In [1]:
```
import pandas as pd
import numpy as np
```

In [2]:
```
data = pd.read_csv("vehicle.csv")
data
```

Out[2]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon
0	1.0	lounge	51.0	882.0	25000.0	1.0	44.907242	8.611559868
1	2.0	pop	51.0	1186.0	32500.0	1.0	45.666359	12.24188995
2	3.0	sport	74.0	4658.0	142228.0	1.0	45.503300	11.41784
3	4.0	lounge	51.0	2739.0	160000.0	1.0	40.633171	17.63460922
4	5.0	pop	73.0	3074.0	106880.0	1.0	41.903221	12.49565029
...	...	...	...	...	...	...	...	...
1544	NaN	NaN	NaN	NaN	NaN	NaN	NaN	length
1545	NaN	NaN	NaN	NaN	NaN	NaN	NaN	concat
1546	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Null values
1547	NaN	NaN	NaN	NaN	NaN	NaN	NaN	find
1548	NaN	NaN	NaN	NaN	NaN	NaN	NaN	search

1549 rows × 11 columns

a) Find mean, median, mode and describe

In [3]:
```
data.mean()
```

Out[3]:
```
ID                   769.500000
engine_power          51.904421
age_in_days         1650.980494
km                 53396.011704
previous_owners        1.123537
lat                   43.541361
Unnamed: 9                  NaN
dtype: float64
```

In [4]:
```
data.median()
```

Out[4]:
```
ID                   769.500000
engine_power          51.000000
age_in_days         1035.000000
km                 39031.000000
previous_owners        1.000000
lat                   44.394096
```

```
Unnamed: 9                  NaN
dtype: float64
```

In [5]:
```
data.mode()
```

Out[5]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon
0	1.0	lounge	51.0	366.0	17000.0	1.0	41.903221	12.49565029
1	2.0	NaN	NaN	790.0	NaN	NaN	NaN	NaN
2	3.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	4.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	5.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...
1533	1534.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1534	1535.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1535	1536.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1536	1537.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1537	1538.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN

1538 rows × 11 columns

In [6]:
```
data.describe()
```

Out[6]:

	ID	engine_power	age_in_days	km	previous_owners	lat	Unnam
count	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	
mean	769.500000	51.904421	1650.980494	53396.011704	1.123537	43.541361	N
std	444.126671	3.988023	1289.522278	40046.830723	0.416423	2.133518	N
min	1.000000	51.000000	366.000000	1232.000000	1.000000	36.855839	N
25%	385.250000	51.000000	670.000000	20006.250000	1.000000	41.802990	N
50%	769.500000	51.000000	1035.000000	39031.000000	1.000000	44.394096	N
75%	1153.750000	51.000000	2616.000000	79667.750000	1.000000	45.467960	N
max	1538.000000	77.000000	4658.000000	235000.000000	4.000000	46.795612	N

Find sum(), cumsum(), count, min and max values

In [7]:
```
data.sum()
```

Out[7]:
```
ID                                                        1183491.0
engine_power                                                79829.0
age_in_days                                               2539208.0
km                                                       82123066.0
previous_owners                                             1728.0
lat                                                      66966.61372
lon               8.61155986812.2418899511.4178417.6346092212.49...
price             8900880042006000570079001075091905600600089501...
Unnamed: 9                                                     0.0
dtype: object
```

In [8]:
```
a = data.head(50)
a.cumsum()
```

Out[8]:

	ID	model	engine_power	age_in_days	km
0	1.0	lounge	51.0	882.0	25000.0
1	3.0	loungepop	102.0	2068.0	57500.0
2	6.0	loungepopsport	176.0	6726.0	199728.0
3	10.0	loungepopsportlounge	227.0	9465.0	359728.0
4	15.0	loungepopsportloungepop	300.0	12539.0	466608.0
5	21.0	loungepopsportloungepoppop	374.0	16162.0	536833.0
6	28.0	loungepopsportloungepoppoplounge	425.0	16893.0	548433.0
7	36.0	loungepopsportloungepoppoploungelounge	476.0	18414.0	597509.0
8	45.0	loungepopsportloungepoppoploungeloungesport	549.0	22463.0	673509.0
9	55.0	loungepopsportloungepoppoploungeloungesportsport	600.0	26116.0	762509.0
10	66.0	loungepopsportloungepoppoploungeloungesportspo...	651.0	26906.0	805795.0
11	78.0	loungepopsportloungepoppoploungeloungesportspo...	702.0	27272.0	823295.0
12	91.0	loungepopsportloungepoppoploungeloungesportspo...	753.0	27728.0	841745.0
13	105.0	loungepopsportloungepoppoploungeloungesportspo...	804.0	31563.0	961745.0
14	120.0	loungepopsportloungepoppoploungeloungesportspo...	855.0	32598.0	1002245.0
15	136.0	loungepopsportloungepoppoploungeloungesportspo...	906.0	33694.0	1030445.0
16	153.0	loungepopsportloungepoppoploungeloungesportspo...	979.0	37894.0	1140445.0
17	171.0	loungepopsportloungepoppoploungeloungesportspo...	1030.0	40117.0	1237293.0
18	190.0	loungepopsportloungepoppoploungeloungesportspo...	1081.0	42978.0	1268293.0
19	210.0	loungepopsportloungepoppoploungeloungesportspo...	1132.0	43403.0	1288323.0
20	231.0	loungepopsportloungepoppoploungeloungesportspo...	1183.0	43800.0	1307360.0
21	253.0	loungepopsportloungepoppoploungeloungesportspo...	1234.0	45686.0	1417360.0

	ID	model	engine_power	age_in_days	km
22	276.0	loungepopsportloungepoppoploungeloungesportspo...	1285.0	46721.0	1425360.0
23	300.0	loungepopsportloungepoppoploungeloungesportspo...	1336.0	47511.0	1452955.0
24	325.0	loungepopsportloungepoppoploungeloungesportspo...	1387.0	49094.0	1467855.0
25	351.0	loungepopsportloungepoppoploungeloungesportspo...	1438.0	49460.0	1477073.0
26	378.0	loungepopsportloungepoppoploungeloungesportspo...	1489.0	53052.0	1601073.0
27	406.0	loungepopsportloungepoppoploungeloungesportspo...	1540.0	56583.0	1701073.0
28	435.0	loungepopsportloungepoppoploungeloungesportspo...	1591.0	57345.0	1729973.0
29	465.0	loungepopsportloungepoppoploungeloungesportspo...	1642.0	58015.0	1733973.0
30	496.0	loungepopsportloungepoppoploungeloungesportspo...	1704.0	60784.0	1793189.0
31	528.0	loungepopsportloungepoppoploungeloungesportspo...	1755.0	64953.0	1892666.0
32	561.0	loungepopsportloungepoppoploungeloungesportspo...	1806.0	65774.0	1914396.0
33	595.0	loungepopsportloungepoppoploungeloungesportspo...	1857.0	69701.0	2054396.0
34	630.0	loungepopsportloungepoppoploungeloungesportspo...	1908.0	70341.0	2086429.0
35	666.0	loungepopsportloungepoppoploungeloungesportspo...	1959.0	73994.0	2224545.0
36	703.0	loungepopsportloungepoppoploungeloungesportspo...	2010.0	74846.0	2241545.0
37	741.0	loungepopsportloungepoppoploungeloungesportspo...	2061.0	77859.0	2300072.0
38	780.0	loungepopsportloungepoppoploungeloungesportspo...	2112.0	78649.0	2343172.0
39	820.0	loungepopsportloungepoppoploungeloungesportspo...	2163.0	80507.0	2356545.0
40	861.0	loungepopsportloungepoppoploungeloungesportspo...	2214.0	84646.0	2475545.0
41	903.0	loungepopsportloungepoppoploungeloungesportspo...	2265.0	85255.0	2504045.0
42	946.0	loungepopsportloungepoppoploungeloungesportspo...	2316.0	86351.0	2587045.0
43	990.0	loungepopsportloungepoppoploungeloungesportspo...	2389.0	90400.0	2685045.0
44	1035.0	loungepopsportloungepoppoploungeloungesportspo...	2440.0	90856.0	2697738.0
45	1081.0	loungepopsportloungepoppoploungeloungesportspo...	2491.0	91618.0	2712324.0
46	1128.0	loungepopsportloungepoppoploungeloungesportspo...	2542.0	92439.0	2739964.0
47	1176.0	loungepopsportloungepoppoploungeloungesportspo...	2593.0	94478.0	2788964.0

In [9]:
```
data.count()
```

Out[9]:
```
ID                1538
model             1538
engine_power      1538
age_in_days       1538
km                1538
previous_owners   1538
lat               1538
```

```
lon               1549
price             1549
Unnamed: 9           0
Unnamed: 10          1
dtype: int64
```

In [10]:
```
data.max()
```

Out[10]:
```
ID                   1538.0
engine_power           77.0
age_in_days          4658.0
km                 235000.0
previous_owners         4.0
lat                46.795612
lon                    sumif
price               lonprice
Unnamed: 9               NaN
dtype: object
```

In [11]:
```
data.min()
```

Out[11]:
```
ID                       1.0
engine_power            51.0
age_in_days            366.0
km                    1232.0
previous_owners          1.0
lat                36.855839
lon                10.00240993
price                      1
Unnamed: 9               NaN
dtype: object
```

Find covariance and correlation (spearman and pearsons

In [12]:
```
from numpy import cov
```

In [13]:
```
print(cov(data['ID'],data['engine_power']))
```

```
[[nan nan]
 [nan nan]]
```

In [14]:
```
from scipy.stats import pearsonr
from scipy.stats import spearmanr
```

In [15]:
```
print(pearsonr(a['ID'],a['engine_power']))
```

```
(-0.28309348116788063, 0.04636002207093489)
```

In [16]:
```
print(spearmanr(a['ID'],a['engine_power']))
```

```
SpearmanrResult(correlation=-0.2700768408837805, pvalue=0.05784835814161204)
```