Used Car Price Prediction

FINAL SEMESTER PROJECT - SUMMER 2021

Syed Muhammad Sabih

Project Statement

For the US Cars Dataset, the analysis pertains to predict the price of the car based on the appropriate features.

Dataset Information

The dataset is from the Kaggle Repository and was scraped from auctionexport.com. The dataset includes information about 28 brands of clean and used vehicles for sale in the US.
The dataset includes 12 features: price, years, brand, model, color, state, mileage, VIN, title status, lot, and the condition.

Feature Description

- Price: The sale price of the vehicle
- Year: Vehicle registration year
- Brand: Brand/Make of the vehicle
- Model: Model of the vehicle
- Color: Color of the vehicle
- State: The location where the vehicle is for sale
- Mileage: Miles traveled by the vehicle
- VIN: Vehicle identification number
- Title status: Clean or salvage title
- lot: lot number from the manufacturer
- condition: time

Library Import

In [92]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from numpy import mean
from numpy import std
from pandas import read_csv

from sklearn.model_selection import train_test_split
from sklearn.impute import KNNImputer
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.pipeline import Pipeline
from matplotlib import pyplot
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn import preprocessing
from sklearn.preprocessing import OneHotEncoder

from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline , FeatureUnion
from sklearn.feature_selection import SelectKBest, chi2 , f_classif
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.preprocessing import Normalizer
import xgboost as xgb
from sklearn.model_selection import KFold, GridSearchCV
from sklearn.metrics import accuracy_score, make_scorer
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import roc_curve, precision_recall_curve
from sklearn.metrics import f1_score, precision_score, recall_score
from sklearn.metrics import classification_report, confusion_matrix, auc

from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn import metrics
from tabulate import tabulate
from sklearn.feature_selection import RFE
from sklearn.pipeline import Pipeline
from matplotlib import pyplot
from sklearn import preprocessing
from sklearn.metrics import roc_auc_score

from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import LinearSVR, SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from xgboost import XGBRegressor
```

Loading the Dataset

In [131]:
```
df = pd.read_csv("C:/Users/smsab/Desktop/UCF/STA - 6704/dataset/USA_cars_datasets.csv")
df
```

Out[131]:

	Unnamed: 0	price	brand	model	year	title_status	mileage	color	vin	lot	state	country	conditio
0	0	6300	toyota	cruiser	2008	clean vehicle	274117.0	black	jtezu11f88k007763	159348797	new jersey	usa	10 da
1	1	2899	ford	se	2011	clean vehicle	190552.0	silver	2fmdk3gc4bbb02217	166951262	tennessee	usa	6 da
2	2	5350	dodge	mpv	2018	clean vehicle	39590.0	silver	3c4pdcgg5jt346413	167655728	georgia	usa	2 da
3	3	25000	ford	door	2014	clean vehicle	64146.0	blue	1ftfw1et4efc23745	167753855	virginia	usa	22 hou
4	4	27700	chevrolet	1500	2018	clean vehicle	6654.0	red	3gcpcrec2jg473991	167763266	florida	usa	22 hou
...	...	...	...	...	...	...	...	...	...	...	...	...	
2494	2494	7800	nissan	versa	2019	clean vehicle	23609.0	red	3n1cn7ap9kl880319	167722715	california	usa	1 da
2495	2495	9200	nissan	versa	2018	clean vehicle	34553.0	silver	3n1cn7ap5jl884088	167762225	florida	usa	21 hou
2496	2496	9200	nissan	versa	2018	clean vehicle	31594.0	silver	3n1cn7ap9jl884191	167762226	florida	usa	21 hou
2497	2497	9200	nissan	versa	2018	clean vehicle	32557.0	black	3n1cn7ap3jl883263	167762227	florida	usa	2 da
2498	2498	9200	nissan	versa	2018	clean vehicle	31371.0	silver	3n1cn7ap4jl884311	167762228	florida	usa	21 hou

2499 rows × 13 columns

Exploratory Data Analysis

Based on the knowledge of cars and in my experience, the price of a used car usually depends on the brand, model, year, title status, mileage, color, and what state the car is located in. For the purpose of this analysis, lets drop the VIN, lot number, country, and condition column.

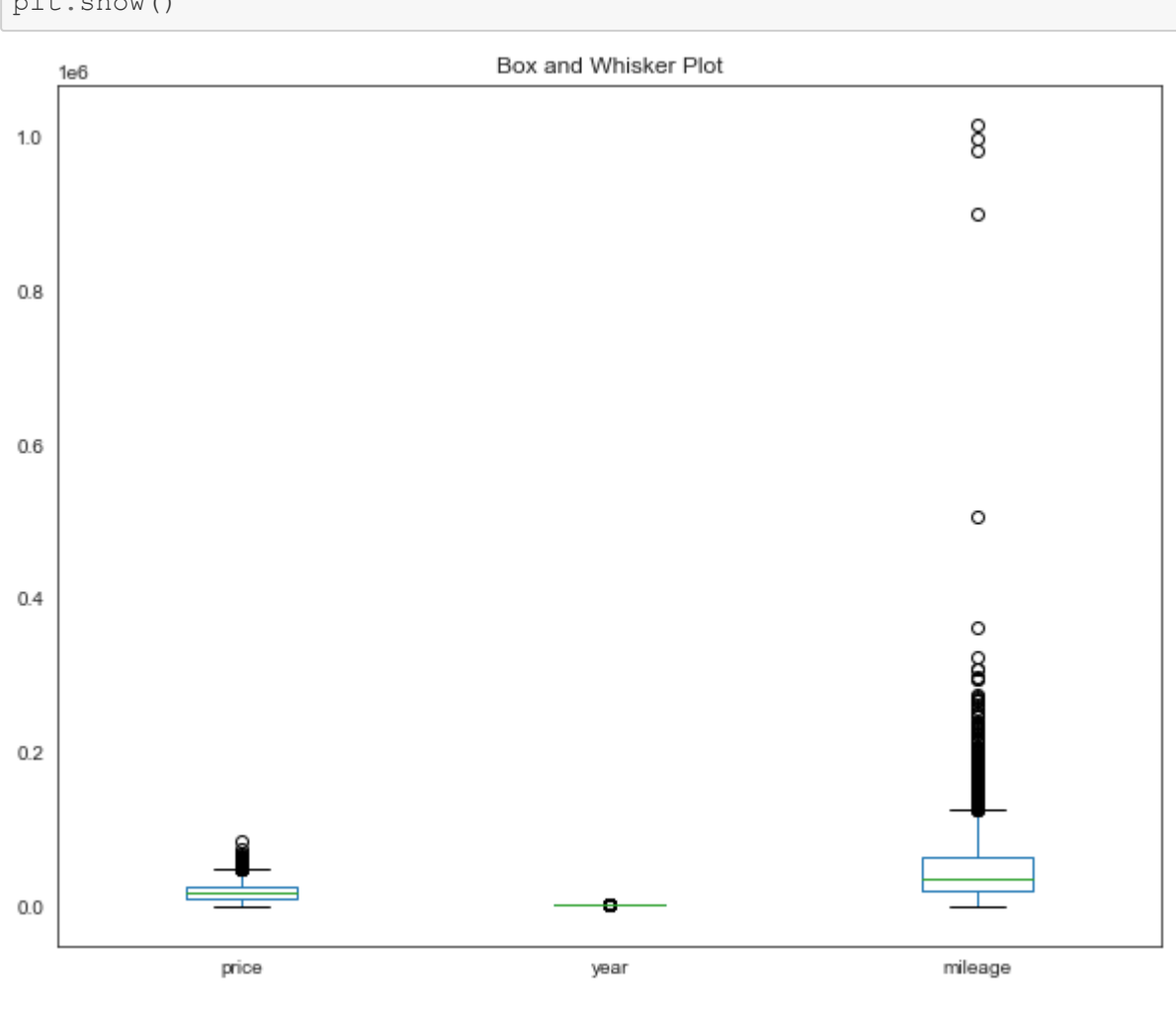
In [132]:
```
#Dropping the irrelevant columns
df = df.drop(["Unnamed: 0", "vin", "lot", "country","condition"], axis=1)
```

In [133]:
```
df.head(10).style.set_properties(**{'background-color': 'black',

                                    'color': 'lawngreen',
                                    'border-color': 'white'})
```

Out[133]:

	price	brand	model	year	title_status	mileage	color	state
0	6300	toyota	cruiser	2008	clean vehicle	274117.000	black	new jersey
1	2899	ford	se	2011	clean vehicle	190552.000	silver	tennessee
2	5350	dodge	mpv	2018	clean vehicle	39590.000	silver	georgia
3	25000	ford	door	2014	clean vehicle	64146.000	blue	virginia
4	27700	chevrolet	1500	2018	clean vehicle	6654.000	red	florida
5	5700	dodge	mpv	2018	clean vehicle	45561.000	white	texas
6	7300	chevrolet	pk	2010	clean vehicle	149050.000	black	georgia
7	13350	gmc	door	2017	clean vehicle	23525.000	gray	california
8	14600	chevrolet	malibu	2018	clean vehicle	9371.000	silver	florida
9	5250	ford	mpv	2017	clean vehicle	63418.000	black	texas

In [134]:
```
#Lets look at the spread of the initial data
boxplot_data = df.plot.box(title="Box and Whisker Plot")
plt.show()
```



At this point, the data is raw, and not been pre-processed. The box and whisker plot will not show promising results.

Investigating Numeric and Categorical Variables

In [135]:
```
#Type of the variables
df.dtypes
```

Out[135]:
```
price             int64
brand            object
model            object
year              int64
title_status     object
mileage         float64
color            object
state            object
dtype: object
```

In [136]:
```
#Descriptive Statistics
pd.set_option('precision',3)
df.describe(include='all')
```

Out[136]:

	price	brand	model	year	title_status	mileage	color	state
count	2499.000	2499	2499	2499.000	2499	2.499e+03	2499	2499
unique	NaN	28	127	NaN	2	NaN	49	44
top	NaN	ford	door	NaN	clean vehicle	NaN	white	pennsylvania
freq	NaN	1235	651	NaN	2336	NaN	707	299
mean	18767.671	NaN	NaN	2016.714	NaN	5.230e+04	NaN	NaN
std	12116.095	NaN	NaN	3.443	NaN	5.971e+04	NaN	NaN
min	0.000	NaN	NaN	1973.000	NaN	0.000e+00	NaN	NaN
25%	10200.000	NaN	NaN	2016.000	NaN	2.147e+04	NaN	NaN
50%	16900.000	NaN	NaN	2018.000	NaN	3.536e+04	NaN	NaN
75%	25555.500	NaN	NaN	2019.000	NaN	6.347e+04	NaN	NaN
max	84900.000	NaN	NaN	2020.000	NaN	1.018e+06	NaN	NaN

In [137]:
```
# Checking for unique columns

print("\n\nUnique column values in dataset\n", df.nunique())
```

```
Unique column values in dataset
 price            790
brand             28
model            127
year              30
title_status       2
mileage         2439
color             49
state             44
dtype: int64
```

Categorical Variables are brand, model, title, color, and state.

Checking for duplicate rows and deleting them

At this point, lets delete any duplicate rows.

In [138]:
```
#Count of the variables before deleting duplicate rows
count_before_removing_dup = pd.DataFrame(df.count())
count_before_removing_dup.style.set_caption("Count of variables before removing duplicates")
```

Out[138]:

Count of variables before removing duplicates

	0
price	2499
brand	2499
model	2499
year	2499
title_status	2499
mileage	2499
color	2499
state	2499

In [139]:
```
#Checking for Duplicate rows
duplicate_rows_df = df[df.duplicated()]
duplicate_rows_df.style.set_caption("Duplicate Rows")
```

Out[139]:

Duplicate Rows

	price	brand	model	year	title_status	mileage	color	state
518	50	chevrolet	door	2008	salvage insurance	172102.000	blue	texas
530	0	chevrolet	door	2003	salvage insurance	194673.000	gray	texas
541	25	chevrolet	pickup	2010	salvage insurance	149189.000	white	colorado
661	26900	chevrolet	traverse	2018	clean vehicle	42941.000	black	missouri

In [140]:
```
print("number of duplicate rows: ", duplicate_rows_df.shape)
```

```
number of duplicate rows:  (4, 8)
```

Deleting 4 duplicate rows

In [141]:
```
#Deleting the Duplicate rows
df = df.drop_duplicates()
duplicate_rows_df = df[df.duplicated()]
print("number of duplicate rows: ", duplicate_rows_df.shape)
```

```
number of duplicate rows:  (0, 8)
```

In [143]:
```
#Count of the data after deleting duplicate rows
count_after_removing_dup = pd.DataFrame(df.count())
count_after_removing_dup.style.set_caption("Count of variables after removing duplicates")
```

Out[143]:

Count of variables after removing duplicates

	0
price	2495
brand	2495
model	2495
year	2495
title_status	2495
mileage	2495
color	2495
state	2495

In [12]:
```
#New shape of the dataset
print(" dataset: ( rows, columns) = ", df.shape)
```

```
 dataset: ( rows, columns) =  (2495, 8)
```

Checking for any missing values

In [13]:
```
#Finding the null values
print(df.isnull().sum())
```

```
price           0
brand           0
model           0
year            0
title_status    0
mileage         0
color           0
state           0
dtype: int64
```

There are no missing values

Modifying the Year Variable

In [14]:
```
#Fixing the year variable to where it shows how old the car is
def mod_year(x):
    return 2021 - x
df['year'] = mod_year(df.year)
df
```

```
<ipython-input-14-67f2d1a5d522>:4: 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/indexin
g.html#returning-a-view-versus-a-copy
  df['year'] = mod_year(df.year)
```

Out[14]:

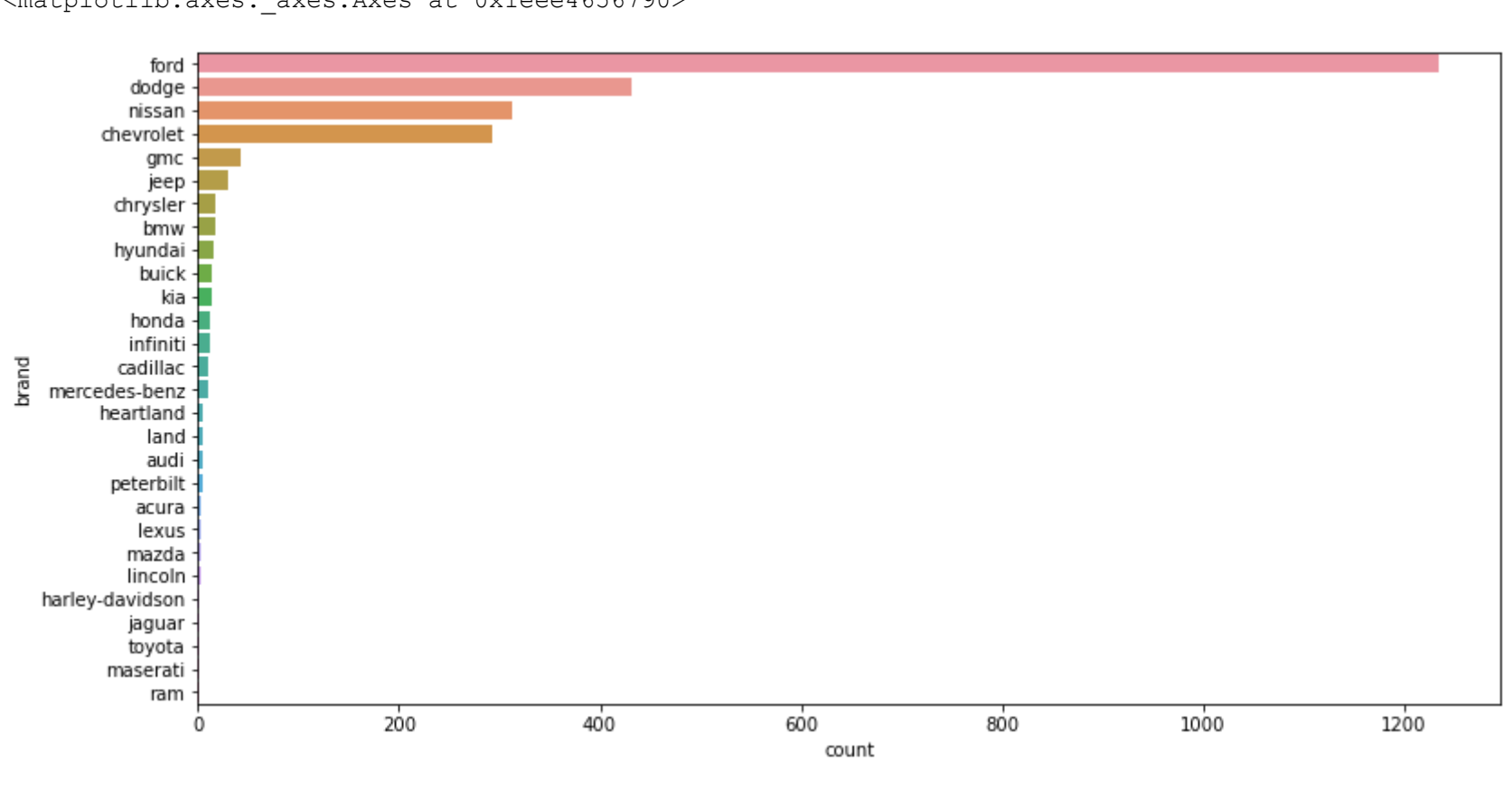
	price	brand	model	year	title_status	mileage	color	state
0	6300	toyota	cruiser	13	clean vehicle	274117.0	black	new jersey
1	2899	ford	se	10	clean vehicle	190552.0	silver	tennessee
2	5350	dodge	mpv	3	clean vehicle	39590.0	silver	georgia
3	25000	ford	door	7	clean vehicle	64146.0	blue	virginia
4	27700	chevrolet	1500	3	clean vehicle	6654.0	red	florida
...	...	...	...	...	...	...	...	...
2494	7800	nissan	versa	2	clean vehicle	23609.0	red	california
2495	9200	nissan	versa	3	clean vehicle	34553.0	silver	florida
2496	9200	nissan	versa	3	clean vehicle	31594.0	silver	florida
2497	9200	nissan	versa	3	clean vehicle	32557.0	black	florida
2498	9200	nissan	versa	3	clean vehicle	31371.0	silver	florida

2495 rows × 8 columns

Visualize the top brands of the vehicle by count

In [15]:
```
brand_count = df['brand'].value_counts().to_frame().reset_index()
brand_count.rename(columns={'index':'brand', 'brand':'count'}, inplace=True)

fig = plt.figure(figsize=(10, 5))

axes = fig.add_axes([0, 0, 1, 1])

sns.barplot(y = brand_count['brand'], x = brand_count['count'], ax=axes)
```

Out[15]: `<matplotlib.axes._axes.Axes at 0x1eee4656790>`



Since we have a larger number of vehicles that are Ford, Dodge, Nissan, Chevorlet, and GMC, lets only take the datapoints that incorporate the top 5 brands for the dataset

In [16]:
```
# Set the index of the DataFrame to the brand name
df1 = df.set_index("brand")
#Drop the brands other than top 5
df1 = df1.drop(["jeep","chrysler","bmw","hyundai","buick","kia","honda","infiniti","cadillac",
              "mercedes-benz","heartland","audi","land","peterbilt","acura","lincoln","mazda",
              "lexus","jaguar","ram","maserati","harley-davidson","toyota"])
```

In [17]:
```
#Reset the index to have brand as a column/feature
df1.reset_index(level=0, inplace=True)
```

In [18]:
```
#Visualize the shape of the dataset
df1
```

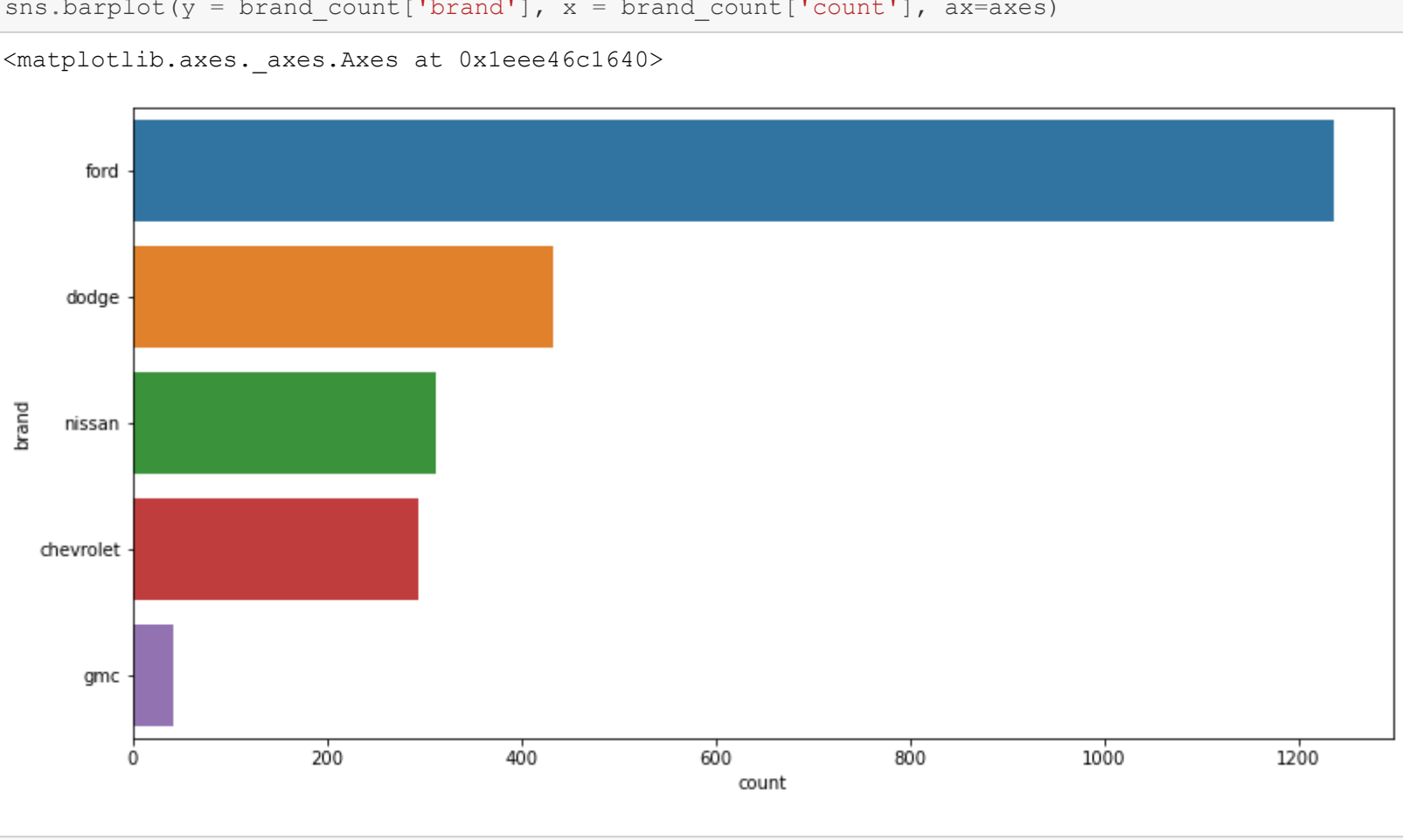
Out[18]:

	brand	price	model	year	title_status	mileage	color	state
0	ford	2899	se	10	clean vehicle	190552.0	silver	tennessee
1	dodge	5350	mpv	3	clean vehicle	39590.0	silver	georgia
2	ford	25000	door	7	clean vehicle	64146.0	blue	virginia
3	chevrolet	27700	1500	3	clean vehicle	6654.0	red	florida
4	dodge	5700	mpv	3	clean vehicle	45561.0	white	texas
...	...	...	...	...	...	...	...	...
2309	nissan	7800	versa	2	clean vehicle	23609.0	red	california
2310	nissan	9200	versa	3	clean vehicle	34553.0	silver	florida
2311	nissan	9200	versa	3	clean vehicle	31594.0	silver	florida
2312	nissan	9200	versa	3	clean vehicle	32557.0	black	florida
2313	nissan	9200	versa	3	clean vehicle	31371.0	silver	florida

2314 rows × 8 columns

In [19]:
```
brand_count = df1['brand'].value_counts().to_frame().reset_index()
brand_count.rename(columns={'index':'brand', 'brand':'count'}, inplace=True)

fig = plt.figure(figsize=(10, 5))

axes = fig.add_axes([0, 0, 1, 1])

sns.barplot(y = brand_count['brand'], x = brand_count['count'], ax=axes)
```

Out[19]: `<matplotlib.axes._axes.Axes at 0x1eee46c1640>`



In [20]:
```
#Number of records removed
no_of_records_removed = df.count()-df1.count()
no_of_records_removed
```

Out[20]:
```
brand           181
color           181
mileage         181
model           181
price           181
state           181
title_status    181
year            181
dtype: int64
```

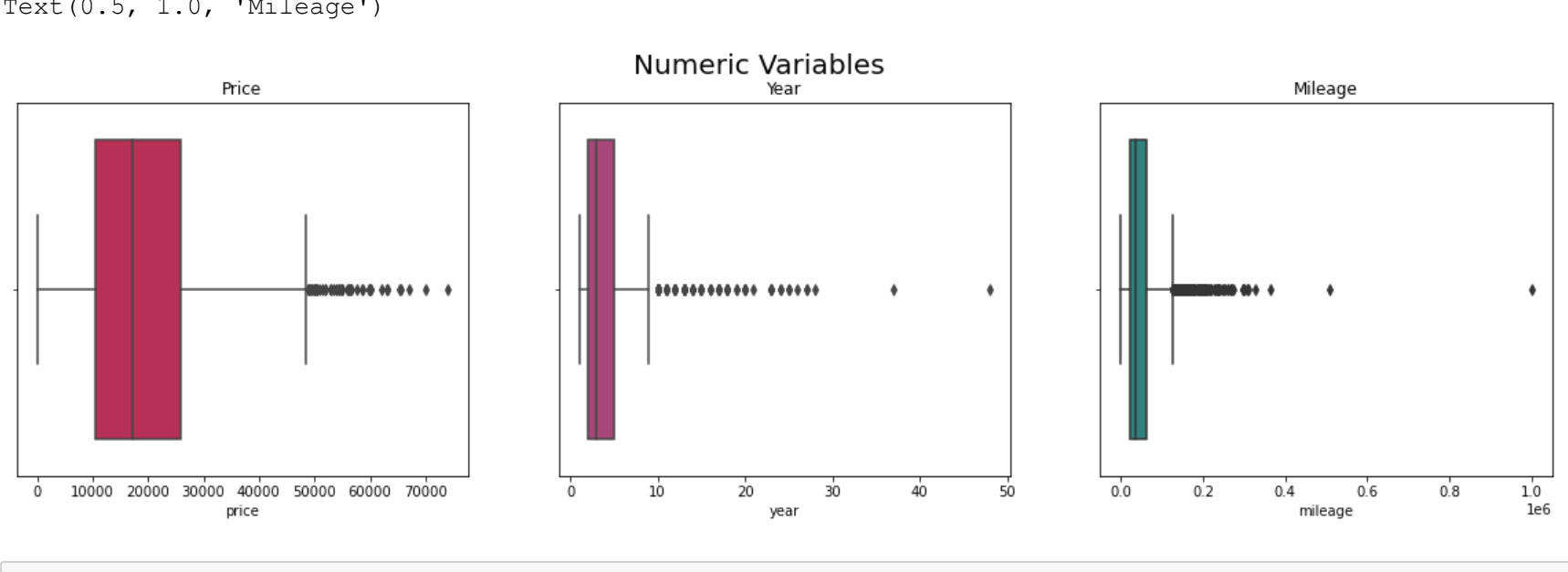
181 records removed

Visualize the numeric variables

Univariate graphs

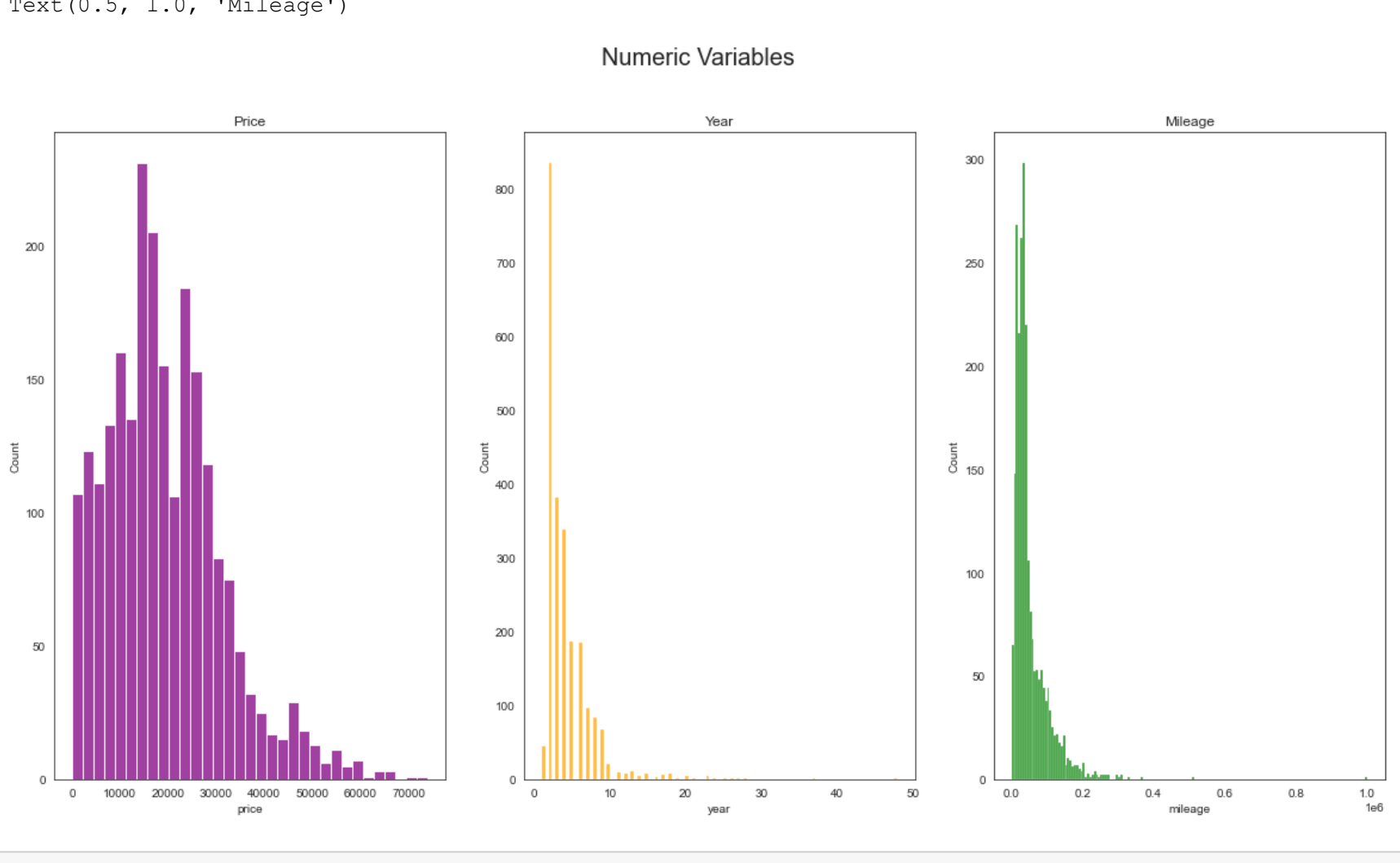
In [21]:
```
#Box Plots for Numeric Variables
fig, axes = plt.subplots(1, 3, figsize=(20, 5))
fig.suptitle('Numeric Variables', fontsize=20)

# Price
sns.boxplot(ax=axes[0], x=df1['price'], palette="rocket")
axes[0].set_title("Price")

# Year
sns.boxplot(ax=axes[1], x=df1['year'], palette="magma")
axes[1].set_title("Year")

# Mileage
sns.boxplot(ax=axes[2], x=df1['mileage'], palette="viridis")
axes[2].set_title("Mileage")
```

Out[21]: `Text(0.5, 1.0, 'Mileage')`



In [144]:
```
#Histogram for Numeric Variables
fig, axes = plt.subplots(1, 3, figsize=(20, 10))
fig.suptitle('Numeric Variables', fontsize=20)

# Price
sns.histplot(ax=axes[0], x=df1['price'], color='purple')
axes[0].set_title("Price")

# Year
sns.histplot(ax=axes[1], x=df1['year'], color='orange')
axes[1].set_title("Year")

# Mileage
sns.histplot(ax=axes[2], x=df1['mileage'], color='green')
axes[2].set_title("Mileage")
```

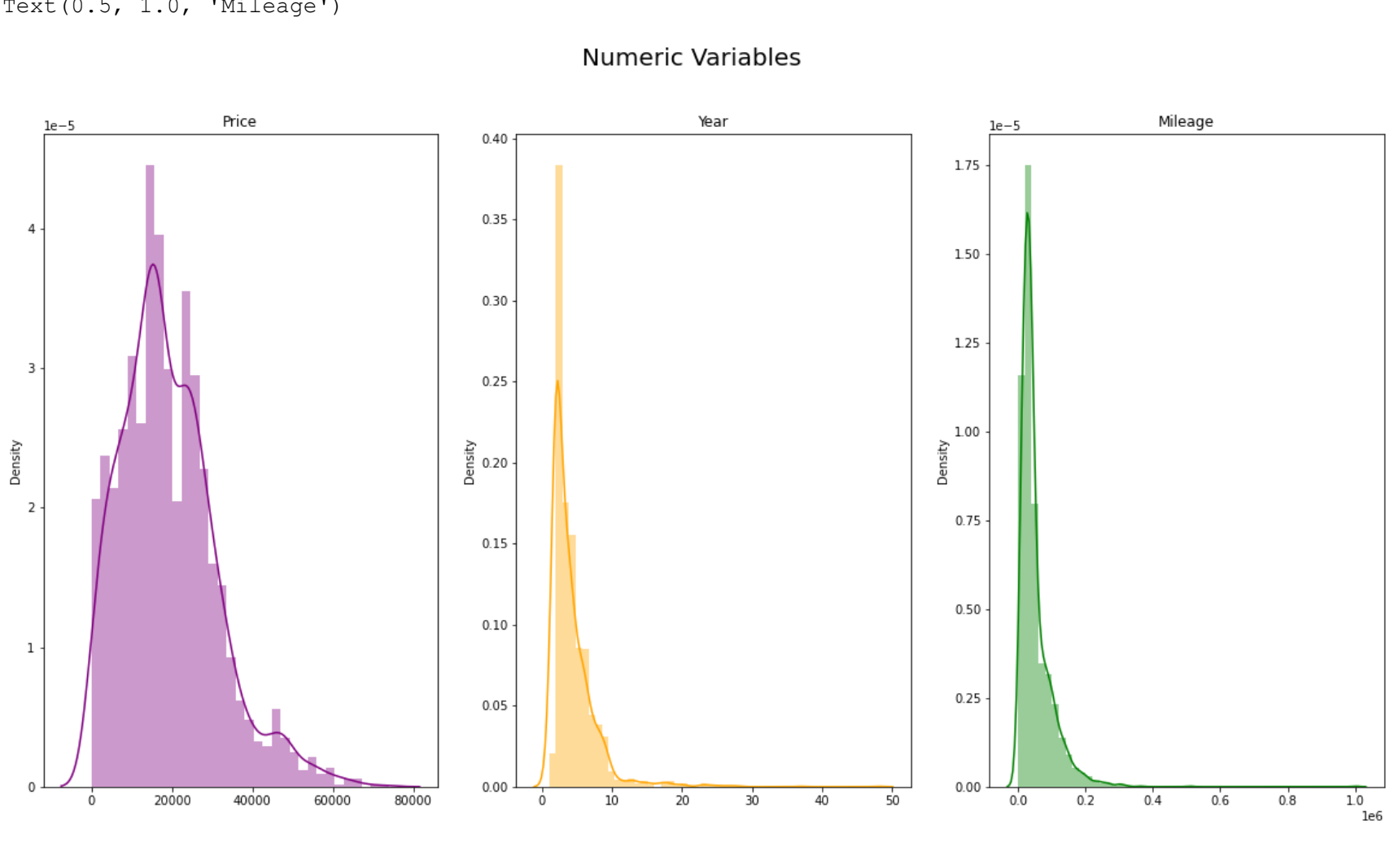
Out[144]: `Text(0.5, 1.0, 'Mileage')`



In [23]:
```
#Density Plot for Numeric Variables
fig, axes = plt.subplots(1, 3, figsize=(20, 10))
fig.suptitle('Numeric Variables', fontsize=20)

# Price
sns.distplot(ax=axes[0], x=df1['price'], color='purple')
axes[0].set_title("Price")

# Year
sns.distplot(ax=axes[1], x=df1['year'], color='orange')
axes[1].set_title("Year")

# Mileage
sns.distplot(ax=axes[2], x=df1['mileage'], color='green')
axes[2].set_title("Mileage")
```

```
C:\Users\smsab\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` i
s a deprecated function and will be removed in a future version. Please adapt your code to use either
`displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function fo
r histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\smsab\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` i
s a deprecated function and will be removed in a future version. Please adapt your code to use either
`displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function fo
r histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\smsab\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` i
s a deprecated function and will be removed in a future version. Please adapt your code to use either
`displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function fo
r histograms).
  warnings.warn(msg, FutureWarning)
```

Out[23]: `Text(0.5, 1.0, 'Mileage')`



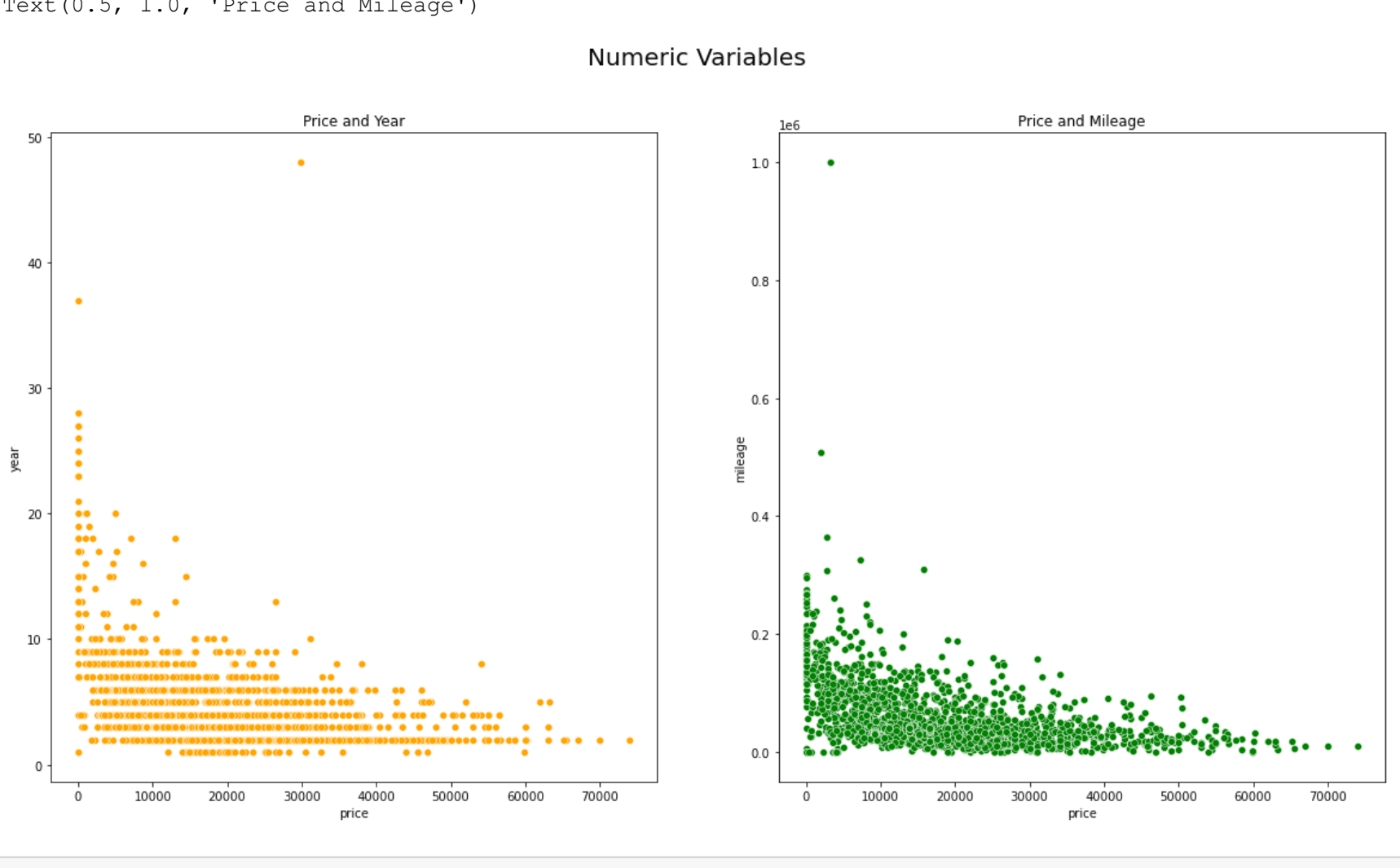
At this point, we want to include the outliers in this analysis, since there are also older cars or salvage cars that cost less. We can see that the price target variable is skewed to the left. Along with the price, we can also see year and mileage variables are also skewed.

Bivariate graphs

Lets investigate the relationship between the price and year, and price and mileage.

In [24]:
```
#Density Plot for Numeric Variables
fig, axes = plt.subplots(1, 2, figsize=(20, 10))
fig.suptitle('Numeric Variables', fontsize=20)

# Price and Year
sns.scatterplot(x="price", y="year", data=df1, color='orange', ax=axes[0])
axes[0].set_title("Price and Year")

#Price and Mileage
sns.scatterplot(x="price", y="mileage", data=df1, color='green', ax=axes[1])
axes[1].set_title("Price and Mileage")
```

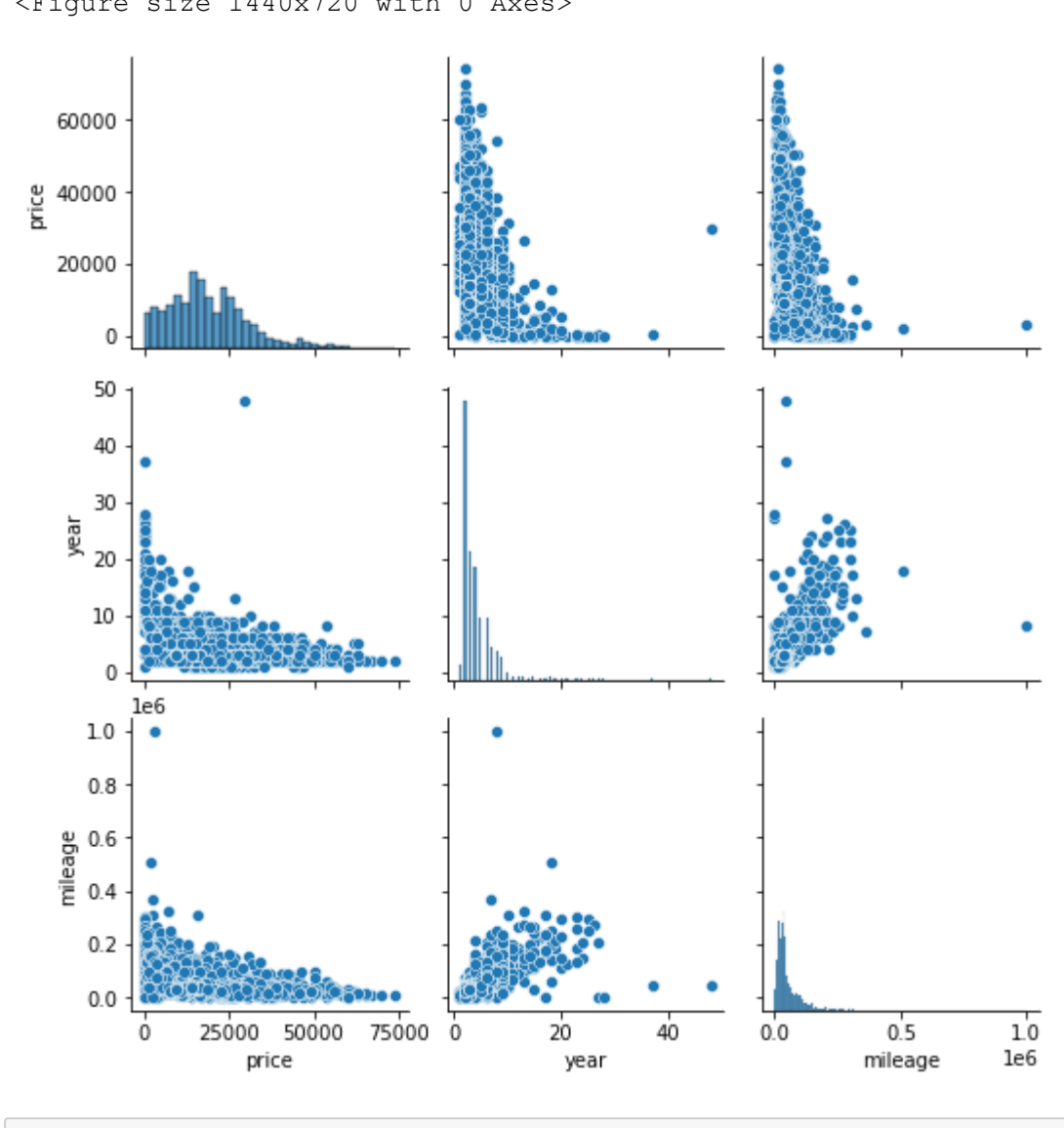
Out[24]: `Text(0.5, 1.0, 'Price and Mileage')`



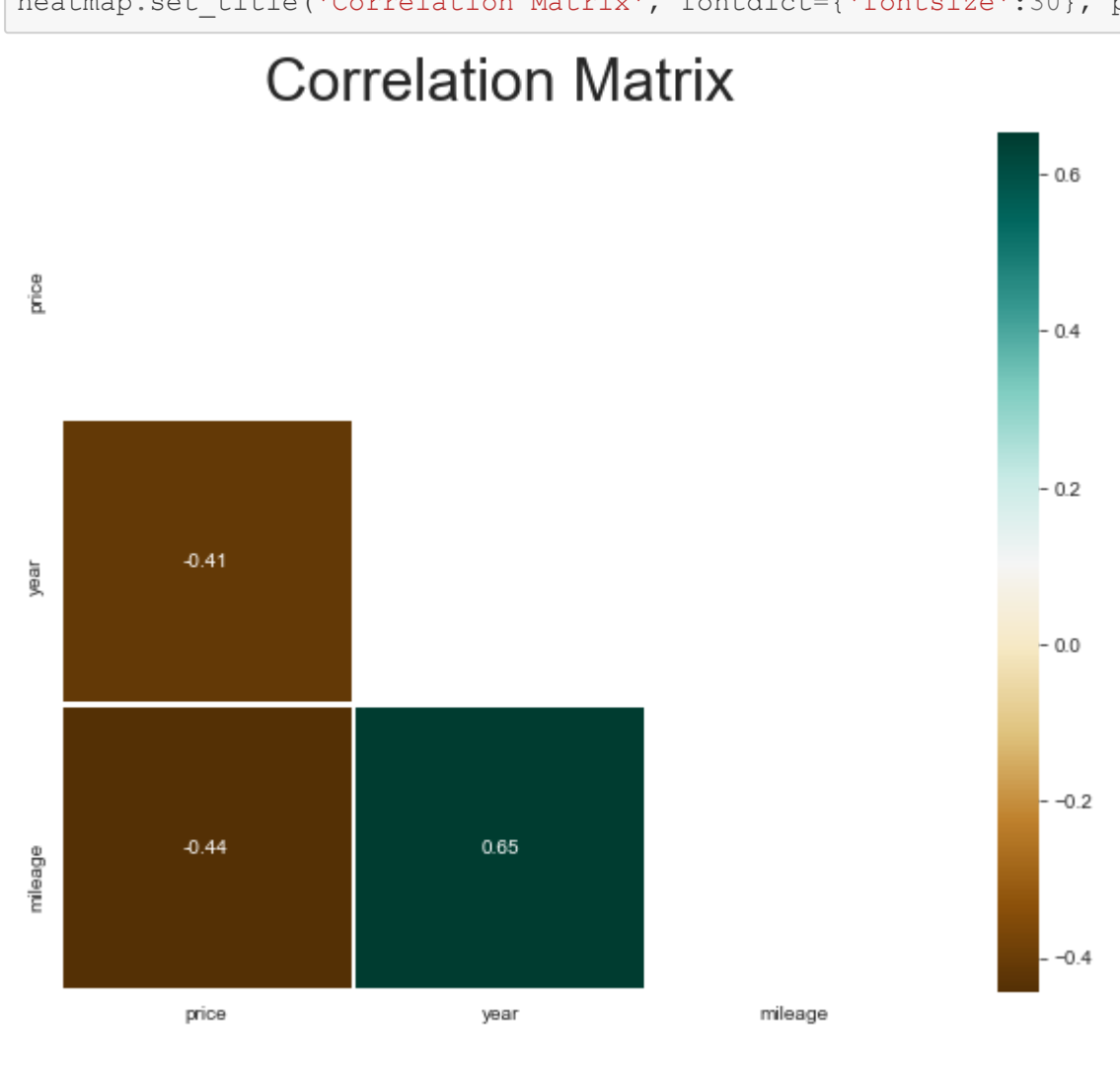
In [25]:
```
plt.figure(figsize=(20, 10))
sns.pairplot(df1)
```

Out[25]: `<seaborn.axisgrid.PairGrid at 0x1eee5a62c40>`

```
<Figure size 1440x720 with 0 Axes>
```



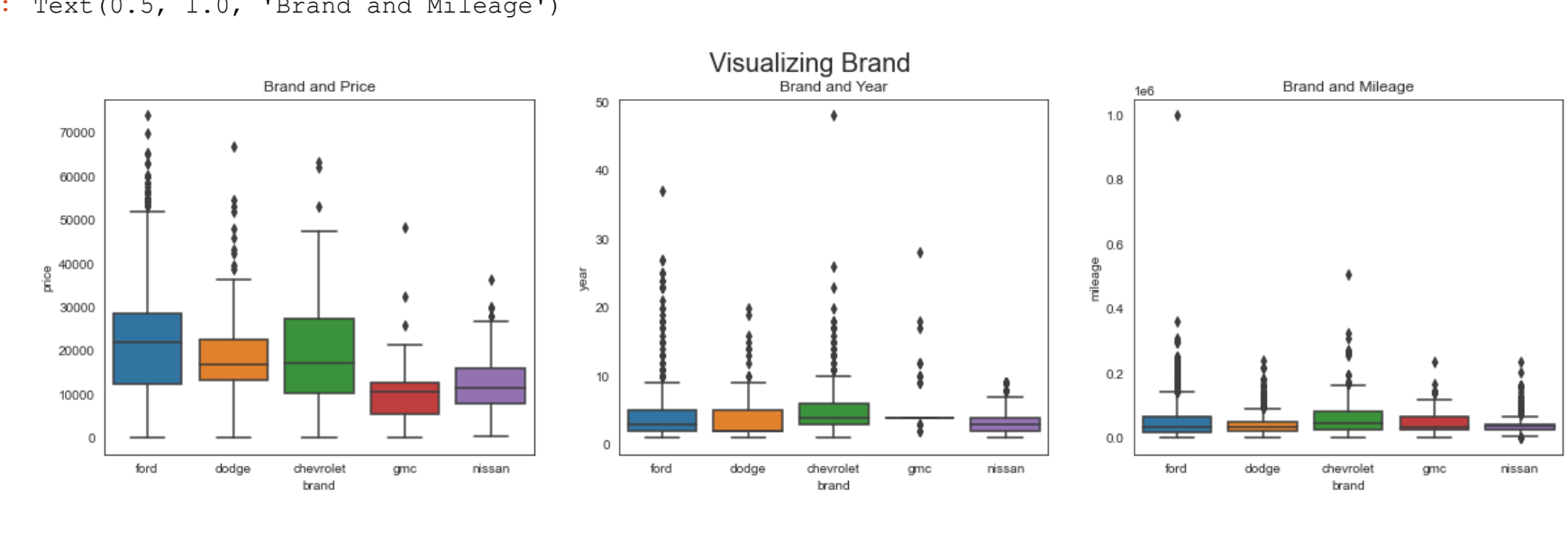
In [26]:
```
#correlation matrix
plt.figure(figsize=(10, 8))
sns.set_style('white')
mask = np.triu(np.ones_like(df1.corr(), dtype=np.bool))
heatmap = sns.heatmap(df1.corr(), mask=mask,annot=True, cmap='BrBG', linewidths = 2)
heatmap.set_title('Correlation Matrix', fontdict={'fontsize':30}, pad=16);
```



Visualize the categorical variables

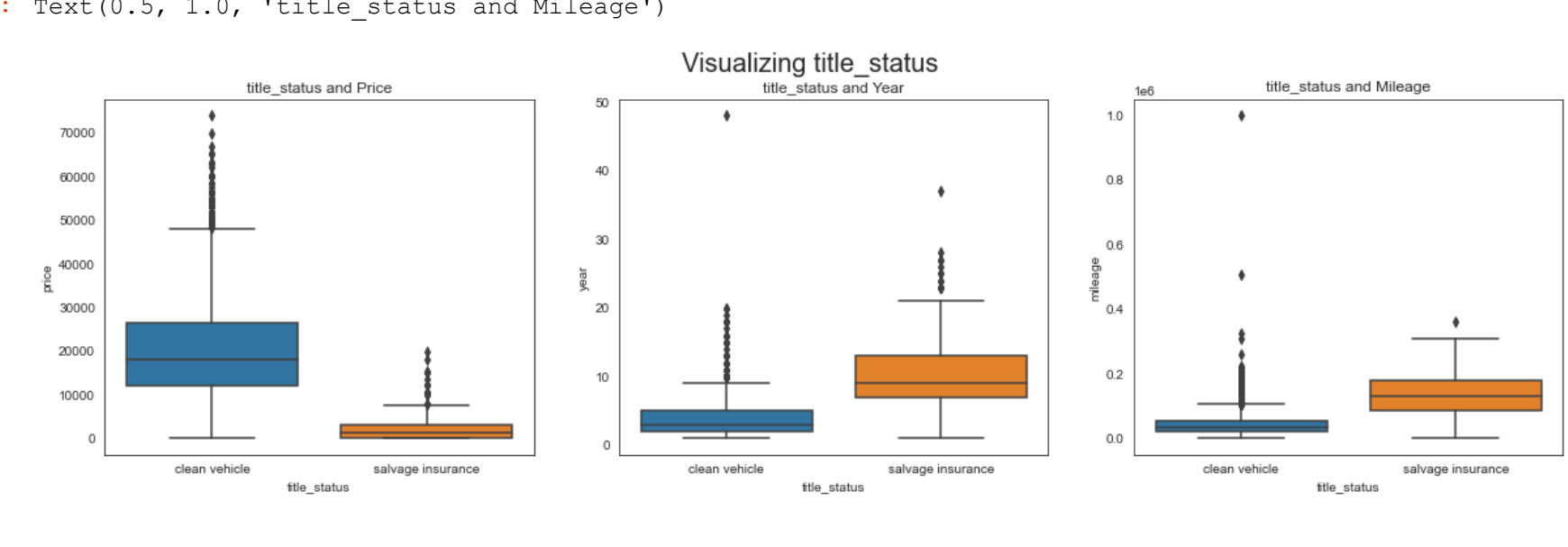
Brand

```
In [27]: fig, axes = plt.subplots(1, 3, figsize=(20, 5))
         fig.suptitle('Visualizing Brand', fontsize=20)

         #Brand and Price
         sns.boxplot(ax=axes[0], x="brand", y="price", data=df1)
         axes[0].set_title("Brand and Price")

         #Brand and Year
         sns.boxplot(ax=axes[1], x="brand", y="year", data=df1)
         axes[1].set_title("Brand and Year")

         #Brand and Mileage
         sns.boxplot(ax=axes[2], x="brand", y="mileage", data=df1)
         axes[2].set_title("Brand and Mileage")
Out[27]: Text(0.5, 1.0, 'Brand and Mileage')
```



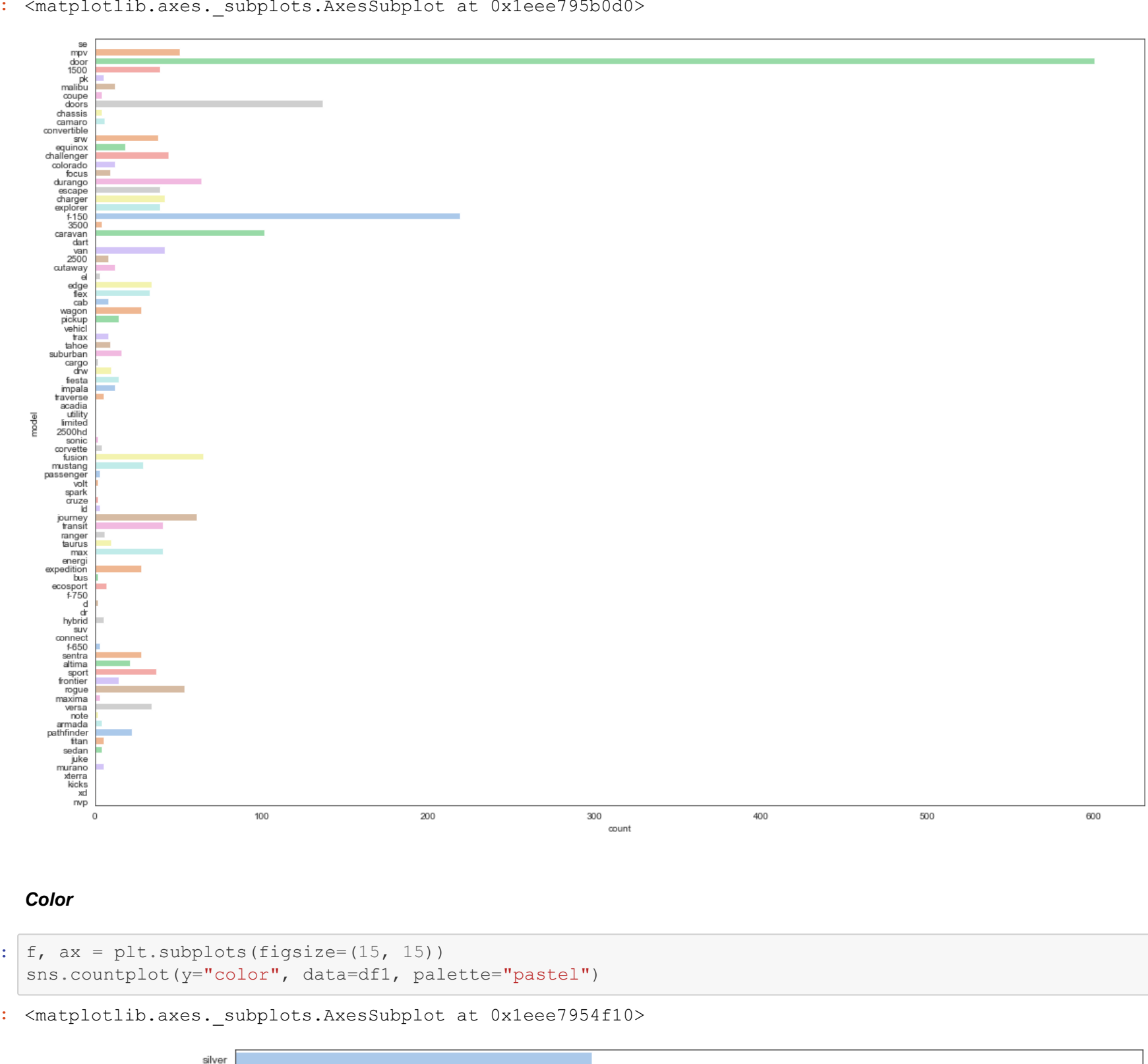
Title Status

```
In [28]: fig, axes = plt.subplots(1, 3, figsize=(20, 5))
         fig.suptitle('Visualizing title_status', fontsize=20)

         #Title Status and Price
         sns.boxplot(ax=axes[0], x="title_status", y="price", data=df1)
         axes[0].set_title("title_status and Price")

         #Title Status and Year
         sns.boxplot(ax=axes[1], x="title_status", y="year", data=df1)
         axes[1].set_title("title_status and Year")

         #Title Status and Mileage
         sns.boxplot(ax=axes[2], x="title_status", y="mileage", data=df1)
         axes[2].set_title("title_status and Mileage")
Out[28]: Text(0.5, 1.0, 'title_status and Mileage')
```



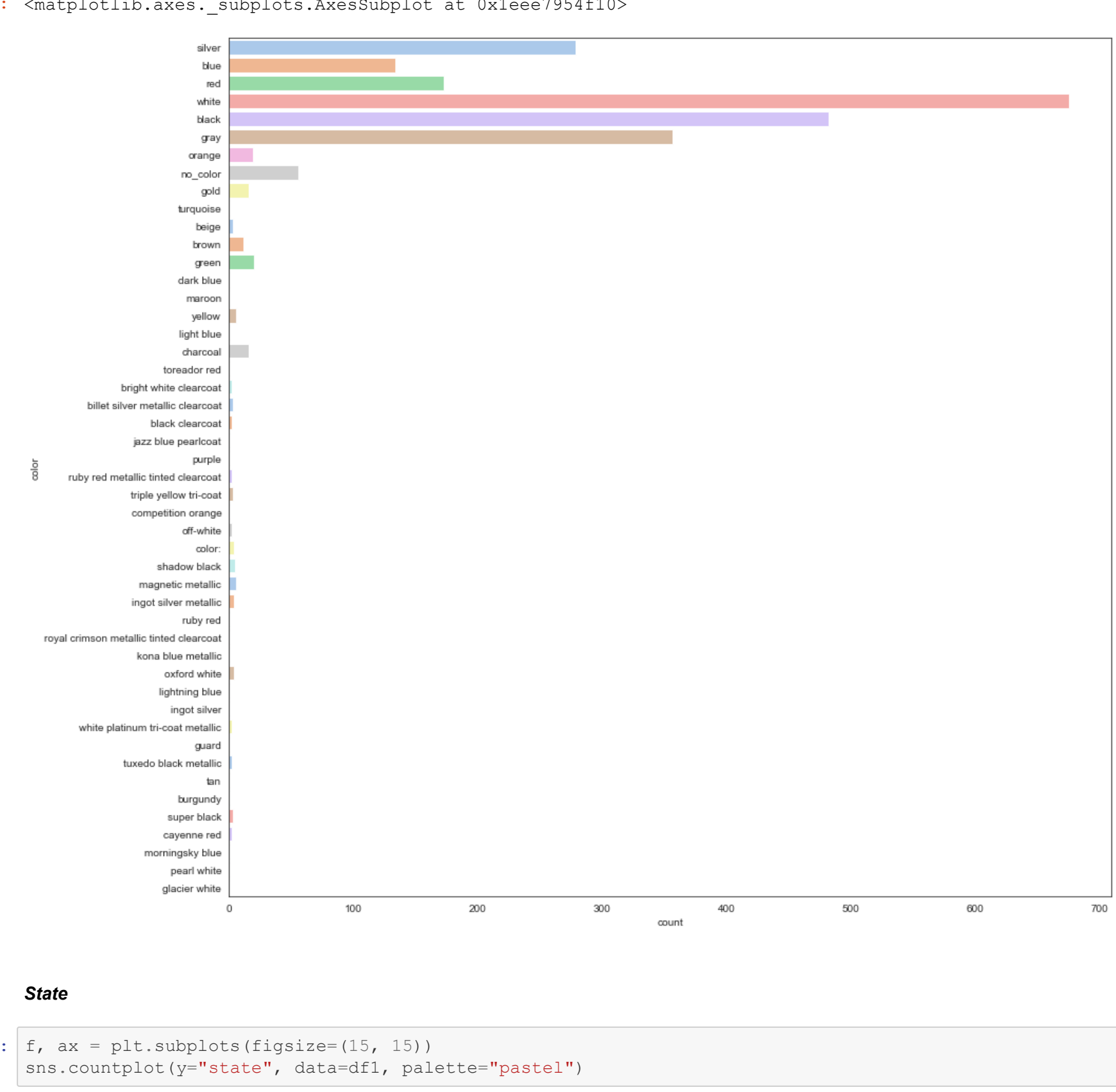
Model

```
In [29]: f, ax = plt.subplots(figsize=(20, 15))
         sns.countplot(y="model", data=df1, palette="pastel")
Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x1eee795b0d0>
```



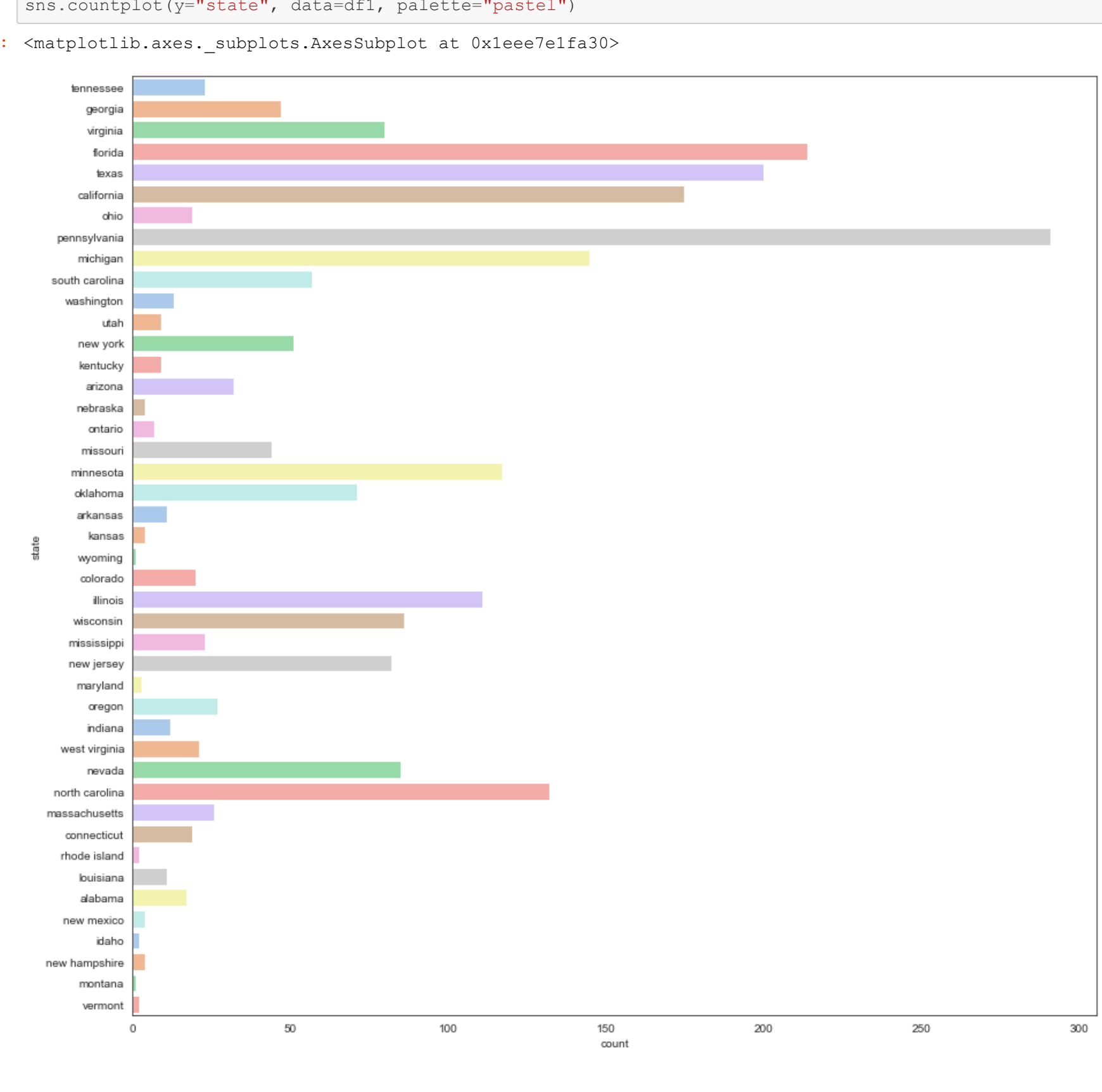
Color

```
In [30]: f, ax = plt.subplots(figsize=(15, 15))
         sns.countplot(y="color", data=df1, palette="pastel")
Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x1eee7954f10>
```



State

```
In [31]: f, ax = plt.subplots(figsize=(15, 15))
         sns.countplot(y="state", data=df1, palette="pastel")
Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x1eee7e1fa30>
```



Data Preparation

Separate the Categorical and Numeric Variables

```
In [32]: df1_categorical = df1[['brand','title_status','model','color','state']]
         df1_categorical
Out[32]:
```

	brand	title_status	model	color	state
0	ford	clean vehicle	se	silver	tennessee
1	dodge	clean vehicle	mpv	silver	georgia
2	ford	clean vehicle	door	blue	virginia
3	chevrolet	clean vehicle	1500	red	florida
4	dodge	clean vehicle	mpv	white	texas
...	...	...	...	...	...
2309	nissan	clean vehicle	versa	red	california
2310	nissan	clean vehicle	versa	silver	florida
2311	nissan	clean vehicle	versa	silver	florida
2312	nissan	clean vehicle	versa	black	florida
2313	nissan	clean vehicle	versa	silver	florida

2314 rows × 5 columns

```
In [33]: df1_numerical = df1[['price','year','mileage']]
         df1_numerical
Out[33]:
```

	price	year	mileage
0	2899	10	190552.0
1	5350	3	39590.0
2	25000	7	64146.0
3	27700	3	6654.0
4	5700	3	45561.0
...	...	...	...
2309	7800	2	23609.0
2310	9200	3	34553.0
2311	9200	3	31594.0
2312	9200	3	32557.0
2313	9200	3	31371.0

2314 rows × 3 columns

OneHot Encode the Categorical Variables

By default, the encoder derives the categories based on the unique values in each feature.
The method below one_hot encodes the categorical features to keep the prefixes for each feature when creating binary variables for categorical predictor levels.

```
In [34]: def onehot_encode(df, columns_with_prefixes):
             df = df.copy()
             for column, prefix in columns_with_prefixes:
                 dummies = pd.get_dummies(df[column], prefix=prefix)
                 df = pd.concat([df, dummies], axis=1)
                 df = df.drop(column, axis=1)
             return df
```

```
In [35]: df1_categorical = onehot_encode(
             df1_categorical,
             columns_with_prefixes=[
                 ('brand', 'br'),
                 ('model', 'md'),
                 ('color', 'cl'),
                 ('state', 'st'),
                 ('title_status', 'ts')
              ]
          )
```

```
In [36]: df1_categorical.describe(include='all')
Out[36]:
```

	br_chevrolet	br_dodge	br_ford	br_gmc	br_nissan	md_1500	md_2500	md_2500hd	md_3500	md_acadia	...	st_texas	st_
count	2314.000	2314.000	2314.000	2314.000	2314.000	2314.000	2314.000	2.314e+03	2314.000	2.314e+03	...	2314.000	2314
mean	0.127	0.187	0.534	0.018	0.135	0.017	0.003	4.322e-04	0.002	4.322e-04	...	0.086	0
std	0.333	0.390	0.499	0.134	0.342	0.129	0.059	2.079e-02	0.042	2.079e-02	...	0.281	0
min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000e+00	0.000	0.000e+00	...	0.000	0
25%	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000e+00	0.000	0.000e+00	...	0.000	0
50%	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000e+00	0.000	0.000e+00	...	0.000	0
75%	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000e+00	0.000	0.000e+00	...	0.000	0
max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000e+00	1.000	1.000e+00	...	1.000	1

8 rows × 188 columns

```
In [37]: df1_categorical
Out[37]:
```

	br_chevrolet	br_dodge	br_ford	br_gmc	br_nissan	md_1500	md_2500	md_2500hd	md_3500	md_acadia	...	st_texas	st_utah
0	0	0	1	0	0	0	0	0	0	0	...	0	0
1	0	1	0	0	0	0	0	0	0	0	...	0	0
2	0	0	1	0	0	0	0	0	0	0	...	0	0
3	1	0	0	0	0	1	0	0	0	0	...	0	0
4	0	1	0	0	0	0	0	0	0	0	...	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2309	0	0	0	0	1	0	0	0	0	0	...	0	0
2310	0	0	0	0	1	0	0	0	0	0	...	0	0
2311	0	0	0	0	1	0	0	0	0	0	...	0	0
2312	0	0	0	0	1	0	0	0	0	0	...	0	0
2313	0	0	0	0	1	0	0	0	0	0	...	0	0

2314 rows × 188 columns

Concatenate the numerical and categorical dataframe

```
In [38]: df_2 = pd.concat([df1_numerical, df1_categorical], axis=1)
         df_2
Out[38]:
```

	price	year	mileage	br_chevrolet	br_dodge	br_ford	br_gmc	br_nissan	md_1500	md_2500	...	st_texas	st_utah	st_vermont
0	2899	10	190552.0	0	0	1	0	0	0	0	...	0	0	0
1	5350	3	39590.0	0	1	0	0	0	0	0	...	0	0	0
2	25000	7	64146.0	0	0	1	0	0	0	0	...	0	0	0
3	27700	3	6654.0	1	0	0	0	0	1	0	...	0	0	0
4	5700	3	45561.0	0	1	0	0	0	0	0	...	1	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2309	7800	2	23609.0	0	0	0	0	1	0	0	...	0	0	0
2310	9200	3	34553.0	0	0	0	0	1	0	0	...	0	0	0
2311	9200	3	31594.0	0	0	0	0	1	0	0	...	0	0	0
2312	9200	3	32557.0	0	0	0	0	1	0	0	...	0	0	0
2313	9200	3	31371.0	0	0	0	0	1	0	0	...	0	0	0

2314 rows × 191 columns

Scaling the input

Standardize features by removing the mean and scaling to unit variance

```
In [39]: scaler = StandardScaler()
         df_2 = pd.DataFrame(scaler.fit_transform(df_2.drop(['price'],axis=1)), columns=df_2.drop(['price'],axis
         =1).columns)
         df_2
Out[39]:
```

	year	mileage	br_chevrolet	br_dodge	br_ford	br_gmc	br_nissan	md_1500	md_2500	md_2500hd	...	st_texas	st_utah	st_ve
0	1.746	2.769	-0.381	-0.479	0.935	-0.136	-0.395	-0.131	-0.059	-0.021	...	-0.308	-0.062	-
1	-0.360	-0.225	-0.381	2.087	-1.070	-0.136	-0.395	-0.131	-0.059	-0.021	...	-0.308	-0.062	-
2	0.844	0.262	-0.381	-0.479	0.935	-0.136	-0.395	-0.131	-0.059	-0.021	...	-0.308	-0.062	-
3	-0.360	-0.878	2.626	-0.479	-1.070	-0.136	-0.395	7.638	-0.059	-0.021	...	-0.308	-0.062	-
4	-0.360	-0.107	-0.381	2.087	-1.070	-0.136	-0.395	-0.131	-0.059	-0.021	...	3.251	-0.062	-
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
2309	-0.661	-0.542	-0.381	-0.479	-1.070	-0.136	2.533	-0.131	-0.059	-0.021	...	-0.308	-0.062	-
2310	-0.360	-0.325	-0.381	-0.479	-1.070	-0.136	2.533	-0.131	-0.059	-0.021	...	-0.308	-0.062	-
2311	-0.360	-0.384	-0.381	-0.479	-1.070	-0.136	2.533	-0.131	-0.059	-0.021	...	-0.308	-0.062	-
2312	-0.360	-0.365	-0.381	-0.479	-1.070	-0.136	2.533	-0.131	-0.059	-0.021	...	-0.308	-0.062	-
2313	-0.360	-0.388	-0.381	-0.479	-1.070	-0.136	2.533	-0.131	-0.059	-0.021	...	-0.308	-0.062	-

2314 rows × 190 columns

```
In [40]: df_2 = pd.concat([df1_numerical['price'],df_2], axis = 1)
         df_2
Out[40]:
```

	price	year	mileage	br_chevrolet	br_dodge	br_ford	br_gmc	br_nissan	md_1500	md_2500	...	st_texas	st_utah	st_vermont
0	2899	1.746	2.769	-0.381	-0.479	0.935	-0.136	-0.395	-0.131	-0.059	...	-0.308	-0.062	-0.029
1	5350	-0.360	-0.225	-0.381	2.087	-1.070	-0.136	-0.395	-0.131	-0.059	...	-0.308	-0.062	-0.029
2	25000	0.844	0.262	-0.381	-0.479	0.935	-0.136	-0.395	-0.131	-0.059	...	-0.308	-0.062	-0.029
3	27700	-0.360	-0.878	2.626	-0.479	-1.070	-0.136	-0.395	7.638	-0.059	...	-0.308	-0.062	-0.029
4	5700	-0.360	-0.107	-0.381	2.087	-1.070	-0.136	-0.395	-0.131	-0.059	...	3.251	-0.062	-0.029
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2309	7800	-0.661	-0.542	-0.381	-0.479	-1.070	-0.136	2.533	-0.131	-0.059	...	-0.308	-0.062	-0.029
2310	9200	-0.360	-0.325	-0.381	-0.479	-1.070	-0.136	2.533	-0.131	-0.059	...	-0.308	-0.062	-0.029
2311	9200	-0.360	-0.384	-0.381	-0.479	-1.070	-0.136	2.533	-0.131	-0.059	...	-0.308	-0.062	-0.029
2312	9200	-0.360	-0.365	-0.381	-0.479	-1.070	-0.136	2.533	-0.131	-0.059	...	-0.308	-0.062	-0.029
2313	9200	-0.360	-0.388	-0.381	-0.479	-1.070	-0.136	2.533	-0.131	-0.059	...	-0.308	-0.062	-0.029

2314 rows × 191 columns

```
In [41]: df_2.describe()
Out[41]:
```

	price	year	mileage	br_chevrolet	br_dodge	br_ford	br_gmc	br_nissan	md_1500	md_2500	...	st_texas
count	2314.000	2.314e+03	2.314e+03	2.314e+03	2.314e+03	2.314e+03	2.314e+03	2.314e+03	2.314e+03	2.314e+03	...	2.314e+03
mean	19088.407	6.939e-16	2.963e-17	1.916e-15	-9.175e-15	4.535e-16	-2.942e-15	3.702e-15	-2.668e-15	-8.020e-16	...	-1.547e-15
std	11944.640	1.000e+00	1.000e+00	1.000e+00	1.000e+00	1.000e+00	1.000e+00	1.000e+00	1.000e+00	1.000e+00	...	1.000e+00
min	0.000	-9.617e-01	-1.010e+00	-3.808e-01	-4.791e-01	-1.070e+00	-1.360e-01	-3.948e-01	-1.309e-01	-5.890e-02	...	-3.076e-01
25%	10607.500	-6.608e-01	-5.859e-01	-3.808e-01	-4.791e-01	-1.070e+00	-1.360e-01	-3.948e-01	-1.309e-01	-5.890e-02	...	-3.076e-01
50%	17175.000	-3.599e-01	-3.089e-01	-3.808e-01	-4.791e-01	9.347e-01	-1.360e-01	-3.948e-01	-1.309e-01	-5.890e-02	...	-3.076e-01
75%	25900.000	2.419e-01	2.344e-01	-3.808e-01	-4.791e-01	9.347e-01	-1.360e-01	-3.948e-01	-1.309e-01	-5.890e-02	...	-3.076e-01
max	74000.000	1.318e+01	1.882e+01	2.626e+00	2.087e+00	9.347e-01	7.355e+00	2.533e+00	7.638e+00	1.698e+01	...	3.251e+00

8 rows × 191 columns

Predictive Modeling

At this point the data looks good to start the process towards modeling. However, there a lot of feature columns in the dataset, which point in the direction of dimensioality reduction for efficient model performance.

Split the dataframe produced into input and output variables

```
In [42]: X = df_2.drop('price', axis = 1).values
         y = df_2['price'].values
```

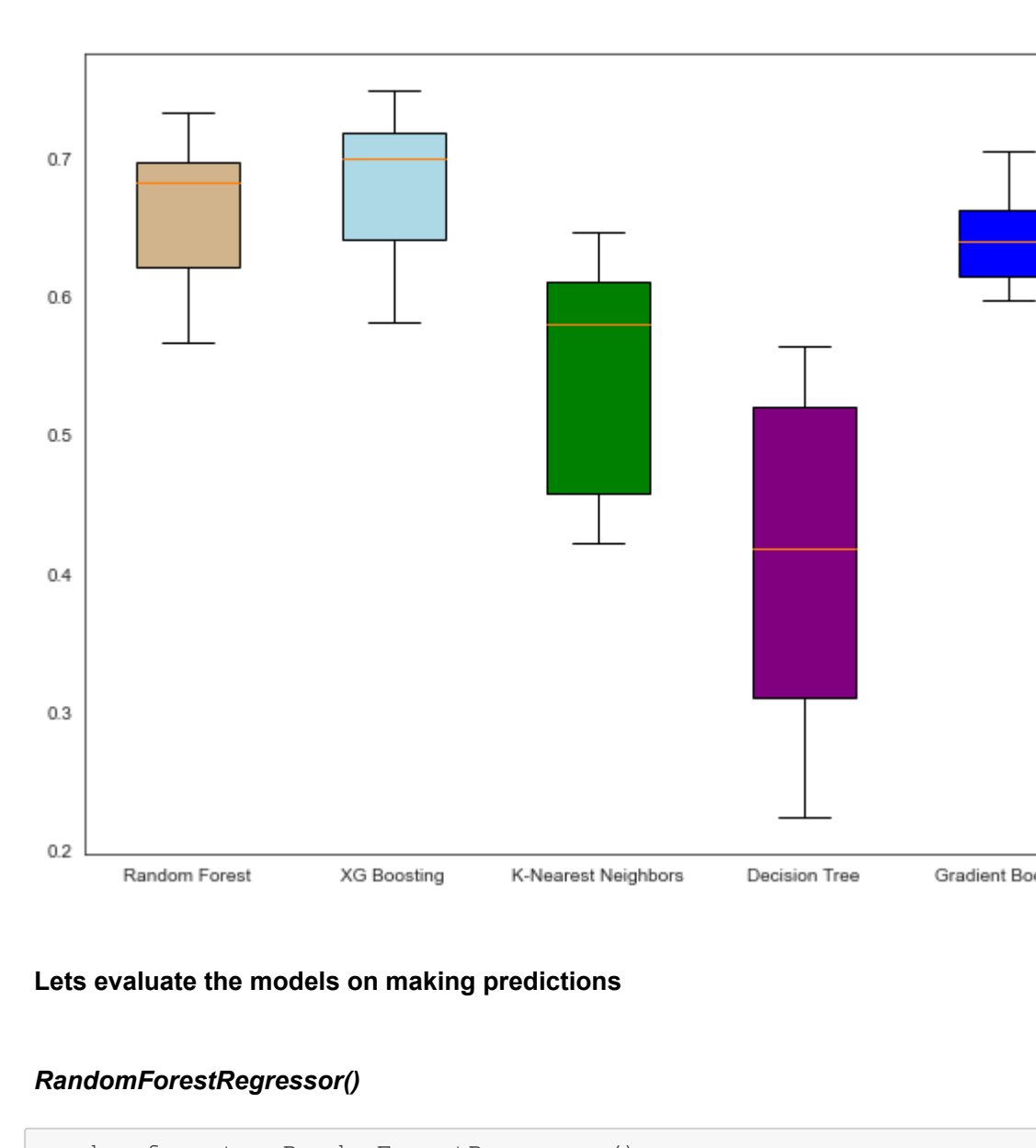
Split the data in to train and test set

```
In [43]: X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=123)

In [44]: np.shape(X_train)
Out[44]: (1619, 190)

In [45]: np.shape(y_train)
Out[45]: (1619,)

In [46]: X_train
Out[46]: array([[ 3.85271023,  2.30189026, -0.38075942, ..., -0.02079276,
                 -3.94063084,  3.94063084],
               [-0.66084357, -0.57925755, -0.38075942, ..., -0.02079276,
                 0.25376648, -0.25376648],
               [ 0.24186719,  0.42246347, -0.38075942, ..., -0.02079276,
                 0.25376648, -0.25376648],
               ...,
               [-0.35993999, -0.16812116, -0.38075942, ..., -0.02079276,
                 0.25376648, -0.25376648],
               [ 0.24186719,  0.13861475, -0.38075942, ..., -0.02079276,
                 0.25376648, -0.25376648],
               [-0.66084357, -0.75878512, -0.38075942, ..., -0.02079276,
                 0.25376648, -0.25376648]])
```

Spot Checking a few Regression models with cross validation on the Training dataset

```
In [47]: from sklearn import model_selection

         #Preparing models
         models = []
         models.append(('Random Forest', RandomForestRegressor()))
         models.append(('XG Boosting', XGBRegressor()))
         models.append(('K-Nearest Neighbors', KNeighborsRegressor()))
         models.append(('Decision Tree', DecisionTreeRegressor()))
         models.append(('Gradient Boosting', GradientBoostingRegressor()))

         #Evaluating each model in turn
         results = []
         names = []
         scoring = 'r2'
         for name, model in models:
             kfold = model_selection.KFold(n_splits=10, shuffle=True, random_state=7)
             cv_results = model_selection.cross_val_score(model, X_train, y_train, cv=kfold, scoring='r2')
             results.append(cv_results)
             names.append(name)
             spotcheck_output = "%s: %.3f" % (name, cv_results.mean())
             print(spotcheck_output)

         Random Forest: 0.660
         XG Boosting: 0.680
         K-Nearest Neighbors: 0.543
         Decision Tree: 0.408
         Gradient Boosting: 0.642
```

```
In [48]: #compare algorithms
         fig=plt.figure(figsize=(10,8))
         fig.suptitle('Base Algorithms Comparison - RSquared', fontsize=20)
         ax=fig.add_subplot(111)
         bplot1=plt.boxplot(results, patch_artist=True)
         ax.set_xticklabels(names)

         colors = ['tan', 'lightblue', 'green', 'purple', 'blue']
         for patch, color in zip(bplot1['boxes'], colors):
             patch.set_facecolor(color)

         plt.show()
```



Lets evaluate the models on making predictions

RandomForestRegressor()

```
In [49]: random_forest = RandomForestRegressor()
         base_rf_predict_model = random_forest.fit(X_train, y_train)
         y_pred = base_rf_predict_model.predict((X_test))

         print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
         print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
         print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
         print("R_2 = {:.2f} %".format((r2_score(y_test, y_pred)*100)))
         print("Variance score = {:.2f} %".format((base_rf_predict_model.score(X_test, y_test)*100)))

         Mean Absolute Error: 3957.5076115107913
         Mean Squared Error: 36840561.981187195
         Root Mean Squared Error: 6069.642656795142
         R_2 = 72.93 %
         Variance score = 72.93 %
```

XGBRegressor()

```
In [50]: xgb_model = XGBRegressor()
         base_xgb_predict_model = xgb_model.fit(X_train, y_train)
         y_pred = base_xgb_predict_model.predict((X_test))

         print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
         print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
         print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
         print("R_2 = {:.2f} %".format((r2_score(y_test, y_pred)*100)))
         print("Variance score = {:.2f} %".format((base_xgb_predict_model.score(X_test, y_test)*100)))

         Mean Absolute Error: 4016.4639647422077
         Mean Squared Error: 35517633.58071563
         Root Mean Squared Error: 5959.667237414823
         R_2 = 73.90 %
         Variance score = 73.90 %
```

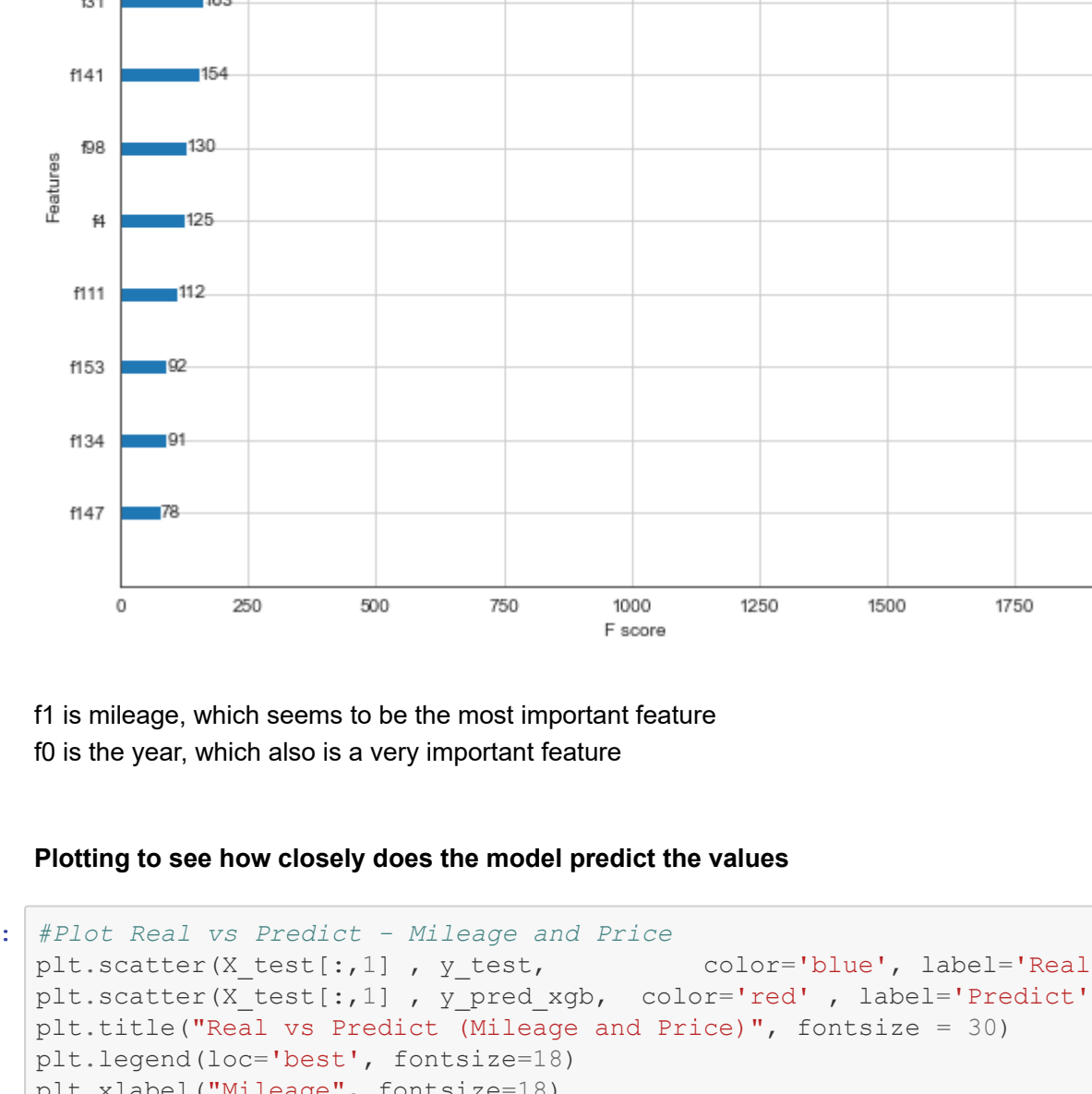
Hyperparameter Tuning for XGBRegressor() to see if we acheive better results

```
In [89]: #XGBoost hyper-parameter tuning
         def hyperParameterTuning(X_train, y_train):
             param_tuning = {
                 'learning_rate': [0.01, 0.1],
                 'max_depth': [3, 5, 7, 10],
                 'min_child_weight': [1, 3, 5],
                 'subsample': [0.5, 0.7, 0.8, 0.95],
                 'colsample_bytree': [0.5, 0.7],
                 'n_estimators' : [100, 200, 500],
                 'objective': ['reg:squarederror']
             }

             xgb_model = XGBRegressor()

             gsearch = GridSearchCV(estimator = xgb_model,
                                    param_grid = param_tuning,
                                    #scoring = 'neg_mean_absolute_error', #MAE
                                    #scoring = 'neg_mean_squared_error',  #MSE
                                    scoring = 'r2',
                                    cv = 5,
                                    n_jobs = -1,
                                    verbose = 1)

             gsearch.fit(X_train,y_train)

             return gsearch.best_params_
```

```
In [90]: #Fit the tuned model on the training dataset
         hyperParameterTuning(X_train, y_train)

         Fitting 5 folds for each of 576 candidates, totalling 2880 fits

         [Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
         [Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:    8.7s
         [Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed:   42.1s
         [Parallel(n_jobs=-1)]: Done 426 tasks      | elapsed:  1.9min
         [Parallel(n_jobs=-1)]: Done 776 tasks      | elapsed:  4.1min
         [Parallel(n_jobs=-1)]: Done 1226 tasks      | elapsed:  6.0min
         [Parallel(n_jobs=-1)]: Done 1776 tasks      | elapsed:  9.0min
         [Parallel(n_jobs=-1)]: Done 2426 tasks      | elapsed: 13.0min
         [Parallel(n_jobs=-1)]: Done 2880 out of 2880 | elapsed: 16.3min finished

Out[90]: {'colsample_bytree': 0.7,
          'learning_rate': 0.1,
          'max_depth': 5,
          'min_child_weight': 1,
          'n_estimators': 500,
          'objective': 'reg:squarederror',
          'subsample': 0.95}
```

```
In [85]: xgb_model = XGBRegressor(
                 objective = 'reg:squarederror',
                 colsample_bytree = 0.7,
                 learning_rate = 0.1,
                 max_depth = 5,
                 min_child_weight = 1,
                 n_estimators = 500,
                 subsample = 0.95)

         xgb_model.fit(X_train, y_train)

         y_pred_xgb = xgb_model.predict(X_test)

         print('MSE: ',mean_squared_error(y_test,y_pred_xgb))
         print('R2: ',r2_score(y_test,y_pred_xgb)*100, '%')
         print('MAE: ', metrics.mean_absolute_error(y_test,y_pred_xgb))
         print('RMSE: ',np.sqrt(mean_squared_error(y_test,y_pred_xgb)))

         MSE:  33511036.622043252
         R2:  75.37912108608108 %
         MAE:  3874.3044465428634
         RMSE:  5788.871791812568
```

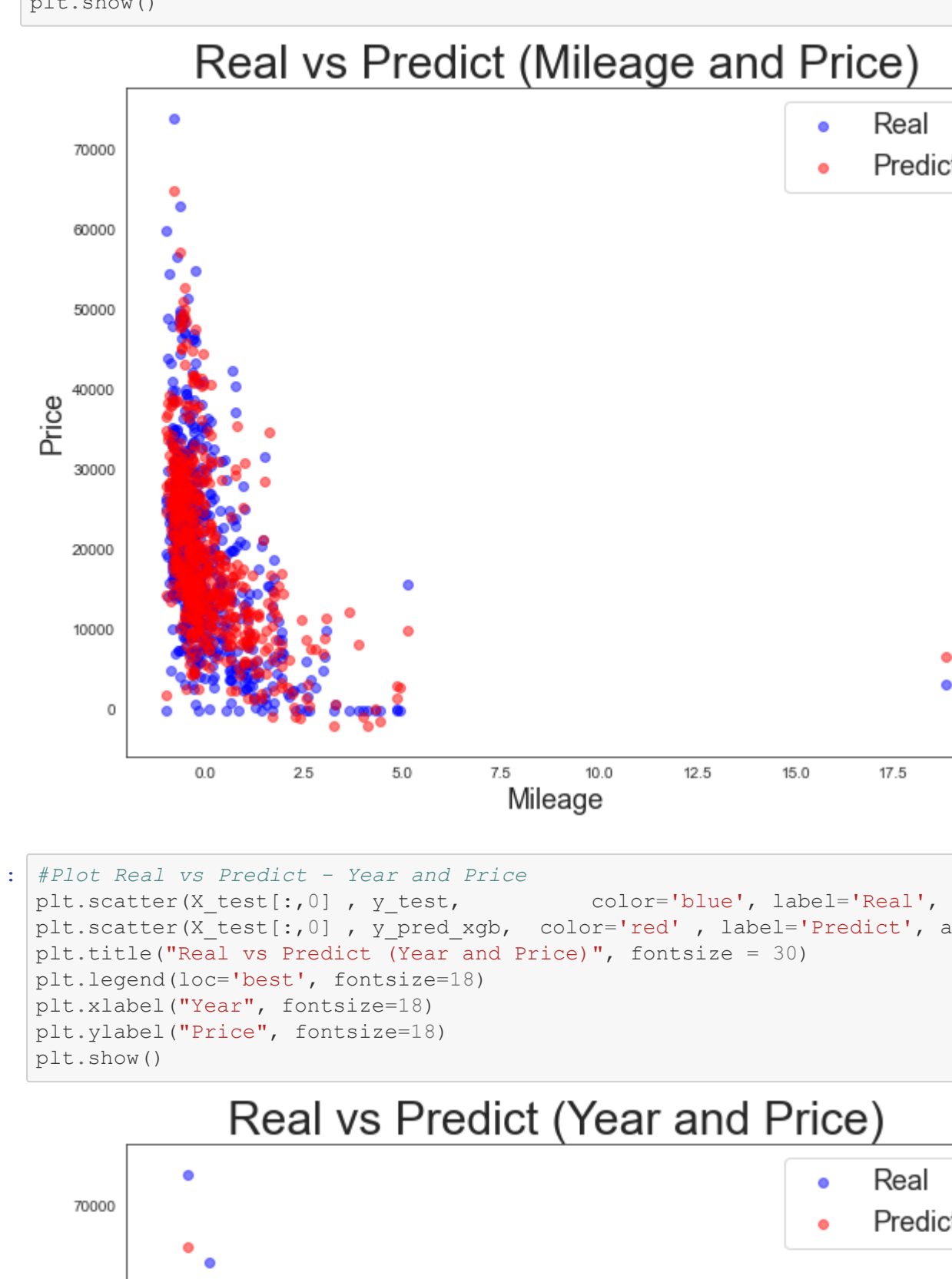
```
In [86]: xgb.plot_importance(xgb_model, max_num_features=10)
         plt.rcParams['figure.figsize'] = [10,8]
         plt.show()
```



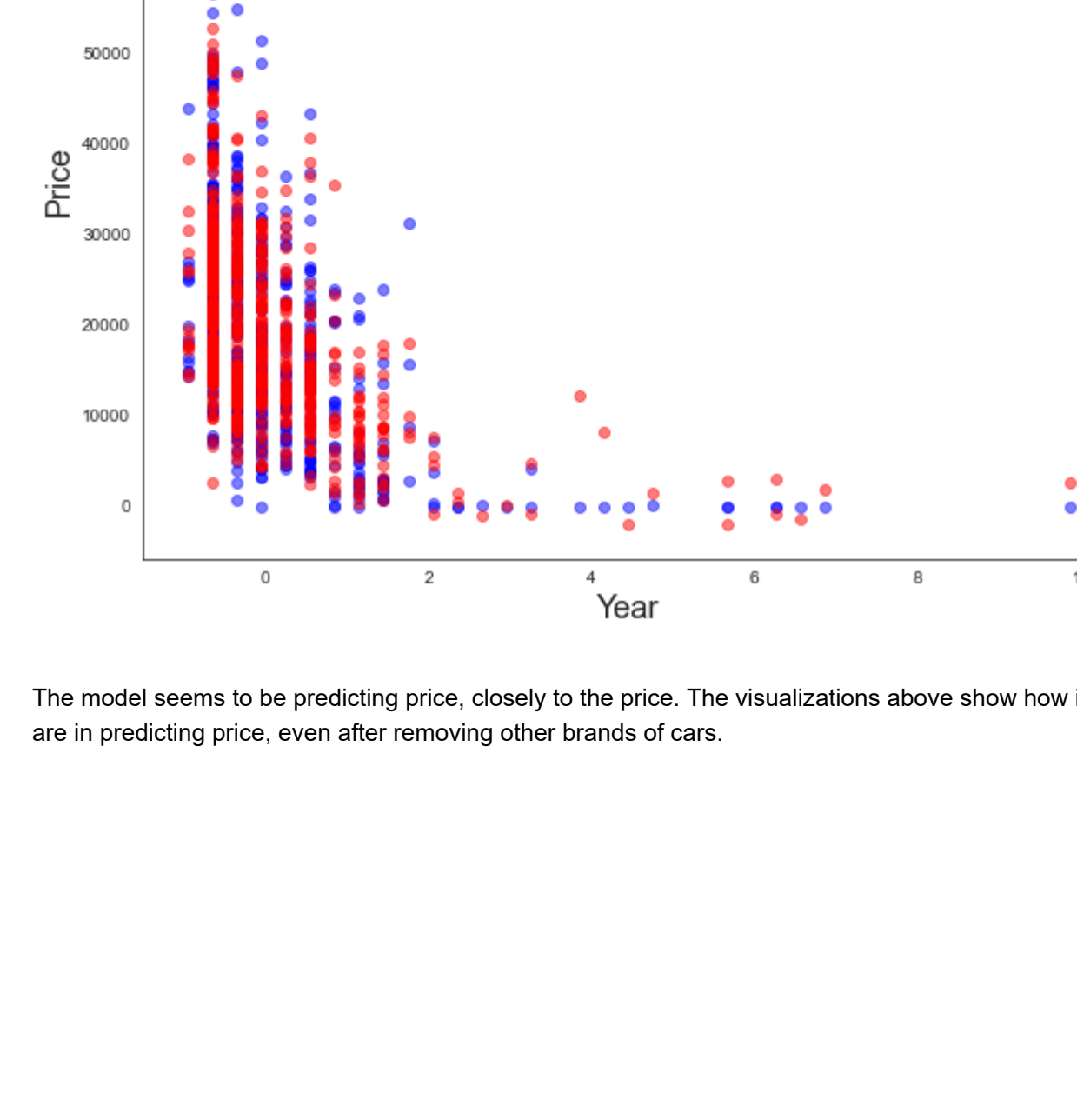
f1 is mileage, which seems to be the most important feature
f0 is the year, which also is a very important feature

Plotting to see how closely does the model predict the values

```
In [87]: #Plot Real vs Predict - Mileage and Price
         plt.scatter(X_test[:,1] , y_test,          color='blue', label='Real',    alpha=0.5)
         plt.scatter(X_test[:,1] , y_pred_xgb,  color='red' , label='Predict', alpha=0.5)
         plt.title("Real vs Predict (Mileage and Price)", fontsize = 30)
         plt.legend(loc='best', fontsize=18)
         plt.xlabel("Mileage", fontsize=18)
         plt.ylabel("Price", fontsize=18)
         plt.show()
```




```
In [145]: #Plot Real vs Predict - Year and Price
          plt.scatter(X_test[:,0] , y_test,          color='blue', label='Real',    alpha=0.5)
          plt.scatter(X_test[:,0] , y_pred_xgb,  color='red' , label='Predict', alpha=0.5)
          plt.title("Real vs Predict (Year and Price)", fontsize = 30)
          plt.legend(loc='best', fontsize=18)
          plt.xlabel("Year", fontsize=18)
          plt.ylabel("Price", fontsize=18)
          plt.show()
```



The model seems to be predicting price, closely to the price. The visualizations above show how imperative the year and mileage columns are in predicting price, even after removing other brands of cars.