EDA

If you are consulting an automobile company, you are trying to understand the factors that influence the sale price of the cars. Specifically, which factors drive the price showing different aspect of analysis

```
# Surpress warnings:
def warn(*args, **kwargs):
    pass
import warnings
warnings.warn = warn

import pandas as pd
import numpy as np
from scipy.stats import skew, kurtosis, zscore, shapiro
import seaborn as sns
import matplotlib.pylab as plt
%matplotlib inline
```

Reading and understanding our data

we will be using the car sales dataset, hosted on IBM Cloud object storage. This dataset can also be found and downloaded from kaggle.com, an open public data source. The dataset contains all the information about cars, a name of a manufacturer, all car's technical parameters and a sale price of a car.

Let's read the data into *pandas* data frame and look at the first 5 rows using the `head()` method.

```
data = pd.read_csv('https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-ML240EN-SkillsNetwork/labs/data/CarPrice_Assignment.csv')
data.head()
```

```
   car_ID  symboling                   CarName fueltype aspiration
doornumber  \
0       1          3        alfa-romero giulia      gas        std
two
1       2          3       alfa-romero stelvio      gas        std
two
2       3          1  alfa-romero Quadrifoglio      gas        std
two
3       4          2               audi 100 ls      gas        std
four
4       5          2                audi 100ls      gas        std
```

```
four

       carbody drivewheel enginelocation  wheelbase  ...
enginesize  \
0  convertible        rwd          front       88.6  ...          130

1  convertible        rwd          front       88.6  ...          130

2    hatchback        rwd          front       94.5  ...          152

3        sedan        fwd          front       99.8  ...          109

4        sedan        4wd          front       99.4  ...          136


   fuelsystem  boreratio  stroke compressionratio horsepower  peakrpm
citympg  \
0        mpfi       3.47    2.68              9.0        111     5000
21
1        mpfi       3.47    2.68              9.0        111     5000
21
2        mpfi       2.68    3.47              9.0        154     5000
19
3        mpfi       3.19    3.40             10.0        102     5500
24
4        mpfi       3.19    3.40              8.0        115     5500
18

   highwaympg    price
0          27  13495.0
1          27  16500.0
2          26  16500.0
3          30  13950.0
4          22  17450.0

[5 rows x 26 columns]
```

We can find more information about the features and types using the `info()` method.

```
data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   car_ID            205 non-null    int64
 1   symboling         205 non-null    int64
 2   CarName           205 non-null    object
 3   fueltype          205 non-null    object
```

```
 4   aspiration        205 non-null    object
 5   doornumber        205 non-null    object
 6   carbody           205 non-null    object
 7   drivewheel        205 non-null    object
 8   enginelocation    205 non-null    object
 9   wheelbase         205 non-null    float64
 10  carlength         205 non-null    float64
 11  carwidth          205 non-null    float64
 12  carheight         205 non-null    float64
 13  curbweight        205 non-null    int64
 14  enginetype        205 non-null    object
 15  cylindernumber    205 non-null    object
 16  enginesize        205 non-null    int64
 17  fuelsystem        205 non-null    object
 18  boreratio         205 non-null    float64
 19  stroke            205 non-null    float64
 20  compressionratio  205 non-null    float64
 21  horsepower        205 non-null    int64
 22  peakrpm           205 non-null    int64
 23  citympg           205 non-null    int64
 24  highwaympg        205 non-null    int64
 25  price             205 non-null    float64
dtypes: float64(8), int64(8), object(10)
memory usage: 41.8+ KB
```

According to the output above, we have 205 entries or rows, as well as 26 features. The "Non-Null Count" column shows the number of non-null entries. If the count is 205 then there is no missing values for that particular feature. The 'price' is our target, or response variable, and the rest of the features are our predictor variables.

We also have a mix of numerical (8 int64 and 8 float64) and object data types (10 object).

The `describe()` function will provide the statistical information about all numeric values.

```
data.describe()

           car_ID   symboling   wheelbase   carlength    carwidth
carheight  \
count  205.000000  205.000000  205.000000  205.000000  205.000000
205.000000
mean   103.000000    0.834146   98.756585  174.049268   65.907805
53.724878
std     59.322565    1.245307    6.021776   12.337289    2.145204
2.443522
min      1.000000   -2.000000   86.600000  141.100000   60.300000
47.800000
25%     52.000000    0.000000   94.500000  166.300000   64.100000
52.000000
50%    103.000000    1.000000   97.000000  173.200000   65.500000
54.100000
```

```
75%     154.000000    2.000000  102.400000  183.100000   66.900000
55.500000
max     205.000000    3.000000  120.900000  208.100000   72.300000
59.800000

        curbweight  enginesize   boreratio      stroke
compressionratio  \
count   205.000000  205.000000  205.000000  205.000000
205.000000
mean   2555.565854  126.907317    3.329756    3.255415
10.142537
std     520.680204   41.642693    0.270844    0.313597
3.972040
min    1488.000000   61.000000    2.540000    2.070000
7.000000
25%    2145.000000   97.000000    3.150000    3.110000
8.600000
50%    2414.000000  120.000000    3.310000    3.290000
9.000000
75%    2935.000000  141.000000    3.580000    3.410000
9.400000
max    4066.000000  326.000000    3.940000    4.170000
23.000000

       horsepower      peakrpm     citympg  highwaympg         price
count  205.000000   205.000000  205.000000  205.000000    205.000000
mean   104.117073  5125.121951   25.219512   30.751220  13276.710571
std     39.544167   476.985643    6.542142    6.886443   7988.852332
min     48.000000  4150.000000   13.000000   16.000000   5118.000000
25%     70.000000  4800.000000   19.000000   25.000000   7788.000000
50%     95.000000  5200.000000   24.000000   30.000000  10295.000000
75%    116.000000  5500.000000   30.000000   34.000000  16503.000000
max    288.000000  6600.000000   49.000000   54.000000  45400.000000
```

Data Cleaning and Wrangling

Here, we will check if we have any missing values.

```
data.isnull().sum()

car_ID              0
symboling           0
CarName             0
fueltype            0
aspiration          0
doornumber          0
carbody             0
drivewheel          0
enginelocation      0
```

```
wheelbase           0
carlength           0
carwidth            0
carheight           0
curbweight          0
enginetype          0
cylindernumber      0
enginesize          0
fuelsystem          0
boreratio           0
stroke              0
compressionratio    0
horsepower          0
peakrpm             0
citympg             0
highwaympg          0
price               0
dtype: int64
```

Also, check for any duplicates by running `duplicated()` function through 'car_ID' records, since each row has a unique car ID value.

```
sum(data.duplicated(subset = 'car_ID')) == 0

True
```

Next, let's look into some of our object variables first. Using `unique()` function, we will describe all categories of the 'CarName' attribute.

```
data["CarName"].unique()

array(['alfa-romero giulia', 'alfa-romero stelvio',
       'alfa-romero Quadrifoglio', 'audi 100 ls', 'audi 100ls',
       'audi fox', 'audi 5000', 'audi 4000', 'audi 5000s (diesel)',
       'bmw 320i', 'bmw x1', 'bmw x3', 'bmw z4', 'bmw x4', 'bmw x5',
       'chevrolet impala', 'chevrolet monte carlo', 'chevrolet vega
2300',
       'dodge rampage', 'dodge challenger se', 'dodge d200',
       'dodge monaco (sw)', 'dodge colt hardtop', 'dodge colt (sw)',
       'dodge coronet custom', 'dodge dart custom',
       'dodge coronet custom (sw)', 'honda civic', 'honda civic cvcc',
       'honda accord cvcc', 'honda accord lx', 'honda civic 1500 gl',
       'honda accord', 'honda civic 1300', 'honda prelude',
       'honda civic (auto)', 'isuzu MU-X', 'isuzu D-Max ',
       'isuzu D-Max V-Cross', 'jaguar xj', 'jaguar xf', 'jaguar xk',
       'maxda rx3', 'maxda glc deluxe', 'mazda rx2 coupe', 'mazda rx-
4',
       'mazda glc deluxe', 'mazda 626', 'mazda glc', 'mazda rx-7 gs',
       'mazda glc 4', 'mazda glc custom l', 'mazda glc custom',
```

```
       'buick electra 225 custom', 'buick century luxus (sw)',
       'buick century', 'buick skyhawk', 'buick opel isuzu deluxe',
       'buick skylark', 'buick century special',
       'buick regal sport coupe (turbo)', 'mercury cougar',
       'mitsubishi mirage', 'mitsubishi lancer', 'mitsubishi
outlander',
       'mitsubishi g4', 'mitsubishi mirage g4', 'mitsubishi montero',
       'mitsubishi pajero', 'Nissan versa', 'nissan gt-r', 'nissan
rogue',
       'nissan latio', 'nissan titan', 'nissan leaf', 'nissan juke',
       'nissan note', 'nissan clipper', 'nissan nv200', 'nissan dayz',
       'nissan fuga', 'nissan otti', 'nissan teana', 'nissan kicks',
       'peugeot 504', 'peugeot 304', 'peugeot 504 (sw)', 'peugeot
604sl',
       'peugeot 505s turbo diesel', 'plymouth fury iii',
       'plymouth cricket', 'plymouth satellite custom (sw)',
       'plymouth fury gran sedan', 'plymouth valiant', 'plymouth
duster',
       'porsche macan', 'porcshce panamera', 'porsche cayenne',
       'porsche boxter', 'renault 12tl', 'renault 5 gtl', 'saab 99e',
       'saab 99le', 'saab 99gle', 'subaru', 'subaru dl', 'subaru brz',
       'subaru baja', 'subaru r1', 'subaru r2', 'subaru trezia',
       'subaru tribeca', 'toyota corona mark ii', 'toyota corona',
       'toyota corolla 1200', 'toyota corona hardtop',
       'toyota corolla 1600 (sw)', 'toyota carina', 'toyota mark ii',
       'toyota corolla', 'toyota corolla liftback',
       'toyota celica gt liftback', 'toyota corolla tercel',
       'toyota corona liftback', 'toyota starlet', 'toyota tercel',
       'toyota cressida', 'toyota celica gt', 'toyouta tercel',
       'vokswagen rabbit', 'volkswagen 1131 deluxe sedan',
       'volkswagen model 111', 'volkswagen type 3', 'volkswagen 411
(sw)',
       'volkswagen super beetle', 'volkswagen dasher', 'vw dasher',
       'vw rabbit', 'volkswagen rabbit', 'volkswagen rabbit custom',
       'volvo 145e (sw)', 'volvo 144ea', 'volvo 244dl', 'volvo 245',
       'volvo 264gl', 'volvo diesel', 'volvo 246'], dtype=object)
```

We can see that the 'CarName' includes both the company name (brand) and the car model. Next, we want to split a company name from the model of a car, as for our model building purpose, we will focus on a company name only.

```
data['brand'] = data.CarName.str.split(' ').str.get(0).str.lower()
#data.CarName.str.split(' ')  split it in list like [alfa-romero,
giulia]
```

Let's view all the `unique()` brands now.

```
data.brand.unique()
```

```
array(['alfa-romero', 'audi', 'bmw', 'chevrolet', 'dodge', 'honda',
       'isuzu', 'jaguar', 'maxda', 'mazda', 'buick', 'mercury',
       'mitsubishi', 'nissan', 'peugeot', 'plymouth', 'porsche',
       'porcshce', 'renault', 'saab', 'subaru', 'toyota', 'toyouta',
       'vokswagen', 'volkswagen', 'vw', 'volvo'], dtype=object)
```

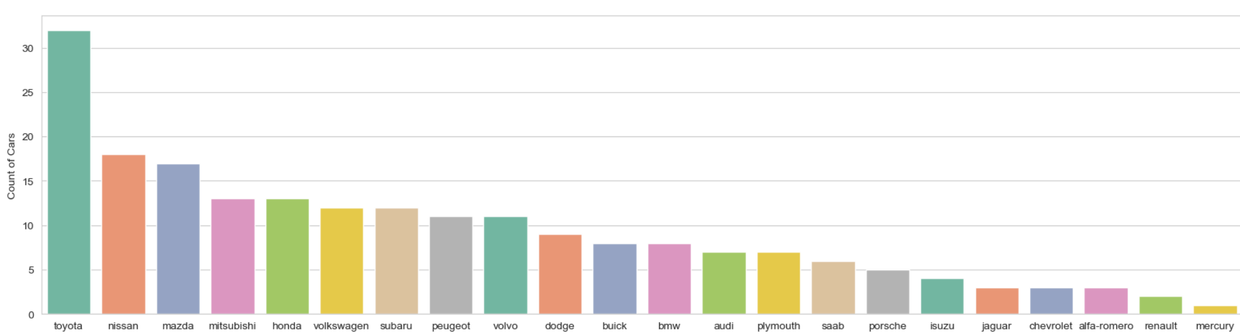
There are some typos in the names of the cars, so they should be corrected.

```
data['brand'] = data['brand'].replace(['vw', 'vokswagen'],
'volkswagen')
data['brand'] = data['brand'].replace(['maxda'], 'mazda')
data['brand'] = data['brand'].replace(['porcshce'], 'porsche')
data['brand'] = data['brand'].replace(['toyouta'], 'toyota')

data.brand.unique()
```

```
array(['alfa-romero', 'audi', 'bmw', 'chevrolet', 'dodge', 'honda',
       'isuzu', 'jaguar', 'mazda', 'buick', 'mercury', 'mitsubishi',
       'nissan', 'peugeot', 'plymouth', 'porsche', 'renault', 'saab',
       'subaru', 'toyota', 'volkswagen', 'volvo'], dtype=object)
```

Let's plot and sort the total number of Brands.

```
palette = sns.color_palette("Set2")
fig, ax = plt.subplots(figsize = (20,5))
plt1 = sns.countplot(x=data['brand'],
order=pd.value_counts(data['brand']).index,palette=palette)
plt1.set(xlabel = 'Brand', ylabel= 'Count of Cars')
plt.show()
plt.tight_layout()
```




```
<Figure size 640x480 with 0 Axes>
```

We can drop 'car_ID', 'symboling', and 'CarName' from our data frame, since they will no longer be needed.

```
data.drop(['car_ID', 'symboling', 'CarName'],axis = 1, inplace = True)
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 24 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   fueltype          205 non-null    object 
 1   aspiration        205 non-null    object 
 2   doornumber        205 non-null    object 
 3   carbody           205 non-null    object 
 4   drivewheel        205 non-null    object 
 5   enginelocation    205 non-null    object 
 6   wheelbase         205 non-null    float64
 7   carlength         205 non-null    float64
 8   carwidth          205 non-null    float64
 9   carheight         205 non-null    float64
 10  curbweight        205 non-null    int64  
 11  enginetype        205 non-null    object 
 12  cylindernumber    205 non-null    object 
 13  enginesize        205 non-null    int64  
 14  fuelsystem        205 non-null    object 
 15  boreratio         205 non-null    float64
 16  stroke            205 non-null    float64
 17  compressionratio  205 non-null    float64
 18  horsepower        205 non-null    int64  
 19  peakrpm           205 non-null    int64  
 20  citympg           205 non-null    int64  
 21  highwaympg        205 non-null    int64  
 22  price             205 non-null    float64
 23  brand             205 non-null    object 
dtypes: float64(8), int64(6), object(10)
memory usage: 38.6+ KB
```

Next, we need to engineer some features, for better visualizations and analysis. We will group our data by 'brand', calculate the average price for each brand, and split these prices into 3 bins: 'Budget', 'Mid-Range', and 'Luxury' cars, naming the newly created column - the 'brand_category'.

Exploratory Data Analysis

Numerical analysis

```
data_comp_avg_price = data[['brand','price']].groupby('brand',
as_index = False).mean().rename(columns={'price':'brand_avg_price'})

data = data.merge(data_comp_avg_price, on = 'brand')
```

We will now check the statistics of our average car price per car brand

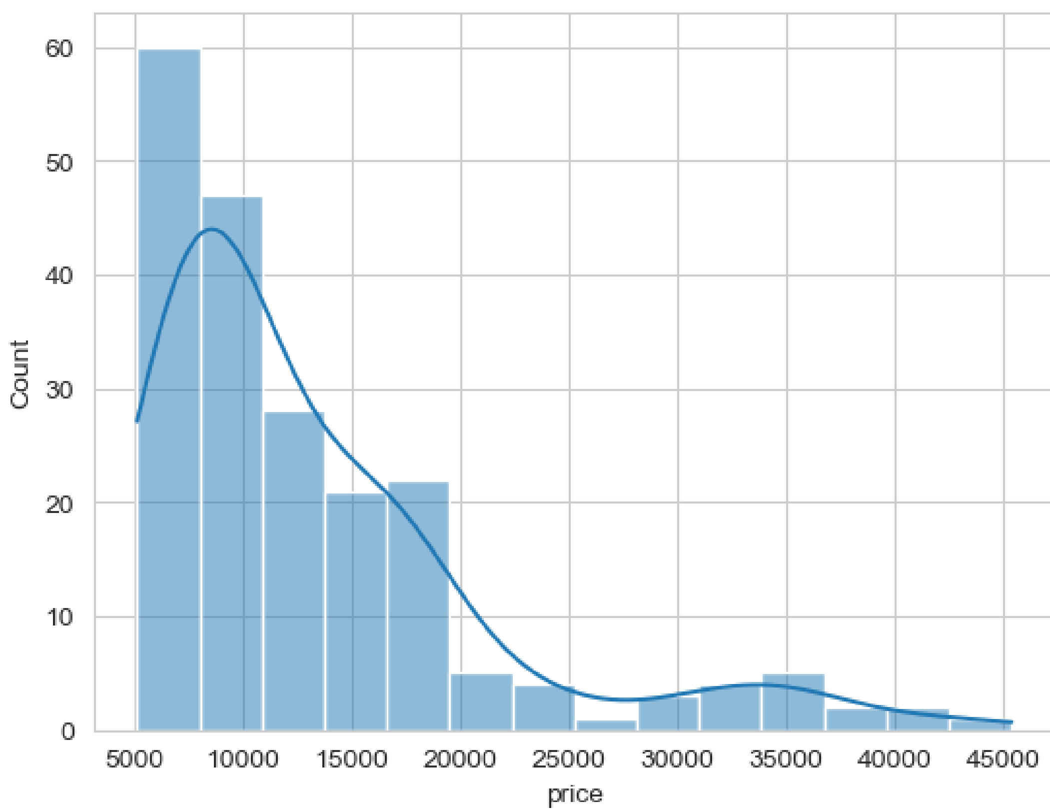
```
data.brand_avg_price.describe()
```

```
count      205.000000
mean     13276.710571
std       7154.179185
min       6007.000000
25%       9239.769231
50%      10077.500000
75%      15489.090909
max      34600.000000
Name: brand_avg_price, dtype: float64
```

```
data['brand_category'] = data['brand_avg_price'].apply(lambda x :
"Budget" if x < 10000
                                                     else ("Mid_Range"
if 10000 <= x < 20000
                                                           else
"Luxury"))
```

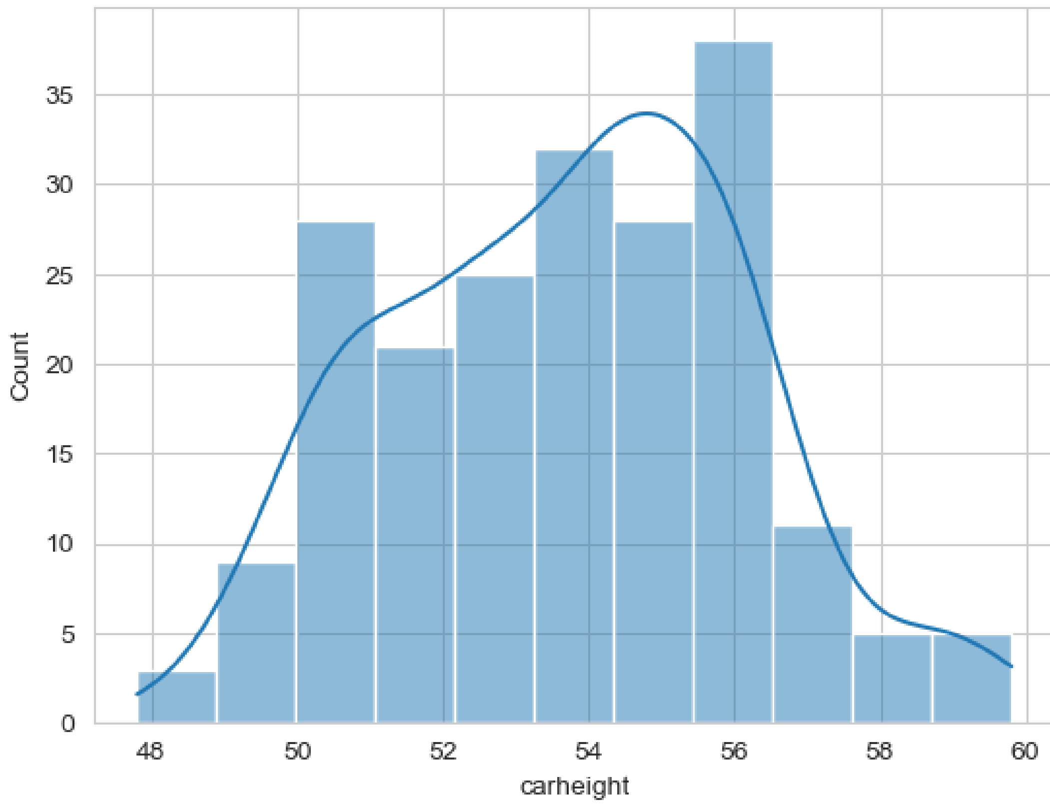
```
palette = sns.color_palette("Set2")
sns.histplot(data.price,kde=True,palette=palette)
```

```
<Axes: xlabel='price', ylabel='Count'>
```



```
palette = sns.color_palette("Set2")
sns.histplot(data.carheight,kde=True,palette=palette)
```

```
<Axes: xlabel='carheight', ylabel='Count'>
```




```
skewness = skew(data['carheight'])
kurt = kurtosis(data['carheight'])
print(f"Skewness: {skewness}, Kurtosis: {kurt}")
```

```
Skewness: 0.06265991683394276, Kurtosis: -0.46218755571934844
```

- The data is almost perfectly symmetrical (no significant skewness).
- The distribution is slightly flat, meaning there are fewer outliers or extreme values than a normal distribution would typically have.

```
stat, p = shapiro(data['carheight'])
print(f"Shapiro-Wilk Test: Statistics={stat}, p-value={p}")
```

```
Shapiro-Wilk Test: Statistics=0.9842308541999559, p-
value=0.021672595956741057
```

Although the skewness and kurtosis indicated a fairly symmetrical distribution, the Shapiro-Wilk test suggests that the data deviates slightly from normality. This could mean there are subtle irregularities that are not captured by skewness and kurtosis alone, such as mild deviations in the tails or some other characteristics that make the distribution not perfectly normal.

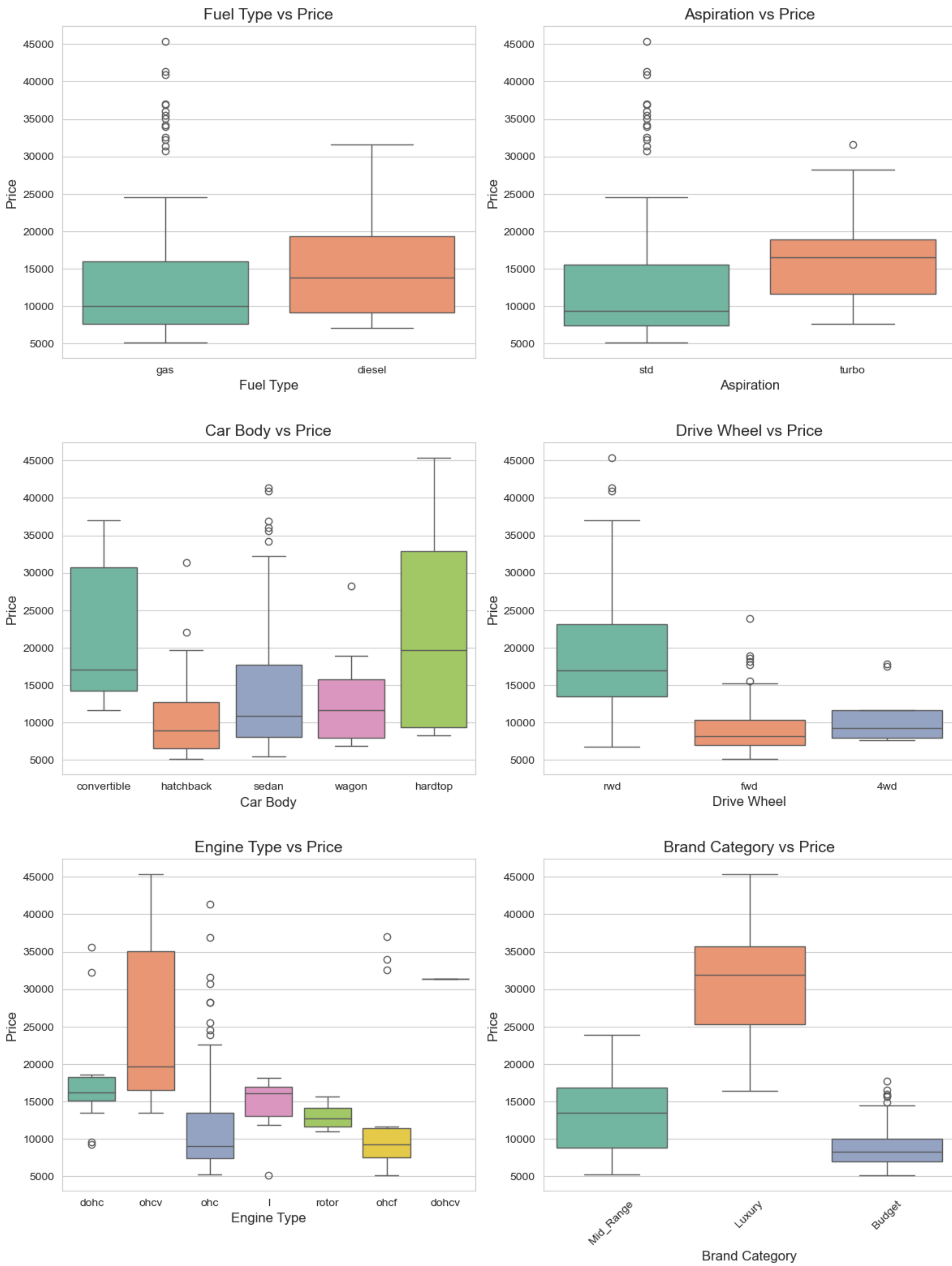
List of Categorical Variables:

- brand_category
- fueltype
- enginetype
- carbody
- doornumber
- enginelocation
- fuelsystem
- cylindernumber
- aspiration
- drivewheel

We will use the `boxplot()` function on the above mentioned categorical variables, to display the mean, variance, and possible outliers, with respect to the price.

```
sns.set_style("whitegrid")
plt.figure(figsize=(12, 20))

palette = sns.color_palette("Set2")

#Fuel Type vs Price
plt.subplot(4, 2, 1)
sns.boxplot(x='fueltype', y='price', data=data, palette=palette)
plt.title('Fuel Type vs Price', fontsize=14)
plt.xlabel('Fuel Type', fontsize=12)
plt.ylabel('Price', fontsize=12)

#Aspiration vs Price
plt.subplot(4, 2, 2)
sns.boxplot(x='aspiration', y='price', data=data, palette=palette)
plt.title('Aspiration vs Price', fontsize=14)
plt.xlabel('Aspiration', fontsize=12)
plt.ylabel('Price', fontsize=12)

#  Car Body vs Price
plt.subplot(4, 2, 3)
sns.boxplot(x='carbody', y='price', data=data, palette=palette)
plt.title('Car Body vs Price', fontsize=14)
plt.xlabel('Car Body', fontsize=12)
plt.ylabel('Price', fontsize=12)

#  Drive Wheel vs Price
plt.subplot(4, 2, 4)
sns.boxplot(x='drivewheel', y='price', data=data, palette=palette)
plt.title('Drive Wheel vs Price', fontsize=14)
```

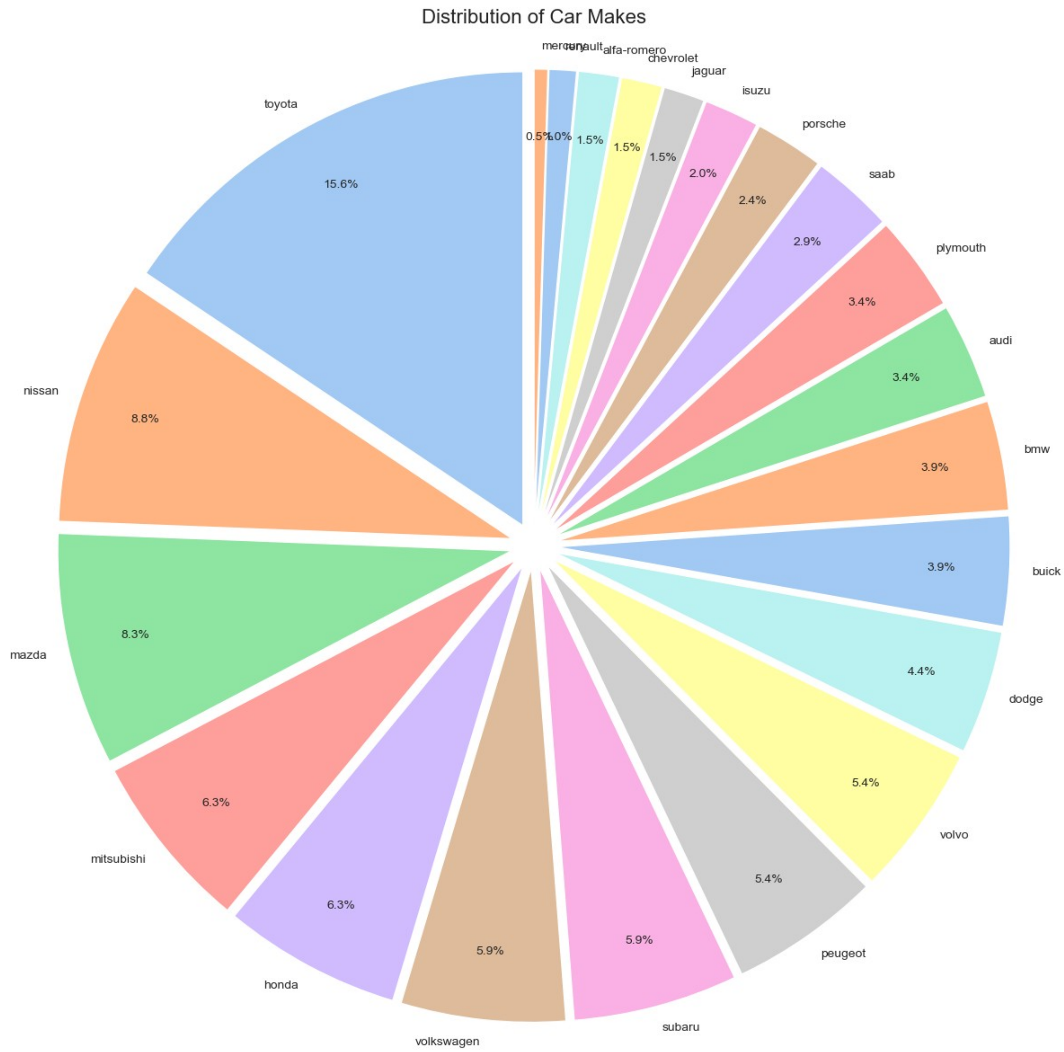
```
plt.xlabel('Drive Wheel', fontsize=12)
plt.ylabel('Price', fontsize=12)

# Engine Type vs Price
plt.subplot(4, 2, 5)
sns.boxplot(x='enginetype', y='price', data=data, palette=palette)
plt.title('Engine Type vs Price', fontsize=14)
plt.xlabel('Engine Type', fontsize=12)
plt.ylabel('Price', fontsize=12)

# Brand Category vs Price
plt.subplot(4, 2, 6)
sns.boxplot(x='brand_category', y='price', data=data, palette=palette)
plt.title('Brand Category vs Price', fontsize=14)
plt.xlabel('Brand Category', fontsize=12)
plt.ylabel('Price', fontsize=12)
plt.xticks(rotation=45)

plt.tight_layout()
plt.show()
```


Fuel Type vs Price
Price
Fuel Type
gas
diesel
Aspiration vs Price
Aspiration
std
turbo
Car Body vs Price
Car Body
convertible
hatchback
sedan
wagon
hardtop
Drive Wheel vs Price
Drive Wheel
rwd
fwd
4wd
Engine Type vs Price
Engine Type
dohc
ohcv
ohc
l
rotor
ohcf
dohcv
Brand Category vs Price
Brand Category
Mid_Range
Luxury
Budget
5000
10000
15000
20000
25000
30000
35000
40000
45000

Next, let's view the list of top features that have high correlation coefficient. The `corr()` function calculates the Pearson'r correlation coefficients with respect to the 'price'.

We can see the how much car is produced by different companies

```
car_make_counts = data['brand'].value_counts()
fig, ax = plt.subplots(figsize=(14, 12))
colors = sns.color_palette('pastel', len(car_make_counts))

explode = [0.05] * len(car_make_counts)
ax.pie(
    car_make_counts,
    labels=car_make_counts.index,
    autopct='%1.1f%%',
    startangle=90,
    colors=colors,
    explode=explode,
    pctdistance=0.85,
    labeldistance=1.05
)

ax.axis('equal')
ax.set_title('Distribution of Car Makes', fontsize=16)
plt.tight_layout()
plt.show()
```



Multivariate Analysis

```
corr_matrix = data.select_dtypes(exclude=['object']).corr()
corr_matrix['price'].sort_values(ascending=False)
```

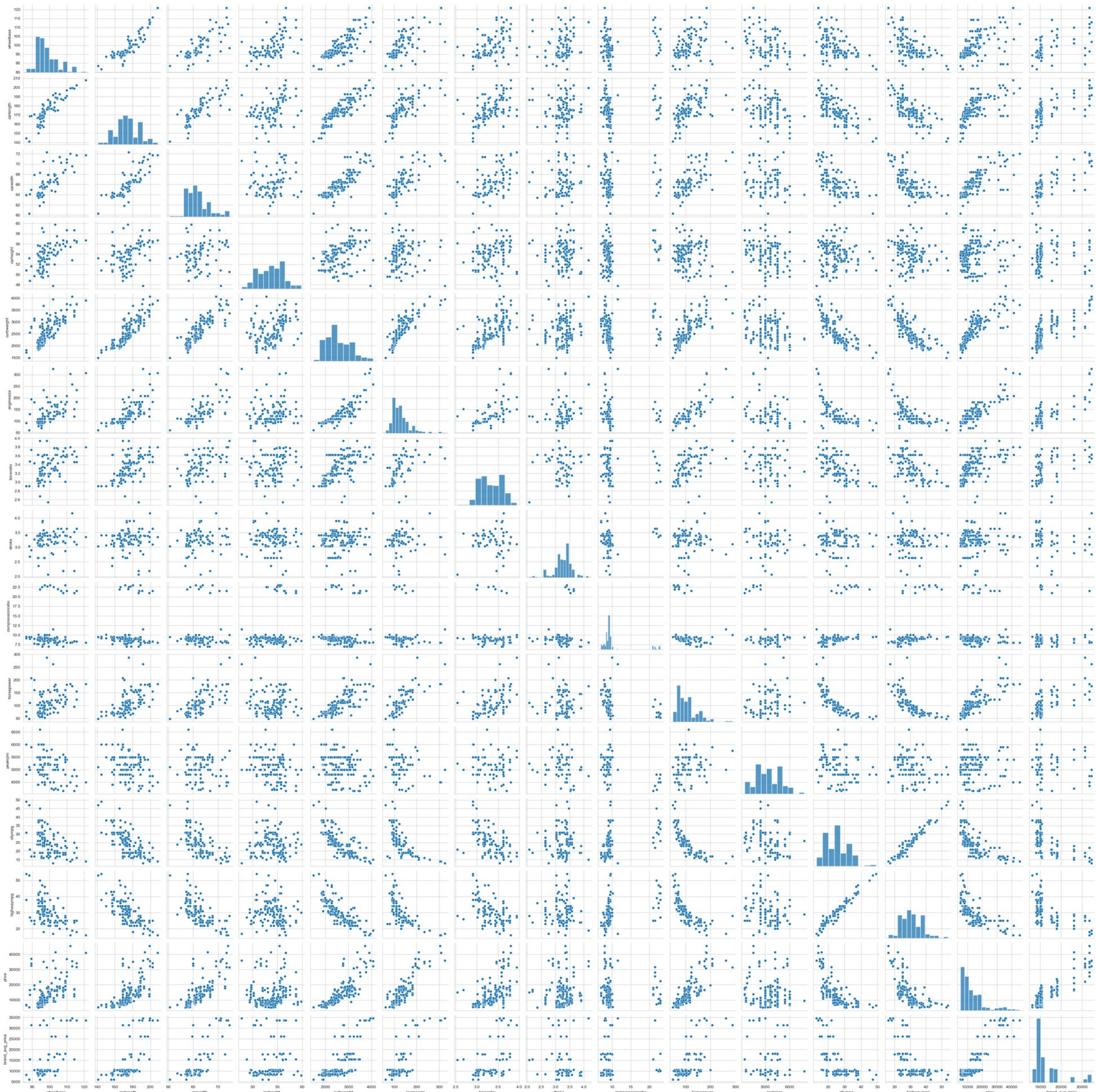
```
price               1.000000
brand_avg_price     0.895520
enginesize          0.874145
curbweight          0.835305
horsepower          0.808139
carwidth            0.759325
carlength           0.682920
wheelbase           0.577816
boreratio           0.553173
carheight           0.119336
stroke              0.079443
compressionratio    0.067984
peakrpm            -0.085267
```

```
citympg            -0.685751
highwaympg         -0.697599
Name: price, dtype: float64
```

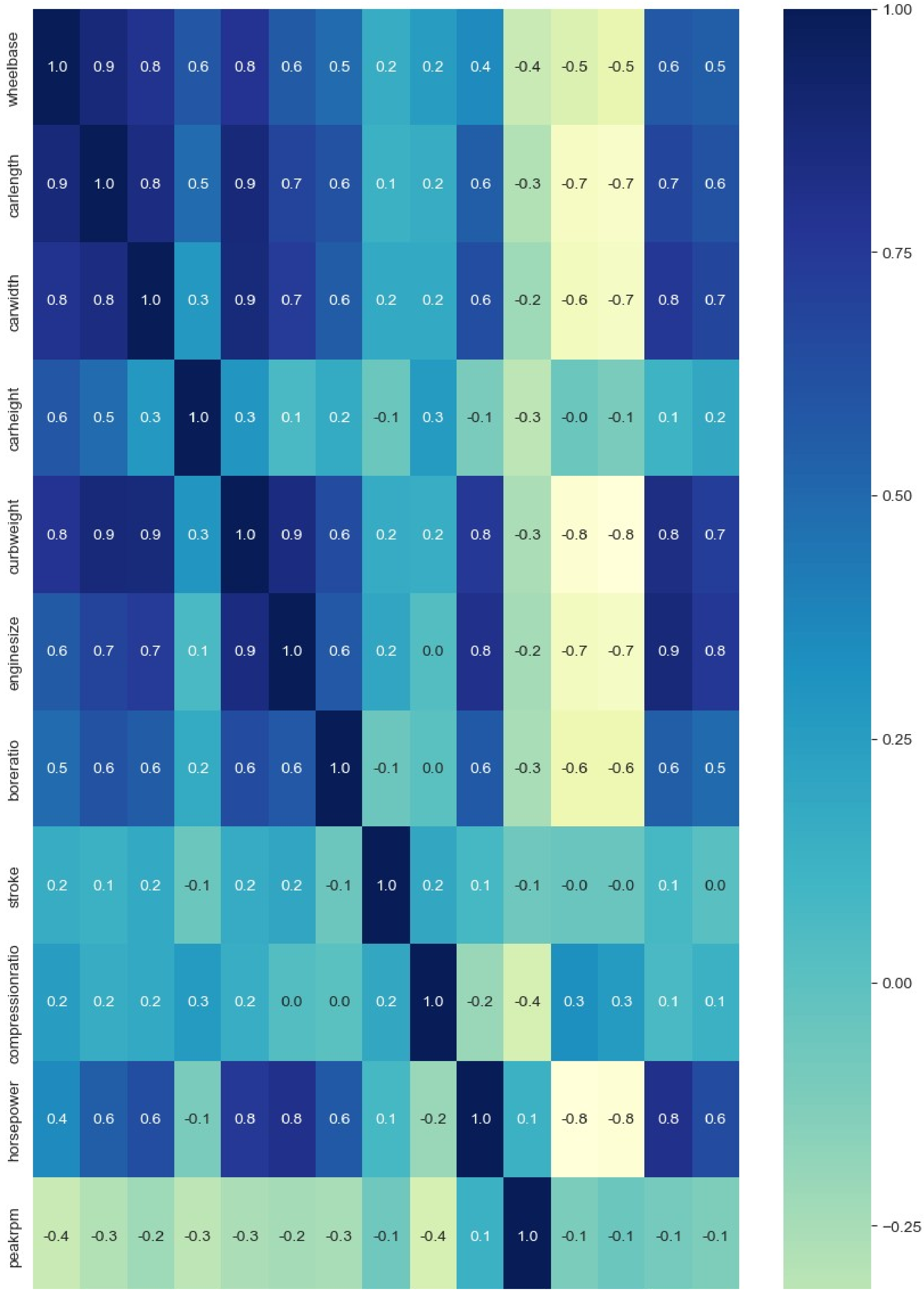
These are strongly correlated numerical features with Car Price.

We can also use the `heatmap()` or `pairplot()` to further explore the relationship between all features and the target variables.

```
sns.pairplot(data,palette=palette)
plt.show()
```

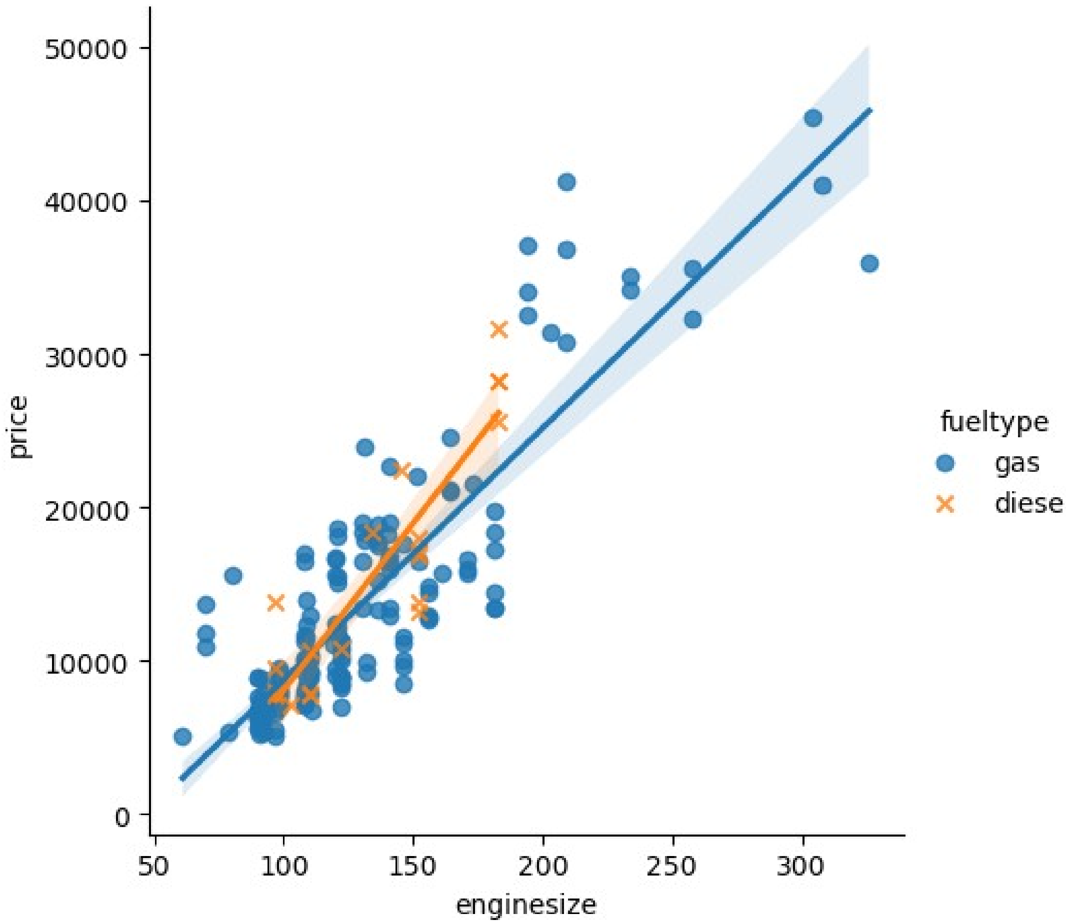


```
plt.figure(figsize=(10, 20))
sns.heatmap(data.select_dtypes(exclude=['object']).corr(),
annot=True,fmt=".1f",cmap='YlGnBu')
plt.show()
```



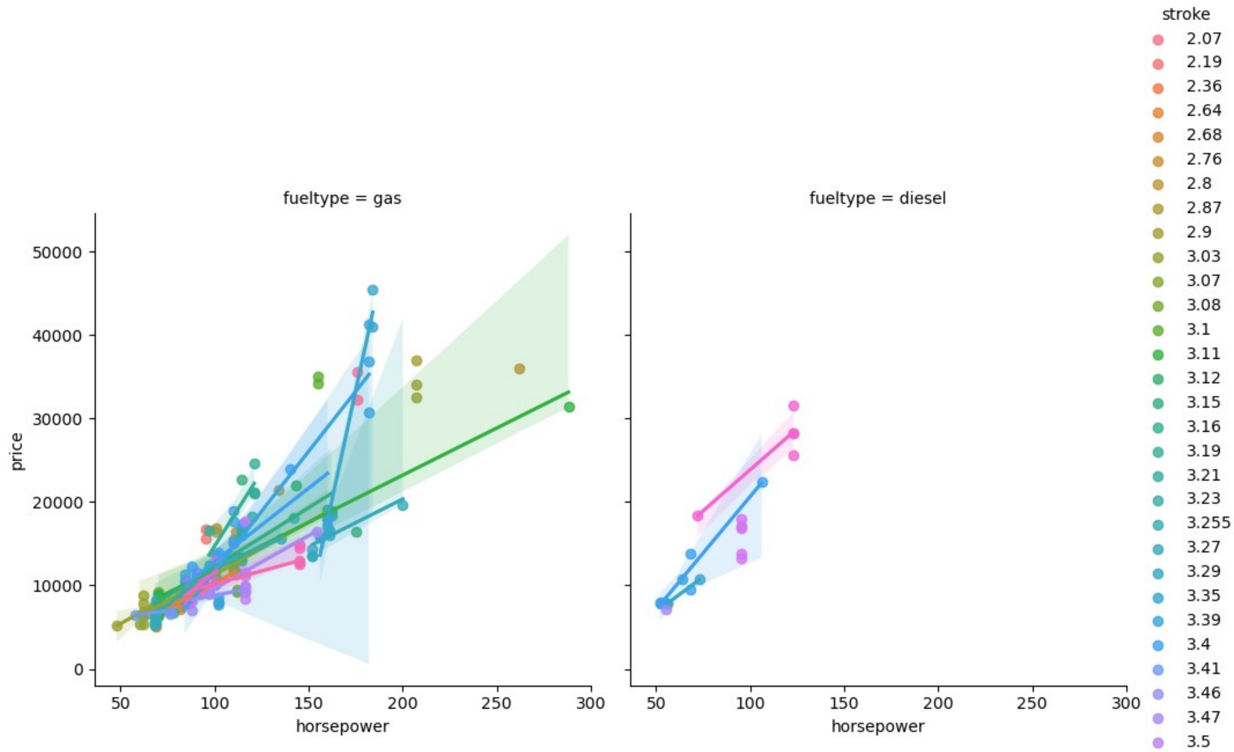
wheelbase
carlength
carwidth
carheight
curbweight
enginesize
boreratio
stroke
compressionratio
horsepower
peakrpm
1.00
0.75
0.50
0.25
0.00
−0.25

```
sns.lmplot(x="enginesize", y="price", hue="fueltype", data=data,
           markers=["o", "x"]);
```

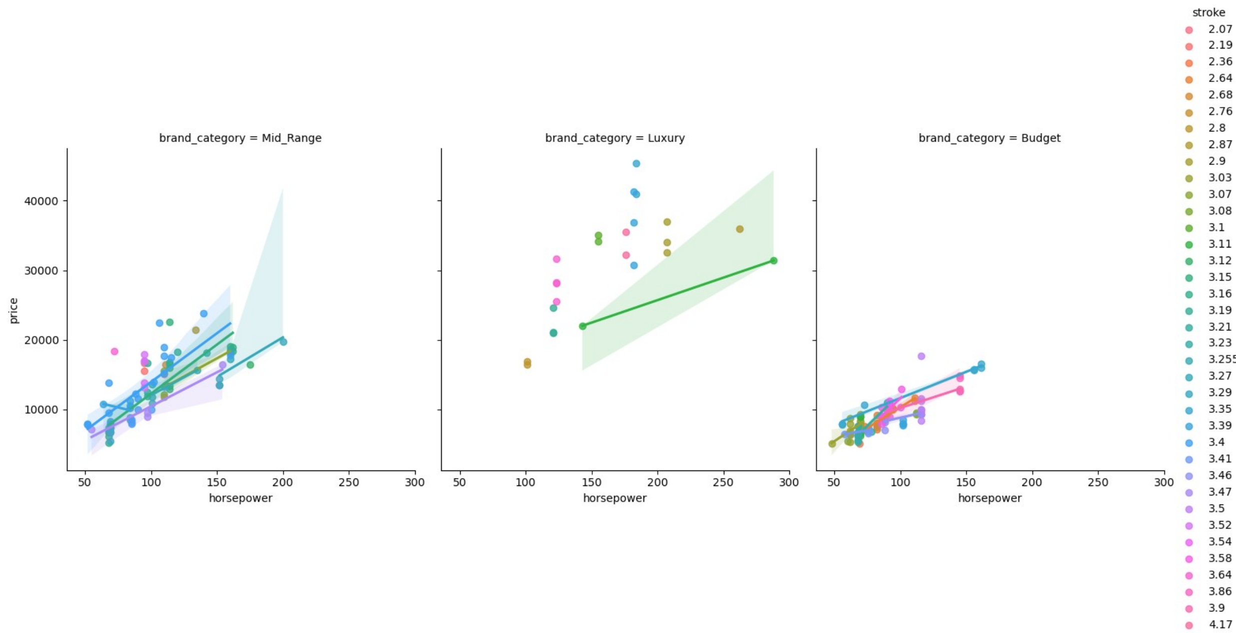



```
sns.lmplot(x="horsepower", y="price", hue="stroke",col='fueltype',
data=data)
```

```
<seaborn.axisgrid.FacetGrid at 0x1f1097b0c20>
```




```
sns.lmplot(x="horsepower", y="price",
hue="stroke",col='brand_category', data=data)

<seaborn.axisgrid.FacetGrid at 0x1f10f708410>
```


brand_category = Mid_Range
brand_category = Luxury
brand_category = Budget
price
horsepower
horsepower
horsepower
stroke
2.07
2.19
2.36
2.64
2.68
2.76
2.8
2.87
2.9
3.03
3.07
3.08
3.1
3.11
3.12
3.15
3.16
3.19
3.21
3.23
3.255
3.27
3.29
3.35
3.39
3.4
3.41
3.46
3.47
3.5
3.52
3.54
3.58
3.64
3.86
3.9
4.17