

Vehicle Price Prediction - Internship Project

The goal of this project is to build a regression model to accurately predict the price of used vehicles based on their features like manufacturer, year, body, etc. reading.

Dependencies

```
In [ ]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import RandomizedSearchCV
from sklearn.preprocessing import LabelEncoder
from scipy.stats import uniform
import re
```

Data Overview

- Importing csv

```
In [247...] data = pd.read_csv("dataset.csv")
```

```
In [248...] # Set the option to display all columns
pd.set_option('display.max_columns', None)
```

```
In [249...] data.head()
```

Out[249...

	name	description	make	model	year	price	engine	cylinders	fuel	mileage	tr
0	2024 Jeep Wagoneer Series II	\n \n Heated Leather Seats, Nav Sy...	Jeep	Wagoneer	2024	74600.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	10.0	
1	2024 Jeep Grand Cherokee Laredo	Al West is committed to offering every custome...	Jeep	Grand Cherokee	2024	50170.0	OHV	6.0	Gasoline	1.0	
2	2024 GMC Yukon XL Denali	NaN	GMC	Yukon XL	2024	96410.0	6.2L V-8 gasoline direct injection, variable v...	8.0	Gasoline	0.0	
3	2023 Dodge Durango Pursuit	White Knuckle Clearcoat 2023 Dodge Durango Pur...	Dodge	Durango	2023	46835.0	16V MPFI OHV	8.0	Gasoline	32.0	
4	2024 RAM 3500 Laramie	\n \n 2024 Ram 3500 Laramie Billet...	RAM	3500	2024	81663.0	24V DDI OHV Turbo Diesel	6.0	Diesel	10.0	

- Shape

In [250...

```
shape = data.shape
print(f"No of rows {shape[0]}")
print(f"No of cols {shape[1]}")
```

No of rows 1002
No of cols 17

- Info

In [251...

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1002 entries, 0 to 1001
Data columns (total 17 columns):
#   Column                Non-Null Count  Dtype
---  -
0   name                   1002 non-null   object
1   description             946 non-null    object
2   make                   1002 non-null   object
3   model                  1002 non-null   object
4   year                   1002 non-null   int64
5   price                  979 non-null    float64
6   engine                 1000 non-null   object
7   cylinders              897 non-null    float64
8   fuel                   995 non-null    object
9   mileage                968 non-null    float64
10  transmission           1000 non-null   object
11  trim                   1001 non-null   object
12  body                   999 non-null    object
13  doors                  995 non-null    float64
14  exterior_color         997 non-null    object
15  interior_color         964 non-null    object
16  drivetrain             1002 non-null   object
dtypes: float64(4), int64(1), object(12)
memory usage: 133.2+ KB
```

In [252...

data.describe()

Out[252...

	year	price	cylinders	mileage	doors
count	1002.000000	979.000000	897.000000	968.000000	995.000000
mean	2023.916168	50202.985700	4.975474	69.033058	3.943719
std	0.298109	18700.392062	1.392526	507.435745	0.274409
min	2023.000000	0.000000	0.000000	0.000000	2.000000
25%	2024.000000	36600.000000	4.000000	4.000000	4.000000
50%	2024.000000	47165.000000	4.000000	8.000000	4.000000
75%	2024.000000	58919.500000	6.000000	13.000000	4.000000
max	2025.000000	195895.000000	8.000000	9711.000000	5.000000

- Columns name

In [253...

list(data.columns)

```
Out[253...] ['name',
             'description',
             'make',
             'model',
             'year',
             'price',
             'engine',
             'cylinders',
             'fuel',
             'mileage',
             'transmission',
             'trim',
             'body',
             'doors',
             'exterior_color',
             'interior_color',
             'drivetrain']
```

- How many nan values are their in each column

```
In [254...] data.isna().sum()
```

```
Out[254...] name          0
description    56
make          0
model         0
year          0
price         23
engine        2
cylinders     105
fuel          7
mileage       34
transmission  2
trim          1
body          3
doors         7
exterior_color 5
interior_color 38
drivetrain    0
dtype: int64
```

- Every Category in each feature

```
In [255...] print("Drive Train: ", list(data['drivetrain'].unique()))
print("Makers Names: ", list(data['make'].unique()))
print("Cylinders: ", list(data['cylinders'].unique()))
print("Fuel Types: ", list(data['fuel'].unique()))
print("cars Body Type: ", list(data['body'].unique()))
print("No. of Doors: ", list(data['doors'].unique()))
```

```
Drive Train:  ['Four-wheel Drive', 'All-wheel Drive', 'Rear-wheel Drive', 'Front-wheel Drive']
Makers Names:  ['Jeep', 'GMC', 'Dodge', 'RAM', 'Nissan', 'Ford', 'Hyundai', 'Chevrolet', 'Volk
swagen', 'Chrysler', 'Kia', 'Mazda', 'Acura', 'Subaru', 'Audi', 'BMW', 'Toyota', 'Buick', 'Mer
cedes-Benz', 'Honda', 'Lincoln', 'Cadillac', 'INFINITI', 'Lexus', 'Land Rover', 'Volvo', 'Gene
sis', 'Jaguar']
Cylinders:  [np.float64(6.0), np.float64(8.0), np.float64(4.0), np.float64(nan), np.float64(3.
0), np.float64(0.0)]
Fuel Types:  ['Gasoline', 'Diesel', 'Hybrid', 'Electric', 'E85 Flex Fuel', 'PHEV Hybrid Fuel',
nan, 'Diesel (B20 capable)']
cars Body Type:  ['SUV', 'Pickup Truck', 'Sedan', 'Passenger Van', 'Cargo Van', nan, 'Hatchbac
k', 'Convertible', 'Minivan']
No. of Doors:  [np.float64(4.0), np.float64(3.0), np.float64(nan), np.float64(2.0), np.float64
(5.0)]
```

Note: You will see nan values in category is it because it is not yet cleaned

Data Cleaning

Data Dropping and Imputation

1. Delete name and description column

```
In [256... cleanedData = data.drop(['name', 'description'], axis=1)
cleanedData.head(2)
```

Out[256...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	body
0	Jeep	Wagoneer	2024	74600.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	10.0	8-Speed Automatic	Series II	SUV
1	Jeep	Grand Cherokee	2024	50170.0	OHV	6.0	Gasoline	1.0	8-Speed Automatic	Laredo	SUV

Name column is to be deleted because the same data are already present in year, make, model, trim columns

2. Remove nan values from price

```
In [257... cleanedData.dropna(subset=['price'], inplace=True)
```

3. Remove nan values from engine

```
In [258... cleanedData[cleanedData['engine'].isna()]
```

Out[258...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	bo
614	Honda	CR-V Hybrid	2025	42150.0	NaN	4.0	Gasoline	1.0	1-Speed CVT with Overdrive	Sport Touring	SI
803	Jeep	Wagoneer	2024	73999.0	NaN	6.0	Gasoline	59.0	8-Speed Automatic	Series II	SI

```
In [259... cleanedData.loc[(cleanedData['make'] == "Honda") & (cleanedData['model'] == "CR-V Hybrid")][:]
```

Out[259...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	body
109	Honda	CR-V Hybrid	2024	42005.0	16V GDI DOHC Hybrid	4.0	Hybrid	1.0	Automatic CVT	Sport Touring	SUV
304	Honda	CR-V Hybrid	2024	36900.0	16V GDI DOHC Hybrid	4.0	Hybrid	1.0	Automatic CVT	Sport	SUV
534	Honda	CR-V Hybrid	2024	40355.0	16V GDI DOHC Hybrid	4.0	Hybrid	68.0	Automatic CVT	Sport-L	SUV

In [260...

```
cleanedData[(cleanedData['make'] == "Jeep") & (cleanedData['model'] == "Wagoneer")& (cleanedData['mileage'] != NaN)]
```

Out[260...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	body
0	Jeep	Wagoneer	2024	74600.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	10.0	8-Speed Automatic	Series II	SUV
250	Jeep	Wagoneer	2024	87488.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	22.0	8-Speed Automatic	Series II	SUV
261	Jeep	Wagoneer	2024	72908.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	NaN	8-Speed Automatic	Series II	SUV

Note: As we can see from above rows containing nan values can be filled by locating similar type of models and makers, and here they both containing same engine as founded

- 1. Honda with CR-V Hybrid have 16V GDI DOHC Hybrid engine and doors 4.0 .
- 2. Jeep with Wagoneer have 24V GDI DOHC Twin Turbo engine.

In [261...

```
cleanedData.loc[614,'engine'] = "16V GDI DOHC Hybrid"  
cleanedData.loc[614,'doors'] = np.float64(4.0)  
cleanedData.loc[803,'engine'] = "24V GDI DOHC Twin Turbo"
```

In [262...

```
cleanedData.isna().sum()
```

Out[262... make 0
model 0
year 0
price 0
engine 0
cylinders 102
fuel 7
mileage 34
transmission 2
trim 1
body 3
doors 6
exterior_color 5
interior_color 37
drivetrain 0
dtype: int64

4. Remove nan values from transmission

```
In [263... cleanedData[cleanedData['transmission'].isna()]
```

Out[263...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	
725	Mercedes-Benz	EQS 450	2024	111245.0	c	NaN	Electric	10.0	NaN	Base 4MATIC	S
940	Ford	Transit-350	2024	52530.0	24V PDI DOHC Flexible Fuel	6.0	E85 Flex Fuel	1.0	NaN	148 WB Medium Roof Cargo	C

```
In [264... cleanedData[(cleanedData['make'] == "Ford") & (cleanedData['model'] == "Transit-350") & (cleanedData['transmission'].notna())]
```

Out[264...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	body	d
793	Ford	Transit-350	2023	57000.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	5581.0	10-Speed Automatic	Base	Cargo Van	
805	Ford	Transit-350	2023	54525.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	0.0	10-Speed Automatic	NaN	Cargo Van	

```
In [265... cleanedData[(cleanedData['make'] == "Mercedes-Benz") & (cleanedData['model'] == "EQS 450") & (cleanedData['transmission'].notna())]
```

Out[265...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	body
253	Mercedes-Benz	EQS 450	2024	110395.0	c	NaN	Electric	5.0	Automatic	Base 4MATIC	Sedan
484	Mercedes-Benz	EQS 450	2024	117985.0	c	NaN	Electric	1.0	Automatic	Base 4MATIC	Sedan
725	Mercedes-Benz	EQS 450	2024	111245.0	c	NaN	Electric	10.0	NaN	Base 4MATIC	Sedan

Note: Same approach is used here looking at the same make, model, engine or body we can find same cars

- Mercedes-Benz of model EQS 450 and body Sedan have transmission Automatic
- Ford of model Transit-350 and engine 24V GDI DOHC Twin Turbo have transmission 10-Speed Automatic

In [266...

```
cleanedData.loc[725,'transmission'] = "Automatic"
cleanedData.loc[940,'transmission'] = "10-Speed Automatic"
```

In [267...

```
cleanedData.isna().sum()
```

Out[267...

make	0
model	0
year	0
price	0
engine	0
cylinders	102
fuel	7
mileage	34
transmission	0
trim	1
body	3
doors	6
exterior_color	5
interior_color	37
drivetrain	0
dtype: int64	

5. Remove nan values from trim

In [268...

```
cleanedData[cleanedData['trim'].isna()]
```

Out[268...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	body	doors
805	Ford	Transit-350	2023	54525.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	0.0	10-Speed Automatic	NaN	Cargo Van	4

In [269...

```
cleanedData[(cleanedData['make'] == "Ford") & (cleanedData['model'] == "Transit-350") & (cleanedData['body'] == "Cargo Van")]
```


Out[269...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	body	d
793	Ford	Transit-350	2023	57000.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	5581.0	10-Speed Automatic	Base	Cargo Van	
805	Ford	Transit-350	2023	54525.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	0.0	10-Speed Automatic	NaN	Cargo Van	



In [270...

```
cleanedData.loc[805, 'trim'] = "base"
```

In [271...

```
cleanedData.isna().sum()
```

Out[271...

```
make          0
model         0
year          0
price         0
engine        0
cylinders    102
fuel          7
mileage      34
transmission  0
trim          0
body          3
doors         6
exterior_color 5
interior_color 37
drivetrain    0
dtype: int64
```

6. Remove nan values from body

In [272...

```
cleanedData[cleanedData['body'].isna()]
```

Out[272...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	bod
164	Dodge	Hornet	2024	41497.0	4 gasoline direct injection, DOHC, Multiair va...	4.0	Gasoline	11.0	6-Speed Automatic	R/T EAWD	Na
235	Dodge	Hornet	2024	41036.0	4 gasoline direct injection, DOHC, Multiair va...	4.0	Gasoline	5.0	6-Speed Automatic	R/T EAWD	Na

687	INFINITI	QX50	2024	49404.0	ER	4.0	Gasoline	7.0	(CVT) CONT VAR.	SPORT	Na
-----	----------	------	------	---------	----	-----	----------	-----	-----------------	-------	----



In [273...

cleanedData[(cleanedData['make'] == "INFINITI") & (cleanedData['model'] == "QX50")][:3]

Out[273...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	bc
167	INFINITI	QX50	2024	48350.0	o 2L I-4 port/direct injection, DOHC, variable...	4.0	Gasoline	3.0	Variable	LUXE	S
335	INFINITI	QX50	2024	45055.0	o 2L I-4 port/direct injection, DOHC, variable...	4.0	Gasoline	25.0	Variable	LUXE	S
687	INFINITI	QX50	2024	49404.0	ER	4.0	Gasoline	7.0	(CVT) CONT VAR.	SPORT	N

In [274...

cleanedData[(cleanedData['make'] == "Dodge") & (cleanedData['model'] == "Hornet") & (cleanedData['body'] == "SUV")]

Out[274...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	body
55	Dodge	Hornet	2024	42855.0	4 gasoline direct injection, DOHC, Multiair va...	4.0	Gasoline	5.0	6-Speed Automatic	R/T EAWD	SUV
164	Dodge	Hornet	2024	41497.0	4 gasoline direct injection, DOHC, Multiair va...	4.0	Gasoline	11.0	6-Speed Automatic	R/T EAWD	NaN
235	Dodge	Hornet	2024	41036.0	4 gasoline direct injection, DOHC, Multiair va...	4.0	Gasoline	5.0	6-Speed Automatic	R/T EAWD	NaN

In [275...

cleanedData.loc[164, 'body'] = "SUV"
cleanedData.loc[235, 'body'] = "SUV"
cleanedData.loc[687, 'body'] = "SUV"

In [276...

cleanedData.isna().sum()

Out[276... make 0
model 0
year 0
price 0
engine 0
cylinders 102
fuel 7
mileage 34
transmission 0
trim 0
body 0
doors 6
exterior_color 5
interior_color 37
drivetrain 0
dtype: int64

7. Remove nan values from fuel

```
In [277... cleanedData[cleanedData['fuel'].isna()]
```

Out[277...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	
128	Subaru	Solterra	2024	39934.0		c	NaN	NaN	5.0	1-Speed Automatic
219	Honda	Prologue	2024	55800.0		c	NaN	NaN	NaN	1-Speed Automatic
315	Honda	Prologue	2024	56550.0		c	NaN	NaN	1.0	1-Speed Automatic
489	Honda	Prologue	2024	55800.0		c	NaN	NaN	NaN	1-Speed Automatic
490	Honda	Prologue	2024	55800.0		c	NaN	NaN	NaN	1-Speed Automatic
610	Chevrolet	Equinox EV	2024	47495.0	<dt>VIN</dt>\n3GN7DNRXPXRS232327		NaN	NaN	0.0	Automatic
726	Jaguar	I-PACE	2024	77053.0	d>\n\n \n<dt>VIN</dt>\nSADHM2S12R1...		NaN	NaN	8.0	Automatic

```
In [278... cleanedData['fuel'].value_counts()
```

Out[278... fuel
Gasoline 647
Hybrid 135
Electric 96
Diesel 72
PHEV Hybrid Fuel 16
E85 Flex Fuel 5
Diesel (B20 capable) 1
Name: count, dtype: int64

Note: Generally all cars have fuel type gasoline so we are going to replace all nan value with Gasoline

```
In [279... cleanedData.fillna({'fuel': "Gasoline"}, inplace=True)
```

8. Remove nan values from doors

```
In [280... cleanedData['doors'].value_counts()
```

```
Out[280... doors
4.0    926
3.0     37
2.0      9
5.0      1
Name: count, dtype: int64
```

- Generally every car comes with 4 doors so nan values in doors columns are going to fill with 4

```
In [281... cleanedData.fillna({'doors':4},inplace=True)
```

```
In [282... cleanedData.isna().sum()
```

```
Out[282... make            0
model            0
year            0
price           0
engine          0
cylinders       102
fuel            0
mileage         34
transmission     0
trim            0
body            0
doors           0
exterior_color   5
interior_color   37
drivetrain       0
dtype: int64
```

9. Remove nan values from exterior_colors

```
In [283... cleanedData[cleanedData['exterior_color'].isna()][:3]
```

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim
					ar 3.6L V-6 DOHC, variable valve control, regu...					
117	Jeep	Wrangler	2024	59456.0		6.0	Gasoline	15.0	Automatic	4-Door Sahara 4x4
137	Acura	ZDX	2024	69850.0	c	0.0	Electric	0.0	Automatic	A-SPEC
373	Mercedes-Benz	EQS 450	2024	114850.0	c	NaN	Electric	8.0	1-Speed Automatic	Base 4MATIC

```
In [284... cleanedData['exterior_color'].value_counts()
```

```
Out[284...] exterior_color
Bright White Clearcoat      80
Black                       31
White                       29
Gray                        25
Summit White                25
..
Aspen White / Super Black   1
Jungle Green                1
Cactus Gray                 1
Pearl White Tricoat         1
Wheatland Yellow           1
Name: count, Length: 262, dtype: int64
```

- It is going to be filled with `Bright White Clearcoat` because most of the cars used it

```
In [285...] cleanedData.fillna({'exterior_color': 'Bright White Clearcoat'},inplace=True)
```

10. Remove nan values from cylinders

```
In [286...] cleanedData[cleanedData['cylinders'].isna()][:3]
```

```
Out[286...]
   make  model  year  price  engine  cylinders  fuel  mileage  transmission  trim  body  d
14  Chevrolet  Blazer EV  2024  51695.0      c      NaN  Electric      4.0  1-Speed Automatic  2LT  SUV
28  Chevrolet  Blazer EV  2024  52190.0      c      NaN  Electric      6.0  1-Speed Automatic  2LT  SUV
33      Kia    EV6  2024  49820.0      c      NaN  Electric     13.0  Automatic      GT  SUV
```

```
In [287...] cleanedData[cleanedData['fuel'] == "Gasoline"]['cylinders'].value_counts()
```

```
Out[287...]
cylinders
4.0      336
6.0      203
8.0       80
3.0       27
Name: count, dtype: int64
```

- We are going to fill `4` in cylinders whose `cylinders` are `Nan` and fuel type is `Gasoline`

```
In [288...] cleanedData.loc[(cleanedData['cylinders'].isna()) & (cleanedData['fuel'] == 'Gasoline'),'cylinders']
```

- Correctly assign `Electric` to EVs and 0 cylinders before general imputation.
- This is based on the observation that EVs often have engine type `C`.

```
In [289...] cleanedData.loc[cleanedData['engine'] == 'C', 'fuel'] = 'Electric'
cleanedData.loc[(cleanedData['cylinders'].isna()) & (cleanedData['fuel'] == 'Electric'),'cylinders']
```

11. Remove nan values from mileage

```
In [290...] cleanedData[cleanedData['mileage'].isna()][:3]
```

Out[290...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim
27	Chrysler	Pacifica	2024	48705.0	24V MPFI DOHC	6.0	Gasoline	NaN	9-Speed Automatic	Touring-L
47	Subaru	Outback	2024	44354.0	16V GDI DOHC Turbo	4.0	Gasoline	NaN	Automatic CVT	Wilderness
63	Jeep	Grand Cherokee L	2024	51360.0	24V MPFI DOHC	6.0	Gasoline	NaN	8-Speed Automatic	Limited

In [291...

cleanedData['mileage'].value_counts()

Out[291...

```
mileage
5.0      113
0.0       109
10.0      103
1.0        58
6.0        50
...
241.0      1
66.0       1
41.0       1
141.0      1
296.0      1
Name: count, Length: 91, dtype: int64
```

- Generally the milage is 5.0 so we are going to replace it with nan values

In [292...

cleanedData.fillna({'mileage': 5.0},inplace=True)

12. Removing unusual data values in engine

In [293...

```
# Drop rows where 'engine' contains the '<dt' tag (case-insensitive)
mask = cleanedData['engine'].astype(str).str.contains(r'<dt', case=False, na=False)
print(f"Removing {mask.sum()} rows containing '<dt' in engine")
# Optional inspect
display(cleanedData.loc[mask, ['engine']].head(10))
# Drop and reset index
cleanedData = cleanedData.loc[~mask].reset_index(drop=True)
print("New shape:", cleanedData.shape)
```

Removing 8 rows containing '<dt' in engine

engine

```
195 >\n\n\n <dt>VIN</dt>\n ZACNDFAN0R3A...
255 dd>\n\n\n <dt>VIN</dt>\n 1V2BMPE85R...
474 >\n\n\n <dt>VIN</dt>\n ZACNDFAN0R3A...
610 <dt>VIN</dt>\n 3GN7DNRPXRS232327
685 <dt>VIN</dt>\n 1FMUK7HH1SGA05728
705 <dt>VIN</dt>\n 3C63R3HLXRG198198
726 d>\n\n\n <dt>VIN</dt>\n SADHM2S12R1...
893 d>\n\n\n <dt>VIN</dt>\n 7FARS4H71SE...
```

New shape: (971, 15)

13. Remove nan values from interior_colors

```
In [294... cleanedData['interior_color'].value_counts()
```

```
Out[294... interior_color
Black                492
Global Black         83
Gray                 76
Jet Black            45
Ebony                37
...
Caramel              1
gray                 1
Dark Palazzo         1
Gray/Black           1
Navy Pier            1
Name: count, Length: 88, dtype: int64
```

- Here **Black** interior is the most commone one

```
In [295... cleanedData.fillna({'interior_color':'Black'},inplace=True)
```

```
In [296... cleanedData.isna().sum()
```

```
Out[296... make                0
model                0
year                0
price               0
engine              0
cylinders           0
fuel               0
mileage            0
transmission        0
trim               0
body               0
doors              0
exterior_color      0
interior_color      0
drivetrain          0
dtype: int64
```

```
In [297... cleanedData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 971 entries, 0 to 970
```

```
Data columns (total 15 columns):
```

#	Column	Non-Null Count	Dtype
0	make	971 non-null	object
1	model	971 non-null	object
2	year	971 non-null	int64
3	price	971 non-null	float64
4	engine	971 non-null	object
5	cylinders	971 non-null	float64
6	fuel	971 non-null	object
7	mileage	971 non-null	float64
8	transmission	971 non-null	object
9	trim	971 non-null	object
10	body	971 non-null	object
11	doors	971 non-null	float64
12	exterior_color	971 non-null	object
13	interior_color	971 non-null	object
14	drivetrain	971 non-null	object

```
dtypes: float64(4), int64(1), object(10)
```

```
memory usage: 113.9+ KB
```

Detecting Outliers

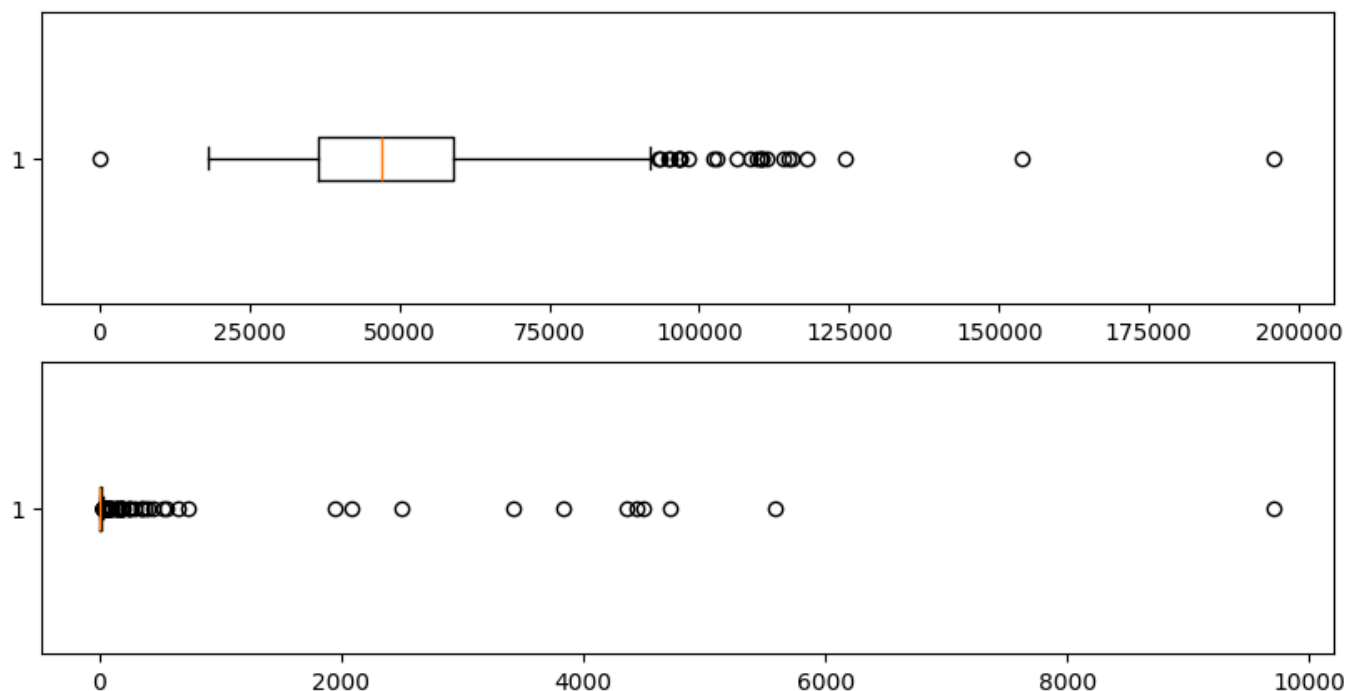
Possible Outliers can exist in:

- price
- mileage

Before Removing Outliers

In [298...

```
fig, axs = plt.subplots(2,1, figsize=(10, 5)) # 2 rows, 2 columns
axs[0].boxplot(cleanedData['price'],orientation='horizontal')
axs[1].boxplot(cleanedData['mileage'],orientation='horizontal')
plt.show()
```



In [299...

```
# Calculate IQR for the 'price' column
Q1_price = cleanedData['price'].quantile(0.25)
Q3_price = cleanedData['price'].quantile(0.75)
IQR_price = Q3_price - Q1_price
lower_bound_price = Q1_price - 1.5 * IQR_price
```



```

upper_bound_price = Q3_price + 1.5 * IQR_price

# Calculate IQR for the 'mileage' column
Q1_mileage = cleanedData['mileage'].quantile(0.25)
Q3_mileage = cleanedData['mileage'].quantile(0.75)
IQR_mileage = Q3_mileage - Q1_mileage
lower_bound_mileage = Q1_mileage - 1.5 * IQR_mileage
upper_bound_mileage = Q3_mileage + 1.5 * IQR_mileage

# Filter the DataFrame to remove outliers from both columns
cleanedData = cleanedData[
    (cleanedData['price'] >= lower_bound_price) &
    (cleanedData['price'] <= upper_bound_price) &
    (cleanedData['mileage'] >= lower_bound_mileage) &
    (cleanedData['mileage'] <= upper_bound_mileage)
]

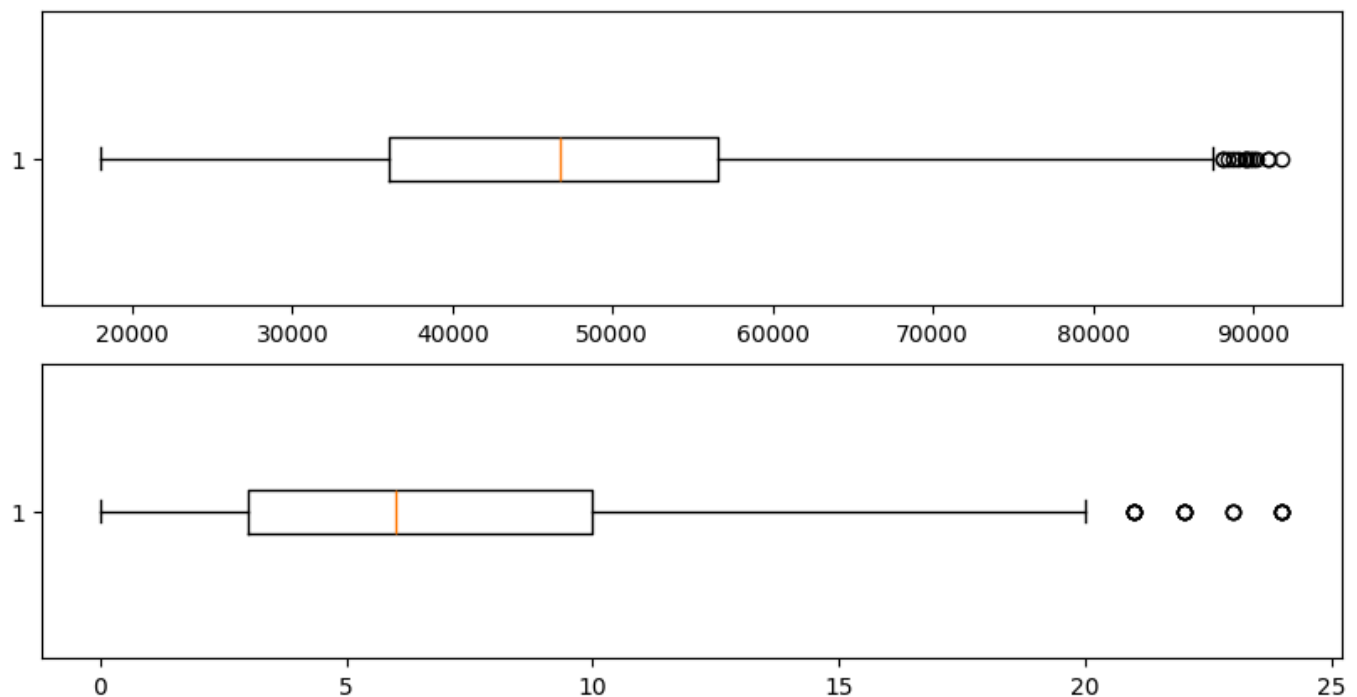
```

After Removing Outliers

```

In [300... fig, axs = plt.subplots(2,1, figsize=(10, 5)) # 2 rows, 2 columns
axs[0].boxplot(cleanedData['price'],orientation='horizontal')
axs[1].boxplot(cleanedData['mileage'],orientation='horizontal')
plt.show()

```



Shape now after cleaning the data

```

In [301... shape = cleanedData.shape
print(f"No. of rows: {shape[0]}")
print(f"No. of rows removed: {data.shape[0]-shape[0]}")

```

No. of rows: 840

No. of rows removed: 162

EDA

1. Create a Histogram of Price to see the distribution of price

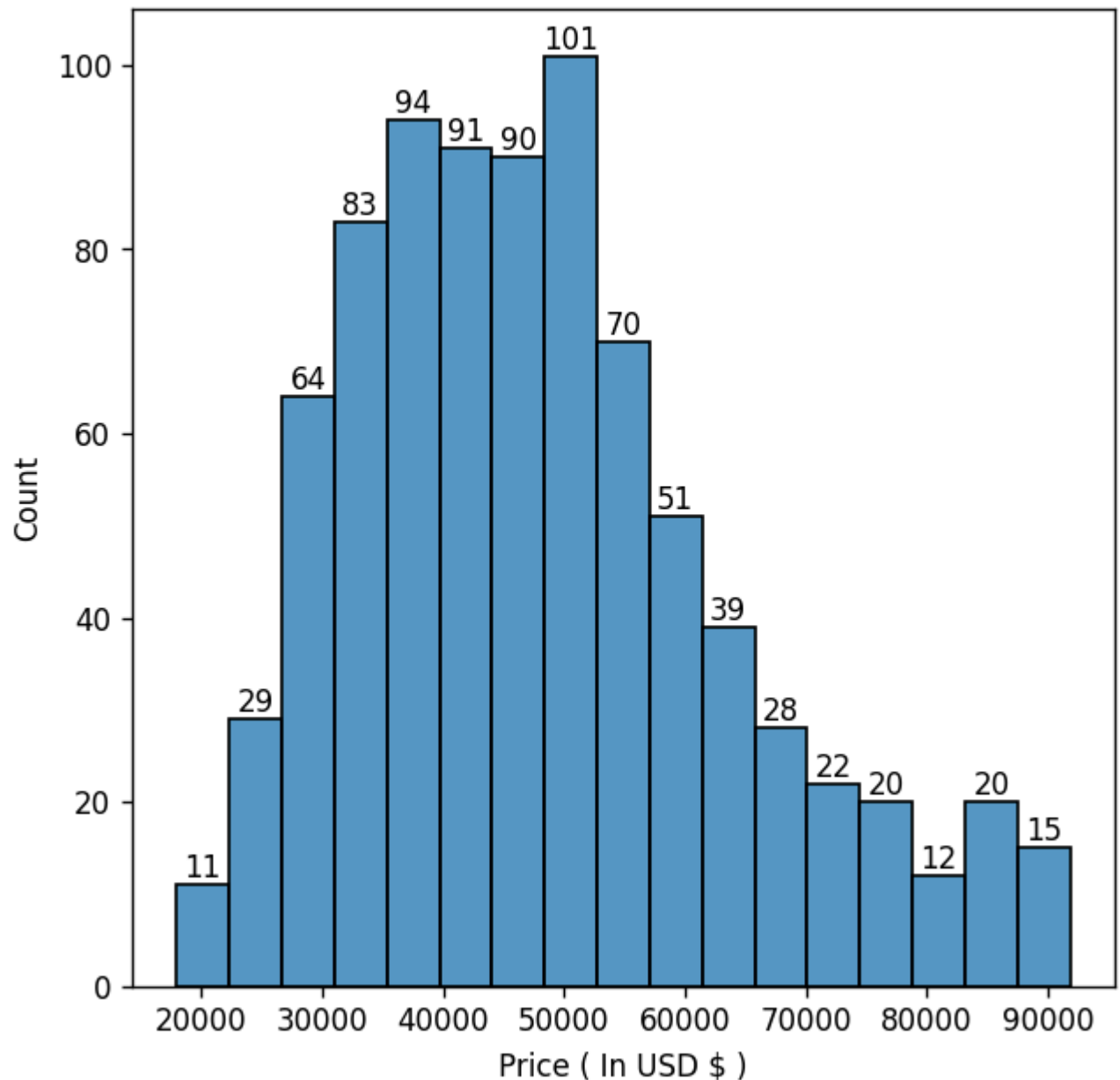
```

In [302... plt.figure(figsize=(6,6),dpi=120)
ax = sns.histplot(cleanedData['price'])
ax.bar_label(ax.containers[0],fontsize = 10)
ax.set_xlabel("Price ( In USD $ )")

```

```
ax.set_ylabel("Count")
ax.set_title("Price Distribution",fontdict={'weight':"bold",'size':24},pad=20)
plt.show()
```

Price Distribution



2. We will create a Bar graph of `make` feature to how many cars in total is made by each maker

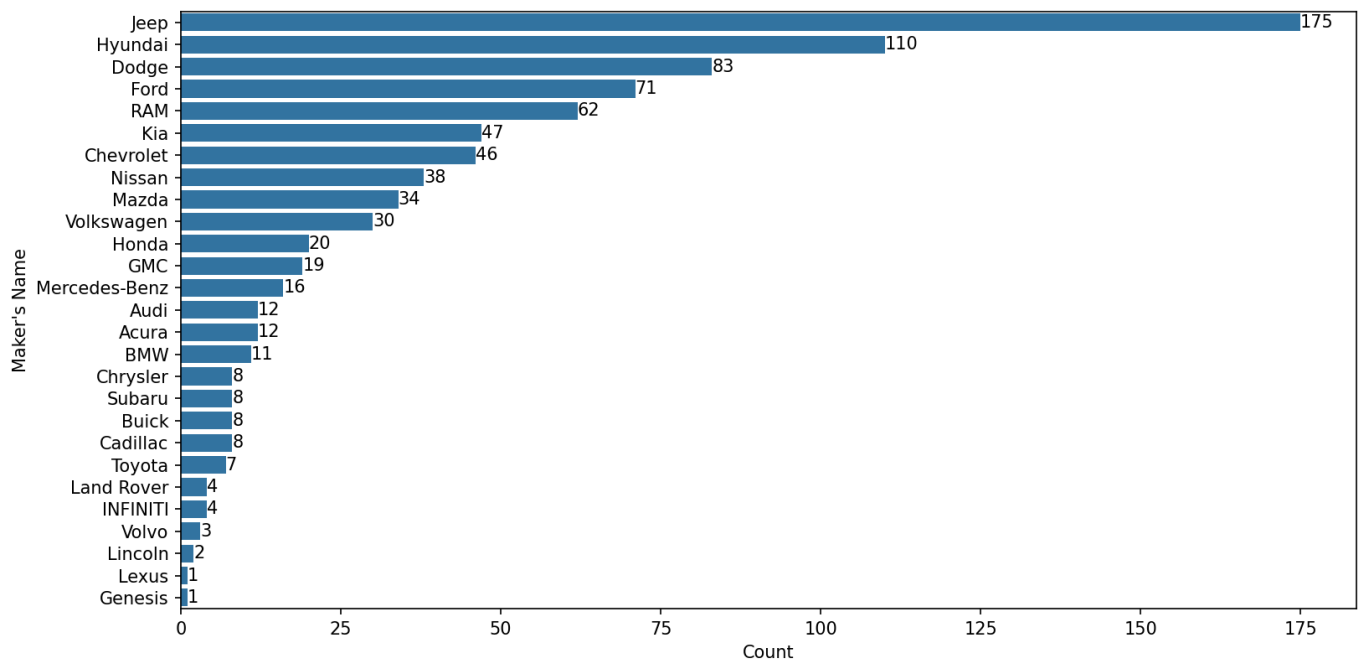
In [303...

```
plt.figure(figsize=(11,6),dpi=150)

ax = sns.barplot(data=cleanedData['make'].value_counts(),errorbar=None,estimator="sum",orient="vertical")
ax.bar_label(ax.containers[0],fontsize = 10)
ax.set_xlabel("Count")
ax.set_ylabel("Maker's Name")
ax.set_title("Value Count of each Car Maker",loc="left",fontdict={'weight':"bold",'size':24},fontstyle="italic")

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

Value Count of each Car Maker

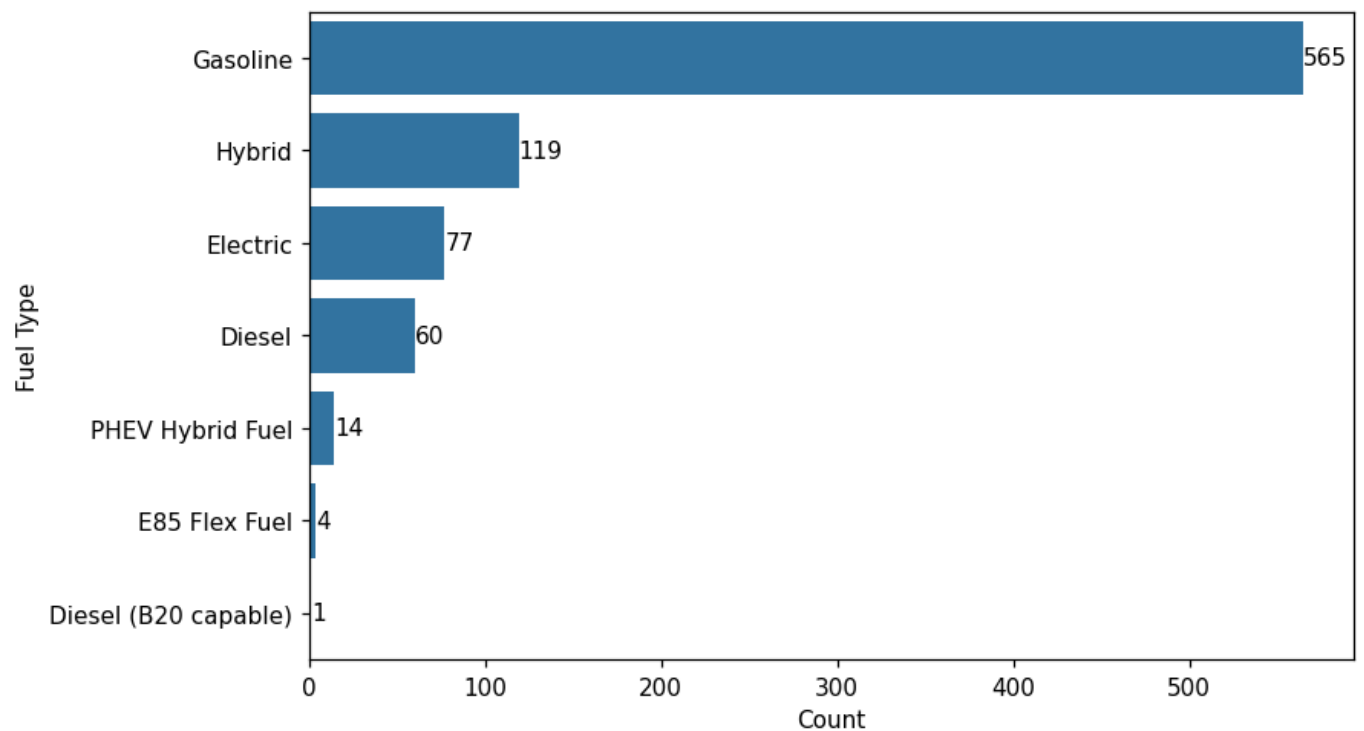


3. Create a Histogram of fuel

In [304...

```
plt.figure(figsize=(8,5),dpi=110)
ax = sns.barplot(cleanedData['fuel'],value_counts(),errorbar=None,orient='y')
ax.bar_label(ax.containers[0],fontsize = 10)
ax.set_xlabel("Count")
ax.set_ylabel("Fuel Type")
ax.set_title("Fuel Distribution",fontdict={'weight':"bold",'size':24},pad=20,loc='left')
plt.show()
```

Fuel Distribution

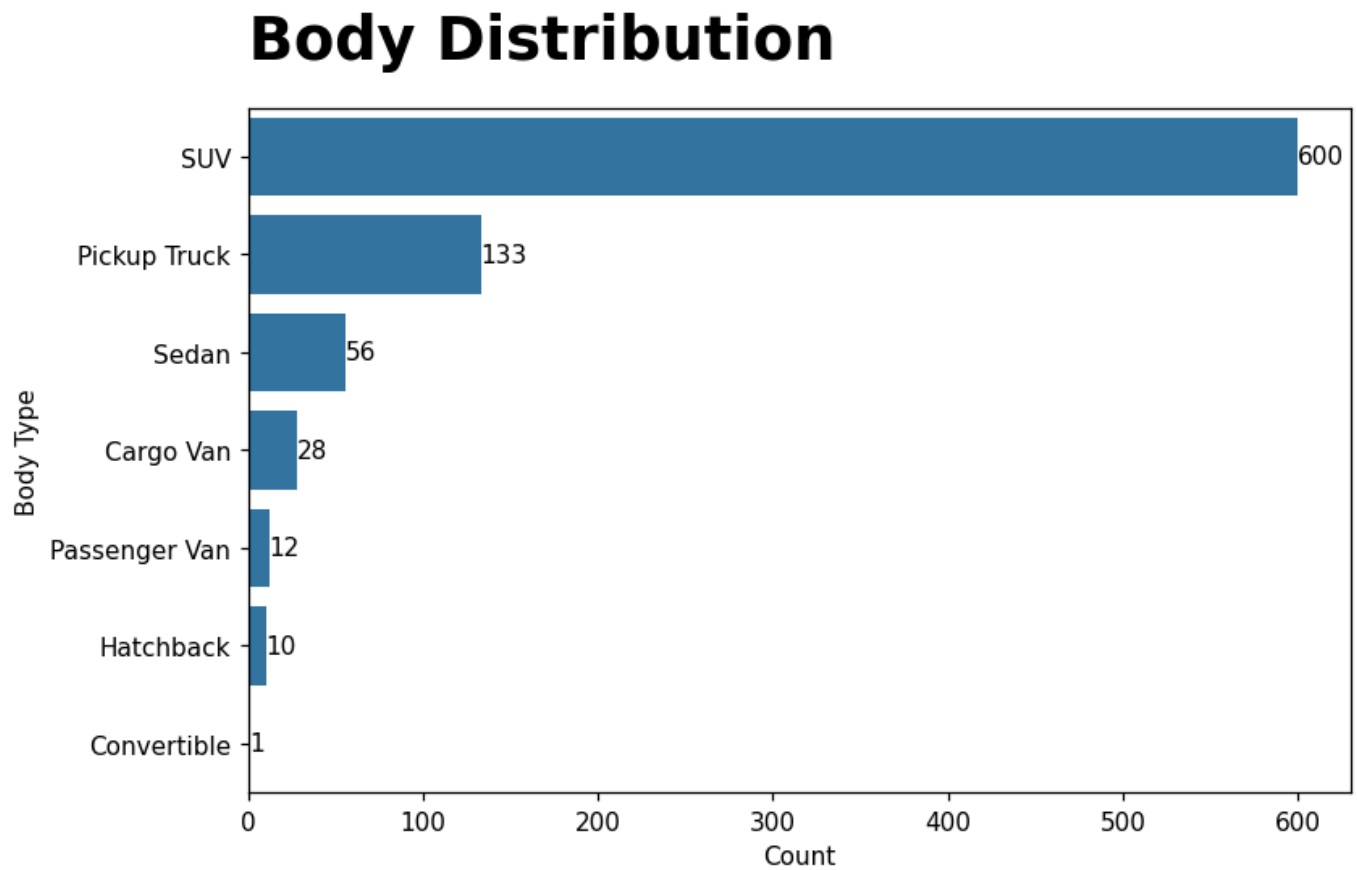


4. Create a Bar graph of Body do see general body type of all cars

In [305...

```
plt.figure(figsize=(8,5),dpi=110)
ax = sns.barplot(cleanedData['body'],value_counts(),errorbar=None,orient='y')
ax.bar_label(ax.containers[0],fontsize = 10)
```

```
ax.set_xlabel("Count")
ax.set_ylabel("Body Type")
ax.set_title("Body Distribution",fontdict={'weight':"bold",'size':24},pad=20,loc='left')
plt.show()
```



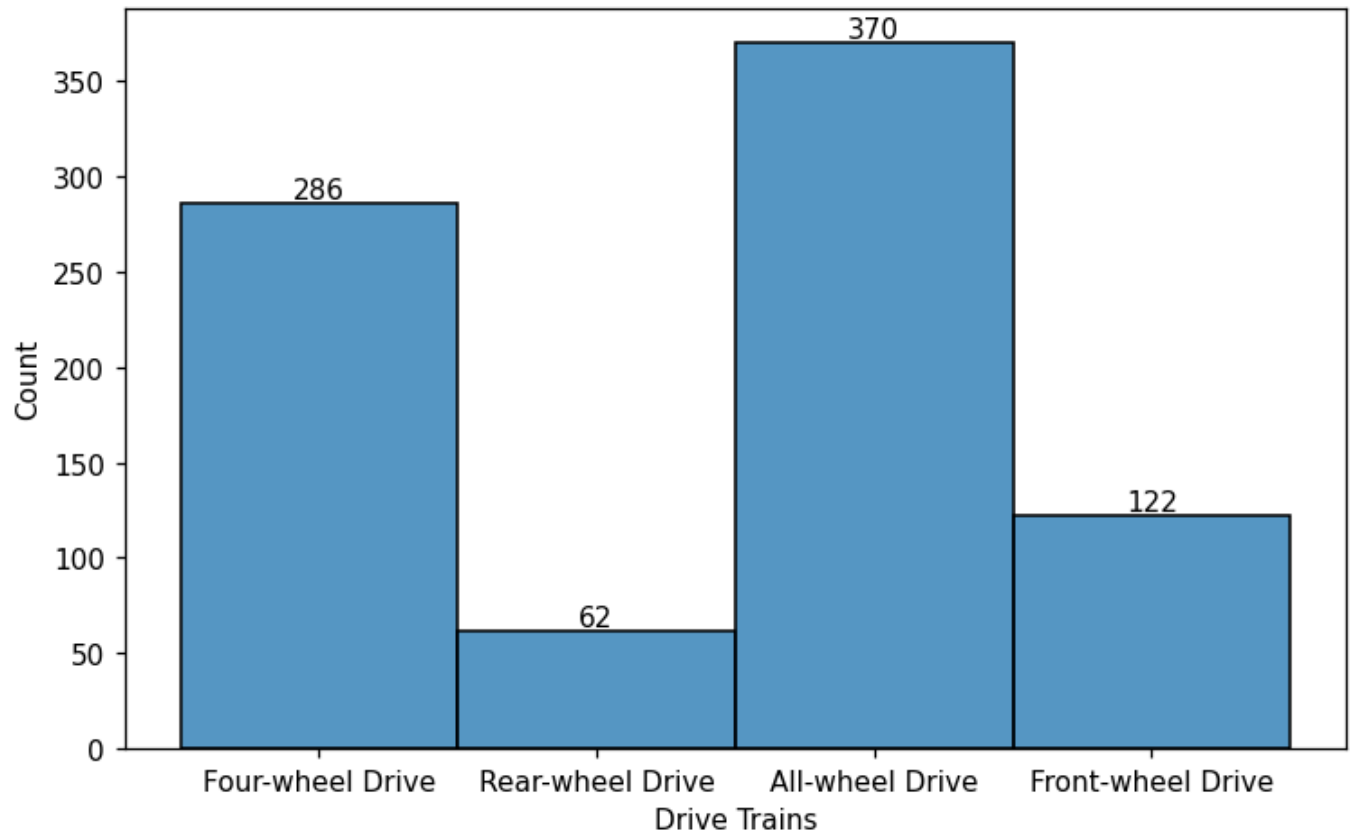
5. Create a Bar Graph of `drivetrain`

In [306...

```
plt.figure(figsize=(7,5),dpi=110)

ax = sns.histplot(cleanedData['drivetrain'])
ax.bar_label(ax.containers[0],fontsize = 10)
ax.tick_params(axis='x')
ax.set_xlabel("Drive Trains")
ax.set_ylabel("Count")
ax.set_title("Types of Drive train",fontdict={'weight':"bold",'size':24},pad=20)
plt.tight_layout()
plt.show()
```

Types of Drive train



6. Create a scatter plot where x axis makers name in ascending order of price and y axis show price (The idea to show how much each company spend)

In [307...

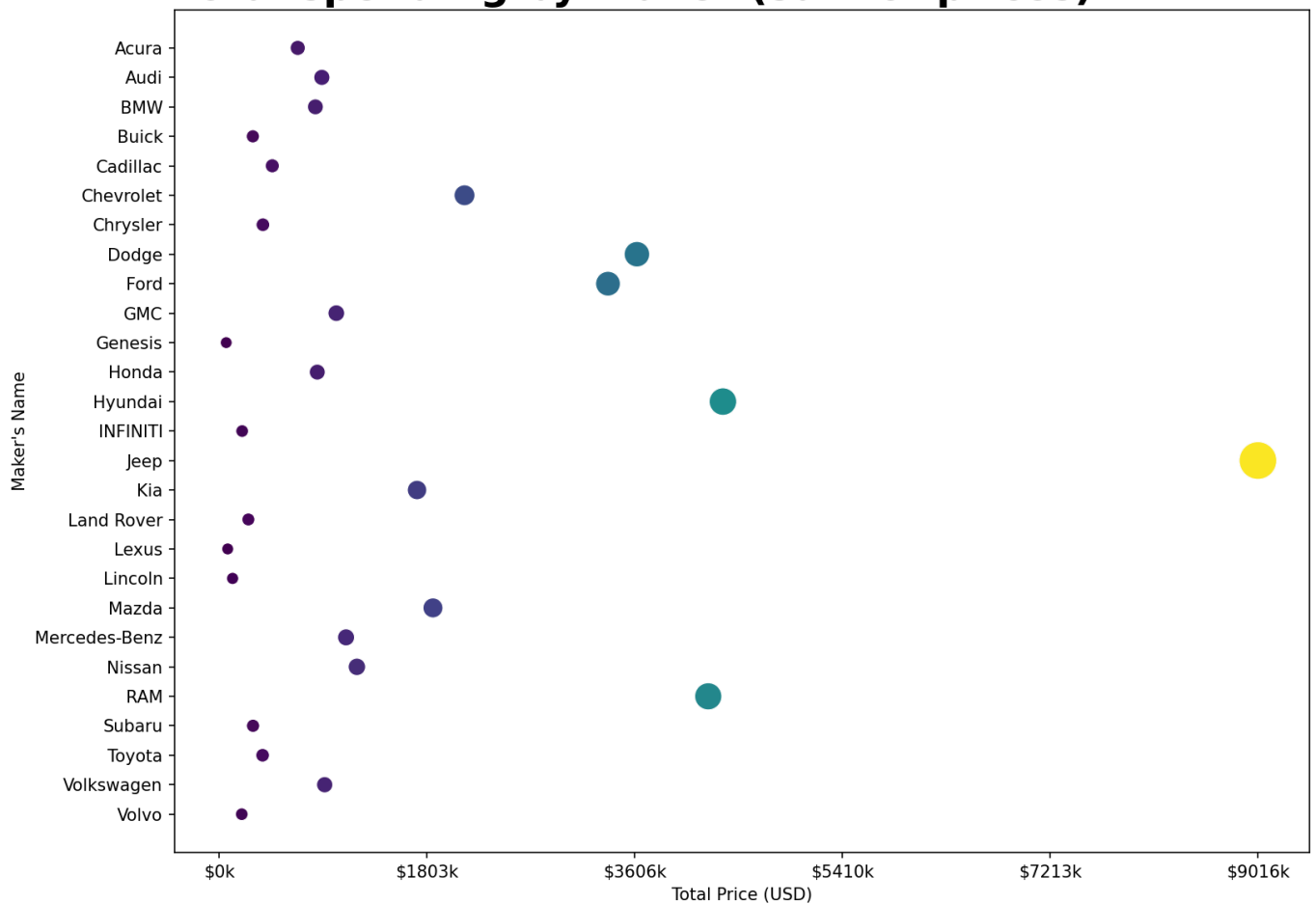
```
import matplotlib.ticker as ticker

make_price = cleanedData.groupby('make', as_index=False)['price'].sum()
make_price
plt.figure(figsize=(11,8), dpi=150)
ax = sns.scatterplot(
    data=make_price,
    x='price',
    y='make',
    size='price',
    hue='price',
    sizes=(50, 500),
    palette='viridis',
    legend=False
)

max_price = make_price['price'].max()
ticks = np.linspace(0, max_price, 6)
ax.set_xticks(ticks)
ax.xaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: f'${x/1000:.0f}k'))

ax.set_xlabel('Total Price (USD)')
ax.set_ylabel("Maker's Name")
ax.set_title("Total spending by maker (sum of prices)", loc='left', fontdict={'weight':'bold'})
plt.tight_layout()
plt.show()
```

Total spending by maker (sum of prices)



Feature Engineering

1. Make a Prediction data for Feature Engineering and Model training

```
In [308... predictionData = cleanedData[['make', 'model', 'year', 'price', 'engine', 'cylinders', 'fuel'
```

```
In [309... predictionData.head()
```

Out[309...

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	body
0	Jeep	Wagoneer	2024	74600.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	10.0	8-Speed Automatic	Series II	SUV
1	Jeep	Grand Cherokee	2024	50170.0	OHV	6.0	Gasoline	1.0	8-Speed Automatic	Laredo	SUV
4	RAM	3500	2024	81663.0	24V DDI OHV Turbo Diesel	6.0	Diesel	10.0	6-Speed Automatic	Laramie	Pickup Truck
6	Jeep	Wagoneer	2024	63862.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	5.0	8-Speed Automatic	Base	SUV
7	Ford	F-350	2024	89978.0	32V DDI OHV Turbo Diesel	8.0	Diesel	15.0	10-Speed Automatic	Lariat Super Duty	Pickup Truck

2. Engine Feature Extraction

In [310...

```
# --- Feature Engineering from 'engine' column ---
predictionData['engine_liters'] = predictionData['engine'].str.extract(r'(\d\.\d*)L', flags=re.IGNORECASE)
predictionData['is_turbo'] = predictionData['engine'].str.contains('Turbo', case=False, na=False)
predictionData['is_hybrid'] = predictionData['engine'].str.contains('Hybrid', case=False, na=False)
predictionData['valve_count'] = predictionData['engine'].str.extract(r'(\d{1,2})V', flags=re.IGNORECASE)

# --- Handle Missing Values in New Columns (Warning-Free Method) ---
# Reassign the column instead of using inplace=True
median_liters = predictionData['engine_liters'].median()
predictionData['engine_liters'] = predictionData['engine_liters'].fillna(median_liters)

median_valves = predictionData['valve_count'].median()
predictionData['valve_count'] = predictionData['valve_count'].fillna(median_valves)

# This syntax is also fine for the binary flags
predictionData['is_turbo'] = predictionData['is_turbo'].fillna(0)
predictionData['is_hybrid'] = predictionData['is_hybrid'].fillna(0)

# --- Clean Up ---
# Drop the original 'engine' column as it's no longer needed
predictionData.drop('engine', axis=1, inplace=True)

print("New engineered features:")
print(predictionData[['engine_liters', 'is_turbo', 'is_hybrid', 'valve_count']].head())
```

New engineered features created without warnings:

	engine_liters	is_turbo	is_hybrid	valve_count
0	3.6	1	0	24.0
1	3.6	0	0	16.0
4	3.6	1	0	24.0
6	3.6	1	0	24.0
7	3.6	1	0	32.0

3. Trim Feature Extraction

```
In [319... # --- Feature Engineering for 'trim' ---

# Calculate how many times each trim appears
trim_counts = predictionData['trim'].value_counts()

# Identify trims that appear less than, say, 5 times
rare_trims = trim_counts[trim_counts < 5].index

# Replace these rare trims with the category 'Other'
predictionData['trim_cleaned'] = predictionData['trim'].replace(rare_trims, 'Other')

# Drop the original trim column
predictionData.drop('trim', axis=1, inplace=True)
```

4. Feature extraction of Model

```
In [323... # --- Feature Engineering for 'model' ---

# Calculate how many times each model appears
model_counts = predictionData['model'].value_counts()

# Identify models that appear less than, say, 10 times
rare_models = model_counts[model_counts < 10].index

# Replace these rare models with the category 'Other'
predictionData['model_cleaned'] = predictionData['model'].replace(rare_models, 'Other')

# Now you can one-hot encode 'model_cleaned' instead of the original 'model'
# Don't forget to drop the original 'model' column
predictionData.drop('model', axis=1, inplace=True)
```

5. Feature Extraction of transmission

```
In [324... # --- Improved Feature Engineering for 'transmission' ---

# 1. Extract the number of speeds (gears) - This part remains the same.
predictionData['gears'] = predictionData['transmission'].str.extract(r'(\d{1,2})-Speed', flag

# 2. Create a categorical 'transmission_type' column
# Define conditions for each transmission type. Order is important: check for CVT first.
conditions = [
    predictionData['transmission'].str.contains('CVT', case=False, na=False),
    predictionData['transmission'].str.contains('Automatic', case=False, na=False)
]

# Define the values to assign for each condition
choices = ['CVT', 'Automatic']

# Create the new column using np.select
# If a value is neither CVT nor Automatic, it will be labeled 'Other'
predictionData['transmission_type'] = np.select(conditions, choices, default='Other')
```



```
# --- Handle Missing Values and Clean Up ---

# Fill any missing gear counts with the median
predictionData['gears'] = predictionData['gears'].fillna(predictionData['gears'].median())

# Drop the original transmission column
predictionData.drop('transmission', axis=1, inplace=True)

# Now, one-hot encode the new 'transmission_type' column along with your other categoricals.

print("Improved transmission features:")
print(predictionData[['gears', 'transmission_type']].head())
```

Improved transmission features:

	gears	transmission_type
0	8.0	Automatic
1	8.0	Automatic
4	6.0	Automatic
6	8.0	Automatic
7	10.0	Automatic

6. Add an Age feature which shows the age of a car

In [311...

```
# Example
current_year = 2024
predictionData.loc[:, 'age'] = current_year - predictionData['year']
```

7. Perform Feature Encoding on make, fuel, body, drive train

In [327...

```
# Assume 'predictionData' is your DataFrame after feature engineering
encodedData = predictionData.copy()

# List of all columns you want to encode
categorical_cols = [
    'make', 'fuel', 'body', 'drivetrain',
    'model_cleaned', 'trim_cleaned', 'transmission_type'
]

# Loop through the columns and apply the encoder
for col in categorical_cols:
    le = LabelEncoder()
    encodedData[col] = le.fit_transform(encodedData[col])

print("Data after Label Encoding:")
print(encodedData.head())
```

Data after Label Encoding:

	make	year	price	cylinders	fuel	mileage	body	doors	drivetrain	\
0	14	2024	74600.0	6.0	4	10.0	5	4.0		1
1	14	2024	50170.0	6.0	4	1.0	5	4.0		1
4	22	2024	81663.0	6.0	0	10.0	4	4.0		1
6	14	2024	63862.0	6.0	4	5.0	5	4.0		3
7	8	2024	89978.0	8.0	0	15.0	4	4.0		1

	engine_liters	is_turbo	is_hybrid	valve_count	age	trim_cleaned	\
0	3.6	1	0	24.0	0		44
1	3.6	0	0	16.0	0		20
4	3.6	1	0	24.0	0		18
6	3.6	1	0	24.0	0		7
7	3.6	1	0	32.0	0		25

	model_cleaned	gears	transmission_type
0	23	8.0	0
1	8	8.0	0
4	1	6.0	0
6	23	8.0	0
7	17	10.0	0

Data Preprocessing

Train and Test Data

```
In [329... X = encodedData.drop(['price'],axis=1)
y = encodedData['price']

X_train,X_test,y_train,y_test = train_test_split(X,y,random_state=45,train_size=0.8,test_size=0.2)
```

Data Scaling

```
In [330... scaler = StandardScaler()

# 1. Fit on training data and transform it
X_train_scaled = scaler.fit_transform(X_train)

# 2. Use the SAME scaler to transform the test data
X_test_scaled = scaler.transform(X_test)

X_train_scaled_df = pd.DataFrame(X_train_scaled,columns=X_train.columns)
X_test_scaled_df = pd.DataFrame(X_test_scaled,columns=X_test.columns)
```

Model Selection and Evaluation

For this project we are going to use Linear Regression

```
In [353... linearModel = LinearRegression()

linearModel.fit(X_train_scaled_df,y_train)

prediction = linearModel.predict(X_test_scaled_df)

mae = mean_absolute_error(y_test, prediction)
rmse = np.sqrt(mean_squared_error(y_test, prediction))
r2 = r2_score(y_test, prediction)

print(f"MAE: ${mae:,.2f}")
```

```
print(f"RMSE: ${rmse:,.2f}")
print(f"R-squared: {r2:.4f}")
```

MAE: \$10,151.26
RMSE: \$12,804.19
R-squared: 0.2889

In [341...

```
regressor = RandomForestRegressor(n_estimators=10, random_state=0, oob_score=True)
regressor.fit(X_train_scaled, y_train)

tunedregressor = RandomForestRegressor(n_estimators=300, max_features=0.24, random_state=0, oo
tunedregressor.fit(X_train_scaled, y_train)
```

C:\Users\Shaurya Srivastava\AppData\Roaming\Python\Python313\site-packages\sklearn\ensemble_forest.py:513: UserWarning: The number of unique classes is greater than 50% of the number of samples.

```
y_type = type_of_target(y)
```

C:\Users\Shaurya Srivastava\AppData\Roaming\Python\Python313\site-packages\sklearn\ensemble_forest.py:611: UserWarning: Some inputs do not have OOB scores. This probably means too few trees were used to compute any reliable OOB estimates.

```
warn(
```

C:\Users\Shaurya Srivastava\AppData\Roaming\Python\Python313\site-packages\sklearn\ensemble_forest.py:513: UserWarning: The number of unique classes is greater than 50% of the number of samples.

```
y_type = type_of_target(y)
```

Out[341...

▼ RandomForestRegressor ⓘ ?
► Parameters

In [333...

```
predictions = regressor.predict(X_test_scaled)

oob_score = regressor.oob_score_
mae = mean_absolute_error(y_test, predictions)
rmse = np.sqrt(mean_squared_error(y_test, predictions))
r2 = r2_score(y_test, predictions)

print(f'Out-of-Bag Score: {oob_score}')
print(f"MAE: ${mae:,.2f}")
print(f"RMSE: ${rmse:,.2f}")
print(f"R-squared: {r2:.4f}")
```

Out-of-Bag Score: 0.7102655005935559
MAE: \$4,246.58
RMSE: \$6,765.76
R-squared: 0.8014

In [342...

```
predictions = tunedregressor.predict(X_test_scaled)

oob_score = tunedregressor.oob_score_
mae = mean_absolute_error(y_test, predictions)
rmse = np.sqrt(mean_squared_error(y_test, predictions))
r2 = r2_score(y_test, predictions)

print(f'Out-of-Bag Score: {oob_score}')
print(f"MAE: ${mae:,.2f}")
print(f"RMSE: ${rmse:,.2f}")
print(f"R-squared: {r2:.4f}")
```

Out-of-Bag Score: 0.8529480528464308
MAE: \$3,919.60
RMSE: \$6,353.10
R-squared: 0.8249

In [343...

```
sample = X_test.iloc[0:1]
```

```

samplePrice = y_test.iloc[0:1]
prediction = tunedregressor.predict(scaler.transform(sample))

sample_dict = sample.iloc[0].to_dict()

print(f"\nSample Data: {sample_dict}")
print(f"Predicted Price: {prediction[0]}\nActual Price: {samplePrice.values[0]}")

```

Sample Data: {'make': 14.0, 'year': 2024.0, 'cylinders': 4.0, 'fuel': 5.0, 'mileage': 5.0, 'body': 5.0, 'doors': 4.0, 'drivetrain': 1.0, 'engine_liters': 3.6, 'is_turbo': 1.0, 'is_hybrid': 1.0, 'valve_count': 16.0, 'age': 0.0, 'trim_cleaned': 45.0, 'model_cleaned': 25.0, 'gears': 8.0, 'transmission_type': 0.0}

Predicted Price: 51541.73333333333

Actual Price: 50755.0

If we add 3000\$ in the predicted price it will match the price of actual price

Hyper parameter tuning for Random Forest Regressor

Only to be used when regressor is not runned

In [336...

```

## Define the search space for continuous hyperparameters
## For example, 'n_estimators' (integer) and 'max_features' (continuous)
param_distributions = {
    'n_estimators': [100, 200, 300],
    'max_features': uniform(0.1, 0.9) # Continuous range from 0.1 to 1.0 (0.1 + 0.9)
}

## Perform Randomized Search
random_search = RandomizedSearchCV(
    estimator=regressor,
    param_distributions=param_distributions,
    n_iter=50, # Number of random combinations to try
    cv=5,      # 5-fold cross-validation
    scoring='neg_mean_squared_error', # Metric for evaluation
    random_state=42
)

## Fit the search to your data
random_search.fit(X_train_scaled, y_train)

## Get the best hyperparameters
best_params = random_search.best_params_
best_params

```

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

```
orest.py:513: UserWarning: The number of unique classes is greater than 50% of the number of samples.
  y_type = type_of_target(y)
C:\Users\Shaurya Srivastava\AppData\Roaming\Python\Python313\site-packages\sklearn\ensemble\_forest.py:513: UserWarning: The number of unique classes is greater than 50% of the number of samples.
  y_type = type_of_target(y)
C:\Users\Shaurya Srivastava\AppData\Roaming\Python\Python313\site-packages\sklearn\ensemble\_forest.py:513: UserWarning: The number of unique classes is greater than 50% of the number of samples.
  y_type = type_of_target(y)
C:\Users\Shaurya Srivastava\AppData\Roaming\Python\Python313\site-packages\sklearn\ensemble\_forest.py:513: UserWarning: The number of unique classes is greater than 50% of the number of samples.
  y_type = type_of_target(y)
```

```
Out[336... {'max_features': np.float64(0.2403950683025824), 'n_estimators': 300}
```