AUTOMOBILE PRICE PREDICTION

Step-1: Import all the required libraries which are used to train the model and visualise the data

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
import plotly
import plotly.express as px
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn import metrics
```

Step-2: Read the data

In [2]:
```
df=pd.read_csv("/home/silpa/Downloads/Automobile_data.csv")
df
```

Out[2]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine siz
0	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	13
1	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	13
2	1	?	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...	15
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8	...	10
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4	...	13
...	...	...	...	...	...	...	...	...	...	...	...	.
200	-1	95	volvo	gas	std	four	sedan	rwd	front	109.1	...	14
201	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.1	...	14
202	-1	95	volvo	gas	std	four	sedan	rwd	front	109.1	...	17
203	-1	95	volvo	diesel	turbo	four	sedan	rwd	front	109.1	...	14
204	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.1	...	14

205 rows × 26 columns

EXPLORATORY DATA ANALYSIS

Step-3: To know number of rows and columns in the data set

In [3]:
```
print(df.shape)
```

```
(205, 26)
```

Step-4: Describe the dataset which shows the minimum value, maximum value, mean value, count, standard deviation, etc.

In [4]:
```
df.describe()
```

Out[4]:

	symboling	wheel-base	length	width	height	curb-weight	engine-size	compression-ratio	
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	20
mean	0.834146	98.756585	174.049268	65.907805	53.724878	2555.565854	126.907317	10.142537	2
std	1.245307	6.021776	12.337289	2.145204	2.443522	520.680204	41.642693	3.972040	
min	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000000	7.000000	1
25%	0.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97.000000	8.600000	1
50%	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.000000	9.000000	2
75%	2.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	141.000000	9.400000	3
max	3.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326.000000	23.000000	4

Step-5: Checking for missing values

In [5]:
```
df.isna().sum()
```

Out[5]:
```
symboling            0
normalized-losses    0
make                 0
fuel-type            0
aspiration           0
num-of-doors         0
body-style           0
drive-wheels         0
engine-location      0
wheel-base           0
length               0
width                0
height               0
curb-weight          0
engine-type          0
num-of-cylinders     0
engine-size          0
fuel-system          0
bore                 0
stroke               0
compression-ratio    0
horsepower           0
peak-rpm             0
city-mpg             0
highway-mpg          0
price                0
dtype: int64
```

Step-6: There is no null values in the dataset but there is '?' suymbol.So replacing them in to np.nan.

In [6]:
```
for colm in df.columns:
    df[colm].replace({'?':np.nan},inplace=True)
df
```

Out[6]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine-siz
0	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	13
1	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	13

2	1	NaN	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...	15
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8	...	10
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4	...	13
...	...	...	...	...	...	...	...	...	...	...	...	.
200	-1	95	volvo	gas	std	four	sedan	rwd	front	109.1	...	14
201	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.1	...	14
202	-1	95	volvo	gas	std	four	sedan	rwd	front	109.1	...	17
203	-1	95	volvo	diesel	turbo	four	sedan	rwd	front	109.1	...	14
204	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.1	...	14

205 rows × 26 columns

Step-7: Cheking missing values again

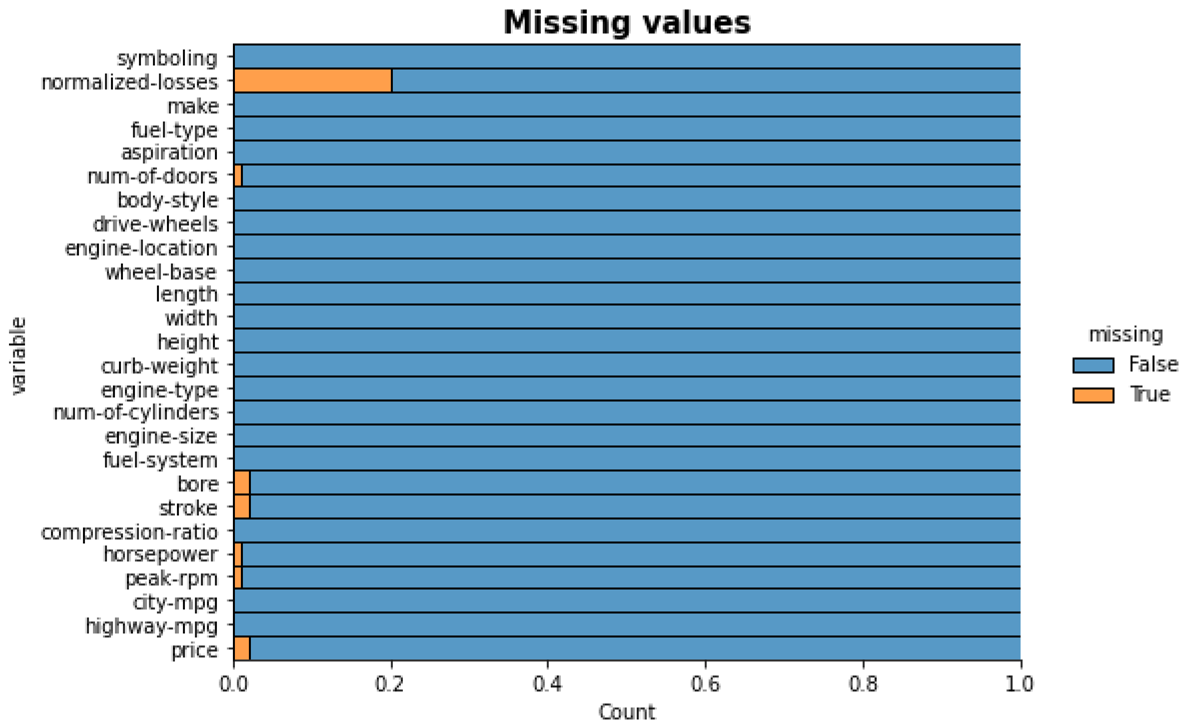
In [7]:
```
df.isna().sum()
```

Out[7]:
```
symboling             0
normalized-losses    41
make                  0
fuel-type             0
aspiration            0
num-of-doors          2
body-style            0
drive-wheels          0
engine-location       0
wheel-base            0
length                0
width                 0
height                0
curb-weight           0
engine-type           0
num-of-cylinders      0
engine-size           0
fuel-system           0
bore                  4
stroke                4
compression-ratio     0
horsepower            2
peak-rpm              2
city-mpg              0
highway-mpg           0
price                 4
dtype: int64
```

Step-8: Plotting missing values

In [8]:
```
# To create a heatmap of missing values of the df
sns.displot(data=df.isna().melt(value_name="missing"),
    y="variable",
    hue="missing",
    multiple="fill",
    height=5,
    aspect=1.5
)
plt.title("Missing values",fontsize=15,fontweight='bold')
```

Out[8]:
```
Text(0.5, 1.0, 'Missing values')
```



Step-9: Handling the two missing values in 'num of doors'. So we are looking at the 'make' and 'body style' corresponding to the missing value and checking the same model's number of doors.

In [9]:
```
df[(df["num-of-doors"].isna() == True)]
```

Out[9]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine-size	sy
27	1	148	dodge	gas	turbo	NaN	sedan	fwd	front	93.7	...	98	
63	0	NaN	mazda	diesel	std	NaN	sedan	fwd	front	98.8	...	122	

2 rows × 26 columns

Step-10: From the above data we can find that the 'body style' is sedan and 'make' is dodge and mazda. Then check the number of doors in dodge and mazda.

In [10]:
```
df['num-of-doors'][(df['body-style']=='sedan') & (df['make']=='mazda')]
```

Out[10]:
```
53    four
54    four
60    four
62    four
63     NaN
65    four
66    four
Name: num-of-doors, dtype: object
```

In [11]:
```
df['num-of-doors'][(df['body-style']=='sedan') & (df['make']=='dodge')]
```

Out[11]:
```
25    four
26    four
27     NaN
Name: num-of-doors, dtype: object
```

Step-11: Both have four doors. So, fill the missing values in 'num of doors' by four

In [12]:
```
df['num-of-doors'] = df['num-of-doors'].fillna('four')
```

```
a=df['num-of-doors'].map({'two':2,'four':4})          # dictionary mapping
df['num-of-doors']=a
df['num-of-doors'] = df['num-of-doors'].astype(str).astype(int)  # converting datatype
```

Step-12: Filling the missing values in the numerical columns with mean

In [13]:
```
ncol = ['normalized-losses','bore', 'stroke', 'horsepower', 'peak-rpm','price']

for col in ncol:
    df[col]=pd.to_numeric(df[col])
    df[col].fillna(df[col].mean(), inplace=True)
df.head()
```

Out[13]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine-size
0	3	122.0	alfa-romero	gas	std	2	convertible	rwd	front	88.6	...	130
1	3	122.0	alfa-romero	gas	std	2	convertible	rwd	front	88.6	...	130
2	1	122.0	alfa-romero	gas	std	2	hatchback	rwd	front	94.5	...	152
3	2	164.0	audi	gas	std	4	sedan	fwd	front	99.8	...	109
4	2	164.0	audi	gas	std	4	sedan	4wd	front	99.4	...	136

5 rows × 26 columns

Step-13: Checking missing value again

In [14]:
```
print(df.isnull().sum())
```

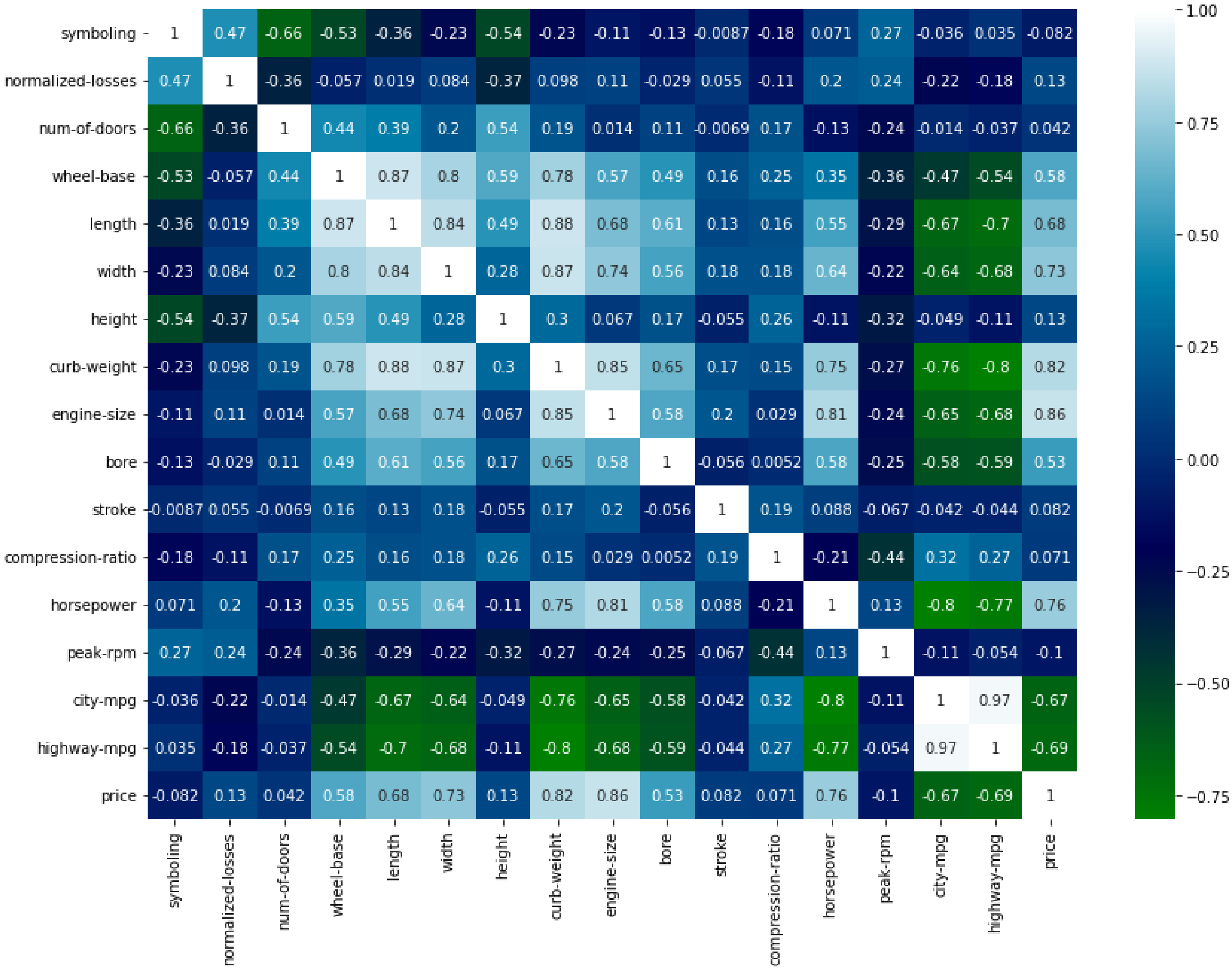
```
symboling            0
normalized-losses    0
make                 0
fuel-type            0
aspiration           0
num-of-doors         0
body-style           0
drive-wheels         0
engine-location      0
wheel-base           0
length               0
width                0
height               0
curb-weight          0
engine-type          0
num-of-cylinders     0
engine-size          0
fuel-system          0
bore                 0
stroke               0
compression-ratio    0
horsepower           0
peak-rpm             0
city-mpg             0
highway-mpg          0
price                0
dtype: int64
```

Step-14: Checking the correlation between different variables

In [15]:

```python
plt.figure(figsize=(14,10))
sns.heatmap(df.corr(),annot=True,cmap="ocean")
```

Out[15]: <AxesSubplot:>



> Positive Correlation:

** Price : wheel_base, length, width, curb_weight, engine_size, bore, horsepower

** wheelbase : length, width, height, curb_weight, engine_size, price

** horsepower : length, width, curb_weight, engine_size, bore, price

** Highway mpg : city mpg

> Negative Correlation:

** Price : highway_mpg, city_mpg

** highway_mpg : wheel base, length, width, curb_weight, engine_size, bore, horsepower, price

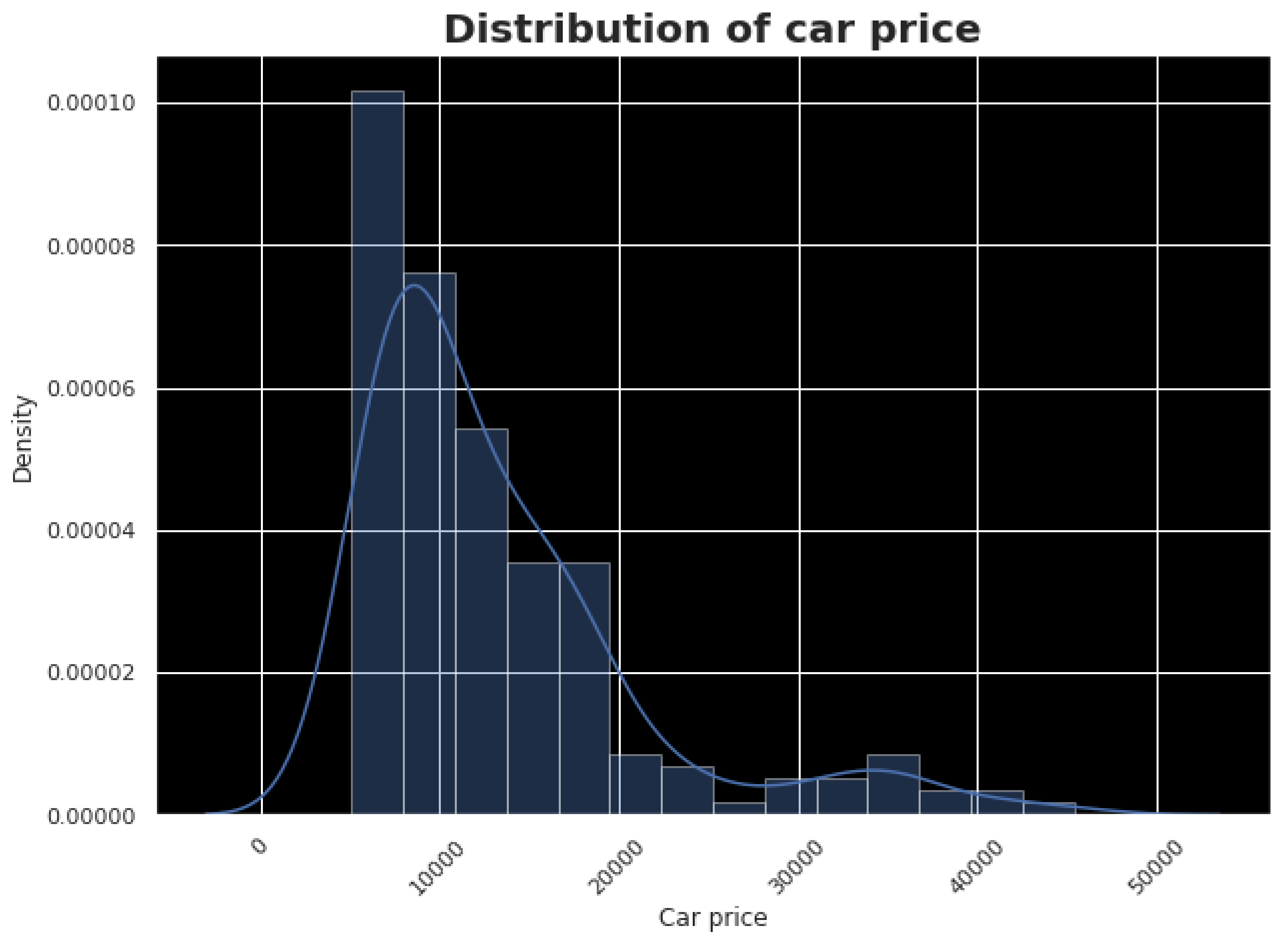
** city-mpg : wheel base, length, width, curb_weight, horsepower, engine_size, bore, price

Step-15: Plotting the disdtribution of car price

In [38]:

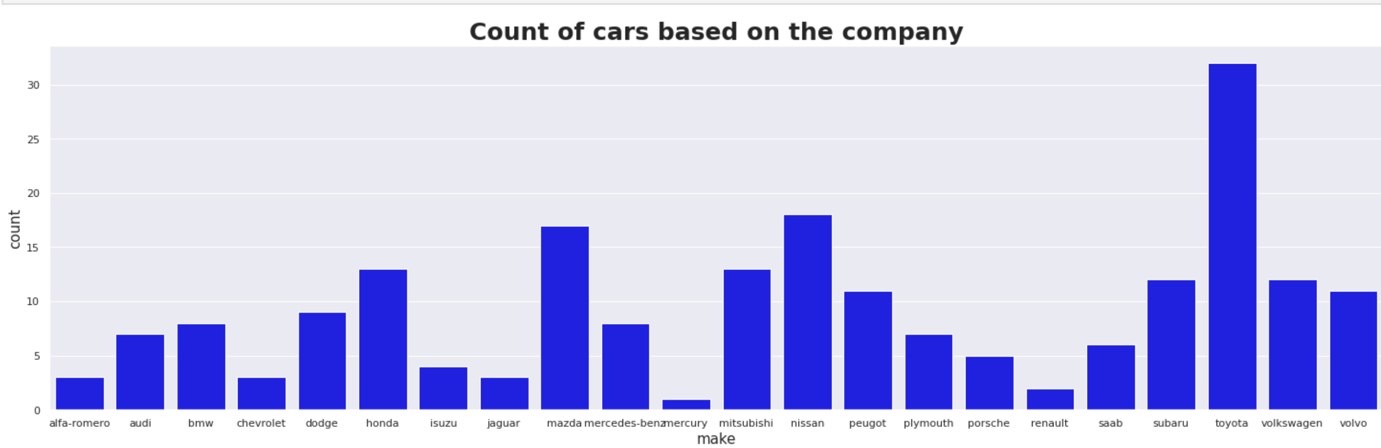
```python
ax=plt.axes()
ax.set(facecolor='black')
```

```
sns.set(rc={'figure.figsize':(10,7)},style='darkgrid')
ax.set_title('Distribution of car price',fontsize=20,fontweight='bold')
sns.distplot(df['price'])
plt.xticks(rotation=45)
plt.xlabel('Car price')
plt.show()
```



Step-16: Count plot of cars based on the company

In [17]:
```
plt.figure(figsize=(25,7))
sns.countplot(df['make'],color='blue')
plt.xlabel('make',fontsize=15)
plt.ylabel('count',fontsize=15)
plt.title('Count of cars based on the company',fontsize=25,fontweight='bold')
plt.show()
```

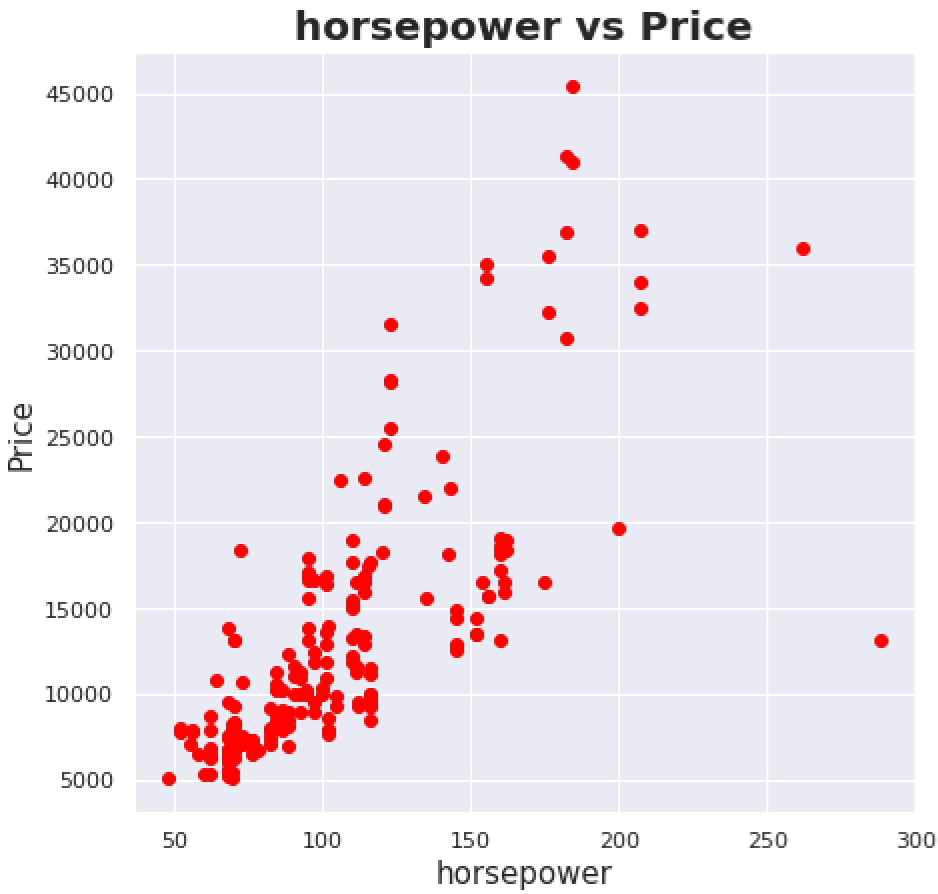


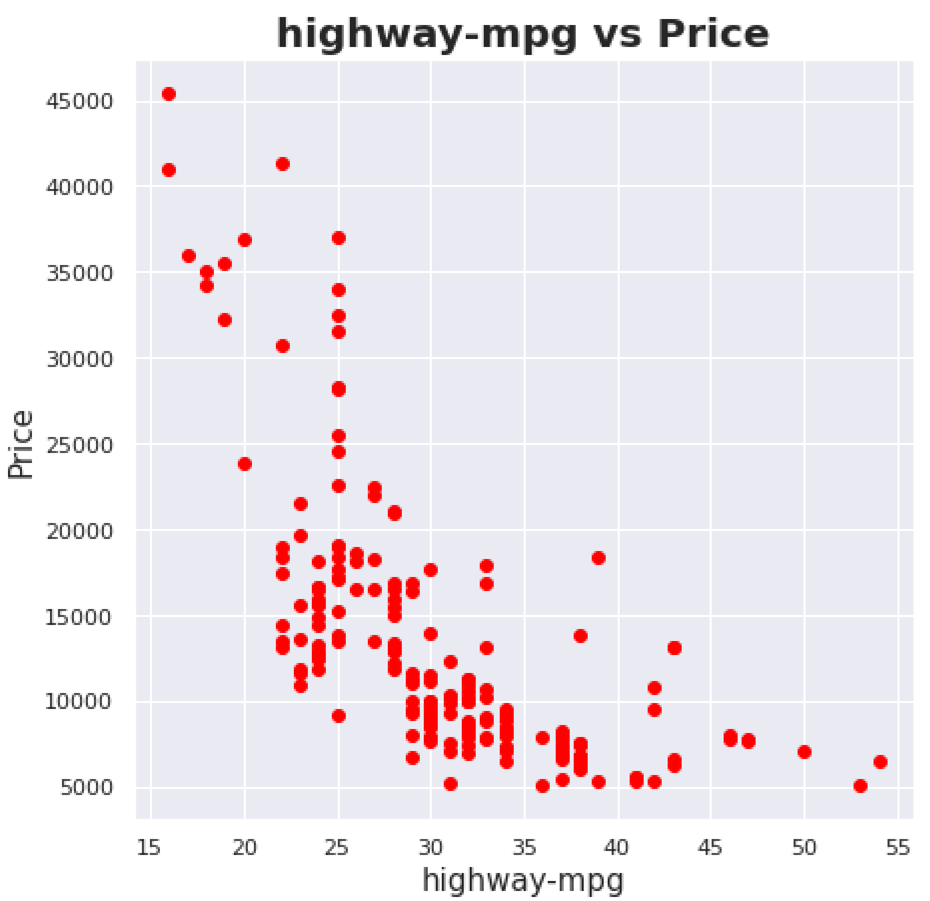
** From the graph we can see that, Toyota is the leading producer of cars followed by nissan and mazda

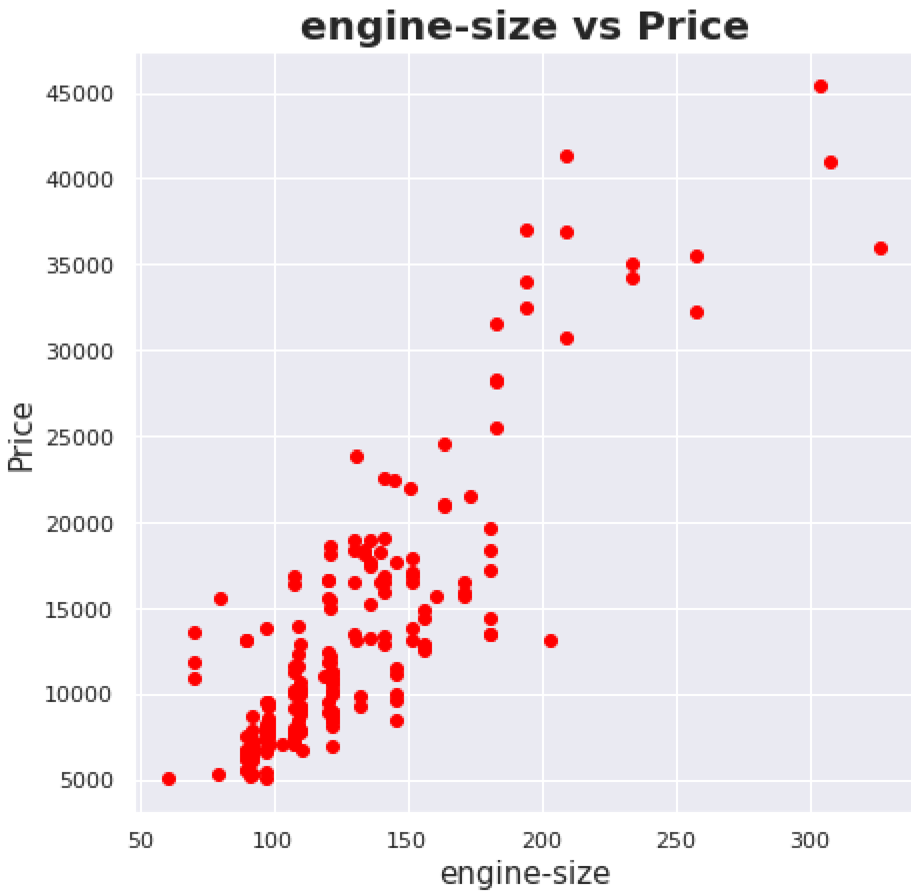
Step-17: Checking how the horse power,highway mpg,engine size and curb weight affect the price

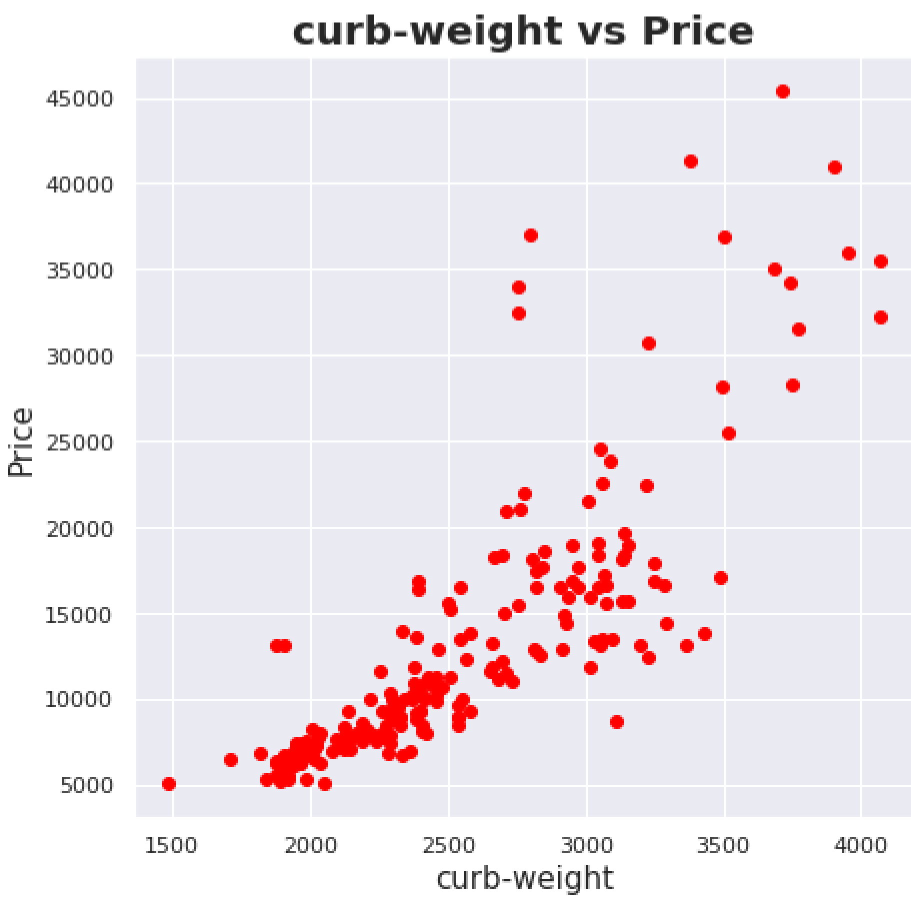
In [18]:

```
c=['horsepower','highway-mpg','engine-size','curb-weight']
for j in c:
    plt.figure(figsize=(7,7))
    plt.scatter(x=j,y='price',data=df,color='red')
    plt.xlabel(j,fontsize=15)
    plt.ylabel('Price',fontsize=15)
    plt.title(j+ ' vs Price',fontsize=20,fontweight='bold')
```





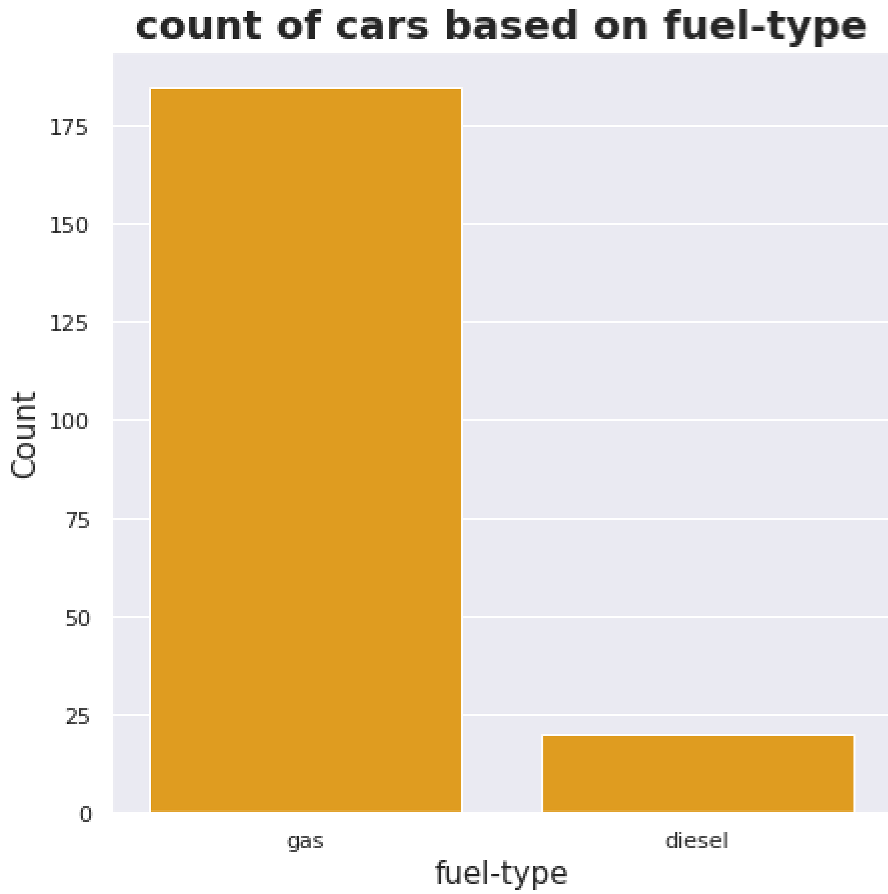


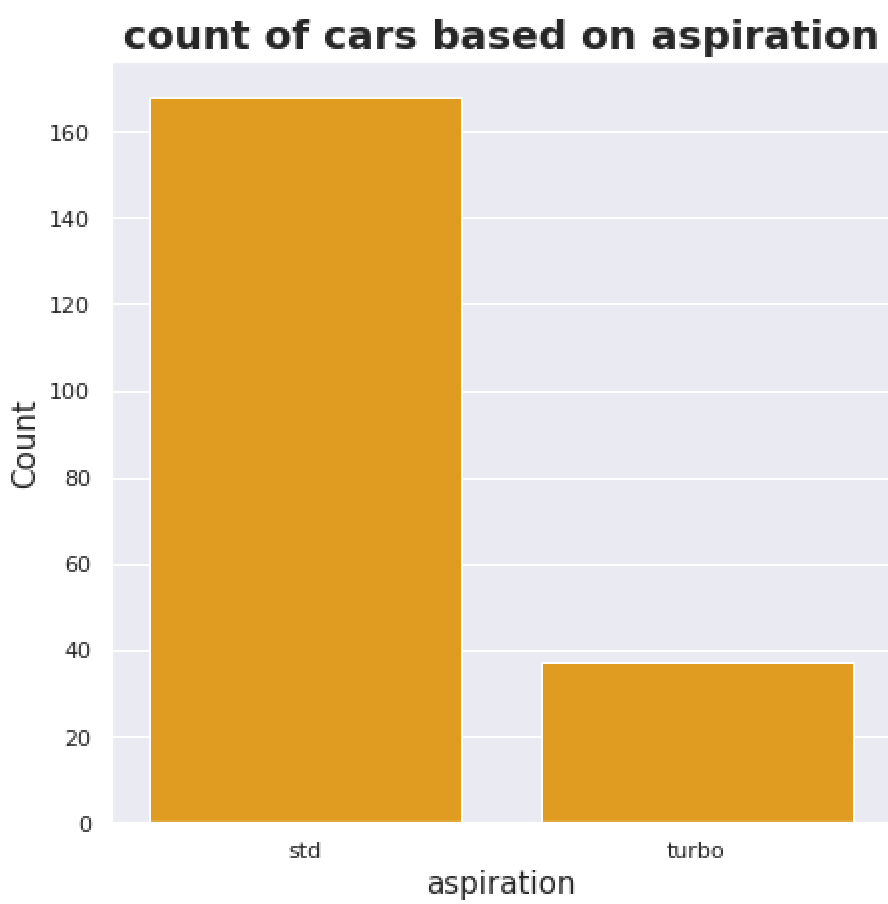


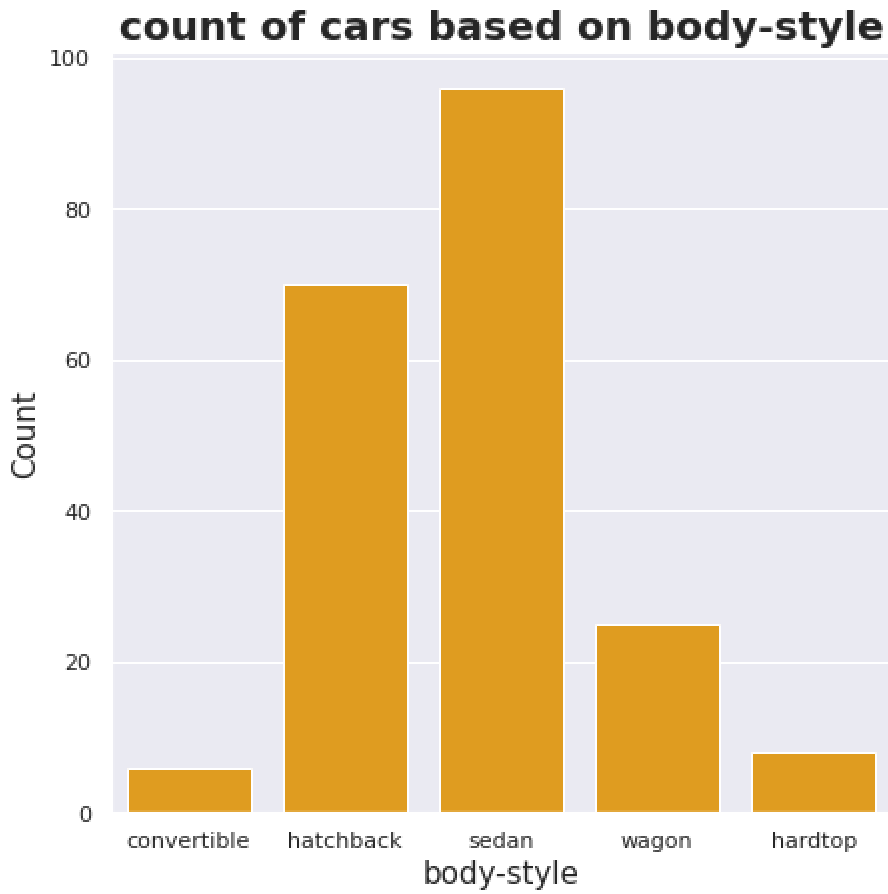
Step-18: Plotting count of cars based on different features

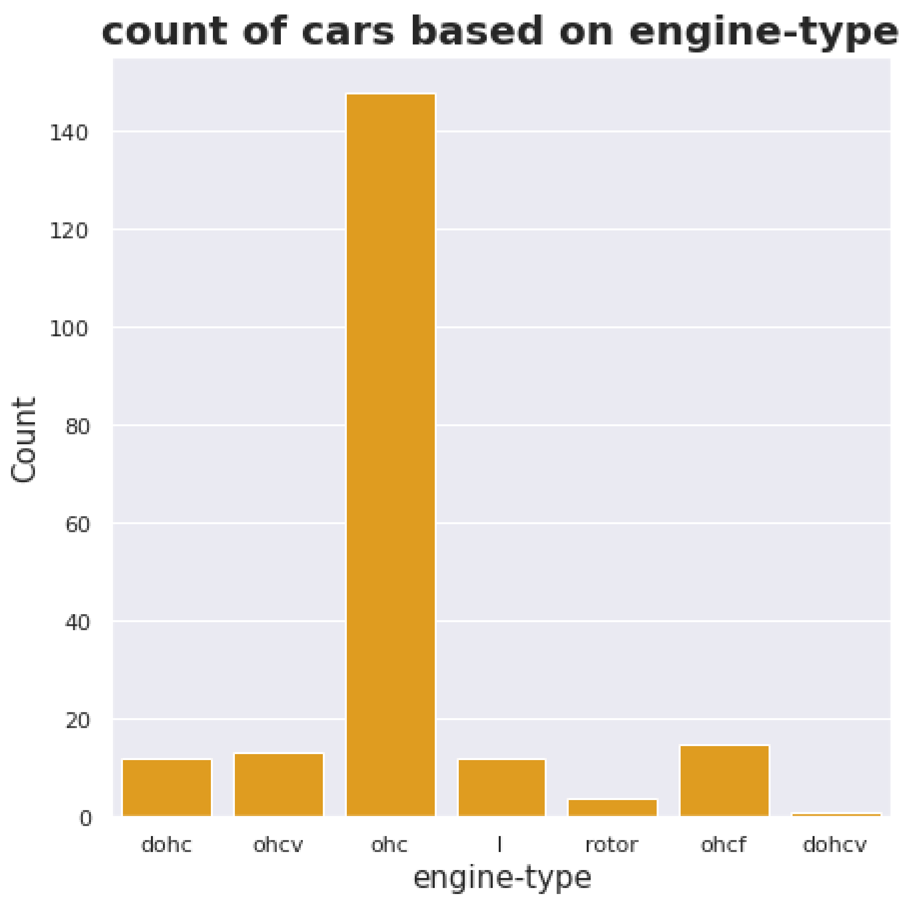
In [19]:
```
col=['fuel-type', 'aspiration', 'body-style','engine-type', 'fuel-system']
for i in col:
    plt.subplots(figsize=(7,7))
    sns.countplot(x=i,data=df,color='orange')
    plt.xlabel(i,fontsize=15)
```

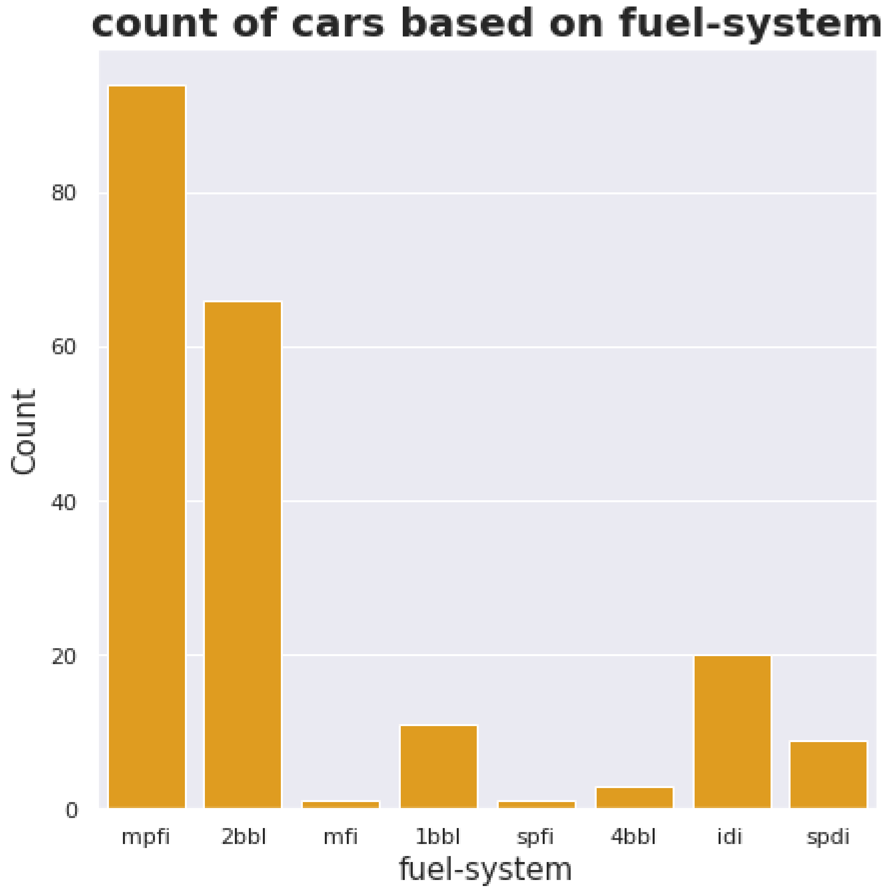
```
    plt.ylabel('Count',fontsize=15)
    plt.title('count of cars based on ' +i,fontsize=20,fontweight='bold')
```





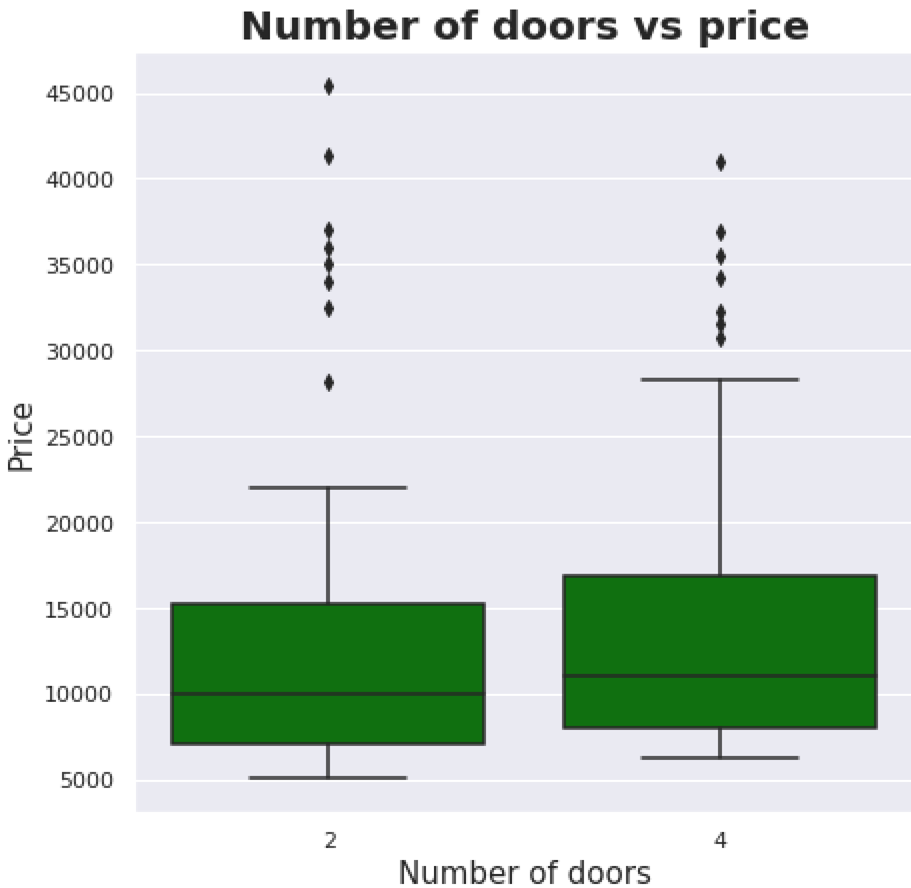

count of cars based on body-style
100
80
60
40
20
0
Count
convertible
hatchback
sedan
wagon
hardtop
body-style


count of cars based on engine-type
140
120
100
80
60
40
20
0
Count
dohc
ohcv
ohc
l
rotor
ohcf
dohcv
engine-type



Step-18: Relation between number of doors and price in boxplot

In [20]:
```
plt.subplots(figsize=(7,7))
sns.set_style("darkgrid")
sns.boxplot(x='num-of-doors',y='price',color='green',data=df)
plt.xlabel('Number of doors',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.title('Number of doors vs price',fontsize=20,fontweight='bold')
plt.show()
```



** From the boxplot we can understand that the average price of a vehicle with two doors is 10000, and the average price of a vehicle with four doors is 12000.

DATA CLEANING

Step-19: Checking the object data type columns in the dataframe

In [21]:
```
df.select_dtypes(include='object')
```

Out[21]:

	make	fuel-type	aspiration	body-style	drive-wheels	engine-location	engine-type	num-of-cylinders	fuel-system
0	alfa-romero	gas	std	convertible	rwd	front	dohc	four	mpfi
1	alfa-romero	gas	std	convertible	rwd	front	dohc	four	mpfi
2	alfa-romero	gas	std	hatchback	rwd	front	ohcv	six	mpfi
3	audi	gas	std	sedan	fwd	front	ohc	four	mpfi
4	audi	gas	std	sedan	4wd	front	ohc	five	mpfi
...	...	...	...	...	...	...	...	...	...
200	volvo	gas	std	sedan	rwd	front	ohc	four	mpfi
201	volvo	gas	turbo	sedan	rwd	front	ohc	four	mpfi
202	volvo	gas	std	sedan	rwd	front	ohcv	six	mpfi
203	volvo	diesel	turbo	sedan	rwd	front	ohc	six	idi
204	volvo	gas	turbo	sedan	rwd	front	ohc	four	mpfi

205 rows × 9 columns

Step-20: Convert categorical features to dummy variables

In [22]:
```
dummy=pd.get_dummies(df[['make','fuel-type','body-style', 'aspiration','drive-wheels',
                         'engine-location','engine-type','num-of-cylinders','fuel-system
dummy
```

Out[22]:

	make_audi	make_bmw	make_chevrolet	make_dodge	make_honda	make_isuzu	make_jaguar	make_maz
0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	
3	1	0	0	0	0	0	0	
4	1	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	
200	0	0	0	0	0	0	0	
201	0	0	0	0	0	0	0	
202	0	0	0	0	0	0	0	
203	0	0	0	0	0	0	0	
204	0	0	0	0	0	0	0	

205 rows × 49 columns

Step-21: Dropping the categorical columns from the dataframe df

In [23]:
```
df.drop(['make','fuel-type', 'aspiration','body-style','drive-wheels','engine-location',
        'num-of-cylinders','drive-wheels','engine-type','fuel-system'],axis=1,inplace=Tr
```

Step-22: Concat the dataframes

In [24]:
```
dfe=pd.concat([df,dummy],axis=1)
```

MODEL BUILDING

Step-23: Assigning input and output

In [25]:
```
x = dfe.drop("price",axis = 1).values
y = dfe["price"].values
```

Step-24: Split data for train and test

In [26]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=0)
```

Step-24: MinMaxScaler: It transforms data by scaling features to a given range

In [27]:
```
scaler=MinMaxScaler()
scaler.fit(x_train)
x_train=scaler.transform(x_train)
x_test=scaler.transform(x_test)
```

Step-25: Training and Predicting data

In [28]:
```
from sklearn.linear_model import LinearRegression   # Using Linear Regression
reg=LinearRegression()
reg.fit(x_train,y_train)
y_pred=reg.predict(x_test)
y_pred
```

Out[28]:
```
array([ 6317.49121234, 16279.25392884, 11415.57552673, -7498.03462069,
        9973.95321452, 11244.5168697 ,  5727.62674462,  4463.62557424,
       16165.08430352,  8323.51425568, 20427.37350994, 27181.45334551,
       12729.08315618, 14581.71849619,  6481.09359812, 10327.54271017,
       10864.15290736, 17042.14781679,  8620.13518081,  8012.56059349,
        9308.6426538 , 14990.29945036, 11434.6403626 , 11365.32092726,
       17616.51217513,  6971.63955767,  7396.11547906, 15509.88764122,
        7546.67581655,  5791.03344207,  9049.11448554, 11959.89341155,
       22694.86536296,  9279.52096138,  7277.64141404, 29293.50463344,
       14229.20438957, 14654.47618507,  4649.82351011, 37206.53011509,
        5235.2674832 , 12651.18929658, 34777.97286691, 21379.65645375,
       10828.45867882,  7670.19903561,  6605.30701906, 13136.61885706,
       10172.61881449, 10683.82963658, 19635.84795323,  6842.93281529,
        7255.97541734,  9756.98232837, 17449.71964832, 17396.42779201,
        8960.91296904, 17956.79718565, 10334.40348454,  6365.40562905,
        3125.09668801, 14392.30817763])
```

Step-26: Model Evaluation

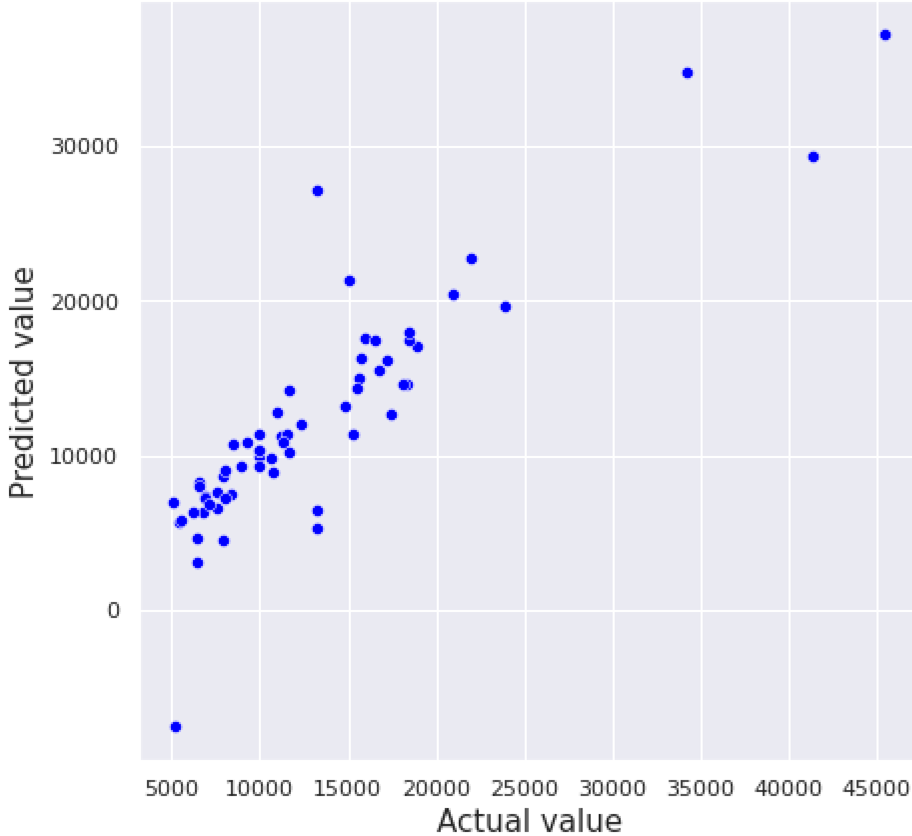
In [29]:
```
dif=pd.DataFrame({'Actual Value':y_test,'Predicted Value':y_pred})
print(dif)
```

```
    Actual Value  Predicted Value
0         6795.0      6317.491212
1        15750.0     16279.253929
2        15250.0     11415.575527
3         5151.0     -7498.034621
4         9995.0      9973.953215
..           ...              ...
57       18420.0     17956.797186
58        9960.0     10334.403485
59        6229.0      6365.405629
60        6479.0      3125.096688
61       15510.0     14392.308178

[62 rows x 2 columns]
```

In [30]:
```
plt.subplots(figsize=(7,7))
ax = sns.scatterplot(x=y_test, y=y_pred,color='blue')
plt.xlabel("Actual value",fontsize=15)
plt.ylabel("Predicted value",fontsize=15)
```

Out[30]:
```
Text(0, 0.5, 'Predicted value')
```



In [31]:
```
print("y intercept : ",reg.intercept_)
```

```
y intercept :  10291.759068734822
```

In [32]:
```
print("coefficients:",reg.coef_)
```

```
coefficients: [ 7.03865875e+02 -3.46167020e+02  1.16376348e+03  1.00803440e+04
 -9.56327628e+03  6.91928571e+03 -1.60903865e+03  1.43060592e+04
  2.71641294e+04 -8.17542031e+03 -1.86470740e+03 -1.53873389e+04
 -5.52843825e+03  5.29499596e+03 -2.08350568e+03  2.10945186e+03
  4.70574191e+02  6.01887547e+03 -2.56721711e+03 -4.70973235e+03
 -9.60658414e+02 -3.35342442e+03 -6.24588301e+02 -1.71145149e+03
  4.83908998e+03  2.18278728e-11 -4.29784193e+03 -8.80163815e+02
 -2.96356235e+03 -4.23608093e+03  7.18325912e+03 -4.00177669e-11
  2.41511793e+03 -3.02960800e+03 -2.11830465e+03 -1.04025905e+03
 -5.25296047e+02 -7.13350032e+03 -3.80189308e+03 -3.90392484e+03
 -3.80409167e+03 -4.70633956e+03  1.80667568e+03  1.99556441e+03
  3.51854050e+03  7.18325912e+03  1.04591891e-11 -2.96356235e+03
  1.99761291e+02  4.15365112e+03 -2.38554668e+03  5.46059843e+03
 -1.35915801e+03  3.76388434e+03  1.49604437e+03  0.00000000e+00
  3.90876748e+03  5.46059843e+03  2.81580333e+03  2.08116509e+02
  7.13350032e+03  2.22224857e+03  2.11066630e+03  1.11920550e+03
  3.24581422e+03]
```

In [33]:
```
print('MAE:', metrics.mean_absolute_error(y_test,y_pred))  # Mean Absolute Error (MAE)

print('MSE:', metrics.mean_squared_error(y_test,y_pred))   # Mean Squared Error (MSE)

print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test,y_pred)))  # Root Mean Squared

print('R^2 Score:', metrics.r2_score(y_test,y_pred))    # R-squared (R2)
```

```
MAE: 2243.300306103572
MSE: 14223461.941464137
RMSE: 3771.400527849586
R^2 Score: 0.7632813583401515
```

Training and Predicting using Decision Tree Regression

In [34]:
```
from sklearn.tree import DecisionTreeRegressor      # Using Decision Tree Regression
dt=DecisionTreeRegressor(max_depth=4)
dt.fit(x_train,y_train)
yd_pred = dt.predict(x_test)
yd_pred
```

Out[34]:
```
array([ 6402.        , 14793.43592847,  9480.74074074,  6402.        ,
        9480.74074074, 14793.43592847,  6402.        ,  6402.        ,
       14793.43592847,  6402.        , 22835.        , 35978.66666667,
       13309.625     , 14793.43592847,  6402.        , 14793.43592847,
       14793.43592847, 17277.5       ,  7945.71428571,  6402.        ,
       13309.625     , 14793.43592847,  9480.74074074, 14793.43592847,
       14793.43592847,  7945.71428571,  7945.71428571, 14793.43592847,
        7945.71428571,  7945.71428571,  7945.71428571, 14793.43592847,
       14793.43592847,  9480.74074074,  7945.71428571, 33690.66666667,
        7945.71428571, 14793.43592847,  6402.        , 40960.        ,
        6402.        , 14793.43592847, 35978.66666667, 14793.43592847,
        9480.74074074,  7945.71428571,  6402.        , 14793.43592847,
       14793.43592847,  7945.71428571, 21406.25      ,  7945.71428571,
        7945.71428571,  9480.74074074, 14793.43592847, 14793.43592847,
        9480.74074074, 14793.43592847,  9480.74074074,  6402.        ,
        6402.        , 14793.43592847])
```

In [35]:
```
print('MAE:', metrics.mean_absolute_error(y_test,yd_pred))   # Mean Absolute Error (MAE)

print('MSE:', metrics.mean_squared_error(y_test,yd_pred))    # Mean Squared Error (MSE)

print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test,yd_pred)))  # Root Mean Squared

print('R^2 Score:', metrics.r2_score(y_test,yd_pred))  # R-squared (R2)
```

```
MAE: 2416.618657914397
MSE: 16400319.731546937
RMSE: 4049.730822109901
R^2 Score: 0.7270522868752888
```

Training and Predicting using Random Forest Regression

In [36]:
```
from sklearn.ensemble import RandomForestRegressor
model=RandomForestRegressor(n_estimators=100)
model.fit(x_train,y_train)
yr_pred=model.predict(x_test)
yr_pred
```

Out[36]:
```
array([ 6075.81      , 16509.97      , 12915.14508706,  5793.        ,
        9761.36      , 14315.38879353,  5892.63      ,  7575.48      ,
       17484.76629353,  6742.13      , 19516.70666667, 35590.18      ,
       12357.5       , 14616.80333333,  6403.55      , 14308.47629353,
       12812.9825    , 17726.88258706,  8705.42      ,  6481.91      ,
       10311.97129353, 15687.45333333, 11404.69333333, 14838.50629353,
       17121.98129353,  7234.94      ,  7636.33      , 14391.11333333,
        8004.73      ,  6845.78      ,  8405.99333333, 12908.33175373,
       15989.11758706, 10102.75166667,  7173.9       , 33079.92      ,
        9030.15      , 16238.60017413,  5978.64      , 37209.46      ,
        6298.11      , 14692.98767413, 34855.41      , 12622.18212687,
       10155.32212687,  7821.83      ,  6714.61      , 14008.24      ,
       13440.9013806 ,  8706.68333333, 19109.3238806 ,  7395.21      ,
        8285.25      ,  9134.81833333, 17561.65758706, 17210.5188806 ,
       10022.79833333, 17260.77258706,  9043.13      ,  6347.51      ,
        5977.8       , 12947.1525    ])
```

In [37]:
```
print('MAE:', metrics.mean_absolute_error(y_test,yr_pred))   # Mean Absolute Error (MAE)

print('MSE:', metrics.mean_squared_error(y_test,yr_pred))    # Mean Squared Error (MSE)
```

```python
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test,yr_pred)))  # Root Mean Squared

print('R^2 Score:', metrics.r2_score(y_test,yr_pred))  # R-squared (R2)
```

```
MAE: 2106.959881038357
MSE: 15010295.838633325
RMSE: 3874.3123052528076
R^2 Score: 0.7501862165162868
```