Predicting Fuel efficiency using Ridge regression

In [1]:
```
#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn. metrics import r2_score, mean_absolute_error, mean_squared_error
```

Reading the data

In [13]:
```
df = pd.read_csv('data/auto-mpg.csv')
df.head()
```

Out[13]:

	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

In [3]:
```
df.shape
```

Out[3]:
```
(398, 9)
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64
 2   displacement  398 non-null    float64
 3   horsepower    398 non-null    object
 4   weight        398 non-null    int64
 5   acceleration  398 non-null    float64
 6   model year    398 non-null    int64
 7   origin        398 non-null    int64
 8   car name      398 non-null    object
dtypes: float64(3), int64(4), object(2)
memory usage: 28.1+ KB
```

Data Preprocessing

In [5]:
```
#checking for null values
df.isnull().sum()
```

```
mpg             0
```

Out[5]:
```
cylinders       0
displacement    0
horsepower      0
weight          0
acceleration    0
model year      0
origin          0
car name        0
dtype: int64
```

In [9]:
```
#cleaning column horsepower
df[df.horsepower.str.isdigit()==False]
```

Out[9]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name
32	25.0	4	98.0	?	2046	19.0	71	1	ford pinto
126	21.0	6	200.0	?	2875	17.0	74	1	ford maverick
330	40.9	4	85.0	?	1835	17.3	80	2	renault lecar deluxe
336	23.6	4	140.0	?	2905	14.3	80	1	ford mustang cobra
354	34.5	4	100.0	?	2320	15.8	81	2	renault 18i
374	23.0	4	151.0	?	3035	20.5	82	1	amc concord dl

In [15]:
```
#replacing '?' with nan
df['horsepower'] = df.horsepower.replace('?', np.nan)
```

In [16]:
```
df.isnull().sum()
```

Out[16]:
```
mpg             0
cylinders       0
displacement    0
horsepower      6
weight          0
acceleration    0
model year      0
origin          0
car name        0
dtype: int64
```

In [17]:
```
#filling null values with median
df['horsepower'] = df['horsepower'].fillna(df['horsepower'].median())
```

In [18]:
```
df.isnull().sum()
```

Out[18]:
```
mpg             0
cylinders       0
displacement    0
horsepower      0
weight          0
acceleration    0
model year      0
origin          0
car name        0
dtype: int64
```

In [19]:
```
#checking datatypes of features
df.dtypes
```

Out[19]:
```
mpg             float64
cylinders         int64
displacement    float64
horsepower       object
```

```
weight            int64
acceleration    float64
model year        int64
origin            int64
car name         object
dtype: object
```

In [20]:

```python
#converting horsepower to numerical varialbe
df['horsepower'] = df['horsepower'].astype('float64')
```

In [21]:

```python
#dropping car name column
df = df.drop('car name', axis=1)
df.head()
```

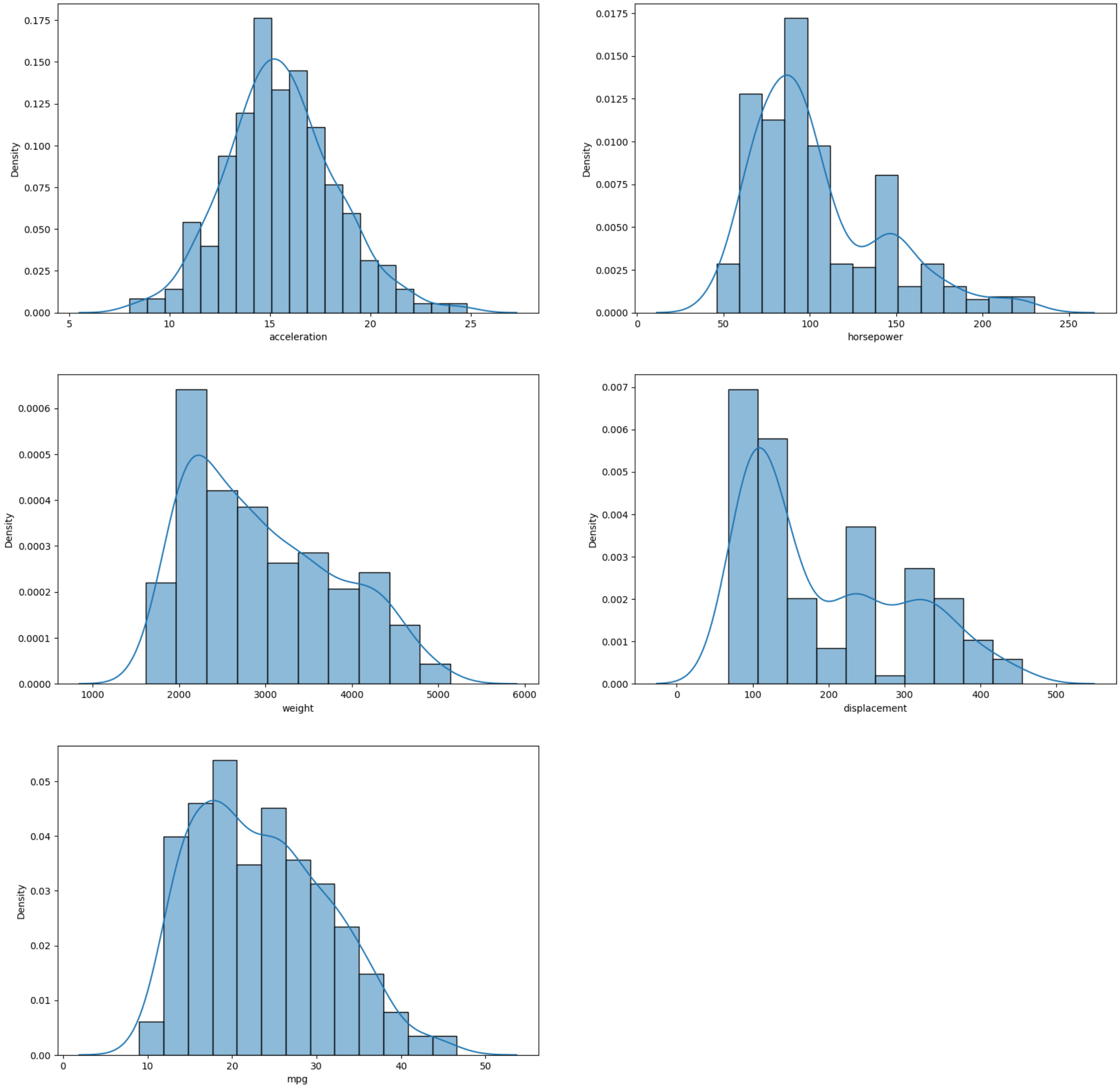
Out[21]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin
0	18.0	8	307.0	130.0	3504	12.0	70	1
1	15.0	8	350.0	165.0	3693	11.5	70	1
2	18.0	8	318.0	150.0	3436	11.0	70	1
3	16.0	8	304.0	150.0	3433	12.0	70	1
4	17.0	8	302.0	140.0	3449	10.5	70	1

Exploratory data analysis

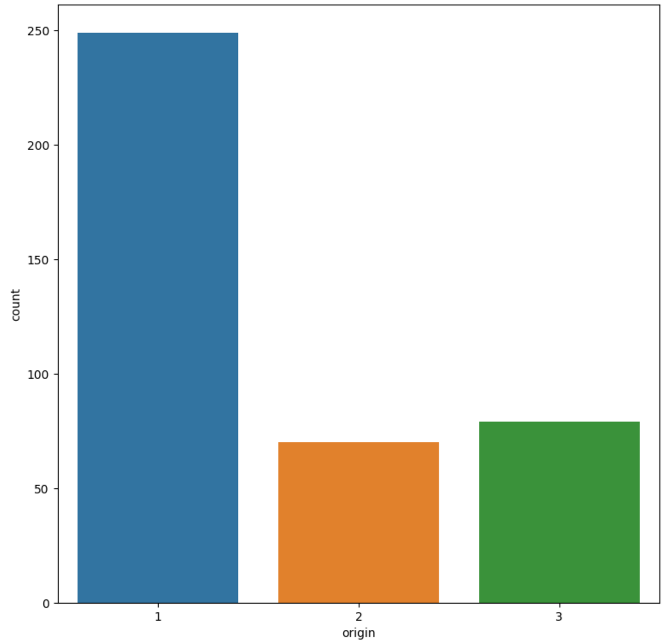
In [33]:

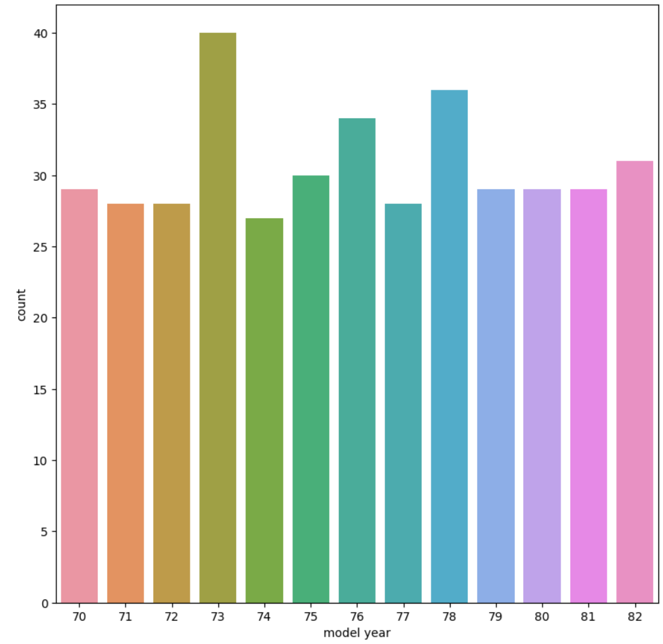
```python
#plotting distribution of features
num_cols = ["acceleration", "horsepower", "weight", "displacement", "mpg"]

plt.figure(figsize=(20,20))
for i in range(1, len(num_cols)+1):
    plt.subplot(3, 2, i)
    sns.histplot(df[num_cols[i-1]], kde=True,
    stat="density", kde_kws=dict(cut=3))
```

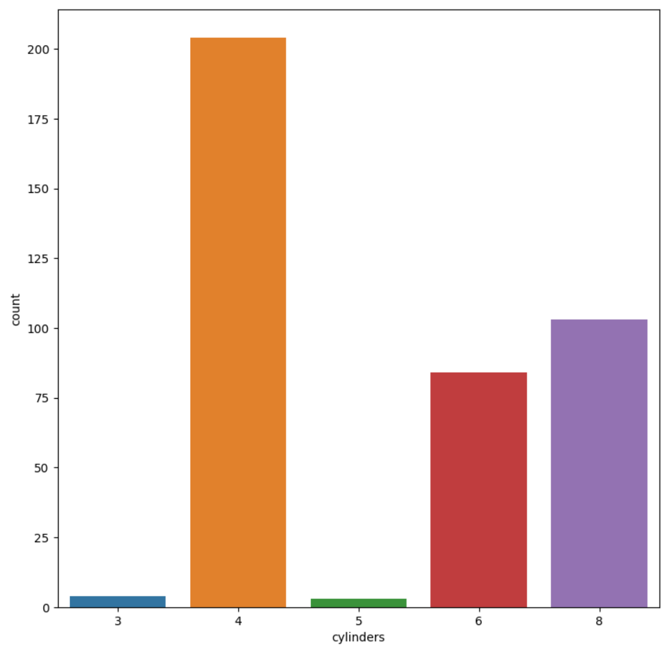


- The distribution of acceleraiton is normal
- horsepower follows a righskewed distribution which means small number of cars have high horesepower
- The distirbutions of weigh, displacement and mpg are also right skewed

In [37]:
```
cat_cols = ["origin", "model year", "cylinders"]

plt.figure(figsize=(20,20))
for i in range(1, len(cat_cols)+1):
    plt.subplot(2, 2, i)
    sns.countplot(data=df, x=cat_cols[i-1])
```



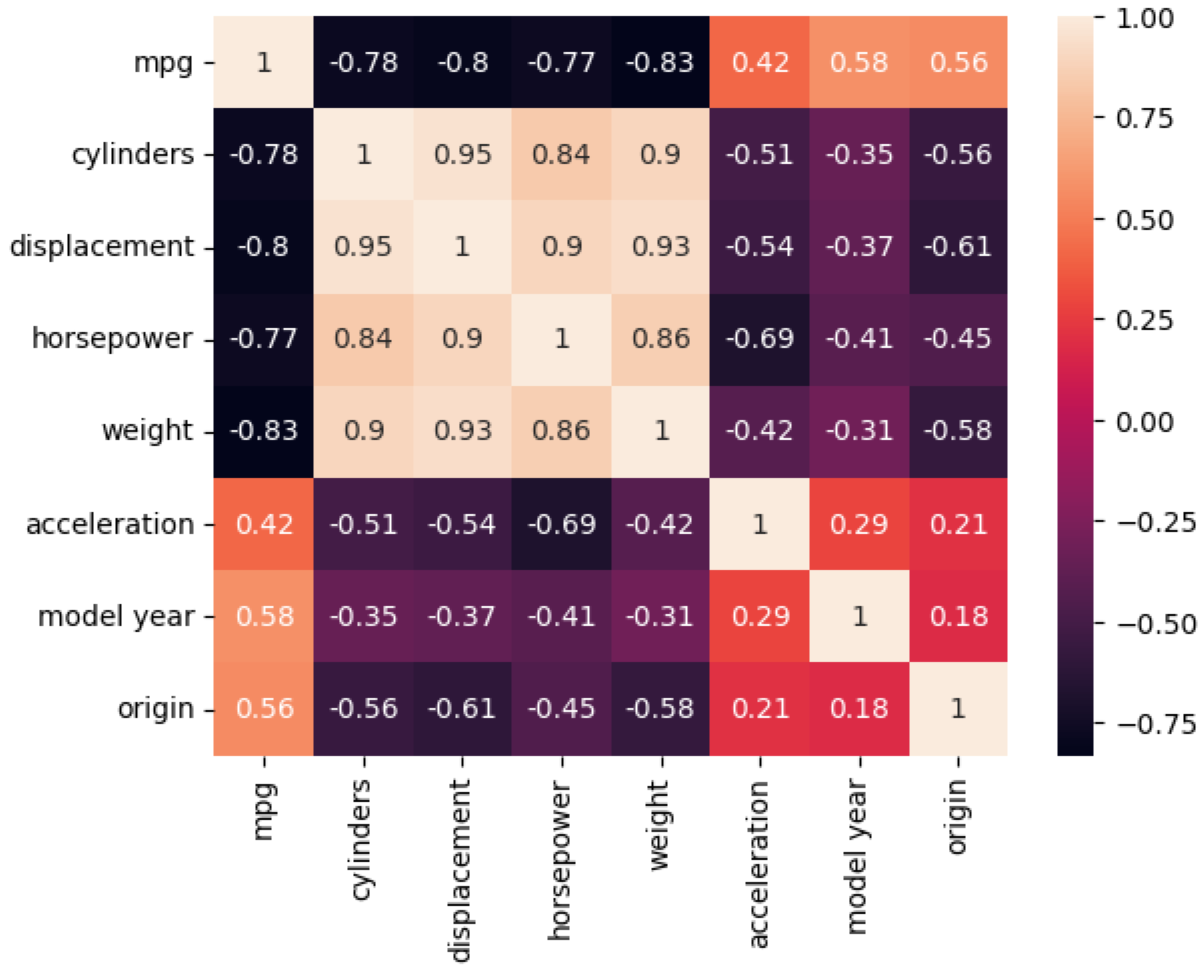




- Most of the cars are of origin 1 (American)
- Majority of cars have 4 cylinders
- Number of cars with 3 or 5 cylinders are very low
- Year 1973 has more number of cars

In [39]:
```
#heatmap
sns.heatmap(df.corr(numeric_only=True), annot=True)
```

Out[39]:
```
<AxesSubplot: >
```



- mpg has a strong negative correlation with cylinders, horespower, displacement and weight
- acceleration and horsepower seems to have a negative correlation
- cylinders have strong positive correlation with displacement and weight
- diplacement has strong positve correlationwith horsepower

Seperating dependent and independent variables

In [47]:
```
X = df.drop('mpg', axis=1)
y = df[['mpg']]
```

In [ ]:
```
#standrdizing the data
from sklearn import preprocessing

X_scaled = preprocessing.scale(X)
X_scaled = pd.DataFrame(X_scaled, columns=X.columns)

y_scaled = preprocessing.scale(y)
y_scaled = pd.DataFrame(y_scaled, columns=y.columns)
```

Model training

In [50]:
```
#splitting dataset into train and test sets
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_scaled, test_size=0.3, r
```

- #### Linear regression model

In [51]:
```
lr = LinearRegression()
lr.fit(X_train, y_train)

for i, col in enumerate(X_train.columns):
    print('The coefficent for {} is {}'.format(col, lr.coef_[0][i]))
```

```
The coefficent for cylinders is -0.08561436895562707
The coefficent for displacement is 0.30441822535930246
The coefficent for horsepower is -0.09718466302484263
The coefficent for weight is -0.7628632829136761
The coefficent for acceleration is 0.021591275172924626
The coefficent for model year is 0.3749408074118714
The coefficent for origin is 0.12302637024556856
```

Model evaluation

In [53]:
```
y_pred = lr.predict(X_test)

r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print('R2 score: ', r2)
print('Mean absolute: ', mae)
print('Mean squared error: ', mse)
print('Root mean squared error: ', rmse)
```

```
R2 score:  0.8472274567567305
Mean absolute:  0.2960772496395954
Mean squared error:  0.14658208429020428
Root mean squared error:  0.38286039791313525
```

- #### Ridge regression

In [67]:
```
#finding value for alpha
from sklearn.model_selection import GridSearchCV

ridge_regressor = Ridge()

parameters = {'alpha':[1,2,5,10,20,30,40,50,60,70,80,90]}
ridgecv = GridSearchCV(ridge_regressor, parameters, scoring='neg_mean_squared_error', cv
ridgecv.fit(X_train, y_train)
```

Out[67]:
```
▸ GridSearchCV
▸ estimator: Ridge
    ▸ Ridge
```

In [68]:
```
ridgecv.best_params_
```

Out[68]:
```
{'alpha': 1}
```

In [69]:
```
ridgecv.best_score_
```

Out[69]:
```
-0.21128276888504183
```

In [71]:
```
y_pred = ridgecv.predict(X_test)

r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print('R2 score: ', r2)
print('Mean absolute: ', mae)
print('Mean squared error: ', mse)
print('Root mean squared error: ', rmse)
```

```
R2 score:  0.8480557970107935
Mean absolute:  0.2953247183707148
Mean squared error:  0.14578730900948722
Root mean squared error:  0.3818210431726979
```

In [76]:
```
ridge1 = Ridge(alpha=1)

ridge1.fit(X_train, y_train)
for i, col in enumerate(X_train.columns):
    print('The coefficent for {} is {}'.format(col, ridge1.coef_[0][i]))
```

```
The coefficent for cylinders is -0.07121896528742029
The coefficent for displacement is 0.2545922110228855
The coefficent for horsepower is -0.10562163061671638
The coefficent for weight is -0.7257272526332574
The coefficent for acceleration is 0.013936782414360338
The coefficent for model year is 0.37123495928305966
The coefficent for origin is 0.1203017141809628
```

In [77]:
```
ridge1 = Ridge(alpha=100000)

ridge1.fit(X_train, y_train)
for i, col in enumerate(X_train.columns):
    print('The coefficent for {} is {}'.format(col, ridge1.coef_[0][i]))
```

```
The coefficent for cylinders is -0.0020812622699733843
The coefficent for displacement is -0.0021491698921673303
The coefficent for horsepower is -0.0020869049192098863
The coefficent for weight is -0.002272781885832798
The coefficent for acceleration is 0.0011095344715934758
The coefficent for model year is 0.0015994823467540237
The coefficent for origin is 0.001432841735828801
```

In [ ]:
```
!jupyter nbconvert --to webpdf --allow-chromium-download fuel_efficiency_prediction.ipyn
```