

DS1_C5_S1_Challenge

In [1]:

```
#Import the required Library  
import pandas as pd  
import warnings  
warnings.filterwarnings('ignore')  
import matplotlib.pyplot as plt  
import statistics as st
```

In [6]:

```
car = pd.read_excel(r'E:\Aishwarya official\Aishwarya Data Scince\course 5\DS1_C4_S5_Car_Data\car.xlsx')
```

Out[6]:

	Sl. No.	Make	Model	Variant	Displacement	Cylinders	Valves_Per_Cylinder	Drivetrain
0	0	Tata	Nano Genx	Xt	624.0	2.0	2.0	RW (Rear Wheel Drive)
1	1	Tata	Nano Genx	Xe	624.0	2.0	2.0	RW (Rear Wheel Drive)
2	2	Tata	Nano Genx	Emax Xm	624.0	2.0	2.0	RW (Rear Wheel Drive)
3	3	Tata	Nano Genx	Xta	624.0	2.0	2.0	RW (Rear Wheel Drive)
4	4	Tata	Nano Genx	Xm	624.0	2.0	2.0	RW (Rear Wheel Drive)
...
1271	1271	Honda	City	Vx Mt Diesel	1498.0	4.0	4.0	FW (Front Wheel Drive)
1272	1272	Honda	City	Zx Mt Diesel	1498.0	4.0	4.0	FW (Front Wheel Drive)
1273	1273	Honda	City	Zx Cvt Petrol	1497.0	4.0	4.0	FW (Front Wheel Drive)
1274	1274	Honda	City	V Cvt Petrol	1497.0	4.0	4.0	FW (Front Wheel Drive)
1275	1275	Mitsubishi	Montero	3.2 At	3200.0	4.0	4.0	AWD (All Wheel Drive)

1276 rows × 139 columns

Task 1

In [9]:

```
for item in car.columns:  
    print(item, " ", car[item].isna().sum())
```

```
Cylinder_Configuration    13  
Engine_Location          43  
Fuel_System              8  
Fuel_Tank_Capacity_litre  69  
Fuel_Type                0  
Height_mm               1  
Length_mm              0  
Width_mm               12  
Body_Type              6  
Doors                  4  
City_Mileage_km_litre   555  
Highway_Mileage_km_litre 800  
ARAI_Certified_Mileage   114  
ARAI_Certified_Mileage_for_CNG 1249  
Kerb_Weight            365  
Gears                 105  
Ground_Clearance       289  
Front_Brakes           25  
Rear_Brakes            25  
Front_Suspension       59
```

In [8]:

```
car.isnull().sum()
```

Out[8]:

```
Sl. No.          0  
Make            75  
Model           0  
Variant         0  
Displacement    12  
  
...  
USB_Ports       1247  
Heads-Up_Display 1225  
Welcome_Lights  1207  
Battery         1263  
Electric_Range  1259  
Length: 139, dtype: int64
```

In [23]:

```
cr = car[['Make', 'Displacement', 'Fuel_Tank_Capacity_litre', 'City_Mileage_km_litre', 'Highway_Mileage']]
cr.dropna(inplace=True)
cr
```

Out[23]:

	Make	Displacement	Fuel_Tank_Capacity_litre	City_Mileage_km_litre	Highway_Mileage
6	Datsun	799.0	28.0	21.38	
7	Datsun	799.0	28.0	21.38	
8	Datsun	799.0	28.0	21.38	
9	Datsun	799.0	28.0	21.38	
24	Suzuki	1196.0	40.0	12.00	
...	
1271	Honda	1498.0	40.0	22.60	
1272	Honda	1498.0	40.0	22.60	
1273	Honda	1497.0	40.0	18.00	
1274	Honda	1497.0	40.0	14.30	
1275	Mitsubishi	3200.0	88.0	8.25	

338 rows × 6 columns



In [38]:

```
cr=cr.groupby(['Make'])['Displacement', 'Fuel_Tank_Capacity_litre', 'City_Mileage_km_litre', 'Highway_Mileage_km_litre']
cr
```

Out[38]:

	Displacement	Fuel_Tank_Capacity_litre	City_Mileage_km_litre	Highway_Mileage_km_litre
Make				
Audi	18098.0	375.0	41.30	
Bentley	22741.0	360.0	15.50	
Bmw	28919.0	788.0	171.32	2
Datsun	3196.0	112.0	85.52	
Dc	2000.0	60.0	8.00	
Fiat	11516.0	405.0	130.00	1
Force	10384.0	252.0	56.00	
Ford	7594.0	240.0	26.30	
Honda	28946.0	796.0	309.50	3
Hyundai	32460.0	1101.0	415.20	4
Icml	21934.0	550.0	94.60	1
Isuzu	5998.0	152.0	27.60	
Jaguar	23974.0	690.0	64.81	1
Lamborghini	6498.0	90.0	3.60	
Mahindra	76908.0	2225.0	548.05	6
Maserati	12369.0	231.0	13.80	
Mitsubishi	15585.0	438.0	40.75	
Nissan	10364.0	341.0	112.90	1
Porsche	11988.0	270.0	21.30	
Premier	8061.0	276.0	82.00	1
Renault	13260.0	450.0	126.20	1
Skoda	50630.0	1782.0	418.60	5
Suzuki	47594.0	1693.0	825.68	9
Tata	41682.0	1279.0	510.48	5
Toyota	68947.0	2129.0	629.01	7
Volkswagen	12881.0	450.0	171.00	1
Volvo	5549.0	177.0	38.25	

In [41]:

```

mean = []
mode = []
median = []

for col in cr:
    mean.append(st.mean(cr[col]))
    mode.append(st.mode(cr[col]))
    median.append(st.median(cr[col]))

row_head = ['mean', 'mode', 'median']
col_name = ['Displacement', 'Fuel_Tank_Capacity_litr', 'City_Mileage_km_litre', 'Highway_Milea

# create dataframe of mean , median ,mode
d_data = pd.DataFrame ([mean, mode, median], columns = col_name)
d_data

# insert column
d_data.insert(0, "Measures", row_head)
d_data

```

Out[41]:

	Measures	Displacement	Fuel_Tank_Capacity_litr	City_Mileage_km_litre	Highway_Mileage_km
0	mean	22225.037037	656.0	184.713704	219.90
1	mode	18098.000000	450.0	41.300000	54.60
2	median	13260.000000	405.0	85.520000	122.32

In [44]:

```

mean= []
SD =[]
CV=[]

# iterate each column
for col in cr:
    col_mean= cr[col].mean()    #creating mean of each column
    mean.append(col_mean)       #storing the calculated mean in mean named folder
    col_std= cr[col].std()      #calculating standard deviation of each column
    SD.append(col_std)         #storing the calculated SD in SD name folder
    CV.append(col_std/col_mean*100)

row_head = ['mean', 'SD', 'CV']
col_name = ['Displacement', 'Fuel_Tank_Capacity_litr', 'City_Mileage_km_litre', 'Highway_Mileage_km']

# create dataframe of mean , median , mode
d_data1 = pd.DataFrame ([mean, SD, CV], columns = col_name)
d_data1

# insert column
d_data1.insert(0, "Measures", row_head)
d_data1

```

Out[44]:

	Measures	Displacement	Fuel_Tank_Capacity_litr	City_Mileage_km_litre	Highway_Mileage_km
0	mean	22225.037037	656.000000	184.713704	219.90
1	SD	19612.814181	630.529753	223.802065	255.17
2	CV	88.246486	96.117340	121.161593	116.03

In [21]:

```

su = cr[cr.Make == 'Suzuki']
to = cr[cr.Make == 'Mahindra']
ma = cr[cr.Make == 'Toyota']

```

In [55]:

```

Suzuki_data = su['Displacement'].tolist()
Mahindra_data = to['Displacement'].tolist()
Toyota_data = ma['Displacement'].tolist()

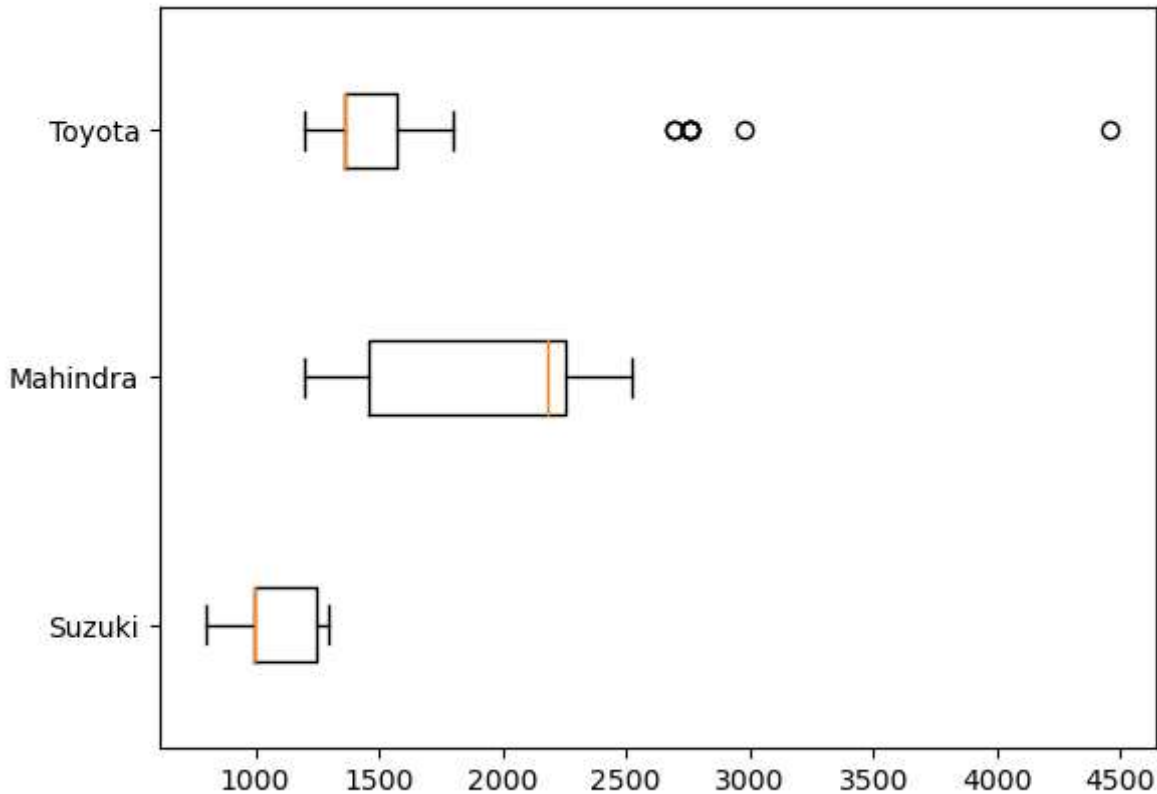
```

In [56]:

```
plt.boxplot([Suzuki_data, Mahindra_data, Toyota_data], vert=0)
plt.yticks([1,2,3],['Suzuki', 'Mahindra', 'Toyota'])
```

Out[56]:

```
(<matplotlib.axis.YTick at 0x1ccd97de3d0>,
 <matplotlib.axis.YTick at 0x1ccd97c1d30>,
 <matplotlib.axis.YTick at 0x1ccd97f3880>],
 [Text(0, 1, 'Suzuki'), Text(0, 2, 'Mahindra'), Text(0, 3, 'Toyota')])
```



Task 2

In [54]:

```
import seaborn as sns
```

In [71]:

```
make = car.groupby(['Make'])['Displacement', 'Fuel_Tank_Capacity_litre', 'City_Mileage_km_li
```


In [72]:

```
corr = make[['Displacement', 'Fuel_Tank_Capacity_litre', 'City_Mileage_km_litre', 'Cylinders',  
corr
```

Out[72]:

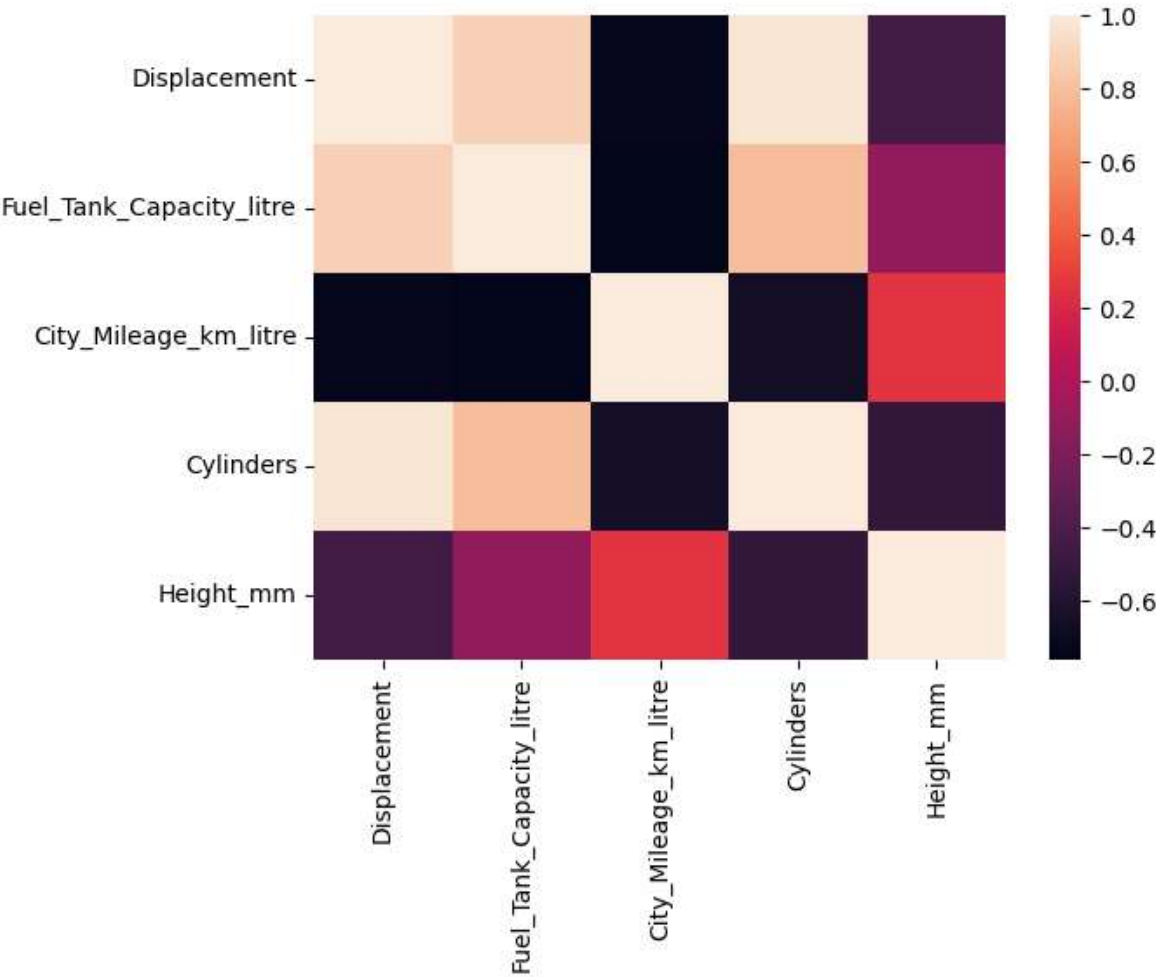
	Displacement	Fuel_Tank_Capacity_litre	City_Mileage_km_litre	Cylinder:
Displacement	1.000000	0.881811	-0.736779	0.971032
Fuel_Tank_Capacity_litre	0.881811	1.000000	-0.758070	0.792271
City_Mileage_km_litre	-0.736779	-0.758070	1.000000	-0.666116
Cylinders	0.971032	0.792271	-0.666116	1.000000
Height_mm	-0.448780	-0.114598	0.252883	-0.522741

In [73]:

```
sns.heatmap(corr)
```

Out[73]:

<AxesSubplot:>



In [67]:

```
make['Displacement'].corr(make['City_Mileage_km_litre'])
```

Out[67]:

-0.7367789216015502

In []:

```
make['Displacement'].corr(make[''])
```

In [68]:

```
make['Displacement'].corr(make['Cylinders'])
```

Out[68]:

0.9710315137022268

In [70]:

```
make['Displacement'].corr(make['Height_mm'])
```

Out[70]:

-0.4487804365986555

Conclusion : - From above heatmap and correlation coefficient its observable that number of cylinders have the highest correlation with mileage and followed by displacement