## Data Visualisation - Graded Questions

Note - This stub file doesn't contain the conceptual questions asked on the platform

## ▼ I) Marks Analysis

In the 'Marks.csv' file, you can find the scores obtained by 200 students in 4 subjects of a standardised test. The different columns - Score A, Score B, Score C and Score D indicate the score obtained by a particular student in the respective subjects A, B, C and D.

Load the dataset to your notebook and answer the following questions

```
#Load the necessary Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
#Load the dataset
df1 = pd.read_csv('Marks.csv')
df1.head()
```

	Score A	Score B	Score C	Score D	
0	230.1	37.8	69.2	22.1	ıl.
1	44.5	39.3	45.1	10.4	
2	17.2	45.9	69.3	12.0	
3	151.5	41.3	58.5	16.5	
4	180.8	10.8	58.4	17.9	

**Q1)** Load the dataset and plot a histogram for the Score A column by keeping the number of bins to 6. Which bin range among the following has the highest frequency?

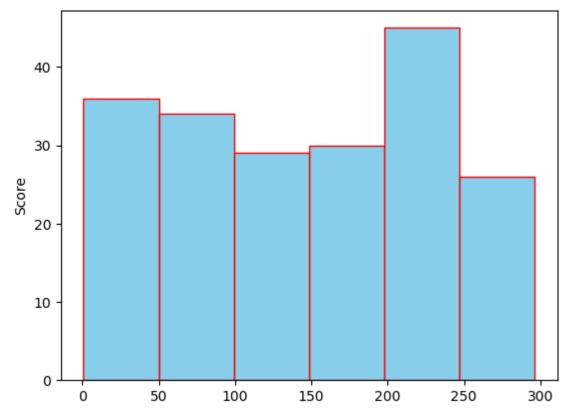
(Note - The bin ranges mentioned in the options are approximate values for the bin ranges that you'll actually get when you plot the histogram)

```
a)0-50
```

b)50-100

c) 150-200

d)200-250 - Correct

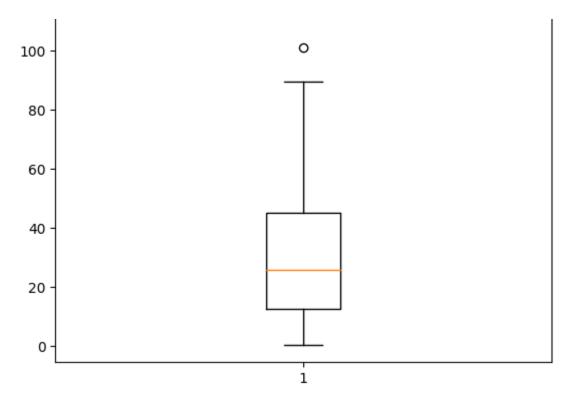


## Q2) Plot a box plot for the column Score C and choose the correct option.

A - The 25th percentile lies between 20 and 40

2 of 8 19/10/23, 11:02

0



## II) Superstore Data

In the superstore.csv file, you have the details of orders purchased in an American online retail store. Load the dataset, observe and analyse the different columns and answer the following questions.

```
#Load the dataset
df2 = pd.read_csv('superstore.csv')
df2.head()
```

	Order ID	Ship Mode	Segment	Region	Product ID	Sales	Quant:
0	CA-2016-152156	Second Class	Consumer	South	FUR- BO-10001798	261.9600	
1	CA-2016-152156	Second Class	Consumer	South	FUR- CH-10000454	731.9400	
2	CA-2016-138688	Second Class	Corporate	West	OFF- LA-10000240	14.6200	
3	US-2015-108966	Standard Class	Consumer	South	FUR- TA-10000577	957.5775	
4	US-2015-108966	Standard Class	Consumer	South	OFF- ST-10000760	22.3680	

**Q4)** Plot a pie-chart to find the Ship Mode through which most of the orders are being delivered.

```
a)Standard Class - correct
```

- b)First Class
- c)Second Class
- d)Same Day

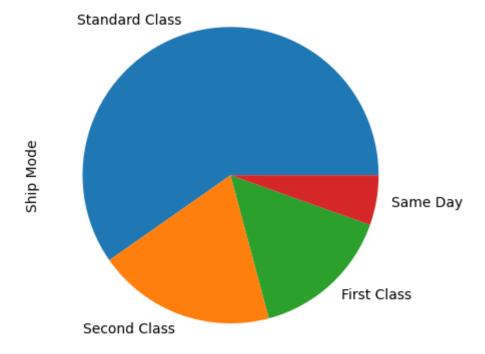
## df2['Ship Mode'].value\_counts()

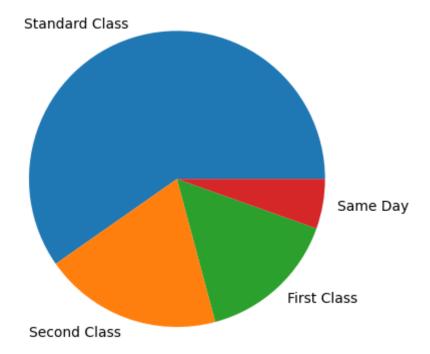
Standard Class 5968 Second Class 1945 First Class 1538 Same Day 543

Name: Ship Mode, dtype: int64

#Your code here
df2['Ship Mode'].value\_counts().plot.pie()

<Axes: ylabel='Ship Mode'>





**Q5)** Plot a bar chart comparing the average Discount across all the Regions and report back the Region getting the highest average discount

Note - You need to clean the Discount column first

- a)Central correct
- b)South
- c)West
- d)East

## df2.head()

	Order ID	Ship Mode	Segment	Region	Product ID	Sales	Quant
0	CA-2016-152156	Second Class	Consumer	South	FUR- BO-10001798	261.9600	
1	CA-2016-152156	Second Class	Consumer	South	FUR- CH-10000454	731.9400	
2	CA-2016-138688	Second Class	Corporate	West	OFF- LA-10000240	14.6200	
3	US-2015-108966	Standard Class	Consumer	South	FUR- TA-10000577	957.5775	
4	US-2015-108966	Standard Class	Consumer	South	OFF- ST-10000760	22.3680	

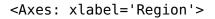
111 1 1 //

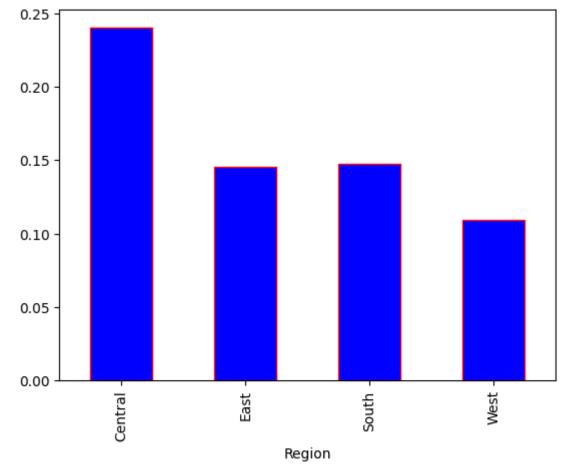
```
atz['Discount'].value_counts()
              4798
    0%
    0.20%
              3657
    0.70%
               418
    0.80%
               300
    0.30%
               227
    0.40%
               206
    0.60%
               138
    0.10%
                94
    0.50%
                66
    0.15%
                52
    0.32%
                27
    0.45%
                11
    Name: Discount, dtype: int64
df2['Discount values'] = df2['Discount'].str.strip('%').astype('float')
df2['Discount values'].value counts()
    0.00
             4798
    0.20
             3657
    0.70
              418
    0.80
              300
    0.30
              227
    0.40
              206
    0.60
              138
               94
    0.10
    0.50
               66
               52
    0.15
    0.32
               27
               11
    0.45
    Name: Discount values, dtype: int64
df2.groupby('Region').mean()
    <ipython-input-70-625368922aac>:1: FutureWarning: The default value of nume
      df2.groupby('Region').mean()
                                                                  扁
                   Sales Quantity
                                       Profit Discount values
      Region
                                                                  11.
     Central 215.772661 3.779595 17.092709
                                                      0.240353
       East
              238.336110 3.728230 32.135808
                                                      0.145365
      South
              241.803645 3.832716 28.857673
                                                      0.147253
      West
              226.493233 3.829535 33.849032
                                                      0.109335
region wise avg discount = df2.groupby('Region')['Discount values'].mean()
region wise avg discount
    Region
    Central
                0.240353
    East
                0.145365
```

South 0.147253 West 0.109335

Name: Discount values, dtype: float64

# Plot a bar chart comparing the average Discount across all the Regions and # report back the Region getting the highest average discount region\_wise\_avg\_discount.plot.bar(color='blue', edgecolor='red')





```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
```

## When to use scatter plots?

- Scatter plots are used to convey the relationship between two numerical variables
- Scatter plots are sometimes called correlation plots because they show how two variables are correlated

```
# Read Toyota.csv, Handle "??","????" at the time of reading
cars_data = pd.read_csv('Toyota.csv', na_values=['??', '????'], index_col=0)
```

## cars\_data

	Price	Age	KM	FuelType	HP	MetColor	Automatic	CC	Door
0	13500	23.0	46986.0	Diesel	90.0	1.0	0	2000	thre
1	13750	23.0	72937.0	Diesel	90.0	1.0	0	2000	•
2	13950	24.0	41711.0	Diesel	90.0	NaN	0	2000	•
3	14950	26.0	48000.0	Diesel	90.0	0.0	0	2000	•
4	13750	30.0	38500.0	Diesel	90.0	0.0	0	2000	•
									• 1
1431	7500	NaN	20544.0	Petrol	86.0	1.0	0	1300	•
1432	10845	72.0	NaN	Petrol	86.0	0.0	0	1300	•
1433	8500	NaN	17016.0	Petrol	86.0	0.0	0	1300	
1434	7250	70.0	NaN	NaN	86.0	1.0	0	1300	
1435	6950	76.0	1.0	Petrol	110.0	0.0	0	1600	

1436 rows × 10 columns

### cars data.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 1436 entries, 0 to 1435
Data columns (total 10 columns):

Data	Cocamins	(cocac io cocamins)	•
#	Column	Non-Null Count	Dtype
0	Price	1436 non-null	int64
1	Age	1336 non-null	float64
2	KM	1421 non-null	float64
3	FuelType	e 1336 non-null	object
_			

```
ΗP
                                    tloat64
                    1430 non-null
     5
         MetColor
                    1286 non-null
                                    float64
     6
         Automatic 1436 non-null
                                    int64
     7
                    1436 non-null
                                    int64
     8
                    1436 non-null
         Doors
                                    object
     9
         Weight 1436 non-null
                                    int64
    dtypes: float64(4), int64(4), object(2)
    memory usage: 123.4+ KB
cars data.isnull().sum()
    Price
                   0
                 100
    Age
    KΜ
                  15
    FuelType
                 100
    HP
                   6
                 150
    MetColor
    Automatic
                   0
    CC
                   0
    Doors
                   0
                   0
    Weight
    dtype: int64
## Drop null values
cars data.dropna(inplace=True)
cars data.info()
    <class 'pandas.core.frame.DataFrame'>
    Int64Index: 1096 entries, 0 to 1435
    Data columns (total 10 columns):
     #
         Column
                    Non-Null Count Dtype
     - - -
         -----
                    -----
                                    ----
                    1096 non-null
     0
         Price
                                    int64
     1
         Age
                    1096 non-null
                                    float64
     2
         KM
                    1096 non-null
                                    float64
     3
         FuelType 1096 non-null
                                    object
     4
                    1096 non-null
                                    float64
         HP
     5
         MetColor
                    1096 non-null
                                    float64
     6
                                    int64
         Automatic 1096 non-null
     7
         CC
                    1096 non-null
                                    int64
         Doors
                                    object
     8
                    1096 non-null
         Weight
                    1096 non-null
                                    int64
    dtypes: float64(4), int64(4), object(2)
```

matplotlib.pyplot.scatter(x, y, s=None, c=None, marker=None, cmap=None, norm=None, vmin=None, vmax=None, alpha=None, linewidths=None, , edgecolors=None, plotnonfinite=False, data=None, \*kwarqs)

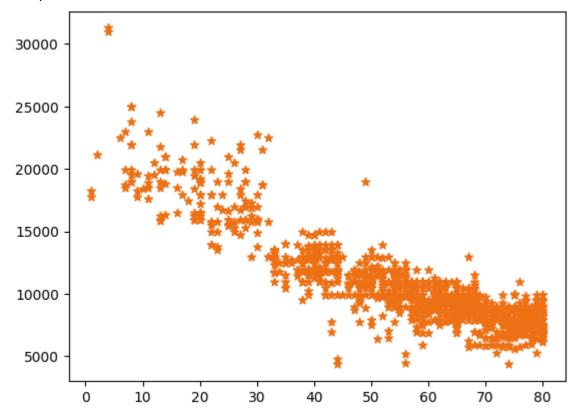
```
cars_data.isnull().sum()
Price 0
```

memory usage: 94.2+ KB

```
Age 0 KM 0 FuelType 0 HP 0 MetColor 0 Automatic 0 CC 0 Doors 0 Weight 0 dtype: int64
```

#Scatter plot of Age Vs Price
plt.scatter(cars\_data['Age'], cars\_data['Price'], marker='\*', color='#ed7014')

<matplotlib.collections.PathCollection at 0x7c86dd3e9ae0>



# write the analysis observed from plot

## Histogram

# What is a histogram?

- It is a graphical representation of data using bars of different heights
- Histogram groups numbers into ranges and the height of each bar depicts the frequency of each range or bin

#### Mhan ta uga histaarama?

## when to use mstograms:

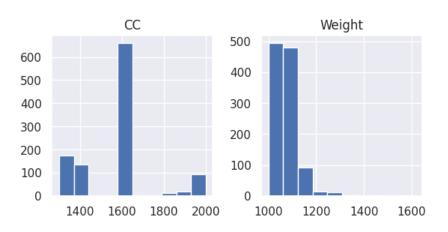
• To represent the frequency distribution of numerical variables

```
cars_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1096 entries, 0 to 1435
Data columns (total 10 columns):
#
     Column
                Non-Null Count
                                 Dtype
0
     Price
                1096 non-null
                                 int64
1
                1096 non-null
                                 float64
     Age
2
                                 float64
     ΚM
                1096 non-null
3
                                 object
     FuelType
                1096 non-null
4
                                 float64
     HP
                1096 non-null
5
     MetColor
                1096 non-null
                                 float64
6
     Automatic
                1096 non-null
                                 int64
7
     CC
                1096 non-null
                                 int64
8
     Doors
                1096 non-null
                                 object
9
     Weight
                1096 non-null
                                 int64
dtypes: float64(4), int64(4), object(2)
memory usage: 94.2+ KB
```

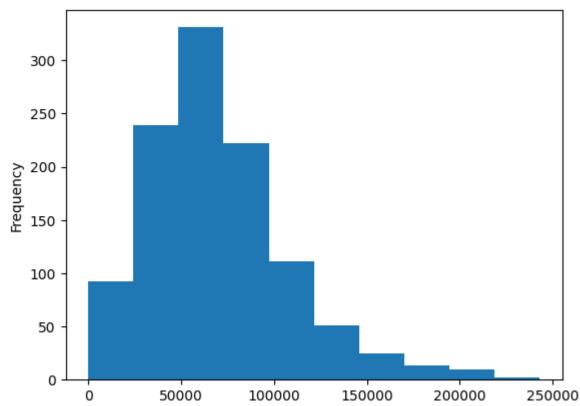
cars\_data.hist(figsize=(10, 10))

```
array([[<Axes: title={'center': 'Price'}>,
         <Axes: title={'center': 'Age'}>, <Axes: title={'center': 'KM'}>],
        [<Axes: title={'center': 'HP'}>,
         <Axes: title={'center': 'MetColor'}>,
         <Axes: title={'center': 'Automatic'}>],
        [<Axes: title={'center': 'CC'}>,
         <Axes: title={'center': 'Weight'}>, <Axes: >]], dtype=object)
              Price
                                           Age
                                                                         ΚM
 400
                                                          300
                              200
                                                          250
 300
                              150
                                                           200
 200
                                                           150
                              100
                                                           100
 100
                               50
                                                            50
   0
                                                            0
                               0
        10000
               20000
                       30000
                                        25
                                               50
                                                     75
                                                                     100000
                                                                              200000
               HP
                                         MetColor
                                                                      Automatic
                                                          1000
 600
                              600
                                                          800
 400
                                                          600
                              400
                                                           400
 200
                              200
                                                           200
   0
                               0
                                                            0
                                            0.5
          100
                  150
                                  0.0
                                                      1.0
                                                               0.0
                                                                         0.5
                                                                                   1.0
```



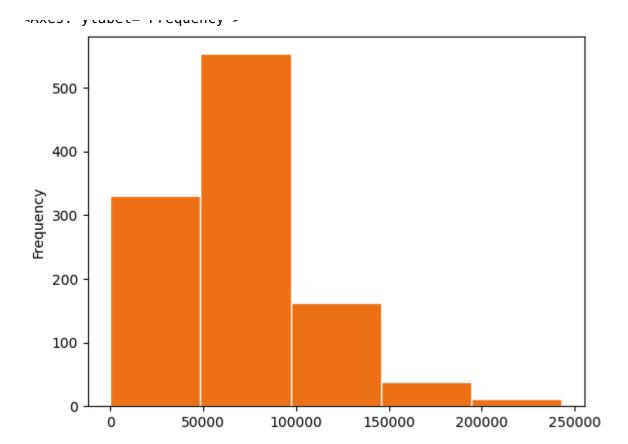
# do some formatting
cars\_data['KM'].plot.hist()

<Axes: ylabel='Frequency'>



cars\_data['KM'].plot.hist(color='#ed7014', bins=5, edgecolor='white')

<Ayes. vlahel='Frequency'>



## Bar plot

What is a bar plot?

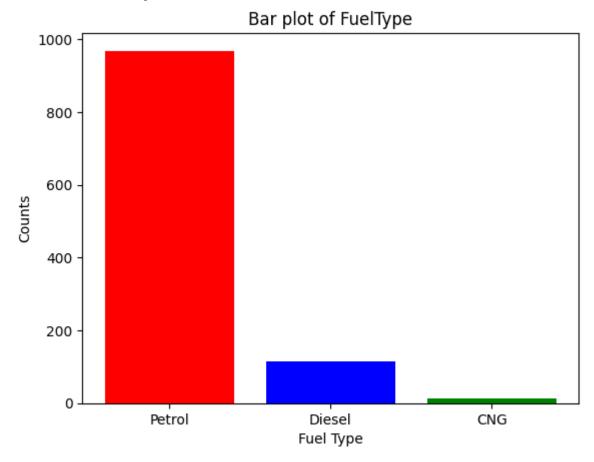
• A bar plot is a plot that presents categorical data with rectangular bars with lengths proportional to the counts that they represent

# When to use bar plot?

• To represent the frequency distribution of categorical variables • A bar diagram makes it easy to compare sets of data between different groups

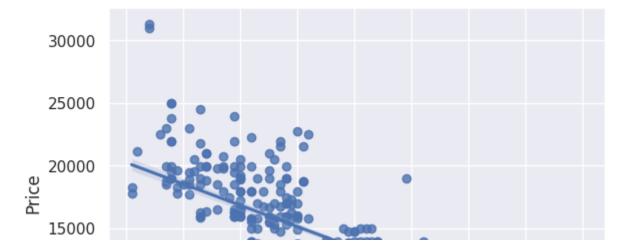
```
pit.yiabei( counts )
plt.title('Bar plot of FuelType')
plt.bar(fuels.index, fuels, color=['red', 'blue','green'])
```

<BarContainer object of 3 artists>



## Seaborn

- · Seaborn is a Python data visualization library based on matplotlib
- It provides a high-level interface for drawing attractive and informative statistical graphics

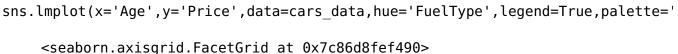


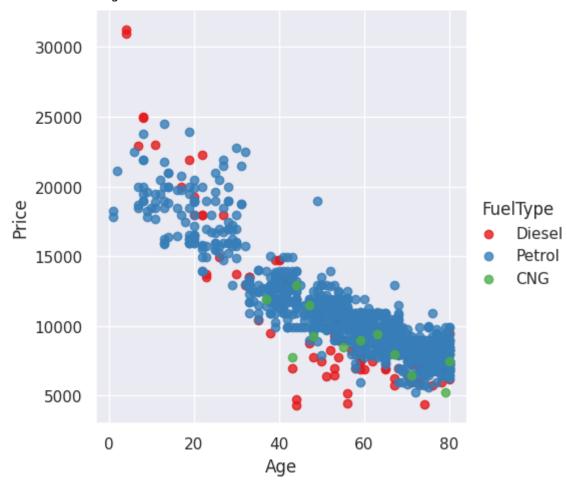


By default, fit\_reg = True

o It estimates and plots a regression model relating the x and y variables

# Using hue parameter, including another variable to show the fuel types categories with different colors





```
sns.distplot(cars data['Age'])
```

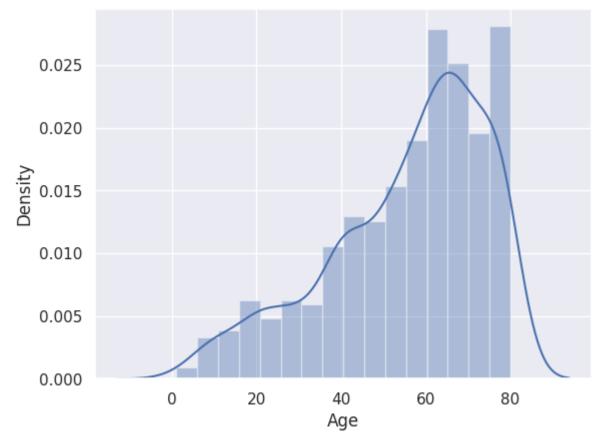
<ipython-input-68-67ef1d320a1e>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0

Please adapt your code to use either `displot` (a figure-level function wisimilar flexibility) or `histplot` (an axes-level function for histograms)

For a guide to updating your code to use the new functions, please see <a href="https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751">https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751</a>

```
sns.distplot(cars_data['Age'])
<Axes: xlabel='Age', ylabel='Density'>
```



sns.distplot(cars data['Age'],kde=False)

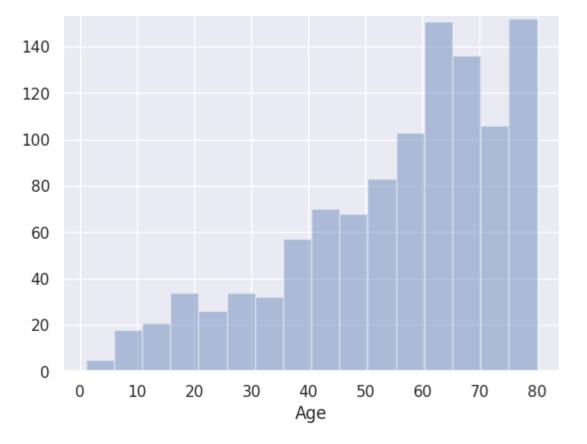
<ipython-input-69-0f8bc2d269a0>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0

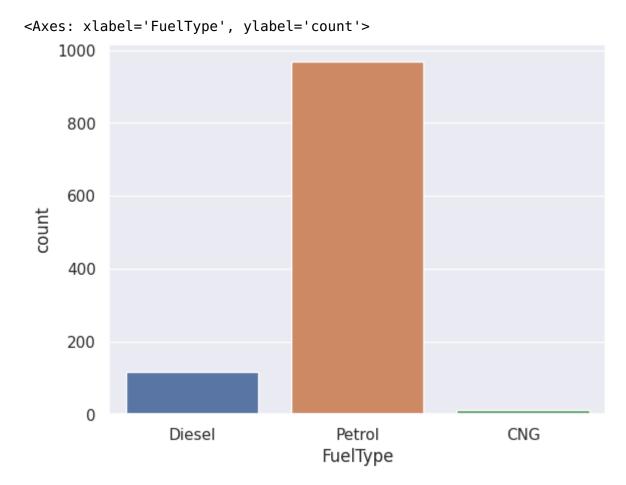
Please adapt your code to use either `displot` (a figure-level function wisimilar flexibility) or `histplot` (an axes-level function for histograms)

For a guide to updating your code to use the new functions, please see <a href="https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751">https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751</a>

```
sns.distplot(cars_data['Age'],kde=False)
<Axes: xlabel='Age'>
```



sns.countplot(x='FuelType',data=cars\_data)

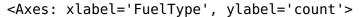


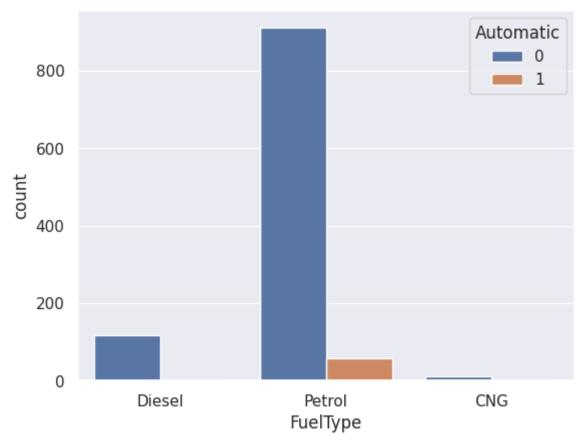
pd.crosstab(index=cars\_data['Automatic'],columns=cars\_data['FuelType'],dropna=Tr

Evaltura CNC Discal Datus

rueriype	CNG	ntezer	retrot	ш
Automatic				ılı
0	12	116	910	
1	0	0	58	

sns.countplot(x='FuelType',data=cars\_data,hue='Automatic')

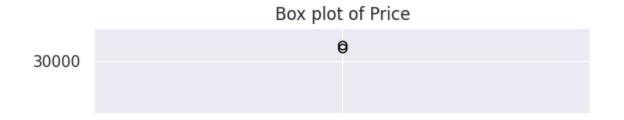


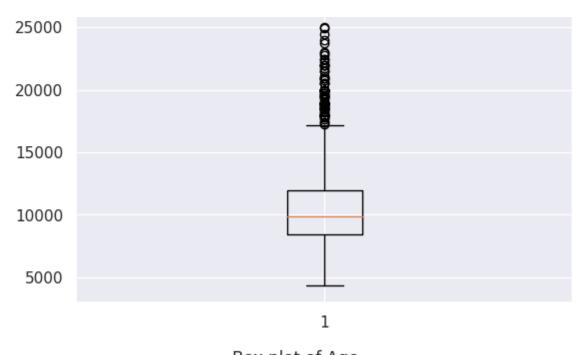


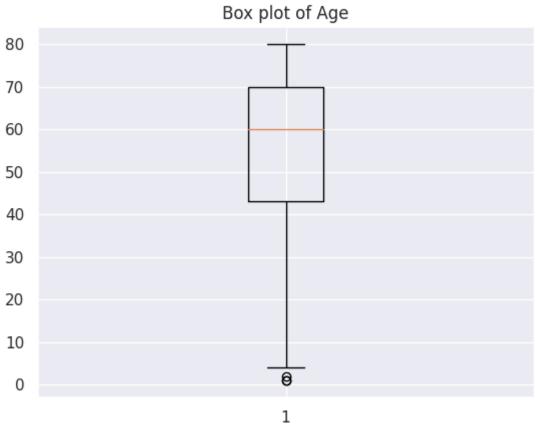
## Box and whiskers plot - numerical variable

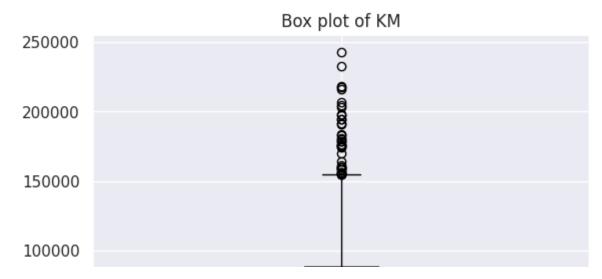
Box and whiskers plot of Price to visually interpret the five-number summary

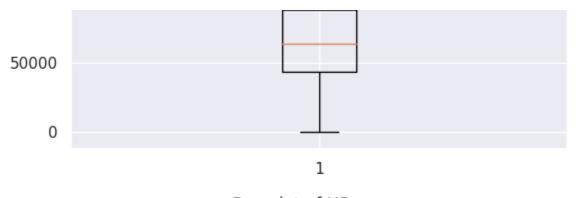
```
# box plot of all numerical columns
# verify the stastical info
for col in cars_data.select_dtypes(include=['float64', 'int64']).columns:
   plt.boxplot(cars_data[col])
   plt.title(f"Box plot of {col}")
   plt.show()
```



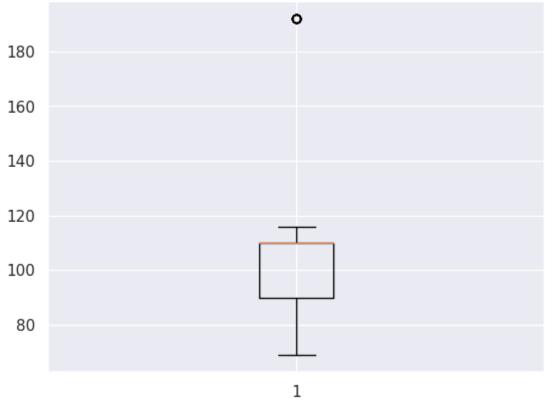




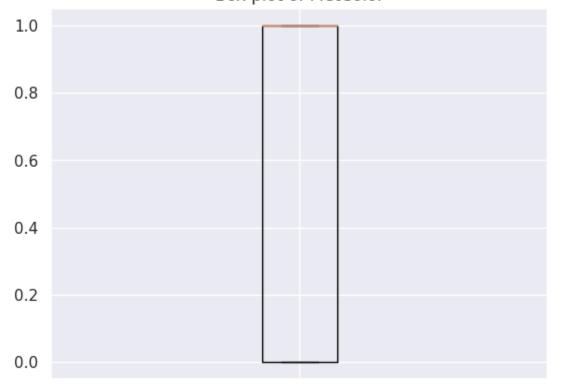




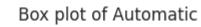


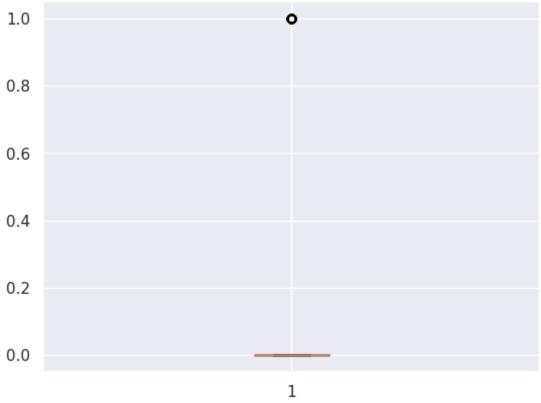


# Box plot of MetColor

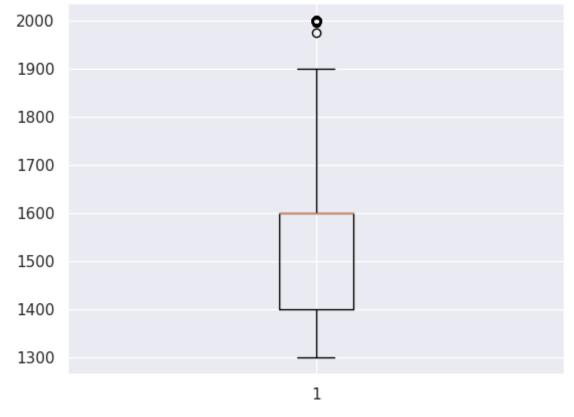


1

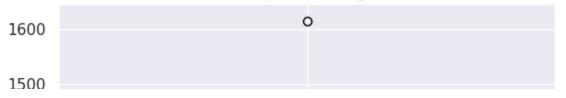


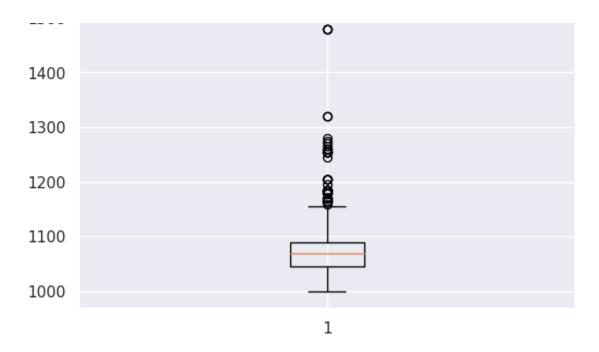


# Box plot of CC



# Box plot of Weight



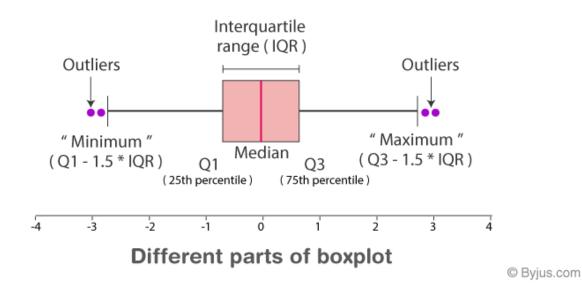


A box plot (aka box and whisker plot) uses boxes and lines to depict the distributions of one or more groups of numeric data.

Box limits indicate the range of the central 50% of the data, with a central line marking the median value.

Lines extend from each box to capture the range of the remaining data,

with dots placed past the line edges to indicate outliers.



11950.0

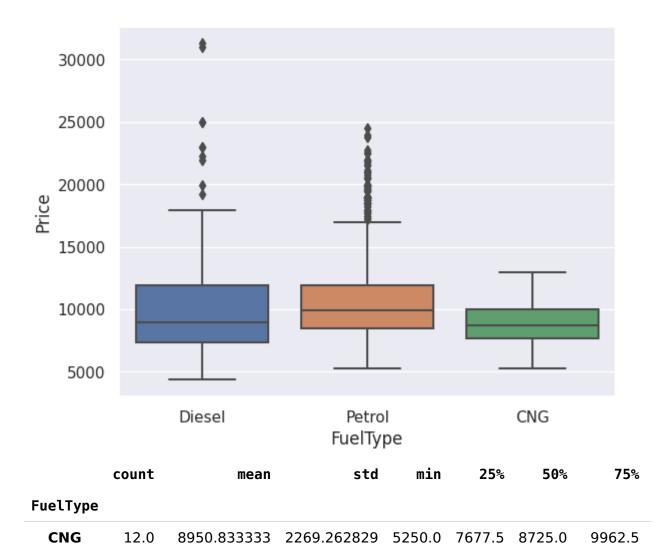
Diesel

Petrol

```
# box plot of numerical columns vs categorical column
# verify the stastical info
```

# box plot of numerical columns vs categorical column
sns.boxplot(x=cars\_data['FuelType'],y=cars\_data['Price'])
plt.show()

# verify the stastical info
cars\_data.groupby('FuelType')['Price'].describe()



#create two subplots and plot Box bolt and histogram plot of the same numerical
fig,ax=plt.subplots(1,2,figsize=(10,8))
sns.boxplot(y=cars\_data['Price'],ax=ax[0])
sns.histplot(cars\_data['Price'],ax=ax[1],kde=False)
plt.show()



116.0 10550.956897 5233.610064 4350.0 7325.0 8950.0

968.0 10780.233471 3408.043316 5250.0 8500.0 9940.0 11950.0

