CS109A Introduction to Data Science:

Homework 9: ANNs

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In [1]:
```
# RUN THIS CELL FOR FORMAT
import requests
from IPython.core.display import HTML
styles = requests.get("https://raw.githubusercontent.com/Harvard-IACS/2018-CS109A
HTML(styles)
```

Out[1]:

Import libraries:

In [2]:
```
import random
random.seed(112358)

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.utils import resample
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.linear_model import LogisticRegressionCV

import keras
from keras.models import Sequential
from keras.layers import Dense

%matplotlib inline

import seaborn as sns
pd.set_option('display.width', 1500)
pd.set_option('display.max_columns', 100)

from keras import regularizers


from sklearn.utils import shuffle
```

```
C:\ProgramData\Anaconda3\lib\site-packages\h5py\__init__.py:36: FutureWarning:
Conversion of the second argument of issubdtype from `float` to `np.floating` i
s deprecated. In future, it will be treated as `np.float64 == np.dtype(float).t
ype`.
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
```

Neural Networks

Neural networks are, of course, a large and complex topic that cannot be covered in a single homework. Here we'll focus on the key idea of NNs: they are able to learn a mapping from example input data (of fixed size) to example output data (of fixed size). We'll also partially explore what patterns the neural network learns and how well they generalize.

In this question we'll see if Neural Networks can learn a (limited) version of the Fourier Transform. (The Fourier Transform takes in values from some function and returns a set of sine and cosine functions which, when added together, approximate the original function.)

In symbols: $\mathcal{F}(s) = \int_{-\infty}^{\infty} f(x)e^{-2\pi ixs}\,dx$. In words, the value of the transformed function at some point, s, is the value of an integral which measures, in some sense, how much the original f(x) looks like a wave with period s. As an example, with $f(x) = 4cos(x) + sin(2x)$, $\mathcal{F}(s)$ is 0 everywhere except at -2, -1, 1, and 2, mapping to the waves of period 1 and 1/2. The values at these points are linked to the magnitude of the waves, and their phases (roughly: sin waves versus cosine waves).

The only thing about the Fourier transform that matters for this pset is this: function goes in, re-write in terms of sine and cosine comes out.

In our specific problem, we'll train a network to map from 1000 sample values from a function (equally spaced along 0 to 2π) to the four features of the sine and cosine waves that make up that function. Thus, the network is attempting to learn a mapping from a 1000-entry vector down to a 4-entry vector. Our X_train dataset is thus N by 1000 and our y_train is N by 4.

Questions 1.1 and 1.2 will get you used to the format of the data.

We'll use 6 data files in this question:

- `sinewaves_X_train.npy` and `sinewaves_y_train.npy` : a (10,000 by 1,000) and (10,000 by 4) training dataset. Examples were generated by randomly selecting a,b,c,d in the interval [0,1] and building the curve $a\sin(b\,x) + c\cos(d\,x)$
- `sinewaves_X_test.npy` and `sinewaves_y_test.npy` : a (2,000 by 1,000) and (2,000 by 4) test dataset, generated in the same way as the training data
- `sinewaves_X_extended_test` and `sinewaves_y_extended_test` : a (9 by 1,000) and (9 by 4) test dataset, testing whether the network can generalize beyond the training data (e.g. to negative values of a)

These datasets are read in to their respective variables for you.

Question 1 [50pts]

1.1 Plot the first row of the `X_train` training data and visually verify that it is a sinusoidal curve.

1.2 The first row of the `y_train` data is $[0.024, 0.533, 0.018, 0.558]$. Visually or numerically verify that the first row of X_train is 1000 equally-spaced samples in $[0, 10\pi]$ from the function $f(x) = 0.024\sin(0.533\,x) + 0.018\cos(0.558\,x)$. This pattern (y_train is the true parameters of the curve in X_train) will always hold.

1.3 Use `Sequential` and `Dense` from Keras to build a fully-connected neural network. You can choose any number of layers and any number of nodes in each layer.

1.4 Compile your model via the line `model.compile(loss='mean_absolute_error', optimizer='adam')` and display the `.summary()` . Explain why the first layer in your network has the indicated number of parameters.

1.5 Fit your model to the data for 50 epochs using a batch size of 32 and a validation split of 0.2. You can train for longer if you wish- the fit tends to improve over time.

1.6 Use the `plot_predictions` function to plot the model's predictions on `X_test` to the true values in `y_test` (by default, it will only plot the first few rows). Report the model's overall loss on the test set. Comment on how well the model performs on this unseen data. Do you think it has accurately learned how to map from sample data to the coefficients that generated the data?

1.7 Examine the model's performance on the 9 train/test pairs in the `extended_test` variables. Which examples does the model do well on, and which examples does it struggle with?

1.8 Is there something that stands out about the difficult examples, especially with respect to the data the model was trained on? Did the model learn the mapping we had in mind? Would you say the model is overfit, underfit, or neither?

Hint:

- Keras's documentation and examples of a Sequential model are a good place to start.
- A strong model can achieve validation error of around 0.03 on this data and 0.02 is very good.

In [3]:
```python
def plot_predictions(model, test_x, test_y, count=None):
    # Model - a Keras or SKlearn model that takes in (n,1000) training data and p
    # test_x - a (n,1000) input dataset
    # test_y - a (n,4) output dataset
    # This function will plot the sine curves in the training data and those imp
    # It will also print the predicted and actual output values.

    #helper function that takes the n by 4 output and reverse-engineers
    #the sine curves that output would create
    def y2x(y_data):
        #extract parameters
        a=y_data[:,0].reshape(-1,1)
        b=y_data[:,1].reshape(-1,1)
        c=y_data[:,2].reshape(-1,1)
        d=y_data[:,3].reshape(-1,1)

        #build the matching training data
        x_points = np.linspace(0,10*np.pi,1000)
        x_data = a*np.sin(np.outer(b,x_points)) + c*np.cos(np.outer(d,x_points))
        return x_data

    #if <20 examples, plot all. If more, just plot 5
    if count==None:
        if test_x.shape[0]>20:
            count=5
        else:
            count=test_x.shape[0]

    #build predictions
    predicted = model.predict(test_x)
    implied_x = y2x(predicted)
    for i in range(count):
        plt.plot(test_x[i,:],label='true')
        plt.plot(implied_x[i,:],label='predicted')
        plt.legend()
        plt.ylim(-2.1,2.1)
        plt.xlabel("x value")
        plt.xlabel("y value")
        plt.title("Curves using the Neural Network's Approximate Fourier Transfo
        plt.show()
        print("true:", test_y[i,:])
        print("predicted:", predicted[i,:])
```

In [4]:
```python
X_train = np.load('data/sinewaves_X_train.npy')
y_train = np.load('data/sinewaves_y_train.npy')

X_test = np.load('data/sinewaves_X_test.npy')
y_test = np.load('data/sinewaves_y_test.npy')

X_extended_test = np.load('data/sinewaves_X_extended_test.npy')
y_extended_test = np.load('data/sinewaves_y_extended_test.npy')
```

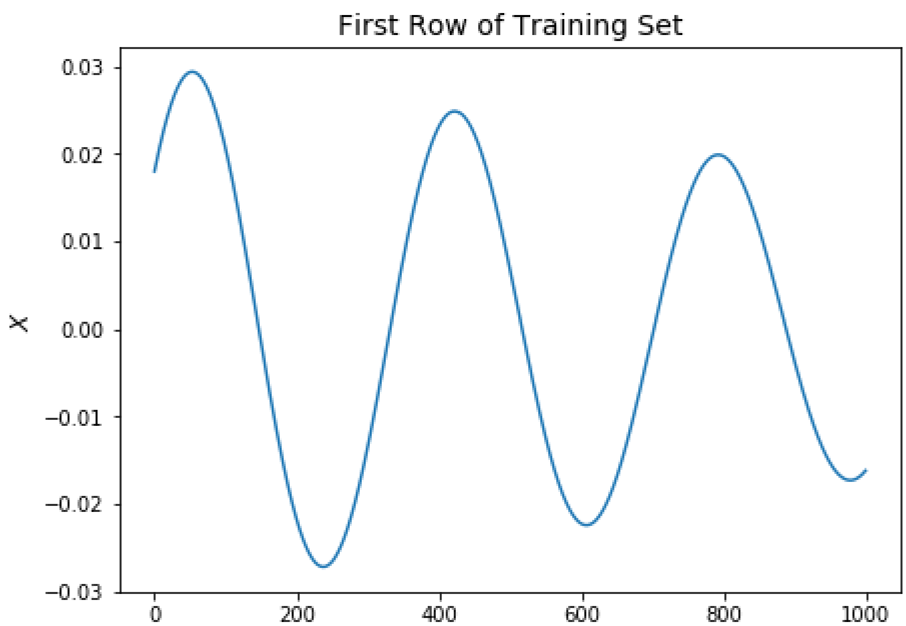
Answers:

1.1 Plot the first row of the `X_train` training data and visually verify that it is a sinusoidal curve

In [5]:
```
# your code here
display(X_train.shape)
fig, ax = plt.subplots(1,1, figsize=(7,5))
ax.plot(X_train[0,], label=r'$X$')
ax.set_ylabel(r'$X$', fontsize=12)
ax.set_title('First Row of Training Set', fontsize=14)
```

```
(10000, 1000)
```

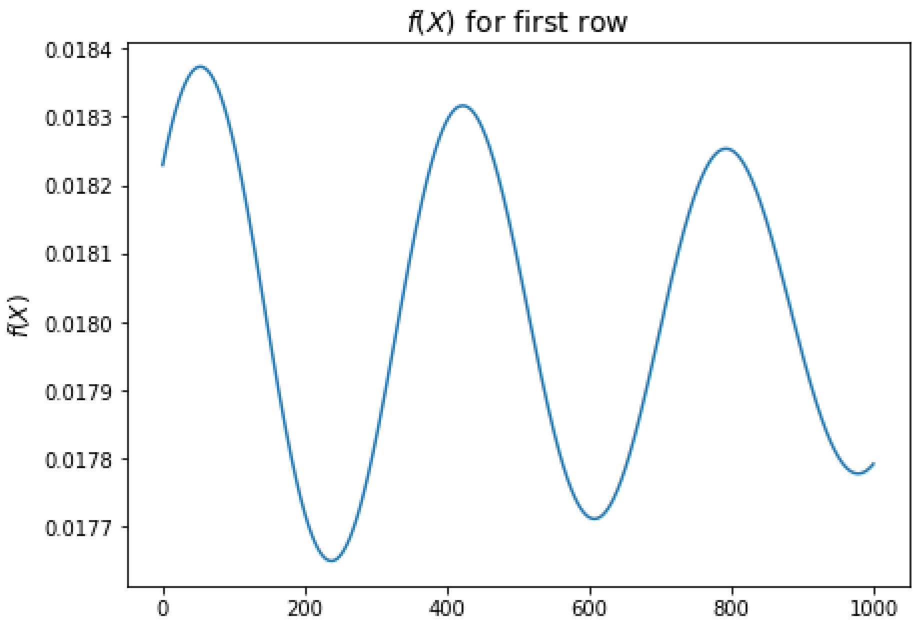
Out[5]:
```
Text(0.5,1,'First Row of Training Set')
```



1.2 The first row of the `y_train` data is $[0.024, 0.533, 0.018, 0.558]$. Visually or numerically verify that the first row of X_train is 1000 equally-spaced points in $[0, 10\pi]$ from the function $f(x) = 0.024 \sin(0.533\, x) + 0.018 \cos(0.558\, x)$...

In [6]:
```
# your code here
f_x = 0.024*np.sin(0.533*X_train[0]) + 0.018*np.cos(0.558*X_train[0])
fig, ax = plt.subplots(1,1, figsize=(7,5))
ax.plot(f_x, label=r'$f(X)$')
ax.set_ylabel(r'$f(X)$', fontsize=12)
ax.set_title('$f(X)$ for first row', fontsize=14)
```

Out[6]: `Text(0.5,1,'$f(X)$ for first row')`



1.3 Use `Sequential` and `Dense` from Keras to build a fully-connected neural network. You can choose any number of layers and any number of nodes in each layer.

In [7]:
```
# your code here
H = 150
L = 10
input_dim = 1000

model = keras.models.Sequential()

# hidden layers (L)
for i in range(L):
    model.add(keras.layers.Dense(H, input_dim=input_dim,
                kernel_initializer='normal',
                activation='relu'))
# output layer
model.add(keras.layers.Dense(4, kernel_initializer='normal',
                activation='linear'))
```

Answer:

We use this combination of number of nodes and number of layers, because it gives us a validation error of approximately 0.02 - as desired in the question.

1.4 Compile your model via the line `model.compile(loss='mean_absolute_error',` optimizer='adam') and display the .summary() . Explain why the first layer in your network has the indicated number of parameters.

In [8]:
```
# your code here
model.compile(loss='mean_absolute_error', optimizer='adam')
display(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_1 (Dense)              (None, 150)               150150    
_________________________________________________________________
dense_2 (Dense)              (None, 150)               22650     
_________________________________________________________________
dense_3 (Dense)              (None, 150)               22650     
_________________________________________________________________
dense_4 (Dense)              (None, 150)               22650     
_________________________________________________________________
dense_5 (Dense)              (None, 150)               22650     
_________________________________________________________________
dense_6 (Dense)              (None, 150)               22650     
_________________________________________________________________
dense_7 (Dense)              (None, 150)               22650     
_________________________________________________________________
dense_8 (Dense)              (None, 150)               22650     
_________________________________________________________________
dense_9 (Dense)              (None, 150)               22650     
_________________________________________________________________
dense_10 (Dense)             (None, 150)               22650     
_________________________________________________________________
dense_11 (Dense)             (None, 4)                 604       
=================================================================
Total params: 354,604
Trainable params: 354,604
Non-trainable params: 0
_________________________________________________________________
```

```
None
```

Answer:

Each of the input dimensions go into each of the nodes in the first layer. We have 150 nodes in each hidden layer and 1000 input dimensions. So for each of the nodes in the first hidden layer, we have 1 parameter to give the weights for affine transformations for each of the input dimensions going into it and one parameter for the activation function. Thus, we have $150 * 1000 = 150000$ total affine transformations + 150 activation functions = 150150 parameters.

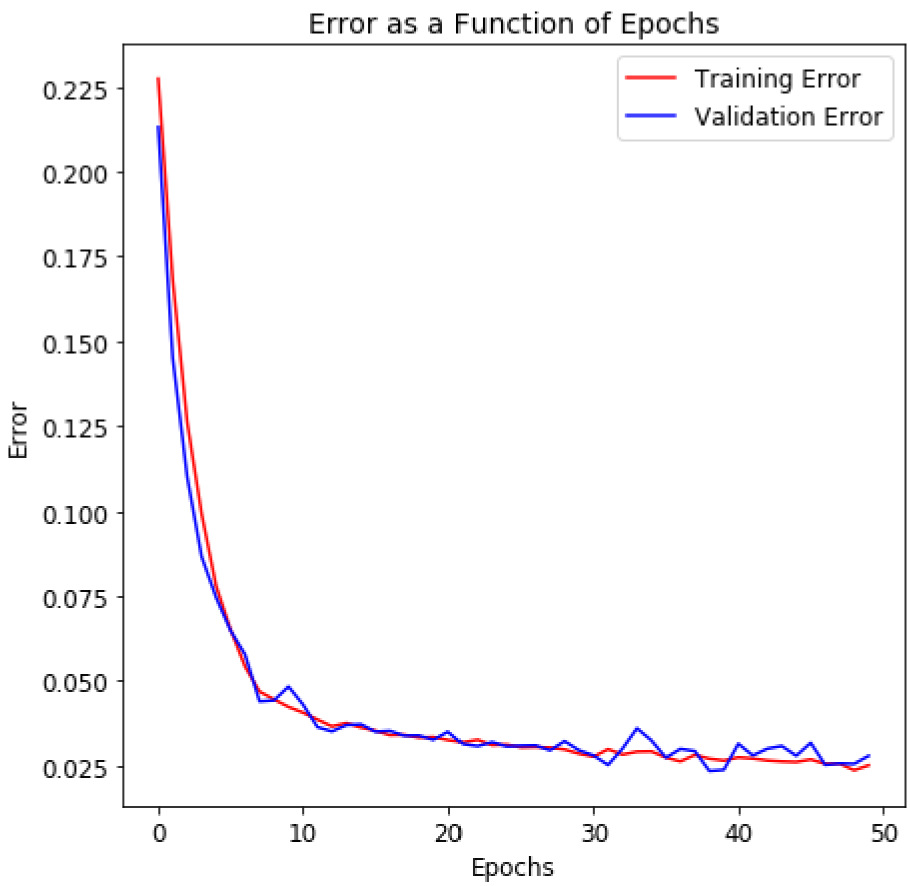
1.5 Fit your model to the data for 50 epochs using a batch size of 32 and a validation split of .2. You can train for longer if you wish- the fit tends to improve over time.

In [9]:
```
# your code here
#f_x = y_train[1]*np.sin(0.533*X_train) + 0.018*np.cos(0.558*X_train[0])
model_history = model.fit(X_train, y_train, batch_size=32, epochs=50, verbose=1,
                          shuffle = True, validation_split=0.2)
```

```
Train on 8000 samples, validate on 2000 samples
Epoch 1/50
8000/8000 [==============================] - 3s 328us/step - loss: 0.2274 - v
al_loss: 0.2132
Epoch 2/50
8000/8000 [==============================] - 3s 348us/step - loss: 0.1683 - v
al_loss: 0.1451
Epoch 3/50
8000/8000 [==============================] - 2s 301us/step - loss: 0.1262 - v
al_loss: 0.1102
Epoch 4/50
8000/8000 [==============================] - 2s 249us/step - loss: 0.0992 - v
al_loss: 0.0866
Epoch 5/50
8000/8000 [==============================] - 2s 233us/step - loss: 0.0780 - v
al_loss: 0.0746
Epoch 6/50
8000/8000 [==============================] - 3s 316us/step - loss: 0.0651 - v
al_loss: 0.0648
```

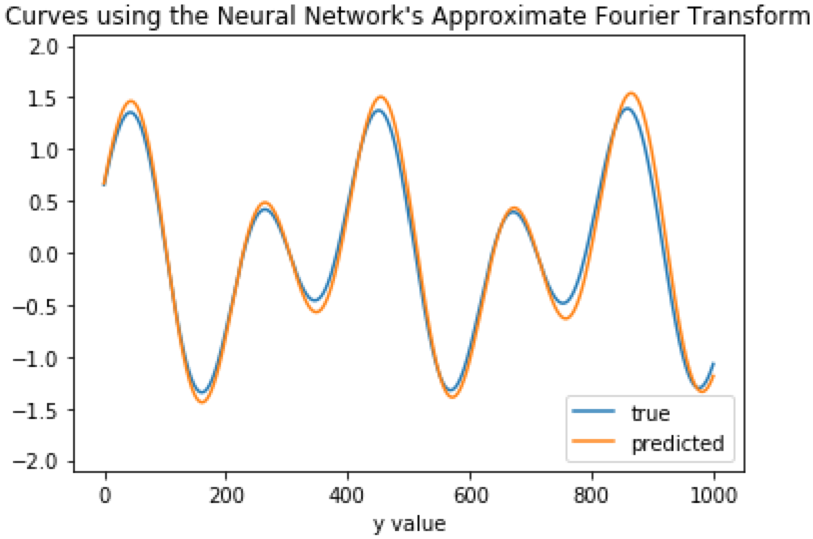
In [10]:
```
fig, ax = plt.subplots(1,1, figsize=(7,7))
ax.plot(model_history.history['loss'], color='red', label='Training Error')
ax.plot(model_history.history['val_loss'], color='blue', label='Validation Error
ax.set_xlabel('Epochs', fontsize=12)
ax.set_ylabel('Error', fontsize=12)
ax.legend(loc='best', fontsize=12)
ax.tick_params(labelsize=12)
ax.set_title('Error as a Function of Epochs', fontsize=14)
```

Out[10]:
```
Text(0.5,1,'Error as a Function of Epochs')
```

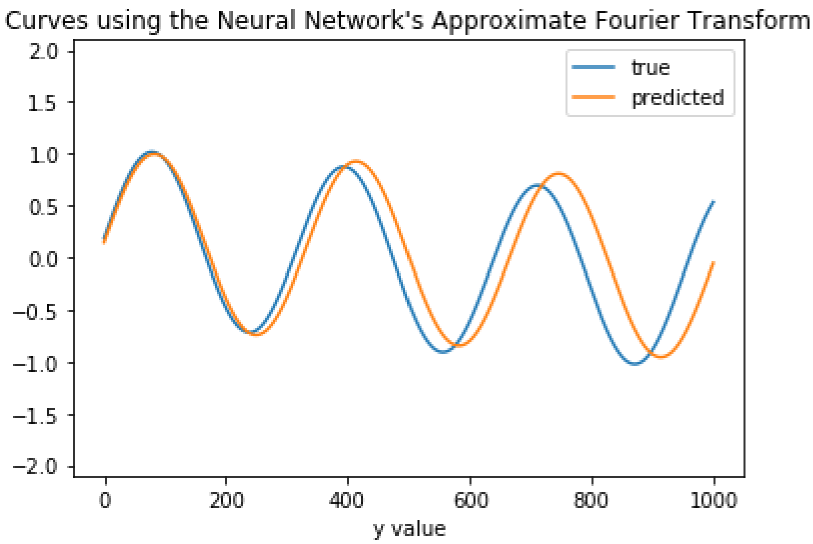


1.6 Use the `plot_predictions` function to plot the model's predictions on `X-test` to the true values in `y_test` (by default, it will only plot the first few rows). Report the model's overall loss on the test set. Comment on how well the model performs on this unseen data. Do you think it has accurately learned how to map from sample data to the coefecients that generated the data?

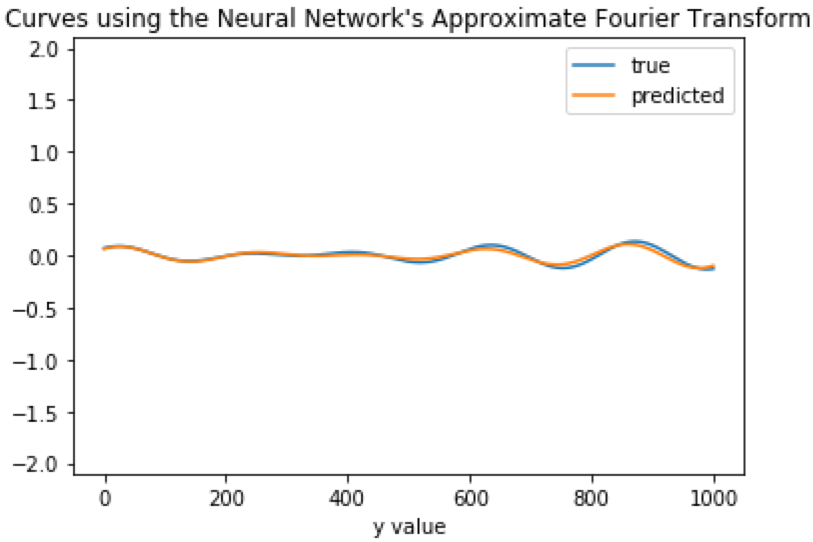
In [11]:
```
# your code here
plot_predictions(model, test_x=X_test, test_y=y_test)
```



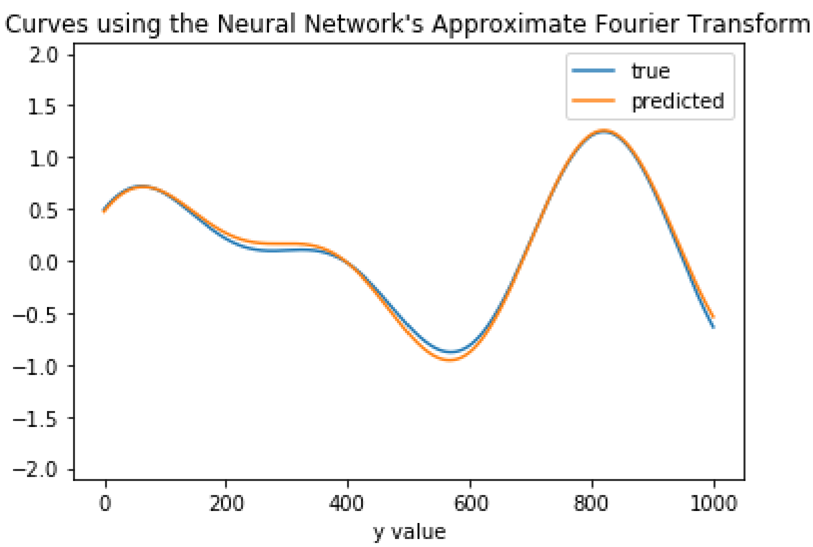

```
true: [0.86199664 0.98175913 0.65523998 0.4870337 ]
predicted: [0.9595372  0.9766133  0.6695246  0.48006696]
```



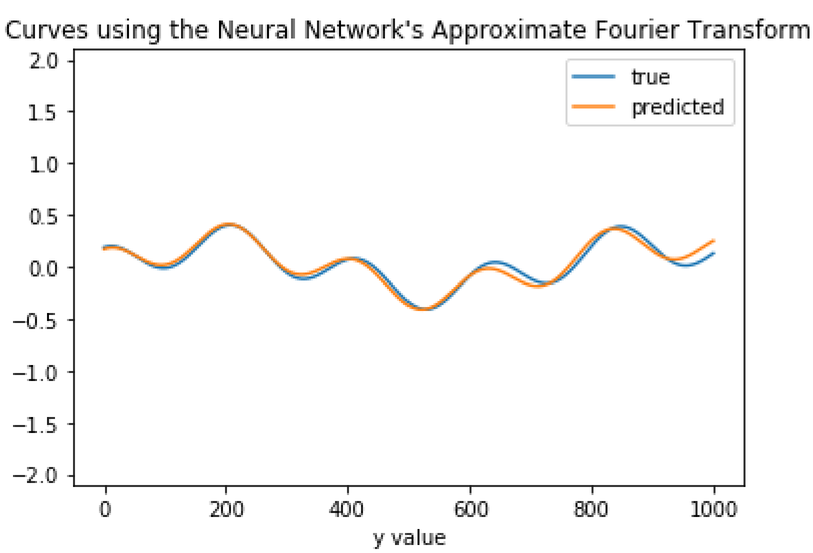

```
true: [0.8406355  0.63159555 0.18328701 0.11174618]
predicted: [0.85639256 0.6023923  0.1431007  0.08182629]
```




```
true: [0.06591224 0.75183886 0.06986143 0.91352303]
predicted: [0.06331608 0.77830607 0.06437665 0.9119868 ]
```




```
true: [0.75610725 0.30861152 0.49522059 0.48394499]
predicted: [0.78434676 0.30377597 0.4744247  0.48862427]
```




```
true: [0.2229353  0.27885697 0.18696198 0.94846283]
```

```
predicted: [0.24616541 0.2753426  0.16997257 0.9648801 ]
```

In [12]:
```
print('\nTotal loss on the Test Set: %s'%model.evaluate(X_test, y_test))
```

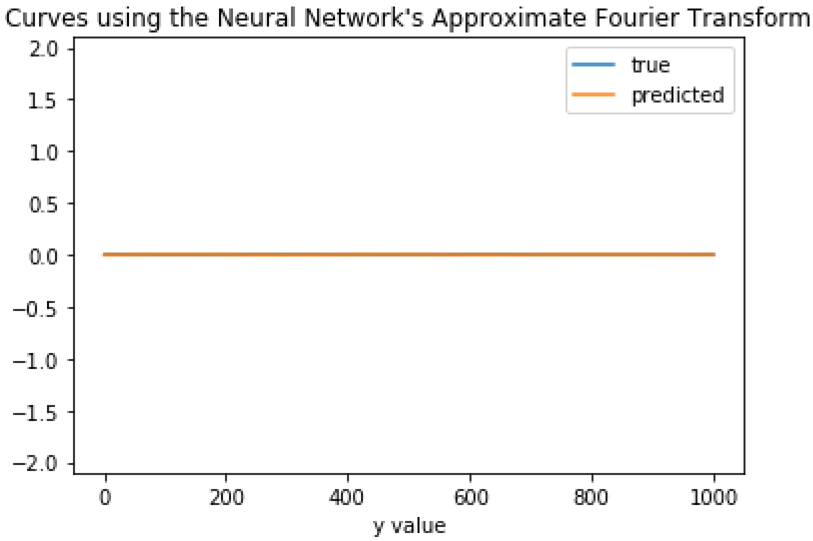
```
2000/2000 [==============================] - 0s 78us/step

Total loss on the Test Set: 0.026937744656443596
```

Answer:

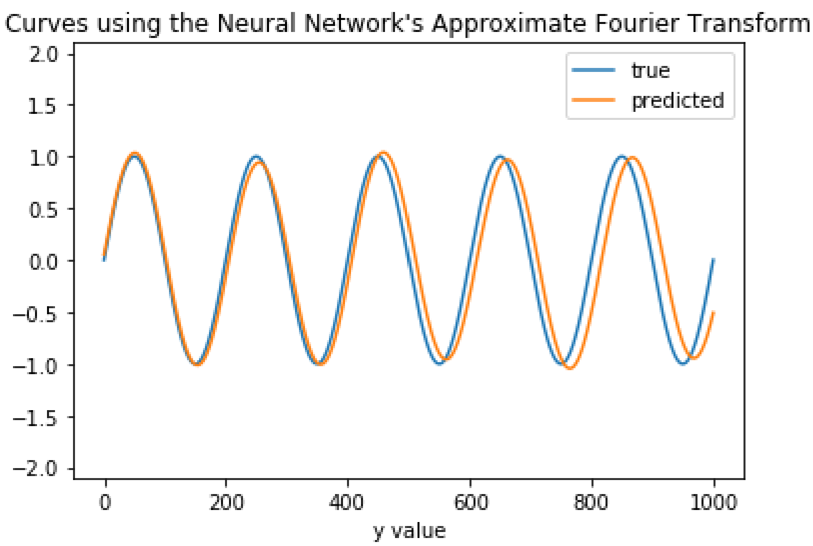
We see above that our total loss on the test set is 0.027 and which similar to the validation error in the last step of our first network. Thus, it seems that the model is performing pretty well on the test data set.

1.7 Examine the model's performance on the 9 train/test pairs in the `extended_test` variables. Which examples does the model do well on, and which examples does it struggle with?

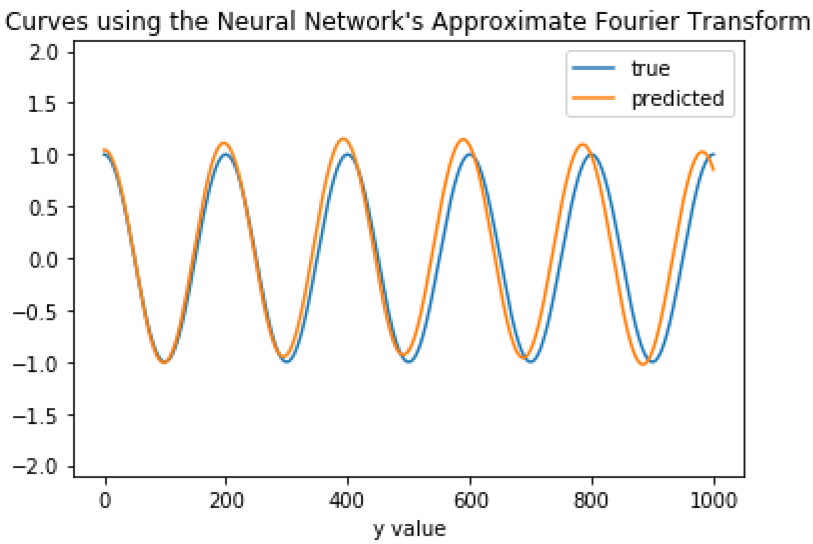
In [13]:
```
# your code here
plot_predictions(model, test_x=X_extended_test, test_y=y_extended_test)
```



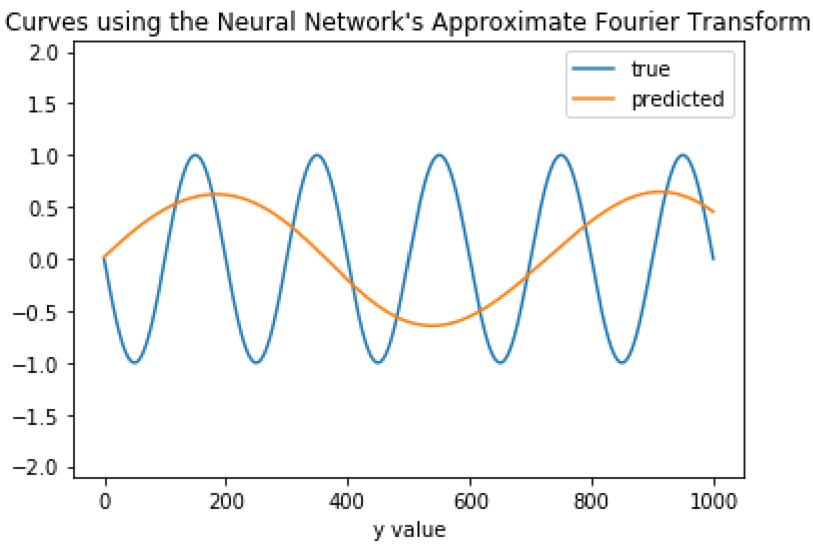

```
true: [0. 0. 0. 0.]
predicted: [ 0.00442269  0.5893971  -0.00272386  0.53924876]
```



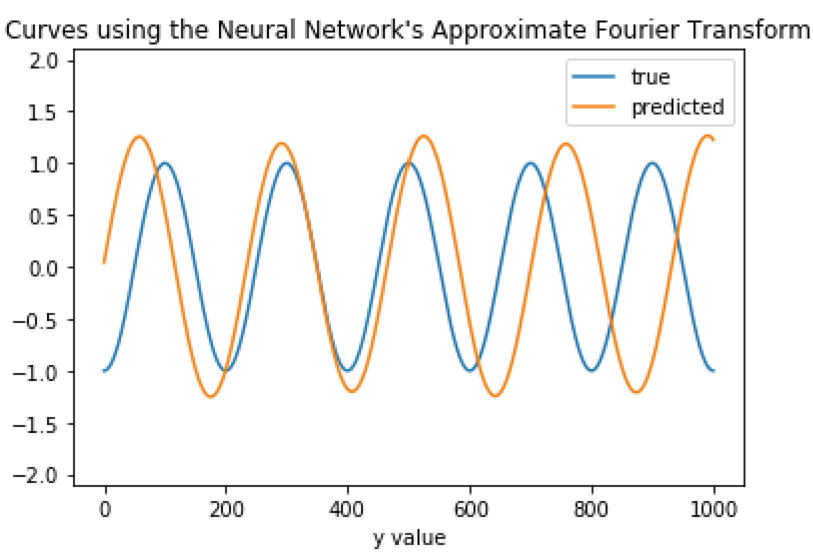

```
true: [1. 1. 0. 0.]
predicted: [0.9936381  0.9809843  0.05198237 0.4012767 ]
```




```
true: [0. 0. 1. 1.]
predicted: [0.11199296 0.10689051 1.04355    1.0181174 ]
```

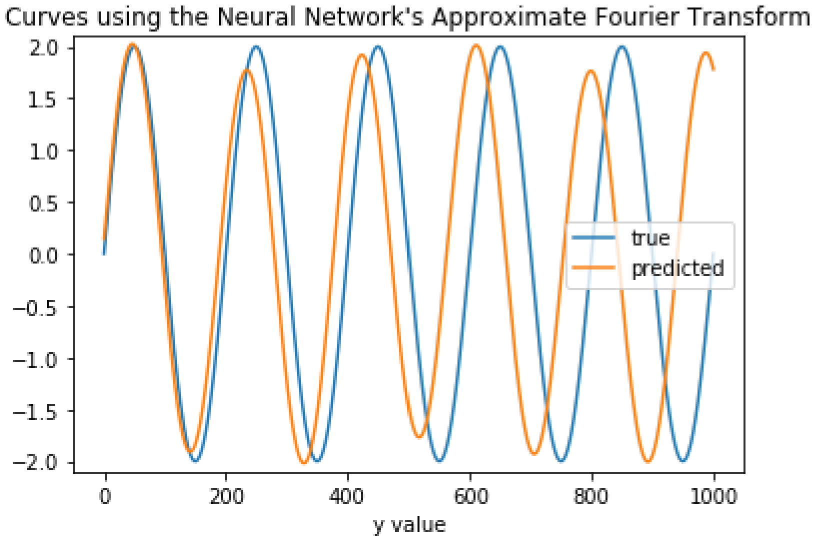



```
true: [-1.  1.  0.  0.]
predicted: [0.6367775  0.2755617  0.01624243 0.6258744 ]
```

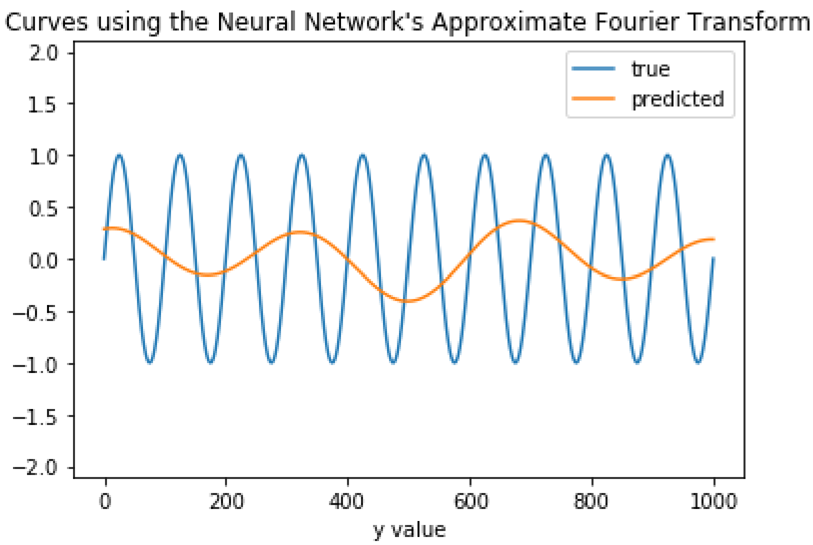



```
true: [ 0.  0. -1.  1.]
```

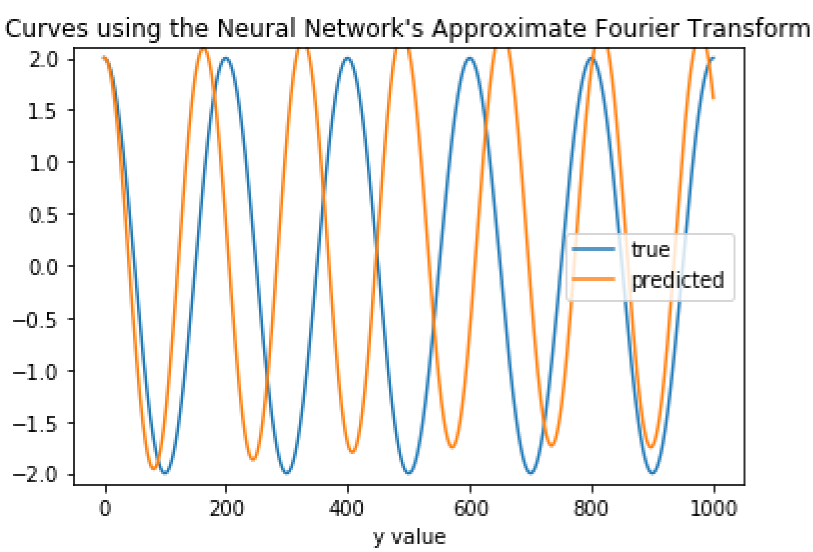
```
predicted: [1.2249901  0.85803723 0.04229444 0.41388756]
```



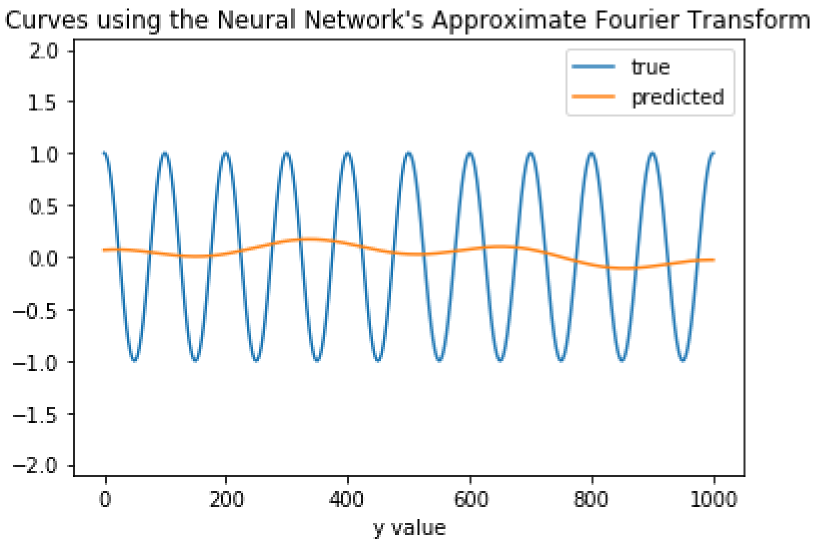

```
true: [2. 1. 0. 0.]
predicted: [1.9021856  1.0639334  0.14350896 0.36344826]
```




```
true: [1. 2. 0. 0.]
predicted: [0.13192807 0.32657635 0.28636286 0.5960197 ]
```



```
true: [0. 0. 2. 1.]
predicted: [0.27125457 0.06802007 2.0052361  1.2256857 ]
```




```
true: [0. 0. 1. 2.]
predicted: [0.10532093 0.1361649  0.06428452 0.5971668 ]
```

In [14]:
```python
model.evaluate(X_extended_test, y_extended_test, steps=9)
```

```
9/9 [==============================] - 0s 1ms/step
```

Out[14]:
```
0.44034892320632935
```

Answer:

As we can see above the model performs well on samples: (1:3, 5) and struggles with samples: (4, 6:9). Thus, we get a loss that is a lot higher compared to the train or the test set.

1.8 Is there something that stands out about the difficult observations, especially with respect to the data the model was trained on? Did the model learn the mapping we had in mind? Would you say the model is overfit, underfit, or neither?

Answer:

We can see that the model is always predicting values for [a,b,c,d] in the range [0,1] - which is what we trained it on. However, the true values in the difficult samples are either < 0 or > 1.

This means that the model only learned the mapping from the training set but could not be generalized to the `extended_test` set which had values outside of the training set. Thus, the model was overfit on the train set.

Regulrizing Neural Networks

In this problem set we have already explored how ANN are able to learn a mapping from example input data (of fixed size) to example output data (of fixed size), and how well the neural network can generalize. In this problem we focus on issues of overfitting and regularization in Neural Networks.

As we have explained in class, ANNs can be prone to overfitting, where they learn specific patterns present in the training data, but the patterns don't generalize to fresh data.

There are several methods used to improve ANN generalization. One approach is to use an achitecutre just barely wide/deep enough to fit the data. The idea here is that smaller networks are less expressive and thus less able to overfit the data.

However, it is difficult to know a priori the correct size of the ANN, and computationally costly to hunt for a correct size. Given this, other methodologies are used to fight overfitting and improve the ANN generalization. These, like other techniques to combat overfitting, fall under the umbrella of Regularization.

In this problem you are asked to regularize a network given to you below. The train dataset can be generated using the code also given below.

Question 2 [50 pts]

2.1 Data Download and Exploration: For this problem, we will be working with the MNIST dataset (Modified National Institute of Standards and Technology database) which is a large database of handwritten digits and commonly used for training various image processing systems.

We will be working directly with the download from `keras MNIST dataset` of 60,000 28x28 grayscale images of the 10 digits, along with a test set of 10,000 images.

Please refer to the code below to process the data.

For pedagogical simplicity, we will only use the digits labeled `4` and `9`, and we want to use a total of 800 samples for training.

2.2 Data Exploration and Inspection: Use `imshow` to display a handwritten 4 and a handwritten 9.

2.3 Overfit an ANN: Build a fully connected network (FCN) using `keras`:

1. Nodes per Layer: 100,100,100,2 (<-the two-class 'output' layer)
2. Activation function: reLU
3. Loss function: binary_crossentropy
4. Output unit: Sigmoid
5. Optimizer: sgd (use the defaults; no other tuning)
6. Epochs: no more than 2,000
7. Batch size: 128
8. Validation size: .5

This NN trained on the dataset you built in 2.1 will overfit to the training set. Plot the training accuracy and validation accuracy as a function of epochs and explain how you can tell it is overfitting.

2.4 Explore Regularization: Your task is to regularize this FCN. You are free to explore any method or combination of methods. If you are using anything besides the methods we have covered in class, give a citation and a short explanation. You should always have an understanding of the methods you are using.

Save the model using `model.save(filename)` and submit in canvas along with your notebook.

We will evaluate your model on a test set we've kept secret.

1. Don't try to use extra data from NMIST. We will re-train your model on training set under the settings above.
2. Keep the architecture above as is. In other words keep the number of layers, number of nodes, activation function, and loss fucntion the same. You can change the number of epochs (max 2000), batch size, optimizer and of course add elements that can help to regularize (e.g. drop out, L2 norm etc). You can also do data augmentation.
3. You *may* import new modules, following the citation rule above.

Grading: Your score will be based on how much you can improve on the test score via regularization:

1. (0-1] percent will result into 10 pts
2. (1-2] percent will result into 20 pts
3. (2-3] percent will result into 30 pts
4. Above 3 percent will result in 35 pts

5. Top 15 groups or single students will be awarded an additional 10 pts
6. The overall winner(s) will be awarded an additional 5 pts

2.1 Data Download and Exploration: For this problem, we will be working with the MNIST dataset (Modified National Institute of Standards and Technology database) which is a large database of handwritten digits and commonly used for training various image processing systems. We will be working directly with the download from `keras MNIST dataset` of 60,000 28x28 grayscale images of the 10 digits, along with a test set of 10,000 images.

Please refer to the code below to process the data.

For pedagogical simplicity, we will only use the digits labeled `4` and `9` , and we want to use a total of 800 samples for training.

In [15]:

```
## Read and Setup train and test splits in one
from keras.datasets import mnist
from random import randint

(x_train, y_train), (x_test, y_test) = mnist.load_data()

#shuffle the data before we do anything
x_train, y_train = shuffle(x_train, y_train, random_state=1)
```

In [16]:

```
## separating 4s and 9s select 800 points
# your code here
display(x_train.shape)
display(y_train.shape)

# mask for 4 & 9
msk_train = ((y_train==4) | (y_train==9))
msk_test = ((y_test==4) | (y_test==9))

# random sampling
rand = []
for i in range(800):
    rand.append(randint(0,msk_train.sum()))


# filter data
y_train_filtered = y_train[msk_train][rand]
x_train_filtered = x_train[msk_train][rand]
y_test_filtered = y_test[msk_test]
x_test_filtered = x_test[msk_test]
```

```
(60000, 28, 28)
```

```
(60000,)
```

In [17]:
```
# sanity check
display(y_train_filtered.shape)
display(x_train_filtered.shape)
display(y_test_filtered.shape)
display(x_test_filtered.shape)
```

```
(800,)

(800, 28, 28)

(1991,)

(1991, 28, 28)
```

In [18]:
```
# Preprocess data using keras.utils.to_categorical
# your code here
y_train_clean = keras.utils.to_categorical(y=y_train_filtered.reshape(-1,1),
                                           num_classes=len(np.unique(y_train)),
                                           dtype='uint8')[:,[4,9]]
y_test_clean = keras.utils.to_categorical(y=y_test_filtered.reshape(-1,1),
                                          num_classes=len(np.unique(y_test)),
                                          dtype='uint8')[:,[4,9]]
```

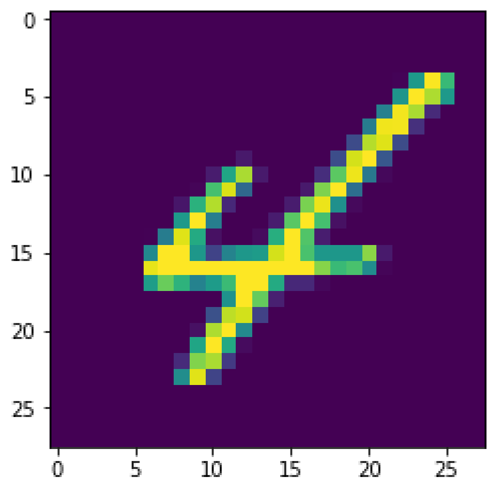
In [19]:
```
# scale the data otherwise reLU can become unstable
# your code here
from sklearn.preprocessing import StandardScaler

nrow_train = x_train_filtered.shape[0]
nrow_test = x_test_filtered.shape[0]
col = x_train_filtered.shape[1]
depth = x_train_filtered.shape[2]

x_train_reshaped = x_train_filtered.reshape(nrow_train, col*depth)
x_test_reshaped = x_test_filtered.reshape(nrow_test, col*depth)


scaler = StandardScaler().fit(x_train_reshaped)
x_train_clean = scaler.transform(x_train_reshaped)
x_test_clean = scaler.transform(x_test_reshaped)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:475: Dat
aConversionWarning: Data with input dtype uint8 was converted to float64 by Sta
ndardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:475: Dat
aConversionWarning: Data with input dtype uint8 was converted to float64 by Sta
ndardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:475: Dat
aConversionWarning: Data with input dtype uint8 was converted to float64 by Sta
ndardScaler.
  warnings.warn(msg, DataConversionWarning)
```

2.2 Data Exploration and Inspection: Use `imshow` to display a handwritten 4 and a handwritten 9.

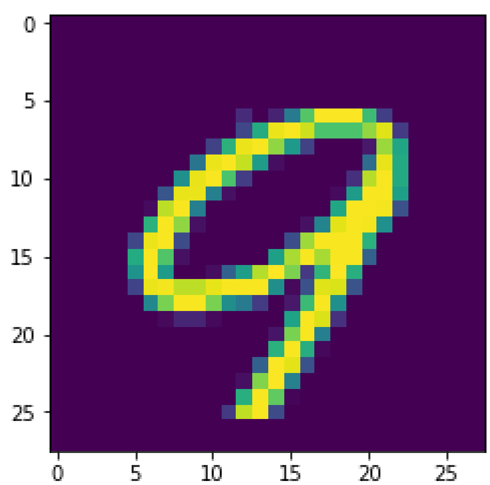
In [20]:
```
# your code here
plt.imshow(x_train_filtered[y_train_clean[:,0]==1,:,:][5,:,:])
```

Out[20]: `<matplotlib.image.AxesImage at 0x82f5d3ce10>`



In [21]:
```
plt.imshow(x_train_filtered[y_train_clean[:,1]==1,:,:][5,:,:])
```

Out[21]: `<matplotlib.image.AxesImage at 0x82f5d99ef0>`



2.3 Overfit an ANN: Build a fully connected network (FCN) using `keras` :

1. Nodes per Layer: 100,100,100,2 (<-the two-class 'output' layer)
2. Activation function: reLU
3. Loss function: binary_crossentropy
4. Output unit: Sigmoid
5. Optimizer: sgd (use the defaults; no other tuning)
6. Epochs: no more than 1,000
7. Batch size: 128
8. Validation size: .5

This NN trained on the dataset you built in 2.1 will overfit to the training set. Plot the training accuracy and validation accuracy as a function of epochs and explain how you can tell it is overfitting.

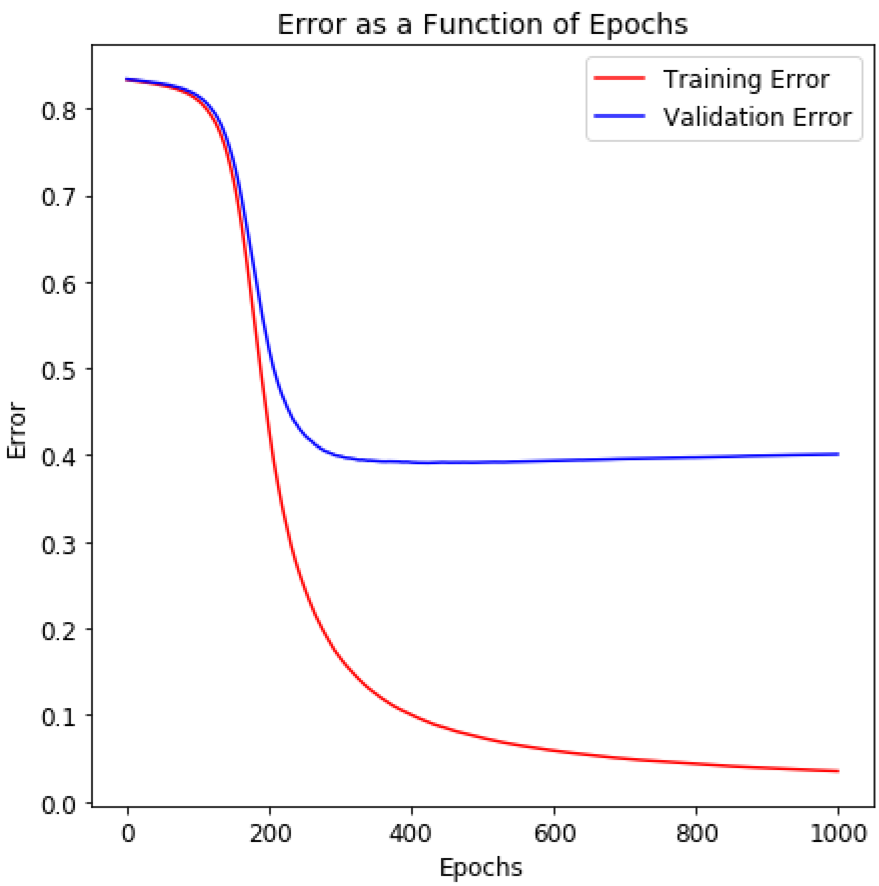
In [22]:
```
# your code here
H = 100
L = 3
input_dim = col*depth
```

In [23]:
```
model2 = keras.models.Sequential()

# hidden layers (L)
for i in range(L):
    model2.add(keras.layers.Dense(H, input_dim=input_dim,
                kernel_initializer='normal',
                activation='relu'))
# output layer
model2.add(keras.layers.Dense(2, kernel_initializer='normal',
                activation='sigmoid'))

# compile
model2.compile(loss='binary_crossentropy', optimizer='sgd')

model2_history = model2.fit(x_train_clean, y_train_clean, batch_size=128, epochs
```

```
Train on 400 samples, validate on 400 samples
Epoch 1/1000
400/400 [==============================] - 0s 753us/step - loss: 0.6941 - val
_loss: 0.6952
Epoch 2/1000
400/400 [==============================] - 0s 58us/step - loss: 0.6939 - val_
loss: 0.6949
Epoch 3/1000
400/400 [==============================] - 0s 60us/step - loss: 0.6937 - val_
loss: 0.6947
Epoch 4/1000
400/400 [==============================] - 0s 98us/step - loss: 0.6935 - val_
loss: 0.6945
Epoch 5/1000
400/400 [==============================] - 0s 95us/step - loss: 0.6933 - val_
loss: 0.6944
Epoch 6/1000
400/400 [==============================] - 0s 68us/step - loss: 0.6931 - val_
loss: 0.6943
```

In [24]:
```
#your code here
fig, ax = plt.subplots(1,1, figsize=(7,7))
ax.plot(np.sqrt(model2_history.history['loss']), color='red', label='Training Err
ax.plot(np.sqrt(model2_history.history['val_loss']), color='blue', label='Valida
ax.set_xlabel('Epochs', fontsize=12)
ax.set_ylabel('Error', fontsize=12)
ax.legend(loc='best', fontsize=12)
ax.tick_params(labelsize=12)
ax.set_title('Error as a Function of Epochs', fontsize=14)
```

Out[24]:
```
Text(0.5,1,'Error as a Function of Epochs')
```



In [25]:
```
y_pred = model2.predict_classes(x_test_clean)
model2_acc = accuracy_score(y_test_clean[:,1], y_pred)
model2_acc
```

Out[25]:
```
0.9417378201908588
```

Answer:

As we can we in the above plot that the trainig error is decreasing with the increase in the number of epochs but the validation error is more or less remaining constant or rather increasing slightly. In short, the training error and validation error are diverging from each other which tells us that the model is clearly overfitting.

2.4 Explore Regularization: Your task is to regularize this FCN. You are free to explore any method or combination of methods. If you are using anything besides the methods we have covered in class, give a citation and a short explanation. You should always have an understanding of the methods you are using.

Save the model using `model.save(filename)` and submit in canvas along with your notebook.

In [26]:
```
model3 = keras.models.Sequential()

# hidden layers (L)
model3.add(keras.layers.Dense(H, input_dim=input_dim,
                              kernel_initializer='normal',
                              bias_regularizer=regularizers.l2(0.01),
                              kernel_regularizer=regularizers.l2(0.01),
                              activation='relu'))

# output layer
model3.add(keras.layers.Dense(2, kernel_initializer='normal',
                              activity_regularizer=regularizers.l2(0.01),
                              activation='sigmoid'))

# compile
model3.compile(loss='binary_crossentropy', optimizer='sgd')

model3_history = model3.fit(x_train_clean, y_train_clean, batch_size=150, epochs
                            validation_split=0.2, verbose=1)
```

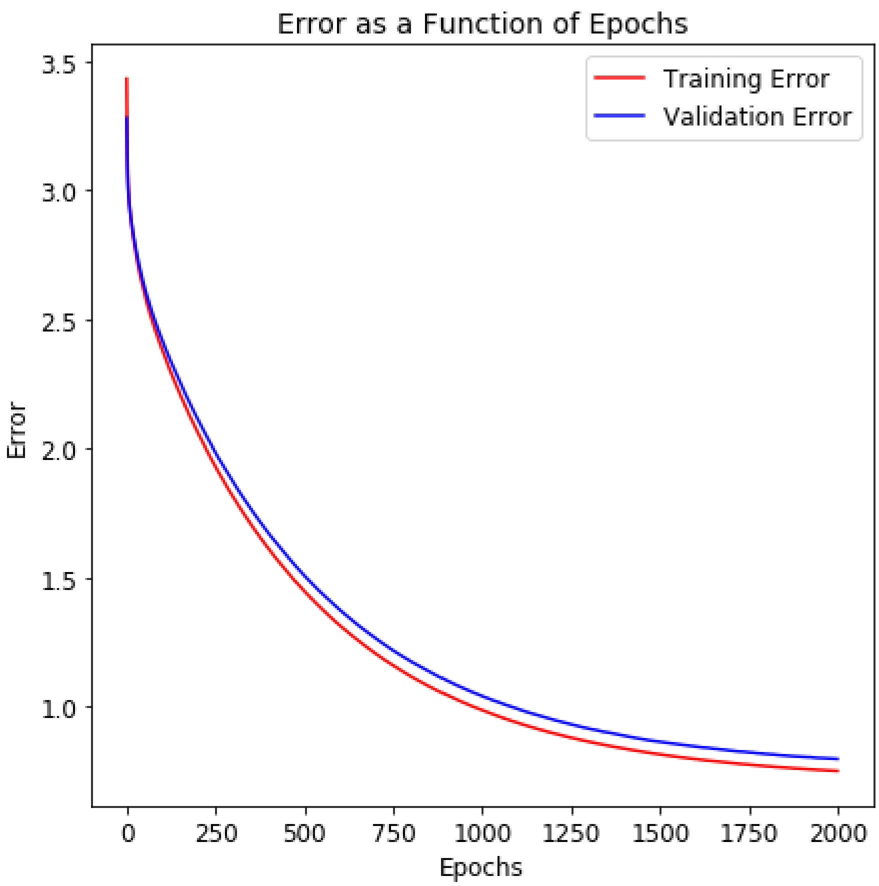
```
Train on 640 samples, validate on 160 samples
Epoch 1/2000
640/640 [==============================] - 0s 461us/step - loss: 3.4316 - val
_loss: 3.2794
Epoch 2/2000
640/640 [==============================] - 0s 40us/step - loss: 3.2461 - val_
loss: 3.1566
Epoch 3/2000
640/640 [==============================] - 0s 36us/step - loss: 3.1377 - val_
loss: 3.0837
Epoch 4/2000
640/640 [==============================] - 0s 44us/step - loss: 3.0728 - val_
loss: 3.0380
Epoch 5/2000
640/640 [==============================] - 0s 47us/step - loss: 3.0308 - val_
loss: 3.0074
Epoch 6/2000
640/640 [==============================] - 0s 50us/step - loss: 3.0009 - val_
loss: 2.9840
```

In [27]:
```
y_pred = model3.predict_classes(x_test_clean)
model3_acc = accuracy_score(y_test_clean[:,1], y_pred)
model3_acc
```

Out[27]:
```
0.9698643897538926
```

In [28]:
```
fig, ax = plt.subplots(1,1, figsize=(7,7))
ax.plot(model3_history.history['loss'], color='red', label='Training Error')
ax.plot(model3_history.history['val_loss'], color='blue', label='Validation Error
ax.set_xlabel('Epochs', fontsize=12)
ax.set_ylabel('Error', fontsize=12)
ax.legend(loc='best', fontsize=12)
ax.tick_params(labelsize=12)
ax.set_title('Error as a Function of Epochs', fontsize=14)
```

Out[28]:
```
Text(0.5,1,'Error as a Function of Epochs')
```



In [29]:
```
model3.save('cs109_HW9_Q2_4.h5')
```

In [30]:
```
from keras.models import load_model
m = load_model('cs109_HW9_Q2_4.h5')
y_pred = m.predict_classes(x_test_clean)
m_acc = accuracy_score(y_test_clean[:,1], y_pred)
m_acc
```

Out[30]:
```
0.9698643897538926
```

Answer:

Keeping the architecture same as 2.3, the following methods were tried for regularization: `Dropout` , `L1` , `L2` , `Sparse Representation` . Of those, we find that `Dropout` gives almost the same accuracy as the original model and `L1` gives a much lower accuracy on the test set. Hence, after much trial and error, the following regularization combination was used:

1. `L2` on `kernel` ($\lambda = 0.015$) and `bias` ($\lambda = 0.015$) of the hidden layers (i.e. `Sparse Representation`) and
2. `L2` on activation function ($\lambda = 0.015$) of the output layer

In addition, the following changes were made to the model in 2.3:

1. batch_size=150,
2. epochs=2000,
3. validation_split=0.2

In [ ]:

```

```