MLND CAPSTONE PROJECT

Project Summary:

In this project, we will train a model that can decode sequences of digits from natural images, and create an app that prints the numbers it sees in real time using Tensorflow

The data that we will be using is Street View House Numbers (SVHN), a large-scale dataset of house numbers in Google Street View images.

Download matlab data

```
# Import required modules
from __future__ import print_function
import matplotlib.pyplot as plt
import numpy as np
import os
import sys
import tarfile
import tensorflow as tf

from IPython.display import display, Image
from scipy import ndimage
from six.moves.urllib.request import urlretrieve
from six.moves import cPickle as pickle

%matplotlib inline
```

```
# Download SVHN data from Stanford University repo
from urllib import urlretrieve

url = 'http://ufldl.stanford.edu/housenumbers/'

def maybe_download(filename, force=False):
  """Download a file if not present, and make sure it's the right size."""
  if force or not os.path.exists(filename):
    filename, _ = urlretrieve(url + filename, filename)
  statinfo = os.stat(filename)
  print('Found and downloaded', filename)
  return filename
```

```
# Download train, test and extra 32_32 matlab files for cropped digits
train_filename = maybe_download('train_32x32.mat')
test_filename = maybe_download('test_32x32.mat')
extra_filename = maybe_download('extra_32x32.mat')
```

```
Found and downloaded train_32x32.mat
Found and downloaded test_32x32.mat
Found and downloaded extra_32x32.mat
```

```
# Load matlab files using scipy.io library
import scipy.io as sio

train_data = sio.loadmat('train_32x32.mat', variable_names='X').get('X')
train_labels = sio.loadmat('train_32x32.mat', variable_names='y').get('y')
test_data = sio.loadmat('test_32x32.mat', variable_names='X').get('X')
test_labels = sio.loadmat('test_32x32.mat', variable_names='y').get('y')
# extra_data = sio.loadmat('extra_32x32.mat', variable_names='X').get('X')
# extra_labels = sio.loadmat('extra_32x32.mat', variable_names='y').get('y')

print("train data: ", train_data.shape, train_labels.shape)
print("test data: ", test_data.shape, test_labels.shape)
# print("extra data: ", extra_data.shape, extra_labels.shape)
```

```
train data:  (32, 32, 3, 73257) (73257, 1)
test data:  (32, 32, 3, 26032) (26032, 1)
```

```
plt.rcParams['figure.figsize'] = (15.0, 15.0)
f, ax = plt.subplots(nrows=1, ncols=10)

for i, j in enumerate(np.random.randint(0, train_labels.shape[0], size=10)):
    ax[i].axis('off')
    ax[i].set_title(train_labels[j], loc='center')
    ax[i].imshow(train_data[:,:,:,j])
```

Pre-processing Data

```
# first we will normalize image data in range of -1 and 1.
train_data = train_data.astype('float32') / 128.0 - 1
test_data = test_data.astype('float32') / 128.0 - 1

# reshaping np array so that we can access data in CNN friendly format i.e. [i,:,:,:] from [:,:,:,i]
train_data = np.transpose(train_data, (3, 0, 1, 2))
test_data = np.transpose(test_data,(3, 0, 1, 2))

#chaning class labels range 1-10 to 0-9
train_labels[train_labels == 10] = 0
test_labels[test_labels == 10] = 0

# processing labels in CNN friendly format i.e. 1-hot-encoding
num_labels = 10
train_labels = train_labels[:,0]
test_labels = test_labels[:,0]
train_labels = (np.arange(num_labels) == train_labels[:, None]).astype(np.float32)
test_labels = (np.arange(num_labels) == test_labels[:, None]).astype(np.float32)

print("train data: ", train_data.shape, train_labels.shape)
print("test data: ", test_data.shape, test_labels.shape)
print("sample one-hot encoding train label: ", train_labels[3])
```

```
train data:  (73257, 32, 32, 3) (73257, 10)
test data:  (26032, 32, 32, 3) (26032, 10)
sample one-hot encoding train label:  [ 0.  0.  0.  1.  0.  0.  0.  0.  0.  0.]
```

```
# Create Validation data from Train data
#from sklearn.model_selection import train_test_split
from sklearn.cross_validation import train_test_split

train_data, valid_data, train_labels, valid_labels = train_test_split(train_data, train_labels,
                                                                      test_size=0.1, random_state=42)

print("train data: ", train_data.shape, train_labels.shape)
print("valid data: ", valid_data.shape, valid_labels.shape)
```

```
train data:  (65931, 32, 32, 3) (65931, 10)
valid data:  (7326, 32, 32, 3) (7326, 10)
```

```
# shuffle dataset
from sklearn.utils import shuffle

train_data, train_labels = shuffle(train_data, train_labels, random_state=0)
test_data, test_labels = shuffle(test_data, test_labels, random_state=0)

print("train data: ", train_data.shape, train_labels.shape)
print("test data: ", test_data.shape, test_labels.shape)
print("valid data: ", valid_data.shape, valid_labels.shape)
```

```
train data:  (65931, 32, 32, 3) (65931, 10)
test data:  (26032, 32, 32, 3) (26032, 10)
valid data:  (7326, 32, 32, 3) (7326, 10)
```

```
# Create pickle file to save processed data
pickle_file = 'SVHN_single.pickle'

try:
  f = open(pickle_file, 'wb')
  save = {
    'train_data': train_data,
    'train_labels': train_labels,
    'test_data': test_data,
    'test_labels': test_labels
    }
  pickle.dump(save, f, pickle.HIGHEST_PROTOCOL)
  f.close()
except Exception as e:
  print('Unable to save data to', pickle_file, ':', e)
  raise

statinfo = os.stat(pickle_file)
print('Compressed pickle size:', statinfo.st_size)
```

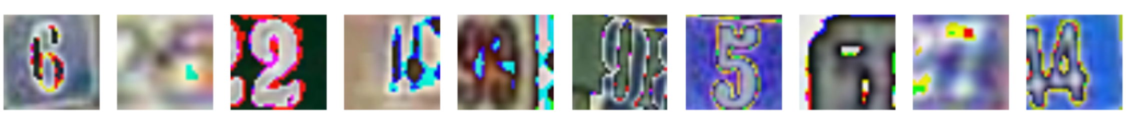
```
Compressed pickle size: 1133720175
```

Training the Model

```
# lets load data from pickle file we previously stored
data_file = 'SVHN_single.pickle' # redefined varaible in case you have completed above steps previously.

print('Tring to load pickle from %s' % data_file)

with open(data_file, 'rb') as file:
    svhn_datasets = pickle.load(file)
    train_data = svhn_datasets['train_data']
    train_labels = svhn_datasets['train_labels']
    test_data = svhn_datasets['test_data']
    test_labels = svhn_datasets['test_labels']
    del svhn_datasets # free up memory
    print('pickle loaded successfully!')

print("train data: ", train_data.shape, train_labels.shape)
print("test data: ", test_data.shape, test_labels.shape)
print("valid data: ", valid_data.shape, valid_labels.shape)
```

```
Tring to load pickle from SVHN_single.pickle
pickle loaded successfully!
train data:  (65931, 32, 32, 3) (65931, 10)
test data:  (26032, 32, 32, 3) (26032, 10)
valid data:  (7326, 32, 32, 3) (7326, 10)
```

```
# Check to make sure image from pickle file is valid

plt.rcParams['figure.figsize'] = (15.0, 15.0)
f, ax = plt.subplots(nrows=1, ncols=10)

for i, j in enumerate(np.random.randint(0, train_labels.shape[0], size=10)):
    ax[i].axis('off')
    # we will not display labels here as 1-hot-encoding cannot be viewed properly in little place
    ax[i].imshow(train_data[j,:,:,:])
```



Prepare CNN using TensorFlow

```
# Weight initialization

def weight_variable(shape):
  initial = tf.truncated_normal(shape, stddev=0.1)
  return tf.Variable(initial)

def bias_variable(shape):
  initial = tf.constant(0.1, shape=shape)
  return tf.Variable(initial)


# 2D Convolution and 2x2 Pooling

def conv2d(x, W):
  return tf.nn.conv2d(x, W, strides=[1, 1, 1, 1], padding='SAME')

def max_pool_2x2(x):
  return tf.nn.max_pool(x, ksize=[1, 2, 2, 1],
                        strides=[1, 2, 2, 1], padding='SAME')
```

```
def accuracy(predictions, labels):
  return (100.0 * np.sum(np.argmax(predictions, 1) == np.argmax(labels, 1))
          / predictions.shape[0])
```

Covnet Model: conv1/pool1/conv2/pool2/fc1/dropout/fc2/softmax

```
graph = tf.Graph()

with graph.as_default():

    # placeholders for input data batch_size x 32 x 32 x 3 and labels batch_size x 10
    x = tf.placeholder(tf.float32, shape=[None, 32, 32, 3])
    y_ = tf.placeholder(tf.float32, shape=[None, 10])

    # Optimizer
    global_step = tf.Variable(0)
    learning_rate = tf.train.exponential_decay(1e-4, global_step=global_step, decay_steps=10000, decay_rate=0.97)

    # Conv Layer 1: with 32 filters of size 5 x 5
    W_conv1 = weight_variable([5, 5, 3, 32])
    b_conv1 = bias_variable([32])

    x_image = tf.reshape(x, [-1, 32, 32, 3])
    h_conv1 = tf.nn.relu(conv2d(x_image, W_conv1) + b_conv1)

    # Pool
    h_pool1 = max_pool_2x2(h_conv1)

    # Conv Layer 2:  with 64 filters of size 5 x 5
    W_conv2 = weight_variable([5, 5, 32, 64])
    b_conv2 = bias_variable([64])

    h_conv2 = tf.nn.relu(conv2d(h_pool1, W_conv2) + b_conv2)

    # Pool
    h_pool2 = max_pool_2x2(h_conv2)


    W_fc1 = weight_variable([8 * 8 * 64, 1024])
    b_fc1 = bias_variable([1024])

    # flatening output of pool layer to feed in FC layer
    h_pool2_flat = tf.reshape(h_pool2, [-1, 8*8*64])

    # FC layer
    h_fc1 = tf.nn.relu(tf.matmul(h_pool2_flat, W_fc1) + b_fc1)

    # Dropout
    keep_prob = tf.placeholder(tf.float32)
    h_fc1_drop = tf.nn.dropout(h_fc1, keep_prob)

    W_fc2 = weight_variable([1024, 10])
    b_fc2 = bias_variable([10])

    # Output
    y_conv = tf.matmul(h_fc1_drop, W_fc2) + b_fc2

    cross_entropy = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(y_conv, y_))
    train_step = tf.train.AdamOptimizer(learning_rate).minimize(cross_entropy, global_step)
    correct_prediction = tf.equal(tf.argmax(y_conv, 1), tf.argmax(y_, 1))
    accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
    saver = tf.train.Saver()
```

```
batch_size = 64
num_steps = 20001

with tf.Session(graph=graph) as session:
    session.run(tf.initialize_all_variables())
    print('Initialized')
    for i in xrange(num_steps):
        offset = (i * batch_size) % (train_labels.shape[0] - batch_size)
        batch_data = train_data[offset:(offset + batch_size), :, :]
        batch_labels = train_labels[offset:(offset + batch_size), :]
        feed_dict = {x: batch_data, y_: batch_labels, keep_prob: 0.5}
        if i%500 == 0:
            train_accuracy = accuracy.eval(feed_dict={x:batch_data, y_: batch_labels, keep_prob: 1.0})
            valid_accuracy = accuracy.eval(feed_dict={x:valid_data, y_: valid_labels, keep_prob: 1.0})
            print("step: %d, training accuracy: %g, validation accuracy: %g" %
                  (i,train_accuracy, valid_accuracy ))
        train_step.run(feed_dict={x: batch_data, y_: batch_labels, keep_prob: 0.5})

    test_accuracy = []
    for i in xrange(len(test_labels)/batch_size):
        batch_data = test_data[i * batch_size: (i * batch_size) + batch_size]
        batch_labels = test_labels[i * batch_size: (i * batch_size) + batch_size, :]
        test_accuracy.append(accuracy.eval(feed_dict={
                    x: batch_data,
                    y_: batch_labels,
                    keep_prob: 1.0}))
    print('test accuracy %g' % np.mean(test_accuracy))
    session.close()
    print('session closed!')
```

```
Initialized
step: 0, training accuracy: 0.0625, validation accuracy: 0.0649741
step: 500, training accuracy: 0.359375, validation accuracy: 0.460415
step: 1000, training accuracy: 0.6875, validation accuracy: 0.665438
step: 1500, training accuracy: 0.828125, validation accuracy: 0.751433
step: 2000, training accuracy: 0.796875, validation accuracy: 0.800983
step: 2500, training accuracy: 0.875, validation accuracy: 0.827054
step: 3000, training accuracy: 0.921875, validation accuracy: 0.840158
step: 3500, training accuracy: 0.875, validation accuracy: 0.857084
step: 4000, training accuracy: 0.8125, validation accuracy: 0.861862
step: 4500, training accuracy: 0.796875, validation accuracy: 0.869369
step: 5000, training accuracy: 0.90625, validation accuracy: 0.872918
step: 5500, training accuracy: 0.875, validation accuracy: 0.880562
step: 6000, training accuracy: 0.953125, validation accuracy: 0.880835
step: 6500, training accuracy: 0.953125, validation accuracy: 0.883702
step: 7000, training accuracy: 0.96875, validation accuracy: 0.886432
step: 7500, training accuracy: 0.890625, validation accuracy: 0.889435
step: 8000, training accuracy: 0.90625, validation accuracy: 0.890117
step: 8500, training accuracy: 0.984375, validation accuracy: 0.892984
step: 9000, training accuracy: 0.921875, validation accuracy: 0.892028
step: 9500, training accuracy: 0.921875, validation accuracy: 0.893257
step: 10000, training accuracy: 0.9375, validation accuracy: 0.894895
step: 10500, training accuracy: 0.9375, validation accuracy: 0.894758
step: 11000, training accuracy: 0.921875, validation accuracy: 0.89626
step: 11500, training accuracy: 0.953125, validation accuracy: 0.900628
step: 12000, training accuracy: 0.96875, validation accuracy: 0.902402
step: 12500, training accuracy: 0.96875, validation accuracy: 0.894895
step: 13000, training accuracy: 0.953125, validation accuracy: 0.89858
step: 13500, training accuracy: 0.953125, validation accuracy: 0.902675
step: 14000, training accuracy: 0.984375, validation accuracy: 0.90445
step: 14500, training accuracy: 0.921875, validation accuracy: 0.902266
step: 15000, training accuracy: 0.96875, validation accuracy: 0.903904
step: 15500, training accuracy: 0.984375, validation accuracy: 0.901993
step: 16000, training accuracy: 0.96875, validation accuracy: 0.904996
step: 16500, training accuracy: 0.953125, validation accuracy: 0.906088
step: 17000, training accuracy: 1, validation accuracy: 0.907999
step: 17500, training accuracy: 0.984375, validation accuracy: 0.909091
step: 18000, training accuracy: 0.9375, validation accuracy: 0.907316
step: 18500, training accuracy: 0.984375, validation accuracy: 0.910456
step: 19000, training accuracy: 0.984375, validation accuracy: 0.908954
step: 19500, training accuracy: 0.96875, validation accuracy: 0.910046
step: 20000, training accuracy: 1, validation accuracy: 0.908135
test accuracy 0.889278
session closed!
```