Convolutional networks for MNIST

In [1]:
```
import tensorflow as tf
import matplotlib.pyplot as plt
import numpy as np
from tensorflow import keras
import time
```

```
/software/Anaconda3-5.0.1-el7-x86_64/envs/DL_GPU_cuda_9.0/lib/python3.
6/site-packages/h5py/__init__.py:36: FutureWarning: Conversion of the
second argument of issubdtype from `float` to `np.floating` is depreca
ted. In future, it will be treated as `np.float64 == np.dtype(float).t
ype`.
  from ._conv import register_converters as _register_converters
```

In [2]:
```
def one_hot(values,n_values=10):
    n_v = np.maximum(n_values,np.max(values) + 1)
    oh=np.eye(n_v)[values]
    return oh

X = np.load('/project2/cmsc25025/mnist/MNIST.npy').reshape(-1,28,28,1).as
Y = one_hot(np.load('/project2/cmsc25025/mnist/MNIST_labels.npy'))
n = 70000
train_set = (X[:int(5/7 * n)], Y[:int(5/7 * n)])
val_set = (X[int(5/7 * n):int(6/7 * n)], Y[int(5/7 * n):int(6/7 * n)])
test_set = (X[int(6/7 * n):n], Y[int(6/7 * n):n])
```

In [3]:
```
def show_image(X, nr, nc):
    plt.figure(figsize=(nc*2, nr*2))
    for i in range(nr*nc):
        plt.subplot(nr, nc, i+1)
        plt.imshow(X[i].T[0].T, cmap='gray')
        plt.axis('off')
    plt.axis('off')
    plt.show()

def show_layer_image(layer, nr, nc):
    plt.figure(figsize=(nc*2, nr*2))
    for i in range(nr*nc):
        plt.subplot(nr, nc, i+1)
        plt.imshow(layer[i][0], cmap='gray')
        plt.axis('off')
    plt.axis('off')
    plt.show()
```

(a) Compute the total number of parameters in the original model. And run this model. You shouldn't run more than 20 epochs. (On the RCC with 8 cores it takes about 90 seconds per epoch with all the training data.) You can do this with only 10000 training data to expedite the experiments. For each experiment plot the error rate on training and validation as a function of the epoch number. Show an image with the 32 5 × 5 filters that are estimated in the first layer of the model

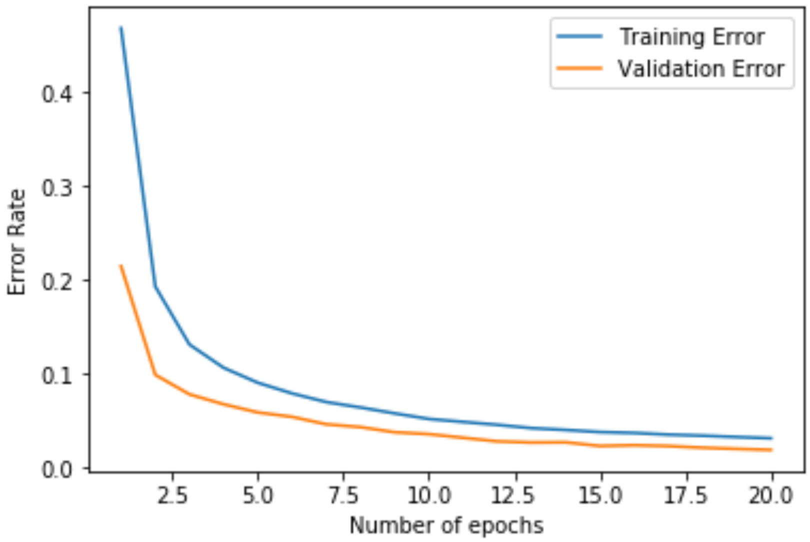
In [83]:
```
def getModel(f1 = 32, f2 = 64, numF = 5, depth = 1):
    model = keras.models.Sequential()
    model.add(keras.layers.InputLayer((28,28,1)))
    model.add(keras.layers.Conv2D(filters=f1, kernel_size=(numF,numF), pa
    model.add(keras.layers.MaxPool2D())
    model.add(keras.layers.Dropout(rate=0.4))
    for i in range(depth):
        model.add(keras.layers.Conv2D(filters=f2, kernel_size=(numF,numF)
    model.add(keras.layers.MaxPool2D())
    model.add(keras.layers.Dropout(rate=0.4))
    model.add(keras.layers.Flatten())
    model.add(keras.layers.Dense(units=1024, activation='relu'))
    model.add(keras.layers.Dense(units=10, activation='softmax'))
    model.compile(optimizer=tf.train.AdadeltaOptimizer(0.1),
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model
```

In [5]:
```
errors = []
model = getModel()
epocs = 20
hist = model.fit(x=train_set[0], y=train_set[1],
          epochs=epocs, batch_size=500,
          shuffle=True,
          validation_data=val_set)
train_errors = 1- np.array(hist.history.get('acc'))
val_errors = 1- np.array(hist.history.get('val_acc'))
```

```
Train on 50000 samples, validate on 10000 samples
Epoch 1/20
50000/50000 [==============================] - 17s 332us/step - loss:
1.6022 - acc: 0.5313 - val_loss: 0.7473 - val_acc: 0.7849
Epoch 2/20
50000/50000 [==============================] - 4s 88us/step - loss: 0.
6168 - acc: 0.8064 - val_loss: 0.3722 - val_acc: 0.9005
Epoch 3/20
50000/50000 [==============================] - 4s 88us/step - loss: 0.
4331 - acc: 0.8683 - val_loss: 0.2835 - val_acc: 0.9213
Epoch 4/20
50000/50000 [==============================] - 4s 88us/step - loss: 0
```

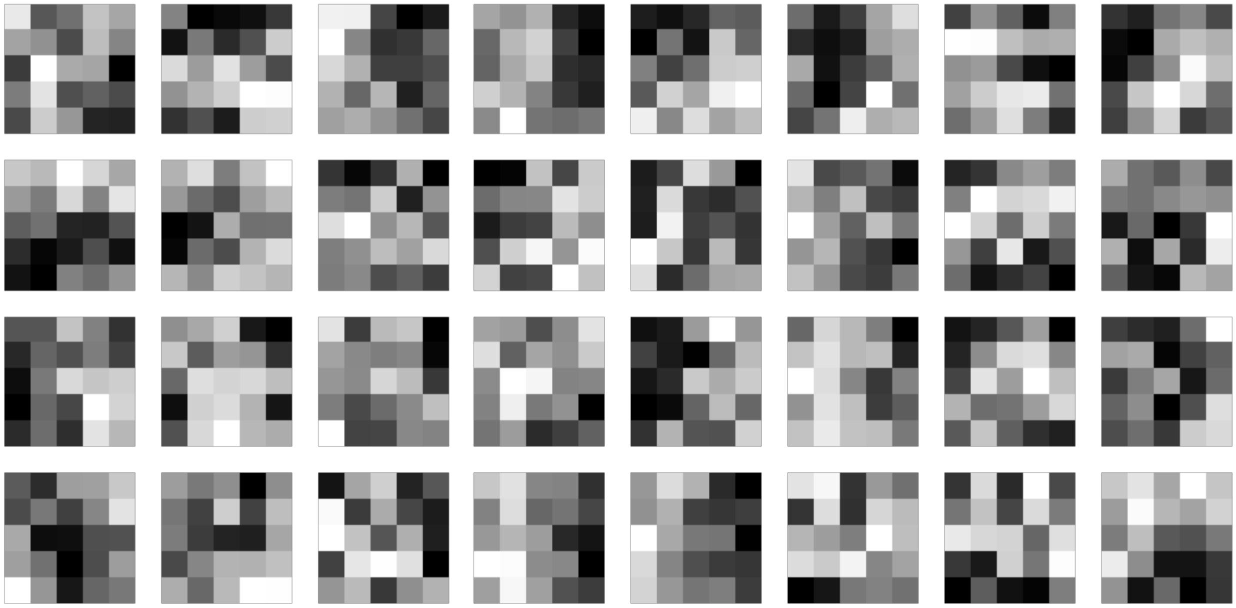
```
3548 - acc: 0.8931 - val_loss: 0.2375 - val_acc: 0.9319
Epoch 5/20
50000/50000 [==============================] - 4s 87us/step - loss: 0.
3026 - acc: 0.9090 - val_loss: 0.2029 - val_acc: 0.9406
Epoch 6/20
50000/50000 [==============================] - 4s 88us/step - loss: 0.
2648 - acc: 0.9203 - val_loss: 0.1813 - val_acc: 0.9453
Epoch 7/20
50000/50000 [==============================] - 5s 93us/step - loss: 0.

2336 - acc: 0.9295 - val_loss: 0.1557 - val_acc: 0.9532
Epoch 8/20
50000/50000 [==============================] - 5s 91us/step - loss: 0.
2152 - acc: 0.9353 - val_loss: 0.1435 - val_acc: 0.9562
Epoch 9/20
50000/50000 [==============================] - 4s 87us/step - loss: 0.
1930 - acc: 0.9416 - val_loss: 0.1277 - val_acc: 0.9617
Epoch 10/20
50000/50000 [==============================] - 4s 88us/step - loss: 0.
1765 - acc: 0.9475 - val_loss: 0.1167 - val_acc: 0.9637
Epoch 11/20
50000/50000 [==============================] - 4s 87us/step - loss: 0.
1652 - acc: 0.9507 - val_loss: 0.1065 - val_acc: 0.9676
Epoch 12/20
50000/50000 [==============================] - 4s 87us/step - loss: 0.
1551 - acc: 0.9538 - val_loss: 0.0984 - val_acc: 0.9714
Epoch 13/20
50000/50000 [==============================] - 4s 87us/step - loss: 0.
1444 - acc: 0.9573 - val_loss: 0.0908 - val_acc: 0.9726
Epoch 14/20
50000/50000 [==============================] - 4s 87us/step - loss: 0.
1358 - acc: 0.9592 - val_loss: 0.0858 - val_acc: 0.9724
Epoch 15/20
50000/50000 [==============================] - 4s 88us/step - loss: 0.
1292 - acc: 0.9615 - val_loss: 0.0789 - val_acc: 0.9763
Epoch 16/20
50000/50000 [==============================] - 4s 88us/step - loss: 0.
1242 - acc: 0.9624 - val_loss: 0.0785 - val_acc: 0.9755
Epoch 17/20
50000/50000 [==============================] - 4s 87us/step - loss: 0.
1173 - acc: 0.9642 - val_loss: 0.0734 - val_acc: 0.9764
Epoch 18/20
50000/50000 [==============================] - 4s 87us/step - loss: 0.
1133 - acc: 0.9653 - val_loss: 0.0684 - val_acc: 0.9782
Epoch 19/20
50000/50000 [==============================] - 4s 88us/step - loss: 0.
1094 - acc: 0.9668 - val_loss: 0.0655 - val_acc: 0.9794
Epoch 20/20
50000/50000 [==============================] - 4s 87us/step - loss: 0.
1050 - acc: 0.9681 - val_loss: 0.0626 - val_acc: 0.9805
```

In [6]:
```
plt.plot(range(1,epocs+1), train_errors)
plt.plot(range(1,epocs+1), val_errors)
plt.legend(["Training Error", "Validation Error"])
plt.xlabel('Number of epochs')
plt.ylabel('Error Rate')
plt.show()
```



It appears that the more epocs, the lower the error. However, there are dimishing returns to adding more epocs as the decrease in error rate decreases. This is the expected behavior as evidently more iterations will improve the model. The time per epoc is constant and thus, the benefit from each epoc is decreasing.

In [8]:
```
show_layer_image(model.layers[0].get_weights()[0].T, 4, 8)
```



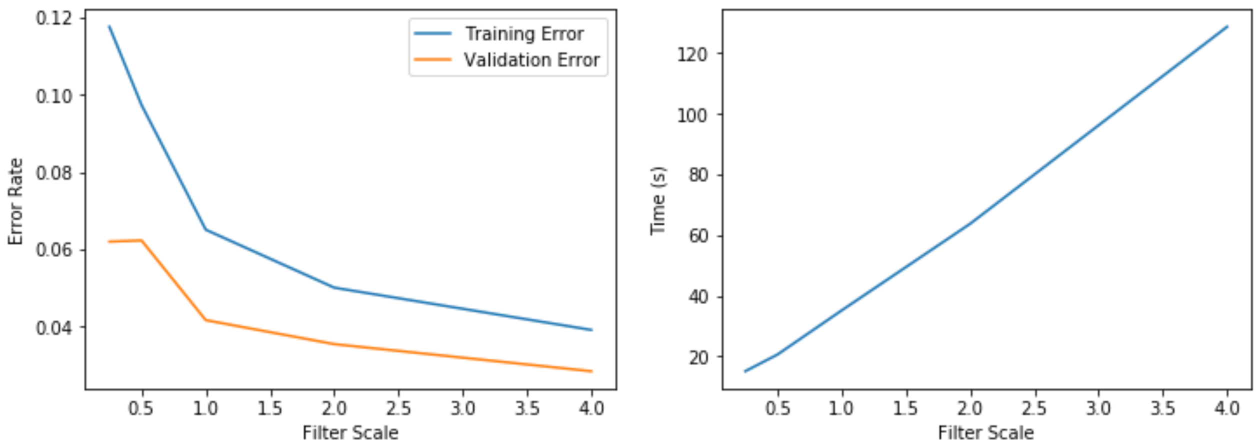
(b) Experiment with changing parameters of the network:

i. Keep the same number of layers and change layer parameters reducing number of parameters by half and doubling the number parameters. Try a few different options. Report the results.

In [10]:
```
filter_parameters = [(8,16), (16,32), (32, 64), (64,128), (128,256)]
filter_scale = [0.25, 0.5, 1, 2, 4]
ftrain_errors = []
fval_errors = []
ftime = []
for f in filter_parameters:
    print("Running with", f, "filters")
    model = getModel(f1 = f[0], f2= f[1])
    start = time.time()
    hist = model.fit(x=train_set[0], y=train_set[1],
              epochs=7, batch_size=500,
              shuffle=True,
              validation_data=val_set)
    ftime.append(time.time() - start)
    ftrain_errors.append(1- hist.history.get('acc')[-1])
    fval_errors.append(1- hist.history.get('val_acc')[-1])
```

```
Running with (8, 16) filters
Train on 50000 samples, validate on 10000 samples
Epoch 1/7
50000/50000 [==============================] - 3s 64us/step - loss: 2.
0927 - acc: 0.3421 - val_loss: 1.6321 - val_acc: 0.7480
Epoch 2/7
50000/50000 [==============================] - 2s 38us/step - loss: 1.
1438 - acc: 0.6796 - val_loss: 0.5992 - val_acc: 0.8548
Epoch 3/7
50000/50000 [==============================] - 2s 38us/step - loss: 0.
6996 - acc: 0.7820 - val_loss: 0.4072 - val_acc: 0.8975
Epoch 4/7
50000/50000 [==============================] - 2s 39us/step - loss: 0.
5562 - acc: 0.8270 - val_loss: 0.3316 - val_acc: 0.9138
Epoch 5/7
50000/50000 [==============================] - 2s 38us/step - loss: 0.
4773 - acc: 0.8544 - val_loss: 0.2894 - val_acc: 0.9225
Epoch 6/7
50000/50000 [==============================] - 2s 38us/step - loss: 0.
```

In [18]:
```
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(filter_scale, ftrain_errors)
plt.plot(filter_scale, fval_errors)
plt.legend(["Training Error", "Validation Error"])
plt.xlabel('Filter Scale')
plt.ylabel('Error Rate')
plt.subplot(1, 2, 2)
plt.plot(filter_scale, ftime)
plt.xlabel('Filter Scale')
plt.ylabel('Time (s)')
plt.show()
```

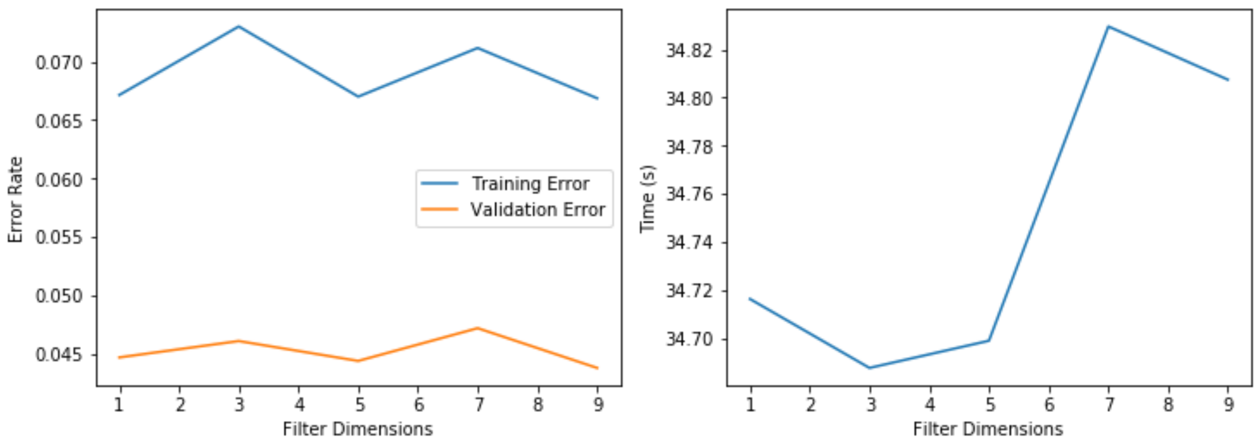


The results from the number of numbers is extremely similar to the results from the number of epochs. As the number of filters increases, the error rate decreases at a decreasing rate. Thus, the more filters we have, the better the results. The runtime appears to increase linearly. Thus, increasing the filter size has diminishing returns.

In [8]:
```
filterdd_parameters = [1,3,5,7,9]
fdtrain_errors = []
fdval_errors = []
fdtime = []
for fd in filterdd_parameters:
    print("Running with dimension:", fd,"x",fd)
    model = getModel(numF = 5)
    start = time.time()
    hist = model.fit(x=train_set[0], y=train_set[1],
                epochs=7, batch_size=500,
                shuffle=True,
                validation_data=val_set)
    fdtime.append(time.time() - start)
    fdtrain_errors.append(1- hist.history.get('acc')[-1])
    fdval_errors.append(1- hist.history.get('val_acc')[-1])
```

```
Running with dimension: 1 x 1
Train on 50000 samples, validate on 10000 samples
Epoch 1/7
50000/50000 [==============================] - 6s 119us/step - loss: 1
.6473 - acc: 0.5246 - val_loss: 0.6766 - val_acc: 0.7936
Epoch 2/7
50000/50000 [==============================] - 5s 95us/step - loss: 0.
6006 - acc: 0.8105 - val_loss: 0.3547 - val_acc: 0.9023
Epoch 3/7
50000/50000 [==============================] - 5s 95us/step - loss: 0.
4223 - acc: 0.8715 - val_loss: 0.2804 - val_acc: 0.9179
Epoch 4/7
50000/50000 [==============================] - 5s 94us/step - loss: 0.
3439 - acc: 0.8958 - val_loss: 0.2299 - val_acc: 0.9327
Epoch 5/7
50000/50000 [==============================] - 5s 95us/step - loss: 0.
2929 - acc: 0.9100 - val_loss: 0.1943 - val_acc: 0.9437
Epoch 6/7
50000/50000 [==============================] - 5s 94us/step - loss: 0.
```

In [19]:
```
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(filterdd_parameters, fdtrain_errors)
plt.plot(filterdd_parameters, fdval_errors)
plt.legend(["Training Error", "Validation Error"])
plt.xlabel('Filter Dimensions')
plt.ylabel('Error Rate')
plt.subplot(1, 2, 2)
plt.plot(filterdd_parameters, fdtime)
plt.xlabel('Filter Dimensions')
plt.ylabel('Time (s)')
plt.show()
```



The filter demensions have interesting results. The error rate does not seem to depend very much on the dimensions (kernal size) of the filter. The results were best with a kernal size of 5x5 and 9x9. Also, the difference in time is extremely small as shown by the scale on the time graph. Thus, I will conclude that dimensions of filters does not have a very significant impact on the results.

ii. Design a deeper network with the same number of parameters as the original net- work. Report the results.

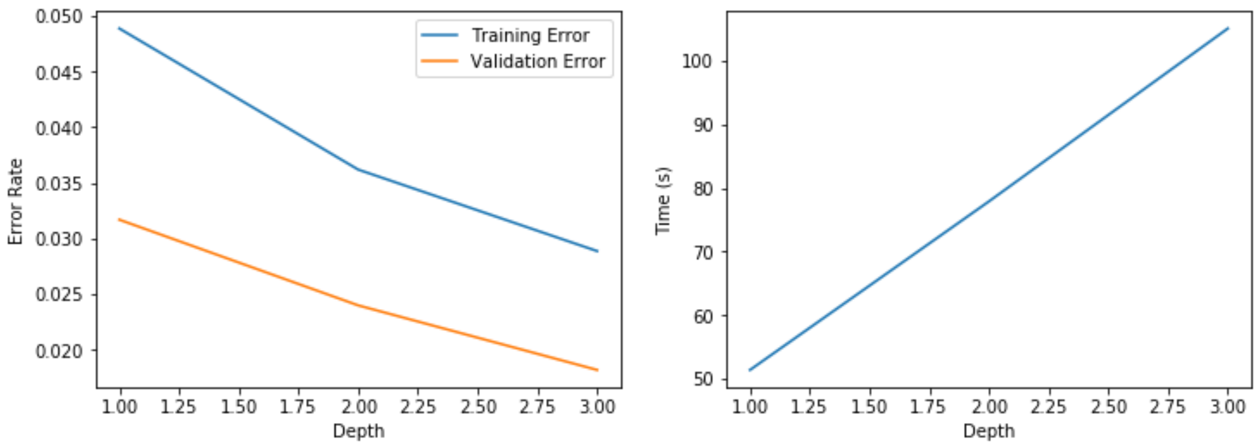
In [6]:
```
depth_parameters = [1,2,3]
dtrain_errors = []
dval_errors = []
dtime = []
for d in depth_parameters:
    print("Running with depth:", d)
    model = getModel(depth = d)
    start = time.time()
    hist = model.fit(x=train_set[0], y=train_set[1],
                     epochs=10, batch_size=500,
                     shuffle=True,
```

```
            validation_data=val_set)
    dtime.append(time.time() - start)
    dtrain_errors.append(1- hist.history.get('acc')[-1])
    dval_errors.append(1- hist.history.get('val_acc')[-1])
```

```
Running with depth: 1
Train on 50000 samples, validate on 10000 samples
Epoch 1/10
50000/50000 [==============================] - 7s 145us/step - loss: 1
.5498 - acc: 0.5629 - val_loss: 0.5914 - val_acc: 0.8489
Epoch 2/10
50000/50000 [==============================] - 5s 95us/step - loss: 0.
5708 - acc: 0.8199 - val_loss: 0.3554 - val_acc: 0.8991
Epoch 3/10
50000/50000 [==============================] - 5s 97us/step - loss: 0.
4085 - acc: 0.8762 - val_loss: 0.2715 - val_acc: 0.9210

Epoch 4/10
50000/50000 [==============================] - 5s 98us/step - loss: 0.
3292 - acc: 0.9008 - val_loss: 0.2200 - val_acc: 0.9358
Epoch 5/10
50000/50000 [==============================] - 5s 98us/step - loss: 0.
2772 - acc: 0.9168 - val_loss: 0.1815 - val_acc: 0.9481
Epoch 6/10
50000/50000 [==============================] - 5s 98us/step - loss: 0.
2405 - acc: 0.9286 - val_loss: 0.1581 - val_acc: 0.9538
Epoch 7/10
50000/50000 [==============================] - 5s 97us/step - loss: 0.
2164 - acc: 0.9354 - val_loss: 0.1409 - val_acc: 0.9571
Epoch 8/10
50000/50000 [==============================] - 5s 98us/step - loss: 0.
1940 - acc: 0.9415 - val_loss: 0.1259 - val_acc: 0.9631
Epoch 9/10
50000/50000 [==============================] - 5s 97us/step - loss: 0.
1766 - acc: 0.9467 - val_loss: 0.1150 - val_acc: 0.9649
Epoch 10/10
50000/50000 [==============================] - 5s 98us/step - loss: 0.
1622 - acc: 0.9511 - val_loss: 0.1044 - val_acc: 0.9683
Running with depth: 2
Train on 50000 samples, validate on 10000 samples
Epoch 1/10
50000/50000 [==============================] - 9s 175us/step - loss: 1
.5677 - acc: 0.5054 - val_loss: 0.5011 - val_acc: 0.8464
Epoch 2/10
50000/50000 [==============================] - 8s 152us/step - loss: 0
.4848 - acc: 0.8479 - val_loss: 0.2783 - val_acc: 0.9140
Epoch 3/10
50000/50000 [==============================] - 8s 152us/step - loss: 0
.3158 - acc: 0.9023 - val_loss: 0.1953 - val_acc: 0.9385
Epoch 4/10
50000/50000 [==============================] - 8s 151us/step - loss: 0
```

```
.2393 - acc: 0.9259 - val_loss: 0.1455 - val_acc: 0.9539
Epoch 5/10
50000/50000 [==============================] - 8s 152us/step - loss: 0
.1971 - acc: 0.9395 - val_loss: 0.1216 - val_acc: 0.9604
Epoch 6/10
50000/50000 [==============================] - 8s 154us/step - loss: 0
.1684 - acc: 0.9475 - val_loss: 0.1059 - val_acc: 0.9645
Epoch 7/10
50000/50000 [==============================] - 8s 154us/step - loss: 0
.1489 - acc: 0.9550 - val_loss: 0.0896 - val_acc: 0.9711
Epoch 8/10
50000/50000 [==============================] - 8s 154us/step - loss: 0
.1366 - acc: 0.9567 - val_loss: 0.0841 - val_acc: 0.9715
Epoch 9/10
50000/50000 [==============================] - 8s 154us/step - loss: 0
.1264 - acc: 0.9613 - val_loss: 0.0759 - val_acc: 0.9749
Epoch 10/10
50000/50000 [==============================] - 8s 154us/step - loss: 0
.1165 - acc: 0.9638 - val_loss: 0.0706 - val_acc: 0.9760
Running with depth: 3
Train on 50000 samples, validate on 10000 samples
Epoch 1/10
50000/50000 [==============================] - 11s 228us/step - loss:
1.6069 - acc: 0.4522 - val_loss: 0.4728 - val_acc: 0.8527
Epoch 2/10
50000/50000 [==============================] - 10s 206us/step - loss:
0.3954 - acc: 0.8759 - val_loss: 0.1936 - val_acc: 0.9416
Epoch 3/10
50000/50000 [==============================] - 10s 207us/step - loss:
0.2352 - acc: 0.9280 - val_loss: 0.1416 - val_acc: 0.9566
Epoch 4/10
50000/50000 [==============================] - 10s 206us/step - loss:
0.1795 - acc: 0.9444 - val_loss: 0.1020 - val_acc: 0.9665
Epoch 5/10
50000/50000 [==============================] - 10s 206us/step - loss:
0.1507 - acc: 0.9527 - val_loss: 0.0903 - val_acc: 0.9723
Epoch 6/10
50000/50000 [==============================] - 10s 206us/step - loss:
0.1312 - acc: 0.9594 - val_loss: 0.0763 - val_acc: 0.9742
Epoch 7/10
50000/50000 [==============================] - 10s 207us/step - loss:
0.1162 - acc: 0.9633 - val_loss: 0.0703 - val_acc: 0.9759
Epoch 8/10
50000/50000 [==============================] - 10s 208us/step - loss:
0.1058 - acc: 0.9666 - val_loss: 0.0634 - val_acc: 0.9795
Epoch 9/10
50000/50000 [==============================] - 10s 208us/step - loss:
0.0971 - acc: 0.9697 - val_loss: 0.0565 - val_acc: 0.9813
Epoch 10/10
50000/50000 [==============================] - 10s 207us/step - loss:
```

In [17]:
```
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(depth_parameters, dtrain_errors)
plt.plot(depth_parameters, dval_errors)
plt.legend(["Training Error", "Validation Error"])
plt.xlabel('Depth')
plt.ylabel('Error Rate')
plt.subplot(1, 2, 2)
plt.plot(depth_parameters, dtime)
plt.xlabel('Depth')
plt.ylabel('Time (s)')
plt.show()
```



The error rate decreases slightly as depth increases. This is the expected behavior as a more complex network will better represent the input data. However, it is important to note that the increase in time is extremely dramatic. This is also expected as a more complex network takes a lot longer to train. I didn't test anything above a depth of 3 as I figured it would take too long.

iii. Once you pick the best configuration try it on the full training set and report the result

We will use 20 epochs, filter sizes of 128 and 256, filter dimensions of 5x5 and a depth of 3 as this gets the best results. However, it should be noted that it takes ~8-10 minutes to run on the full data set. However, as a classifier is normally trained once, I feel like this is accepetable.

In [29]:
```
model = getModel(f1 = 64, f2 = 128, numF = 5, depth = 3)
hist = model.fit(x=train_set[0], y=train_set[1],
                 epochs=20, batch_size=500,
                 shuffle=True,
                 validation_data=val_set)
test_error = 1- model.evaluate(test_set[0], test_set[1])[1]
print("The training error rate is", 1- hist.history.get('acc')[-1])
```

```
print("The validaiton error rate is", 1- hist.history.get('val_acc')[-1])
print("The testing error rate is", test_error)
```

```
Train on 50000 samples, validate on 10000 samples
Epoch 1/20
50000/50000 [==============================] - 24s 480us/step - loss:
1.3335 - acc: 0.5761 - val_loss: 0.3720 - val_acc: 0.8831
Epoch 2/20
50000/50000 [==============================] - 21s 415us/step - loss:
0.3039 - acc: 0.9060 - val_loss: 0.1561 - val_acc: 0.9515
Epoch 3/20
50000/50000 [==============================] - 21s 418us/step - loss:
0.1867 - acc: 0.9431 - val_loss: 0.1166 - val_acc: 0.9613
Epoch 4/20
50000/50000 [==============================] - 21s 417us/step - loss:
0.1402 - acc: 0.9562 - val_loss: 0.0894 - val_acc: 0.9702
Epoch 5/20
50000/50000 [==============================] - 21s 418us/step - loss:
0.1149 - acc: 0.9636 - val_loss: 0.0719 - val_acc: 0.9763
Epoch 6/20
50000/50000 [==============================] - 21s 418us/step - loss:
0.1004 - acc: 0.9685 - val_loss: 0.0660 - val_acc: 0.9766
Epoch 7/20
50000/50000 [==============================] - 21s 418us/step - loss:
0.0900 - acc: 0.9717 - val_loss: 0.0542 - val_acc: 0.9825
Epoch 8/20
50000/50000 [==============================] - 21s 419us/step - loss:
0.0819 - acc: 0.9740 - val_loss: 0.0493 - val_acc: 0.9840
Epoch 9/20
50000/50000 [==============================] - 21s 419us/step - loss:
0.0763 - acc: 0.9765 - val_loss: 0.0495 - val_acc: 0.9834
Epoch 10/20
50000/50000 [==============================] - 21s 422us/step - loss:
0.0698 - acc: 0.9781 - val_loss: 0.0455 - val_acc: 0.9846
Epoch 11/20
50000/50000 [==============================] - 21s 420us/step - loss:
0.0651 - acc: 0.9794 - val_loss: 0.0436 - val_acc: 0.9851
Epoch 12/20
50000/50000 [==============================] - 21s 421us/step - loss:
0.0628 - acc: 0.9801 - val_loss: 0.0411 - val_acc: 0.9857
Epoch 13/20
50000/50000 [==============================] - 21s 420us/step - loss:
0.0587 - acc: 0.9824 - val_loss: 0.0382 - val_acc: 0.9870
Epoch 14/20
50000/50000 [==============================] - 21s 419us/step - loss:
0.0546 - acc: 0.9827 - val_loss: 0.0371 - val_acc: 0.9868
Epoch 15/20
50000/50000 [==============================] - 21s 419us/step - loss:
0.0530 - acc: 0.9834 - val_loss: 0.0353 - val_acc: 0.9876
Epoch 16/20
```

```
50000/50000 [==============================] - 21s 419us/step - loss:
0.0511 - acc: 0.9838 - val_loss: 0.0339 - val_acc: 0.9884
Epoch 17/20
50000/50000 [==============================] - 21s 419us/step - loss:
0.0473 - acc: 0.9852 - val_loss: 0.0344 - val_acc: 0.9877
Epoch 18/20
50000/50000 [==============================] - 21s 419us/step - loss:
0.0443 - acc: 0.9862 - val_loss: 0.0322 - val_acc: 0.9894
Epoch 19/20
50000/50000 [==============================] - 21s 420us/step - loss:
0.0436 - acc: 0.9863 - val_loss: 0.0321 - val_acc: 0.9892
Epoch 20/20
50000/50000 [==============================] - 21s 422us/step - loss:
0.0444 - acc: 0.9864 - val_loss: 0.0296 - val_acc: 0.9899
10000/10000 [==============================] - 3s 300us/step
The training error rate is 0.013640000224113491
The validaiton error rate is 0.010100001096725486
The testing error rate is 0.011700000000000044
```

This error rate is extremely good and thus our optimal model performed extremely well. It does take a long time and the error decreases marginally after the first 8 or so epochs. However, the marginal increase is defintely beneficial if this model was actually going to be used in practice and thus the time cost is worth the increase in accuracy.

(c) Handling variability. A transformed data set /project/cmsc25025/mnist/MNIST TRANSFOR has been created by taking each digit, rotating it by a random angle between [-40,-20]or [20,40], applying a random shift of +/– 3 pixels in each direction and applying a random scale between [.9, 1.1].

In [5]:
```
XT = np.load('/project2/cmsc25025/mnist/MNIST_TEST_TRANS.npy').reshape(-1
n = 70000
trans_train_set = (XT[:int(5/7 * n)], Y[:int(5/7 * n)])
trans_val_set = (XT[int(5/7 * n):int(6/7 * n)], Y[int(5/7 * n):int(6/7 *
trans_test_set = (XT[int(6/7 * n):n], Y[int(6/7 * n):n])
```

Display a few of these examples alongside the original digits.

In [10]:
```
XXT = []
for i in range(10):
    XXT.append(X[i])
    XXT.append(XT[i])

XXT = np.array(XXT)
show_image(XXT,2,10)
```

Using the original architecture to test on this data set. The classification rate drops dramatically.

In [7]:
```
model = getModel()
hist = model.fit(x=trans_train_set[0], y=trans_train_set[1],
              epochs=10, batch_size=500,
              shuffle=True,
              validation_data=trans_val_set)
test_error = 1- model.evaluate(trans_test_set[0], trans_test_set[1])[1]
print("The training error rate is", 1- hist.history.get('acc')[-1])
print("The validaiton error rate is", 1- hist.history.get('val_acc')[-1])
print("The testing error rate is", test_error)
```

```
Train on 50000 samples, validate on 10000 samples
Epoch 1/10
50000/50000 [==============================] - 5s 101us/step - loss: 2
.3022 - acc: 0.1135 - val_loss: 2.3019 - val_acc: 0.1135
Epoch 2/10
50000/50000 [==============================] - 4s 87us/step - loss: 2.
3017 - acc: 0.1136 - val_loss: 2.3015 - val_acc: 0.1135
Epoch 3/10
50000/50000 [==============================] - 4s 87us/step - loss: 2.
3013 - acc: 0.1136 - val_loss: 2.3013 - val_acc: 0.1135
Epoch 4/10
50000/50000 [==============================] - 4s 87us/step - loss: 2.
3011 - acc: 0.1136 - val_loss: 2.3011 - val_acc: 0.1135
Epoch 5/10
50000/50000 [==============================] - 4s 87us/step - loss: 2.
3010 - acc: 0.1136 - val_loss: 2.3010 - val_acc: 0.1135
Epoch 6/10
50000/50000 [==============================] - 4s 87us/step - loss: 2.
3009 - acc: 0.1136 - val_loss: 2.3009 - val_acc: 0.1135
Epoch 7/10
50000/50000 [==============================] - 4s 87us/step - loss: 2.
3008 - acc: 0.1136 - val_loss: 2.3008 - val_acc: 0.1135
Epoch 8/10
50000/50000 [==============================] - 4s 87us/step - loss: 2.
3007 - acc: 0.1136 - val_loss: 2.3007 - val_acc: 0.1135
Epoch 9/10
50000/50000 [==============================] - 4s 88us/step - loss: 2.
3006 - acc: 0.1136 - val_loss: 2.3007 - val_acc: 0.1135
Epoch 10/10
50000/50000 [==============================] - 4s 88us/step - loss: 2.
3006 - acc: 0.1136 - val_loss: 2.3006 - val_acc: 0.1135
10000/10000 [==============================] - 1s 72us/step
The training error rate is 0.8864399997144937
The validaiton error rate is 0.8864999998360872
The testing error rate is 0.8936
```

Try to propose changes to the network architecture so that still training on the original training set you would perform better on the transformed test set. Perform some experiments using a transformed validation set and show the final results on the transformed test set.

First, I will run the model with the original train data and the transformed validation set.

In [85]:
```
model = getModel()
hist = model.fit(x=train_set[0], y=train_set[1],
              epochs=10, batch_size=500,
              shuffle=True,
              validation_data=trans_val_set)
print("The transformed validation error rate is", 1- hist.history.get('va
```

```
Train on 50000 samples, validate on 10000 samples
Epoch 1/10
50000/50000 [==============================] - 8s 164us/step - loss: 1
.6698 - acc: 0.5278 - val_loss: 2.2973 - val_acc: 0.1282
Epoch 2/10
50000/50000 [==============================] - 4s 88us/step - loss: 0.
5667 - acc: 0.8221 - val_loss: 2.2980 - val_acc: 0.1135
Epoch 3/10
50000/50000 [==============================] - 4s 88us/step - loss: 0.
3891 - acc: 0.8839 - val_loss: 2.2979 - val_acc: 0.1135
Epoch 4/10
50000/50000 [==============================] - 4s 88us/step - loss: 0.
3165 - acc: 0.9056 - val_loss: 2.2977 - val_acc: 0.1135
Epoch 5/10
50000/50000 [==============================] - 4s 88us/step - loss: 0.
2709 - acc: 0.9195 - val_loss: 2.2973 - val_acc: 0.1135
Epoch 6/10
50000/50000 [==============================] - 4s 88us/step - loss: 0.
2345 - acc: 0.9289 - val_loss: 2.2964 - val_acc: 0.1135
Epoch 7/10
50000/50000 [==============================] - 4s 88us/step - loss: 0.
2130 - acc: 0.9362 - val_loss: 2.2957 - val_acc: 0.1144
Epoch 8/10
50000/50000 [==============================] - 4s 88us/step - loss: 0.
1921 - acc: 0.9426 - val_loss: 2.2952 - val_acc: 0.1142
Epoch 9/10
50000/50000 [==============================] - 4s 88us/step - loss: 0.
1761 - acc: 0.9472 - val_loss: 2.2949 - val_acc: 0.1152
Epoch 10/10
50000/50000 [==============================] - 4s 89us/step - loss: 0.
1630 - acc: 0.9499 - val_loss: 2.2943 - val_acc: 0.1159
The transformed validation error rate is 0.8840999994426966
```

To prevent overfitting and increase the accuracy in the validation set, I tried multiple things. This includes using a lower number of filters, using a lower kernal size changing the depth, changing the dropout rate and adding a regularizer. Generally, I tried to make changes that would make the model less specific and thus overfit less.

Here is the best model that I came up with:

In [95]:
```
def getTransformedModel(f1 = 32, f2 = 64, numF = 5, depth = 1):
    model = keras.models.Sequential()
    model.add(keras.layers.InputLayer((28,28,1)))
    model.add(keras.layers.Conv2D(filters=f1, kernel_size=(numF,numF), pa
    model.add(keras.layers.MaxPool2D())
    model.add(keras.layers.Dropout(rate=0.4))
    for i in range(depth):
        model.add(keras.layers.Conv2D(filters=f2, kernel_size=(numF,numF)
    model.add(keras.layers.MaxPool2D())
    model.add(keras.layers.Dropout(rate=0.4))
    model.add(keras.layers.Flatten())
    model.add(keras.layers.Dense(units=1024, activation='relu'))
    model.add(keras.layers.Dense(units=10, activation='softmax'))
    model.compile(optimizer=tf.train.AdadeltaOptimizer(0.1),
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model
```

In [96]:
```
model = getTransformedModel(f1 = 16, f2=64)
hist = model.fit(x=train_set[0], y=train_set[1],
              epochs=10, batch_size=500,
              shuffle=True,
              validation_data=trans_val_set)
print("The transformed validation error rate is", 1- hist.history.get('va
```

```
Train on 50000 samples, validate on 10000 samples
Epoch 1/10
50000/50000 [==============================] - 8s 157us/step - loss: 1
.8966 - acc: 0.5349 - val_loss: 2.5617 - val_acc: 0.1652
Epoch 2/10
50000/50000 [==============================] - 3s 70us/step - loss: 0.
8918 - acc: 0.8034 - val_loss: 2.5478 - val_acc: 0.1687
Epoch 3/10
50000/50000 [==============================] - 4s 70us/step - loss: 0.
7137 - acc: 0.8548 - val_loss: 2.5348 - val_acc: 0.1553
Epoch 4/10
50000/50000 [==============================] - 4s 70us/step - loss: 0.
6284 - acc: 0.8769 - val_loss: 2.5221 - val_acc: 0.1527
Epoch 5/10
50000/50000 [==============================] - 4s 70us/step - loss: 0.
5673 - acc: 0.8943 - val_loss: 2.5105 - val_acc: 0.1279
Epoch 6/10
50000/50000 [==============================] - 4s 70us/step - loss: 0.
5229 - acc: 0.9030 - val_loss: 2.5001 - val_acc: 0.1289
Epoch 7/10
50000/50000 [==============================] - 4s 70us/step - loss: 0.
4846 - acc: 0.9127 - val_loss: 2.4907 - val_acc: 0.1222
Epoch 8/10
50000/50000 [==============================] - 4s 70us/step - loss: 0.
4506 - acc: 0.9214 - val_loss: 2.4824 - val_acc: 0.1374
Epoch 9/10
50000/50000 [==============================] - 4s 70us/step - loss: 0.
4223 - acc: 0.9270 - val_loss: 2.4743 - val_acc: 0.1649
Epoch 10/10
50000/50000 [==============================] - 4s 70us/step - loss: 0.
3974 - acc: 0.9320 - val_loss: 2.4671 - val_acc: 0.1743
The transformed validation error rate is 0.8256999976933003
```

None of my proposed changes worked too well. The best error rate I got from making changes was 0.83 when I used regularization and less filters on the first filter layer. Unfortunately, this is still very high. It is interesting to see how hard it is to make a model that can work on transformed data. I generally found that the validation error rate decreased as more epochs were run. This makes sense as more epochs specifies the model more, but the goal is to have a model that can be trained with more epochs and not have the validiation error rate decrease.

```
In [ ]:
```

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