

DATA HANDLING IN PYTHON

CODE

```
import pandas as pd
```

```
data=pd.read_csv("auto-mpg.csv")
```

```
type(data)
```

OUTPUT



```
pandas.core.frame.DataFrame
def __init__(data=None, index: Axes | None=None, columns: Axes | None=None,
dtype: Dtype | None=None, copy: bool | None=None) -> None
```

Two-dimensional, size-mutable, potentially heterogeneous tabular data.

Data structure also contains labeled axes (rows and columns).
Arithmetic operations align on both row and column labels. Can be
thought of as a dict-like container for Series objects. The primary

```
data.shape
```



```
(398, 9)
```

```
nrow_count=data.shape[0]
print(nrow_count)
```



```
398
```

```
ncol_count=data.shape[1]
print(ncol_count)
```



```
9
```

```
data.columns
```



```
Index(['mpg', 'cylinders', 'displacement', 'horsepower', 'weight',
'acceleration', 'model year', 'origin', 'car name'],
dtype='object')
```

```
data.columns=['miles_per_gallon', 'cylinders', 'displacement', 'horsepower', 'weight',
'acceleration', 'model year', 'origin', 'car name']
```

```
data.columns
```



```
Index(['miles_per_gallon', 'cylinders', 'displacement', 'horsepower', 'weight',
'acceleration', 'model year', 'origin', 'car name'],
dtype='object')
```

CODE

```
data.rename(columns={'displacement':'disp'},inplace=True)
```

```
data.head()
```

OUTPUT



	miles_per_gallon	cylinders	disp	horsepower	weight	acceleration	model year	origin
0	18.0	8	307.0	130	3504	12.0	70	1
1	15.0	8	350.0	165	3693	11.5	70	1

```
data.head(3)
```



	miles_per_gallon	cylinders	disp	horsepower	weight	acceleration	model year	origin
0	18.0	8	307.0	130	3504	12.0	70	1

```
data.tail()
```

	miles_per_gallon	cylinders	disp	horsepower	weight	acceleration	model year	orig
393	27.0	4	140.0	86	2790	15.6	82	
394	44.0	4	97.0	52	2130	24.6	82	

```
data.tail(3)
```

	miles_per_gallon	cylinders	disp	horsepower	weight	acceleration	model year	orig
395	32.0	4	135.0	84	2295	11.6	82	

CODE

```
data.at[200,'cylinders']
```

6

```
#data.get_value(200,'cylinders')
```

```
data_cyl=data.loc[:,'car name']
```

```
data_cyl.head()
```

OUTPUT

```
0    chevrolet chevelle malibu
1         buick skylark 320
2      plymouth satellite
3         amc rebel sst
4         ford torino
Name: car name, dtype: object
```

CODE

```
import numpy as np
```

```
var1=[np.nan,np.nan,np.nan,10.1,12,123.14,0.121]
var2=[40.2,11.78,7801,0.25,34.2,np.nan,np.nan]
var3=[1234,np.nan,34.5,np.nan,78.25,14.5,np.nan]
df=pd.DataFrame({'Attr_1':var1,'Attr_2':var2,'Attr_3':var3})
print(df)
```

OUTPUT

	Attr_1	Attr_2	Attr_3
0	NaN	40.20	1234.00
1	NaN	11.78	NaN
2	NaN	7801.00	34.50
3	10.100	0.25	NaN
4	12.000	34.20	78.25
5	123.140	NaN	14.50
6	0.121	NaN	NaN

CODE

```
miss_val=df[df['Attr_1'].isnull()]
print(miss_val)
```

OUTPUT

	Attr_1	Attr_2	Attr_3
0	NaN	40.20	1234.0
1	NaN	11.78	NaN
2	NaN	7801.00	34.5

```
np.mean(data[['miles_per_gallon']])
```

23.514572864321607

```
np.median(data[['miles_per_gallon']])
```

23.0

```
np.var(data[['miles_per_gallon']])
```

```
miles_per_gallon    60.936119
dtype: float64
```

```
np.std(data[['miles_per_gallon']])
```

```
↗ miles_per_gallon    7.806159  
dtype: float64
```

IRIS DATASET

CODE

```
from sklearn import datasets
```

```
iris=datasets.load_iris()
```

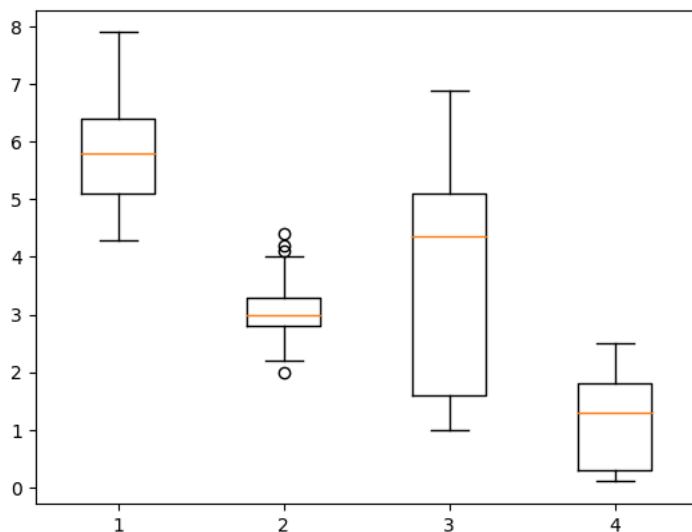
```
import matplotlib.pyplot as plt
```

```
X=iris.data[:, :4]
```

```
plt.boxplot(X)
```

OUTPUT

```
↗ {'whiskers': [<matplotlib.lines.Line2D at 0x7f16ee3a3910>,  
<matplotlib.lines.Line2D at 0x7f16ee3a1c90>,  
<matplotlib.lines.Line2D at 0x7f16ee3a2da0>,  
<matplotlib.lines.Line2D at 0x7f16ee3a2f50>,  
<matplotlib.lines.Line2D at 0x7f16ee7a49a0>,  
<matplotlib.lines.Line2D at 0x7f16edf91600>,  
<matplotlib.lines.Line2D at 0x7f16edf91450>,  
<matplotlib.lines.Line2D at 0x7f16edf92a70>],  
'caps': [<matplotlib.lines.Line2D at 0x7f16ee3a3730>,  
<matplotlib.lines.Line2D at 0x7f16ee3a26e0>,  
<matplotlib.lines.Line2D at 0x7f16ee3a3130>,  
<matplotlib.lines.Line2D at 0x7f16ee3a3d00>,  
<matplotlib.lines.Line2D at 0x7f16edf902e0>,  
<matplotlib.lines.Line2D at 0x7f16edf92b00>,  
<matplotlib.lines.Line2D at 0x7f16edf91060>,  
<matplotlib.lines.Line2D at 0x7f16edf929b0>],  
'boxes': [<matplotlib.lines.Line2D at 0x7f16ee3a3190>,  
<matplotlib.lines.Line2D at 0x7f16ee3a3b20>,  
<matplotlib.lines.Line2D at 0x7f16ee7a47f0>,  
<matplotlib.lines.Line2D at 0x7f16edf92110>],  
'medians': [<matplotlib.lines.Line2D at 0x7f16ee3a12a0>,  
<matplotlib.lines.Line2D at 0x7f16ee3a23b0>,  
<matplotlib.lines.Line2D at 0x7f16edf923e0>,  
<matplotlib.lines.Line2D at 0x7f16edf93880>],  
'fliers': [<matplotlib.lines.Line2D at 0x7f16ee3a3340>,  
<matplotlib.lines.Line2D at 0x7f16ee7a4dc0>,  
<matplotlib.lines.Line2D at 0x7f16edf900d0>,  
<matplotlib.lines.Line2D at 0x7f16edf93220>],  
'means': []}
```

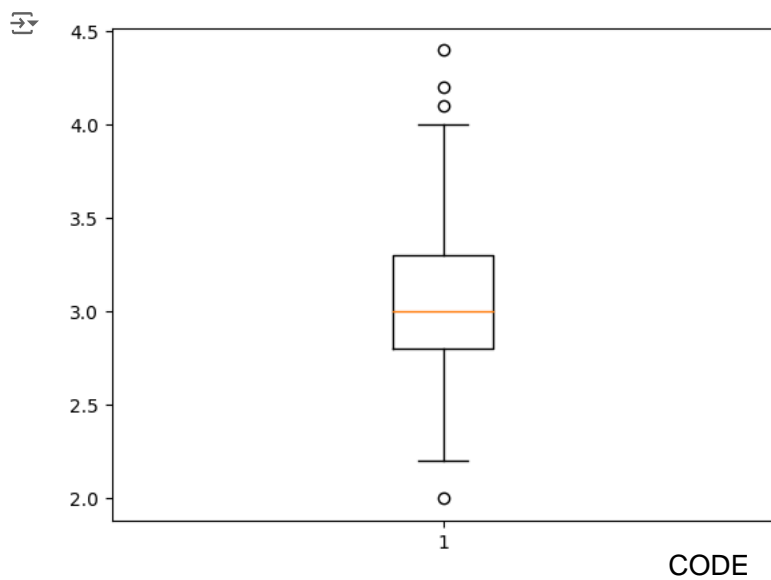


CODE

```
plt.show()
```

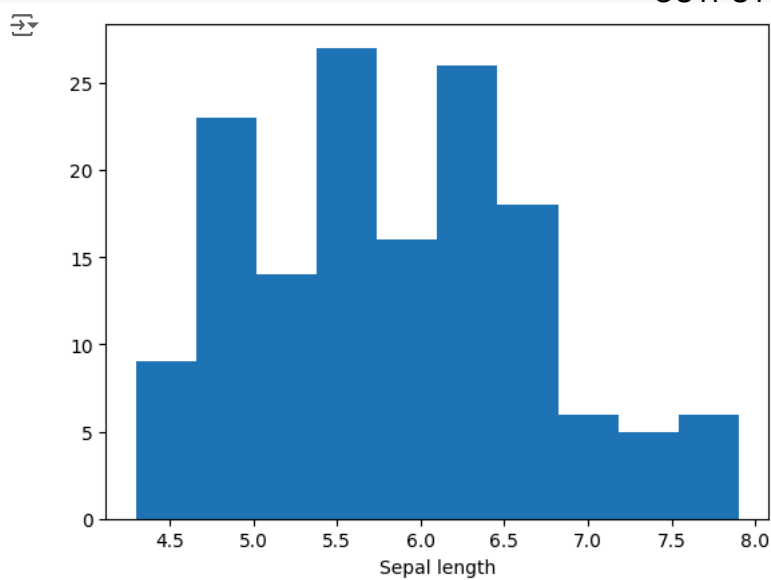
```
plt.boxplot(X[:,1])  
plt.show()
```

OUTPUT



```
X=iris.data[:, :1]
plt.hist(X)
plt.xlabel('Sepal length')
plt.show()
```

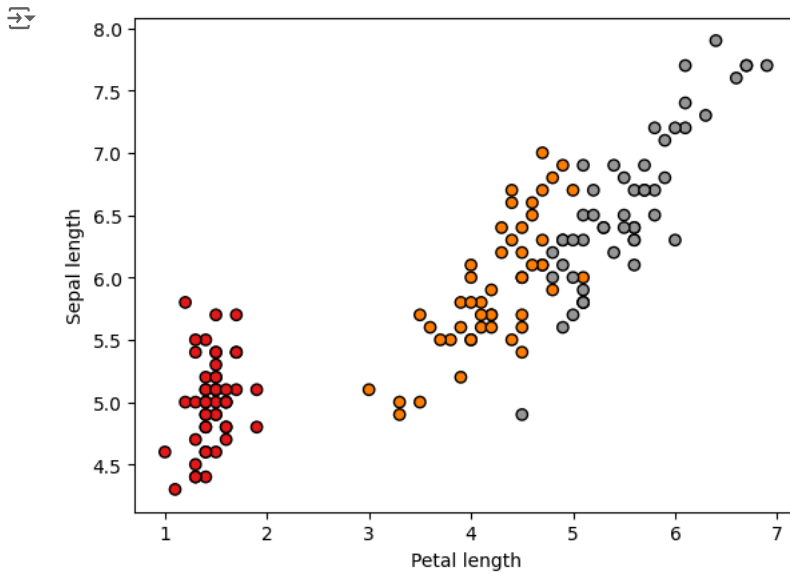
OUTPUT



CODE

```
X=iris.data[:, :4]
y=iris.target
plt.scatter(X[:, 2], X[:, 0], c=y, cmap=plt.cm.Set1, edgecolor='k')
plt.xlabel('Petal length')
plt.ylabel('Sepal length')
plt.show()
```

OUTPUT



DATA PRE-PROCESSING

CODE

```
df=pd.read_csv('auto-mpg.csv')
```

```
miss_val=df[df['horsepower'].isnull()]
print(miss_val)
```

OUTPUT

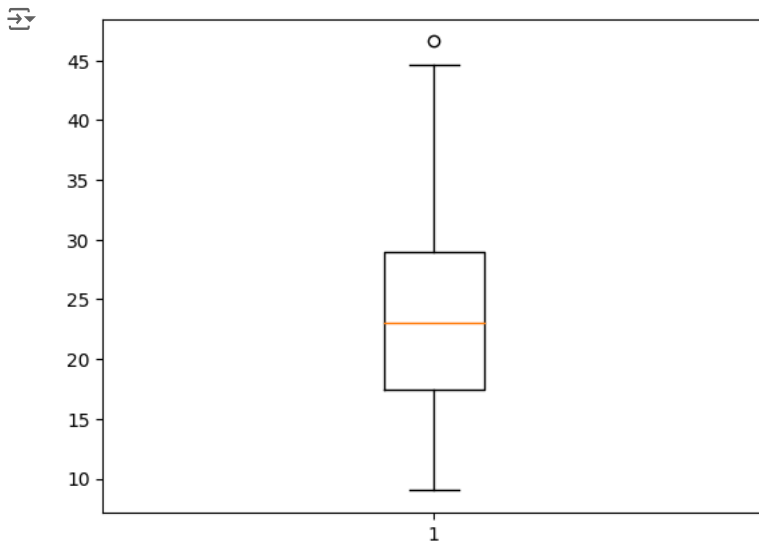
```
Empty DataFrame
Columns: [mpg, cylinders, displacement, horsepower, weight, acceleration, model year, origin, car name]
Index: []
```

Finding Outliers(Option 1):

CODE

```
X=data['miles_per_gallon']
plt.boxplot(X)
plt.show()
```


OUTPUT

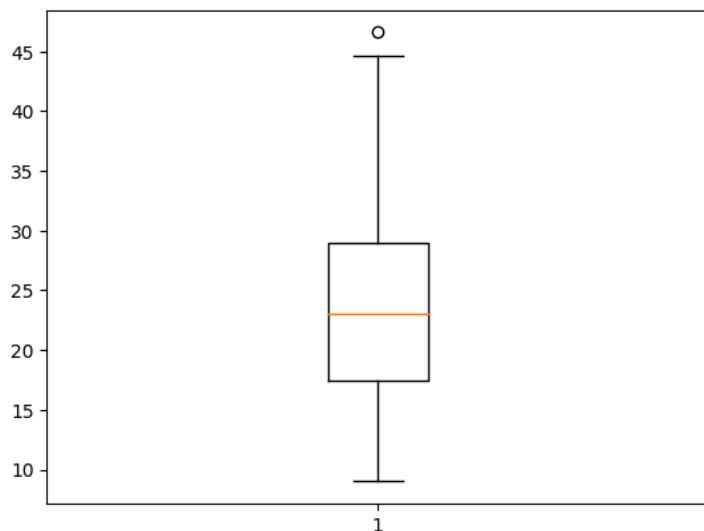


CODE

```
outliers=plt.boxplot(X[:,,])['fliers'][0].get_data([1])
outliers
```

OUTPUT

 (array([1.]), array([46.6]))



Finding Outliers(Option 2):


CODE

```
def find_outlier(ds, col):
    quart1 = ds[col].quantile(0.25)
    quart3 = ds[col].quantile(0.75)
    IQR = quart3 - quart1 #Inter-quartile range
    low_val = quart1 - 1.5*IQR
    high_val = quart3 + 1.5*IQR
    ds = ds.loc[(ds[col] < low_val) | (ds[col] > high_val)]
    return ds
```

```
outliers=find_outlier(data,'miles_per_gallon')
```

outliers

OUTPUT

 miles_per_gallon cylinders disp horsepower weight acceleration model year orig:


miles_per_gallon	cylinders	disp	horsepower	weight	acceleration	model year	orig:
18.0	8	307.0	130	3504	12.0	70	1
15.0	8	350.0	165	3693	11.5	70	1
18.0	8	318.0	150	3436	11.0	70	1
16.0	8	304.0	150	3433	12.0	70	1
17.0	8	302.0	140	3449	10.5	70	1
...
27.0	4	140.0	86	2790	15.6	82	1
44.0	4	97.0	52	2130	24.6	82	2
32.0	4	135.0	84	2295	11.6	82	1
28.0	4	120.0	79	2625	18.6	82	1
31.0	4	119.0	82	2720	19.4	82	1

Removing records with missing values / outliers:

CODE

```
data.dropna(axis=0, how='any')
```

OUTPUT



	miles_per_gallon	cylinders	disp	horsepower	weight	acceleration	model year	origin	car name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino
...
393	27.0	4	140.0	86	2790	15.6	82	1	ford mustang gl
394	44.0	4	97.0	52	2130	24.6	82	2	vw pickup
395	32.0	4	135.0	84	2295	11.6	82	1	dodge rampage
396	28.0	4	120.0	79	2625	18.6	82	1	ford ranger
397	31.0	4	119.0	82	2720	19.4	82	1	chevy s-10

398 rows × 9 columns

CODE

```
def remove_outlier(ds, col):
    quart1 = ds[col].quantile(0.25)
    quart3 = ds[col].quantile(0.75)
    IQR = quart3 - quart1 #Interquartile range
    low_val = quart1 - 1.5*IQR
    high_val = quart3 + 1.5*IQR
    df_out = ds.loc[(ds[col] > low_val) & (ds[col] < high_val)]
```

```
return df_out
```

```
data=remove_outlier(data,'miles_per_gallon')
```

Inputing Standard Values

CODE

```
hp_mean = np.mean(data['horsepower'])
inputedrows = data[data['horsepower'].isnull()]
inputedrows = inputedrows.replace(np.nan, hp_mean)
missval_removed_rows = data.dropna(subset=['horsepower'])
data_mod = pd.concat([missval_removed_rows,inputedrows],ignore_index=True)
data_mod
```

OUTPUT

	miles_per_gallon	cylinders	disp	horsepower	weight	acceleration	model year	origin	car name
0	18.0	8	307.0	130.000000	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165.000000	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150.000000	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150.000000	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140.000000	3449	10.5	70	1	ford torino
...
392	21.0	6	200.0	104.570332	2875	17.0	74	1	ford maverick
393	40.9	4	85.0	104.570332	1835	17.3	80	2	renault lecar deluxe
394	23.6	4	140.0	104.570332	2905	14.3	80	1	ford mustang cobra
395	34.5	4	100.0	104.570332	2320	15.8	81	2	renault 18i
396	23.0	4	151.0	104.570332	3035	20.5	82	1	amc concord dl

397 rows × 9 columns