TF Mutiple Hidden Layers: Regression on Boston Data

This is adapted from Frossard's tutorial (http://www.cs.toronto.edu/~frossard/post/tensorflow/).
This approach is not batched, and the number of layers is fixed.

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Import the Libraries and Tools

In [16]:
```
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.contrib import learn
from sklearn import cross_validation
from sklearn import preprocessing
from sklearn import metrics
from __future__ import print_function

%matplotlib inline
```

Import the Boston Data

We don't worry about adding column names to the data.

In [17]:
```
boston = learn.datasets.load_dataset('boston')
#print( "boston = ", boston )
x, y = boston.data, boston.target
y.resize( y.size, 1 ) #make y = [[x], [x], [x], ... ]

train_x, test_x, train_y, test_y = cross_validation.train_test_split(
                                    x, y, test_size=0.2, random_state=42)

print( "Dimension of Boston test_x = ", test_x.shape )
print( "Dimension of test_y = ", test_y.shape )

print( "Dimension of Boston train_x = ", train_x.shape )
print( "Dimension of train_y = ", train_y.shape )
```

```
Dimension of Boston test_x =  (102, 13)
Dimension of test_y =  (102, 1)
Dimension of Boston train_x =  (404, 13)
Dimension of train_y =  (404, 1)
```

We scale the inputs to have mean 0 and standard variation 1.

In [18]:
```
scaler = preprocessing.StandardScaler( )
train_x = scaler.fit_transform( train_x )
test_x  = scaler.fit_transform( test_x )
```

We verify that we have 13 features...

In [19]:
```
numFeatures =  train_x.shape[1]

print( "number of features = ", numFeatures )
```

```
number of features =  13
```

Input & Output Place-Holders

Define 2 place holders to the graph, one for the inputs one for the outputs...

In [20]:
```
with tf.name_scope("IO"):
    inputs = tf.placeholder(tf.float32, [None, numFeatures], name="X")
    outputs = tf.placeholder(tf.float32, [None, 1], name="Yhat")
```

Define the Coeffs for the Layers

For each layer the input vector will be multiplied by a matrix h of dim n x m, where n is the dimension of the input vector and m the dimention of the output vector. Then a bias vector of dimension m is added to the product.

In [21]:

```
with tf.name_scope("LAYER"):
    # network architecture
    Layers = [numFeatures, 52, 39, 26, 13, 1]

    h1   = tf.Variable(tf.random_normal([Layers[0], Layers[1]], 0, 0.1, dtyp
    h2   = tf.Variable(tf.random_normal([Layers[1], Layers[2]], 0, 0.1, dtyp
    h3   = tf.Variable(tf.random_normal([Layers[2], Layers[3]], 0, 0.1, dtyp
    h4   = tf.Variable(tf.random_normal([Layers[3], Layers[4]], 0, 0.1, dtyp
    hout = tf.Variable(tf.random_normal([Layers[4], Layers[5]], 0, 0.1, dtyp

    b1   = tf.Variable(tf.random_normal([Layers[1]], 0, 0.1, dtype=tf.float3
    b2   = tf.Variable(tf.random_normal([Layers[2]], 0, 0.1, dtype=tf.float3
    b3   = tf.Variable(tf.random_normal([Layers[3]], 0, 0.1, dtype=tf.float3
    b4   = tf.Variable(tf.random_normal([Layers[4]], 0, 0.1, dtype=tf.float3
    bout = tf.Variable(tf.random_normal([Layers[5]], 0, 0.1, dtype=tf.float3
```

Define the Layer operations as a Python funtion

In [22]:

```
def model( inputs, layers ):
    [h1, b1, h2, b2, h3, b3, hout, bout] = layers
    y1 = tf.add( tf.matmul(inputs, h1), b1 )
    y1 = tf.nn.sigmoid( y1 )

    y2 = tf.add( tf.matmul(y1, h2), b2 )
    y2 = tf.nn.sigmoid( y2 )

    y3 = tf.add( tf.matmul(y2, h3), b3 )
    y3 = tf.nn.sigmoid( y3 )

    y4 = tf.add( tf.matmul(y3, h4), b4 )
    y4 = tf.nn.sigmoid( y4 )

    yret  = tf.matmul(y4, hout) + bout
    return yret
```

Define the operations that are performed

We define what happens to the inputs (x), when they are provided, and what we do with the outputs of the layers (compare them to the y values), and the type of minimization that must be done.

In [23]:
```
with tf.name_scope("train"):
    learning_rate = 0.50
    yout = model( inputs, [h1, b1, h2, b2, h3, b3, hout, bout] )

    cost_op = tf.reduce_mean( tf.pow( yout - outputs, 2 ))
    #cost_op = tf.reduce_sum( tf.pow( yout - outputs, 2 ))
    #cost_op =  tf.reduce_mean(-tf.reduce_sum( yout * tf.log( outputs ) ) )

    #train_op = tf.train.GradientDescentOptimizer(learning_rate).minimize(co
    #train_op = tf.train.AdamOptimizer( learning_rate=learning_rate ).minimi
    train_op = tf.train.AdagradOptimizer( learning_rate=learning_rate ).mini
```

Train the Model

We are now ready to go through many sessions, and in each one train the model. Here we train on the whole x-train and y-train data, rather than batching into smaller groups.

In [24]:

```
# define variables/constants that control the training
epoch = 0
last_cost = 0
max_epochs = 50000
tolerance = 1e-6

print( "Beginning Training" )

sess = tf.Session() # Create TensorFlow session
with sess.as_default():

    # initialize the variables
    init = tf.initialize_all_variables()
    sess.run(init)

    # start training until we stop, either because we've reached the max
    # number of epochs, or successive errors are close enough to each other
    # (less than tolerance)

    costs = []
    epochs= []
    while True:
        # Do the training
        sess.run( train_op, feed_dict={inputs: train_x, outputs: train_y} )

        # Update the user every 1000 epochs
        if epoch % 1000==0:
            cost = sess.run(cost_op, feed_dict={inputs: train_x, outputs: tr
            costs.append( cost )
            epochs.append( epoch )

            print( "Epoch: %d - Error: %.4f" %(epoch, cost) )

            # time to stop?
            if epoch > max_epochs :
                # or abs(last_cost - cost) < tolerance:
                print( "STOP!" )
                break
            last_cost = cost

        epoch += 1

    # we're done...
    # print some statistics...

    print( "Test Cost =", sess.run(cost_op, feed_dict={inputs: test_x, outpu

    # compute the predicted output for test_x
    pred_y = sess.run( yout, feed_dict={inputs: test_x, outputs: test_y} )

    print( "\nPrediction\nreal\tpredicted" )
    for (y, yHat ) in zip( test_y, pred_y )[0:10]:
        print( "%1.1f\t%1.1f" % (y, yHat ) )
```

```
Beginning Training
Epoch: 0 - Error: 406.0418
Epoch: 1000 - Error: 5.6299
Epoch: 2000 - Error: 3.2823
Epoch: 3000 - Error: 2.7294
Epoch: 4000 - Error: 2.5422
Epoch: 5000 - Error: 2.3896
Epoch: 6000 - Error: 2.2441
Epoch: 7000 - Error: 2.1843
Epoch: 8000 - Error: 2.1206
Epoch: 9000 - Error: 1.7072
Epoch: 10000 - Error: 1.3639
Epoch: 11000 - Error: 1.0263
Epoch: 12000 - Error: 0.8089
Epoch: 13000 - Error: 0.6670
Epoch: 14000 - Error: 0.5102
Epoch: 15000 - Error: 0.4037
Epoch: 16000 - Error: 0.3435
Epoch: 17000 - Error: 0.2700
Epoch: 18000 - Error: 0.2161
Epoch: 19000 - Error: 0.1671
Epoch: 20000 - Error: 0.1435
Epoch: 21000 - Error: 0.1176
Epoch: 22000 - Error: 0.0976
Epoch: 23000 - Error: 0.0816
Epoch: 24000 - Error: 0.0662
Epoch: 25000 - Error: 0.0612
Epoch: 26000 - Error: 0.0524
Epoch: 27000 - Error: 0.0458
Epoch: 28000 - Error: 0.0407
Epoch: 29000 - Error: 0.0340
Epoch: 30000 - Error: 0.0336
Epoch: 31000 - Error: 0.0303
Epoch: 32000 - Error: 0.0278
Epoch: 33000 - Error: 0.0257
Epoch: 34000 - Error: 0.0238
Epoch: 35000 - Error: 0.0210
Epoch: 36000 - Error: 0.0193
Epoch: 37000 - Error: 0.0196
Epoch: 38000 - Error: 0.0182
Epoch: 39000 - Error: 0.0173
Epoch: 40000 - Error: 0.0165
Epoch: 41000 - Error: 0.0158
Epoch: 42000 - Error: 0.0152
Epoch: 43000 - Error: 0.0147
Epoch: 44000 - Error: 0.0139
Epoch: 45000 - Error: 0.0127
Epoch: 46000 - Error: 0.0159
Epoch: 47000 - Error: 0.0135
Epoch: 48000 - Error: 0.0131
Epoch: 49000 - Error: 0.0128
Epoch: 50000 - Error: 0.0089
Epoch: 51000 - Error: 0.0045
STOP!
Test Cost = 13.6573

Prediction
```

```
real    predicted
23.0    29.9
32.0    36.7
13.0    19.3
22.0    24.5
16.0    18.5
20.0    19.6
17.0    19.4
14.0    17.1
19.0    27.2
16.0    21.7
```

R2 score

In [25]:

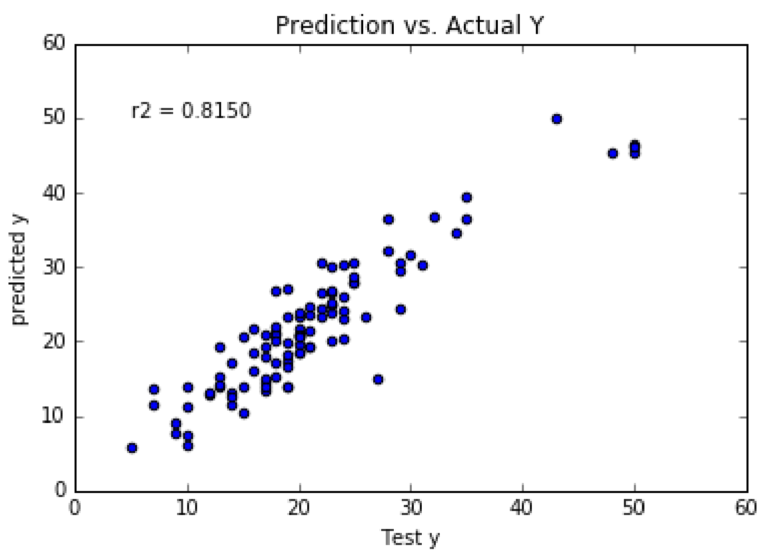
```
r2 =  metrics.r2_score(test_y, pred_y)
print( "mean squared error = ", metrics.mean_squared_error(test_y, pred_y))
print( "r2 score (coef determination) = ", metrics.r2_score(test_y, pred_y))
```

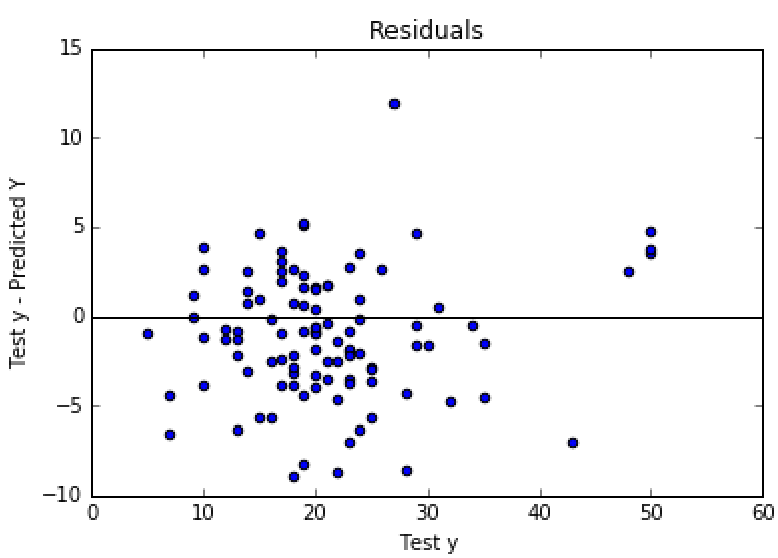
```
mean squared error =  13.6573081195
r2 score (coef determination) =  0.81498519045
```

Plot Prediction vs. Real Housing Price

In [41]:

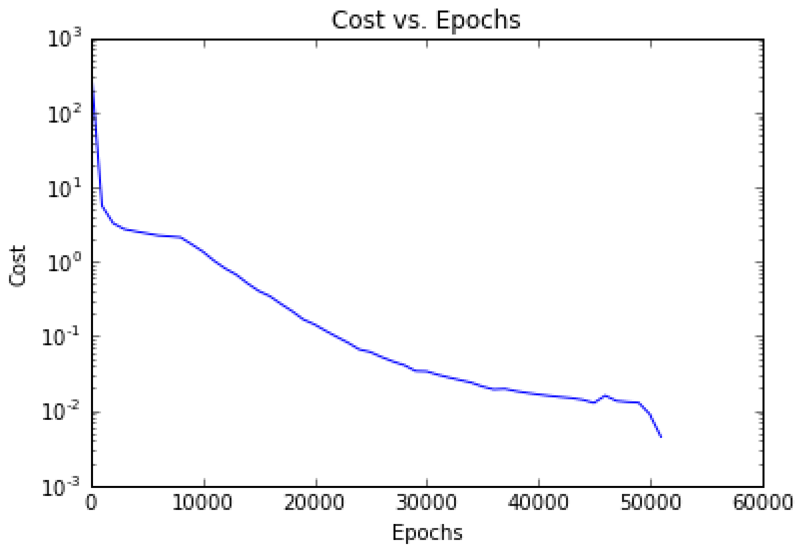
```
fig = plt.figure()
plt.scatter( test_y, pred_y )
plt.text(5, 50, r'r2 = %1.4f' % r2)
plt.xlabel( "Test y" )
plt.ylabel( "predicted y" )
plt.title( "Prediction vs. Actual Y" )
#plt.save( "images/sigmoid_adagrad_52_39_26_13_1.png")
plt.show()
fig.savefig('PredVsRealBoston.png', bbox_inches='tight')

fig = plt.figure()
plt.scatter( test_y, test_y - pred_y )
plt.axhline(0, color='black')
plt.xlabel( "Test y" )
plt.ylabel( "Test y - Predicted Y" )
plt.title( "Residuals" )
plt.show()
fig.savefig('ResidualsBoston.png', bbox_inches='tight')
```





Plot Cost vs Epochs

In [42]:
```
fig = plt.figure()
plt.semilogy( epochs, costs )
plt.xlabel( "Epochs" )
plt.ylabel( "Cost" )
plt.title( "Cost vs. Epochs")
plt.show()
fig.savefig('CostVsEpochs.png', bbox_inches='tight')
```



In [ ]: