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In [ ]: #Cris Chou
#Cyc180001
#HW8
from matplotlib.colors import Normalize
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

```
In [ ]: df = pd.read_csv(r"C:\Users\C\Desktop\school\CS 4375\hw8\Auto.csv") #switch to file loc
print(df.head())
print(df.shape)
print('\nDescription of mpg, weight, and year\n', df.loc[:,['mpg','weight','year']].desc
print("The range for mpg was from 9-46.6, for weight, 1613-5140, and for year, 70-82. T
print("\nThe data types for each column are \n", df.dtypes)
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	\
0	18.0	8	307.0	130	3504	12.0	70.0	
1	15.0	8	350.0	165	3693	11.5	70.0	
2	18.0	8	318.0	150	3436	11.0	70.0	
3	16.0	8	304.0	150	3433	12.0	70.0	
4	17.0	8	302.0	140	3449	NaN	70.0	

	origin	name
0	1	chevrolet chevelle malibu
1	1	buick skylark 320
2	1	plymouth satellite
3	1	amc rebel sst
4	1	ford torino

(392, 9)

Description of mpg, weight, and year

	mpg	weight	year
count	392.000000	392.000000	390.000000
mean	23.445918	2977.584184	76.010256
std	7.805007	849.402560	3.668093
min	9.000000	1613.000000	70.000000
25%	17.000000	2225.250000	73.000000
50%	22.750000	2803.500000	76.000000
75%	29.000000	3614.750000	79.000000
max	46.600000	5140.000000	82.000000

The range for mpg was from 9-46.6, for weight, 1613-5140, and for year, 70-82. The averages respectively, were 23.459, 2977.584, and 76.01

The data types for each column are

mpg	float64
cylinders	int64
displacement	float64
horsepower	int64
weight	int64
acceleration	float64
year	float64
origin	int64
name	object
dtype:	object

```
In [ ]: #change using catecode
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```
df.cylinders = df.cylinders.astype('category').cat.codes
df.origin = df.origin.astype('category')
print("\n After\n")
print(df.dtypes)
```

After

```
mpg          float64
cylinders    int8
displacement float64
horsepower   int64
weight       int64
acceleration float64
year         float64
origin       category
name         object
dtype: object
```

```
In [ ]: #deleting NAs
df.dropna(inplace=True)
print(df.shape)
```

(389, 9)

```
In [ ]: #modify columns
averageMPG = df.mpg.mean()
df['mpg_high'] = np.where(df.mpg > averageMPG, 1,0)
df = df.drop(columns=['mpg', 'name'])
print(df.head())
```

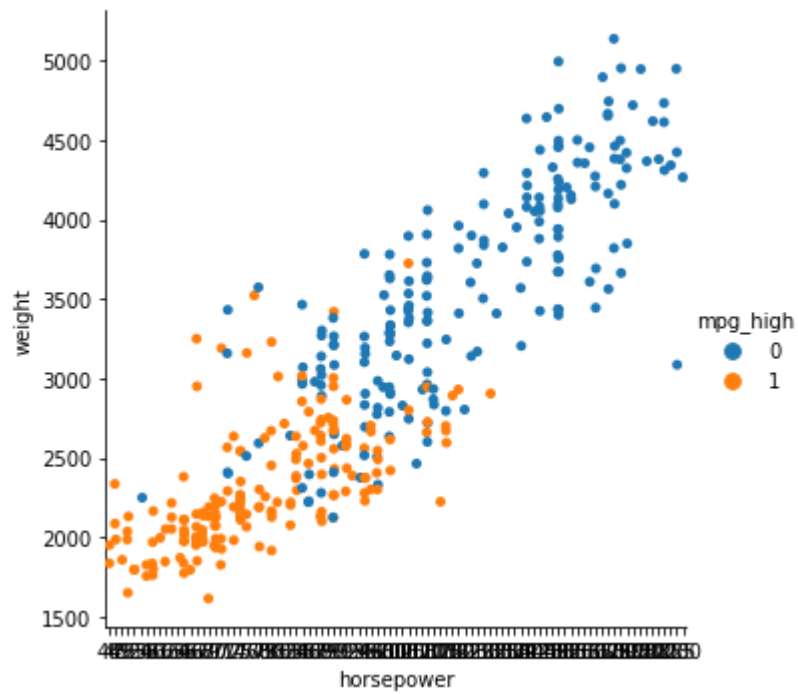
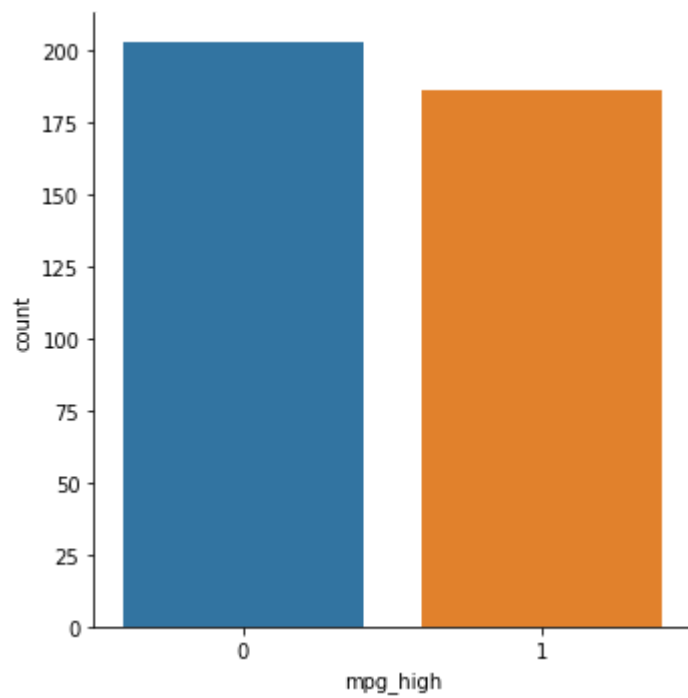
	cylinders	displacement	horsepower	weight	acceleration	year	origin	\
0	4	307.0	130	3504	12.0	70.0	1	
1	4	350.0	165	3693	11.5	70.0	1	
2	4	318.0	150	3436	11.0	70.0	1	
3	4	304.0	150	3433	12.0	70.0	1	
6	4	454.0	220	4354	9.0	70.0	1	

	mpg_high
0	0
1	0
2	0
3	0
6	0

```
In [ ]: #data exploration with graphs

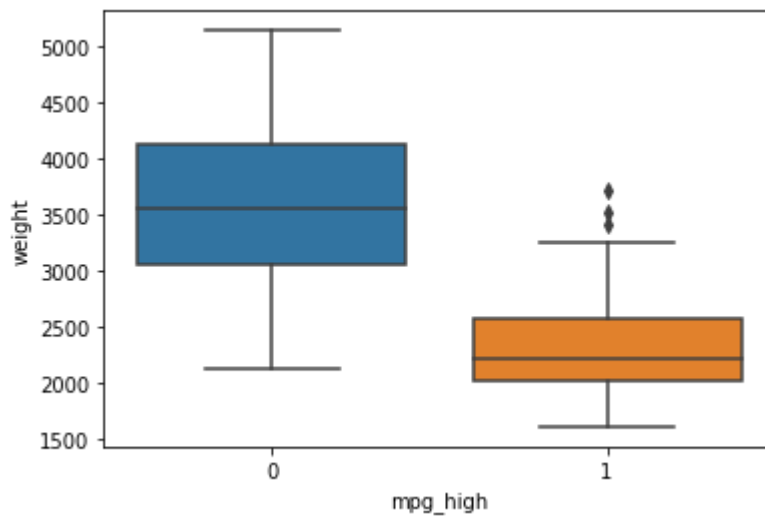
sns.catplot(x="mpg_high", kind="count", data=df)
#plt.show()
#in the data there is almost an even amount of cars with high and not high mpg
sns.catplot(x="horsepower", y="weight", hue = "mpg_high",data=df)
#plt.show()
#in the data it seems that cars with less mpg trend towards higher horsepower and heavi
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Out[ ]: <seaborn.axisgrid.FacetGrid at 0x222d174fa60>
```



```
In [ ]: sns.boxplot(x = "mpg_high", y = "weight", data = df)
        #plt.show()
        #cars with lower mpg seem to average heavier weight
```

```
Out[ ]: <AxesSubplot:xlabel='mpg_high', ylabel='weight'>
```



```
In [ ]: #train test
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
X = df.iloc[:,0:6]
y = df.iloc[:,7]
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=.2,random_state=1234)
print("Train size", X_train.shape)
print("Test size", X_test.shape)
```

Train size (311, 6)

Test size (78, 6)

```
In [ ]: #Logistic regression
logreg = LogisticRegression(solver = "lbfgs")
logreg.fit(X_train,y_train)

logPred = logreg.predict(X_test)
import sklearn.metrics as metrics
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.metrics import classification_report
print("mse= ", metrics.mean_squared_error(y_test,logPred))
print("correlation= ",metrics.r2_score(y_test,logPred))
print("Logistic Regression \n")
print(classification_report(y_test, logPred))
```

mse= 0.14102564102564102

correlation= 0.387142857142857

Logistic Regression

	precision	recall	f1-score	support
0	0.98	0.80	0.88	50
1	0.73	0.96	0.83	28
accuracy			0.86	78
macro avg	0.85	0.88	0.85	78
weighted avg	0.89	0.86	0.86	78

```
In [ ]: #Decision tree
from sklearn.tree import DecisionTreeClassifier
```

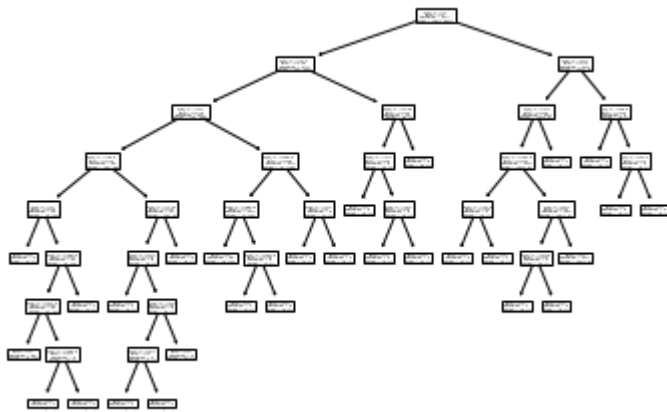
```

clf = DecisionTreeClassifier()
clf.fit(X_train,y_train)
treePred = clf.predict(X_test)
print("Decision Tree: \n")
print(classification_report(y_test,treePred))
from sklearn import tree
tree.plot_tree(clf)
plt.show()

```

Decision Tree:

	precision	recall	f1-score	support
0	0.96	0.92	0.94	50
1	0.87	0.93	0.90	28
accuracy			0.92	78
macro avg	0.91	0.92	0.92	78
weighted avg	0.93	0.92	0.92	78



In []:

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Analysis:
The Logistic Regression had higher accuracy for predicting when a car did not have mpg_
Decision Tree out performed Logistic Regression in terms of accuracy. Thus the Decision
It performed better because the target was a binary factor. There were also a few outli
Logistic Regression is not flexible towards outliers.
'''

```