hw7-hagmann-tim

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1 Homework 7: Machine Learning with Spark

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Note: This notebook is hosted on Amazon EC2 with Python *2.7* and Spark *2.2* and Jupyter Notebook. The easiest way to replicate it is using a docker image like *jupyter/all-spark-notebook*. To use it after intalling docker simply run the following command:

```
docker run -it --rm -p 8888:8888 --name spark jupyter/all-spark-notebook
```

2 Problem 1 (25%)

Question: Attached file *auto_mpg_original.csv* contains a set of data on automobile characteristics and fuel consumption. File *auto_mpg_description.csv* contains the description of the data. Import data into Spark. Randomly select *10-20%* of you data for testing and use remaining data for training. Find all *null values* in all *numerical* columns. Replace *nulls*, if any, with *average values* for respective columns using *Spark Data Frame API*.

2.0.1 Setup spark

The first step of the analysis is to setup the spark context and load all the necessary libraries

```
In [1]: # Load spark
        import findspark
        findspark.init("/home/tim/spark")

        # Import libraries
        import os
        import pyspark
        from pyspark import SparkContext, SparkConf
        from pyspark.sql import Row
        import pyspark.mllib
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        from IPython.display import display, HTML
```

```
In [2]: # Start spark context
        conf = SparkConf().setAppName("hw7").setMaster("local[*]")
        sc = SparkContext(conf=conf)
```

```
In [3]: from pyspark.ml.feature import Imputer
        from pyspark.mllib.regression import LabeledPoint
        from pyspark.mllib.regression import LinearRegressionWithSGD
        from pyspark.mllib.tree import DecisionTree
        from pyspark.sql.functions import *
        from pyspark.sql import SQLContext
        from pyspark.sql.functions import lit
        sqlContext = SQLContext(sc)
```

2.0.2 Load data

Next we can load the data and split the csv file by *comma* delimited mode.

```
In [4]: # Read data
        auto = sc.textFile("/home/tim/e63-coursework/hw7/data/auto_mpg_original-1.csv",
                           use_unicode=False)

        # Split data
        autordd = auto.map(lambda line: line.split(","))
```

With that we can add the column names and split the dataset into numerical and categorical variables.

```
In [5]: # Create dataframe
        df = autordd.map(lambda line: Row(mpg = line[0], cylinders = line[1],
                                          displacement=line[2], horsepower=line[3],
                                          weight=line[4], acceleration=line[5],
                                          my=line[6], origin=line[7],
                                          name=line[8])).toDF()

        # Define numeric variables
        df_num = df.select(df.mpg.cast('float'), df.displacement.cast('float'),
                           df.horsepower.cast('float'), df.weight.cast('float'),
                           df.acceleration.cast('float'), df.cylinders.cast('float'),
                           df.my.cast('float'), df.origin.cast('float'))

        # Define categorical variables
        df_cat = df.select(df.name.cast('string'))
```

2.0.3 Numerical variables

Next we can have a look at the summary statistic of the numerical variabels.

```
In [6]: # Calculate summary
        df_num_summary = df_num.describe()
```

```
# Show numeric variabels I
df_num_summary['summary', 'mpg', 'displacement', 'horsepower', 'weight'].show()
```

```
+-------+-----------------+------------------+------------------+------------------+
|summary|              mpg|      displacement|        horsepower|            weight|
+-------+-----------------+------------------+------------------+------------------+
|  count|              405|               406|               405|               406|
|   mean|23.49333333144953| 194.7795566502463|104.83703703703704|2979.4137931034484|
| stddev|7.77823691931324 6|104.92245837948875|38.655601865131466| 847.0043282393509|
|    min|              9.0|              68.0|              46.0|            1613.0|
|    max|             46.6|             455.0|             230.0|            5140.0|
+-------+-----------------+------------------+------------------+------------------+
```

```
In [7]: # Show numeric variable II
        df_num_summary['summary', 'acceleration', 'cylinders', 'my', 'origin'].show()
```

```
+-------+------------------+------------------+-----------------+------------------+
|summary|      acceleration|         cylinders|               my|            origin|
+-------+------------------+------------------+-----------------+------------------+
|  count|               406|               406|              406|               406|
|   mean|15.519704440544391| 5.475369458128079|75.92118226600985|1.5689655172413792|
| stddev| 2.803358855032557|1.7121596315485292|3.748737345455887|0.7974789993244706|
|    min|               8.0|               3.0|             70.0|               1.0|
|    max|              24.8|               8.0|             82.0|               3.0|
+-------+------------------+------------------+-----------------+------------------+
```

The above count statistics show, that there are NA's present. This appears to be the case for *mpg* and *horsepower*.

2.0.4 Impute Values

With Spark 2.2. there is a new the impute function available. With the help of this function the null values can be replaced with the group mean.

```
In [8]: # Impute NA's with the average (new function on Spark 2.2)
        imputer = Imputer(inputCols=df_num.columns, outputCols=["{}".format(c)
                                                                 for c in df_num.columns])
        df_num = imputer.setStrategy("mean").fit(df_num).transform(df_num)
```

2.0.5 Join numeric and categorical together

Having imputed the numerical variables, the next step is to join the dataframe back into one.

```
In [9]: # Add ID variable
        df_num = df_num.withColumn("row_id", monotonically_increasing_id())
        df_cat = df_cat.withColumn("row_id", monotonically_increasing_id())

        # Join dataframe
        df2 = df_num.join(df_cat, "row_id").drop("row_id")

        # Show data
        df2.show(5)
```

```
+----+------------+----------+------+------------+---------+----+------+-------+
| mpg|displacement|horsepower|weight|acceleration|cylinders|  my|origin|   name|
+----+------------+----------+------+------------+---------+----+------+-------+
|25.0|       110.0|      87.0|2672.0|        17.5|      4.0|70.0|   2.0|peugeot|
|26.0|       121.0|     113.0|2234.0|        12.5|      4.0|70.0|   2.0|    bmw|
|27.2|       119.0|      97.0|2300.0|        14.7|      4.0|78.0|   3.0| datsun|
|25.0|        97.5|      80.0|2126.0|        17.0|      4.0|72.0|   1.0|  dodge|
|25.0|       140.0|      92.0|2572.0|        14.9|      4.0|76.0|   1.0|  capri|
+----+------------+----------+------+------------+---------+----+------+-------+
only showing top 5 rows
```

Note: In order to use the categorical variable *name* we use *1-of-k binary encoding*. This is not necessary for the analysis in problem 2.

2.0.6 Select variables

For the following analysis in problem 2, only variables *mpg* and *horsepower* are used. That is we only select those values.

```
In [10]: # Select variables
         df3 = df2.select(df2.mpg.cast('float'), df2.horsepower.cast('float'))

         # Show data
         df3.show(5)
```

```
+----+----------+
| mpg|horsepower|
+----+----------+
|25.0|      87.0|
|26.0|     113.0|
|27.2|      97.0|
|25.0|      80.0|
|25.0|      92.0|
+----+----------+
only showing top 5 rows
```

2.0.7 Labeled points (could also be done in problem 2)

In order to programmatically tell the ML Algorithm the features and target variables we're adding labeled points to the data.

```
In [11]: # Create labeled points
         df_labeled = df3.rdd.map(lambda r : LabeledPoint(r[0], r[1:]))
         df_labeled.take(5)
```

```
Out[11]: [LabeledPoint(25.0, [87.0]),
          LabeledPoint(26.0, [113.0]),
          LabeledPoint(27.2000007629, [97.0]),
          LabeledPoint(25.0, [80.0]),
          LabeledPoint(25.0, [92.0])]
```

2.0.8 Creat test and train dataframes

In order to control for overfitting we're creating datasets for training (80%) and testing (20%) the models.

```
In [12]: # Test and learning set.
         df_train, df_test = df_labeled.randomSplit([.8, .2], seed=123)

         # Cache data
         df_train = df_train.cache()
         df_test = df_test.cache()
```

2.0.9 Summary of the data

```
In [13]: # Get values
         print "Training data size: %d" % df_train.count()
         print "Test data size: %d" % df_test.count()
         print "Total data size: %d " % df3.count()
         print "Train + Test size : %d" % (df_train.count() + df_test.count())
```

```
Training data size: 315
Test data size: 91
Total data size: 406
Train + Test size : 406
```

There are 315 observation in the training set and 91 in the testset. This is equal to the number of observations in the overall dataset.

3 Problem 2 (25%)

Question: Look initially at two variables in the data set from the previous problem: the *horsepower* and the *mpg* (miles per gallon). Treat *mpg* as a feature and *horsepower* as the target variable (label). Use *MLlib* linear regression to identify the model for the relationship. Use the *test data* to illustrate *accuracy* of the *linear regression model* and its ability to predict the relationship. Calculate *two standard measures* of model *accuracy*. Create a *diagram* using any technique of convenience to presents the model (straight line), and the original test data. Please label your axes and use different colors for original data and predicted data.

3.0.1 Accuracy functions

We're first defining the accuracy function. We're measaring the *mean squared error*, *mean absolut error* and the *root mean squared log error*.

In [14]:
```
# MSE
def squared_error(actual, pred):
    return (pred - actual)**2

# MAE
def abs_error(actual, pred):
    return np.abs(pred - actual)

# RMSLE
def squared_log_error(pred, actual):
    return (np.log(pred + 1) - np.log(actual + 1))**2
```

3.0.2 Regression model

Next we're calculating a linear regression model.

In [ ]:
```
# Calculate model
fit_lin = LinearRegressionWithSGD.train(df_train, 1000, .0001, intercept=False)
print("Linear Model Info:" + str (fit_lin))
```

3.0.3 Prediction

Having the above model we're next calculating the estimated values on the test set. Based on that we can calculate the accuracy rate.

In [16]:
```
# Calculate true vs. prediction
tbl_pred = df_test.map(lambda x: (x.label, fit_lin.predict(x.features)))

# Calculate two accuracy measures
mse = tbl_pred.map(lambda (t, p): squared_error(t, p)).mean()
mae = tbl_pred.map(lambda (t, p): abs_error(t, p)).mean()
rmsle = np.sqrt(tbl_pred.map(lambda(t,p):squared_log_error(t,p)).mean())

# Print output
print ("Linear model: Mean squared error: %2.4f" % mse)
print ("Linear model: Mean absolute error: %2.4f" % mae)
print ("Linear model: Root mean squared log error: %2.4f" % rmsle)
```

```
Linear model: Mean squared error: 242.6391
Linear model: Mean absolute error: 12.3945
Linear model: Root mean squared log error: 0.6914
```

It appears that we're producing a bit of error. However, we have to be careful with the interpretation as we didn't standartize the model. Furthermore, in order to make the accuracy measures comparable we would have to calculate a baseline model. Without all this there is however another method assessing the goodness of fit and that is to visualize the model in a scatterplot.

3.0.4 Visualization

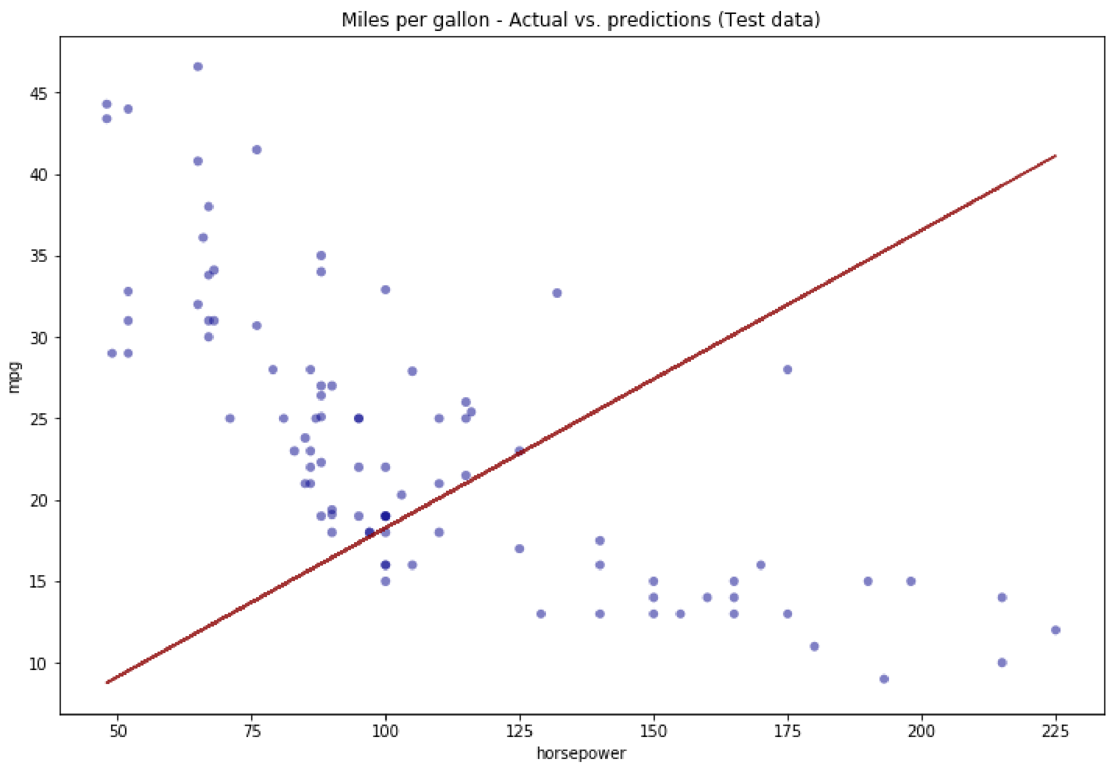
Having calculated the accuracy rate a good indicator for the goodness of fit is to visualize the data.

```
In [17]: pd_train_pred = df_train.map(lambda p: (float(p.label), float(fit_lin.predict(p.feature
                                                 float(p.features[0]))).toDF().toPandas()
         pd_test_pred = df_test.map(lambda p: (float(p.label), float(fit_lin.predict(p.features)
                                               float(p.features[0]))).toDF().toPandas()
         pd_train_pred.columns = ['mpg', 'mpg_pred', 'horsepower']
         pd_test_pred.columns = ['mpg', 'mpg_pred', 'horsepower']
```

3.0.5 Plot I: Actual vs. prediction (test data)

In order to see the goodness of fit we're visualizing the model on top of a scatterplot.

```
In [18]: plt.figure(1, figsize=(12,8))
         plt.scatter(pd_test_pred['horsepower'], pd_test_pred['mpg'],
                     c='darkblue', alpha=0.5, edgecolor="")
         plt.plot(pd_test_pred['horsepower'], pd_test_pred['mpg_pred'],
                  c='darkred', alpha=0.8)
         plt.xlabel('horsepower')
         plt.ylabel('mpg')
         plt.title('Miles per gallon - Actual vs. predictions (Test data)')
         plt.show()
```

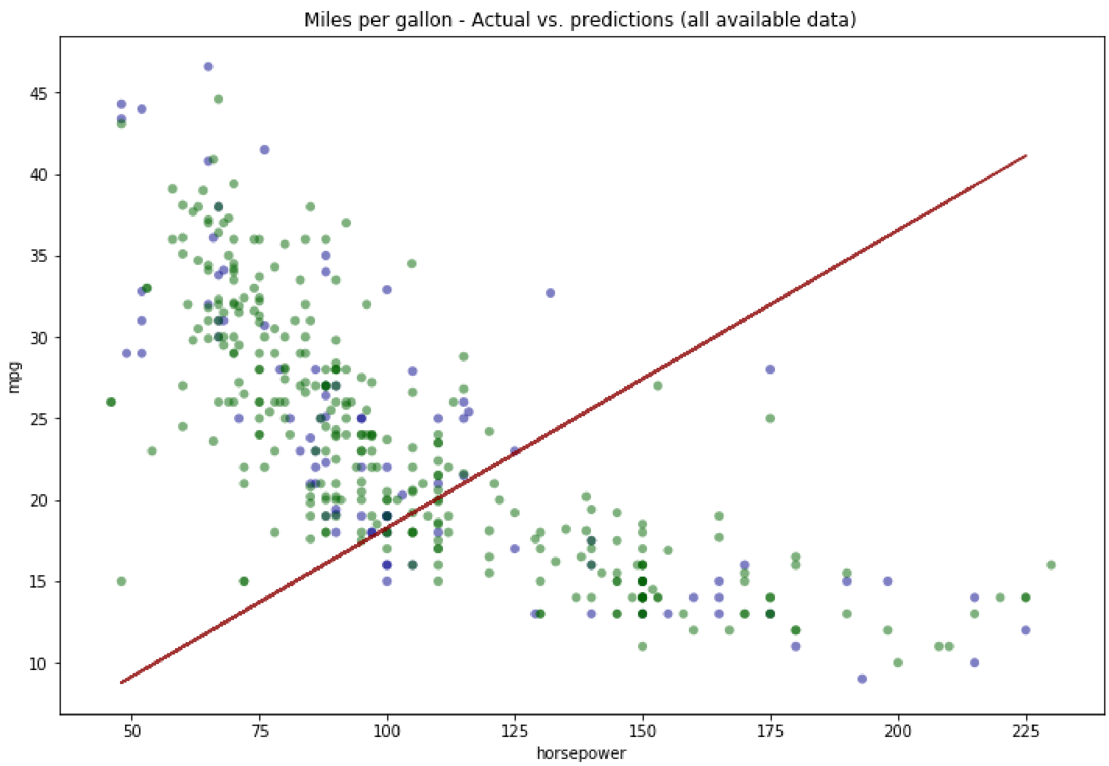


As can be seen above, the model is quit a bad fit for the data. This is because the data appears no be of a polynomic nature. If we'd like to stick to the regression method, a good next step would be to fit fit a model with a quadratic term and an intercept. However, an alternative would be to fit a non-linear model such as a regression tree. This is what we're going to do in problem 4.

3.0.6 Plot I: Actual vs. prediction (all data) [optional]

Because we only took 20% of the data as test. I also visualized the overall data to the model. However, the conclusion is the same as above.

```
In [19]: plt.figure(1, figsize=(12,8))
         plt.scatter(pd_test_pred['horsepower'], pd_test_pred['mpg'],
                     c='darkblue', alpha=0.5, edgecolor="")
         plt.scatter(pd_train_pred['horsepower'], pd_train_pred['mpg'],
                     c='darkgreen', alpha=0.5, edgecolor="")
         plt.plot(pd_test_pred['horsepower'], pd_test_pred['mpg_pred'],
                  c='darkred', alpha=0.8)
         plt.xlabel('horsepower')
         plt.ylabel('mpg')
         plt.title('Miles per gallon - Actual vs. predictions (all available data)')
         plt.show()
```



4 Problem 3 (25%)

Question: Consider attached file *Bike-Sharing-Dataset.zip*. This is the bike set discussed in class. Do *not* use all columns of the data set. Retain the following variables: *season, yr, mnth, hr, holiday, weekday, workingday, weathersit, temp, atemp, hum, windspeed, cnt*. Discard others. Regard *cnt* as the target variable and all other variables as features. Please note that some of those are categorical variables. Identify categorical variables and use *1-of-k binary encoding* for those variables. If there are any null values in numerical columns, replace those with average values for those columns using *Spark DataFrame API*. Train your model using *LinearRegressionSGD* method. Use test data (15% of all) to assess the quality of prediction for *cnt* variable. Calculate at least two performance metrics of your model.

4.0.1 Functions

The following functions are used in this problem set.

```
In [20]: def get_mapping(rdd, idx):
             return rdd.map(lambda fields: fields[idx]).distinct()
                                                   .zipWithIndex().collectAsMap()

         def extract_features(record):
             cat_vec = np.zeros(cat_len)
```

```
    i = 0
    step = 0
    for field in record[0:8] :
        m = mappings[i]
        idx = m[field]
        cat_vec[idx + step] = 1
        i = i + 1
        step = step + len(m)
    num_vec = np.array([float(field) for field in record[8:12]])
    return np.concatenate((cat_vec, num_vec))

def extract_label(record):
    return float(record[-1])
```

4.0.2 Creat spark context

```
In [21]: from pyspark.sql import SparkSession
         spark = SparkSession.builder.master("local").appName("p3_df_count")
                                    .getOrCreate()
```

4.0.3 Load data

We're first loading the from the csv file as well as droping some unwanted variables.

```
In [22]: # Load data
         df_bike = spark.read.csv("file:///home/tim/e63-coursework/hw7/data/hour.csv",
                               nullValue='NA', header=True)

In [23]: # Select data and arrange (categories first)
         df_bike = df_bike.select(df_bike.season.cast('float'), df_bike.yr.cast('float'),
                               df_bike.mnth.cast('float'), df_bike.hr.cast('float'),
                               df_bike.holiday.cast('float'), df_bike.weekday.cast('float'),
                               df_bike.workingday.cast('float'), df_bike.weathersit.cast('flo
                               df_bike.temp.cast('float'), df_bike.atemp.cast('float'),
                               df_bike.hum.cast('float'), df_bike.windspeed.cast('float'),
                               df_bike.cnt.cast('float'))
```

4.0.4 Impute missings

Next we're imputing missing values with the average value

```
In [24]: # Impute NA's with the average (new function on Spark 2.2)
         imputer = Imputer(inputCols=df_bike.columns, outputCols=["{}".format(c)
                                                            for c in df_bike.columns])
         x = imputer.setStrategy("mean").fit(df_bike).transform(df_bike)
```

4.0.5 Look at the data

Next we can have a first look at the data

```
In [25]: df_bike.show(5)

+------+---+----+---+-------+-------+----------+----------+----+------+----+---------+----+
|season| yr|mnth| hr|holiday|weekday|workingday|weathersit|temp| atemp| hum|windspeed| cnt|
+------+---+----+---+-------+-------+----------+----------+----+------+----+---------+----+
|   1.0|0.0| 1.0|0.0|    0.0|    6.0|       0.0|       1.0|0.24|0.2879|0.81|      0.0|16.0|
|   1.0|0.0| 1.0|1.0|    0.0|    6.0|       0.0|       1.0|0.22|0.2727| 0.8|      0.0|40.0|
|   1.0|0.0| 1.0|2.0|    0.0|    6.0|       0.0|       1.0|0.22|0.2727| 0.8|      0.0|32.0|
|   1.0|0.0| 1.0|3.0|    0.0|    6.0|       0.0|       1.0|0.24|0.2879|0.75|      0.0|13.0|
|   1.0|0.0| 1.0|4.0|    0.0|    6.0|       0.0|       1.0|0.24|0.2879|0.75|      0.0| 1.0|
+------+---+----+---+-------+-------+----------+----------+----+------+----+---------+----+
only showing top 5 rows
```

4.0.6 Seting type

Next we're setting the type of the variables

```
In [26]: # Select data and arrange (categories first)
         df_bike = df_bike.select(df_bike.season.cast('int'), df_bike.yr.cast('int'),
                                  df_bike.mnth.cast('int'), df_bike.hr.cast('int'),
                                  df_bike.holiday.cast('int'), df_bike.weekday.cast('int'),
                                  df_bike.workingday.cast('int'), df_bike.weathersit.cast('int')
                                  df_bike.temp.cast('float'), df_bike.atemp.cast('float'),
                                  df_bike.hum.cast('float'), df_bike.windspeed.cast('float'),
                                  df_bike.cnt.cast('float'))
         df_bike.show(5)

+------+---+----+---+-------+-------+----------+----------+----+------+----+---------+----+
|season| yr|mnth| hr|holiday|weekday|workingday|weathersit|temp| atemp| hum|windspeed| cnt|
+------+---+----+---+-------+-------+----------+----------+----+------+----+---------+----+
|     1|  0|   1|  0|      0|      6|         0|         1|0.24|0.2879|0.81|      0.0|16.0|
|     1|  0|   1|  1|      0|      6|         0|         1|0.22|0.2727| 0.8|      0.0|40.0|
|     1|  0|   1|  2|      0|      6|         0|         1|0.22|0.2727| 0.8|      0.0|32.0|
|     1|  0|   1|  3|      0|      6|         0|         1|0.24|0.2879|0.75|      0.0|13.0|
|     1|  0|   1|  4|      0|      6|         0|         1|0.24|0.2879|0.75|      0.0| 1.0|
+------+---+----+---+-------+-------+----------+----------+----+------+----+---------+----+
only showing top 5 rows
```

We are left with 12 variables (features). The first eight are categorical, while the last 4 are numeric variables. The target variable is *cnt*

4.0.7 Get mapping

Next we're getting the mapping of the values

```
In [27]: rdd_bike = df_bike.rdd
         mappings = [get_mapping(rdd_bike, i) for i in range(0,8)]
         print (mappings)
```

```
[{1: 0, 2: 1, 3: 2, 4: 3}, {0: 0, 1: 1}, {1: 0, 2: 1, 3: 2, 4: 3, 5: 4, 6: 5, 7: 6, 8: 7, 9: 8,
```

4.0.8 Summary data

```
In [28]: cat_len = np.sum(map(len, mappings))
         print(rdd_bike.first()[8:12])
         num_len = len(rdd_bike.first()[8:12])
         total_len = num_len + cat_len
```

```
(0.23999999463558197, 0.28790000081062317, 0.8100000023841858, 0.0)
```

```
In [29]: print "Feature vector length for categorical features: %d" % cat_len
         print "Feature vector length for numerical features: %d" % num_len
         print "Total feature vector length: %d" % total_len
```

```
Feature vector length for categorical features: 57
Feature vector length for numerical features: 4
Total feature vector length: 61
```

There are 57 categorical features (dummys) and 4 numerical features in the data.

4.0.9 Define labeled points

Next we're defining the labeled points

```
In [30]: rdd_bike.take(5)
```

```
Out[30]: [Row(season=1, yr=0, mnth=1, hr=0, holiday=0, weekday=6, workingday=0, weathersit=1, te
          Row(season=1, yr=0, mnth=1, hr=1, holiday=0, weekday=6, workingday=0, weathersit=1, te
          Row(season=1, yr=0, mnth=1, hr=2, holiday=0, weekday=6, workingday=0, weathersit=1, te
          Row(season=1, yr=0, mnth=1, hr=3, holiday=0, weekday=6, workingday=0, weathersit=1, te
          Row(season=1, yr=0, mnth=1, hr=4, holiday=0, weekday=6, workingday=0, weathersit=1, te
```

```
In [31]: rdd_bike2 = rdd_bike.map(lambda r: LabeledPoint(extract_label(r),
                                                         extract_features(r)))
         first_point = rdd_bike2.first()
         print ("Label: " + str(first_point.label))
         print ("Linear Model feature vector:\n" + str(first_point.features))
         print ("Linear Model feature vector length: " + str(len(first_point.features)))
```

```
Label: 16.0
Linear Model feature vector:
[1.0,0.0,0.0,0.0,1.0,0.0,1.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0,1.0,0.0,0.0,0.0,0.0,0.0
Linear Model feature vector length: 61
```

4.0.10 Creat test and train

We're spliting the data into 85% training and 15% testing data

```
In [32]: df_train, df_test = rdd_bike2.randomSplit([.85, .15], seed=123)
         df_train = df_train.cache()
         df_test = df_test.cache()
```

4.0.11 Linear regression

Next we're calculating the regression model with all the features against the training data.

```
In [33]: fit_lin = LinearRegressionWithSGD.train(df_train, 500, .0001)
         print(fit_lin)
```

```
(weights=[0.116168979055,0.226422311253,0.26017070975,0.207218347234,0.304143328575,0.5058370187
```

4.0.12 Prediction

With the above model we can predict the values from the test dataset.

```
In [34]: df_pred = df_test.map(lambda p: (p.label, fit_lin.predict(p.features)))
         print ("Linear Model predictions: " + str(df_pred.take(10)))
```

```
Linear Model predictions: [(36.0, 2.9554706504526154), (110.0, 2.649529971102679), (53.0, 2.5569
```

4.0.13 Accuracy

Next we can calculate the accuracy of our model.

```
In [35]: mse2 = df_pred.map(lambda (t, p): squared_error(t, p)).mean()
         mae2 = df_pred.map(lambda (t, p): abs_error(t, p)).mean()
         rmsle2=np.sqrt(df_pred.map(lambda(t,p):squared_log_error(t,p)).mean())
         print ("Linear model: - Mean squared error: %2.4f" % mse)
         print ("Linear model: - Mean absolute error: %2.4f" % mae)
         print ("Linear model: - Root mean squared log error: %2.4f" % rmsle)
```

```
Linear model: - Mean squared error: 242.6391
Linear model: - Mean absolute error: 12.3945
Linear model: - Root mean squared log error: 0.6914
```

The model has a MSE of 242.64 and a MAE of 12.39 while the RMSLE is at 0.69.

5 Problem 4 (25%)

Question: Use a *Decision Tree model* to predict *mpg* values in *auto_mpg_original.txt* data. Assess accuracy of your prediction using at least two performance metrics.

5.0.1 Functions

The below problem needs the following functions to be solved.

```
In [36]: def extract_features(record):
             cat_vec = np.zeros(cat_len)
             i = 0
             step = 0
             for field in record[0:4] :
                 m = mappings[i]
                 idx = m[field]
                 cat_vec[idx + step] = 1
                 i = i + 1
                 step = step + len(m)
             num_vec = np.array([float(field) for field in record[4:8]])
             return np.concatenate((cat_vec, num_vec))

         def extract_features_dt(record):
             return np.array(map(float, record[0:8]))
```

5.0.2 Prepare data

First we're preparing the dataframe. We're using the same dataframe as used in problem 1 & 2. That means we can pick up from dataframe2 (df2). The advantage of the regression tree is that we can simply hash the car name for our analyis.

```
In [37]: # Prepare data
         df_car = df2.select(df2.cylinders.cast('int'), df2.my.cast('int'),
                             abs(hash(df2.name)).alias('name').cast('int'),
                             df2.origin.cast('int'), df2.acceleration, df2.displacement,
                             df2.horsepower, df2.weight, df2.mpg)
         rdd_car = df_car.rdd
```

5.0.3 Create mapping

Next we can create the mapping.

```
In [38]: # Create Mapping
         mappings = [get_mapping(rdd_car, i) for i in range(0,4)]
         print (mappings)

[{8: 4, 3: 0, 4: 1, 5: 2, 6: 3}, {70: 0, 71: 1, 72: 2, 73: 3, 74: 4, 75: 5, 76: 6, 77: 7, 78: 8,
```

5.0.4 Feature description

Next we can output the features used for the prediction.

```
In [39]: print "Length of categorical features: %d" % np.sum(map(len, mappings))
         print "Length of numerical features: %d" % len(rdd_car.first()[4:9])
         print "Total feature vector length: %d" % (np.sum(map(len, mappings)) + len(rdd_car.fir
```

```
Length of categorical features: 59
Length of numerical features: 5
Total feature vector length: 64
```

5.0.5 Label points

Next we can label the dataset.

```
In [40]: df_car2 = rdd_car.map(lambda r: LabeledPoint(extract_label(r),
                                                       extract_features_dt(r)))
```

```
In [41]: df_car2.take(5)
```

```
Out[41]: [LabeledPoint(25.0, [4.0,70.0,1304410654.0,2.0,17.5,110.0,87.0,2672.0]),
          LabeledPoint(26.0, [4.0,70.0,1064022512.0,2.0,12.5,121.0,113.0,2234.0]),
          LabeledPoint(27.2000007629, [4.0,78.0,1936435720.0,3.0,14.6999998093,119.0,97.0,2300.0
          LabeledPoint(25.0, [4.0,72.0,420531909.0,1.0,17.0,97.5,80.0,2126.0]),
          LabeledPoint(25.0, [4.0,76.0,1355140489.0,1.0,14.8999996185,140.0,92.0,2572.0])]
```

```
In [42]: first_point = df_car2.first()
         print ("Label: " + str(first_point.label))
         print ("Linear Model feature vector:\n" + str(first_point.features))
         print ("Linear Model feature vector length: " + str(len(first_point.features)))
```

```
Label: 25.0
Linear Model feature vector:
[4.0,70.0,1304410654.0,2.0,17.5,110.0,87.0,2672.0]
Linear Model feature vector length: 8
```

5.0.6 Split data

In order to control for overfitting we're splitting the dataset. We're using the same split as in problem 1, i.e., 80% training and 20% test set.

```
In [43]: # Split data
         df_train, df_test = df_car2.randomSplit([.8, .2], seed=123)

         df_train = df_train.cache()
         df_test = df_test.cache()
```

5.0.7 Regression tree

Next we can build the regression tree with the *DecisionTree* method. It thas a default tree depth of 5. As we're using the labelpoint we don't have to input any categorical features.

```
In [44]: fit_tree = DecisionTree.trainRegressor(df_train,{})
```

5.0.8 Prediction

With the above model we can predict the values in the test set.

```
In [45]: preds = fit_tree.predict(df_test.map(lambda p: p.features))
         actual = df_test.map(lambda p: p.label)
         tbl_pred = actual.zip(preds)
```

5.0.9 Tree caracteristics

Next we can output the tree characteristics.

```
In [46]: print ("Decision tree predictions: " + str(tbl_pred.take(5)))
         print ("Decision tree depth: " + str(fit_tree.depth()))
         print ("Decision tree number of nodes: " + str(fit_tree.numNodes()))

         testErr = tbl_pred.filter(lambda (v, p): v != p).count() / float(df_test.count())
         print('Test error = ' + str(testErr))
```

```
Decision tree predictions: [(44.0, 39.099998474121094), (19.0, 18.40909090909091), (18.0, 20.390
Decision tree depth: 5
Decision tree number of nodes: 63
Test error = 1.0
```

The tree has 63 nodes and tree depth of 5.

5.0.10 Accuracy

Next we can have a look at the accuracy of the model.

```
In [47]: mse = tbl_pred.map(lambda (t, p): squared_error(t, p)).mean()
         mae = tbl_pred.map(lambda (t, p): abs_error(t, p)).mean()
         rmsle = np.sqrt(tbl_pred.map(lambda (t, p): squared_log_error(t, p)).mean())
         print "Decision tree: Mean squared error: %2.4f" % mse
         print "Decision tree: Mean absolute error: %2.4f" % mae
         print "Decision tree: Root mean squared log error: %2.4f" % rmsle
```

```
Decision tree: Mean squared error: 24.0046
Decision tree: Mean absolute error: 3.3218
Decision tree: Root mean squared log error: 0.2085
```

The above tree achieves a MSE of 24, a MAE of 3.3 and a RMSLE of 0.2. comparing that with the simple linear regression model from problem 2 (MSE: 242.64, MAE: 12.39 and RMSLE: 0.69) the regression tree clearly outperforms the regression model. This was to be expected as we're using much more features. Furthermore, as already mentioned in problem 2, some of the data shows a non-linear relationship with the target variable.

5.0.11 Output tree (optional)

Last but not least we can have a look at the actual tree.

```
In [ ]: print(fit_tree.toDebugString())
```

```
DecisionTreeModel regressor of depth 5 with 63 nodes
  If (feature 0 <= 5.0)
   If (feature 7 <= 2219.0)
    If (feature 1 <= 77.0)
     If (feature 4 <= 19.5)
      If (feature 7 <= 2075.0)
       Predict: 31.023809523809526
      Else (feature 7 > 2075.0)
       Predict: 27.366666666666667
     Else (feature 4 > 19.5)
      If (feature 1 <= 71.0)
       Predict: 22.333333333333332
      Else (feature 1 > 71.0)
       Predict: 25.25
    Else (feature 1 > 77.0)
     If (feature 6 <= 58.0)
      If (feature 1 <= 78.0)
       Predict: 43.099998474121094
      Else (feature 1 > 78.0)
       Predict: 39.099998474121094
     Else (feature 6 > 58.0)
      If (feature 5 <= 91.0)
       Predict: 36.236841804102845
      Else (feature 5 > 91.0)
       Predict: 34.14117656034582
   Else (feature 7 > 2219.0)
    If (feature 1 <= 78.0)
     If (feature 7 <= 2300.0)
      If (feature 4 <= 18.200000762939453)
       Predict: 26.35384618318998
      Else (feature 4 > 18.200000762939453)
       Predict: 21.5
     Else (feature 7 > 2300.0)
      If (feature 7 <= 2865.0)
       Predict: 23.181250035762787
      Else (feature 7 > 2865.0)
       Predict: 20.285714285714285
    Else (feature 1 > 78.0)
     If (feature 7 <= 2560.0)
      If (feature 0 <= 3.0)
       Predict: 23.700000762939453
      Else (feature 0 > 3.0)
       Predict: 32.24285738808768
```

```
    Else (feature 7 > 2560.0)
     If (feature 5 <= 135.0)
      Predict: 29.521481619940865
     Else (feature 5 > 135.0)
      Predict: 26.671428544180735
 Else (feature 0 > 5.0)
  If (feature 6 <= 129.0)
   If (feature 1 <= 78.0)
    If (feature 5 <= 232.0)
     If (feature 7 <= 3465.0)
      Predict: 20.390909108248625
     Else (feature 7 > 3465.0)
      Predict: 18.18571444920131
    Else (feature 5 > 232.0)
     If (feature 4 <= 16.5)
      Predict: 18.40909090909091
     Else (feature 4 > 16.5)
      Predict: 16.444444444444443
   Else (feature 1 > 78.0)
    If (feature 2 <= 1.488979555E9)
     If (feature 7 <= 3420.0)
      Predict: 20.866666793823242
     Else (feature 7 > 3420.0)
      Predict: 17.600000381469727
    Else (feature 2 > 1.488979555E9)
     If (feature 1 <= 81.0)
      Predict: 24.714285714285715
     Else (feature 1 > 81.0)
      Predict: 38.0
  Else (feature 6 > 129.0)
   If (feature 7 <= 4054.0)
    If (feature 6 <= 150.0)
     If (feature 1 <= 76.0)
      Predict: 15.2
     Else (feature 1 > 76.0)
      Predict: 17.845454822887074
    Else (feature 6 > 150.0)
     If (feature 7 <= 3613.0)
      Predict: 15.566666920979818
     Else (feature 7 > 3613.0)
      Predict: 26.0
   Else (feature 7 > 4054.0)
    If (feature 1 <= 74.0)
     If (feature 7 <= 4278.0)
      Predict: 14.545454545454545
     Else (feature 7 > 4278.0)
      Predict: 12.636363636363637
    Else (feature 1 > 74.0)
```

```
If (feature 1 <= 77.0)
 Predict: 15.26923076923077
Else (feature 1 > 77.0)
 Predict: 17.199999809265137
```

As can be seen above, the tree uses a multitude of features that the tree selected as spliting points.