Project: Create a neural network class

Based on previous code examples, develop a neural network class that is able to classify any dataset provided. The class should create objects based on the desired network architecture:

1. Number of inputs
2. Number of hidden layers
3. Number of neurons per layer
4. Number of outputs
5. Learning rate

The class must have the train, and predict functions.

Test the neural network class on the datasets provided below: Use the input data to train the network, and then pass new inputs to predict on. Print the expected label and the predicted label for the input you used. Print the accuracy of the training after predicting on different inputs.

Use matplotlib to plot the error that the train method generates.

Don't forget to install Keras and tensorflow in your environment!

Import the needed Packages

In [3]:

```
import numpy as np
import matplotlib.pyplot as plt

# Needed for the mnist data
from keras.datasets import mnist
from keras.utils import to_categorical
```

```
Using TensorFlow backend.
```

Define the class

In [4]:

```
class NeuralNetwork:
```

```python
class NeuralNetwork:

    def __init__(self, architecture, alpha):
        '''
            layers: List of integers which represents the architecture of the networ
            alpha:  Learning rate.
        '''
        np.random.seed(666)
        _inputs, _layer, _neurons, _output = architecture
        _layer = _layer if _layer < 3 else 2
        # Initialize values
        self.alpha         = alpha
        self.layers        = _layer
        self.neurons       = _neurons
        # Weights
        self.initialW = np.random.randn(_inputs, _neurons)
        self.middleW  = np.zeros( (_layer - 1, _neurons, _neurons) )
        self.lastW    = np.random.randn(_neurons, _output)
        # This will be used in the predict function
        self.calcW    = []
        # Bias
        self.initialb    = np.random.randn(_neurons)
        self.middleb     = np.random.randn(_layer - 1, _neurons)
        self.lastb       = np.random.randn(_output)
        for i in range(_layer - 1):
            self.middleW[i] = np.random.randn(_neurons, _neurons)

        pass


    def __repr__(self):
        # construct and return a string that represents the network
        # architecture
        return "NeuralNetwork: {}".format( "-".join(str(l) for l in self.layers))

    @staticmethod
    def softmax(X):
        # applies the softmax function to a set of values

        expX = np.exp(X)
        return expX / expX.sum(axis=1, keepdims=True)

    @staticmethod
    def sigmoid(x):
        # the sigmoid for a given input value

        return 1.0 / (1.0 + np.exp(-x))

    @staticmethod
    def sigmoid_deriv(x):
        # the derivative of the sigmoid

        return x * (1 - x)

    def predict(self, inputs):
```

```python
    def predict(self, inputs):
        self.calcW = np.zeros( (self.layers, inputs.shape[0], self.neurons) )
        # Lvl 1
        self.calcW[0] = self.sigmoid( np.dot(inputs, self.initialW) + self.initialb
        # Lvl 2
        for i in range(self.layers - 1):
            self.calcW[i + 1] = self.sigmoid( np.dot(self.calcW[i], self.middleW[i]

        # Lvl 3 (last)
        return self.softmax( np.dot(self.calcW[len(self.calcW)-1], self.lastW) + sel

    def train(self, inputs, labels, epochs = 1000, displayUpdate = 100):
        # Define the training step for the network. It should include the forward a
        # steps, the updating of the weights, and it should print the error every '
        # It must return the errors so that they can be displayed with matplotlib
        err = []
        for i in range(epochs):
            # Forward propagation
            pred    = self.predict(inputs)
            lvl_err = labels - pred
            err.append( np.average(np.abs(lvl_err)) )

            # Back propagation
            lvl_delta_last   = lvl_err * self.sigmoid_deriv(pred)
            lvl_err_middle   = np.dot(lvl_delta_last, self.lastW.T)
            lvl_delta_middle = lvl_err_middle * self.sigmoid_deriv(self.calcW[-1])

            b_delta_last = np.sum(lvl_delta_last)

            self.lastb += b_delta_last * self.alpha
            self.lastW += np.dot(self.calcW[-1].T, lvl_delta_last) * self.alpha

            # First W & B
            self.initialW += np.dot(inputs.T, lvl_delta_middle) * self.alpha
            b_delta_last   = np.sum(lvl_delta_middle)
            self.initialb += b_delta_last * self.alpha

            # Middle W & B
            for j in range(self.layers - 1):
                tmp  = (len(self.middleW) - 1) - j
                tmp2 = (len(self.calcW) - 2) - j

                lvl_err_middle     = np.dot(lvl_delta_middle, self.middleW[tmp])
                self.middleW[tmp] += np.dot(self.calcW[tmp2].T, lvl_delta_middle) *
                b_delta_middle     = np.sum(lvl_delta_middle)
                self.middleb[j]   += b_delta_middle * self.alpha
                lvl_delta_middle   = lvl_err_middle * self.sigmoid_deriv(self.calcW[

            if i % displayUpdate == 0:
                print("Error: ", err[-1])

        return err
```

Test datasets

XOR

In [11]:

```
XOR_inputs = np.array([
                [0,0],
                [0,1],
                [1,0],
                [1,1]])
hot_labels = np.zeros((4, 2))
labels     = np.array([1,0,1,0])
XOR_labels = np.array([[0,1,1,0]]).T
for i in range(4): hot_labels[i, XOR_labels[i]] = 1
```

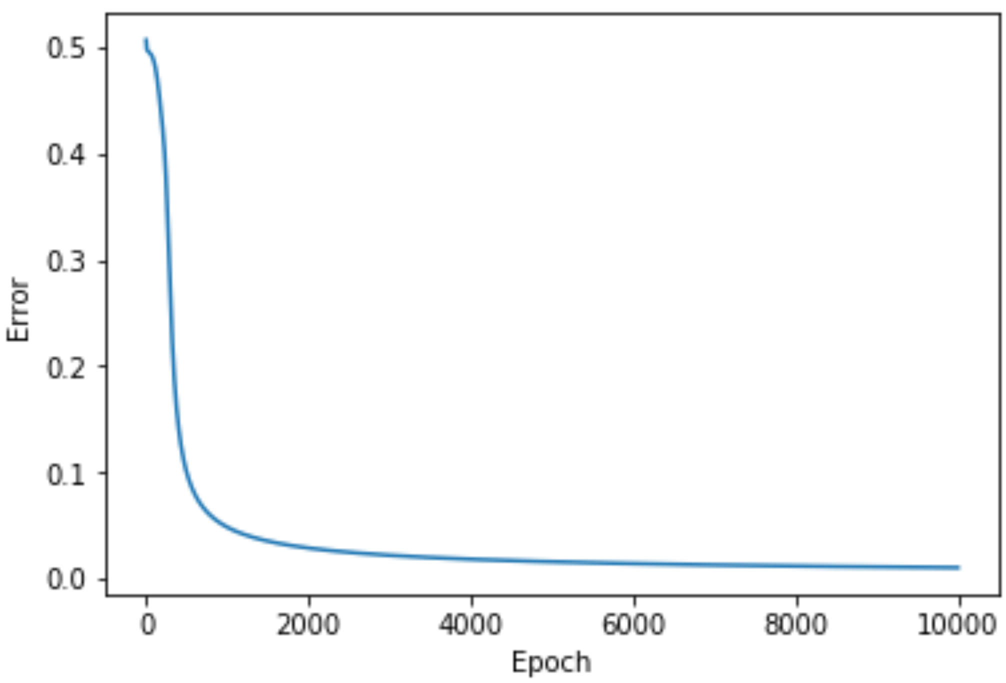
In [20]:

```
# inputs, hlayers, neurons, outputs
architecture = [2, 1, 4, 2]

nn = NeuralNetwork(architecture, 1)
err = nn.train(XOR_inputs, hot_labels, 10000, 1000)

f, p = plt.subplots(1,1)
p.set_xlabel('Epoch')
p.set_ylabel('Error')

p.plot(err)
```

```
Error:  0.5067163741471821
Error:  0.04836028039265587
Error:  0.028752759268767726
Error:  0.021923531109867556
Error:  0.018216148489197056
Error:  0.015819794609415714
Error:  0.014116101570139556
Error:  0.012829509561431224
Error:  0.011816417975138119
Error:  0.010993769576483035
```

Out[20]:

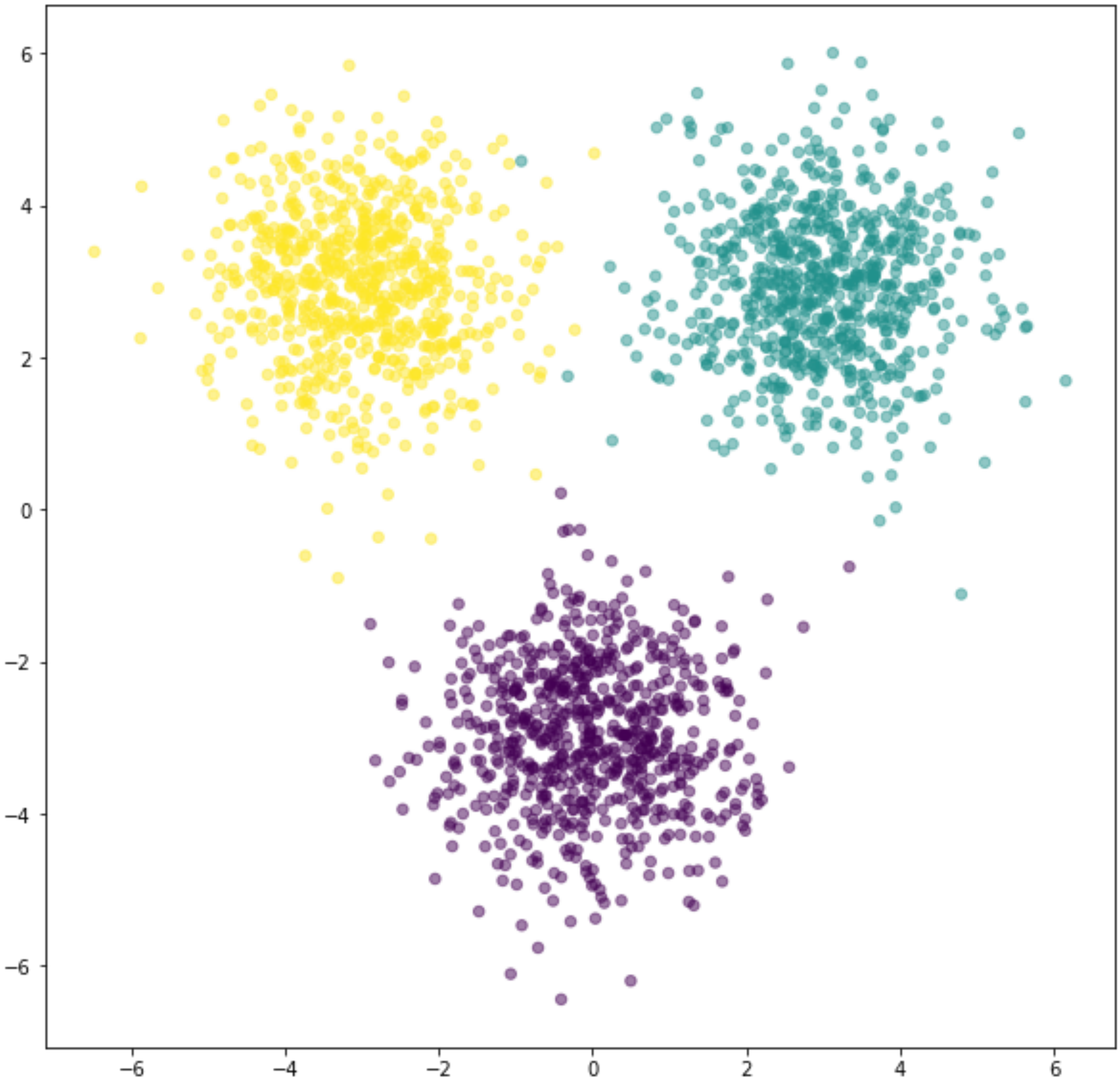
```
[<matplotlib.lines.Line2D at 0xb2b6fb5c0>]
```



Multiple classes

In [22]:

```
# Creates the data points for each class
class_1 = np.random.randn(700, 2) + np.array([0, -3])
class_2 = np.random.randn(700, 2) + np.array([3, 3])
class_3 = np.random.randn(700, 2) + np.array([-3, 3])

feature_set = np.vstack([class_1, class_2, class_3])

labels = np.array([0]*700 + [1]*700 + [2]*700)

one_hot_labels = np.zeros((2100, 3))

for i in range(2100):
    one_hot_labels[i, labels[i]] = 1

plt.figure(figsize=(10,10))
plt.scatter(feature_set[:,0], feature_set[:,1], c=labels, s=30, alpha=0.5)
plt.show()
```



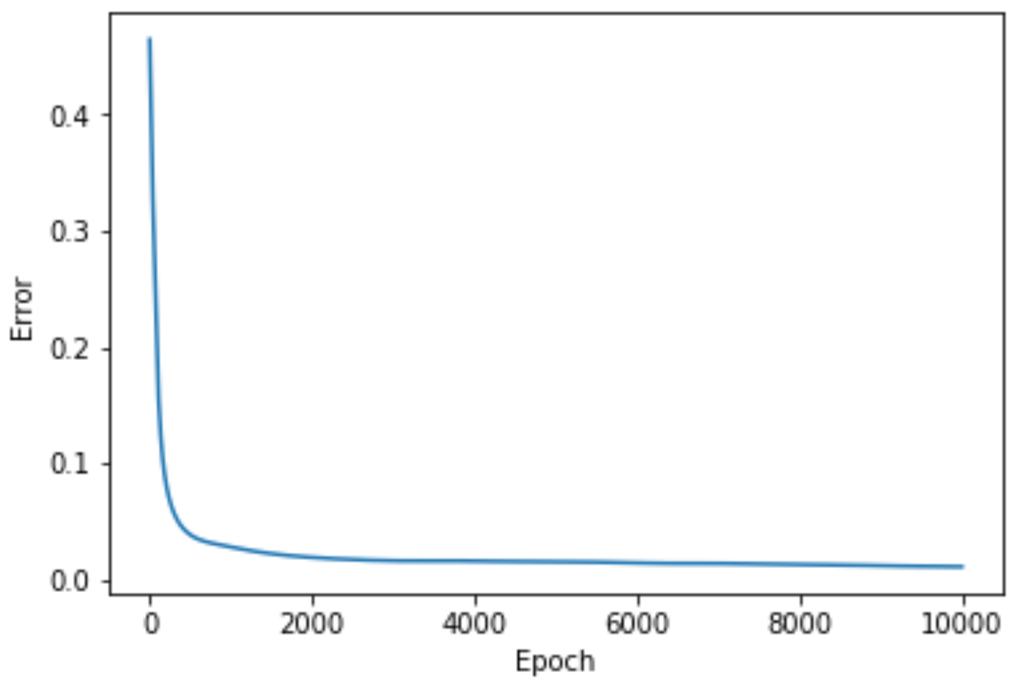
In [23]:

```
#TODO: Test the class with the multiple classes data
architecture2 = [2, 2, 5, 3]
nn2 = NeuralNetwork(architecture2, 0.001)
err2 = nn2.train(feature_set, one_hot_labels, 10000, 1000)

f, p2 = plt.subplots(1,1)
p2.set_xlabel('Epoch')
p2.set_ylabel('Error')

p2.plot(err2)
```

```
Error:  0.46463379955635614
Error:  0.027878488151728 61
Error:  0.018878519925421167
Error:  0.016054310456823987
Error:  0.01573267924167125
Error:  0.015387847818728621
Error:  0.014267821141488562
Error:  0.013751510650309016
Error:  0.012907678971188 04
Error:  0.011750090726241707
```

Out[23]:

```
[&lt;matplotlib.lines.Line2D at 0xb2bc7b208&gt;]
```



On the mnist data set

Train the network to classify hand drawn digits.

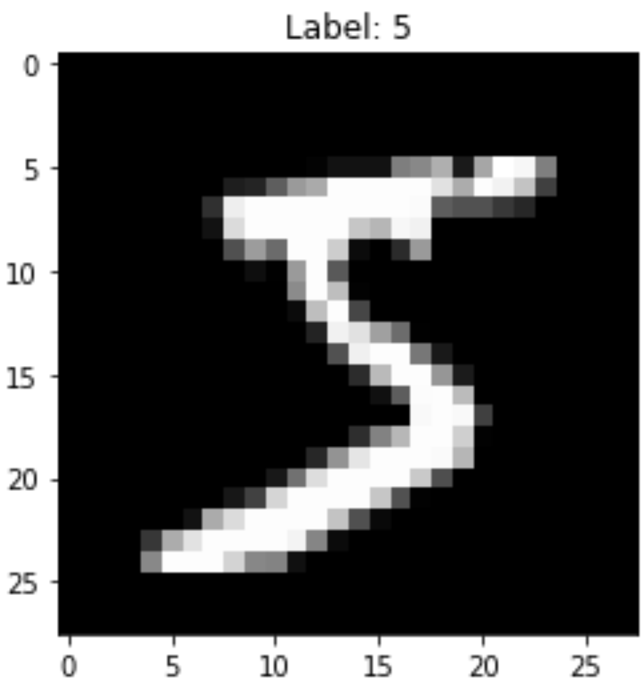
For this data set, if the training step is taking too long, you can try to adjust the architecture of the network to have fewer layers, or you could try to train it with fewer input. The data has already been loaded and preprocesed so that it can be used with the network.

In [24]:

```
# Load the train and test data from the mnist data set
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()

# Plot a sample data point
plt.title("Label: " + str(train_labels[0]))
plt.imshow(train_images[0], cmap="gray")
```

Out[24]:

```
<matplotlib.image.AxesImage at 0xb2bc7b7f0>
```



In [25]:

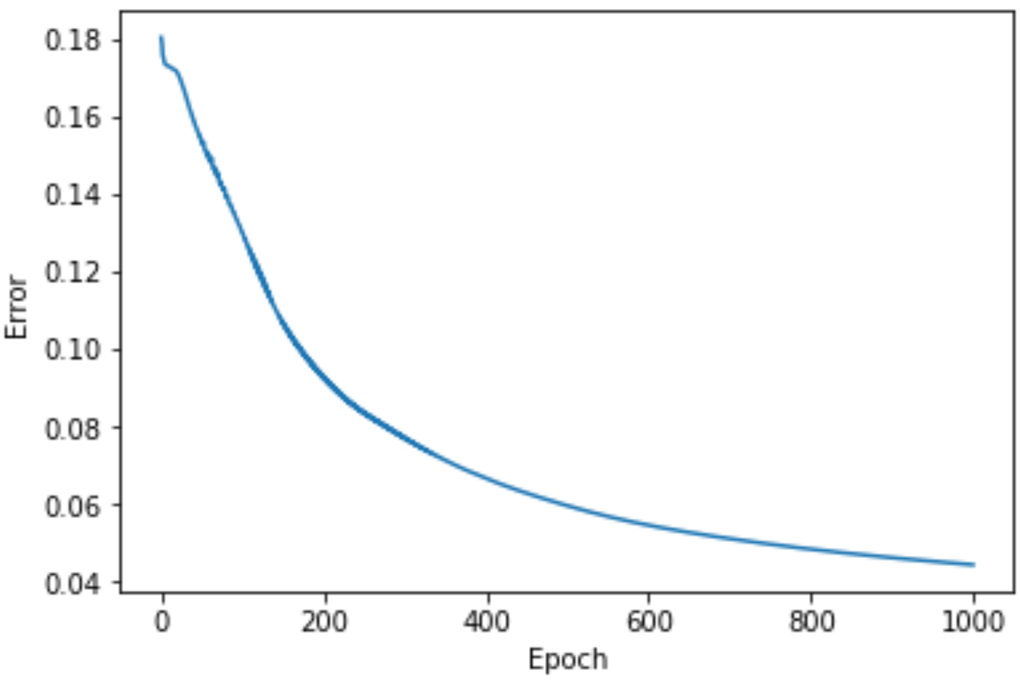
```
# Standardize the data

# Flatten the images
train_images = train_images.reshape((60000, 28 * 28))
# turn values from 0-255 to 0-1
train_images = train_images.astype('float32') / 255

test_images = test_images.reshape((10000, 28 * 28))
test_images = test_images.astype('float32') / 255

# Create one hot encoding for the labels
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)
```

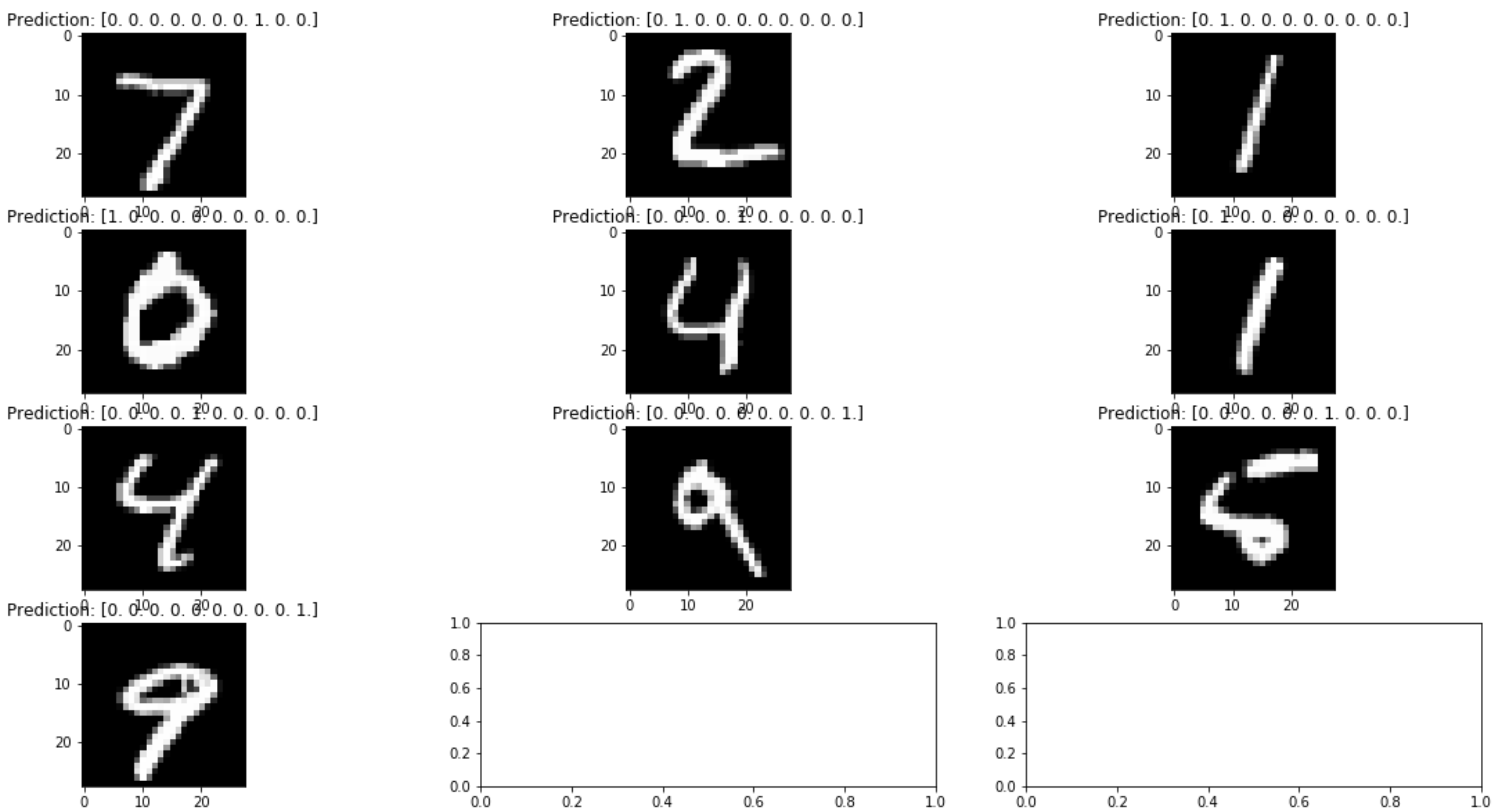
In [32]:

```
# Test the class with the mnist data. Test the training of the network with the test
# record the accuracy of the classification.

architecture3 = [784, 2, 64, 10]
nn3 = NeuralNetwork(architecture3, 0.0008)
err3 = nn3.train(train_images[0:5000], train_labels[0:5000], 1000, 100)

f, p3 = plt.subplots(1,1)
p3.set_xlabel('Epoch')
p3.set_ylabel('Error')

p3.plot(err3)

tests = nn3.predict(test_images[0:1000])
# create one hot encoding on the test data
one_hot_test_labels = to_categorical(test_labels[0:1000])

np.set_printoptions(precision=3, suppress= True, linewidth=75)
# turn predictions to one hot encoding labels
predictions = np.copy(tests)
predictions[predictions > 0.5] = 1
predictions[predictions < 0.5] = 0

error_predictions = []
for index, (prediction, label) in enumerate(zip(predictions[0:10], one_hot_test_labe
    if not np.array_equal(prediction,label):
        error_predictions.append((index, prediction, label))

#show results
f, plots = plt.subplots((len(error_predictions)+3-1)//3, 3, figsize=(20,10))
plots = [plot for sublist in plots for plot in sublist]
```

```python
for img, plot in zip(error_predictions, plots):
    plot.imshow(test_images[img[0]].reshape(28,28), cmap = "gray")
    plot.set_title('Prediction: ' + str(img[1]))
```

```
Error:  0.18045419948360583
Error:  0.13025334277365422
Error:  0.09227545105263922
Error:  0.07681549432831902
Error:  0.06662816270086987
Error:  0.059602499575617224
Error:  0.0545662032192668 7
Error:  0.051091232272253345
Error:  0.04837405990516209
Error:  0.046177804375707475
```





After predicting on the *test_images*, use matplotlib to display some of the images that were not correctly classified. Then, answer the following questions:

1. **Why do you think those were incorrectly classified?**
   IMO, the images had poor quality and bad hand writting causing my NN to get confused at some times.

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2. **What could you try doing to improve the classification accuracy?**
   Before using the NN I would create a image proccesing pipeline that would make the images more clear (e.g. GaussianBlur) so that the hand writting could be more readable.

In [ ]:

```

```