CapStone Project

This project will try to create a convolution Neural network, train it with Street view house numbers and calculate the accuracy of predicting of house numbers

Data set http://ufldl.stanford.edu/housenumbers/ (http://ufldl.stanford.edu/housenumbers/)

For visualization of the house numbers images you can have a look at the site provided above

In [2]:

```
import tensorflow as tf
import scipy.io as scp
import numpy as np
import random
from scipy import misc
import matplotlib.pyplot as plt

%matplotlib inline
```

In [2]:

```
# Load the data
testData = scp.loadmat('../../data/svhn/test_32x32.mat')
trainData = scp.loadmat('../../data/svhn/train_32x32.mat')

logs_path = '/home/ubuntu/tensorFlowLogs/'
```

In [3]:

```
testDataX = testData['X'].astype('float32') / 128.0 - 1
testDataY = testData['y']

trainDataX = trainData['X'].astype('float32') / 128.0 - 1
trainDataY = trainData['y']
```

In [4]:

```
print type(trainDataX)
print type(trainDataY)

print 'train Data image shape : ', trainDataX.shape
print 'train data output shape : ', trainDataY.shape
print 'test data image shape : ', testDataX.shape
print 'test data output shape : ', testDataY.shape
```

```
<type 'numpy.ndarray'>
<type 'numpy.ndarray'>
train Data image shape :  (32, 32, 3, 73257)
train data output shape :  (73257, 1)
test data image shape :  (32, 32, 3, 26032)
test data output shape :  (26032, 1)
```

In [5]:

```
# try tansposing the array
def transposeArray(data):
    xtrain = []
    trainLen = data.shape[3]
    for x in xrange(trainLen):
        xtrain.append(data[:,:,:,x])

    xtrain = np.asarray(xtrain)
    return xtrain
```

In [6]:

```
trainDataX = transposeArray(trainDataX)
testDataX = transposeArray(testDataX)


print 'New train data image shape : ', trainDataX.shape
```

```
New train data image shape :  (73257, 32, 32, 3)
```

In [7]:

```
def OnehotEndoding(Y):
    Ytr=[]
    for el in Y:
        temp=np.zeros(10)
        if el==10:
            temp[0]=1
        elif el==1:
            temp[1]=1
        elif el==2:
            temp[2]=1
        elif el==3:
            temp[3]=1
        elif el==4:
            temp[4]=1
        elif el==5:
            temp[5]=1
        elif el==6:
            temp[6]=1
        elif el==7:
            temp[7]=1
        elif el==8:
            temp[8]=1
        elif el==9:
            temp[9]=1
        Ytr.append(temp)

    return np.asarray(Ytr)
```

Converting the label to one hot encoding as the prediction really improves. This make sense as well.

In [8]:

```
# convert y to one hot encoding
trainDataY = OnehotEndoding(trainDataY)
testDataY = OnehotEndoding(testDataY)
print 'train data output shape : ', trainDataY.shape
print 'test data output shape : ', testDataY.shape
```

```
train data output shape :  (73257, 10)
test data output shape :  (26032, 10)
```

In [9]:

```
#Neural network parameters
height = 32
width = 32
channel = 3
tags = 10
patch = 5
depth = 16
num_hidden = 128
dropout = 0.75 # Dropout, probability to keep units

learning_rate = 1e-4
```

In [10]:

```
stddev = 1e-1
tf_X = tf.placeholder("float", shape=[None, height, width, channel], name = "X-Input")
tf_Y = tf.placeholder("float", shape=[None, tags], name = "LabeledData")

convW1 = tf.Variable(tf.random_normal([patch, patch, channel, depth], stddev=stddev), na
me="ConvW1")
bias1 = tf.Variable(tf.random_normal([depth], stddev=stddev), name="Bias1")

convW2 = tf.Variable(tf.random_normal([patch, patch, depth, depth], stddev=stddev), nam
e="ConvW2")
bias2 = tf.Variable(tf.random_normal([depth], stddev=stddev), name = "Bias2")

w3 = tf.Variable(tf.random_normal([height // 4 * width // 4 * depth, num_hidden], stdde
v=stddev), name="w3")
bias3 = tf.Variable(tf.random_normal([num_hidden]), name="bias3")

w4 = tf.Variable(tf.random_normal([num_hidden, tags], stddev=stddev), name="w4")
bias4 = tf.Variable(tf.random_normal([tags], stddev=stddev), name="bias4")

keep_prob = tf.placeholder(tf.float32) #dropout (keep probability)
```

Here is the model I have tried to build

Input Image : 32x32x3 first Convolution Hidden layer : 5x5x3x16 Padding : Same, Stride : [1,2,2,1] Output of first Convolution Hidden layer : 16x16x16

Second Convolution Hidden layer : 5x5x16x16 Padding : Same, Stride : [1,2,2,1] Output of Second Convolution Hidden layer : 8x8x16

third Hidden Layer fully connected : 8x8x16 Output of third Hidden layer : 64

Fourth Hidden Layer : 64 x 10

In [11]:

```
#model

def model(X):

    #first layer : Convolution
    conv = tf.nn.conv2d(X, convW1, [1,1,1,1], padding='SAME')
    hidden1 = tf.nn.relu(conv + bias1)

    #second layer : pooling
    hidden2 = tf.nn.max_pool(hidden1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1],
padding='SAME')

    #third layer : convolution
    conv2 = tf.nn.conv2d(hidden2, convW2, [1,1,1,1], padding='SAME')
    hidden3 = tf.nn.relu(conv2 + bias2)

    #fourth layer : pooling
    hidden4 = tf.nn.max_pool(hidden3, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1],
padding='SAME')

    #reshape it to a single Dimensional
    shape = hidden4.get_shape()

    #5th layer : fully connected
    newInput = tf.reshape(hidden4, [-1, shape[1].value * shape[2].value * shape[3].value
])
    hidden5 = tf.nn.relu(tf.matmul(newInput, w3) + bias3)

    dp5 = tf.nn.dropout(hidden5, keep_prob)

    return tf.matmul(dp5, w4) + bias4
```

In [12]:

```
with tf.name_scope('Model'):
    pred = model(tf_X)
with tf.name_scope('loss'):
    loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(pred, tf_Y))


# Optimizer.
with tf.name_scope('AdamOptimizer'):
    optimizer = tf.train.AdamOptimizer(learning_rate).minimize(loss)

with tf.name_scope('accuracy'):
    accuracy = tf.reduce_mean(tf.cast(tf.equal(tf.argmax(tf.nn.softmax(pred),1),tf.argma
x(tf_Y,1)), "float"))

# Create a summary to monitor cost tensor
tf.scalar_summary("loss", loss)
# Create a summary to monitor accuracy tensor
tf.scalar_summary("accuracy", accuracy)
# Merge all summaries into a single op
merged_summary_op = tf.merge_all_summaries()
```

In [13]:

```
def Accuracy(X, Y, message, sess):
    print message, sess.run(accuracy, feed_dict= {tf_X: X, tf_Y: Y, keep_prob:1.0})
```

Ran the model with epoch 50000 and batch size of 128. Received accuracy of around 89% on the test data

Could not run the accuracy on the training set as I was getting OOM exceptions. The training data is huge so cannot run on my 8 core machine. Please refer to the "convHouse.log" file for correct accuracy.

In [ ]:

```
with tf.Session() as sess:
    tf.initialize_all_variables().run()

    # op to write logs to Tensorboard
    summary_writer = tf.train.SummaryWriter(logs_path, graph=tf.get_default_graph())

    epoch = 50000
    batch_size = 128
    print('Initialized')

    p = np.random.permutation(range(len(trainDataX)))
    trX, trY = trainDataX[p], trainDataY[p]
    start = 0
    end = 0

    for step in range(epoch):
        start = end
        end = start + batch_size

        if start >= len(trainDataX):
            start = 0
            end = start + batch_size

        if end >= len(trainDataX):
            end = len(trainDataX) - 1
        if start == end:
            start = 0
            end = start + batch_size

        #print step, start, end

        #batch = np.random.choice(len(trainDataX) - 1, batch_size)
        inX, outY = trX[start:end], trY[start:end]
        _, summary = sess.run([optimizer, merged_summary_op], feed_dict= {tf_X: inX, tf
_Y: outY, keep_prob:0.75})
        summary_writer.add_summary(summary, step)

        if step % 500 == 0:
            print 'cost at each step :', step, 'is :', sess.run(loss, feed_dict={tf_X:
inX, tf_Y: outY, keep_prob:1.0})

    #Accuracy(trX, trY, 'accuracy of training data : ', sess)
    Accuracy(testDataX, testDataY, 'accuracy of test data : ', sess)
```

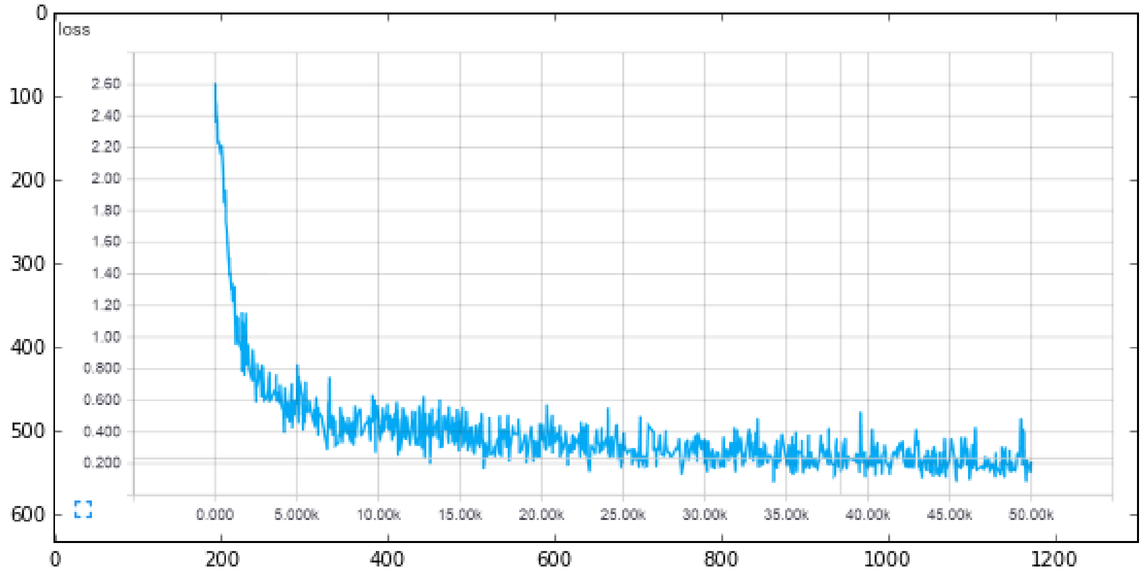
Below figures show the growth of loss and accuracy. Loss decreases with step size and accuracu increases with step size

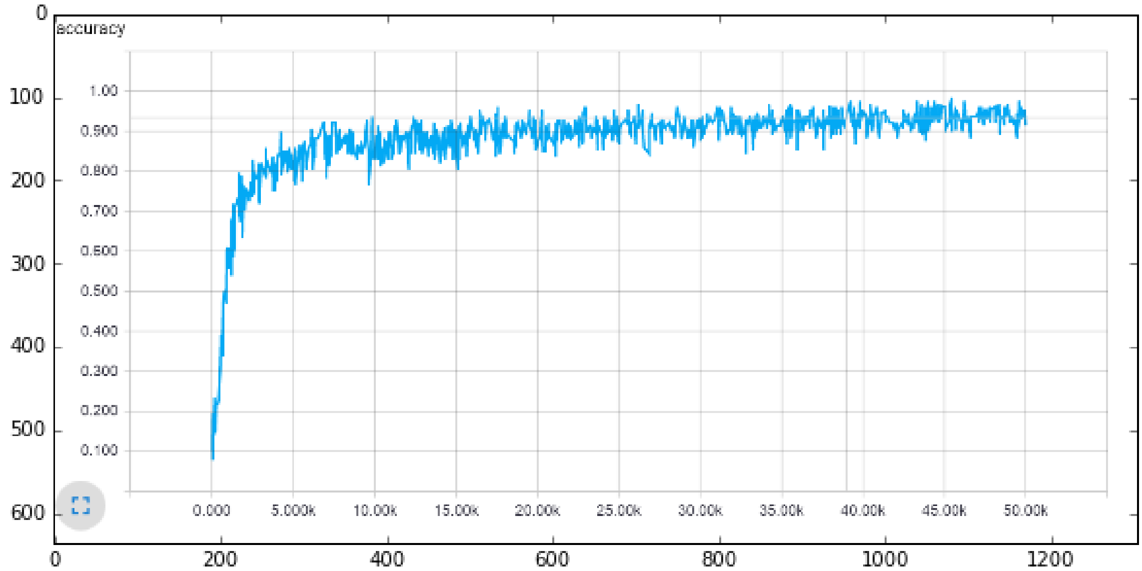
In [21]:

```
fig = plt.figure(figsize=(10,10))
lossImg = misc.imread('loss.PNG')
accuracyImg = misc.imread('accuracy.PNG')

plt.imshow(lossImg)
plt.show()

fig = plt.figure(figsize=(10,10))
plt.imshow(accuracyImg)
plt.show()
```





Initialized cost at each step : 0 is : 2.6576 cost at each step : 500 is : 1.92077 cost at each step : 1000 is : 1.37282 cost at each step : 1500 is : 0.870127 cost at each step : 2000 is : 0.711635 cost at each step : 2500 is : 0.486733 cost at each step : 3000 is : 0.630811 cost at each step : 3500 is : 0.612623 cost at each step : 4000 is : 0.689234 cost at each step : 4500 is : 0.424147 cost at each step : 5000 is : 0.561107 cost at each step : 5500 is : 0.625011 cost at each step : 6000 is : 0.448621 cost at each step : 6500 is : 0.482624 cost at each step : 7000 is : 0.473487 cost at each step : 7500 is : 0.356364 cost at each step : 8000 is : 0.498098 cost at each step : 8500 is : 0.281976 cost at each step : 9000 is : 0.357416 cost at each step : 9500 is : 0.252303 cost at each step : 10000 is : 0.497836 cost at each step : 10500 is : 0.449012 cost at each step : 11000 is : 0.358522 cost at each step : 11500 is : 0.285492 cost at each step : 12000 is : 0.395516 cost at each step : 12500 is : 0.25675 cost at each step : 13000 is : 0.311785 cost at each step : 13500 is : 0.346169 cost at each step : 14000 is : 0.426077 cost at each step : 14500 is : 0.272177 cost at each step : 15000 is : 0.30715 cost at each step : 15500 is : 0.30222 cost at each step : 16000 is : 0.290662 cost at each step : 16500 is : 0.258701 cost at each step : 17000 is : 0.294812 cost at each step : 17500 is : 0.277403 cost at each step : 18000 is : 0.365175 cost at each step : 18500 is : 0.275363 cost at each step : 19000 is : 0.307067 cost at each step : 19500 is : 0.267246 cost at each step : 20000 is : 0.240689 cost at each step : 20500 is : 0.275802 cost at each step : 21000 is : 0.181096 cost at each step : 21500 is : 0.2127 cost at each step : 22000 is : 0.237906 cost at each step : 22500 is : 0.462042 cost at each step : 23000 is : 0.256202 cost at each step : 23500 is : 0.415456 cost at each step : 24000 is : 0.36995 cost at each step : 24500 is : 0.317184 cost at each step : 25000 is : 0.254055 cost at each step : 25500 is : 0.350063 cost at each step : 26000 is : 0.158022 cost at each step : 26500 is : 0.29065 cost at each step : 27000 is : 0.184727 cost at each step : 27500 is : 0.217466 cost at each step : 28000 is : 0.159578 cost at each step : 28500 is : 0.306664 cost at each step : 29000 is : 0.162781 cost at each step : 29500 is : 0.206243 cost at each step : 30000 is : 0.187358 cost at each step : 30500 is : 0.283236 cost at each step : 31000 is : 0.184029 cost at each step : 31500 is : 0.366909 cost at each step : 32000 is : 0.169825 cost at each step : 32500 is : 0.175509 cost at each step : 33000 is : 0.196755 cost at each step : 33500 is : 0.195132 cost at each step : 34000 is : 0.185456 cost at each step : 34500 is : 0.175545 cost at each step : 35000 is : 0.176949 cost at each step : 35500 is : 0.14594 cost at each step : 36000 is : 0.33098 cost at each step : 36500 is : 0.197402 cost at each step : 37000 is : 0.290938 cost at each step : 37500 is : 0.298807 cost at each step : 38000 is : 0.261421 cost at each step : 38500 is : 0.19854 cost at each step : 39000 is : 0.115448 cost at each step : 39500 is : 0.198216 cost at each step : 40000 is : 0.126958 cost at each step : 40500 is : 0.167211 cost at each step : 41000 is : 0.149497 cost at each step : 41500 is : 0.137184 cost at each step : 42000 is : 0.2285 cost at each step : 42500 is : 0.163846 cost at each step : 43000 is : 0.0905895 cost at each step : 43500 is : 0.121242 cost at each step : 44000 is : 0.170001 cost at each step : 44500 is : 0.148984 cost at each step : 45000 is : 0.144387 cost at each step : 45500 is : 0.13648 cost at each step : 46000 is : 0.100441 cost at each step : 46500 is : 0.124121 cost at each step : 47000 is : 0.138372 cost at each step : 47500 is : 0.326166 cost at each step : 48000 is : 0.231229 cost at each step : 48500 is : 0.182549 cost at each step : 49000 is : 0.0651341 cost at each step : 49500 is : 0.190509 accuracy of test data : 0.894822