SORAN AUTOMOBILE SALES ANALYSIS

In [2]:
```
#pip install missingno
```

In [3]:
```
# Import Libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import missingno as msno
sns.set()
from subprocess import check_output
import warnings
warnings.filterwarnings("ignore")
from scipy.stats import skew, kurtosis
```

In [4]:
```
# Load data and view top 5

Carsales = pd.read_excel(r"Car_Sales.xlsx")
Carsales
```

Out[4]:

	car	price	body	mileage	engV	engType	registration	year	model	drive
0	Ford	15500.0	crossover	68	2.5	Gas	yes	2010	Kuga	full
1	Mercedes-Benz	20500.0	sedan	173	1.8	Gas	yes	2011	E-Class	rear
2	Mercedes-Benz	35000.0	other	135	5.5	Petrol	yes	2008	CL 550	rear
3	Mercedes-Benz	17800.0	van	162	1.8	Diesel	yes	2012	B 180	front
4	Mercedes-Benz	33000.0	vagon	91	NaN	Other	yes	2013	E-Class	NaN
...	...	...	...	...	...	...	...	...	...	...
9571	Hyundai	14500.0	crossover	140	2.0	Gas	yes	2011	Tucson	front
9572	Volkswagen	2200.0	vagon	150	1.6	Petrol	yes	1986	Passat B2	front
9573	Mercedes-Benz	18500.0	crossover	180	3.5	Petrol	yes	2008	ML 350	full
9574	Lexus	16999.0	sedan	150	3.5	Gas	yes	2008	ES 350	front
9575	Audi	22500.0	other	71	3.6	Petrol	yes	2007	Q7	full

9576 rows × 10 columns

Overview of dataset

In [5]:
```
Carsales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9576 entries, 0 to 9575
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   car           9576 non-null   object
 1   price         9576 non-null   float64
 2   body          9576 non-null   object
 3   mileage       9576 non-null   int64
 4   engV          9142 non-null   float64
 5   engType       9576 non-null   object
 6   registration  9576 non-null   object
 7   year          9576 non-null   int64
 8   model         9576 non-null   object
 9   drive         9065 non-null   object
dtypes: float64(2), int64(2), object(6)
memory usage: 748.2+ KB
```

In [6]:
```
# Dimensionality :To check the Dimension of our dataset
Carsales.shape
```

Out[6]:
```
(9576, 10)
```

In [7]:
```
# statistical summary of the dataset
Carsales.describe().astype(int)
```

Out[7]:

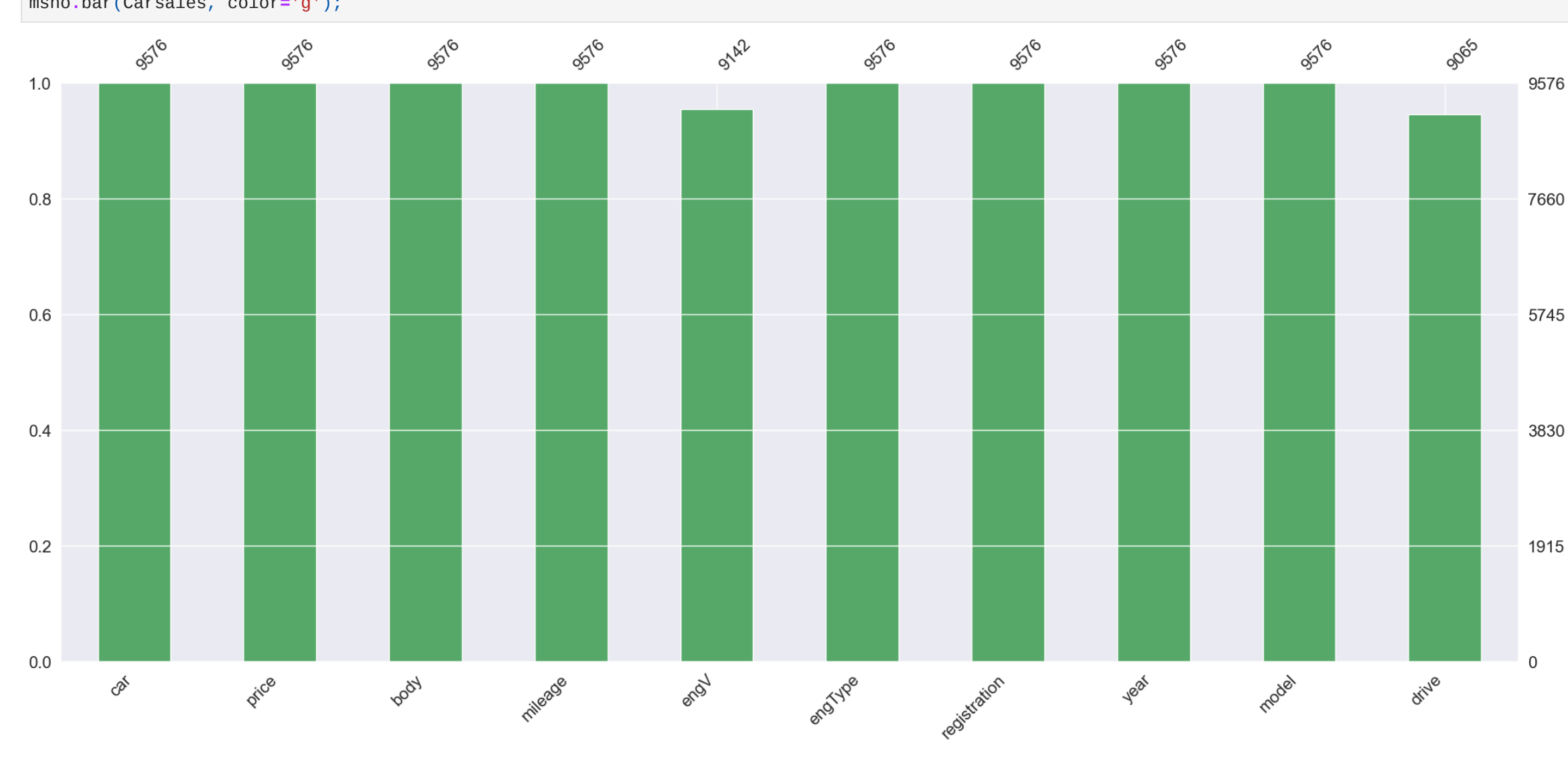
	price	mileage	engV	year
count	9576	9576	9142	9576
mean	15633	138	2	2006
std	24106	98	5	7
min	0	0	0	1953
25%	4999	70	1	2004
50%	9200	128	2	2008
75%	16700	194	2	2012
max	547800	999	99	2016

In [8]:
```
#missing values :To check for the missing values in thed dataset
Carsales.isnull().sum()
```

Out[8]:
```
car               0
price             0
body              0
mileage           0
engV            434
engType           0
registration      0
year              0
model             0
drive           511
dtype: int64
```

- We have a huge chunk of missing values in the dataset, sum of 434 missing values in engV and sum of 511 in drive

In [9]:
```
# Visualizing the missing data for a clearer view
msno.bar(Carsales, color='g');
```



- The engV and drive have unequal bars compared to other variables. So its clear where our missing values are

In [10]:
```
# Another way to visualize the missing Data
plt.figure(figsize=(10,5))
sns.heatmap(Carsales.isnull(), cbar=True, cmap='cividis');
```

- Another clear view of the missing values using the Heatmap, pointing directly to where we have the missing values in the dataset

In [ ]:

Preprofiling

- This shows the Raw Broad Overview of the dataset

In [45]:
```
#pip install -U pandas-profiling
```

In [12]:
```
from pandas_profiling import ProfileReport
```

In [13]:
```
carsales_profile = ProfileReport(Carsales, title='Carsales_Raw_Overview')
carsales_profile
```

```
Summarize dataset:    0%|          | 0/5 [00:00<?, ?it/s]
Generate report structure:    0%|          | 0/1 [00:00<?, ?it/s]
Render HTML:    0%|          | 0/1 [00:00<?, ?it/s]
```

Carsales_Raw_Overview — Overview | Variables | Interactions | Correlations | Missing values | Sample | Duplicate rows

Overview

Overview | Alerts 14 | Reproduction

Dataset statistics

Number of variables	10
Number of observations	9576
Missing cells	945
Missing cells (%)	1.0%
Duplicate rows	110
Duplicate rows (%)	1.1%
Total size in memory	748.2 KiB
Average record size in memory	80.0 B

Variable types

Categorical	4
Numeric	4
Boolean	1
Unsupported	1

Variables

Select Columns

car

Out[13]:

Data Cleaning

In [14]:
```
# make a copy of df - .copy()
carsales1 = Carsales.copy()
carsales1.head(3)
```

Out[14]:

	car	price	body	mileage	engV	engType	registration	year	model	drive
0	Ford	15500.0	crossover	68	2.5	Gas	yes	2010	Kuga	full
1	Mercedes-Benz	20500.0	sedan	173	1.8	Gas	yes	2011	E-Class	rear
2	Mercedes-Benz	35000.0	other	135	5.5	Petrol	yes	2008	CL 550	rear

Rename column names

In [15]:
```
# Displaying the Raw Dataset Columns
Carsales.columns
```

Out[15]:
```
Index(['car', 'price', 'body', 'mileage', 'engV', 'engType', 'registration',
       'year', 'model', 'drive'],
      dtype='object')
```

In [16]:
```
Carsales.columns = ['Car_brand', 'Price', 'BodyType', 'Mileage', 'EngineValue', 'EngineType', 'Registration',
     'Year', 'CarModel', 'DriveType']
Carsales.head(3)
```

Out[16]:

	Car_brand	Price	BodyType	Mileage	EngineValue	EngineType	Registration	Year	CarModel	DriveType
0	Ford	15500.0	crossover	68	2.5	Gas	yes	2010	Kuga	full
1	Mercedes-Benz	20500.0	sedan	173	1.8	Gas	yes	2011	E-Class	rear
2	Mercedes-Benz	35000.0	other	135	5.5	Petrol	yes	2008	CL 550	rear

Handling Duplicates

In [17]:
```
# Displaying the duplicate values we have in the dataset
Carsales.duplicated().sum()
```

Out[17]:
```
113
```

In [18]:
```
# drop duplicate rows
Carsales.drop_duplicates(inplace=True)
```

In [19]:
```
Carsales.shape
```

Out[19]:
```
(9463, 10)
```

In [20]:
```
# Double checking for duplicate values
Carsales.duplicated().sum()
```

Out[20]:
```
0
```

Handling missing values

Replacing the missing data in EngineValue and DriveType

In [21]:
```
Carsales.isnull().sum()
```

Out[21]:
```
Car_brand         0
Price             0
BodyType          0
Mileage           0
EngineValue     434
EngineType        0
Registration      0
Year              0
CarModel          0
DriveType       510
dtype: int64
```

In [22]:
```
# filling missing values for drive : Using the mode of the DriveType
Carsales["DriveType"].mode()
```

Out[22]:
```
0    front
Name: DriveType, dtype: object
```

In [23]:
```
#fill missing values with the mode = "front"
Carsales["DriveType"] =  Carsales["DriveType"].fillna('front')
```

In [24]:
```
#fill missing values for EngineValue with the median
Carsales["EngineValue"] = Carsales.groupby(['Car_brand', 'BodyType'])['EngineValue'].transform(lambda x: x.fillna(x.median()))
```

In [25]:
```
# Double checking to see if the missing values are sorted
Carsales.isnull().sum()
```

Out[25]:
```
Car_brand        0
Price            0
BodyType         0
Mileage          0
EngineValue     10
EngineType       0
Registration     0
Year             0
CarModel         0
DriveType        0
dtype: int64
```

In [26]:
```
# checking for the left-over missing values in EngineValue

Carsales[Carsales.EngineValue.isnull()]
```

Out[26]:

	Car_brand	Price	BodyType	Mileage	EngineValue	EngineType	Registration	Year	CarModel	DriveType
319	Tesla	58000.0	hatch	52	NaN	Other	yes	2013	Model S	front
1437	Tesla	178500.0	crossover	0	NaN	Other	yes	2016	Model X	full
2486	Tesla	185000.0	crossover	1	NaN	Other	yes	2016	Model X	full
5084	GAZ	0.0	crossover	1	NaN	Petrol	yes	1963	69	full
6773	UAZ	3000.0	other	1	NaN	Other	yes	1985	3303	full
8569	Tesla	176900.0	crossover	0	NaN	Other	yes	2016	Model X	full
8824	Fisker	0.0	other	100	NaN	Other	yes	2001	Karma	front
8905	Changan	6028.0	crossover	101	NaN	Other	yes	2005	Ideal	front
9360	Barkas	5500.0	van	80	NaN	Petrol	yes	2015	B1000	front
9566	UAZ	850.0	van	255	NaN	Other	yes	1981	3962	front

In [27]:
```
#drop the remaining NaN values
Carsales.dropna(subset=['EngineValue'],inplace=True)
Carsales.isnull().sum()
```

Out[27]:
```
Car_brand       0
Price           0
BodyType        0
Mileage         0
EngineValue     0
EngineType      0
Registration    0
Year            0
CarModel        0
DriveType       0
dtype: int64
```

Now its clear that the missing values sorted

In [28]:
```
Carsales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9453 entries, 0 to 9575
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Car_brand     9453 non-null   object
 1   Price         9453 non-null   float64
 2   BodyType      9453 non-null   object
 3   Mileage       9453 non-null   int64
 4   EngineValue   9453 non-null   float64
 5   EngineType    9453 non-null   object
 6   Registration  9453 non-null   object
 7   Year          9453 non-null   int64
 8   CarModel      9453 non-null   object
 9   DriveType     9453 non-null   object
dtypes: float64(2), int64(2), object(6)
memory usage: 812.4+ KB
```

In [29]:
```
Carsales.Price[Carsales.Price==0].count()
```

Out[29]:
```
238
```

In [30]:
```
# Dropping entries with price <= 0

Carsales = Carsales.drop(Carsales[Carsales.Price <=0].index)
```

In [31]:
```
Carsales.Price[Carsales.Price==0].count()
```

Out[31]:
```
0
```

In [32]:
```
Carsales.Mileage[Carsales.Mileage==0].count()
```

Out[32]:
```
281
```

In [212…
```
# Dropping entries with Mileage <= 0

Carsales = Carsales.drop(Carsales[Carsales.Mileage <=0].index)
```

In [213…
```
Carsales.Mileage[Carsales.Mileage==0].count()
```

Out[213]:
```
0
```

In [ ]:

Post profiling

In [33]:
```
carsales_profile2 = ProfileReport(Carsales, title='Carsales_after_data_cleaning')
carsales_profile2
```

```
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]
```

Carsales_after_data_cleaning — Overview | Variables | Interactions | Correlations | Missing values | Sample | Duplicate rows

Overview

Overview | Alerts 11 | Reproduction

Dataset statistics

Number of variables	10
Number of observations	9215
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	24
Duplicate rows (%)	0.3%
Total size in memory	1.0 MiB
Average record size in memory	116.7 B

Variable types

Categorical	4
Numeric	4
Boolean	1
Unsupported	1

Variables

Select Columns

Car_brand

Out[33]:

In [ ]:

In [34]:
```
Carsales.head()
```

Out[34]:

	Car_brand	Price	BodyType	Mileage	EngineValue	EngineType	Registration	Year	CarModel	DriveType
0	Ford	15500.0	crossover	68	2.5	Gas	yes	2010	Kuga	full
1	Mercedes-Benz	20500.0	sedan	173	1.8	Gas	yes	2011	E-Class	rear
2	Mercedes-Benz	35000.0	other	135	5.5	Petrol	yes	2008	CL 550	rear
3	Mercedes-Benz	17800.0	van	162	1.8	Diesel	yes	2012	B 180	front
4	Mercedes-Benz	33000.0	vagon	91	2.0	Other	yes	2013	E-Class	front

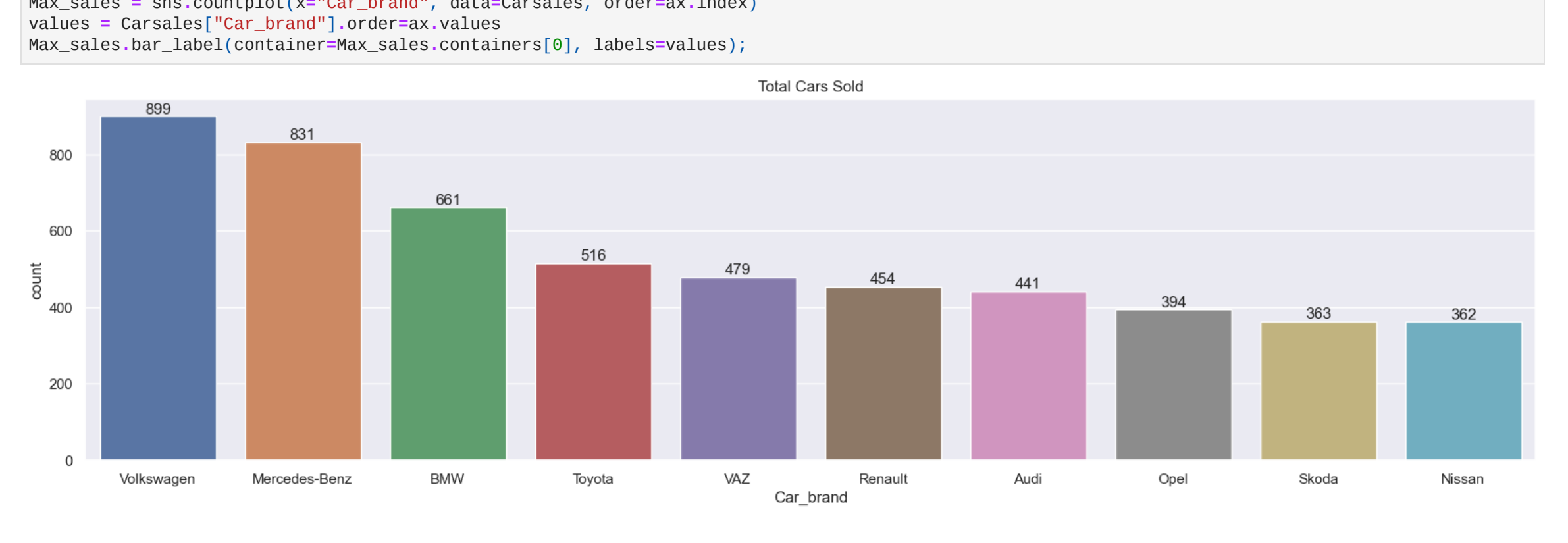
Exploratory Data Analysis Of Car Sales

Questions:

- Which type of cars are sold maximum?
- What is the correlation between price and mileage?
- How many cars are registered?
- Does the registration status influence car price?
- What is the car price distribution based on Engine Value?
- Which car type has the highest pricing?

In [ ]:
```
# 1. Which type of cars are sold most?
```

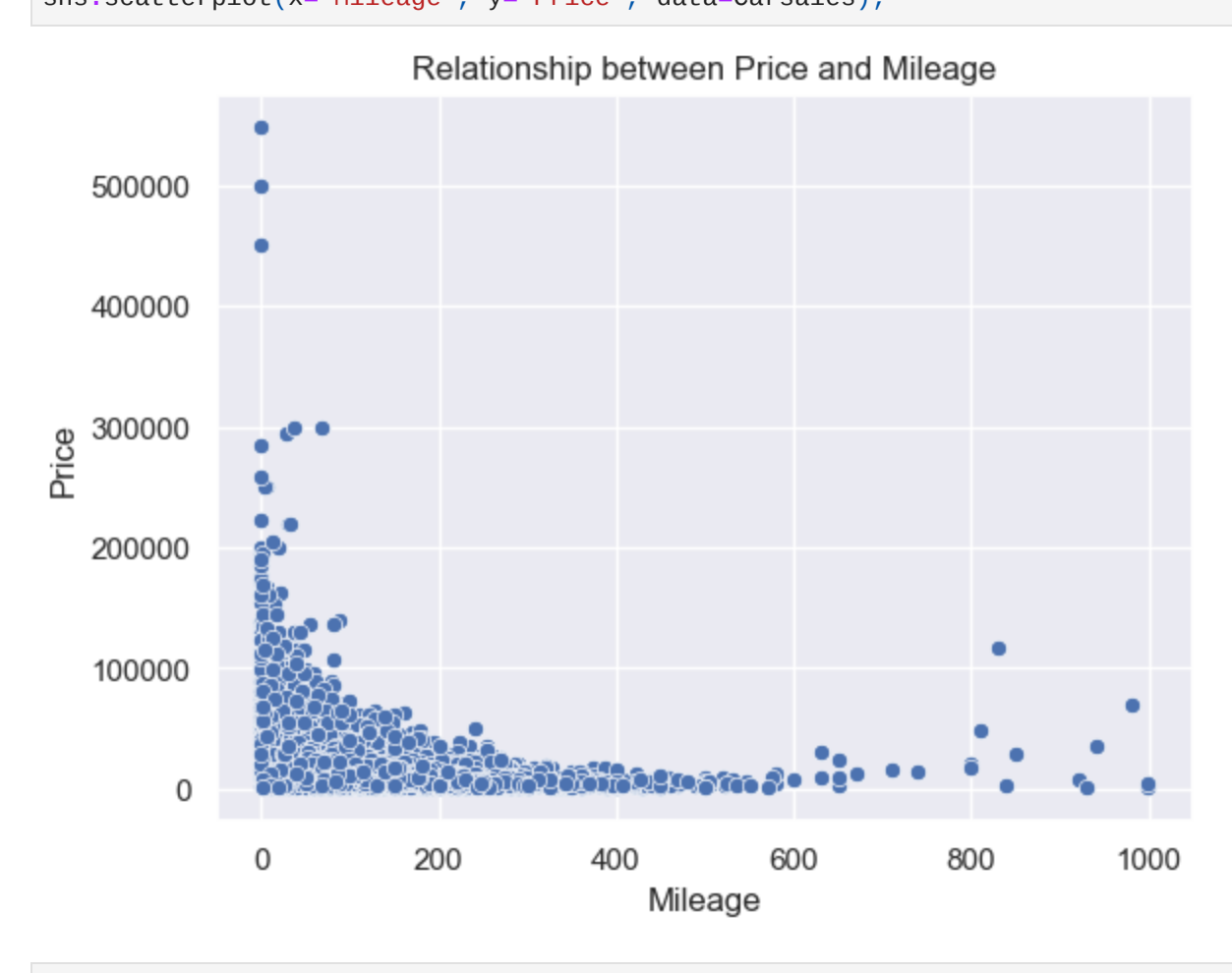
In [36]:
```
# Car brand that's most sold

plt.figure(figsize=(20,5))
plt.title('Total Cars Sold')

ax = Carsales["Car_brand"].value_counts().head(10)
Max_sales = sns.countplot(x="Car_brand", data=Carsales, order=ax.index)
values = Carsales["Car_brand"].order=ax.values
Max_sales.bar_label(container=Max_sales.containers[0], labels=values);
```



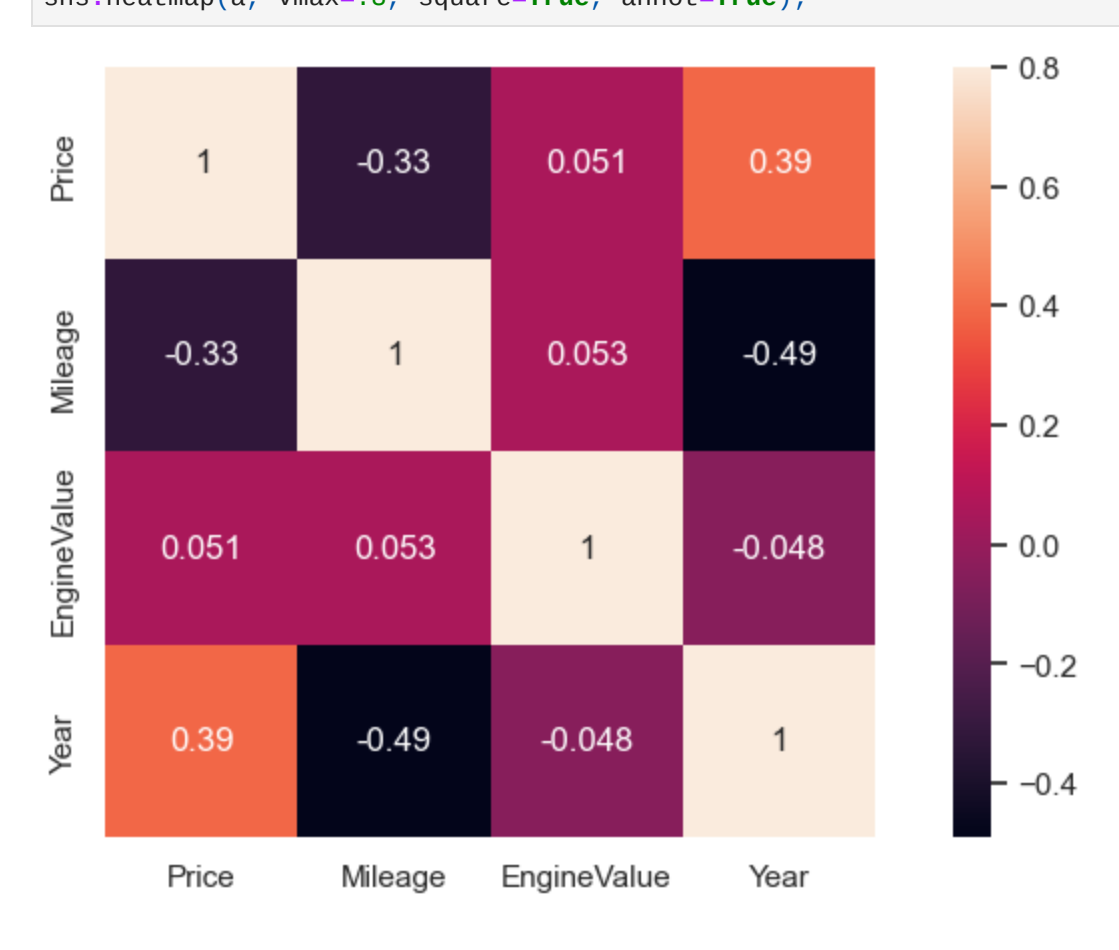
- Volkswagen is the most sold car, followed by Mercedes-Bens and BMW. The Chat above shows the top 10 most sold cars

In [147]:
```
# 2. What is the correlation between price and mileage?
```

In [37]:
```
plt.title('Relationship between Price and Mileage')
sns.scatterplot(x='Mileage', y='Price', data=Carsales);
```



In [38]:
```
# Correlation
a = Carsales.corr()
f, ax = plt.subplots(figsize=(10,5))
sns.heatmap(a, vmax=.8, square=True, annot=True);
```



- From the relationship plot above between 'price and mileage', it shows that there's a negative relationship between the two.
- Backing it up with the correlation heatmap directly above it clearly dispace the negative correlation of (-0.46) between the price and the mileage.
- The strong relationship/correlation is between the Price and the Year. This means that generally the Car Price is strongly influenced by the year.

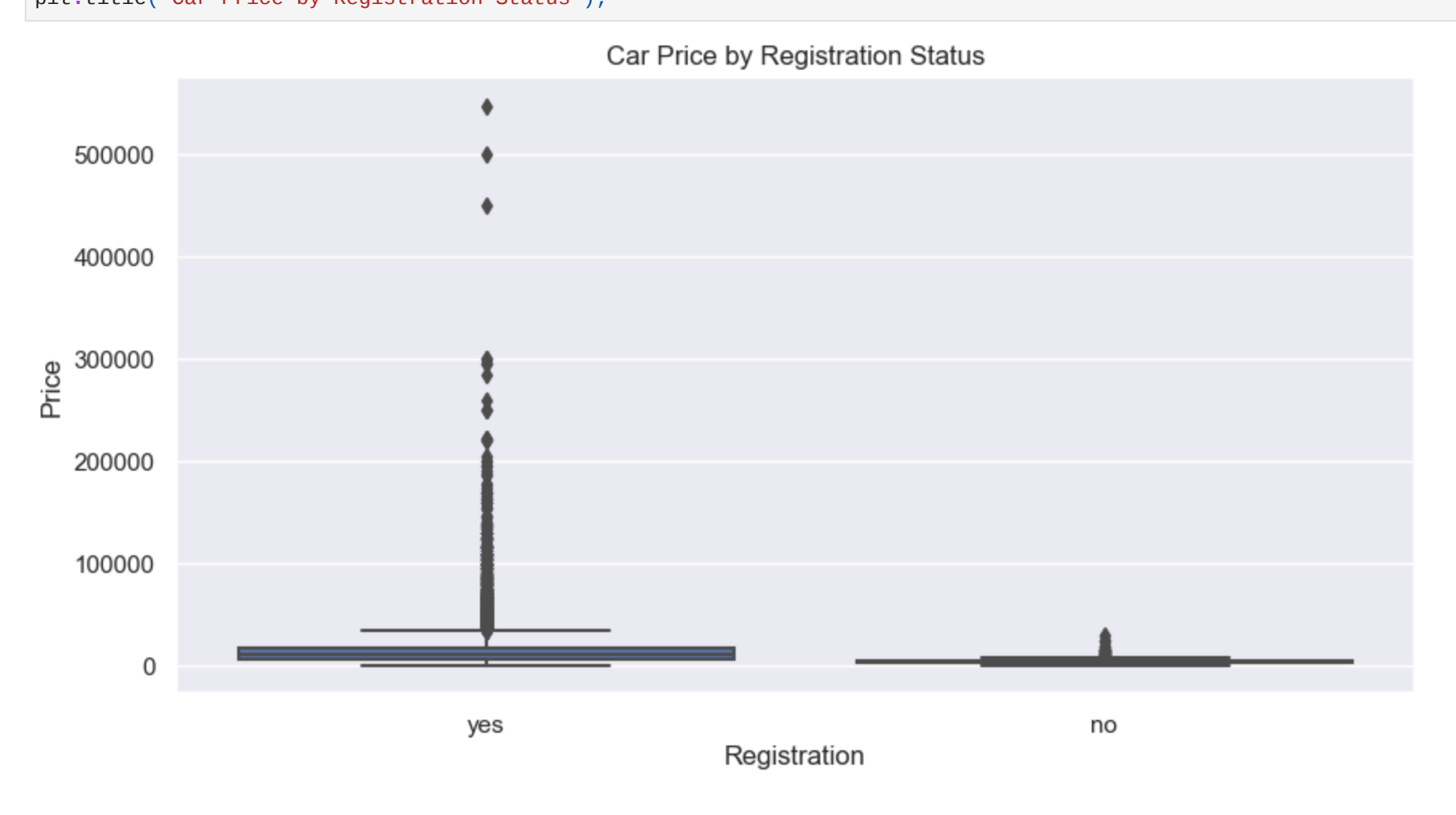
In [175…
```
# 3. How many cars are registered?
```

In [39]:
```
Carsales["Registration"].value_counts()
```

Out[39]:
```
yes    8661
no      554
Name: Registration, dtype: int64
```

In [ ]:
```
# 4. Does the registration status influence car price?.
```

In [53]:
```
plt.figure(figsize=(10,5))
sns.boxplot(x='Registration',y='Price',data=Carsales)
plt.title("Car Price by Registration Status");
```



- Yes! The Registered cars are of high Price compare to Unregistered cars

In [41]:
```
Carsales.tail(10)
```

Out[41]:

	Car_brand	Price	BodyType	Mileage	EngineValue	EngineType	Registration	Year	CarModel	DriveType
9565	Mercedes-Benz	8900.0	hatch	155	1.5	Petrol	yes	2005	A 150	front
9567	Jeep	13990.0	crossover	210	3.0	Diesel	yes	2006	Grand Cherokee	full
9568	Mercedes-Benz	5000.0	vagon	248	2.0	Gas	yes	1996	E-Class	rear
9569	Volkswagen	18000.0	crossover	155	2.0	Diesel	yes	2011	Tiguan	full
9570	Toyota	14474.0	crossover	115	2.0	Petrol	yes	2007	Rav 4	full
9571	Hyundai	14500.0	crossover	140	2.0	Gas	yes	2011	Tucson	front
9572	Volkswagen	2200.0	vagon	150	1.6	Petrol	yes	1986	Passat B2	front
9573	Mercedes-Benz	18500.0	crossover	180	3.5	Petrol	yes	2008	ML 350	full
9574	Lexus	16999.0	sedan	150	3.5	Gas	yes	2008	ES 350	front
9575	Audi	22500.0	other	71	3.6	Petrol	yes	2007	Q7	full

In [ ]:
```
# 5. What is the car price distribution based on Engine Value?
```

In [42]:
```
# Count of total Engine Value

Carsales['EngineValue'].value_counts()
```

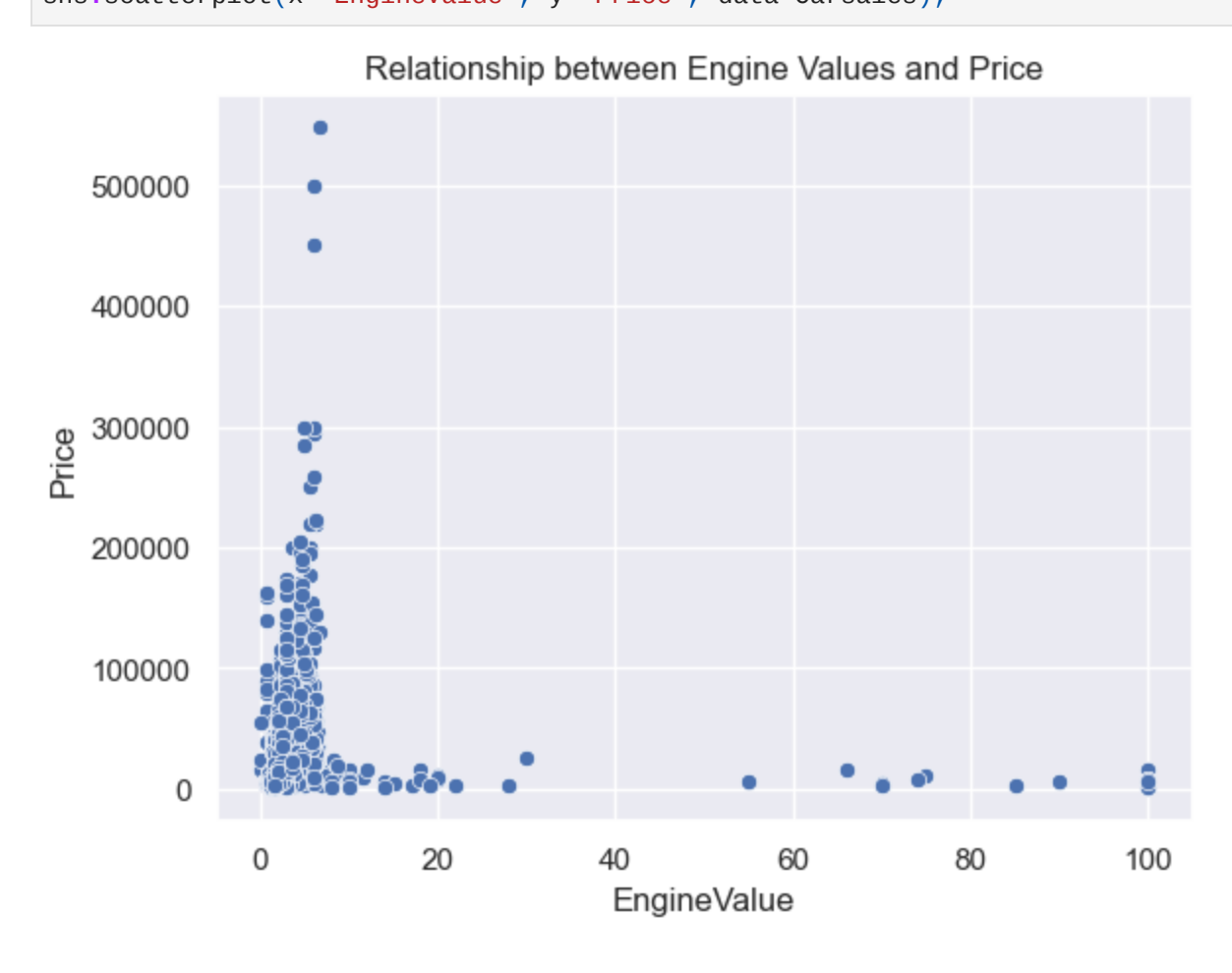
Out[42]:
```
2.00     1548
1.60     1250
1.50      729
3.00      627
1.80      597
         ...
1.78        1
1.36        1
55.00       1
1.59        1
74.00       1
Name: EngineValue, Length: 119, dtype: int64
```

In [43]:
```
# Each Engine Value by Price

EngVal = Carsales.groupby('EngineValue')['Price'].sum().reset_index().head(20)
EngVal
```

Out[43]:

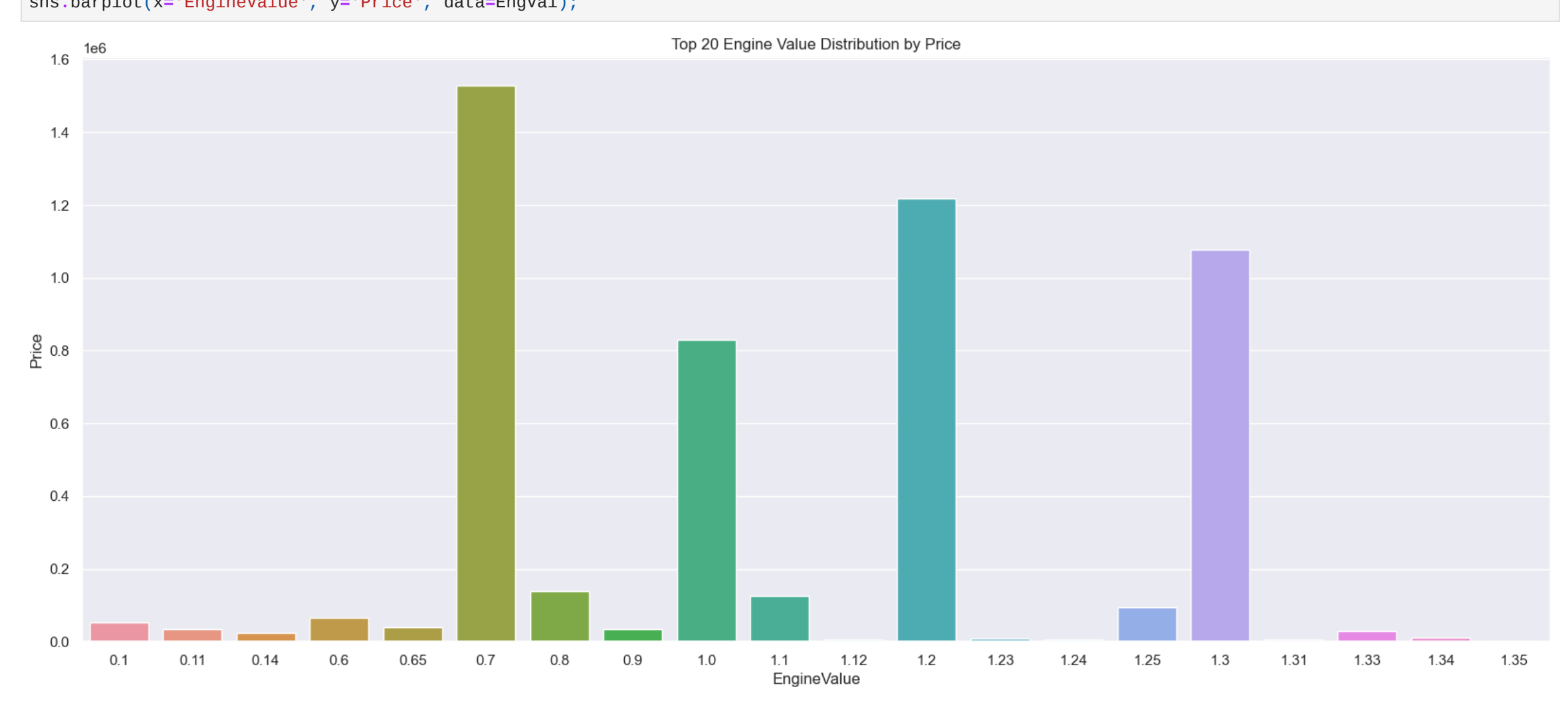
	EngineValue	Price
0	0.10	5.400000e+04
1	0.11	3.340000e+04
2	0.14	2.430000e+04
3	0.60	6.579900e+04
4	0.65	3.888800e+04
5	0.70	1.529240e+06
6	0.80	1.390940e+05
7	0.90	3.529889e+04
8	1.00	8.300753e+05
9	1.10	1.249419e+05
10	1.12	5.800000e+03
11	1.20	1.219030e+06
12	1.23	8.900000e+03
13	1.24	5.799000e+03
14	1.25	9.431099e+04
15	1.30	1.076508e+06
16	1.31	5.700000e+03
17	1.33	3.059409e+04
18	1.34	9.800000e+03
19	1.35	1.555000e+03

In [45]:
```
# Distribution of Engine Values by Price

plt.title('Relationship between Engine Values and Price')

sns.scatterplot(x='EngineValue', y='Price', data=Carsales);
```



- This shows there's a negative relationship between the price and the Engine Value

In [47]:
```
# Top 20 Engine Value distribution by Price

plt.figure(figsize=(20,8))
plt.title('Top 20 Engine Value Distribution by Price')
sns.barplot(x='EngineValue', y='Price', data=EngVal);
```



- From the barplot chart it also clearly shows theres no even or positive distribution between the Price and Engine Value by this I mean the Engine Value can be high and the Price low, also the Engine Value can be Low and the Price high

In [ ]:
```
# 6. Which car type has the highest pricing?
```

In [48]:
```
High_Pricing_Car = Carsales.loc[Carsales["Price"] == Carsales['Price'].max(), ['Car_brand','Price','BodyType', 'Mileage', 'EngineValue', 'EngineType
High_Pricing_Car
```

Out[48]:

	Car_brand	Price	BodyType	Mileage	EngineValue	EngineType	Registration	Year	CarModel	DriveType
7621	Bentley	547800.0	sedan	0	6.75	Petrol	yes	2016	Mulsanne	rear

In [ ]: