CIND 820 Final results and codes

November 28, 2021

[26]:
```
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
import dask.dataframe as dd
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LinearRegression
from sklearn import metrics
```

[27]:
```
! pip install phik
import phik
from phik.report import plot_correlation_matrix
```

```
Requirement already satisfied: phik in /opt/conda/lib/python3.7/site-packages
(0.12.0)
Requirement already satisfied: matplotlib>=2.2.3 in
/opt/conda/lib/python3.7/site-packages (from phik) (3.2.1)
Requirement already satisfied: pandas>=0.25.1 in /opt/conda/lib/python3.7/site-
packages (from phik) (1.0.3)
Requirement already satisfied: numpy>=1.18.0 in /opt/conda/lib/python3.7/site-
packages (from phik) (1.18.4)
Requirement already satisfied: scipy>=1.5.2 in /opt/conda/lib/python3.7/site-
packages (from phik) (1.7.3)
Requirement already satisfied: joblib>=0.14.1 in /opt/conda/lib/python3.7/site-
packages (from phik) (1.0.1)
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>=2.2.3->phik) (2.4.7)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.7/site-
packages (from matplotlib>=2.2.3->phik) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
```

```
/opt/conda/lib/python3.7/site-packages (from matplotlib>=2.2.3->phik) (1.2.0)
Requirement already satisfied: python-dateutil>=2.1 in
/opt/conda/lib/python3.7/site-packages (from matplotlib>=2.2.3->phik) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in /opt/conda/lib/python3.7/site-
packages (from pandas>=0.25.1->phik) (2020.1)
Requirement already satisfied: six in /opt/conda/lib/python3.7/site-packages
(from cycler>=0.10->matplotlib>=2.2.3->phik) (1.14.0)
```

[28]:
```
pip install pandas-profiling
```

```
Requirement already satisfied: pandas-profiling in
/opt/conda/lib/python3.7/site-packages (3.1.0)
Requirement already satisfied: scipy>=1.4.1 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (1.7.3)
Requirement already satisfied: missingno>=0.4.2 in
/opt/conda/lib/python3.7/site-packages (from pandas-profiling) (0.5.0)
Requirement already satisfied: numpy>=1.16.0 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (1.18.4)
Requirement already satisfied: htmlmin>=0.1.12 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (0.1.12)
Requirement already satisfied: markupsafe~=2.0.1 in
/opt/conda/lib/python3.7/site-packages (from pandas-profiling) (2.0.1)
Requirement already satisfied: matplotlib>=3.2.0 in
/opt/conda/lib/python3.7/site-packages (from pandas-profiling) (3.2.1)
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: 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: jinja2>=2.11.1 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (2.11.2)
Requirement already satisfied: joblib~=1.0.1 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (1.0.1)
Requirement already satisfied: seaborn>=0.10.1 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (0.10.1)
Requirement already satisfied: requests>=2.24.0 in
/opt/conda/lib/python3.7/site-packages (from pandas-profiling) (2.26.0)
Requirement already satisfied: multimethod>=1.4 in
/opt/conda/lib/python3.7/site-packages (from pandas-profiling) (1.6)
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: phik>=0.11.1 in /opt/conda/lib/python3.7/site-
packages (from pandas-profiling) (0.12.0)
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: 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: 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: 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: cycler>=0.10 in /opt/conda/lib/python3.7/site-
packages (from matplotlib>=3.2.0->pandas-profiling) (0.10.0)
Requirement already satisfied: typing-extensions>=3.7.4.3 in
/opt/conda/lib/python3.7/site-packages (from pydantic>=1.8.1->pandas-profiling)
(4.0.0)
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: 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) (2.0.8)
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: 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>=1.5 in /opt/conda/lib/python3.7/site-
packages (from python-dateutil>=2.1->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.
```

[29]:
```python
from pandas_profiling import ProfileReport as pp
```

[30]:
```python
!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: scipy>=1.4.1 in /opt/conda/lib/python3.7/site-
packages (from feature_engine) (1.7.3)
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: pandas>=1.0.3 in /opt/conda/lib/python3.7/site-
packages (from feature_engine) (1.0.3)
Requirement already satisfied: numpy>=1.18.2 in /opt/conda/lib/python3.7/site-
packages (from feature_engine) (1.18.4)
Requirement already satisfied: statsmodels>=0.11.1 in
/opt/conda/lib/python3.7/site-packages (from feature_engine) (0.11.1)
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: 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: patsy>=0.5 in /opt/conda/lib/python3.7/site-
packages (from statsmodels>=0.11.1->feature_engine) (0.5.1)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.7/site-
packages (from python-dateutil>=2.6.1->pandas>=1.0.3->feature_engine) (1.14.0)
```

[31]:
```python
from sklearn.ensemble import RandomForestRegressor
!pip install xgboost
import xgboost as xgb
from sklearn.inspection import permutation_importance
from sklearn.model_selection import RandomizedSearchCV
```

```
Requirement already satisfied: xgboost in /opt/conda/lib/python3.7/site-packages
(1.5.1)
Requirement already satisfied: scipy in /opt/conda/lib/python3.7/site-packages
(from xgboost) (1.7.3)
Requirement already satisfied: numpy in /opt/conda/lib/python3.7/site-packages
(from xgboost) (1.18.4)
```

[32]:
```python
# Load Canadian dataset
df = pd.read_csv("ca-dealers-used.csv",dtype={'fuel_type': 'object',␣
↪'engine_block': 'object'})
```

[33]:
```
# Check the datatypes of each attributes
df.dtypes
```

[33]:
```
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
```

[34]:
```
# check total number of records for the raw data
len(df)
```

[34]:
```
393603
```

[35]:
```
# first 5 records
df.head(5)
```

[35]:
```
             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]
```

[36]:
```python
# For the first dataset, we will only select records from Toronto, ON
df=df[df.state == "ON"]
```

[37]:
```python
df=df[df.city == "Toronto"]
```

[38]:
```python
# drop irrelevant columns for this research
drop_columns = ['id', 'vin', 'stock_no',␣
↪'seller_name','street','city','state','zip']
df = df.drop(columns = drop_columns)
```

[39]:
```python
# EDA analysis
# check data types of the remainning attributes
df.dtypes
```

[39]:
```
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
```

[40]:
```
# summary of the dataset
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
```

[41]:
```
# Check missing values in each column, as these missing values need to be␣
↪handled properly
missing_values_count = df.isnull().sum()
missing_values_count
```

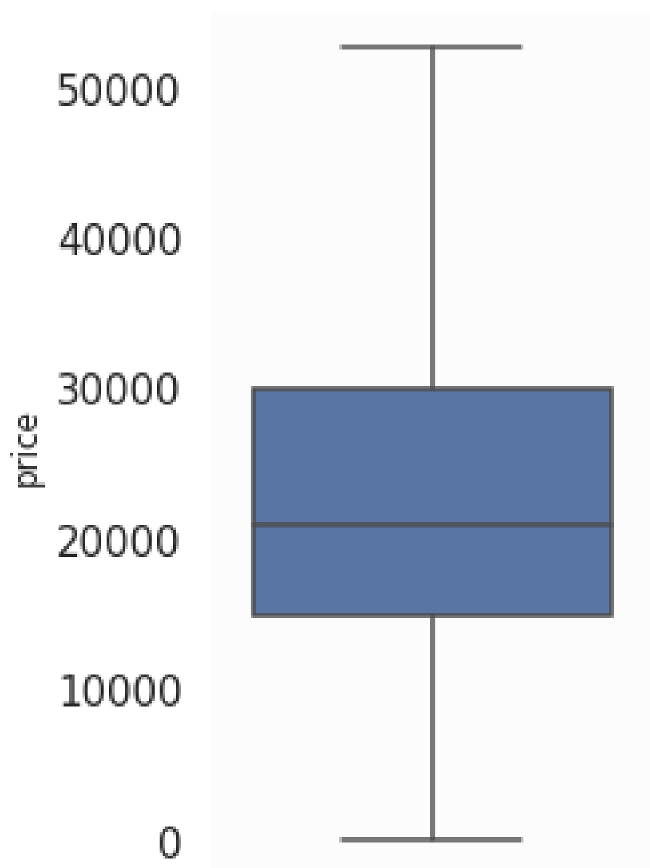
[41]:
```
price           1187
miles           1769
year               0
make               0
model            191
trim            1044
body_type       1556
vehicle_type    1720
drivetrain       736
transmission     722
fuel_type       2383
engine_size     2391
```

```
engine_block    2444
dtype: int64
```

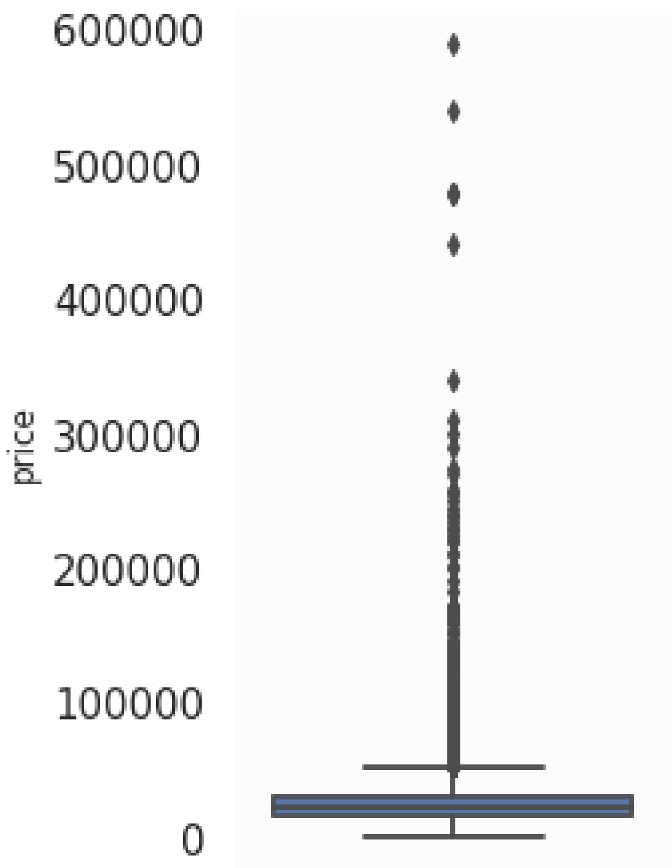
[42]:
```
# Some EDA analysis on price as it is most important attribute for this␣
↪research, first lets check the statistics summary and distribution of price
df['price'].describe()
```

[42]:
```
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
```

[43]:
```
# Boxplot for price
plt.figure(figsize=(3,6))
sns.boxplot(y='price', data=df, showfliers=False);
```

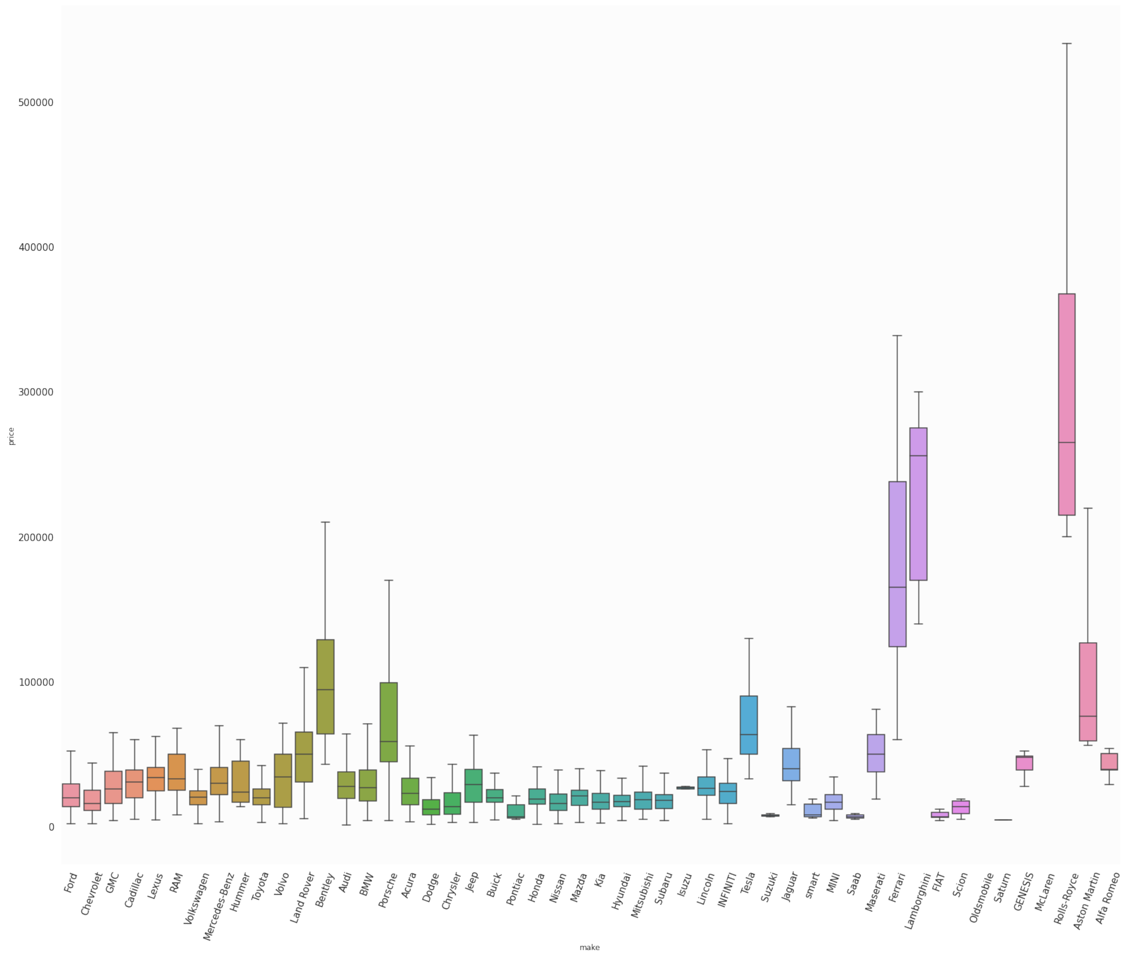


[44]:
```python
# Box plot for price with outliers, we can see that there are a lot extreme␣
↪high prices
plt.figure(figsize=(3,6))
sns.boxplot(y='price', data=df, showfliers=False)
sns.boxplot(y='price', data=df);
```



[45]:
```python
# Prices by different brands, some brands have high average prices and max␣
↪prices
plt.figure(figsize=(30,25))
plt.xticks(rotation=70)
sns.boxplot(y='price', x='make', data=df, showfliers=False)
```

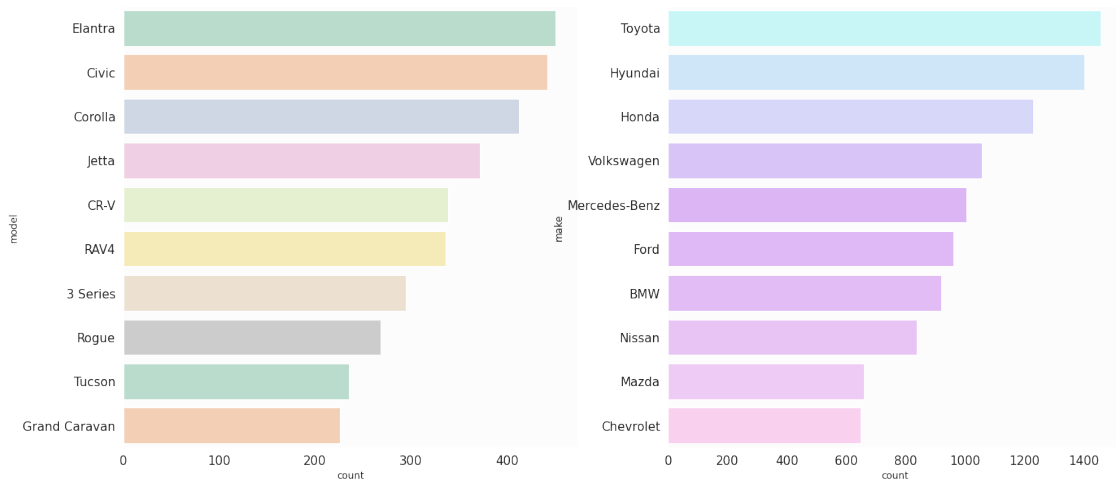
[45]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6bc606c4d0>



[46]:

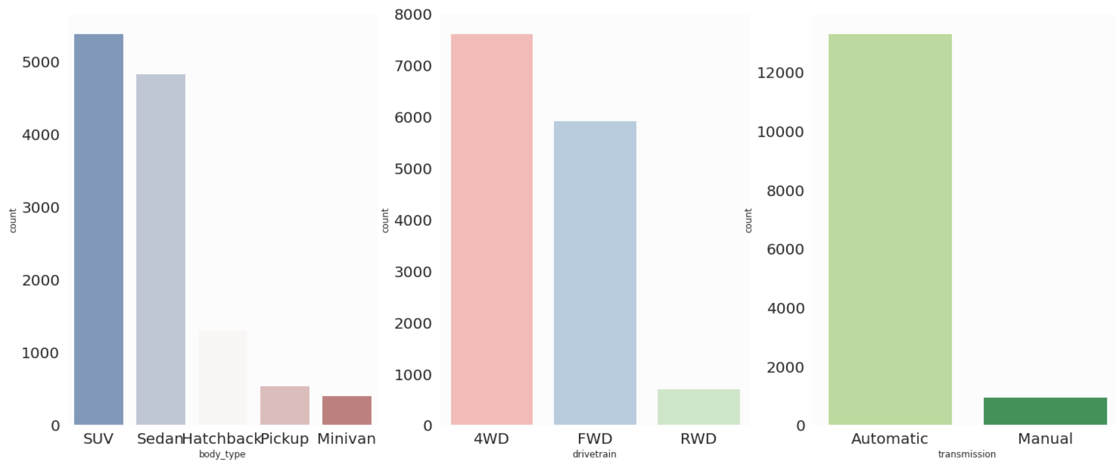
```
# Lets check some other attributes just to get familiar with our dataset. Count␣
↪by top 10 most popular brand and model.
colors = ["#C0FDFF",␣
↪"#C8E7FF","#D0D1FF","#D8BBFF","#DEAAFF","#E2AFFF","#E5B3FE","#ECBCFD","#F3C4FB","#FFCBF2"]
sns.set_palette(sns.color_palette(colors))


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()
```



[47]:

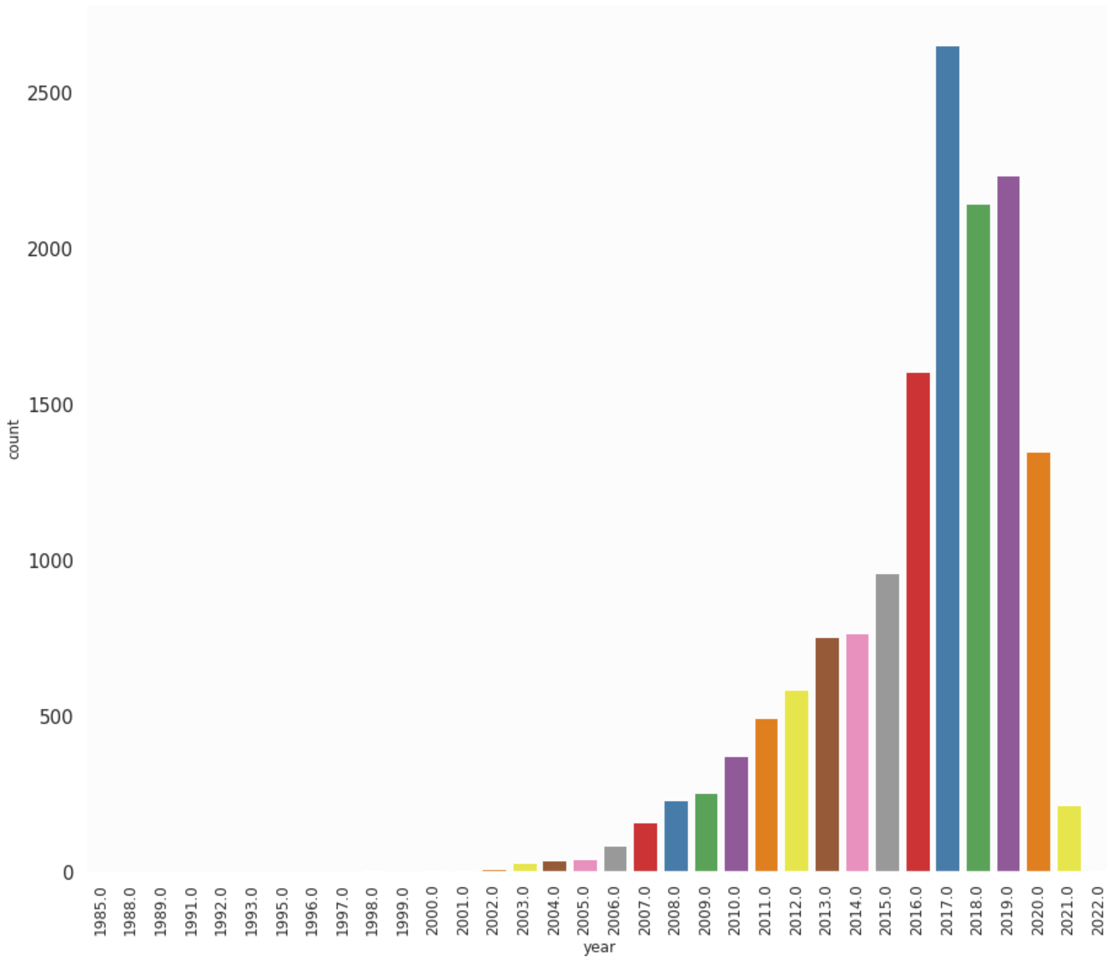
```
# Countplot by body_type, drivetrain and transmission
fig, ax =plt.subplots(1,3,figsize=(25, 10))
sns.set(rc={"axes.facecolor":"#fcfcfc", "axes.grid":False,'xtick.labelsize':
 ↪15,'ytick.labelsize':15})
sns.countplot(x ='body_type',data = df,order=df.body_type.value_counts().iloc[:
 ↪5].index, ax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



[48]:

```
# Year is another important atrributes, lets use bar chart to check the number␣
 ↪of cars 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=12);
```



[49]:
```
# Data cleaning and preprocessing:
# Lets drop records without prices, since these records will be useless for our␣
↪analysis
df_tor=df.dropna(subset=['price'])
```

[50]:
```
# Using pandas profiling to inspect our dataset. Pandas profiling gives you␣
↪very detailed information on variables and correlations
profile = pp(df_tor)
profile.to_notebook_iframe()
```

```
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>
```

[51]:
```
# Save the profiling as 'profile_bf_cleaning_tor'
profile.to_file("profile_bf_cleaning_tor.html")
```

```
Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```

[52]:
```
# check the 2 and 98 percentile of the data.
rr=sorted(df_tor["price"])
quantile1, quantile3= np.percentile(rr,[2,98])
print(quantile1,quantile3)
```

```
4999.0 72320.79999999971
```

[53]:
```
# There are extreme values exist on both side of the distribution. Also the␣
↪difference between 75% value and max value is very large so lets leave 2%␣
↪values at both ends of a distribution. As extreme values will impact the␣
↪performance of our model.
# From a real-world prespecitve, price range between 4990 and 72321 seems␣
↪reasonable.
# Remove records with prices <4990 and price > 72321.
df_tor=df_tor[(df_tor.price < 72321) & (df_tor.price > 4990 )]
```

[54]:
```
# Transform price from float to int
df_tor['price'] = df_tor.price.astype(int)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

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

[55]:
```
# 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 )]
```

[56]:
```python
# Below attributes have missing values, they need to be cleaned up:
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

[56]:
```
price              0
miles           1545
year               0
make               0
model            163
trim             933
body_type       1401
vehicle_type    1556
drivetrain       649
transmission     638
fuel_type       2138
engine_size     2142
engine_block    2176
dtype: int64
```

[57]:
```python
# 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)
```

[58]:
```python
# There are records with missing values in 'model'.These records have to be␣
↪removed as model can't be replaced based on other attributes without␣
↪changing the reality of the instances.
df_tor=df_tor.dropna(subset=['model'])
```

[59]:
```python
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

[59]:
```
price              0
miles           1532
year               0
make               0
model              0
body_type       1244
vehicle_type    1394
drivetrain       636
transmission     625
fuel_type       1975
engine_size     1979
engine_block    2013
dtype: int64
```

[60]:
```python
# I am droping records with missnig drivetrain and transmission as well since␣
↪they are only account for less than 1% of total records.
```

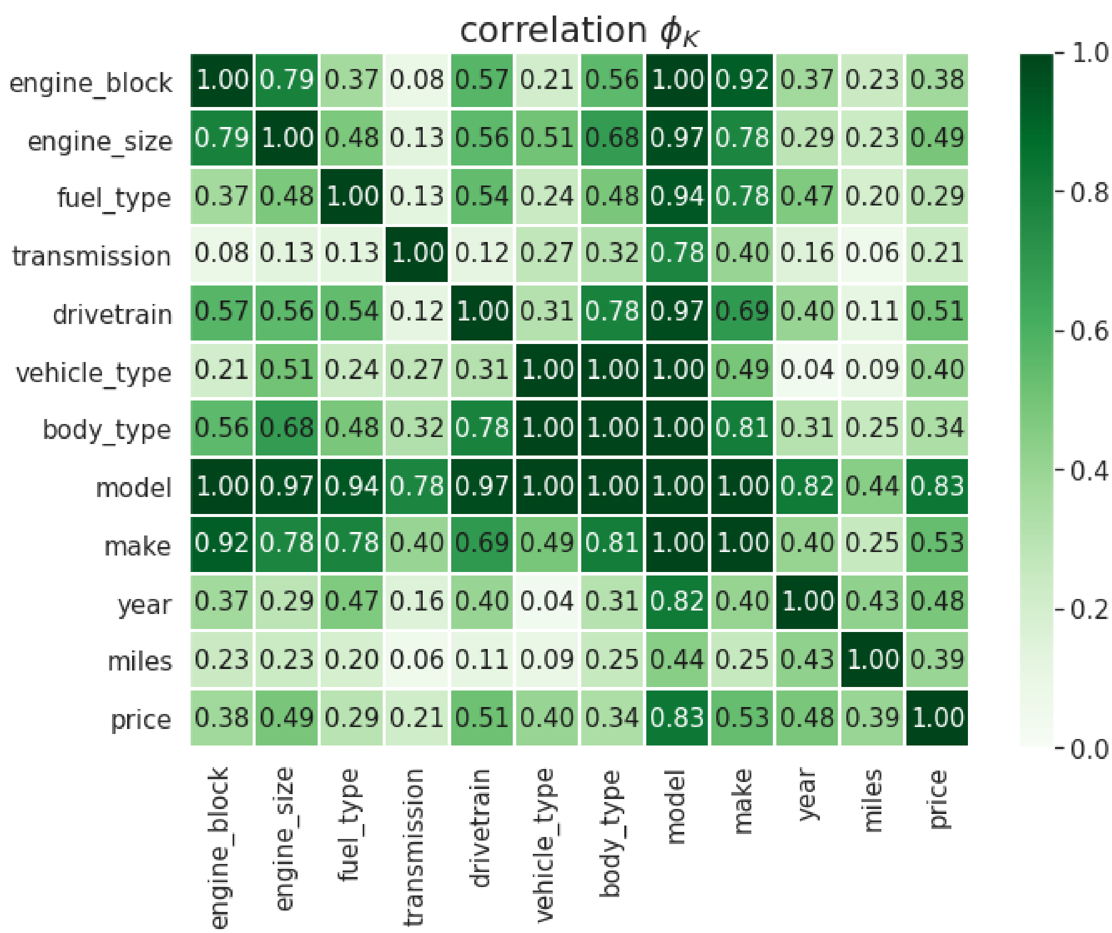
```python
df_tor=df_tor.dropna(subset=['drivetrain','transmission'])
```

[61]:
```python
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

[61]:
```
price              0
miles           1430
year               0
make               0
model              0
body_type       1160
vehicle_type    1305
drivetrain         0
transmission       0
fuel_type       1327
engine_size     1359
engine_block    1373
dtype: int64
```

[62]:
```python
# check correlation using Phi_K Correlation Analyzer
phik_overview = df_tor.phik_matrix()
plot_correlation_matrix(phik_overview.values,
                        x_labels=phik_overview.columns,
                        y_labels=phik_overview.index,
                        vmin=0, vmax=1, color_map="Greens",
                        title=r"correlation $\phi_K$",
                        fontsize_factor=1.5,
                        figsize=(10, 8))
plt.tight_layout()
```

```
interval columns not set, guessing: ['price', 'miles', 'year', 'engine_size']
```



[63]:

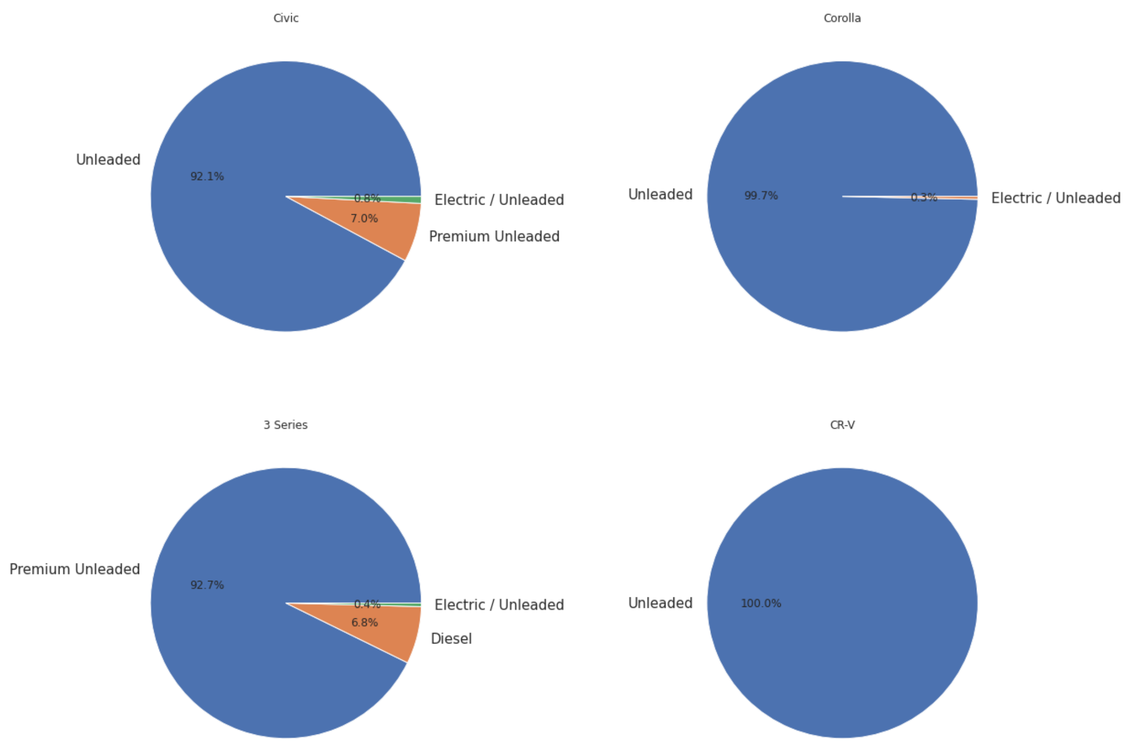
```
### Fuel_type can be an important feature, instead of simply dropping all the records and also for the purpose of learning, lets try to replace these missing values.
# Phi_K Correlation heatmap indicates that fuel_type has a high correlation with car model
# Pie charts show that these brands prefer to produce cars with certain fuel_type
plt.figure(figsize=(20,15))
plt.subplot(221)
df_tor["fuel_type"][df_tor["model"]=='Civic'].value_counts().plot.pie(autopct = '%.1f%%', title="Civic")
plt.axis('off')

plt.subplot(222)
df_tor["fuel_type"][df_tor["model"]=='Corolla'].value_counts().plot.pie(autopct= '%.1f%%', title="Corolla")
plt.axis('off')
```

```
plt.subplot(223)
df_tor["fuel_type"][df_tor["model"]=='3 Series'].value_counts().plot.
 ↪pie(autopct = '%.1f%%', title="3 Series")
plt.axis('off')

plt.subplot(224)
df_tor["fuel_type"][df_tor["model"]=='CR-V'].value_counts().plot.pie(autopct =␣
 ↪'%.1f%%', title="CR-V")
plt.axis('off')

plt.show()
# model Civic has 92.1% cars with premim unleaded fuel_type
# model Corolla has 99.7% cars with unleaded fuel_type
# model 3 Series has 92.7 % cars with unleaded fuel_type
# model CR-V has 100% with unleaded fuel_type
```



[64]:
```
# The approach used here is to replace missing fuel_type with the most common␣
 ↪value for each car model. First, I will create a dataframe with total count␣
 ↪of each fuel type by car model,and only keep the highest fuel_type for each␣
 ↪model.
```

```
fuel_count = df_tor.groupby(['fuel_type','model'], sort=True).size().
↪reset_index(name='Count').sort_values(['model','Count'],ascending=False).
↪groupby(['model']).first()
```

[65]:
```
# Reset the index for 'model to make it accessble for the next step.
fuel_count.reset_index(inplace=True)
fuel_pair = fuel_count[['model','fuel_type']]
```

[66]:
```
# create a panda series for model and its corresponding highest fuel_type
fuel_replace = pd.Series(fuel_pair.fuel_type.values,index = fuel_pair.model)
```

[67]:
```
# Replace the missing fuel_type using the panda series just created. The␣
↪missing value is replaced by most common value for that brand.
df_tor['fuel_type'] = df_tor['fuel_type'].fillna(df_tor['model'].apply(lambda x:
↪ fuel_replace.get(x)))
```

[68]:
```
# dropping the remaining records since they cant be replaced.
df_tor=df_tor.dropna(subset=['fuel_type'])
```

[69]:
```
# Miles
# Replacing missing values in miles with median value of each year. Median is␣
↪less impacted by extreme values compared to mean. we will first get all the␣
↪median number by year.
miles_median = dict(df_tor.groupby('year')['miles'].median())
```

[70]:
```
df_tor['miles'] = df_tor['miles'].fillna(df_tor['year'].apply(lambda x:
↪miles_median.get(x)))
```

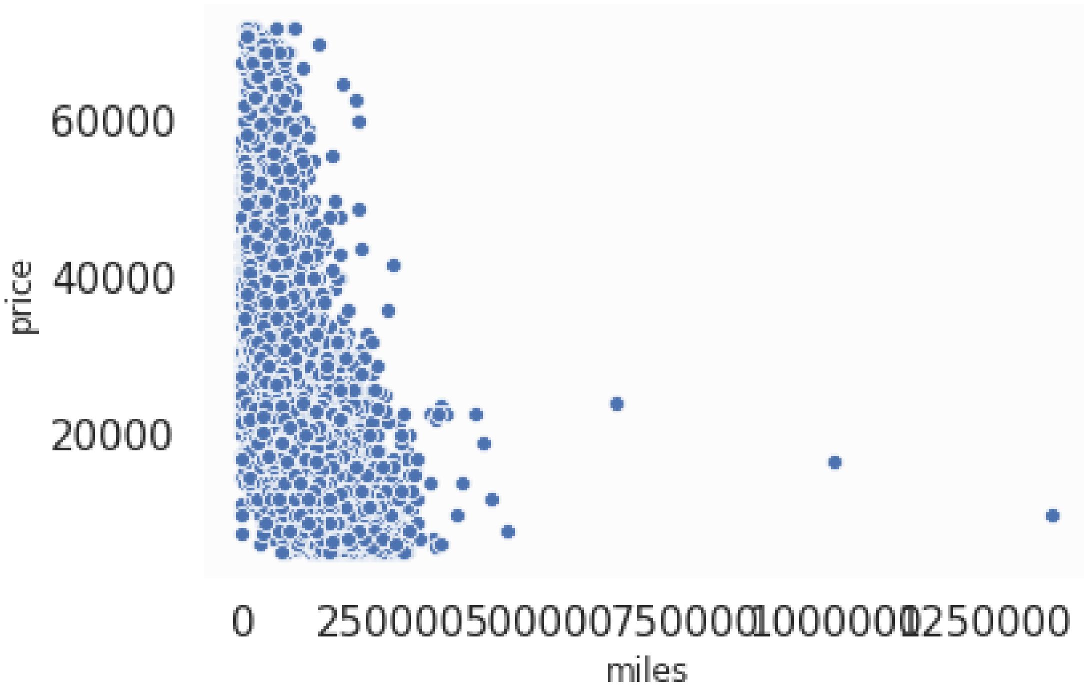
[71]:
```
# Removing the left missing values in miles because no information is available␣
↪for that year.
df_tor=df_tor.dropna(subset=['miles'])
```

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

[72]:
```
price              0
miles              0
year               0
make               0
model              0
body_type       1091
vehicle_type    1229
drivetrain         0
transmission       0
fuel_type          0
engine_size     1284
engine_block    1296
```

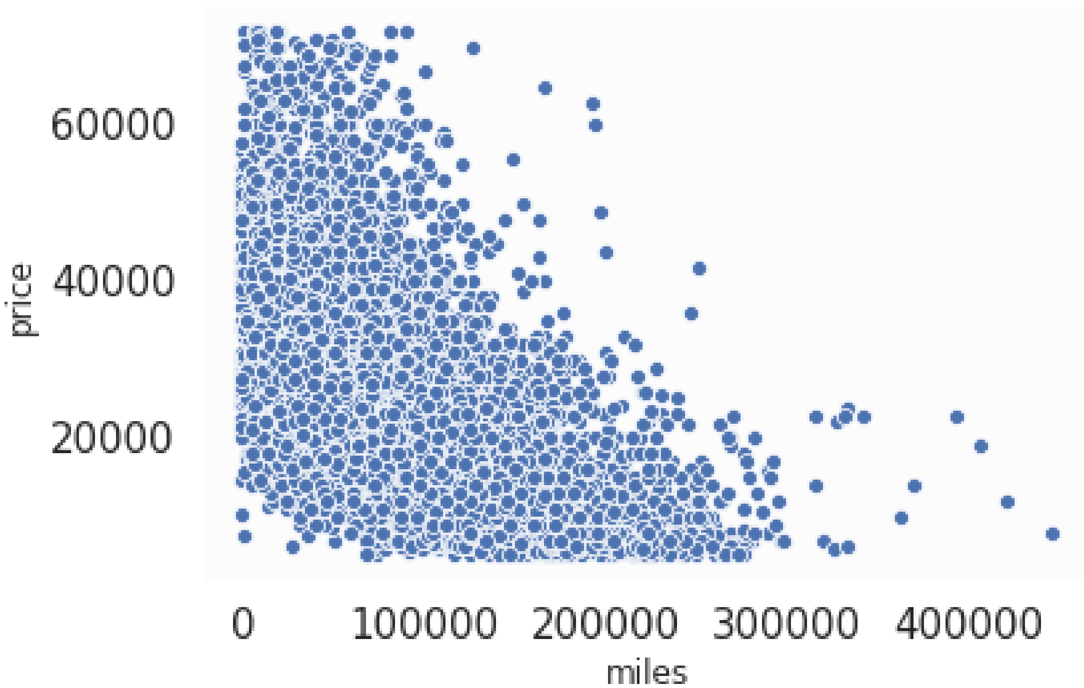
```
dtype: int64
```

[73]:
```
# Lets see if miles has any outliers using scatterplot
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)
```



[74]:
```
# 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 )]
```

[75]:
```
# check the distribution after removing records with miles >1 and < 500000:
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)
```



[76]:
```
# 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 )]
```

[77]:
```
# Body_type
# Phi_K Correlation heatmap indicates that body type has a high correltion with␣
↪vehicle type, thus, we will replace missing body_type based on vehicle type.␣
↪Lets take a look at these two attributes by count
df_bt = df_tor.groupby(['vehicle_type','body_type'], sort=True).size().
↪reset_index(name='Count')
df_bt
```

[77]:

	vehicle_type	body_type	Count
0	Car	Car Van	1
1	Car	Convertible	78
2	Car	Coupe	277
3	Car	Hatchback	993
4	Car	Micro Car	6
5	Car	Mini Mpv	19
6	Car	SUV	1
7	Car	Sedan	4074
8	Car	Targa	3
9	Car	Wagon	104
10	Truck	Car Van	8

```
11         Truck      Cargo Van    111
12         Truck    Chassis Cab     10
13         Truck        Cutaway     22
14         Truck       Mini Mpv      3
15         Truck        Minivan    326
16         Truck  Passenger Van     13
17         Truck         Pickup    436
18         Truck            SUV   4647
```

[78]:
```
# We also find out that there are records missing both attributes
df_tor.loc[(df_tor['vehicle_type'].isna()) & (df_tor['body_type'].isna())].
 ↪count()
```

[78]:
```
price           1079
miles           1079
year            1079
make            1079
model           1079
body_type          0
vehicle_type       0
drivetrain      1079
transmission    1079
fuel_type       1079
engine_size        0
engine_block       0
dtype: int64
```

[79]:
```
# 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') # drop␣
 ↪records which are missing both vehicle type and body type
```

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

[80]:
```
price             0
miles             0
year              0
make              0
model             0
body_type        10
vehicle_type    148
drivetrain        0
transmission      0
fuel_type         0
engine_size     203
engine_block    215
```

```
dtype: int64
```

[81]:
```
# Replacing missing vehicle type based on most common body_type, first lets␣
↪check the distribution of each body type for the vehicle type
df_bodytype = df_tor.groupby(['vehicle_type','body_type'], sort=True).size().
↪reset_index(name='Count')
df_bodytype
```

[81]:

	vehicle_type	body_type	Count
0	Car	Car Van	1
1	Car	Convertible	78
2	Car	Coupe	277
3	Car	Hatchback	993
4	Car	Micro Car	6
5	Car	Mini Mpv	19
6	Car	SUV	1
7	Car	Sedan	4074
8	Car	Targa	3
9	Car	Wagon	104
10	Truck	Car Van	8
11	Truck	Cargo Van	111
12	Truck	Chassis Cab	10
13	Truck	Cutaway	22
14	Truck	Mini Mpv	3
15	Truck	Minivan	326
16	Truck	Passenger Van	13
17	Truck	Pickup	436
18	Truck	SUV	4647

[82]:
```
# 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'
```

[83]:
```
# Now lets deal with missing vehicle type, similarly we will replace missing␣
↪vehicle type based on most common body_type, lets first check the␣
↪distribution of vehicle type for each 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 incosistent data points are probably entered by mistake.
```

[83]:

	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	78
5	Coupe	Car	277
6	Cutaway	Truck	22
7	Hatchback	Car	993
8	Micro Car	Car	6
9	Mini Mpv	Car	19
10	Mini Mpv	Truck	3
11	Minivan	Truck	326
12	Passenger Van	Truck	13
13	Pickup	Truck	436
14	SUV	Car	1
15	SUV	Truck	4647
16	Sedan	Car	4084
17	Targa	Car	3
18	Wagon	Car	104

[84]:
```python
# Lets first drop these inconsistent records:
df_tor = df_tor.drop(df_tor[(df_tor['body_type'] == 'Car Van') &␣
↪(df_tor['vehicle_type'] == 'Car')].index) # car van shouldn't be mapped to␣
↪car
```

[85]:
```python
df_tor = df_tor.drop(df_tor[(df_tor['body_type'] == 'Mini Mpv') &␣
↪(df_tor['vehicle_type'] == 'Truck')].index) # mini mpv shouldn't be mapped␣
↪to truck
```

[86]:
```python
df_tor = df_tor.drop(df_tor[(df_tor['body_type'] == 'SUV') &␣
↪(df_tor['vehicle_type'] == 'Car')].index) # SUV shouldnt be mapped to car
```

[87]:
```python
# Replacing missing vehicle type based on its body type, first create a new␣
↪dataframe by body_type with most common vehicle type by count
df_vechile = df_tor.groupby(['body_type','vehicle_type'], sort=True).size().
↪reset_index(name='Count')
df_vechile
```

[87]:

	body_type	vehicle_type	Count
0	Car Van	Truck	8
1	Cargo Van	Truck	111
2	Chassis Cab	Truck	10
3	Convertible	Car	78
4	Coupe	Car	277
5	Cutaway	Truck	22
6	Hatchback	Car	993

```
7        Micro Car         Car      6
8         Mini Mpv         Car     19
9          Minivan       Truck    326
10   Passenger Van       Truck     13
11          Pickup       Truck    436
12             SUV       Truck   4647
13           Sedan         Car   4084
14           Targa         Car      3
15           Wagon         Car    104
```

[88]:
```
# create a padada series with only bodytype and vehicle type, then replace␣
↪missing vehicle type based on bodytype in the panda series.
vechile_pair = df_vechile[['body_type','vehicle_type']]
```

[89]:
```
vechile_replace = pd.Series(vechile_pair.vehicle_type.values,index =␣
↪vechile_pair.body_type)
```

[90]:
```
df_tor['vehicle_type'] = df_tor['vehicle_type'].fillna(df_tor['body_type'].
↪apply(lambda x: vechile_replace.get(x)))
```

[91]:
```
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

[91]:
```
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     202
engine_block    214
dtype: int64
```

[92]:
```
# After above data cleaning process, I find that the information provided by␣
↪these two attributes are kind of overlaping with each other. The body type␣
↪is really a granular level of vehicle type. The decision here is to only␣
↪keep body_type
df_tor=df_tor.drop(["vehicle_type"],axis=1)
```

[93]:
```
# 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'
```

[94]:
```
# Phi_K Correlation heatmap indicates engine_block is highly correlated with␣
↪car models. We will replace the missing values with most commonly used␣
↪engine block type for each car model
```

[95]:
```
# Same coding approach will be used here as previously as to replace missing␣
↪engine block by most common value by each make/brand.
block_count = df_tor.groupby(['engine_block','model'], sort=True).size().
↪reset_index(name='Count').sort_values(['model','Count'],ascending=False).
↪groupby(['model']).first()
```

[96]:
```
block_count.reset_index(inplace=True)
```

[97]:
```
block_pair = block_count[['model','engine_block']]
```

[98]:
```
block_replace = pd.Series(block_pair.engine_block.values,index = block_pair.
↪model)
df_tor['engine_block'] = df_tor['engine_block'].fillna(df_tor['model'].
↪apply(lambda x: block_replace.get(x)))
```

[99]:
```
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

[99]:
```
price             0
miles             0
year              0
make              0
model             0
body_type         0
drivetrain        0
transmission      0
fuel_type         0
engine_size     202
engine_block      4
dtype: int64
```

[100]:
```
# dropping remaining 4 records since they cant be replaced.
df_tor=df_tor.dropna(subset=['engine_block'])
```

[101]:
```
# Engine_size
# Lets first change engine size of all electric cars to 0
df_tor.loc[df_tor.fuel_type == 'Electric', 'engine_size'] = 0
```

[102]:
```
# Pandas Profiling report indicates engine_size is highly correlated with car␣
↪models . We will replace the missing values with most commonly used engine␣
↪size for each car model
```

```
size_count = df_tor.groupby(['engine_size','model'], sort=True).size().
→reset_index(name='Count').sort_values(['model','Count'],ascending=False).
→groupby(['model']).first()
```

[103]:
```
# Same coding approach is used here as to replace missng engine size based on␣
→engine block.
size_count.reset_index(inplace=True)
```

[104]:
```
size_pair = size_count[['model','engine_size']]
```

[105]:
```
size_replace = pd.Series(size_pair.engine_size.values,index = size_pair.model)
```

[106]:
```
df_tor['engine_size'] = df_tor['engine_size'].fillna(df_tor['model'].
→apply(lambda x: size_replace.get(x)))
```

[107]:
```
missing_values_count = df_tor.isnull().sum()
missing_values_count
```

[107]:
```
price           0
miles           0
year            0
make            0
model           0
body_type       0
drivetrain      0
transmission    0
fuel_type       0
engine_size     0
engine_block    0
dtype: int64
```

[108]:
```
len(df_tor)
```

[108]:
```
11281
```

[109]:
```
df_tor.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11281 entries, 446 to 393573
Data columns (total 11 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   price          11281 non-null  int64
 1   miles          11281 non-null  float64
 2   year           11281 non-null  float64
 3   make           11281 non-null  object
 4   model          11281 non-null  object
```

```
 5   body_type     11281 non-null  object
 6   drivetrain    11281 non-null  object
 7   transmission  11281 non-null  object
 8   fuel_type     11281 non-null  object
 9   engine_size   11281 non-null  float64
 10  engine_block  11281 non-null  object
dtypes: float64(3), int64(1), object(7)
memory usage: 1.0+ MB
```

[110]:
```
# check each make by count
df_tor.make.value_counts().to_frame()
```

[110]:

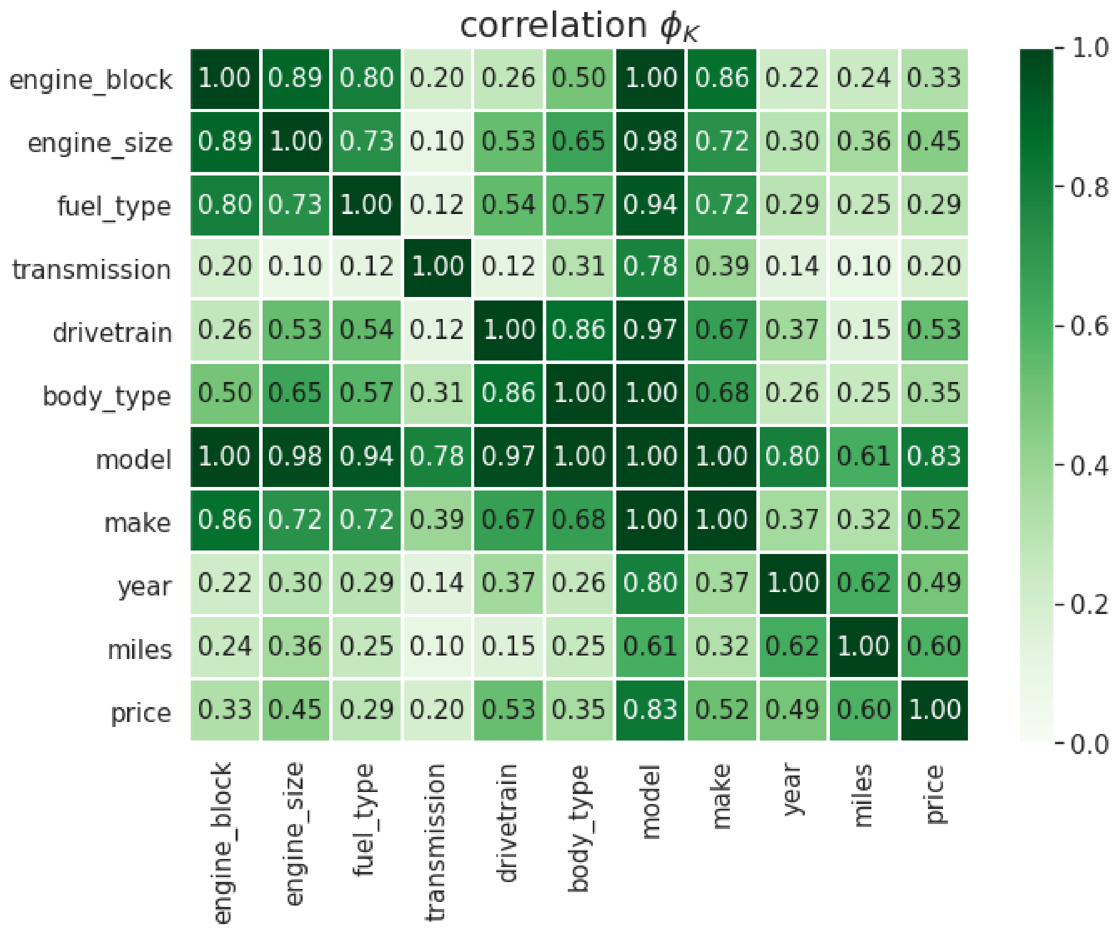
	make
Hyundai	1237
Toyota	1125
Volkswagen	889
Honda	827
Ford	780
BMW	747
Mercedes-Benz	687
Nissan	647
Mazda	520
Chevrolet	518
Kia	382
Lexus	364
Audi	344
Dodge	296
Jeep	226
Acura	201
Land Rover	147
GMC	133
Subaru	132
INFINITI	130
Cadillac	112
RAM	107
Buick	105
MINI	92
Lincoln	77
Chrysler	71
Jaguar	69
Volvo	68
Mitsubishi	66
Porsche	62
GENESIS	25
Maserati	18
Tesla	17
FIAT	15

```
Scion            13
Pontiac           7
smart             7
Hummer            6
Alfa Romeo        6
Aston Martin      4
Suzuki            1
Saab              1
```

[111]:
```
# Some brands have too few samples. For the precision of our models, 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', 'Saab','Suzuki','Tesla']
for brand in rm_brands:
    df_tor = df_tor[~(df_tor['make'] == brand)]
```

[112]:
```
# check correlation using Phi_K Correlation Analyzer after data cleaning
phik_overview = df_tor.phik_matrix()
plot_correlation_matrix(phik_overview.values,
                        x_labels=phik_overview.columns,
                        y_labels=phik_overview.index,
                        vmin=0, vmax=1, color_map="Greens",
                        title=r"correlation $\phi_K$",
                        fontsize_factor=1.5,
                        figsize=(10, 8))
plt.tight_layout()
```

```
interval columns not set, guessing: ['price', 'miles', 'year', 'engine_size']
```



[113]:

```
# check panada profiling after data cleaning
profile1 = pp(df_tor)
profile1.to_notebook_iframe()
```

```
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>
```

[114]:

```
# Save the profile as 'profile_clead_tor'
profile1.to_file("profile_clead_tor.html")
```

```
Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```

[115]:
```python
# total number of records after data cleaning
len(df_tor)
```

[115]: 11186

[116]:
```python
# The end of data cleaning and processing for toronto data
```

[117]:
```python
# 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.
```

[118]:
```python
# Load data. since the raw dataset is huge, we need to transform it in a dask␣
↪dataframe first
df2 = dd.read_csv("us-dealers-used.csv",dtype={'fuel_type': 'object',␣
↪'engine_block': 'object','zip': 'object', 'year': 'float64'})
```

[119]:
```python
# drop irrelevant columns for this research
drop_column = ['id', 'vin', 'stock_no', 'seller_name','street','zip']
df2 = df2.drop(columns = drop_column)
```

[120]:
```python
# onley select city as Boston
df2 =df2[df2.state == "MA"]
df2=df2[df2.city == "Boston"]
```

[121]:
```python
# transform dask dataframe into pandas dataframe
df_bs = df2.compute()
```

[122]:
```python
# check number of records before data cleaning and processing
len(df_bs)
```

[122]: 12780

[123]:
```python
# drop state, city and trim
df_bs=df_bs.drop(["state","city","trim"],axis=1)
```

[124]:
```python
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
```

[125]:
```
# Overall, the missing value only account for a very small portion of the whole␣
↪dataset
missing_values_count = df_bs.isnull().sum()
missing_values_count
```

[125]:
```
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
```

[126]:
```
# sample data:
df_bs.head(20)
```

[126]:
```
         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
```

[127]:
```
# Lets drop records without prices, since these records will be useless for our␣
↪analysis
df_bs=df_bs.dropna(subset=['price'])
```

[128]:
```
# check panda profiling for the dataset
profile2 = pp(df_bs)
profile2.to_notebook_iframe()
```

```
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>
```

[129]:
```
# Save the profile as profile_bf_cleaing_bos
profile2.to_file("profile_bf_cleaing_bos.html")
```

```
Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```

[130]:
```
# 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
```

[131]:
```
missing_values_count = df_bs.isnull().sum()
missing_values_count
```

[131]:
```
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
```

[132]:
```
len(df_bs)
```

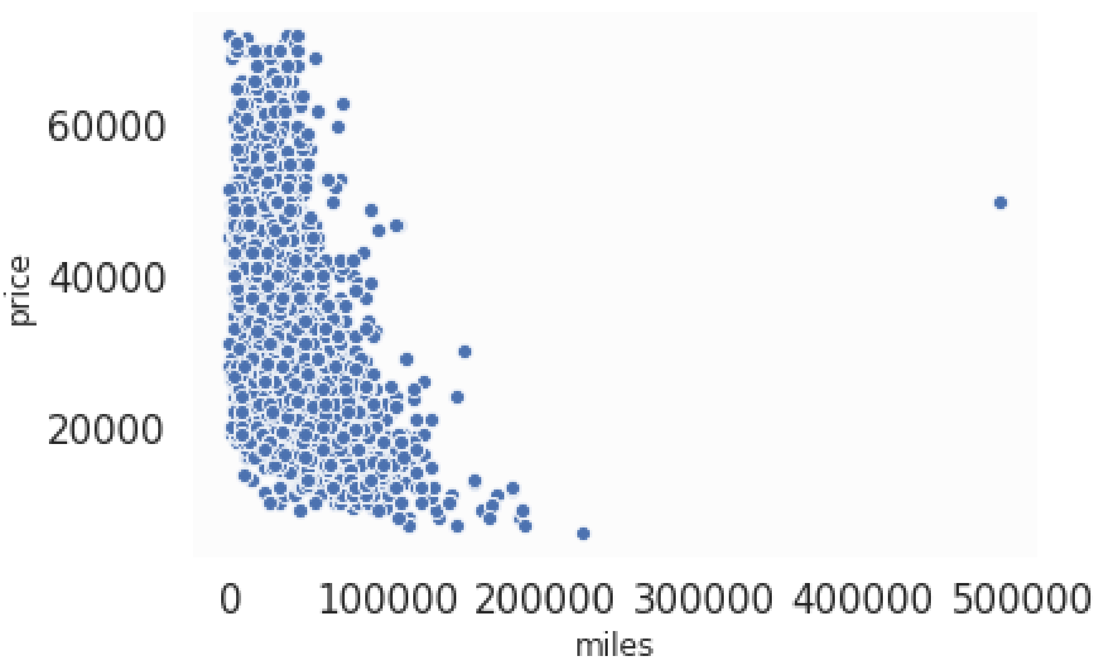
[132]:
```
12495
```

[133]:
```
# Price:
# Keep the same price range as toronto
df_bs=df_bs[(df_bs.price < 72321) & (df_bs.price > 4990)]
```

[134]:
```
# Transform price from float to int.
df_bs['price'] = df_bs.price.astype(int)
```

[135]:
```
# 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)]
```

[136]:
```
# Miles
# Lets see if miles has any outliers using scatterplot
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)
```

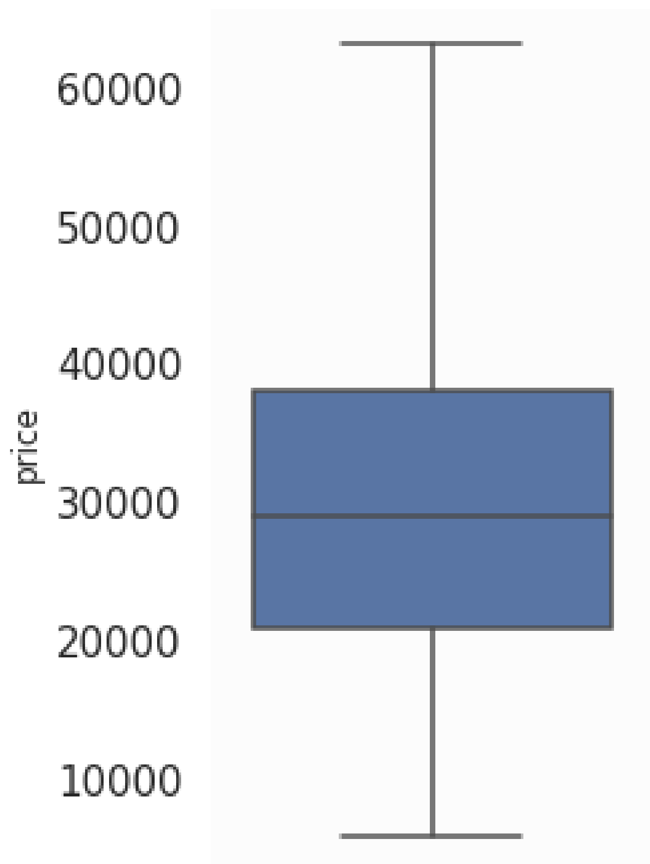


[137]:
```
# Remove outliers where miles below 1 and larger than 300000
df_bs=df_bs[(df_bs.miles < 300000) & (df_bs.miles > 1 )]
```

[138]:
```
# Engine_block
# Change engine block of all electric cars to 'N/A'
df_bs.loc[df_bs.fuel_type == 'Electric', 'engine_block'] = 'N/A'
```

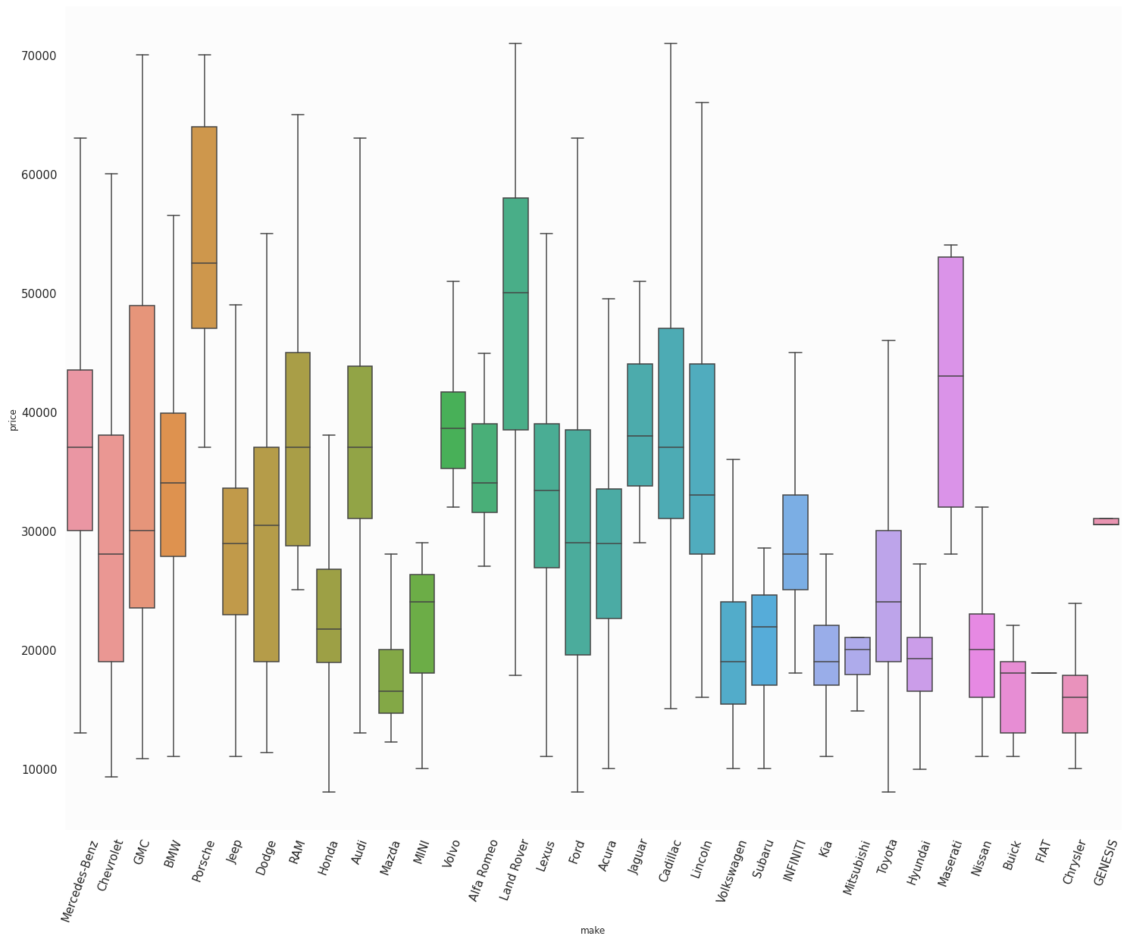
[139]:
```
# Engine_size
# Change engine size of all electric cars to 0
df_bs.loc[df_bs.fuel_type == 'Electric', 'engine_size'] = 0
```

[140]:
```
# boxplot for price
plt.figure(figsize=(3,6))
sns.boxplot(y='price', data=df_bs, showfliers=False);
```



[141]:
```python
# check price range by brand for Boston:
plt.figure(figsize=(25,20))
plt.xticks(rotation=70)
sns.boxplot(y='price', x='make', data=df_bs, showfliers=False)
```

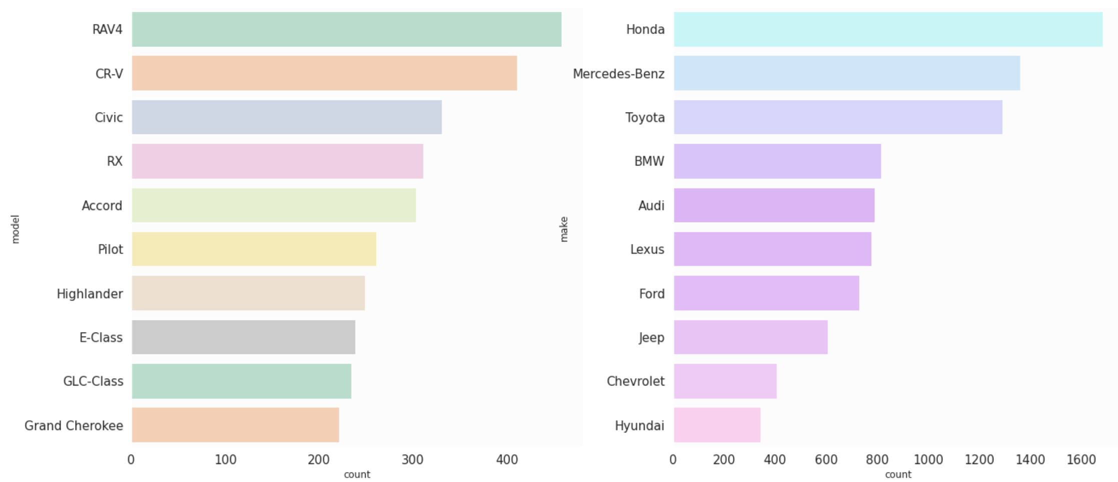
[141]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6c29c5ac90>



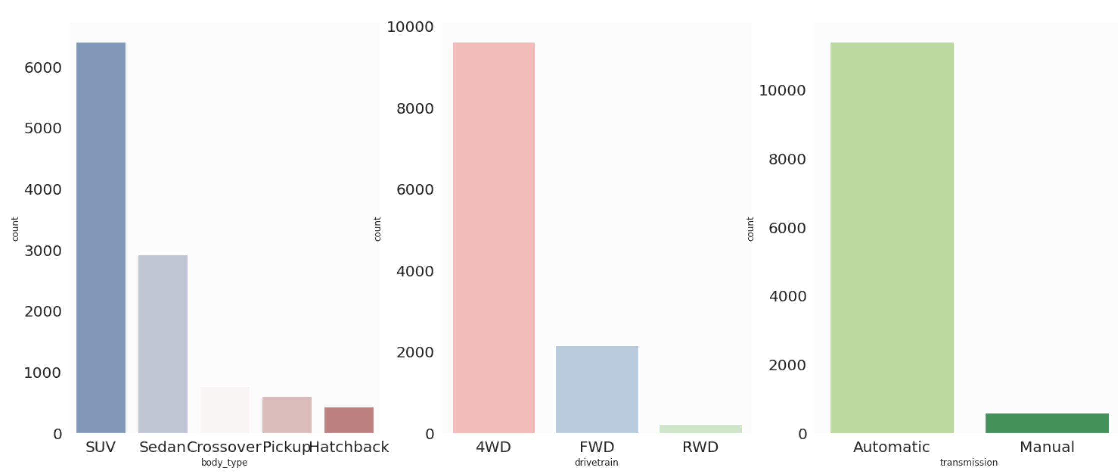
[142]:
```python
# Top 10 make and model by count for Boston:
colors = ["#C0FDFF",␣
↪"#C8E7FF","#D0D1FF","#D8BBFF","#DEAAFF","#E2AFFF","#E5B3FE","#ECBCFD","#F3C4FB","#FFCBF2"]
sns.set_palette(sns.color_palette(colors))


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)
```

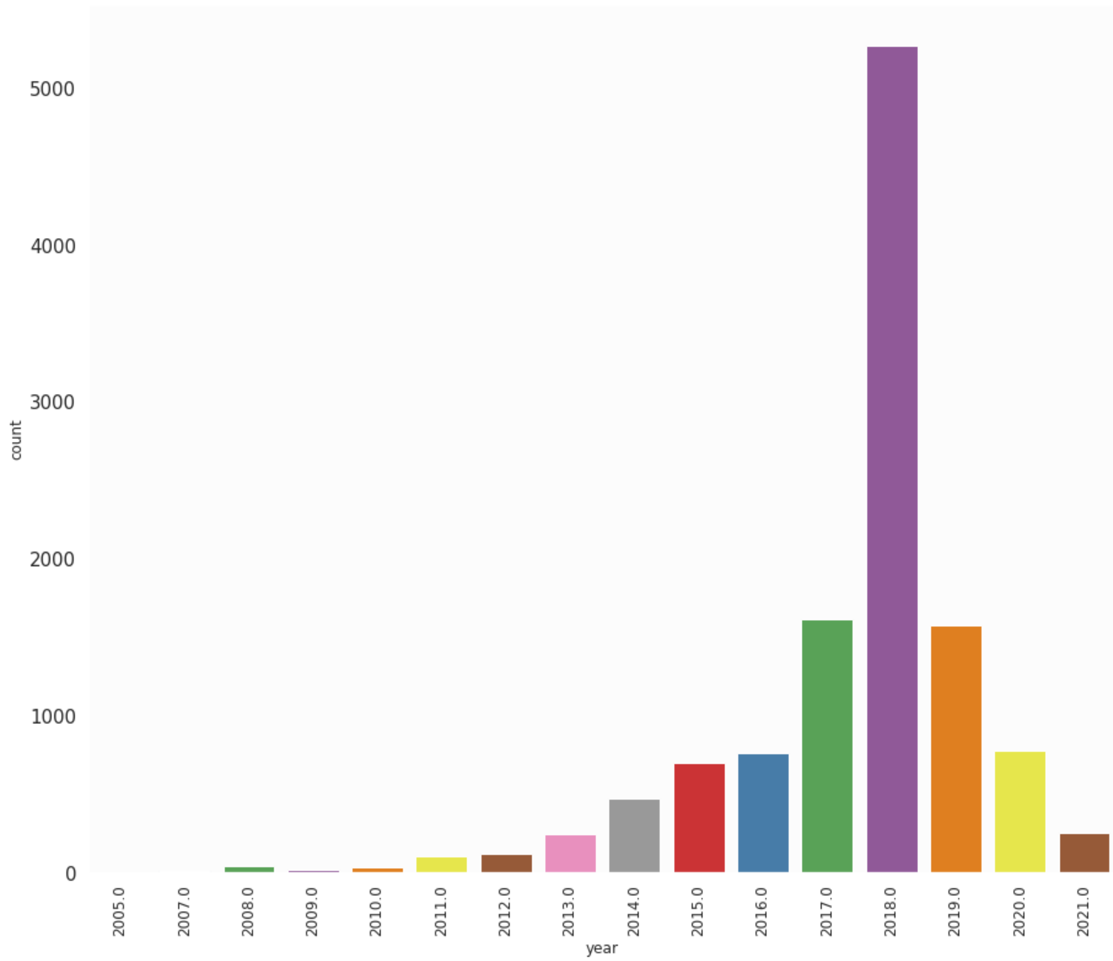
```
sns.countplot(y ='model',data = df_bs,order=df_bs.model.value_counts().iloc[:
↪10].index, ax= ax[0],palette = "Pastel2")
fig.show()
```



[143]:
```
# Top 5 body_type, drivetrain and transmission by count
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()
```



[144]:
```
# distribution for year manufactured by count
plt.figure(figsize=(15, 13))
ax = sns.countplot(x = 'year', data=df_bs, palette='Set1')
ax.set_xticklabels(ax.get_xticklabels(), rotation=90,fontsize=12);
```



[145]:
```
# check body_type and vehicle_type, we found some inconsistent data there.
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.
```

[145]:

	body_type	vehicle_type	Count
0	Cargo Van	Truck	63
1	Chassis Cab	Truck	10
2	Convertible	Car	60

```
3           Coupe          Car   441
4       Crossover          Car     9
5       Crossover        Truck   765
6       Hatchback          Car   442
7        Mini Mpv        Truck     7
8         Minivan        Truck   114
9   Passenger Van        Truck    16
10         Pickup        Truck   610
11       Roadster          Car     5
12            SUV          Car    16
13            SUV        Truck  6396
14          Sedan          Car  2932
15          Wagon          Car   118
```

[146]:
```
# lets drop these records:
df_bs = df_bs.drop(df_bs[(df_bs['body_type'] == 'Crossover') &␣
↪(df_bs['vehicle_type'] == 'Car')].index) # crossover shouln't be mapped to␣
↪car
df_bs = df_bs.drop(df_bs[(df_bs['body_type'] == 'SUV') & (df_bs['vehicle_type']␣
↪== 'Car')].index) # SUV shouldn't be mppaed to car
```

[147]:
```
# check brand by count:
df_bs.make.value_counts().to_frame()
```

[147]:

	make
Honda	1684
Mercedes-Benz	1361
Toyota	1283
BMW	799
Audi	791
Lexus	776
Ford	731
Jeep	606
Chevrolet	407
Hyundai	344
Acura	334
Land Rover	319
Nissan	275
Cadillac	274
Volvo	185
Porsche	178
INFINITI	170
Lincoln	167
Subaru	156
Kia	145
Alfa Romeo	137
MINI	137

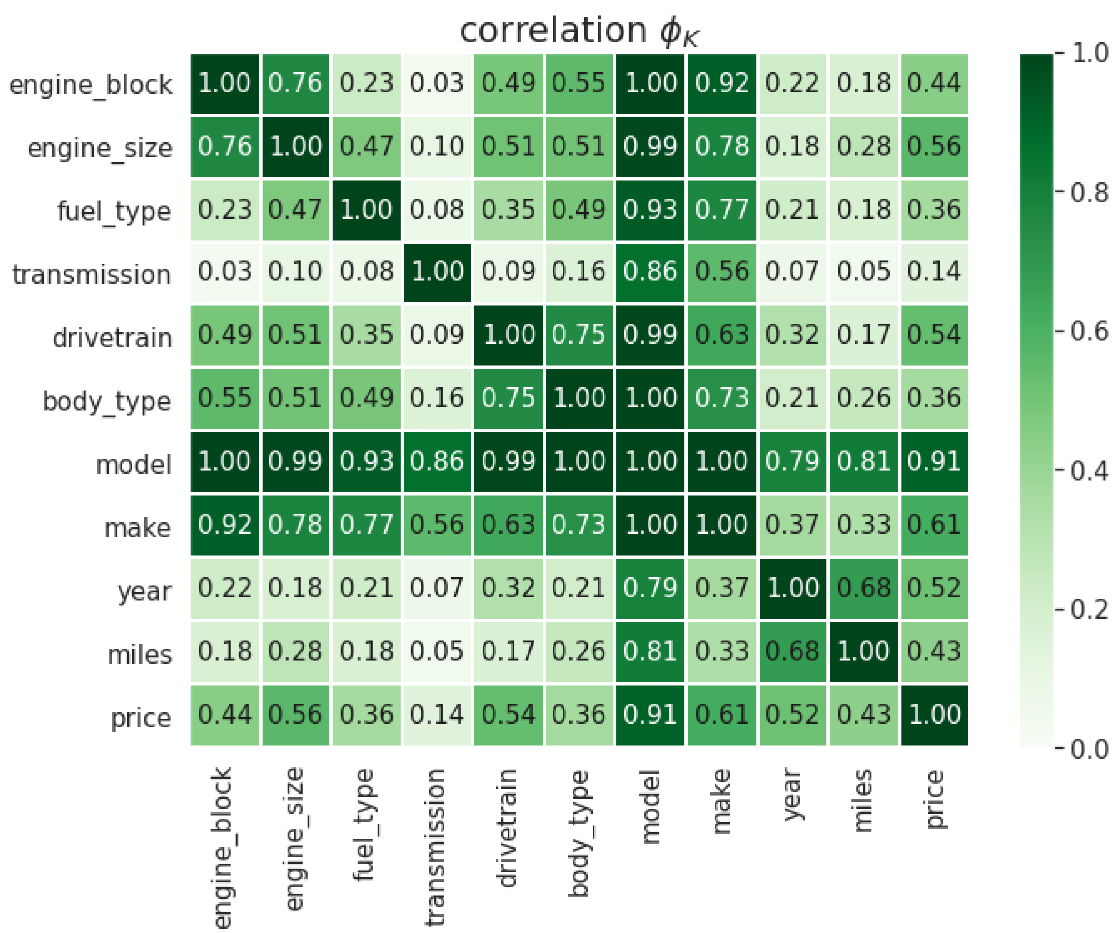
```
Volkswagen      120
Dodge           112
RAM              94
GMC              89
Jaguar           88
Mazda            74
Buick            50
Mitsubishi       30
Chrysler         29
Maserati         24
GENESIS           5
FIAT              5
```

[148]:
```
# 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)]
```

[149]:
```
# Vehicle_type will be dropped for Boston dataset as well
df_bs=df_bs.drop(["vehicle_type"],axis=1)
```

[150]:
```
# check correlation using Phi_K Correlation Analyzer after data cleaning
phik_overview = df_bs.phik_matrix()
plot_correlation_matrix(phik_overview.values,
                        x_labels=phik_overview.columns,
                        y_labels=phik_overview.index,
                        vmin=0, vmax=1, color_map="Greens",
                        title=r"correlation $\phi_K$",
                        fontsize_factor=1.5,
                        figsize=(10, 8))
plt.tight_layout()
```

```
interval columns not set, guessing: ['price', 'miles', 'year', 'engine_size']
```



[151]:
```
# check data profiling after data cleaning:
profile3 = pp(df_bs)
profile3.to_notebook_iframe()
```

```
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>
```

[152]:
```
# save the data profile as 'profile_cleaned_bos'
profile2.to_file("profile_cleaned_bos.html")
```

```
Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```

[153]:
```python
# total number of Boston dataset after cleaning
len(df_bs)
```

[153]: 11969

[154]:
```python
# feature engineering
# 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. This will help to improve the performence of our models
# The method usded here is MinMaxScaler
# The price is not scaled because it would be easier to interpret on the␣
↪performance result if we keep it this way
scaler = MinMaxScaler()
num_vars= ['year', 'miles', 'engine_size']
df_tor[num_vars] = scaler.fit_transform(df_tor[num_vars])
```

[155]:
```python
# The first model we will implement is Linear Regression, however, linear␣
↪regression as other regression models 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 order to avoid bias, 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 as well
# lets make a copy of cleaned dataset first
df_tor_model = df_tor.copy()
```

[156]:
```python
# Upon further checking, a lot of the model only appear once in our dataset! So␣
↪the approach we use here first is to use rarelabel encoder. All models that␣
↪appear less than 20 times are labelled as 'Rare' here.
# Set the threshold first, 20/ 11186 (total record of toronto dataset) = 0.002
rare_encoder = RareLabelCategoricalEncoder(
    tol=0.002,
    n_categories=10, variables=["model"])
```

[157]:
```python
# Implement the encoding on the dataset, this will also help us to reduce the␣
↪dimensionality of our dataset.
rare_encoder.fit(df_tor_model)
```

[157]:
```
RareLabelEncoder(ignore_format=False, max_n_categories=None, n_categories=10,
                 replace_with='Rare', tol=0.002, variables=['model'])
```

[158]:
```python
df_tor_model = rare_encoder.transform(df_tor_model)
```

[159]:
```
# Now we will apply dummy encoding on the dataset
# First, Define a function to generate dummy variables and merge 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 dataset
df_tor_model = dummies('make', df_tor_model)
df_tor_model = dummies('model', df_tor_model)
df_tor_model = dummies('drivetrain', df_tor_model)
df_tor_model = dummies('transmission', df_tor_model)
df_tor_model = dummies('fuel_type', df_tor_model)
df_tor_model = dummies('body_type', df_tor_model)
df_tor_model = dummies('engine_block', df_tor_model)
```

[160]:
```
# check some sample data
df_tor_model.head()
```

[160]:

	price	miles	year	engine_size	make_Audi	make_BMW	make_Buick	\
446	39455	0.293181	0.869565	0.684932	0	0	0	
732	6450	0.742471	0.391304	0.739726	0	0	0	
992	24962	0.178778	0.869565	0.205479	0	0	0	
993	24962	0.173431	0.869565	0.205479	0	0	0	
996	24962	0.173431	0.869565	0.205479	0	0	0	

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

	body_type_Passenger Van	body_type_Pickup	body_type_SUV	\
446	0	1	0	
732	0	1	0	
992	0	0	0	
993	0	0	0	
996	0	0	0	

	body_type_Sedan	body_type_Targa	body_type_Wagon	engine_block_I	\
446	0	0	0	0	
732	0	0	0	0	
992	0	0	0	1	
993	0	0	0	1	

```
996                 0                 0                 0                1

     engine_block_N/A  engine_block_V
446                 0               1
732                 0               1
992                 0               0
993                 0               0
996                 0               0

[5 rows x 179 columns]
```

[161]:
```python
# Split train and test data for model implemetation using 8:2 ratio:
X_train, X_test, Y_train, Y_test = train_test_split(df_tor_model.
 ↪drop('price',axis=1), df_tor_model['price'], test_size=0.20,␣
 ↪random_state=141)
```

[162]:
```python
# build model evaluation dataframe for later use.
model_evaluation  = pd.DataFrame(columns=('r2', 'rmse','mae' ))
```

[163]:
```python
# Using linear regression algorithm on the tranning set
lrm = LinearRegression()
lrm.fit(X_train,Y_train)
```

[163]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

[164]:
```python
# performance evaluation, the measurement used here are r square, RMSE and MAE
# measure the performance on testing dataset
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))
lrm_mae = metrics.mean_absolute_error(Y_test, lrm_predict)

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

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)
print('The mae for the testing set is:', lrm_mae)
```

```
For the linear regressor, the root mean square error for the testing set is:
5067.514807859321
The r2 score for the testing set is: 0.8198440976466574
The mae for the testing set is: 3647.3118170148527
```

[165]:
```
# To test whether it is overfitting, we apply the model on trainning dataset as␣
↪well and compare the socres:
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))
lrm_mae_train = metrics.mean_absolute_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 training set is:', lrm_r2_train)
print('The mae for the training set is:', lrm_mae_train)
# With somewhat similiar results, it seems that overfitting is not a probelm.
```

```
For the linear regressor, the root mean square error for the training set is:
4897.770432892777
The r2 score for the training set is: 0.8398875751860665
The mae for the training set is: 3494.133494564074
```

[166]:
```
# We will apply linear regression on Boston dataset as well and compare the␣
↪differences
# First we will scale the numberic values as we did for Toronto dataset
scaler = MinMaxScaler()
num_vars= ['year', 'miles', 'engine_size']
df_bs[num_vars] = scaler.fit_transform(df_bs[num_vars])
```

[167]:
```
# copy the Boston dataset
df_bs_model = df_bs.copy()
```

[168]:
```
# All models that appear less than 20 times are labelled as 'Rare' here.
# Set the threshold first, 20/total record of boston dataset = 0.0017
rare_encoder = RareLabelCategoricalEncoder(
    tol=0.002,
    n_categories=10, variables=["model"])
```

[169]:
```
# Apply rare encoder on the dataset
rare_encoder.fit(df_bs_model)
```

[169]:
```
RareLabelEncoder(ignore_format=False, max_n_categories=None, n_categories=10,
                 replace_with='Rare', tol=0.002, variables=['model'])
```

[170]:
```
df_bs_model = rare_encoder.transform(df_bs_model)
```

[171]:
```
# create a function to generate dummy variables and merge 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_bs_model = dummies('make', df_bs_model)
df_bs_model = dummies('model', df_bs_model)
df_bs_model = dummies('drivetrain', df_bs_model)
df_bs_model = dummies('transmission', df_bs_model)
df_bs_model = dummies('fuel_type', df_bs_model)
df_bs_model = dummies('body_type', df_bs_model)
df_bs_model = dummies('engine_block', df_bs_model)
```

[172]:
```
# check some sample data after encoding:
df_bs_model.head()
```

[172]:
```
      price     miles    year  engine_size  make_Alfa Romeo  make_Audi  \
141   22998  0.394358  0.5000     0.672131                0          0
512   10998  0.157576  0.6250     0.098361                0          0
882   58998  0.138755  0.8125     0.672131                0          0
4772  58498  0.096166  0.7500     0.672131                0          0
5289  58998  0.204385  0.7500     0.803279                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  …
4772         0           0              0               0  …
5289         0           0              0               0  …

      body_type_Mini Mpv  body_type_Minivan  body_type_Passenger Van  \
141                    0                  0                        0
512                    0                  0                        0
882                    0                  0                        0
4772                   0                  0                        0
5289                   0                  0                        0

      body_type_Pickup  body_type_Roadster  body_type_SUV  body_type_Sedan  \
141                  0                   0              0                0
512                  0                   0              0                0
882                  0                   0              1                0
4772                 0                   0              1                0
5289                 0                   0              1                0

      body_type_Wagon  engine_block_I  engine_block_V
141                 0               0               1
```

```
512                     0                 1                 0
882                     0                 0                 1
4772                    0                 0                 1
5289                    0                 0                 1

[5 rows x 173 columns]
```

[173]:
```python
# Split train and test data using 8:2 ratio:
x_train, x_test, y_train, y_test = train_test_split(df_bs_model.
 ↪drop('price',axis=1), df_bs_model['price'], test_size=0.20, random_state=141)
```

[174]:
```python
# Apply linear regression model
lrm2 = LinearRegression()
lrm2.fit(x_train,y_train)
```

[174]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

[175]:
```python
# measure the performance on testing dataset
# The result is better than Toronto dataset
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))
lrm2_mae = metrics.mean_absolute_error(y_test, lrm2_predict)

model_evaluation = model_evaluation.append(pd.DataFrame({'r2':[lrm2_r2], 'rmse':
 ↪[lrm2_rmse],'mae':[lrm2_mae]}, index = ['Linear Regression Boston']))

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)
print('The mae score for the testing set is:', lrm2_mae)
```

```
For the linear regressor, the root mean square error for the testing set is:
4634.348636185853
The r2 score for the testing set is: 0.8621068736923854
The mae score for the testing set is: 3348.0899784919793
```

[176]:
```python
# 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))
lrm2_mae_train = metrics.mean_absolute_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 training set is:', lrm2_r2_train)
print('The mae score for the trainin set is:', lrm2_mae_train)
# With similar scores, it seems that overfitting is not a probelm.
```

```
For the linear regressor, the root mean square error for the training set is:
4591.121286043685
The r2 score for the training set is: 0.8618153488281346
The mae score for the trainin set is: 3271.925645638851
```

[177]:
```
# Next we will apply more advanced methods on these two datasets: Random Forest␣
 ↪and XGBoost
```

[178]:
```
# We will use the traning and testing dataset prepared in the previous stage
# For Toronto dataset:
rfr = RandomForestRegressor()
```

[179]:
```
# Randomized Search CV, there are a lot of parameters to tune, we only select 5␣
 ↪most important ones here:
from sklearn.model_selection import RandomizedSearchCV
n_estimators=[100,200,300,400,500,600,700,800,900,1000,1100,1200]
max_features=['auto','sqrt']
max_depth=[5,10,15,20,25,30]
min_samples_split=[2,5,10,15,100]
min_samples_leaf=[1,2,5,10,12]
```

[180]:
```
# creating random grid for later use
random_grid={'n_estimators': n_estimators,'max_features': max_features,
            'max_depth': max_depth,'min_samples_split': min_samples_split,
            'min_samples_leaf': min_samples_leaf}
print(random_grid)
```

```
{'n_estimators': [100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1100,
1200], 'max_features': ['auto', 'sqrt'], 'max_depth': [5, 10, 15, 20, 25, 30],
'min_samples_split': [2, 5, 10, 15, 100], 'min_samples_leaf': [1, 2, 5, 10, 12]}
```

[181]:
```
# Use the random grid to search for best hyperparameters
# Random search of parameters, using 5 fold cross validation, number of␣
 ↪iteration is 10.
rfr_tor = RandomizedSearchCV(estimator = rfr, param_distributions =␣
 ↪random_grid, n_iter = 10, cv = 5, random_state=14, n_jobs = 1)
```

[182]:
```
rfr_tor.fit(X_train,Y_train)
```

[182]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=RandomForestRegressor(bootstrap=True,
```

```
                                                    ccp_alpha=0.0,
                                                    criterion='mse',
                                                    max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=0.0,
                                                    n_estimators=100,
                                                    n_jobs=None,
oob_score=Fals…
                   iid='deprecated', n_iter=10, n_jobs=1,
                   param_distributions={'max_depth': [5, 10, 15, 20, 25, 30],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 2, 5, 10, 12],
                                        'min_samples_split': [2, 5, 10, 15,
                                                              100],
                                        'n_estimators': [100, 200, 300, 400,
                                                         500, 600, 700, 800,
                                                         900, 1000, 1100,
                                                         1200]},
                   pre_dispatch='2*n_jobs', random_state=14, refit=True,
                   return_train_score=False, scoring=None, verbose=0)
```

[183]:
```
# Best parameters combination after tuning:
rfr_tor.best_params_
```

[183]:
```
{'n_estimators': 500,
 'min_samples_split': 5,
 'min_samples_leaf': 1,
 'max_features': 'sqrt',
 'max_depth': 25}
```

[184]:
```
# Best estimators:
rfr_tor.best_estimator_
```

[184]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=25, max_features='sqrt', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=5, min_weight_fraction_leaf=0.0,
                      n_estimators=500, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

[185]:
```
# Re-train the model using the best estimators from previous result
rfr_tor_be = RandomForestRegressor(bootstrap=True, ccp_alpha=0.0,␣
↪criterion='mse',
                      max_depth=25, max_features='sqrt', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=5, min_weight_fraction_leaf=0.0,
                      n_estimators=500, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

[186]:
```
rfr_tor_be.fit(X_train,Y_train)
```

[186]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=25, max_features='sqrt', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=5, min_weight_fraction_leaf=0.0,
                      n_estimators=500, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

[187]:
```
# evaluate the precting result on the testing dataset:
rfr_tor_predict = rfr_tor_be.predict(X_test)

rfr_tor_r2 = metrics.r2_score(Y_test, rfr_tor_predict)
rfr_tor_rmse = math.sqrt(metrics.mean_squared_error(Y_test, rfr_tor_predict))
rfr_tor_mae = metrics.mean_absolute_error(Y_test, rfr_tor_predict)

model_evaluation = model_evaluation.append(pd.DataFrame({'r2':[rfr_tor_r2],␣
↪'rmse':[rfr_tor_rmse],'mae':[rfr_tor_mae]}, index = ['Random Forest␣
↪Toronto']))

print('For the random forest, the root mean square error for the testing set is:
↪', rfr_tor_rmse)
print('The r2 score for the testing set is:', rfr_tor_r2)
print('The mae score for the testing set is:', rfr_tor_mae)
```

```
For the random forest, the root mean square error for the testing set is:
3419.84214471145
The r2 score for the testing set is: 0.9179515157179154
The mae score for the testing set is: 2274.2650320404096
```

[188]:
```
# Lets check the top 5 feature by importances:
rfr_tor_be.feature_importances_

temp2 =df_tor_model.drop(columns=['price'])
feature_rank = pd.DataFrame(rfr_tor_be.feature_importances_,temp2.
↪columns,columns=['importances']).sort_values(['importances'],ascending=False)
```

```
feature_rank.head(5)
```

[188]:
```
                 importances
year                0.221972
miles               0.209709
drivetrain_FWD      0.088269
engine_size         0.087559
engine_block_V      0.029811
```

[189]:
```
# To test whether it is overfitting, again we calculate the score for the␣
 ↪training set as well:
rfr_tor_predict_train = rfr_tor.predict(X_train)

rfr_tor_r2_train = metrics.r2_score(Y_train, rfr_tor_predict_train)
rfr_tor_rmse_train = math.sqrt(metrics.mean_squared_error(Y_train,␣
 ↪rfr_tor_predict_train))
rfr_tor_mae_train = metrics.mean_absolute_error(Y_train, rfr_tor_predict_train)

print('For the random forest, the root mean square error for the training set␣
 ↪is:', rfr_tor_rmse_train)
print('The r2 score for the trainging set is:', rfr_tor_r2_train)
print('The r2 score for the training set is:', rfr_tor_mae_train)
# There is a very slight overfitting problem based on the r2 score and rmse
```

```
For the random forest, the root mean square error for the training set is:
2429.4296420888436
The r2 score for the trainging set is: 0.9606053871579714
The r2 score for the training set is: 1609.1813094180486
```

[190]:
```
# For Boston dataset, the approach will be the same
# Use the random grid to search for best hyperparameters
# Random search of parameters, using 5 fold cross validation,
rfr_bs = RandomizedSearchCV(estimator = rfr, param_distributions = random_grid,␣
 ↪n_iter = 10, cv = 5, random_state=14, n_jobs = 1)
```

[191]:
```
# Search for the best parameters
rfr_bs.fit(x_train,y_train)
```

[191]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=RandomForestRegressor(bootstrap=True,
                                                   ccp_alpha=0.0,
                                                   criterion='mse',
                                                   max_depth=None,
                                                   max_features='auto',
                                                   max_leaf_nodes=None,
                                                   max_samples=None,
                                                   min_impurity_decrease=0.0,
```

```
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=0.0,
                                                    n_estimators=100,
                                                    n_jobs=None,
oob_score=Fals…
                   iid='deprecated', n_iter=10, n_jobs=1,
                   param_distributions={'max_depth': [5, 10, 15, 20, 25, 30],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 2, 5, 10, 12],
                                        'min_samples_split': [2, 5, 10, 15,
                                                              100],
                                        'n_estimators': [100, 200, 300, 400,
                                                         500, 600, 700, 800,
                                                         900, 1000, 1100,
                                                         1200]},
                   pre_dispatch='2*n_jobs', random_state=14, refit=True,
                   return_train_score=False, scoring=None, verbose=0)
```

[192]:
```
# Best parameters for Boston dataset:
rfr_bs.best_params_
```

[192]:
```
{'n_estimators': 500,
 'min_samples_split': 5,
 'min_samples_leaf': 1,
 'max_features': 'sqrt',
 'max_depth': 25}
```

[193]:
```
# Best estimators:
rfr_bs.best_estimator_
```

[193]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=25, max_features='sqrt', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=5, min_weight_fraction_leaf=0.0,
                      n_estimators=500, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

[194]:
```
rfr_bs = RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=25, max_features='sqrt', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=5, min_weight_fraction_leaf=0.0,
                      n_estimators=500, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

[195]:
```
rfr_bs.fit(x_train,y_train)
```

[195]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=25, max_features='sqrt', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=5, min_weight_fraction_leaf=0.0,
                      n_estimators=500, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

[196]:
```
# evaluate the prediction result on Boston dataset:
rfr_bs_predict = rfr_bs.predict(x_test)

rfr_bs_r2 = metrics.r2_score(y_test, rfr_bs_predict)
rfr_bs_rmse = math.sqrt(metrics.mean_squared_error(y_test, rfr_bs_predict))
rfr_bs_mae = metrics.mean_absolute_error(y_test, rfr_bs_predict)

model_evaluation = model_evaluation.append(pd.DataFrame({'r2':[rfr_bs_r2],␣
 ↪'rmse':[rfr_bs_rmse],'mae':[rfr_bs_mae]}, index = ['Random Forest Boston']))

print('For the random forest, the root mean square error for the testing set is:
 ↪', rfr_bs_rmse)
print('The r2 score for the testing set is:', rfr_bs_r2)
print('The mae score for the testing set is:', rfr_bs_mae)
```

```
For the random forest, the root mean square error for the testing set is:
1682.7312997289766
The r2 score for the testing set is: 0.9818199631305511
The mae score for the testing set is: 1094.435580137958
```

[197]:
```
# Lets check the top 5 feature by importances:
rfr_bs.feature_importances_

temp3 =df_bs_model.drop(columns=['price'])
feature_rank_bs = pd.DataFrame(rfr_bs.feature_importances_,temp3.
 ↪columns,columns=['importances']).sort_values(['importances'],ascending=False)
feature_rank_bs.head(5)
```

[197]:

	importances
miles	0.144425
year	0.138921
engine_size	0.117500
drivetrain_FWD	0.062034
fuel_type_Premium Unleaded	0.059921

[198]:
```
# apply the model on the trainning dataset to see if its overfitting:
rfr_bs_predict_train = rfr_bs.predict(x_train)
```

```
rfr_bs_r2_train = metrics.r2_score(y_train, rfr_bs_predict_train)
rfr_bs_rmse_train = math.sqrt(metrics.mean_squared_error(y_train,␣
↪rfr_bs_predict_train))
rfr_bs_mae_train = metrics.mean_absolute_error(y_train, rfr_bs_predict_train)

print('For the random forest, the root mean square error for the training set␣
↪is:', rfr_bs_rmse_train)
print('The r2 score for the training set is:', rfr_bs_r2_train)
print('The mae score for the training set is:', rfr_bs_mae_train)

# The score is slightly better than test dataset.
```

```
For the random forest, the root mean square error for the training set is:
1270.905470638837
The r2 score for the training set is: 0.9894111505651663
The mae score for the training set is: 862.15143511153
```

[199]:
```
# Next, lets apply XGBoost:
model_xgb = xgb.XGBRegressor()
```

[200]:
```
# For XGboost, we will use hyperparameter tunning as well. There are a lot of␣
↪parameters to tune, only the most important ones are selected here:
n_estimators = [100,200,300]
max_depth = [10,20,30]
learning_rate=[0.05,0.1,0.15]
min_child_weight=[1,3,5]
```

[201]:
```
# create parameter_grid for later use in RandomizedSearchCV :
parameter_grid = {
    'n_estimators': n_estimators,
    'max_depth':max_depth,
    'learning_rate':learning_rate,
    'min_child_weight':min_child_weight,
    }
```

[202]:
```
# Set up the grid search with 5-fold cross validation, the number of iteration␣
↪is 10
xgb_tor = RandomizedSearchCV(estimator=model_xgb,
            param_distributions=parameter_grid,
            cv=5,
            n_jobs = 1,
            n_iter= 10,
            random_state=14)
```

[203]:
```
# Search for the best parameters
xgb_tor.fit(X_train, Y_train)
```

[203]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=XGBRegressor(base_score=None, booster=None,
                                          colsample_bylevel=None,
                                          colsample_bynode=None,
                                          colsample_bytree=None,
                                          enable_categorical=False, gamma=None,
                                          gpu_id=None, importance_type=None,
                                          interaction_constraints=None,
                                          learning_rate=None,
                                          max_delta_step=None, max_depth=None,
                                          min_child_weight=None, missing=nan,
                                          monot…
                                          scale_pos_weight=None, subsample=None,
                                          tree_method=None,
                                          validate_parameters=None,
                                          verbosity=None),
                   iid='deprecated', n_iter=10, n_jobs=1,
                   param_distributions={'learning_rate': [0.05, 0.1, 0.15],
                                        'max_depth': [10, 20, 30],
                                        'min_child_weight': [1, 3, 5],
                                        'n_estimators': [100, 200, 300]},
                   pre_dispatch='2*n_jobs', random_state=14, refit=True,
                   return_train_score=False, scoring=None, verbose=0)
```

[204]:
```
# Best parameters for Boston dataset:
xgb_tor.best_params_
```

[204]:
```
{'n_estimators': 300,
 'min_child_weight': 1,
 'max_depth': 10,
 'learning_rate': 0.1}
```

[205]:
```
# Best estimators:
xgb_tor.best_estimator_
```

[205]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.1, max_delta_step=0,
             max_depth=10, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=300, n_jobs=8,
             num_parallel_tree=1, objective='reg:squarederror',
             predictor='auto', random_state=0, reg_alpha=0, reg_lambda=1,
             scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

[206]:
```
xgb_tor = xgb.XGBRegressor(base_score=0.5, booster='gbtree',␣
↪colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.1, max_delta_step=0,
             max_depth=10, min_child_weight=1, missing=np.nan,
             monotone_constraints='()', n_estimators=300, n_jobs=8,
             num_parallel_tree=1, objective='reg:squarederror',
             predictor='auto', random_state=0, reg_alpha=0, reg_lambda=1,
             scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

[207]:
```
# train the model with best parameters
xgb_tor.fit(X_train, Y_train)
```

[207]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.1, max_delta_step=0,
             max_depth=10, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=300, n_jobs=8,
             num_parallel_tree=1, objective='reg:squarederror',
             predictor='auto', random_state=0, reg_alpha=0, reg_lambda=1,
             scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

[208]:
```
# evaluate the prediction result on the testing dataset:
xgb_tor_predict = xgb_tor.predict(X_test)

xgb_tor_r2 = metrics.r2_score(Y_test, xgb_tor_predict)
xgb_tor_rmse = math.sqrt(metrics.mean_squared_error(Y_test, xgb_tor_predict))
xgb_tor_mae = metrics.mean_absolute_error(Y_test, xgb_tor_predict)

model_evaluation = model_evaluation.append(pd.DataFrame({'r2':[xgb_tor_r2],␣
↪'rmse':[xgb_tor_rmse],'mae':[xgb_tor_mae]}, index = ['XGB_Toronto']))

print('For the xgb, the root mean square error for the testing set is:',␣
↪xgb_tor_rmse)
print('The r2 score for the testing set is:', xgb_tor_r2)
print('The ame score for the testing set is:', xgb_tor_mae)
```

```
For the xgb, the root mean square error for the testing set is:
3171.866588155776
The r2 score for the testing set is: 0.9294189253145879
The ame score for the testing set is: 1994.8169222397928
```

[209]:
```python
# Lets check the top 10 feature by importances type 'total_gain':
tor_score = xgb_tor.get_booster().get_score(importance_type='total_gain')
tor_score_list = list(tor_score.items())
tor_fe_score = pd.DataFrame(tor_score_list,columns = ['feature','score'] ).
 ↪sort_values(['score'],ascending=False)
tor_fe_score['score'] = tor_fe_score['score'].astype(int)
tor_fe_score.head(10)
```

[209]:

	feature	score
143	drivetrain_FWD	1699787833344
0	miles	1663765839872
1	year	1195905253376
2	engine_size	966477676544
156	fuel_type_Unleaded	180427751424
171	engine_block_I	104526159872
19	make_Land Rover	44506972160
27	make_Porsche	42090418176
24	make_Mercedes-Benz	29995022336
168	body_type_Sedan	29613146112

[210]:
```python
# apply the model on the trainning dataset to check overfitting:
xgb_tor_predict_train = xgb_tor.predict(X_train)

xgb_tor_r2_train = metrics.r2_score(Y_train, xgb_tor_predict_train)
xgb_tor_rmse_train = math.sqrt(metrics.mean_squared_error(Y_train,␣
 ↪xgb_tor_predict_train))
xgb_tor_mae_train = metrics.mean_absolute_error(Y_train, xgb_tor_predict_train)

print('For the random forest, the root mean square error for the training set␣
 ↪is:', xgb_tor_rmse_train)
print('The r2 score for the training set is:', xgb_tor_r2_train)
print('The ame score for the training set is:', xgb_tor_mae_train)
```

```
For the random forest, the root mean square error for the training set is:
1255.6350128213571
The r2 score for the training set is: 0.9894766256699343
The ame score for the training set is: 820.0267756892252
```

[211]:
```python
# For Boston dataset, the approach will be the same
# Use the random grid to search for best hyperparameters
# Random search of parameters, using 5 fold cross validation,
# Set up the grid search with 5-fold cross validation
xgb_bs = RandomizedSearchCV(estimator=model_xgb,
            param_distributions=parameter_grid,
            cv=5,
            n_jobs = 1,
            n_iter= 10,
```

```
                random_state=14)
```

[212]:
```
# Search for the best parameters
xgb_bs.fit(x_train, y_train)
```

[212]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=XGBRegressor(base_score=None, booster=None,
                                          colsample_bylevel=None,
                                          colsample_bynode=None,
                                          colsample_bytree=None,
                                          enable_categorical=False, gamma=None,
                                          gpu_id=None, importance_type=None,
                                          interaction_constraints=None,
                                          learning_rate=None,
                                          max_delta_step=None, max_depth=None,
                                          min_child_weight=None, missing=nan,
                                          monot…
                                          scale_pos_weight=None, subsample=None,
                                          tree_method=None,
                                          validate_parameters=None,
                                          verbosity=None),
                   iid='deprecated', n_iter=10, n_jobs=1,
                   param_distributions={'learning_rate': [0.05, 0.1, 0.15],
                                        'max_depth': [10, 20, 30],
                                        'min_child_weight': [1, 3, 5],
                                        'n_estimators': [100, 200, 300]},
                   pre_dispatch='2*n_jobs', random_state=14, refit=True,
                   return_train_score=False, scoring=None, verbose=0)
```

[213]:
```
# Best estimators:
xgb_bs.best_estimator_
```

[213]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.1, max_delta_step=0,
             max_depth=30, min_child_weight=3, missing=nan,
             monotone_constraints='()', n_estimators=200, n_jobs=8,
             num_parallel_tree=1, objective='reg:squarederror',
             predictor='auto', random_state=0, reg_alpha=0, reg_lambda=1,
             scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

[214]:
```
xgb_bs = xgb.XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.1, max_delta_step=0,
```

```
                max_depth=20, min_child_weight=3, missing=np.nan,
                monotone_constraints='()', n_estimators=200, n_jobs=8,
                num_parallel_tree=1, objective='reg:squarederror',
                predictor='auto', random_state=0, reg_alpha=0, reg_lambda=1,
                scale_pos_weight=1, subsample=1, tree_method='exact',
                validate_parameters=1, verbosity=None)
```

[215]:
```
xgb_bs.fit(x_train, y_train)
```

[215]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.1, max_delta_step=0,
             max_depth=20, min_child_weight=3, missing=nan,
             monotone_constraints='()', n_estimators=200, n_jobs=8,
             num_parallel_tree=1, objective='reg:squarederror',
             predictor='auto', random_state=0, reg_alpha=0, reg_lambda=1,
             scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

[216]:
```
# evaluate the prediction result on the testing dataset:
xgb_bs_predict = xgb_bs.predict(x_test)

model_evaluation_xgb  = pd.DataFrame(columns=('r2', 'rmse'))

xgb_bs_r2 = metrics.r2_score(y_test, xgb_bs_predict)
xgb_bs_rmse = math.sqrt(metrics.mean_squared_error(y_test, xgb_bs_predict))
xgb_bs_mae = metrics.mean_absolute_error(y_test, xgb_bs_predict)

model_evaluation = model_evaluation.append(pd.DataFrame({'r2':[xgb_bs_r2],␣
↪'rmse':[xgb_bs_rmse],'mae':[xgb_bs_mae]}, index = ['XGB_Boston']))

print('For the xgb, the root mean square error for the testing set is:',␣
↪xgb_bs_rmse)
print('The r2 score for the testing set is:', xgb_bs_r2)
print('The mae score for the testing set is:', xgb_bs_mae)
```

```
For the xgb, the root mean square error for the testing set is:
874.0396789971427
The r2 score for the testing set is: 0.9950951298836093
The mae score for the testing set is: 222.6755883034409
```

[223]:
```
bs_score = xgb_bs.get_booster().get_score(importance_type='total_gain')
bs_score_list= list(bs_score.items())
bs_fe_score = pd.DataFrame(bs_score_list,columns = ['feature','score'] ).
↪sort_values(['score'],ascending=False)
bs_fe_score['score'] = bs_fe_score['score'].astype(int)
```

```
bs_fe_score.head(10)
```

[223]:

	feature	score
2	engine_size	1465724960768
146	drivetrain_FWD	1450551803904
1	year	1444843225088
0	miles	564732493824
155	fuel_type_Unleaded	447817318400
154	fuel_type_Premium Unleaded	404856045568
19	make_Land Rover	105801687040
15	make_INFINITI	64585494528
116	model_Rare	58281861120
152	fuel_type_Electric / Premium Unleaded	49610526720

[218]:
```
# apply the model on the trainning dataset to check overfitting:
xgb_bs_predict_train = xgb_bs.predict(x_train)

xgb_bs_r2_train = metrics.r2_score(y_train, xgb_bs_predict_train)
xgb_bs_rmse_train = math.sqrt(metrics.mean_squared_error(y_train,␣
 ↪xgb_bs_predict_train))
xgb_bs_mae_train = metrics.mean_absolute_error(y_train, xgb_bs_predict_train)


print('For the random forest, the root mean square error for the training set␣
 ↪is:', xgb_bs_rmse_train)
print('The r2 score for the testing set is:', xgb_bs_r2_train)
print('The mae score for the testing set is:', xgb_bs_mae_train)
```

```
For the random forest, the root mean square error for the training set is:
231.36480575233568
The r2 score for the testing set is: 0.999649072931969
The mae score for the testing set is: 85.89960014482702
```

[219]:
```
# Compare the final scores in a dataframe:
model_evaluation.sort_values(by=['r2'], ascending=False)
```

[219]:

	r2	rmse	mae
XGB_Boston	0.995095	874.039679	222.675588
Random Forest Boston	0.981820	1682.731300	1094.435580
XGB_Toronto	0.929419	3171.866588	1994.816922
Random Forest Toronto	0.917952	3419.842145	2274.265032
Linear Regression Boston	0.862107	4634.348636	3348.089978
Linear Regression Toronto	0.819844	5067.514808	3647.311817

[ ]:
```

```