CIND 820 data cleaning ver3

November 5, 2021

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import matplotlib.image as mpimg
import math
import dask.dataframe as dd

from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from string import ascii_letters
```

[2]:
```
# Load data
df = pd.read_csv("ca-dealers-used.csv",dtype={'fuel_type': 'object',␣
↪'engine_block': 'object'})
```

[3]:
```
df.dtypes
```

[3]:
```
id                 object
vin                object
price             float64
miles             float64
stock_no           object
year              float64
make               object
model              object
trim               object
body_type          object
vehicle_type       object
drivetrain         object
transmission       object
fuel_type          object
engine_size       float64
engine_block       object
seller_name        object
street             object
```

```
city               object
state              object
zip                object
dtype: object
```

[4]:
```
len(df)
```

[4]:
```
393603
```

[5]:
```
df.head(5)
```

[5]:
```
             id                vin     price    miles  stock_no    year  \
0  b39ea795-eca9  19UNC1B01HY800062  179999.0   9966.0    V-P4139  2017.0
1  026cb5b1-6e3e  19UNC1B02HY800023  179995.0   5988.0  PPAP70374  2017.0
2  5cd5d5b2-5cc2  19UNC1B02HY800071  168528.0  24242.0     B21085  2017.0
3  b32473ed-5922  19UNC1B02LY800001  220000.0   6637.0     AP5333  2020.0
4  ac40c9fc-0676  19UNC1B02LY800001  220000.0   6637.0     AP5333  2020.0

    make model  trim body_type  … drivetrain transmission  \
0  Acura   NSX  Base     Coupe  …        4WD    Automatic
1  Acura   NSX  Base     Coupe  …        4WD    Automatic
2  Acura   NSX  Base     Coupe  …        4WD    Automatic
3  Acura   NSX  Base     Coupe  …        4WD    Automatic
4  Acura   NSX  Base     Coupe  …        4WD    Automatic

                    fuel_type engine_size  engine_block  \
0  Electric / Premium Unleaded         3.5             V
1  Electric / Premium Unleaded         3.5             V
2  Electric / Premium Unleaded         3.5             V
3  Electric / Premium Unleaded         3.5             V
4  Electric / Premium Unleaded         3.5             V

             seller_name                          street                 city  \
0        edmundston honda                475 Rue Victoria           Edmundston
1  garage daniel lessard  2795 Route-du-prsident-kennedy  Notre-dame-des-pins
2          lougheed acura           1388 Lougheed Highway            Coquitlam
3        drive autogroup         1305 Parkway Suite 600            Pickering
4         acura pickering              575 Kingston Road            Pickering

  state      zip
0    NB  E3V 2K7
1    QC  G0M 1K0
2    BC  V3K 6S4
3    ON  L1V 3P2
4    ON  L1V 3N7

[5 rows x 21 columns]
```

[6]:
```python
# Only select records from Toronto
df=df[df.state == "ON"]
```

[7]:
```python
df=df[df.city == "Toronto"]
```

[8]:
```python
# drop irrelevant columns for this research
drop_columns = ['id', 'vin', 'stock_no',␣
↪'seller_name','street','city','state','zip']
```

[9]:
```python
df = df.drop(columns = drop_columns)
```

[10]:
```python
# EDA analysis
# check data types
df.dtypes
```

[10]:
```
price            float64
miles            float64
year             float64
make              object
model             object
trim              object
body_type         object
vehicle_type      object
drivetrain        object
transmission      object
fuel_type         object
engine_size      float64
engine_block      object
dtype: object
```

[11]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 14998 entries, 39 to 393573
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   price         13811 non-null  float64
 1   miles         13229 non-null  float64
 2   year          14998 non-null  float64
 3   make          14998 non-null  object
 4   model         14807 non-null  object
 5   trim          13954 non-null  object
 6   body_type     13442 non-null  object
 7   vehicle_type  13278 non-null  object
 8   drivetrain    14262 non-null  object
 9   transmission  14276 non-null  object
```

```
 10  fuel_type     12615 non-null  object
 11  engine_size   12607 non-null  float64
 12  engine_block  12554 non-null  object
dtypes: float64(4), object(9)
memory usage: 1.6+ MB
```

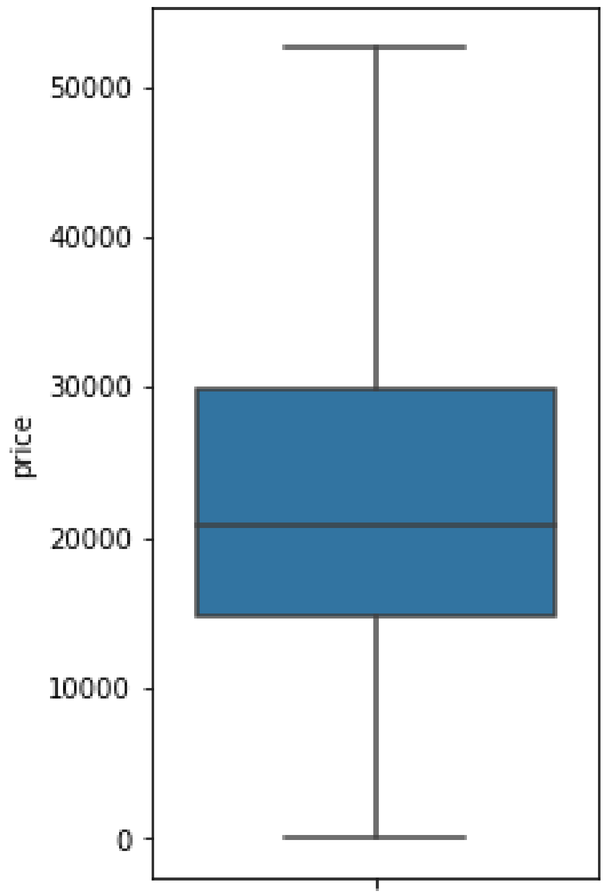
[12]:
```python
# Check missing values
missing_values_count = df.isnull().sum()
missing_values_count
```

[12]:
```
price           1187
miles           1769
year               0
make               0
model            191
trim            1044
body_type       1556
vehicle_type    1720
drivetrain       736
transmission     722
fuel_type       2383
engine_size     2391
engine_block    2444
dtype: int64
```

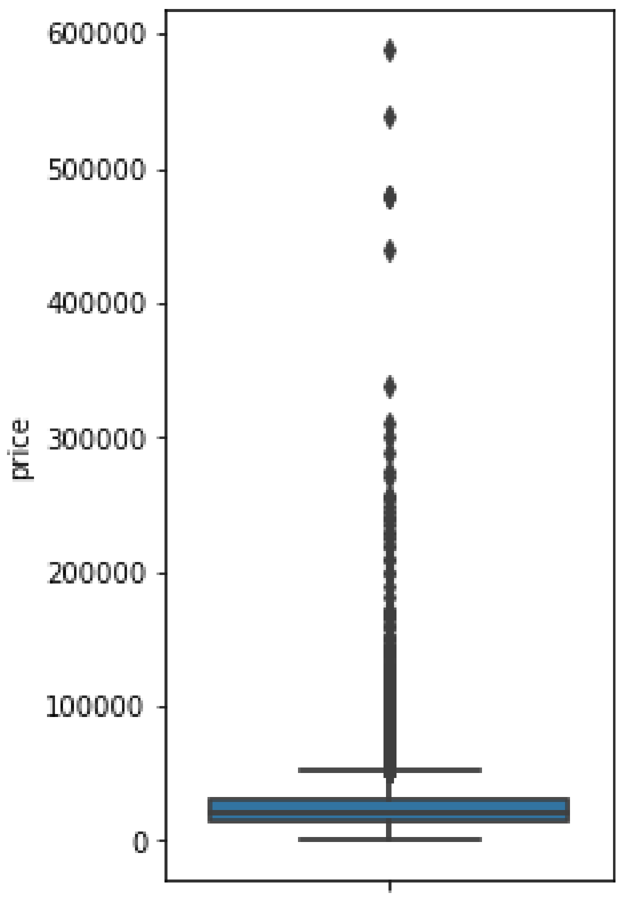
[13]:
```python
df['price'].describe()
```

[13]:
```
count     13811.000000
mean      25069.024835
std       21359.905212
min           0.000000
25%       14855.500000
50%       20900.000000
75%       29950.000000
max      589000.000000
Name: price, dtype: float64
```

[14]:
```python
# Boxplot for price
plt.figure(figsize=(3,6))
sns.boxplot(y='price', data=df, showfliers=False);
```

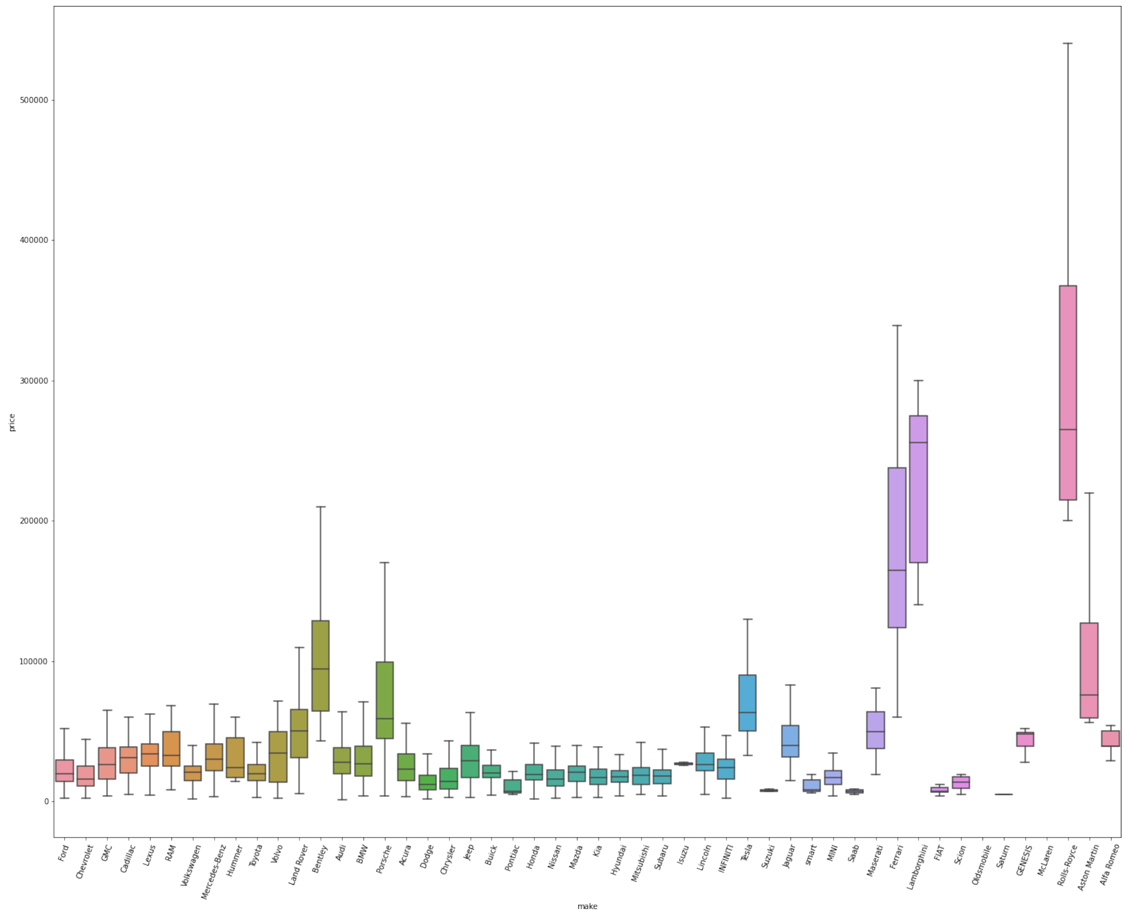


[15]:
```
# Box plot for price with outliers, we can see that there are a lot extreme␣
 ↪high prices
plt.figure(figsize=(3,6))
sns.boxplot(y='price', data=df, showfliers=False)
sns.boxplot(y='price', data=df);
```



[16]:
```
# Prices by different brands
plt.figure(figsize=(25,20))
plt.xticks(rotation=70)
sns.boxplot(y='price', x='make', data=df, showfliers=False)
```

[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f92d7595cd0>

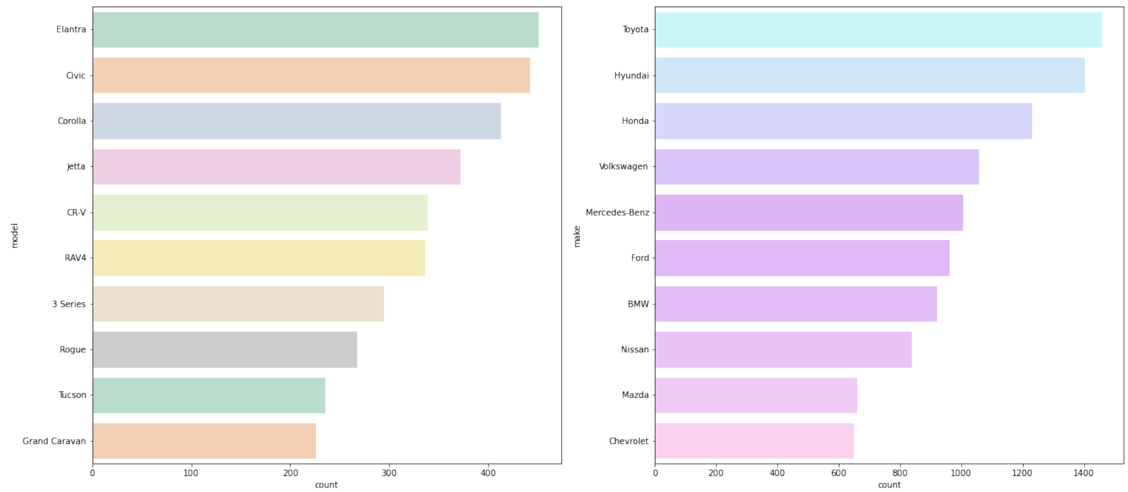


[17]:

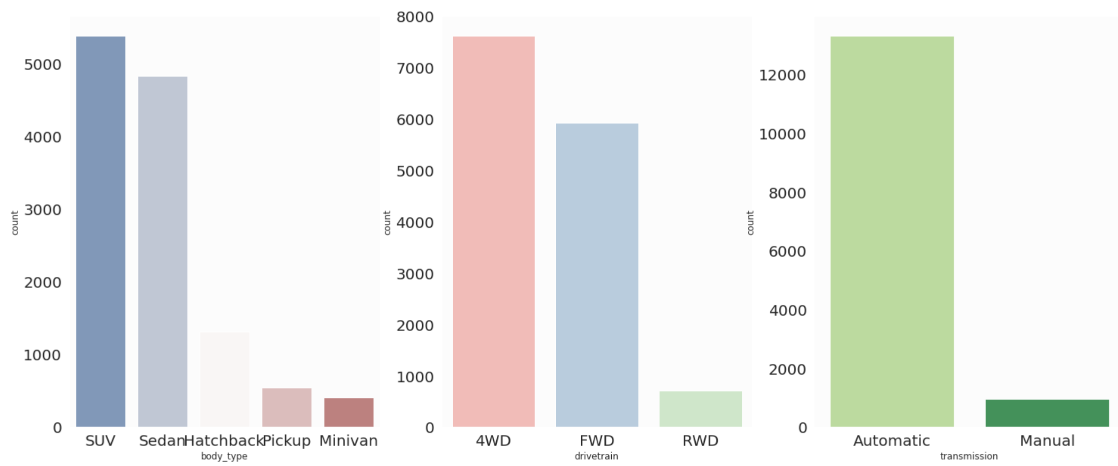
```
# Count by top 10 most popular brand and model
colors = ["#C0FDFF",␣
↪"#C8E7FF","#D0D1FF","#D8BBFF","#DEAAFF","#E2AFFF","#E5B3FE","#ECBCFD","#F3C4FB","#FFCBF2"]
sns.set_palette(sns.color_palette(colors))



fig, ax =plt.subplots(1,2,figsize=(22, 10))
sns.set(rc={"axes.facecolor":"#fcfcfc", "axes.grid":False,'xtick.labelsize':
↪20,'ytick.labelsize':20})
sns.countplot(y ='make',data = df,order=df.make.value_counts().iloc[:10].index,␣
↪ax = ax[1],palette = colors)
sns.countplot(y ='model',data = df,order=df.model.value_counts().iloc[:10].
↪index, ax= ax[0],palette = "Pastel2")
fig.show()
```

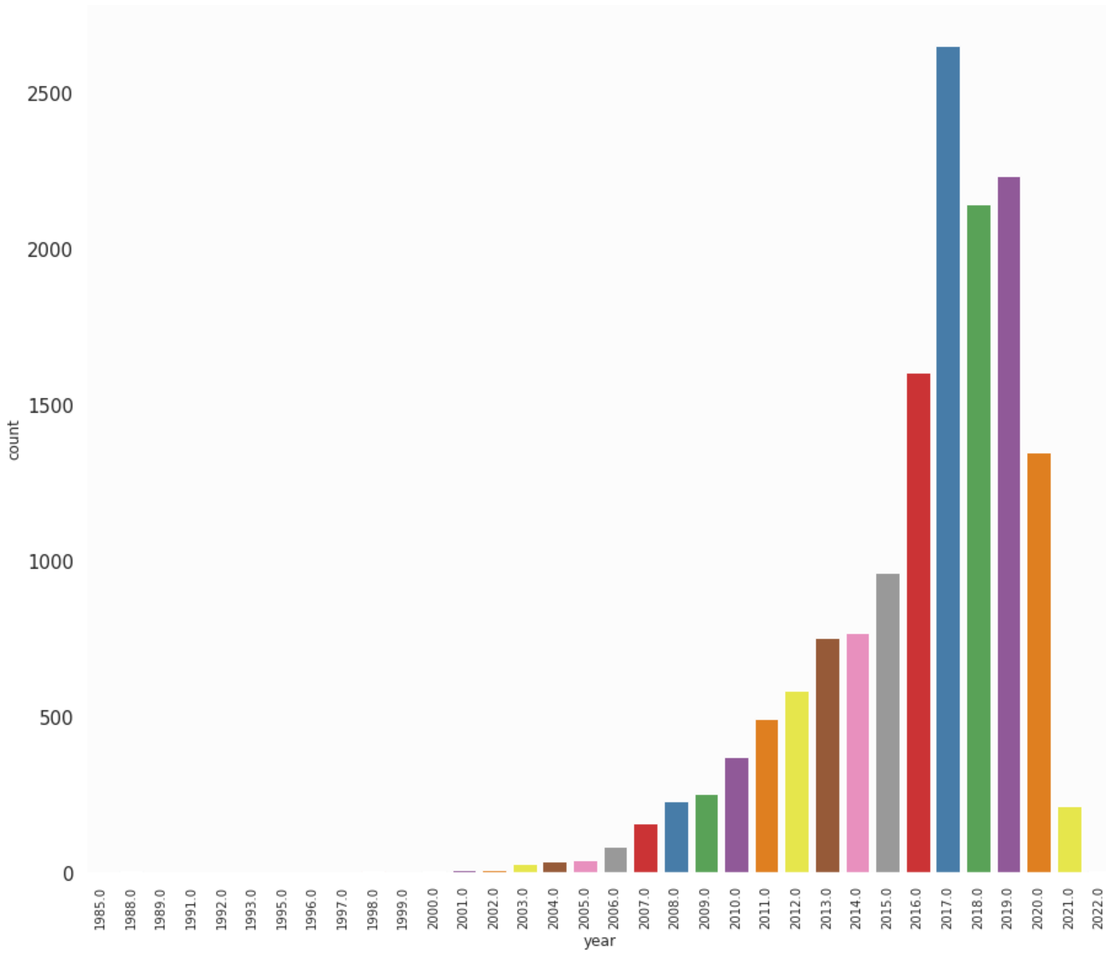


[18]:
```
# Countplot by body_type, drivetrain and transmission
fig, ax =plt.subplots(1,3,figsize=(25, 10))
sns.set(rc={"axes.facecolor":"#fcfcfc", "axes.grid":False,'xtick.labelsize':
↪15,'ytick.labelsize':15})
sns.countplot(x ='body_type',data = df,order=df.body_type.value_counts().iloc[:
↪5].index, ax = ax[0],palette="vlag")
sns.countplot(x ='drivetrain',data = df,order=df.drivetrain.value_counts().
↪iloc[:5].index, ax = ax[1],palette="Pastel1")
sns.countplot(x ='transmission',data = df,order=df.transmission.value_counts().
↪iloc[:5].index, ax = ax[2],palette="YlGn")
fig.show()
```



[19]:
```
# Count by year
plt.figure(figsize=(15, 13))
```

```
ax = sns.countplot(x = 'year', data=df, palette='Set1')
ax.set_xticklabels(ax.get_xticklabels(), rotation=90,fontsize=10);
```



[20]:
```
# Sample data:
df.tail(20)
```

[20]:

	price	miles	year	make	model \
393008	9990.0	96588.0	2013.0	Hyundai	Sonata Hybrid
393022	NaN	154300.0	2013.0	Hyundai	Sonata Hybrid
393040	38998.0	15365.0	2020.0	Hyundai	Sonata Hybrid
393067	8995.0	112000.0	2012.0	Kia	Optima
393134	16999.0	103590.0	2016.0	Kia	Optima
393144	14950.0	90000.0	2016.0	Kia	Optima
393177	13888.0	97123.0	2015.0	Kia	Optima
393232	18990.0	64476.0	2017.0	Kia	Optima
393235	18990.0	64476.0	2017.0	Kia	Optima
393236	18990.0	64476.0	2017.0	Kia	Optima

393237	18990.0	64476.0	2017.0	Kia	Optima
393241	27654.0	99.0	2019.0	Kia	Niro
393279	16647.0	122138.0	2017.0	Kia	Niro
393454	38140.0	8500.0	2020.0	Kia	Niro
393545	62988.0	22352.0	2020.0	Land Rover	Range Rover Evoque
393546	62988.0	22352.0	2020.0	Land Rover	Range Rover Evoque
393561	26450.0	56000.0	2017.0	BMW	3 Series
393568	45880.0	69000.0	2018.0	Mercedes-Benz	GLC-Class
393570	43880.0	65000.0	2018.0	Mercedes-Benz	GLC-Class
393573	46800.0	19833.0	2018.0	Mercedes-Benz	GLC-Class

	trim	body_type	vehicle_type	drivetrain	transmission \
393008	Hybrid	Sedan	Car	FWD	Automatic
393022	Hybrid	Sedan	Car	FWD	Automatic
393040	SEL	Sedan	Car	FWD	Automatic
393067	Hybrid	Sedan	Car	FWD	Automatic
393134	EX Hybrid	Sedan	Car	FWD	Automatic
393144	EX Hybrid	Sedan	Car	FWD	Automatic
393177	EX Hybrid	Sedan	Car	FWD	Automatic
393232	EX Plug-In Hybrid	Sedan	Car	FWD	Automatic
393235	EX Plug-In Hybrid	Sedan	Car	FWD	Automatic
393236	EX Plug-In Hybrid	Sedan	Car	FWD	Automatic
393237	EX Plug-In Hybrid	Sedan	Car	FWD	Automatic
393241	LX	Hatchback	Car	FWD	Automatic
393279	EX	Hatchback	Car	FWD	Automatic
393454	EX	Hatchback	Car	FWD	Automatic
393545	HSE	SUV	Truck	4WD	Automatic
393546	HSE	SUV	Truck	4WD	Automatic
393561	330e	Sedan	Car	RWD	Automatic
393568	GLC350e	SUV	Truck	4WD	Automatic
393570	GLC350e	SUV	Truck	4WD	Automatic
393573	GLC350e	SUV	Truck	4WD	Automatic

	fuel_type	engine_size	engine_block
393008	Electric / Unleaded	2.4	I
393022	Electric / Unleaded	2.4	I
393040	Electric / Unleaded	2.0	I
393067	Electric / Unleaded	2.4	I
393134	Electric / Unleaded	2.4	I
393144	Electric / Unleaded	2.4	I
393177	Electric / Unleaded	2.4	I
393232	Electric / Unleaded	2.0	I
393235	Electric / Unleaded	2.0	I
393236	Electric / Unleaded	2.0	I
393237	Electric / Unleaded	2.0	I
393241	Electric / Unleaded	1.6	I
393279	Electric / Unleaded	1.6	I

```
393454  Electric / Unleaded         1.6           I
393545  Electric / Unleaded         2.0           I
393546  Electric / Unleaded         2.0           I
393561  Electric / Unleaded         2.0           I
393568  Electric / Unleaded         2.0           I
393570  Electric / Unleaded         2.0           I
393573  Electric / Unleaded         2.0           I
```

[21]:
```
# Data cleaning and preprocessing:
# Lets drop records without prices, since these records will be useless for our␣
↪analysis
df_tor=df.dropna(subset=['price'])
```

[22]:
```
pip install pandas-profiling
```

```
Requirement already satisfied: pandas-profiling in
/opt/conda/lib/python3.7/site-packages (3.1.0)
Requirement already satisfied: missingno>=0.4.2 in
/opt/conda/lib/python3.7/site-packages (from pandas-profiling) (0.5.0)
Requirement already satisfied: jinja2>=2.11.1 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (2.11.2)
Requirement already satisfied: markupsafe~=2.0.1 in
/opt/conda/lib/python3.7/site-packages (from pandas-profiling) (2.0.1)
Requirement already satisfied: phik>=0.11.1 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (0.12.0)
Requirement already satisfied: pydantic>=1.8.1 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (1.8.2)
Requirement already satisfied: tqdm>=4.48.2 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (4.62.3)
Requirement already satisfied: scipy>=1.4.1 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (1.4.1)
Requirement already satisfied: multimethod>=1.4 in
/opt/conda/lib/python3.7/site-packages (from pandas-profiling) (1.6)
Requirement already satisfied: PyYAML>=5.0.0 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (5.3.1)
Requirement already satisfied: tangled-up-in-unicode==0.1.0 in
/opt/conda/lib/python3.7/site-packages (from pandas-profiling) (0.1.0)
Requirement already satisfied: matplotlib>=3.2.0 in
/opt/conda/lib/python3.7/site-packages (from pandas-profiling) (3.2.1)
Requirement already satisfied: joblib~=1.0.1 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (1.0.1)
Requirement already satisfied: requests>=2.24.0 in
/opt/conda/lib/python3.7/site-packages (from pandas-profiling) (2.26.0)
Requirement already satisfied: htmlmin>=0.1.12 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (0.1.12)
Requirement already satisfied: visions[type_image_path]==0.7.4 in
/opt/conda/lib/python3.7/site-packages (from pandas-profiling) (0.7.4)
```

```
Requirement already satisfied: pandas!=1.0.0,!=1.0.1,!=1.0.2,!=1.1.0,>=0.25.3 in
/opt/conda/lib/python3.7/site-packages (from pandas-profiling) (1.0.3)
Requirement already satisfied: numpy>=1.16.0 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (1.18.4)
Requirement already satisfied: seaborn>=0.10.1 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (0.10.1)
Requirement already satisfied: typing-extensions>=3.7.4.3 in
/opt/conda/lib/python3.7/site-packages (from pydantic>=1.8.1->pandas-profiling)
(3.10.0.2)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/opt/conda/lib/python3.7/site-packages (from matplotlib>=3.2.0->pandas-
profiling) (2.4.7)
Requirement already satisfied: kiwisolver>=1.0.1 in
/opt/conda/lib/python3.7/site-packages (from matplotlib>=3.2.0->pandas-
profiling) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.7/site-
packages (from matplotlib>=3.2.0->pandas-profiling) (0.10.0)
Requirement already satisfied: python-dateutil>=2.1 in
/opt/conda/lib/python3.7/site-packages (from matplotlib>=3.2.0->pandas-
profiling) (2.8.1)
Requirement already satisfied: certifi>=2017.4.17 in
/opt/conda/lib/python3.7/site-packages (from requests>=2.24.0->pandas-profiling)
(2020.4.5.2)
Requirement already satisfied: charset-normalizer~=2.0.0; python_version >= "3"
in /opt/conda/lib/python3.7/site-packages (from requests>=2.24.0->pandas-
profiling) (2.0.7)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in
/opt/conda/lib/python3.7/site-packages (from requests>=2.24.0->pandas-profiling)
(1.25.9)
Requirement already satisfied: idna<4,>=2.5; python_version >= "3" in
/opt/conda/lib/python3.7/site-packages (from requests>=2.24.0->pandas-profiling)
(2.9)
Requirement already satisfied: attrs>=19.3.0 in /opt/conda/lib/python3.7/site-
packages (from visions[type_image_path]==0.7.4->pandas-profiling) (19.3.0)
Requirement already satisfied: networkx>=2.4 in /opt/conda/lib/python3.7/site-
packages (from visions[type_image_path]==0.7.4->pandas-profiling) (2.4)
Requirement already satisfied: imagehash; extra == "type_image_path" in
/opt/conda/lib/python3.7/site-packages (from
visions[type_image_path]==0.7.4->pandas-profiling) (4.2.1)
Requirement already satisfied: Pillow; extra == "type_image_path" in
/opt/conda/lib/python3.7/site-packages (from
visions[type_image_path]==0.7.4->pandas-profiling) (7.1.2)
Requirement already satisfied: pytz>=2017.2 in /opt/conda/lib/python3.7/site-
packages (from pandas!=1.0.0,!=1.0.1,!=1.0.2,!=1.1.0,>=0.25.3->pandas-profiling)
(2020.1)
Requirement already satisfied: six in /opt/conda/lib/python3.7/site-packages
(from cycler>=0.10->matplotlib>=3.2.0->pandas-profiling) (1.14.0)
Requirement already satisfied: decorator>=4.3.0 in
```

```
/opt/conda/lib/python3.7/site-packages (from
networkx>=2.4->visions[type_image_path]==0.7.4->pandas-profiling) (4.4.2)
Requirement already satisfied: PyWavelets in /opt/conda/lib/python3.7/site-
packages (from imagehash; extra ==
"type_image_path"->visions[type_image_path]==0.7.4->pandas-profiling) (1.1.1)
Note: you may need to restart the kernel to use updated packages.
```

[23]:
```
# Using pandas profiling to inspect our dataset. Pandas profiling gives you␣
↪very detailed information on variables and correlations
from pandas_profiling import ProfileReport as pp
```

[24]:
```
profile = pp(df_tor)
profile
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

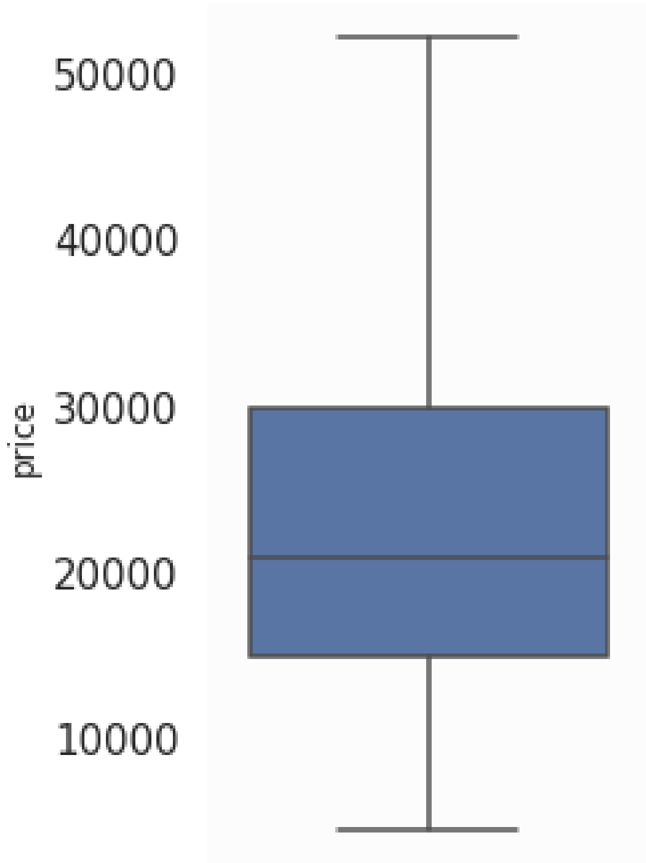
[24]:

[25]:
```
rr=sorted(df_tor["price"])
quantile1, quantile3= np.percentile(rr,[1,99])
print(quantile1,quantile3)
```

```
4490.0 93999.0
```

[26]:
```
# There are extreame values exist on both side of the distribution. Also the␣
↪difference between 75% value and max value is too large so lets leave 1%␣
↪values at both ends of a distribution.These values either do not make sense␣
↪or will significantly impact our models.
# Remove records with prices <4490 and price > 93999.
df_tor=df_tor[(df_tor.price < 93999) & (df_tor.price > 4490 )]
```

[27]:
```
plt.figure(figsize=(3,6))
sns.boxplot(y='price', data=df_tor, showfliers=False);
```



[28]:
```
# Any car that was made before 1990 should be considered as vintage or classic␣
↪car. There is a special group of people who colloect these type␣
↪cars,however, these cars should not be inlcuded in this study. cars made in␣
↪2022 are probably entered by mistake
df_tor=df_tor[(df_tor.year > 1990) & (df_tor.year < 2022 )]
```

[29]:
```
# Below attributes have missing values,we need to clean them up.
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

[29]:
```
price              0
miles           1557
year               0
make               0
model            168
trim             947
body_type       1418
vehicle_type    1572
drivetrain       665
```

```
transmission     654
fuel_type       2171
engine_size     2177
engine_block    2217
dtype: int64
```

[30]:
```
len(df_tor)
```

[30]:
```
13523
```

[31]:
```
# The trim attributes has too much inconsistent data with high cardinality, so␣
↪we will drop this column.
df_tor=df_tor.drop(["trim"],axis=1)
```

[32]:
```
# There are records with missing values in 'model'.These records have to be␣
↪removed as model cant be replaced easily without changing the reality of the␣
↪instances.
df_tor=df_tor.dropna(subset=['model'])
```

[33]:
```
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

[33]:
```
price              0
miles           1544
year               0
make               0
model              0
body_type       1256
vehicle_type    1405
drivetrain       652
transmission     641
fuel_type       2003
engine_size     2009
engine_block    2049
dtype: int64
```

[34]:
```
# I am droping records with missnig drivetrain and transmission as well since␣
↪they are only account for less than 1% of total records.
df_tor=df_tor.dropna(subset=['drivetrain','transmission'])
```

[35]:
```
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

[35]:
```
price              0
miles           1439
year               0
make               0
```

```
model              0
body_type       1169
vehicle_type    1313
drivetrain         0
transmission       0
fuel_type       1338
engine_size     1375
engine_block    1394
dtype: int64
```

[36]:

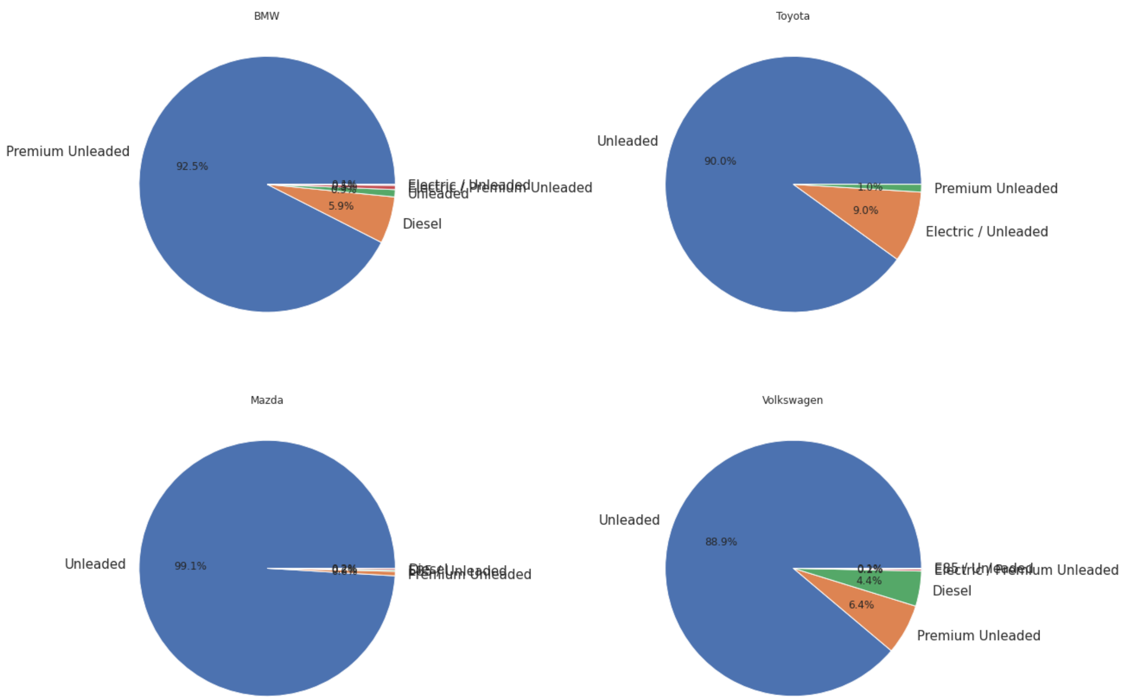
```
# Fuel_type can be an important feature, instead of simply dropping all the␣
↪records and also for the purpose of learning, lets try to replace these␣
↪missing values.
# Panadas profiling indicates that fuel_type has a relative high correlation␣
↪with make. We will select 4 random car brands and compare its fuel_type in␣
↪pie charts.
# Pie charts show that these brands prefer to produce cars with certain␣
↪fuel_type
plt.figure(figsize=(20,15))
plt.subplot(221)
df_tor["fuel_type"][df_tor["make"]=='BMW'].value_counts().plot.pie(autopct = '%.
↪1f%%', title="BMW")
plt.axis('off')

plt.subplot(222)
df_tor["fuel_type"][df_tor["make"]=='Toyota'].value_counts().plot.pie(autopct =␣
↪'%.1f%%', title="Toyota")
plt.axis('off')

plt.subplot(223)
df_tor["fuel_type"][df_tor["make"]=='Mazda'].value_counts().plot.pie(autopct =␣
↪'%.1f%%', title="Mazda")
plt.axis('off')

plt.subplot(224)
df_tor["fuel_type"][df_tor["make"]=='Volkswagen'].value_counts().plot.
↪pie(autopct = '%.1f%%', title="Volkswagen")
plt.axis('off')

plt.show()
```



[37]:
```python
# The approach here is to replace missing fuel_type with the most common value
↪for each brand. We first try to create a list with each brand and its most
↪commonly used fuel_type
fuel_count = df_tor.groupby(['fuel_type','make'], sort=True).size().
↪reset_index(name='Count').sort_values(['make','Count'],ascending=False).
↪groupby(['make']).first()
```

[38]:
```python
fuel_count.reset_index(inplace=True)
```

[39]:
```python
fuel_pair = fuel_count[['make','fuel_type']]
```

[40]:
```python
fuel_replace = pd.Series(fuel_pair.fuel_type.values,index = fuel_pair.make)
```

[41]:
```python
# Replace with missing fuel_type:
df_tor['fuel_type'] = df_tor['fuel_type'].fillna(df_tor['make'].apply(lambda x:
↪fuel_replace.get(x)))
```

[42]:
```python
# Miles
# miles has a strong negative correlation with year as shown below:
df_tor.corr()
```

[42]:

	price	miles	year	engine_size
price	1.000000	-0.476104	0.474156	0.311024
miles	-0.476104	1.000000	-0.717641	0.273222

```
year         0.474156 -0.717641  1.000000    -0.291305
engine_size  0.311024  0.273222 -0.291305     1.000000
```

[43]:
```
# Replacing missing values in miles with median value of each year.
miles_median =  dict(df_tor.groupby('year')['miles'].median())
```

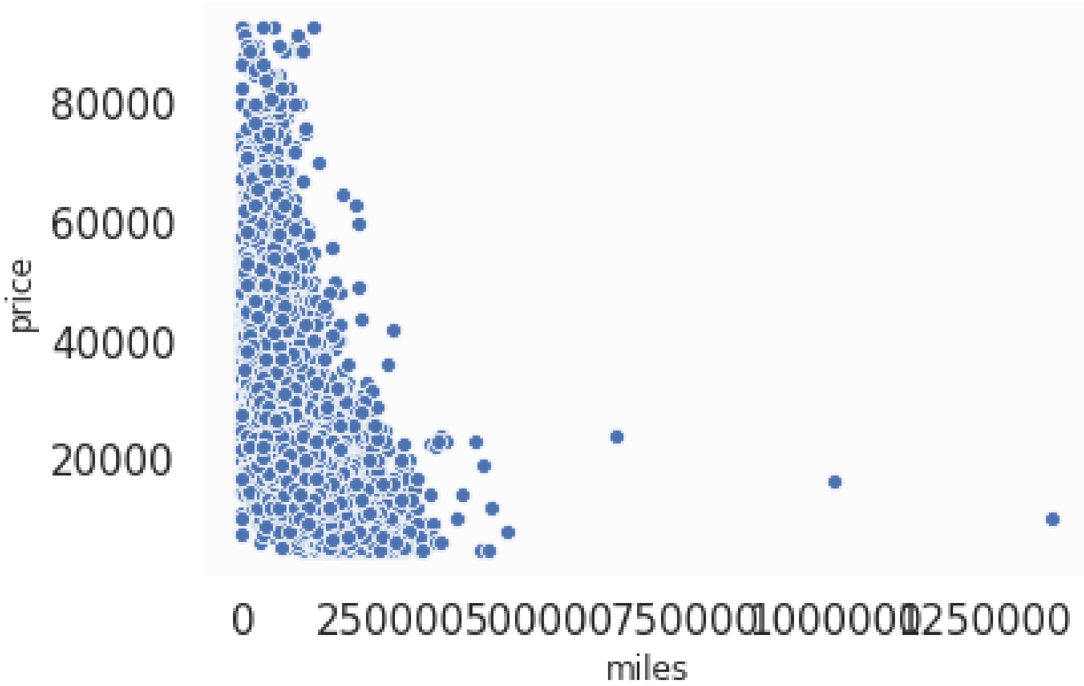
[44]:
```
df_tor['miles'] = df_tor['miles'].fillna(df_tor['year'].apply(lambda x:␣
 ↪miles_median.get(x)))
```

[45]:
```
# Removing the left missing values in miles because no information available␣
 ↪for that year.
df_tor=df_tor.dropna(subset=['miles'])
```

[46]:
```
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

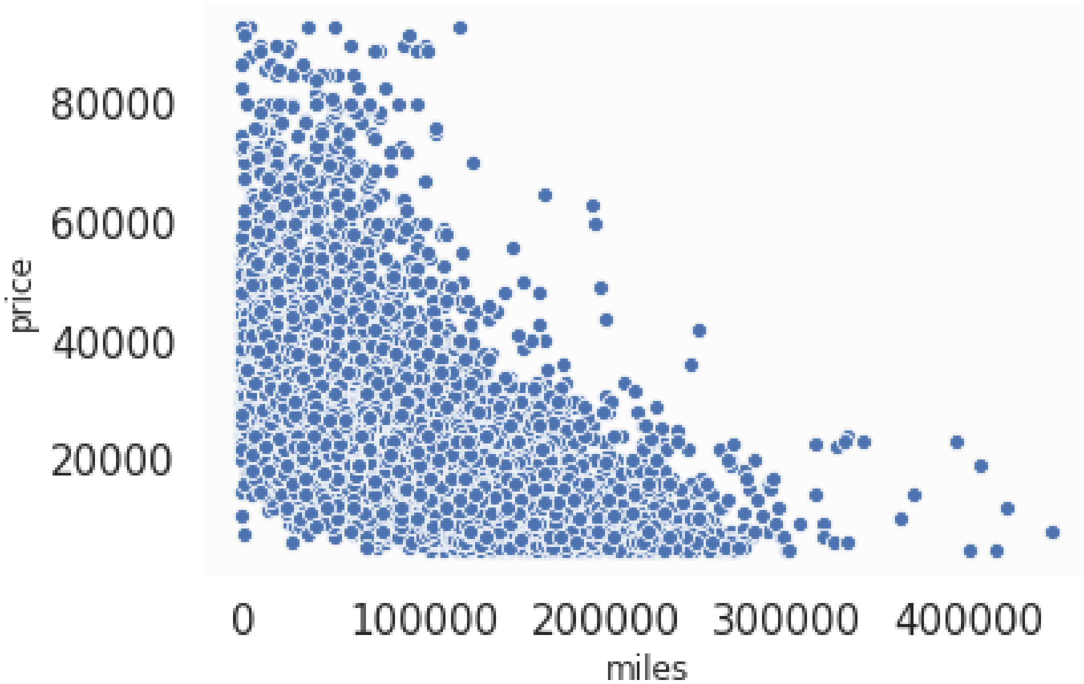
[46]:
```
price              0
miles              0
year               0
make               0
model              0
body_type       1169
vehicle_type    1313
drivetrain         0
transmission       0
fuel_type          0
engine_size     1375
engine_block    1394
dtype: int64
```

[47]:
```
# Lets see if miles has any outliers
ax = sns.scatterplot(x="miles", y="price", data=df_tor)
ax.get_xaxis().get_major_formatter().set_scientific(False)
ax.get_yaxis().get_major_formatter().set_scientific(False)
```



[48]:
```
# From the scatterplot above we can easily see some outliers, let's first only␣
↪keep cars between 1 miles and 500000 miles.
df_tor=df_tor[(df_tor.miles < 500000) & (df_tor.miles > 1 )]
```

[49]:
```
#Miles is another important feature, lets see if it has any outliers:
ax = sns.scatterplot(x="miles", y="price", data=df_tor)
ax.get_xaxis().get_major_formatter().set_scientific(False)
ax.get_yaxis().get_major_formatter().set_scientific(False)
```



[50]:
```
# There are still several instances where miles > 300000, lets remove those as␣
↪well
df_tor=df_tor[(df_tor.miles < 300000) & (df_tor.miles > 1 )]
```

[51]:
```
# Body_type
# Pandas profiling indicates that body type has a high correltion with vehicle␣
↪type, we will replace missing body_type based on vehicle type. Lets take a␣
↪look at these two attributes together.
df_bt = df_tor.groupby(['vehicle_type','body_type'], sort=True).size().
↪reset_index(name='Count')
df_bt
```

[51]:

	vehicle_type	body_type	Count
0	Car	Car Van	1
1	Car	Convertible	84
2	Car	Coupe	293
3	Car	Hatchback	1008
4	Car	Micro Car	6
5	Car	Mini Mpv	20
6	Car	SUV	1
7	Car	Sedan	4127
8	Car	Targa	4
9	Car	Wagon	107
10	Truck	Car Van	8

```
11         Truck      Cargo Van    111
12         Truck    Chassis Cab     10
13         Truck        Cutaway     22
14         Truck       Mini Mpv      4
15         Truck        Minivan    336
16         Truck  Passenger Van     13
17         Truck         Pickup    438
18         Truck            SUV   4730
```

[52]:
```
# We find out that there are records missing both attributes
df_tor.loc[(df_tor['vehicle_type'].isna()) & (df_tor['body_type'].isna())].
↪count()
```

[52]:
```
price           1154
miles           1154
year            1154
make            1154
model           1154
body_type          0
vehicle_type       0
drivetrain      1154
transmission    1154
fuel_type       1154
engine_size        0
engine_block       0
dtype: int64
```

[53]:
```
# Lets drop these records because the values cant be replaced by the approach␣
↪we are using.
df_tor=df_tor.dropna(subset=['vehicle_type','body_type'],how = 'all')
```

[54]:
```
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

[54]:
```
price             0
miles             0
year              0
make              0
model             0
body_type        11
vehicle_type    155
drivetrain        0
transmission      0
fuel_type         0
engine_size     217
engine_block    236
dtype: int64
```

[55]:
```
len(df_tor)
```

[55]: 11489

[56]:
```
# Replacing missing body_type based on vehicle type
df_bodytype = df_tor.groupby(['vehicle_type','body_type'], sort=True).size().
↪reset_index(name='Count')
df_bodytype
```

[56]:

	vehicle_type	body_type	Count
0	Car	Car Van	1
1	Car	Convertible	84
2	Car	Coupe	293
3	Car	Hatchback	1008
4	Car	Micro Car	6
5	Car	Mini Mpv	20
6	Car	SUV	1
7	Car	Sedan	4127
8	Car	Targa	4
9	Car	Wagon	107
10	Truck	Car Van	8
11	Truck	Cargo Van	111
12	Truck	Chassis Cab	10
13	Truck	Cutaway	22
14	Truck	Mini Mpv	4
15	Truck	Minivan	336
16	Truck	Passenger Van	13
17	Truck	Pickup	438
18	Truck	SUV	4730

[57]:
```
# The approach is to replace the missing value with most common body type for␣
↪each vehicle type
df_tor.loc[(df_tor['vehicle_type'] == 'Car') & (df_tor['body_type'].
↪isna()),'body_type'] = 'Sedan'
df_tor.loc[(df_tor['vehicle_type'] == 'Truck') & (df_tor['body_type'].
↪isna()),'body_type'] = 'SUV'
```

[58]:
```
# Now lets deal with missing vehicle type, similarly we will replace missing␣
↪vehicle type based on body_type:
df_vechile = df_tor.groupby(['body_type','vehicle_type'], sort=True).size().
↪reset_index(name='Count')
df_vechile
# We can see that in most cases, each body_type corresponding to one vehicle␣
↪type. Some outliers are probably entered by mistake.
```

[58]:

	body_type	vehicle_type	Count
0	Car Van	Car	1
1	Car Van	Truck	8
2	Cargo Van	Truck	111
3	Chassis Cab	Truck	10
4	Convertible	Car	84
5	Coupe	Car	293
6	Cutaway	Truck	22
7	Hatchback	Car	1008
8	Micro Car	Car	6
9	Mini Mpv	Car	20
10	Mini Mpv	Truck	4
11	Minivan	Truck	336
12	Passenger Van	Truck	13
13	Pickup	Truck	438
14	SUV	Car	1
15	SUV	Truck	4730
16	Sedan	Car	4138
17	Targa	Car	4
18	Wagon	Car	107

[59]:

```
# Lets first drop these 'ourlier' records:
df_tor = df_tor.drop(df_tor[(df_tor['body_type'] == 'Car Van') &␣
↪(df_tor['vehicle_type'] == 'Car')].index)
```

[60]:

```
df_tor = df_tor.drop(df_tor[(df_tor['body_type'] == 'Mini Mpv') &␣
↪(df_tor['vehicle_type'] == 'Truck')].index)
```

[61]:

```
df_tor = df_tor.drop(df_tor[(df_tor['body_type'] == 'SUV') &␣
↪(df_tor['vehicle_type'] == 'Car')].index)
```

[62]:

```
# Replacing missing vehicle type based on its body type
df_vechile = df_tor.groupby(['body_type','vehicle_type'], sort=True).size().
↪reset_index(name='Count')
df_vechile
```

[62]:

	body_type	vehicle_type	Count
0	Car Van	Truck	8
1	Cargo Van	Truck	111
2	Chassis Cab	Truck	10
3	Convertible	Car	84
4	Coupe	Car	293
5	Cutaway	Truck	22
6	Hatchback	Car	1008
7	Micro Car	Car	6
8	Mini Mpv	Car	20
9	Minivan	Truck	336

```
10  Passenger Van       Truck     13
11         Pickup       Truck    438
12            SUV       Truck   4730
13          Sedan         Car   4138
14          Targa         Car      4
15          Wagon         Car    107
```

[63]:
```python
vechile_pair = df_vechile[['body_type','vehicle_type']]
vechile_replace = pd.Series(vechile_pair.vehicle_type.values,index =␣
↪vechile_pair.body_type)
df_tor['vehicle_type'] = df_tor['vehicle_type'].fillna(df_tor['body_type'].
↪apply(lambda x: vechile_replace.get(x)))
```

[64]:
```python
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

[64]:
```
price             0
miles             0
year              0
make              0
model             0
body_type         0
vehicle_type      1
drivetrain        0
transmission      0
fuel_type         0
engine_size     216
engine_block    235
dtype: int64
```

[65]:
```python
# dropping that one record since no information is available
df_tor=df_tor.dropna(subset=['vehicle_type'])
```

[66]:
```python
# Engine_block
# Lets first change engine block of all electric cars to 'N/A'
df_tor.loc[df_tor.fuel_type == 'Electric', 'engine_block'] = 'N/A'
```

[67]:
```python
# Pandas Profiling report indicates engine_block is highly correlated with car␣
↪makes. We will replace the missing values with most commonly used engine␣
↪block type
```

[68]:
```python
block_count = df_tor.groupby(['engine_block','make'], sort=True).size().
↪reset_index(name='Count').sort_values(['make','Count'],ascending=False).
↪groupby(['make']).first()
```

[69]:
```python
block_count.reset_index(inplace=True)
```

[70]:
```
block_pair = block_count[['make','engine_block']]
```

[71]:
```
block_replace = pd.Series(block_pair.engine_block.values,index = block_pair.
 ↪make)
df_tor['engine_block'] = df_tor['engine_block'].fillna(df_tor['make'].
 ↪apply(lambda x: block_replace.get(x)))
```

[72]:
```
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

[72]:
```
price              0
miles              0
year               0
make               0
model              0
body_type          0
vehicle_type       0
drivetrain         0
transmission       0
fuel_type          0
engine_size      215
engine_block       6
dtype: int64
```

[73]:
```
# dropping those 6 records since no information is available
df_tor=df_tor.dropna(subset=['engine_block'])
```

[74]:
```
# Engine_size
# Lets first change engine size of all electric cars to 0
df_tor.loc[df_tor.fuel_type == 'Electric', 'engine_size'] = 0
```

[75]:
```
# Pandas Profiling report indicates engine_block is highly correlated with␣
 ↪engine_block . We will replace the missing values with most commonly used␣
 ↪engine size for each engine block
size_count = df_tor.groupby(['engine_size','engine_block'], sort=True).size().
 ↪reset_index(name='Count').
 ↪sort_values(['engine_block','Count'],ascending=False).
 ↪groupby(['engine_block']).first()
```

[76]:
```
size_count.reset_index(inplace=True)
```

[77]:
```
size_pair = size_count[['engine_block','engine_size']]
```

[78]:
```
size_replace = pd.Series(size_pair.engine_size.values,index = size_pair.
 ↪engine_block)
```

[79]:
```
df_tor['engine_size'] = df_tor['engine_size'].fillna(df_tor['engine_block'].
↪apply(lambda x: size_replace.get(x)))
```

[80]:
```
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

[80]:
```
price           0
miles           0
year            0
make            0
model           0
body_type       0
vehicle_type    0
drivetrain      0
transmission    0
fuel_type       0
engine_size     0
engine_block    0
dtype: int64
```

[81]:
```
len(df_tor)
```

[81]:
```
11476
```

[82]:
```
df_tor.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11476 entries, 446 to 393573
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   price         11476 non-null  float64
 1   miles         11476 non-null  float64
 2   year          11476 non-null  float64
 3   make          11476 non-null  object
 4   model         11476 non-null  object
 5   body_type     11476 non-null  object
 6   vehicle_type  11476 non-null  object
 7   drivetrain    11476 non-null  object
 8   transmission  11476 non-null  object
 9   fuel_type     11476 non-null  object
 10  engine_size   11476 non-null  float64
 11  engine_block  11476 non-null  object
dtypes: float64(4), object(8)
memory usage: 1.1+ MB
```

[83]:

```
profile = pp(df_tor)
profile
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

[83]:

[84]:

```
df_tor.make.value_counts().to_frame()
```

[84]:

	make
Hyundai	1243
Toyota	1133
Volkswagen	890
Honda	834
Ford	787
BMW	760
Mercedes-Benz	707
Nissan	656
Chevrolet	526
Mazda	526
Kia	387
Lexus	367
Audi	352
Dodge	308
Jeep	229
Acura	203
Land Rover	174
GMC	135
Subaru	133
INFINITI	130
Cadillac	121
RAM	107
Buick	106
MINI	92
Jaguar	80
Lincoln	79
Porsche	76
Chrysler	71
Volvo	70

```
Mitsubishi       66
GENESIS          25
Tesla            22
Maserati         19
FIAT             15
Scion            13
smart             7
Pontiac           7
Hummer            6
Alfa Romeo        6
Aston Martin      5
Saturn            1
Saab              1
Suzuki            1
```

[85]:
```
# Some brands have too few samples. For the precision of our future model, I␣
↪choose to remove the car brands which have less than 20 samples. It will␣
↪narrow the capability of our model, but in return lower the bias and␣
↪variance.
rm_brands = ['Maserati', 'FIAT', 'Scion', 'smart', 'Pontiac', 'Alfa Romeo',␣
↪'Hummer', 'Aston Martin', 'Saturn', 'Saab','Suzuki']
for brand in rm_brands:
    df_tor = df_tor[~(df_tor['make'] == brand)]
```

[86]:
```
# The end of data cleaning and processing for toronto data
```

[87]:
```
# Another dataset is selected for comparison for our reserch purpose. The city␣
↪selected is Boston, since it is comparable to Toronto.
# The same data cleaning and processing approach will be applied to the new␣
↪dataset.
```

[88]:
```
# Load data
import dask.dataframe as dd
df2 = dd.read_csv("us-dealers-used.csv",dtype={'fuel_type': 'object',␣
↪'engine_block': 'object','zip': 'object', 'year': 'float64'})
```

[89]:
```
# drop irrelevant columns for this research
drop_column = ['id', 'vin', 'stock_no', 'seller_name','street','zip']
```

[90]:
```
df2 = df2.drop(columns = drop_column)
```

[91]:
```
df2 =df2[df2.state == "MA"]
```

[92]:
```
# onley select city as Boston
df2=df2[df2.city == "Boston"]
```

[93]:
```
df_bs = df2.compute()
```

[94]:
```
len(df_bs)
```

[94]:
```
12780
```

[95]:
```
# drop state, city and trim
df_bs=df_bs.drop(["state","city","trim"],axis=1)
```

[96]:
```
df_bs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 12780 entries, 141 to 9367
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   price         12664 non-null  float64
 1   miles         12760 non-null  float64
 2   year          12780 non-null  float64
 3   make          12780 non-null  object
 4   model         12775 non-null  object
 5   body_type     12761 non-null  object
 6   vehicle_type  12757 non-null  object
 7   drivetrain    12772 non-null  object
 8   transmission  12767 non-null  object
 9   fuel_type     12749 non-null  object
 10  engine_size   12655 non-null  float64
 11  engine_block  12629 non-null  object
dtypes: float64(4), object(8)
memory usage: 1.3+ MB
```

[97]:
```
missing_values_count = df_bs.isnull().sum()
missing_values_count
```

[97]:
```
price           116
miles            20
year              0
make              0
model             5
body_type        19
vehicle_type     23
drivetrain        8
transmission     13
fuel_type        31
engine_size     125
engine_block    151
dtype: int64
```

[98]:
```python
# sample data:
df_bs.head(20)
```

[98]:

	price	miles	year	make	model	body_type
141	22998.0	87571.0	2013.0	Mercedes-Benz	CLS-Class	Coupe
512	10998.0	34998.0	2015.0	Chevrolet	Spark	Hatchback
882	58998.0	30819.0	2018.0	Mercedes-Benz	GLS-Class	SUV
3534	79998.0	10492.0	2019.0	Porsche	Cayenne	SUV
4772	58498.0	21363.0	2017.0	Mercedes-Benz	GLS-Class	SUV
5289	58998.0	45391.0	2017.0	Mercedes-Benz	GLE-Class	SUV
6160	NaN	8.0	2021.0	BMW	8 Series	Sedan
6700	23498.0	58970.0	2017.0	GMC	Savana Cargo	Cargo Van
8004	53998.0	27262.0	2014.0	BMW	6 Series	Sedan
8339	43900.0	37212.0	2012.0	Porsche	Boxster	Roadster
8657	22498.0	87571.0	2013.0	Mercedes-Benz	CLS-Class	Coupe
9003	189998.0	31385.0	2014.0	Ferrari	458 Spider	Convertible
9491	40998.0	62303.0	2015.0	Mercedes-Benz	S-Class	Sedan
9643	299998.0	559.0	2020.0	Bentley	Mulsanne	Sedan
10280	84998.0	18663.0	2018.0	Porsche	Panamera	Hatchback
10650	122998.0	28419.0	2018.0	Mercedes-Benz	G-Class	SUV
11316	83998.0	17534.0	2018.0	BMW	M5	Sedan
11771	122998.0	28419.0	2018.0	Mercedes-Benz	G-Class	SUV
12567	122998.0	28419.0	2018.0	Mercedes-Benz	G-Class	SUV
13906	49998.0	24160.0	2017.0	Mercedes-Benz	CLS-Class	Coupe

	vehicle_type	drivetrain	transmission	fuel_type	engine_size
141	Car	4WD	Automatic	Premium Unleaded	4.7
512	Car	FWD	Automatic	Unleaded	1.2
882	Truck	4WD	Automatic	Premium Unleaded	4.7
3534	Truck	4WD	Automatic	Premium Unleaded	2.9
4772	Truck	4WD	Automatic	Premium Unleaded	4.7
5289	Truck	4WD	Automatic	Premium Unleaded	5.5
6160	Car	4WD	Automatic	Premium Unleaded	4.4
6700	Truck	RWD	Automatic	Unleaded	4.8
8004	Car	RWD	Automatic	Premium Unleaded	4.4
8339	Car	RWD	Manual	Premium Unleaded	3.4
8657	Car	4WD	Automatic	Premium Unleaded	4.7
9003	Car	RWD	Automatic	Premium Unleaded	4.5
9491	Car	4WD	Automatic	Premium Unleaded	4.7
9643	Car	RWD	Automatic	Premium Unleaded	6.8
10280	Car	4WD	Automatic	Premium Unleaded	2.9
10650	Truck	4WD	Automatic	Premium Unleaded	5.5
11316	Car	4WD	Automatic	Premium Unleaded	4.4
11771	Truck	4WD	Automatic	Premium Unleaded	5.5
12567	Truck	4WD	Automatic	Premium Unleaded	5.5
13906	Car	4WD	Automatic	Premium Unleaded	4.7

```
      engine_block
141              V
512              I
882              V
3534             V
4772             V
5289             V
6160             V
6700             V
8004             V
8339             H
8657             V
9003             V
9491             V
9643             V
10280            V
10650            V
11316            V
11771            V
12567            V
13906            V
```

[99]:
```
# Lets drop records without prices, since these records will be useless for our␣
↪analysis
df_bs=df_bs.dropna(subset=['price'])
```

[100]:
```
profile = pp(df_bs)
profile
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

[100]:

[101]:
```
# We will simply drop records with missing values, since they only account for␣
↪a very small percentage of the whole dataset.
df_bs=df_bs.
↪dropna(subset=['miles','model','body_type','vehicle_type','drivetrain','transmission','fuel
```

[102]:
```python
missing_values_count = df_bs.isnull().sum()
missing_values_count
```

[102]:
```
price           0
miles           0
year            0
make            0
model           0
body_type       0
vehicle_type    0
drivetrain      0
transmission    0
fuel_type       0
engine_size     0
engine_block    0
dtype: int64
```

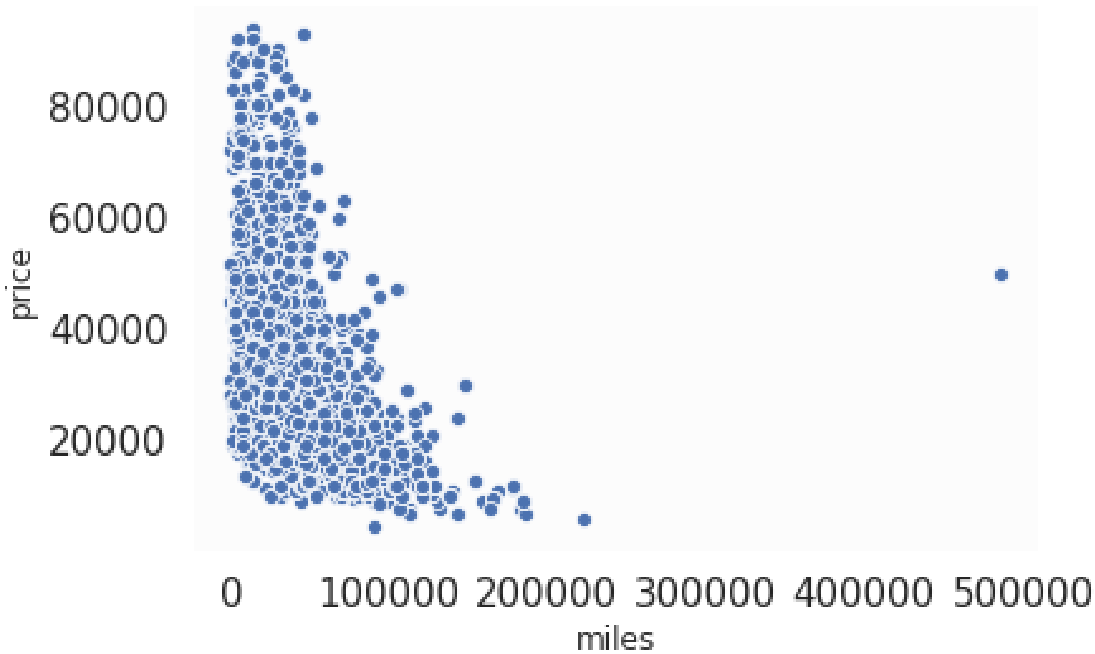
[103]:
```python
len(df_bs)
```

[103]:
```
12495
```

[104]:
```python
# Price:
# Keep the same price range as toronto
df_bs=df_bs[(df_bs.price < 93999) & (df_bs.price > 4490 )]
```

[105]:
```python
# Year
# Any car that was made before 1990 should be considered as vintage or classic␣
↪car. There is a special group of people who colloect these cars,however,␣
↪these cars should not be inlcuded in this study.
df_bs=df_bs[(df_bs.year > 1990)]
```

[106]:
```python
# Miles
# Lets see if miles has any outliers
ax = sns.scatterplot(x="miles", y="price", data=df_bs)
ax.get_xaxis().get_major_formatter().set_scientific(False)
ax.get_yaxis().get_major_formatter().set_scientific(False)
```

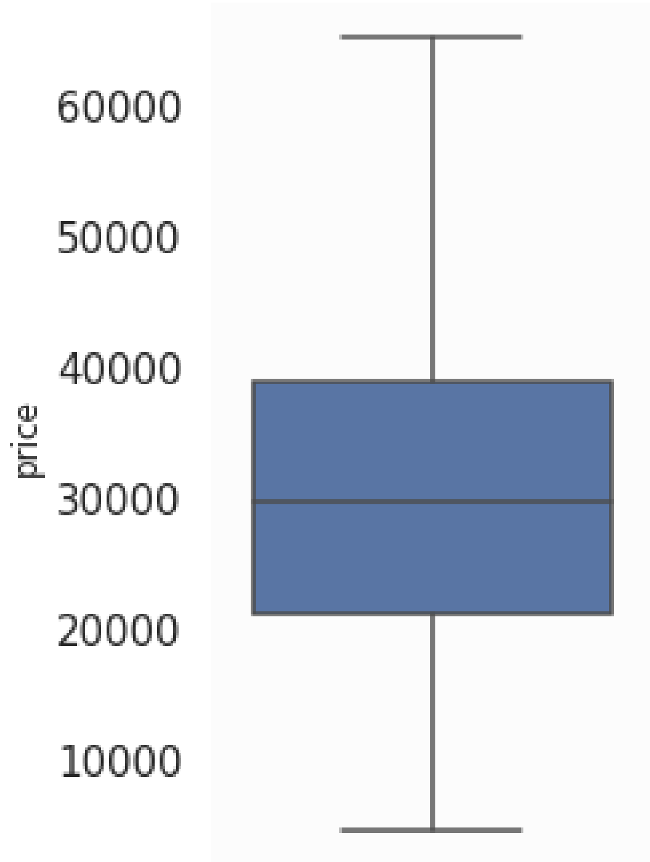


[107]:
```
# Remove outliers
df_bs=df_bs[(df_bs.miles < 300000) & (df_bs.miles > 1 )]
```

[108]:
```
# Engine_block
# Change engine block of all electric cars to 'N/A'
df_bs.loc[df_bs.fuel_type == 'Electric', 'engine_block'] = 'N/A'
```

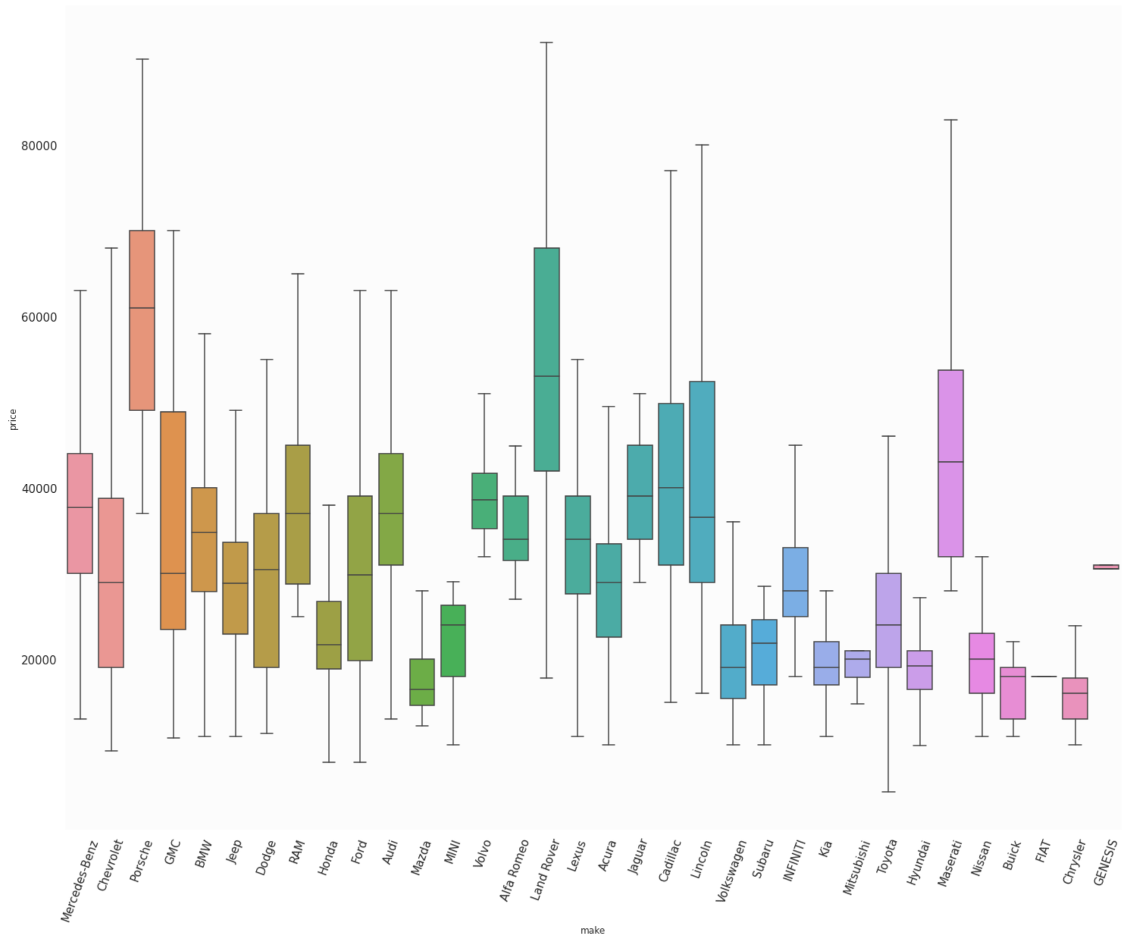
[109]:
```
# Engine_size
# Change engine size of all electric cars to 0
df_bs.loc[df_bs.fuel_type == 'Electric', 'engine_size'] = 0
```

[110]:
```
plt.figure(figsize=(3,6))
sns.boxplot(y='price', data=df_bs, showfliers=False);
```



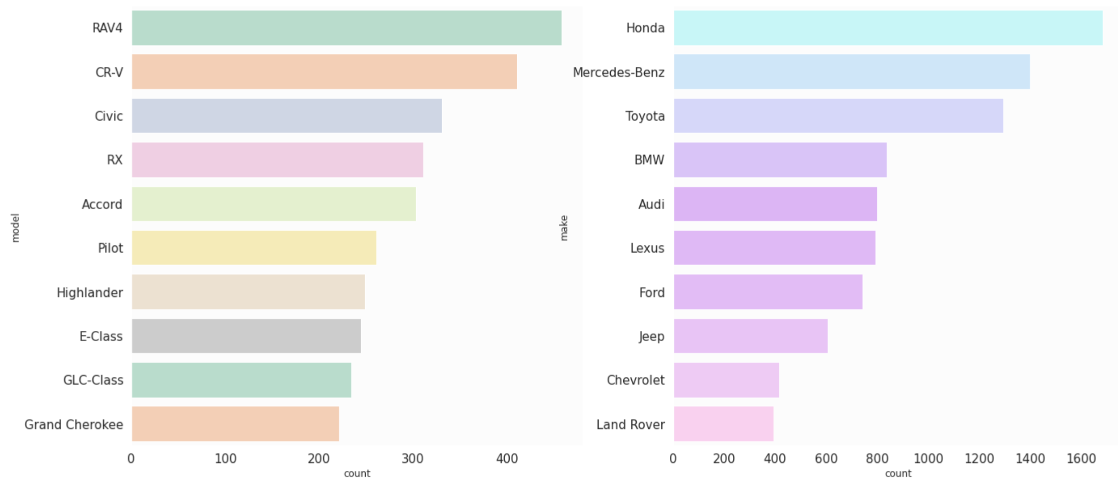
[111]:
```
plt.figure(figsize=(25,20))
plt.xticks(rotation=70)
sns.boxplot(y='price', x='make', data=df_bs, showfliers=False)
```

[111]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9254660950>



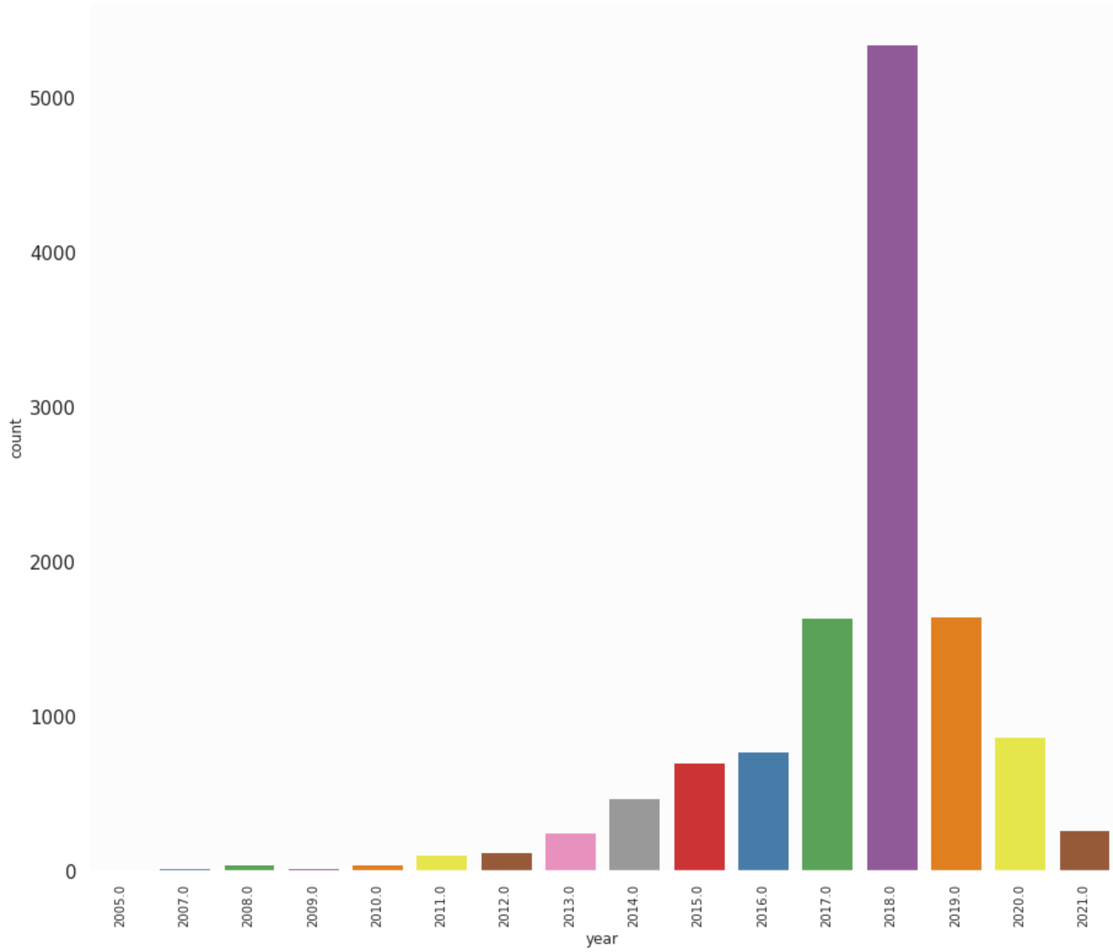
[112]:
```
colors = ["#C0FDFF",␣
↪"#C8E7FF","#D0D1FF","#D8BBFF","#DEAAFF","#E2AFFF","#E5B3FE","#ECBCFD","#F3C4FB","#FFCBF2"]
sns.set_palette(sns.color_palette(colors))


fig, ax =plt.subplots(1,2,figsize=(22, 10))
sns.set(rc={"axes.facecolor":"#fcfcfc", "axes.grid":False,'xtick.labelsize':
↪20,'ytick.labelsize':20})
sns.countplot(y ='make',data = df_bs,order=df_bs.make.value_counts().iloc[:10].
↪index, ax = ax[1],palette = colors)
sns.countplot(y ='model',data = df_bs,order=df_bs.model.value_counts().iloc[:
↪10].index, ax= ax[0],palette = "Pastel2")
fig.show()
```



[113]:
```
fig, ax =plt.subplots(1,3,figsize=(25, 10))
sns.set(rc={"axes.facecolor":"#fcfcfc", "axes.grid":False,'xtick.labelsize':
 ↪15,'ytick.labelsize':15})
sns.countplot(x ='body_type',data = df_bs,order=df_bs.body_type.value_counts().
 ↪iloc[:5].index, ax = ax[0],palette="vlag")
sns.countplot(x ='drivetrain',data = df_bs,order=df_bs.drivetrain.
 ↪value_counts().iloc[:5].index, ax = ax[1],palette="Pastel1")
sns.countplot(x ='transmission',data = df_bs,order=df_bs.transmission.
 ↪value_counts().iloc[:5].index, ax = ax[2],palette="YlGn")
fig.show()
```

[114]:
```
plt.figure(figsize=(15, 13))
ax = sns.countplot(x = 'year', data=df_bs, palette='Set1')
ax.set_xticklabels(ax.get_xticklabels(), rotation=90,fontsize=10);
```



[115]:
```
# Now lets deal with missing vehicle type, similarly we will replace missing␣
↪vehicle type based on body_type:
df_bv = df_bs.groupby(['body_type','vehicle_type'], sort=True).size().
↪reset_index(name='Count')
df_bv
# We can see that in most cases, each body_type corresponding to one vehicle␣
↪type. Some outliers are probably entered by mistake.
```

[115]:

	body_type	vehicle_type	Count
0	Cargo Van	Truck	63
1	Chassis Cab	Truck	10
2	Convertible	Car	64
3	Coupe	Car	468
4	Crossover	Car	9
5	Crossover	Truck	765
6	Hatchback	Car	468
7	Mini Mpv	Truck	7

```
8          Minivan        Truck    114
9    Passenger Van        Truck     16
10          Pickup        Truck    623
11        Roadster          Car      5
12             SUV          Car     16
13             SUV        Truck   6576
14           Sedan          Car   2965
15           Wagon          Car    118
```

[116]:
```
df_bs = df_bs.drop(df_bs[(df_bs['body_type'] == 'Crossover') &
 ↪(df_bs['vehicle_type'] == 'Car')].index)
df_bs = df_bs.drop(df_bs[(df_bs['body_type'] == 'SUV') & (df_bs['vehicle_type']
 ↪== 'Car')].index)
```

[117]:
```
df_bs.make.value_counts().to_frame()
```

[117]:

	make
Honda	1684
Mercedes-Benz	1397
Toyota	1284
BMW	823
Audi	798
Lexus	794
Ford	744
Jeep	606
Chevrolet	417
Land Rover	393
Hyundai	344
Acura	334
Cadillac	294
Nissan	275
Porsche	232
Lincoln	186
Volvo	185
INFINITI	170
Subaru	156
Kia	145
Alfa Romeo	137
MINI	137
Volkswagen	120
Dodge	112
RAM	94
Jaguar	93
GMC	89
Mazda	74
Buick	50
Mitsubishi	30

```
Chrysler         29
Maserati         26
FIAT              5
GENESIS           5
```

[118]:
```
# Remove the car brands which have less than 20 samples. It will narrow the␣
↪capability of our model, but in return lower the bias and variance.
rm_brands = ['FIAT', 'GENESIS']
for brand in rm_brands:
    df_bs = df_bs[~(df_bs['make'] == brand)]
```

[119]:
```
profile = pp(df_bs)
profile
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

[119]:

[120]:
```
# Before we start to train the models, We also need to normalize the values in␣
↪the numerical features ("year" ,"engine_size" "miles"), as they do not have␣
↪the same scale as the other newly created columns.
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
num_vars= ['year', 'miles', 'engine_size']
df_tor[num_vars] = scaler.fit_transform(df_tor[num_vars])
```

[121]:
```
# The first model we will implement is Linear Regression, however, linear␣
↪regression can not handle categorical data directly. Thus, we need to apply␣
↪encoding first.
# Most of our categorical features have more than two values. If we use␣
↪LabelEncoder then these values will be treated as ordinal ones by the␣
↪machine learning model.
# In this case, we will select One-hot encoder, also called as dummy encoding,␣
↪however, model feature has a high cardinality, we need to avoid curse of␣
↪dimensionality
df_tor_lr = df_tor.copy()
```

[122]:
```
!pip install feature_engine
from feature_engine.encoding import RareLabelEncoder as␣
↪RareLabelCategoricalEncoder
```

```
Requirement already satisfied: feature_engine in /opt/conda/lib/python3.7/site-
packages (1.1.2)
Requirement already satisfied: statsmodels>=0.11.1 in
/opt/conda/lib/python3.7/site-packages (from feature_engine) (0.11.1)
Requirement already satisfied: numpy>=1.18.2 in /opt/conda/lib/python3.7/site-
packages (from feature_engine) (1.18.4)
Requirement already satisfied: pandas>=1.0.3 in /opt/conda/lib/python3.7/site-
packages (from feature_engine) (1.0.3)
Requirement already satisfied: scikit-learn>=0.22.2 in
/opt/conda/lib/python3.7/site-packages (from feature_engine) (0.22.2.post1)
Requirement already satisfied: scipy>=1.4.1 in /opt/conda/lib/python3.7/site-
packages (from feature_engine) (1.4.1)
Requirement already satisfied: patsy>=0.5 in /opt/conda/lib/python3.7/site-
packages (from statsmodels>=0.11.1->feature_engine) (0.5.1)
Requirement already satisfied: python-dateutil>=2.6.1 in
/opt/conda/lib/python3.7/site-packages (from pandas>=1.0.3->feature_engine)
(2.8.1)
Requirement already satisfied: pytz>=2017.2 in /opt/conda/lib/python3.7/site-
packages (from pandas>=1.0.3->feature_engine) (2020.1)
Requirement already satisfied: joblib>=0.11 in /opt/conda/lib/python3.7/site-
packages (from scikit-learn>=0.22.2->feature_engine) (1.0.1)
Requirement already satisfied: six in /opt/conda/lib/python3.7/site-packages
(from patsy>=0.5->statsmodels>=0.11.1->feature_engine) (1.14.0)
```

[123]:
```
# Upon further checking, a lot of the model only appear once in our dataset! So␣
↪the approach we use here first is rarelabel encoder. All models that appear␣
↪less than 20 times are labelled as 'Rare'.
rare_encoder = RareLabelCategoricalEncoder(
    tol=0.0018,
    n_categories=10, variables=["model"])
```

[124]:
```
rare_encoder.fit(df_tor_lr)
```

[124]:
```
RareLabelEncoder(ignore_format=False, max_n_categories=None, n_categories=10,
                 replace_with='Rare', tol=0.0018, variables=['model'])
```

[125]:
```
df_tor_lr = rare_encoder.transform(df_tor_lr)
```

[126]:
```
# Define a function to generate dummy variables and mergek it with data frame

def dummies(x,df):
    temp = pd.get_dummies(df[[x]], drop_first=True)
    df = pd.concat([df,temp], axis=1)
```

```
    df.drop([x], axis=1, inplace=True)
    return df

# Apply function to the cars_new df
df_tor_lr = dummies('make', df_tor_lr)
df_tor_lr = dummies('model', df_tor_lr)
df_tor_lr = dummies('body_type', df_tor_lr)
df_tor_lr = dummies('vehicle_type', df_tor_lr)
df_tor_lr = dummies('drivetrain', df_tor_lr)
df_tor_lr = dummies('transmission', df_tor_lr)
df_tor_lr = dummies('fuel_type', df_tor_lr)
df_tor_lr = dummies('engine_block', df_tor_lr)
```

[127]:

```
df_tor_lr.head()
```

[127]:

```
       price     miles      year  engine_size  make_Audi  make_BMW  \
446  39455.0  0.290890  0.869565     0.684932          0         0
732   6450.0  0.736667  0.391304     0.739726          0         0
992  24962.0  0.177380  0.869565     0.205479          0         0
993  24962.0  0.172075  0.869565     0.205479          0         0
996  24962.0  0.172075  0.869565     0.205479          0         0

     make_Buick  make_Cadillac  make_Chevrolet  make_Chrysler  …  \
446           0              0               0              0  …
732           0              0               0              0  …
992           0              0               1              0  …
993           0              0               1              0  …
996           0              0               1              0  …

     fuel_type_Electric / E85  fuel_type_Electric / Premium Unleaded  \
446                         0                                       0
732                         0                                       0
992                         0                                       1
993                         0                                       1
996                         0                                       1

     fuel_type_Electric / Unleaded  fuel_type_Premium Unleaded  \
446                              0                           0
732                              0                           0
992                              0                           0
993                              0                           0
996                              0                           0

     fuel_type_Premium Unleaded / Unleaded  fuel_type_Unleaded  \
446                                      0                   0
732                                      0                   0
992                                      0                   0
```

```
993                                        0                   0
996                                        0                   0

     fuel_type_Unleaded / Unleaded  engine_block_I  engine_block_N/A  \
446                              1               0                 0
732                              0               0                 0
992                              0               1                 0
993                              0               1                 0
996                              0               1                 0

     engine_block_V
446               1
732               1
992               0
993               0
996               0

[5 rows x 192 columns]
```

[128]:
```
# Split train and test data using 8:2 ratio:
X_train, X_test, Y_train, Y_test = train_test_split(df_tor_lr.
 ↪drop('price',axis=1), df_tor_lr['price'], test_size=0.20, random_state=141)
```

[129]:
```
model_evaluation  = pd.DataFrame(columns=('r2', 'rmse'))
```

[130]:
```
from sklearn.linear_model import LinearRegression
lrm = LinearRegression()
lrm.fit(X_train,Y_train)
```

[130]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

[131]:
```
# Overall the performence and accuracy is just mediocre with R2 score around 82%
from sklearn import metrics
lrm_predict = lrm.predict(X_test)

lrm_r2 = metrics.r2_score(Y_test, lrm_predict)
lrm_rmse = math.sqrt(metrics.mean_squared_error(Y_test, lrm_predict))

model_evaluation = model_evaluation.append(pd.DataFrame({'r2':[lrm_r2], 'rmse':
 ↪[lrm_rmse]}, index = ['Linear Regression']))

print('For the linear regressor, the root mean square error for the testing set␣
 ↪is:', lrm_rmse)
print('The r2 score for the testing set is:', lrm_r2)
```

```
For the linear regressor, the root mean square error for the testing set is:
5576.616035914864
```

The r2 score for the testing set is: 0.82619340703072

[132]:
```
# To test whether it is overfitting, we calculate the score for the training␣
↪set as well:
lrm_predict_train = lrm.predict(X_train)

lrm_r2_train = metrics.r2_score(Y_train, lrm_predict_train)
lrm_rmse_train = math.sqrt(metrics.mean_squared_error(Y_train,␣
↪lrm_predict_train))

print('For the linear regressor, the root mean square error for the training␣
↪set is:', lrm_rmse_train)
print('The r2 score for the testing set is:', lrm_r2_train)
# With similar rmse and r2 score, it seems that overfitting is not a probelm.
```

For the linear regressor, the root mean square error for the training set is:
5725.808257497235
The r2 score for the testing set is: 0.8217534983075683

[133]:
```
# We will apply linear regression on Boston dataset as well and compare the␣
↪difference:
scaler = MinMaxScaler()
num_vars= ['year', 'miles', 'engine_size']
df_bs[num_vars] = scaler.fit_transform(df_bs[num_vars])
```

[134]:
```
df_bs_lr = df_bs.copy()
```

[135]:
```
rare_encoder.fit(df_bs_lr)
```

[135]:
```
RareLabelEncoder(ignore_format=False, max_n_categories=None, n_categories=10,
                 replace_with='Rare', tol=0.0018, variables=['model'])
```

[136]:
```
df_bs_lr = rare_encoder.transform(df_bs_lr)
```

[137]:
```
def dummies(x,df):
    temp = pd.get_dummies(df[[x]], drop_first=True)
    df = pd.concat([df,temp], axis=1)
    df.drop([x], axis=1, inplace=True)
    return df

# Apply function to the cars_new df
df_bs_lr = dummies('make', df_bs_lr)
df_bs_lr = dummies('model', df_bs_lr)
df_bs_lr = dummies('body_type', df_bs_lr)
df_bs_lr = dummies('vehicle_type', df_bs_lr)
df_bs_lr = dummies('drivetrain', df_bs_lr)
df_bs_lr = dummies('transmission', df_bs_lr)
```

```
df_bs_lr = dummies('fuel_type', df_bs_lr)
df_bs_lr = dummies('engine_block', df_bs_lr)
```

[138]:
```
df_bs_lr.head()
```

[138]:
```
        price     miles    year  engine_size  make_Alfa Romeo  make_Audi  \
141   22998.0  0.394358  0.5000     0.611940                0          0
512   10998.0  0.157576  0.6250     0.089552                0          0
882   58998.0  0.138755  0.8125     0.611940                0          0
3534  79998.0  0.047205  0.8750     0.343284                0          0
4772  58498.0  0.096166  0.7500     0.611940                0          0

      make_BMW  make_Buick  make_Cadillac  make_Chevrolet  …  \
141          0           0              0               0  …
512          0           0              0               1  …
882          0           0              0               0  …
3534         0           0              0               0  …
4772         0           0              0               0  …

      fuel_type_E85 / Premium Unleaded  fuel_type_E85 / Unleaded  \
141                                  0                         0
512                                  0                         0
882                                  0                         0
3534                                 0                         0
4772                                 0                         0

      fuel_type_E85 / Unleaded; Unleaded / Unleaded  \
141                                               0
512                                               0
882                                               0
3534                                              0
4772                                              0

      fuel_type_Electric / Premium Unleaded  \
141                                       0
512                                       0
882                                       0
3534                                      0
4772                                      0

      fuel_type_Electric / Premium Unleaded; Premium Unleaded  \
141                                                         0
512                                                         0
882                                                         0
3534                                                        0
4772                                                        0
```

```
      fuel_type_Electric / Unleaded  fuel_type_Premium Unleaded  \
141                               0                           1
512                               0                           0
882                               0                           1
3534                              0                           1
4772                              0                           1

      fuel_type_Unleaded  engine_block_I  engine_block_V
141                    0               0               1
512                    1               1               0
882                    0               0               1
3534                   0               0               1
4772                   0               0               1

[5 rows x 179 columns]
```

[139]:
```
# Split train and test data using 8:2 ratio:
x_train, x_test, y_train, y_test = train_test_split(df_bs_lr.
 ↪drop('price',axis=1), df_bs_lr['price'], test_size=0.20, random_state=141)
```

[140]:
```
lrm2 = LinearRegression()
lrm2.fit(x_train,y_train)
```

[140]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

[141]:
```
# The r2 score is higher and RMSE is somewhat similiar to toronto.
lrm2_predict = lrm2.predict(x_test)

lrm2_r2 = metrics.r2_score(y_test, lrm2_predict)
lrm2_rmse = math.sqrt(metrics.mean_squared_error(y_test, lrm2_predict))

model_evaluation_bs = model_evaluation.append(pd.DataFrame({'r2':[lrm2_r2],␣
 ↪'rmse':[lrm2_rmse]}, index = ['Linear Regression']))

print('For the linear regressor, the root mean square error for the testing set␣
 ↪is:', lrm2_rmse)
print('The r2 score for the testing set is:', lrm2_r2)
```

```
For the linear regressor, the root mean square error for the testing set is:
5122.596901444411
The r2 score for the testing set is: 0.8736260197642974
```

[142]:
```
# Again, to test whether it is overfitting, we calculate the score for the␣
 ↪training set as well:
lrm2_predict_train = lrm2.predict(x_train)

lrm2_r2_train = metrics.r2_score(y_train, lrm2_predict_train)
```

```
lrm2_rmse_train = math.sqrt(metrics.mean_squared_error(y_train,␣
↪lrm2_predict_train))

print('For the linear regressor, the root mean square error for the training␣
↪set is:', lrm2_rmse_train)
print('The r2 score for the testing set is:', lrm2_r2_train)
# With similar rmse and r2 score, it seems that overfitting is not a probelm.
```

```
For the linear regressor, the root mean square error for the training set is:
5304.935843152996
The r2 score for the testing set is: 0.8639902539603114
```

[ ]:
```
# Next we will apply more advanced methods on these two datasets: Random Forest␣
↪and XGB
```