Decision Tree and Random Forest

The goal: predict gas consumption (low or high, 0 or 1) in 48 of the US states based on petrol tax (in cents), per capita income (dollars), paved highways (in miles) and the proportion of population with the driving license. 1) Import Libraries 2) Import Dataset 3) Perform basic EDA – your choice (come up with 3 insights) 4) Classification:
a. Train a basic decision tree preparing variables as necessary for the model b. Analyze the results of the decision tree classification following our example 5) Classification: Random Forest a. Train a basic random forest model preparing variables as necessary for the model b. Analyze the results of the random forest classification following our example

Import Libraries and data set

Import the usual libraries for pandas and plotting

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

1. Get the Data: Use pandas to read petroleum cnsumption**

In [2]:
```
df = pd.read_csv('petrol_consumption_low_high.csv')
```

2. Check out the info(), head(), and describe() methods on petrol consumption

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48 entries, 0 to 47
Data columns (total 5 columns):
Petrol_tax                      48 non-null float64
Average_income                  48 non-null int64
Paved_Highways                  48 non-null int64
Population_Driver_licence(%)    48 non-null float64
Petrol_Consumption              48 non-null int64
dtypes: float64(2), int64(3)
memory usage: 2.0 KB
```

In [67]:
```
df.head()
```

Out[67]:

	Petrol_tax	Average_income	Paved_Highways	Population_Driver_licence(%)	Petrol_Consumptio
0	8.0	5319	11868	0.451	
1	8.0	4399	431	0.544	
2	7.5	4870	2351	0.529	
3	10.0	5342	1333	0.571	
4	8.5	4574	2619	0.551	

In [5]:
```
df.describe()
```

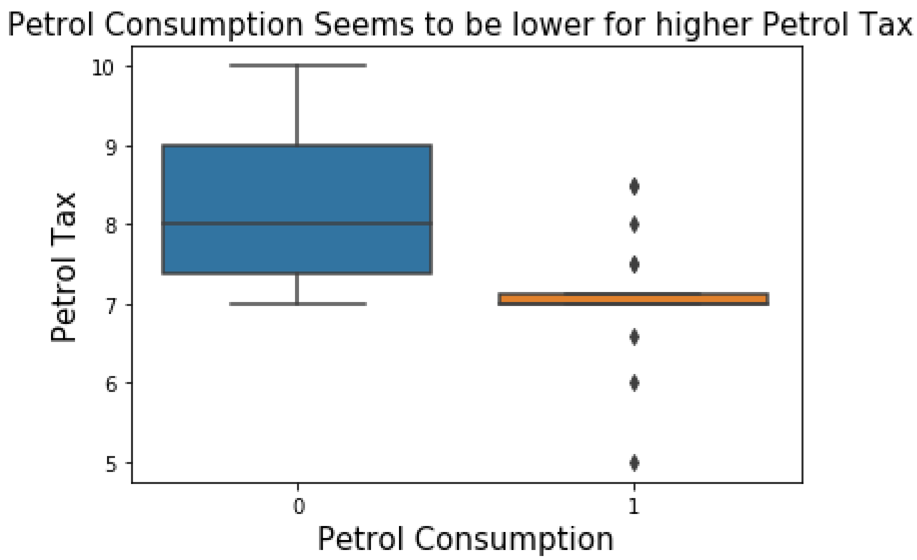
Out[5]:

	Petrol_tax	Average_income	Paved_Highways	Population_Driver_licence(%)	Petrol_Consui
count	48.000000	48.000000	48.000000	48.000000	48.(
mean	7.668333	4241.833333	5565.416667	0.570333	0.4
std	0.950770	573.623768	3491.507166	0.055470	0.4
min	5.000000	3063.000000	431.000000	0.451000	0.(
25%	7.000000	3739.000000	3110.250000	0.529750	0.(
50%	7.500000	4298.000000	4735.500000	0.564500	0.(
75%	8.125000	4578.750000	7156.000000	0.595250	1.(
max	10.000000	5342.000000	17782.000000	0.724000	1.(

3a. Exploratory Data Analysis - Explore the data in a meaningful way in order to find variables of interest. Create at least 6 visualizations that are meaningful and document your observations with a markdown cell for each visualization

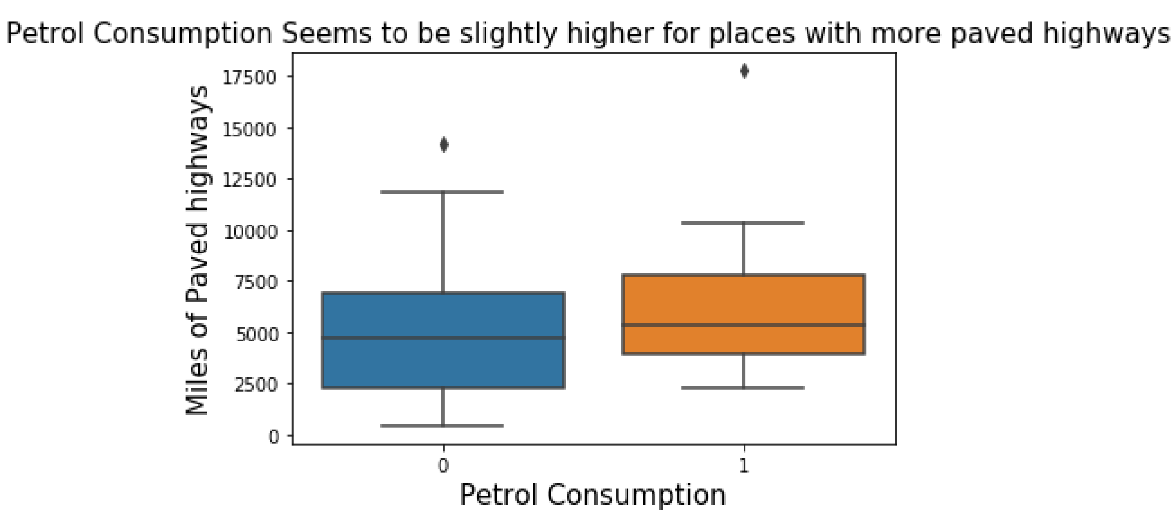
In [8]:
```
sns.boxplot(x=df['Petrol_Consumption'],y=df['Petrol_tax'])
plt.title("Petrol Consumption Seems to be lower for higher Petrol Tax ", fontsize=15)
plt.xlabel("Petrol Consumption",fontsize=15)
plt.ylabel("Petrol Tax",fontsize=15)
```

Out[8]:
```
Text(0, 0.5, 'Petrol Tax')
```



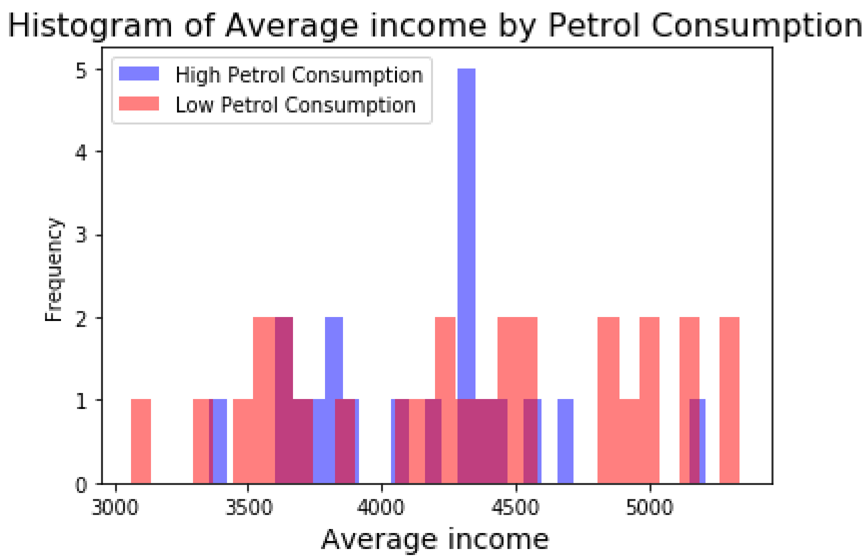
In [11]:
```
sns.boxplot(x=df['Petrol_Consumption'],y=df['Paved_Highways'])
plt.title("Petrol Consumption Seems to be slightly higher for places with more paved highways ", fontsize=15)
plt.xlabel("Petrol Consumption",fontsize=15)
plt.ylabel("Miles of Paved highways",fontsize=15)
```

Out[11]:
```
Text(0, 0.5, 'Miles of Paved highways')
```



In [13]:
```
df[df['Petrol_Consumption']==1]['Average_income'].plot.hist(bins=30,alpha=0.5,
color='blue', label='High Petrol Consumption')
df[df['Petrol_Consumption']==0]['Average_income'].plot.hist(bins=30,alpha=0.5,
color='red', label='Low Petrol Consumption')
plt.legend(fontsize=10)
plt.title ("Histogram of Average income by Petrol Consumption", fontsize=16)
plt.xlabel("Average income", fontsize=14)
```

Out[13]:
```
Text(0.5, 0, 'Average income')
```

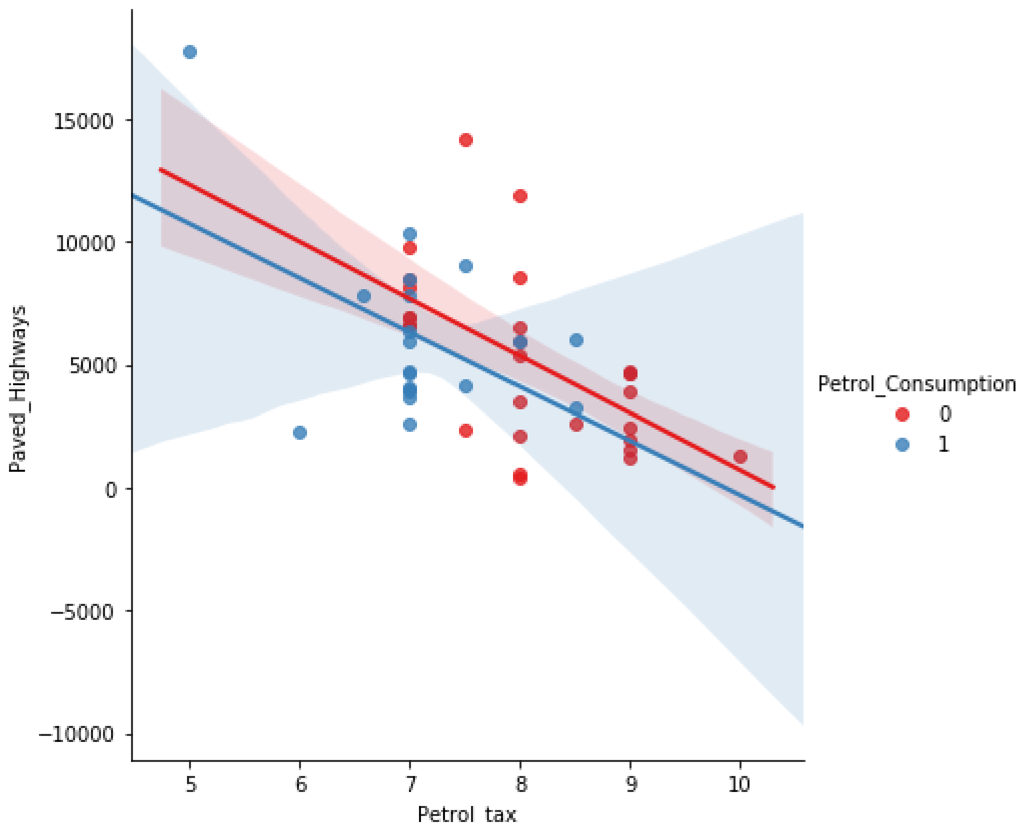


In [15]:
```
plt.figure(figsize=(14,7))
sns.lmplot(y='Paved_Highways',x='Petrol_tax',data=df,hue='Petrol_Consumption',
palette='Set1',size=6)
```

```
C:\Users\p2840013\AppData\Local\Continuum\anaconda3_school\lib\site-packages
\seaborn\regression.py:546: UserWarning: The `size` paramter has been renamed
to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```

Out[15]: <seaborn.axisgrid.FacetGrid at 0x2260988c5c0>

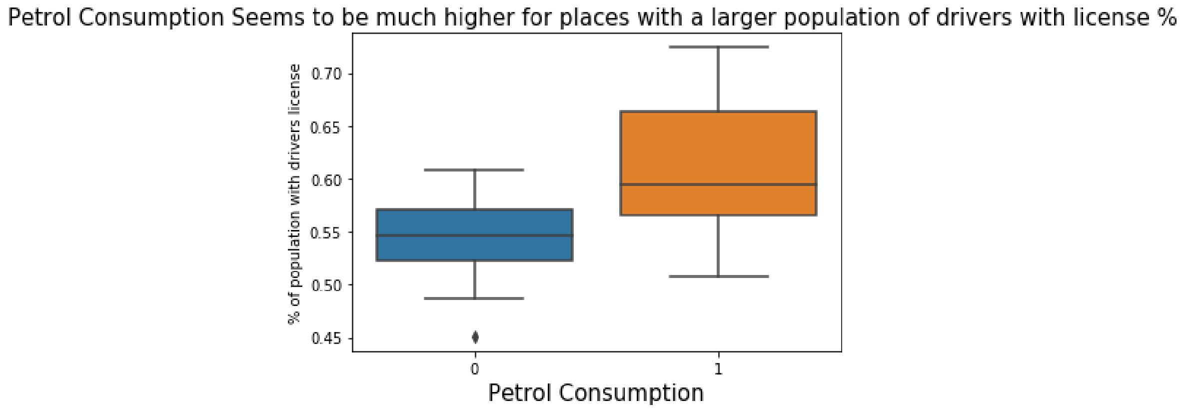
<Figure size 1008x504 with 0 Axes>



In [ ]:
```
##Interesting to see that there is a tiny negative correlation between tax and
miles of highways.
```

In [18]:
```
sns.boxplot(x=df['Petrol_Consumption'],y=df['Population_Driver_licence(%)'])
plt.title("Petrol Consumption Seems to be much higher for places with a larger population of drivers with license % ", fontsize=15)
plt.xlabel("Petrol Consumption",fontsize=15)
plt.ylabel("% of population with drivers license",fontsize=10)
```

Out[18]:
```
Text(0, 0.5, '% of population with drivers license')
```



In [21]:

```
print(df.corr())
plt.figure(figsize=(10,7))
sns.heatmap(df.corr(),annot=True,linewidths=2)

#Based on the output below there are moderate correlations between.....
#Petrol_Consumption & Population_Driver_licence(%) .556
#Petrol_Consumption & Petrol_tax -.529
#Paved_Highways & Petrol_tax -.522

#but not really and STRONG correlations
```

```
                              Petrol_tax  Average_income  Paved_Highways  \
Petrol_tax                      1.000000        0.012665       -0.522130
Average_income                  0.012665        1.000000        0.050163
Paved_Highways                 -0.522130        0.050163        1.000000
Population_Driver_licence(%)   -0.288037        0.157070       -0.064129
Petrol_Consumption             -0.529411       -0.146339        0.141632

                              Population_Driver_licence(%)  Petrol_Consumptio
n
Petrol_tax                                       -0.288037           -0.52941
1
Average_income                                    0.157070           -0.14633
9
Paved_Highways                                   -0.064129            0.14163
2
Population_Driver_licence(%)                      1.000000            0.55610
3
Petrol_Consumption                                0.556103            1.00000
0
```

Out[21]: `<matplotlib.axes._subplots.AxesSubplot at 0x22609a7e470>`

3b. Prepare the data as necessary with consideration to missing values, scaling, categorical variables, etc.

In [24]:
```
#No categorical variables in the data set
print(df.isna().sum())
#No missing values in the data set
```

```
Petrol_tax                      0
Average_income                  0
Paved_Highways                  0
Population_Driver_licence(%)    0
Petrol_Consumption              0
dtype: int64
```

4. Setting up the Data

Prepare the data for analysis by creating a new dataframe without the first

row of headings and verify the results

In [25]:
```
df_final = pd.get_dummies(df,drop_first=True)
```

In [27]:
```
df_final.head()
```

Out[27]:

	Petrol_tax	Average_income	Paved_Highways	Population_Driver_licence(%)	Petrol_Consumptic
0	8.0	5319	11868	0.451	
1	8.0	4399	431	0.544	
2	7.5	4870	2351	0.529	
3	10.0	5342	1333	0.571	
4	8.5	4574	2619	0.551	

5. Create your Train Test Split based on Petrol_Consumption as the target

and verify your work

In [28]:
```
from sklearn.model_selection import train_test_split
X = df_final.drop('Petrol_Consumption',axis=1)
y = df_final['Petrol_Consumption']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)
```

In [29]:
```
X.head()
```

Out[29]:

	Petrol_tax	Average_income	Paved_Highways	Population_Driver_licence(%)
0	8.0	5319	11868	0.451
1	8.0	4399	431	0.544
2	7.5	4870	2351	0.529
3	10.0	5342	1333	0.571
4	8.5	4574	2619	0.551

6. Show your work to train the Decision Tree Model - first create an instance of DecisionTreeClassifier() called dtree and fit it to the training data.

In [30]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [31]:
```
dtree = DecisionTreeClassifier(criterion='gini',max_depth=None)
```

In [32]:
```
dtree.fit(X_train,y_train)
```

Out[32]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False, random_state=None,
                       splitter='best')
```

7. Predictions and Evaluation of Decision Tree

Create predictions from the test set and create a classification report and a confusion matrix.

In [33]:
```
predictions = dtree.predict(X_test)
```

In [34]:
```
from sklearn.metrics import classification_report,confusion_matrix
```

In [36]:
```
print(classification_report(y_test,predictions))
cm=confusion_matrix(y_test,predictions)
print(cm)
print ("Accuracy of prediction:",round((cm[0,0]+cm[1,1])/cm.sum(),3))
```

```
              precision    recall  f1-score   support

           0       0.80      0.80      0.80        10
           1       0.60      0.60      0.60         5

   micro avg       0.73      0.73      0.73        15
   macro avg       0.70      0.70      0.70        15
weighted avg       0.73      0.73      0.73        15

[[8 2]
 [2 3]]
Accuracy of prediction: 0.733
```

8. What would be the accuracy of a prediction with a baseline model just using the % of 0's and 1's in the overall data set? We can use this to see if we perform better than a baseline or simple model based on raw data observations

There were 20 High's and 28 Lows.

9. Training the Random Forest model: Create an instance of the RandomForestClassifier class and fit it to the training data from the previous step.

In [59]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [60]:
```
rfc = RandomForestClassifier(n_estimators=100)
```

In [61]:
```
rfc.fit(X_train, y_train)
```

Out[61]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

10. Predictions and Evaluation: predict with the y_test values and evaluate the model.

In [62]:
```
rfc_pred = rfc.predict(X_test)
```

11. Create a classification report from the results.

In [63]:
```
cr = classification_report(y_test,predictions)
```

In [64]:
```
print(cr)
```

```
              precision    recall  f1-score   support

           0       0.80      0.80      0.80        10
           1       0.60      0.60      0.60         5

   micro avg       0.73      0.73      0.73        15
   macro avg       0.70      0.70      0.70        15
weighted avg       0.73      0.73      0.73        15
```

12. Show the Confusion Matrix for the predictions.

In [65]:
```
cm = confusion_matrix(y_test,rfc_pred)
print(cm)
```

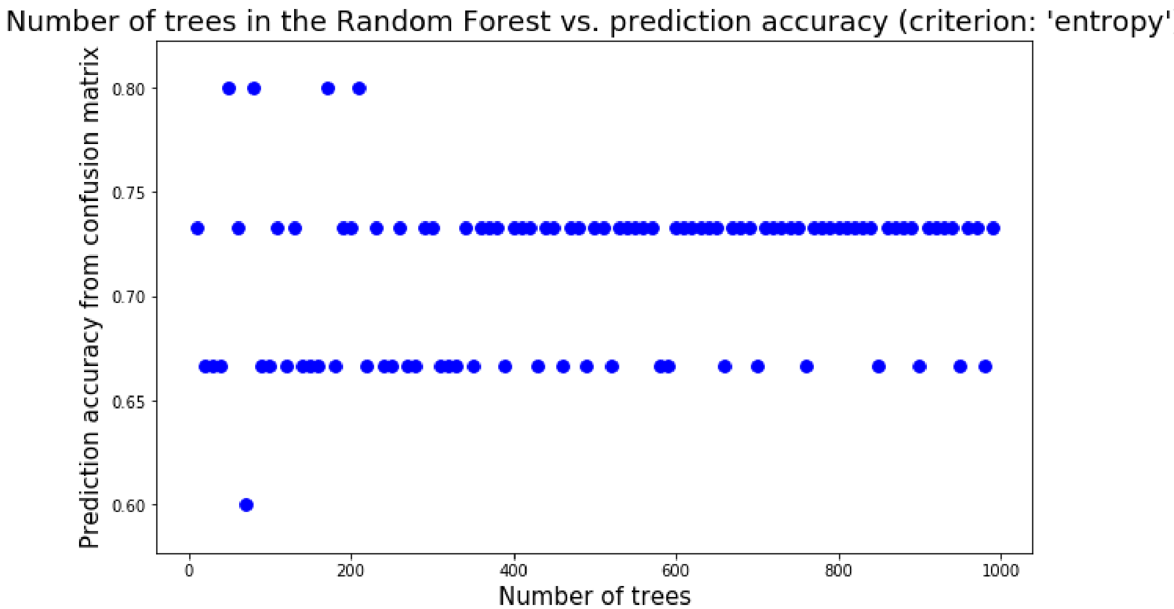
```
[[9 1]
 [1 4]]
```

13. Run a loop with increasing number of trees in the random forest and checking accuracy of confusion matrix with criterion 'gini' or 'entropy'

In [57]:
```
nsimu = 100
accuracy=[0]*nsimu
ntree = [0]*nsimu
for i in range(1,nsimu):
    rfc = RandomForestClassifier(n_estimators=i*5,min_samples_split=10,max_dep
th=None,criterion='entropy')
    rfc.fit(X_train, y_train)
    rfc_pred = rfc.predict(X_test)
    cm = confusion_matrix(y_test,rfc_pred)
    accuracy[i] = (cm[0,0]+cm[1,1])/cm.sum()
    ntree[i]=i*10
```

In [58]:
```
plt.figure(figsize=(10,6))
plt.scatter(x=ntree[1:nsimu],y=accuracy[1:nsimu],s=60,c='blue')
plt.title("Number of trees in the Random Forest vs. prediction accuracy (crite
rion: 'entropy')", fontsize=18)
plt.xlabel("Number of trees", fontsize=15)
plt.ylabel("Prediction accuracy from confusion matrix", fontsize=15)
```

Out[58]:
```
Text(0, 0.5, 'Prediction accuracy from confusion matrix')
```



14. Evaluate the decision tree classification in your own words.

The decision tree had and F1 of .73 which is not great because it is somewhat close to 1. What was not good was the overall error rate of 10/21 = .476. The sensitivity or Recall was 3/5 = .60

15. Evaluate the random forest model in your own words.

RM also had an F1 of .73 but had an overall error rate of only 2/15 = .133. The sensitivity was 4/5 = .8

16. Which model performed better and why? Did the models perform better than a baseline model?

Although both models had a similar F1 score, the random forest model was better due to the much lower Overall Error Rate of .133 vs. the decision trees OER of .476. The RFM also had a Sensitivity that was .2 higher, .8 vs. .6. Since .8 is closer to one the RFM had a better sensitivity rate. These were both better than the baseline model.