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 [331…
```
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 scipy.stats import uniform
```

Data Overview

- Importing csv

In [332…
```
data = pd.read_csv("dataset.csv")
```

In [333…
```
# Set the option to display all columns
pd.set_option('display.max_columns', None)
```

In [334…
```
data.head()
```

Out[334…

	name	description	make	model	year	price	engine	cylinders	fuel	mileage	tra
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 [335…

```
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 [336…

```
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 [337…

```
data.describe()
```

Out[337…

	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

- How many nan values are their in each column

In [338…

```
data.isna().sum()
```

Out[338...
```
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 [339...
```python
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 Droping and Imputation

1. Delete name and description column

In [340...
```python
cleanedData = data.drop(['name', 'description'], axis=1)
cleanedData.head(2)
```

Out[340...

	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 engine

In [341...

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

Out[341...

	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	S
803	Jeep	Wagoneer	2024	73999.0	NaN	6.0	Gasoline	59.0	8-Speed Automatic	Series II	S

In [342...

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

Out[342...

	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
614	Honda	CR-V Hybrid	2025	42150.0	NaN	4.0	Gasoline	1.0	1-Speed CVT with Overdrive	Sport Touring	SUV
637	Honda	CR-V Hybrid	2024	36900.0	16V GDI DOHC Hybrid	4.0	Hybrid	1.0	Automatic CVT	Sport	SUV
673	Honda	CR-V Hybrid	2024	37505.0	16V GDI DOHC Hybrid	4.0	Hybrid	0.0	Automatic CVT	Sport-L	SUV

In [343...

```
cleanedData[(cleanedData['make'] == "Jeep") & (cleanedData['model'] == "Wagoneer")& (cleanedD
```

Out[343...

	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
399	Jeep	Wagoneer	2024	75888.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	NaN	8-Speed Automatic	Series II	SUV
650	Jeep	Wagoneer	2024	84935.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	1.0	8-Speed Automatic	Series II	SUV
772	Jeep	Wagoneer	2024	79487.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	18.0	8-Speed Automatic	Series II	SUV
803	Jeep	Wagoneer	2024	73999.0	NaN	6.0	Gasoline	59.0	8-Speed Automatic	Series II	SUV
970	Jeep	Wagoneer	2024	74625.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	10.0	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 [344...

```
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 [345...

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

Out[345…
```
make              0
model             0
year              0
price            23
engine            0
cylinders       105
fuel              7
mileage          34
transmission      2
trim              1
body              3
doors             6
exterior_color    5
interior_color   38
drivetrain        0
dtype: int64
```

3. Remove nan values from transmission

In [346…
```
cleanedData[cleanedData['transmission'].isna()]
```

Out[346…

	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
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

In [347…
```
cleanedData[(cleanedData['make'] == "Ford") & (cleanedData['model'] == "Transit-350") & (clea
```

Out[347…

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	body
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 [348…
```
cleanedData[(cleanedData['make'] == "Mercedes-Benz") & (cleanedData['model'] == "EQS 450") &
```

Out[348…

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	trim	b
142	Mercedes-Benz	EQS 450	2024	NaN	c	NaN	Electric	8.0	Automatic	Base 4MATIC	Se
253	Mercedes-Benz	EQS 450	2024	110395.0	c	NaN	Electric	5.0	Automatic	Base 4MATIC	Se
328	Mercedes-Benz	EQS 450	2024	NaN	c	NaN	Electric	10.0	Automatic	Base 4MATIC	Se
372	Mercedes-Benz	EQS 450	2024	NaN	c	NaN	Electric	4.0	Automatic	Base 4MATIC	Se
484	Mercedes-Benz	EQS 450	2024	117985.0	c	NaN	Electric	1.0	Automatic	Base 4MATIC	Se
725	Mercedes-Benz	EQS 450	2024	111245.0	c	NaN	Electric	10.0	NaN	Base 4MATIC	Se

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

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

In [349…

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

In [350…

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

Out[350…

```
make               0
model              0
year               0
price             23
engine             0
cylinders        105
fuel               7
mileage           34
transmission       0
trim               1
body               3
doors              6
exterior_color     5
interior_color    38
drivetrain         0
dtype: int64
```

4. Remove nan values from trim

In [351…

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

Out[351…

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

In [352…

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

Out[352…

	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 [353…

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

In [354…

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

Out[354…

```
make               0
model              0
year               0
price             23
engine             0
cylinders        105
fuel               7
mileage           34
transmission       0
trim               0
body               3
doors              6
exterior_color     5
interior_color    38
drivetrain         0
dtype: int64
```

5. Remove nan values from body

In [355…

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

Out[355…

	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 [356…

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

Out[356…

	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
799	INFINITI	QX50	2024	46855.0	o 2L I-4 port/direct injection, DOHC, variable...	4.0	Gasoline	11.0	Variable	LUXE	S

In [357…

```
cleanedData[(cleanedData['make'] == "Dodge") & (cleanedData['model'] == "Hornet") & (cleanedD
```

Out[357…

	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	SU\
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\
243	Dodge	Hornet	2024	48595.0	4 gasoline direct injection, DOHC, Multiair va...	4.0	Gasoline	0.0	6-Spd Aisin F21-250 PHEV Auto Trans	Hornet R/T Plus Eawd	SU\
511	Dodge	Hornet	2024	46490.0	4 gasoline direct injection, DOHC, Multiair va...	4.0	Gasoline	21.0	6-Speed Automatic	R/T Plus EAWD	SU\

In [358…

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

In [359…

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

Out[359…

```
make                0
model               0
year                0
price              23
engine              0
cylinders         105
fuel                7
mileage            34
transmission        0
trim                0
body                0
doors               6
exterior_color      5
interior_color     38
drivetrain          0
dtype: int64
```

6. Remove nan values from fuel

In [360…
```
cleanedData[cleanedData['fuel'].isna()]
```

Out[360…

	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>\n 3GN7DNRPXRS232327	NaN	NaN	0.0	Automatic
726	Jaguar	I-PACE	2024	77053.0	d>\n\n \n <dt>VIN</dt>\n SADHM2S12R1...	NaN	NaN	8.0	Automatic

In [361…
```
cleanedData['fuel'].value_counts()
```

Out[361…
```
fuel
Gasoline                664
Hybrid                  137
Electric                 99
Diesel                   73
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 [362…
```
cleanedData.fillna({'fuel':"Gasoline"},inplace=True)
```

7. Remove nan values from doors

In [363…
```
cleanedData['doors'].value_counts()
```

Out[363…
```
doors
4.0    948
3.0     37
2.0     10
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 [364…
```
cleanedData.fillna({'doors':4},inplace=True)
```

In [365…

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

Out[365…

```
make                0
model               0
year                0
price              23
engine              0
cylinders         105
fuel                0
mileage            34
transmission        0
trim                0
body                0
doors               0
exterior_color      5
interior_color     38
drivetrain          0
dtype: int64
```

8. Remove nan values from exterior_colors

In [366…

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

Out[366…

	make	model	year	price	engine	cylinders	fuel	mileage	transmission	t
117	Jeep	Wrangler	2024	59456.0	ar 3.6L V-6 DOHC, variable valve control, regu...	6.0	Gasoline	15.0	Automatic	4-D Sah
137	Acura	ZDX	2024	69850.0	c	0.0	Electric	0.0	Automatic	A-SI
373	Mercedes-Benz	EQS 450	2024	114850.0	c	NaN	Electric	8.0	1-Speed Automatic	B 4MA
608	Mercedes-Benz	Sprinter 2500	2023	58665.0	gasoline direct injection, DOHC, variable valv...	4.0	Gasoline	0.0	Automatic	H R
612	Mercedes-Benz	Sprinter 2500	2024	65129.0	diesel direct injection, DOHC, intercooled tur...	4.0	Diesel	0.0	Automatic	H R

In [367…

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

Out[367...

```
exterior_color
Bright White Clearcoat       81
Black                        32
White                        29
Gray                         27
Diamond Black                26
                             ..
Aspen White / Super Black     1
Jungle Green                  1
Cactus Gray                   1
Pearl White Tricoat           1
Wheatland Yellow              1
Name: count, Length: 263, dtype: int64
```

- It is going to be filled with `Black` because `Bright White Clearcoat` already as 81 and by adding more numbers to it fill make the data unfair

In [368...

```
cleanedData.fillna({'exterior_color': 'Black'},inplace=True)
```

Doubt: Is doing this good or not?

9. Remove nan values from price

In [369...

```
cleanedData.fillna({'price':round(cleanedData['price'].mean(),2)},inplace=True)
```

10. Remove nan values from cylinders

In [370...

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

Out[370…

	make	model	year	price	engine	cylinders	fuel	mileage	transmission
14	Chevrolet	Blazer EV	2024	51695.0	c	NaN	Electric	4.0	1-Speed Automatic
28	Chevrolet	Blazer EV	2024	52190.0	c	NaN	Electric	6.0	1-Speed Automatic
33	Kia	EV6	2024	49820.0	c	NaN	Electric	13.0	Automatic
35	Ford	Mustang Mach-E	2024	47790.0	c	NaN	Electric	5.0	1-Speed Automatic
49	Hyundai	IONIQ 5	2024	44195.0	c	NaN	Electric	14.0	1-Speed Automatic
...	...	...	...	...	...	...	...	...	...
884	BMW	i7	2024	195895.0	c	NaN	Electric	0.0	1-Speed Automatic
893	Honda	CR-V	2025	38305.0	d>\n\n \n <dt>VIN</dt>\n 7FARS4H71SE...	NaN	Gasoline	0.0	Automatic CVT
941	Hyundai	IONIQ 5	2024	38201.0	c	NaN	Electric	12.0	Automatic
944	Kia	EV6	2024	41528.0	c	NaN	Electric	13.0	Automatic
978	Kia	EV6	2024	43439.0	c	NaN	Electric	14.0	Automatic

105 rows × 15 columns

In [371…

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

Out[371…

```
cylinders
4.0    347
6.0    207
8.0     82
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 [372…

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

- We are going to fill `0` in cylinders whose `cylinders` are `Nan` and fuel type is `Electric`

In [373…

```
cleanedData.loc[(cleanedData['cylinders'].isna()) & (cleanedData['fuel'] == 'Electric'),'cyli
```

11. Remove nan values from mileage

In [374…

```
cleanedData[cleanedData['mileage'].isna()][:5]
```

Out[374...

	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
73	Jeep	Wagoneer	2024	63057.0	24V GDI DOHC Twin Turbo	6.0	Gasoline	NaN	8-Speed Automatic	Base
84	Jeep	Grand Cherokee L	2024	49390.0	OHV	6.0	Gasoline	NaN	8-Speed Automatic	Limited

In [375...

```
cleanedData['mileage'].value_counts()
```

Out[375...

```
mileage
5.0      116
0.0      110
10.0     108
1.0       58
6.0       50
        ...
697.0      1
66.0       1
41.0       1
141.0      1
296.0      1
Name: count, Length: 95, dtype: int64
```

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

In [376...

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

Doubt: Is doing this a good option?

12. Remove nan values from interior_colors

In [377...

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

Out[377…

```
interior_color
Black           510
Global Black     84
Gray             77
Jet Black        45
Ebony            43
               ...
Caramel           1
gray              1
Dark Palazzo      1
Gray/Black        1
Navy Pier         1
Name: count, Length: 91, dtype: int64
```

- Here `Black` interior is the most commone one

In [378…

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

In [379…

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

Out[379…

```
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 [380…

```
cleanedData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1002 entries, 0 to 1001
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   make            1002 non-null   object 
 1   model           1002 non-null   object 
 2   year            1002 non-null   int64  
 3   price           1002 non-null   float64
 4   engine          1002 non-null   object 
 5   cylinders       1002 non-null   float64
 6   fuel            1002 non-null   object 
 7   mileage         1002 non-null   float64
 8   transmission    1002 non-null   object 
 9   trim            1002 non-null   object 
 10  body            1002 non-null   object 
 11  doors           1002 non-null   float64
 12  exterior_color  1002 non-null   object 
 13  interior_color  1002 non-null   object 
 14  drivetrain      1002 non-null   object 
dtypes: float64(4), int64(1), object(10)
memory usage: 117.6+ KB
```

Achievement

Without removing any data we successully cleaned our dataset with right values

Detecting Outliers

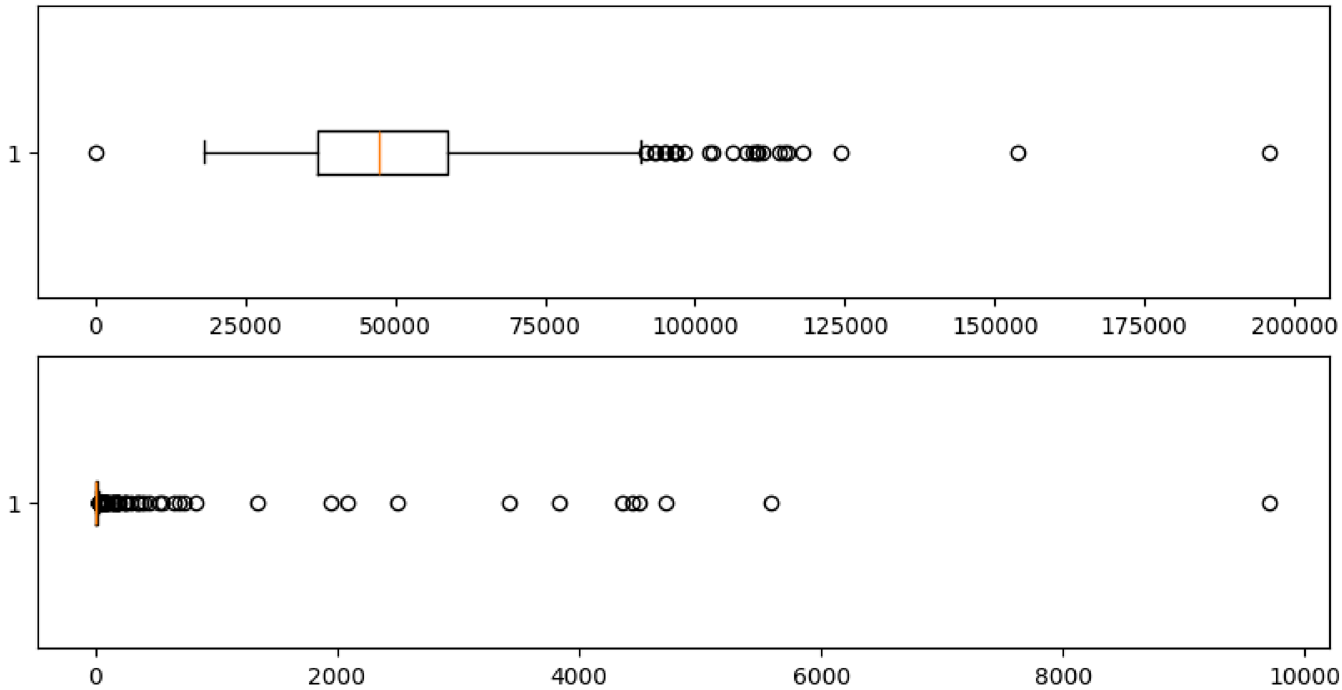
Possible Outliers can exist in:

- price
- mileage

Before Removing Outliers

In [381...

```
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 [382...

```
cleanedData = cleanedData[(cleanedData['price'] < 100000) & (cleanedData['price'] > 10)]
```

In [383...

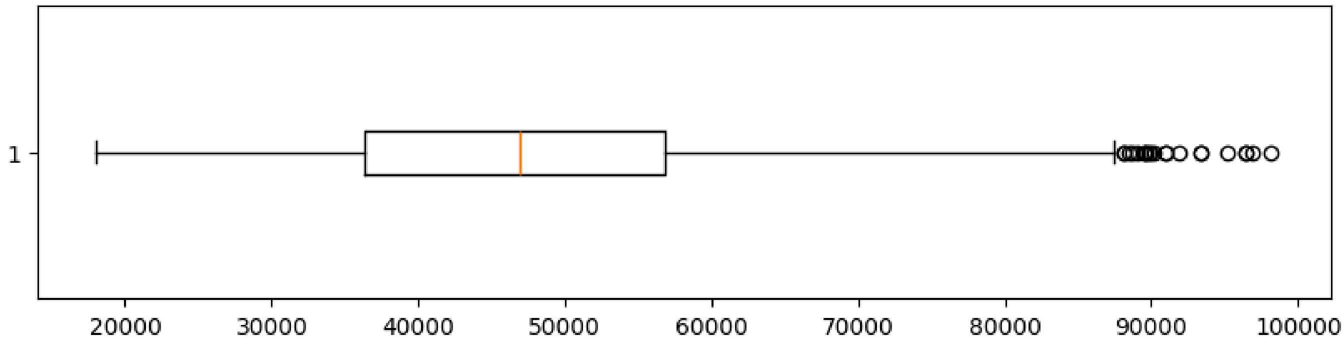
```
cleanedData = cleanedData[cleanedData['mileage'] < 30]
```

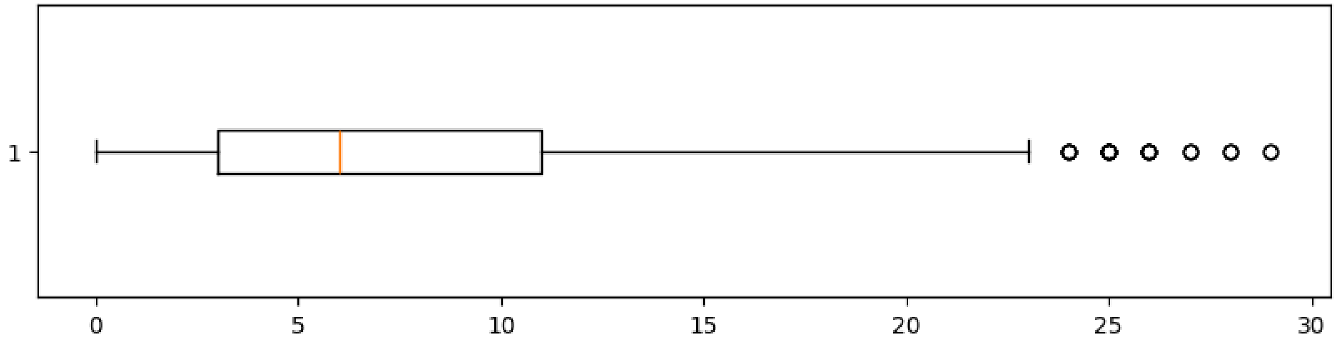
Note: I dont know if i handeled the outliers correctly or not

After Removing Outliers

In [384...

```
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 [385…

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

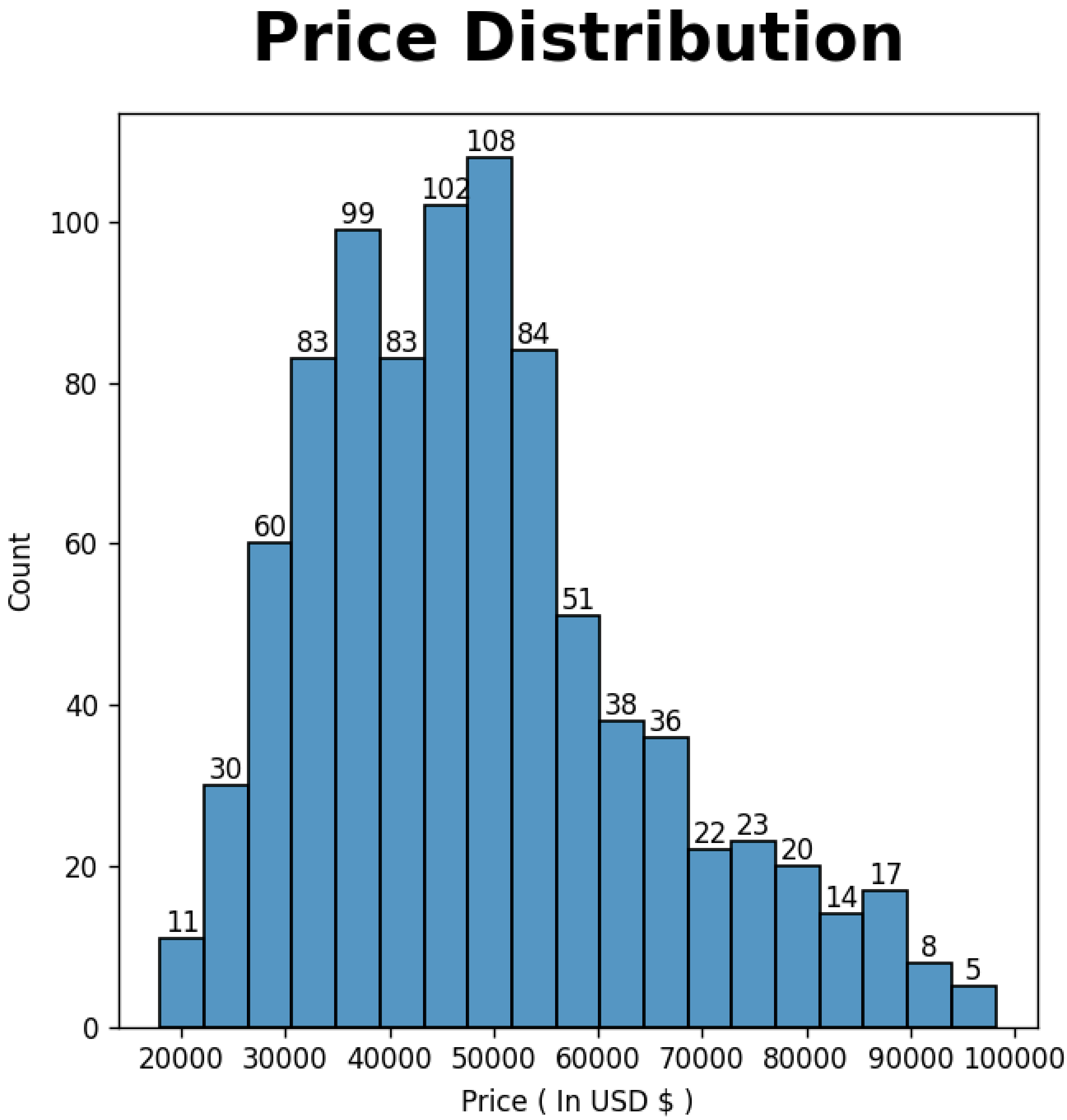
```
No. of rows: 894
No. of rows removed: 108
```

EDA

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

In [386…

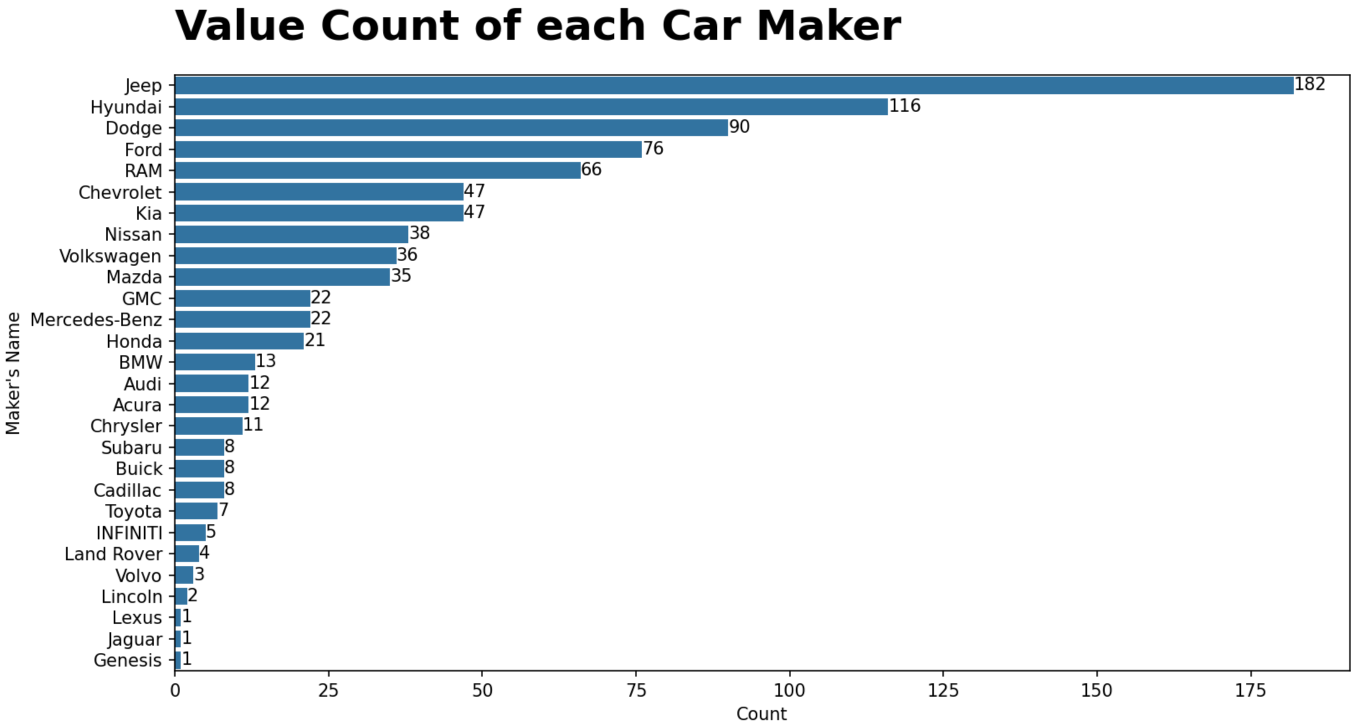
```
plt.figure(figsize=(6,6),dpi=120)
ax = sns.histplot(cleanedData['price'])
ax.bar_label(ax.containers[0],fontsize = 10)
ax.set_xlabel("Price ( In USD $ )")
ax.set_ylabel("Count")
ax.set_title("Price Distribution",fontdict={'weight':"bold",'size':24},pad=20)
plt.show()
```



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

In [387…

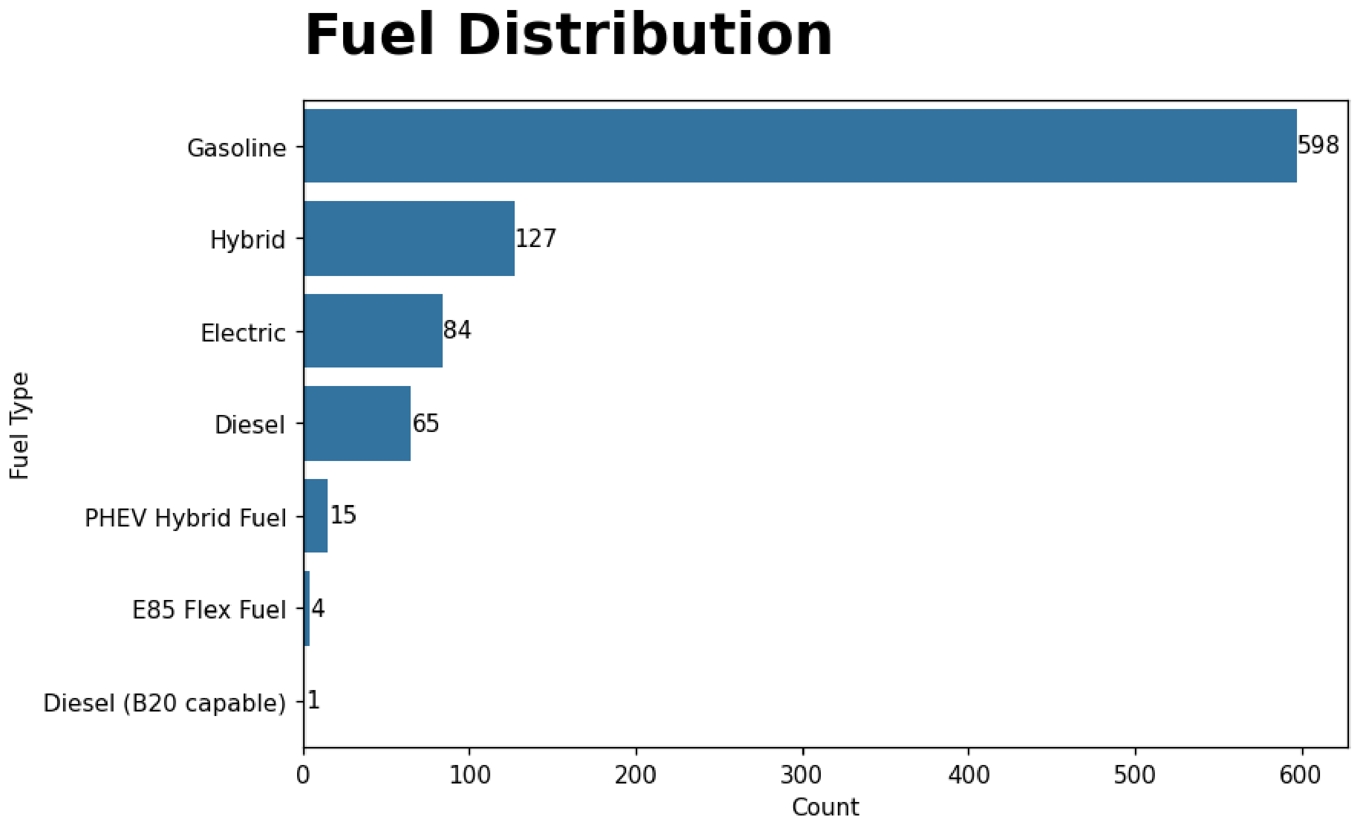
```
plt.figure(figsize=(11,6),dpi=150)

ax = sns.barplot(data=cleanedData['make'].value_counts(),errorbar=None,estimator="sum",orient
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},

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



3. Create a Histogram of fuel

In [388…

```
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()
```

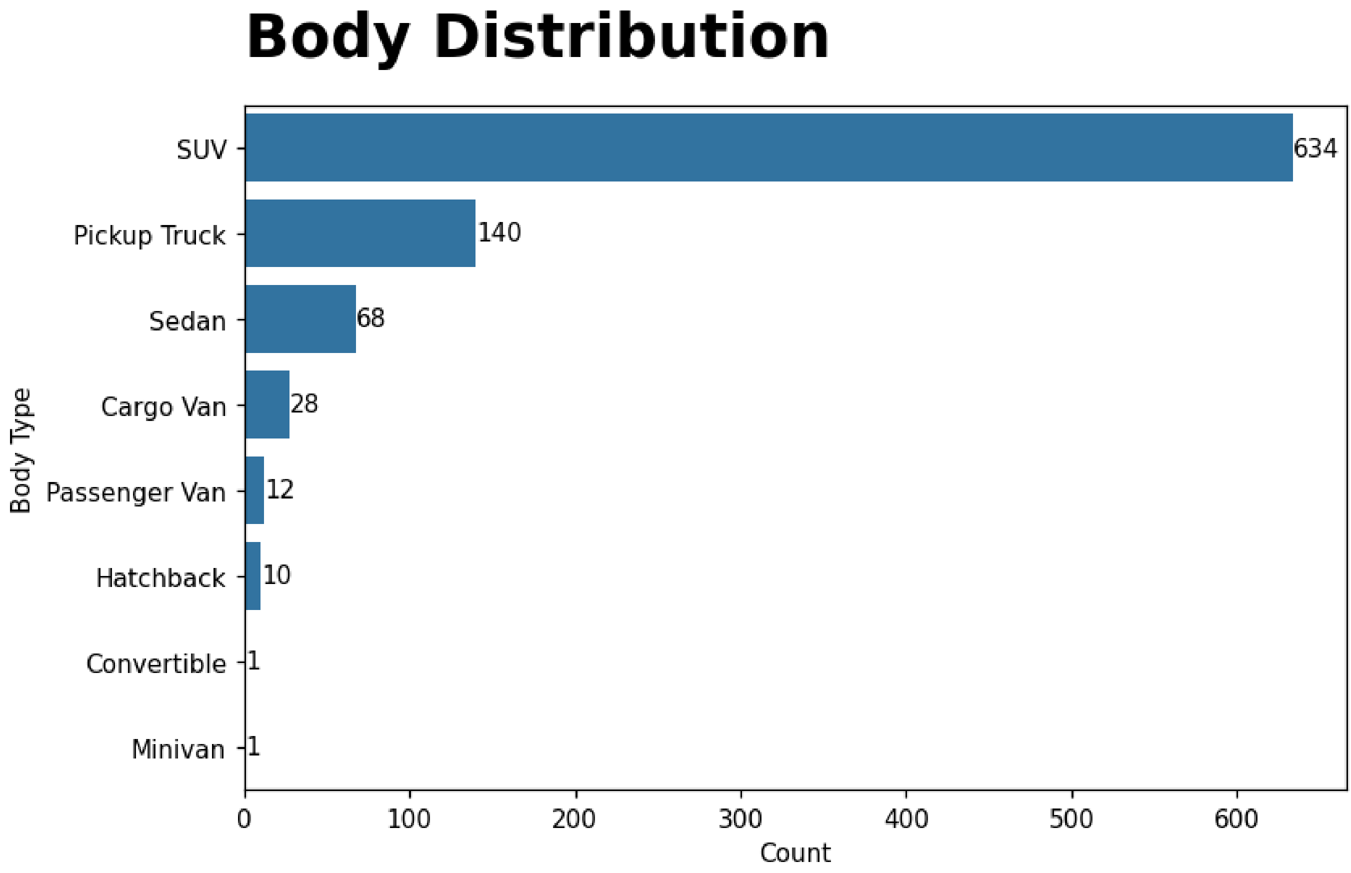


4. Create a Bar graph of `Body` do see general body type of all cars

In [389…

```
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)
```

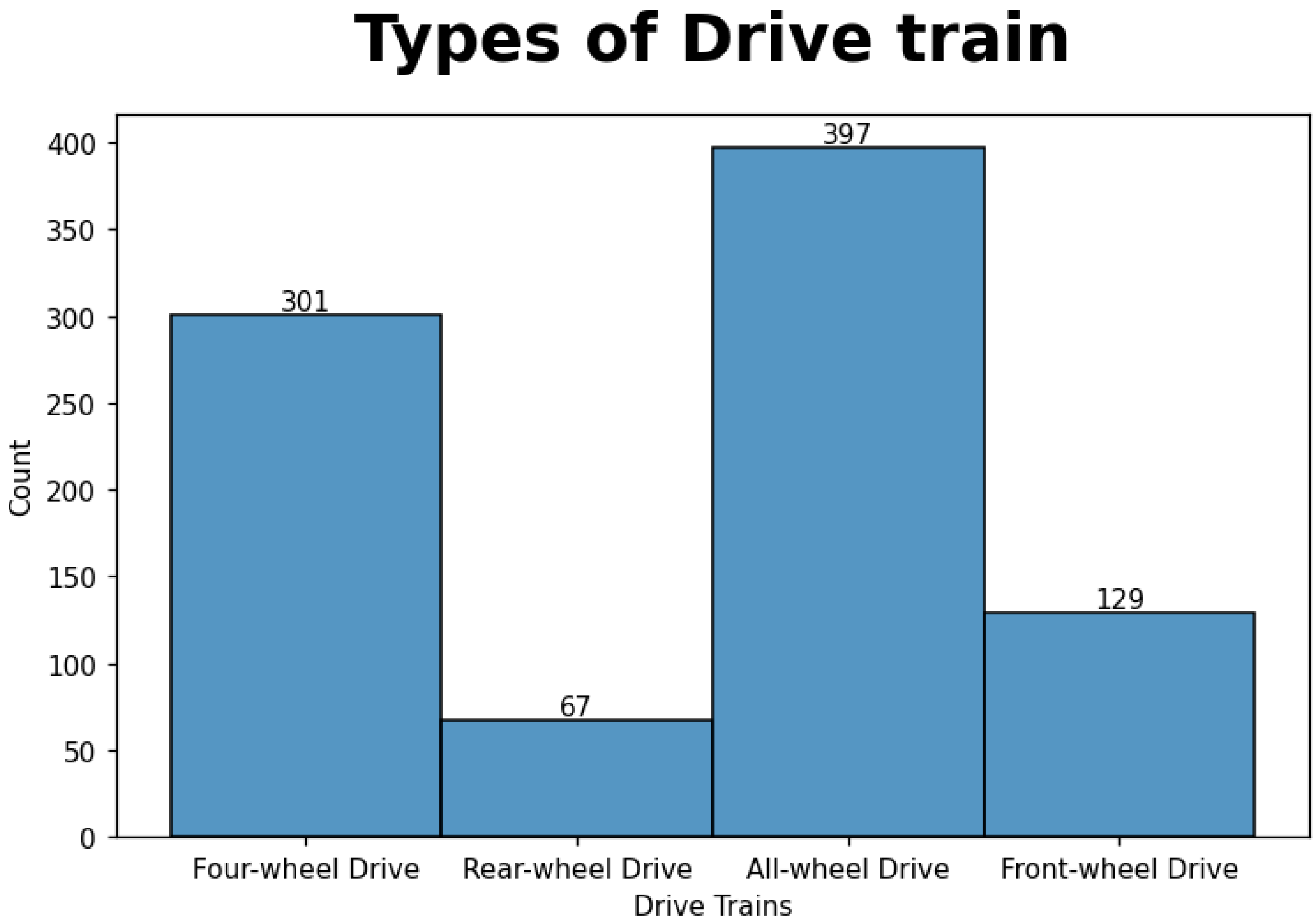
```
ax.set_xlabel("Count")
ax.set_ylabel("Body Type")
ax.set_title("Body Distribution",fontdict={'weight':"bold",'size':24},pad=20,loc='left')
plt.show()
```



5. Create a Bar Graph of `drivetrain`

In [390…

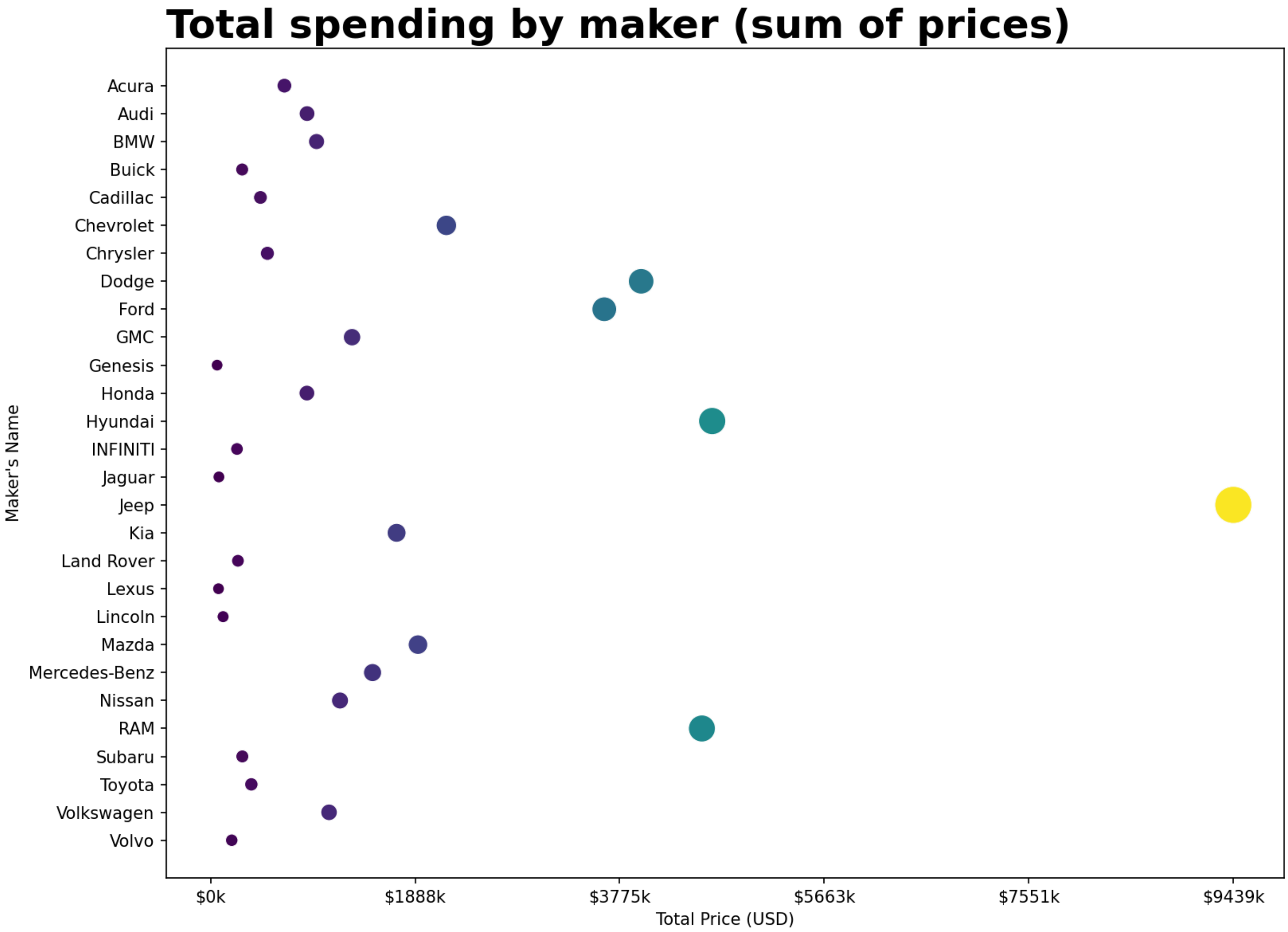
```
plt.figure(figsize=(7,5),dpi=110)

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()
```



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 [391…

```
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()
```



Feature Engineering

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

In [392…

```
predictionData = cleanedData[['make', 'year', 'price', 'cylinders', 'fuel', 'mileage', 'body'
```

In [393…

```
predictionData.head()
```

Out[393…

	make	year	price	cylinders	fuel	mileage	body	doors	drivetrain
0	Jeep	2024	74600.0	6.0	Gasoline	10.0	SUV	4.0	Four-wheel Drive
1	Jeep	2024	50170.0	6.0	Gasoline	1.0	SUV	4.0	Four-wheel Drive
2	GMC	2024	96410.0	8.0	Gasoline	0.0	SUV	4.0	Four-wheel Drive
4	RAM	2024	81663.0	6.0	Diesel	10.0	Pickup Truck	4.0	Four-wheel Drive
6	Jeep	2024	63862.0	6.0	Gasoline	5.0	SUV	4.0	Rear-wheel Drive

2. Add an Age feauture which shows the age of a car

In [394…

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

```
C:\Users\Shaurya Srivastava\AppData\Local\Temp\ipykernel_11784\2453037954.py:3: SettingWithCop
yWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/
indexing.html#returning-a-view-versus-a-copy
  predictionData.loc[:,'age'] = current_year - predictionData['year']
```

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

In [395…

```python
# Example Fix
encodedData = pd.get_dummies(predictionData, columns=['make', 'fuel', 'body','drivetrain'], d
encodedData
```

Out[395…

	year	price	cylinders	mileage	doors	age	make_Audi	make_BMW	make_Buick	make_Cad
0	2024	74600.0	6.0	10.0	4.0	0	False	False	False	F
1	2024	50170.0	6.0	1.0	4.0	0	False	False	False	F
2	2024	96410.0	8.0	0.0	4.0	0	False	False	False	F
4	2024	81663.0	6.0	10.0	4.0	0	False	False	False	F
6	2024	63862.0	6.0	5.0	4.0	0	False	False	False	F
...	...	...	...	...	...	...	...	...	...	
996	2024	69315.0	6.0	0.0	4.0	0	False	False	False	F
997	2024	59037.0	4.0	10.0	3.0	0	False	False	False	F
998	2024	49720.0	4.0	0.0	4.0	0	False	False	False	F
999	2024	69085.0	6.0	20.0	4.0	0	False	False	False	F
1000	2024	43495.0	6.0	6.0	4.0	0	False	False	False	F

894 rows × 49 columns

Data Preprocessing

Train and Test Data

In [396…

```python
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
```

Data Scaling

In [397…

```python
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 [398…

```
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: $7,216.15
RMSE: $9,140.43
R-squared: 0.6885
```

In [408…

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

tunedregressor = RandomForestRegressor(n_estimators=100, max_features=0.57,random_state=0, oo
tunedregressor.fit(X_train_scaled_df, y_train)
```

```
C:\Users\Shaurya Srivastava\AppData\Roaming\Python\Python313\site-packages\sklearn\ensemble\_f
orest.py:611: UserWarning: Some inputs do not have OOB scores. This probably means too few tre
es were used to compute any reliable OOB estimates.
  warn(
```

Out[408…

RandomForestRegressor

▶ Parameters

In [400…

```
predictions = regressor.predict(X_test_scaled_df)

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: 0.49022696177874137
MAE: $6,290.23
RMSE: $8,853.63
R-squared: 0.7078
```

In [409…

```
predictions = tunedregressor.predict(X_test_scaled_df)

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: 0.689879206075898
MAE: $5,984.16
RMSE: $8,276.86
R-squared: 0.7446
```

In [402…

```
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: {'year': 2024, 'cylinders': 3.0, 'mileage': 6.0, 'doors': 4.0, 'age': 0, 'make_Au
di': False, 'make_BMW': False, 'make_Buick': True, 'make_Cadillac': False, 'make_Chevrolet': F
alse, 'make_Chrysler': False, 'make_Dodge': False, 'make_Ford': False, 'make_GMC': False, 'mak
e_Genesis': False, 'make_Honda': False, 'make_Hyundai': False, 'make_INFINITI': False, 'make_J
aguar': False, 'make_Jeep': False, 'make_Kia': False, 'make_Land Rover': False, 'make_Lexus':
False, 'make_Lincoln': False, 'make_Mazda': False, 'make_Mercedes-Benz': False, 'make_Nissan':
False, 'make_RAM': False, 'make_Subaru': False, 'make_Toyota': False, 'make_Volkswagen': Fals
e, 'make_Volvo': False, 'fuel_Diesel (B20 capable)': False, 'fuel_E85 Flex Fuel': False, 'fuel
_Electric': False, 'fuel_Gasoline': True, 'fuel_Hybrid': False, 'fuel_PHEV Hybrid Fuel': Fals
e, 'body_Convertible': False, 'body_Hatchback': False, 'body_Minivan': False, 'body_Passenger
Van': False, 'body_Pickup Truck': False, 'body_SUV': True, 'body_Sedan': False, 'drivetrain_Fo
ur-wheel Drive': False, 'drivetrain_Front-wheel Drive': True, 'drivetrain_Rear-wheel Drive': F
alse}
Predicted Price: 30682.113392857147
Actual Price: 27075.0
```

```
C:\Users\Shaurya Srivastava\AppData\Roaming\Python\Python313\site-packages\sklearn\utils\valid
ation.py:2749: UserWarning: X does not have valid feature names, but RandomForestRegressor was
fitted with feature names
  warnings.warn(
```

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

Hyper parameter tuning for Randome Forest Regressor

In [403…

```
# 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_df, y_train)

# Get the best hyperparameters
```

```
best_params = random_search.best_params_
best_params
```

Out[403…

```
{'max_features': np.float64(0.5722807884690141), 'n_estimators': 100}
```