Data Handling and Visualization (CSE2026) - Record

Submitted From,

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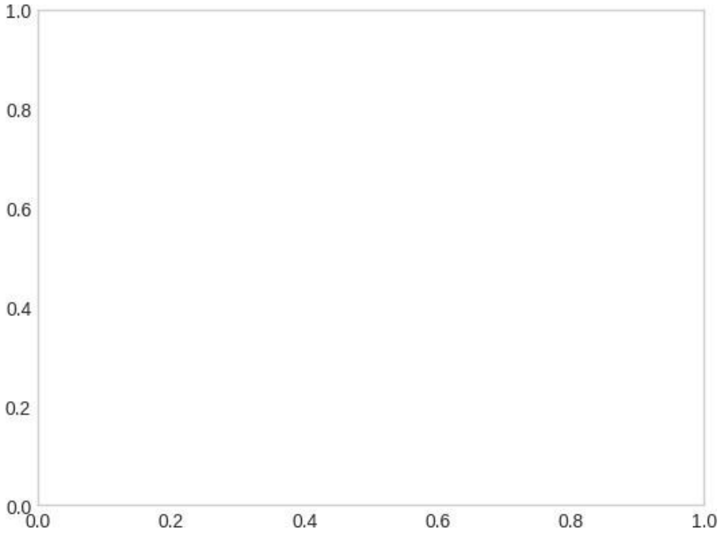
LABSHEET 1

```
from matplotlib import pyplot as plt plt.style.use('seaborn-whitegrid') import numpy as np
```

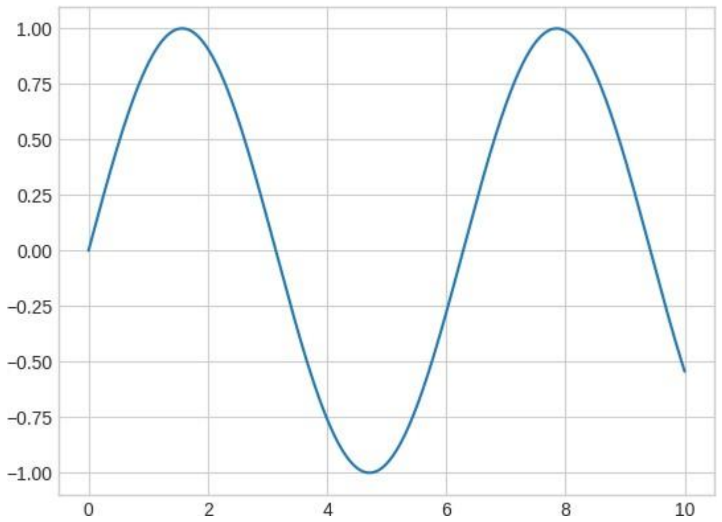
```
print("step 1")
```

```
step 1
<ipython-input-4-240c5389bdd3>:2: MatplotlibDeprecationWarning: The seaborn styles shipped by Matplotlib are deprecated since 3.6,
  plt.style.use('seaborn-whitegrid')
```

```
fig = plt.figure()
ax = plt.axes()
ax.grid()
```



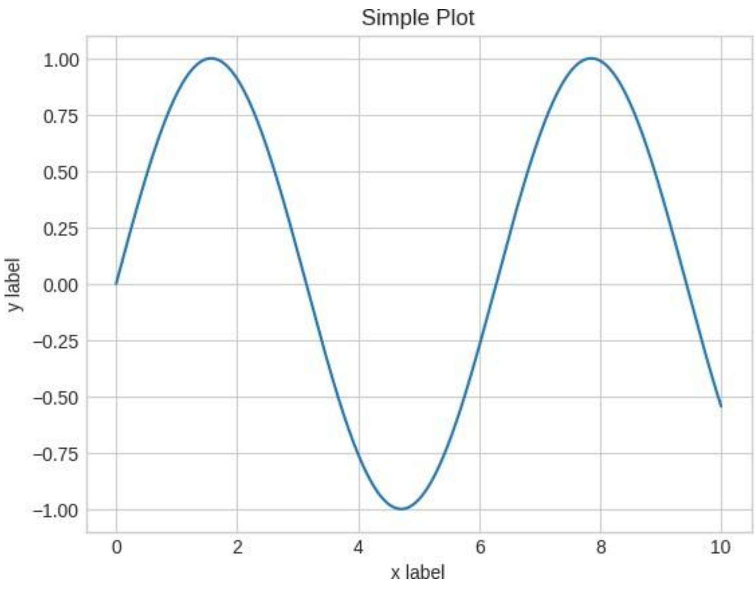

```
fig = plt.figure()
ax = plt.axes()
x = np.linspace(0, 10, 1000)
ax.plot(x, np.sin(x));
```



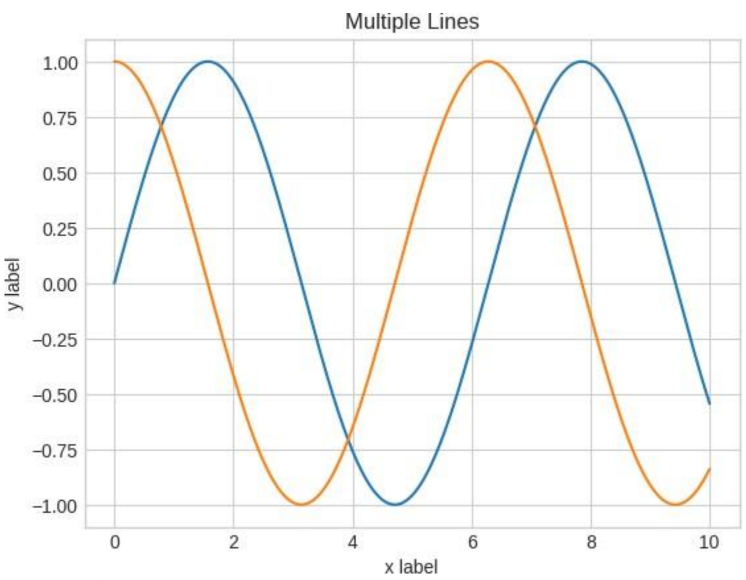
1

```
# Lets add a title and labels to the plot
fig  =  plt.figure()
ax = plt.axes()


x = np.linspace(0, 10, 1000) ax.plot(x, np.sin(x))
ax.set_title('Simple  Plot')  #  Add  a  title
ax.set_xlabel('x   label')   #   Add   x   label
ax.set_ylabel('y label'); # Add y label
```

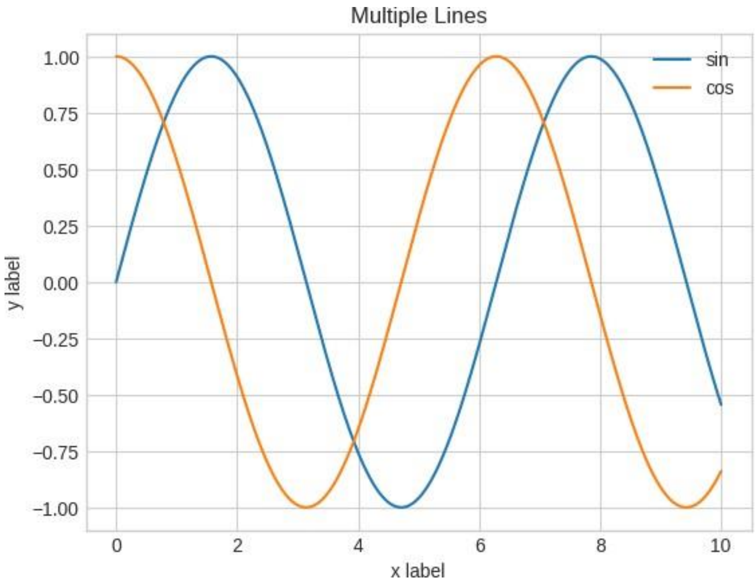



```
# Lets add a title to the plot above
fig = plt.figure() ax = plt.axes()
x  =  np.linspace(0,  10,  1000)
ax.plot(x,           np.sin(x))
ax.plot(x,           np.cos(x))
#ax.plot(x,          np.tan(x))
ax.set_title('Multiple Lines');
ax.set_xlabel('x        label')
ax.set_ylabel('y        label')
plt.show()
```

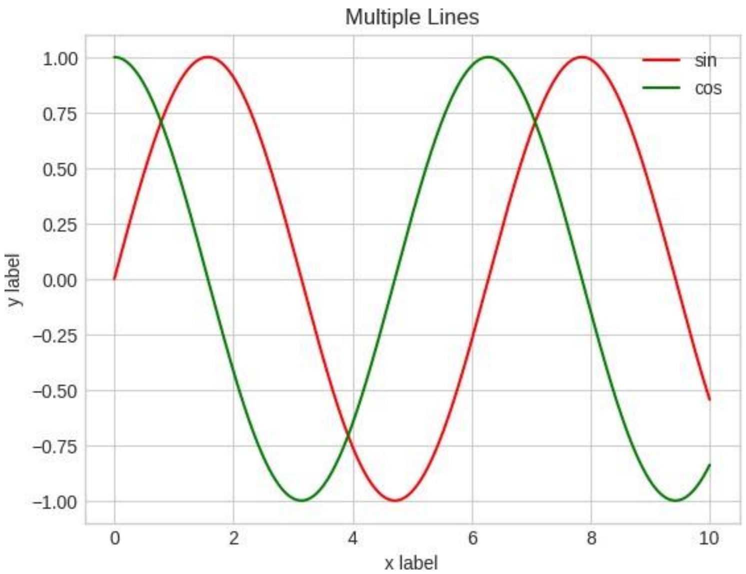



```
fig = plt.figure() ax
= plt.axes()
x   =   np.linspace(0,   10,   1000)
ax.plot(x, np.sin(x), label = 'sin')
ax.plot(x, np.cos(x), label = 'cos')
ax.set_title('Multiple      Lines');
ax.set_xlabel('x              label')
ax.set_ylabel('y label') ax.legend()
# ax.legend(loc=1) plt.show()
```

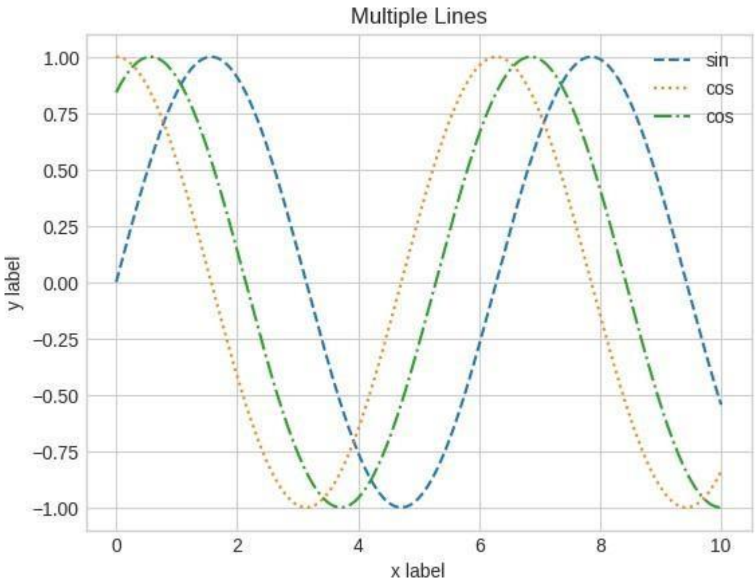
2



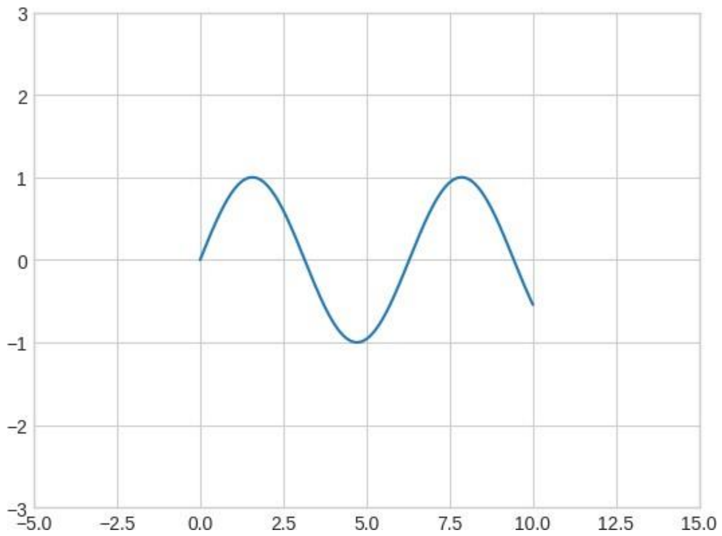

```
fig = plt.figure()
  ax = plt.axes()
x = np.linspace(0, 10, 1000) ax.plot(x, np.sin(x), label = 'sin', color = 'red') #
  specify color by name ax.plot(x, np.cos(x), label = 'cos', color = 'g')       #
  short color code (rgbcmyk) ax.set_title('Multiple Lines'); ax.set_xlabel('x
  label') ax.set_ylabel('y label') ax.legend();
```



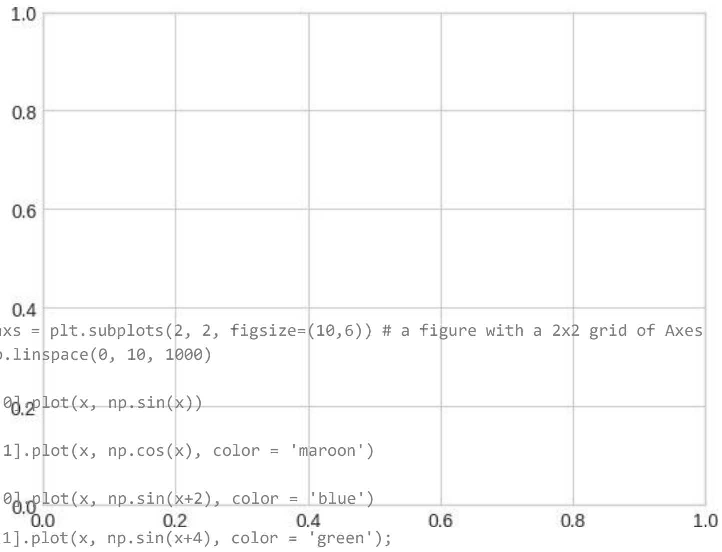

```
  fig = plt.figure() ax
  = plt.axes()
  # ax.grid(linestyle = '--')
x = np.linspace(0, 10, 1000) ax.plot(x, np.sin(x), label =
  'sin', linestyle = 'dashed') ax.plot(x, np.cos(x), label =
  'cos', linestyle = 'dotted') ax.plot(x, np.sin(x+1), label =
  'cos', linestyle = 'dashdot') ax.set_title('Multiple
  Lines'); ax.set_xlabel('x label') ax.set_ylabel('y label')
  ax.legend();
```




```
fig  =  plt.figure()
  ax = plt.axes()
x = np.linspace(0, 10, 1000)
  ax.plot(x, np.sin(x))
ax.set_xlim(-5, 15)
  ax.set_ylim(-3,
  3);
```



```
fig, ax = plt.subplots()        # a figure with a single Axes
```



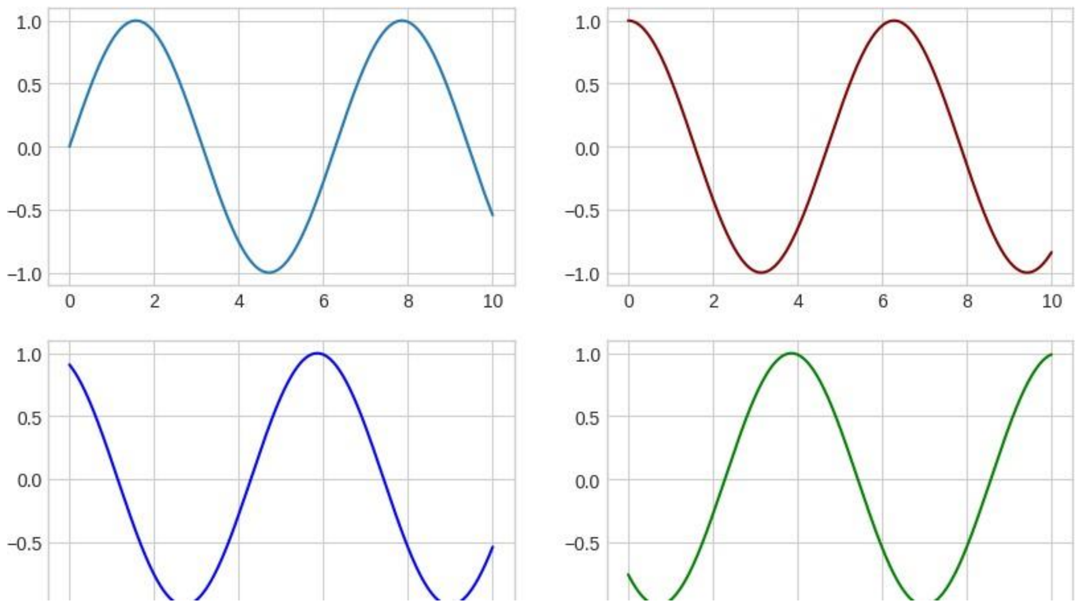

```
fig, axs = plt.subplots(2, 2, figsize=(10,6)) # a figure with a 2x2 grid of Axes
x = np.linspace(0, 10, 1000)

axs[0,0].plot(x, np.sin(x))

axs[0,1].plot(x, np.cos(x), color = 'maroon')

axs[1,0].plot(x, np.sin(x+2), color = 'blue')

axs[1,1].plot(x, np.sin(x+4), color = 'green');
```



LABSHEET 2

pandas

```
import pandas as pd data=pd.read_csv(r'C:\Users\Thejas
Venugopal\Downloads\nyc_weather.csv') data.head()
```

	EST	Temperature	DewPoint	Humidity	Sea Level PressureIn	VisibilityMiles	WindSpeedMP
0	1/1/2016	38	23	52	30.03	10	8.
1	1/2/2016	36	18	46	30.02	10	7.
2	1/3/2016	40	21	47	29.86	10	8.
3	1/4/2016	25	9	44	30.05	10	9.

pandas series

```
import numpy as np
d=np.array(['a','b','c','d']
) s=pd.Series(d) print(s)
```

```
0    a
1    b
2    c
3    d
dtype: object
```

with d being a dictionary

```
d={'a':1.,'b':2,'c':3}
s=pd.Series(d,index=['b','c','d'])
s
```

```
b 2.0
c    3.0
d    NaN
dtype: float64
```

changing the index

```
d=np.array(['a','b','c','d'])
s=pd.Series(d,index=[100,101,102,103])
print(s)
```

```
100    a
101    b
102    c
103    d
dtype: object
```

dtype = float

```
n=np.array([1,2,3])
s1=pd.Series(n,dtype=float)
s1
```

```
0    1.0
1    2.0
2    3.0
dtype: float64
```


syntax

pd.Series(data,index=[ ],dtype=, name=, copy=,)

combining 2 arrays to make an object

```
a1=np.array([1,2,3])
a2=np.array(['a','b','z']
) s2=pd.Series(a1,a2) s2
```

```
a
  1 b
  2 z
  3
dtype: int32
```

handling missing values

```
d={'a':1.,'b':2,'c':3}
s=pd.Series(d,index=['b','c','d'])
print(s)
```

```
b 2.0
c    3.0
d    NaN
dtype: float64
```

```
s.isna().sum()
```

```
1
```

```
s.dropna()
```

```
b 2.0 c 3.0
dtype: float64
```

```
d={'a':1.,'b':2,'c':3}
 s=pd.Series(d,index=['b','c','d'
 ]) print(s)
```

```
b 2.0  c
 3.0    d
 NaN
 dtype: float64
```

```
s.fillna(2)
```

```
b 2.0  c
 3.0    d
 2.0
 dtype: float64
```

accessing elements from the index

```
series=pd.Series([1,2,3,4,5],index=['a','b','c','d','e'])
series[1]
```

```
2
```

```
series[:3]
```

```
a 1  b
 2   c
 3
 dtype: int64
```

```
series['a']
```

```
1
```



```
series[['a','c','e']]
```

```
a 1  c
 3   e
 5
 dtype: int64
```

```
series1=pd.Series([103,1079,978],index=[' a hundred and three','one thousand seventy nine','nine hundred seventy eight']) series1['nine
hundred seventy eight']
```

```
978
```

DATA FRAME

```
import pandas as pd data = {'Name':['Alice', 'Bob',
'Claire', 'David'],
        'Age':[20, 21, 20, 22]}
df = pd.DataFrame(data) print(df)
```

```
      Name Age
0     Alice 20
1     Bob 21
2     Claire 20
```

```
3     David 22
```

```
# creating a dataframe from a list of dictionary data
= [{'Name': 'Alice', 'Age': 20},
        {'Name': 'Bob', 'Age': 21},
        {'Name': 'Claire', 'Age': 20},
        {'Name': 'David', 'Age': 22}]
df = pd.DataFrame(data) print(df)
```

```
       Name Age
0      Alice 20
1      Bob 21
2      Claire 20
3      David 22
```

```
pd.DataFrame(df)
```

	Name	Age
0	Alice	20
1	Bob	21
2	Claire	20
3	David	22

```
Start coding or generate with AI.
```

LABSHEET 3

Data Cleaning and Data Preprocessing:

1. Data cleaning is the process of changing or eliminating garbage, incorrect, duplicate, corrupted, or incomplete data in a dataset.
2. There's no such absolute way to describe the precise steps in the data cleaning process because the processes may vary from dataset to dataset.

☐ Data Cleaning Cycle

Missing Values:

```
# import the pandas library
import pandas as pd import
numpy as np
df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three'])
print(df)
# df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

# print (df)
```

```
one  two   three a 0.375319 -
0.763927 -0.762393 c -1.093644
1.335944 -0.668966 e -0.013401
0.155461 -0.843651 f 0.423813
0.900266 -0.828664 h -0.644593
2.654895 1.211697
```

Check for Missing Values:

To make detecting missing values easier (and across different array dtypes),Pandas provides the **isnull()** and **notnull()** functions, which are also methods on Series and DataFrame objects –

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```
import pandas as pd
import numpy as np
df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',

'h'],columns=['one', 'two', 'three']) df =

df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

# print (df['one'].isnull())
# print(df)
print(df["one"].isnull())
```

```
a False b
True
c False  d
True     e
False    f
False    g
True     h
False
Name: one, dtype: bool
```

Replacing the Missing Values

```
#Replace the missing values by 0 import pandas as pd import numpy as np df =
pd.DataFrame(np.random.randn(3, 3), index=['a', 'c', 'e'],columns=['one',
'two', 'three']) df =
df.reindex(['a', 'b', 'c'])
print (df) print ("NaN replaced
with '0':") print (df.fillna(0))
```

```
        one       two      three
a  -0.961858  -1.671248  0.556286
b  NaN  NaN  NaN  c  -0.386504  -
0.709324  0.622838  NaN  replaced
with '0':
        one       two      three
a  -0.961858  -1.671248  0.556286
b  0.000000  0.000000  0.000000  c
-0.386504  -0.709324  0.622838
```

Fill NA Forward and Backward

```
# Method          Action
pad/fill          Fill methods Forward
bfill/backfill    Fill methods Backward
```

```
import pandas as pd
import numpy as np
df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three']) df =
df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])
print(df) print (df.fillna(method='pad'))
```

```
          one       two     three
a 0.109813 -1.940379 -0.444834 b
     NaN    NaN    NaN c -0.208020
0.309864 0.819870 d     NaN    NaN
     NaN e -0.465764 0.215614
1.031519 f 1.189843 3.814140
0.954030 g       NaN    NaN    NaN
h 0.480653 0.552598 -0.888482
one  two   three a 0.109813 -
1.940379 -0.444834 b 0.109813 -
1.940379 -0.444834 c -0.208020
0.309864 0.819870 d -0.208020
0.309864 0.819870 e -0.465764
0.215614 1.031519 f 1.189843
3.814140 0.954030 g 1.189843
3.814140 0.954030 h 0.480653
0.552598 -0.888482
```

```
import pandas as pd
import numpy as np
df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three']) df =
df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h']) print
(df.fillna(method='bfill'))
```

```
          one       two      three
a -1.204446 2.137228 -0.388020
b 1.327178 2.355456 -1.347412 c
1.327178 2.355456 -1.347412 d -
0.228600 1.300295 0.939832 e -
0.228600 1.300295 0.939832 f -
0.938383  2.278881  -0.098408  g
0.726762  0.456629  -1.167753  h
0.726762 0.456629 -1.167753
```

Drop Missing Values:

Use dropna function along with the axis argument.

By default, axis=0, i.e., along row, which means that if any value within a row is NA then the whole row is excluded.

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```
'h'],columns=['one', 'two', 'three']) print(df) df =
df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])
print(df) print (df.dropna())
```

```
one  two   three a -0.481989 -
1.249458 -2.316982 c 1.119240 -
1.054186 -0.972090 e -0.991040 -
0.749165 0.259387 f -1.300768 -
0.000567 -0.056870 h 0.497341
0.984014 -1.094049 one  two
    three
a -0.481989 -1.249458 -2.316982
b NaN      NaN   NaN c 1.119240 -1.054186 -0.972090
d    NaN   NaN   NaN e -
0.991040 -0.749165 0.259387 f -
1.300768 -0.000567 -0.056870 g
    NaN   NaN   NaN h 0.497341
0.984014 -1.094049 one  two
    three a -0.481989 -1.249458
-2.316982 c 1.119240 -1.054186
-0.972090
e    -0.991040 -0.749165
0.259387 f -1.300768 -0.000567
-0.056870 h 0.497341 0.984014 -
1.094049
```

Replace Missing (or) Generic Values:

We can achieve this by applying the **replace** method.

Replacing NA with a scalar value is equivalent behavior of the **fillna()** function.

```
import pandas as pd import
numpy as np
df = pd.DataFrame({'one':[10,20,30,40,50,2000],
'two':[1000,0,30,40,50,60]})
print(df) print
(df.replace({1000:10,2000:60}))
```

```
    one  two  0
10 1000
1    20     0
2    30
      30
3    40
      40
4    50
      50
5    2000
      60   one
     two
0   10 10
1   20      0
2   30 30
3   40 40

4   50 50
5   60 60
```

```
import pandas as pd
import numpy as np
df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
```

Data Preprocessing

1. Load data in Pandas
2. Drop columns that aren’t useful
3. Drop rows with missing values
4. Create dummy variables
5. Take care of missing data
6. Convert the data frame to NumPy

Download Titanic-Dataset from Kaggle.com.

Here we are going to use train.csv dataset for preprocessing.

```
import pandas as pd import
numpy as np from google.colab
import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
df = pd.read_csv(r"C:\Users\Thejas Venugopal\Downloads\train (1).csv")
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890 Data
columns (total 12 columns):
 #   Column       Non-Null Count Dtype
-----            -------------- ------
     -------
 0                              int64
 1   PassengerId 891 non-null   int64
 2   Survived     891 non-null  int64
 3   Pclass       891 non-null  object
 4   Name         891 non-null  object
 5   Sex          891 non-null  float64
 6   Age          714 non-null  int64
 7   SibSp        891 non-null  int64
 8   Parch        891 non-null  object
 9   Ticket       891 non-null  float64
     Fare         891 non-null  object
10  Cabin         204 non-null  object
11  Embarked      889 non-null
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

Drop the Columns that are not required

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```
cols=['Name','Ticket','Cabin']
df=df.drop(cols,axis=0)
df.info()
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
C:\Users\THEJAS~1\AppData\Local\Temp/ipykernel_20436/1019933480.py in <module>
      1 cols=['Name','Ticket','Cabin']
----> 2 df=df.drop(cols)
      3 df.info()
c:\Users\Thejas    Venugopal\anaconda3\lib\site-packages\pandas\util\_decorators.py    in
wrapper(*args, **kwargs)
    309                     stacklevel=stacklevel,
    310                     )
--> 311             return func(*args, **kwargs)
    312
    313         return wrapper
c:\Users\Thejas    Venugopal\anaconda3\lib\site-packages\pandas\core\frame.py    in
drop(self, labels, axis, index, columns, level, inplace, errors)
   4904                 weight 1.0  0.8
   4905                 """
-> 4906    return super().drop(  4907
   labels=labels,
   4908             axis=axis,
c:\Users\Thejas    Venugopal\anaconda3\lib\site-packages\pandas\core\generic.py    in
drop(self, labels, axis, index, columns, level, inplace, errors) 4148 for axis,
labels in axes.items(): 4149 if labels is not None:
-> 4150    obj = obj._drop_axis(labels, axis, level=level,
errors=errors) 4151
   4152         if inplace:
c:\Users\Thejas Venugopal\anaconda3\lib\site-packages\pandas\core\generic.py in
_drop_axis(self, labels, axis, level, errors)
   4183                 new_axis = axis.drop(labels, level=level, errors=errors)
   4184                 else:
-> 4185 new_axis = axis.drop(labels, errors=errors) 4186 result =
   self.reindex(**{axis_name: new_axis})
   4187

c:\Users\Thejas   Venugopal\anaconda3\lib\site-packages\pandas\core\indexes\base.py   in
drop(self, labels, errors)
   6015             if mask.any():
   6016             if errors != "ignore":
-> 6017                 raise KeyError(f"{labels[mask]} not found in axis")
```

Drop the rows having no values

```
df = df.dropna()
df.info()
```

```
<class  'pandas.core.frame.DataFrame'>
Int64Index: 712 entries, 0 to 890 Data
columns (total 9 columns):

 #   Column        Non-Null Count Dtype
```

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```
-----            ----------------------  ------
    -------
 0  PassengerId 712 non-null     int64
 1  Survived    712 non-null     int64
 2  Pclass      712 non-null     int64
 3  Sex         712 non-null     object
 4  Age         712 non-null     float64
 5  SibSp       712 non-null     int64
 6  Parch       712 non-null     int64
 7  Fare        712 non-null     float64
 8  Embarked    712 non-null     object
dtypes: float64(2), int64(5), object(2)
memory usage: 55.6+ KB
```

Creating Dummy variables

Instead of wasting our data, let's convert the Pclass, Sex and Embarked to columns in Pandas and drop them after conversion.

```
dummies = [] cols = ['Pclass', 'Sex',
'Embarked'] for col in cols:
   dummies.append(pd.get_dummies(df[col]))
```

Transfor the eigth columns

```
titanic_dummies = pd.concat(dummies, axis=1)
```

Concatenate the values with data frame

```
df = pd.concat((df,titanic_dummies), axis=1)
```

Remove the unwanted cols

```
df = df.drop(['Pclass', 'Sex', 'Embarked'], axis=1)
```

Take care of Missing data

Let's compute a **median or interpolate()** all the ages and fill those missing age values. Pandas has an interpolate() function that will replace all the missing NaNs to interpolated values.

```
df['Age'] = df['Age'].interpolate()
print(df)
```

Min Max Scaler and Standardization

Normalization is a rescaling of the data from the original range so that all values are within the new range of 0 and 1.

A value is normalized as follows:

y = (x – min) / (max – min)

```
from sklearn.preprocessing import MinMaxScaler
data = [[-1, 2], [-0.5, 6], [0, 10], [1, 18]]
scaler = MinMaxScaler() print(scaler.fit(data))
MinMaxScaler()          print(scaler.data_max_)
print(scaler.transform(data))
```

```
MinMaxScaler()
 [ 1. 18.]

 [[0. 0. ]
  [0.25 0.25]
  [0.5 0.5 ]
  [1. 1. ]]
```

Data Standardization

Standardizing a dataset involves rescaling the distribution of values so that the mean of observed values is 0 and the standard deviation is 1.

A value is standardized as follows: y = (x

– mean) / standard_deviation

Where the mean is calculated as:

mean = sum(x) / count(x)

And the standard_deviation is calculated as: standard_deviation =

sqrt(sum((x – mean)^2) / count(x))

```
from numpy import asarray
from sklearn.preprocessing import StandardScaler
# define data
data = asarray([[100, 0.001],
 [8, 0.05],
 [50, 0.005],
 [88, 0.07],
 [4, 0.1]])
 print(data)
```

```
# define standard scaler scaler
= StandardScaler()
# transform data
scaled = scaler.fit transform(data)
```

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LABSHEET 4

```
import numpy as np import pandas as pd
```

```
# Example dataset data
= {
    'Feature1': [10, 20, 30, 40, 50],
    'Feature2': [5, 15, 25, 35, 45] }

# Create a DataFrame df
= pd.DataFrame(data)

# Display the original data
print("Original    Data:")
print(df)
```

```
Original  Data:  Feature1
      Feature2
   0        10        5
   1        20        15
   2        30        25
   3        40        35
   4        50        45
```

```
# Function to normalize data using Z-score def
zscore_normalization(df):
    normalized_df = df.copy() for column in normalized_df.columns:
    mean       =       normalized_df[column].mean()       std       =
    normalized_df[column].std()       normalized_df[column]       =
    (normalized_df[column] - mean) / std
    return normalized_df

# Normalize the DataFrame normalized_df
= zscore_normalization(df)

#   Display   the   normalized   data
print("\nNormalized     Data     (Z-
score):") print(normalized_df)
```

```
Normalized Data (Z-score):
   Feature1 Feature2
0  -1.264911 -1.264911
1  -0.632456 -0.632456
2  0.000000 0.000000
3  0.632456 0.632456
4  1.264911 1.264911
```

LABSHEET 5

```
from google.colab import files df
= files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving train.csv to train.csv
```

```
import pandas as pd
import numpy as np
```

```
data = pd.read_csv('./train.csv')
data.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	493	0	1	Molson, Mr. Harry Markland	male	55.0	0	0	113787	30.5000	C30	S
1	53	1	1	Harper, Mrs. Henry Sleeper (Myna Haxtun)	female	49.0	1	0	PC 17572	76.7292	D33	C
2	388	1	2	Buss, Miss. Kate	female	36.0	0	0	27849	13.0000	NaN	S
3	192	0	2	Carbines, Mr. William	male	19.0	0	0	28424	13.0000	NaN	S
4	687	0	3	Panula, Mr. Jaako Arnold	male	14.0	4	1	3101295	39.6875	NaN	S

```
cols = ['Name', 'Ticket', 'Cabin']
filtered_data = data.drop(cols, axis = 1)
filtered_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 712 entries, 0 to 711 Data
columns (total 9 columns):
 #  Column        Non-Null Count  Dtype
------ -----------      -------------------------   ---------
 0      PassengerId 712 non-null    int64
 1      Survived 712 non-null int64
 2      Pclass   712 non-null int64
 3      Sex      712 non-null object
 4      Age      566 non-null float64
 5      SibSp    712 non-null int64
 6      Parch    712 non-null int64
 7      Fare     712 non-null float64
 8      Embarked 710 non-null  object dtypes: float64(2), int64(5), object(2)
memory usage: 50.2+ KB
```

```
data = data.dropna()
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 148 entries, 0 to 695 Data
columns (total 12 columns):
                                   ---------
 0   PassengerId 148 non-null
 1   Survived       148 non-null int64
 2   Pclass         148 non-null int64
 3   Name  148 non-null           int64
 4   Sex   148 non-null           object
 5   Age   148 non-null           object
 6   SibSp 148 non-null           float64
 7   Parch 148 non-null           int64
 8   Ticket         148 non-null  int64
 9   Fare  148 non-null           object
 10  Cabin 148 non-null           float64
```

```
11  Embarked        148 non-null object         #  Column           Non-Null Count  Dtype
                                 object    ------          --------------------
```

```
dtypes:  float64(2),  int64(5),  object(5)
memory usage: 15.0+ KB
```

```
data.head()
```

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	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
									113787			
0	493	0	1	Molson, Mr. Harry Markland	male	55.0	0	0		30.5000	C30	S
1	53	1	1	Harper, Mrs. Henry Sleeper (Myna Haxtun)	female	49.0	1	0	PC 17572	76.7292	D33	C
9	752	1	3	Moor, Master. Meier	male	6.0	0	1	392096	12.4750	E121	S
10	541	1	1	Crosby, Miss. Harriet R	female	36.0	0	2	WE/P 5735	71.0000	B22	S

```
dummies = [] cols = ['Pclass', 'Sex',
'Embarked'] for col in cols:
  dummies.append(pd.get_dummies(data[col]))
```

```
dummies
```

```
 [  1 2 3 0  1 0                                   7
1  1 0                                             7
2  0 1                                             2
3  0 1                                             3
4  0 0.. .. .. ..                                  3
707 0 0                                            3

708  1 0 0
709  0 0 1
710  0 1 0
711  1 0 0

[712 rows x 3 columns], female
     male
0         0     1
1         1       0
```

```
2         1       0
3         0     1
4         0     1
..       ... ...
707       1     0
708       0       1
709       0       1
710       0       1
711       0       1

[712 rows x 2 columns],
     C  Q  S 0
         0 0 1
1    1 0 0
2    0 0 1
3    0 0 1
4    0 0 1
.. .. .. ..
707  1 0 0
708  1 0 0
709  0 0 1
710  0 0 1
711  0 0 1

[712 rows x 3 columns]]
```

```
titanic_dummies = pd.concat(dummies, axis = 1)
  titanic_dummies
```

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	1	2	3	female	male	C	Q	S
	1	0	0					
0	0	1	0	0	1			
1	1	0	0	1	0	1	0	0
2	0	1	0	1	0	0	0	1
3	0	1	0	0	1	0	0	1
4	0	0	1	0	1	0	0	1
...	...	...	...	...	... ...	... ...		
707	0	0	1	1	0	1	0	0
708	1	0	0	0	1	1	0	0
709	0	0	1	0	1	0	0	1
710	0	1	0	0	1	0	0	1
711	1	0	0	0	1	0	0	1

712 rows × 8 columns

```
data.drop(['Pclass', 'Sex', 'Embarked'], axis = 1)
```

	PassengerId	Survived	Name	Age	SibSp	Parch	Ticket	Fare	Cabin
0	493	0	Molson, Mr. Harry Markland	55.0	0	0	113787	30.5000	C30
1	53	1	Harper, Mrs. Henry Sleeper (Myna Haxtun)	49.0	1	0	PC 17572	76.7292	D33
2	388	1	Buss, Miss. Kate	36.0	0	0	27849	13.0000	NaN
3	192	0	Carbines, Mr. William	19.0	0	0	28424	13.0000	NaN
4	687	0	Panula, Mr. Jaako Arnold	14.0	4	1	3101295	39.6875	NaN
...	...	...	...	...	...	...	...	...	...
707	859	1	Baclini, Mrs. Solomon (Latifa Qurban)	24.0	0	3	2666	19.2583	NaN
708	65	0	Stewart, Mr. Albert A	NaN	0	0	PC 17605	27.7208	NaN
709	130	0	Ekstrom, Mr. Johan	45.0	0	0	347061	6.9750	NaN
710	21	0	Fynney, Mr. Joseph J	35.0	0	0	239865	26.0000	NaN
711	476	0	Clifford, Mr. George Quincy	NaN	0	0	110465	52.0000	A14

712 rows × 9 columns

```
data['Age'] = data['Age'].interpolate() print(data)
```

```
     PassengerId Survived Pclass                                        Name \
0            493  0        1        Molson, Mr. Harry Markland
1            53   1        1 Harper, Mrs. Henry Sleeper (Myna Haxtun)
2            388  1        2        Buss, Miss. Kate
3            192  0        2        Carbines, Mr. William
4            687  0        3        Panula, Mr. Jaako Arnold
..           ...       ...     ...                                       ...
707          859  1        3        Baclini, Mrs. Solomon (Latifa Qurban)
708          65   0        1        Stewart, Mr. Albert A
709          130  0        3        Ekstrom, Mr. Johan
710          21   0        2        Fynney, Mr. Joseph J
711          476  0        1        Clifford, Mr. George Quincy


          Sex Age SibSp Parch      Ticket     Fare Cabin Embarked
0      male 55.0   0        0        113787 30.5000 C30          S
1      female 49.0 1        0 PC 17572 76.7292 D33      C
2      female 36.0 0        0        27849 13.0000 NaN  S
3      male 19.0 0 0 28424 13.0000 NaN S 4 male 14.0 4 1 3101295 39.6875 NaN S
.. ... ... ... ... ... ... ... ...
707    female 24.0 0        3        2666 19.2583 NaN   C
708    male 34.5   0        0 PC 17605 27.7208 NaN      C
709    male 45.0   0        0        347061 6.9750 NaN  S
710    male 35.0   0        0        239865 26.0000 NaN          S
711    male 35.0   0        0        110465 52.0000 A14          S

[712 rows x 12 columns]
```

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```
from sklearn.preprocessing import MinMaxScaler
data = [[-1, 1], [-0.5, 6], [0, 10], [1, 10]]
scaler = MinMaxScaler()
print(scaler.fit(data))
print(scaler.data_max_)
print(scaler.transform(data))
```

```
MinMaxScaler()
[ 1. 10.]
[[0.         0.        ]
 [0.25       0.55555556]
 [0.5        1.        ]
 [1.         1.        ]]
```

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LABSHEET 6

```
import matplotlib.pyplot as plt # import seaborn as sn

# print a empty figure
# linespace 10 points with 1000 data points
# styles
# sin x and cos x
# legend values, colors, setting x, y title and other stuff
# line styles (different styles for each line)
# setting access limits (interval limits)
# subplot (printing multiple plots)
# 0 1 y = sin and then 0 1 x = sin
```

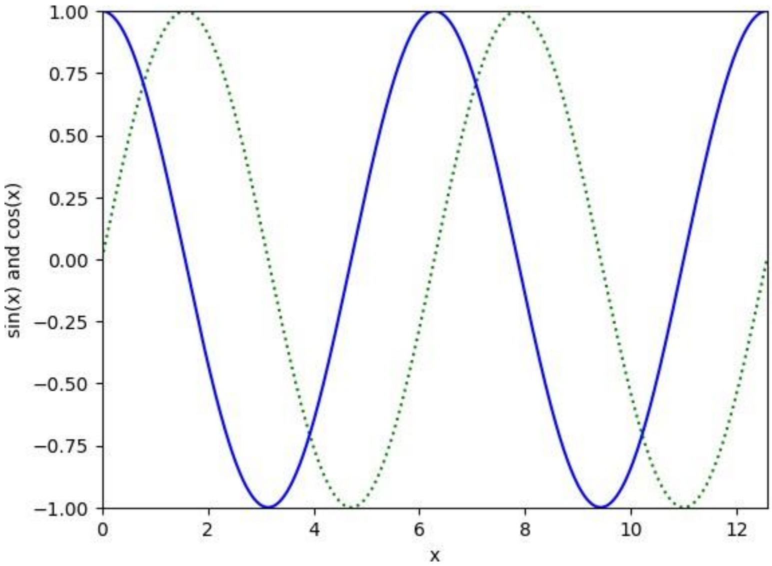
Code Text

```
# print a empty figure
fig   =   plt.figure()
plt.show()
```

```
<Figure size 640x480 with 0 Axes>
```

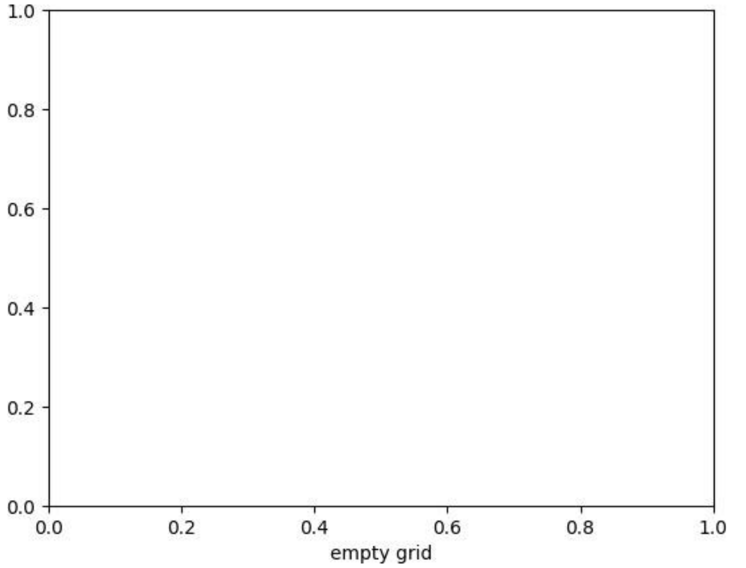
```
# print sin wave until 4pi import

numpy as np

x = np.linspace(0, 4*np.pi, 1000)
y = np.sin(x)  z = np.cos(x)  a =
np.tan(x)
plt.plot(x, y, color="green", linestyle="dotted")
plt.plot(x, z, color="blue")


# Set the x-axis and y-axis limits
plt.xlim(0, 4*np.pi) plt.ylim(-1,
1)


# Set the x-axis and y-axis labels
plt.xlabel('x')
plt.ylabel('sin(x) and cos(x)')


# Show the plot
# plt.show()
```

```
Text(0, 0.5, 'sin(x) and cos(x)')
```

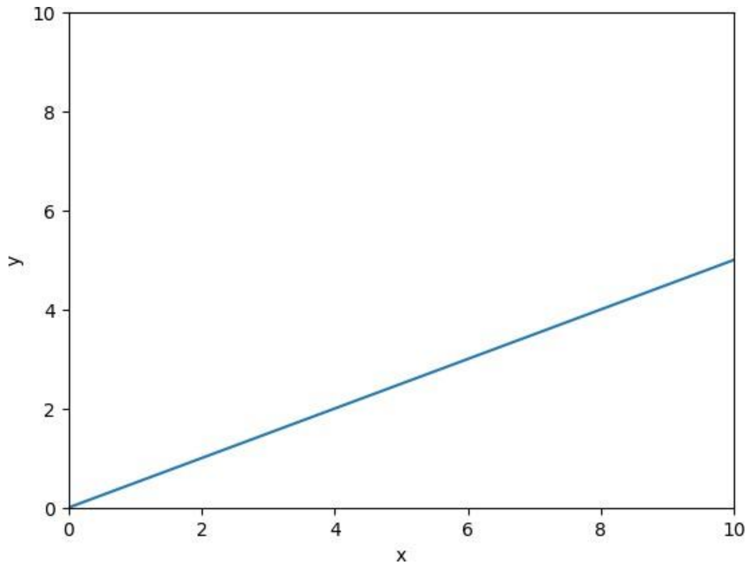



```
plt.xlabel('empty grid')
```

```
Text(0.5, 0, 'empty grid')
```




```
x = np.linspace(0, 10, 1000) y =
  np.linspace(0,   5,   1000)   #
  plt.plot(np.sin(x),   np.cos(y))
  plt.plot(x, y)


  # Set the x-axis and y-axis limits
  plt.xlim(0, 10) plt.ylim(0, 10)


  # Set the x-axis and y-axis
  labels plt.xlabel('x')
  plt.ylabel('y')


  # Show the plot plt.show()
```




```
  # printing a subplot x =
  np.array([0, 1, 2, 3]) y =
  np.array([3, 8, 1, 10])
plt.subplot(2, 1, 1)
  plt.plot(x,y)


  #plot 2:
  #x = np.array([0, 1, 2, 3])
  #y = np.array([10, 20, 30, 40])
```

```
#plt.subplot(2, 1, 2)
#plt.plot(x,y)
```

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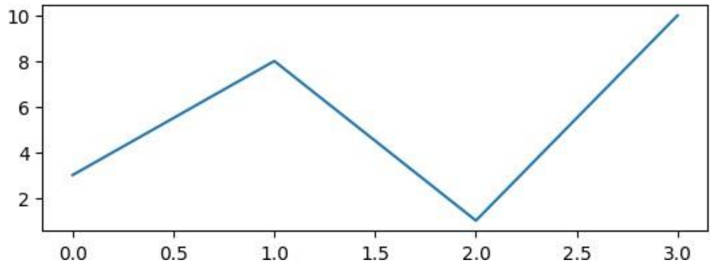
```
[<matplotlib.lines.Line2D at 0x7a4d87f00ca0>]
```



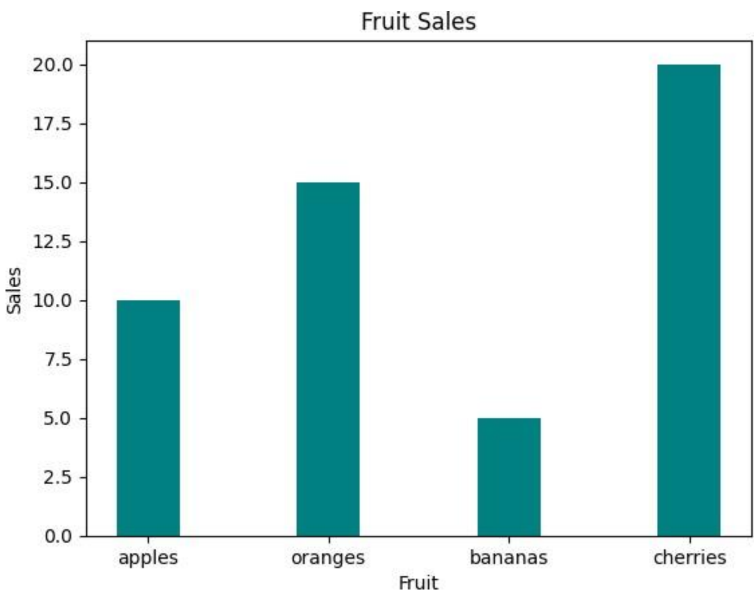

```
# barchar example with dictionary import
matplotlib.pyplot as plt

# Define the data data = {'apples': 10, 'oranges': 15, 'bananas':
5, 'cherries': 20}

#  Create  a  bar  chart  plt.bar(list(data.keys()),  list(data.values()),
width=0.35, color="teal")

# Add title and axis labels
plt.title('Fruit    Sales')
plt.xlabel('Fruit')
plt.ylabel('Sales')

# Show the plot plt.show()
```




```
# example of horizontal barchart with dictionary

# Define the data
data = {'apples': 10, 'oranges': 15, 'bananas': 5, 'cherries': 20}

# Create a horizontal bar chart
plt.barh(list(data.keys()), list(data.values()), color="purple", height=0.3)
```

```
# Add title and axis labels
plt.title('Fruit Sales') #
plt.xlabel('Sales')
# plt.ylabel('Fruit')


# Show the plot show_plot
= plt.show()
```

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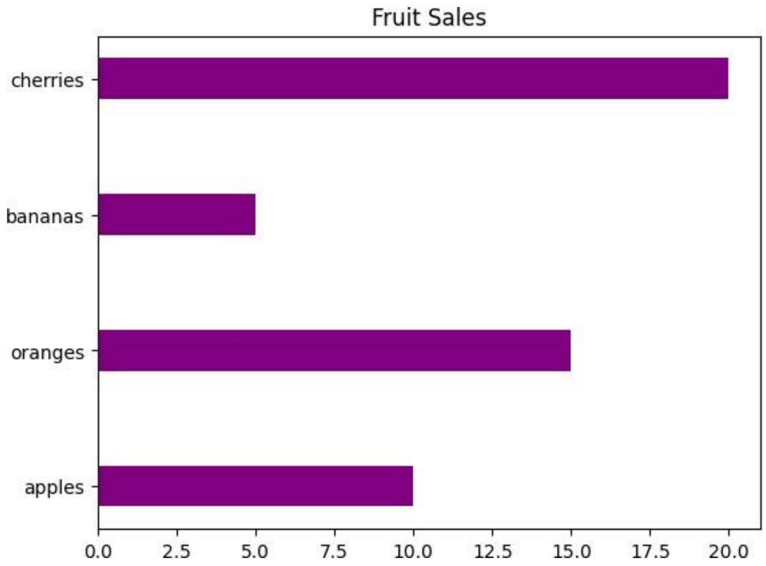
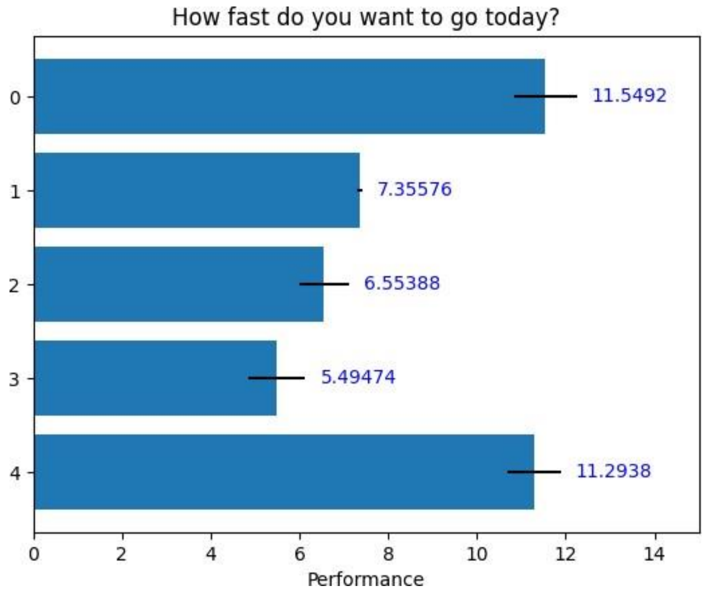



```
AttributeError                            Traceback (most recent call last)
<ipython-input-56-dbd46437747f> in <cell line: 16>()
     14 # Show the plot
     15 show_plot = plt.show()
---> 16 show_plot.set_xlabel('something')

AttributeError: 'NoneType' object has no attribute 'set_xlabel'
```

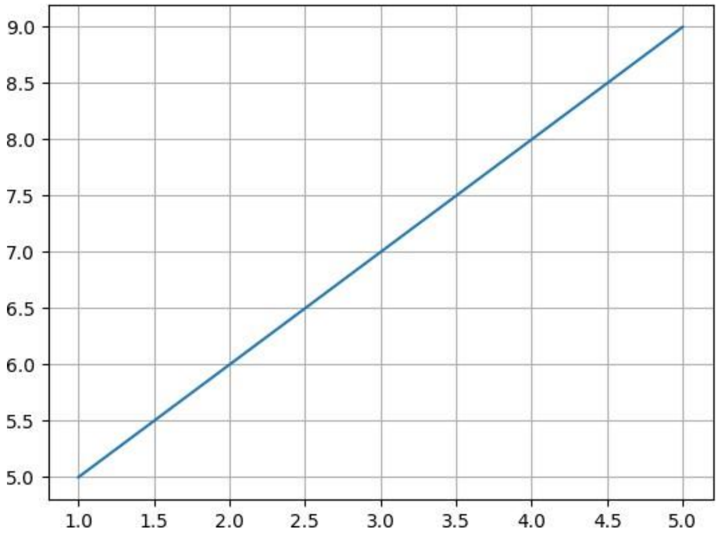
```
fig, ax = plt.subplots()

 # Example data people = ('Tom', 'Thejas', 'Harry',
 'Slim',  'Jim')  y_pos  =  np.arange(len(people))
 performance = 3 + 10 * np.random.rand(len(people))
 error = np.random.rand(len(people))
hbars = ax.barh(y_pos, performance, xerr=error, align='center')
 ax.invert_yaxis()                    ax.set_xlabel('Performance')
 ax.set_title('How fast do you want to go today?')

 # Label with given captions, custom padding and annotate
 options ax.bar_label(hbars, padding=8, color='b')
 ax.set_xlim(right=15) plt.show()
```




```
print(np.arange(10, 20, 2))
```

```
[10 12 14 16 18]
```

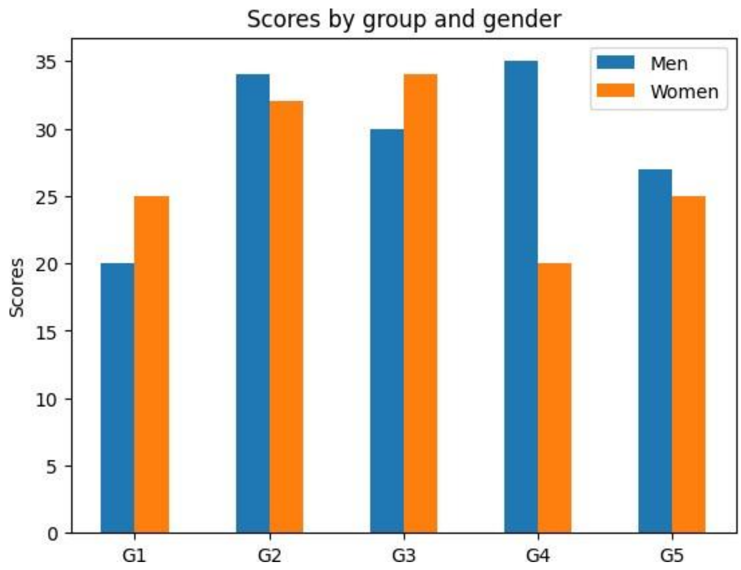
```
# pprint a axis plot with ax.grid() import

matplotlib.pyplot as plt

# Create a figure and an axes object ax
= plt.subplot()


# Plot some data ax.plot([1, 2, 3, 4,
5], [5,6,7,8,9])


# Enable the grid ax.grid(True)


# Show the plot plt.show()
```



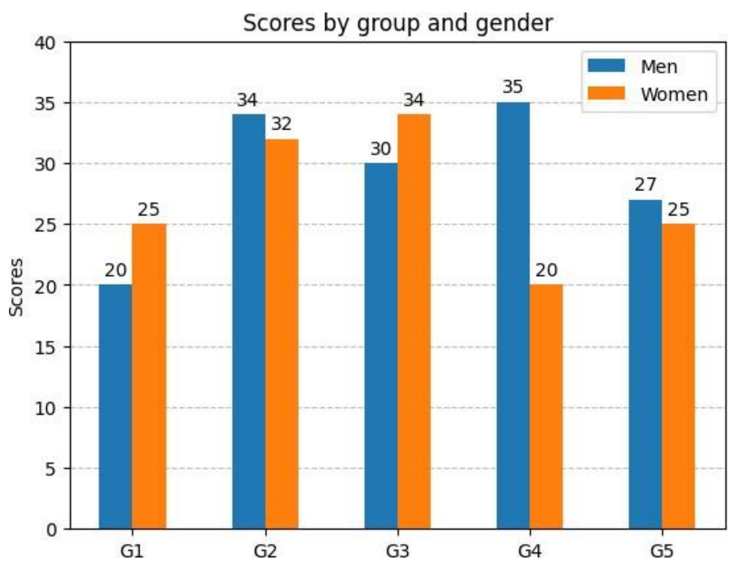

```
print(np.arange(10, 20, 2))
```

```
[10 12 14 16 18]
```

```
# grouped bar charts example import
numpy as np import matplotlib.pyplot
as plt labels = ['G1', 'G2', 'G3',
'G4', 'G5'] men_means = [20, 34, 30,
35, 27] women_means = [25, 32, 34, 20,
25]
x = np.arange(len(labels))
# width of the individual component width
= 0.25
fig, ax = plt.subplots() rects1 = ax.bar(x - width/2, men_means,
width, label='Men') rects2 = ax.bar(x + width/2, women_means,
width, label='Women')


# Add some text for labels, title and custom x-axis tick labels,
etc. ax.set_ylabel('Scores') ax.set_title('Scores by group and
gender') ax.set_xticks(x) ax.set_xticklabels(labels) ax.legend();
plt.show()
```

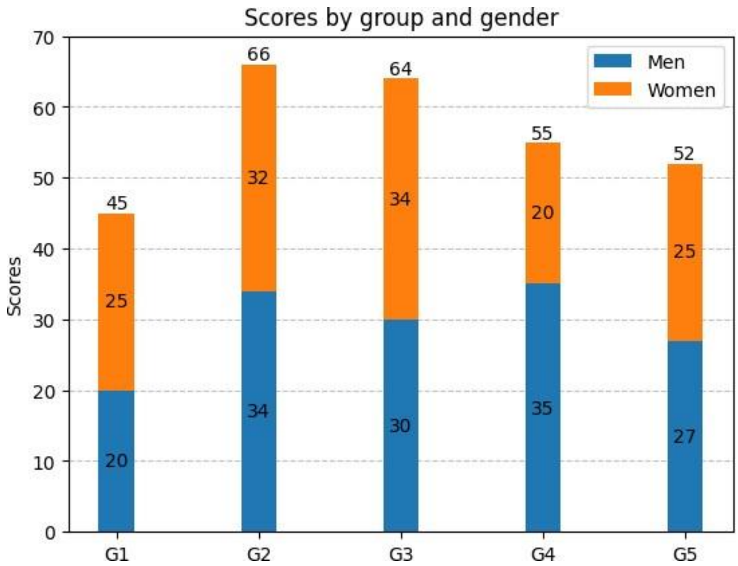



```
# adding labels to individual bars with their scores

fig, ax = plt.subplots() ax.grid(linestyle='--',
color='0.75', axis = 'y') ax.set_axisbelow(True)
rects1 = ax.bar(x - width/2, men_means, width, label='Men')
rects2 = ax.bar(x + width/2, women_means, width,
label='Women')
ax.set_ylabel('Scores')
ax.set_title('Scores by group and
gender') ax.set_xticks(x)
ax.set_xticklabels(labels) ax.legend()

#   Adding   the   bar   labels
ax.bar_label(rects1, padding=3)
ax.bar_label(rects2, padding=3)
ax.set_ylim(0,40);
```



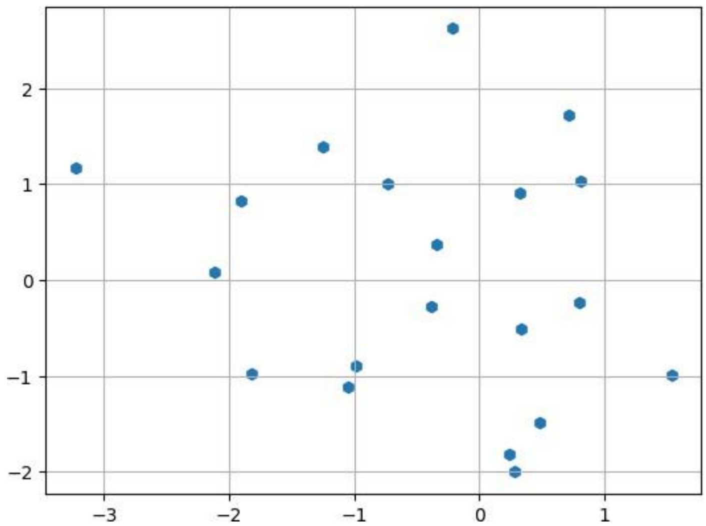
```
fig, ax = plt.subplots() ax.grid(linestyle='--', color='0.75',
axis = 'y'); ax.set_axisbelow(True) # set this to true for
enabling gridlines

p1 = ax.bar(labels, men_means, width, label='Men') p2 =
ax.bar(labels,  women_means,  width,  bottom=men_means,
label='Women')
ax.set_ylabel('Scores')
ax.set_title('Scores by group and
gender') ax.legend()


# Label with label_type 'center'
ax.bar_label(p1, label_type='center')
ax.bar_label(p2, label_type='center')
ax.bar_label(p2) ax.set_ylim(0,70)
```

```
(0.0, 70.0)
```

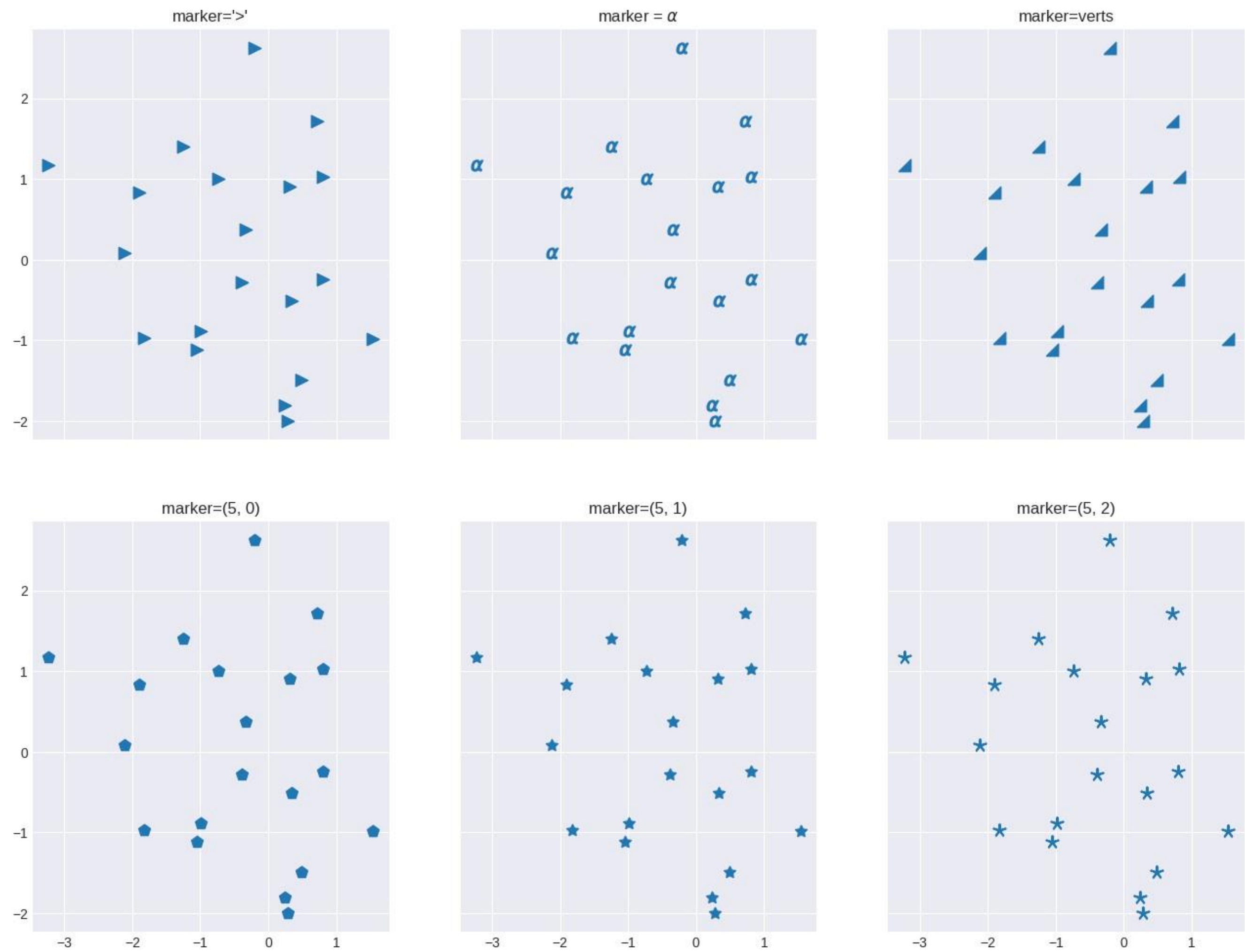



```
# scatter plot x =
np.random.randn(20) y
= np.random.randn(20)
fig, ax = plt.subplots() ax.grid(True) ax.scatter(x, y,
marker = 'h') # can change to any marker
```

```
<matplotlib.collections.PathCollection at 0x7b29651475e0>
```

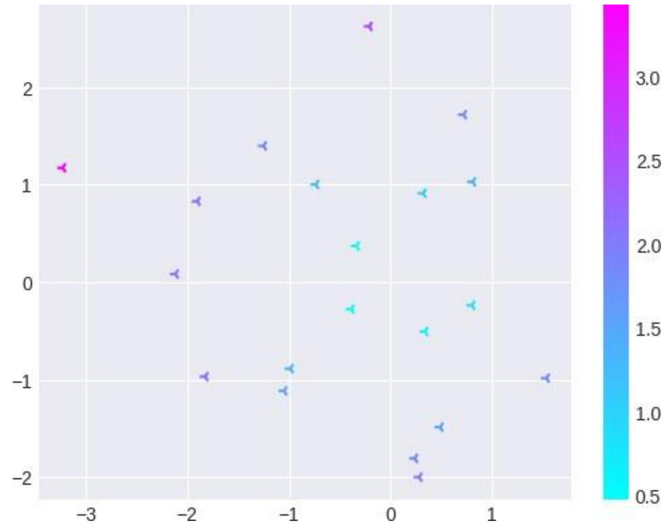


```
fig, axs = plt.subplots(2, 3, sharex=True, sharey=True, figsize=(16,12));
  # plt.style.use('seaborn-darkgrid')
  # marker symbol axs[0, 0].scatter(x, y,
  s=80,         marker=">")         axs[0,
  0].set_title("marker='>'")


  # marker from TeX axs[0, 1].scatter(x, y, s=80,
  marker=r'$\alpha$') axs[0, 1].set_title("marker =
  " + r'$\alpha$')
  # axs[0, 1].set_title(f"marker = {r'$\alpha$'}")


  # marker from path verts = [[-1, -1], [1, -
  1], [1, 1], [-1, -1]] axs[0, 2].scatter(x, y,
  s=80,          marker=verts)          axs[0,
  2].set_title("marker=verts")
 axs[1, 0].scatter(x, y, s=80, marker=(5, 0))
  axs[1, 0].set_title("marker=(5, 0)")


  # regular star marker axs[1, 1].scatter(x, y,
  s=80,       marker=(5,       1))       axs[1,
  1].set_title("marker=(5, 1)")


  #    regular    asterisk    marker    axs[1,
  2].scatter(x, y, s=80, marker=(5, 2)) axs[1,
  2].set_title("marker=(5, 2)");
```



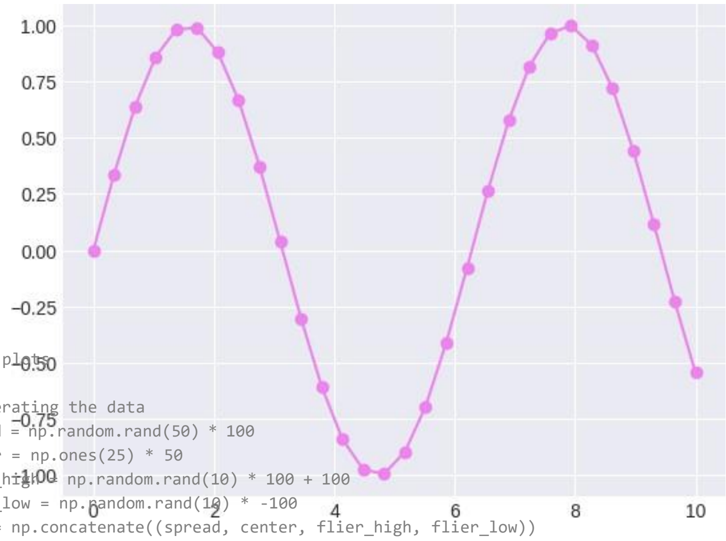
```
# setting the colors with
matplotlib plt.style.use('seaborn-
darkgrid') z1 = np.sqrt(x**2 +
y**2)

fig, ax = plt.subplots() pos = ax.scatter(x, y, c=z1,
cmap='cool', marker='3')

fig.colorbar(pos);
```

```
<ipython-input-51-3dd43bf91bb6>:2: MatplotlibDeprecationWarning: The seaborn styles shipped by Matplotlib are deprecated since 3.6,
  plt.style.use('seaborn-darkgrid')
```



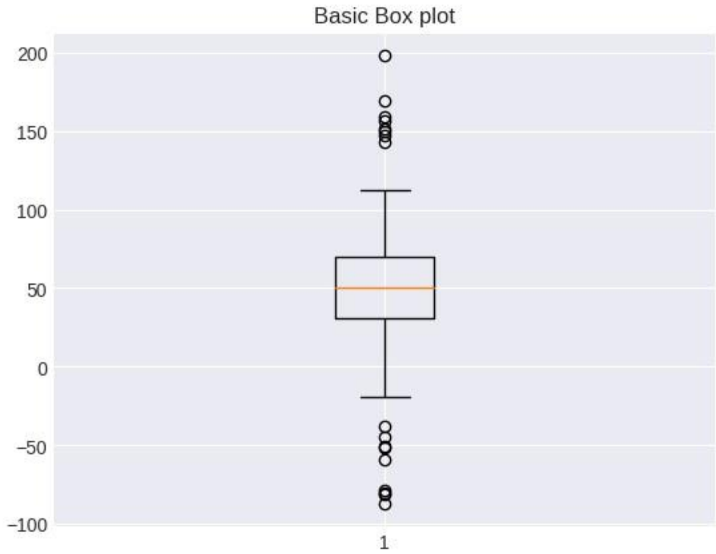

```
x = np.random.randn(100)
  y = np.random.randn(100)
z1 = np.sqrt(x**2 + y**2) z2 =
  np.random.randint(10, 200, size=len(x))
fig, ax = plt.subplots()
  # pos = ax.scatter(x, y, c=z1, s=z2, alpha = 0.55, cmap='viridis')
  pos = ax.scatter(x, y, c = z1, s = z2, alpha = 0.55, cmap='RdPu_r')
  fig.colorbar(pos);
```


```
x = np.linspace(0, 10, 30) y
  = np.sin(x)
plt.plot(x, y, 'o-', color='violet');
```




```
# Box plots

# Generating the data
spread = np.random.rand(50) * 100
center = np.ones(25) * 50
flier_high = np.random.rand(10) * 100 + 100
flier_low = np.random.rand(10) * -100
data = np.concatenate((spread, center, flier_high, flier_low))


# Visualization of the data using box plot (basic)
fig, ax = plt.subplots() ax.boxplot(data)
ax.set_title("Basic Box plot")
```

```
Text(0.5, 1.0, 'Basic Box plot')
```




```
# Notched boxplot without outliers
```

LABSHEET 7

```
import pandas as pd
```

Code Text

```
df = pd.read_csv('train.csv')
df
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	C

```
df.dtypes
```

```
PassengerId     int64
Survived        int64
Pclass          int64
Name           object
Sex            object
Age           float64
SibSp           int64
Parch           int64
Ticket         object
Fare          float64
Cabin          object
Embarked       object
dtype: object
```

```
df.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

```
df.isna().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```



```
age_mean_value=df['Age'].mean()
df['Age']=df['Age'].fillna(age_mean_value)
```

```
df.drop("Cabin",axis=1,inplace=True)
```

```
df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	S

```
filtered_age = df[df.Age>40] filtered_age
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	S
11	12	1	1	Bonnell, Miss. Elizabeth	female	58.0	0	0	113783	26.5500	S
15	16	1	2	Hewlett, Mrs. (Mary D Kingcome)	female	55.0	0	0	248706	16.0000	S
33	34	0	2	Wheadon, Mr. Edward H	male	66.0	0	0	C.A. 24579	10.5000	S
35	36	0	1	Holverson, Mr. Alexander Oskar	male	42.0	1	0	113789	52.0000	S
...	...	...	...	...	...	...	...	...	...	...	...
862	863	1	1	Swift, Mrs. Frederick Joel (Margaret Welles Ba...	female	48.0	0	0	17466	25.9292	S
865	866	1	2	Bystrom, Mrs. (Karolina)	female	42.0	0	0	236852	13.0000	S
871	872	1	1	Beckwith, Mrs. Richard Leonard (Sallie Monypeny)	female	47.0	1	1	11751	52.5542	S
873	874	0	3	Vander Cruyssen, Mr. Victor	male	47.0	0	0	345765	9.0000	S
879	880	1	1	Potter Mrs Thomas Jr (Lily Alexenia Wilson)	female	56 0	0	1	11767	83 1583	C

```
# let's sort the column Name in ascending order sorted_passengers =
df.sort_values('Name',ascending=True,kind ='heapsort')
```

```
sorted_passengers.head(10)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked

845	846	0	3	Abbing, Mr. Anthony	male	42.0	0	0	C.A. 5547	7.5500	S
746	747	0	3	Abbott, Mr. Rossmore Edward	male	16.0	1	1	C.A. 2673	20.2500	S
279	280	1	3	Abbott, Mrs. Stanton (Rosa Hunt)	female	35.0	1	1	C.A. 2673	20.2500	S
308	309	0	2	Abelson, Mr. Samuel	male	30.0	1	0	P/PP 3381	24.0000	C
874	875	1	2	Abelson, Mrs. Samuel (Hannah Wizosky)	female	28.0	1	0	P/PP 3381	24.0000	C
365	366	0	3	Adahl, Mr. Mauritz Nils Martin	male	30.0	0	0	C 7076	7.2500	S
401	402	0	3	Adams, Mr. John	male	26.0	0	0	341826	8.0500	S
40	41	0	3	Ahlin, Mrs. Johan (Johanna Persdotter Larsson)	female	40.0	1	0	7546	9.4750	S
855	856	1	3	Aks, Mrs. Sam (Leah Rosen)	female	18.0	0	1	392091	9.3500	S
207	208	1	3	Albimona, Mr. Nassef Cassem	male	26.0	0	0	2699	18.7875	C

```
merged_df = pd.merge(df.head(2),df.tail(2),how='outer',indicator=True)
  merged_df
```


	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked	_merge
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S	left_only
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C	left_only
2	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C	right_only

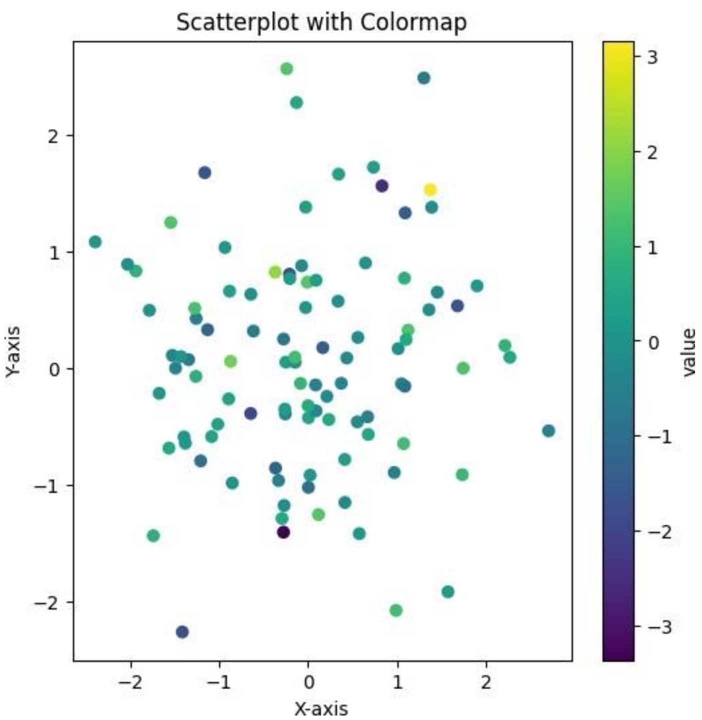
```
group_df = df.groupby('Name')
```

```
group_df
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x111f7ad50>
```

LABSHEET 8

```
import pandas as pd import numpy as np import matplotlib.pyplot as plt
# Sample dataframe with multiple columns data
= pd.DataFrame({
    "x": np.random.randn(100),
    "y": np.random.randn(100),
    "value": np.random.randn(100)
})
# Define the colormap and alpha values
cmap = "viridis" alpha = 1
# Create the scatterplot plt.figure(figsize=(6, 6)) plt.scatter(data["x"],
data["y"], c=data["value"], cmap=cmap, alpha=alpha)
#   Customize   the   plot   (optional)
plt.xlabel("X-axis")   plt.ylabel("Y-
axis")  plt.title("Scatterplot  with
Colormap")
plt.colorbar(label="value")
# Show the plot plt.show()
```




```
import  pandas  as  pd  import
  numpy        as        np
  print(np.random.randn(100)
  )
```

```
[ 7.25060198e-01  2.53900412e+00  1.26528031e+00  1.84136990e+00  -2.60848832e+00 -
   5.59983281e-01 4.35035456e-01 -7.00367135e-02
    1.96931749e+00 1.04382097e+00 -5.23481680e-01 4.38611173e-01
   -6.03314609e-02 -1.62331938e+00 -1.75368806e-01 -1.45327854e-01
    7.11162067e-01 -1.24752326e+00 1.10879435e+00 6.15797150e-01
    3.22382085e-02 -4.94204444e-01 -1.56553377e+00 1.86476127e+00
   -1.53372917e+00  6.21845005e-01  1.08857491e+00  -1.69076421e+00  -3.80722950e+00
    4.70410313e-01 8.77562643e-01 -8.95285501e-01
    9.83561836e-01 9.32718991e-01 -6.78531171e-01 9.14953408e-05 -2.21344622e+00 -
   6.15124358e-02 -9.18144802e-02 7.84013469e-01
    9.64181023e-01 -1.75737978e+00 1.19471319e+00 -1.02246958e-01
    7.73172607e-01 1.02398382e+00 1.47867589e-01 -2.44199793e+00
```

```
-8.49499655e-01 1.88210306e-01 -2.61106287e-01 -9.53558247e-01
 -8.54821744e-01 -3.80648950e-01 -5.87306646e-01 5.54602769e-01
  1.40580004e+00 1.08580790e+00 -8.33862936e-01 7.08280769e-01
-1.43281505e+00 -1.93642975e-01 6.86796860e-01 5.50748349e-01
  7.79495185e-01 -2.71795003e-01 -1.16407843e+00 1.38373041e+00
-2.90569948e-01  1.27385062e+00  -4.24752220e-01  5.69263764e-01  -1.45006382e+00
8.39335515e-01 -9.49539071e-01 -2.04611107e+00
  1.00680640e+00 2.59974257e-01 -1.29858485e+00 9.67979863e-01
-9.72496062e-01 -1.72551385e+00 -5.42038103e-01 4.26256470e-01
```



```
 6.57253328e-01 -1.75193447e+00 -1.22202143e+00 -6.31901884e-01
-9.24312354e-01 1.76235295e+00 -6.83714121e-01 5.19175365e-01
-3.18749238e-01 -1.69096151e-01 -4.49121798e-01 3.98598713e-01
 8.80300195e-01 -6.39043290e-02 -4.47122464e-01 -1.65126924e-01]
```

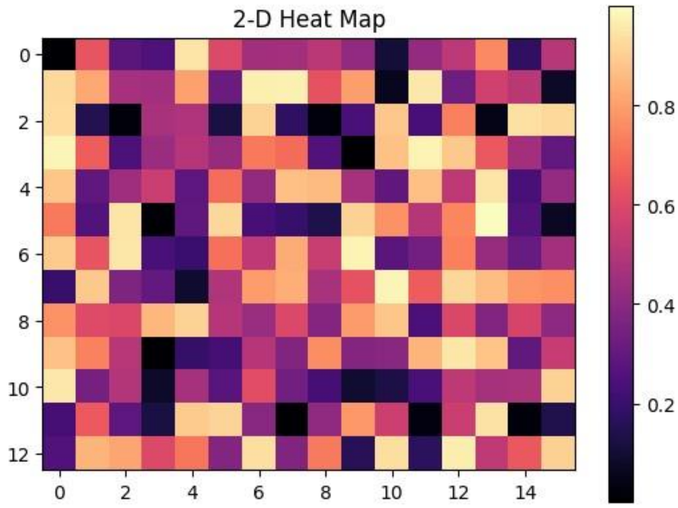
Start coding or g enerate with AI.

Double-click (or enter) to edit

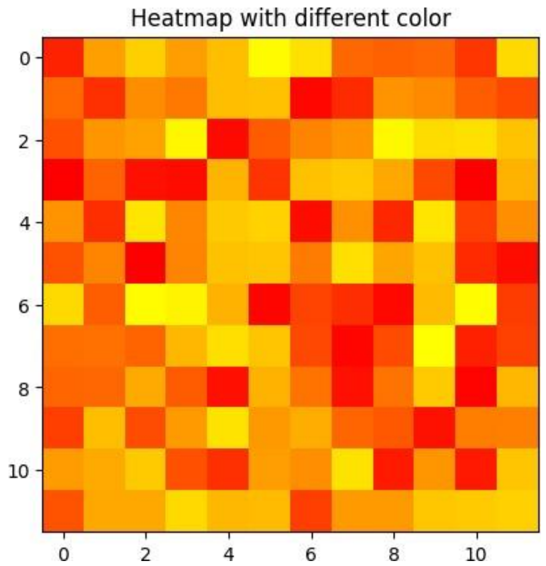
LABSHEET 9

```
# Program to plot 2-D Heat map
# using matplotlib.pyplot.imshow() method
import    numpy    as    np    import
matplotlib.pyplot   as   plt   data   =
np.random.random(( 13 , 16 )) plt.imshow(
data,cmap="magma" )
plt.title( "2
```

```
-D Heat Map" )   plt.colorbar() plt.show()
```



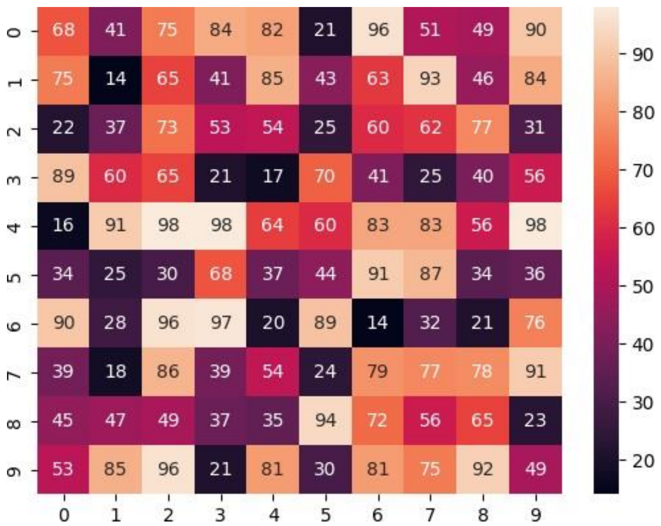

```
# Program to plot 2-D Heat map
# using matplotlib.pyplot.imshow() method
import    numpy    as    np    import
matplotlib.pyplot as plt
data = np.random.random((12, 12))
plt.imshow(data, cmap='autumn')
plt.title("Heatmap with different color")
plt.show()
```




```
# importing the modules import
numpy as np import seaborn as
sns import matplotlib.pyplot as
plt


# generating 2-D 10x10 matrix of random numbers
# from 1 to 100 data =
 np.random.randint(low=14,
 high=100,
```



```
                        size=(10, 10))
#   plotting   the   heatmap   hm   =
sns.heatmap(data=data,annot=True)   #
displaying   the   plotted   heatmap
plt.show()
```



All the IPython Notebooks in **Python Seaborn Module** lecture series by **Dr. Milaan Parmar** are available @ **GitHub**

LABSHEET 10

Open in Colab

Seaborn Color Palettes

Color is an utmost important aspect of figure styling because it reveals pattern in the data if used effectively; or hide those patterns if used poorly. Even professionals often assume usage of color to portray data as a solved problem. They just pick a palette from a drop-down menu (probably either a grayscale ramp or a rainbow), set start and end points & finally press apply. But it isn't that simple and thus many visualizations fail to represent the underlying data as appropriately as they could.

Primary objective with choice of color is to illuminate datapoints that are concealed in huge datasets. Quoting Robert Simmon:

> Although the basics are straightforward, a number of issue complicate color choices in visualization. Among them: The relationship between the light we see and the colors we perceive is extremely complicated. There are multiple types of data, each suited to a different color scheme. A significant number of people (mostly men), are color blind. Arbitrary color choices can be confusing for viewers unfamiliar with a data set. Light colors on a dark field are perceived differently than dark colors on a bright field, which can complicate some visualization tasks, such as target detection.

One of the most fundamental and important aspects of color selection is the mapping of numbers to colors. This mapping allows us to pseudocolor an image or object based on varying numerical data. By far, the most common color map used in scientific visualization is the rainbow color map. Research paper on **Diverging Color Maps for Scientific Visualization** by Kenneth Moreland very well deals with the extended color concepts, if the topic interests you for further analysis.

With all that been said, let us now focus on what Seaborn has to offer BUT before doing that let me once again remind you that Seaborn runs on top of Matplotlib so any color that is supported by **Matplotlib** will be supported by Seaborn as well. So at first, let us understand what Matplotlib has to offer:

- an RGB or RGBA tuple of float values in [0, 1] (e.g., (0.1, 0.2, 0.5) or (0.1, 0.2, 0.5, 0.3))
- a hex RGB or RGBA string (e.g., '#0F0F0F' or '#0F0F0F0F')
- a string representation of a float value in [0, 1] inclusive for gray level (e.g., '0.5') one of {'b', 'g', 'r', 'c', 'm', 'y', 'k', 'w'}
- a X11/CSS4 color name
- a name from the xkcd color survey prefixed with 'xkcd:' (e.g., 'xkcd:sky blue') one of {'C0', 'C1', 'C2', 'C3', 'C4', 'C5', 'C6', 'C7', 'C8', 'C9'}

- one of {'tab:blue', 'tab:orange', 'tab:green', 'tab:red', 'tab:purple', 'tab:brown', 'tab:pink', 'tab:gray', 'tab:olive', 'tab:cyan'} which are the **Tableau** Colors from the 'T10' categorical palette (which is the default color cycle).

Note that all string specifications of color, other than "CN", are NOT case-sensitive. Let us briefly go through a couple of common supported colors here:

- RGB/RGBA tuples are 4-tuples where the respective tuple components represent Red, Green, Blue, and Alpha (opacity) values for a color. Each value is a floating point number between 0.0 and 1.0. For example, the tuple (1, 0, 0, 1) represents an opaque red, while (0, 1, 0, 0.5) represents a half transparent green.
- This is actually another way of representing RGBA codes and common Color Conversion Calculators can be used to translate values. Here is a **Hex to RGBA** and **RGB to Hex** Color converter for your future assistance.
- Dictionary of values from {'C0', 'C1', 'C2', 'C3', 'C4', 'C5', 'C6', 'C7', 'C8', 'C9'} represent **Color Quantization**. I have attached a link in the provided notebook that shall guide you to an online book where on Page-29 you could find specifics.

My sole purpose of keeping you posted of Matplotlib background every now and then is only to ensure that when you get to production-level and try to customize a plot as per your analysis, you should know what is ACTUALLY running in the background. This shall empower you to accordingly tweak parameters here and there. Let us now look into few Seaborn options for colors:

```
# Importing required Libraries:
import numpy as np import
pandas as pd
import matplotlib.pyplot as plt import
seaborn as sns
%matplotlib inline

# Setting a figure size for all the plots we shall be drawing in this kernel:
sns.set(rc={"figure.figsize": (6, 6)})
```

☐ Building color palettes:

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```
current_palette = sns.color_palette()
sns.palplot(current_palette)
```

The most important function for working with discrete color palettes is **`color_palette()`** . This function provides an interface to many (though not all) of the possible ways you can generate colors in seaborn, and it's used internally by any function that has a **`palette`** argument (and in some cases for a **`color`** argument when multiple colors are needed).

`color_palette()` will accept the name of any seaborn palette or matplotlib colormap (except **`jet`** , which you should never use). It can also take a list of colors specified in any valid matplotlib format (RGB tuples, hex color codes, or HTML color names). The return value is always a list of RGB tuples.

Finally, calling **`color_palette()`** with no arguments will return the current default color cycle.

```
sns.palplot(sns.color_palette("hls", 8))
```

```
sns.palplot(sns.color_palette("husl", 8))
```

Let me explain these Qualitative (or categorical) palettes. These are best when you want to distinguish discrete chunks of data that do not have an inherent ordering. Ideally, when importing Seaborn, the default color cycle is changed to a set of six colors that evoke the standard matplotlib color cycle. But when we have more than 6, say 8 categories in our data to distinguish, then the most common way is using **`hls`** color space, which is a simple transformation of RGB values.

Then there is also **`hls_palette()`** function that lets you control the lightness and saturation of colors.

All of it displayed above is just the basic Seaborn aesthetics. Let us now look at xkcd_rgb dictionary that has 954 colors in it. Let us try to pull a few out of it:

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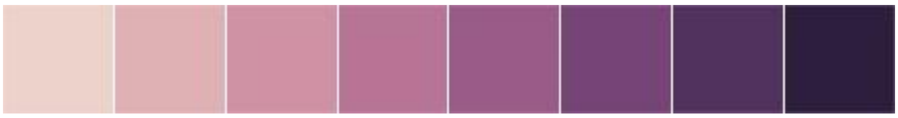
```
sample_colors = ["windows blue", "amber", "greyish", "faded green", "dusty purple", "pale red",
sns.palplot(sns.xkcd_palette(sample_colors))
```

Other style is **`cubehelix`** color palette that makes sequential palettes with a linear increase or decrease in brightness and some variation in **hue**. Actually let us plot this color palette in a Density contour plot:

```
# Default Matplotlib Cubehelix version:
sns.palplot(sns.color_palette("cubehelix", 8))
```

```
# Default Seaborn Cubehelix version:
sns.palplot(sns.cubehelix_palette(8))
```



```
# Density Plot with Seaborn defaults:
x, y = np.random.multivariate_normal([0, 0], [[1, -.5], [-.5, 1]], size=300).T
sample_cmap = sns.cubehelix_palette(light=1, as_cmap=True)
sns.kdeplot(x, y, cmap=sample_cmap, shade=True)
```

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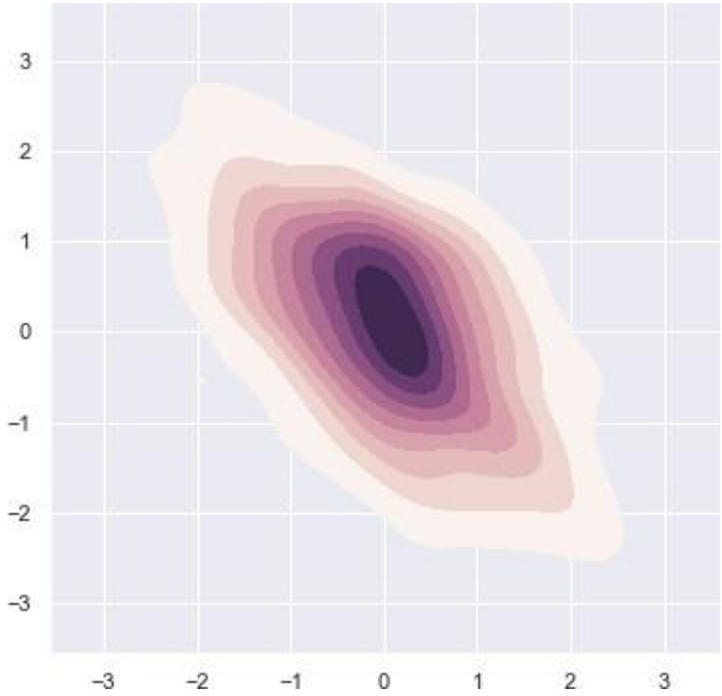
```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
  warnings.warn(
```

<AxesSubplot:>



Interactive widget to create a sequential cubehelix palette:

Let us now play with the parameters to have some fun and choose best parameters:

```
sns.choose_cubehelix_palette(as_cmap=True)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-1-230a1c9055e9> in <cell line: 1>()
----> 1 sns.choose_cubehelix_palette(as_cmap=True)

NameError: name 'sns' is not defined
```

Note that this app only works in this Jupyter Notebook as of now to help choose best parameters for our plot:

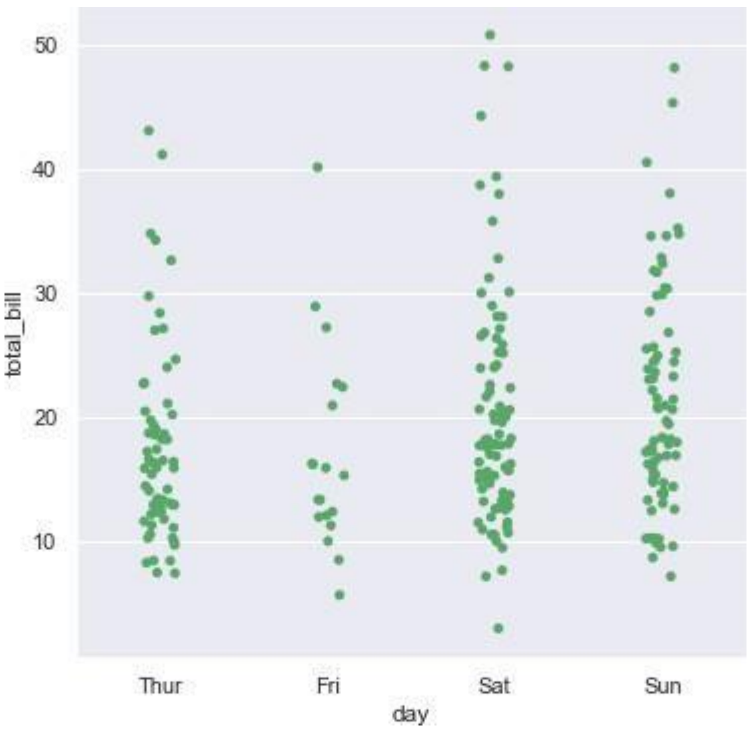
```
sns.palplot(sns.cubehelix_palette(n_colors=8, start=1.7, rot=0.2, dark=0, light=.95, reverse=Tru
```

start is always between 0 and 3. rot an abbreviation for rotation is kept between -1 and 1. reverse converses the color ordering and hue refers to plot appearance.

Generic Seaborn Plots:

```
# Loading up built-in dataset: tips
= sns.load_dataset("tips")

# Creating Strip plot for day-wise revenue:
sns.stripplot(x="day", y="total_bill", data=tips, color="g")
```

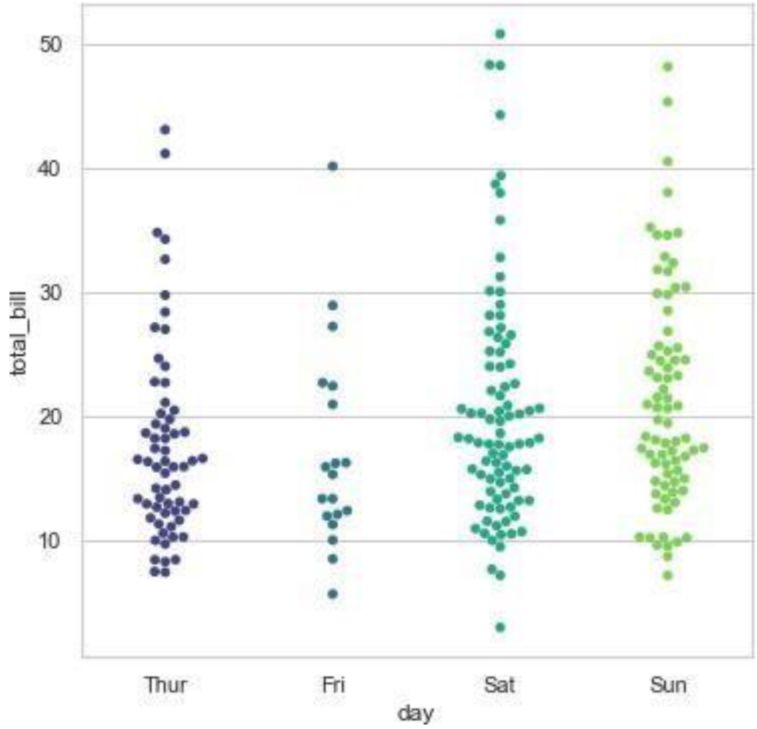
<AxesSubplot:xlabel='day', ylabel='total_bill'>



This does the job for us but let us try to get better results by plotting each day in different color instead of same color. For this, we shall replace **`color`** parameter with **`palette`** parameter:

```
# Set Theme:
sns.set_style('whitegrid')

# Creating Strip plot for day-wise revenue: sns.swarmplot(x="day",
y="total_bill", data=tips, palette="viridis")
```

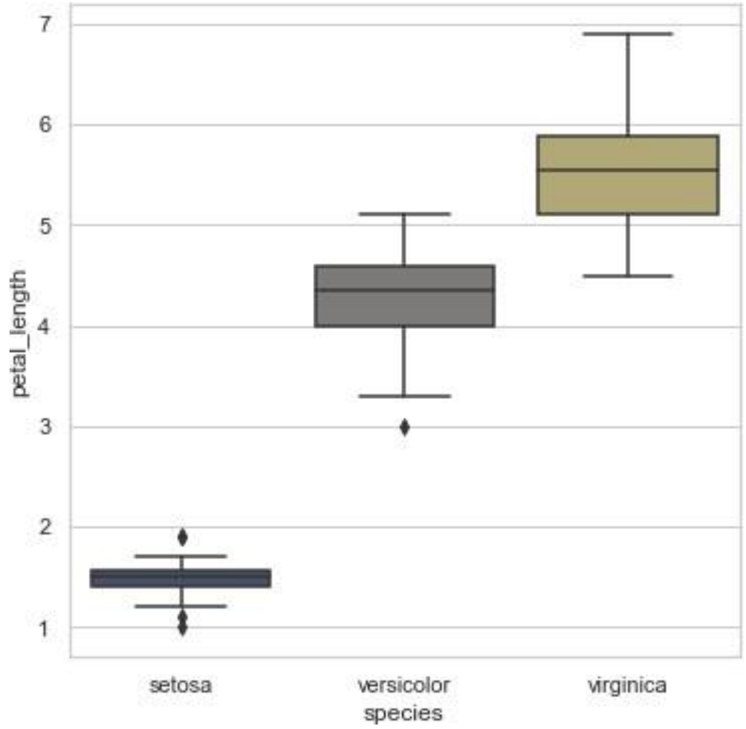
```
<AxesSubplot:xlabel='day', ylabel='total_bill'>
```



Similarly, let us plot one more and for a change, this time we shall plot a Violin plot:

```
iris = sns.load_dataset("iris")
sns.boxplot(x="species", y="petal_length", data=iris, palette="cividis")
```

```
<AxesSubplot:xlabel='species', ylabel='petal_length'>
```



There are multiple such palette available for us to play around with like magma, warm grey, gunmetal, dusky blue, cool blue, deep teal, viridian, twilight blue and many more. For customized

color brewing, we may also use color brewer that also offers interesting color palettes for working with Qualitative data. The cool thing about it is that you can use the an interactive Ipython widget function to make the selection of the palette. For this, you only need to use `choose_colorbrewer_palette()` .

There are multiple such palette available for us to play around with like magma, warm grey, gunmetal, dusky blue, cool blue, deep teal, viridian, twilight blue and many more. For customized color brewing, we may also use color brewer that also offers interesting color palettes for working with Qualitative data. A nice feature of the **Color Brewer website** is that it provides some guidance on which palettes are color blind safe.

The cool thing about it is that you can use the an interactive Ipython widget function to make the selection of the palette. For this, you only need to use `choose_colorbrewer_palette()` . To access this on your web browser, please access **ColorBrewer** link provided in the notebook.

I also found a nice representation of Color Schemes in Seaborn, that I found somewhere on web, so thought of sharing it in your Resource bucket to check out if you wish to. Let's have a look at it

LABSHEET 11

```
#Installation
#pip install seaborn
```

Seaborn2

Figure

Figure

It refers to the whole figure that you see. It is possible to have multiple sub-plots (Axes) in the same figure.

Axes

An Axes refers to the actual plot in the figure. A figure can have multiple Axes but a given Axes can be part of only one figure.

Axis

An Axis refers to an actual axis (x-axis/y-axis) in a specific plot.

Four sub-plots (Axes) in a single figure.

Figure2

Seaborn

Seaborn - can create complicated plot types from Pandas data with relatively simple commands Plotting in seaborn

is either : Axes-level functions OR Figure-level function

PLOT CATEGORIES IN SEABORN

I. Relational plots : This plot is used to understand the relation between two variables.

II. Categorical plots: This plot deals with categorical variables and how they can be visualized.

III. Distribution plots: This plot is used for examining univariate and bivariate distributions **IV. Matrix plots:** A matrix plot is an array of scatterplots.

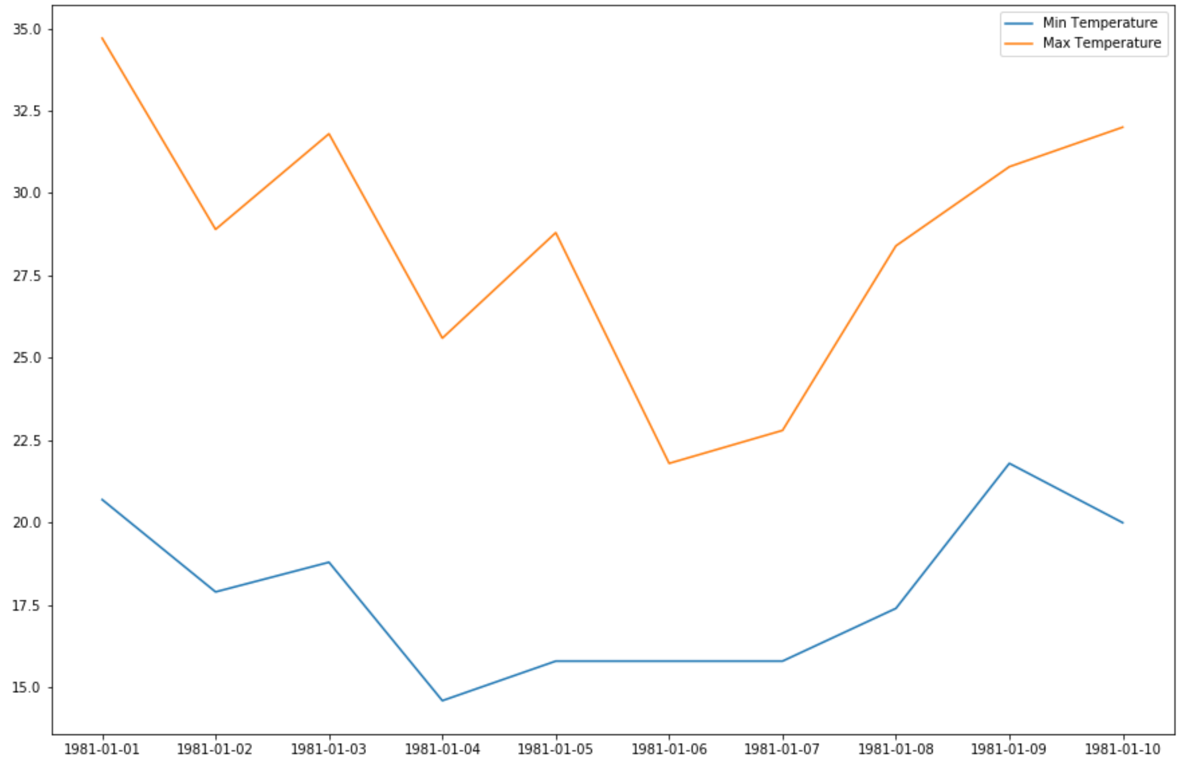
V. Regression plots: The regression plots in seaborn are primarily intended to add a visual guide that helps to emphasize patterns in a dataset during exploratory data analyses.

Seaborn

```
#Import necessary Packages import
numpy as np import pandas as pd
import matplotlib.pyplot as plt from
matplotlib.pyplot import figure
import seaborn as sns

%matplotlib inline
```

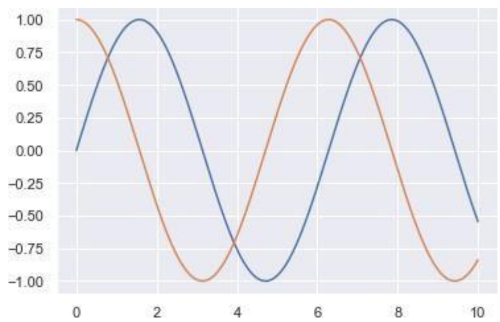
```
#Simple Plotting with Seaborn
#Data dates = ['1981-01-01', '1981-01-02', '1981-01-03', '1981-01-04', '1981-
01-05',
        '1981-01-06', '1981-01-07', '1981-01-08', '1981-01-09', '1981-01-10' ]
min_temperature = [20.7, 17.9, 18.8, 14.6, 15.8, 15.8, 15.8, 17.4, 21.8, 20.0]
max_temperature = [34.7, 28.9, 31.8, 25.6, 28.8, 21.8, 22.8, 28.4, 30.8, 32.0]
#Plotting   fig,axes   =   plt.subplots(nrows=1,   ncols=1,
figsize=(15,10))     axes.plot(dates,     min_temperature,
label='Min  Temperature')  axes.plot(dates,  max_temperature,
label = 'Max Temperature') axes.legend()
```

```
<matplotlib.legend.Legend at 0x1c0d2b24748>
```




```
#seaborn style as the default matplotlib style sns.set()
```

```
#Simple   sine   plot   x   =
np.linspace(0, 10, 1000)
plt.plot(x, np.sin(x), x, np.cos(x));
```



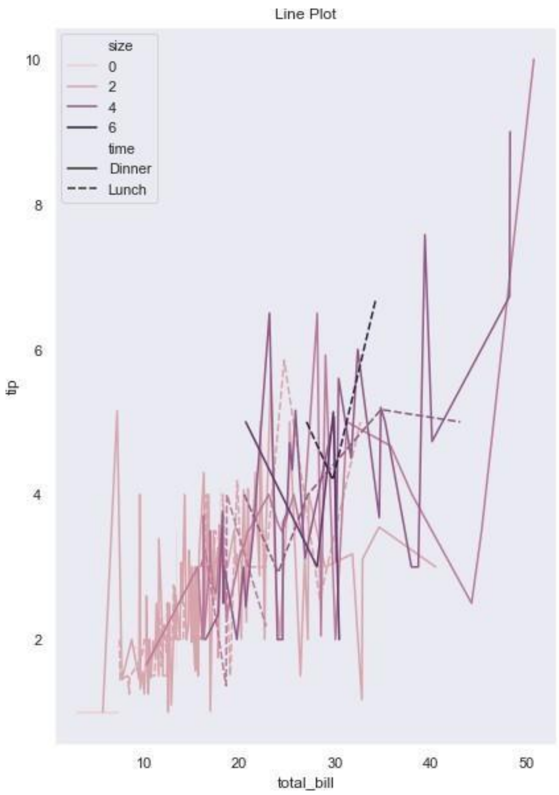

```
# I. Relational Plots
```

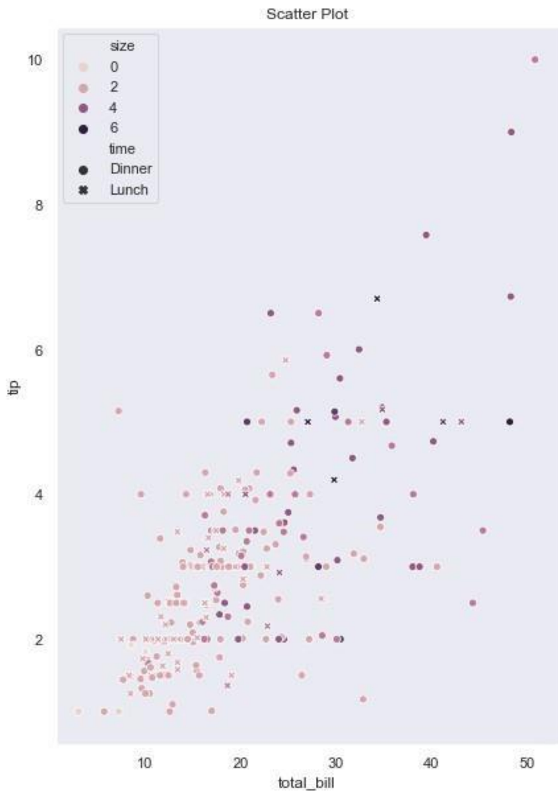
```
# Line plot : The line plot is one of the most basic plot in seaborn library.
#This plot is mainly used to visualize the data in form of some time series, i.e. in continuous
manner. sns.set(style="dark") fig, ax = plt.subplots(ncols=2, nrows=1, figsize=(15,10))
```

```
#Loading Data with Seaborn df

=   sns.load_dataset("tips")

print(df.head())
```

```
#lineplot        sns.lineplot(x="total_bill",        y="tip",        hue="size",        style="time",
data=df,ax=ax[0]).set_title("Line Plot")



#scatterplot
Sct_plt=sns.scatterplot(x="total_bill", y="tip", hue="size", style="time", data=df,ax=ax[1]).set_title("Scatter Plot")


#Saving Plot
Sct_plt.figure.savefig('Scatter_plot1.png')
print('Plot Saved')
```

```
   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
Plot Saved
```

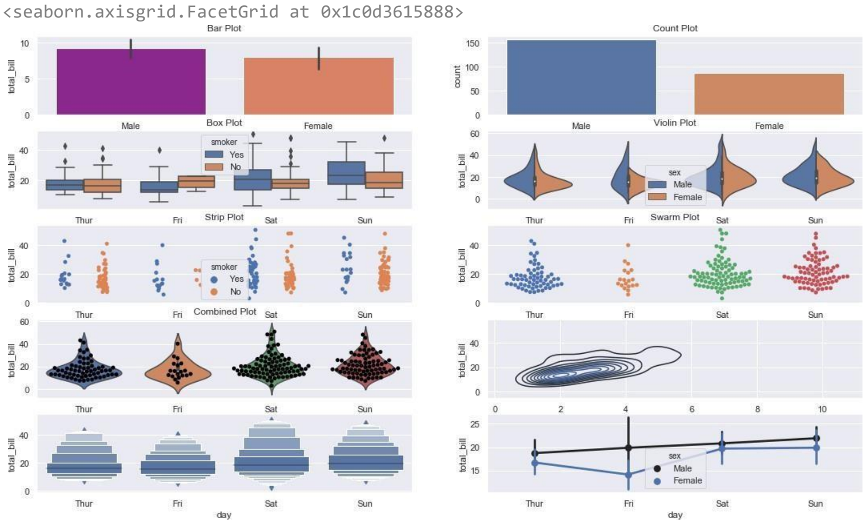


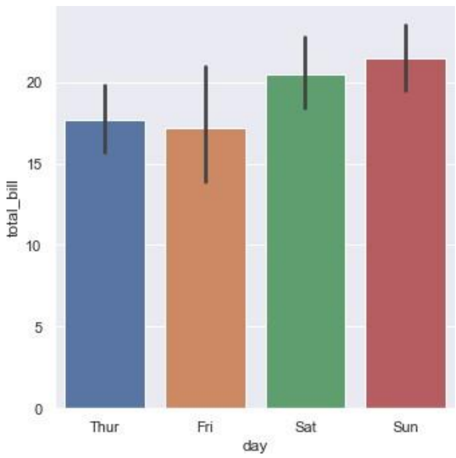



```
#II. Categorical Plots
#Plots are basically used for visualizing the relationship between variables.
#Variables can be either be completely numerical or a category like a group, class or division.
sns.set_style('darkgrid')    fig,    ax
=plt.subplots(nrows=5,ncols=2)
fig.set_size_inches(18.5, 10.5)


#Data
# 'tips' dataset contains information about people who probably had food at a restaurant #
whether or not they left a tip for the waiters, their gender, whether they smoke and so on.
df = sns.load_dataset('tips')


#barplot - basically used to aggregate the categorical data according to some methods and by default its the mean sns.barplot(x
='sex', y ='total_bill', data = df,palette ='plasma', estimator = np.std,ax=ax[0,0]).set_title('Bar Plot')



#countplot -Counts the categories and returns a count of their occurrences sns.countplot(x
='sex', data = df,ax=ax[0,1]).set_title('Count Plot')


#boxplot - known as the box and whisker plot.
#It shows the distribution of the quantitative data that represents the comparisons between variables sns.boxplot(x
='day', y ='total_bill', data = df, hue ='smoker',ax=ax[1,0]).set_title('Box Plot')
```

```
# Similar to the boxplot except that it provides a higher, more advanced visualization # Uses
the kernel density estimation to give a better description about the data distribution.
sns.violinplot(x ='day', y ='total_bill', data = df, hue ='sex', split = True,ax=ax[1,1]).set_title('Violin Plot')


#Stripplot - scatter plot based on the category sns.stripplot(x ='day', y ='total_bill', data = df, jitter = True, hue ='smoker',
dodge = True,ax=ax[2,0]).set_title('Strip Plot')


#Swarmplot-similar to stripplot except the fact that the points are adjusted so that they do not overlap.
sns.swarmplot(x ='day', y ='total_bill', data = df,ax=ax[2,1]).set_title('Swarm Plot')


#Combining the idea of a violin plot and a stripplot to form this plot sns.violinplot(x ='day', y
='total_bill', data = df,ax=ax[3,0]) sns.swarmplot(x ='day', y ='total_bill', data = df, color
='black',ax=ax[3,0]).set_title('Combined Plot')


#     Density     Plot     sns.kdeplot(df['tip'],
df['total_bill'],ax=ax[3,1])


#boxenplot    sns.boxenplot(x="day",    y="total_bill",color="b",    scale="linear",
data=df,ax=ax[4,0])


#Ridgeplot    sns.pointplot(x="day",    y="total_bill",color="b",    hue="sex",
data=df,ax=ax[4,1])


#catplot
#General plot - provides a parameter called 'kind' to choose the kind of plot ,better that writing the plots separately. #The
kind parameter can be bar, violin, swarm etc.
sns.catplot(x ='day', y ='total_bill', data = df, kind ='bar')
```

```
<seaborn.axisgrid.FacetGrid at 0x1c0d3615888>
```





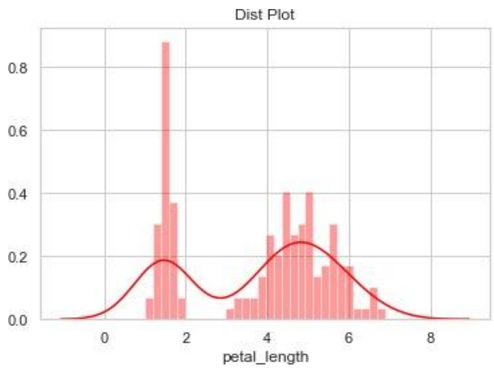
III. **Distribution plots** in seaborn is used for examining univariate and bivariate distributions. 4 main types of distribution plots :

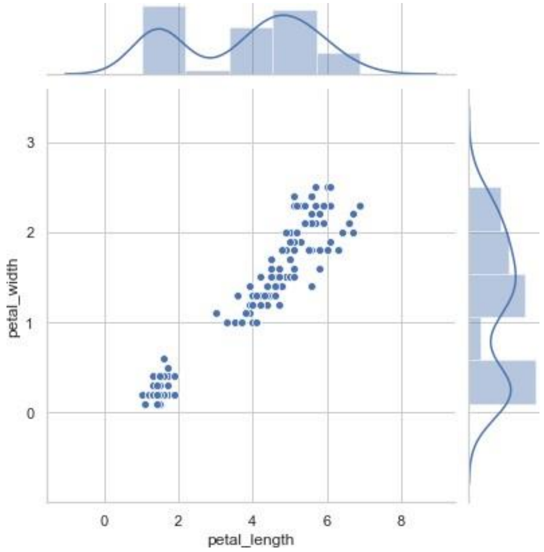
```
joinplot
distplot
pairplot rugplot
```

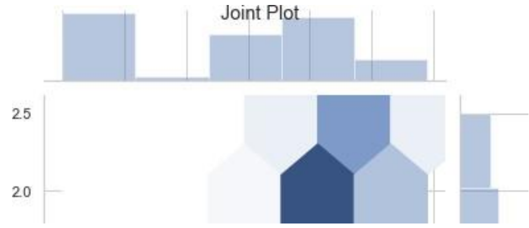
```
sns.set_style('whitegrid')

#Data - 'iris' df =
sns.load_dataset('iris')
print(df.head())

#Displot- used for univariant set of observations and visualizes it through a histogram #i.e.
only one observation and hence we choose one particular column of the dataset.
#KDE is a way to estimate the probability density function (PDF) of the random variable that “underlies” the sample.
#KDE is a means of data smoothing.
#bins is used to set the number of bins you want in your plot and it actually depends on your dataset.
#color is used to specify the color of the plot sns.distplot(df['petal_length'], kde = True,
color ='red', bins = 30).set_title('Dist Plot')

#Joinplot/jointgrid- draw a plot of two variables with bivariate and univariate graphs. It basically combines two different plots.
#Plot a bi-variate distribution along with marginal distributions in the same plot
#Joint Distribution of two variables can be visualised using scatter plot/regplot or kdeplot.
#Marginal Distribution of variables can be visualised by histograms and/or kde plot
#KDE shows the density where the points match up the most
#The Axes-level function to use for joint distribution must be passed to JointGrid.plot_joint().
#The Axes-level function to use for marginal distribution must be passed to JointGrid.plot_marginals()
jointgrid = sns.JointGrid(x='petal_length', y='petal_width', data=df)
jointgrid.plot_joint(sns.scatterplot)
jointgrid.plot_marginals(sns.distplot)

#jointplot() to plot bi-variate distribution along with marginal distributions.
#It uses JointGrid() and JointGrid.plot_joint() in the background.
g=sns.jointplot(x = 'petal_length',y = 'petal_width',data = df,kind = 'hex') g.fig.suptitle('Joint
Plot')

#Pairplot- pairwise relation across the entire dataframe
#hue sets up the categorical separation between the entries in the dataset.
#palette is used for designing the plots.
g=sns.pairplot(df, hue ="species", palette ='coolwarm') g.fig.suptitle("Pair
Plot 1")
g.add_legend()

#PairGrid() - creates Axes for each pair of variables
#PairGrid.map() - draws the plot on each Axes using data corresponding to that pair of variables
pairgrid = sns.PairGrid(data=df) pairgrid = pairgrid.map_offdiag(sns.scatterplot) pairgrid =
pairgrid.map_diag(plt.hist)

#Different kind of plots on Upper Triangular Axes, Diagonal Axes and Lower Triangular Axes.
pairgrid = sns.PairGrid(data=df) pairgrid = pairgrid.map_upper(sns.scatterplot) pairgrid =
pairgrid.map_diag(plt.hist) pairgrid = pairgrid.map_lower(sns.kdeplot)

#Avoid Redundancy
g = sns.PairGrid(df, diag_sharey=False, corner=True) g.map_lower(sns.scatterplot)
g.map_diag(sns.kdeplot)
```

```
   sepal_length sepal_width petal_length petal_width species
0           5.1         3.5          1.4         0.2  setosa
1           4.9         3.0          1.4         0.2  setosa
2           4.7         3.2          1.3         0.2  setosa
3           4.6         3.1          1.5         0.2  setosa
4           5.0         3.6          1.4         0.2  setosa
```

<seaborn.axisgrid.PairGrid at 0x1c0d2b15888>







LABSHEET 12

Load the Pacakges

To get started, open a Colab notebook and load the Pandas, Matplotlib, and Wordcloud packages.

Code Text

```
import pandas as pd import
matplotlib.pyplot as plt from
wordcloud import WordCloud from
wordcloud import STOPWORDS
```

Mount the drive and read the CSV file from the drive.

Here we are going to use netflix_titles.csv dataset downloaded from kaggle.

Since it is text visualization we are going to consider only one column.

```
from google.colab import drive

drive.mount('/content/drive/')
```

```
Mounted at /content/drive/
```

```
df=pd.read_csv('/content/drive/My Drive/Data/netflix_titles.csv', usecols=['cast'])
df.head()
```

	cast
0	NaN
1	Ama Qamata, Khosi Ngema, Gail Mabalane, Thaban...
2	Sami Bouajila, Tracy Gotoas, Samuel Jouy, Nabi...
3	NaN
4	Mayur More, Jitendra Kumar, Ranjan Raj, Alam K...

Perform Prepeocessing to remove the records containing NaN

```
ndf=df.dropna()
ndf.head()
```

	cast
1	Ama Qamata, Khosi Ngema, Gail Mabalane, Thaban...
2	Sami Bouajila, Tracy Gotoas, Samuel Jouy, Nabi...
4	Mayur More, Jitendra Kumar, Ranjan Raj, Alam K...
5	Kate Siegel, Zach Gilford, Hamish Linklater, H...
6	Vanessa Hudgens, Kimiko Glenn, James Marsden, ...

The wordcloud package requires single string instead of column.

Joining the all text data of the coloumn 'cast' to single string to make text visualization easy

```
text = " ".join(item for item in ndf['cast']) print(text)
```

```
Ama Qamata, Khosi Ngema, Gail Mabalane, Thabang Molaba, Dillon Windvogel, Natasha Thahane, Arno Greeff, Xolile Tshabalala, Getmore
```

Sometimes, there will be words in your dataframe that are insignificant and don't add any insight. We can take these out using the STOPWORDS module which is included in Wordcloud.

```
stopwords = set(STOPWORDS)
```

Create a basic word cloud

56

By instantiating WordCloud and then appending generate(text), we can pass in our big list of words and WordCloud will calculate the word frequencies, and determine the sizes, and colours of each of the words shown based on their frequencies within the text.

The other bits of Matplotlib code turn off the axes and ticks to make the word cloud look a bit neater.

```
wordcloud = WordCloud(background_color="white").generate(text) plt.imshow(wordcloud, interpolation='bilinear') plt.axis("off") plt.margins(x=0, y=0)
plt.show()
```


```
wordcloud = WordCloud(background_color="white",
                      max_words=100,
                      max_font_size=300,
                      width=800,
                      height=500,
                      colormap="magma"
                     ).generate(text)
plt.figure(figsize=(20,20))
  plt.imshow(wordcloud, interpolation='bilinear')
  plt.axis("off")      plt.margins(x=0,      y=0)
  plt.savefig("cloud.jpg",          format="jpg")
  plt.show()
```


Lee
David
Paul
James
Richard
Peter
Robert
Smith
Anthony
Jack
Taylor
George
Scott
Nick
Chris
Joe
Lewis
Adam
Jacob
Christian
Martin
Morgan
Aaron
Al
Ryan
Jennifer
Kevin
Jone
Chen
Sarah
Choi
Kim
Mike
Matt
Han
William
Mark
Kang
Andrea
Jordan
Daniel
Johnson
Park
Ahmed
Carlo
Steven
Sharma
Kumar
Thomas
Wilson
Young
Jung
Anna
Andrew
Stephen
Yu
Lui
Amy
Yang
Alex
Singh
Jason
Ali
Sam
Dan
Lin
Evan
Tom
Jr
Davi
ho
Tim
Edward
Kate
Wang
Christopher
Sean

LABSHEET 13

A time series is the series of data points listed in time order.

A time series is a sequence of successive equal interval points in time.

A time-series analysis consists of methods for analyzing time series data in order to extract meaningful insights and other useful characteristics of data.

For performing time series analysis download stock_data.csv

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

```
# reading the dataset using read_csv df =
pd.read_csv(r"stock_data.csv")          #
displaying the first five rows of dataset
df.head()
```

	Date	Open	High	Low	Close	Volume	Name
0	1/3/2006	39.69	41.22	38.79	40.91	24232729	AABA
1	1/4/2006	41.22	41.90	40.77	40.97	20553479	AABA
2	1/5/2006	40.93	41.73	40.85	41.53	12829610	AABA
3	1/6/2006	42.88	43.57	42.80	43.21	29422828	AABA
4	1/9/2006	43.10	43.66	42.82	43.42	16268338	AABA

We have used the ‘parse_dates’ parameter in the read_csv function to convert the ‘Date’ column to the DatetimeIndex format.

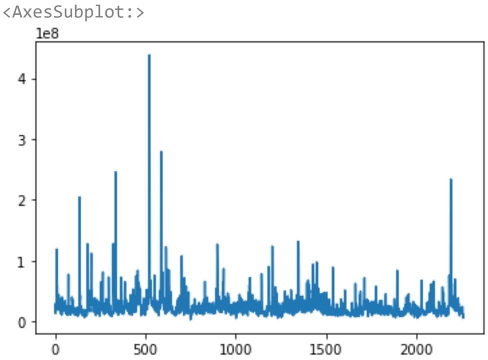
By default, Dates are stored in string format which is not the right format for time series data analysis.

Now, removing the unwanted columns from dataframe i.e. ‘Unnamed: 0’.

Example 1: Plotting a simple line plot for time series data.

```
df['Volume'].plot()
```

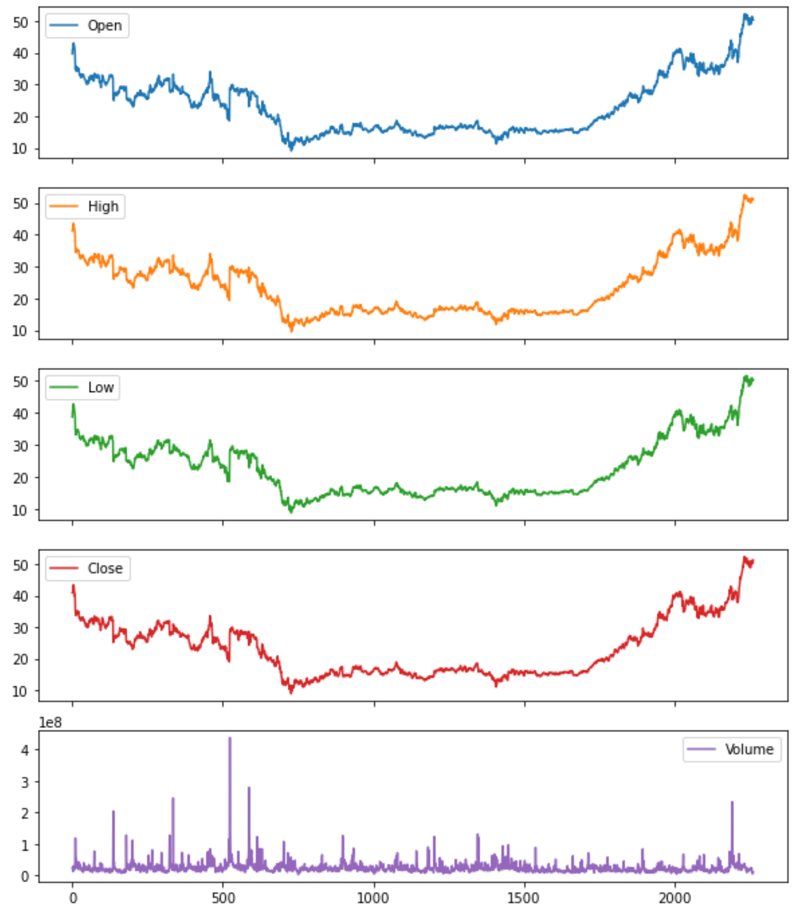
<AxesSubplot:>



Example 2: Now let’s plot all other columns using subplot.

```
df.plot(subplots=True, figsize=(10, 12))
```

```
array([<AxesSubplot:>,     <AxesSubplot:>,     <AxesSubplot:>,     <AxesSubplot:>,
       <AxesSubplot:>], dtype=object)
```



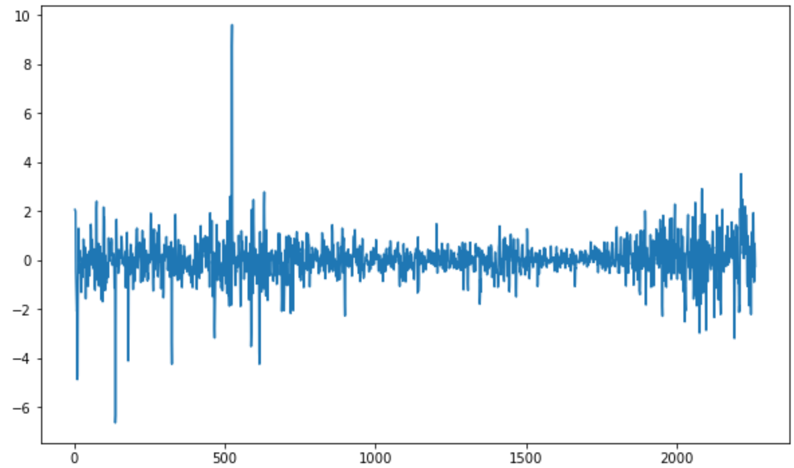
Resampling: Resampling is a methodology of economically using a data sample to improve the accuracy and quantify the uncertainty of a population parameter. Resampling for months or weeks and making bar plots is another very simple and widely used method of finding seasonality. Here we are going to make a bar plot of month data for 2016 and 2017.

Example 3:

Differencing: Differencing is used to make the difference in values of a specified interval. By default, it's one, we can specify different values for plots. It is the most popular method to remove trends in the data.

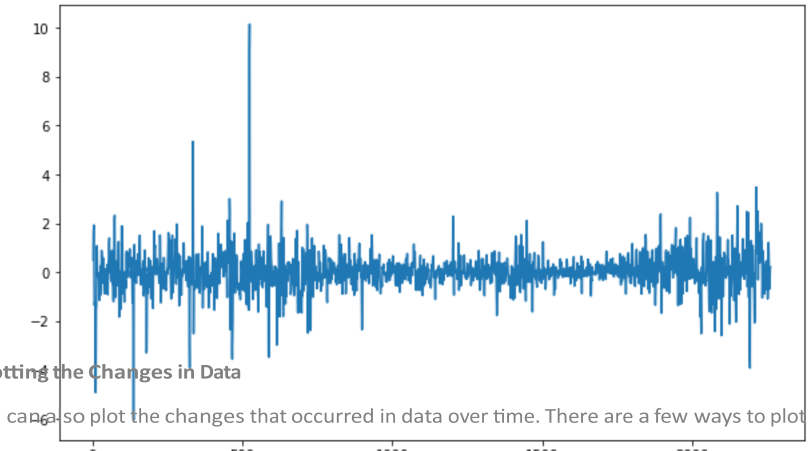
```
df.Low.diff(2).plot(figsize=(10, 6))
```

```
<AxesSubplot:>
```



```
df.High.diff(2).plot(figsize=(10, 6))
```


<AxesSubplot:>



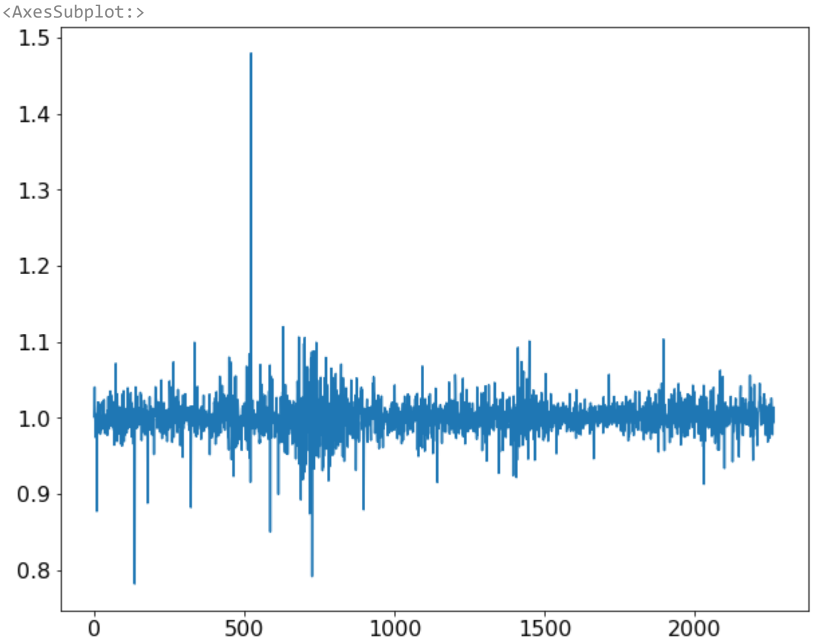
Plotting the Changes in Data

We can also plot the changes that occurred in data over time. There are a few ways to plot changes in data.

Shift: The shift function can be used to shift the data before or after the specified time interval. We can specify the time, and it will shift the data by one day by default. That means we will get the previous day's data. It is helpful to see previous day data and today's data simultaneously side by side.

```
df['Change'] = df.Close.div(df.Close.shift())
  df['Change'].plot(figsize=(10, 8), fontsize=16)
```

<AxesSubplot:>



.div() function helps to fill up the missing data values.

Actually, div() means division.

If we take df. div(6) it will divide each element in df by 6.

We do this to avoid the null or missing values that are created by the 'shift()' operation.

Double-click (or enter) to edit