Notebook - Used Car Price Prediction Linear Regression

January 8, 2020

1 Project: Linear Regression Price Predictor for Used Cars

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

from sklearn.linear_model import LinearRegression, Lasso, LassoCV, Ridge,␣
↪RidgeCV, ElasticNet, ElasticNetCV

import statsmodels.api as sm
import statsmodels.formula.api as smf
import patsy

import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
sns.set_style('whitegrid')
```

1.0.1 Section 1: DataFrame Loading, Cleaning

[2]:
```
# Returns you all the variables in the current environment

# dir()

# Refer to this link: https://stackoverflow.com/questions/633127/
↪viewing-all-defined-variables
# To find out out to view all defined variables in the current environment
```

[3]:
```
df_main = pd.read_csv('cars.csv')
df_main.sample(5)
```

[3]:
```
      manufacturer_name model_name transmission body_type  production_year  \
11264            Toyota     innova       Số tay       MPV             2015
8175             Toyota   fortuner   Số tự động       SUV             2019
11456            Toyota       vios       Số tay     Sedan             2010
6897             Toyota       vios       Số tay     Sedan             2015
19544            Toyota   fortuner   Số tự động       SUV             2019
```

```
       number_of_seat  odometer_value color_body engine_fuel  engine_type  \
11264               7        170000.0        NaN        Xăng          NaN
8175                7          7000.0  Xám (ghi)      Diesel          NaN
11456               5         98500.0        Bạc        Xăng          NaN
6897                5         62000.0  Xám (ghi)        Xăng          NaN
19544               7          7000.0  Xám (ghi)      Diesel          NaN

       engine_capacity                drivetrain         price  \
11264              NaN                       NaN  4.900000e+08
8175               NaN    RFD - Dẫn động cầu sau  1.030000e+09
11456              NaN  FWD - Dẫn động cầu trước  3.000000e+08
6897               NaN  FWD - Dẫn động cầu trước  3.700000e+08
19544              NaN    RFD - Dẫn động cầu sau  1.030000e+09

                                                     url
11264  http://oto.com.vn/mua-ban-xe-toyota-innova-ha-…
8175   http://oto.com.vn/mua-ban-xe-toyota-fortuner-h…
11456  http://oto.com.vn/mua-ban-xe-toyota-vios-phu-t…
6897   http://oto.com.vn/mua-ban-xe-toyota-vios-ha-no…
19544  http://oto.com.vn/mua-ban-xe-toyota-fortuner-h…
```

[4]:
```
df_main.columns
```

[4]:
```
Index(['manufacturer_name', 'model_name', 'transmission', 'body_type',
       'production_year', 'number_of_seat', 'odometer_value', 'color_body',
       'engine_fuel', 'engine_type', 'engine_capacity', 'drivetrain', 'price',
       'url'],
      dtype='object')
```

[5]:
```
df_main.describe()
```

[5]:
```
       production_year  number_of_seat  odometer_value  engine_type  \
count     20540.000000    20540.000000    1.719800e+04          0.0
mean       2013.443427        5.433009    7.035604e+04          NaN
std           4.853385        1.231451    1.859967e+05          NaN
min        1965.000000        0.000000    1.000000e+00          NaN
25%        2010.000000        5.000000    3.000000e+04          NaN
50%        2015.000000        5.000000    5.500000e+04          NaN
75%        2017.000000        5.000000    1.080000e+05          NaN
max        2019.000000       47.000000    1.800000e+07          NaN

       engine_capacity         price
count      1138.000000  2.054000e+04
mean       1591.660808  1.455116e+09
std         491.286989  3.845170e+09
min          20.000000  0.000000e+00
```

```
25%        1496.000000  3.700000e+08
50%        1496.000000  4.760000e+08
75%        1496.000000  8.800000e+08
max        5700.000000  1.790000e+10
```

[6]:
```python
df_clean = df_main.drop(['color_body',
       'engine_fuel', 'engine_type', 'engine_capacity', 'drivetrain',␣
 ↪'url'],axis=1) # Dropping columns that I used for my own reference

# We see that we have NA entries in this dataset.
# We want to drop these NA values or they will pose problems for us later
# The null values can be attributed to the fact that some data is not keyed in␣
 ↪the listing itself,
# or formatting issues due to the varying ways of which people organize the␣
 ↪information of the car in a single listing

df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20540 entries, 0 to 20539
Data columns (total 8 columns):
manufacturer_name    20540 non-null object
model_name           20540 non-null object
transmission         19288 non-null object
body_type            20539 non-null object
production_year      20540 non-null int64
number_of_seat       20540 non-null int64
odometer_value       17198 non-null float64
price                20540 non-null float64
dtypes: float64(2), int64(2), object(4)
memory usage: 1.3+ MB
```

[7]:
```python
# We now have 20540 rows

df_clean.dropna(inplace=True)
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 17027 entries, 0 to 20539
Data columns (total 8 columns):
manufacturer_name    17027 non-null object
model_name           17027 non-null object
transmission         17027 non-null object
body_type            17027 non-null object
production_year      17027 non-null int64
number_of_seat       17027 non-null int64
odometer_value       17027 non-null float64
```

```
price                  17027 non-null float64
dtypes: float64(2), int64(2), object(4)
memory usage: 1.2+ MB
```

[8]:
```
# Taking a look at our data
df_clean.sample(5)
```

[8]:
```
      manufacturer_name model_name transmission  body_type  production_year  \
11675           Hyundai     accent       Số tay      Sedan             2018
259              Daewoo      matiz       Số tay  Hatchback             2001
10507            Toyota      camry   Số tự động      Sedan             2007
19910            Toyota       vios       Số tay      Sedan             2015
14123            Toyota       vios       Số tay      Sedan             2015

       number_of_seat  odometer_value        price
11675               5         11000.0  476000000.0
259                 5      10000000.0          0.0
10507               5        150000.0  432000000.0
19910               5         62000.0  370000000.0
14123               5         62000.0  370000000.0
```

[9]:
```
print(df_clean.columns,'\n',len(df_clean.columns))

# We have 12 features in our columns
```

```
Index(['manufacturer_name', 'model_name', 'transmission', 'body_type',
       'production_year', 'number_of_seat', 'odometer_value', 'price'],
      dtype='object')
 8
```

1.0.2 Section 2: Data Categorizing

1.1 Section 2.1: One-hot encoding TRANSMISSION Column

[10]:
```
# Here, we see that there only two options for transmission - Auto or Manual (i.
 ↪e., Auto or not).
# Therefore, we can do 1-hot encoding for this

df_clean['transmission'].value_counts()
```

[10]:
```
Số tự động    11396
Số tay         5625
Số hỗn hợp        6
Name: transmission, dtype: int64
```

[11]:
```
# Transmission conversion -> 1 for auto, 0 for manual
```

```
df_clean['transmission_convert'] = df_clean['transmission'].apply(lambda x: 1␣
↪if x == 'Số tự động' else 0)
df_clean.drop('transmission',axis=1,inplace=True)
df_clean.rename(columns={'transmission_convert':"transmission"}, inplace=True) ␣
↪# Renaming column back
df_clean.sample(5)
```

[11]:

```
      manufacturer_name model_name body_type  production_year  number_of_seat  \
8307             Toyota     innova       MPV             2015               7
18573               Kia     cerato     Sedan             2010               5
15772            Toyota   fortuner       SUV             2019               7
20478            Toyota      camry     Sedan             2016               5
14865            Toyota      camry     Sedan             2016               5

       odometer_value         price  transmission
8307         170000.0  4.900000e+08             0
18573        108000.0  3.800000e+08             1
15772          7000.0  1.030000e+09             1
20478         36000.0  9.800000e+08             1
14865         36000.0  9.800000e+08             1
```

[12]:

```
indexNames = df_clean[ df_clean['price'] == 0 ].index
df_clean.drop(indexNames , inplace=True)
df_clean.describe()
```

[12]:

```
       production_year  number_of_seat  odometer_value         price  \
count     17026.000000    17026.000000    17026.000000  1.702600e+04
mean       2014.233819        5.380242    68174.348878  1.689566e+09
std           4.207260        1.169015    57817.070771  4.178914e+09
min        1965.000000        2.000000        1.000000  3.600000e+07
25%        2010.000000        5.000000    30000.000000  3.700000e+08
50%        2016.000000        5.000000    55000.000000  4.900000e+08
75%        2018.000000        5.000000   108000.000000  8.850000e+08
max        2019.000000       47.000000  1000000.000000  1.790000e+10

       transmission
count  17026.000000
mean       0.669329
std        0.470468
min        0.000000
25%        0.000000
50%        1.000000
75%        1.000000
max        1.000000
```

[13]:

```
# Performing whitespace stripping prior to dtype manipulation
#df_clean['body_type'].apply(str.strip)
```

```
#df_clean['body_type'].apply(str.lstrip)

# Inspection of the type of Vehicles
df_clean['body_type'].value_counts()
#df_clean['engine_capacity'].value_counts()
```

[13]:
```
Sedan              9885
SUV                2501
Hatchback          2264
MPV                1145
Pick-up Truck      1111
Van/Minivan          69
CUV                  32
Truck                13
Sport Car             2
City Car              2
Special Purpose       1
Coupe                 1
Name: body_type, dtype: int64
```

[14]:
```
df_clean.head()
```

[14]:
```
  manufacturer_name     model_name body_type  production_year  number_of_seat  \
0               Kia         cerato     Sedan             2018               5
1            Toyota         innova       MPV             2016               7
2            Toyota         innova       MPV             2014               8
3            Toyota  corolla-altis     Sedan             2009               5
4               Kia            rio     Sedan             2015               5

   odometer_value        price  transmission
0         15000.0  608000000.0             1
1        151000.0  583000000.0             0
2         82000.0  520000000.0             1
3        127000.0  470000000.0             1
4         70000.0  366000000.0             0
```

1.2 Section 2.2: Datetime conversion

[15]:
```
# Converting reg_date to datetime, and Manufactured year to int

#df_clean['REG_DATE'] = pd.to_datetime(df_clean['REG_DATE'])
df_clean['production_year'] = df_clean['production_year'].astype(int)
df_clean[['production_year']].dtypes
```

[15]:
```
production_year    int32
dtype: object
```

[16]:
```
df_clean.dtypes
```

[16]:
```
manufacturer_name     object
model_name            object
body_type             object
production_year        int32
number_of_seat         int64
odometer_value       float64
price                float64
transmission           int64
dtype: object
```

[17]:
```
# ONLY RUN THIS CELL ONCE!
#df_main['SCRAPE_DATE'] = \
#pd.to_datetime(df_main['SCRAPE_DATE']).dt.year # Convert scrape date to␣
 ↪integer to perform operations on them
```

[18]:
```
#df_main['SCRAPE_DATE'] # Checking dtype
```

1.2.1 Section 2.2.1: Adding a Car Age Column

[19]:
```
# Converting current scrape date from main dataframe to datetime object using␣
 ↪pandas
from datetime import date

# Obtaining number of years from year of manufacture to current year (metric␣
 ↪for how new the car is)
current_year = date.today().year
df_clean['car_age'] = current_year - df_clean['production_year'] # Obtaining␣
 ↪values for age of car
df_clean['car_age'].astype(int)
```

[19]:
```
0         2
1         4
2         6
3        11
4         5
         ..
20535     3
20536     3
20537     9
20538     1
20539    13
Name: car_age, Length: 17026, dtype: int32
```

[20]:
```
# Rearranging Columns
#df_clean = df_clean[['BRAND', 'PRICE', 'DEPRE_VALUE_PER_YEAR', 'MILEAGE_KM',␣
↪'COE_FROM_SCRAPE_DATE', 'DAYS_OF_COE_LEFT',
#                       'REG_DATE', 'MANUFACTURED_YEAR', 'CAR_AGE',␣
↪'DEREG_VALUE_FROM_SCRAPE_DATE', 'OMV', 'ARF',
#                       'ENGINE_CAPACITY_CC', 'ROAD_TAX_PER_YEAR',␣
↪'CURB_WEIGHT_KG',
#                       'NO_OF_OWNERS', 'VEHICLE_TYPE', 'TRANSMISSION']]
df_clean.head()
```

[20]:
```
  manufacturer_name     model_name body_type  production_year  number_of_seat  \
0               Kia         cerato     Sedan             2018               5
1            Toyota         innova       MPV             2016               7
2            Toyota         innova       MPV             2014               8
3            Toyota  corolla-altis     Sedan             2009               5
4               Kia            rio     Sedan             2015               5

   odometer_value        price  transmission  car_age
0         15000.0  608000000.0             1        2
1        151000.0  583000000.0             0        4
2         82000.0  520000000.0             1        6
3        127000.0  470000000.0             1       11
4         70000.0  366000000.0             0        5
```

1.3 Section 2.3:BODY_TYPE To Dummy Variables

[21]:
```
# Making Dummy Variables out of Vehicle Types:

x_vehtype_dummy = patsy.
↪dmatrix('body_type',data=df_clean,return_type='dataframe')
x_vehtype_dummy.head()

# Do we drop the "Intercept" column?
```

[21]:
```
   Intercept  body_type[T.City Car]  body_type[T.Coupe]  \
0        1.0                    0.0                 0.0
1        1.0                    0.0                 0.0
2        1.0                    0.0                 0.0
3        1.0                    0.0                 0.0
4        1.0                    0.0                 0.0

   body_type[T.Hatchback]  body_type[T.MPV]  body_type[T.Pick-up Truck]  \
0                     0.0               0.0                         0.0
1                     0.0               1.0                         0.0
2                     0.0               1.0                         0.0
3                     0.0               0.0                         0.0
```

```
4                   0.0             0.0                        0.0

   body_type[T.SUV]  body_type[T.Sedan]  body_type[T.Special Purpose]  \
0               0.0                 1.0                           0.0
1               0.0                 0.0                           0.0
2               0.0                 0.0                           0.0
3               0.0                 1.0                           0.0
4               0.0                 1.0                           0.0

   body_type[T.Sport Car]  body_type[T.Truck]  body_type[T.Van/Minivan]
0                     0.0                 0.0                       0.0
1                     0.0                 0.0                       0.0
2                     0.0                 0.0                       0.0
3                     0.0                 0.0                       0.0
4                     0.0                 0.0                       0.0
```

[22]:
```
#df_clean_memory = df_clean.memory_usage(index=True).sum()
x_vehtype_dummy_memory = x_vehtype_dummy.memory_usage(index=True).sum()
#print("df_clean_memory dataset uses ",df_clean_memory/ 1024**2," MB")
#print("x_vehtype_dummy_memory dataset uses ",x_vehtype_dummy_memory/ 1024**2,"␣
↪MB")
df_clean2 = df_clean.join(x_vehtype_dummy)
df_clean2
```

[22]:
```
      manufacturer_name     model_name      body_type  production_year  \
0                   Kia         cerato          Sedan             2018
1                Toyota         innova            MPV             2016
2                Toyota         innova            MPV             2014
3                Toyota  corolla-altis          Sedan             2009
4                   Kia            rio          Sedan             2015
…                     …              …              …                …
20535              Ford         ranger  Pick-up Truck             2017
20536            Toyota       fortuner            SUV             2017
20537       Rolls-Royce        phantom          Sedan             2011
20538            Toyota       fortuner            SUV             2019
20539            Toyota          camry          Sedan             2007

       number_of_seat  odometer_value         price  transmission  car_age  \
0                   5         15000.0  6.080000e+08             1        2
1                   7        151000.0  5.830000e+08             0        4
2                   8         82000.0  5.200000e+08             1        6
3                   5        127000.0  4.700000e+08             1       11
4                   5         70000.0  3.660000e+08             0        5
…                   …               …             …             …        …
20535               5         55000.0  7.900000e+08             1        3
20536               7         55000.0  8.850000e+08             0        3
20537               4         30000.0  1.790000e+10             1        9
```

```
20538              7         7000.0  1.030000e+09            1        1
20539              5       150000.0  4.320000e+08            1       13

       Intercept  …  body_type[T.Coupe]  body_type[T.Hatchback]  \
0            1.0  …                 0.0                     0.0
1            1.0  …                 0.0                     0.0
2            1.0  …                 0.0                     0.0
3            1.0  …                 0.0                     0.0
4            1.0  …                 0.0                     0.0
…              …  …                   …                       …
20535        1.0  …                 0.0                     0.0
20536        1.0  …                 0.0                     0.0
20537        1.0  …                 0.0                     0.0
20538        1.0  …                 0.0                     0.0
20539        1.0  …                 0.0                     0.0

       body_type[T.MPV]  body_type[T.Pick-up Truck]  body_type[T.SUV]  \
0                   0.0                         0.0               0.0
1                   1.0                         0.0               0.0
2                   1.0                         0.0               0.0
3                   0.0                         0.0               0.0
4                   0.0                         0.0               0.0
…                     …                           …                 …
20535               0.0                         1.0               0.0
20536               0.0                         0.0               1.0
20537               0.0                         0.0               0.0
20538               0.0                         0.0               1.0
20539               0.0                         0.0               0.0

       body_type[T.Sedan]  body_type[T.Special Purpose]  \
0                     1.0                           0.0
1                     0.0                           0.0
2                     0.0                           0.0
3                     1.0                           0.0
4                     1.0                           0.0
…                       …                             …
20535                 0.0                           0.0
20536                 0.0                           0.0
20537                 1.0                           0.0
20538                 0.0                           0.0
20539                 1.0                           0.0

       body_type[T.Sport Car]  body_type[T.Truck]  body_type[T.Van/Minivan]
0                         0.0                 0.0                       0.0
1                         0.0                 0.0                       0.0
2                         0.0                 0.0                       0.0
3                         0.0                 0.0                       0.0
```

```
4                   0.0                0.0                  0.0
…                 …                …                  …
20535               0.0                0.0                  0.0
20536               0.0                0.0                  0.0
20537               0.0                0.0                  0.0
20538               0.0                0.0                  0.0
20539               0.0                0.0                  0.0

[17026 rows x 21 columns]
```

1.4 Section 2.4: Car Brand Categorization. Includes:

- Splitting them into Dummy Variables
- Indexing them into price range categories (perhaps better metric over vehicle types)
- Converting lesser-known brands into "others"

[23]:
```
# Renaming Brand Names to their actual names

#df_clean2.loc[df_clean2['BRAND'] == 'Aston','BRAND'] = 'Aston Martin'
#df_clean2.loc[df_clean2['BRAND'] == 'Land','BRAND'] = 'Land Rover'
#df_clean2.loc[df_clean2['BRAND'] == 'Alfa', 'BRAND'] = 'Alfa Romeo'
#df_clean2.head()
```

[24]:
```
# Cleaning whitespaces from the values in "Brand" to prevent any messup later
#df_clean2['manufacturer_name'].apply(str.strip)

# Checking the number of brands in the dataset
print("# Of rows in DataFrame in Brands Column:\n", df_clean2.loc[:
 ↪,'manufacturer_name'])
print("\nValue Counts of Brands:\n", df_clean2.loc[:,'manufacturer_name'].
 ↪value_counts())
print("\n# of Brands:", len(df_clean2.loc[:,'manufacturer_name'].
 ↪value_counts()))

# New Column ATAS
# New Column Budget Cars
# Top 20 brands
# Am I comfortable with grouping uncommon cars into others?
```

```
# Of rows in DataFrame in Brands Column:
 0                Kia
1             Toyota
2             Toyota
3             Toyota
4                Kia
            …
20535           Ford
```

```
20536         Toyota
20537    Rolls-Royce
20538         Toyota
20539         Toyota
Name: manufacturer_name, Length: 17026, dtype: object

Value Counts of Brands:
 Toyota           8693
Kia              2228
Mercedes-Benz    1207
Hyundai          1182
Ford             1178
Mazda            1098
Rolls-Royce      1046
Lexus              70
Honda              55
Chevrolet          54
Mitsubishi         32
LandRover          28
BMW                25
Audi               23
Nissan             23
Daewoo             16
Suzuki             13
Porsche             7
Cadillac            7
Bentley             5
Jaguar              4
Acura               4
Isuzu               4
Renault             3
Peugeot             3
Mini                2
Volkswagen          2
Zotye               2
Cửu Long            2
Fuso                1
Subaru              1
FAW                 1
Hino                1
Thaco               1
Samco               1
Infiniti            1
Fiat                1
Ssangyong           1
Maserati            1
Name: manufacturer_name, dtype: int64
```

```
# of Brands: 39
```

1.5 Section 3: Data Visualization

- EDA
- Correlation Matrix
- Pairplots

1.6 Section 3.1: Preliminary Correlation Exploration

1.6.1 Section 3.1.1: Analysis without Car Brands and Vehicle Types for Feature Dropping

[25]:
```
df_clean2.columns
```

[25]:
```
Index(['manufacturer_name', 'model_name', 'body_type', 'production_year',
       'number_of_seat', 'odometer_value', 'price', 'transmission', 'car_age',
       'Intercept', 'body_type[T.City Car]', 'body_type[T.Coupe]',
       'body_type[T.Hatchback]', 'body_type[T.MPV]',
       'body_type[T.Pick-up Truck]', 'body_type[T.SUV]', 'body_type[T.Sedan]',
       'body_type[T.Special Purpose]', 'body_type[T.Sport Car]',
       'body_type[T.Truck]', 'body_type[T.Van/Minivan]'],
      dtype='object')
```

[26]:
```
df_price_no_brands = df_clean2[['model_name', 'body_type', 'production_year',
       'number_of_seat', 'odometer_value', 'price', 'transmission',
       'car_age']]
df_price_no_brands.head()
```

[26]:
```
      model_name body_type  production_year  number_of_seat  odometer_value  \
0         cerato     Sedan             2018               5         15000.0
1         innova       MPV             2016               7        151000.0
2         innova       MPV             2014               8         82000.0
3  corolla-altis     Sedan             2009               5        127000.0
4            rio     Sedan             2015               5         70000.0

         price  transmission  car_age
0  608000000.0             1        2
1  583000000.0             0        4
2  520000000.0             1        6
3  470000000.0             1       11
4  366000000.0             0        5
```

[27]:
```
# Corr Matrix
df_price_no_brands.corr()
```

[27]:
```
                 production_year  number_of_seat  odometer_value     price  \
production_year         1.000000        0.236846       -0.722899 -0.154397
number_of_seat          0.236846        1.000000        0.112451 -0.277573
odometer_value         -0.722899        0.112451        1.000000 -0.207174
price                  -0.154397       -0.277573       -0.207174  1.000000
transmission           -0.101326       -0.298632       -0.142373  0.199955
car_age                -1.000000       -0.236846        0.722899  0.154397

                 transmission   car_age
production_year     -0.101326 -1.000000
number_of_seat      -0.298632 -0.236846
odometer_value      -0.142373  0.722899
price                0.199955  0.154397
transmission         1.000000  0.101326
car_age              0.101326  1.000000
```

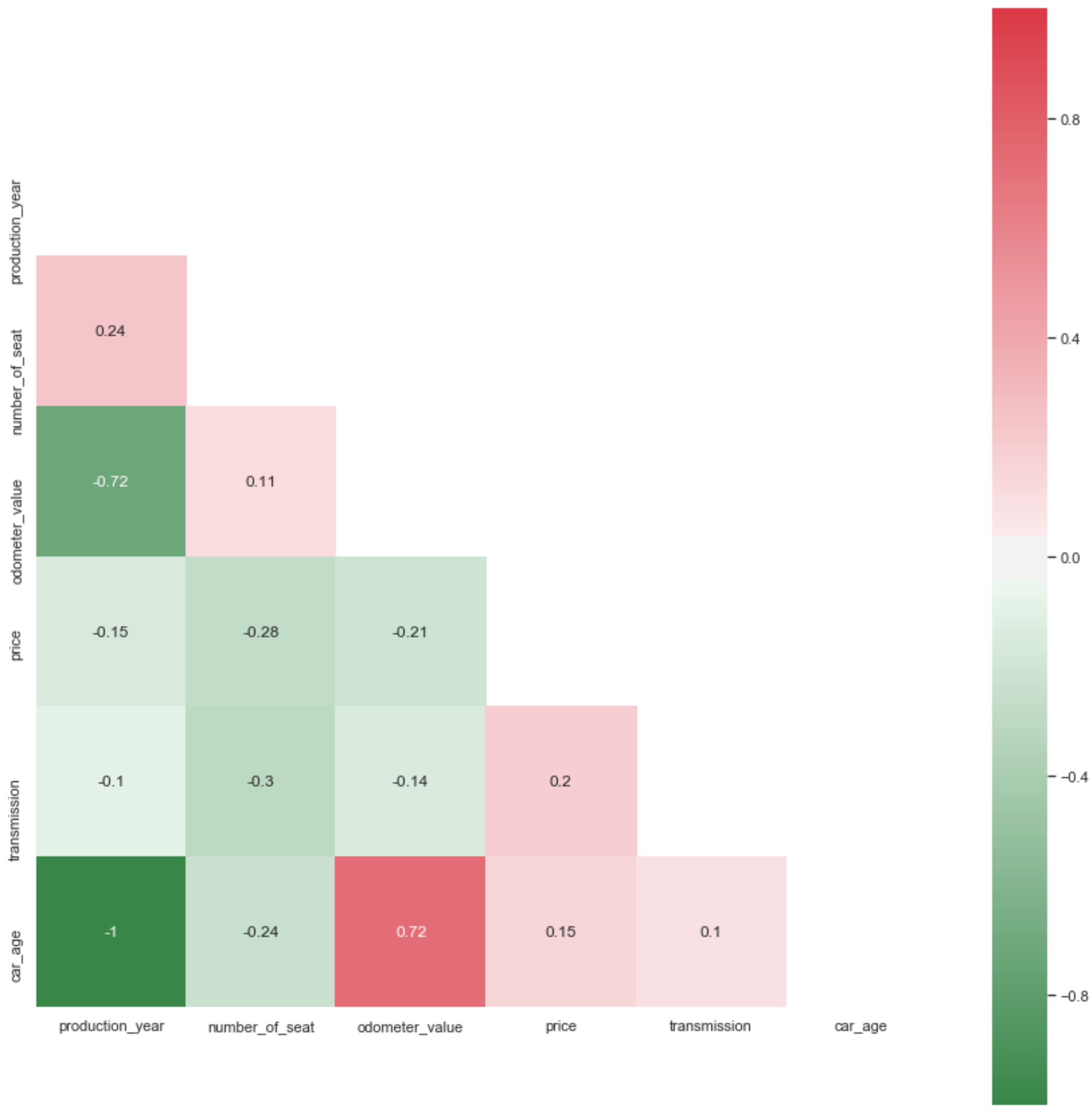
[28]:
```
# How each feature relates to price
df_price_no_brands.corr()['price'].sort_values(ascending=False)
```

[28]:
```
price              1.000000
transmission       0.199955
car_age            0.154397
production_year   -0.154397
odometer_value    -0.207174
number_of_seat    -0.277573
Name: price, dtype: float64
```

[29]:
```
# Corr Matrix Heatmap Visualization

sns.set(style="white")

# Generate a mask for the upper triangle
mask = np.zeros_like(df_price_no_brands.corr(), dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure to control size of heatmap
fig, ax = plt.subplots(figsize=(15,15))

# Create a custom color palette
cmap = \
sns.diverging_palette(133, 10,
                      as_cmap=True)  # as_cmap returns a matplotlib colormap␣
 ↪object rather than a list of colors
# Green = Good (low correlation), Red = Bad (high correlation) between the␣
 ↪independent variables

# Plot the heatmap
```

```
sns.heatmap(df_price_no_brands.corr(), mask=mask, annot=True,
            square=True, cmap=cmap , vmin=-1, vmax=1,ax=ax);

# Prevent Heatmap Cut-Off Issue
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

[29]: (6.0, 0.0)



1.6.2 Section 3.1.2: Removing Independent Variables with High Correlation to each other

[30]:
```
df_price_no_brands.drop(['production_year','body_type'],axis=1,inplace=True)
df_price_no_brands.columns
```

```
D:\Application\Anaconda2\envs\py3\lib\site-packages\pandas\core\frame.py:4117:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  errors=errors,
```

[30]:
```
Index(['model_name', 'number_of_seat', 'odometer_value', 'price',
       'transmission', 'car_age'],
      dtype='object')
```

1.6.3 Section 3.1.3: Re-Visualizing New Correlation Matrix (with a few features dropped)

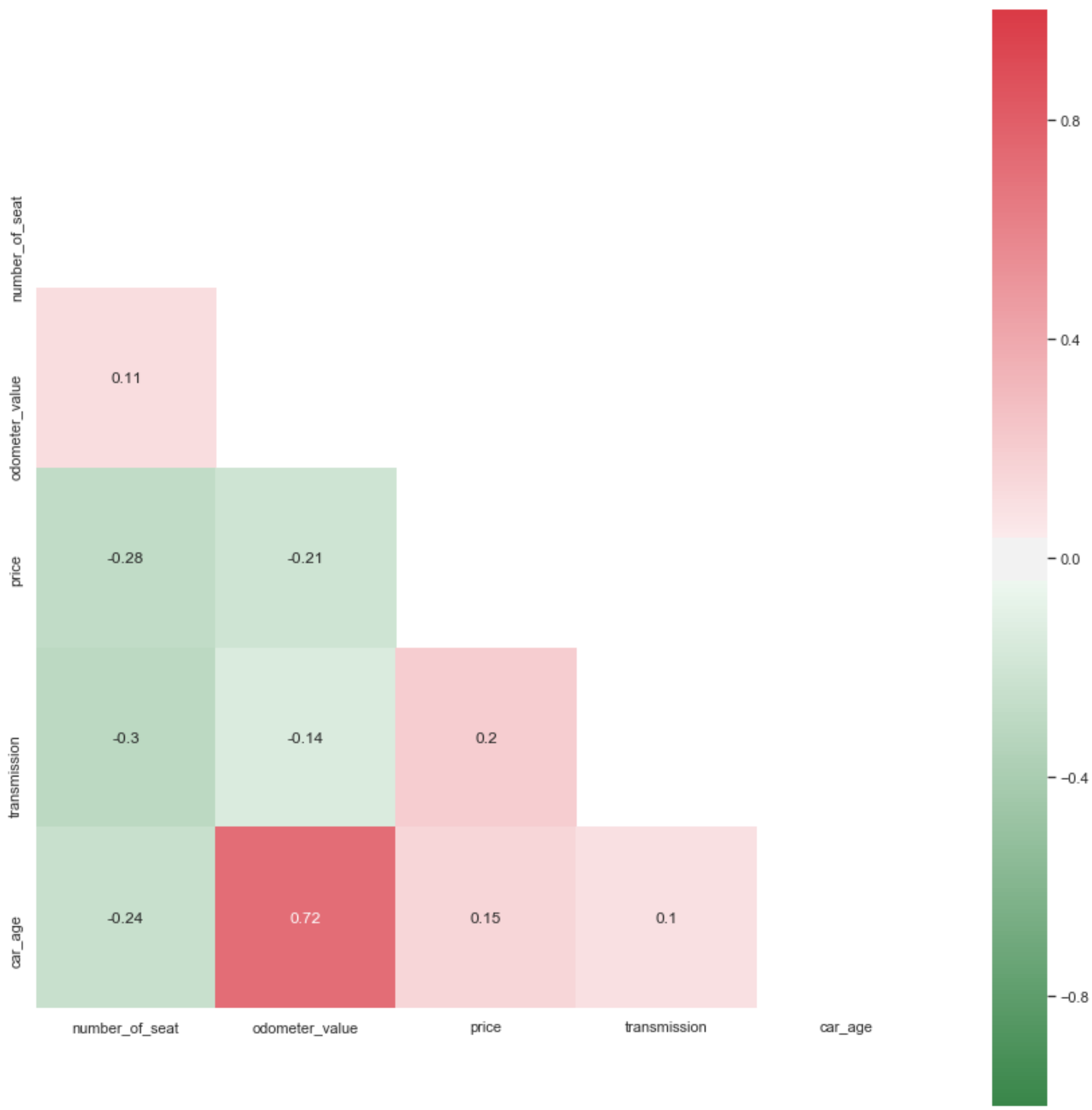
From the above Corr Matrix, we can observe that a few Independent Variables are highly correlated with each other. Interestingly, this makes sense due to how a few of the independent variables are calculated. Therefore, some of these features can be dropped.

Production Year and Car Age: Obviously, production year can be dropped, since Car Age is derived from year of manufacture. And since car age is more intuitive, **Production Year** column will be dropped. From the correlation matrix, they have a correlation of **-1**.

[31]:
```
# Re-visualizing the correlation matrix

sns.set(style="white")

# Creating the data
data = df_price_no_brands.corr()



# Generate a mask for the upper triangle
mask = np.zeros_like(data, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure to control size of heatmap
fig, ax = plt.subplots(figsize=(15,15))

# Create a custom color palette
cmap = \
sns.diverging_palette(133, 10,
```

```
                        as_cmap=True)  # as_cmap returns a matplotlib colormap␣
↪object rather than a list of colors
# Green = Good (low correlation), Red = Bad (high correlation) between the␣
↪independent variables

# Plot the heatmap
sns.heatmap(data, mask=mask, annot=True,
            square=True, cmap=cmap , vmin=-1, vmax=1,ax=ax);

# Prevent Heatmap Cut-Off Issue
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

[31]: (5.0, 0.0)

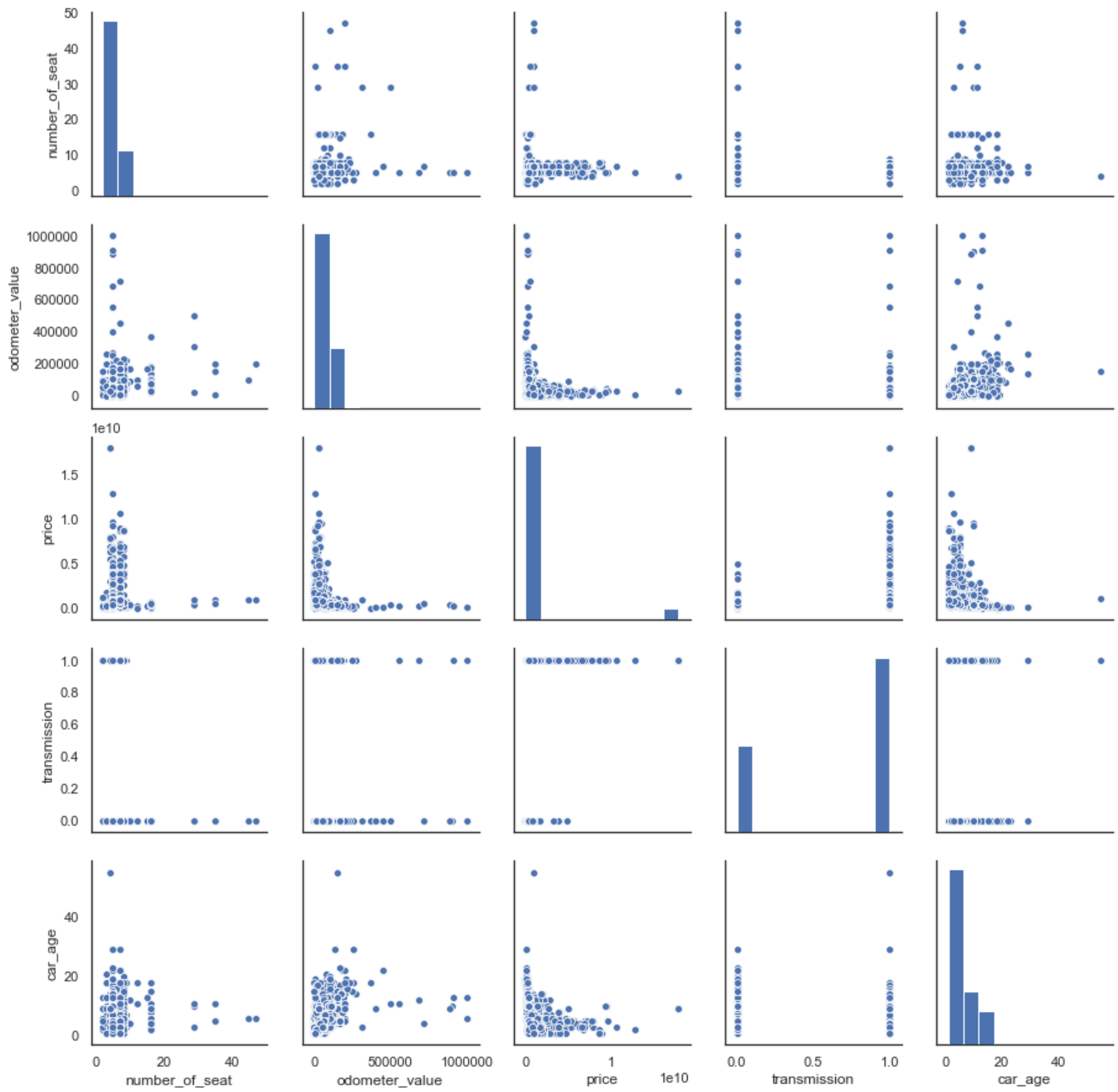


[32]:
```
# Correlations of the independent variables (features) to dependent variable␣
↪(target, price)
df_price_no_brands.corr()['price'].sort_values(ascending=False)
```

[32]:
```
price             1.000000
transmission      0.199955
car_age           0.154397
odometer_value   -0.207174
number_of_seat   -0.277573
Name: price, dtype: float64
```

Section 3.1.3.1: Pairplot after Feature Selection

[33]:
```
# Performing a pairplot to visualize the data trends of the variables

# We can see that price and mileage hold a negative linear relationship
# COE from the scrape date doesn't seem to have a very clear relatonship here
# Days of COE seems to have a slight linear r/s
# Car age doesn't seem to have a very distinct relationship here. But␣
↪generally, the younger the car, the higher the price
# OMV has a clear increasing linear rs with price with price
# Engine capacity seems to also have a increasing linear r/s  with price, with␣
↪a few outliers in the center
# Perhaps it's because a lot of the higher-priced cars (higher brands) are␣
↪produced in that engine capacity range?
# Curb weight seems to have a linear r/s too.

sns.pairplot(df_price_no_brands);
```



[34]:
```
df_price_no_brands.columns
```

[34]:
```
Index(['model_name', 'number_of_seat', 'odometer_value', 'price',
       'transmission', 'car_age'],
      dtype='object')
```

1.6.4 Section 3.2: Preliminary Model fitting to check R^2 Value and P>|t| values of Price and the leftover Independent Variables

[35]:
```
# Slicing Data into Independent Variables (Features) and Dependent Variable␣
↪(Target)
#df_price_no_brands.dropna(inplace=True)
X = df_price_no_brands[ ['number_of_seat', 'odometer_value', 'transmission',
```

```
        'car_age'] ].astype(float)
X = sm.add_constant(X)
y = df_price_no_brands['price'].astype(int)
```

```
C:\Users\nam.nguyen\AppData\Roaming\Python\Python37\site-
packages\numpy\core\fromnumeric.py:2389: FutureWarning: Method .ptp is
deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```

[36]:
```
X.head()
```

[36]:

	const	number_of_seat	odometer_value	transmission	car_age
0	1.0	5.0	15000.0	1.0	2.0
1	1.0	7.0	151000.0	0.0	4.0
2	1.0	8.0	82000.0	1.0	6.0
3	1.0	5.0	127000.0	1.0	11.0
4	1.0	5.0	70000.0	0.0	5.0

[37]:
```
y.head()
```

[37]:
```
0    608000000
1    583000000
2    520000000
3    470000000
4    366000000
Name: price, dtype: int32
```

[38]:
```
# model / fit / summarize
import statsmodels.api as sm

lsm = sm.OLS(y, X)
results = lsm.fit()
results.summary()
```

[38]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.295
Model:                            OLS   Adj. R-squared:                  0.295
Method:                 Least Squares   F-statistic:                     1778.
Date:                Wed, 08 Jan 2020   Prob (F-statistic):               0.00
Time:                        09:09:32   Log-Likelihood:            -3.6918e+05
No. Observations:               17026   AIC:                         7.384e+05
Df Residuals:                   17021   BIC:                         7.384e+05
Df Model:                           4
Covariance Type:            nonrobust
```

```
==============================================================================
==
                    coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--
const          5.674e+07   3.02e+07      1.879      0.060   -2.46e+06
1.16e+08
number_of_seat  9.707e+07   4.78e+06     20.301      0.000    8.77e+07
1.06e+08
odometer_value  6404.3877    137.269     46.656      0.000    6135.325
6673.450
transmission    1.404e+08   1.11e+07     12.677      0.000    1.19e+08
1.62e+08
car_age        -1.243e+08   1.92e+06    -64.822      0.000   -1.28e+08
-1.21e+08
==============================================================================
Omnibus:                     7813.001   Durbin-Watson:                   2.046
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            45536.917
Skew:                          -2.166   Prob(JB):                         0.00
Kurtosis:                       9.740   Cond. No.                     5.70e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 5.7e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

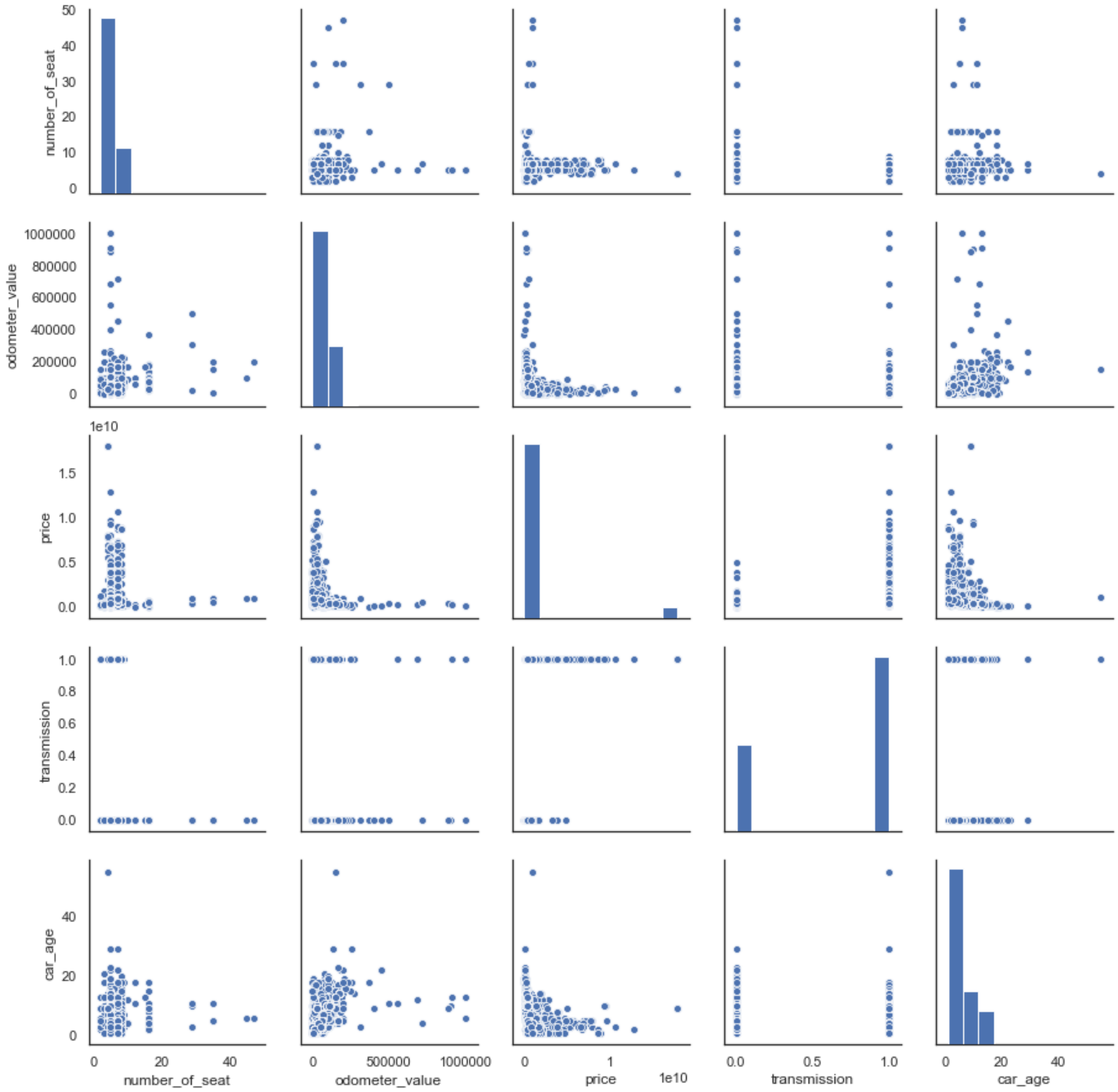
1.6.5 Section 3.2.1: Optimizing R^2 Value

Section 3.2.1.1: Checking Distributions & Pairplots of all Variables

Pairplot of Price vs Independent Variables (without any transformation)

[39]:
```
# Performing a pairplot to visualize the data trends of the variables

# We can see that price and mileage hold a negative linear relationship
# COE from the scrape date doesn't seem to have a very clear relatonship here
# Days of COE seems to have a slight linear r/s
# Car age doesn't seem to have a very distinct relationship here. But
 ↪generally, the younger the car, the higher the price
# OMV has a clear increasing linear rs with price with price
# Engine capacity seems to also have a increasing linear r/s  with price, with
 ↪a few outliers in the center
```

```
# Perhaps it's because a lot of the higher-priced cars (higher brands) are
↪produced in that engine capacity range?
# Curb weight seems to have a linear r/s too.

sns.pairplot(df_price_no_brands);
```

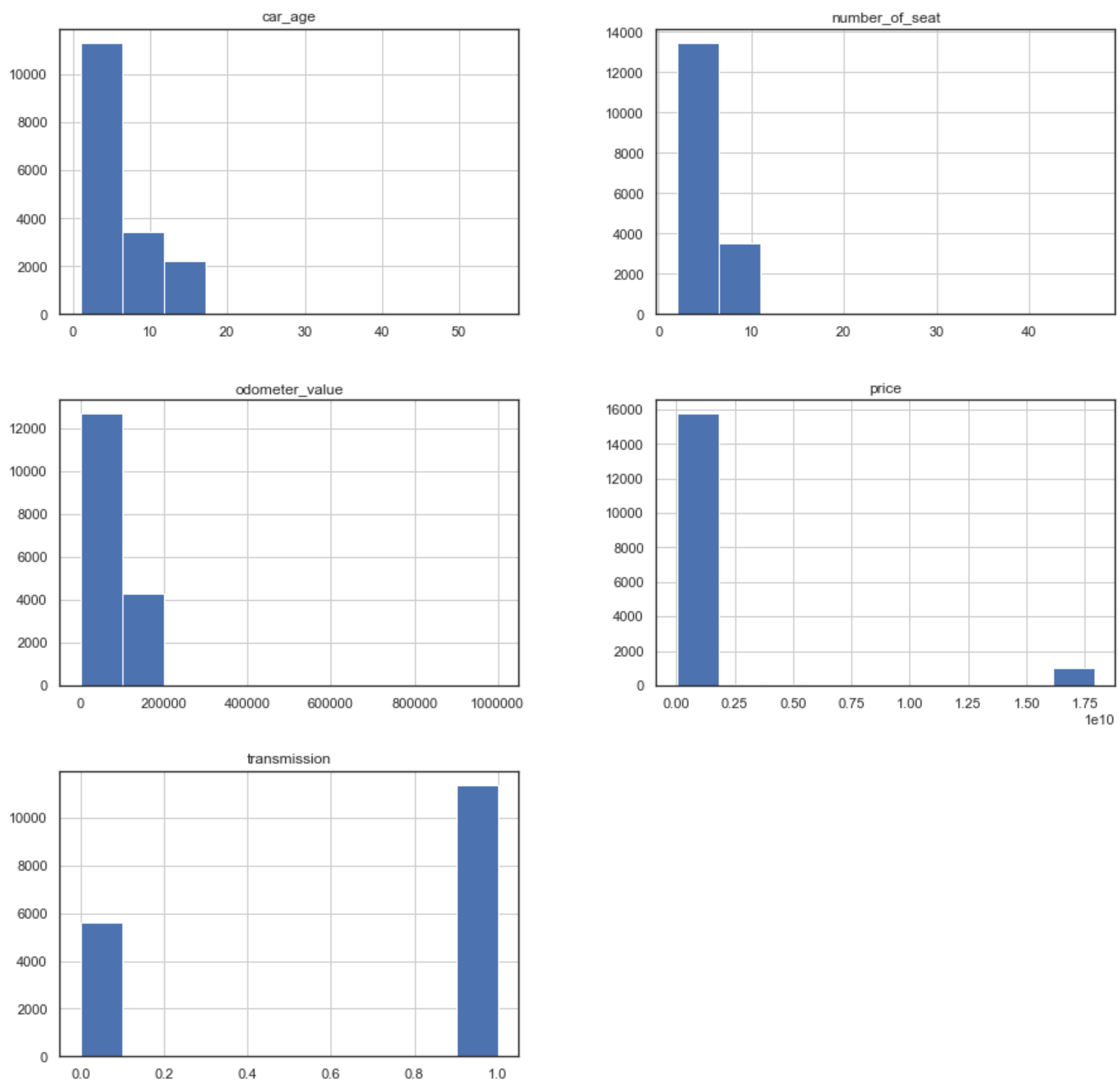


Histograph of all Variables (Columns) in DataFrame

[40]:
```
fig, ax = plt.subplots(figsize=(15,15))
pd.DataFrame.hist(df_price_no_brands,ax=ax)
```

```
D:\Application\Anaconda2\envs\py3\lib\site-packages\ipykernel_launcher.py:2:
UserWarning: To output multiple subplots, the figure containing the passed axes
is being cleared
```

```
[40]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x0000027329B8D408>,
             <matplotlib.axes._subplots.AxesSubplot object at 0x0000027329F4E8C8>],
            [<matplotlib.axes._subplots.AxesSubplot object at 0x000002732C123A88>,
             <matplotlib.axes._subplots.AxesSubplot object at 0x00000273293B9F48>],
            [<matplotlib.axes._subplots.AxesSubplot object at 0x00000273294006C8>,
             <matplotlib.axes._subplots.AxesSubplot object at 0x000002732C15C988>]],
           dtype=object)
```



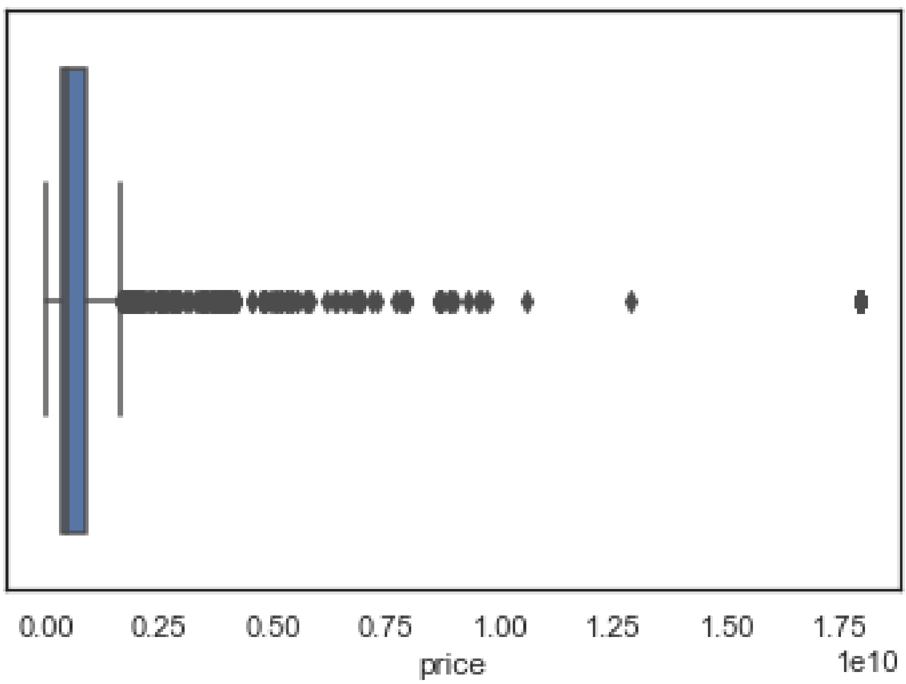

```
[41]: # From the above graphs, it would make sense to apply log transform on the
      ↪following variables to make them
      # more normally distributed
      # Mileage
```

```
# Engine Cap
# Price
# OMV
```

1.7 Distribution of Price

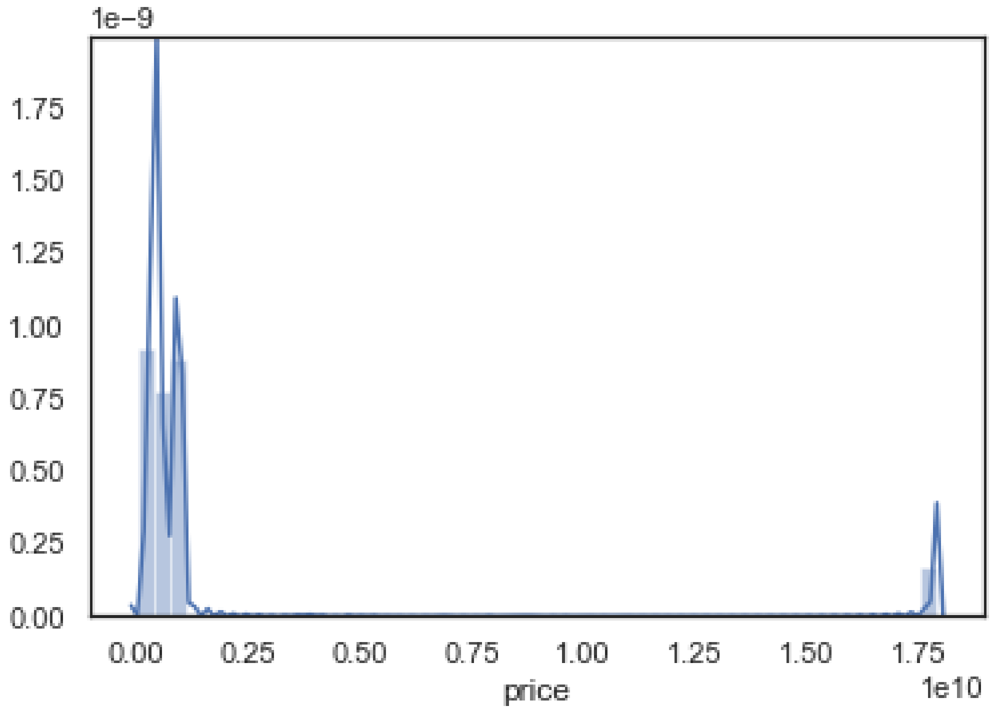
[42]:
```
sns.boxplot(df_price_no_brands['price'])  #
```

[42]: <matplotlib.axes._subplots.AxesSubplot at 0x27329de2848>



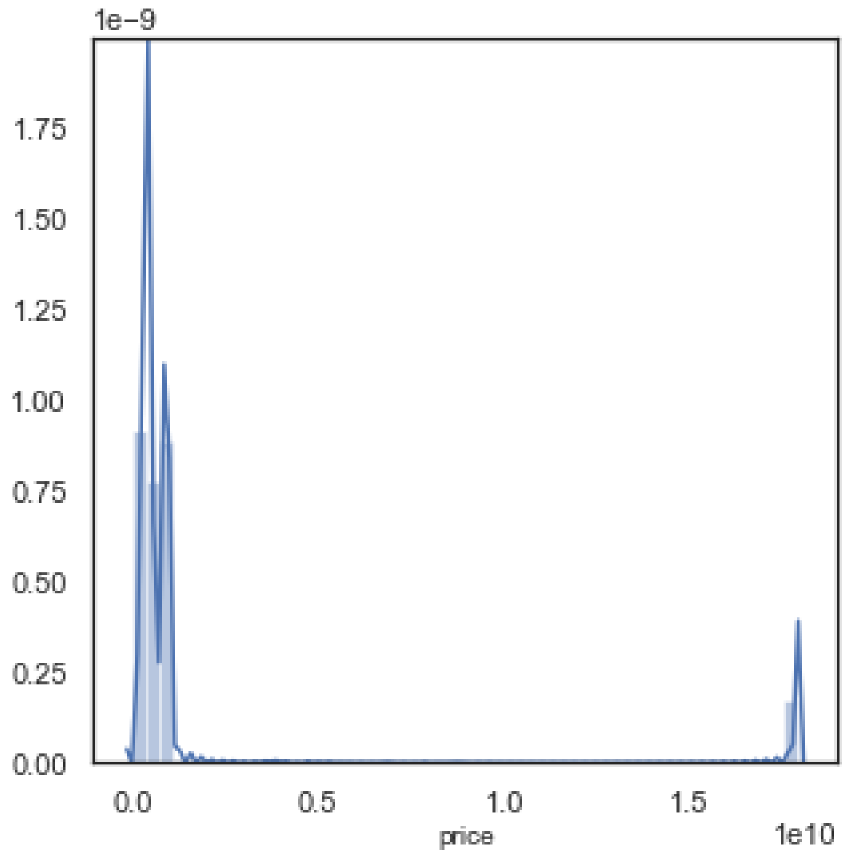
[43]:
```
sns.distplot(df_price_no_brands['price'])  # Your dependent variable 'must' be␣
↪normally distributed
```

[43]: <matplotlib.axes._subplots.AxesSubplot at 0x27329604048>



[44]:
```
# We see that price is right-skewed. Therefore, we can try applying a log onto␣
↪price, then visualize the data again.
```

[45]:
```
fig, ax = plt.subplots(figsize=(5,5))
sns.distplot(df_price_no_brands['price'],ax=ax)
plt.xlabel('price',size=10)
plt.savefig("price_no_log.png",transparent=True)
```



1.7.1 Section 3.2.1: Logging Mileage ONLY

[46]:
```
# Creating a copy of the dataframe to work log on
df_price_no_brands_only_mileage_logged = df_price_no_brands.copy()
```

[47]:
```
# Log Mileage
df_price_no_brands_only_mileage_logged["odometer_value_log"] =␣
↪df_price_no_brands_only_mileage_logged['odometer_value'].apply(np.log)
df_price_no_brands_only_mileage_logged
```

[47]:
```
          model_name  number_of_seat  odometer_value         price  \
0             cerato               5         15000.0  6.080000e+08
1             innova               7        151000.0  5.830000e+08
2             innova               8         82000.0  5.200000e+08
3      corolla-altis               5        127000.0  4.700000e+08
4                rio               5         70000.0  3.660000e+08
…                  …               …               …             …
20535         ranger               5         55000.0  7.900000e+08
20536       fortuner               7         55000.0  8.850000e+08
```

```
20537        phantom              4       30000.0  1.790000e+10
20538       fortuner              7        7000.0  1.030000e+09
20539          camry              5      150000.0  4.320000e+08

       transmission  car_age  odometer_value_log
0                 1        2            9.615805
1                 0        4           11.925035
2                 1        6           11.314475
3                 1       11           11.751942
4                 0        5           11.156251
…             …       …               …
20535             1        3           10.915088
20536             0        3           10.915088
20537             1        9           10.308953
20538             1        1            8.853665
20539             1       13           11.918391

[17026 rows x 7 columns]
```

[48]:
```python
# Rearranging columns

df_price_no_brands_only_mileage_logged = \
df_price_no_brands_only_mileage_logged[['price', 'odometer_value_log',
       'car_age', 'transmission']]
```

[49]:
```python
df_price_no_brands_only_mileage_logged.columns
df_price_no_brands_only_mileage_logged.describe()
```

[49]:

	price	odometer_value_log	car_age	transmission
count	1.702600e+04	17026.000000	17026.000000	17026.000000
mean	1.689566e+09	10.704260	5.766181	0.669329
std	4.178914e+09	1.053606	4.207260	0.470468
min	3.600000e+07	0.000000	1.000000	0.000000
25%	3.700000e+08	10.308953	2.000000	0.000000
50%	4.900000e+08	10.915088	4.000000	1.000000
75%	8.850000e+08	11.589887	10.000000	1.000000
max	1.790000e+10	13.815511	55.000000	1.000000

[50]:
```python
# Slicing Data into Independent Variables (Features) and Dependent Variable␣
↪(Target)
X = df_price_no_brands_only_mileage_logged[ [ 'odometer_value_log',
       'car_age', 'transmission'] ].astype(float)
X = sm.add_constant(X)
y = df_price_no_brands_only_mileage_logged['price'].astype(int)


# model / fit / summarize
```

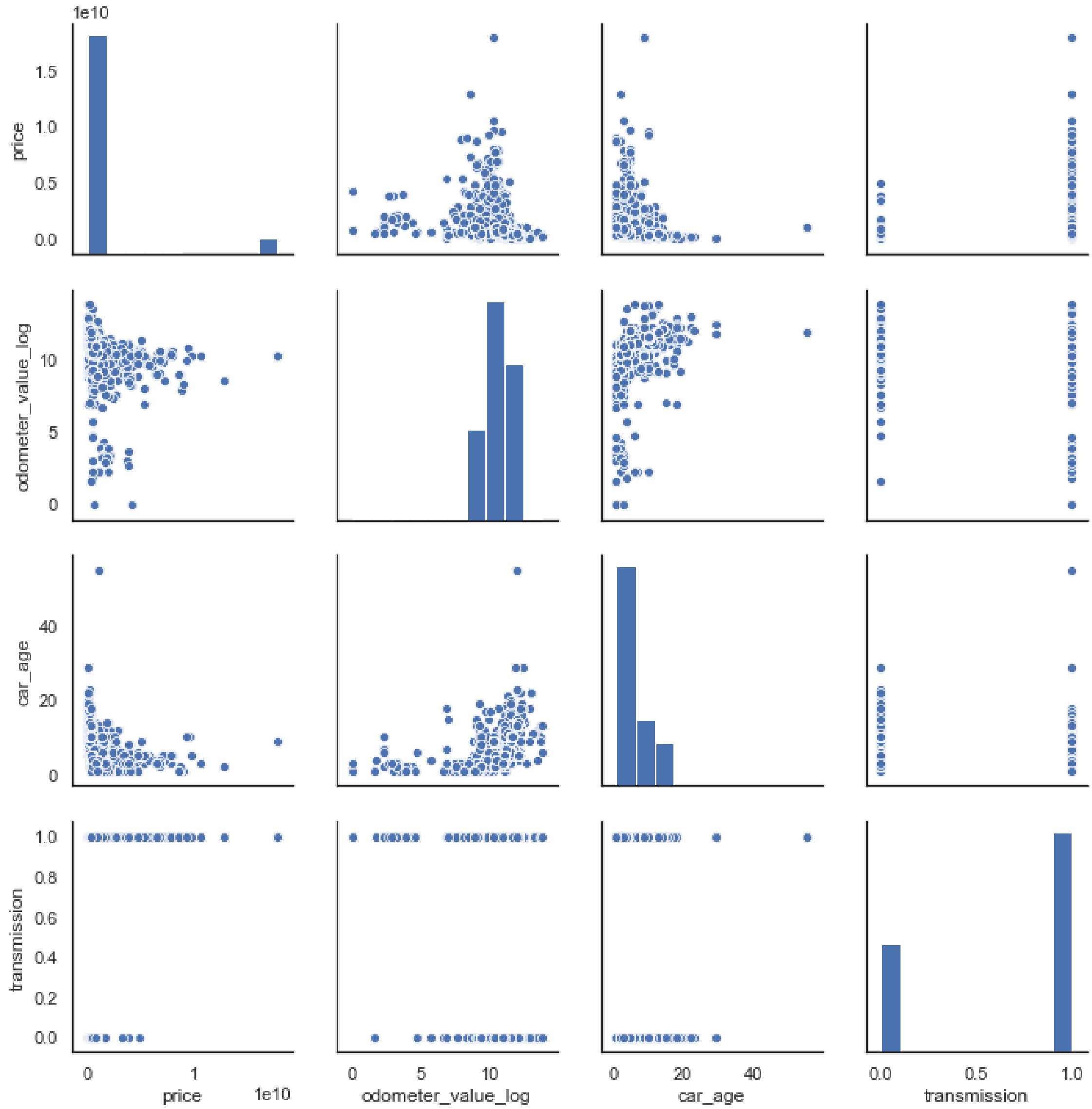
```python
import statsmodels.api as sm

lsm = sm.OLS(y, X)
results = lsm.fit()
results.summary()
```

```
C:\Users\nam.nguyen\AppData\Roaming\Python\Python37\site-
packages\numpy\core\fromnumeric.py:2389: FutureWarning: Method .ptp is
deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```

[50]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.225
Model:                            OLS   Adj. R-squared:                  0.225
Method:                 Least Squares   F-statistic:                     1648.
Date:                Wed, 08 Jan 2020   Prob (F-statistic):               0.00
Time:                        09:09:42   Log-Likelihood:            -3.6999e+05
No. Observations:               17026   AIC:                         7.400e+05
Df Residuals:                   17022   BIC:                         7.400e+05
Df Model:                           3
Covariance Type:            nonrobust
================================================================================
======
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
------
const             -2.329e+09   7.29e+07    -31.943      0.000   -2.47e+09
-2.19e+09
odometer_value_log  3.152e+08    7.2e+06     43.807      0.000    3.01e+08
3.29e+08
car_age           -1.217e+08   1.79e+06    -68.188      0.000   -1.25e+08
-1.18e+08
transmission       7.356e+07   1.15e+07      6.376      0.000    5.09e+07
9.62e+07
==============================================================================
Omnibus:                     6905.208   Durbin-Watson:                   2.041
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            38017.599
Skew:                          -1.886   Prob(JB):                         0.00
Kurtosis:                       9.274   Cond. No.                         181.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
```

```
specified.
"""
```

[51]:
```
# Visualizing Pairplots of Price vs Other Features and Only Mileage logged

sns.pairplot(df_price_no_brands_only_mileage_logged);
```



1.7.2 Section 3.2.2: Normal Price with Logged Mileage and Squared Engine CC

[52]:
```
# Creating a copy of the dataframe to work log on
#df_price_no_brands_mileage_logged_squared_engine_cap =␣
↪df_price_no_brands_only_mileage_logged.copy()
```

[53]:
```
# Square Engine CC
#df_price_no_brands_mileage_logged_squared_engine_cap["engine_squared"] = \
#df_price_no_brands_mileage_logged_squared_engine_cap['engine_capacity'].
↪apply(lambda x: x**2)
```

[54]:
```
#df_price_no_brands_mileage_logged_squared_engine_cap.columns
```

[55]:
```
# Rearrange columns
#df_price_no_brands_mileage_logged_squared_engine_cap = \
#df_price_no_brands_mileage_logged_squared_engine_cap[['PRICE', 'MILEAGE_LOG',␣
↪'COE_FROM_SCRAPE_DATE', 'DAYS_OF_COE_LEFT',
#        'CAR_AGE', 'OMV', 'ENGINE_SQUARED', 'CURB_WEIGHT_KG',
#        'NO_OF_OWNERS', 'TRANSMISSION']]
```

[56]:
```
# Slicing Data into Independent Variables (Features) and Dependent Variable␣
↪(Target)
#X = df_price_no_brands_mileage_logged_squared_engine_cap[␣
↪['odometer_value_log', 'car_age',
#        'transmission', 'engine_squared'] ].astype(float)
#X = sm.add_constant(X)
#y = df_price_no_brands_only_mileage_logged['price'].astype(int)



# model / fit / summarize
#import statsmodels.api as sm

#lsm = sm.OLS(y, X)
#results = lsm.fit()
#results.summary()
```

[57]:
```
# Visualizing Pairplots of the distributions

#sns.pairplot(df_price_no_brands_mileage_logged_squared_engine_cap);
```

[58]:
```
# Viewing Corr Matrix of Price vs Independent Variables (only logged mileage␣
↪and squared engine CC)

#sns.set(style="white")
#data = df_price_no_brands_mileage_logged_squared_engine_cap.corr()

# Generate a mask for the upper triangle
```

```
#mask = np.zeros_like(data, dtype=np.bool)
#mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure to control size of heatmap
#fig, ax = plt.subplots(figsize=(15,15))

# Create a custom color palette
#cmap = \
#sns.diverging_palette(133, 10,
#                         as_cmap=True)  # as_cmap returns a matplotlib colormap␣
↪object rather than a list of colors
# Green = Good (low correlation), Red = Bad (high correlation) between the␣
↪independent variables

# Plot the heatmap
#sns.heatmap(data, mask=mask, annot=True,
#             square=True, cmap=cmap , vmin=-1, vmax=1,ax=ax);

# Prevent Heatmap Cut-Off Issue
#bottom, top = ax.get_ylim()
#ax.set_ylim(bottom + 0.5, top - 0.5)
```

1.7.3 Section 3.2.3: Logged Price with Logged Mileage and Squared Engine CC

[59]:

```
#df_logged_price_no_brands_mileage_logged_squared_engine_cap =␣
↪df_price_no_brands_mileage_logged_squared_engine_cap.copy()
```

[60]:

```
# Logging Price
#df_logged_price_no_brands_mileage_logged_squared_engine_cap['price_log'] =\
#df_logged_price_no_brands_mileage_logged_squared_engine_cap['price'].apply(np.
↪log)
```

[61]:

```
# Rearrange columns
#df_logged_price_no_brands_mileage_logged_squared_engine_cap = \
#df_logged_price_no_brands_mileage_logged_squared_engine_cap[['price_log',␣
↪'odometer_value_log', 'car_age',
#       'transmission', 'engine_squared']]
```

[62]:

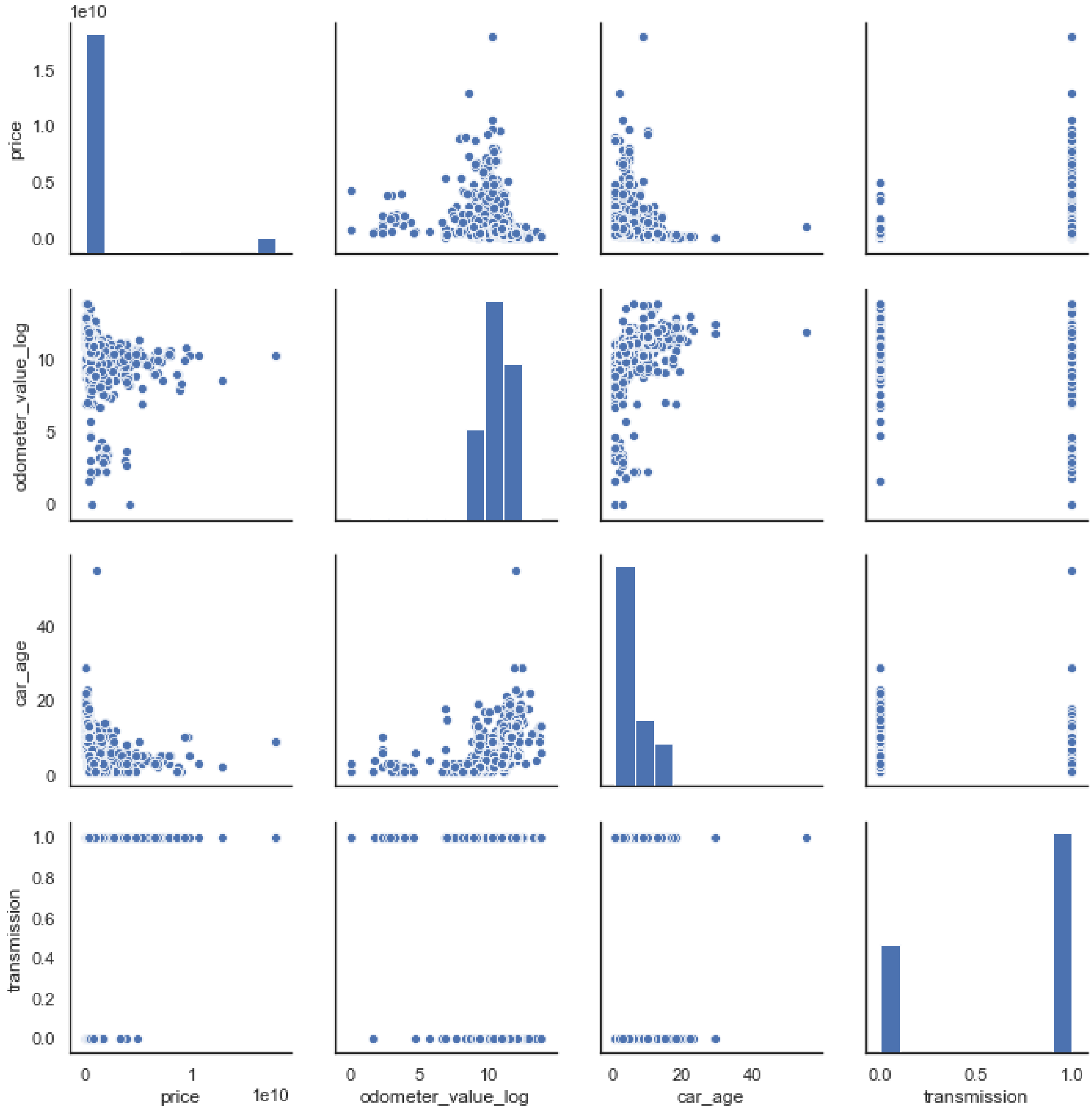
```
# Slicing Data into Independent Variables (Features) and Dependent Variable␣
↪(Target)
#X = df_logged_price_no_brands_mileage_logged_squared_engine_cap[␣
↪['odometer_value_log', 'car_age',
#       'transmission', 'engine_squared'] ].astype(float)
#X = sm.add_constant(X)
#y = df_logged_price_no_brands_mileage_logged_squared_engine_cap['price_log'].
↪astype(float)
```

```
# model / fit / summarize
#import statsmodels.api as sm

#lsm = sm.OLS(y, X)
#results = lsm.fit()
#results.summary()
```

1.7.4 Section 3.2.3: Logged Price with Logged Mileage only (no engine squared)

[63]:
```
df_logged_price_no_brands_only_mileage_logged =␣
↪df_price_no_brands_only_mileage_logged.copy()
```

[64]:
```
sns.pairplot(df_logged_price_no_brands_only_mileage_logged);
plt.savefig("log_price_and_mileage.png")
```



[65]:
```
# Logging Price
df_logged_price_no_brands_only_mileage_logged['price'] =␣
↪df_logged_price_no_brands_only_mileage_logged['price'].apply(np.log)

# Renaming column
df_logged_price_no_brands_only_mileage_logged.rename(columns={'price':
↪'price_log'},inplace=True)
```

[66]:
```
df_logged_price_no_brands_only_mileage_logged.columns
```

[66]:
```
Index(['price_log', 'odometer_value_log', 'car_age', 'transmission'],
dtype='object')
```

[67]:
```
df_logged_price_no_brands_only_mileage_logged.head()
```

[67]:

	price_log	odometer_value_log	car_age	transmission
0	20.225685	9.615805	2	1
1	20.183698	11.925035	4	0
2	20.069339	11.314475	6	1
3	19.968243	11.751942	11	1
4	19.718144	11.156251	5	0

[68]:
```
df_logged_price_no_brands_only_mileage_logged.dropna(inplace=True)
df_logged_price_no_brands_only_mileage_logged.describe()
```

[68]:

	price_log	odometer_value_log	car_age	transmission
count	17026.000000	17026.000000	17026.000000	17026.000000
mean	20.313010	10.704260	5.766181	0.669329
std	0.986852	1.053606	4.207260	0.470468
min	17.399029	0.000000	1.000000	0.000000
25%	19.729014	10.308953	2.000000	0.000000
50%	20.009916	10.915088	4.000000	1.000000
75%	20.601098	11.589887	10.000000	1.000000
max	23.608067	13.815511	55.000000	1.000000

[69]:
```
# Slicing Data into Independent Variables (Features) and Dependent Variable␣
↪(Target)
X = df_logged_price_no_brands_only_mileage_logged[['odometer_value_log',␣
↪'car_age', 'transmission']].astype(float)
X = sm.add_constant(X)
y = df_logged_price_no_brands_only_mileage_logged['price_log'].astype(float)


# model / fit / summarize
import statsmodels.api as sm

lsm = sm.OLS(y, X)
results = lsm.fit()
results.summary()
```

[69]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              price_log   R-squared:                       0.142
Model:                            OLS   Adj. R-squared:                  0.142
Method:                 Least Squares   F-statistic:                     937.1
Date:                Wed, 08 Jan 2020   Prob (F-statistic):               0.00
Time:                        09:09:55   Log-Likelihood:                -22632.
No. Observations:               17026   AIC:                         4.527e+04
```

```
Df Residuals:                   17022   BIC:                         4.530e+04
Df Model:                           3
Covariance Type:            nonrobust
================================================================================
======
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
------
const                23.1053      0.101    229.692      0.000      22.908
23.302
odometer_value_log   -0.2934      0.010    -29.552      0.000      -0.313
-0.274
car_age               0.0118      0.002      4.780      0.000       0.007
0.017
transmission          0.4192      0.016     26.336      0.000       0.388
0.450
==============================================================================
Omnibus:                     6772.075   Durbin-Watson:                   2.037
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            26406.582
Skew:                           1.998   Prob(JB):                         0.00
Kurtosis:                       7.611   Cond. No.                         181.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

1.7.5 R^2 Summary from Linear Regression Models

Price vs Original Independent Variables:
R^2: **0.295**
R^2 Adjusted: **0.295**
df_price_no_brands

Logged Price vs Independent Variables (Logged Mileage): R^2: **0.142**
R^2 Adjusted: **0.142**
df_logged_price_no_brands_only_mileage_logged

1.8 Section 3.3: Analysis of Car Brands, Vehicle Types, Brand Categorization

1.8.1 3.3.1: Further breaking down dataframe into finalized features (with log price, log mileage)

[70]:
```
df_finalized_features = df_clean2.copy()
```

[71]:
```
# Applying log to the desired features
df_finalized_features['price'] = df_clean2['price'].apply(np.log)
df_finalized_features['odometer_value'] = df_clean2['odometer_value'].apply(np.
↪log)


# Renaming features
df_finalized_features.rename(columns={'price':'price_log',
                                       'odometer_value':
↪'odometer_value_log'},inplace=True)
```

[72]:
```
df_finalized_features.columns
```

[72]:
```
Index(['manufacturer_name', 'model_name', 'body_type', 'production_year',
       'number_of_seat', 'odometer_value_log', 'price_log', 'transmission',
       'car_age', 'Intercept', 'body_type[T.City Car]', 'body_type[T.Coupe]',
       'body_type[T.Hatchback]', 'body_type[T.MPV]',
       'body_type[T.Pick-up Truck]', 'body_type[T.SUV]', 'body_type[T.Sedan]',
       'body_type[T.Special Purpose]', 'body_type[T.Sport Car]',
       'body_type[T.Truck]', 'body_type[T.Van/Minivan]'],
      dtype='object')
```

[73]:
```
# Rearranging Columns and removing unwanted variables
#df_finalized_features = df_finalized_features[['BRAND','PRICE_LOG',␣
↪'MILEAGE_LOG', 'COE_FROM_SCRAPE_DATE', 'DAYS_OF_COE_LEFT',
#        'CAR_AGE', 'OMV', 'ENGINE_CAPACITY_CC', 'CURB_WEIGHT_KG',
#        'NO_OF_OWNERS', 'TRANSMISSION', 'Intercept', 'VEHICLE_TYPE[T.Luxury␣
↪Sedan]',
#        'VEHICLE_TYPE[T.MPV]', 'VEHICLE_TYPE[T.Mid-Sized Sedan]',
#        'VEHICLE_TYPE[T.SUV]', 'VEHICLE_TYPE[T.Sports Car]',
#        'VEHICLE_TYPE[T.Stationwagon]']]
```

[74]:
```
df_logged_price_no_brands_only_mileage_logged.columns
```

[74]:
```
Index(['price_log', 'odometer_value_log', 'car_age', 'transmission'],
dtype='object')
```

[75]:
```
df_finalized_features.columns
```

[75]:
```
Index(['manufacturer_name', 'model_name', 'body_type', 'production_year',
       'number_of_seat', 'odometer_value_log', 'price_log', 'transmission',
       'car_age', 'Intercept', 'body_type[T.City Car]', 'body_type[T.Coupe]',
       'body_type[T.Hatchback]', 'body_type[T.MPV]',
       'body_type[T.Pick-up Truck]', 'body_type[T.SUV]', 'body_type[T.Sedan]',
       'body_type[T.Special Purpose]', 'body_type[T.Sport Car]',
       'body_type[T.Truck]', 'body_type[T.Van/Minivan]'],
      dtype='object')
```

1.8.2 3.3.2: Joining Brand Dummy Variables into Main Dataframe

[76]:
```python
# Creating a new DataFrame for this Brand Categorization
df_categorized_car_brands = df_finalized_features.copy()
```

[77]:
```python
print(df_categorized_car_brands['manufacturer_name'].value_counts())
print(len(df_categorized_car_brands['manufacturer_name'].value_counts()))
```

```
Toyota           8693
Kia              2228
Mercedes-Benz    1207
Hyundai          1182
Ford             1178
Mazda            1098
Rolls-Royce      1046
Lexus              70
Honda              55
Chevrolet          54
Mitsubishi         32
LandRover          28
BMW                25
Audi               23
Nissan             23
Daewoo             16
Suzuki             13
Porsche             7
Cadillac            7
Bentley             5
Jaguar              4
Acura               4
Isuzu               4
Renault             3
Peugeot             3
Mini                2
Volkswagen          2
Zotye               2
Cửu Long            2
Fuso                1
Subaru              1
FAW                 1
Hino                1
Thaco               1
Samco               1
Infiniti            1
Fiat                1
Ssangyong           1
Maserati            1
Name: manufacturer_name, dtype: int64
```

39

[78]:
```
# Creating the relevant columns
df_categorized_car_brands['EXOTIC'] = 0 # Create EXOTIC column
df_categorized_car_brands["ULTRA_LUXURY"] = 0
df_categorized_car_brands["LUXURY"] = 0
df_categorized_car_brands["MID_LEVEL"] = 0
df_categorized_car_brands["ECONOMY"] = 0
```

[79]:
```
# Labelling Car Brands into Exotic
df_categorized_car_brands.loc[(df_clean2['manufacturer_name'] == "Aston␣
 ↪Martin") |
              (df_clean2['manufacturer_name'] == "Ferrari") |
              (df_clean2['manufacturer_name'] == "Lamborghini") |
              (df_clean2['manufacturer_name'] == "McLaren") |
              (df_clean2['manufacturer_name'] == "Hummer"),
              'EXOTIC'] = 1

# Labelling Car Brands into Ultra Luxury
df_categorized_car_brands.loc[(df_clean2['manufacturer_name'] == "Bentley") |
              (df_clean2['manufacturer_name'] == "Land Rover") |
              (df_clean2['manufacturer_name'] == "Maserati") |
              (df_clean2['manufacturer_name'] == "Porsche") |
              (df_clean2['manufacturer_name'] == "Rolls-Royce"),
              "ULTRA_LUXURY"] = 1

# Labelling Car Brands into Luxury

df_categorized_car_brands.loc[(df_clean2['manufacturer_name'] == "Audi") |
              (df_clean2['manufacturer_name'] == "BMW") |
              (df_clean2['manufacturer_name'] == "Jeep") |
              (df_clean2['manufacturer_name'] == "Lexus") |
              (df_clean2['manufacturer_name'] == "Lotus") |
              (df_clean2['manufacturer_name'] == "Mercedes-Benz") |
              (df_clean2['manufacturer_name'] == "Volvo") |
              (df_clean2['manufacturer_name'] == "Peugeot"),
              "LUXURY"] = 1


# Labelling Car Brands into Mid-Level

df_categorized_car_brands.loc[(df_clean2['manufacturer_name'] == "Infiniti") |
              (df_clean2['manufacturer_name'] == "MINI") |
              (df_clean2['manufacturer_name'] == "Volkswagen") |
              (df_clean2['manufacturer_name'] == "Renault") |
              (df_clean2['manufacturer_name'] == "Peugeot"),
              "MID_LEVEL"] = 1
```

```
# (df_clean2['manufacturer_name'] == "Opel") & "Alfa Romeo" will be considered␣
↪as "Others" because it is not a very common brand in Singapore

# Labelling Car Brands into Economy

df_categorized_car_brands.loc[(df_clean2['manufacturer_name'] == "Chevrolet") |
              (df_clean2['manufacturer_name'] == "Citroen") |
              (df_clean2['manufacturer_name'] == "Ford") |
              (df_clean2['manufacturer_name'] == "Honda") |
              (df_clean2['manufacturer_name'] == "Hyundai") |
              (df_clean2['manufacturer_name'] == "Kia") |
              (df_clean2['manufacturer_name'] == "Mazda") |
              (df_clean2['manufacturer_name'] == "Mitsubishi") |
              (df_clean2['manufacturer_name'] == "Nissan") |
              (df_clean2['manufacturer_name'] == "Suzuki") |
              (df_clean2['manufacturer_name'] == "Toyota"),
              "ECONOMY"] = 1

# (df_clean2['manufacturer_name'] == "Ssangyong") will be considered as␣
↪"Others" because it is not a common brand in Singapore

# Changing Uncommon Car brands to "Others"
df_categorized_car_brands.loc[(df_clean2['manufacturer_name'] == 'Opel') |
                  (df_clean2['manufacturer_name'] == 'Ssangyong') |
                  (df_clean2['manufacturer_name'] == 'Proton') |
                  (df_clean2['manufacturer_name'] == 'Daihatsu') |
                  (df_clean2['manufacturer_name'] == 'Fiat') |
                  (df_clean2['manufacturer_name'] == 'Alfa Romeo') |
                  (df_clean2['manufacturer_name'] == 'Skoda') |
                  (df_clean2['manufacturer_name'] == 'Hummer')|
                  (df_clean2['manufacturer_name'] == 'Aston Martin')|
                  (df_clean2['manufacturer_name'] == 'Lotus')|
                  (df_clean2['manufacturer_name'] == 'Ford')|
                  (df_clean2['manufacturer_name'] == 'Jeep'),
                  'manufacturer_name'] = "Others"



# Group uncommon cars into "Others". There are too many brands to work with.
```

[80]:
```
print(df_categorized_car_brands['manufacturer_name'].value_counts())
print(len(df_categorized_car_brands['manufacturer_name'].value_counts()))
```

```
Toyota           8693
Kia              2228
Mercedes-Benz    1207
```

```
Hyundai          1182
Others           1180
Mazda            1098
Rolls-Royce      1046
Lexus              70
Honda              55
Chevrolet          54
Mitsubishi         32
LandRover          28
BMW                25
Audi               23
Nissan             23
Daewoo             16
Suzuki             13
Porsche             7
Cadillac            7
Bentley             5
Acura               4
Jaguar              4
Isuzu               4
Renault             3
Peugeot             3
Mini                2
Zotye               2
Cửu Long            2
Volkswagen          2
Subaru              1
Fuso                1
Samco               1
FAW                 1
Infiniti            1
Thaco               1
Maserati            1
Hino                1
Name: manufacturer_name, dtype: int64
37
```

Brand Dummy Variables Creation

[81]:
```
x_brand_dummy = patsy.dmatrix('manufacturer_name',␣
↪data=df_categorized_car_brands, return_type='dataframe')
x_brand_dummy.head()
```

[81]:
```
   Intercept  manufacturer_name[T.Audi]  manufacturer_name[T.BMW]  \
0        1.0                        0.0                       0.0
1        1.0                        0.0                       0.0
2        1.0                        0.0                       0.0
3        1.0                        0.0                       0.0
```

```
4       1.0                         0.0                          0.0

   manufacturer_name[T.Bentley]  manufacturer_name[T.Cadillac]  \
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

   manufacturer_name[T.Chevrolet]  manufacturer_name[T.Cửu Long]  \
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

   manufacturer_name[T.Daewoo]  manufacturer_name[T.FAW]  \
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

   manufacturer_name[T.Fuso]  …  manufacturer_name[T.Porsche]  \
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

   manufacturer_name[T.Renault]  manufacturer_name[T.Rolls-Royce]  \
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

   manufacturer_name[T.Samco]  manufacturer_name[T.Subaru]  \
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

   manufacturer_name[T.Suzuki]  manufacturer_name[T.Thaco]  \
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

   manufacturer_name[T.Toyota]  manufacturer_name[T.Volkswagen]  \
0                          0.0                              0.0
1                          1.0                              0.0
2                          1.0                              0.0
3                          1.0                              0.0
4                          0.0                              0.0

   manufacturer_name[T.Zotye]
0                         0.0
1                         0.0
2                         0.0
3                         0.0
4                         0.0

[5 rows x 37 columns]
```

[82]:
```
df_categorized_car_brands.drop('Intercept',axis=1,inplace=True)# Drop intercept␣
↪because already have intercept from previous vehicle type
df_categorized_car_brands = df_categorized_car_brands.join(x_brand_dummy)
df_categorized_car_brands
```

[82]:
```
      manufacturer_name     model_name      body_type  production_year  \
0                   Kia         cerato          Sedan             2018
1                Toyota         innova            MPV             2016
2                Toyota         innova            MPV             2014
3                Toyota  corolla-altis          Sedan             2009
4                   Kia            rio          Sedan             2015
…                   …              …              …               …
20535            Others         ranger  Pick-up Truck             2017
20536            Toyota       fortuner            SUV             2017
20537       Rolls-Royce        phantom          Sedan             2011
20538            Toyota       fortuner            SUV             2019
20539            Toyota          camry          Sedan             2007

       number_of_seat  odometer_value_log  price_log  transmission  car_age  \
0                   5            9.615805  20.225685             1        2
1                   7           11.925035  20.183698             0        4
2                   8           11.314475  20.069339             1        6
3                   5           11.751942  19.968243             1       11
4                   5           11.156251  19.718144             0        5
…                 …                 …          …           …      …
20535               5           10.915088  20.487544             1        3
20536               7           10.915088  20.601098             0        3
```

```
20537              4         10.308953  23.608067             1        9
20538              7          8.853665  20.752825             1        1
20539              5         11.918391  19.883936             1       13

       body_type[T.City Car]  …  manufacturer_name[T.Porsche]  \
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
…                          …  …                             …
20535                    0.0  …                           0.0
20536                    0.0  …                           0.0
20537                    0.0  …                           0.0
20538                    0.0  …                           0.0
20539                    0.0  …                           0.0

       manufacturer_name[T.Renault]  manufacturer_name[T.Rolls-Royce]  \
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
…                                 …                                 …
20535                           0.0                               0.0
20536                           0.0                               0.0
20537                           0.0                               1.0
20538                           0.0                               0.0
20539                           0.0                               0.0

       manufacturer_name[T.Samco]  manufacturer_name[T.Subaru]  \
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
…                               …                            …
20535                         0.0                          0.0
20536                         0.0                          0.0
20537                         0.0                          0.0
20538                         0.0                          0.0
20539                         0.0                          0.0

       manufacturer_name[T.Suzuki]  manufacturer_name[T.Thaco]  \
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
…                                 …                             …
20535                              0.0                            0.0
20536                              0.0                            0.0
20537                              0.0                            0.0
20538                              0.0                            0.0
20539                              0.0                            0.0

       manufacturer_name[T.Toyota]  manufacturer_name[T.Volkswagen]  \
0                              0.0                              0.0
1                              1.0                              0.0
2                              1.0                              0.0
3                              1.0                              0.0
4                              0.0                              0.0
…                             …                               …
20535                          0.0                              0.0
20536                          1.0                              0.0
20537                          0.0                              0.0
20538                          1.0                              0.0
20539                          1.0                              0.0

       manufacturer_name[T.Zotye]
0                             0.0
1                             0.0
2                             0.0
3                             0.0
4                             0.0
…                            …
20535                         0.0
20536                         0.0
20537                         0.0
20538                         0.0
20539                         0.0

[17026 rows x 62 columns]
```

1.8.3 3.3.4 : Only Brand Segregation

[83]:
```
df_categorized_car_brands.columns
```

[83]:
```
Index(['manufacturer_name', 'model_name', 'body_type', 'production_year',
       'number_of_seat', 'odometer_value_log', 'price_log', 'transmission',
       'car_age', 'body_type[T.City Car]', 'body_type[T.Coupe]',
       'body_type[T.Hatchback]', 'body_type[T.MPV]',
       'body_type[T.Pick-up Truck]', 'body_type[T.SUV]', 'body_type[T.Sedan]',
       'body_type[T.Special Purpose]', 'body_type[T.Sport Car]',
```

```
 'body_type[T.Truck]', 'body_type[T.Van/Minivan]', 'EXOTIC',
 'ULTRA_LUXURY', 'LUXURY', 'MID_LEVEL', 'ECONOMY', 'Intercept',
 'manufacturer_name[T.Audi]', 'manufacturer_name[T.BMW]',
 'manufacturer_name[T.Bentley]', 'manufacturer_name[T.Cadillac]',
 'manufacturer_name[T.Chevrolet]', 'manufacturer_name[T.Cửu Long]',
 'manufacturer_name[T.Daewoo]', 'manufacturer_name[T.FAW]',
 'manufacturer_name[T.Fuso]', 'manufacturer_name[T.Hino]',
 'manufacturer_name[T.Honda]', 'manufacturer_name[T.Hyundai]',
 'manufacturer_name[T.Infiniti]', 'manufacturer_name[T.Isuzu]',
 'manufacturer_name[T.Jaguar]', 'manufacturer_name[T.Kia]',
 'manufacturer_name[T.LandRover]', 'manufacturer_name[T.Lexus]',
 'manufacturer_name[T.Maserati]', 'manufacturer_name[T.Mazda]',
 'manufacturer_name[T.Mercedes-Benz]', 'manufacturer_name[T.Mini]',
 'manufacturer_name[T.Mitsubishi]', 'manufacturer_name[T.Nissan]',
 'manufacturer_name[T.Others]', 'manufacturer_name[T.Peugeot]',
 'manufacturer_name[T.Porsche]', 'manufacturer_name[T.Renault]',
 'manufacturer_name[T.Rolls-Royce]', 'manufacturer_name[T.Samco]',
 'manufacturer_name[T.Subaru]', 'manufacturer_name[T.Suzuki]',
 'manufacturer_name[T.Thaco]', 'manufacturer_name[T.Toyota]',
 'manufacturer_name[T.Volkswagen]', 'manufacturer_name[T.Zotye]'],
dtype='object')
```

[84]:

```
df_categorized_car_brands[['manufacturer_name', 'model_name', 'body_type',␣
↪'production_year', 'Intercept',
       'number_of_seat', 'odometer_value_log', 'price_log', 'transmission',␣
↪'car_age', 'EXOTIC', 'ULTRA_LUXURY', 'LUXURY',
       'MID_LEVEL', 'ECONOMY']]
```

[84]:

```
      manufacturer_name     model_name      body_type  production_year  \
0                   Kia         cerato          Sedan             2018
1                Toyota         innova            MPV             2016
2                Toyota         innova            MPV             2014
3                Toyota  corolla-altis          Sedan             2009
4                   Kia            rio          Sedan             2015
…                     …              …              …                …
20535            Others         ranger   Pick-up Truck             2017
20536            Toyota       fortuner            SUV             2017
20537       Rolls-Royce        phantom          Sedan             2011
20538            Toyota       fortuner            SUV             2019
20539            Toyota          camry          Sedan             2007

       Intercept  number_of_seat  odometer_value_log  price_log  transmission  \
0            1.0               5            9.615805  20.225685             1
1            1.0               7           11.925035  20.183698             0
2            1.0               8           11.314475  20.069339             1
3            1.0               5           11.751942  19.968243             1
4            1.0               5           11.156251  19.718144             0
```

```
…       …          …          …         …          …
20535      1.0          5       10.915088  20.487544          1
20536      1.0          7       10.915088  20.601098          0
20537      1.0          4       10.308953  23.608067          1
20538      1.0          7        8.853665  20.752825          1
20539      1.0          5       11.918391  19.883936          1

       car_age  EXOTIC  ULTRA_LUXURY  LUXURY  MID_LEVEL  ECONOMY
0            2       0             0       0          0        1
1            4       0             0       0          0        1
2            6       0             0       0          0        1
3           11       0             0       0          0        1
4            5       0             0       0          0        1
…          …      …            …      …        …        …
20535        3       0             0       0          0        1
20536        3       0             0       0          0        1
20537        9       0             1       0          0        0
20538        1       0             0       0          0        1
20539       13       0             0       0          0        1

[17026 rows x 15 columns]
```

[85]:
```
# Finding out new R^2 from log transformations of Log Price and Log Independent␣
↪Variables (except Mileage)

# Slicing Variables
#df_categorized_car_brands.dropna(inplace=True)
X = df_categorized_car_brands[[ 'odometer_value_log', 'transmission',␣
↪'car_age', 'EXOTIC', 'ULTRA_LUXURY', 'LUXURY',
       'MID_LEVEL', 'ECONOMY']]
X = sm.add_constant(X)
y = df_categorized_car_brands['price_log'].astype(float)

# Initially my coefficients were difficult to interpret.
# Therefore I transformed it using log for better explanation purposes

# model / fit / summarize
import statsmodels.api as sm

lsm = sm.OLS(y, X)
results = lsm.fit()
results.summary()
```

[85]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
```

```
Dep. Variable:              price_log   R-squared:                       0.858
Model:                            OLS   Adj. R-squared:                  0.858
Method:                 Least Squares   F-statistic:                 1.473e+04
Date:                Wed, 08 Jan 2020   Prob (F-statistic):               0.00
Time:                        09:09:56   Log-Likelihood:                -7294.2
No. Observations:               17026   AIC:                         1.460e+04
Df Residuals:                   17018   BIC:                         1.467e+04
Df Model:                           7
Covariance Type:            nonrobust
================================================================================
======
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
------
const                20.3377      0.058    348.707      0.000      20.223
20.452
odometer_value_log    0.0873      0.004     20.334      0.000       0.079
0.096
transmission          0.3163      0.007     48.207      0.000       0.303
0.329
car_age              -0.0964      0.001    -81.884      0.000      -0.099
-0.094
EXOTIC            -8.213e-16   7.55e-17    -10.872      0.000   -9.69e-16
-6.73e-16
ULTRA_LUXURY          2.8997      0.043     66.779      0.000       2.815
2.985
LUXURY               -0.8710      0.043    -20.190      0.000      -0.956
-0.786
MID_LEVEL            -0.1835      0.127     -1.445      0.149      -0.432
0.065
ECONOMY              -0.8510      0.042    -20.236      0.000      -0.933
-0.769
==============================================================================
Omnibus:                     4696.531   Durbin-Watson:                   1.927
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            64009.643
Skew:                           0.945   Prob(JB):                         0.00
Kurtosis:                      12.309   Cond. No.                     1.43e+18
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 1.31e-30. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
"""
```

1.8.4 R^2 Summary from Linear Regression Models

Price vs Original Independent Variables:
R^2: **0.225**
R^2 Adjusted: **0.225**
df_price_no_brands

Logged Price vs Independent Variables (Logged Mileage): R^2: **0.142**
R^2 Adjusted: **0.142**
df_logged_price_no_brands_only_mileage_logged

Logged Price vs Independent Variables (Logged Mileage) + Categorized Car Brands: R^2: **0.858**
R^2 Adjusted: **0.858**
df_categorized_car_brands

[ ]:
```

```

1.9 Section 4.2: Cross-Validation Using Models other than LR

1.9.1 Section 4.2.1 : Using LassoCV to find best Alpha Value for L1 Regularization

[86]:
```
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.linear_model import LinearRegression, Lasso, Ridge, ElasticNet
from sklearn.linear_model import LassoCV, RidgeCV, ElasticNetCV
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
```

[87]:
```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold  #Kfold will allow you to do cross␣
 ↪validation

X = df_categorized_car_brands[[ 'odometer_value_log', 'transmission',␣
 ↪'car_age', 'EXOTIC', 'ULTRA_LUXURY', 'LUXURY',
       'MID_LEVEL', 'ECONOMY']]
y = df_categorized_car_brands['price_log']

# hold out 20% of the data for final testing

X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size = 0.
 ↪2, random_state=10)
X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val,␣
 ↪test_size = 0.2, random_state=20)
```

[88]:
```
## Scale the data (a MUST if you're doing regularization)
std = StandardScaler()
std.fit(X_train.values)

## Scale the Predictors on both the train/validation (the whole 80%) and test␣
 ↪set (the whole 20%)
X_train_scaled = std.transform(X_train.values)
```

```
X_val_scaled = std.transform(X_val.values)

# LassoCV does 2 things for you. It trains your model, and it also chooses the␣
↪best lambda/alpha for you.
# But of course, you have to feed it a list of lambdas to try.

# The best part about LambdaCV is that it does all 3 for you:
# Fit
# Finding best lambda
# Doing Cross-Validation

from sklearn.model_selection import KFold   #Kfold will allow you to do cross␣
↪validation

# Run the cross validation, find the best alpha, refit the model on all the␣
↪data with that alpha

alphavec = 10**np.linspace(-3,3,200) # Defining a vector of lambdas (alpha) to␣
↪try from
kf = KFold(n_splits=5, shuffle=True, random_state = 1000)  # Creating a␣
↪partitioned randomized-state data

lasso_model = LassoCV(alphas = alphavec, cv=kf)  # If you want to use Ridge,␣
↪use RidgeCV
lasso_model.fit(X_train_scaled, y_train)

# This is the best alpha value it found - not far from the value
# selected using simple validation
lasso_model.alpha_
```

[88]:
```
0.001
```

[89]:
```
# These are the (standardized) coefficients found when it refit using that best␣
↪alpha
list(zip(X_train.columns, lasso_model.coef_))
```

[89]:
```
[('odometer_value_log', 0.08470542643925862),
 ('transmission', 0.14717164938035499),
 ('car_age', -0.39641272099307434),
 ('EXOTIC', 0.0),
 ('ULTRA_LUXURY', 0.7648896286058525),
 ('LUXURY', -0.16175046659662895),
 ('MID_LEVEL', -0.0035497269716694884),
 ('ECONOMY', -0.20246361609994537)]
```

[90]:
```
def RMSE(y_true, y_pred):
    return np.sqrt(np.mean((y_true - y_pred)**2))

# Make predictions on the test set using the new model
# (the model is already using the best alpha. It is a LassoCV initialization)
val_set_pred = lasso_model.predict(X_val_scaled)

# Find the MAE and R^2 on the test set using this model
print(f"LassoCV Best Lambda (alpha): {lasso_model.alpha_}")
print(f"LassoCV RMSE: {RMSE(y_val, val_set_pred)}")
print(f"LassoCV R^2 Score: {r2_score(y_val, val_set_pred)}")
```

```
LassoCV Best Lambda (alpha): 0.001
LassoCV RMSE: 0.38373913501898876
LassoCV R^2 Score: 0.8435895300489282
```

1.9.2 Section 4.2.2: Using RidgeCV to find best Alpha Value for L2 Regularization

[91]:
```
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.linear_model import LinearRegression, Lasso, Ridge, ElasticNet
from sklearn.linear_model import LassoCV, RidgeCV, ElasticNetCV
from sklearn.preprocessing import StandardScaler, PolynomialFeatures


from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold  #Kfold will allow you to do cross␣
 ↪validation

X = df_categorized_car_brands[[ 'odometer_value_log', 'transmission',␣
 ↪'car_age', 'EXOTIC', 'ULTRA_LUXURY', 'LUXURY',
       'MID_LEVEL', 'ECONOMY']]
y = df_categorized_car_brands['price_log']


# hold out 20% of the data for final testing

X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size = 0.
 ↪2, random_state=10)
X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val,␣
 ↪test_size = 0.2, random_state=20)
```

[92]:
```
# Use RidgeCV to find the optimal ALPHA value for L2 regularization

## Scale the data (a MUST if you're doing regularization)
std = StandardScaler()
std.fit(X_train.values)
```

```python
# Scale the Predictors on both the train and validation set (for RidgeCV)
X_train_scaled = std.transform(X_train.values)
X_val_scaled = std.transform(X_val.values)

# Run the cross-validation, find the best alpha, refit the model on all the␣
↪data with that alpha (RidgeCV does this for you)
alphavec = 10 ** np.linspace(-3,3,200) # alpha varies from 0.001 to 1000
kf = KFold(n_splits=5, shuffle=True, random_state=1000)

ridge_model = RidgeCV(alphas=alphavec, cv=kf)
ridge_model.fit(X_train_scaled, y_train)  # Fit your scaled train input and␣
↪your y train values

# This is the best alpha value found
ridge_model.alpha_
```

[92]: 25.23539170434766

[93]:
```python
# display all coefficients in the model with optimal alpha
list(zip(X_train.columns, ridge_model.coef_))
```

[93]:
```
[('odometer_value_log', 0.0876069492402216),
 ('transmission', 0.1487559385087927),
 ('car_age', -0.3988572527834823),
 ('EXOTIC', 0.0),
 ('ULTRA_LUXURY', 0.7373005062921066),
 ('LUXURY', -0.19249255412014488),
 ('MID_LEVEL', -0.006751763592785005),
 ('ECONOMY', -0.2424662145775657)]
```

[94]:
```python
def RMSE(y_true, y_pred):
    return np.sqrt(np.mean((y_true - y_pred)**2))

# Make predictions on the test set using the new model and save it into a␣
↪variable
val_set_pred = lasso_model.predict(X_val_scaled)


# Find the MAE and R^2 on the test set using this model
print(f"Best Lambda (alpha) RidgeCV: {ridge_model.alpha_}")
print(f"RidgeCV MAE: {RMSE(y_val, val_set_pred)}")
print(f"RidgeCV R^2 Score: {r2_score(y_val, val_set_pred)}")
```

```
Best Lambda (alpha) RidgeCV: 25.23539170434766
RidgeCV MAE: 0.38373913501898876
RidgeCV R^2 Score: 0.8435895300489282
```

1.9.3 Section 4.2.3: Using ElasticnetCV to find best Alpha Value

[95]:
```
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.linear_model import LinearRegression, Lasso, Ridge, ElasticNet
from sklearn.linear_model import LassoCV, RidgeCV, ElasticNetCV
from sklearn.preprocessing import StandardScaler, PolynomialFeatures


from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold  #Kfold will allow you to do cross␣
↪validation

X = df_categorized_car_brands[[ 'odometer_value_log', 'transmission',␣
↪'car_age', 'EXOTIC', 'ULTRA_LUXURY', 'LUXURY',
       'MID_LEVEL', 'ECONOMY']]
y = df_categorized_car_brands['price_log']

# hold out 20% of the data for final testing

X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size = 0.
↪2, random_state=10)
X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val,␣
↪test_size = 0.2, random_state=20)
```

[96]:
```
# Using ElasticNetCV to find the optimal ALPHA value
# Scale the data as before (scaling is a must for regularization)
std = StandardScaler()
std.fit(X_train.values) # (60% of the data)

# Scale the Predictors on both the train and validation set
X_train_scaled = std.transform(X_train.values)
X_val_scalred = std.transform(X_val.values)

# Run the cross-validation, find the best alpha, refit the model and all the␣
↪data using that alpha (ElasticNetCV does this for you)
alphavec = 10 ** np.linspace(-3,3,200)  # alpha varies from 0.001 to 1000
kf = KFold(n_splits=5, shuffle=True, random_state=1000)

elasticnet_model = ElasticNetCV(alphas = alphavec, cv=kf)
elasticnet_model.fit(X_train_scaled, y_train)  # Fitting standardscaled input␣
↪and true y values into model to train it

elasticnet_model.alpha_
```

[96]:
```
0.001
```

[97]:
```
# display all coefficients in the model with optimal alpha
list(zip(X_train.columns, elasticnet_model.coef_))
```

[97]:
```
[('odometer_value_log', 0.08709220005311995),
 ('transmission', 0.14816022550936267),
 ('car_age', -0.3987944732203305),
 ('EXOTIC', 0.0),
 ('ULTRA_LUXURY', 0.7526732782206628),
 ('LUXURY', -0.17604684112050104),
 ('MID_LEVEL', -0.005087419957232235),
 ('ECONOMY', -0.22129368702501492)]
```

[98]:
```
def RMSE(y_true, y_pred):
    return np.sqrt(np.mean((y_true - y_pred)**2))

# Use this model to do prediction on a validation data set
val_set_pred = elasticnet_model.predict(X_val_scaled)

# Find the MAE and R^2 on the test set using this model
print(f'Best Lambda (Alpha) ElasticNetCV: {elasticnet_model.alpha_}')
print(f'ElasticNetCV RMSE: {RMSE(y_val, val_set_pred)}')  # mae is a defined␣
↪function above
print(f'ElasticNetCV R^2 Score: {r2_score(y_val, val_set_pred)}')  # r2_score␣
↪is an imported module
```

```
Best Lambda (Alpha) ElasticNetCV: 0.001
ElasticNetCV RMSE: 0.38350590470075996
ElasticNetCV R^2 Score: 0.843779599679487
```

1.9.4 Section 4.2.3: Summary from the above Train-Validation Sets

LassoCV Best Lambda (alpha): 0.001 LassoCV RMSE: 0.38373913501898876 LassoCV R^2 Score: 0.8435895300489282

Best Lambda (alpha) RidgeCV: 25.23539170434766 RidgeCV MAE: 0.38373913501898876 RidgeCV R^2 Score: 0.8435895300489282

Best Lambda (Alpha) ElasticNetCV: 0.001 ElasticNetCV RMSE: 0.38350590470075996 ElasticNetCV R^2 Score: 0.843779599679487

1.9.5 Section 4.3: Picking Model with the best R^2 score (Train and Cross-Validation)

[99]:
```
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.linear_model import LinearRegression, Lasso, Ridge, ElasticNet
from sklearn.linear_model import LassoCV, RidgeCV, ElasticNetCV
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
```

```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold  #Kfold will allow you to do cross␣
↪validation

X = df_categorized_car_brands[[ 'odometer_value_log', 'transmission',␣
↪'car_age', 'EXOTIC', 'ULTRA_LUXURY', 'LUXURY',
       'MID_LEVEL', 'ECONOMY']]
y = df_categorized_car_brands['price_log']

# Create 80% of train data. The code below will automate the cross-validation
X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size = 0.
↪2, random_state=10)
```

[100]:

```
## cross validation using KFold (on the 100% dataset, without manually␣
↪splitting)
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold

def RMSE(y_true, y_pred):
    return np.sqrt(np.mean((y_true - y_pred)**2))


#Feature transform/scaling so that we can run our ridge/lasso/elasticnet model
scaler = StandardScaler()
X_train_val_scaled = scaler.fit_transform(X_train_val.values)

#Feature transform/scaling so that we can run our poly model
poly = PolynomialFeatures(degree=2)
X_train_val_poly = poly.fit_transform(X_train_val.values)

kf = KFold(n_splits=5, shuffle=True, random_state = 1000)

lm = LinearRegression()
cvs_lm = cross_val_score(lm, X_train_val, y_train_val, cv=kf, scoring='r2')
print("Linear Regression Cross Val Score: {}".format(cvs_lm))
# print(f'ElasticNetCV RMSE: {round(RMSE(y_val, val_set_pred),3)}')
print('Linear regression cv R^2:', round(np.mean(cvs_lm),3), '+-', round(np.
↪std(cvs_lm),3),'\n' )


lm_ridge = Ridge(alpha= 25.23539170434766 )
cvs_ridge = cross_val_score(lm_ridge, X_train_val_scaled, y_train_val, cv=kf,␣
↪scoring='r2')
print("Ridge Cross Val Score: {}".format(cvs_ridge))
# print(f'ElasticNetCV RMSE: {round(RMSE(y_val, val_set_pred),3)}')
print('Ridge regression cv R^2:', round(np.mean(cvs_ridge),3), '+-', round(np.
↪std(cvs_ridge),3),'\n' )
```

```python
lm_lasso = Lasso(alpha=0.001)
cvs_lasso = cross_val_score(lm_lasso, X_train_val_scaled, y_train_val, cv=kf,␣
↪scoring='r2')
print("Lasso Cross Val Score: {}".format(cvs_lasso))
# print(f'ElasticNetCV RMSE: {round(RMSE(y_val, val_set_pred),3)}')
print('Lasso regression cv R^2:', round(np.mean(cvs_lasso),3), '+-', round(np.
↪std(cvs_lasso),3),'\n' )


lm_elasticnet = ElasticNet(alpha=0.001 )
cvs_elasticnet = cross_val_score(lm_elasticnet, X_train_val_scaled,␣
↪y_train_val, cv=kf, scoring='r2')
print("Elastic Net Cross Val Score: {}".format(cvs_elasticnet))
# print(f'ElasticNetCV RMSE: {round(RMSE(y_val, val_set_pred),3)}')
print('ElasticNet regression cv R^2:', round(np.mean(cvs_elasticnet),3), '+-',␣
↪round(np.std(cvs_elasticnet),3),'\n' )


lm_poly = LinearRegression()
cvs_poly = cross_val_score(lm_poly, X_train_val_poly, y_train_val, cv=kf,␣
↪scoring='r2')
print("Poly Regression Cross Val Score: {}".format(cvs_poly))
# print(f'ElasticNetCV RMSE: {round(RMSE(y_val, val_set_pred),3)}')
print('Degree 2 polynomial Regression cv R^2:', round(np.mean(cvs_poly),3),␣
↪'+-', round(np.std(cvs_poly),3) )
```

```
Linear Regression Cross Val Score: [0.85352277 0.86759166 0.84863217 0.85471994
0.84724817]
Linear regression cv R^2: 0.854 +- 0.007

Ridge Cross Val Score: [0.85342813 0.86762171 0.84882679 0.85501083 0.84722059]
Ridge regression cv R^2: 0.854 +- 0.007

Lasso Cross Val Score: [0.85350301 0.86721532 0.84914978 0.85352675 0.84771586]
Lasso regression cv R^2: 0.854 +- 0.007

Elastic Net Cross Val Score: [0.85350324 0.86742934 0.84894665 0.8542459
0.84748116]
ElasticNet regression cv R^2: 0.854 +- 0.007

Poly Regression Cross Val Score: [0.90227071 0.90362012 0.89025832 0.89516535
0.89900252]
Degree 2 polynomial Regression cv R^2: 0.898 +- 0.005
```

```
[101]: # From the code above, it seems like Linear Regression provides similar results␣
       ↪as compared to the rest.
       # Therefore, will choose to use linear regression for it's simplicity and ease␣
       ↪of use
```

2 Section 5: Model Testing (On whole DataSet)

2.1 Section 5.1: Training Model on 80% DataSet

```
[102]: df_categorized_car_brands.columns
```

```
[102]: Index(['manufacturer_name', 'model_name', 'body_type', 'production_year',
              'number_of_seat', 'odometer_value_log', 'price_log', 'transmission',
              'car_age', 'body_type[T.City Car]', 'body_type[T.Coupe]',
              'body_type[T.Hatchback]', 'body_type[T.MPV]',
              'body_type[T.Pick-up Truck]', 'body_type[T.SUV]', 'body_type[T.Sedan]',
              'body_type[T.Special Purpose]', 'body_type[T.Sport Car]',
              'body_type[T.Truck]', 'body_type[T.Van/Minivan]', 'EXOTIC',
              'ULTRA_LUXURY', 'LUXURY', 'MID_LEVEL', 'ECONOMY', 'Intercept',
              'manufacturer_name[T.Audi]', 'manufacturer_name[T.BMW]',
              'manufacturer_name[T.Bentley]', 'manufacturer_name[T.Cadillac]',
              'manufacturer_name[T.Chevrolet]', 'manufacturer_name[T.Cửu Long]',
              'manufacturer_name[T.Daewoo]', 'manufacturer_name[T.FAW]',
              'manufacturer_name[T.Fuso]', 'manufacturer_name[T.Hino]',
              'manufacturer_name[T.Honda]', 'manufacturer_name[T.Hyundai]',
              'manufacturer_name[T.Infiniti]', 'manufacturer_name[T.Isuzu]',
              'manufacturer_name[T.Jaguar]', 'manufacturer_name[T.Kia]',
              'manufacturer_name[T.LandRover]', 'manufacturer_name[T.Lexus]',
              'manufacturer_name[T.Maserati]', 'manufacturer_name[T.Mazda]',
              'manufacturer_name[T.Mercedes-Benz]', 'manufacturer_name[T.Mini]',
              'manufacturer_name[T.Mitsubishi]', 'manufacturer_name[T.Nissan]',
              'manufacturer_name[T.Others]', 'manufacturer_name[T.Peugeot]',
              'manufacturer_name[T.Porsche]', 'manufacturer_name[T.Renault]',
              'manufacturer_name[T.Rolls-Royce]', 'manufacturer_name[T.Samco]',
              'manufacturer_name[T.Subaru]', 'manufacturer_name[T.Suzuki]',
              'manufacturer_name[T.Thaco]', 'manufacturer_name[T.Toyota]',
              'manufacturer_name[T.Volkswagen]', 'manufacturer_name[T.Zotye]'],
             dtype='object')
```

```
[103]: from sklearn.metrics import mean_squared_error, r2_score
       from sklearn.linear_model import LinearRegression, Lasso, Ridge, ElasticNet
       from sklearn.linear_model import LassoCV, RidgeCV, ElasticNetCV
       from sklearn.preprocessing import StandardScaler, PolynomialFeatures

       from sklearn.model_selection import train_test_split
```

```
from sklearn.model_selection import KFold  #Kfold will allow you to do cross␣
↪validation

X = df_categorized_car_brands[[ 'odometer_value_log', 'transmission',␣
↪'car_age', 'Intercept', 'EXOTIC', 'ULTRA_LUXURY', 'LUXURY',
       'MID_LEVEL', 'ECONOMY']]
#X = sm.add_constant(X)
y = df_categorized_car_brands['price_log']

# Create 80% of train data. The code below will automate the cross-validation
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,␣
↪random_state=20)
```

[104]:
```
# model / fit / summarize
import statsmodels.api as sm

lm_model = LinearRegression()
lm_model = sm.OLS(y_train, X_train)  # no need sm.add_constant because there's␣
↪already an intercept
results = lm_model.fit()
results.summary()
```

[104]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              price_log   R-squared:                       0.857
Model:                            OLS   Adj. R-squared:                  0.857
Method:                 Least Squares   F-statistic:                 1.166e+04
Date:                Wed, 08 Jan 2020   Prob (F-statistic):               0.00
Time:                        09:10:00   Log-Likelihood:                -5816.0
No. Observations:               13620   AIC:                         1.165e+04
Df Residuals:                   13612   BIC:                         1.171e+04
Df Model:                           7
Covariance Type:            nonrobust
================================================================================
======
                         coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
------
odometer_value_log     0.0986      0.005     20.025      0.000       0.089
0.108
transmission           0.3180      0.007     43.278      0.000       0.304
0.332
car_age               -0.1001      0.001    -74.934      0.000      -0.103
-0.097
```

```
Intercept               20.2943      0.066    308.872      0.000      20.166
20.423
EXOTIC               -3.762e-15   3.97e-17    -94.650      0.000   -3.84e-15
-3.68e-15
ULTRA_LUXURY             2.8605      0.048     59.911      0.000       2.767
2.954
LUXURY                  -0.9081      0.047    -19.165      0.000      -1.001
-0.815
MID_LEVEL                0.0300      0.153      0.196      0.845      -0.271
0.331
ECONOMY                 -0.9093      0.046    -19.720      0.000      -1.000
-0.819
==============================================================================
Omnibus:                     3150.158   Durbin-Watson:                   2.005
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            30622.838
Skew:                           0.833   Prob(JB):                         0.00
Kurtosis:                      10.155   Cond. No.                     1.50e+18
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 9.54e-31. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
"""
```

2.1.1 R^2 Summary from Linear Regression Models

Best Data Set (80% of data on train, 20% on test)
Logged Price vs Independent Variables (Logged Mileage) + Categorized Car Brands: R^2: **0.857**
R^2 Adjusted: **0.857**
df_categorized_car_brands

Price vs Original Independent Variables:
R^2: **0.295**
R^2 Adjusted: **0.295**
df_price_no_brands

Logged Price vs Independent Variables (Logged Mileage): R^2: **0.142**
R^2 Adjusted: **0.142**
df_logged_price_no_brands_only_mileage_logged

Logged Price vs Independent Variables (Logged Mileage) + Categorized Car Brands: R^2: **0.858**
R^2 Adjusted: **0.858**
df_categorized_car_brands

2.2 Section 5.2: Testing Model on 20% DataSet

[105]:
```
from sklearn.metrics import mean_squared_error, r2_score
#Mean Absolute Error (MAE)
def mae(y_true, y_pred):
    return np.mean(np.abs(y_pred - y_true))

# Create prediction variable for test set
model_test_pred = results.predict(X_test)

# Check accuracy of test
print("Linear Regression Test Scores:\n")
print("Linear Regression MAE: {}".format(mae(y_test, model_test_pred))) # MAE
print("Linear Regression MSE: {}".format(mean_squared_error(y_test,␣
↪model_test_pred))) # Mean Squared Error (MSE)
print("Linear Regression RMSE: {}".format(RMSE(y_test, model_test_pred))) #␣
↪Root Mean squared error
print("Linear Regression R2 Score: {}".format(r2_score(y_test,␣
↪model_test_pred)))# R^2 Score
```

```
Linear Regression Test Scores:

Linear Regression MAE: 0.24679311662778855
Linear Regression MSE: 0.14010916191613537
Linear Regression RMSE: 0.37431158399939396
Linear Regression R2 Score: 0.862591947195551
```

3 Section 6: Checking Linear Regression Assumptions

3.0.1 Plot 3 Graphs

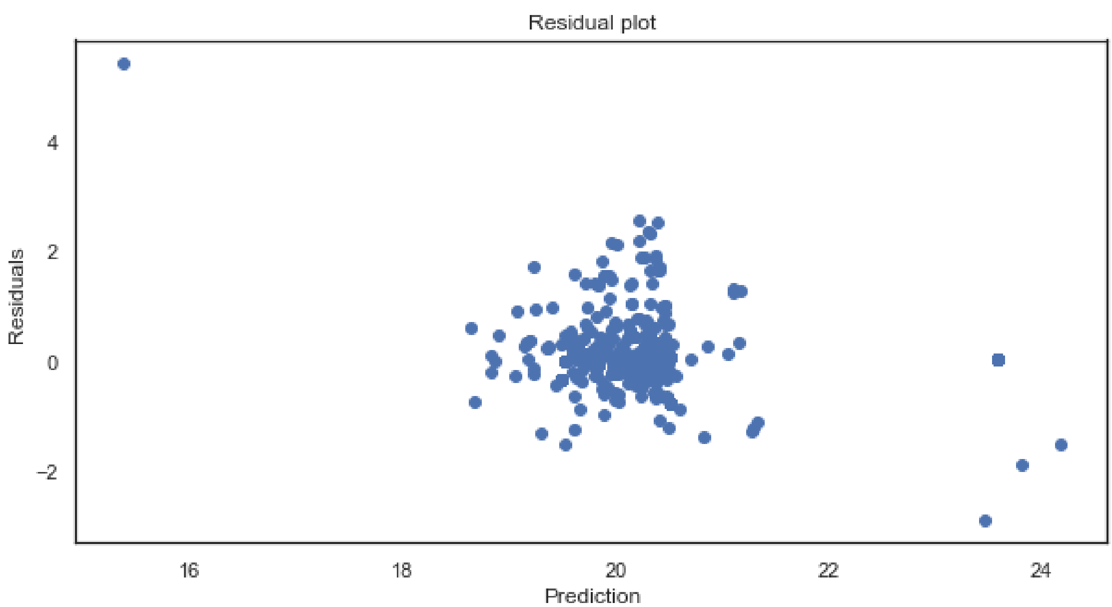
- residue
- QQ plot

[106]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import patsy
import scipy.stats as stats

import statsmodels.api as sm
import statsmodels.formula.api as smf
from sklearn import preprocessing
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
%matplotlib inline
```

3.1 Section 6.1: Plotting the Residuals

[107]:
```
# Defining Graph size
plt.figure(figsize=(10,5))

# Defining the residue and model predicted results
df_categorized_car_brands['PREDICTIONS'] = results.predict(X_test)
df_categorized_car_brands['RESIDUE'] = y_test - model_test_pred

# Plot your predicted values on the x-axis, and your residuals on the y-axis on␣
↪Residue Plot
plt.scatter(df_categorized_car_brands['PREDICTIONS'],␣
↪df_categorized_car_brands['RESIDUE'])
plt.title("Residual plot")
plt.xlabel("Prediction")
plt.ylabel("Residuals")
```

[107]: Text(0, 0.5, 'Residuals')



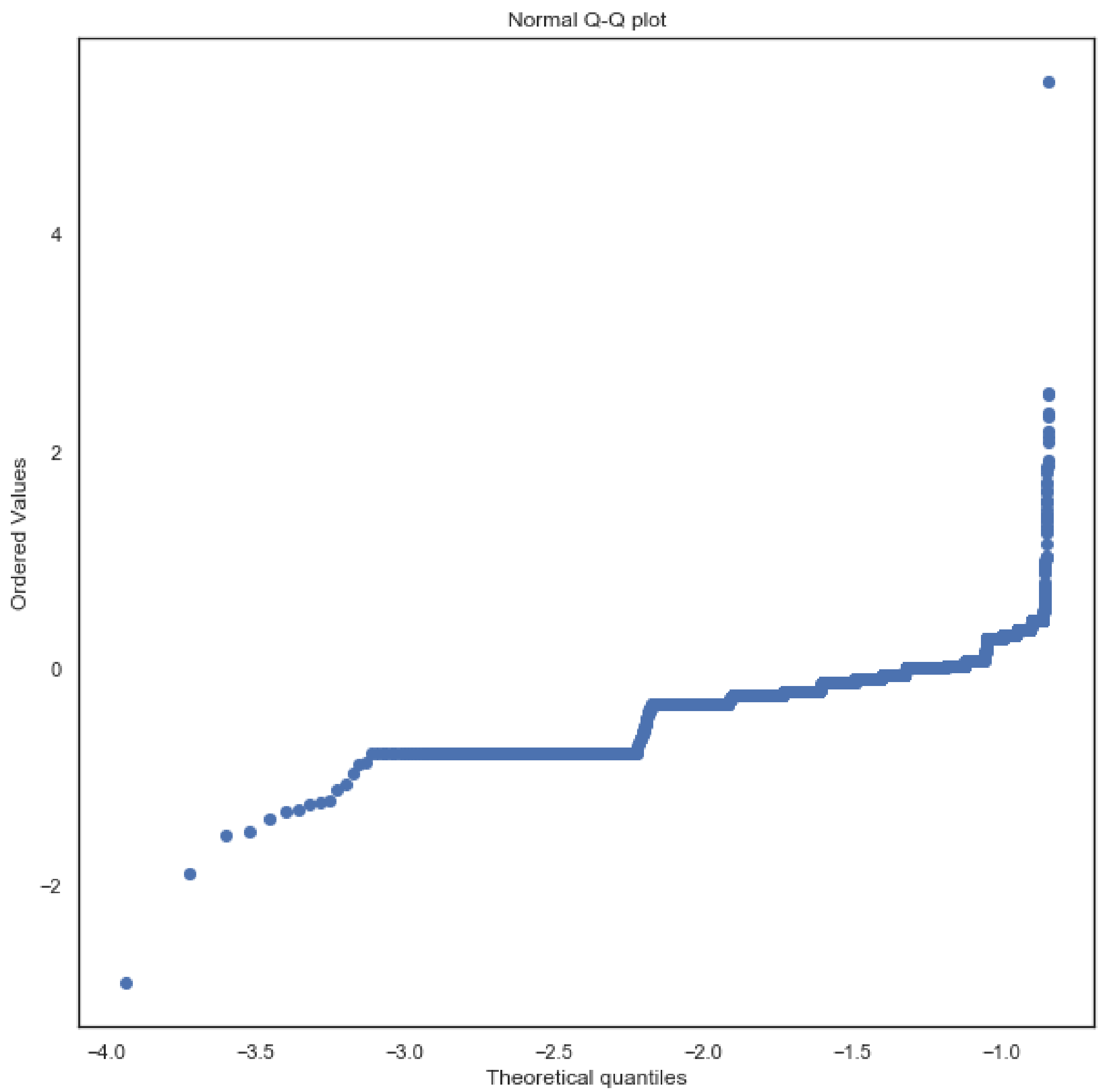
3.2 Section 6.2: QQ Plot

[108]:
```
# Defining the residue and model predicted results
df_categorized_car_brands['PREDICTIONS'] = results.predict(X_test)
df_categorized_car_brands['RESIDUE'] = y_test - model_test_pred

# diagnose/inspect residual normality using QQplot:
plt.figure(figsize=(10,10))
```

```
stats.probplot(df_categorized_car_brands['RESIDUE'], dist="norm", plot=plt)
plt.title("Normal Q-Q plot")
```

```
D:\Application\Anaconda2\envs\py3\lib\site-
packages\scipy\stats\_distn_infrastructure.py:901: RuntimeWarning: invalid value
encountered in greater
  return (a < x) & (x < b)
D:\Application\Anaconda2\envs\py3\lib\site-
packages\scipy\stats\_distn_infrastructure.py:901: RuntimeWarning: invalid value
encountered in less
  return (a < x) & (x < b)
D:\Application\Anaconda2\envs\py3\lib\site-
packages\scipy\stats\_distn_infrastructure.py:1892: RuntimeWarning: invalid
value encountered in less_equal
  cond2 = cond0 & (x <= _a)
```

[108]:
```
Text(0.5, 1.0, 'Normal Q-Q plot')
```


Normal Q-Q plot
Ordered Values
Theoretical quantiles
4
2
0
−2
−4.0
−3.5
−3.0
−2.5
−2.0
−1.5
−1.0

[ ]: