E-63 Big Data Analytics - Assignment 09 - TensorFlow

Shanaka De Soysa

Problem 1.

Please considered attached Excel file called Reduced_Car_Data.xlsx. This is the data set we used previously except that we have now removed several descriptive variables and left only: Displacement, Horsepower and Weight . Please build a regression model using TensorFlow that will predict the gasoline consumption (MPG - Miles Per Gallon) of cars based on three remaining variables. Please extract a percentage of data to serve as a training set and a percentage to serve as the test set. Please report on the accuracy of your model.

In [1]:
```
# Import tensorflow and other libraries.
from __future__ import absolute_import
from __future__ import division
from __future__ import print_function

import math
import tensorflow as tf
import matplotlib.pyplot as plt
import numpy as np
import xlrd

%matplotlib inline
```

In [2]:
```
# Settings
DATA_FILE = 'data/Reduced_Car_Data.xlsx'
LOG_FILE = 'logs/Reduced_Car_Data'
NUM_OF_EPOCHS = 5000
LEARN_RATE = 1.0e-7
```

In [3]:
```
# Step 1: read in data from the .xls file
book = xlrd.open_workbook(DATA_FILE, encoding_override="utf-8")
sheet = book.sheet_by_index(0)
data = np.asarray([sheet.row_values(i) for i in range(1, sheet.nrows)])
n_samples = sheet.nrows - 1
```

Please extract a percentage of data to serve as a training set and a percentage to serve as the test set.

In [4]:
```
# Split training and test data
print(n_samples)
np.random.seed(1234)
msk = np.random.rand(len(data)) < 0.75
train = data[msk]
test = data[~msk]
print('training/test data set length: {0}/{1}'.format(len(train), len(te
st)))
```

```
100
training/test data set length: 76/24
```

In [5]:
```
# Step 2: create placeholders for input X (number of fire) and label Y
# (number of theft)
X = tf.placeholder(tf.float32, [None, 3], name='X')
Y = tf.placeholder(tf.float32, [None, 1], name='Y')
```

In [6]:
```
# Step 3: create weight and bias, initialized to 0
W = tf.Variable(tf.zeros([3, 1]), name="weights")
B = tf.Variable(tf.zeros([1]), name="bias")
```

In [7]:
```
# Step 4: build model to predict Y
with tf.name_scope("Wx_b") as scope:
    product = tf.matmul(X, W)
    Y_predicted = product + B
```

In [8]:
```
# Add summary ops to collect data
W_hist = tf.summary.histogram("weight", W)
B_hist = tf.summary.histogram("biases", B)
Y_hist = tf.summary.histogram("y", Y_predicted)
```

In [9]:
```
# Step 5: use the square error as the loss function
# Cost function sum((y_-y)**2)
with tf.name_scope("cost") as scope:
    cost = tf.reduce_mean(tf.square(Y - Y_predicted))
    cost_sum = tf.summary.scalar("cost", cost)
```

In [10]:
```
# Step 6: using gradient descent with learning rate of 0.01 to minimize
 loss
with tf.name_scope("train") as scope:
    train_step =
tf.train.GradientDescentOptimizer(LEARN_RATE).minimize(cost)
```

In [11]:
```
# Calculate accuracy of the model using RMSE
RMSE = tf.sqrt(tf.reduce_mean(tf.square(tf.subtract(Y, Y_predicted))))
```

In [12]:
```
# Traing dataset
train_X = train[:, 1:4]
train_Y = train[:, 4]
train_X = np.array(train_X)
train_Y = np.transpose([train_Y])

all_feed = {X: train_X, Y: train_Y}

sess = tf.Session()

# Merge all the summaries and write them out to logs
merged = tf.summary.merge_all()
writer = tf.summary.FileWriter(LOG_FILE, sess.graph)

init = tf.global_variables_initializer()
sess.run(init)

for i in range(NUM_OF_EPOCHS):
    # Record summary data, and the accuracy every 10 steps
    if i % 100 == 0:
        result = sess.run(merged, feed_dict=all_feed)
        writer.add_summary(result, i)
    else:
        sess.run(train_step, feed_dict=all_feed)

    if i % 1000 == 0:
        print("After %d iteration:" % i)
        #print("W: %s" % sess.run(W))
        #print("b: %f" % sess.run(B))
        print("cost: %f" % sess.run(cost, feed_dict=all_feed))
        print("RMSE: %f" % sess.run(RMSE, feed_dict=all_feed))
```

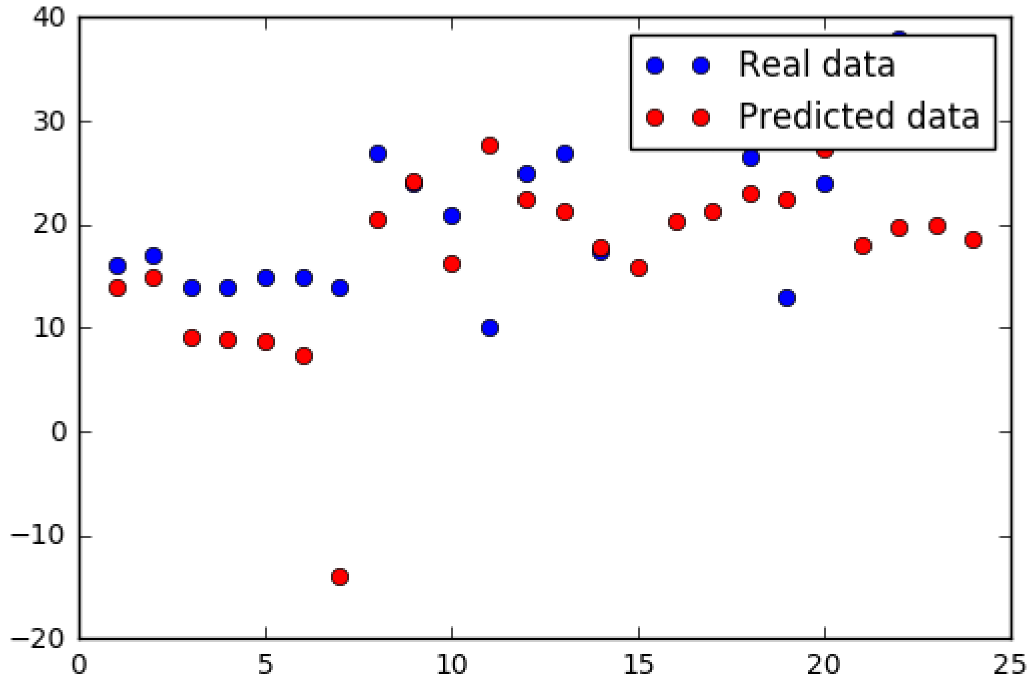
```
After 0 iteration:
cost: 610.105286
RMSE: 24.700310
After 1000 iteration:
cost: 116.813362
RMSE: 10.808023
After 2000 iteration:
cost: 104.587120
RMSE: 10.226785
After 3000 iteration:
cost: 101.781685
RMSE: 10.088691
After 4000 iteration:
cost: 101.118835
RMSE: 10.055786
```

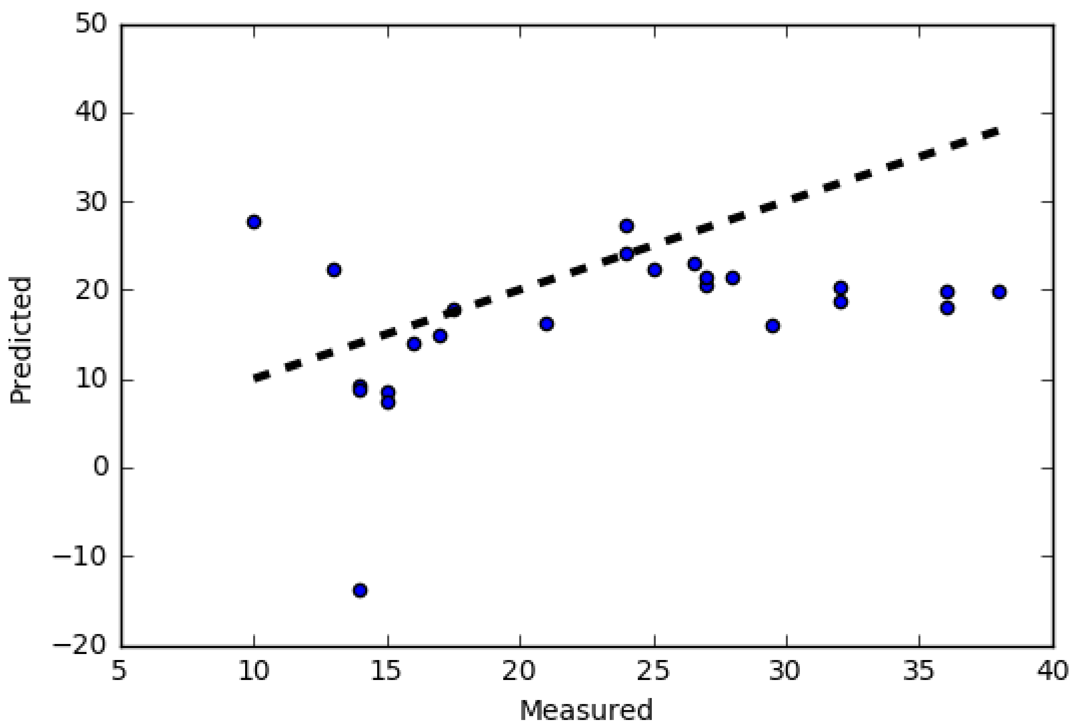
In [13]:
```
W_value, B_value = sess.run([W, B])

print(W_value, B_value)
# close the writer when you're done using it
writer.flush()
writer.close()
```

```
[[-0.12670228]
 [-0.0379815 ]
 [ 0.01695694]] [ 0.00208244]
```

In [14]:
```
# Get predictions for Test dataset
test_X = test[:, 1:4]
test_Y = test[:, 4]
test_X = np.array(test_X)
test_Y = np.transpose([test_Y])

all_feed = {X: test_X, Y: test_Y}

pred_Y = sess.run(Y_predicted, feed_dict=all_feed)
RMSE_Test = sess.run(RMSE, feed_dict=all_feed)

square = np.square(test_Y - pred_Y)
#print("Sum of square errors: {0}".format(np.sum(square)))
#print("Root sum of square errors: {0}".format(math.sqrt(np.sum(squar
e))))
print("Accuracy of the model, RMSE: {0}".format(RMSE_Test))

plt.plot(range(1, len(test) + 1), test_Y, 'bo', label='Real data')
plt.plot(range(1, len(test) + 1), pred_Y, 'ro', label='Predicted data')
plt.legend()
plt.show()

fig, ax = plt.subplots()
ax.scatter(test_Y, pred_Y)
ax.plot([test_Y.min(), test_Y.max()], [
        test_Y.min(), test_Y.max()], 'k--', lw=3)
ax.set_xlabel('Measured')
ax.set_ylabel('Predicted')
plt.show()
```

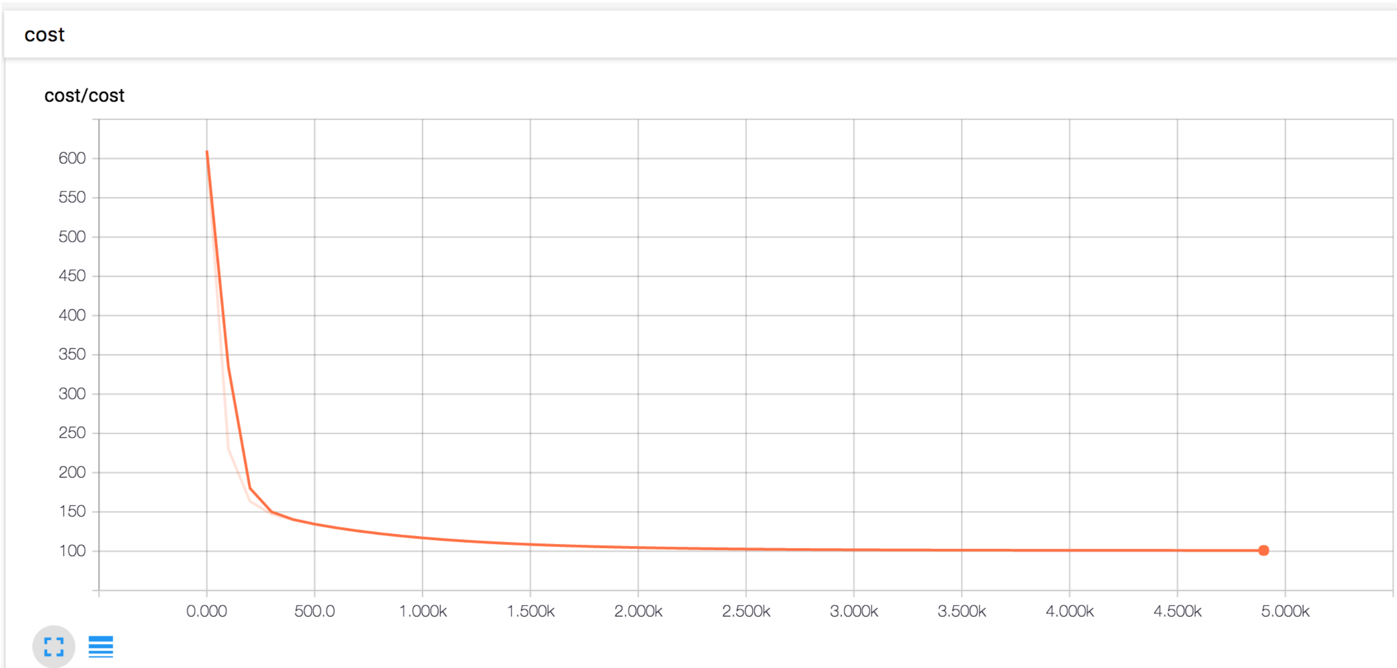
```
Accuracy of the model, RMSE: 11.02444076538086
```



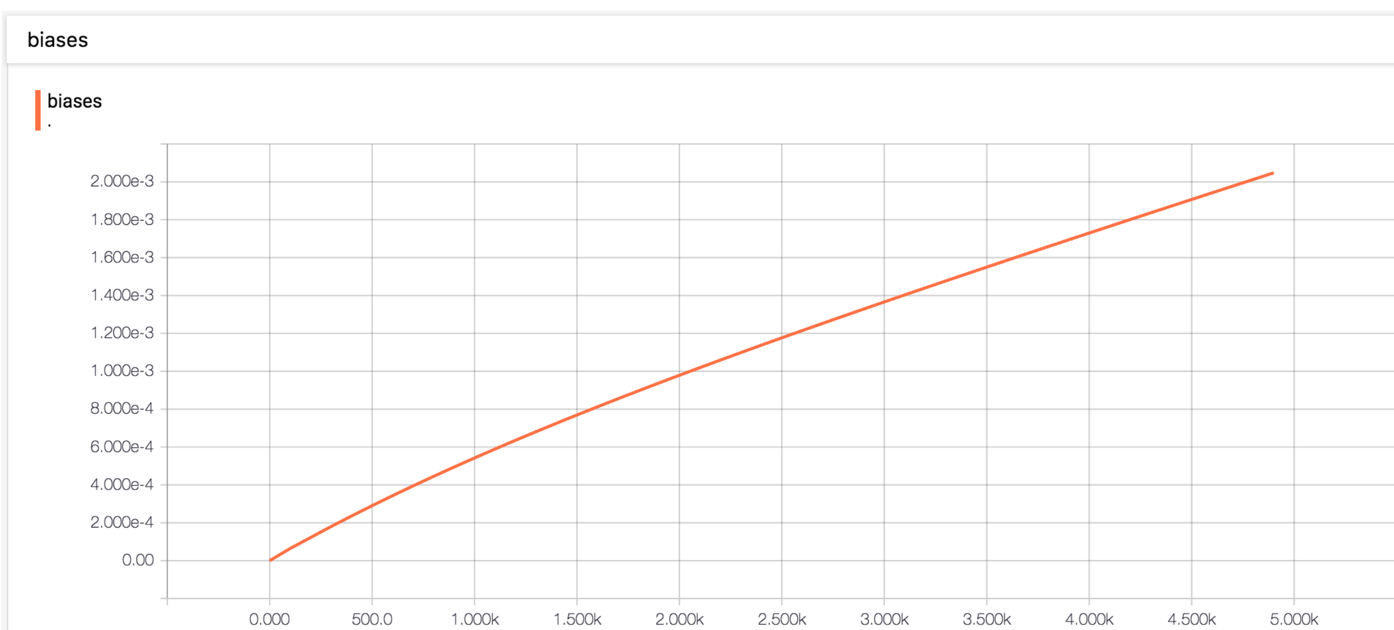


In [19]:
```
# Close the session
sess.close()
```

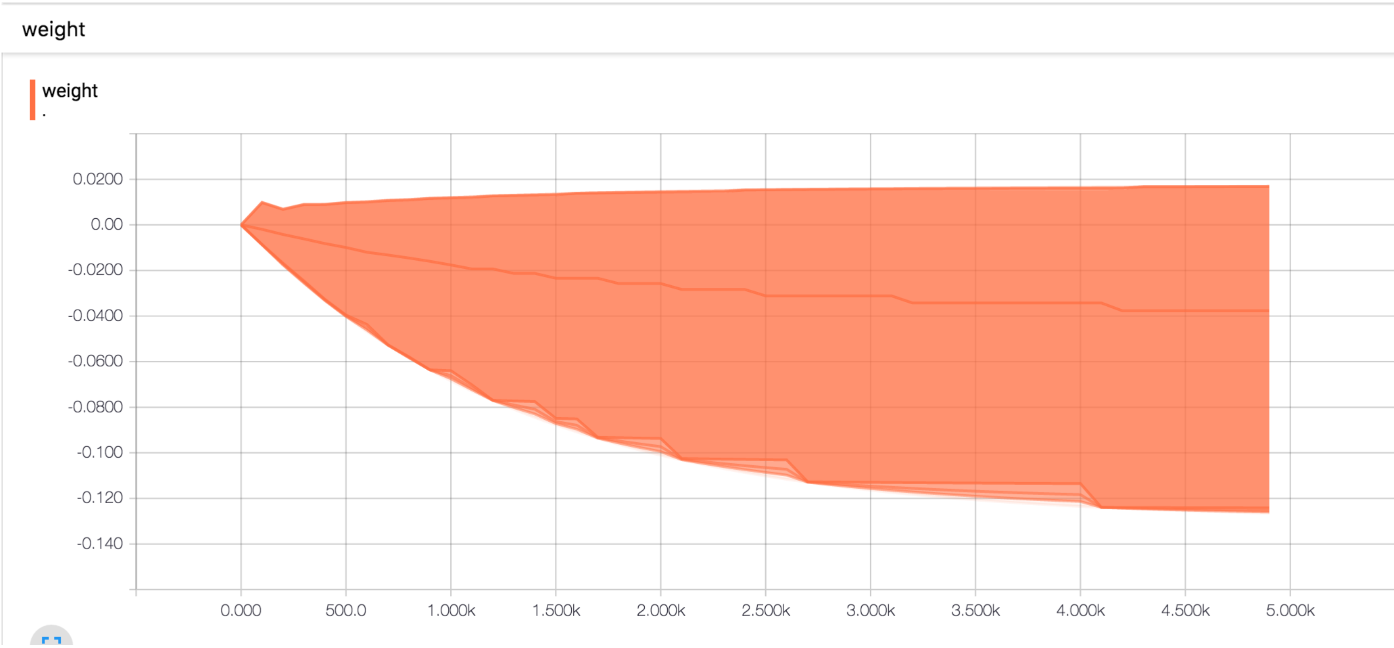
TensorBoard Cost Graph



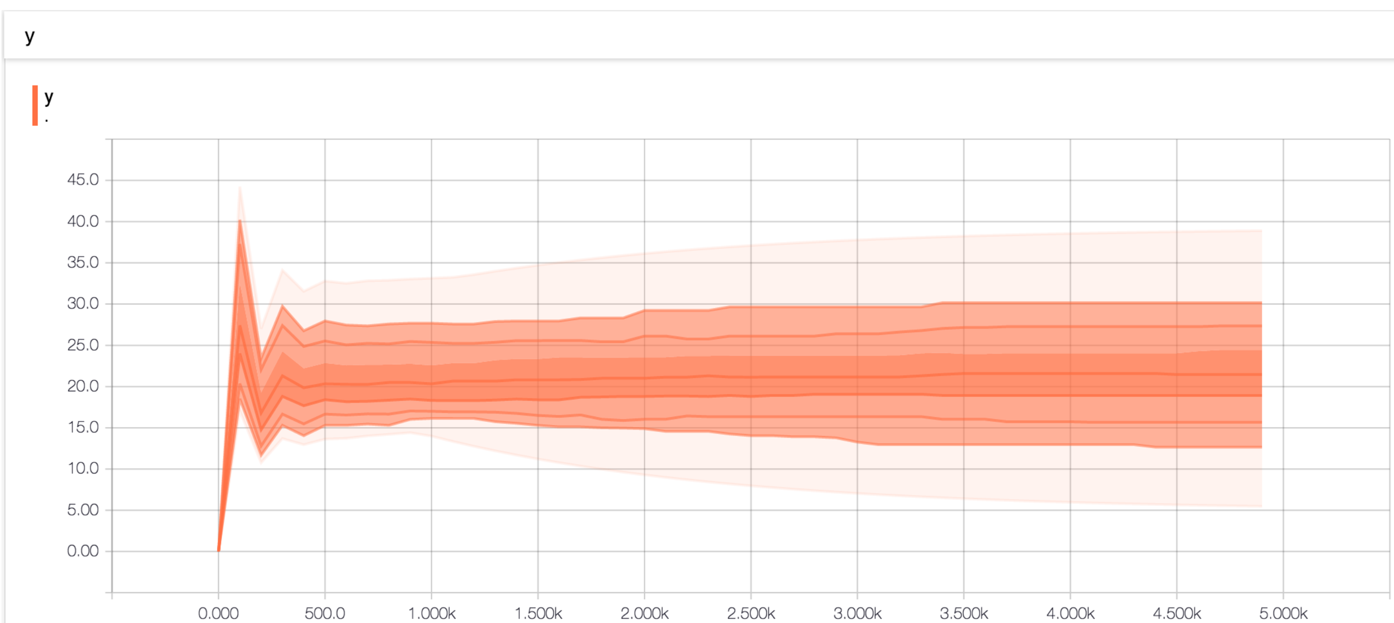
TensorBoard Bias Distribution Graph



TensorBoard Weight Distribution Graph



TensorBoard Y Distribution Graph



Problem 2.

Consider the attached file linear_regression.py and the attached data file fire_theft.xls. Compare results of this original solution to a solution with new feature quadratic in X (the number of fires), and then with a solution cubic in X. For all three solutions, plot the diagram of predicted values vs. original target values. You can have three different diagrams or you can present all those curves and data on one diagram. Either way is fine. Perform these calculations using the same set of parameters. Present TensorBoard Graphs for all three solutions and point to any differences between them.

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

Define function to normalize features

In [2]:
```
def feature_normalize(dataset):
    mu = np.mean(dataset, axis=0)
    sigma = np.std(dataset, axis=0)
    return (dataset - mu) / sigma
```

Define function for linear regression with different parameters and scale

In [3]:
```
def analyse_fire_theft_regression(scale='linear',
                                  learning_rate=1.0e-3,
                                  num_of_epochs=100,
                                  data_file='data/fire_theft.xls',
                                  log_file='logs/fire_theft'):
    # Step 1: read in data from the .xls file
    book = xlrd.open_workbook(data_file, encoding_override="utf-8")
    sheet = book.sheet_by_index(0)
    data = np.asarray([sheet.row_values(i) for i in range(1,
sheet.nrows)])
    n_samples = sheet.nrows - 1

    # Normalize features
    all_xs = feature_normalize(data.T[0])
    all_xs = np.transpose([all_xs])
    all_ys = np.transpose([data.T[1]])

    # Step 2: create placeholders for input X (number of fire) and label
 Y
    # (number of theft)
    X = tf.placeholder(tf.float32, [None, 1], name='X')
    Y = tf.placeholder(tf.float32, [None, 1], name='Y')

    # Step 3: create weight and bias, initialized to 0
    W1 = tf.Variable(tf.zeros([1, 1]), name="weights")
    W2 = tf.Variable(tf.zeros([1, 1]), name="weights")
```

```
    W3 = tf.Variable(tf.zeros([1, 1]), name="weights")
    B = tf.Variable(tf.zeros([1]), name="bias")

    # Step 4: build model to predict Y
    with tf.name_scope("Wx_b") as scope:
        # Linear by default
        Y_predicted = X * W1 + B

        if scale == 'quadratic':
            Y_predicted = X ** 2 * W2 + X * W1 + B
        if scale == 'cubic':
            Y_predicted = X ** 3 * W3 + X ** 2 * W2 + X * W1 + B

    # Add summary ops to collect data
    W_hist = tf.summary.histogram("weight", [W1, W2, W3])
    B_hist = tf.summary.histogram("biases", B)
    Y_hist = tf.summary.histogram("y", Y_predicted)

    # Step 5: use the square error as the loss function
    with tf.name_scope("loss") as scope:
        loss = tf.reduce_mean(tf.square(Y - Y_predicted), name='loss')
        los_sum = tf.summary.scalar("loss", loss)

    # Step 6: using gradient descent with learning rate of 0.01 to minim
ize
    # loss

    with tf.name_scope("train") as scope:
        train_step = tf.train.GradientDescentOptimizer(
            learning_rate).minimize(loss)

    # Calculate accuracy of the model using RMSE
    RMSE = tf.sqrt(tf.reduce_mean(tf.square(tf.subtract(Y,
Y_predicted))))

    sess = tf.Session()

    # Merge all the summaries and write them out to logs
    merged = tf.summary.merge_all()
    writer = tf.summary.FileWriter(log_file, sess.graph)

    init = tf.global_variables_initializer()
    sess.run(init)

    all_feed = {X: all_xs, Y: all_ys}

    for i in range(num_of_epochs):
        # Record summary data, and the accuracy every 10 steps
        if i % 10 == 0:
            result = sess.run(merged, feed_dict=all_feed)
            writer.add_summary(result, i)
        else:
            sess.run(train_step, feed_dict=all_feed)

        #if i % 10 == 0:
            #print("After %d iteration:" % i)
            #print("W: %s" % sess.run(W))
```

```
            #print("b: %f" % sess.run(B))
            #print("loss: %f" % sess.run(loss, feed_dict=all_feed))
            #print("RMSE: %f" % sess.run(RMSE, feed_dict=all_feed))

    B_val, W1_val, W2_val, W3_val = sess.run([B, W1, W2, W3])
    print("Type: {0}, B: {1} W1: {2}, W2: {3}, W3: {4}"
          .format(scale, B_val, W1_val, W2_val, W3_val))

    print("loss: {0}".format(sess.run(loss, feed_dict=all_feed)))
    print("RMSE: {0}".format(sess.run(RMSE, feed_dict=all_feed)))

    # Step 9: output the values of w and b
    all_feed = {X: all_xs}

    pred_Y = sess.run(Y_predicted, feed_dict=all_feed)

    writer.flush()
    writer.close()
    sess.close()

    X, Y = all_xs, all_ys
    plt.plot(X, Y, 'bo', label='Real data')
    plt.plot(X, pred_Y, 'ro', label='Predicted data')
    plt.xlabel('Standardized X')
    plt.ylabel('Y')

    plt.legend()
    plt.show()

    fig, ax = plt.subplots()
    ax.scatter(Y, pred_Y)
    ax.plot([Y.min(), Y.max()], [Y.min(), Y.max()], 'k--', lw=3)
    ax.set_xlabel('Measured')
    ax.set_ylabel('Predicted')
    plt.show()
```

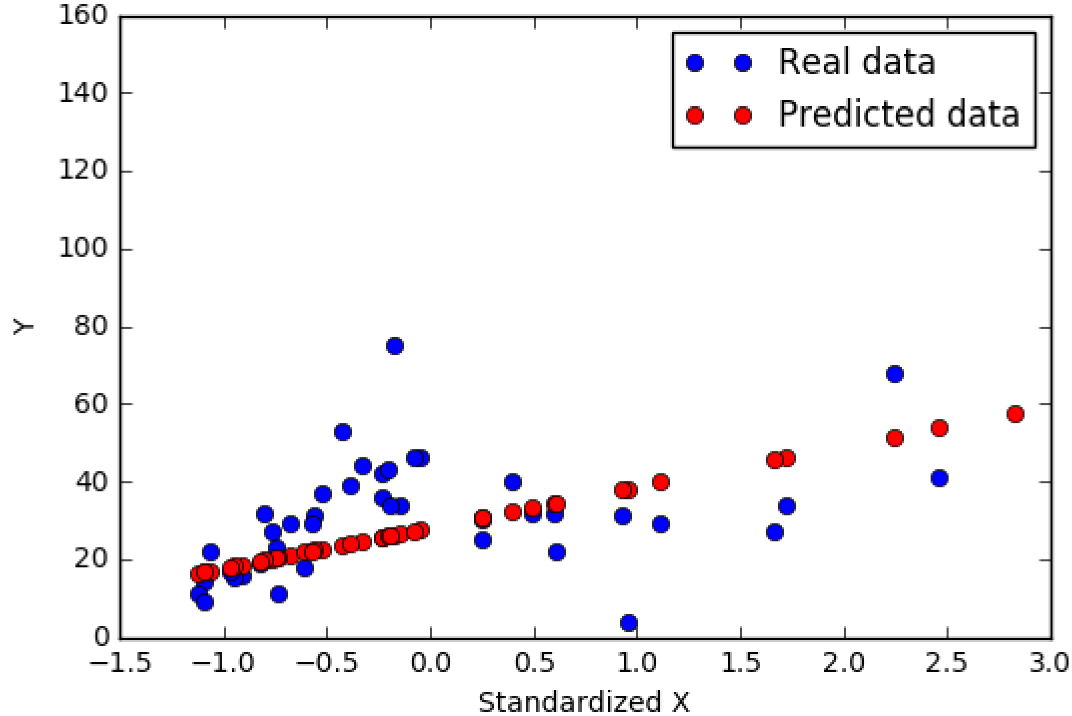
Parameters for Regression

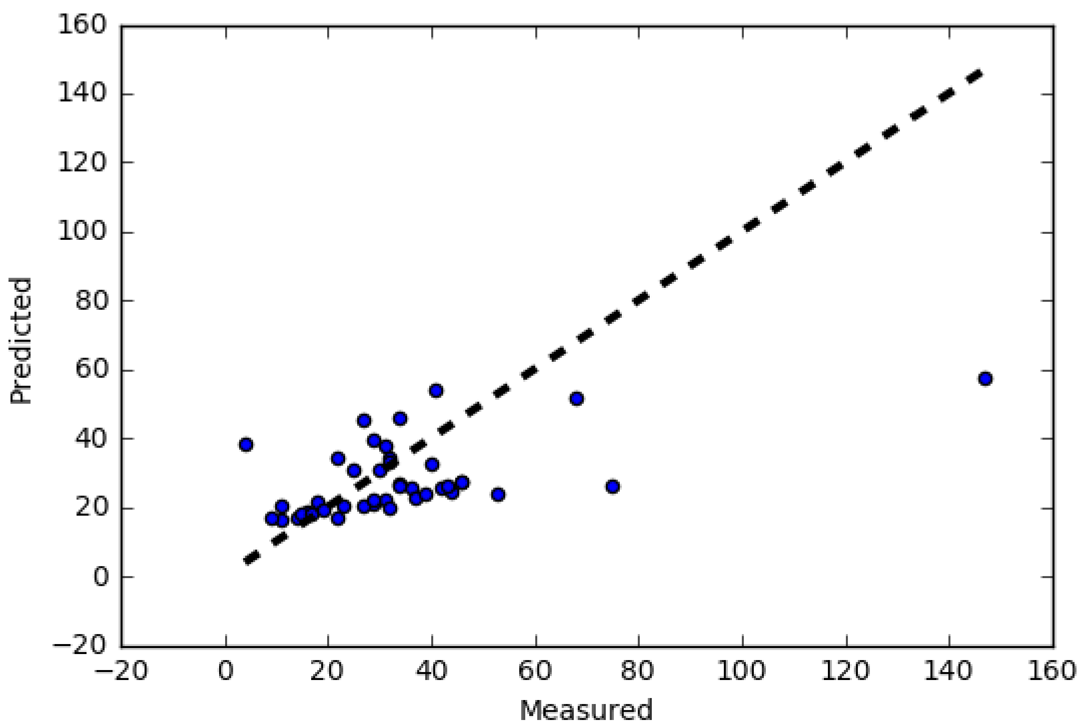
In [4]:
```
DATA_FILE = 'data/fire_theft.xls'
LOG_FILE = 'logs/fire_theft'
LEARN_RATE = 1.0e-3
NUM_OF_EPOCHS = 1000
```

Linear regression in linear scale

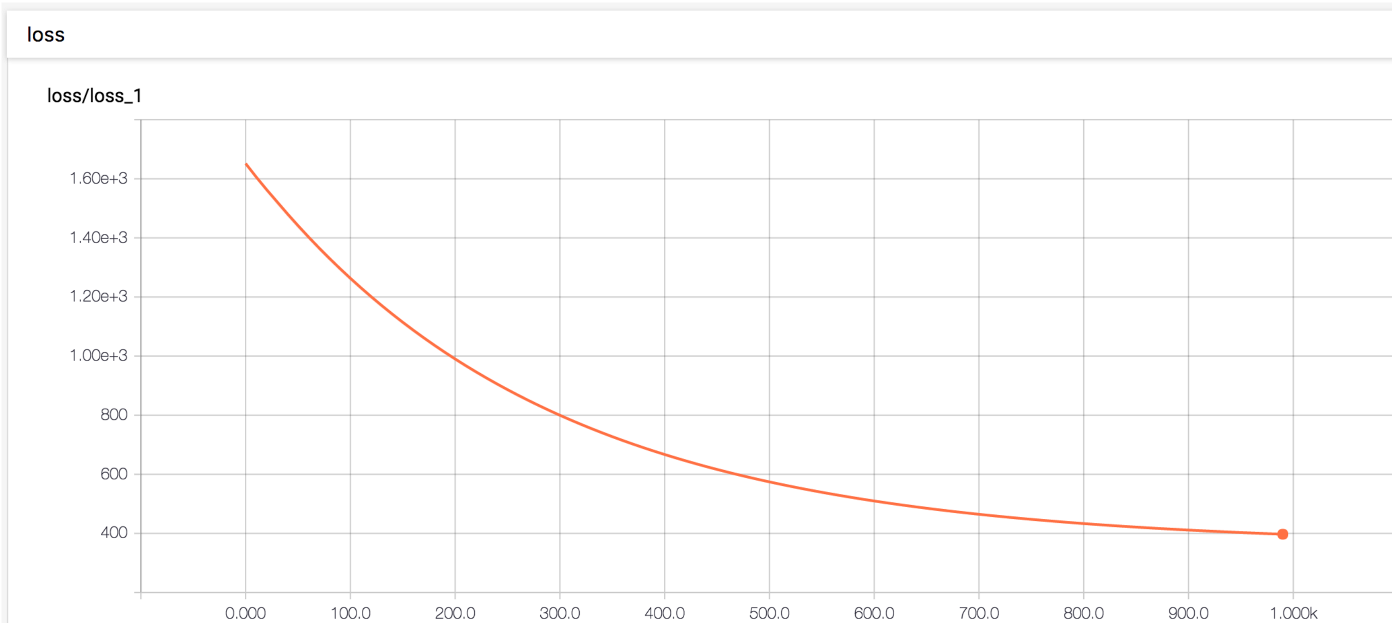
In [5]:
```
analyse_fire_theft_regression(scale='linear', learning_rate=LEARN_RATE,
num_of_epochs=NUM_OF_EPOCHS)
```

```
Type: linear, B: [ 28.11161613] W1: [[ 10.47589397]], W2: [[ 0.]], W3:
 [[ 0.]]
loss: 395.964111328125
RMSE: 19.898847579956055
```

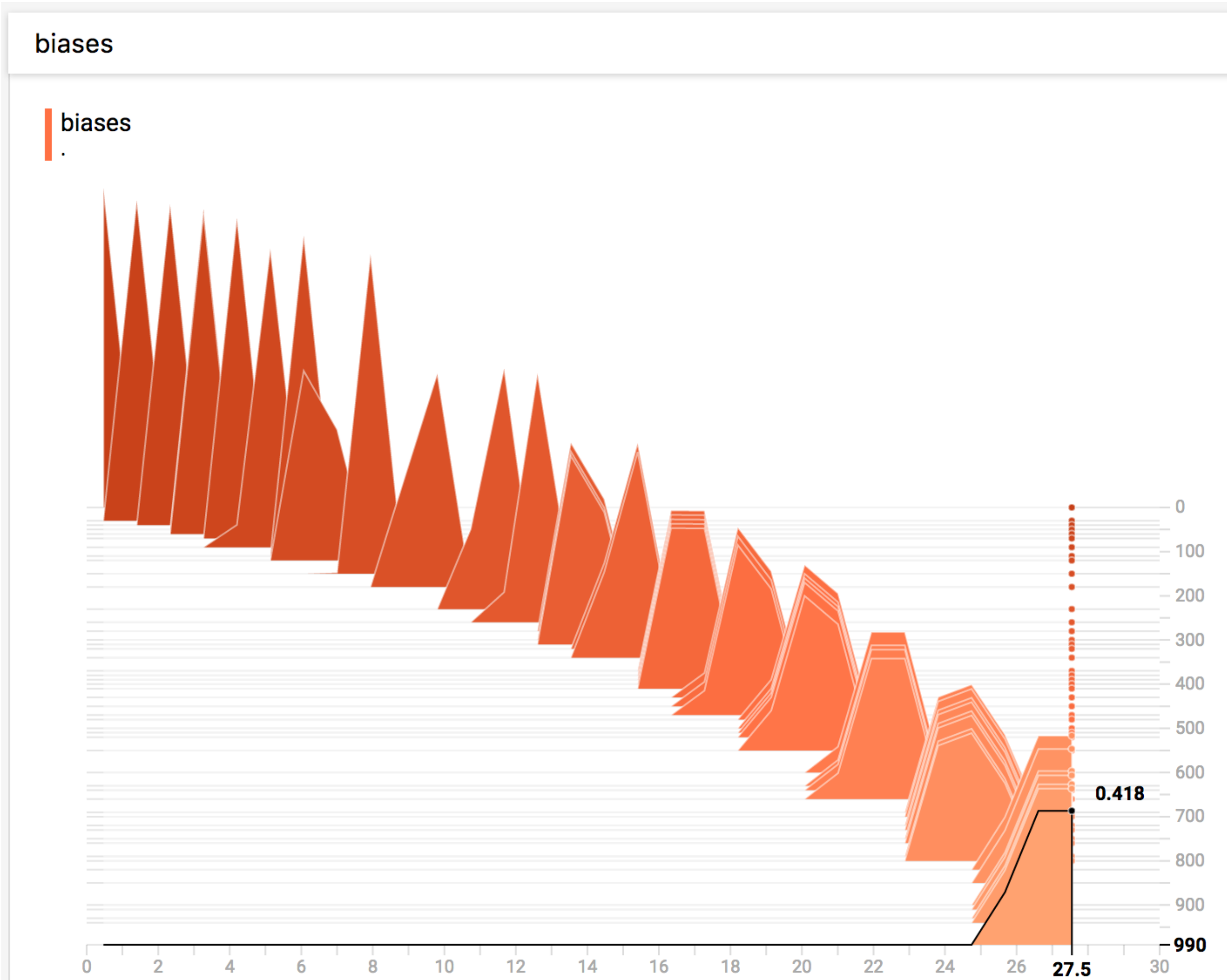




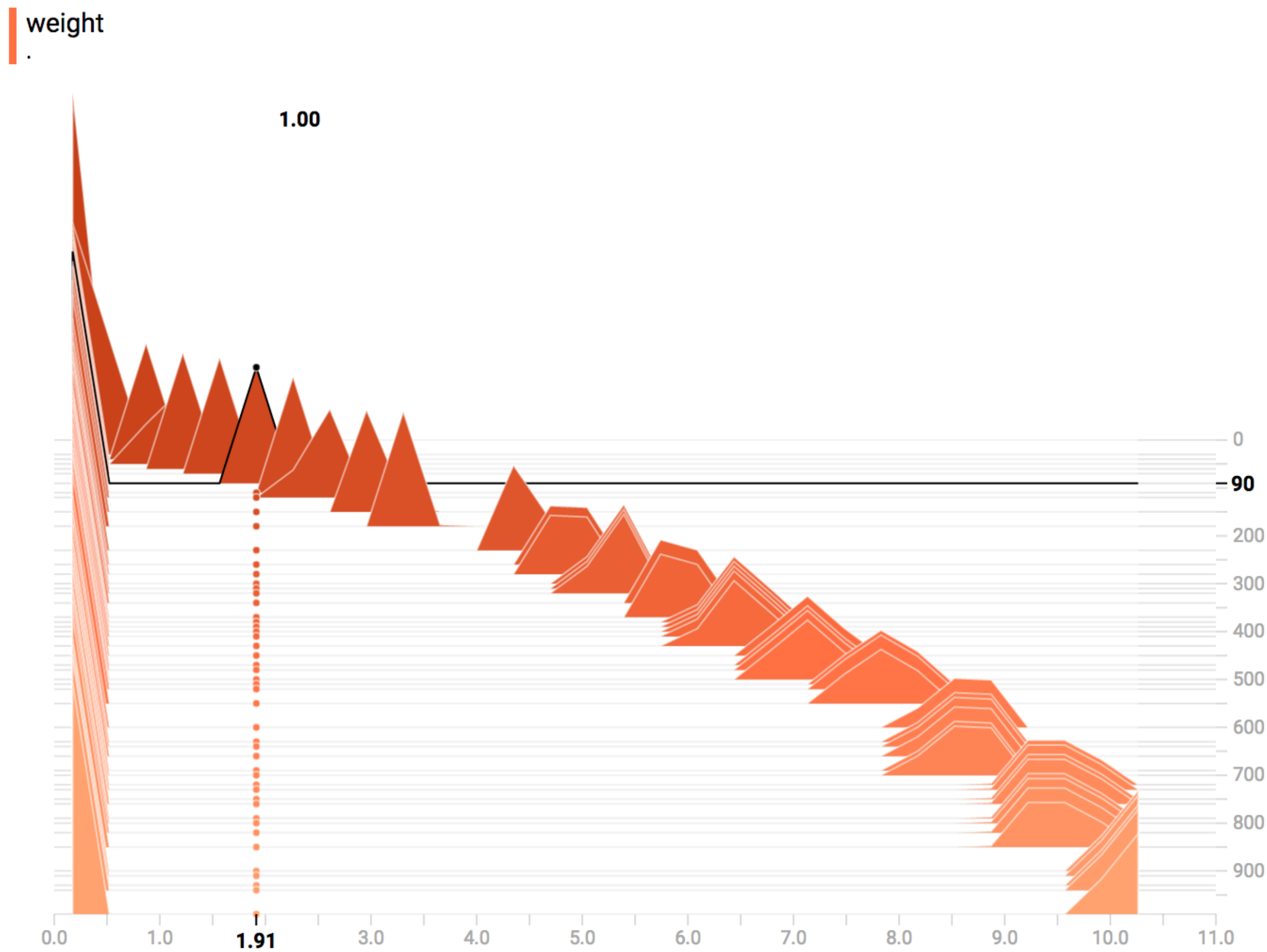
Linear TensorBoard loss



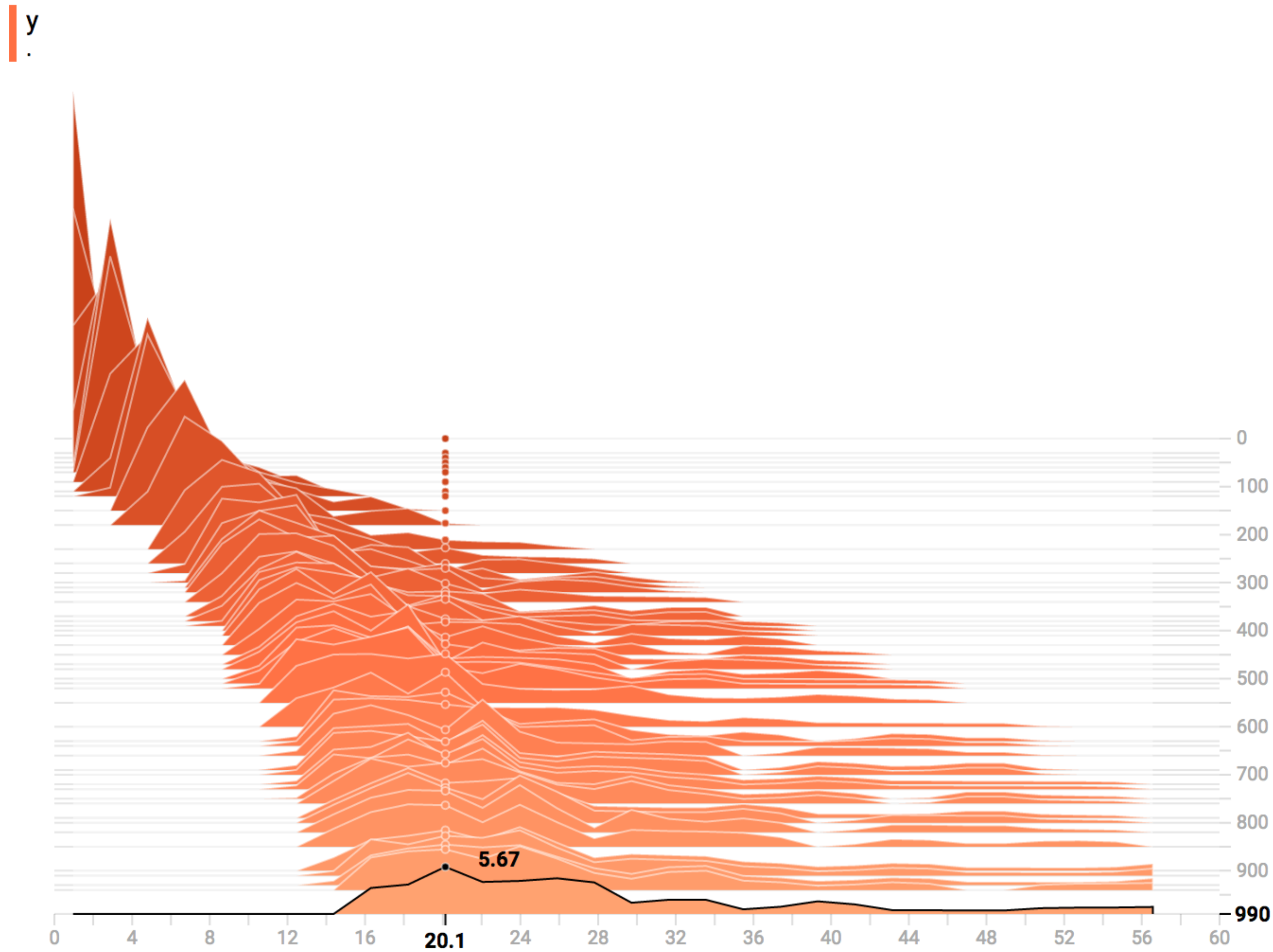
Linear TensorBoard Bias Histogram



Linear TensorBoard Weight Histogram



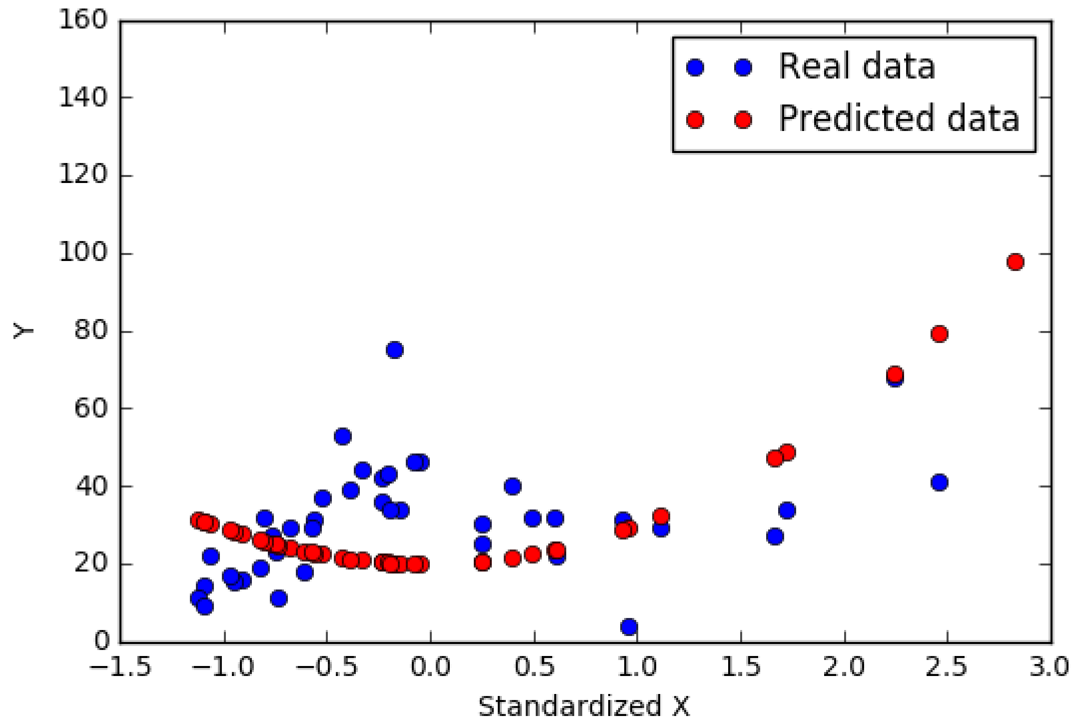
Linear TensorBoard Y Histogram

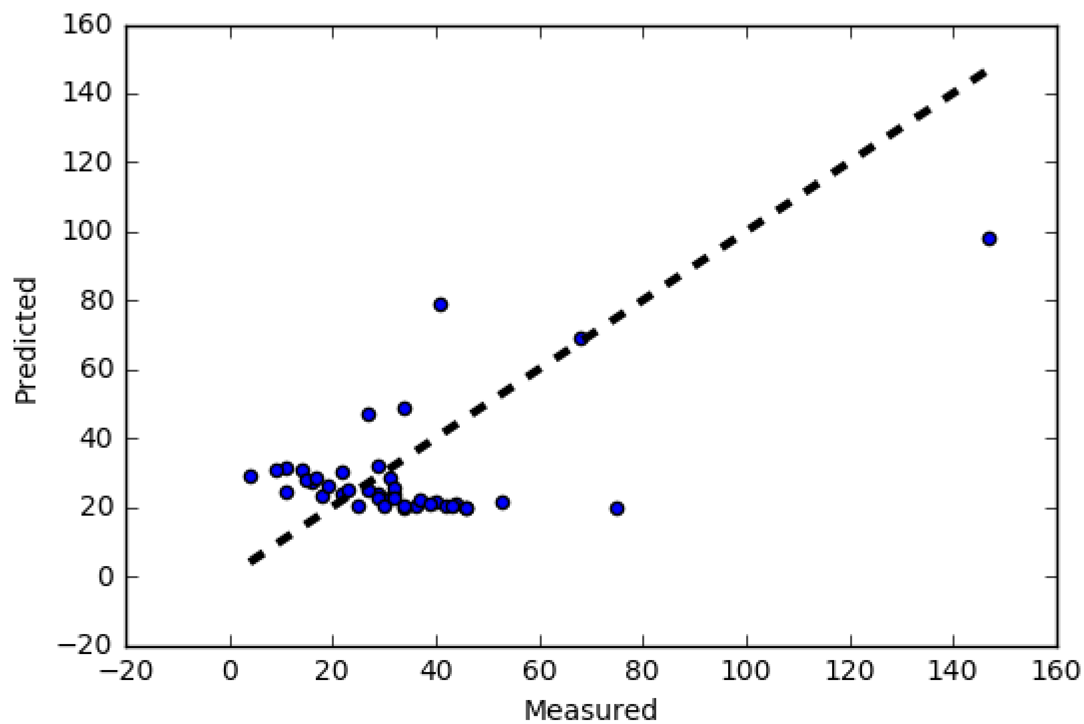


Quadratic scale

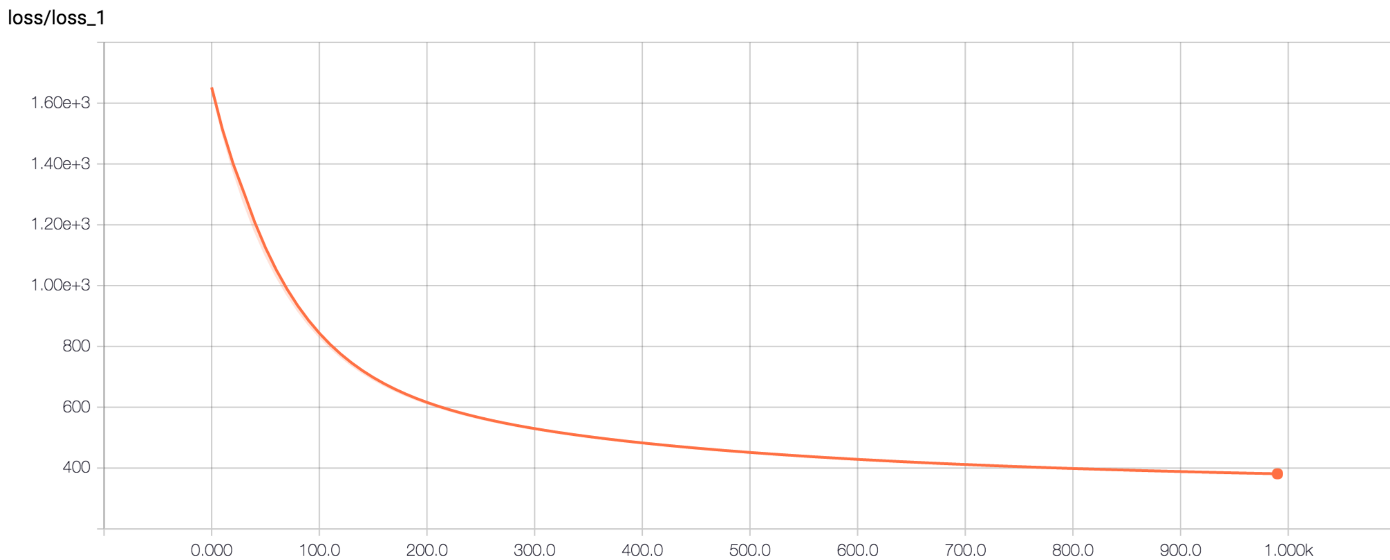
In [5]:
```
analyse_fire_theft_regression(scale='quadratic', learning_rate=LEARN_RAT
E, num_of_epochs=NUM_OF_EPOCHS)
```

```
Type: quadratic, B: [ 19.83799744] W1: [[ 0.48119235]], W2: [[ 9.604850
77]], W3: [[ 0.]]
loss: 380.387451171875
RMSE: 19.503524780273438
```





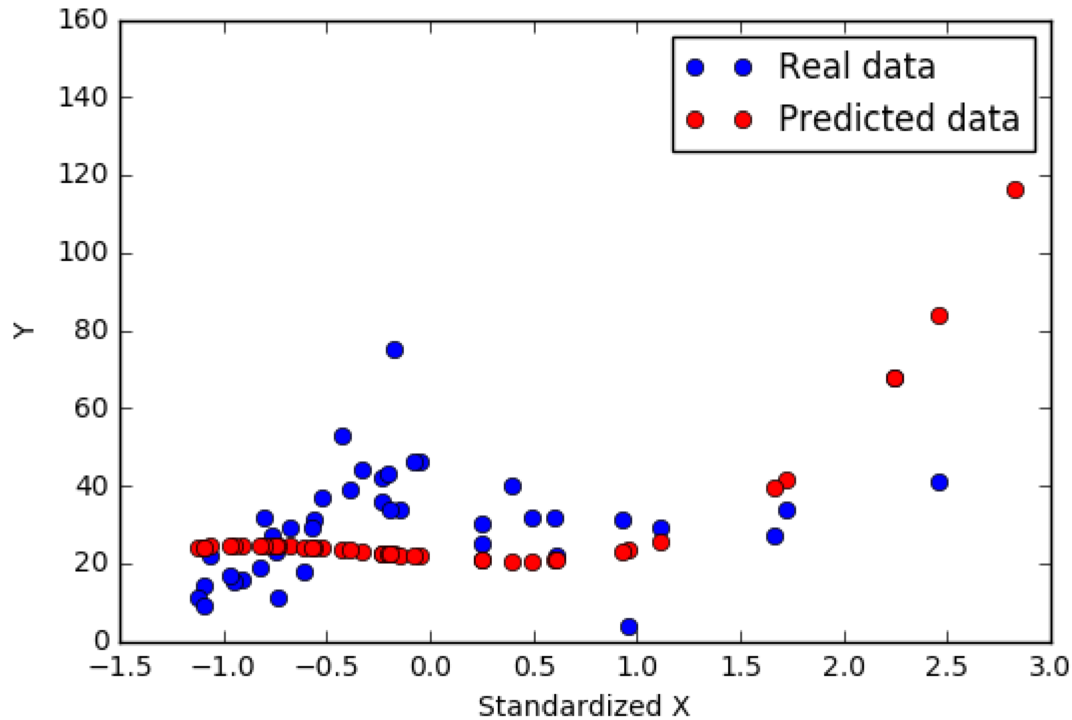
Quadratic TensorBoard loss

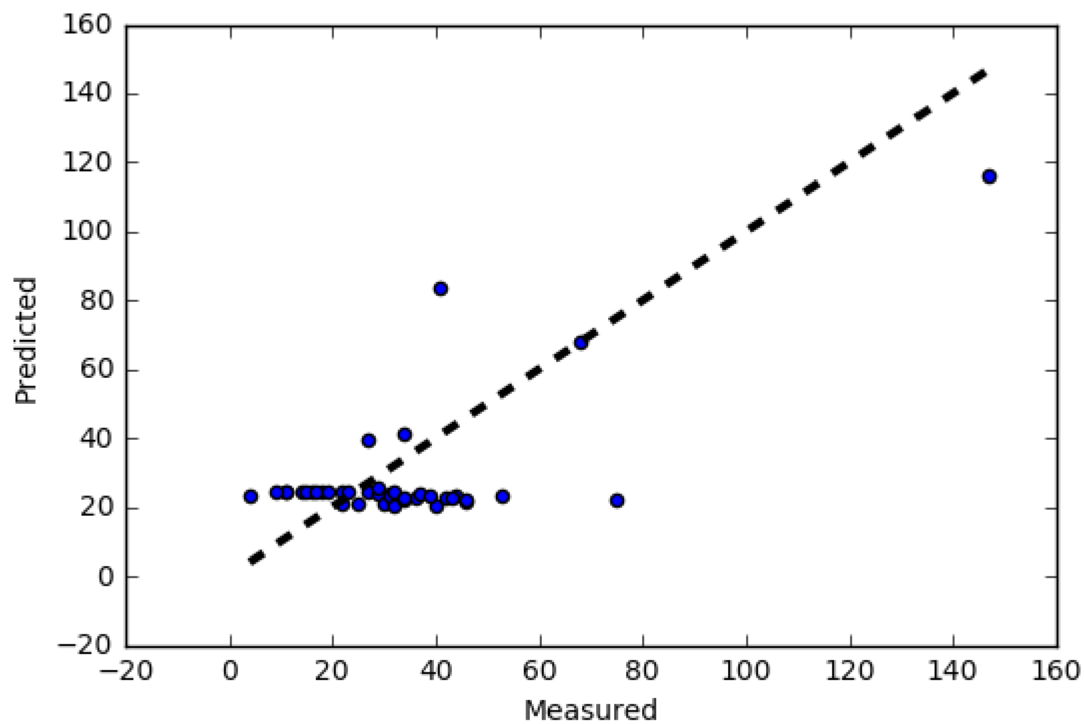


Cubic scale

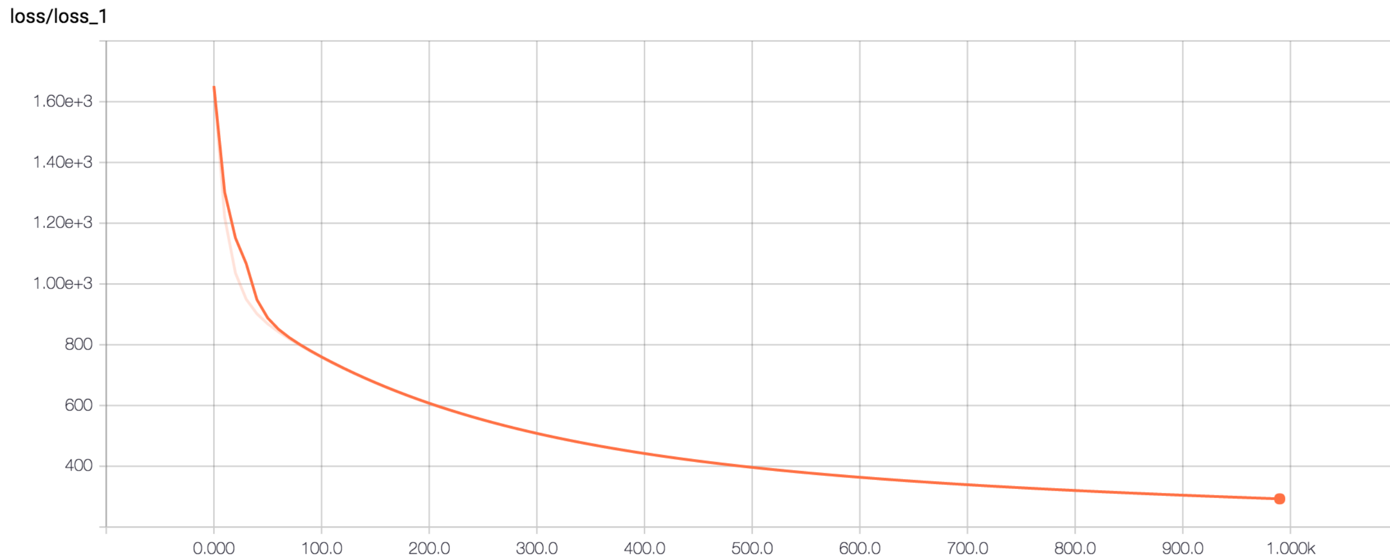
In [5]:
```
analyse_fire_theft_regression(scale='cubic', learning_rate=LEARN_RATE, n
um_of_epochs=NUM_OF_EPOCHS)
```

```
Type: cubic, B: [ 21.50963211] W1: [[-4.10484743]], W2: [[ 2.6649460
8]], W3: [[ 3.76151562]]
loss: 291.59600830078125
RMSE: 17.076183319091797
```





Cubic TensorBoard loss



Conclusion

Looking at the loss graphs quadratic and cubic models converged quicker than linear model. We can see the both quadratic and cubic reduced loss to 600 in about 200 steps although linear model took 450 steps. Also we can see the RMSE dropped 19.90, 19.50, 17.08 in linear, quad and cubic models respectively.

Problem 3.

Consider the attached file logistic_regression_mnist.py. We have stated the results of that program in class but left many details unexplained. Search through TensorFlow API documentation and the Internet and describe for us what is the meaning and purpose of functions used in step 5 and step 6. Demonstrate that you can run the code successfully. Fetch for us the TensorBoard Graph. Vary parameter batch_size through values: 8, 64, 128, 256 and report and plot changes in the execution time and accuracy. Keep other parameters the same as in the original program. Similarly, vary parameter learning_rate through values 0.001, 0.005, 0.01, 0.02 and 0.05. Report and plot changes in the execution time and accuracy.

Search through TensorFlow API documentation and the Internet and describe for us what is the meaning and purpose of functions used in step 5 and step 6.

Cross-entropy can be used to mathematically compare similarity of two graphs. To use cross entropy, we need to convert both the actual outcome vector and the prediction outcome vector values into a probability distribution. We use softmax to transform prediction outcome to a probability distribution. In step 5 we use this probability error as the loss funstion.

Then in step 6 we use gradient descent as the optimizer.

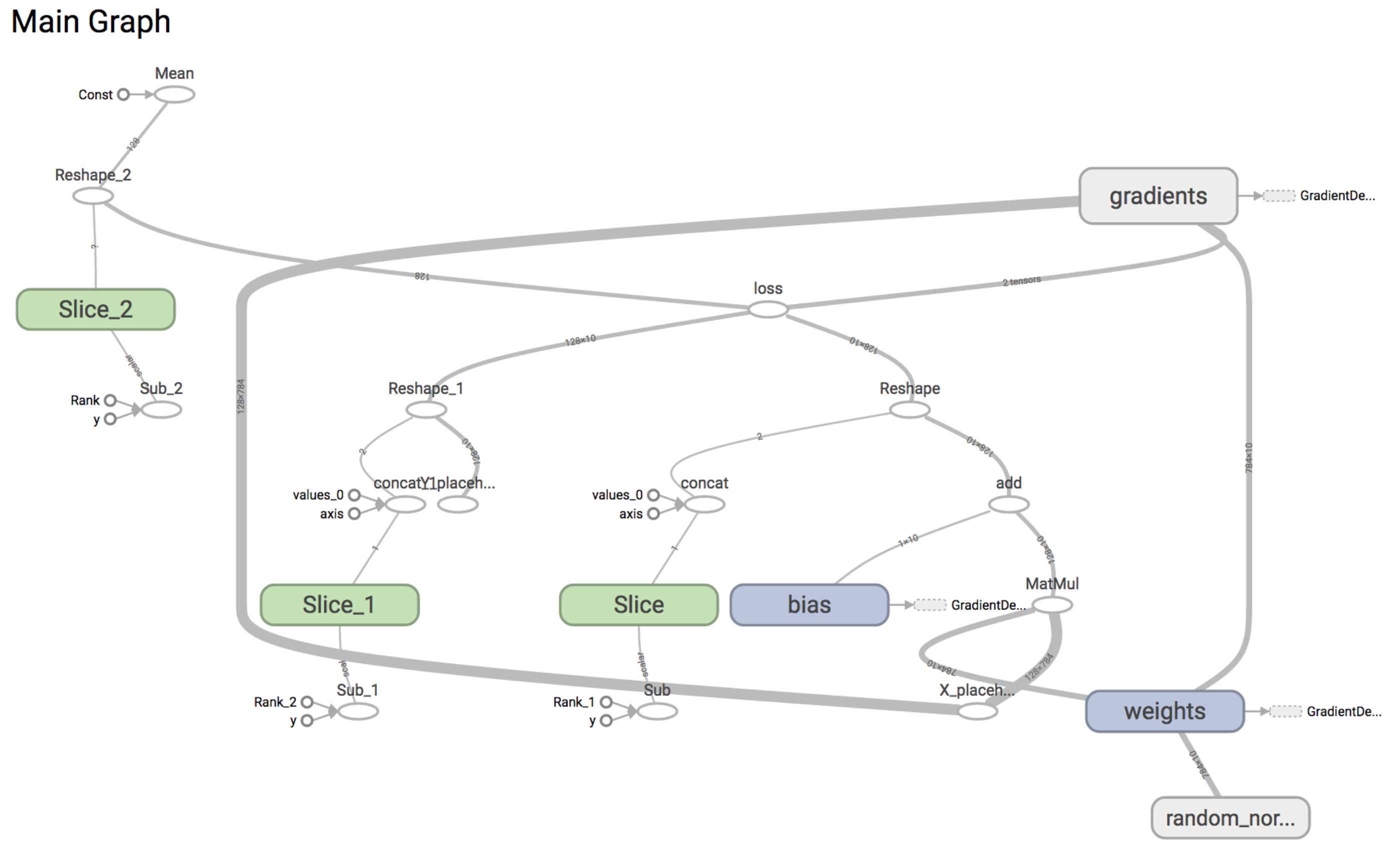
In [3]:
```
import time
import tensorflow as tf
import numpy as np
from tensorflow.examples.tutorials.mnist import input_data
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

Define function for logistic regression with varying parameters

In [2]:
```
def analyse_logistic_regression_mnist(learning_rate=0.01,
                                      batch_size=128,
                                      n_epochs=30,
                                      log_file="logs/logistic_mnist",
                                      debug=False):
    # Step 1: Read in data
    # using TF Learn's built in function to load MNIST data to the folde
r mnist
    mnist = input_data.read_data_sets('./mnist', one_hot=True)

    # Step 2: create placeholders for features and labels
    # each image in the MNIST data is of shape 28*28 = 784
    # therefore, each image is represented with a 1x784 tensor
    # there are 10 classes for each image, corresponding to digits 0 -
 9.
    # each lable is one hot vector.
    X = tf.placeholder(tf.float32, [batch_size, 784], name='X_placeholde
r')
    Y = tf.placeholder(tf.float32, [batch_size, 10], name='Y_placeholde
r')

    # Step 3: create weights and bias
    # w is initialized to random variables with mean of 0, stddev of 0.0
1
    # b is initialized to 0
    # shape of w depends on the dimension of X and Y so that Y = tf.matm
ul(X, w)
    # shape of b depends on Y
    w = tf.Variable(tf.random_normal(
        shape=[784, 10], stddev=0.01), name='weights')
    b = tf.Variable(tf.zeros([1, 10]), name="bias")

    # Step 4: build model
    # the model that returns the logits.
    # this logits will be later passed through softmax layer
    logits = tf.matmul(X, w) + b

    # Step 5: define loss function
    # use cross entropy of softmax of logits as the loss function
    entropy = tf.nn.softmax_cross_entropy_with_logits(
        logits=logits, labels=Y, name='loss')
    # computes the mean over all the examples in the batch
    loss = tf.reduce_mean(entropy)
```

```
    # Step 6: define training op
    # using gradient descent with learning rate of 0.01 to minimize loss
    optimizer = tf.train.GradientDescentOptimizer(learning_rate).minimiz
e(loss)

    with tf.Session() as sess:
        # to visualize using TensorBoard
        writer = tf.summary.FileWriter(log_file, sess.graph)

        start_time = time.time()
        sess.run(tf.global_variables_initializer())
        n_batches = int(mnist.train.num_examples / batch_size)
        for i in range(n_epochs):  # train the model n_epochs times
            total_loss = 0

            for _ in range(n_batches):
                X_batch, Y_batch = mnist.train.next_batch(batch_size)
                _, loss_batch = sess.run([optimizer, loss],
                                         feed_dict={X: X_batch, Y: Y_bat
ch})
                total_loss += loss_batch
            avg_loss = total_loss / n_batches
            if debug:
                print('Average loss epoch {0}: {1}'
                      .format(i, avg_loss))
        total_time = time.time() - start_time
        if debug:
            print('Total time: {0} seconds'.format(total_time))

        # should be around 0.35 after 25 epochs
        if debug:
            print('Optimization Finished!')

        # test the model
        n_batches = int(mnist.test.num_examples / batch_size)
        total_correct_preds = 0
        for i in range(n_batches):
            X_batch, Y_batch = mnist.test.next_batch(batch_size)
            _, loss_batch, logits_batch = sess.run(
                [optimizer, loss, logits], feed_dict={X: X_batch, Y: Y_b
atch})
            preds = tf.nn.softmax(logits_batch)
            correct_preds = tf.equal(
                tf.argmax(preds, 1), tf.argmax(Y_batch, 1))
            accuracy = tf.reduce_sum(tf.cast(correct_preds, tf.float32))
            total_correct_preds += sess.run(accuracy)

        accuracy = total_correct_preds / mnist.test.num_examples
        if debug:
            print('Accuracy {0}'.
                  format(accuracy))

        writer.close()
    print('Time: {0}, Avg. Loss: {1}, Accuracy: {2}'.
          format(total_time, avg_loss, accuracy))
    return [total_time, avg_loss, accuracy]
```

TensorBoard Graph



Vary parameter batch_size through values: 8, 64, 128, 256 and report and plot changes in the execution time and accuracy. Keep other parameters the same as in the original program.

In [12]:
```
batch_sizes = [8, 64, 128, 256]
#batch_sizes = [128, 256]

batch_result = [analyse_logistic_regression_mnist(batch_size=x) for x in
 batch_sizes]
```

```
Extracting ./mnist/train-images-idx3-ubyte.gz
Extracting ./mnist/train-labels-idx1-ubyte.gz
Extracting ./mnist/t10k-images-idx3-ubyte.gz
Extracting ./mnist/t10k-labels-idx1-ubyte.gz
Time: 78.24736404418945, Avg. Loss: 0.259334195193479, Accuracy: 0.9255
Extracting ./mnist/train-images-idx3-ubyte.gz
Extracting ./mnist/train-labels-idx1-ubyte.gz
Extracting ./mnist/t10k-images-idx3-ubyte.gz
Extracting ./mnist/t10k-labels-idx1-ubyte.gz
Time: 22.4779269695282, Avg. Loss: 0.30729271814105674, Accuracy: 0.917
3
Extracting ./mnist/train-images-idx3-ubyte.gz
Extracting ./mnist/train-labels-idx1-ubyte.gz
Extracting ./mnist/t10k-images-idx3-ubyte.gz
Extracting ./mnist/t10k-labels-idx1-ubyte.gz
Time: 17.838057041168213, Avg. Loss: 0.3366956442316651, Accuracy: 0.91
22
Extracting ./mnist/train-images-idx3-ubyte.gz
Extracting ./mnist/train-labels-idx1-ubyte.gz
Extracting ./mnist/t10k-images-idx3-ubyte.gz
Extracting ./mnist/t10k-labels-idx1-ubyte.gz
Time: 15.168068885803223, Avg. Loss: 0.3779068417916788, Accuracy: 0.90
41
```

Creating a dataframe to hold batch results

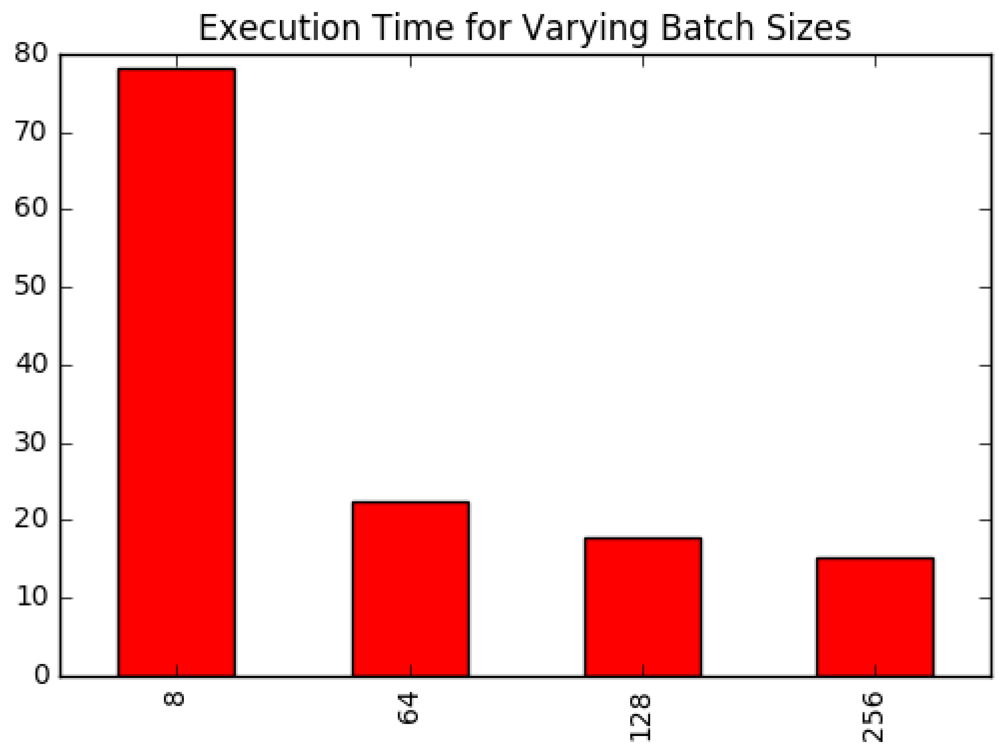
In [13]:
```
cols = ['Time', 'Loss', 'Accuracy']
df = pd.DataFrame(batch_result, index=batch_sizes, columns=cols)
df
```

Out[13]:

	Time	Loss	Accuracy
8	78.247364	0.259334	0.9255
64	22.477927	0.307293	0.9173
128	17.838057	0.336696	0.9122
256	15.168069	0.377907	0.9041

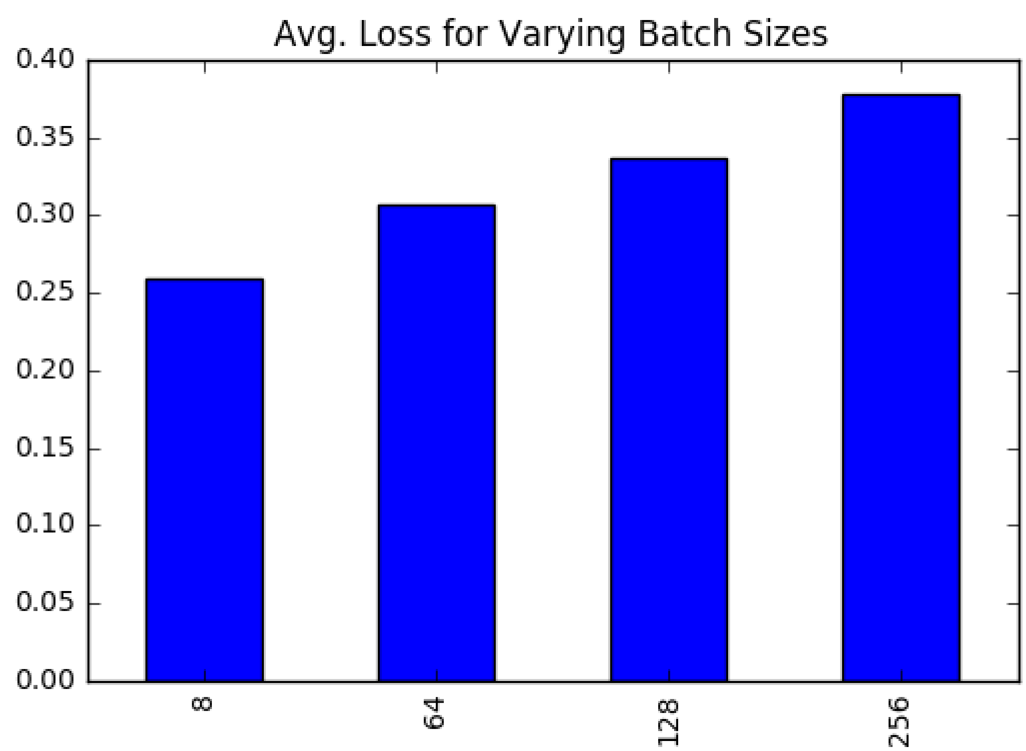
In [14]:
```
df.Time.plot(kind='bar', color='r', title='Execution Time for Varying Ba
tch Sizes')
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x12d8fb1d0>



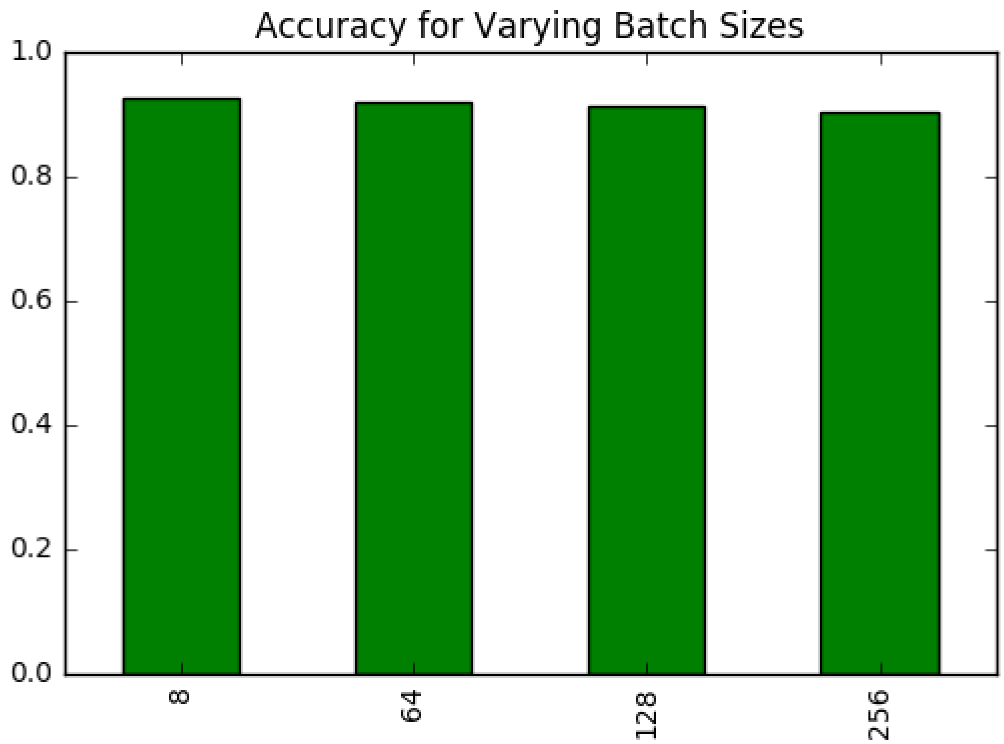
In [15]:
```
df.Loss.plot(kind='bar', color='b', title='Avg. Loss for Varying Batch S
izes')
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x12d904358>



```
In [16]: df.Accuracy.plot(kind='bar', color='g', title='Accuracy for Varying Batc
h Sizes')
```

```
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x11b780390>
```



Similarly, vary parameter learning_rate through values 0.001, 0.005, 0.01, 0.02 and 0.05. Report and plot changes in the execution time and accuracy.

In [17]:
```
learning_rates = [0.001, 0.005, 0.01, 0.02, 0.05]

batch_result = [analyse_logistic_regression_mnist(learning_rate=x) for x
 in learning_rates]
```

```
Extracting ./mnist/train-images-idx3-ubyte.gz
Extracting ./mnist/train-labels-idx1-ubyte.gz
Extracting ./mnist/t10k-images-idx3-ubyte.gz
Extracting ./mnist/t10k-labels-idx1-ubyte.gz
Time: 19.71430516242981, Avg. Loss: 0.5647743087270599, Accuracy: 0.875
3
Extracting ./mnist/train-images-idx3-ubyte.gz
Extracting ./mnist/train-labels-idx1-ubyte.gz
Extracting ./mnist/t10k-images-idx3-ubyte.gz
Extracting ./mnist/t10k-labels-idx1-ubyte.gz
Time: 18.63776993751526, Avg. Loss: 0.3773252709414853, Accuracy: 0.904
1
Extracting ./mnist/train-images-idx3-ubyte.gz
Extracting ./mnist/train-labels-idx1-ubyte.gz
Extracting ./mnist/t10k-images-idx3-ubyte.gz
Extracting ./mnist/t10k-labels-idx1-ubyte.gz
Time: 19.455049991607666, Avg. Loss: 0.3368964605814927, Accuracy: 0.91
2
Extracting ./mnist/train-images-idx3-ubyte.gz
Extracting ./mnist/train-labels-idx1-ubyte.gz
Extracting ./mnist/t10k-images-idx3-ubyte.gz
Extracting ./mnist/t10k-labels-idx1-ubyte.gz
Time: 19.392534971237183, Avg. Loss: 0.3075909244986403, Accuracy: 0.91
71
Extracting ./mnist/train-images-idx3-ubyte.gz
Extracting ./mnist/train-labels-idx1-ubyte.gz
Extracting ./mnist/t10k-images-idx3-ubyte.gz
Extracting ./mnist/t10k-labels-idx1-ubyte.gz
Time: 19.44957685470581, Avg. Loss: 0.2805567752127047, Accuracy: 0.922
3
```

Creating a dataframe with batch results

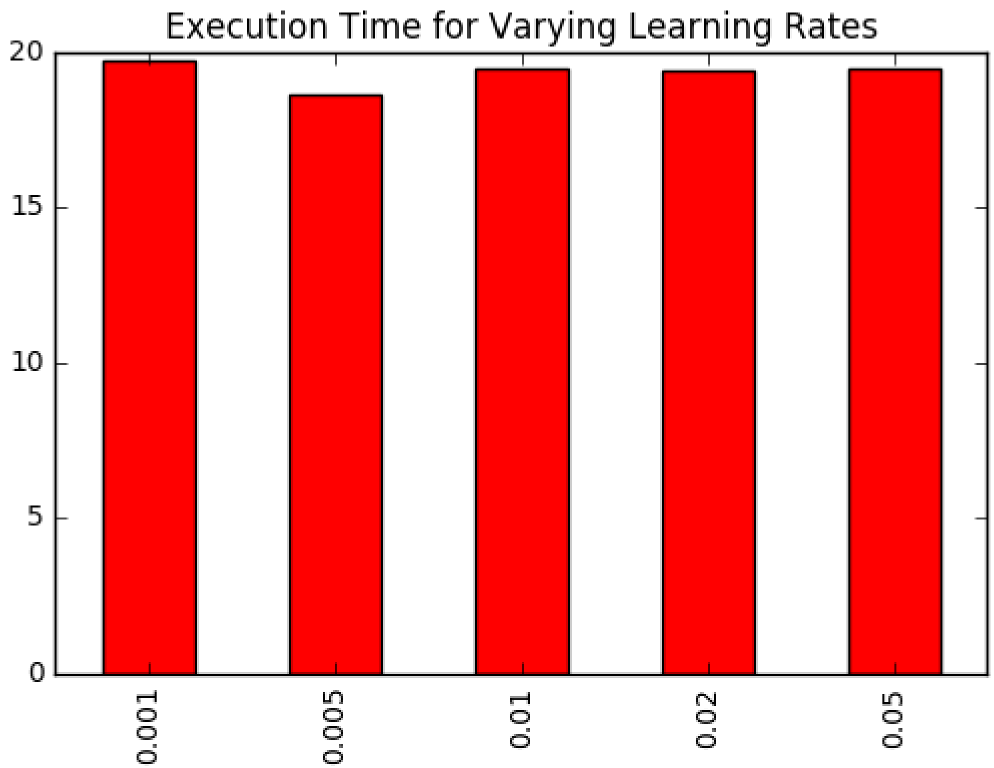
In [18]:
```
cols = ['Time', 'Loss', 'Accuracy']
df = pd.DataFrame(batch_result, index=learning_rates, columns=cols)
df
```

Out[18]:

	Time	Loss	Accuracy
0.001	19.714305	0.564774	0.8753
0.005	18.637770	0.377325	0.9041
0.010	19.455050	0.336896	0.9120
0.020	19.392535	0.307591	0.9171
0.050	19.449577	0.280557	0.9223

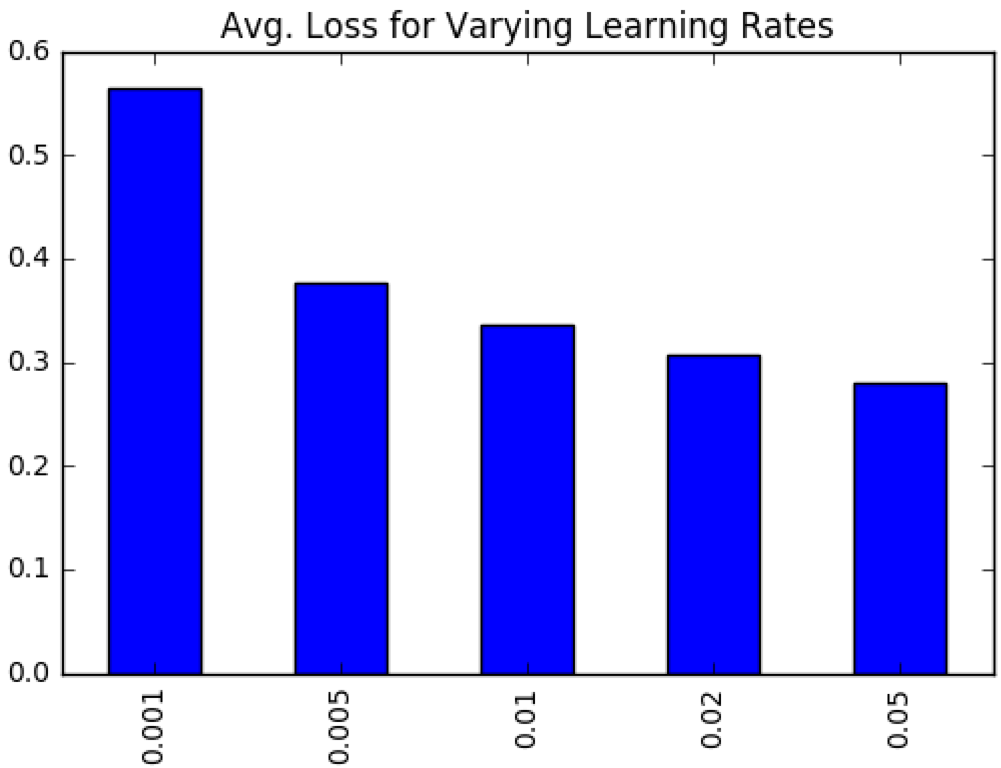
In [19]:
```
%matplotlib inline
df.Time.plot(kind='bar', color='r', title='Execution Time for Varying Le
arning Rates')
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x122c6cb00>



In [20]:
```
df.Loss.plot(kind='bar', color='b', title='Avg. Loss for Varying Learnin
g Rates')
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x122c88cc0>



In [21]:
```
df.Accuracy.plot(kind='bar', color='g', title='Accuracy for Varying Lear
ning Rates')
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x122cbfe48>