Final Project: Car Price Prediction Model

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FinalReport

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Class : *AAI 500 − Probability & Stats for AI*

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0.0.1 1. Data Preprocessing

Statement - One of the single biggest problems with our dataset was the data itself. There were many unreadable characters as well as data fields which had been incorrectly input or difficult to work with. We created a program to mitigate these issues.
1) The special characters were simply deleted. This made a few of the make fields empty so model was copied into them to ensure they weren't completely blank.
2) Each field had special considerations, so for each field we made a small preprocessing functions and added them to a dictionary so that it would get used on the correct column.

[1]:
```
# Imports
import data_fix as dfix
import data_utils_g1 as du
import matplotlib.pyplot as plt
import numpy
import statsmodels.stats.api as sms
from statsmodels.compat import lzip
import pandas as pd
import seaborn as sns
from sklearn.linear_model import LinearRegression
import statsmodels.formula.api as smf
# Setting up warnings
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
# scrub the datafile
dfix.init()
```

```python
# This function will automatically prompt for a file and a save location using a dialog selector
data = dfix.scrub_txt_file()
```

```
Replacing all special characters for clean read
Asking for cleaned data file save location
Printing save location:
C:/Users/chris/Documents/School/Masters/zz_GIT/2022-msaai-500-final-
project/data/sanitized/sanitized_1.txt
C:/Users/chris/Documents/School/Masters/zz_GIT/2022-msaai-500-final-
project/data/sanitized/sanitized_1_final.csv
```

[3]:
```python
# display the data
display(data.head(15))
```

```
          ID  Price  Levy   Manufacturer     Model Prod_year     Category  \
0   45654403  13328  1399          LEXUS    RX 450      2010         Jeep
1   44731507  16621  1018      CHEVROLET   EQUINOX      2011         Jeep
2   45774419   8467     0          HONDA       FIT      2006    Hatchback
3   45769185   3607   862           FORD    ESCAPE      2011         Jeep
4   45809263  11726   446          HONDA       FIT      2014    Hatchback
5   45802912  39493   891        HYUNDAI  SANTA FE      2016         Jeep
6   45656768   1803   761         TOYOTA     PRIUS      2010    Hatchback
7   45816158    549   751        HYUNDAI    SONATA      2013        Sedan
8   45641395   1098   394         TOYOTA     CAMRY      2014        Sedan
9   45756839  26657     0          LEXUS    RX 350      2007         Jeep
10  45621750    941  1053  MERCEDES-BENZ     E 350      2014        Sedan
11  45814819   8781     0           FORD   TRANSIT      1999     Microbus
12  45815568   3000     0           OPEL    VECTRA      1997  Goods wagon
13  45661288   1019  1055          LEXUS    RX 450      2013         Jeep
14  45732604  59464   891        HYUNDAI  SANTA FE      2016         Jeep

   Leather_interior Fuel_type Engine_volume Turbo Mileage Cylinders  \
0               Yes    Hybrid           3.5        186005         6
1                No    Petrol             3        192000         6
2                No    Petrol           1.3        200000         4
3               Yes    Hybrid           2.5        168966         4
4               Yes    Petrol           1.3         91901         4
5               Yes    Diesel             2        160931         4
6               Yes    Hybrid           1.8        258909         4
7               Yes    Petrol           2.4        216118         4
8               Yes    Hybrid           2.5        398069         4
9               Yes    Petrol           3.5        128500         6
10              Yes    Diesel           3.5        184467         6
11               No       CNG             4             0         8
12               No       CNG           1.6        350000         4
13              Yes    Hybrid           3.5        138038         6
14              Yes    Diesel             2         76000         4
```

```
   Gear_box_type Drive_wheels Doors             Wheel   Color Airbags
0      Automatic    Front-Rear   4-5        Left wheel  Silver      12
1      Tiptronic    Front-Rear   4-5        Left wheel   Black       8
2       Variator         Front   4-5  Right-hand drive   Black       2
3      Automatic    Front-Rear   4-5        Left wheel   White       0
4      Automatic         Front   4-5        Left wheel  Silver       4
5      Automatic         Front   4-5        Left wheel   White       4
6      Automatic         Front   4-5        Left wheel   White      12
7      Automatic         Front   4-5        Left wheel    Grey      12
8      Automatic         Front   4-5        Left wheel   Black      12
9      Automatic    Front-Rear   4-5        Left wheel  Silver      12
10     Automatic          Rear   4-5        Left wheel   White      12
11        Manual          Rear   2-3        Left wheel    Blue       0
12        Manual         Front   4-5        Left wheel   White       4
13     Automatic         Front   4-5        Left wheel   White      12
14     Automatic         Front   4-5        Left wheel   White       4
```

For main section of cleaning code please see file data_fix.py Appendix-1 We were also give a data dictionary which we stored in case it was needed later.

[4]:
```
# Given data dictionary
data_dict= {"ID": "Unique identifier/key", "Price": "Price of the car", "Levy":␣
↪"Tax applied to purchase price",
            "Manufacturer": "Name of car manufacturer", "Model": "Model of the␣
↪car",
            "Prod_year": "Year the car was produced", "Category": "Category by␣
↪body type of the car",
            "Leather_interior": "Whether or not the car has a leather␣
↪interior", "Fuel_type": "Fuel type of the car",
            "Engine_volume": "Engine size/volume of the car", "Mileage": "Total␣
↪mileage on the car",
            "Cylinders": "Number of cylinders", "Gear_box_type": "Type of gear␣
↪box", "Drive_wheels":
            "Drive wheels on the car", "Doors": "Number of doors on the car",␣
↪"Wheel": "Side of the steering wheel",
            "Color": "Exterior color of the car", "Airbags": "Number of airbags␣
↪in the car"}

file_name = "..\data\data_dictionary.txt"
# we created a utility library and saved it as data_utils_g1.py
du.save_py_dict(data_dict)
```

```
Asking for dictionary save file path
```

[4]:
```
'C:/Users/chris/Documents/School/Masters/zz_GIT/2022-msaai-500-final-
project/data/data_dictionary.json'
```

We looked at the data just to see what unique values we were dealing with

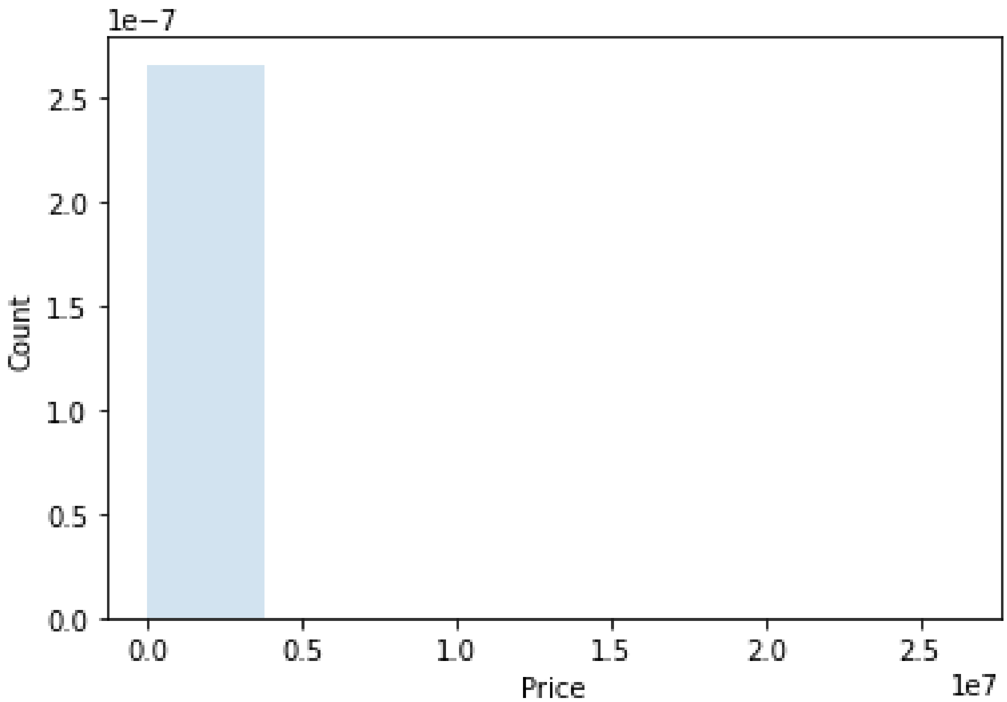
[5]:
```python
# we found quickly we would need to deal with model a little differently
print('Gearbox Uniques', data.Gear_box_type.unique())
print('Cylinders Uniques', data.Cylinders.unique())
print('Manufacturer Uniques', data.Manufacturer.unique())
model = data.Model.unique()
print('Number of Model Uniques', len(model))
```

```
Gearbox Uniques ['Automatic' 'Tiptronic' 'Variator' 'Manual']
Cylinders Uniques ['6' '4' '8' '1' '12' '3' '2' '16' '5' '7' '9' '10' '14']
Manufacturer Uniques ['LEXUS' 'CHEVROLET' 'HONDA' 'FORD' 'HYUNDAI' 'TOYOTA'
'MERCEDES-BENZ'
 'OPEL' 'PORSCHE' 'BMW' 'JEEP' 'VOLKSWAGEN' 'AUDI' 'RENAULT' 'NISSAN'
 'SUBARU' 'DAEWOO' 'KIA' 'MITSUBISHI' 'SSANGYONG' 'MAZDA' 'GMC' 'FIAT'
 'INFINITI' 'ALFA ROMEO' 'SUZUKI' 'ACURA' 'LINCOLN' 'VAZ' 'GAZ' 'CITROEN'
 'LAND ROVER' 'MINI' 'DODGE' 'CHRYSLER' 'JAGUAR' 'ISUZU' 'SKODA'
 'DAIHATSU' 'BUICK' 'TESLA' 'CADILLAC' 'PEUGEOT' 'BENTLEY' 'VOLVO'
 'IVECO DAYLY' 'HAVAL' 'HUMMER' 'SCION' 'GONOW' 'UAZ' 'MERCURY' 'ZAZ'
 'ROVER' 'SEAT' 'LANCIA' 'MOSKVICH' 'MASERATI' 'FERRARI' 'SAAB'
 'LAMBORGHINI' 'ROLLS-ROYCE' 'PONTIAC' 'SATURN' 'ASTON MARTIN' 'GREATWALL']
Number of Model Uniques 1481
```

We also tried looking and sampling the data in different ways to make sense of it.

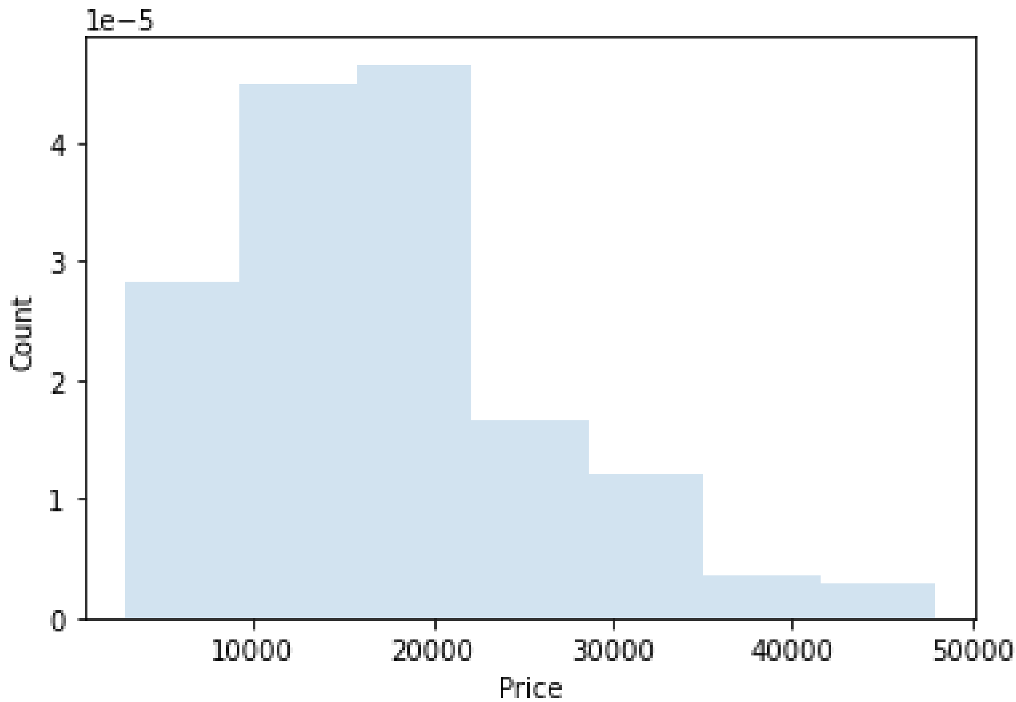
[6]:
```python
data_types = {}
data_types['Price'] = 'int32'
data_types['Mileage'] = 'int32'
data_types['Prod_year'] = 'int32'
data_types['Airbags'] = 'int32'
data = data.astype(data_types)
data = data.sort_values(by=['ID'])

# label the plot
plt.xlabel("Price")
plt.ylabel("Count")

# create histogram
plt.hist(data['Price'], bins=7, density=True, histtype='stepfilled',
         alpha=0.2, label='histogram of data')
```

[6]:
```
(array([2.66069995e-07, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
        0.00000000e+00, 0.00000000e+00, 1.38318775e-11]),
 array([1.00000000e+00, 3.75821514e+06, 7.51642929e+06, 1.12746434e+07,
        1.50328576e+07, 1.87910717e+07, 2.25492859e+07, 2.63075000e+07]),
 [<matplotlib.patches.Polygon at 0x20d57b95490>])
```



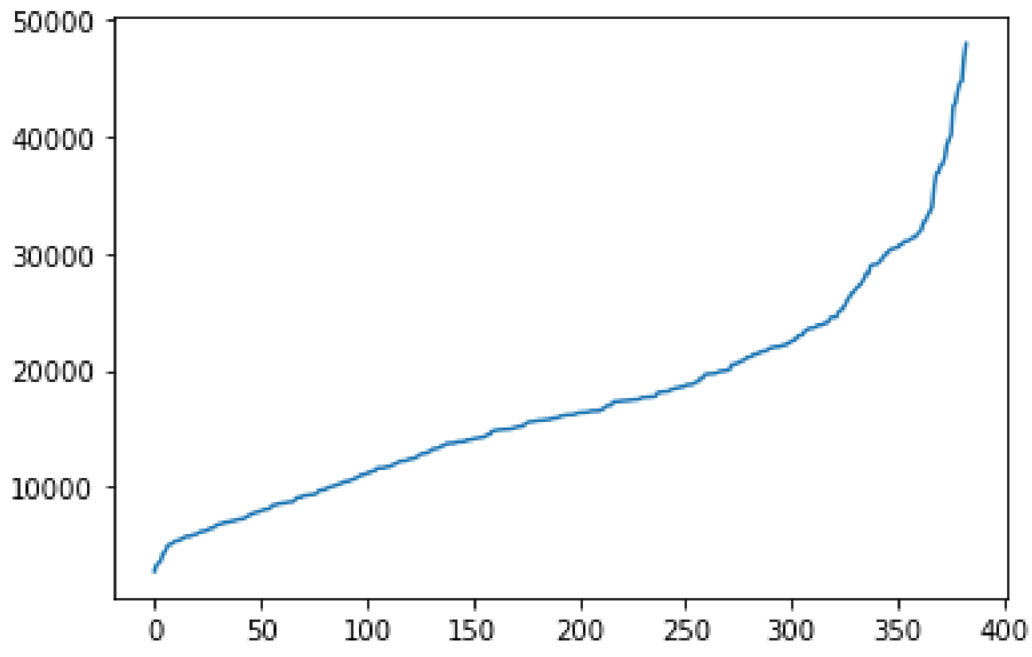
[7]:
```
# This function samples the data at number 'n' per sample
sample = du.random_mean_sample(data['Price'], 50)

# label the plot
plt.xlabel("Price")
plt.ylabel("Count")

# create histogram
# note this is a sorted sample set and we remove the last one
# we know from looking at the data the last sample is messed up from a large␣
↪outlier
plt.hist(sample[:-1], bins=7, density=True, histtype='stepfilled',
         alpha=0.2, label='histogram of data')
```

[7]:
```
(array([2.83228923e-05, 4.49120149e-05, 4.65304659e-05, 1.65891226e-05,
        1.21383824e-05, 3.64151472e-06, 2.83228923e-06]),
 array([ 2805.,  9258., 15711., 22164., 28617., 35070., 41523., 47976.]),
 [<matplotlib.patches.Polygon at 0x20d5a7cc550>])
```



[8]:
```
sample2 = sample[:-1]
plt.plot(sample2)
print('Number of samples', len(sample2))
```

```
Number of samples 383
```



[9]:
```python
mu = numpy.mean(sample2, axis=0)
sigma = numpy.std(sample2, axis=0)
print('The mean of the sampled set is: ', mu)
print('The sigma of the sampled set is: ', sigma)
```

```
The mean of the sampled set is:  17214.720626631854
The sigma of the sampled set is:  8602.999216089052
```

In conclusion, we cleaned the data enough to where we could start really looking at it and deciding how we would create a model for it.

0.0.2 2. Outlier Handling

Statement - The problem with massive outliers is that they can skew the data and make it harder to work with or understand. Many times we would want a model to be resistant against such outliers so training with them is encouraged. There are 2 main reasons we will remove some outliers for our project.
1) The point of this model is to predict the price of a car. We wouldn't want to give someone a prediction that is well over value which could inflate the market or make it difficult to sell their vehicle. We also wouldn't want to tell them to give away their car for free, or just a dollar. Some cars can be cheap but generally transactions like that are prices of people giving the car to a family or friend.
2) When observing the data there was a car that was sold for 26 million. This is obviously a data error of some form. Maybe the van also contained quite a few gold bars. Reguardless of why, this is multiple powers of 10 outside of the normal range, and with this in mind we should remove outliers of this nature.

[10]:
```python
# set plot style
plt.style.use('seaborn')

# Get Path
path = 'C:/Users/chris/Documents/School/Masters/zz_GIT/
 ↪2022-msaai-500-final-project/data/sanitized/sanitized_1_final.csv'

# Reading the dataset
data = pd.read_csv(path)
print("The shape of the dataframe is: ", data.shape)
```

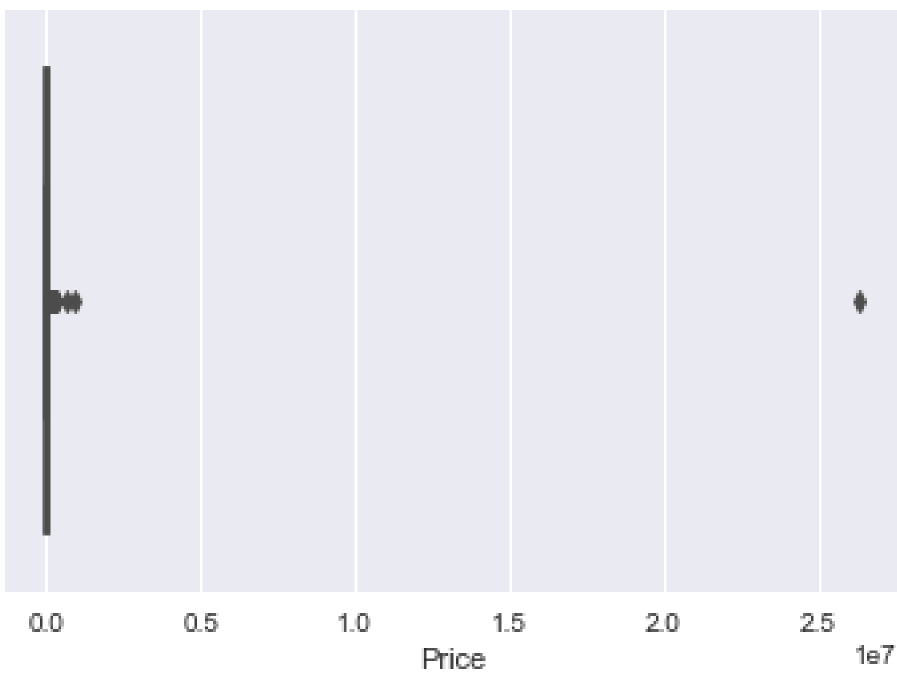
```
The shape of the dataframe is:  (19237, 20)
```

[11]:
```python
# Understand the data
data.describe()
```

[11]:
```
        Unnamed: 0            ID         Price           Levy      Prod_year  \
count   19237.0000  1.923700e+04  1.923700e+04   19237.000000   19237.000000
mean     9618.0000  4.557654e+07  1.855593e+04     632.528669    2010.912824
```

```
std      5553.3879  9.365914e+05  1.905813e+05    567.721688     5.668673
min         0.0000  2.074688e+07  1.000000e+00      0.000000  1939.000000
25%      4809.0000  4.569837e+07  5.331000e+03      0.000000  2009.000000
50%      9618.0000  4.577231e+07  1.317200e+04    642.000000  2012.000000
75%     14427.0000  4.580204e+07  2.207500e+04    917.000000  2015.000000
max     19236.0000  4.581665e+07  2.630750e+07  11714.000000  2020.000000

       Engine_volume       Mileage     Cylinders       Airbags
count   19237.000000  1.923700e+04  19237.000000  19237.000000
mean        2.307990  1.532236e+06      4.582991      6.582627
std         0.877805  4.840387e+07      1.199933      4.320168
min         0.000000  0.000000e+00      1.000000      0.000000
25%         1.800000  7.013900e+04      4.000000      4.000000
50%         2.000000  1.260000e+05      4.000000      6.000000
75%         2.500000  1.888880e+05      4.000000     12.000000
max        20.000000  2.147484e+09     16.000000     16.000000
```

[12]:
```
# This is a boxplot of the data, notice the massive outlier
plt.figure(figsize=(6,4))
sns.boxplot(x=data['Price'])
plt.show()
```



As shown in the box plot above there is at least 1 super outlier that completely harms the data. Using a systematic attempt it was removed.

[13]:
```python
# Use data utils function for group 2
# This is the column to base the decision on
decision_column = 'Price'
# Function Call to our utils library - see Appendix-2
Q3, Q1, filtered_data = du.remove_outliers2(data, decision_column)

# print nice answer
print(f'The lower data limit is ${Q1:.2f} and the upper data limit is ${Q3:.
↪2f}')

# Understand the data
filtered_data.describe()
```

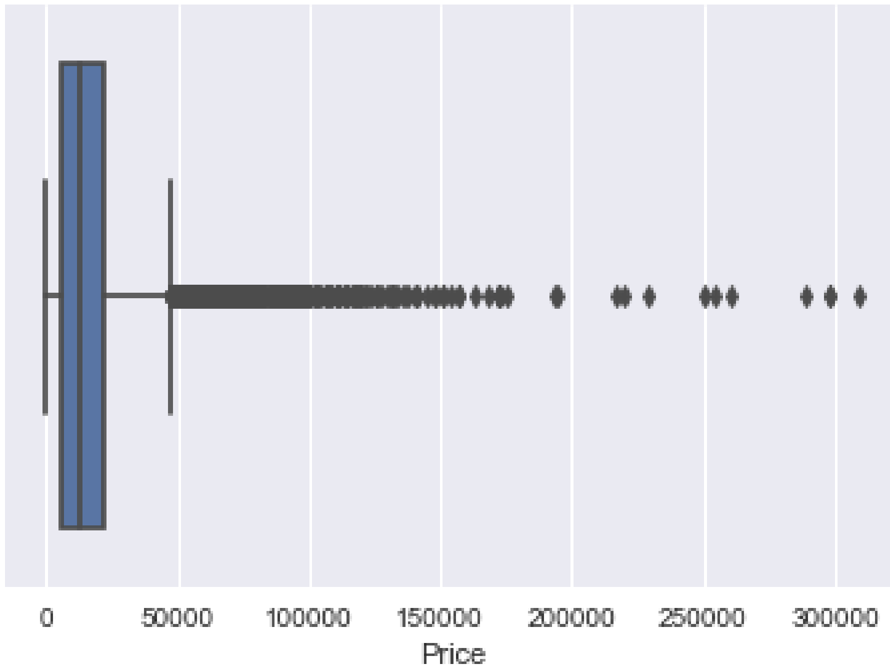
```
The lower data limit is $3.00 and the upper data limit is $345384.78
```

[13]:

	Unnamed: 0	ID	Price	Levy	Prod_year
count	19217.000000	1.921700e+04	19217.000000	19217.000000	19217.000000
mean	9618.009887	4.557636e+07	17128.202061	632.751782	2010.913670
std	5553.556104	9.370593e+05	18279.641947	567.652166	5.666155
min	0.000000	2.074688e+07	6.000000	0.000000	1939.000000
25%	4808.000000	4.569837e+07	5331.000000	0.000000	2009.000000
50%	9618.000000	4.577234e+07	13172.000000	642.000000	2012.000000
75%	14426.000000	4.580204e+07	22110.000000	917.000000	2015.000000
max	19236.000000	4.581665e+07	308906.000000	11714.000000	2020.000000

	Engine_volume	Mileage	Cylinders	Airbags
count	19217.000000	1.921700e+04	19217.000000	19217.000000
mean	2.308102	1.421973e+06	4.582453	6.583286
std	0.877367	4.588801e+07	1.198624	4.319785
min	0.000000	0.000000e+00	1.000000	0.000000
25%	1.800000	7.019400e+04	4.000000	4.000000
50%	2.000000	1.260210e+05	4.000000	6.000000
75%	2.500000	1.888880e+05	4.000000	12.000000
max	20.000000	2.147484e+09	16.000000	16.000000

[14]:
```python
# This is a boxplot of the data, with outliers removed
plt.figure(figsize=(6,4))
sns.boxplot(x=filtered_data['Price'])
plt.show()
```



As we can see from the table and the box plot, although there are still outliers, the ones that massively skewed the data have been removed. In my opinion, more could have been removed from the bottom but we decided that it would be even on both the left and the right sides of the data.
Upper percentile from base data = 0.99985
Lower percentile from base data = 0.00015

In conclusion, this removal was required to make an accurate model for suggesting what a costumer should sell their car for in the market.

0.0.3 3. Quantization of Categorical Variable

When we analyze the car sales data, we have the following

[15]:
```
#read training data from csv file to dataframe
df = pd.read_csv('TrainingData.csv')
#display data types
df.dtypes
```

[15]:
```
Unnamed: 0              int64
ID                      int64
Price                   int64
Levy                    int64
Manufacturer           object
Model                  object
```

```
Prod_year              int64
Category              object
Leather_interior      object
Fuel_type             object
Engine_volume        float64
Turbo                 object
Mileage                int64
Cylinders              int64
Gear_box_type         object
Drive_wheels          object
Doors                 object
Wheel                 object
Color                 object
Airbags                int64
dtype: object
```

We can see there are columns data are "object" type. Which mean they are categorical variables. We cannot use categorical variables in the linear regression model. We have to quantize the categorical varibles to a integer or flow data type. After research we found following two methods that can use for categorical variable quantization.

3.1 Quantization with Calculating Group Mean First option of variable quntization is calculated group mean against Price. Then find proper digit for every different category type, then assigned the number. Where we will use Category column data as a test. We display all the different type of data in the category column:

[16]:
```python
print(df.Category.unique())
```

```
['Jeep' 'Hatchback' 'Sedan' 'Microbus' 'Goods wagon' 'Universal' 'Coupe'
 'Minivan' 'Cabriolet' 'Limousine' 'Pickup']
```

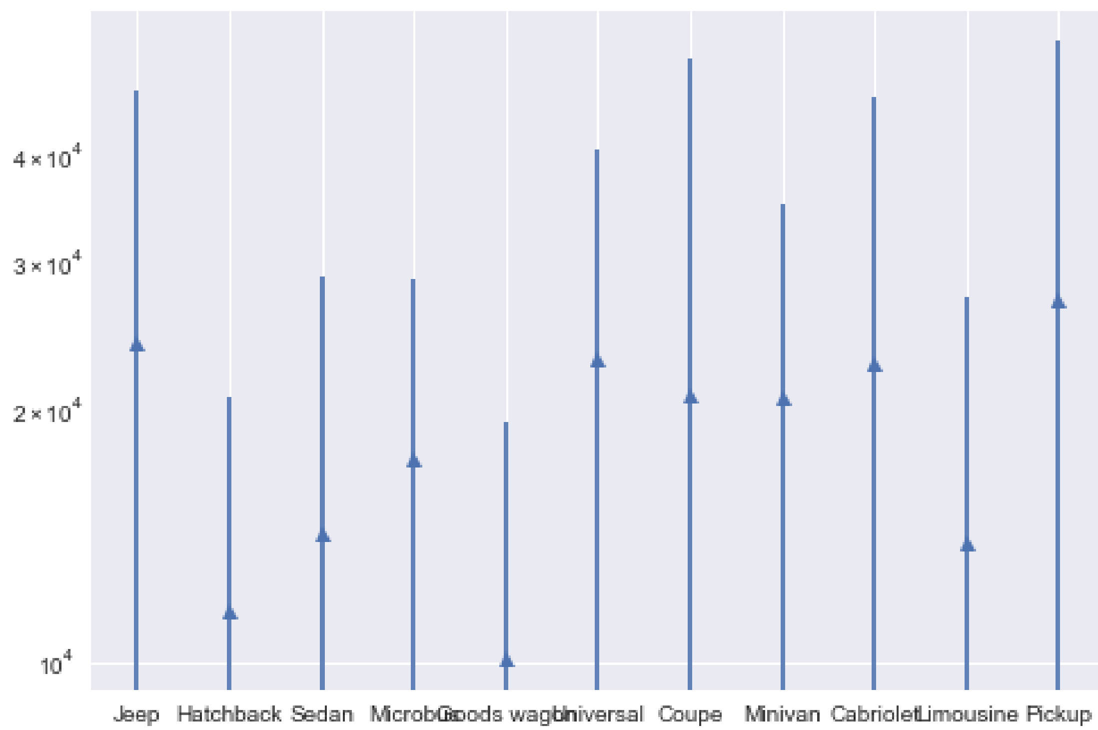
We can see there are 11 types for data in Category columne. Now we need calculated Group mean price for each different type of car category:

[17]:
```python
# Make sure price data type is int
data_types = {}
data_types['Price'] = 'int32'
df = df.astype(data_types)
# store call type of cars in array
categoryarray = df.Category.unique()
# Creaete Price mean array
pricemeanarray = []
# Create Standard Deviations array
pricesdarray = []
#for loop calculate mean and SD for every type of car
for x in categoryarray:
    comm = "Category == '"+x+"'"
    df2 = df.query(comm)
```

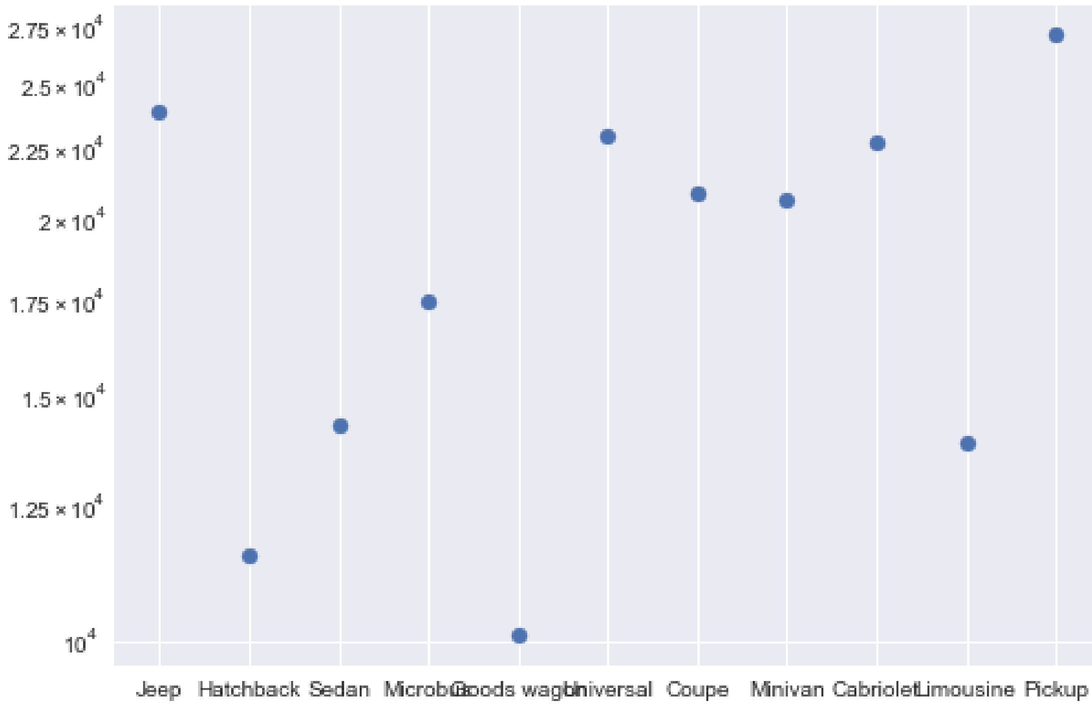
```
    price = df2['Price']
    mean = price.mean()
    sd = price.std()
    pricemeanarray.append(round(mean,2))
    pricesdarray.append(round(sd,2))
#print results
print("Group Mean Price is ", pricemeanarray)
print("Standard Deviation is ",pricesdarray)
print("Group Name is", categoryarray)
```

```
Group Mean Price is  [23927.76, 11509.12, 14261.48, 17483.68, 10101.57,
22919.33, 20849.0, 20655.98, 22713.38, 13856.0, 27078.91]
Standard Deviation is  [23895.86, 9099.94, 14492.03, 11025.5, 9177.41, 17805.5,
31293.12, 14400.32, 24383.81, 13314.98, 27637.63]
Group Name is ['Jeep' 'Hatchback' 'Sedan' 'Microbus' 'Goods wagon' 'Universal'
'Coupe'
 'Minivan' 'Cabriolet' 'Limousine' 'Pickup']
```

[18]:
```
#plot the data for review and set price axis at log for better visibility
fig, ax = plt.subplots()
ax.errorbar(categoryarray, pricemeanarray, pricesdarray, linestyle='None',␣
 ↪marker='^')
ax.set_yscale('log')
```



[19]:
```python
#plot data without standard deviations
fig, ax = plt.subplots()
ax.scatter(categoryarray,pricemeanarray)
ax.set_yscale('log')
```



Now bese on the price mean in every type car, we can find the max price and min price for normalization. base on $UnitStep = \frac{MaxPrice - MinPrice}{1000}$. And assign the unit step price back to every typ of car for a number in the $(0, 1)$ interval.

[20]:
```python
#imprt numpy library
import numpy as np
pricemeanarrayln = np.log(pricemeanarray)
#find max mean and min mean and calcuate unit step
minimean = pricemeanarrayln.min()
unitstep = (pricemeanarrayln.max()-pricemeanarrayln.min())/1000
#assign the unit step back to every car type
pricemeanarraynormal = (pricemeanarrayln - minimean)/unitstep/1000
#Plot data for better visibility
fig, ax = plt.subplots()
ax.scatter(categoryarray,pricemeanarraynormal)
```

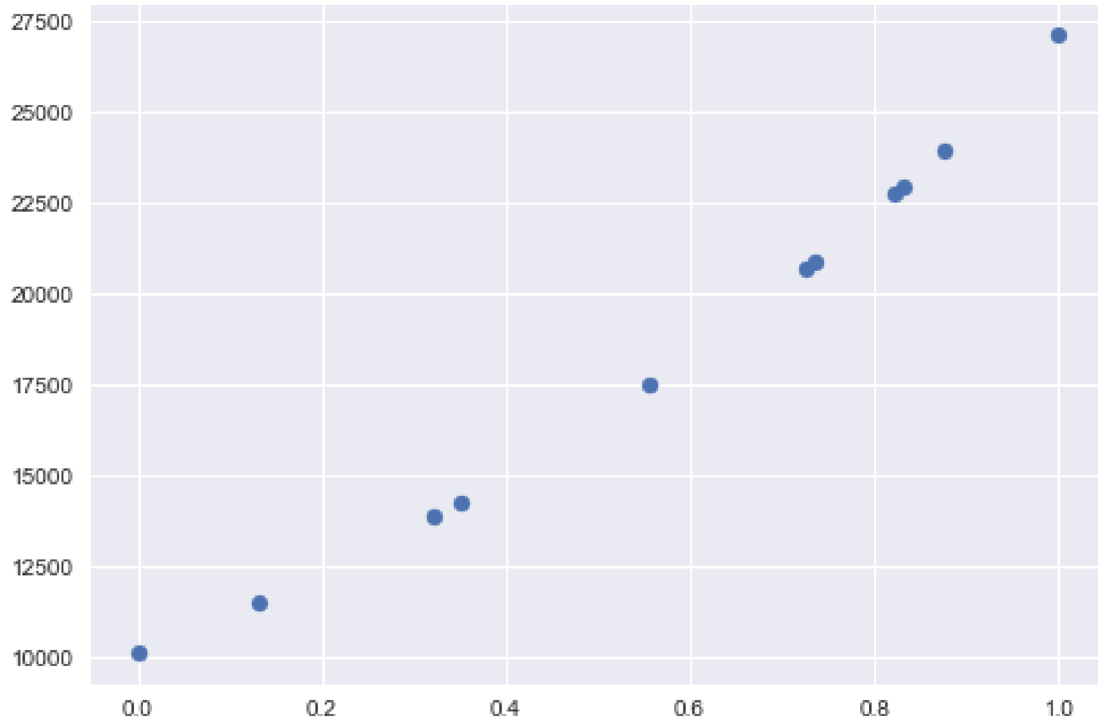
[20]: <matplotlib.collections.PathCollection at 0x20d59922e50>

[21]:
```
#loop to print out all different number assignment for the car category
j = len(categoryarray)
i = 0
for i in range(j):
    print(categoryarray[i], "normallization number is ",␣
 ↪pricemeanarraynormal[i])
    i = i+1
```

```
Jeep normallization number is  0.8745356666201155
Hatchback normallization number is  0.13229249056919942
Sedan normallization number is  0.349745270699173
Microbus normallization number is  0.5563298412491332
Goods wagon normallization number is  0.0
Universal normallization number is  0.8308685039568255
Coupe normallization number is  0.7348558300196918
Minivan normallization number is  0.7254232613366441
Cabriolet normallization number is  0.8217144550817334
Limousine normallization number is  0.32049378734106937
Pickup normallization number is  0.9999999999999999
```

[22]:
```
#plot data with number assigned to every different car category
fig, ax = plt.subplots()
ax.scatter(pricemeanarraynormal, pricemeanarray)
```

[22]: <matplotlib.collections.PathCollection at 0x20d59ca85e0>



We can see that we should be able to use this mothed for the Category Column. However, we also found another solution for variable quantization called One-Hot-Encoding.

3.2 One-Hot-Encoding (Add Dummies) After more research, we found another solution for variable quantization is called One-Hot_Encoding which is adding dummy variable columnes for every category and substract one $n - 1$. We will test this in Category Column again:

[23]:
```
print(df.Category.unique())
```

```
['Jeep' 'Hatchback' 'Sedan' 'Microbus' 'Goods wagon' 'Universal' 'Coupe'
 'Minivan' 'Cabriolet' 'Limousine' 'Pickup']
```

Again, we see there are 11 different car categories in total. Now we apply One-Hot-Encoding to Category columns simply by using get_dummies() fuction in Pandas dataframe

[24]:
```
#assign category data out to categry sub data frame for testing
category = df.Category
#try one-hot-encoding
pd.get_dummies(category)
```

[24]:

	Cabriolet	Coupe	Goods wagon	Hatchback	Jeep	Limousine	Microbus	\
0	0	0	0	0	1	0	0	
1	0	0	0	0	1	0	0	

```
2               0      0            0          1     0          0         0
3               0      0            0          0     1          0         0
4               0      0            0          1     0          0         0
…          …    …          …      …   …       …       …
13448           0      0            0          0     0          0         0
13449           0      0            0          0     0          0         0
13450           0      0            0          1     0          0         0
13451           0      0            0          0     1          0         0
13452           0      0            0          0     0          0         0

       Minivan  Pickup  Sedan  Universal
0            0       0      0          0
1            0       0      0          0
2            0       0      0          0
3            0       0      0          0
4            0       0      0          0
…        …     …    …      …
13448        0       0      1          0
13449        0       0      1          0
13450        0       0      0          0
13451        0       0      0          0
13452        0       0      1          0

[13453 rows x 11 columns]
```

Now we can try this in the main training data frame:

[25]:
```python
pd.get_dummies(df, columns=["Category"], drop_first = True)
```

[25]:
```
       Unnamed: 0        ID  Price  Levy Manufacturer       Model  Prod_year  \
0               0  45654403  13328  1399        LEXUS      RX 450       2010
1               1  44731507  16621  1018    CHEVROLET     EQUINOX       2011
2               2  45774419   8467     0        HONDA         FIT       2006
3               3  45769185   3607   862         FORD      ESCAPE       2011
4               4  45809263  11726   446        HONDA         FIT       2014
…             …       …     …     …       …          …        …
13448       13462  45802417  21103  1104      HYUNDAI    GRANDEUR       2015
13449       13463  44631202  13172   530      HYUNDAI     ELANTRA       2013
13450       13464  45669073  19757   353       TOYOTA       PRIUS       2015
13451       13465  45647811   1019   917          BMW          X5       2013
13452       13466  45768173    125  1750       TOYOTA  HIGHLANDER       2008

      Leather_interior Fuel_type  Engine_volume  … Category_Coupe  \
0                  Yes    Hybrid            3.5  …              0
1                   No    Petrol            3.0  …              0
2                   No    Petrol            1.3  …              0
3                  Yes    Hybrid            2.5  …              0
4                  Yes    Petrol            1.3  …              0
```

```
…                 …        …             …   …             …
13448           Yes      LPG           3.0  …             0
13449           Yes   Petrol           1.6  …             0
13450            No   Hybrid           1.8  …             0
13451           Yes   Diesel           3.0  …             0
13452           Yes   Hybrid           3.3  …             0

       Category_Goods wagon  Category_Hatchback Category_Jeep  \
0                         0                  0             1
1                         0                  0             1
2                         0                  1             0
3                         0                  0             1
4                         0                  1             0
…                       …                  …             …
13448                     0                  0             0
13449                     0                  0             0
13450                     0                  1             0
13451                     0                  0             1
13452                     0                  0             0

      Category_Limousine Category_Microbus Category_Minivan Category_Pickup  \
0                      0                 0                0               0
1                      0                 0                0               0
2                      0                 0                0               0
3                      0                 0                0               0
4                      0                 0                0               0
…                    …                 …                …               …
13448                  0                 0                0               0
13449                  0                 0                0               0
13450                  0                 0                0               0
13451                  0                 0                0               0
13452                  0                 0                0               0

       Category_Sedan  Category_Universal
0                   0                   0
1                   0                   0
2                   0                   0
3                   0                   0
4                   0                   0
…                 …                   …
13448               1                   0
13449               1                   0
13450               0                   0
13451               0                   0
13452               1                   0

[13453 rows x 29 columns]
```

Looks like one-hot-encoding is much simply solution compare to calculate group mean.

3.3 Conclution After research, we have found that there are two method for variable quantization. One if calculate group mean and one is One-Hot-Encoding. As group we have decide to use One-Hot-Encoding for all the categorical variable columns except two columns. Which are Manufacture and Models. We can see following:

[26]:
```
print("Total unique value in Manufacturer columne is ",len(df.Manufacturer.
 ↪unique()))
print("Total unique value in Model columne is ",len(df.Model.unique()))
```

```
Total unique value in Manufacturer columne is  64
Total unique value in Model columne is  1227
```

These number are large and Model is heavely depend on manufacturer (we will show that in following section). Then we decide to use group mean calculation for these two columns.

0.0.4 4. Column Independence Analyzation

One of assumption made for linear regression model was X column data are independent to each other. Only Y column data is dependent data. In our case Y is price. Now we need to test the independency of X columns. First, we needed load training data:

[27]:
```
df = pd.read_csv('TrainingData.csv')
df
```

[27]:
```
       Unnamed: 0        ID  Price  Levy Manufacturer       Model  Prod_year  \
0               0  45654403  13328  1399        LEXUS      RX 450       2010
1               1  44731507  16621  1018    CHEVROLET     EQUINOX       2011
2               2  45774419   8467     0        HONDA         FIT       2006
3               3  45769185   3607   862         FORD      ESCAPE       2011
4               4  45809263  11726   446        HONDA         FIT       2014
…               …         …     …     …           …           …
13448       13462  45802417  21103  1104      HYUNDAI    GRANDEUR       2015
13449       13463  44631202  13172   530      HYUNDAI     ELANTRA       2013
13450       13464  45669073  19757   353       TOYOTA       PRIUS       2015
13451       13465  45647811   1019   917          BMW          X5       2013
13452       13466  45768173    125  1750       TOYOTA  HIGHLANDER       2008

        Category Leather_interior Fuel_type  Engine_volume Turbo  Mileage  \
0           Jeep              Yes    Hybrid            3.5   NaN   186005
1           Jeep               No    Petrol            3.0   NaN   192000
2      Hatchback               No    Petrol            1.3   NaN   200000
3           Jeep              Yes    Hybrid            2.5   NaN   168966
4      Hatchback              Yes    Petrol            1.3   NaN    91901
…            …                …         …              …     …        …
13448      Sedan              Yes       LPG            3.0   NaN   273249
13449      Sedan              Yes    Petrol            1.6   NaN    75000
13450  Hatchback               No    Hybrid            1.8   NaN   105000
```

```
13451       Jeep              Yes    Diesel            3.0   NaN   137802
13452      Sedan              Yes    Hybrid            3.3   NaN   287274

      Cylinders Gear_box_type Drive_wheels Doors            Wheel   Color  \
0             6     Automatic   Front-Rear   4-5       Left wheel  Silver
1             6     Tiptronic   Front-Rear   4-5       Left wheel   Black
2             4      Variator        Front   4-5 Right-hand drive   Black
3             4     Automatic   Front-Rear   4-5       Left wheel   White
4             4     Automatic        Front   4-5       Left wheel  Silver
…           …           …          …   …              …     …
13448         4     Automatic        Front   4-5       Left wheel   Black
13449         4     Tiptronic        Front   4-5       Left wheel   White
13450         4     Automatic        Front   4-5       Left wheel  Silver
13451         6     Automatic   Front-Rear   4-5       Left wheel   Black
13452         6     Automatic   Front-Rear   4-5       Left wheel   White

      Airbags
0          12
1           8
2           2
3           0
4           4
…         …
13448       4
13449       8
13450       8
13451       0
13452      12

[13453 rows x 20 columns]
```

We know that there are different type data in the training data set. We have to analyze them in following 3 different ways.

4.1 Heat Map for Columns With Digit Data Now let's seperate the data frame and creat a new data frame ddf encoding as "Digit Data Frame".

[28]:
```python
ddf = df[['Price','Levy', 'Prod_year', 'Engine_volume', 'Mileage', 'Cylinders',
   'Airbags']]
ddf
```

[28]:

	Price	Levy	Prod_year	Engine_volume	Mileage	Cylinders	Airbags
0	13328	1399	2010	3.5	186005	6	12
1	16621	1018	2011	3.0	192000	6	8
2	8467	0	2006	1.3	200000	4	2
3	3607	862	2011	2.5	168966	4	0
4	11726	446	2014	1.3	91901	4	4

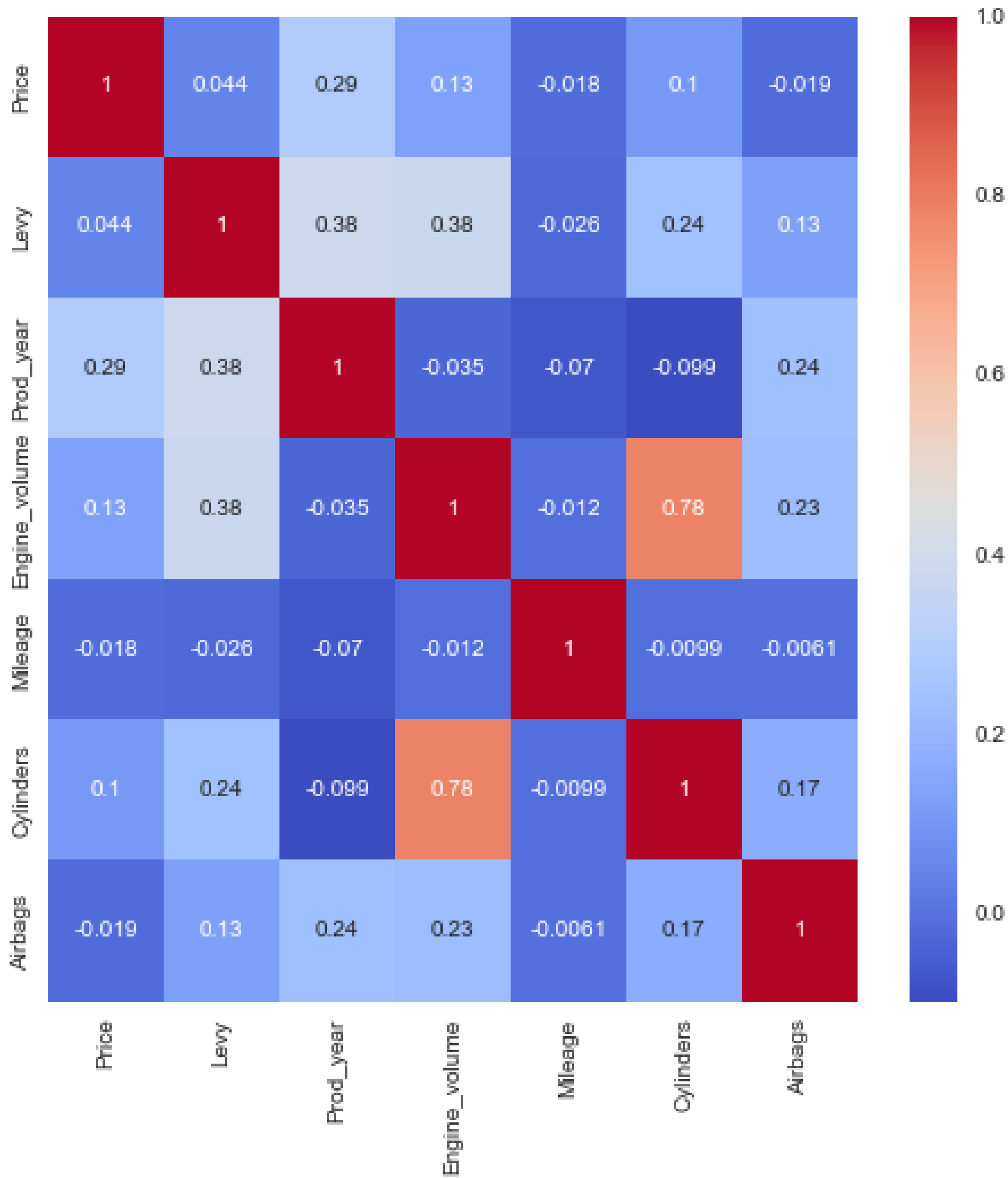
```
...     ...   ...        ...            ...       ...       ...      ...
13448  21103  1104       2015                3.0    273249            4         4
13449  13172   530       2013                1.6     75000            4         8
13450  19757   353       2015                1.8    105000            4         8
13451   1019   917       2013                3.0    137802            6         0
13452    125  1750       2008                3.3    287274            6        12

[13453 rows x 7 columns]
```

[29]:
```python
# find correlation numbers
ddf.corr()
```

[29]:
```
                  Price      Levy  Prod_year  Engine_volume   Mileage  \
Price          1.000000  0.043694   0.287841       0.130153 -0.017634
Levy           0.043694  1.000000   0.381583       0.375368 -0.026169
Prod_year      0.287841  0.381583   1.000000      -0.034592 -0.069824
Engine_volume  0.130153  0.375368  -0.034592       1.000000 -0.012121
Mileage       -0.017634 -0.026169  -0.069824      -0.012121  1.000000
Cylinders      0.104799  0.241199  -0.099391       0.782648 -0.009870
Airbags       -0.019300  0.126134   0.238808       0.225086 -0.006051

               Cylinders   Airbags
Price           0.104799 -0.019300
Levy            0.241199  0.126134
Prod_year      -0.099391  0.238808
Engine_volume   0.782648  0.225086
Mileage        -0.009870 -0.006051
Cylinders       1.000000  0.170400
Airbags         0.170400  1.000000
```

[30]:
```python
# plot heat map base on the correlation numbers
plt.figure(figsize=(8,8))
sns.heatmap(ddf.corr(), annot=True, cmap='coolwarm')
```

[30]: <AxesSubplot:>



We can see that base on the heat map most columns are good with indenpendency. Only exception is column Engine_volume and Cylinders. Which it makes alot sense that when Engine_vlume increase the Cylinders will increase too.

4.2 Analyze the Categorical Variable Column with Heat-Map-like Plot We cannot get correlation number from corr() function in the Pandas dataframe to create heat Map. However, we can pivot the data apparance to compare two categorical variable columns. When data appare only in one row and one column for majority of data in two columns. We can see the dependency of the two categorical variable column. We need to load categorical variable only column to a new data frame "cdf" as categorical data frame.

[31]:
```
cdf = df[['Manufacturer','Model', 'Category', 'Leather_interior', 'Fuel_type',␣
↪'Gear_box_type', 'Drive_wheels', 'Doors', 'Wheel', 'Color']]
cdf
```

[31]:
```
      Manufacturer       Model   Category Leather_interior Fuel_type  \
0            LEXUS      RX 450       Jeep              Yes    Hybrid
1        CHEVROLET     EQUINOX       Jeep               No    Petrol
2            HONDA         FIT  Hatchback               No    Petrol
3             FORD      ESCAPE       Jeep              Yes    Hybrid
4            HONDA         FIT  Hatchback              Yes    Petrol
…                …           …          …                …         …
13448      HYUNDAI    GRANDEUR      Sedan              Yes       LPG
13449      HYUNDAI     ELANTRA      Sedan              Yes    Petrol
13450       TOYOTA       PRIUS  Hatchback               No    Hybrid
13451          BMW          X5       Jeep              Yes    Diesel
13452       TOYOTA  HIGHLANDER      Sedan              Yes    Hybrid

      Gear_box_type Drive_wheels Doors             Wheel   Color
0         Automatic   Front-Rear   4-5        Left wheel  Silver
1         Tiptronic   Front-Rear   4-5        Left wheel   Black
2          Variator        Front   4-5  Right-hand drive   Black
3         Automatic   Front-Rear   4-5        Left wheel   White
4         Automatic        Front   4-5        Left wheel  Silver
…                 …          …    …                 …       …
13448     Automatic        Front   4-5        Left wheel   Black
13449     Tiptronic        Front   4-5        Left wheel   White
13450     Automatic        Front   4-5        Left wheel  Silver
13451     Automatic   Front-Rear   4-5        Left wheel   Black
13452     Automatic   Front-Rear   4-5        Left wheel   White

[13453 rows x 10 columns]
```

4.2.1 Manufacturer vs Model

[32]:
```
# Training Data Frame is too large, let try first 50
cdf1 = cdf.head(50)
# count the Manufacturer and Model data apparence
cdf_counts = cdf1.groupby(['Manufacturer', 'Model']).size()
cdf_counts = cdf_counts.reset_index(name = 'count')
# pivate the data
cdf_counts = cdf_counts.pivot(index = 'Model', columns = 'Manufacturer', values␣
↪= 'count')
cdf_counts
```

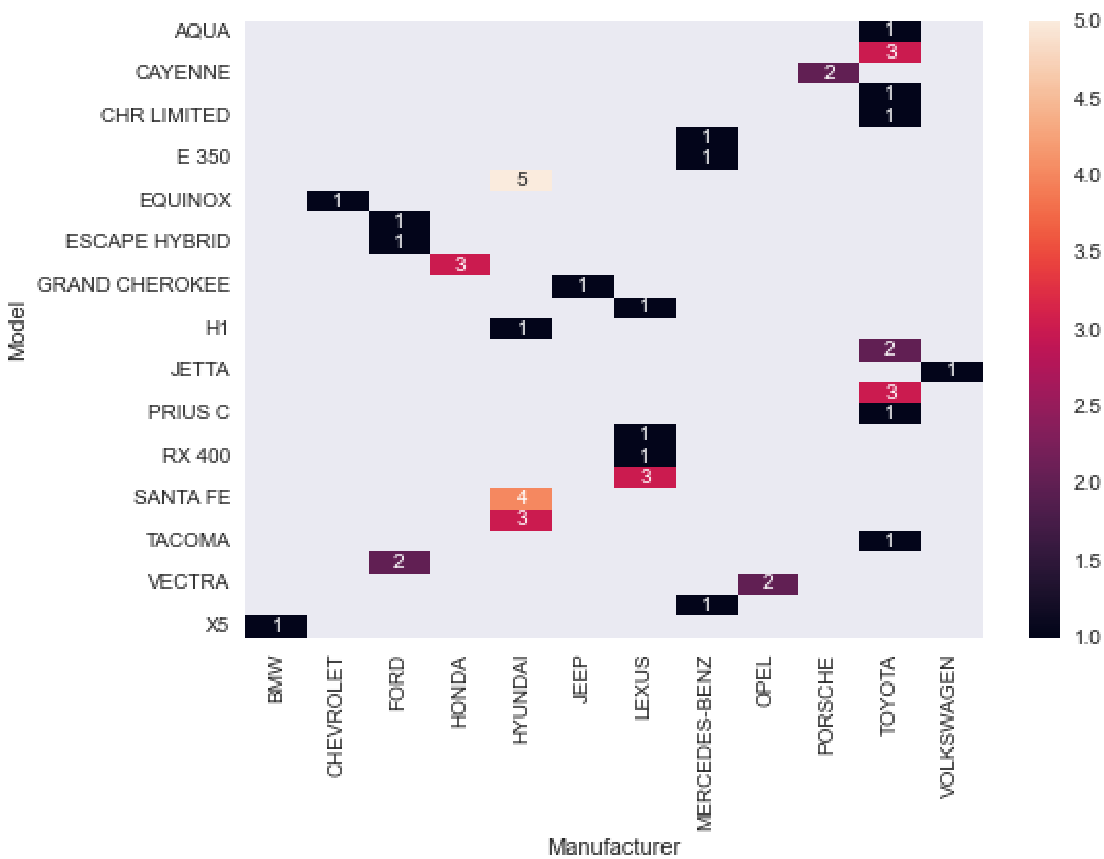
[32]:

```
Manufacturer    BMW  CHEVROLET  FORD  HONDA  HYUNDAI  JEEP  LEXUS  \
Model
AQUA            NaN        NaN   NaN    NaN      NaN   NaN    NaN
CAMRY           NaN        NaN   NaN    NaN      NaN   NaN    NaN
CAYENNE         NaN        NaN   NaN    NaN      NaN   NaN    NaN
CHR             NaN        NaN   NaN    NaN      NaN   NaN    NaN
CHR LIMITED     NaN        NaN   NaN    NaN      NaN   NaN    NaN
E 220           NaN        NaN   NaN    NaN      NaN   NaN    NaN
E 350           NaN        NaN   NaN    NaN      NaN   NaN    NaN
ELANTRA         NaN        NaN   NaN    NaN      5.0   NaN    NaN
EQUINOX         NaN        1.0   NaN    NaN      NaN   NaN    NaN
ESCAPE          NaN        NaN   1.0    NaN      NaN   NaN    NaN
ESCAPE HYBRID   NaN        NaN   1.0    NaN      NaN   NaN    NaN
FIT             NaN        NaN   NaN    3.0      NaN   NaN    NaN
GRAND CHEROKEE  NaN        NaN   NaN    NaN      NaN   1.0    NaN
GX 470          NaN        NaN   NaN    NaN      NaN   NaN    1.0
H1              NaN        NaN   NaN    NaN      1.0   NaN    NaN
HIGHLANDER      NaN        NaN   NaN    NaN      NaN   NaN    NaN
JETTA           NaN        NaN   NaN    NaN      NaN   NaN    NaN
PRIUS           NaN        NaN   NaN    NaN      NaN   NaN    NaN
PRIUS C         NaN        NaN   NaN    NaN      NaN   NaN    NaN
RX 350          NaN        NaN   NaN    NaN      NaN   NaN    1.0
RX 400          NaN        NaN   NaN    NaN      NaN   NaN    1.0
RX 450          NaN        NaN   NaN    NaN      NaN   NaN    3.0
SANTA FE        NaN        NaN   NaN    NaN      4.0   NaN    NaN
SONATA          NaN        NaN   NaN    NaN      3.0   NaN    NaN
TACOMA          NaN        NaN   NaN    NaN      NaN   NaN    NaN
TRANSIT         NaN        NaN   2.0    NaN      NaN   NaN    NaN
VECTRA          NaN        NaN   NaN    NaN      NaN   NaN    NaN
VITO            NaN        NaN   NaN    NaN      NaN   NaN    NaN
X5              1.0        NaN   NaN    NaN      NaN   NaN    NaN

Manufacturer    MERCEDES-BENZ  OPEL  PORSCHE  TOYOTA  VOLKSWAGEN
Model
AQUA                      NaN   NaN      NaN     1.0         NaN
CAMRY                     NaN   NaN      NaN     3.0         NaN
CAYENNE                   NaN   NaN      2.0     NaN         NaN
CHR                       NaN   NaN      NaN     1.0         NaN
CHR LIMITED               NaN   NaN      NaN     1.0         NaN
E 220                     1.0   NaN      NaN     NaN         NaN
E 350                     1.0   NaN      NaN     NaN         NaN
ELANTRA                   NaN   NaN      NaN     NaN         NaN
EQUINOX                   NaN   NaN      NaN     NaN         NaN
ESCAPE                    NaN   NaN      NaN     NaN         NaN
ESCAPE HYBRID             NaN   NaN      NaN     NaN         NaN
FIT                       NaN   NaN      NaN     NaN         NaN
GRAND CHEROKEE            NaN   NaN      NaN     NaN         NaN
```

```
GX 470                    NaN    NaN      NaN      NaN         NaN
H1                        NaN    NaN      NaN      NaN         NaN
HIGHLANDER                NaN    NaN      NaN      2.0         NaN
JETTA                     NaN    NaN      NaN      NaN         1.0
PRIUS                     NaN    NaN      NaN      3.0         NaN
PRIUS C                   NaN    NaN      NaN      1.0         NaN
RX 350                    NaN    NaN      NaN      NaN         NaN
RX 400                    NaN    NaN      NaN      NaN         NaN
RX 450                    NaN    NaN      NaN      NaN         NaN
SANTA FE                  NaN    NaN      NaN      NaN         NaN
SONATA                    NaN    NaN      NaN      NaN         NaN
TACOMA                    NaN    NaN      NaN      1.0         NaN
TRANSIT                   NaN    NaN      NaN      NaN         NaN
VECTRA                    NaN    2.0      NaN      NaN         NaN
VITO                      1.0    NaN      NaN      NaN         NaN
X5                        NaN    NaN      NaN      NaN         NaN
```

[33]:
```python
#plot heat map
sns.heatmap(cdf_counts, annot = True)
```

[33]: `<AxesSubplot:xlabel='Manufacturer', ylabel='Model'>`



We can see that the data apperance on the row of model is depend on the manufacturer. This is normal, as model normally is manufacturer trade mark, they are only depend on manufacturer. For example, when Tesla first time create the Model 3 cars, the idea was use Model E. However, Model E is trade mark of Ford. That is why Tesla is using Model 3. Solution of handling of the data is in section 4.5

4.2.2 Manufacturer vs Category

[34]:

```python
# count the Manufacturer and Category data apperance
cdf_counts = cdf.groupby(['Manufacturer', 'Category']).size()
cdf_counts = cdf_counts.reset_index(name = 'count')
# pivate the data
cdf_counts = cdf_counts.pivot(index = 'Category', columns = 'Manufacturer',␣
↪values = 'count')
cdf_counts
```

[34]:

Manufacturer	ACURA	ALFA ROMEO	ASTON MARTIN	AUDI	BENTLEY	BMW	BUICK	\
Category								
Cabriolet	NaN	NaN	NaN	NaN	NaN	9.0	NaN	
Coupe	NaN	1.0	1.0	9.0	1.0	61.0	NaN	
Goods wagon	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
Hatchback	NaN	1.0	NaN	23.0	NaN	14.0	NaN	
Jeep	4.0	NaN	NaN	44.0	NaN	300.0	3.0	
Limousine	NaN	NaN	NaN	NaN	NaN	1.0	NaN	
Microbus	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
Minivan	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
Pickup	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
Sedan	7.0	1.0	NaN	88.0	1.0	330.0	6.0	
Universal	NaN	NaN	NaN	3.0	NaN	5.0	NaN	

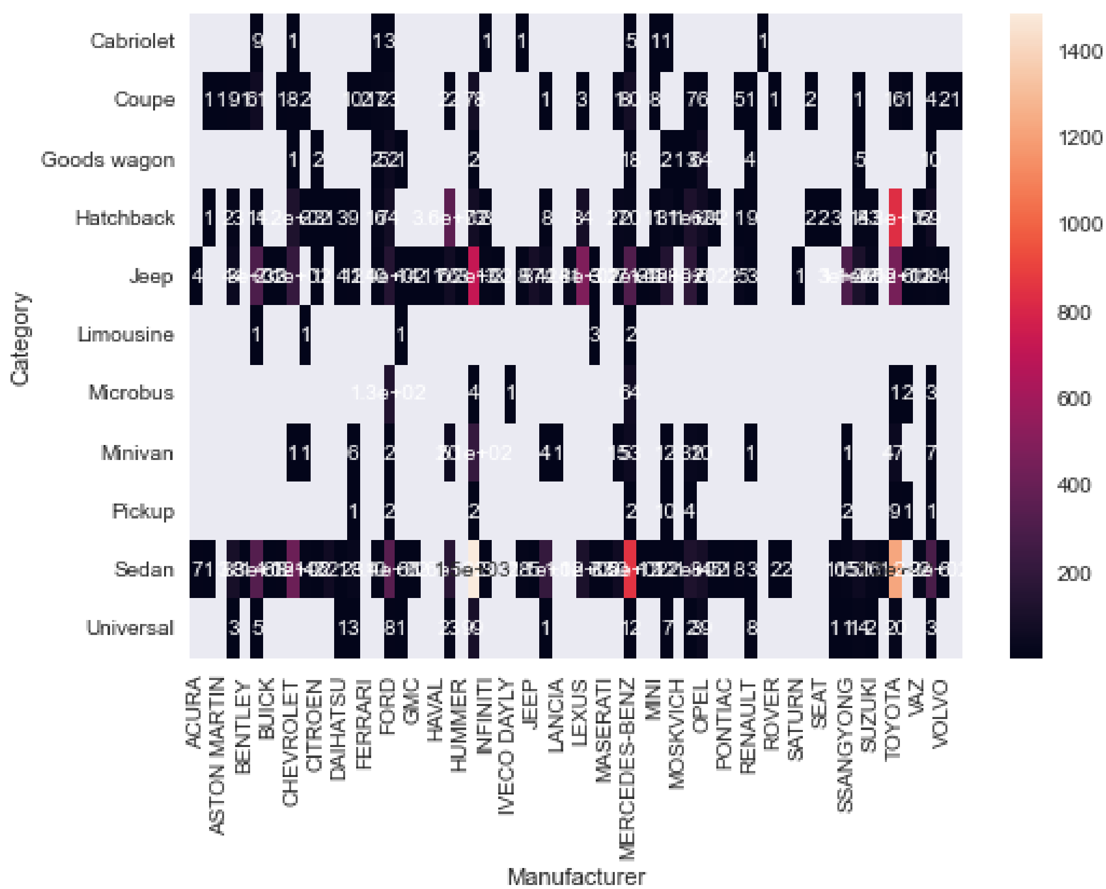
Manufacturer	CADILLAC	CHEVROLET	CHRYSLER	…	SSANGYONG	SUBARU	SUZUKI	\
Category				…				
Cabriolet	NaN	1.0	NaN	…	NaN	NaN	NaN	
Coupe	1.0	8.0	2.0	…	NaN	1.0	NaN	
Goods wagon	NaN	1.0	NaN	…	NaN	5.0	NaN	
Hatchback	NaN	122.0	2.0	…	NaN	14.0	13.0	
Jeep	3.0	212.0	NaN	…	302.0	108.0	28.0	
Limousine	NaN	NaN	1.0	…	NaN	NaN	NaN	
Microbus	NaN	NaN	NaN	…	NaN	NaN	NaN	
Minivan	NaN	1.0	1.0	…	1.0	NaN	NaN	
Pickup	NaN	NaN	NaN	…	2.0	NaN	NaN	
Sedan	8.0	407.0	14.0	…	15.0	52.0	16.0	
Universal	NaN	NaN	NaN	…	1.0	14.0	2.0	

Manufacturer	TESLA	TOYOTA	UAZ	VAZ	VOLKSWAGEN	VOLVO	ZAZ
Category							
Cabriolet	NaN	NaN	NaN	NaN	NaN	NaN	NaN

```
Coupe            NaN    16.0  1.0   NaN        4.0    2.0  1.0
Goods wagon      NaN     NaN  NaN   NaN       10.0    NaN  NaN
Hatchback        NaN   830.0  NaN   1.0       59.0    NaN  NaN
Jeep             NaN   453.0  6.0  12.0       18.0    4.0  NaN
Limousine        NaN     NaN  NaN   NaN        NaN    NaN  NaN
Microbus         NaN     1.0  2.0   NaN        3.0    NaN  NaN
Minivan          NaN    47.0  NaN   NaN        7.0    NaN  NaN
Pickup           NaN     9.0  1.0   NaN        1.0    NaN  NaN
Sedan            1.0  1223.0  NaN  22.0      286.0    6.0  NaN
Universal        NaN    20.0  NaN   NaN        3.0    NaN  NaN

[11 rows x 64 columns]
```

[35]:
```python
#plot heat map
sns.heatmap(cdf_counts, annot = True)
```

[35]: <AxesSubplot:xlabel='Manufacturer', ylabel='Category'>



Unlike the 4.2.1 Manufacturer vs Model, Manufacturer vs Category showing independence as categoery data appearance is distribute every where across manufacturer. This is normal, because manufacturer cannot trade mark car category. All manufacturer can make any category of cars as they like.

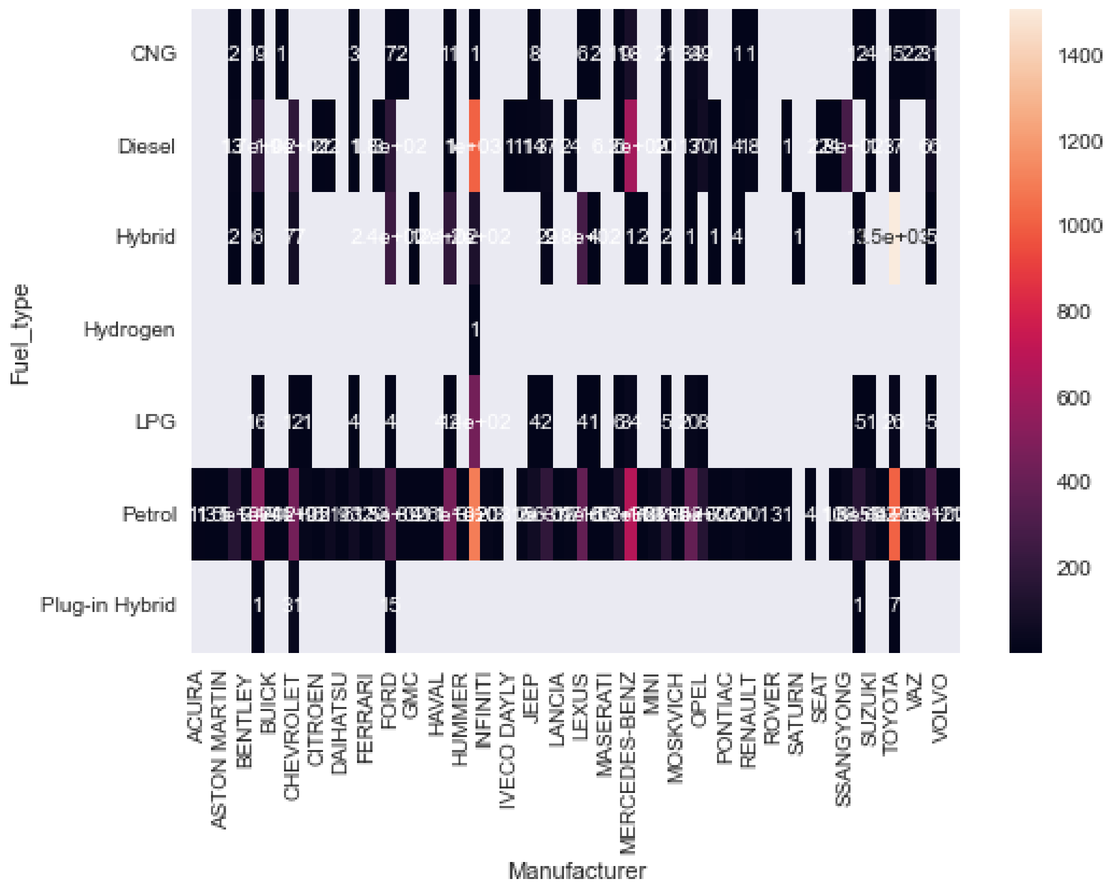
4.2.3 Manufacturer vs Fuel Type

[36]:
```
# count the Manufacturer and Fuel Type data apparence
cdf_counts = cdf.groupby(['Manufacturer', 'Fuel_type']).size()
cdf_counts = cdf_counts.reset_index(name = 'count')
# pivate the data
cdf_counts = cdf_counts.pivot(index = 'Fuel_type', columns = 'Manufacturer',␣
↪values = 'count')
cdf_counts
```

[36]:
```
Manufacturer    ACURA  ALFA ROMEO  ASTON MARTIN   AUDI  BENTLEY    BMW  BUICK  \
Fuel_type
CNG               NaN         NaN           NaN    2.0      NaN   19.0    NaN
Diesel            NaN         NaN           NaN   13.0      NaN  172.0    NaN
Hybrid            NaN         NaN           NaN    2.0      NaN    6.0    NaN
Hydrogen          NaN         NaN           NaN    NaN      NaN    NaN    NaN
LPG               NaN         NaN           NaN    NaN      NaN   16.0    NaN
Petrol           11.0         3.0           1.0  150.0      2.0  506.0    9.0
Plug-in Hybrid    NaN         NaN           NaN    NaN      NaN    1.0    NaN

Manufacturer    CADILLAC  CHEVROLET  CHRYSLER  …  SSANGYONG  SUBARU  SUZUKI  \
Fuel_type                                      …
CNG                  1.0        NaN       NaN  …        NaN    12.0     4.0
Diesel               NaN      188.0       NaN  …      283.0     NaN     1.0
Hybrid               NaN       77.0       NaN  …        NaN    13.0     NaN
Hydrogen             NaN        NaN       NaN  …        NaN     NaN     NaN
LPG                  NaN       12.0       1.0  …        NaN     5.0     1.0
Petrol              11.0      444.0      19.0  …       38.0   163.0    53.0
Plug-in Hybrid       NaN       31.0       NaN  …        NaN     1.0     NaN

Manufacturer    TESLA  TOYOTA  UAZ   VAZ  VOLKSWAGEN  VOLVO  ZAZ
Fuel_type
CNG               NaN    15.0  2.0   2.0        31.0    NaN  NaN
Diesel            NaN    37.0  NaN   NaN        66.0    NaN  NaN
Hybrid            NaN  1507.0  NaN   NaN         5.0    NaN  NaN
Hydrogen          NaN     NaN  NaN   NaN         NaN    NaN  NaN
LPG               NaN    26.0  NaN   NaN         5.0    NaN  NaN
Petrol            1.0  1007.0  8.0  33.0       284.0   12.0  1.0
Plug-in Hybrid    NaN     7.0  NaN   NaN         NaN    NaN  NaN

[7 rows x 64 columns]
```

[37]:
```
#plot heat map
sns.heatmap(cdf_counts, annot = True)
```

[37]: <AxesSubplot:xlabel='Manufacturer', ylabel='Fuel_type'>



Same to 4.2.2 Manufacturer vs Category, Manufactuer vs Fuel Type is also showing independency of the fuel type with one exception of Hydrogen. Looks like we don't have enough traning data for the Hydrogen type. This could lead to large error during the training the model at Hydrogen fuel type.

4.2.4 Manufacturer vs Gear Box Type

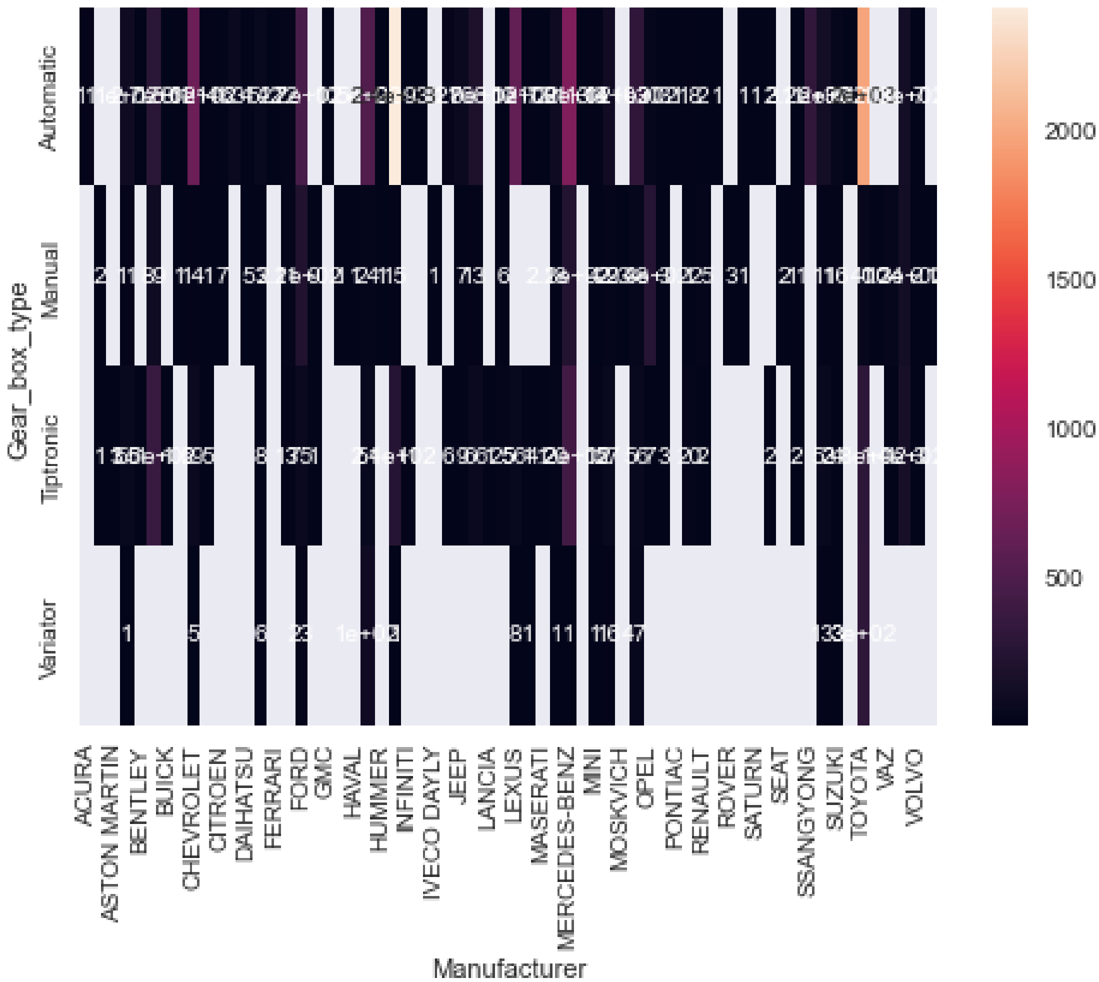
[38]:
```
# count the Manufacturer and Fuel Type data apperence
cdf_counts = cdf.groupby(['Manufacturer', 'Gear_box_type']).size()
cdf_counts = cdf_counts.reset_index(name = 'count')
# pivate the data
cdf_counts = cdf_counts.pivot(index = 'Gear_box_type', columns =␣
↪'Manufacturer', values = 'count')
cdf_counts
```

[38]:
```
Manufacturer   ACURA  ALFA ROMEO  ASTON MARTIN   AUDI  BENTLEY    BMW  BUICK  \
Gear_box_type
Automatic       11.0         NaN           NaN  100.0      1.0  271.0    8.0
```

```
Manual             NaN         2.0          NaN   11.0     NaN   89.0    NaN
Tiptronic          NaN         1.0          1.0   55.0     1.0  360.0    1.0
Variator           NaN         NaN          NaN    1.0     NaN    NaN    NaN

Manufacturer   CADILLAC  CHEVROLET  CHRYSLER  …  SSANGYONG  SUBARU  SUZUKI  \
Gear_box_type                                 …
Automatic          11.0      664.0      14.0  …      321.0   117.0    36.0
Manual              1.0       14.0       1.0  …        NaN    11.0    16.0
Tiptronic           NaN       69.0       5.0  …        NaN    53.0     4.0
Variator            NaN        5.0       NaN  …        NaN    13.0     3.0

Manufacturer   TESLA  TOYOTA   UAZ   VAZ  VOLKSWAGEN  VOLVO  ZAZ
Gear_box_type
Automatic        1.0  1976.0   NaN   NaN       128.0    7.0  NaN
Manual           NaN    40.0  10.0  34.0       119.0    2.0  1.0
Tiptronic        NaN   284.0   NaN   1.0       144.0    3.0  NaN
Variator         NaN   299.0   NaN   NaN         NaN    NaN  NaN

[4 rows x 64 columns]
```

[39]:
```
#plot heat map
sns.heatmap(cdf_counts, annot = True)
```

[39]:
```
<AxesSubplot:xlabel='Manufacturer', ylabel='Gear_box_type'>
```



We can see the gear box type has distribute on more than one manufacturer. This show the independency of these two columns.

4.2.5 Category vs Wheel

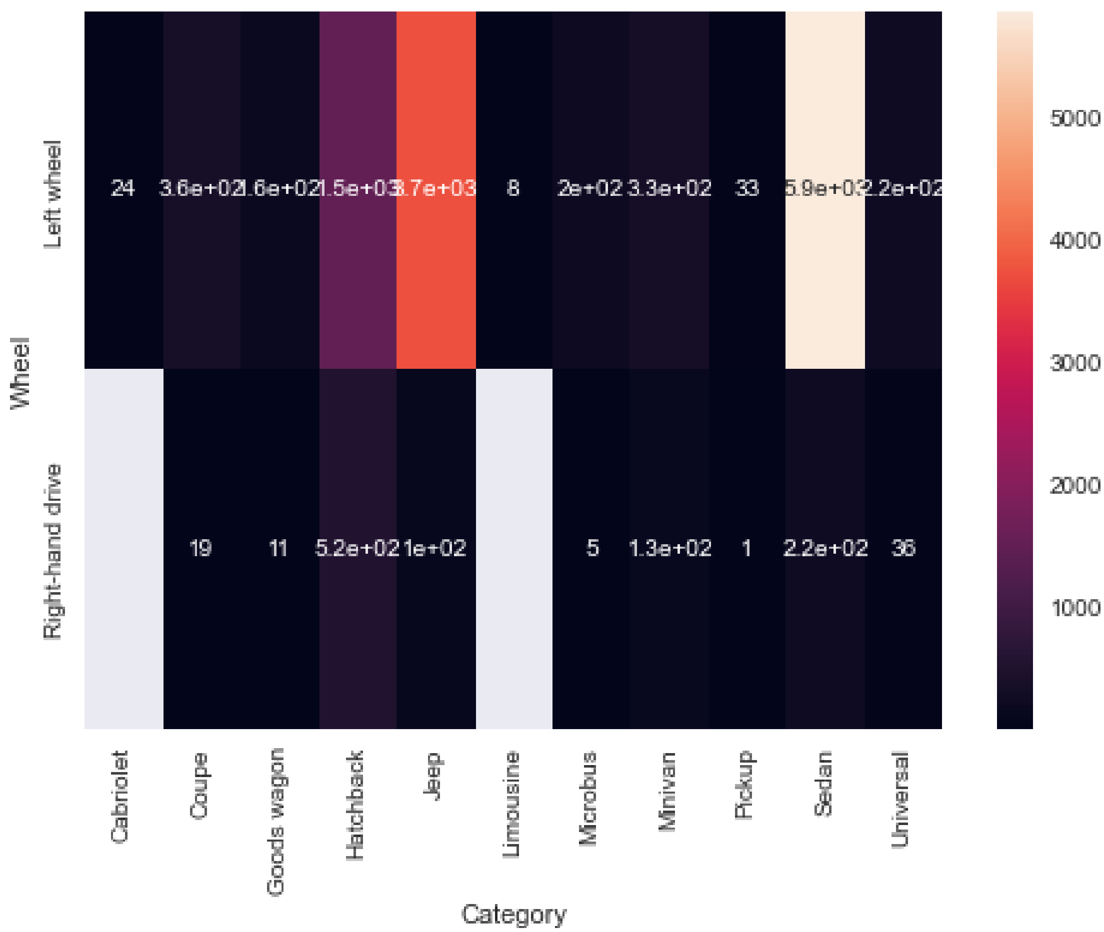
[40]:
```
# count the Category and Wheel data apparence
cdf_counts = cdf.groupby(['Category', 'Wheel']).size()
cdf_counts = cdf_counts.reset_index(name = 'count')
# pivate the data
cdf_counts = cdf_counts.pivot(index = 'Wheel', columns = 'Category', values =
↪'count')
cdf_counts
```

[40]:
```
Category          Cabriolet  Coupe  Goods wagon  Hatchback    Jeep  Limousine  \
Wheel
Left wheel             24.0  357.0        156.0     1473.0  3727.0        8.0
Right-hand drive        NaN   19.0         11.0      525.0   105.0        NaN
```

```
Category           Microbus  Minivan  Pickup   Sedan  Universal
Wheel
Left wheel            200.0    328.0    33.0  5870.0      217.0
Right-hand drive        5.0    134.0     1.0   224.0       36.0
```

[41]:
```
#plot heat map
sns.heatmap(cdf_counts, annot = True)
```

[41]: <AxesSubplot:xlabel='Category', ylabel='Wheel'>



We can see heat map has showing the clearly independency for Category vs Wheel

4.2.6 Fuel Type vs Wheel

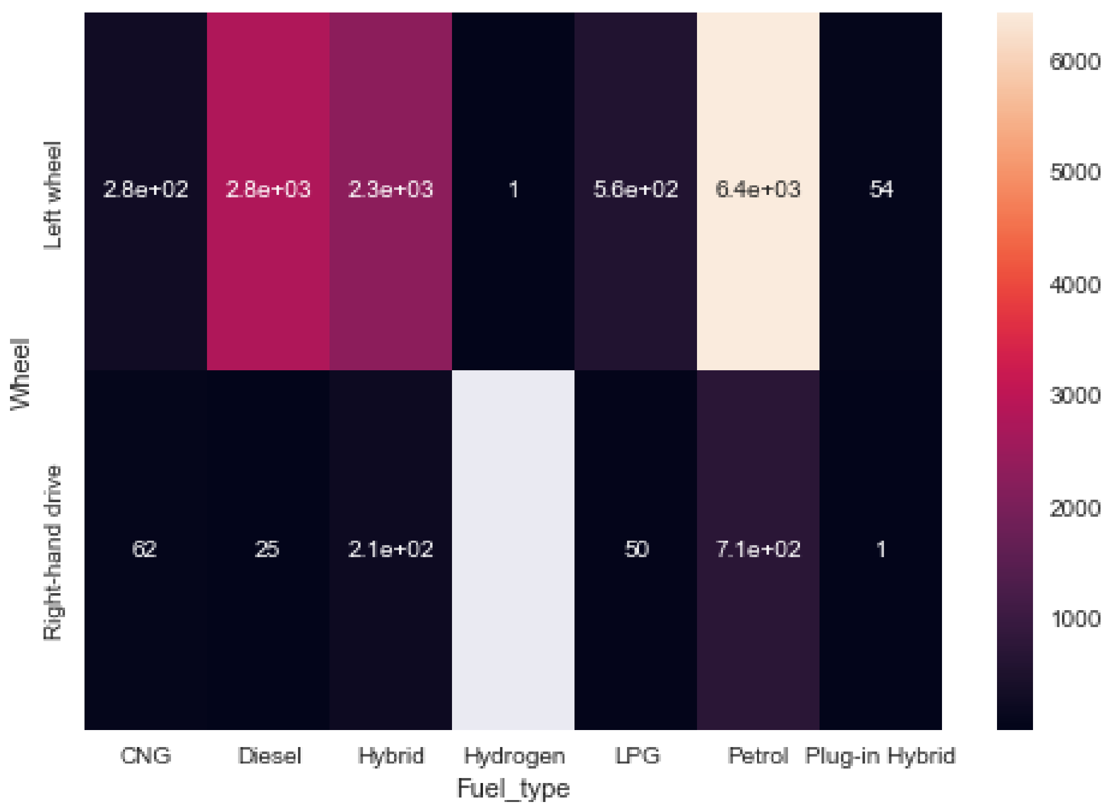
[42]:
```
# count the Fuel type and Wheel data apparence
cdf_counts = cdf.groupby(['Fuel_type', 'Wheel']).size()
cdf_counts = cdf_counts.reset_index(name = 'count')
# pivate the data
```

```
cdf_counts = cdf_counts.pivot(index = 'Wheel', columns = 'Fuel_type', values =
 ↪'count')
cdf_counts
```

[42]:
```
Fuel_type            CNG   Diesel   Hybrid   Hydrogen    LPG   Petrol  \
Wheel
Left wheel         280.0   2785.0   2276.0        1.0  563.0   6434.0
Right-hand drive    62.0     25.0    212.0        NaN   50.0    710.0

Fuel_type          Plug-in Hybrid
Wheel
Left wheel                   54.0
Right-hand drive              1.0
```

[43]:
```
#plot heat map
sns.heatmap(cdf_counts, annot = True)
```

[43]: <AxesSubplot:xlabel='Fuel_type', ylabel='Wheel'>



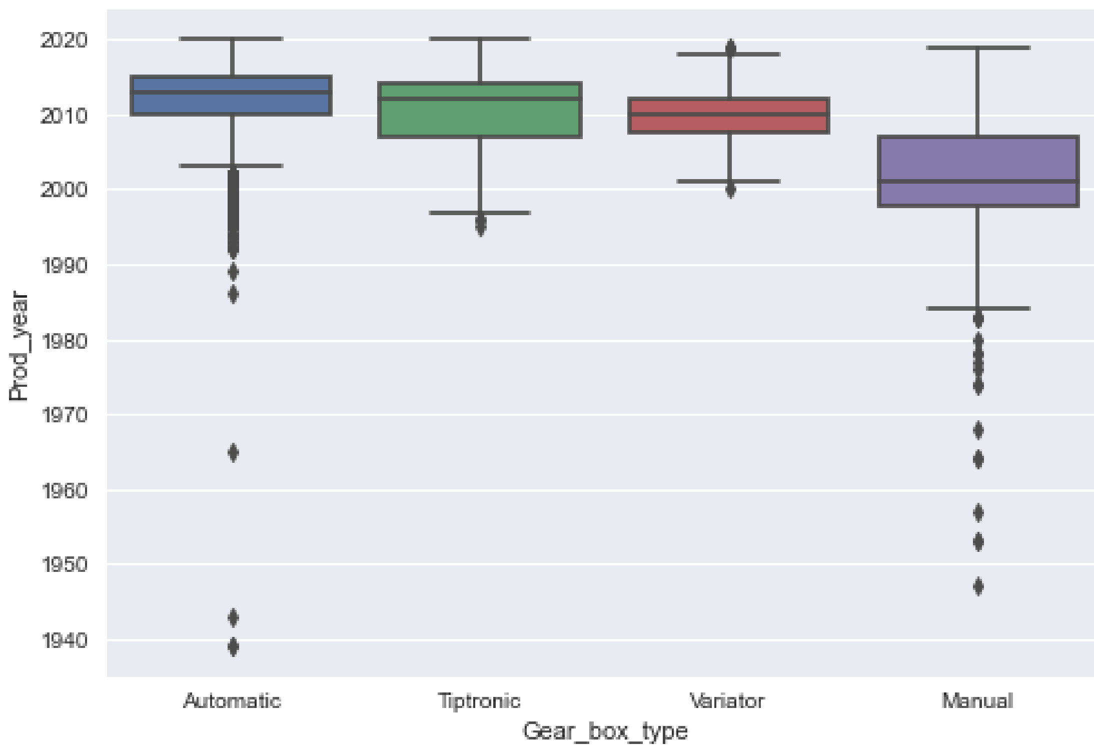
We can see heat map has showing the clearly independency for Fuel Type vs Wheel

4.3 Analyze the Categorical Variable Column with Digit Variable Column Now we have to analyze the categorical variable column with regular digit variable column. We are using box plot to analyze these different type data column indenpendency.

4.3.1 Production Year vs Gear Box Type

[44]:
```
sns.boxplot(y='Prod_year',x="Gear_box_type", data=df)
```

[44]: <AxesSubplot:xlabel='Gear_box_type', ylabel='Prod_year'>

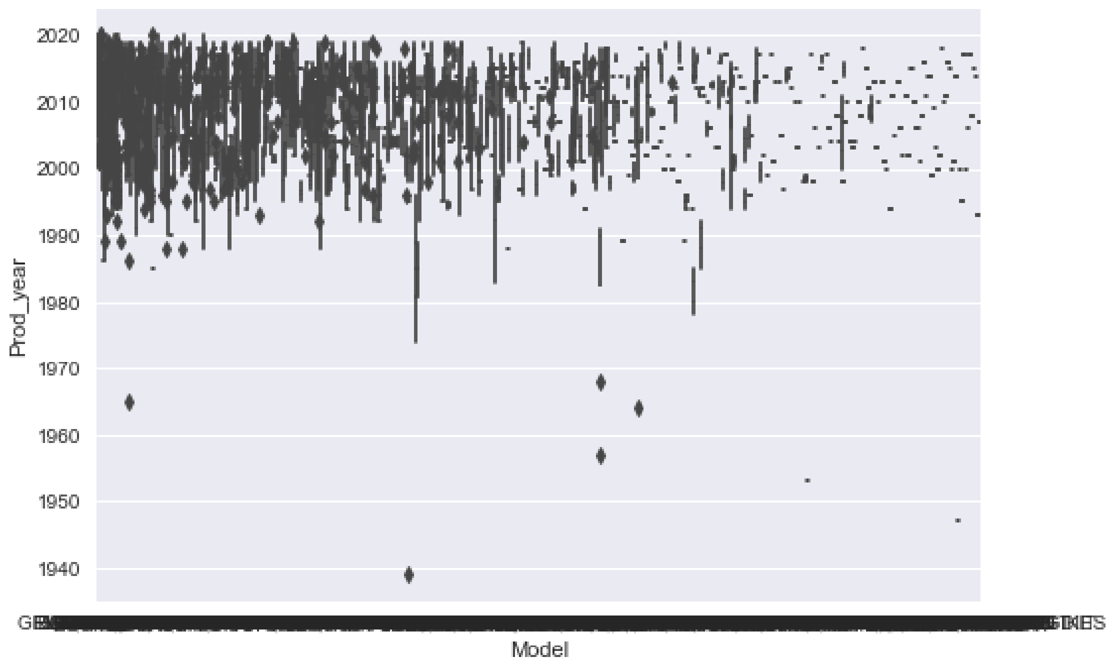


From the box plot we can see that production year and gear box type are indenpendent, because one production year can have more than one gear box type. Gear box type are not year specific in the morjorty of the data.

4.3.2 Production Year vs Model Type

[45]:
```
sns.boxplot(y='Prod_year',x="Model", data=df)
```

[45]: <AxesSubplot:xlabel='Model', ylabel='Prod_year'>



From the box plot we can see that production year and model are indenpendent, because one production year can have more than one model made. Car models are not year specific in the morjorty case of the data.

4.4 Special Case of Engine Volume with Turbo Column When we first time processing the data, we have seperate the Engine Volumn with/with-out Turbo. And we have created Turbo as new column for easy processing. Then we know Turbo is dependent to Engine Volumn. We need to find way to combine the Turbo column back to Engine Volume column. We will use group mean to calculate the coefficient of car has Turbo and not has Turbo.

$X_{EngineVolue}(\hat{\theta}X_{Turbo})$

[46]:
```
#replace null data with 0
df['Turbo']=df['Turbo'].fillna(0)
#set a new data frame with Price Engine_volume and Turbo
tdf= df[['Price','Engine_volume','Turbo']]
tdf
```

[46]:

	Price	Engine_volume	Turbo
0	13328	3.5	0
1	16621	3.0	0
2	8467	1.3	0
3	3607	2.5	0
4	11726	1.3	0
…	…	…	…
13448	21103	3.0	0

```
13449  13172            1.6      0
13450  19757            1.8      0
13451   1019            3.0      0
13452    125            3.3      0

[13453 rows x 3 columns]
```

[47]:
```
#drop non turbo
tdf = tdf.drop(tdf[tdf.Turbo == 0].index)
tdf
```

[47]:
```
       Price  Engine_volume  Turbo
23      7840            2.0  Turbo
25     20385            2.2  Turbo
30     15681            2.0  Turbo
34     24462            3.0  Turbo
42     20165            1.4  Turbo
…      …             …     …
13403  21639            2.4  Turbo
13415  11917            1.4  Turbo
13431  16621            2.0  Turbo
13432  17249            2.0  Turbo
13441  16308            2.2  Turbo

[1341 rows x 3 columns]
```

[48]:
```
#create data frame with non turbo car
ntdf = df[['Price','Engine_volume','Turbo']]
ntdf = ntdf.drop(ntdf[ntdf.Turbo == "Turbo"].index)
ntdf
```

[48]:
```
       Price  Engine_volume Turbo
0      13328            3.5      0
1      16621            3.0      0
2       8467            1.3      0
3       3607            2.5      0
4      11726            1.3      0
…      …             …    …
13448  21103            3.0      0
13449  13172            1.6      0
13450  19757            1.8      0
13451   1019            3.0      0
13452    125            3.3      0

[12112 rows x 3 columns]
```

[49]:
```
#calcuate Theta hat
withturbopricemean = tdf['Price'].mean()
withoutturbopricemean = ntdf['Price'].mean()
Thetahat = withturbopricemean/withoutturbopricemean
print("\u0302\u0398 is", Thetahat)
```

```
ˆΘ is 1.7554345902046502
```

4.5 Make, Model, and Turbo Handling Statement - The problem with make and model was that they weren't very usable in their current state. We had many choices for regression, but for most of our predictions with categorical data we wanted to use the One Hot Code approach. This would be impractical for how many different make and models there were. Also, we decided to simplify turbo by calculating a coefficient for it and then multiplying it into the engine volume.
1) The Make is almost superceeded by the Model in terms of defining a category. For this we merged the two columns
2) We decided that average mean would be a better representation categorically for the Model column.
3) Turbo was easier to deal with as a coefficient multiplied into engine volume

[50]:
```
# Get Path
path = 'C:/Users/chris/Documents/School/Masters/zz_GIT/
↪2022-msaai-500-final-project/data/sanitized/FilterData.csv'

# Reading the dataset
data = pd.read_csv(path)

# Show sample of the dataset
display(data.head(10))
```

```
   Unnamed: 0        ID  Price  Levy Manufacturer     Model  Prod_year  \
0           0  45654403  13328  1399        LEXUS    RX 450       2010
1           1  44731507  16621  1018    CHEVROLET   EQUINOX       2011
2           2  45774419   8467     0        HONDA       FIT       2006
3           3  45769185   3607   862         FORD    ESCAPE       2011
4           4  45809263  11726   446        HONDA       FIT       2014
5           5  45802912  39493   891      HYUNDAI  SANTA FE       2016
6           6  45656768   1803   761       TOYOTA     PRIUS       2010
7           7  45816158    549   751      HYUNDAI    SONATA       2013
8           8  45641395   1098   394       TOYOTA     CAMRY       2014
9           9  45756839  26657     0        LEXUS    RX 350       2007

    Category Leather_interior Fuel_type  Engine_volume Turbo  Mileage  \
0       Jeep              Yes    Hybrid            3.5   NaN   186005
1       Jeep               No    Petrol            3.0   NaN   192000
2  Hatchback               No    Petrol            1.3   NaN   200000
3       Jeep              Yes    Hybrid            2.5   NaN   168966
4  Hatchback              Yes    Petrol            1.3   NaN    91901
5       Jeep              Yes    Diesel            2.0   NaN   160931
```

```
6  Hatchback              Yes     Hybrid           1.8    NaN    258909
7      Sedan              Yes     Petrol           2.4    NaN    216118
8      Sedan              Yes     Hybrid           2.5    NaN    398069
9       Jeep              Yes     Petrol           3.5    NaN    128500

   Cylinders Gear_box_type Drive_wheels Doors             Wheel   Color  \
0          6     Automatic   Front-Rear   4-5        Left wheel  Silver
1          6     Tiptronic   Front-Rear   4-5        Left wheel   Black
2          4      Variator        Front   4-5  Right-hand drive   Black
3          4     Automatic   Front-Rear   4-5        Left wheel   White
4          4     Automatic        Front   4-5        Left wheel  Silver
5          4     Automatic        Front   4-5        Left wheel   White
6          4     Automatic        Front   4-5        Left wheel   White
7          4     Automatic        Front   4-5        Left wheel    Grey
8          4     Automatic        Front   4-5        Left wheel   Black
9          6     Automatic   Front-Rear   4-5        Left wheel  Silver

   Airbags
0       12
1        8
2        2
3        0
4        4
5        4
6       12
7       12
8       12
9       12
```

First, we need to combine the two columns. This can be a simple set of column manipulations

[51]:
```
# Make new column
data_combo = data['Manufacturer'] + '-' + data['Model']

# Make a copy to preserve original for re-run purposes
data2 = data.copy()

# Insert out new column
data2.insert(loc = 4,
          column = 'MakeModel',
          value = data_combo)

# Drop old columns
data2.drop(['Manufacturer', 'Model'], axis=1, inplace=True)

# Show sample of the dataset
display(data2.head(10))
```

```
   Unnamed: 0        ID  Price  Levy          MakeModel  Prod_year   Category  \
```

```
0          0  45654403  13328  1399      LEXUS-RX 450      2010       Jeep
1          1  44731507  16621  1018  CHEVROLET-EQUINOX      2011       Jeep
2          2  45774419   8467     0           HONDA-FIT      2006  Hatchback
3          3  45769185   3607   862         FORD-ESCAPE      2011       Jeep
4          4  45809263  11726   446           HONDA-FIT      2014  Hatchback
5          5  45802912  39493   891    HYUNDAI-SANTA FE      2016       Jeep
6          6  45656768   1803   761        TOYOTA-PRIUS      2010  Hatchback
7          7  45816158    549   751      HYUNDAI-SONATA      2013      Sedan
8          8  45641395   1098   394        TOYOTA-CAMRY      2014      Sedan
9          9  45756839  26657     0        LEXUS-RX 350      2007       Jeep

  Leather_interior Fuel_type  Engine_volume Turbo  Mileage  Cylinders  \
0              Yes    Hybrid            3.5   NaN   186005          6
1               No    Petrol            3.0   NaN   192000          6
2               No    Petrol            1.3   NaN   200000          4
3              Yes    Hybrid            2.5   NaN   168966          4
4              Yes    Petrol            1.3   NaN    91901          4
5              Yes    Diesel            2.0   NaN   160931          4
6              Yes    Hybrid            1.8   NaN   258909          4
7              Yes    Petrol            2.4   NaN   216118          4
8              Yes    Hybrid            2.5   NaN   398069          4
9              Yes    Petrol            3.5   NaN   128500          6

  Gear_box_type Drive_wheels Doors             Wheel   Color  Airbags
0     Automatic   Front-Rear   4-5        Left wheel  Silver       12
1     Tiptronic   Front-Rear   4-5        Left wheel   Black        8
2      Variator        Front   4-5  Right-hand drive   Black        2
3     Automatic   Front-Rear   4-5        Left wheel   White        0
4     Automatic        Front   4-5        Left wheel  Silver        4
5     Automatic        Front   4-5        Left wheel   White        4
6     Automatic        Front   4-5        Left wheel   White       12
7     Automatic        Front   4-5        Left wheel    Grey       12
8     Automatic        Front   4-5        Left wheel   Black       12
9     Automatic   Front-Rear   4-5        Left wheel  Silver       12
```

Next, we need to mean all the various cars by MakeModel set values

[52]:
```python
# get all unique make-model combos
categoryarray = data2.MakeModel.unique()

# loop and query required mean information
pricemeanarray = []
pricesdarray = []
for x in categoryarray:
    comm = "MakeModel == '"+x+"'"
    df = data2.query(comm)
    price = df['Price']
    mean = price.mean()
```

```
    sd = price.std()
    pricemeanarray.append(round(mean,2))
    pricesdarray.append(round(sd,2))

# convert to numpy array
npArray = np.array(pricemeanarray)
```

Below is shown the values that will be used to scale all numbers between 0 and 1

[53]:
```
# show values
print('The minimum average of any MakeModel is:', npArray.min())
print('The maximum average of any MakeModel is:', npArray.max())
print('The number of MakeModel uniques is:', len(categoryarray))
```

```
The minimum average of any MakeModel is: 34.0
The maximum average of any MakeModel is: 297930.0
The number of MakeModel uniques is: 1490
```

Finally, we create a lookup table and do replacements into a final dataframe

[54]:
```
# formula to convert all average values from 0 to 1
replace_weight = (npArray-npArray.min())/npArray.max()

# create lookup table
replace_table = {'Value':replace_weight,'MakeModel':categoryarray}
replace_table = pd.DataFrame(replace_table)

# Show sample of the dataset
display(replace_table.head(10))
```

	Value	MakeModel
0	0.035710	LEXUS-RX 450
1	0.029261	CHEVROLET-EQUINOX
2	0.037106	HONDA-FIT
3	0.027494	FORD-ESCAPE
4	0.133393	HYUNDAI-SANTA FE
5	0.038329	TOYOTA-PRIUS
6	0.048425	HYUNDAI-SONATA
7	0.042147	TOYOTA-CAMRY
8	0.055940	LEXUS-RX 350
9	0.033829	MERCEDES-BENZ-E 350

[55]:
```
# replace values from lookuptable
result = data2.replace(dict(zip(replace_table.MakeModel, replace_table.Value)))

# Show sample of the dataset
display(result.head(10))
```

	Unnamed: 0	ID	Price	Levy	MakeModel	Prod_year	Category \
0	0	45654403	13328	1399	0.035710	2010	Jeep

```
1           1  44731507  16621  1018   0.029261       2011        Jeep
2           2  45774419   8467     0   0.037106       2006   Hatchback
3           3  45769185   3607   862   0.027494       2011        Jeep
4           4  45809263  11726   446   0.037106       2014   Hatchback
5           5  45802912  39493   891   0.133393       2016        Jeep
6           6  45656768   1803   761   0.038329       2010   Hatchback
7           7  45816158    549   751   0.048425       2013       Sedan
8           8  45641395   1098   394   0.042147       2014       Sedan
9           9  45756839  26657     0   0.055940       2007        Jeep

  Leather_interior Fuel_type  Engine_volume Turbo  Mileage  Cylinders  \
0              Yes    Hybrid            3.5   NaN   186005          6
1               No    Petrol            3.0   NaN   192000          6
2               No    Petrol            1.3   NaN   200000          4
3              Yes    Hybrid            2.5   NaN   168966          4
4              Yes    Petrol            1.3   NaN    91901          4
5              Yes    Diesel            2.0   NaN   160931          4
6              Yes    Hybrid            1.8   NaN   258909          4
7              Yes    Petrol            2.4   NaN   216118          4
8              Yes    Hybrid            2.5   NaN   398069          4
9              Yes    Petrol            3.5   NaN   128500          6

  Gear_box_type Drive_wheels Doors             Wheel   Color  Airbags
0     Automatic   Front-Rear   4-5        Left wheel  Silver       12
1     Tiptronic   Front-Rear   4-5        Left wheel   Black        8
2      Variator        Front   4-5  Right-hand drive   Black        2
3     Automatic   Front-Rear   4-5        Left wheel   White        0
4     Automatic        Front   4-5        Left wheel  Silver        4
5     Automatic        Front   4-5        Left wheel   White        4
6     Automatic        Front   4-5        Left wheel   White       12
7     Automatic        Front   4-5        Left wheel    Grey       12
8     Automatic        Front   4-5        Left wheel   Black       12
9     Automatic   Front-Rear   4-5        Left wheel  Silver       12
```

[56]:
```python
# sort values by ID which will allow them to be sudo random
result = result.sort_values(by=['ID'])
```

[57]:
```python
# Split dataset

# data length
n = len(result)
# amount for testing/validation each
t = int(n*.15)
# amount for training
training = n-t*2

#create data sets
```

```
result.sort_values(by=['ID'])
training = result.head(training)
test = result.tail(t*2).head(t)
validation = result.tail(t)

# show values
print('The amount of training records is:', len(training))
print('The amount of test records is:', len(test))
print('The amount of validation records is:', len(validation))
```

```
The amount of training records is: 13453
The amount of test records is: 2882
The amount of validation records is: 2882
```

[58]:
```
# Save progress to files as artifacts
training.to_csv('C:/Users/chris/Documents/School/Masters/zz_GIT/
↪2022-msaai-500-final-project/data/sanitized/TrainingData2.
↪csv',index=False,line_terminator='\n')
test.to_csv('C:/Users/chris/Documents/School/Masters/zz_GIT/
↪2022-msaai-500-final-project/data/sanitized/TestData2.
↪csv',index=False,line_terminator='\n')
validation.to_csv('C:/Users/chris/Documents/School/Masters/zz_GIT/
↪2022-msaai-500-final-project/data/sanitized/ValidationData2.
↪csv',index=False,line_terminator='\n')
replace_table.to_csv('C:/Users/chris/Documents/School/Masters/zz_GIT/
↪2022-msaai-500-final-project/data/sanitized/MakeModelReplaceTable.
↪csv',index=False,line_terminator='\n')
```

The coeffience for turbo was calculated to be 1.7554345902046502. As we had already separated turbo from engine volume, it was easy to make a direct substitution.

[59]:
```
# replace values from Turbo to the coefficient
result = result.replace( 'Turbo', 1.7554345902046502)
result['Turbo'] = result['Turbo'].fillna(1)

# Show sample of the dataset
display(result.head(20))
```

	Unnamed: 0	ID	Price	Levy	MakeModel	Prod_year	Category	\
11207	11219	20746880	157	0	0.046772	1939	Limousine	
13212	13225	23242980	200	0	0.141307	2017	Jeep	
13558	13572	24367759	85702	0	0.299423	2013	Microbus	
3640	3643	24701923	130	0	0.058867	2006	Jeep	
5504	5509	24940334	25089	0	0.057150	1999	Limousine	
19041	19061	25368573	12544	0	0.029406	2002	Sedan	
11412	11424	26248496	150	0	0.081655	2012	Microbus	
15835	15852	26327387	87021	0	0.299423	2013	Microbus	
14948	14964	26465408	43000	0	0.041607	2011	Jeep	
10254	10265	26556126	157	0	0.000485	1939	Cabriolet	

14140	14154	26556811	60	0	0.038329	2012	Hatchback
2490	2493	28135943	3136	0	0.019542	1998	Sedan
4466	4469	28548396	5000	0	0.027766	2004	Universal
9490	9500	29267633	120	0	0.039800	2003	Sedan
14915	14931	30551412	370	0	0.174190	2018	Jeep
8046	8054	30601481	150	0	0.000389	2010	Sedan
9874	9885	31756996	18660	382	0.052501	2014	Sedan
12320	12333	31881664	3700	0	0.092797	2001	Sedan
11146	11158	32089280	50	0	0.056752	2012	Sedan
252	253	32116317	50	0	0.056752	2013	Sedan

	Leather_interior	Fuel_type	Engine_volume	Turbo	Mileage	Cylinders	\
11207	Yes	Petrol	2.4	1.000000	126000	4	
13212	Yes	Petrol	2.7	1.000000	95000	4	
13558	Yes	Diesel	2.2	1.755435	225000	6	
3640	Yes	Petrol	4.4	1.000000	90000	8	
5504	Yes	Petrol	5.4	1.000000	99000	8	
19041	Yes	CNG	2.5	1.000000	220000	6	
11412	Yes	Diesel	3.2	1.755435	200000	6	
15835	Yes	Diesel	2.2	1.755435	240000	8	
14948	Yes	Diesel	3.0	1.000000	190000	6	
10254	Yes	Petrol	5.0	1.000000	129000	8	
14140	Yes	Hybrid	1.8	1.000000	100000	4	
2490	Yes	Petrol	2.8	1.000000	299689	6	
4466	No	Diesel	2.2	1.755435	312000	4	
9490	Yes	Petrol	3.2	1.000000	130000	6	
14915	Yes	Petrol	4.0	1.000000	15000	8	
8046	Yes	Petrol	5.5	1.000000	15000	8	
9874	Yes	Hybrid	2.4	1.000000	114000	4	
12320	Yes	Diesel	2.2	1.000000	0	4	
11146	No	Hybrid	1.5	1.000000	150000	2	
252	No	Hybrid	1.5	1.000000	130000	4	

	Gear_box_type	Drive_wheels	Doors	Wheel	Color	Airbags
11207	Automatic	Rear	4-5	Left wheel	White	0
13212	Automatic	Front-Rear	5	Left wheel	Black	10
13558	Manual	Rear	2-3	Left wheel	White	4
3640	Tiptronic	Front-Rear	4-5	Left wheel	Black	8
5504	Automatic	Front-Rear	4-5	Left wheel	White	4
19041	Tiptronic	Rear	4-5	Left wheel	Silver	8
11412	Manual	Rear	4-5	Left wheel	Silver	2
15835	Manual	Rear	4-5	Left wheel	White	2
14948	Tiptronic	Front-Rear	4-5	Left wheel	Grey	12
10254	Automatic	Rear	4-5	Left wheel	Silver	0
14140	Automatic	Front	4-5	Left wheel	Silver	12
2490	Tiptronic	Front	4-5	Left wheel	Silver	6
4466	Automatic	Front	4-5	Left wheel	Black	4
9490	Tiptronic	Rear	4-5	Left wheel	Black	8

```
14915     Automatic   Front-Rear   4-5        Left wheel     Black       12
8046      Tiptronic   Front-Rear   4-5        Left wheel     Black       12
9874      Automatic        Front   4-5        Left wheel      Blue       10
12320     Automatic         Rear   4-5  Right-hand drive      Blue        4
11146     Automatic         Rear   4-5  Right-hand drive      Blue        0
252       Automatic         Rear   4-5  Right-hand drive  Sky blue        0
```

[60]:

```python
# Combine the columns into 1 unified column
combo = result['Turbo'].astype(float) * result['Engine_volume'].astype(float)
display(combo.head(20))
```

```
11207    2.400000
13212    2.700000
13558    3.861956
3640     4.400000
5504     5.400000
19041    2.500000
11412    5.617391
15835    3.861956
14948    3.000000
10254    5.000000
14140    1.800000
2490     2.800000
4466     3.861956
9490     3.200000
14915    4.000000
8046     5.500000
9874     2.400000
12320    2.200000
11146    1.500000
252      1.500000
dtype: float64
```

[61]:

```python
# Drop old columns
result.drop(['Engine_volume', 'Turbo'], axis=1, inplace=True)

# Insert out new column
result.insert(loc = 10,
          column = 'Engine_volume',
          value = combo)

# display results
display(result.head(20))
```

```
       Unnamed: 0        ID  Price  Levy  MakeModel  Prod_year   Category  \
11207       11219  20746880    157     0   0.046772       1939  Limousine
13212       13225  23242980    200     0   0.141307       2017       Jeep
13558       13572  24367759  85702     0   0.299423       2013   Microbus
3640         3643  24701923    130     0   0.058867       2006       Jeep
```

5504	5509	24940334	25089	0	0.057150	1999	Limousine
19041	19061	25368573	12544	0	0.029406	2002	Sedan
11412	11424	26248496	150	0	0.081655	2012	Microbus
15835	15852	26327387	87021	0	0.299423	2013	Microbus
14948	14964	26465408	43000	0	0.041607	2011	Jeep
10254	10265	26556126	157	0	0.000485	1939	Cabriolet
14140	14154	26556811	60	0	0.038329	2012	Hatchback
2490	2493	28135943	3136	0	0.019542	1998	Sedan
4466	4469	28548396	5000	0	0.027766	2004	Universal
9490	9500	29267633	120	0	0.039800	2003	Sedan
14915	14931	30551412	370	0	0.174190	2018	Jeep
8046	8054	30601481	150	0	0.000389	2010	Sedan
9874	9885	31756996	18660	382	0.052501	2014	Sedan
12320	12333	31881664	3700	0	0.092797	2001	Sedan
11146	11158	32089280	50	0	0.056752	2012	Sedan
252	253	32116317	50	0	0.056752	2013	Sedan

	Leather_interior	Fuel_type	Mileage	Engine_volume	Cylinders \
11207	Yes	Petrol	126000	2.400000	4
13212	Yes	Petrol	95000	2.700000	4
13558	Yes	Diesel	225000	3.861956	6
3640	Yes	Petrol	90000	4.400000	8
5504	Yes	Petrol	99000	5.400000	8
19041	Yes	CNG	220000	2.500000	6
11412	Yes	Diesel	200000	5.617391	6
15835	Yes	Diesel	240000	3.861956	8
14948	Yes	Diesel	190000	3.000000	6
10254	Yes	Petrol	129000	5.000000	8
14140	Yes	Hybrid	100000	1.800000	4
2490	Yes	Petrol	299689	2.800000	6
4466	No	Diesel	312000	3.861956	4
9490	Yes	Petrol	130000	3.200000	6
14915	Yes	Petrol	15000	4.000000	8
8046	Yes	Petrol	15000	5.500000	8
9874	Yes	Hybrid	114000	2.400000	4
12320	Yes	Diesel	0	2.200000	4
11146	No	Hybrid	150000	1.500000	2
252	No	Hybrid	130000	1.500000	4

	Gear_box_type	Drive_wheels	Doors	Wheel	Color	Airbags
11207	Automatic	Rear	4-5	Left wheel	White	0
13212	Automatic	Front-Rear	5	Left wheel	Black	10
13558	Manual	Rear	2-3	Left wheel	White	4
3640	Tiptronic	Front-Rear	4-5	Left wheel	Black	8
5504	Automatic	Front-Rear	4-5	Left wheel	White	4
19041	Tiptronic	Rear	4-5	Left wheel	Silver	8
11412	Manual	Rear	4-5	Left wheel	Silver	2
15835	Manual	Rear	4-5	Left wheel	White	2

```
14948     Tiptronic   Front-Rear   4-5        Left wheel      Grey        12
10254     Automatic         Rear   4-5        Left wheel    Silver         0
14140     Automatic        Front   4-5        Left wheel    Silver        12
2490      Tiptronic        Front   4-5        Left wheel    Silver         6
4466      Automatic        Front   4-5        Left wheel     Black         4
9490      Tiptronic         Rear   4-5        Left wheel     Black         8
14915     Automatic   Front-Rear   4-5        Left wheel     Black        12
8046      Tiptronic   Front-Rear   4-5        Left wheel     Black        12
9874      Automatic        Front   4-5        Left wheel      Blue        10
12320     Automatic         Rear   4-5  Right-hand drive      Blue         4
11146     Automatic         Rear   4-5  Right-hand drive      Blue         0
252       Automatic         Rear   4-5  Right-hand drive  Sky blue         0
```

[62]:

```python
# Split dataset

# data length
n = len(result)
# amount for testing/validation each
t = int(n*.15)
# amount for training
training = n-t*2

#create data sets
result.sort_values(by=['ID'])
training = result.head(training)
test = result.tail(t*2).head(t)
validation = result.tail(t)

# show values
print('The amount of training records is:', len(training))
print('The amount of test records is:', len(test))
print('The amount of validation records is:', len(validation))
```

```
The amount of training records is: 13453
The amount of test records is: 2882
The amount of validation records is: 2882
```

[63]:

```python
# Save the portioned out data sets
training.to_csv('C:/Users/chris/Documents/School/Masters/zz_GIT/
 ↪2022-msaai-500-final-project/data/sanitized/TrainingData3.
 ↪csv',index=False,line_terminator='\n')
test.to_csv('C:/Users/chris/Documents/School/Masters/zz_GIT/
 ↪2022-msaai-500-final-project/data/sanitized/TestData3.
 ↪csv',index=False,line_terminator='\n')
validation.to_csv('C:/Users/chris/Documents/School/Masters/zz_GIT/
 ↪2022-msaai-500-final-project/data/sanitized/ValidationData3.
 ↪csv',index=False,line_terminator='\n')
```

[64]:
```
# Save total dataset
result.to_csv('C:/Users/chris/Documents/School/Masters/zz_GIT/
↪2022-msaai-500-final-project/data/sanitized/FilterData3.
↪csv',index=False,line_terminator='\n')
```

In conclusion, we cleaned up the Manufacturer, Model, and Turbo columns so that they could more easily be used with a machine learning calculator.

0.0.5 5. Normality and Homoscedasticity

5.1 Visualizations

[65]:
```
df = pd.read_csv('TrainingDatacopy.csv') # Import Training dataset
```

[66]:
```
df # display dataset
```

[66]:
```
       Unnamed: 0        ID  Price  Levy Manufacturer       Model  Prod_year  \
0               0  45654403  13328  1399        LEXUS      RX 450       2010
1               1  44731507  16621  1018    CHEVROLET     EQUINOX       2011
2               2  45774419   8467     0        HONDA         FIT       2006
3               3  45769185   3607   862         FORD      ESCAPE       2011
4               4  45809263  11726   446        HONDA         FIT       2014
…             …         …      …     …            …           …
13448       13462  45802417  21103  1104      HYUNDAI    GRANDEUR       2015
13449       13463  44631202  13172   530      HYUNDAI     ELANTRA       2013
13450       13464  45669073  19757   353       TOYOTA       PRIUS       2015
13451       13465  45647811   1019   917          BMW          X5       2013
13452       13466  45768173    125  1750       TOYOTA  HIGHLANDER       2008

        Category Leather_interior Fuel_type  Engine_volume Turbo  Mileage  \
0           Jeep              Yes    Hybrid            3.5   NaN   186005
1           Jeep               No    Petrol            3.0   NaN   192000
2      Hatchback               No    Petrol            1.3   NaN   200000
3           Jeep              Yes    Hybrid            2.5   NaN   168966
4      Hatchback              Yes    Petrol            1.3   NaN    91901
…            …                …        …              …     …        …
13448      Sedan              Yes       LPG            3.0   NaN   273249
13449      Sedan              Yes    Petrol            1.6   NaN    75000
13450  Hatchback               No    Hybrid            1.8   NaN   105000
13451       Jeep              Yes    Diesel            3.0   NaN   137802
13452      Sedan              Yes    Hybrid            3.3   NaN   287274

       Cylinders Gear_box_type Drive_wheels Doors             Wheel   Color  \
0              6     Automatic   Front-Rear   4-5        Left wheel  Silver
1              6     Tiptronic   Front-Rear   4-5        Left wheel   Black
2              4      Variator        Front   4-5  Right-hand drive   Black
3              4     Automatic   Front-Rear   4-5        Left wheel   White
4              4     Automatic        Front   4-5        Left wheel  Silver
```

```
…               …          …          …   …           …     …
13448           4      Automatic        Front    4-5        Left wheel   Black
13449           4      Tiptronic        Front    4-5        Left wheel   White
13450           4      Automatic        Front    4-5        Left wheel  Silver
13451           6      Automatic   Front-Rear    4-5        Left wheel   Black
13452           6      Automatic   Front-Rear    4-5        Left wheel   White

       Airbags
0           12
1            8
2            2
3            0
4            4
…          …
13448        4
13449        8
13450        8
13451        0
13452       12

[13453 rows x 20 columns]
```

Calculating the mean and sd of each colomb and ploting it

[67]:

```python
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Manufacturer = df.groupby("Manufacturer").agg([np.mean, np.std]) # get the mean␣
↪and sd of each Manufacturer
Manufacturer.head()
```

[67]:

```
                Unnamed: 0                          ID                \
                      mean          std           mean           std
Manufacturer
ACURA          4564.000000  3268.083842   4.574356e+07  6.440942e+04
ALFA ROMEO     7122.666667  5994.084528   4.413522e+07  2.038803e+06
ASTON MARTIN  13325.000000          NaN   4.343235e+07           NaN
AUDI           6761.299401  3915.354419   4.550577e+07  1.446298e+06
BENTLEY        3502.500000  1724.633439   4.580029e+07  1.906996e+04

                      Price                           Levy               \
                       mean           std            mean          std
Manufacturer
ACURA           7148.818182  11325.108466    1120.181818   217.452440
ALFA ROMEO     11687.000000   7594.850821       0.000000     0.000000
ASTON MARTIN   54000.000000           NaN       0.000000          NaN
AUDI           14677.694611  18101.019038     592.347305   501.062160
BENTLEY       197574.500000  31045.523228    1409.500000  1993.334016
```

```
              Prod_year           Engine_volume                   Mileage  \
                   mean       std          mean       std            mean
Manufacturer
ACURA       2012.272727  2.148996      3.154545  0.603927   115578.909091
ALFA ROMEO  2006.333333  6.110101      1.800000  0.400000   159066.666667
ASTON MARTIN 2007.000000       NaN     4.300000       NaN    72000.000000
AUDI        2011.257485  4.986686      2.557485  0.622220   159040.874251
BENTLEY     2014.000000  2.828427      5.400000  1.979899    30844.500000

                           Cylinders            Airbags
                      std       mean       std       mean       std
Manufacturer
ACURA        83051.903917  5.272727  1.009050  11.818182  0.603023
ALFA ROMEO   77727.815699  4.000000  0.000000   8.666667  4.163332
ASTON MARTIN          NaN  8.000000       NaN   8.000000       NaN
AUDI        105756.328017  5.125749  1.423468   5.107784  5.049192
BENTLEY      34868.142487  8.000000  0.000000   6.000000  8.485281
```

[68]:

```python
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Model = df.groupby("Model").agg([np.mean, np.std]) # get the mean and sd of␣
 ↪each Model
Model.head()
```

[68]:

```
        Unnamed: 0                         ID                        Price  \
              mean          std          mean           std           mean
Model
100     6186.500000  2740.038777  4.580760e+07   1387.343505   12819.000000
100 NX  6437.000000          NaN  4.580841e+07           NaN    5331.000000
1000    6856.071429  3878.590931  4.577009e+07  11481.524776    3595.142857
1111     448.000000          NaN  4.581583e+07           NaN    4000.000000
114     1196.500000   388.201623  4.578842e+07  31828.997542    6821.000000

                            Levy              Prod_year            \
                std         mean         std        mean       std
Model
100     17352.400410  1103.500000  266.579257  2015.000000  1.414214
100 NX           NaN   765.000000         NaN  2015.000000       NaN
1000     9818.111693  1003.928571  115.020041  2016.142857  1.747840
1111             NaN     0.000000         NaN  1988.000000       NaN
114      4767.313919   780.000000  422.849855  2017.500000  0.707107

       Engine_volume                 Mileage               Cylinders      \
                mean       std          mean           std      mean  std
Model
100         3.000000  0.000000  107087.000000  51343.023382      6.0  0.0
100 NX      2.000000       NaN   70395.000000           NaN      4.0  NaN
```

```
1000        2.392857  0.212908   92423.857143  63686.659608       4.0  0.0
1111        1.300000       NaN    1000.000000           NaN       4.0  NaN
114         2.000000  0.000000   19141.000000  27069.461797       4.0  0.0

          Airbags
             mean       std
Model
100     12.000000  0.000000
100 NX  12.000000       NaN
1000    11.142857  3.207135
1111     6.000000       NaN
114     12.000000  0.000000
```

[69]:
```python
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Prod_year = df.groupby("Prod_year").agg([np.mean, np.std]) # get the mean and␣
 ↪sd of each Prod_year
Prod_year.head()
```

[69]:
```
          Unnamed: 0                    ID                    Price  \
                mean          std       mean           std       mean
Prod_year
1939         10742.0   674.579869  23651503.0  4.107757e+06     157.0
1943          6607.0          NaN  32171534.0           NaN  119172.0
1947         12849.0          NaN  38169002.0           NaN     150.0
1953          6068.5  4182.536611  45806976.0  1.200950e+04   26030.0
1957          9493.0          NaN  45598183.0           NaN    7527.0

                         Levy      Engine_volume            Mileage  \
                  std mean  std            mean       std      mean
Prod_year
1939          0.00000  0.0  0.0             3.7  1.838478  127500.0
1943              NaN  0.0  NaN             2.2       NaN   69000.0
1947              NaN  0.0  NaN             2.0       NaN  165000.0
1953      36367.91597  0.0  0.0             1.3  0.989949   75000.0
1957              NaN  0.0  NaN             2.0       NaN       0.0

                    Cylinders           Airbags
                 std     mean       std    mean       std
Prod_year
1939     2121.320344      6.0  2.828427     0.0  0.000000
1943             NaN      4.0       NaN     0.0       NaN
1947             NaN      6.0       NaN     0.0       NaN
1953   106066.017178      4.0  0.000000     0.5  0.707107
1957             NaN      4.0       NaN     0.0       NaN
```

[70]:
```
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Category = df.groupby("Category").agg([np.mean, np.std]) # get the mean and sd␣
↪of each Manufacturer
Category.head()
```

[70]:
```
             Unnamed: 0                            ID                \
                   mean          std             mean           std
Category
Cabriolet   6363.500000  4212.239196  4.451887e+07  4.215474e+06
Coupe       6604.984043  3930.272031  4.553782e+07  1.044755e+06
Goods wagon 6687.317365  3759.574294  4.545019e+07  1.211668e+06
Hatchback   6815.745746  3868.225046  4.547701e+07  9.571325e+05
Jeep        6781.034447  3854.852763  4.559810e+07  8.304853e+05

                    Price                       Levy                Prod_year  \
                     mean           std         mean          std        mean
Category
Cabriolet   22713.375000  24383.810415  668.291667  1300.574906  2005.625000
Coupe       20849.000000  31293.115885  574.369681   633.840475  2009.002660
Goods wagon 10101.574850   9177.407033  346.868263   548.012923  2003.395210
Hatchback   11509.121622   9099.941174  387.852352   406.488163  2010.280280
Jeep        23927.755219  23895.863948  806.410491   565.791174  2011.679802

                        Engine_volume                 Mileage               \
                   std           mean       std          mean           std
Category
Cabriolet    15.435173       3.175000  1.508887  1.051495e+05  6.338487e+04
Coupe         6.631038       2.580319  1.113259  1.648396e+05  6.535536e+05
Goods wagon   5.602235       1.909581  0.413075  1.860990e+05  1.857672e+05
Hatchback     4.924418       1.587888  0.328352  1.708472e+06  4.021383e+07
Jeep          5.135037       2.703392  0.968323  1.522663e+06  5.163639e+07

            Cylinders            Airbags
                 mean       std      mean       std
Category
Cabriolet    5.541667  1.910592  6.750000  4.285973
Coupe        4.984043  1.381694  7.047872  3.940605
Goods wagon  4.149701  1.117380  3.317365  2.548540
Hatchback    4.033033  0.538837  5.713714  3.980816
Jeep         5.038100  1.467159  6.348643  4.545722
```

[71]:
```
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Leather_interior = df.groupby("Leather_interior").agg([np.mean, np.std]) # get␣
↪the mean and sd of each Category
Leather_interior.head()
```

[71]:
```
                    Unnamed: 0                      ID                \
                          mean         std        mean           std
Leather_interior
No                 6700.767991  3889.57655  4.541670e+07  1.107811e+06
Yes                6745.146778  3887.03180  4.563454e+07  8.764147e+05

                          Price                     Levy             \
                           mean           std       mean        std
Leather_interior
No                 13212.111976   9694.363096  321.441998  512.450589
Yes                18750.393977  20639.007153  750.608079  527.872505

                    Prod_year           Engine_volume                Mileage  \
                         mean       std          mean       std          mean
Leather_interior
No                 2007.24812  7.065800      1.913050  0.562282  3.851408e+06
Yes                2012.29705  4.347299      2.457899  0.929412  3.687309e+05

                                Cylinders             Airbags
                          std        mean       std       mean       std
Leather_interior
No                 7.537544e+07  4.196563  0.838266  5.402793  3.757911
Yes                2.177216e+07  4.730599  1.288826  7.031761  4.409744
```

[72]:
```python
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Fuel_type = df.groupby("Fuel_type").agg([np.mean, np.std]) # get the mean and
 ↪sd of each Fuel_type
Fuel_type.head()
```

[72]:
```
              Unnamed: 0                           ID                \
                    mean          std            mean           std
Fuel_type
CNG          6808.713450  3767.917404  4.571255e+07  327432.668636
Diesel       6898.616014  3934.489019  4.562604e+07  864330.315066
Hybrid       6699.448151  3896.606238  4.552259e+07  965556.552029
Hydrogen    12900.000000          NaN  4.578407e+07            NaN
LPG          6546.277325  3860.275654  4.571750e+07  336637.263157

                   Price                      Levy                Prod_year  \
                    mean           std        mean         std         mean
Fuel_type
CNG          8521.754386   5614.989618   42.941520  236.271681  2000.058480
Diesel      24452.236655  19436.486185  747.227402  464.784743  2011.017794
Hybrid      10865.248794  11255.074944  564.513666  450.618058  2012.153135
Hydrogen    20385.000000           NaN    0.000000         NaN  2012.000000
LPG         13127.650897   6939.179290  600.355628  500.524575  2012.099511
```

```
              Engine_volume                Mileage                \
         std           mean       std            mean             std
Fuel_type
CNG       4.771258      2.508187  0.872111  2.687239e+07  1.995945e+08
Diesel    5.113699      2.371637  0.617085  1.553383e+05  3.079216e+05
Hybrid    2.691679      2.080587  0.639471  6.090445e+05  2.227282e+07
Hydrogen       NaN      2.400000       NaN  1.168000e+05           NaN
LPG       5.214505      2.200979  0.975098  2.755643e+05  1.875976e+05

          Cylinders           Airbags
               mean       std      mean       std
Fuel_type
CNG        4.941520  1.231110  4.789474  3.289030
Diesel     4.519573  0.998650  5.358719  3.597516
Hybrid     4.270900  0.774392  7.819936  4.730252
Hydrogen   6.000000       NaN  8.000000       NaN
LPG        4.313214  0.874347  4.572594  2.027595
```

[73]:
```python
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Engine_volume = df.groupby("Engine_volume").agg([np.mean, np.std]) # get the
 ↪mean and sd of each Engine_volume
Engine_volume.head()
```

[73]:
```
                Unnamed: 0                      ID                 \
                      mean          std          mean            std
Engine_volume
0.0            6459.000000  3837.944688  4.577727e+07  38652.601313
0.1            9763.333333  3754.805765  4.573134e+07  95395.679092
0.2            6430.857143  3885.309830  4.575547e+07  81747.298012
0.3            4845.000000  3463.409014  4.579100e+07   3482.500897
0.4            5368.937500  4788.372242  4.576323e+07   5440.384520

                      Price                      Levy               Prod_year  \
                       mean           std        mean        std         mean
Engine_volume
0.0            22295.750000  19555.027426   87.000000   0.000000  2014.125000
0.1             4096.666667   4008.297560   96.666667  88.928810  2012.000000
0.2             3203.428571   2599.993773  136.285714  60.362003  2013.428571
0.3             2750.000000    353.553391    0.000000   0.000000  1989.000000
0.4            10646.937500  40650.358430  270.937500  72.250000  2008.375000

                           Mileage                Cylinders            \
                    std           mean           std      mean      std
Engine_volume
0.0            2.748376   76509.875000  43652.808630  4.500000  0.925820
```

```
0.1            1.000000   34849.666667  56087.010977  1.666667  1.154701
0.2            5.061526   84425.428571  36354.532968  4.000000  0.000000
0.3            1.414214    9050.500000  12799.339846  4.000000  0.000000
0.4            1.500000  240989.250000  90321.870633  4.250000  1.000000

                 Airbags
                    mean       std
Engine_volume
0.0             6.500000  4.750940
0.1             0.666667  1.154701
0.2            10.571429  3.779645
0.3             0.000000  0.000000
0.4             0.750000  3.000000
```

[74]:
```
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Turbo = df.groupby("Turbo").agg([np.mean, np.std]) # get the mean and sd of␣
 ↪each Turbo
Turbo.head()
```

[74]:
```
        Unnamed: 0                         ID                      Price  \
              mean          std          mean          std          mean
Turbo
Turbo  6827.780015  3944.710453  4.535829e+07  1.277839e+06  28107.325876

                           Levy              Prod_year            \
                std        mean          std       mean       std
Turbo
Turbo  29011.483365  332.956003  472.143593  2009.534676  5.736219

      Engine_volume                  Mileage                Cylinders  \
               mean       std          mean           std       mean
Turbo
Turbo      2.268456  0.761487  149020.053691  232200.974274  4.724087

                  Airbags
            std       mean       std
Turbo
Turbo  1.370236  7.284116  4.175511
```

[75]:
```
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Mileage = df.groupby("Mileage").agg([np.mean, np.std]) # get the mean and sd of␣
 ↪each Mileage
Mileage.head()
```

[75]:

```
               Unnamed: 0                        ID                         Price  \
                     mean          std         mean            std          mean
Mileage
0              6851.28373  3869.197623  4.560113e+07  841826.411247    9650.640873
13            12503.00000          NaN  4.511549e+07            NaN   17562.000000
21             1626.00000          NaN  4.573209e+07            NaN   96915.000000
98            11920.00000          NaN  4.580355e+07            NaN   61781.000000
102            2353.00000          NaN  4.580441e+07            NaN  116036.000000

                            Levy                 Prod_year           \
                 std        mean         std          mean      std
Mileage
0       14579.513334  470.720238  674.232817   2006.674603  8.43766
13               NaN  780.000000         NaN   2019.000000      NaN
21               NaN 1076.000000         NaN   2020.000000      NaN
98               NaN 1076.000000         NaN   2020.000000      NaN
102              NaN 1325.000000         NaN   2019.000000      NaN

        Engine_volume           Cylinders               Airbags
                 mean      std       mean      std         mean       std
Mileage
0             2.33254 0.972082   4.797619 1.373823     5.559524  4.690037
13            1.40000      NaN   4.000000      NaN     8.000000       NaN
21            2.00000      NaN   4.000000      NaN     4.000000       NaN
98            2.00000      NaN   4.000000      NaN     4.000000       NaN
102           2.50000      NaN   4.000000      NaN    12.000000       NaN
```

[76]:

```
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Cylinders = df.groupby("Cylinders").agg([np.mean, np.std]) # get the mean and␣
 ↪sd of each Cylinders
Cylinders.head()
```

[76]:

```
            Unnamed: 0                        ID                         Price  \
                  mean          std         mean           std          mean
Cylinders
1          7177.500000  4132.779067  4.543316e+07  5.761954e+05  11457.346154
2          7327.967742  3902.378928  4.521648e+07  2.452623e+06   8724.580645
3          6412.479452  4110.485529  4.528243e+07  1.215934e+06   9040.630137
4          6734.788523  3907.853955  4.559849e+07  8.174420e+05  16724.152303
5          7206.447619  3946.242692  4.544938e+07  9.800645e+05  14398.000000

                              Levy                Prod_year             \
                   std        mean        std          mean        std
Cylinders
1         11213.477334  203.423077  377.177642  2003.653846  10.917664
2          5219.861804    5.580645   31.071717  2004.838710   6.588357
```

```
3             6071.861655  509.000000  475.287282  2010.410959   5.756242
4            15139.374535  574.216144  432.739629  2011.390588   5.593106
5             9430.845462  285.428571  415.124908  2007.314286   5.537137

          Engine_volume                 Mileage                 Airbags  \
                   mean       std          mean           std      mean
Cylinders
1              1.800000  0.858371  2.391976e+05  5.481671e+05  3.769231
2              1.725806  0.459687  2.155490e+05  2.393210e+05  4.096774
3              1.000000  0.242097  9.183648e+04  1.364739e+05  3.917808
4              1.948104  0.463192  1.617717e+06  4.961394e+07  6.076747
5              2.483810  0.366145  1.780509e+05  1.633029e+05  6.895238


                std
Cylinders
1          4.615692
2          2.981664
3          2.895175
4          4.014838
5          3.953878
```

[77]:

```python
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Gear_box_type = df.groupby("Gear_box_type").agg([np.mean, np.std]) # get the mean and sd of each Gear_box_type
Gear_box_type.head()
```

[77]:

```
                Unnamed: 0                          ID                \
                      mean          std           mean           std
Gear_box_type
Automatic      6740.620501  3900.778938   4.562335e+07  8.855539e+05
Manual         6657.875392  3881.327520   4.552428e+07  1.050872e+06
Tiptronic      6786.864991  3860.060231   4.541361e+07  1.156489e+06
Variator       6554.425047  3779.494786   4.546443e+07  8.166083e+05

                      Price                        Levy              \
                       mean           std          mean         std
Gear_box_type
Automatic      16103.018733  17166.355543   760.750263  504.793310
Manual         11255.672414  10160.255125   196.938871  493.212721
Tiptronic      26297.362663  25178.956703   399.959032  603.532860
Variator       14733.645161   9377.734773   304.859583  436.273333

                 Prod_year           Engine_volume                 Mileage  \
                      mean       std          mean       std          mean
Gear_box_type
```

```
Automatic      2012.296253  4.371197      2.314123  0.892989  4.491488e+05
Manual         2001.736677  7.502759      2.002978  0.571224  7.925834e+06
Tiptronic      2010.398976  4.917535      2.603305  0.914721  1.609843e+06
Variator       2009.939279  3.502866      1.708918  0.425669  1.725020e+05

                             Cylinders           Airbags
                       std        mean       std       mean        std
Gear_box_type
Automatic      1.728358e+07  4.540307  1.154886  6.485477  4.366770
Manual         1.164411e+08  4.283699  0.954371  3.763323  3.034769
Tiptronic      5.110288e+07  5.082402  1.484968  8.728585  3.616500
Variator       5.001567e+05  4.036053  0.534575  6.368121  3.838118
```

[78]:
```python
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Drive_wheels = df.groupby("Drive_wheels").agg([np.mean, np.std]) # get the mean and sd of each Drive_wheels
Drive_wheels.head()
```

[78]:
```
              Unnamed: 0                          ID                  \
                    mean          std            mean            std
Drive_wheels
Front        6743.358207  3903.206357  4.562159e+07  6.794071e+05
Front-Rear   6734.428014  3845.371774  4.551361e+07  1.101735e+06
Rear         6669.646760  3875.036782  4.541029e+07  1.690082e+06

                    Price                            Levy              Prod_year  \
                     mean           std            mean          std        mean
Drive_wheels
Front        16567.109946  14764.154532  601.084667  426.251979  2011.907385
Front-Rear   19392.729787  25711.478549  801.723050  720.233342  2010.197872
Rear         17061.970140  21410.154504  504.212834  781.520818  2006.355146

                       Engine_volume                  Mileage                \
                   std          mean       std           mean           std
Drive_wheels
Front        4.682728      1.959190  0.548168  9.446060e+05  3.317364e+07
Front-Rear   5.543136      3.136879  0.973050  2.410484e+06  6.305507e+07
Rear         8.363882      2.822618  0.986964  1.636135e+06  5.416453e+07

             Cylinders            Airbags
                  mean       std       mean       std
Drive_wheels
Front        4.103985  0.608329  6.208080  3.931416
Front-Rear   5.702128  1.507671  7.333688  5.104825
Rear         5.332910  1.445680  7.377382  4.480220
```

[79]:
```python
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Doors = df.groupby("Doors").agg([np.mean, np.std]) # get the mean and sd of␣
↪each Doors
Doors.head()
```

[79]:
```
        Unnamed: 0                         ID                    Price  \
              mean          std          mean           std         mean
Doors
2-3    6580.811355  3909.217160  4.545548e+07  1.219538e+06  16115.833333
4-5    6738.336661  3884.735238  4.558121e+07  9.188415e+05  17230.830031
5      6880.390805  4194.538671  4.529159e+07  2.459929e+06  22137.954023

                          Levy                Prod_year            \
                std        mean         std        mean       std
Doors
2-3    25349.464342  297.195971  572.716463  2004.981685  8.158276
4-5    18063.304761  648.288222  551.284653  2011.170359  5.429964
5      21757.378282  303.356322  644.903760  2008.114943  6.290312

      Engine_volume                 Mileage                Cylinders           \
               mean       std          mean           std      mean       std
Doors
2-3        2.376740  1.041043  1.962990e+05  7.683600e+05  4.816850  1.325602
4-5        2.302559  0.870247  1.388665e+06  4.485795e+07  4.569735  1.195875
5          2.535632  0.923464  2.317185e+05  7.475786e+05  5.034483  1.535989

        Airbags
           mean       std
Doors
2-3    5.657509  4.296992
4-5    6.617395  4.297051
5      6.988506  4.357550
```

[80]:
```python
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Wheel = df.groupby("Wheel").agg([np.mean, np.std]) # get the mean and sd of␣
↪each Wheel
Wheel.head()
```

[80]:
```
                    Unnamed: 0                         ID                \
                          mean          std          mean           std
Wheel
Left wheel         6741.531268  3888.284499  4.559948e+07  8.952645e+05
Right-hand drive   6631.505660  3880.523029  4.527907e+07  1.420384e+06

                         Price                         Levy               \
```

```
                        mean           std         mean          std
Wheel
Left wheel        17922.460179  18964.013633  657.199548  518.980228
Right-hand drive   8973.055660   6262.134660  334.945283  838.937448

                     Prod_year           Engine_volume              Mileage  \
                          mean       std          mean       std         mean
Wheel
Left wheel         2011.279109  5.607232      2.356330  0.882962  1.175651e+06
Right-hand drive   2006.460377  4.962878      1.731226  0.564145  3.169987e+06

                                  Cylinders           Airbags
                           std       mean       std      mean       std
Wheel
Left wheel        4.036403e+07  4.615993  1.221364  6.768418  4.354818
Right-hand drive  7.273460e+07  4.194340  0.913629  4.387736  2.807928
```

[81]:
```python
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Color = df.groupby("Color").agg([np.mean, np.std]) # get the mean and sd of␣
 ↪each Color
Color.head()
```

[81]:
```
                Unnamed: 0                          ID                \
                      mean          std           mean           std
Color
Beige          6283.344444  3700.370164  4.538647e+07  1.438808e+06
Black          6659.679192  3919.915393  4.558015e+07  9.541581e+05
Blue           6816.271028  3895.145609  4.554244e+07  1.133235e+06
Brown          6849.928571  3573.151862  4.555830e+07  6.688402e+05
Carnelian red  6906.315385  3754.356430  4.547461e+07  1.036633e+06

                     Price                         Levy              \
                      mean           std          mean          std
Color
Beige          14615.622222  12843.017514  255.511111  470.500695
Black          18843.607173  22682.526792  702.530601  589.833482
Blue           15213.814123  16471.530111  520.590862  490.376794
Brown          20816.293651  21169.678921  566.087302  510.126479
Carnelian red  15916.384615  13467.645652  337.015385  431.431868

                 Prod_year           Engine_volume              Mileage  \
                      mean       std          mean       std         mean
Color
Beige          2005.933333  8.603370      2.188889  0.846200  8.768521e+06
Black          2011.393111  5.085715      2.575747  1.001288  1.943455e+06
Blue           2009.455867  6.980138      2.107684  0.722581  2.424610e+06
```

```
Brown          2011.714286  5.697518      2.263492  0.824971  1.753361e+05
Carnelian red  2008.815385  7.041169      2.027692  0.577621  7.822669e+06

                             Cylinders           Airbags
                       std        mean       std      mean       std
Color
Beige          8.197153e+07   4.644444  1.202162  5.344444  3.963772
Black          5.649943e+07   4.913464  1.421012  7.171933  4.565087
Blue           6.922067e+07   4.425753  1.054365  6.382139  4.368591
Brown          6.878448e+05   4.547619  1.070380  6.722222  4.554802
Carnelian red  8.769436e+07   4.246154  1.012033  7.238462  3.887575
```

[82]:
```python
import warnings #ignore warnings
warnings.filterwarnings("ignore") #ignore warnings
Airbags = df.groupby("Airbags").agg([np.mean, np.std]) # get the mean and sd of␣
↪each Airbags
Airbags.head()
```

[82]:
```
          Unnamed: 0                          ID                       Price  \
                mean          std           mean           std          mean
Airbags
0        6787.172202  3933.915497  4.558636e+07  1.199717e+06  12346.549200
1        7093.827586  4002.144518  4.569624e+07  3.078054e+05  10727.827586
2        6721.338101  3764.847866  4.539457e+07  1.315712e+06  10461.063719
3        6321.133333  3339.346155  4.560057e+07  7.641218e+05   9409.266667
4        6793.495500  3906.865554  4.570344e+07  6.741892e+05  22755.018487

                                   Levy                Prod_year            \
                  std          mean          std          mean        std
Airbags
0        18676.959284  718.694957  619.415904  2010.073801  7.702353
1         8378.223042  177.637931  550.482968  1999.017241  8.888177
2         9096.583458  260.717815  593.811508  2003.270481  6.156355
3         6772.249964  223.566667  520.160365  2003.266667  5.044173
4        16794.336922  662.522987  393.073181  2011.699343  4.936541

        Engine_volume              Mileage               Cylinders  \
                 mean       std         mean          std      mean
Airbags
0            2.547847  1.110414  1.415772e+06  3.506076e+07  5.020295
1            2.137931  0.517358  3.325926e+05  8.039262e+05  4.103448
2            1.901170  0.600270  2.902226e+06  5.261848e+07  4.219766
3            1.993333  0.701689  7.665192e+05  3.633719e+06  4.433333
4            1.959985  0.560632  9.073396e+05  3.694089e+07  4.056677


              std
```

```
Airbags
0         1.610796
1         1.180093
2         0.939484
3         1.104328
4         0.395164
```

[83]:

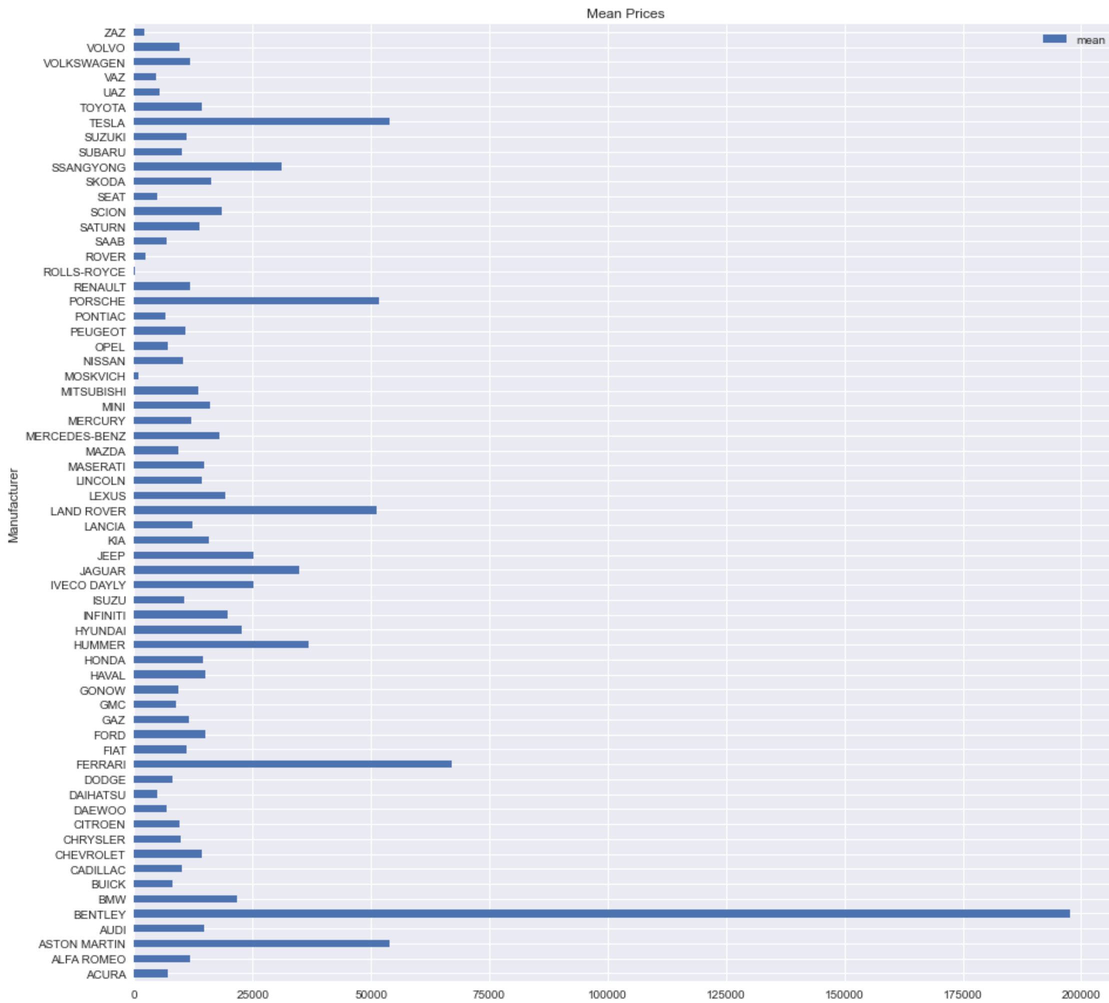
```
manufacturer = Manufacturer['Price'] # get the total mean and sd of price for␣
 ↪each manufacturer
model = Model['Price'] # get the total mean and sd of price for each model
prod_year = Prod_year['Price'] # get the total mean and sd of price for each␣
 ↪prod_year
category = Category['Price'] # get the total mean and sd of price for each␣
 ↪category
leather_interior = Leather_interior['Price'] # get the total mean and sd of␣
 ↪price for each leather_interior
fuel_type = Fuel_type['Price'] # get the total mean and sd of price for each␣
 ↪fuel_type
engine_volume = Engine_volume['Price'] # get the total mean and sd of price for␣
 ↪each engine_volume
turbo = Turbo['Price'] # get the total mean and sd of price for each turbo
mileage = Mileage['Price'] # get the total mean and sd of price for each mileage
cylinders = Cylinders['Price'] # get the total mean and sd of price for each␣
 ↪cylinders
gear_box_type = Gear_box_type['Price'] # get the total mean and sd of price for␣
 ↪each gear_box_type
drive_wheels = Drive_wheels['Price'] # get the total mean and sd of price for␣
 ↪each drive_wheels
doors = Doors['Price'] # get the total mean and sd of price for each doors
wheel = Wheel['Price'] # get the total mean and sd of price for each wheel
color = Color['Price'] # get the total mean and sd of price for each color
airbags = Airbags['Price']# get the total mean and sd of price for each airbags
```

[84]:

```
manufacturer.plot(kind = "barh", y = "mean", legend = True, title = "Mean␣
 ↪Prices", figsize = (15,15)) # plot manufacturer & resize the plot
```

[84]:

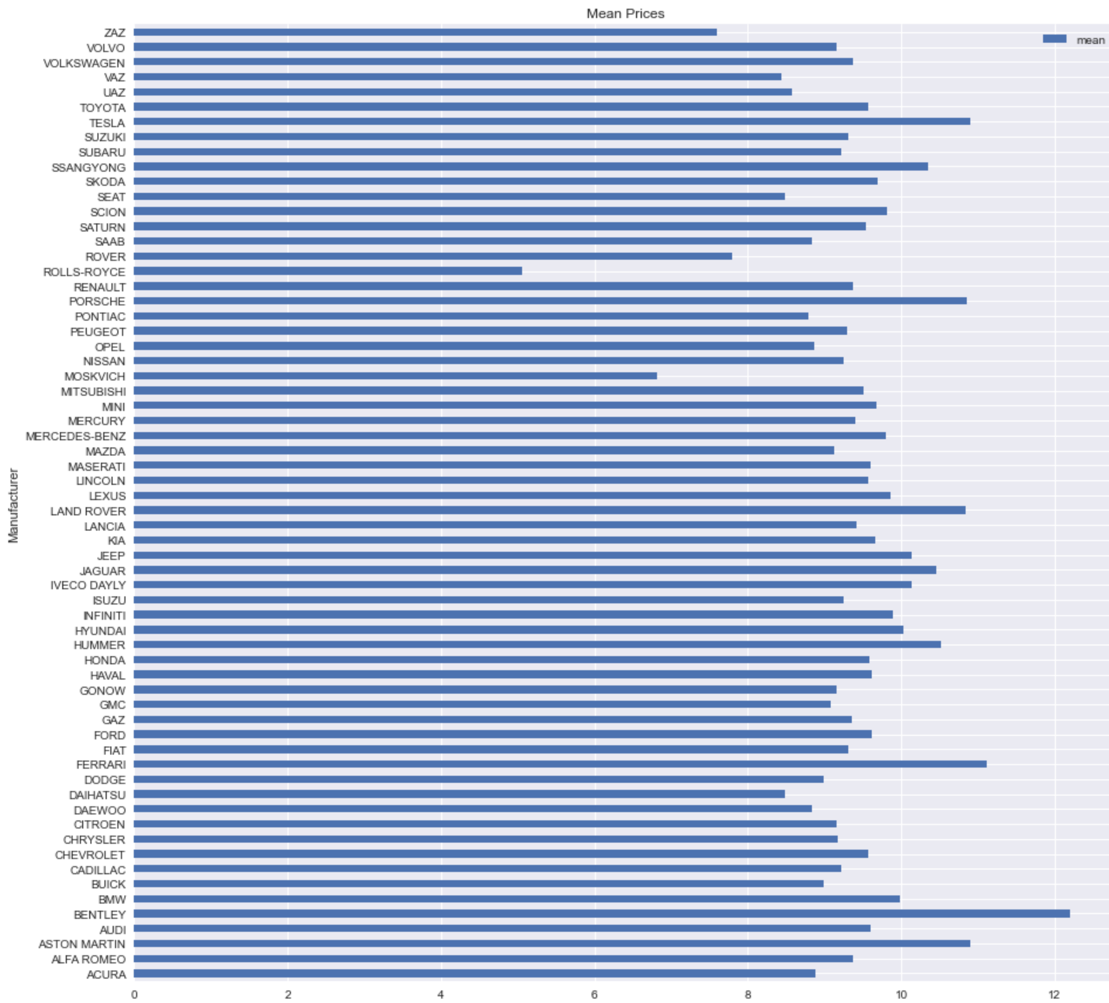
```
<AxesSubplot:title={'center':'Mean Prices'}, ylabel='Manufacturer'>
```



Notice the data is highly skewed, in order to reduce skewness I will use log transformation

```
[85]: data_log1 = np.log(manufacturer) # log
      data_log1.plot(kind = "barh", y = "mean", legend = True, title = "Mean Prices",␣
       ↪figsize = (15,15)) # plot manufacturer & resize the plot
```

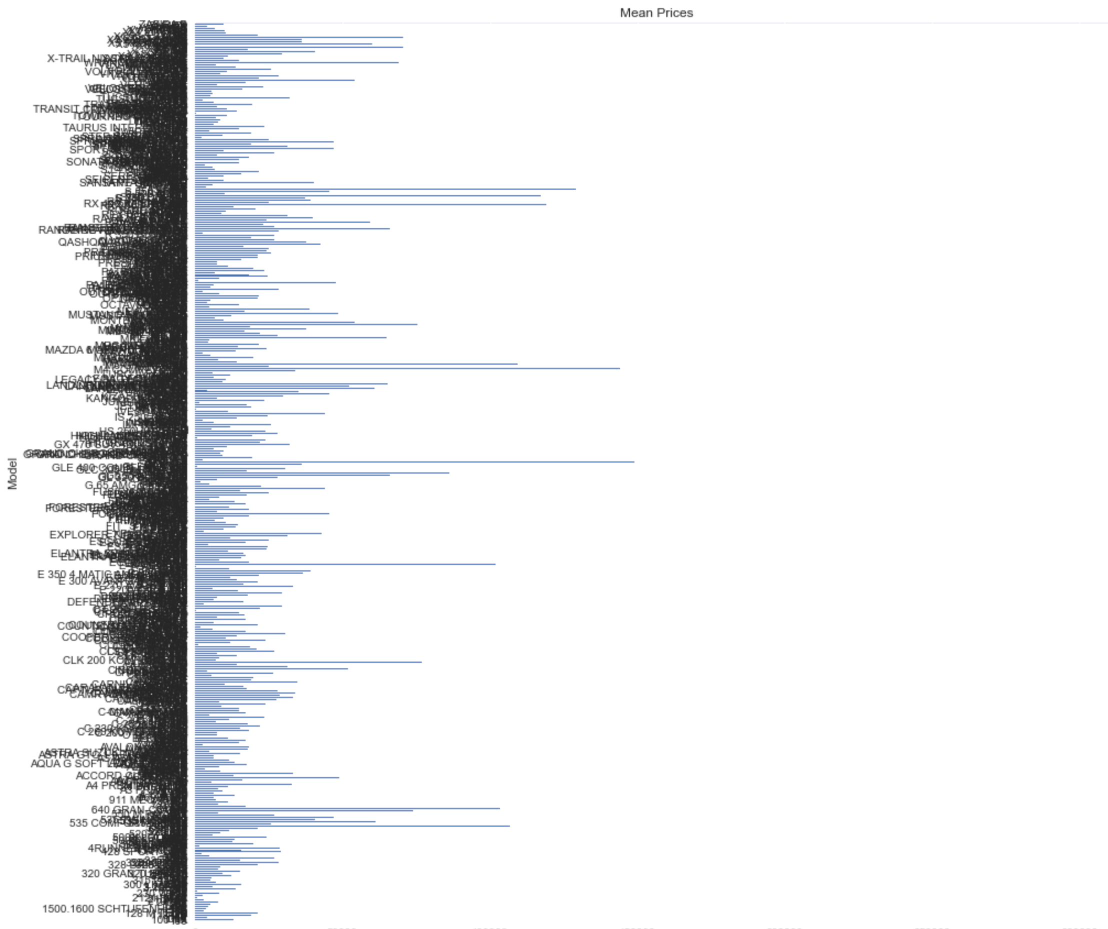
```
[85]: <AxesSubplot:title={'center':'Mean Prices'}, ylabel='Manufacturer'>
```



manufacturer after log transformation

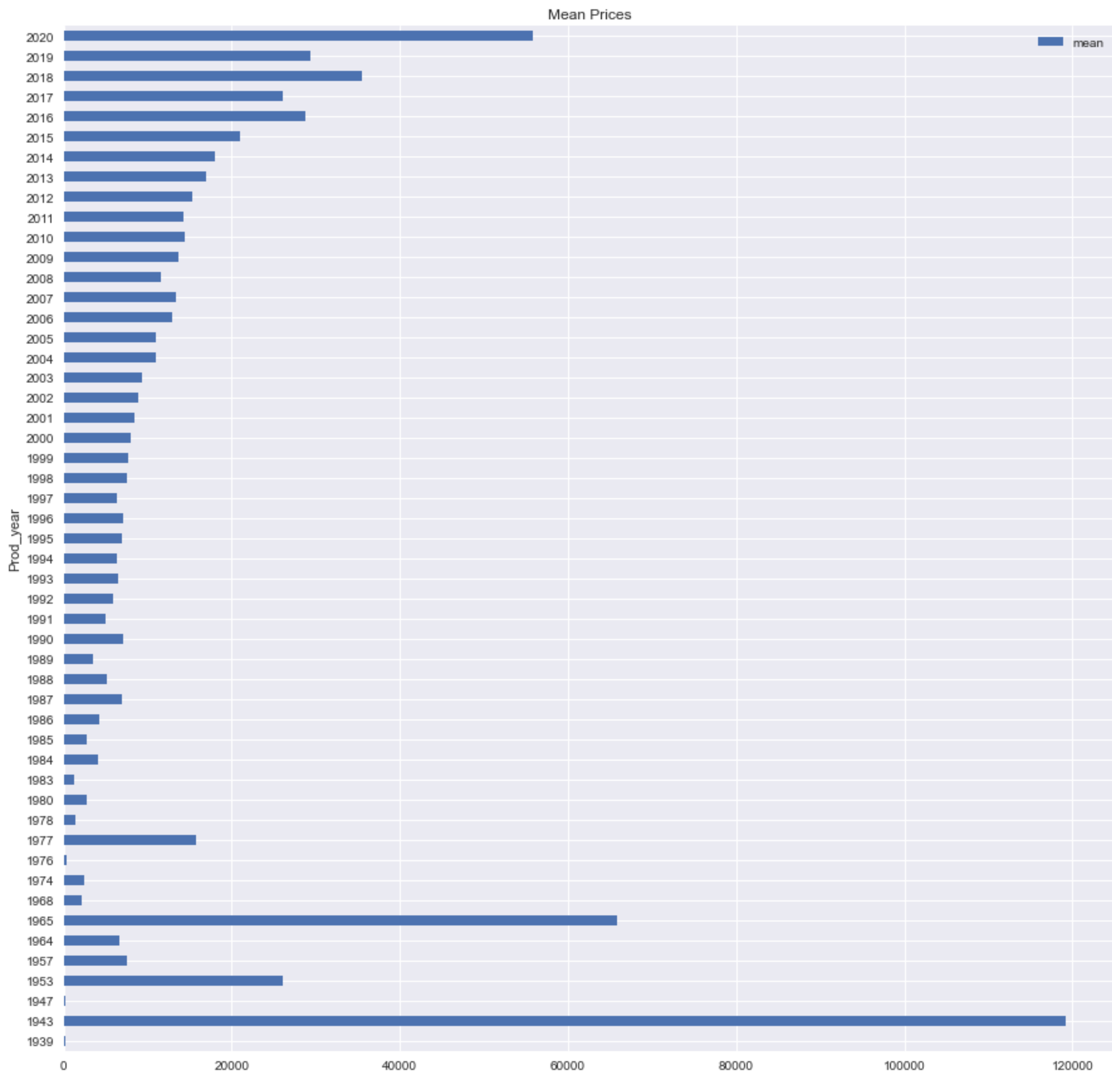
[86]:
```
model.plot(kind = "barh", y = "mean", legend = False,title = "Mean Prices",␣
 ↪figsize = (15,15)) # plot model & resize the plot
```

[86]: <AxesSubplot:title={'center':'Mean Prices'}, ylabel='Model'>




```
[87]: prod_year.plot(kind = "barh", y = "mean", legend = True,title = "Mean Prices",
      ↪figsize = (15,15)) # plot prod_year & resize the plot
```

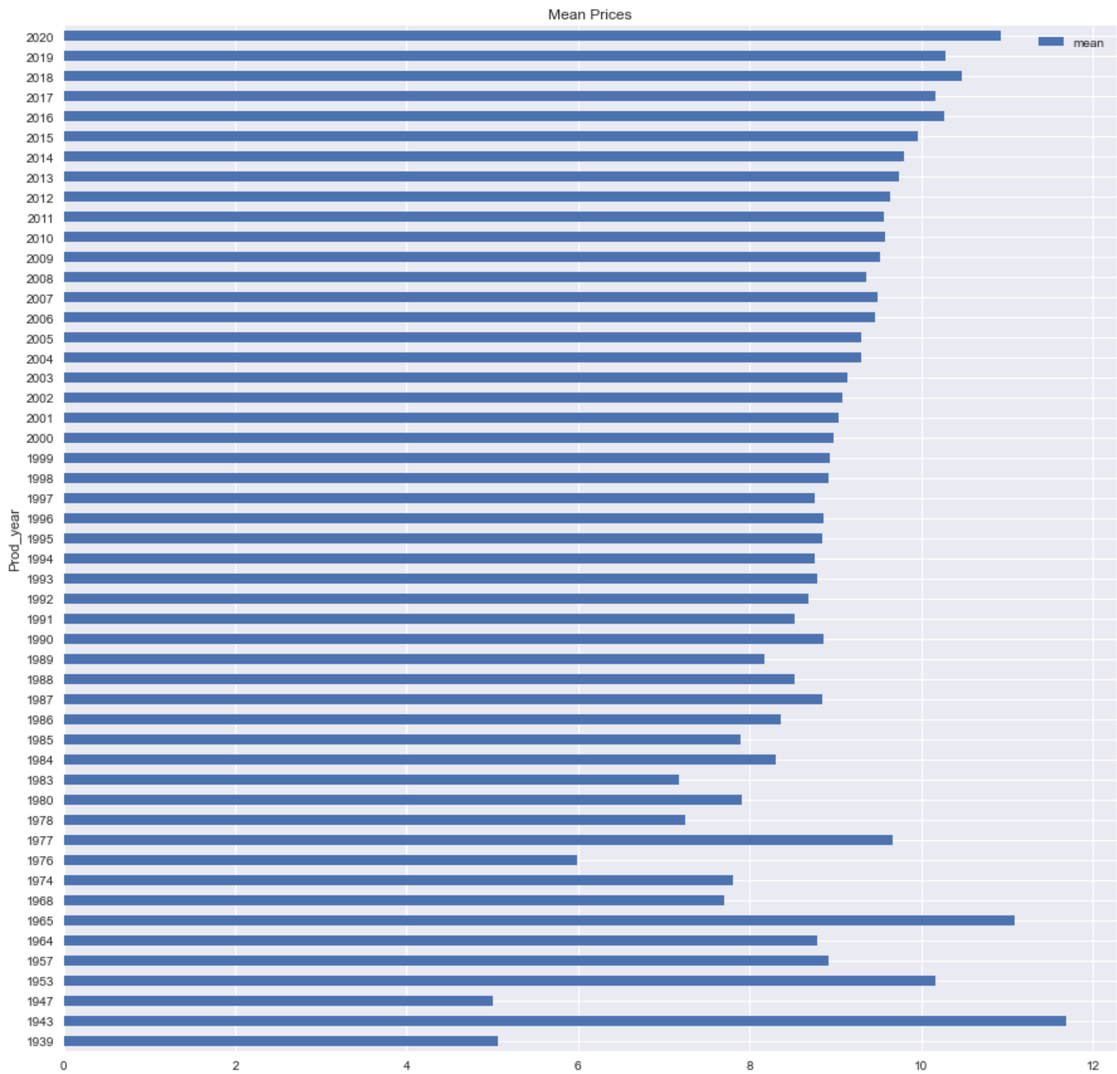
```
[87]: <AxesSubplot:title={'center':'Mean Prices'}, ylabel='Prod_year'>
```



Notice the data is highly skewed, in order to reduce skewness I will use log transformation

[88]:
```
data_log2 = np.log(prod_year) # log
data_log2.plot(kind = "barh", y = "mean", legend = True,title = "Mean Prices",␣
↪figsize = (15,15)) # plot prod_year & resize the plot
```

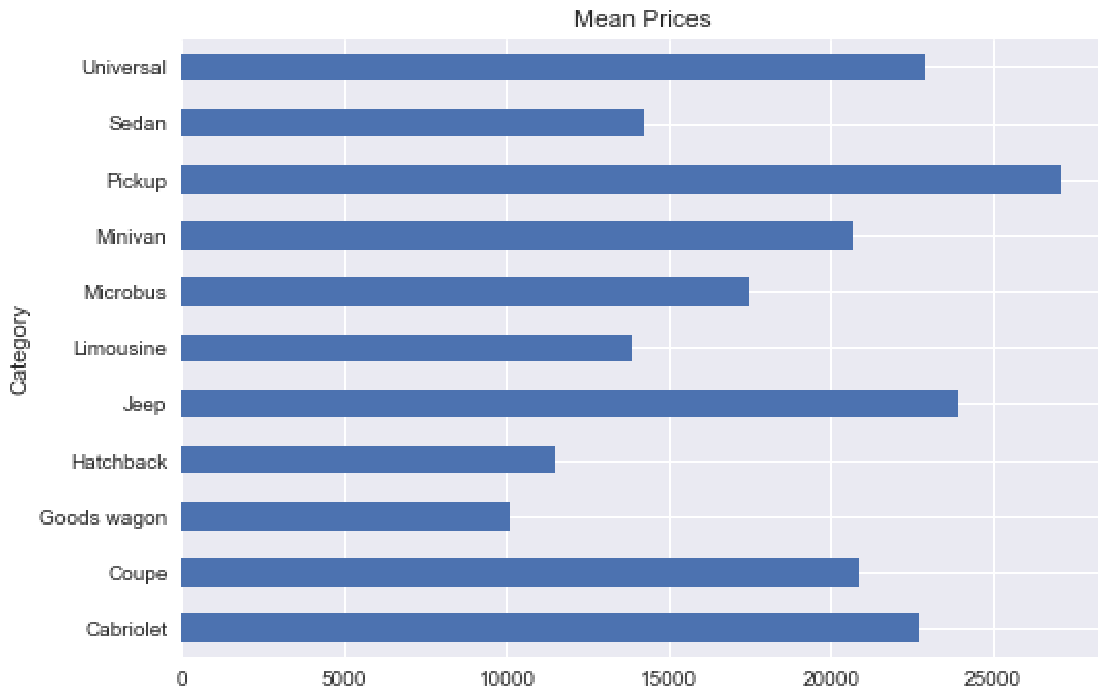
[88]:
```
<AxesSubplot:title={'center':'Mean Prices'}, ylabel='Prod_year'>
```



prod_year after log transformation

[89]:
```
category.plot(kind = "barh", y = "mean", legend = False,title = "Mean Prices") 
 ↪# plot category
```

[89]:
```
<AxesSubplot:title={'center':'Mean Prices'}, ylabel='Category'>
```

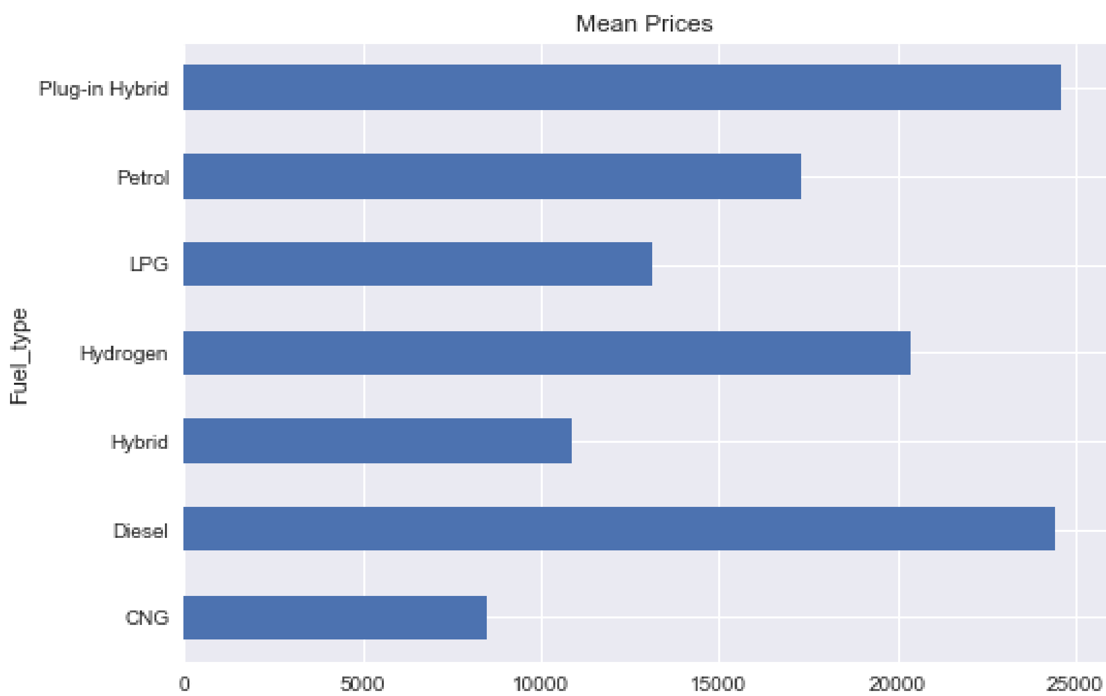



```
[90]: leather_interior.plot(kind = "barh", y = "mean", legend = False,title = "Mean␣
      ↪Prices") # plot leather_interior
```

```
[90]: <AxesSubplot:title={'center':'Mean Prices'}, ylabel='Leather_interior'>
```

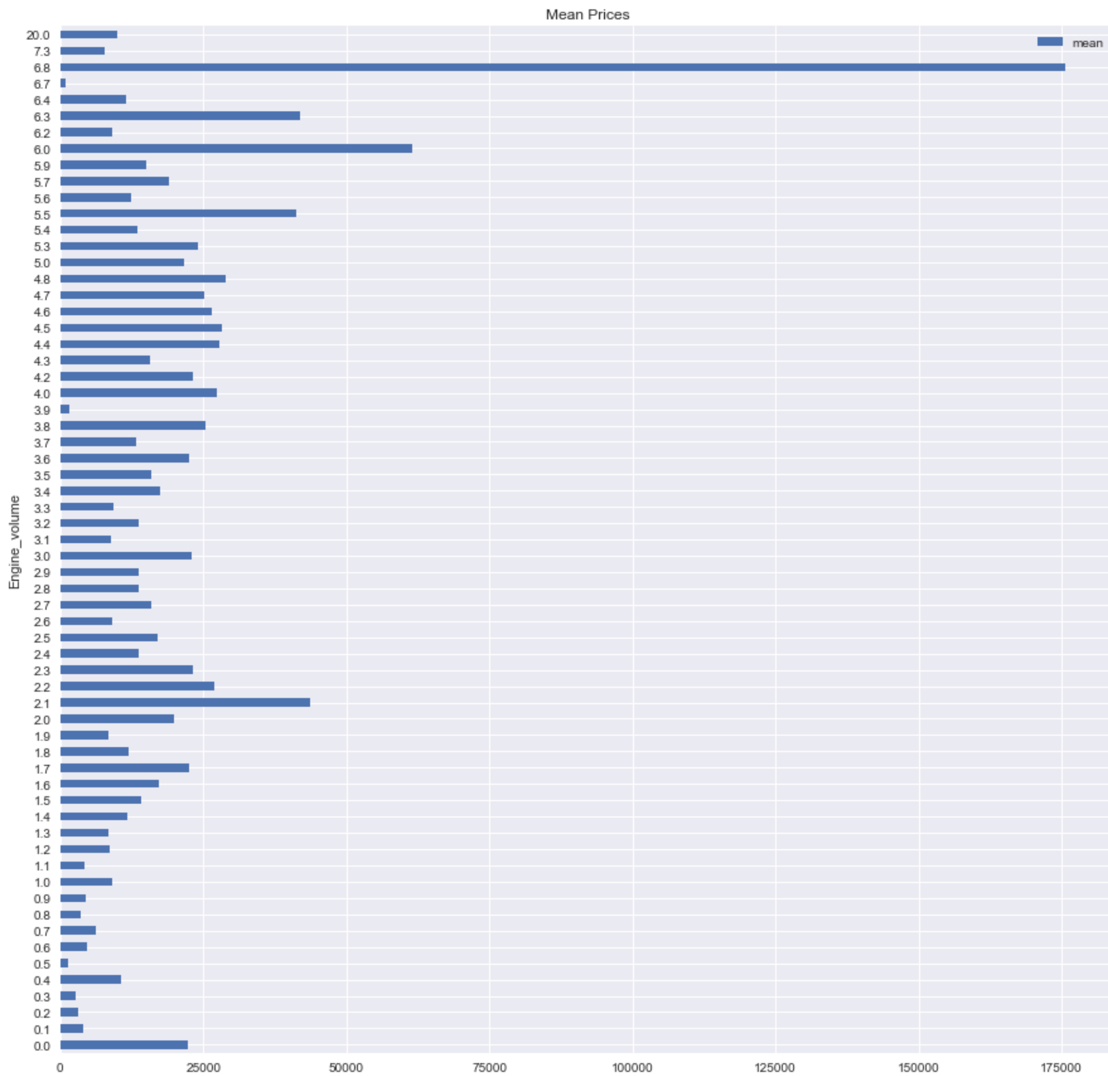
[91]:
```
fuel_type.plot(kind = "barh", y = "mean", legend = False,title = "Mean Prices")␣
↪# plot fuel_type
```

[91]:
```
<AxesSubplot:title={'center':'Mean Prices'}, ylabel='Fuel_type'>
```



[92]:
```python
engine_volume.plot(kind = "barh", y = "mean", legend = True,title = "Mean␣
↪Prices", figsize = (15,15)) # plot engine_volume & resize the plot
```

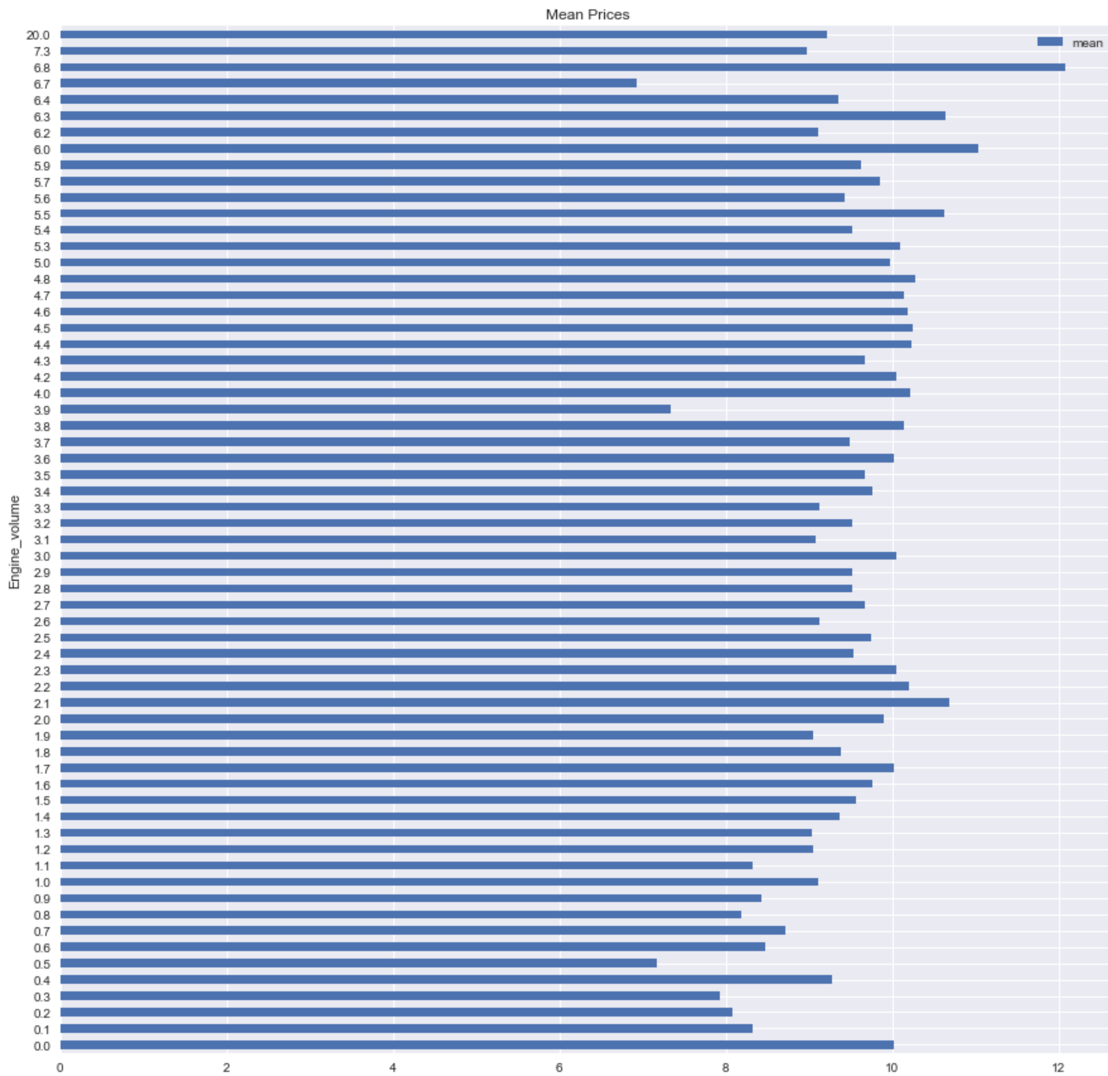
[92]: <AxesSubplot:title={'center':'Mean Prices'}, ylabel='Engine_volume'>



Notice the data is highly skewed, in order to reduce skewness I will use log transformation

[93]:
```
data_log3 = np.log(engine_volume) # log
data_log3.plot(kind = "barh", y = "mean", legend = True,title = "Mean Prices",␣
 ↪figsize = (15,15)) # plot engine_volume & resize the plot
```

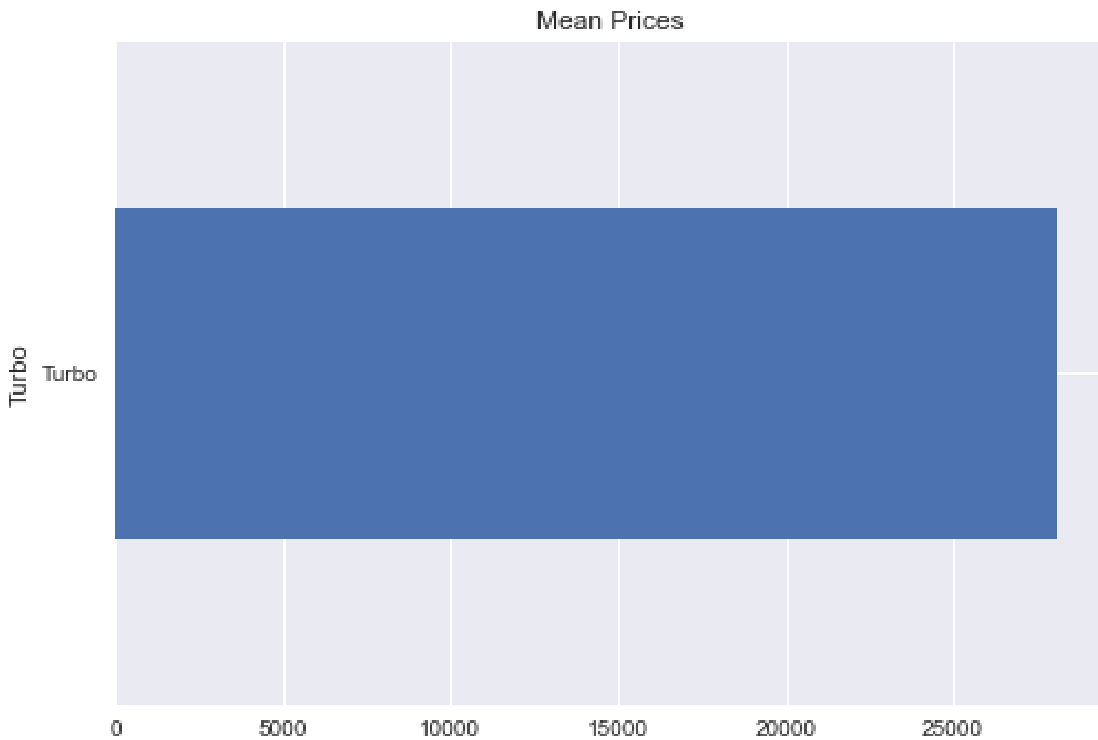
[93]: <AxesSubplot:title={'center':'Mean Prices'}, ylabel='Engine_volume'>



engine_volume after log transformation

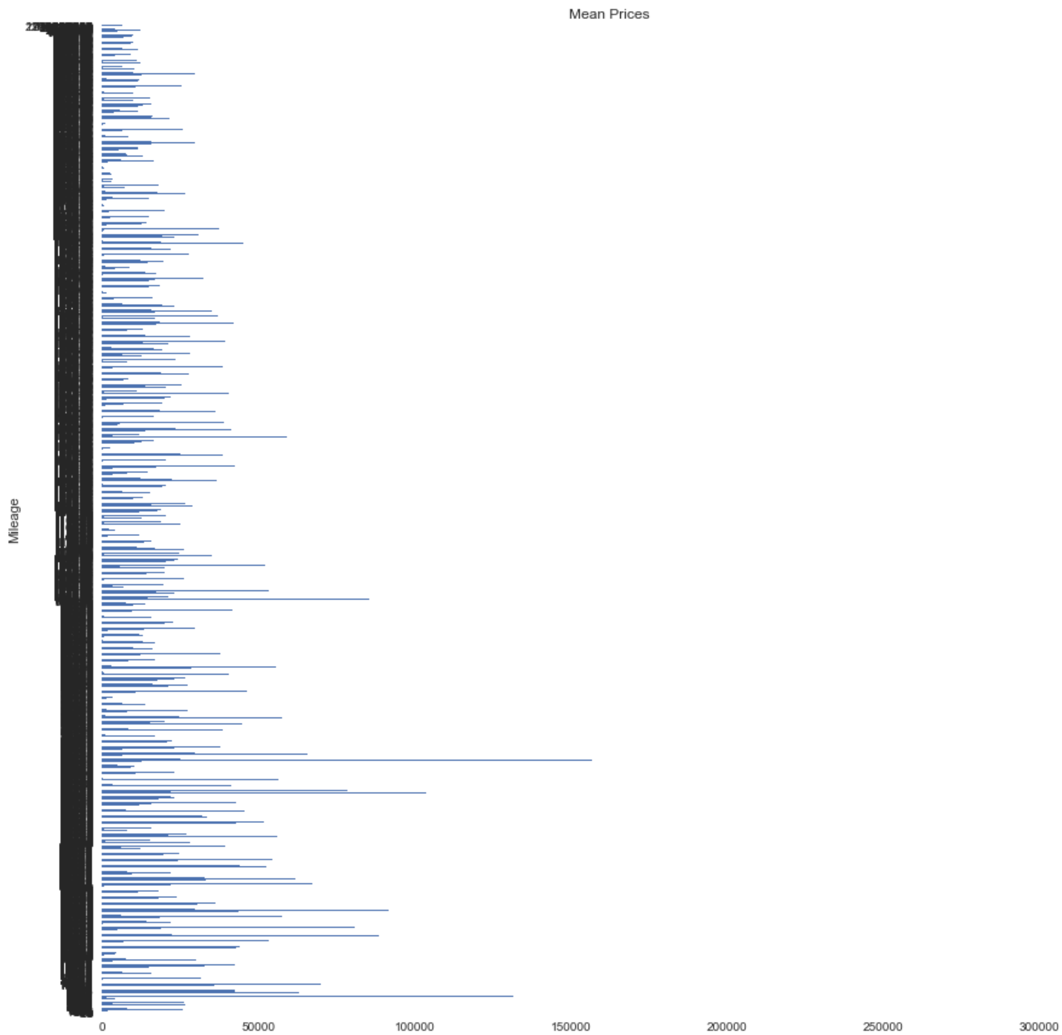
[94]:
```
turbo.plot(kind = "barh", y = "mean", legend = False,title = "Mean Prices") #␣
↪plot turbo
```

[94]: <AxesSubplot:title={'center':'Mean Prices'}, ylabel='Turbo'>



[95]:
```
mileage.plot(kind = "barh", y = "mean", legend = False,title = "Mean Prices",␣
↪figsize = (15,15)) # plot mileage & resize the plot
```

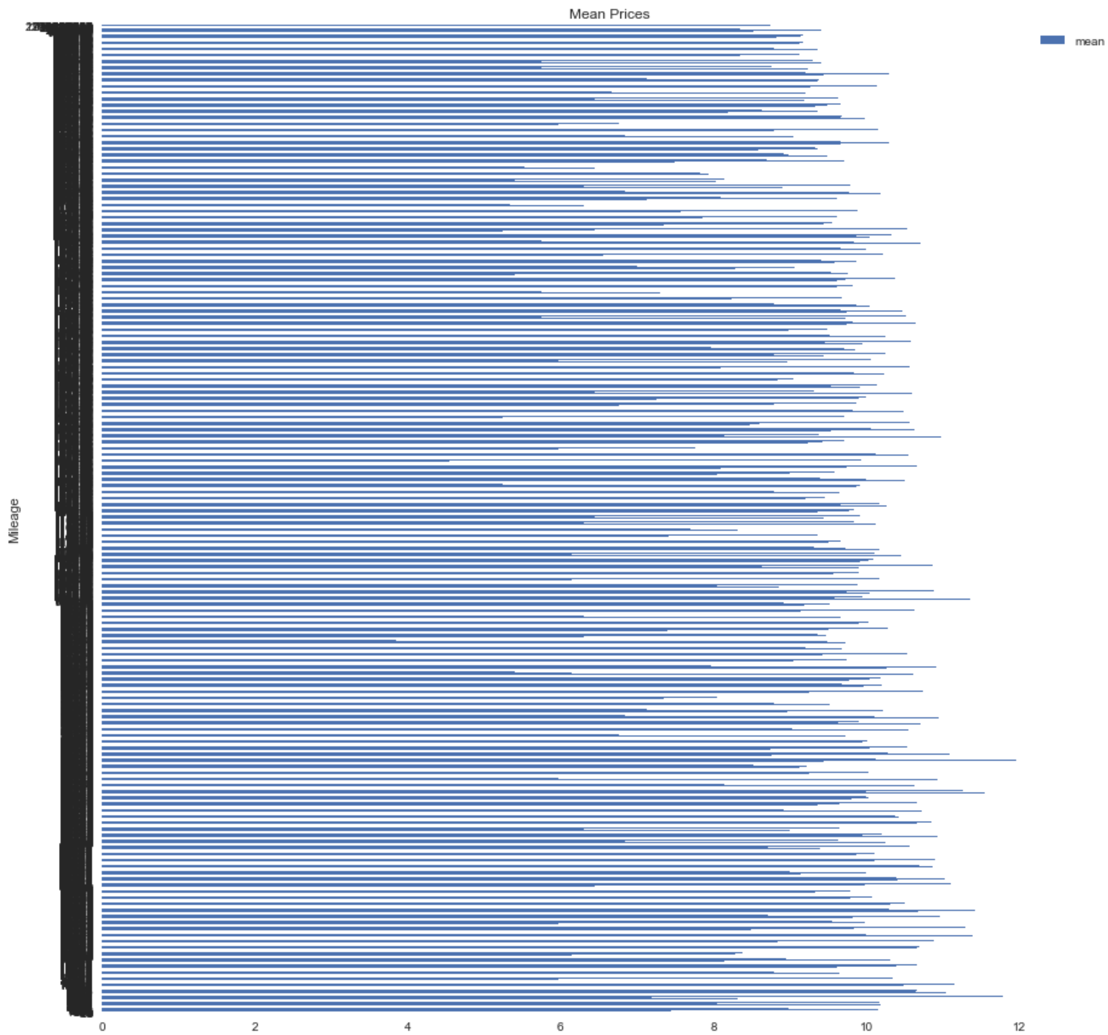
[95]:
```
<AxesSubplot:title={'center':'Mean Prices'}, ylabel='Mileage'>
```



Notice the data is highly skewed, in order to reduce skewness I will use log transformation

[96]:
```
data_log4 = np.log(mileage) # log
data_log4.plot(kind = "barh", y = "mean", legend = True,title = "Mean Prices",␣
 ↪figsize = (15,15)) # plot engine_volume & resize the plot
```

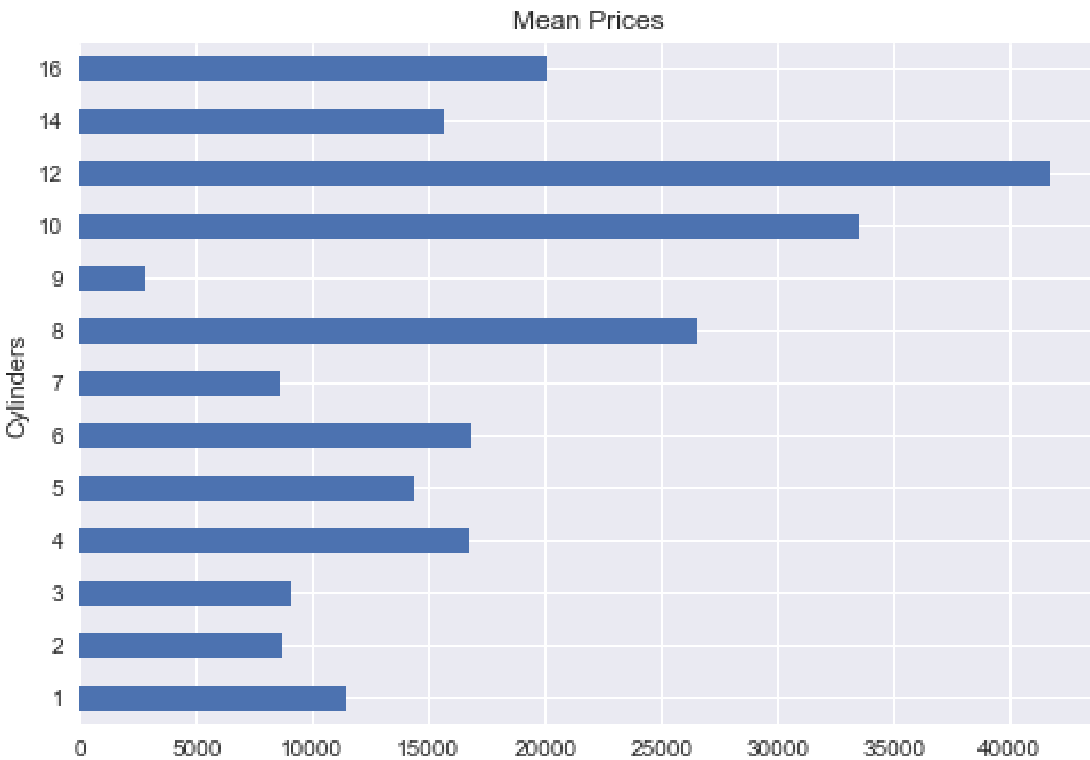
[96]: <AxesSubplot:title={'center':'Mean Prices'}, ylabel='Mileage'>



mileage after log transformation

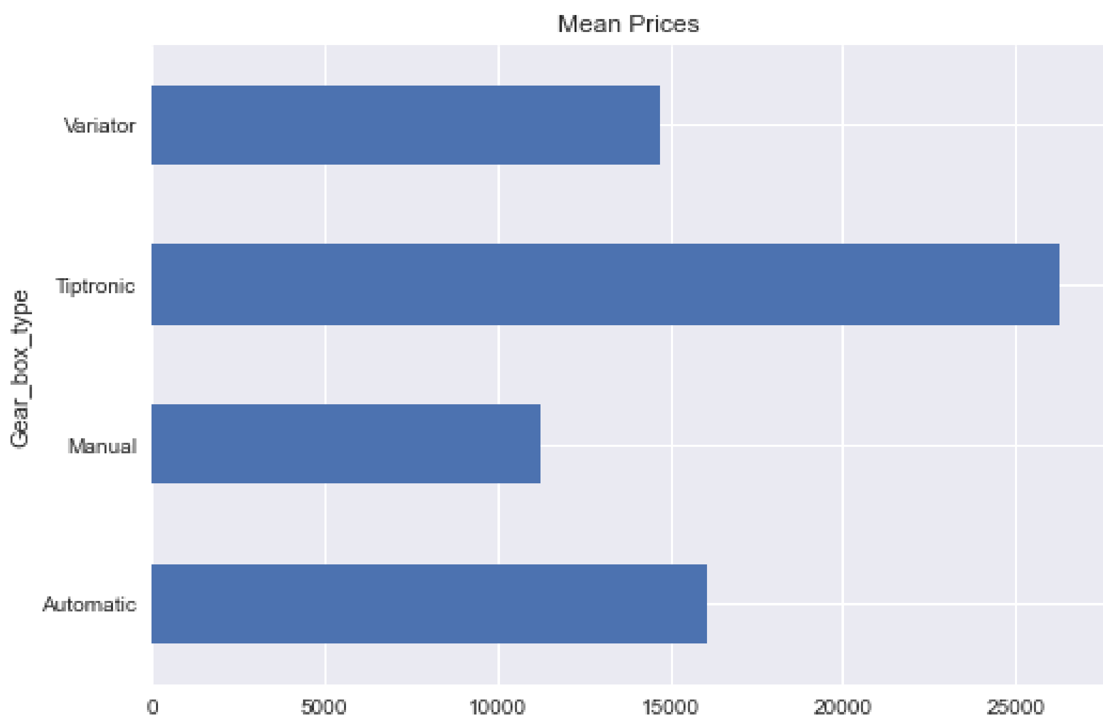
[97]:
```
cylinders.plot(kind = "barh", y = "mean", legend = False,title = "Mean Prices")␣
↪# plot cylinders
```

[97]:
```
<AxesSubplot:title={'center':'Mean Prices'}, ylabel='Cylinders'>
```



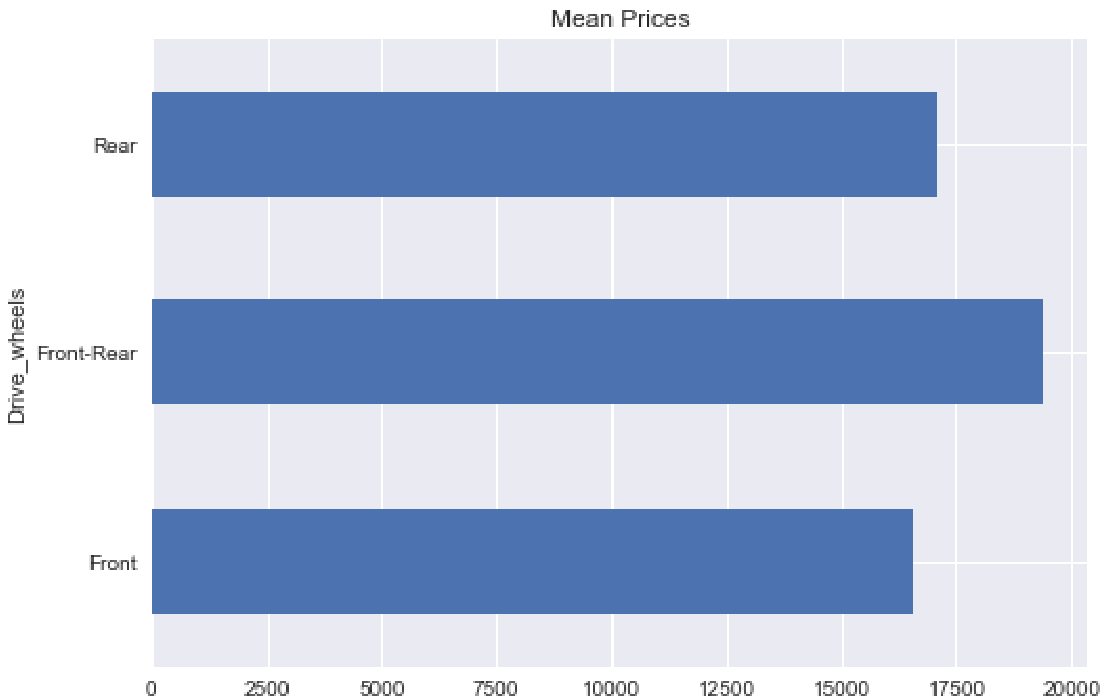
[98]:
```
gear_box_type.plot(kind = "barh", y = "mean", legend = False,title = "Mean␣
↪Prices") # plot gear_box_type
```

[98]: <AxesSubplot:title={'center':'Mean Prices'}, ylabel='Gear_box_type'>



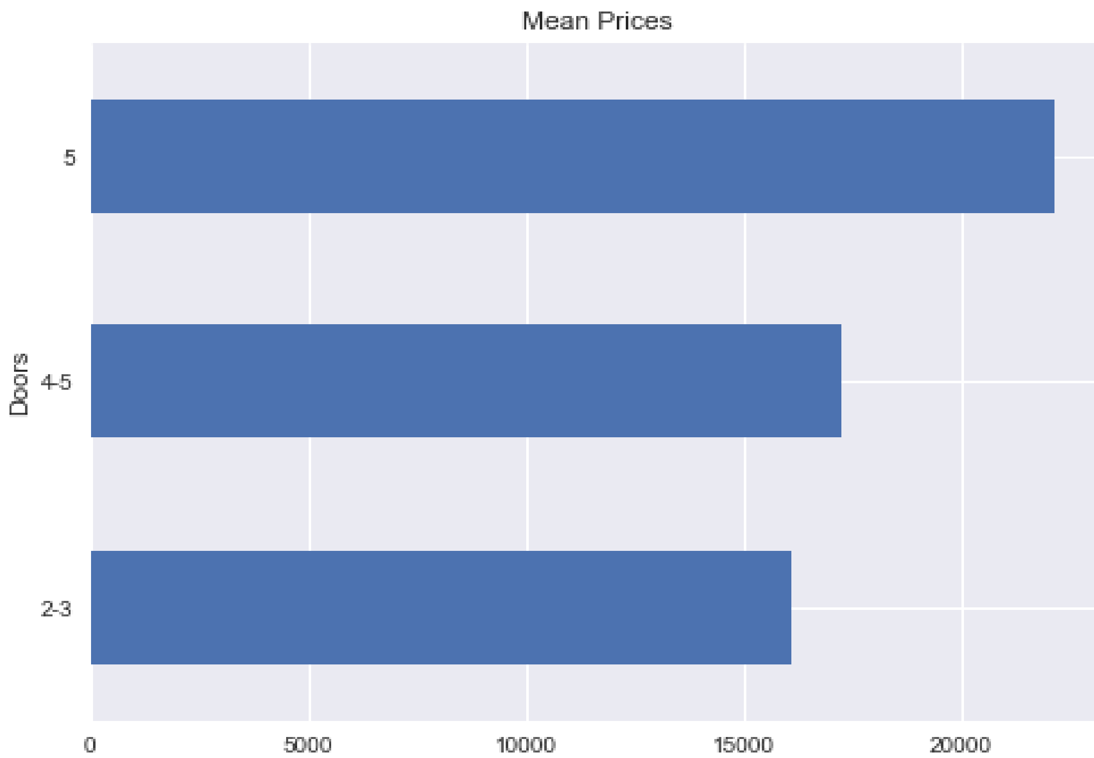
[99]:
```
drive_wheels.plot(kind = "barh", y = "mean", legend = False,title = "Mean␣
↪Prices") # plot drive_wheels
```

[99]:
```
<AxesSubplot:title={'center':'Mean Prices'}, ylabel='Drive_wheels'>
```



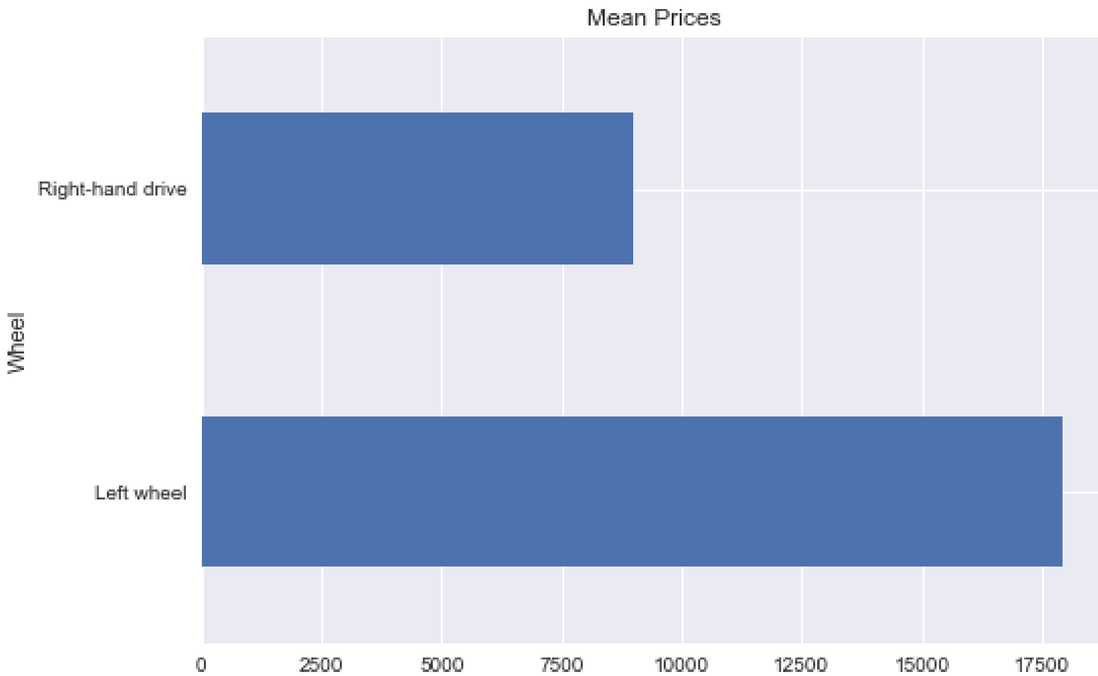
[100]:
```
doors.plot(kind = "barh", y = "mean", legend = False,title = "Mean Prices") #␣
↪plot doors
```

[100]:
```
<AxesSubplot:title={'center':'Mean Prices'}, ylabel='Doors'>
```



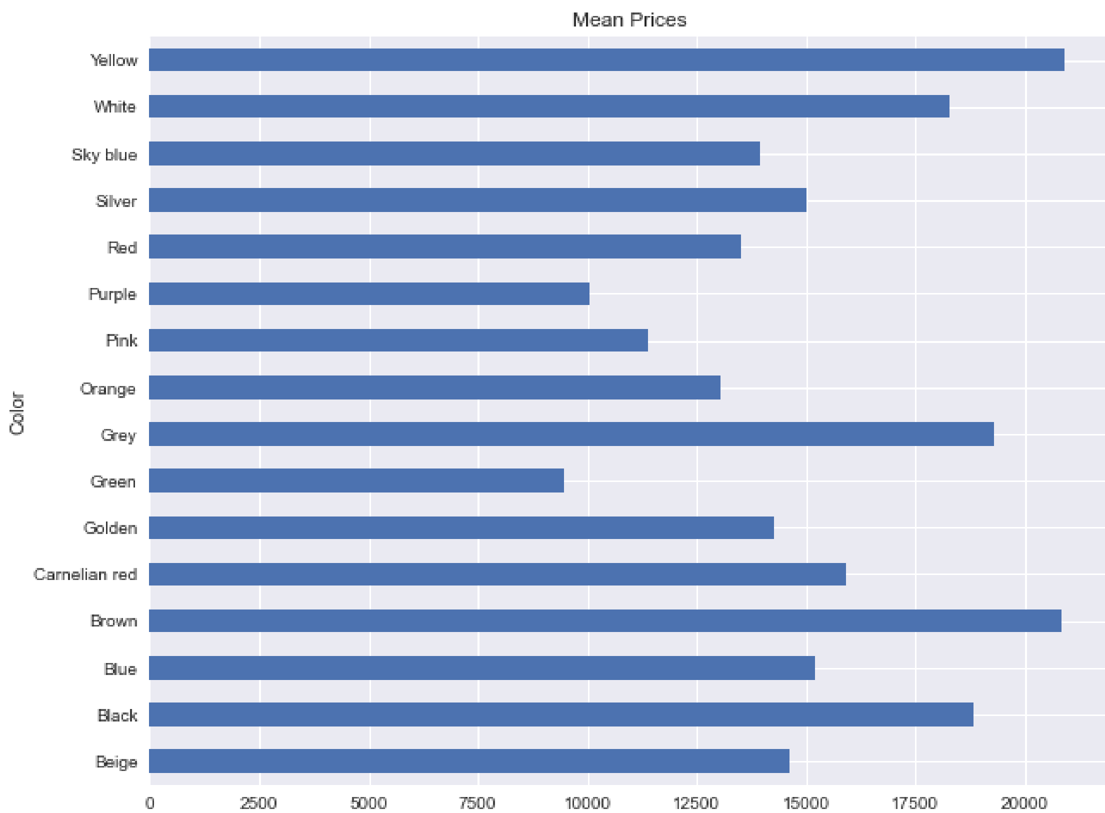
[101]:
```
wheel.plot(kind = "barh", y = "mean", legend = False,title = "Mean Prices") #␣
↪plot wheel
```

[101]: <AxesSubplot:title={'center':'Mean Prices'}, ylabel='Wheel'>



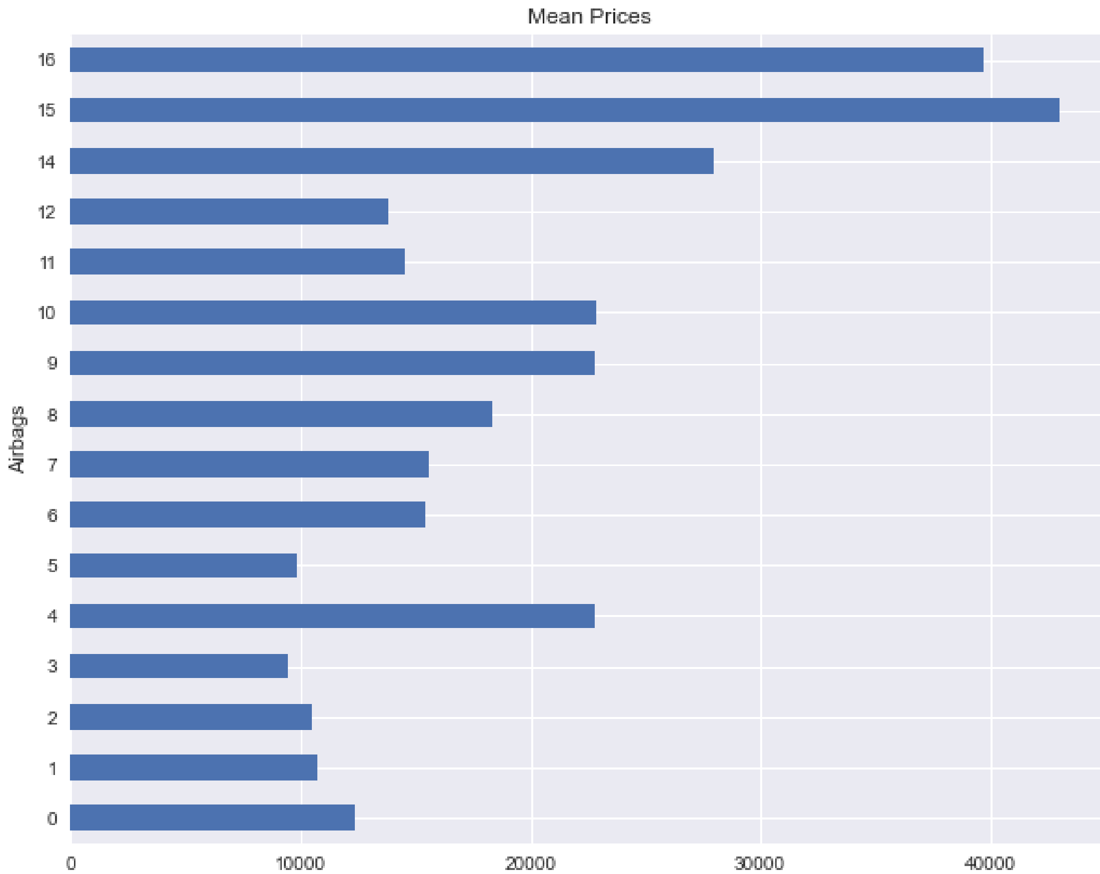
[102]:
```
color.plot(kind = "barh", y = "mean", legend = False,title = "Mean Prices",
  figsize = (10,8)) # plot color & resize the plot
```

[102]: <AxesSubplot:title={'center':'Mean Prices'}, ylabel='Color'>



[103]:
```
airbags.plot(kind = "barh", y = "mean", legend = False,title = "Mean Prices",␣
↪figsize = (10,8)) # plot airbags & resize the plot
```

[103]: <AxesSubplot:title={'center':'Mean Prices'}, ylabel='Airbags'>



5.2 heteroscedasticity (Breusch-Pegan Test) Testing for Heteroskedasticity
Hypothesis:
* The null hypothesis (H0): Signifies that Homoscedasticity is present.
* The alternative hypothesis: (Ha): Signifies that the Homoscedasticity is not present (i.e. heteroscedasticity exists)
First you need to install the numNumPypy, pandas and statsmodels library using: pip3 install numpy pandas statsmodels

[104]:
```
# fit regression model
fit = smf.ols("Price ~ Levy + Manufacturer + Model + Prod_year + Category +␣
↪Leather_interior + Fuel_type + Engine_volume + Turbo + Mileage + Cylinders +␣
↪Gear_box_type + Drive_wheels+ Doors + Wheel  +Color + Airbags", data= df).
↪fit()
```

[105]:
```
# Conduct the Breusch-Pagan test
names = ['Lagrange multiplier statistic', 'p-value','f-value', 'f p-value']
# Get the test result
test_result = sms.het_breuschpagan(fit.resid, fit.model.exog)
lzip(names, test_result)
```

```
[105]: [('Lagrange multiplier statistic', 715.284773129976),
 ('p-value', 1.0),
 ('f-value', 2.0415045099940903),
 ('f p-value', 5.556962926333127e-20)]
```

Output Interpretation:
Here, the Lagrange multiplier statistic for the test comes out to be equal to 715.284 and the corresponding p-value comes out to be equal to 1.0. Since the p-value is greater than 0.05 so we couldn't reject the null hypothesis. Hence, We do not have enough proof to say that heteroscedasticity is present in the regression model.

0.0.6 6. Implementing Linear Regression with Categorical variable Using Sklearn

```
[106]: # Get Path
path = 'C:/Users/chris/Documents/School/Masters/zz_GIT/
 ↪2022-msaai-500-final-project/data/sanitized/FilterData3.csv'

# Reading the dataset
df = pd.read_csv(path)
display(df)
```

```
       Unnamed: 0        ID  Price  Levy  MakeModel  Prod_year   Category  \
0           11219  20746880    157     0   0.046772       1939  Limousine
1           13225  23242980    200     0   0.141307       2017       Jeep
2           13572  24367759  85702     0   0.299423       2013   Microbus
3            3643  24701923    130     0   0.058867       2006       Jeep
4            5509  24940334  25089     0   0.057150       1999  Limousine
…             …       …      …     …        …         …
19212       14885  45816647  15053     0   0.035492       2010  Hatchback
19213         710  45816648  24148   810   0.075149       2016  Hatchback
19214        2168  45816650  20698   697   0.075149       2015  Hatchback
19215       12245  45816651  10976     0   0.025909       2007      Sedan
19216         359  45816654  18817     0   0.042147       2009      Sedan

      Leather_interior Fuel_type  Mileage  Engine_volume  Cylinders  \
0                  Yes    Petrol   126000       2.400000          4
1                  Yes    Petrol    95000       2.700000          4
2                  Yes    Diesel   225000       3.861956          6
3                  Yes    Petrol    90000       4.400000          8
4                  Yes    Petrol    99000       5.400000          8
…                …      …       …              …        …
19212               No    Petrol    83000       2.000000          4
19213               No    Petrol    10200       1.800000          4
19214               No    Petrol    78000       1.800000          4
19215              Yes    Petrol   224823       3.510869          4
19216              Yes    Petrol   230400       2.400000          4

      Gear_box_type Drive_wheels Doors       Wheel    Color   Airbags
```

```
0        Automatic        Rear   4-5  Left wheel   White     0
1        Automatic  Front-Rear     5  Left wheel   Black    10
2           Manual        Rear   2-3  Left wheel   White     4
3        Tiptronic  Front-Rear   4-5  Left wheel   Black     8
4        Automatic  Front-Rear   4-5  Left wheel   White     4
…              …          …    …           …       …     …
19212    Automatic       Front     5  Left wheel  Golden     6
19213    Automatic       Front   4-5  Left wheel   White    10
19214       Manual       Front   4-5  Left wheel  Silver    10
19215    Tiptronic  Front-Rear   4-5  Left wheel   White     0
19216    Automatic       Front   4-5  Left wheel  Silver    12

[19217 rows x 18 columns]
```

[107]:
```
df.shape
df.describe()
```

[107]:
```
         Unnamed: 0            ID          Price          Levy     MakeModel  \
count  19217.000000  1.921700e+04   19217.000000  19217.000000  19217.000000
mean    9618.009887  4.557636e+07   17128.202061    632.751782      0.057377
std     5553.556104  9.370593e+05   18279.641947    567.652166      0.040567
min        0.000000  2.074688e+07       6.000000      0.000000      0.000000
25%     4808.000000  4.569837e+07    5331.000000      0.000000      0.035710
50%     9618.000000  4.577234e+07   13172.000000    642.000000      0.047439
75%    14426.000000  4.580204e+07   22110.000000    917.000000      0.066120
max    19236.000000  4.581665e+07  308906.000000  11714.000000      0.999886

          Prod_year       Mileage  Engine_volume     Cylinders       Airbags
count  19217.000000  1.921700e+04   19217.000000  19217.000000  19217.000000
mean    2010.913670  1.421973e+06       2.479367      4.582453      6.583286
std        5.666155  4.588801e+07       1.068608      1.198624      4.319785
min     1939.000000  0.000000e+00       0.000000      1.000000      0.000000
25%     2009.000000  7.019400e+04       1.800000      4.000000      4.000000
50%     2012.000000  1.260210e+05       2.000000      4.000000      6.000000
75%     2015.000000  1.888880e+05       3.000000      4.000000     12.000000
max     2020.000000  2.147484e+09      20.000000     16.000000     16.000000
```

[108]:
```
df.dtypes
```

[108]:
```
Unnamed: 0            int64
ID                    int64
Price                 int64
Levy                  int64
MakeModel           float64
Prod_year             int64
Category             object
Leather_interior     object
Fuel_type            object
```

```
Mileage                int64
Engine_volume        float64
Cylinders              int64
Gear_box_type         object
Drive_wheels          object
Doors                 object
Wheel                 object
Color                 object
Airbags                int64
dtype: object
```

from the above output we can see if the dataset is following normal distribution

[109]:
```python
# independent variables
X =␣
↪df[['Levy','MakeModel','Prod_year','Category','Leather_interior','Fuel_type','Mileage','Eng
```

[110]:
```python
X = pd.get_dummies(data=X, drop_first=True) # creating a dummy variable
X.head()
```

[110]:
```
   Levy  MakeModel  Prod_year  Mileage  Engine_volume  Cylinders  Airbags  \
0     0   0.046772       1939   126000       2.400000          4        0
1     0   0.141307       2017    95000       2.700000          4       10
2     0   0.299423       2013   225000       3.861956          6        4
3     0   0.058867       2006    90000       4.400000          8        8
4     0   0.057150       1999    99000       5.400000          8        4

   Category_Coupe  Category_Goods wagon  Category_Hatchback  …  Color_Green  \
0               0                     0                   0  …            0
1               0                     0                   0  …            0
2               0                     0                   0  …            0
3               0                     0                   0  …            0
4               0                     0                   0  …            0

   Color_Grey  Color_Orange  Color_Pink  Color_Purple  Color_Red  \
0           0             0           0             0          0
1           0             0           0             0          0
2           0             0           0             0          0
3           0             0           0             0          0
4           0             0           0             0          0

   Color_Silver  Color_Sky blue  Color_White  Color_Yellow
0             0               0            1             0
1             0               0            0             0
2             0               0            1             0
3             0               0            0             0
4             0               0            1             0
```

```
[5 rows x 47 columns]
```

Regression results are easier to interpret when dummy variables are limited to two specidic values, 1 or 0. 1 represents the presence of qualitative attribute, and 0 represents the absence

[111]:
```
# dependent variable
Y = df['Price']
```

[112]:
```
# creating a train and test dataset
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3,␣
 ↪random_state=101)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(13451, 47)
(5766, 47)
(13451,)
(5766,)
```

[113]:
```
# importing linear regression model
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X_train,y_train)
```

[113]:
```
LinearRegression()
```

[114]:
```
# print the intercept
print(model.intercept_)
```

```
-1889774.043681832
```

[115]:
```
coeff_parameter = pd.DataFrame(model.coef_,X.columns,columns=['Coefficient'])
coeff_parameter
```

[115]:

	Coefficient
Levy	-2.504613e+00
MakeModel	2.465659e+05
Prod_year	9.467128e+02
Mileage	6.477146e-07
Engine_volume	2.470109e+03
Cylinders	-4.618217e+02
Airbags	-3.853729e+02
Category_Coupe	-5.478890e+03
Category_Goods wagon	-1.020015e+04
Category_Hatchback	-6.594203e+03
Category_Jeep	-6.550806e+03

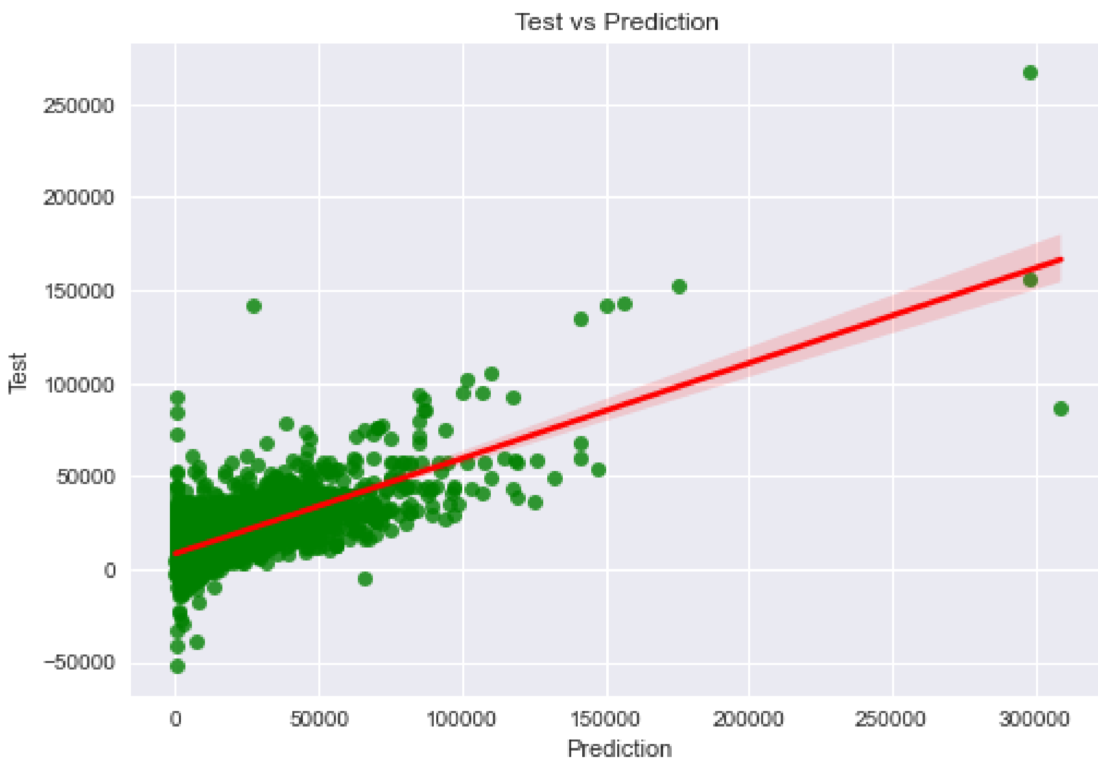
```
Category_Limousine        1.026902e+04
Category_Microbus        -9.985273e+03
Category_Minivan         -7.594809e+03
Category_Pickup          -1.062066e+04
Category_Sedan           -7.787711e+03
Category_Universal       -3.374075e+03
Leather_interior_Yes     -1.893932e+03
Fuel_type_Diesel         -7.773677e+02
Fuel_type_Hybrid         -4.178965e+03
Fuel_type_Hydrogen       -4.709057e+03
Fuel_type_LPG            -3.035668e+03
Fuel_type_Petrol         -1.682828e+03
Fuel_type_Plug-in Hybrid  7.748116e+03
Gear_box_type_Manual      5.035058e+03
Gear_box_type_Tiptronic   7.990753e+03
Gear_box_type_Variator    5.202119e+03
Drive_wheels_Front-Rear  -1.066771e+03
Drive_wheels_Rear        -1.811929e+02
Doors_4-5                 1.693968e+03
Doors_5                   3.842089e+03
Wheel_Right-hand drive   -1.075469e+03
Color_Black              -3.674898e+03
Color_Blue               -3.613971e+03
Color_Brown              -2.203061e+03
Color_Carnelian red      -3.737704e+03
Color_Golden             -2.094258e+03
Color_Green              -1.831197e+03
Color_Grey               -2.635156e+03
Color_Orange             -7.325694e+03
Color_Pink               -3.231098e+02
Color_Purple             -3.984598e+03
Color_Red                -4.720031e+03
Color_Silver             -4.479400e+03
Color_Sky blue           -2.100469e+03
Color_White              -3.700638e+03
Color_Yellow             -4.727896e+03
```

Positive sign indicates that as the predictor variable increases, the target variable also increases. Negative sign indicates that as the predictor variable increases, the target variable dectreases

[116]:
```
# predicted variable
predictions = model.predict(X_test)
predictions
```

[116]:
```
array([ 8241.53657265, 26390.77912694, 30672.4740071 , …,
        5381.73717041, 25613.79114204, 43738.27012917])
```

[117]:
```
plt.title("Test vs Prediction")
ax = sns.regplot(y_test,predictions,scatter_kws={"color": "green"},␣
 ↪line_kws={"color": "red"})
plt.xlabel("Prediction")
plt.ylabel("Test")
plt.show()
```



The graph above shows our model is predicting good results.

[118]:
```
import statsmodels.api as sm
X_train_Sm= sm.add_constant(X_train)
X_train_Sm= sm.add_constant(X_train)
ls=sm.OLS(y_train,X_train_Sm).fit()
print(ls.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Price   R-squared:                       0.519
Model:                            OLS   Adj. R-squared:                  0.518
Method:                 Least Squares   F-statistic:                     308.3
Date:                Sun, 23 Oct 2022   Prob (F-statistic):               0.00
Time:                        20:40:16   Log-Likelihood:            -1.4611e+05
No. Observations:               13451   AIC:                         2.923e+05
```

```
Df Residuals:                   13403   BIC:                         2.927e+05
Df Model:                          47
Covariance Type:            nonrobust
================================================================================
============
                          coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
------------
const               -1.89e+06   5.83e+04    -32.436      0.000      -2e+06
-1.78e+06
Levy                  -2.5046      0.230    -10.906      0.000      -2.955
-2.054
MakeModel           2.466e+05   3240.304     76.093      0.000     2.4e+05
2.53e+05
Prod_year            946.7130     29.036     32.605      0.000     889.798
1003.628
Mileage             6.478e-07   2.75e-06      0.236      0.814   -4.74e-06
6.04e-06
Engine_volume       2470.1093    172.214     14.343      0.000    2132.546
2807.673
Cylinders           -461.8217    143.242     -3.224      0.001    -742.597
-181.046
Airbags             -385.3728     29.227    -13.186      0.000    -442.662
-328.084
Category_Coupe     -5478.8904   2982.037     -1.837      0.066   -1.13e+04
366.323
Category_Goods wagon -1.02e+04  3160.737     -3.227      0.001   -1.64e+04
-4004.659
Category_Hatchback -6594.2028   2986.166     -2.208      0.027   -1.24e+04
-740.897
Category_Jeep      -6550.8066   2980.991     -2.198      0.028   -1.24e+04
-707.643
Category_Limousine  1.027e+04   5695.922      1.803      0.071    -895.791
2.14e+04
Category_Microbus  -9985.2726   3108.386     -3.212      0.001   -1.61e+04
-3892.397
Category_Minivan   -7594.8086   3030.433     -2.506      0.012   -1.35e+04
-1654.733
Category_Pickup    -1.062e+04   3619.903     -2.934      0.003   -1.77e+04
-3525.145
Category_Sedan     -7787.7109   2970.624     -2.622      0.009   -1.36e+04
-1964.870
Category_Universal -3374.0751   3089.181     -1.092      0.275   -9429.306
2681.156
Leather_interior_Yes -1893.9315  316.504     -5.984      0.000   -2514.324
-1273.539
Fuel_type_Diesel    -777.3679    778.584     -0.998      0.318   -2303.503
```

```
748.767
Fuel_type_Hybrid        -4178.9652    794.177     -5.262      0.000   -5735.665
-2622.266
Fuel_type_Hydrogen      -4709.0568   1.27e+04     -0.371      0.710   -2.96e+04
2.01e+04
Fuel_type_LPG           -3035.6685    929.185     -3.267      0.001   -4857.003
-1214.334
Fuel_type_Petrol        -1682.8287    743.436     -2.264      0.024   -3140.069
-225.589
Fuel_type_Plug-in Hybrid 7748.1164   1861.500      4.162      0.000    4099.314
1.14e+04
Gear_box_type_Manual     5035.0576    542.701      9.278      0.000    3971.286
6098.829
Gear_box_type_Tiptronic  7990.7529    344.796     23.175      0.000    7314.904
8666.602
Gear_box_type_Variator   5202.1188    615.723      8.449      0.000    3995.214
6409.023
Drive_wheels_Front-Rear -1066.7713    381.127     -2.799      0.005   -1813.834
-319.709
Drive_wheels_Rear        -181.1929    428.694     -0.423      0.673   -1021.493
659.107
Doors_4-5                1693.9686    718.641      2.357      0.018     285.330
3102.607
Doors_5                  3842.0893   1543.654      2.489      0.013     816.310
6867.868
Wheel_Right-hand drive  -1075.4695    487.496     -2.206      0.027   -2031.030
-119.909
Color_Black             -3674.8979   1316.045     -2.792      0.005   -6254.532
-1095.264
Color_Blue              -3613.9705   1358.297     -2.661      0.008   -6276.424
-951.517
Color_Brown             -2203.0609   1674.879     -1.315      0.188   -5486.059
1079.937
Color_Carnelian red     -3737.7042   1731.025     -2.159      0.031   -7130.757
-344.651
Color_Golden            -2094.2582   1780.667     -1.176      0.240   -5584.616
1396.099
Color_Green             -1831.1963   1553.306     -1.179      0.238   -4875.895
1213.502
Color_Grey              -2635.1564   1335.948     -1.972      0.049   -5253.803
-16.509
Color_Orange            -7325.6929   1654.104     -4.429      0.000   -1.06e+04
-4083.417
Color_Pink               -323.1097   3193.526     -0.101      0.919   -6582.872
5936.652
Color_Purple            -3984.5981   2687.029     -1.483      0.138   -9251.554
1282.358
Color_Red               -4720.0303   1434.898     -3.289      0.001   -7532.632
```

```
-1907.429
Color_Silver          -4479.3995   1319.197     -3.396      0.001   -7065.211
-1893.588
Color_Sky blue        -2100.4688   1888.044     -1.113      0.266   -5801.301
1600.363
Color_White           -3700.6377   1318.468     -2.807      0.005   -6285.022
-1116.254
Color_Yellow          -4727.8962   2059.596     -2.296      0.022   -8764.994
-690.798
==============================================================================
Omnibus:                 6632.088   Durbin-Watson:                   2.016
Prob(Omnibus):              0.000   Jarque-Bera (JB):           146667.419
Skew:                       1.871   Prob(JB):                         0.00
Kurtosis:                  18.738   Cond. No.                     2.12e+10
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.12e+10. This might indicate that there are
strong multicollinearity or other numerical problems.
```

We Use adjusted R-squared to compare the goodness-of-fit for regression models that contain different numbers of independent variables. out R-squared: 0.519 and Adj. R-squared: 0.518, therefor our R-squared is a moderate fit.

The sign of each coefficient indicates the direction of the relationship between a predictor variable and the response variable.

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Appendix-1 data_fix.py

```
##############################################################################
######
# The purpose of this script is to preprocess the given car data
#   It does so by using an initial sanitization sweep
#   Then it uses individual sanitize processors for the different columns
#
# Contributors:
#   Christopher J. Watson
#   Bin Lu
#   Maimuna Bashir
##############################################################################
######
import re
import csv
import pandas as pd
from IPython.display import display
import data_utils_g1 as du


# This dictionary stores the sanitize functions
sanitize_dict = {}


# Column Sanitize Functions
def id_col_preprocess(value):
    regex = "[^0-9]"
    clean_str = re.sub(regex, '', value)
    return clean_str


def price_levy_col_preprocess(value):
    regex = "[^0-9]"
    clean_str = re.sub(regex, '', value)
    if not clean_str and not clean_str.strip():
        clean_str = "0"
    return clean_str


def manuf_preprocess(value):
    clean_str = str(value).upper()
    clean_str = clean_str.strip()
    return clean_str


def model_preprocess(value):
    clean_str = str(value).upper()
    clean_str = clean_str.strip()
    clean_str = clean_str.replace(',', '.')
    clean_str = clean_str.replace('9-MAR', '9-3')
    return clean_str


def engine_col_preprocess(value):
    if len(value)==0:
        clean_str = ["N/A","N/A"]
```

```python
    liter = value.split()
    if liter[-1] == "Turbo":
        clean_str = [liter[0], liter[-1]]
    else:
        clean_str = [liter[-1], ""]
    return clean_str


def do_nothing(value):
    # print("not implemented")
    return value


def drive_weels(value):
    driveWeels = "4x4"
    cleanData = re.sub(driveWeels, "Front-Rear", value)
    return cleanData


def doors(value):
    One = "4-May"
    Two = "2-Mar"
    Three = ">5"
    cleanData = re.sub(One, "4-5", value)  # if there is "4-May" replace it
with "4-5"
    cleanDataTwo = re.sub(Two, "2-3", cleanData)  # if there is "2-Mar"
replace it with "2-3"
    cleanDataTree = re.sub(Three, "5+", cleanDataTwo)  # if there is ">5"
replace it with "5+"
    return cleanDataTree


def production_year_col_preprocess(value):
    regex = "[^0-9]"
    clean_str = re.sub(regex, '', value)
    if not clean_str and not clean_str.strip():
        clean_str = "0"
    if int(clean_str) < 1886:
        clean_str = "0"
    return clean_str


def category_col_preprocess(value):
    clean_str = value
    if len(clean_str)==0:
        clean_str = "N/A"
    return clean_str


def leather_interior_col_preprocess(value):
    clean_str = value
    if len(clean_str)==0:
        clean_str = "N/A"
    if clean_str.casefold() != "yes" and clean_str.casefold()  != "no":
        clean_str = "N/A"
    return clean_str
```

```python
def fuel_type_col_preprocess(value):
    clean_str = value
    if len(clean_str)==0:
        clean_str = "N/A"
    return clean_str


def mileage_col_preprocess(value):
    if len(value)==0:
        clean_str = "0"
    else:
        clean_str, unit = value.split()
    return clean_str


# Initialization Measures
def init():
    global sanitize_dict
    # add all definitions
    sanitize_dict = {'ID': id_col_preprocess, 'Price':
price_levy_col_preprocess, 'Levy': price_levy_col_preprocess,
                     'Manufacturer': manuf_preprocess, 'Model':
model_preprocess,
                     'Prod_year': production_year_col_preprocess,
                     'Category': category_col_preprocess, 'Leather_interior':
leather_interior_col_preprocess,
                     'Fuel_type': fuel_type_col_preprocess,
                     'Engine_volume': engine_col_preprocess, 'Mileage':
mileage_col_preprocess,
                     'Cylinders': do_nothing,
                     'Gear_box_type': do_nothing, 'Drive_wheels':
drive_weels, 'Wheel': drive_weels, 'Doors': doors,
                     'Color': do_nothing, 'Airbags': do_nothing}


# File Scrubbing Function
def scrub_txt_file():
    # THIS SECTION SCRUBS SPECIAL CHARACTERS FROM THE ENTIRE FILE
    # get the file path
    file_path = du.open_file_general()
    print("Replacing all special characters for clean read")
    bad_string = open(file_path, encoding="utf8").read()
    # create regex that only gets basic characters
    regex = "[^a-zA-Z0-9\n\.\,\-\"]"
    clean_str = re.sub(regex, ' ', bad_string)
    # write out sanitized file
    print("Asking for cleaned data file save location")
    clean_file = du.save_file_string(clean_str)
    print("Printing save location:")
    print(clean_file)

    # THIS SECTION CALLS THE SANITIZE METHODS
    # create working variables
    first_row = True
    df_1 = []
    tmp_a_1 = []
```

```
    # open the cleaner file for processing
    with open(clean_file, 'rt', encoding="utf8") as f:
        # list to store the names of columns
        list_of_column_names = []
        reader = csv.reader(f, skipinitialspace=True, quotechar='"')
        # loop to iterate through the rows of csv
        for xrow in reader:
            if first_row:
                # adding the first row header
                for col in xrow:
                    col = col.replace(' ', '_')
                    col = col.replace('.', '')
                    list_of_column_names.append(col)
                list_of_column_names.append("Turbo")
                # set the flag to continue
                first_row = False
            else:
                # create a storing dictionary
                temp_values = {}
                row_temp = xrow
                # sort the columns through the various preprocessors
                for xcol in range(len(list_of_column_names)-1):
                    if list_of_column_names[xcol] == 'Engine_volume':
                        # account for turbo expansion
                        t1 =
sanitize_dict[list_of_column_names[xcol]](row_temp[xcol])
                        temp_values[list_of_column_names[xcol]] = t1[0]

temp_values[list_of_column_names[len(list_of_column_names)-1]] = t1[1]
                    else:
                        temp_values[list_of_column_names[xcol]] = \

sanitize_dict[list_of_column_names[xcol]](row_temp[xcol])
                # add dictionary to dictionary list
                # Account for empty manufacturing slots by using the model
                if not temp_values["Manufacturer"] and not
temp_values["Manufacturer"].strip():
                    temp_values["Manufacturer"] =
sanitize_dict["Manufacturer"](temp_values["Model"])
                tmp_a_1.append(temp_values)
        # move it all to a panda dataframe
        df_1 = pd.json_normalize(tmp_a_1)
        # make final outfile
        final_out = clean_file[:-4] + "_final.csv"
        # create final CSV
        df_1.to_csv(final_out)
        print(final_out)
        # return data for usage in other applications
        return df_1


def main():
    # sets up the variables needed for run
    print("Setting Up Variables")
    init()
    print("Entering Scrubbing Methods")
    # scrub the output
```

```
    display(scrub_txt_file())


if __name__ == "__main__":
    main()
```

Appendix-1 data_fix.py

```
##############################################################################
######
# The purpose of this script is to have utils for group 1 of MSAAI-500 to use
#   to manipulate data more easily
#
# Contributors:
#   Christopher J. Watson
#   Bin Lu
#   Maimuna Bashir
##############################################################################
######

import tkinter as tk
from tkinter import filedialog
import json
import numpy as np

def load_py_dict():
    print("Asking for dictionary data file path")
    data = ''
    file_path = open_file_general()
    with open(file_path) as f:
        data = f.read()
    dict_res = json.loads(data)
    return dict_res


def save_py_dict(data_dict):
    root = tk.Tk()
    root.withdraw()
    print("Asking for dictionary save file path")
    json_object = json.dumps(data_dict, indent=4)
    fd = filedialog.asksaveasfile(mode='w', defaultextension=".json")
    if fd is None:
        return
    fd.write(json_object)
    fd.close()
    return fd.name


# General Save Function
def save_file_string(out_string):
    fd = filedialog.asksaveasfile(mode='w', defaultextension=".txt")
    if fd is None:
        return
    fd.write(out_string)
    fd.close()
    return fd.name


# General file open dialog
def open_file_general():
    # init windows stuff
    root = tk.Tk()
    root.withdraw()
```

```python
    file_path = filedialog.askopenfilename()
    return file_path


def create_enum_dict(unique_list):
    res_dict = {}
    for i in range(len(unique_list)):
        res_dict[str(i)]=unique_list[i]
    return res_dict


# DON'T USE
# Removing the outliers using IRQ
def iqr_outliers(data, col):
    Q3 = np.quantile(data[col], 0.75)
    Q1 = np.quantile(data[col], 0.25)
    IQR = Q3 - Q1

    outlier_free_list = 0
    filtered_data = 0

    lower_range = Q1 - 1.5 * IQR
    upper_range = Q3 + 1.5 * IQR
    outlier_free_list = [x for x in data[col] if (
            (x > lower_range) & (x < upper_range))]
    filtered_data = data.loc[data[col].isin(outlier_free_list)]
    return filtered_data


# This is our decided outlier removal method
# This is a quantile based capping and flooring method
# This simple method seems to be the best out of all of our other attempts
def remove_outliers2(data, col):
    Q3 = np.quantile(data[col], 0.99985)
    Q1 = np.quantile(data[col], 0.00015)

    lower_range = Q1
    upper_range = Q3
    filtered_data = 0
    outlier_free_list = 0

    outlier_free_list = [x for x in data[col] if (
        (x > lower_range) & (x < upper_range))]
    filtered_data = data.loc[data[col].isin(outlier_free_list)]

    return Q3, Q1, filtered_data


def random_mean_sample(data, group_size):
    n = group_size
    a = len(data)
    b = int(len(data) / n)
    res = []
    for i in range(b):
        x = 0
        temp = n if a >= i * n + n else a - i * n
        for j in range(temp):
```

```
            x += data.iloc[n * i + j]
        res.append(int(x / temp))
        res.sort()
    return res
```