

INFOSYS SPRING BOARD INTERNSHIP 6.0

“BUDGETWISE AI BASED EXPENSE FORECASTING TOOL”

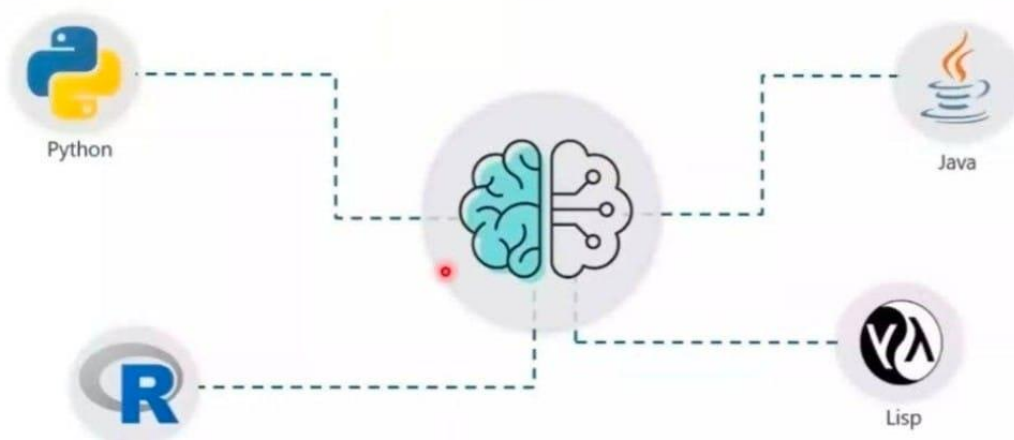
ARTIFICIAL INTELLIGENCE (AI):

John McCarthy is the father of AI in the year 1955. It is defined as the science and engineering of making intelligent machines, especially intelligent computer programs.

APPLICATIONS OF AI:

1. Healthcare
2. Robotics
3. Agriculture
4. Social media

PROGRAMMING LANGUAGES FOR AI

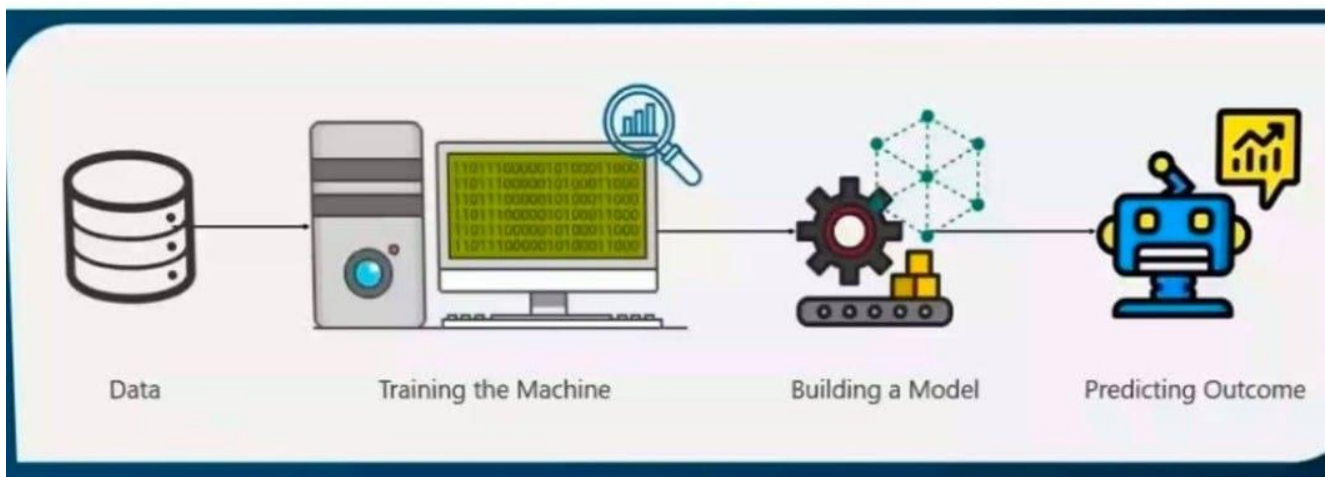


MACHINE LEARNING:

Machine Learning ML was first coined by Arthur Samuel in the year 1959. Machine learning is a subset of AI which provides machines the ability to learn automatically and improve from experience without being explicitly programmed.

APPLICATIONS OF ML:

1. Image recognition
2. Speech recognition
3. Self driving cars
4. Email spam



NUMPY MATRIX:

Numpy stands for "Numerical Python" and is the core library for numeric and scientific computing. It consists of multi dimensional array objects and a collection of routines for processing those arrays.

SINGLE DIMENSIONAL ARRAY:

```
n1=np.array([10,20,30,40,50])
```

n1

O/P: array([10, 20, 30, 40, 50])

MULTIDIMENSIONAL ARRAY:

```
import numpy as np
```

```
n2=np.array([[10,20,30],[40,50,60]])
```

```
n2
```

O/P: array([[10, 20, 30],
[40, 50, 60]])

INITIALIZING NUMPY ARRAY WITH ZEROS:

```
n1=np.zeros((1,2))
```

```
n1
```

O/P: array([[0., 0.]])

- ```
n1=np.zeros((5,5))
```

```
n1
```

O/P: array([[0., 0., 0., 0., 0.],  
[0., 0., 0., 0., 0.],  
[0., 0., 0., 0., 0.],  
[0., 0., 0., 0., 0.],  
[0., 0., 0., 0., 0.]])

## **INITIALIZING NUMPY ARRAY WITH SAME NUMBERS:**

- ```
n1=np.full((2,2),10)
```

```
n1
```

O/P: array([[10, 10],

[10, 10]])

INITIALIZING NUMPY ARRAY:

- `n1=np.arange(10,20)`

`n1`

O/P: `array([10, 11, 12, 13, 14, 15, 16, 17, 18, 19])`

- `import numpy as np`

`n1=np.arange(10,50,5)`

`n1`

O/P: `array([10, 15, 20, 25, 30, 35, 40, 45])`

INITIALISING NUMPY ARRAY WITH RANDOM NUMBERS:

- `n1=np.random.randint(1,100,5)`

`n1`

O/P: `array([69, 68, 94, 66, 72])`

NUMPY SHAPE:

- `n1=np.array([[1,2,3],[4,5,6]])`

`n1.shape`

O/P: `(2, 3)`

- `n1.shape=(3,2)`

`n1.shape`

O/P: `(3, 2)`

JOINING NUMPY ARRAY:

#VSTACK()

```
n1=np.array([10,20,30])
```

```
n2=np.array([40,50,60])
```

```
np.vstack((n1,n2))
```

O/P: array([[10, 20, 30],
[40, 50, 60]])

#HSTACK()

```
n1= np.array([10, 20, 30])
```

```
n2=np.array([40,50,60])
```

```
np.hstack((n1,n2))
```

O/P: array([10, 20, 30, 40, 50, 60])

#COLUMN_STACK()

```
n1=np.array([10,20, 30])
```

```
n2=np.array([40,50,60])
```

```
np.column_stack((n1,n2))
```

O/P: array([[10, 40],
[20, 50],
[30, 60]])

NUMPY TRANSPOSE:

#TRANSPOSE()

```
import numpy as np
```

```
n1.transpose()
```

O/P: array([10, 20, 30])

MATRIX MULTIPLICATION:

```
n1=np.array([[1,2,3],[4,5,6],[7,8,9]])
```

```
n1
```

O/P: array([[1, 2, 3],

[4, 5, 6],

[7, 8, 9]])

- import numpy as np

```
n2 = np.array([[1, 2], [3, 4], [5, 6]])
```

```
n1.dot(n2)
```

O/P: array([[22, 28],

[49, 64],

[76, 100]])

- n2=np.array([[7,8,9],[6,5,4],[5,4,3]])

```
n2
```

O/P: array([[7, 8, 9],

[6, 5, 4],

[5, 4, 3]])

- import numpy as np

```
n1= np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])
```

```
n2=np.array([[7,8,9],[6,5,4],[5,4,3]])
```

```
n2.dot(n1.T)
```

O/P: array([[50, 122, 194],
[28, 73, 118],
[22, 58, 94]])

PANDAS:

Pandas stand for panel Data and is the core library for data analysis. It consists of single & multidimensional data structures for data manipulation.

PANDAS SERIES OBJECT:

#SERIES OBJECT IS ONE-DIMENSIONAL LABELED ARRAY

```
import pandas as pd
```

```
s1=pd.Series([9,7,6,4,5])
```

```
s1
```

O/P:

0

0 9

1 7

0

2 6

3 4

4 5

dtype: int64

CHANGING INDEX:

```
import pandas as pd
```

```
s1=pd.Series([1,2,3],index=['x','y','z'])
```

s1

O/P:

0

x 1

y 2

z 3

dtype: int64

SERIES OBJECT FROM DICTIONARY: You can also create a series object from a dictionary!!

```
import pandas as pd  
pd.Series({'a':10,'b':20,'c':30})
```

O/P:

```
0  
a  10  
b  20  
c  30
```

dtype: int64

CHANGING INDEX POSITION: We can Change the index positions.

```
import pandas as pd  
pd.Series({'a':10,'b':20,'c':30},index=['b','a','g'])
```

O/P:

```
0  
b  20.0
```

0

a 10.0

g NaN

dtype: float64

EXTRACTING INDIVIDUAL ELEMENTS:

#EXTRACTING A SINGLE ELEMENT

```
s1=pd.Series([1,2,3,4,5,6,7,8,9,10])
```

```
s1[5]
```

O/P: np.int64(6)

#EXTRACTING ELEMENTS FROM BACK

```
s1=pd.Series([1,2,3,4,5,6,7,8,9,10])
```

```
s1[-3:]
```

O/P:

0

7 8

0

8 9

9 10

dtype: int64

#EXTRACTING A SEQUENCE OF ELEMENTS

s1=pd.Series([1,2,3,4,5,6,7,8,9,10])

s1[:5]

O/P:

0

0 1

1 2

2 3

3 4

4 5

dtype: int64

#SUM

```
import numpy as np
n1=np.array([10,20])
n2=np.array([30,40])
np.sum([n1,n2])
```

O/P: np.int64(100)

#column wise

```
np.sum([n1,n2],axis=0)
```

O/P: array([40, 60])

#row wise

```
np.sum([n1,n2],axis=1)
```

O/P: array([30, 70])

#ADDITION

```
import numpy as np
n1=np.array([10,20,30])
n1=n1+1
n1
```

O/P: array([11, 21, 31])

#MULTIPLICATION

```
import numpy as np
n1=np.array([10,20,30])
n1=n1*2
```

n1

O/P: array([20, 40, 60])

#SUBTRACTION

import numpy as np

n1=np.array([10,20,30])

n1=n1-1

n1

O/P: array([9, 19, 29])

#DIVISION

import numpy as np

n1=np.array([10,20,30])

n1=n1/2

n1

O/P: array([5., 10., 15.])

#MEAN

import numpy as np

n1=np.array([10,20,30,40,50,60])

np.mean(n1)

O/P: np.float64(35.0)

#standard deviation

import numpy as np

```
n1=np.array([1,5,3,100,4,48])
```

```
np.std(n1)
```

O/P: np.float64(36.59424666377065)

#MEDIAN

```
import numpy as np
```

```
n1=np.array([11,45,5,96,67,85])
```

```
np.median(n1)
```

O/P: np.float64(56.0)

NUMPY MATRIX:

```
n1[0]
```

O/P: array([1, 2, 3])

```
n1[1]
```

O/P: array([4, 5, 6])

```
n1[:,1]
```

O/P: n1[:,1]

```
n1[:,2]
```

O/P: array([3, 6, 9])

BASIC MATH OPERATIONS ON SERIES:

#Adding two series objects

```
import pandas as pd
```

```
s1 = pd.Series([1,2,3,4,5,6,7,8,9])
```

```
s2 = pd.Series([10,20,30,40,50,60,70,80,90])
```

```
s1+s2
```

O/P:

0

0 11

1 22

2 33

3 44

4 55

5 66

6 77

7 88

8 99

dtype: int64

#Adding a scalar value to series elements

```
s1 +5
```

O/P:

0

0 6

1 7

2 8

3 9

4 10

5 11

6 12

7 13

8 14

dtype: int64

DATAFRAME:

This is how we can create a dataframe. Dataframe is a 2-dimensional labelled data structure. A dataframe comprises of rows and columns.

```
import pandas as pd
```

```
pd.DataFrame({"Name":['bob','sam','anne'],'Marks':[76,25,92]})
```


O/P:

| | Name | Marks |
|----------|-------------|--------------|
| 0 | bob | 76 |
| 1 | sam | 25 |
| 2 | anne | 92 |

- `df=pd.DataFrame({"Name":["sam","anne","jennifer"],"Marks": [50,60,70]})`

`df`

O/P:

| | Name | Marks |
|----------|-------------|--------------|
| 0 | sam | 50 |
| 1 | anne | 60 |
| 2 | jennifer | 70 |

- `type(df)`

O/P: **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
```

UPLOADING IRIS DATASET:

```
iris=pd.read_csv('Iris (1).csv')  
from google.colab import files  
uploaded = files.upload()  
for fn in uploaded.keys():  
print('User uploaded file "{name}" with length {length}  
bytes'.format(  
name=fn, length=len(uploaded[fn])))
```

O/P: Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

Saving Iris.csv to Iris (1).csv

User uploaded file "Iris (1).csv" with length 5107 bytes

- iris.head()

O/P:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|----|---------------|--------------|---------------|--------------|-------------|
| 0 | 1 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| 1 | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| 2 | 3 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| 3 | 4 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| 4 | 5 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |

- `import pandas as pd`
- `ds = pd.read_csv('Iris (1).csv')`
- `ds.head()`

O/P:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|----|---------------|--------------|---------------|--------------|-------------|
| 0 | 1 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| 1 | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| 2 | 3 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| 3 | 4 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| 4 | 5 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |


- `ds.head(20)`

O/P:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|----|----|---------------|--------------|---------------|--------------|-------------|
| 0 | 1 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| 1 | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| 2 | 3 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| 3 | 4 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| 4 | 5 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| 5 | 6 | 5.4 | 3.9 | 1.7 | 0.4 | Iris-setosa |
| 6 | 7 | 4.6 | 3.4 | 1.4 | 0.3 | Iris-setosa |
| 7 | 8 | 5.0 | 3.4 | 1.5 | 0.2 | Iris-setosa |
| 8 | 9 | 4.4 | 2.9 | 1.4 | 0.2 | Iris-setosa |
| 9 | 10 | 4.9 | 3.1 | 1.5 | 0.1 | Iris-setosa |
| 10 | 11 | 5.4 | 3.7 | 1.5 | 0.2 | Iris-setosa |
| 11 | 12 | 4.8 | 3.4 | 1.6 | 0.2 | Iris-setosa |
| 12 | 13 | 4.8 | 3.0 | 1.4 | 0.1 | Iris-setosa |
| 13 | 14 | 4.3 | 3.0 | 1.1 | 0.1 | Iris-setosa |
| 14 | 15 | 5.8 | 4.0 | 1.2 | 0.2 | Iris-setosa |
| 15 | 16 | 5.7 | 4.4 | 1.5 | 0.4 | Iris-setosa |
| 16 | 17 | 5.4 | 3.9 | 1.3 | 0.4 | Iris-setosa |
| 17 | 18 | 5.1 | 3.5 | 1.4 | 0.3 | Iris-setosa |
| 18 | 19 | 5.7 | 3.8 | 1.7 | 0.3 | Iris-setosa |
| 19 | 20 | 5.1 | 3.8 | 1.5 | 0.3 | Iris-setosa |

- `ds.tail()`


O/P:



| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|-----|-----|---------------|--------------|---------------|--------------|----------------|
| 145 | 146 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| 146 | 147 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| 147 | 148 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| 148 | 149 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| 149 | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

- `ds.tail(10)`

O/P:



| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|-----|-----|---------------|--------------|---------------|--------------|----------------|
| 140 | 141 | 6.7 | 3.1 | 5.6 | 2.4 | Iris-virginica |
| 141 | 142 | 6.9 | 3.1 | 5.1 | 2.3 | Iris-virginica |
| 142 | 143 | 5.8 | 2.7 | 5.1 | 1.9 | Iris-virginica |
| 143 | 144 | 6.8 | 3.2 | 5.9 | 2.3 | Iris-virginica |
| 144 | 145 | 6.7 | 3.3 | 5.7 | 2.5 | Iris-virginica |
| 145 | 146 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| 146 | 147 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| 147 | 148 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| 148 | 149 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| 149 | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

- `ds.shape`

O/P:

(150, 6)

- `ds.describe()`

O/P:

| | Id | SepallLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm |
|-------|------------|----------------|--------------|---------------|--------------|
| count | 150.000000 | 150.000000 | 150.000000 | 150.000000 | 150.000000 |
| mean | 75.500000 | 5.843333 | 3.054000 | 3.758667 | 1.198667 |
| std | 43.445368 | 0.828066 | 0.433594 | 1.764420 | 0.763161 |
| min | 1.000000 | 4.300000 | 2.000000 | 1.000000 | 0.100000 |
| 25% | 38.250000 | 5.100000 | 2.800000 | 1.600000 | 0.300000 |
| 50% | 75.500000 | 5.800000 | 3.000000 | 4.350000 | 1.300000 |
| 75% | 112.750000 | 6.400000 | 3.300000 | 5.100000 | 1.800000 |
| max | 150.000000 | 7.900000 | 4.400000 | 6.900000 | 2.500000 |

ILOC:
iris.iloc[0:3,0:2]

O/P:

| | Id | SepallLengthCm |
|---|----|----------------|
| 0 | 1 | 5.1 |
| 1 | 2 | 4.9 |
| 2 | 3 | 4.7 |


iris.iloc[0:9,0:8]

O/P:

| | Id | SepallLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|----|----------------|--------------|---------------|--------------|-------------|
| 0 | 1 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| 1 | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| 2 | 3 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| 3 | 4 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| 4 | 5 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| 5 | 6 | 5.4 | 3.9 | 1.7 | 0.4 | Iris-setosa |
| 6 | 7 | 4.6 | 3.4 | 1.4 | 0.3 | Iris-setosa |
| 7 | 8 | 5.0 | 3.4 | 1.5 | 0.2 | Iris-setosa |
| 8 | 9 | 4.4 | 2.9 | 1.4 | 0.2 | Iris-setosa |

ds.iloc[0:3,2:5]

O/P:




| | SepalWidthCm | PetalLengthCm | PetalWidthCm |
|---|--------------|---------------|--------------|
| 0 | 3.5 | 1.4 | 0.2 |
| 1 | 3.0 | 1.4 | 0.2 |
| 2 | 3.2 | 1.3 | 0.2 |

DROPPING COLUMNS:

iris.drop('SepalLengthCm',axis=1)

O/P:




| | Id | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|-----|-----|--------------|---------------|--------------|----------------|
| 0 | 1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| 1 | 2 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| 2 | 3 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| 3 | 4 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| 4 | 5 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| ... | ... | ... | ... | ... | ... |
| 145 | 146 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| 146 | 147 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| 147 | 148 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| 148 | 149 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| 149 | 150 | 3.0 | 5.1 | 1.8 | Iris-virginica |

150 rows × 5 columns

`ds.loc[1:5,('SepalLengthCm','PetalLengthCm')]`

O/P:




| | SepalLengthCm | PetalLengthCm |
|---|---------------|---------------|
| 1 | 4.9 | 1.4 |
| 2 | 4.7 | 1.3 |
| 3 | 4.6 | 1.5 |
| 4 | 5.0 | 1.4 |
| 5 | 5.4 | 1.7 |

LOC:

`iris.loc[0:3,("SepalLengthCm","PetalLengthCm")]`

O/P:



| | SepalLengthCm | PetalLengthCm |
|---|---------------|---------------|
| 0 | 5.1 | 1.4 |
| 1 | 4.9 | 1.4 |
| 2 | 4.7 | 1.3 |
| 3 | 4.6 | 1.5 |

DROPPING ROWS:

`iris.drop([1,2,3],axis=0)`

O/P:



| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|-----|-----|---------------|--------------|---------------|--------------|----------------|
| 0 | 1 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| 4 | 5 | 5.0 | 3.8 | 1.4 | 0.2 | Iris-setosa |
| 5 | 6 | 5.4 | 3.9 | 1.7 | 0.4 | Iris-setosa |
| 6 | 7 | 4.6 | 3.4 | 1.4 | 0.3 | Iris-setosa |
| 7 | 8 | 5.0 | 3.4 | 1.5 | 0.2 | Iris-setosa |
| ... | ... | ... | ... | ... | ... | ... |
| 145 | 146 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| 146 | 147 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| 147 | 148 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| 148 | 149 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| 149 | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

147 rows × 6 columns

MORE PANDAS FUNCTIONS:

iris.mean(numeric_only=True)

O/P:

0

Id 75.500000

SepalLengthCm 5.843333

SepalWidthCm 3.054000

PetalLengthCm 3.758667

PetalWidthCm 1.198667

dtype: float64

iris.median(numeric_only=True)

O/P:

0

Id 75.50

SepalLengthCm 5.80

SepalWidthCm 3.00

0

PetalLengthCm 4.35

PetalWidthCm 1.30

dtype: float64

iris.min()

O/P:

0

Id 1

SepalLengthCm 4.3

SepalWidthCm 2.0

PetalLengthCm 1.0

PetalWidthCm 0.1

Species Iris-setosa

dtype: object

iris.max()

O/P:

| | |
|----------------------|-----------------------|
| | <u>0</u> |
| <u>Id</u> | <u>150</u> |
| <u>SepalLengthCm</u> | <u>7.9</u> |
| <u>SepalWidthCm</u> | <u>4.4</u> |
| <u>PetalLengthCm</u> | <u>6.9</u> |
| <u>PetalWidthCm</u> | <u>2.5</u> |
| <u>Species</u> | <u>Iris-virginica</u> |

dtype: object

LINE PLOT:

```
import numpy as np
```

```
from matplotlib import pyplot as plt
```

```
x=np.arange(1,11)
```

```
y= 2*x
```

```
y
```

O/P:

```
array([ 2,  4,  6,  8, 10, 12, 14, 16, 18, 20])
```

```
x=np.arange(1,11)
```

```
x
```

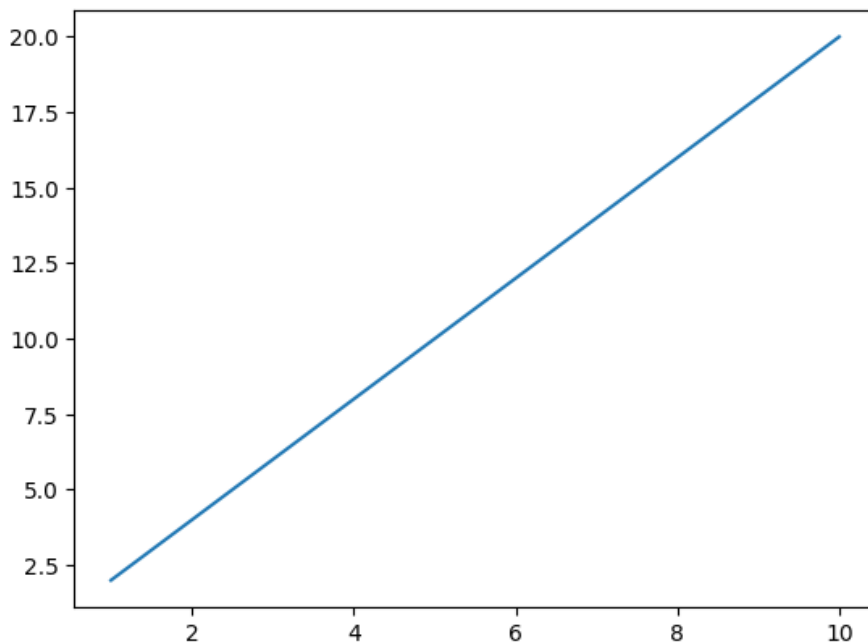
O/P:

```
array([ 1, 2, 3, 4, 5, 6, 7, 8, 9, 10])
```

```
plt.plot(x,y)
```

```
plt.show()
```

O/P:



LINE PLOT: Adding titles & labels

```
plt.plot(x,y)
```

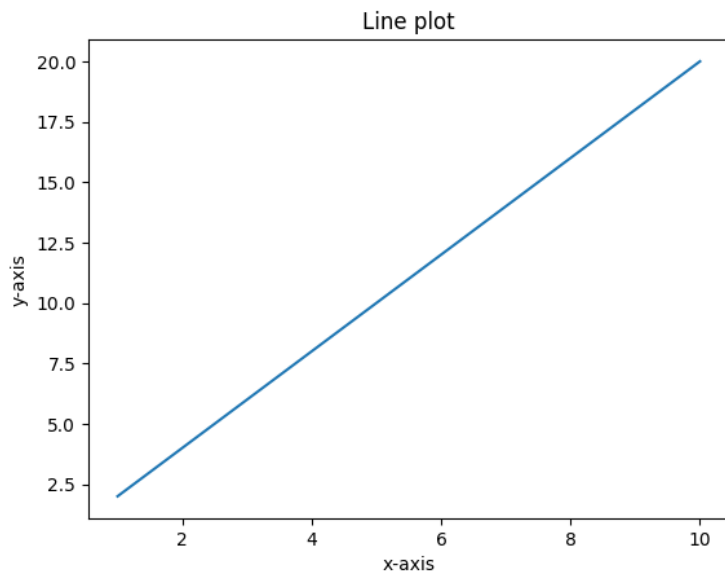
```
plt.title("Line plot")
```

```
plt.xlabel("x-axis")
```

```
plt.ylabel("y-axis")
```

plt.show()

O/P:

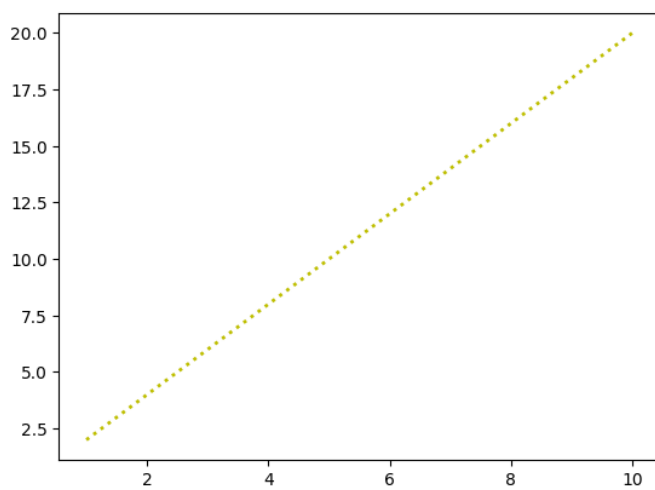


LINE PLOT: Changing line aesthetics

`plt.plot(x,y,color='y',linestyle=':',linewidth=2)`

`plt.show()`

O/P:



LINE PLOT: Adding two lines in the same plot

```
x=np.arange(1,11)
```

```
y1=2*x
```

```
y2=3*x
```

```
plt.plot(x,y1,color='g',linestyle=':',linewidth=2)
```

```
plt.plot(x,y2,color='r',linestyle='-',linewidth=3)
```

```
plt.title("Line plot")
```

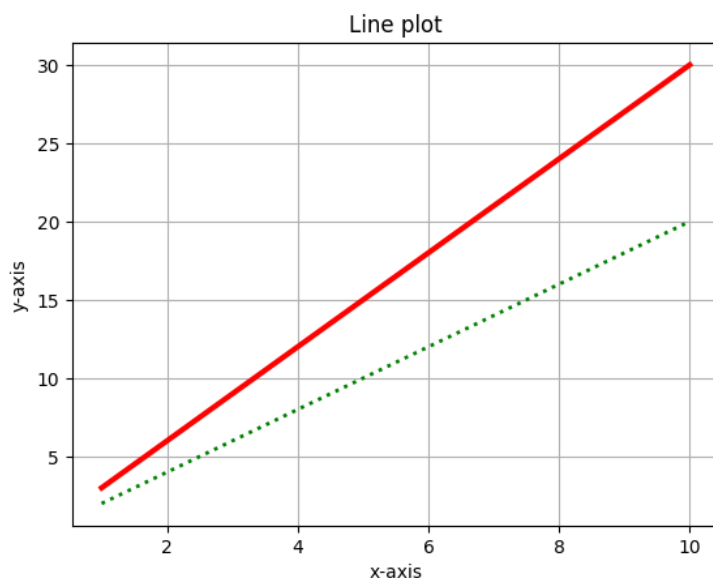
```
plt.xlabel("x-axis")
```

```
plt.ylabel("y-axis")
```

```
plt.grid(True)
```

```
plt.show()
```

O/P:



LINE PLOT: Adding sub-plots

```
x=np.arange(1,11)
```

```
y1=2*x
```

```
y2=3*x
```

```
plt.subplot(1,2,1)
```

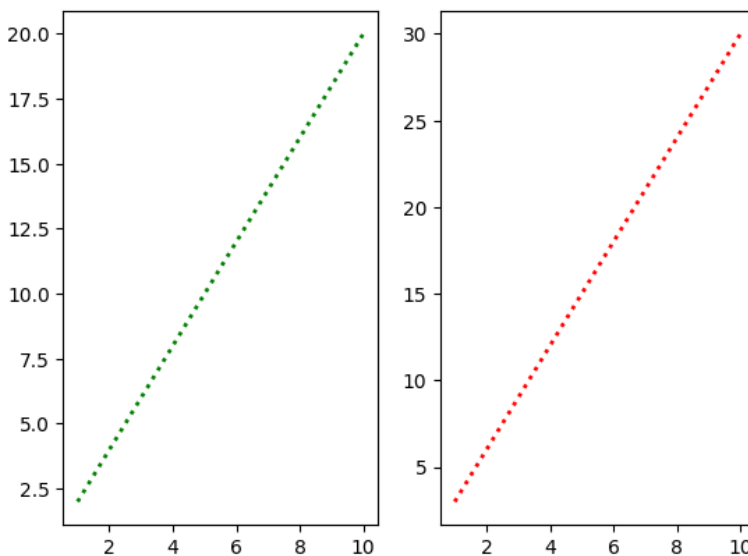
```
plt.plot(x,y1,color='g',linestyle=':',linewidth=2)
```

```
plt.subplot(1,2,2)
```

```
plt.plot(x,y2,color='r',linestyle=':',linewidth=2)
```

```
plt.show()
```

O/P:



BAR PLOT:

```
student = {"bob":87,"matt":56,"sam":27}
```

```
names = list(student.keys())
```

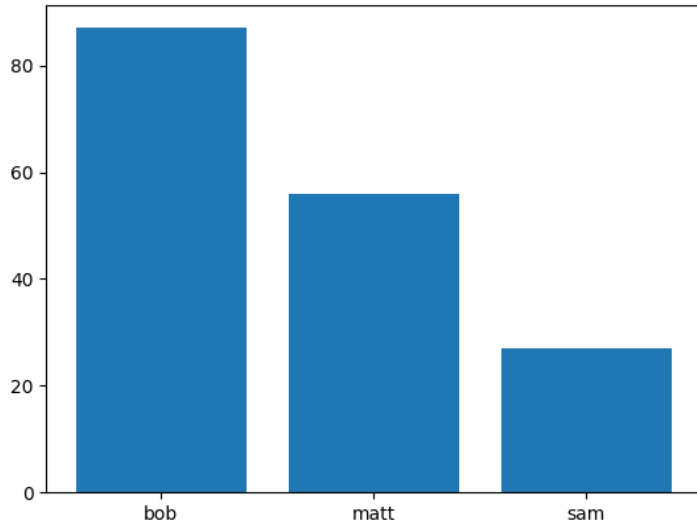
```
values = list(student.values())
```

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

```
plt.bar(names,values)
```

```
plt.show()
```

O/P:



ADDING TITLE AND LABLES:

```
plt.bar(names,values)
```

```
plt.title("Bar Plot")
```

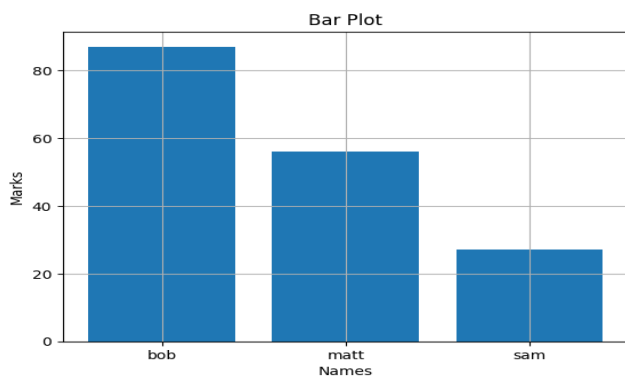
```
plt.xlabel("Names")
```

```
plt.ylabel("Marks")
```

```
plt.grid(True)
```

```
plt.show()
```

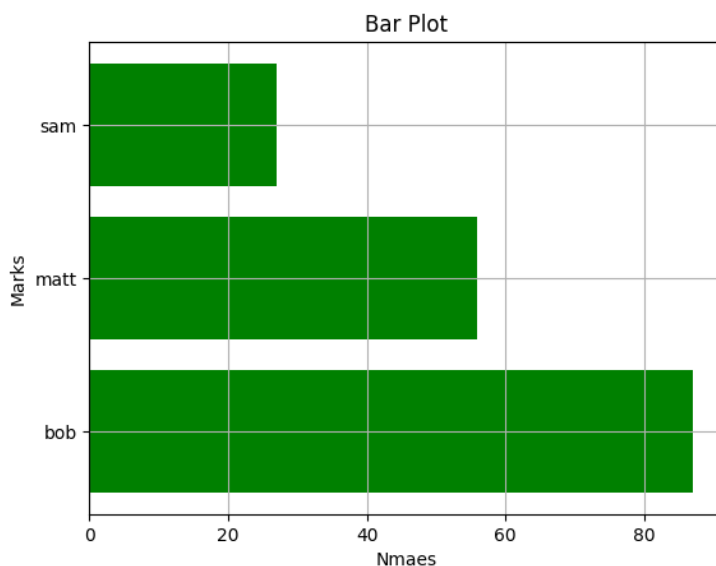
O/P:



HORIZONTAL BAR PLOT:

```
plt.barh(names,values,color='g')  
plt.title("Bar Plot")  
plt.xlabel("Nmaes")  
plt.ylabel("Marks")  
plt.grid(True)  
plt.show()
```

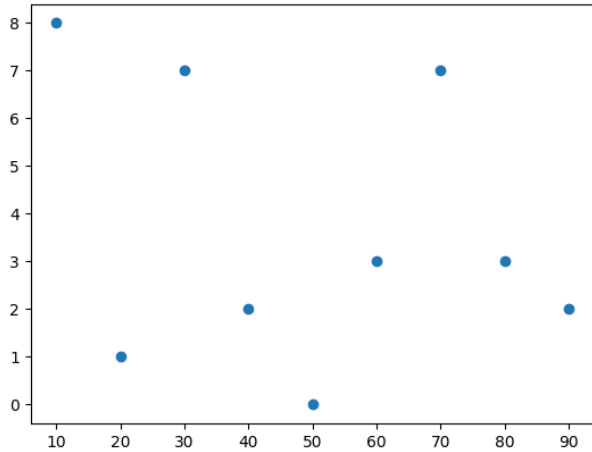
O/P:



SCATTER PLOT:

```
x=[10,20,30,40,50,60,70,80,90]  
a=[8,1,7,2,0,3,7,3,2]  
plt.scatter(x,a)  
plt.show()
```

O/P:



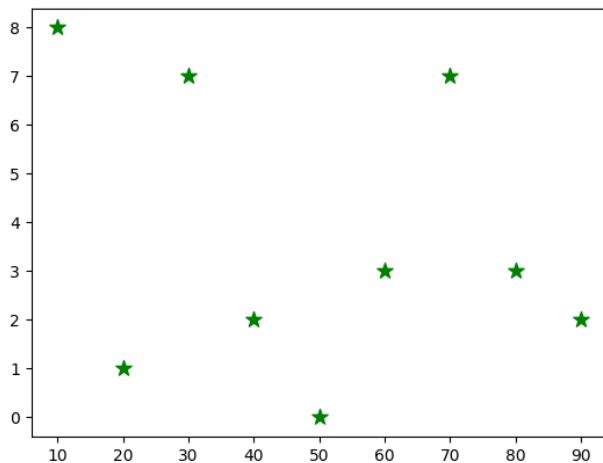
```
x=[10,20,30,40,50,60,70,80,90]
```

```
a=[8,1,7,2,0,3,7,3,2]
```

```
plt.scatter(x,a,marker="*",c="g",s=100)
```

```
plt.show()
```

O/P:



```
x=[10,20,30,40,50,60,70,80,90]
```

```
a=[8,1,7,2,0,3,7,3,2]
```

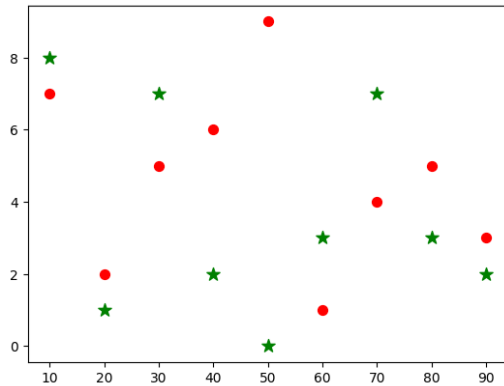
```
b=[7,2,5,6,9,1,4,5,3]
```

```
plt.scatter(x,a,marker="*",c="g",s=100)
```

```
plt.scatter(x,b,marker=".",c="r",s=200)
```

```
plt.show()
```

O/P:



```
x=[10,20,30,40,50,60,70,80,90]
```

```
a=[8,1,7,2,0,3,7,3,2]
```

```
b=[7,2,5,6,9,1,4,5,3]
```

```
plt.subplot(1,2,1)
```

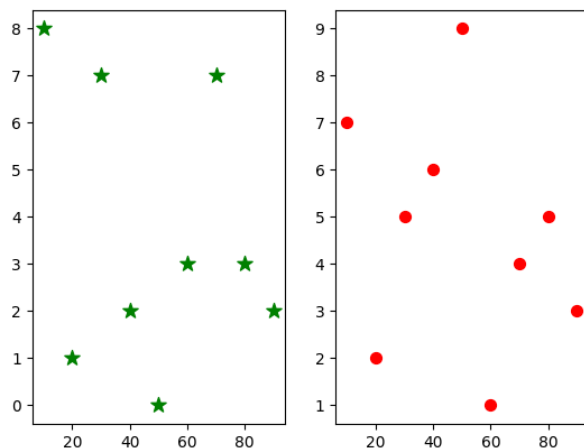
```
plt.scatter(x,a,marker="*",c="g",s=100)
```

```
plt.subplot(1,2,2)
```

```
plt.scatter(x,b,marker=".",c="r",s=200)
```

```
plt.show()
```

O/P:

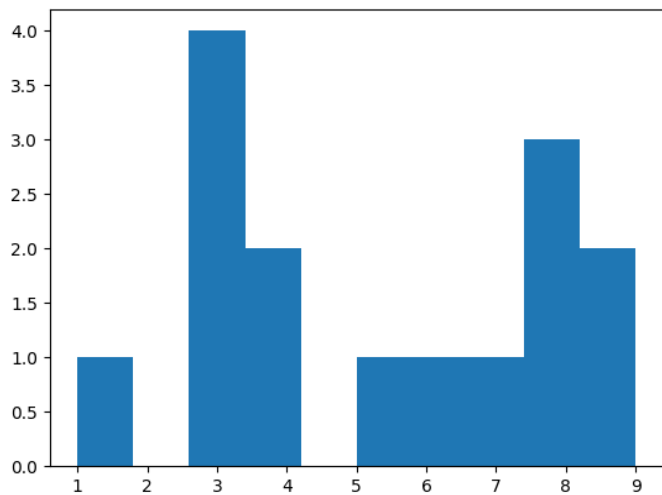


```
data = [1,3,3,3,3,9,9,5,4,4,8,8,8,6,7]
```

```
plt.hist(data)
```

```
plt.show()
```

O/P:

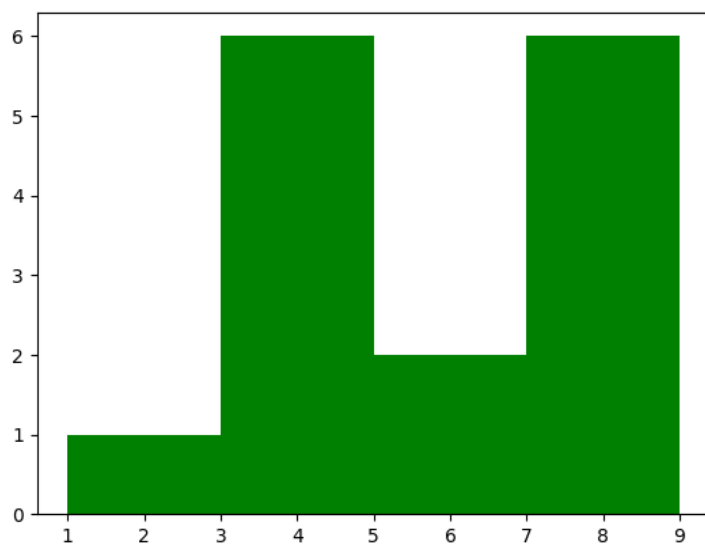


#CHANGING AESTHETICS

```
plt.hist(data,color="g",bins=4)
```

```
plt.show()
```

O/P:



```
iris=pd.read_csv('Iris (1).csv')
```

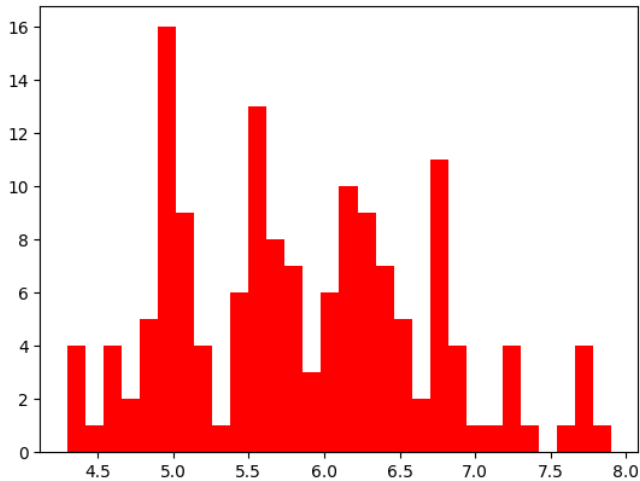
```
iris.head()
```

O/P:

| I d | SepalLeng thCm | SepalWidt hCm | PetalLeng thCm | PetalWidt hCm | Spec ies | |
|--------|-------------------|------------------|-------------------|------------------|-------------|---------------------|
| 0 | 1 | 5.1 | 3.5 | 1.4 | 0.2 | Iris- seto sa |
| 1 | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris- seto sa |
| 2 | 3 | 4.7 | 3.2 | 1.3 | 0.2 | Iris- seto sa |
| 3 | 4 | 4.6 | 3.1 | 1.5 | 0.2 | Iris- seto sa |
| 4 | 5 | 5.0 | 3.6 | 1.4 | 0.2 | Iris- seto sa |

```
plt.hist(iris['SepalLengthCm'],bins=30,color="r")  
plt.show()
```

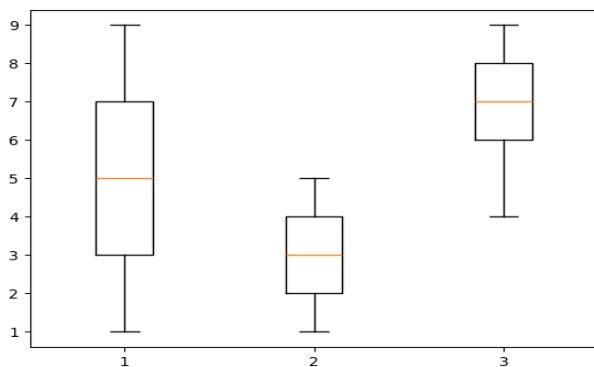
O/P:



#BOXPLOT

```
one = [1,2,3,4,5,6,7,8,9]  
two = [1,2,3,4,5,4,3,2,1]  
three = [6,7,8,9,8,7,6,5,4]  
data = list([one,two,three])  
plt.boxplot(data)  
plt.show()
```

O/P:



VIOLIN-PLOT:

#Creating data

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

```
one = [1,2,3,4,5,6,7,8,9,]
```

```
two = [1,2,3,4,5,4,3,2,1]
```

```
three = [6,7,8,9,8,7,6,5,4]
```

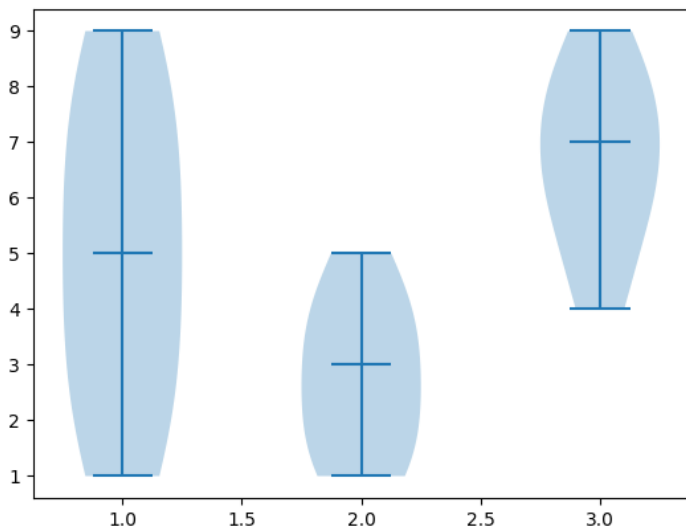
```
data = list([one,two,three])
```

#Making plot

```
plt.violinplot(data,showmedians=True)
```

```
plt.show()
```

O/P:



PIE-CHART:

#Creating data

```
fruit = ['Apple','Orange','Mango','Guava']
```

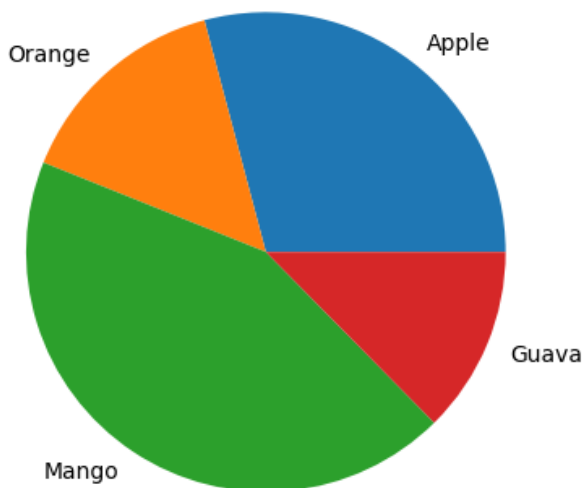
```
quantity = [67,34,100,29]
```

#Making plot

```
plt.pie(quantity,labels=fruit)
```

```
plt.show()
```

O/P:

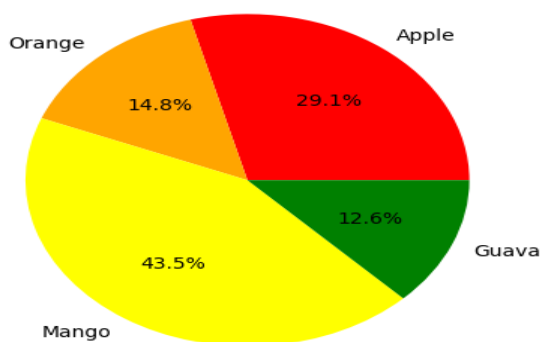


CHANGING COLORS TO PIE-CHART:

```
plt.pie(quantity,labels=fruit,autopct='%0.1f%%',colors=['red','orange','yellow','green'])
```

```
plt.show()
```

O/P:



DOUGHNUT CHART:

#Creating data

```
fruit=['Apple','Mango','Guava','Orange']
```

```
quantity=[67,34,100,29]
```

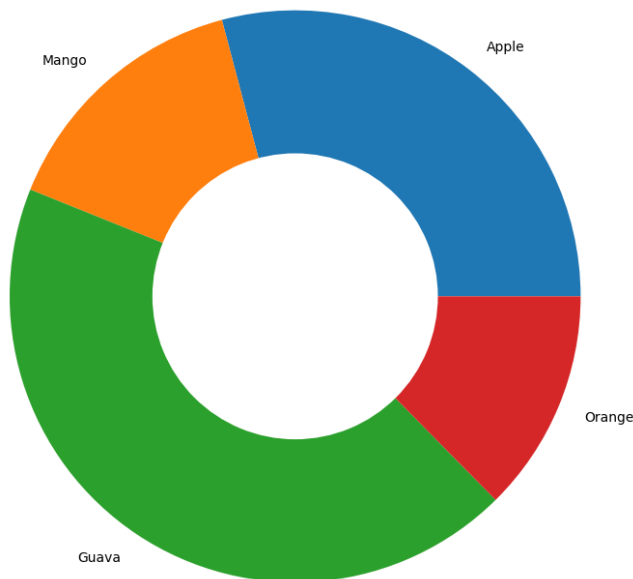
#Making plot

```
plt.pie(quantity,labels=fruit,radius=2)
```

```
plt.pie([1],colors=['w'],radius=1)
```

```
plt.show()
```

O/P:



SEABORN LINE PLOT:

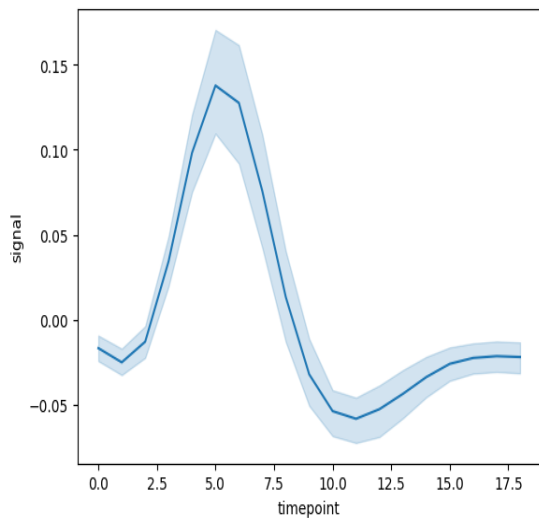
Seaborn is a python data visualization library based on matplotlib it provides a high-level interface for drawing attractive and informative statistical graphics.


```
import seaborn as sns  
from matplotlib import pyplot as plt  
fmri = sns.load_dataset("fmri")  
fmri.head()
```

| | <u>subject</u> | <u>timepoint</u> | <u>event</u> | <u>region</u> | <u>signal</u> |
|----------|----------------|------------------|--------------|-----------------|------------------|
| <u>0</u> | <u>s13</u> | <u>18</u> | <u>stim</u> | <u>parietal</u> | <u>-0.017552</u> |
| <u>1</u> | <u>s5</u> | <u>14</u> | <u>stim</u> | <u>parietal</u> | <u>-0.080883</u> |
| <u>2</u> | <u>s12</u> | <u>18</u> | <u>stim</u> | <u>parietal</u> | <u>-0.081033</u> |
| <u>3</u> | <u>s11</u> | <u>18</u> | <u>stim</u> | <u>parietal</u> | <u>-0.046134</u> |
| <u>4</u> | <u>s10</u> | <u>18</u> | <u>stim</u> | <u>parietal</u> | <u>-0.037970</u> |

```
sns.lineplot(x="timepoint",y="signal",data=fmri)  
plt.show()
```

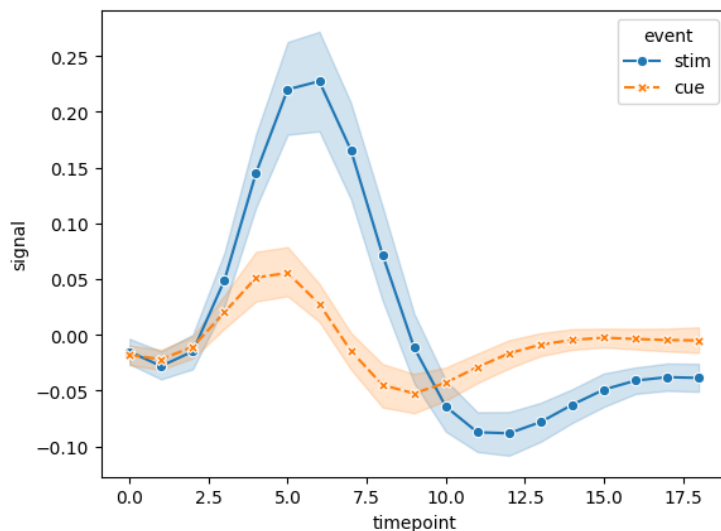
O/P:



```
sns.lineplot(x="timepoint",y="signal",
             hue="event", style="event",
             markers=True, data=fmri)

plt.show()
```

O/P:



#seaborn

```
import numpy as np
```

```
import pandas as pd
```

```
import matplotlib.pyplot as plt
import seaborn as sns
#visualising statistical relationships
ds = sns.load_dataset('tips')
ds.head()
```

O/P:

| | total_bill | tip | sex | smoker | day | time | size |
|----------|-------------------|------------|------------|---------------|------------|-------------|-------------|
| 0 | 16.99 | 1.01 | Female | No | Sun | Dinner | 2 |
| 1 | 10.34 | 1.66 | Male | No | Sun | Dinner | 3 |
| 2 | 21.01 | 3.50 | Male | No | Sun | Dinner | 3 |
| 3 | 23.68 | 3.31 | Male | No | Sun | Dinner | 2 |
| 4 | 24.59 | 3.61 | Female | No | Sun | Dinner | 4 |

```
ds.shape
```

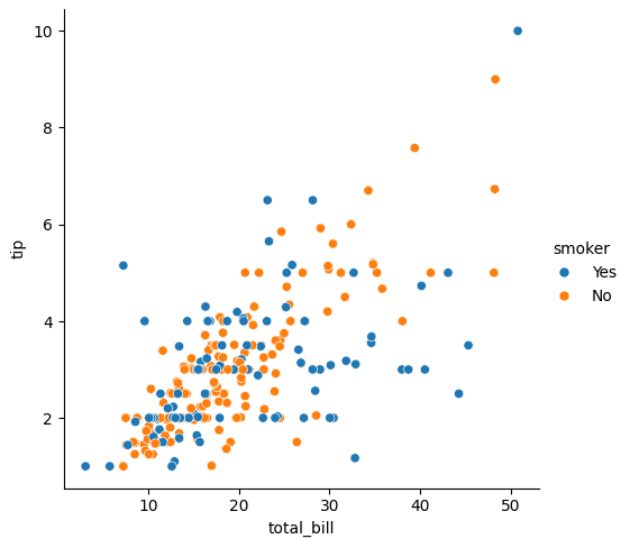
O/P:

(244, 7)

#relating variables with scatter plots

```
sns.relplot(data=ds,x='total_bill',y='tip',hue='smoker')
```

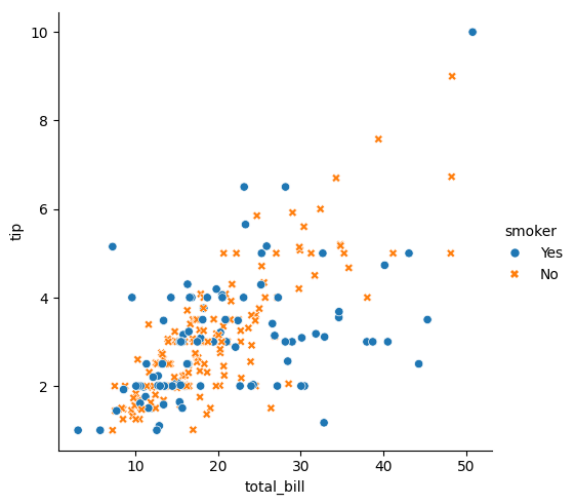
O/P:



#marker

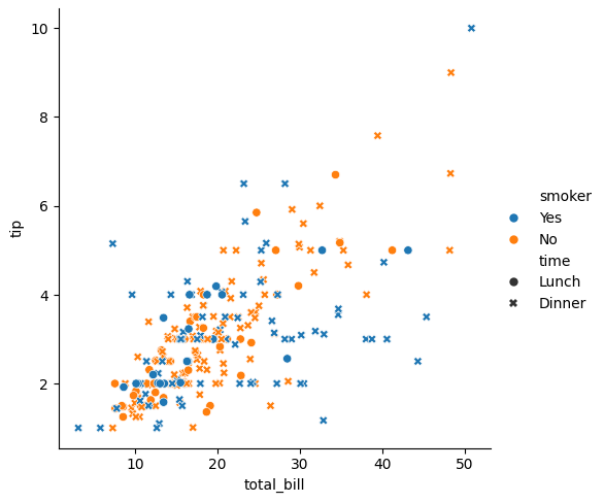
```
sns.relplot(data=ds,x='total_bill',y='tip',hue='smoker',style='smoker')
```

O/P:



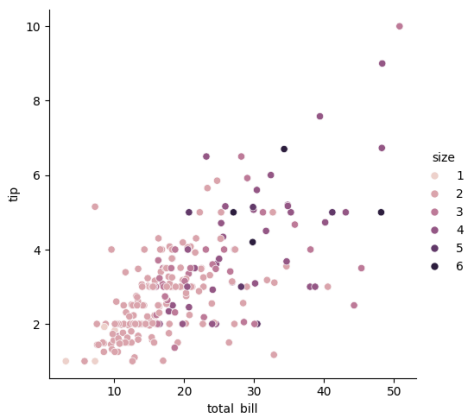
```
sns.relplot(
    data=ds,
    x="total_bill",y="tip",hue="smoker",style="time"
)
```

O/P:



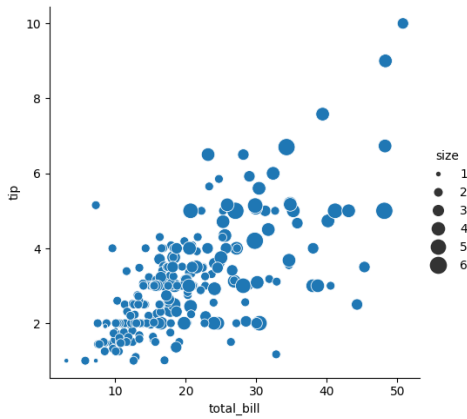
```
sns.relplot(
    data=ds, x="total_bill", y="tip", hue="size",
)
```

O/P:



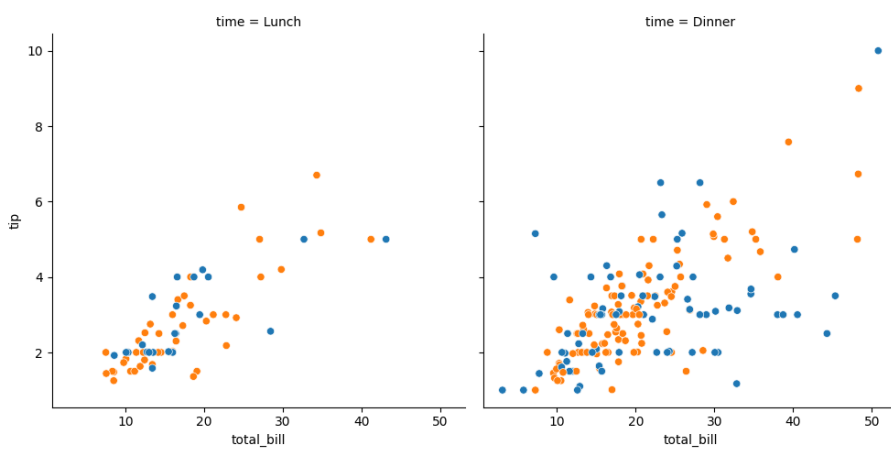
```
sns.relplot(
    data=ds, x="total_bill", y="tip",
    size="size", sizes=(15, 200)
)
```

O/P:



```
sns.relplot(
    data=ds,
    x="total_bill", y="tip", hue="smoker", col="time",
)
```

O/P:



```
import seaborn as sns
fmri = sns.load_dataset('fmri')
fmri.head()
```

O/P:

| subject | timepoint | event | region | signal |
|---------|-----------|-------|--------|--------------------|
| 0 | s13 | 18 | stim | parietal -0.017552 |
| 1 | s5 | 14 | stim | parietal -0.080883 |
| 2 | s12 | 18 | stim | parietal -0.081033 |
| 3 | s11 | 18 | stim | parietal -0.046134 |
| 4 | s10 | 18 | stim | parietal -0.037970 |

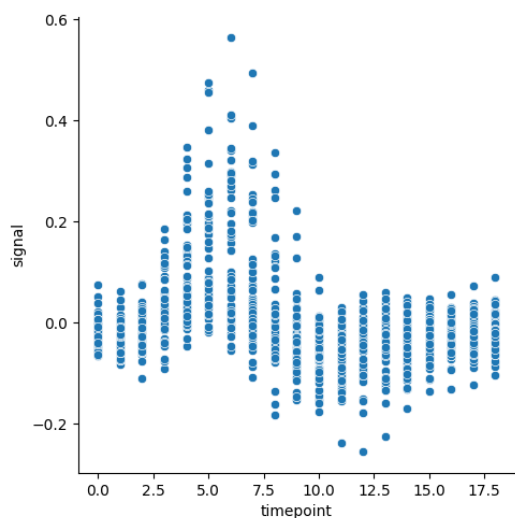
fmri.shape

O/P:

(1064, 5)

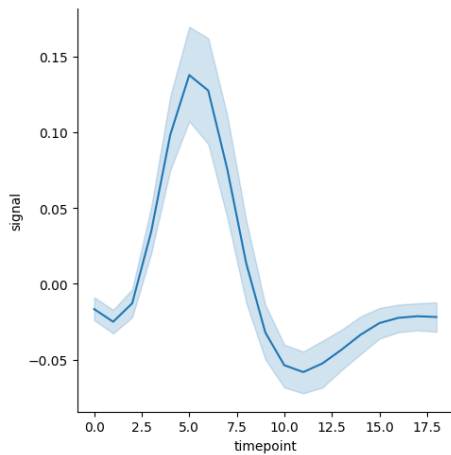
sns.relplot(data=fmri, x='timepoint',y='signal')

O/P:



```
sns.relplot(data=fmri, x='timepoint',y='signal',kind='line')
```

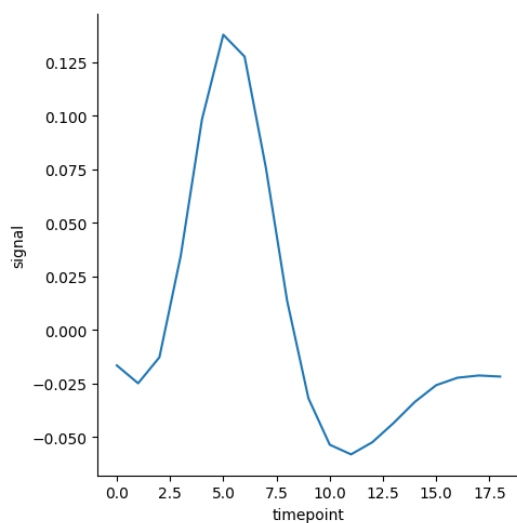
O/P:



```
# remove error band
```

```
sns.relplot(  
    data=fmri,kind='line',  
    x='timepoint',y='signal',errorbar=None  
)
```

O/P:

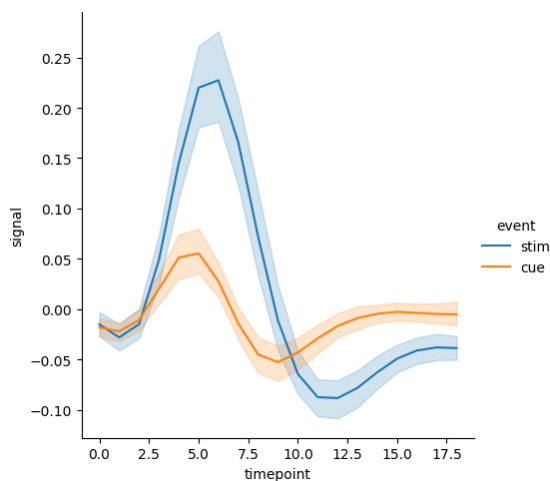


#adding a hue semantic with two level splits

#they plot into two lines and error bands

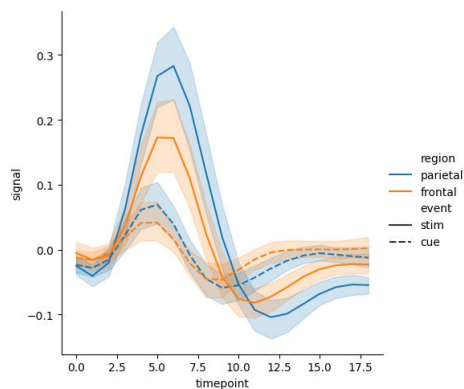
```
sns.relplot(  
    data=fmri,kind='line',  
    x='timepoint',y='signal',  
    hue='event'  
)
```

O/P:



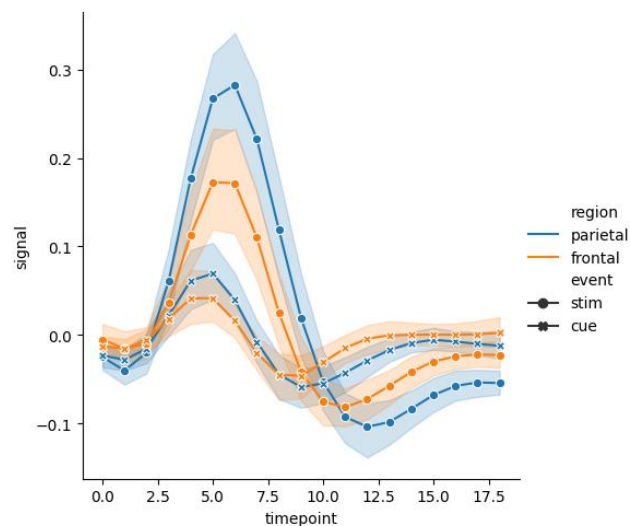
```
sns.relplot(  
    data=fmri,kind='line',  
    x='timepoint',y='signal',  
    hue='region',style='event'  
)
```

O/P:



```
sns.relplot(
    data=fmri,kind='line',
    x='timepoint',y='signal',
    hue='region',style='event',
    dashes=False,markers=True
)
```

O/P:



```
import seaborn as sns
tips = sns.load_dataset('tips')
tips.head()
```

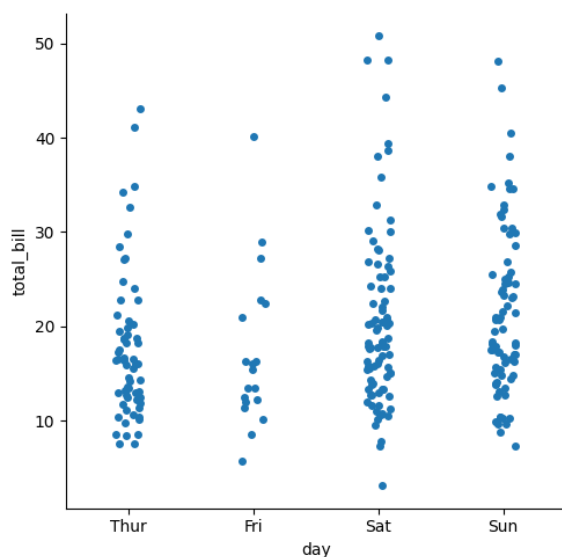
O/P:

| <u>total_bill</u> | <u>tip</u> | <u>sex</u> | <u>smoker</u> | <u>day</u> | <u>time</u> | <u>size</u> |
|-------------------|--------------|-------------|---------------|------------|-------------|------------------------|
| <u>0</u> | <u>16.99</u> | <u>1.01</u> | <u>Female</u> | <u>No</u> | <u>Sun</u> | <u>Dinner</u> <u>2</u> |
| <u>1</u> | <u>10.34</u> | <u>1.66</u> | <u>Male</u> | <u>No</u> | <u>Sun</u> | <u>Dinner</u> <u>3</u> |
| <u>2</u> | <u>21.01</u> | <u>3.50</u> | <u>Male</u> | <u>No</u> | <u>Sun</u> | <u>Dinner</u> <u>3</u> |
| <u>3</u> | <u>23.68</u> | <u>3.31</u> | <u>Male</u> | <u>No</u> | <u>Sun</u> | <u>Dinner</u> <u>2</u> |
| <u>4</u> | <u>24.59</u> | <u>3.61</u> | <u>Female</u> | <u>No</u> | <u>Sun</u> | <u>Dinner</u> <u>4</u> |

#Prevent from overlapping(swarm plot)

```
sns.catplot(data=tips,x='day',y='total_bill')
```

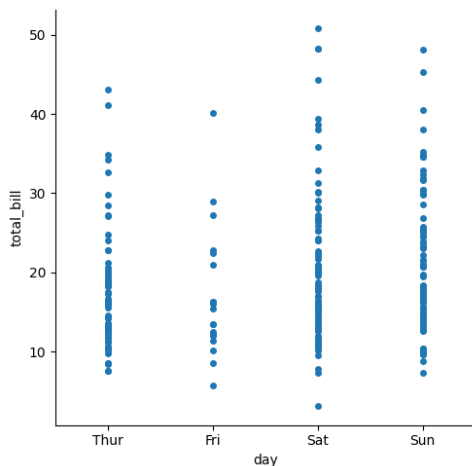
O/P:



#The jitter parameter controls the magnitude of jitter or disables it altogether:

```
sns.catplot(data=tips,x='day',y='total_bill',jitter=False)
```

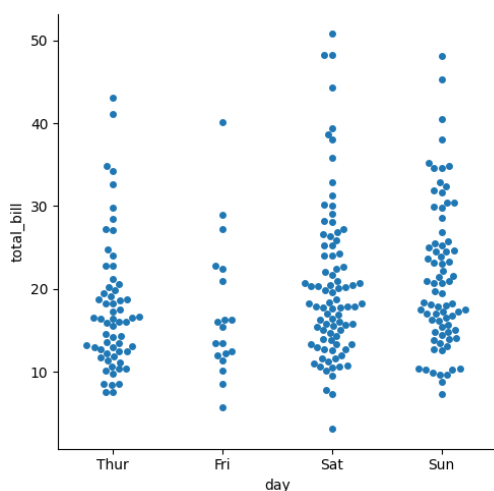
O/P:



#prevent from overlapping(swarm plot)

```
sns.catplot(data=tips,x='day',y='total_bill',kind='swarm')
```

O/P:



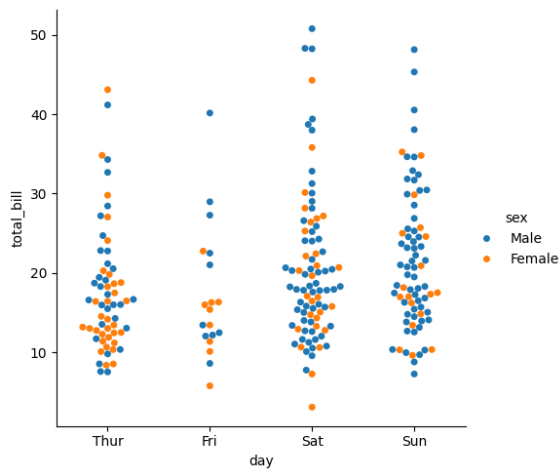
#add the hue semantic

```
import seaborn as sns
```

```
tips = sns.load_dataset('tips')
```

```
sns.catplot(data=tips,x='day',y='total_bill',hue='sex',kind='swarm')
```

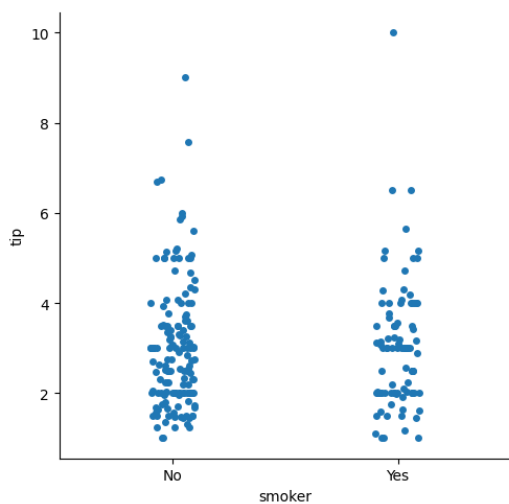
O/P:



#order parameter - to display multiple categorical plot in the same figure

```
sns.catplot(data=tips,x='smoker',y='tip',order=['No','Yes'])
```

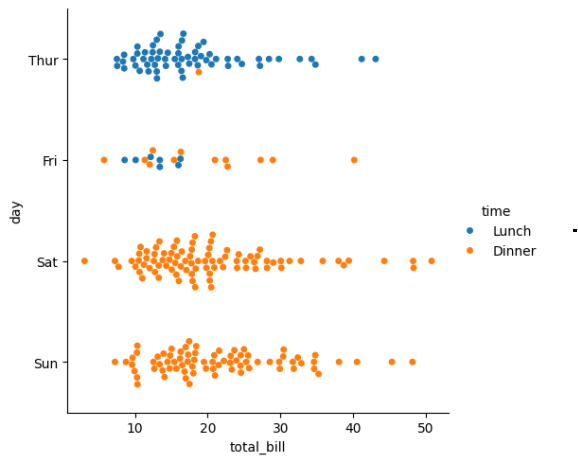
O/P:



#categorical plot on vertical axis

```
sns.catplot(data=tips,x='total_bill',y='day',hue='time',kind='swarm')
)
```

O/P:

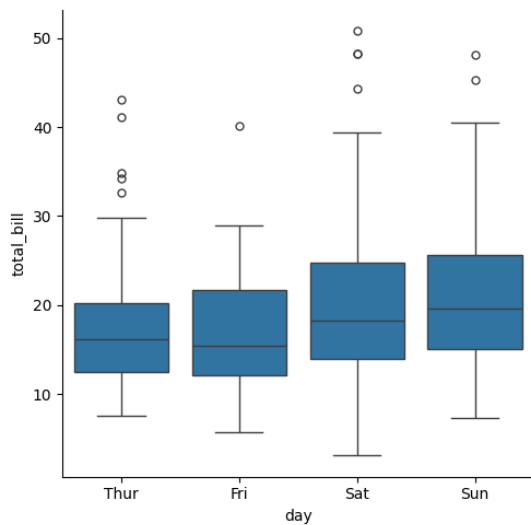


#comparing distribution

#box plots

```
sns.catplot(data=tips,x='day',y='total_bill',kind='box')
```

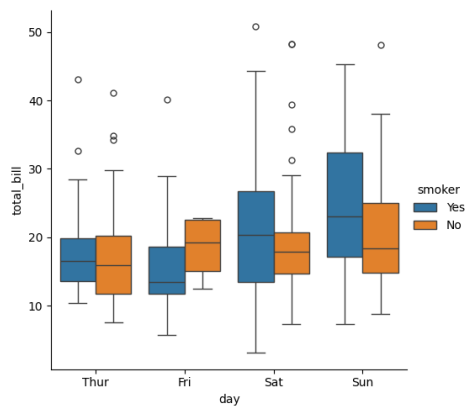
O/P:



#adding hue semantic

```
sns.catplot(data=tips,x='day',y='total_bill',hue='smoker',kind='box')
)
```

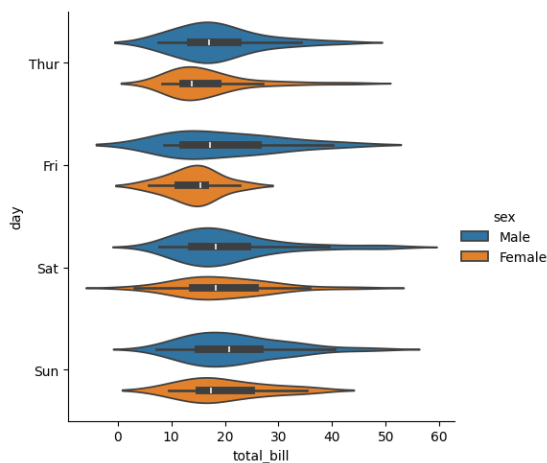
O/P:



#violin plot

```
sns.catplot(data=tips,x='total_bill',y='day',hue='sex',kind='violin')
```

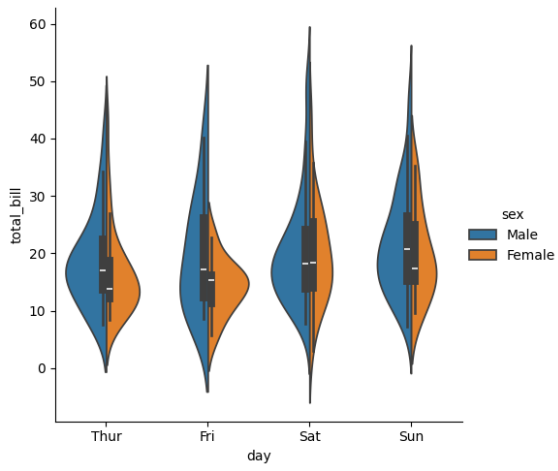
O/P:



#split in the violin plot

```
sns.catplot(data=tips,x='day',y='total_bill',hue='sex',kind='violin',split=True)
```

O/P:



BY
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