plot(epochs, val_loss_values, 'b', label = 'Validation loss')
ax1.set_title('Training and Validation Loss')
ax1.set_xlabel("Epochs")
ax1.set_ylabel("Loss")
ax1.legend()

ax2.plot(epochs, acc,  'bo', label = 'Training accuracy')
ax2.plot(epochs, val_acc, 'b', label = 'Validation accuracy')
ax2.set_title('Training and Validation Accuracy')
ax2.set_xlabel("Epochs")
ax2.set_ylabel("Accuracy")
ax2.legend()

confusion_matrix = metrics.confusion_matrix(y_true=y_test, y_pred=np.
 ↪round(model.predict(X_test)))
heatmap(confusion_matrix, annot = True, cmap='Blues', fmt='g', ax = ax3);
```

```
782/782 [==============================] - 2s 2ms/step - loss: 1.0645 - acc:
0.8495
[1.06448233127594, 0.8495200276374817]
```



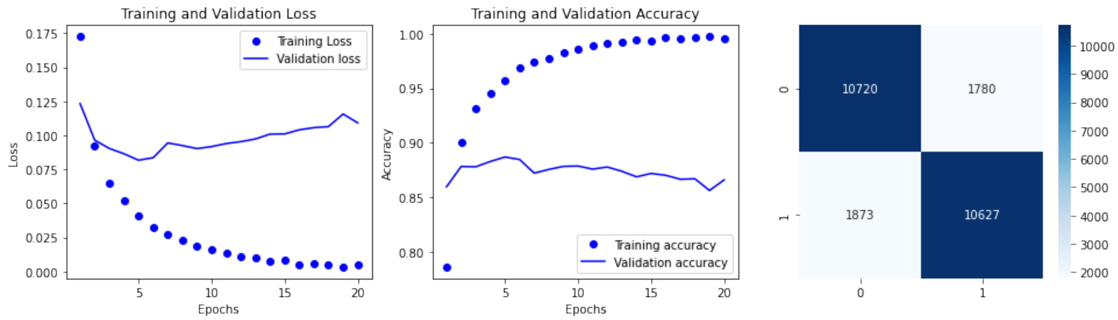
Try using the mse loss function instead of binary_crossentropy

1.6.5 MSE Loss Function

[29]:
```python
# Creating a neural net with shape (1000,16,16,1) and a loss function using mse instead of binary_crossentropy
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 = 'mse',
              metrics = ['acc'])

# Training the neural network
history = model.fit(partial_X_train,
                    partial_y_train,
                    epochs = 20,
                    batch_size = 512,
                    validation_data = (X_val, y_val), verbose = False)

results = model.evaluate(X_test, y_test)
print(results)

history_dict = history.history

acc = history_dict['acc']
val_acc = history_dict['val_acc']
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']
epochs = range(1,len(acc) + 1)

# Plotting metrics
fig, [ax1, ax2, ax3] = plt.subplots(1,3, figsize=(16,4))
```

```
ax1.plot(epochs, loss_values,  'bo', label = 'Training Loss')
ax1.plot(epochs, val_loss_values, 'b', label = 'Validation loss')
ax1.set_title('Training and Validation Loss')
ax1.set_xlabel("Epochs")
ax1.set_ylabel("Loss")
ax1.legend()

ax2.plot(epochs, acc,  'bo', label = 'Training accuracy')
ax2.plot(epochs, val_acc, 'b', label = 'Validation accuracy')
ax2.set_title('Training and Validation Accuracy')
ax2.set_xlabel("Epochs")
ax2.set_ylabel("Accuracy")
ax2.legend()

confusion_matrix = metrics.confusion_matrix(y_true=y_test, y_pred=np.
 ↪round(model.predict(X_test)))
heatmap(confusion_matrix, annot = True, cmap='Blues', fmt='g', ax = ax3);
```

```
782/782 [==============================] - 1s 2ms/step - loss: 0.1192 - acc:
0.8539
[0.11920086294412613, 0.853879988193512]
```



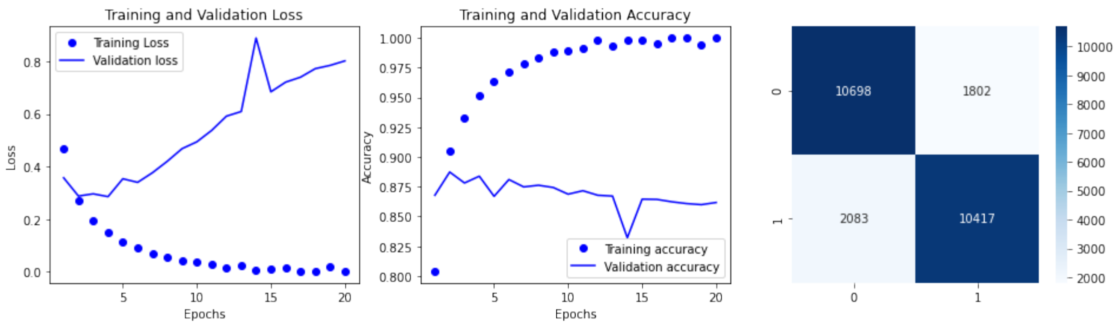
Try using the tanh activation (an activation that was popular in the early days of neural networks) instead of relu.

1.6.6 tanh Activation

[30]:
```
# Creating a neural net with shape (1000,16,16,1) and with tanh activation␣
 ↪functions
model = models.Sequential()
model.add(layers.Dense(16, activation = 'tanh', input_shape = (10000,)))
model.add(layers.Dense(16, activation = 'tanh'))
model.add(layers.Dense(1, activation = 'sigmoid'))

model.compile(optimizer='rmsprop',
```

```
              loss = 'binary_crossentropy',
              metrics = ['acc'])

# Training the neural network
history = model.fit(partial_X_train,
                  partial_y_train,
                  epochs = 20,
                  batch_size = 512,
                  validation_data = (X_val, y_val), verbose = False)

results = model.evaluate(X_test, y_test)
print(results)

history_dict = history.history

acc = history_dict['acc']
val_acc = history_dict['val_acc']
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']
epochs = range(1,len(acc) + 1)

# Plotting metrics
fig, [ax1, ax2, ax3] = plt.subplots(1,3, figsize=(16,4))

ax1.plot(epochs, loss_values,  'bo', label = 'Training Loss')
ax1.plot(epochs, val_loss_values, 'b', label = 'Validation loss')
ax1.set_title('Training and Validation Loss')
ax1.set_xlabel("Epochs")
ax1.set_ylabel("Loss")
ax1.legend()

ax2.plot(epochs, acc,  'bo', label = 'Training accuracy')
ax2.plot(epochs, val_acc, 'b', label = 'Validation accuracy')
ax2.set_title('Training and Validation Accuracy')
ax2.set_xlabel("Epochs")
ax2.set_ylabel("Accuracy")
ax2.legend()

confusion_matrix = metrics.confusion_matrix(y_true=y_test, y_pred=np.
 ↪round(model.predict(X_test)))
heatmap(confusion_matrix, annot = True, cmap='Blues', fmt='g', ax = ax3);
```

```
782/782 [==============================] - 1s 2ms/step - loss: 0.8946 - acc:
0.8446
[0.8946225643157959, 0.8446000218391418]
```


Training and Validation Loss
Training Loss
Validation loss
Loss
Epochs
Training and Validation Accuracy
Training accuracy
Validation accuracy
Accuracy
Epochs
10698
1802
2083
10417