In the Week 4 Exercise, you will build a linear regression model to predict fuel efficiency (miles per gallon) of automobiles.

1. Download the auto-mpg.csv dataset from: Auto-mpg dataset. Load the data as a Pandas data frame and ensure that it imported correctly.

In [1]:
```
import pandas as pd
import numpy as np
```

In [23]:
```
auto_mpg_df  = pd.read_csv('auto-mpg.csv')
auto_mpg_df.head(5)
```

Out[23]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino

2. Begin by prepping the data for modeling:

```
i. Remove the car name column.
```

In [24]:
```
auto_mpg_df_v2 = auto_mpg_df.drop( columns='car name')
auto_mpg_df_v2.head(5)
```

Out[24]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin
0	18.0	8	307.0	130	3504	12.0	70	1
1	15.0	8	350.0	165	3693	11.5	70	1
2	18.0	8	318.0	150	3436	11.0	70	1
3	16.0	8	304.0	150	3433	12.0	70	1
4	17.0	8	302.0	140	3449	10.5	70	1

```
ii. The horsepower column values likely imported as a string data type. Figure
out why and replace any strings with the column mean.
```

In [25]:
```
auto_mpg_df_v2.dtypes # Identifying datatypes. horsepower is in an object.
```

Out[25]:
```
mpg              float64
cylinders          int64
displacement     float64
horsepower        object
weight             int64
acceleration     float64
model year         int64
```

```
origin            int64
dtype: object
```

In [26]:
```
auto_mpg_df_v2.horsepower.unique() # Getting unique values to find incorrect values
```

Out[26]:
```
array(['130', '165', '150', '140', '198', '220', '215', '225', '190',
       '170', '160', '95', '97', '85', '88', '46', '87', '90', '113',
       '200', '210', '193', '?', '100', '105', '175', '153', '180', '110',
       '72', '86', '70', '76', '65', '69', '60', '80', '54', '208', '155',
       '112', '92', '145', '137', '158', '167', '94', '107', '230', '49',
       '75', '91', '122', '67', '83', '78', '52', '61', '93', '148',
       '129', '96', '71', '98', '115', '53', '81', '79', '120', '152',
       '102', '108', '68', '58', '149', '89', '63', '48', '66', '139',
       '103', '125', '133', '138', '135', '142', '77', '62', '132', '84',
       '64', '74', '116', '82'], dtype=object)
```

Horsepower has a '?' which is not an int/float. Replacing '?' with the mean of horsepower

In [27]:
```
auto_mpg_df_v2['horsepower'] = auto_mpg_df_v2['horsepower'].replace('?', np.mean(pd.to_n
auto_mpg_df_v2['horsepower'].unique()
```

Out[27]:
```
array(['130', '165', '150', '140', '198', '220', '215', '225', '190',
       '170', '160', '95', '97', '85', '88', '46', '87', '90', '113',
       '200', '210', '193', 104.46938775510205, '100', '105', '175',
       '153', '180', '110', '72', '86', '70', '76', '65', '69', '60',
       '80', '54', '208', '155', '112', '92', '145', '137', '158', '167',
       '94', '107', '230', '49', '75', '91', '122', '67', '83', '78',
       '52', '61', '93', '148', '129', '96', '71', '98', '115', '53',
       '81', '79', '120', '152', '102', '108', '68', '58', '149', '89',
       '63', '48', '66', '139', '103', '125', '133', '138', '135', '142',
       '77', '62', '132', '84', '64', '74', '116', '82'], dtype=object)
```

    iii. Create dummy variables for the origin column.

In [28]:
```
auto_mpg_dummy_df = pd.get_dummies(auto_mpg_df, columns=['origin'])
auto_mpg_dummy_df.head(5)
```

Out[28]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	car name	origin_1	origin_2	origin_3
0	18.0	8	307.0	130	3504	12.0	70	chevrolet chevelle malibu	1	0	(
1	15.0	8	350.0	165	3693	11.5	70	buick skylark 320	1	0	(
2	18.0	8	318.0	150	3436	11.0	70	plymouth satellite	1	0	(
3	16.0	8	304.0	150	3433	12.0	70	amc rebel sst	1	0	(
4	17.0	8	302.0	140	3449	10.5	70	ford torino	1	0	(

3. Create a correlation coefficient matrix and/or visualization. Are there features highly correlated with mpg?

In [35]:
```
auto_mpg_df_v2.corr(numeric_only=True)
```

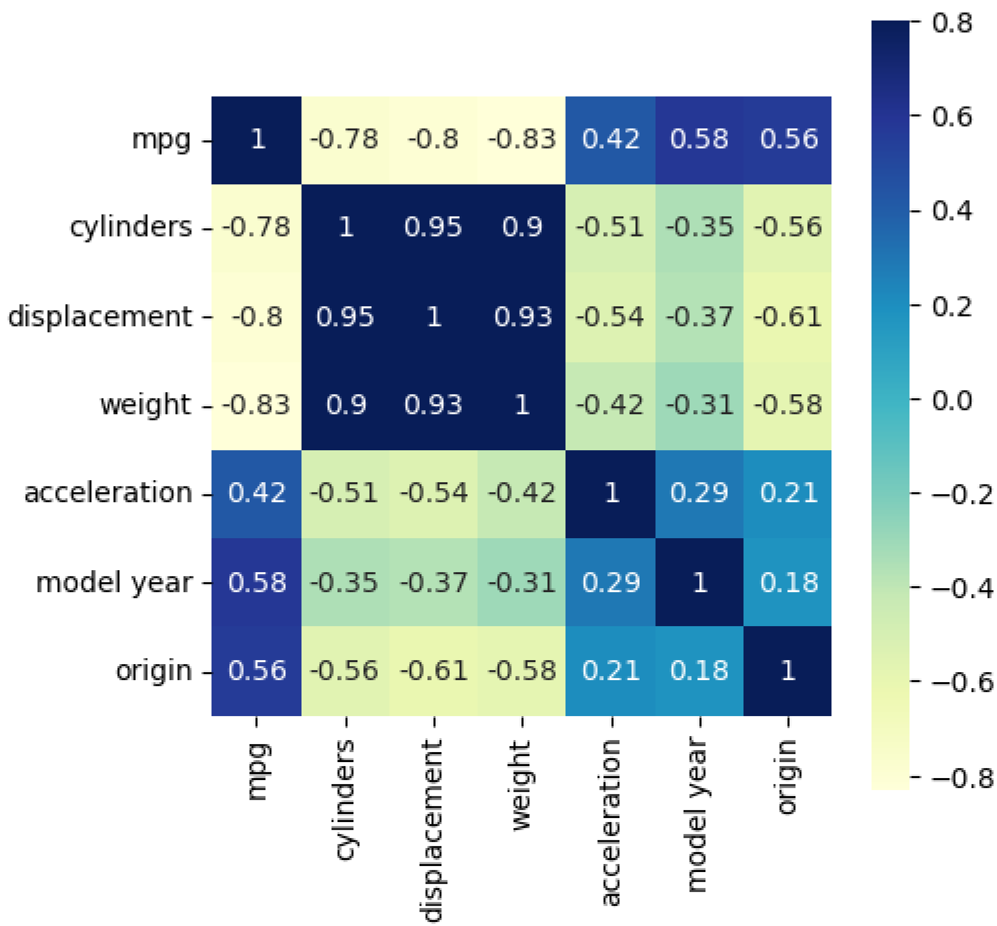
Out[35]:

	mpg	cylinders	displacement	weight	acceleration	model year	origin

mpg	1.000000	-0.775396	-0.804203	-0.831741	0.420289	0.579267	0.563450
cylinders	-0.775396	1.000000	0.950721	0.896017	-0.505419	-0.348746	-0.562543
displacement	-0.804203	0.950721	1.000000	0.932824	-0.543684	-0.370164	-0.609409
weight	-0.831741	0.896017	0.932824	1.000000	-0.417457	-0.306564	-0.581024
acceleration	0.420289	-0.505419	-0.543684	-0.417457	1.000000	0.288137	0.205873
model year	0.579267	-0.348746	-0.370164	-0.306564	0.288137	1.000000	0.180662
origin	0.563450	-0.562543	-0.609409	-0.581024	0.205873	0.180662	1.000000

weight and displacement have a high negative correlation with mpg.

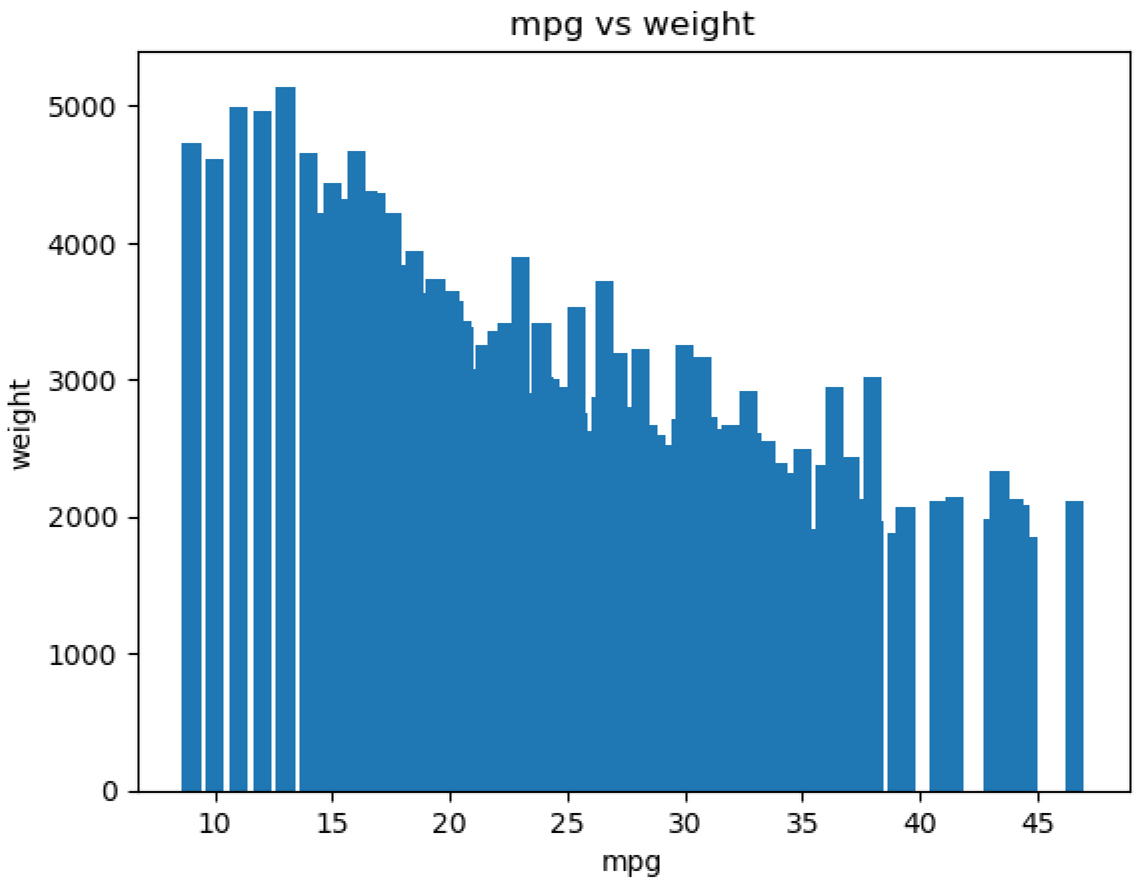
In [36]:
```
import seaborn as sns
import matplotlib.pyplot as plt

corrmat = auto_mpg_df_v2.corr(numeric_only=True)
f, ax = plt.subplots(figsize=(5, 5))
sns.heatmap(corrmat, vmax=.8, square=True,annot=True,cmap='YlGnBu');
plt.show()

#sn.heatmap(corrMatrix, annot=True)
#plt.show(
```



4. Plot mpg versus weight. Analyze this graph and explain how it relates to the corresponding correlation coefficient.

In [37]:
```
plt.bar(auto_mpg_df_v2.mpg,auto_mpg_df_v2.weight)
plt.xlabel("mpg")
plt.ylabel("weight")
plt.title("mpg vs weight")
```

Out[37]: Text(0.5, 1.0, 'mpg vs weight')



From the chart, it is evident that as mpg and weight are negatively correlated. As the weight goes up, mpg decreases.

5. Randomly split the data into 80% training data and 20% test data, where your target is mpg.

In [71]:
```
# Import library
from sklearn.model_selection import train_test_split

# Create training and test sets
y = auto_mpg_df_v2.mpg
x = auto_mpg_df_v2.drop('mpg',axis=1)
```

In [72]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2)
```

In [59]:
```
print("Original dataset :", auto_mpg_df_v2.shape)
print("X train : ", x_train.shape[0])
print("Y train : ", y_train.shape[0])
print("X test : ", x_test.shape[0])
print("Y test : ", y_test.shape[0])
```

```
Original dataset : (398, 8)
X train :  318
Y train :  318
X test :  80
Y test :  80
```

6. Train an ordinary linear regression on the training data.

In [77]:
```
#Load required libraries
from sklearn.linear_model import LinearRegression
```

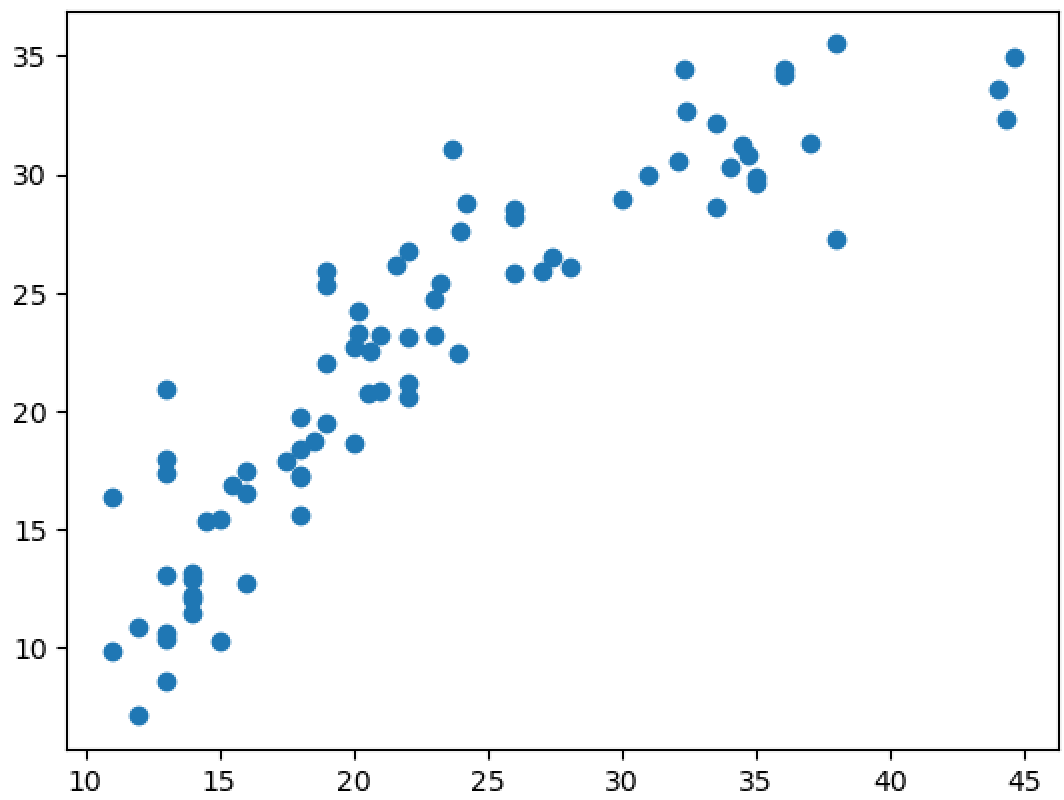
```
lr = LinearRegression()
lr.fit(x_train,y_train)
print('Coeff : ',lr.coef_)
```

```
Coeff :  [-0.34300193  0.01942318 -0.01686394 -0.00696096  0.12717167  0.78037201
  1.30845663]
```

In [62]:
```
predictions = lr.predict(x_test)
predictions
```

Out[62]:
```
array([17.15833798, 20.55112867, 29.83362348, 28.94129021, 18.74043654,
       15.57920859, 10.88233212, 15.30416649, 20.7530766 , 12.19459822,
       19.49923107, 22.51873759, 33.58659401, 29.59154482, 29.98612272,
       19.70675915, 22.05631313, 17.86127535, 13.11055628, 17.33392201,
       22.42987447, 18.39197478, 23.23707597, 30.5670774 , 28.59845855,
       27.2199283 , 24.25178387, 10.36009619, 35.49597197, 28.19560173,
       12.67887322,  8.57524212, 17.9821634 , 20.82756098, 23.15208288,
        7.10140425, 20.90089021, 26.14035753, 32.36000068, 34.47336209,
       21.19254092, 18.64901556, 16.8295314 , 25.38675495, 22.65235264,
       25.91905774, 31.31343344, 10.63355014, 32.15549888, 12.85086135,
       34.20895786, 34.90985895, 31.18652408, 25.31742936, 28.74482854,
       11.49104236, 17.4591845 , 26.06361162,  9.8824107 , 24.69678519,
       23.31753656, 17.29446946, 12.08384313, 30.30844803, 28.48333672,
       31.08796216, 30.78212042, 10.29973106, 15.42631592, 27.59700881,
       25.87441623, 16.31211456, 25.77739861, 34.40673038, 32.63806354,
       13.05622161, 16.53776077, 26.74894996, 23.1858301 , 26.50730341])
```

In [63]:
```
plt.scatter(y_test, predictions)
plt.show()
```



7. Calculate R2, RMSE, and MAE on both the training and test sets and interpret your results.

In [78]:
```
import sklearn.metrics as metrics

print('Score : ',lr.score(x_train,y_train))
# R^2
print('R^2 : ', metrics.r2_score(y_test, predictions))
```

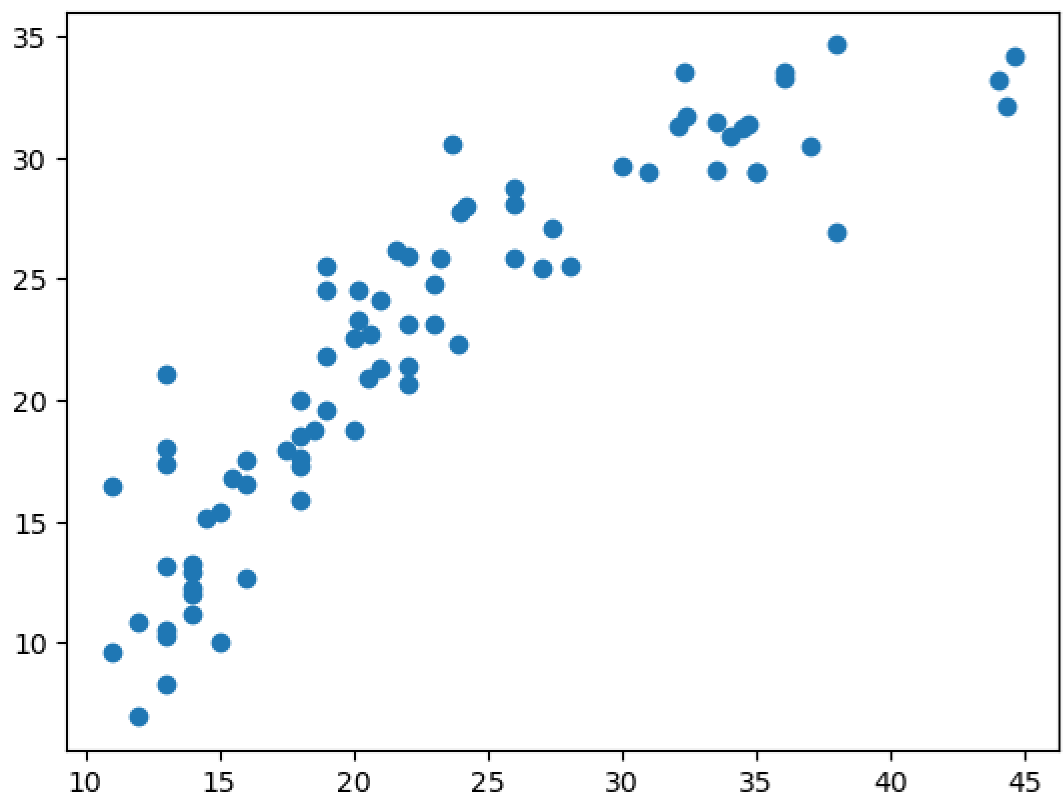
```
#RMSE
print('RMSE : ',np.sqrt(metrics.mean_squared_error(y_test, predictions)))

#MAE
print('MAE : ',metrics.mean_absolute_error(y_test, predictions))
```

```
Score :  0.8150399002132145
R^2 :  -0.8420564032429856
RMSE :  10.393328150906763
MAE :  8.36415376259967
```

8. Pick another regression model and repeat the previous two steps. Note: Do NOT choose logistic regression as it is more like a classification model.

In [68]:

```
from sklearn.linear_model import Lasso

# Creating Lasso Regression model

lasso_reg = Lasso(alpha=0.3)
lasso_reg.fit(x_train,y_train)
predict = lasso_reg.predict(x_test)
plt.scatter(y_test, predict)
plt.show()
```



In [76]:

```
#Regression Score
print('Score : ',lasso_reg.score(x_test,y_test))

# Lasso Regression  R2, RMSE, and MAE on training and test sets
# R^2
print('R^2 : ', metrics.r2_score(y_test, predict))
#RMSE
print('RMSE : ',np.sqrt(metrics.mean_squared_error(y_test, predict)))

#MAE
print('MAE : ',metrics.mean_absolute_error(y_test, predict))
```

```
Score :  0.8382292477165283
R^2 :  -0.8021888931770234
```

```
RMSE :  10.280241852523538
MAE :  8.301966884872297
```