

```
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())

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

## ▼ Missing Values

```
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	-0.039497	1.045655	-0.138289
c	-0.369325	-1.385964	-0.580685
e	0.158656	1.565347	0.087451
f	1.092764	1.218509	-0.550862
h	0.008518	1.282266	0.442202
b	NaN	NaN	NaN
d	NaN	NaN	NaN
g	NaN	NaN	NaN

```
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	-0.662758	0.638865	1.460741
b	NaN	NaN	NaN
c	-0.946790	0.584346	1.968561

NaN replaced with '0':

	one	two	three
a	-0.662758	0.638865	1.460741
b	0.000000	0.000000	0.000000
c	-0.946790	0.584346	1.968561

```
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('-----')
print(df.fillna(method='pad'))
```

	one	two	three
a	0.950124	-1.565339	-1.909730
b	NaN	NaN	NaN
c	0.051079	-0.767547	1.370560
d	NaN	NaN	NaN
e	-0.687186	-0.579887	1.457962
f	0.463522	-1.184759	-0.139350
g	NaN	NaN	NaN
h	-0.318872	0.053867	-2.192390

-----

	one	two	three
a	0.950124	-1.565339	-1.909730
b	0.950124	-1.565339	-1.909730
c	0.051079	-0.767547	1.370560
d	0.051079	-0.767547	1.370560
e	-0.687186	-0.579887	1.457962
f	0.463522	-1.184759	-0.139350
g	0.463522	-1.184759	-0.139350
h	-0.318872	0.053867	-2.192390

```
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	-1.120243	1.486683	-0.093951
b	-0.125297	0.466293	0.824516
c	-0.125297	0.466293	0.824516
d	1.121361	0.520289	-1.270749
e	1.121361	0.520289	-1.270749
f	0.027017	-0.031351	-0.883342
g	-0.720911	0.815735	1.013695
h	-0.720911	0.815735	1.013695

```
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.dropna())
```

	one	two	three
a	0.641054	0.489022	-0.361579
b	NaN	NaN	NaN
c	-0.643466	0.929190	-0.408637
d	NaN	NaN	NaN
e	-1.877724	0.369620	2.092137
f	0.269918	2.400600	-1.373824
g	NaN	NaN	NaN
h	0.962634	1.555593	1.215637

	one	two	three
a	0.641054	0.489022	-0.361579
c	-0.643466	0.929190	-0.408637
e	-1.877724	0.369620	2.092137
f	0.269918	2.400600	-1.373824
h	0.962634	1.555593	1.215637

```
df1 = pd.DataFrame({'one':[1000,23,24,25,26,27], 'two' : [2022,32,25,26,20,22]})
print(df1)
print(df1.replace({1000:22,2022:22}))
```

	one	two
0	1000	2022
1	23	32
2	24	25
3	25	26
4	26	20
5	27	22

	one	two
0	22	22
1	23	32
2	24	25
3	25	26
4	26	20
5	27	22

```
import pandas as pd
df=pd.read_csv('/content/titanic.csv')
df.info()
```

```
df.describe()
```

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

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

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

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

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

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

## ✓ Mix Max Scaler and Standardization

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

```
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)
```

```
scaler = StandardScaler()
scaler.fit(data)
data = scaler.transform(data)
```

data

```
import numpy as np
data = [1,2,2,2,3,1,1,15,2,2,2,3,1,1,2]
mean = np.mean(data)
std = np.std(data)
print("Mean of the dataset is : ",mean)
print("Std deviation is: ",std)
threshold = 3
outlier = []
for i in data:
    z = (i-mean)/std
    if z > threshold:
        outlier.append(i)
print("outlier in dataset is:",outlier)
```

### Interquartile range to detect outliers in dataset

- Q1 = 25%
- Q2 = 50%
- Q3 = 75%

if a dataset has  $2n/2n+1$  data points then,

- Q1 = median of the dataset
- Q2 = meadian of n smallest data points
- Q3 = median of n highest data points

IQR is the range between the first and the third quantiles namely Q1 and Q3

$IQR = Q3 - Q1$

```
#Step1 : import the necessary libraries
import numpy as np
import seaborn as sns
```

```
#Step2 : Take the data and sort it in ascending order
data = [6,2,3,4,5,1,50]
sort_data = np.sort(data)
print(sort_data)
```

```
#step3 : Calculate Q1,Q2,Q3 and IQR
Q1 = np.percentile(data,25,interpolation = 'midpoint')
Q2 = np.percentile(data,50,interpolation = 'midpoint')
Q3 = np.percentile(data,75,interpolation = 'midpoint')
print(" Q1 25 percentile of the given data is : ",Q1)
print(" Q2 50 percentile of the given data is : ",Q2)
print(" Q3 75 percentile of the given data is : ",Q3)

IQR = Q3 - Q1
print("Interquartile range is : ",IQR)

#Step 4:
low_lim=Q1-1.5*IQR
up_lim=Q3+1.5*IQR
print('Low limit is ',low_lim)
print('Up limit is ',up_lim)

#Step 5: Data points greater than the upper limit or less than the lower limit are
outlier = []
for x in data:
    if ((x > up_lim) or (x < low_lim)):
        outlier.append(x)
    print("Outlier in the dataset is ",outlier)

#Step 6: Plot the box plot to highlight outliers
sns.boxplot(data)

import pandas as pd
def load_data():
    df_all = pd.read_csv("/content/2,1 dataset titanic (1).csv")
    #Take a subset
    return df_all.loc[:300,['Survived','Pclass','Sex','Cabin','Embarked']]
df = load_data()
df
```

Finding duplicate rows

```
df.Cabin.duplicated()
```

## Breast Cancer Dataset

### ✓ Principal component analysis

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_breast_cancer
df = pd.read_csv("/content/2.2 dataset breast cancer.csv")
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 33 columns):
 #   Column                Non-Null Count  Dtype
---  -
 0   id                    569 non-null   int64
 1   diagnosis             569 non-null   object
 2   radius_mean           569 non-null   float64
 3   texture_mean          569 non-null   float64
 4   perimeter_mean        569 non-null   float64
 5   area_mean             569 non-null   float64
 6   smoothness_mean       569 non-null   float64
 7   compactness_mean      569 non-null   float64
 8   concavity_mean        569 non-null   float64
 9   concave points_mean   569 non-null   float64
10   symmetry_mean         569 non-null   float64
11   fractal_dimension_mean 569 non-null   float64
12   radius_se             569 non-null   float64
13   texture_se            569 non-null   float64
14   perimeter_se          569 non-null   float64
```



```

      9      ...      21      22      23      24      25      26      27  \
0  0.07871  ...  17.33  184.60  2019.0  0.1622  0.6656  0.7119  0.2654
1  0.05667  ...  23.41  158.80  1956.0  0.1238  0.1866  0.2416  0.1860
2  0.05999  ...  25.53  152.50  1709.0  0.1444  0.4245  0.4504  0.2430
3  0.09744  ...  26.50  98.87   567.7  0.2098  0.8663  0.6869  0.2575
4  0.05883  ...  16.67  152.20  1575.0  0.1374  0.2050  0.4000  0.1625

      28      29      30
0  0.4601  0.11890  0.0
1  0.2750  0.08902  0.0
2  0.3613  0.08758  0.0
3  0.6638  0.17300  0.0
4  0.2364  0.07678  0.0

```

[5 rows x 31 columns]

```

features = breast.feature_names
print(features)

```

```

['mean radius' 'mean texture' 'mean perimeter' 'mean area'
 'mean smoothness' 'mean compactness' 'mean concavity'
 'mean concave points' 'mean symmetry' 'mean fractal dimension'
 'radius error' 'texture error' 'perimeter error' 'area error'
 'smoothness error' 'compactness error' 'concavity error'
 'concave points error' 'symmetry error' 'fractal dimension error'
 'worst radius' 'worst texture' 'worst perimeter' 'worst area'
 'worst smoothness' 'worst compactness' 'worst concavity'
 'worst concave points' 'worst symmetry' 'worst fractal dimension']

```

```
features_labels = np.append(features, 'label')
```

```

breast_dataset.columns = features_labels
breast_dataset.head()

```

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	sy
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	

5 rows x 31 columns

```

breast_dataset['label'].replace(0, 'Benign' , inplace=True)
breast_dataset['label'].replace(1, 'Malignant',inplace=True)
breast_dataset.tail()

```

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791
566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200
568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000

5 rows x 31 columns

```

from sklearn.preprocessing import StandardScaler
x = breast_dataset.loc[:,features].values
x = StandardScaler().fit_transform(x) #normalising the features
print(x.shape)

```

(569, 30)

```
np.mean(x),np.std(x)
```

(-6.118909323768877e-16, 1.0)

```
feat_cols = ['feature'+str(i) for i in range(x.shape[1])]
```

```
normalised_breast = pd.DataFrame(x,columns=feat_cols)
print(normalised_breast)
```

	feature0	feature1	feature2	feature3	feature4	feature5	feature6	\
0	1.097064	-2.073335	1.269934	0.984375	1.568466	3.283515	2.652874	
1	1.829821	-0.353632	1.685955	1.908708	-0.826962	-0.487072	-0.023846	
2	1.579888	0.456187	1.566503	1.558884	0.942210	1.052926	1.363478	
3	-0.768909	0.253732	-0.592687	-0.764464	3.283553	3.402909	1.915897	
4	1.750297	-1.151816	1.776573	1.826229	0.280372	0.539340	1.371011	
..	...	...	...	...	...	...	...	
564	2.110995	0.721473	2.060786	2.343856	1.041842	0.219060	1.947285	
565	1.704854	2.085134	1.615931	1.723842	0.102458	-0.017833	0.693043	
566	0.702284	2.045574	0.672676	0.577953	-0.840484	-0.038680	0.046588	
567	1.838341	2.336457	1.982524	1.735218	1.525767	3.272144	3.296944	
568	-1.808401	1.221792	-1.814389	-1.347789	-3.112085	-1.150752	-1.114873	

	feature7	feature8	feature9	...	feature20	feature21	feature22	\
0	2.532475	2.217515	2.255747	...	1.886690	-1.359293	2.303601	
1	0.548144	0.001392	-0.868652	...	1.805927	-0.369203	1.535126	
2	2.037231	0.939685	-0.398008	...	1.511870	-0.023974	1.347475	
3	1.451707	2.867383	4.910919	...	-0.281464	0.133984	-0.249939	
4	1.428493	-0.009560	-0.562450	...	1.298575	-1.466770	1.338539	
..	...	...	...	...	...	...	...	
564	2.320965	-0.312589	-0.931027	...	1.901185	0.117700	1.752563	
565	1.263669	-0.217664	-1.058611	...	1.536720	2.047399	1.421940	
566	0.105777	-0.809117	-0.895587	...	0.561361	1.374854	0.579001	
567	2.658866	2.137194	1.043695	...	1.961239	2.237926	2.303601	
568	-1.261820	-0.820070	-0.561032	...	-1.410893	0.764190	-1.432735	

	feature23	feature24	feature25	feature26	feature27	feature28	\
0	2.001237	1.307686	2.616665	2.109526	2.296076	2.750622	
1	1.890489	-0.375612	-0.430444	-0.146749	1.087084	-0.243890	
2	1.456285	0.527407	1.082932	0.854974	1.955000	1.152255	
3	-0.550021	3.394275	3.893397	1.989588	2.175786	6.046041	
4	1.220724	0.220556	-0.313395	0.613179	0.729259	-0.868353	
..	...	...	...	...	...	...	
564	2.015301	0.378365	-0.273318	0.664512	1.629151	-1.360158	
565	1.494959	-0.691230	-0.394820	0.236573	0.733827	-0.531855	
566	0.427906	-0.809587	0.350735	0.326767	0.414069	-1.104549	
567	1.653171	1.430427	3.904848	3.197605	2.289985	1.919083	
568	-1.075813	-1.859019	-1.207552	-1.305831	-1.745063	-0.048138	

	feature29
0	1.937015
1	0.281190
2	0.201391
3	4.935010
4	-0.397100
..	...
564	-0.709091
565	-0.973978
566	-0.318409
567	2.219635
568	-0.751207

[569 rows x 30 columns]

```
normalised_breast.tail()
```

	feature0	feature1	feature2	feature3	feature4	feature5	feature6	feature7
564	2.110995	0.721473	2.060786	2.343856	1.041842	0.219060	1.947285	2.320965
565	1.704854	2.085134	1.615931	1.723842	0.102458	-0.017833	0.693043	1.263669
566	0.702284	2.045574	0.672676	0.577953	-0.840484	-0.038680	0.046588	0.105777
567	1.838341	2.336457	1.982524	1.735218	1.525767	3.272144	3.296944	2.658866
568	-1.808401	1.221792	-1.814389	-1.347789	-3.112085	-1.150752	-1.114873	-1.261820

5 rows x 30 columns

```
from sklearn.decomposition import PCA
pca_breast = PCA(n_components=2)
principalComponents_breast = pca_breast.fit_transform(x)
principal_breast_Df = pd.DataFrame(data = principalComponents_breast
                                   , columns = ['principal component 1','principal component 2'])
principal_breast_Df.tail()
```

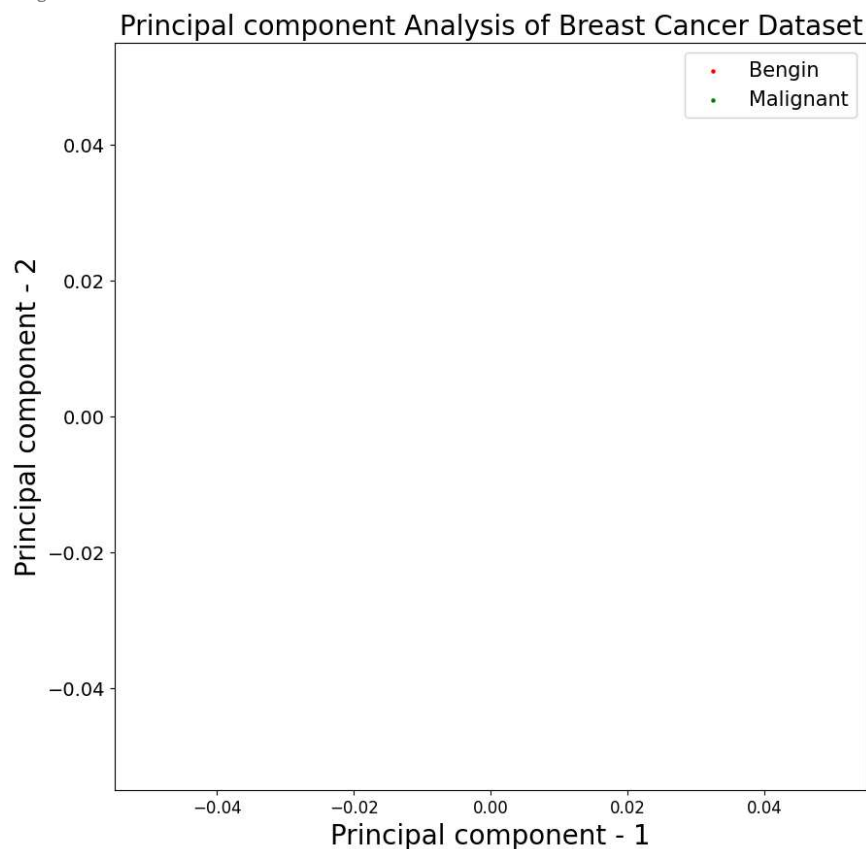
	principal component 1	principal component 2
564	6.439315	-3.576817
565	3.793382	-3.584048
566	1.256179	-1.902297
567	10.374794	1.672010
568	-5.475243	-0.670637

```
print(f"Explained variation per principal component : {pca_breast.explained_variance_ratio_}")
```

```
Explained variation per principal component : [0.44272026 0.18971182]
```

```
import matplotlib.pyplot as plt
plt.figure()
plt.figure(figsize=(10,10))
plt.xticks(fontsize=12)
plt.yticks(fontsize=14)
plt.xlabel("Principal component - 1",fontsize=20)
plt.ylabel("Principal component - 2",fontsize=20)
plt.title("Principal component Analysis of Breast Cancer Dataset",fontsize=20)
targets = ['Benign', 'Malignant']
colors = ['r', 'g']
for target, color in zip(targets, colors):
    indicesToKeep = breast_dataset['label'] == target
    plt.scatter(principal_breast_Df.loc[indicesToKeep, 'principal component 1']
                ,principal_breast_Df.loc[indicesToKeep, 'principal component 2'], c = color , s = 5)
plt.legend(targets,prop={'size': 15})
```

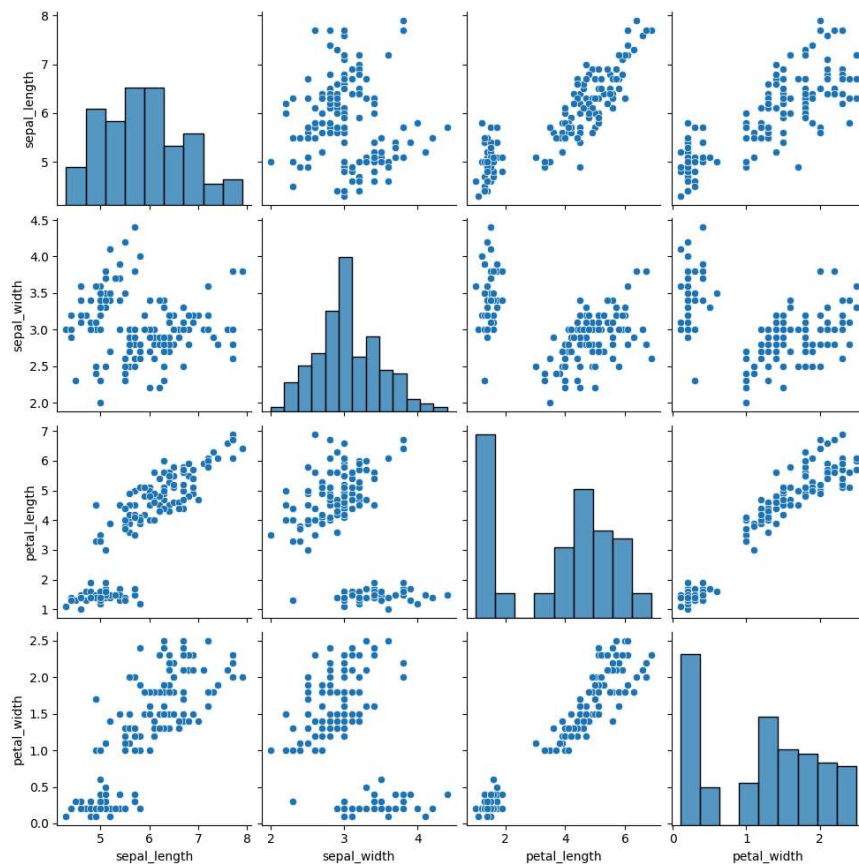
```
<matplotlib.legend.Legend at 0x79406ddbe410>
<Figure size 640x480 with 0 Axes>
```





## ✓ CORRELATION REGRESSION

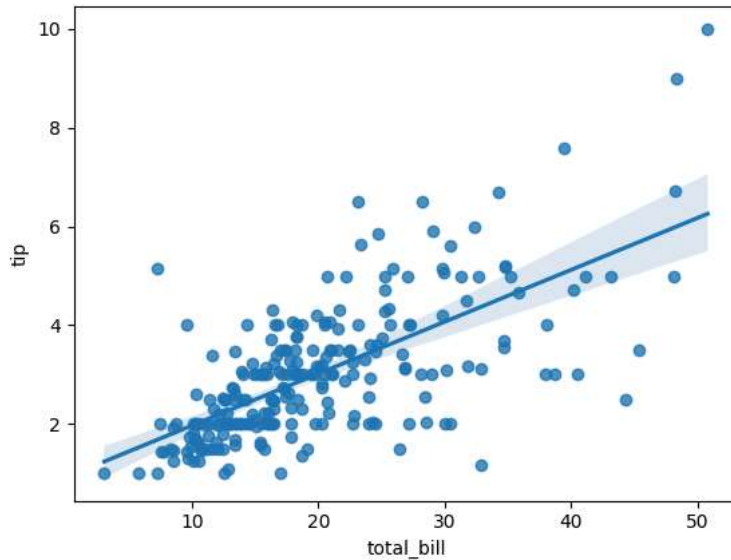
```
import matplotlib.pyplot as plt
import seaborn as sns
df = sns.load_dataset('iris')
#Without regression
sns.pairplot(df, kind="scatter")
plt.show()
```



```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
#   Column      Non-Null Count  Dtype
---  ---
0   sepal_length 150 non-null    float64
1   sepal_width  150 non-null    float64
2   petal_length 150 non-null    float64
3   petal_width  150 non-null    float64
4   species      150 non-null    object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

```
from matplotlib import pyplot as pyplot
df = sns.load_dataset('tips')
sns.regplot(x = "total_bill" , y = "tip" , data =df)
plt.show()
```



```
from scipy import stats
x = [5,7,8,7,2,17,2,9,4,11,12,9,6]
y = [99,86,81,88,111,86,103,87,94,78,77,85,86]
```

```
slope, intercept, r, p, std_err = stats.linregress(x,y)
```

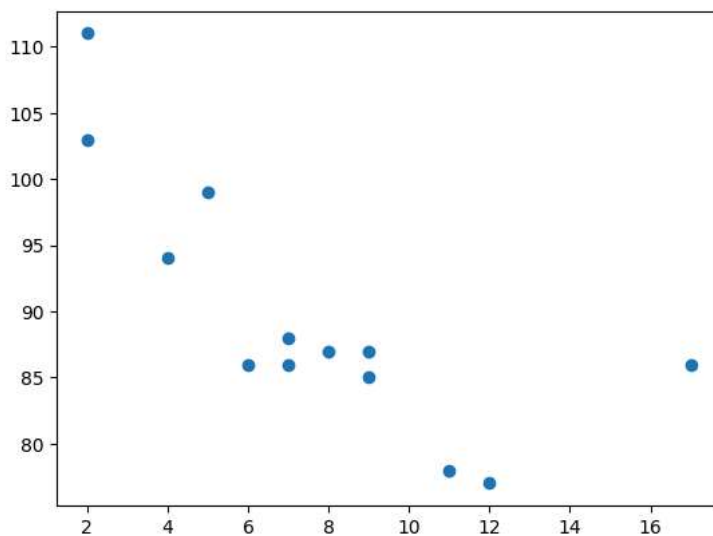
Start coding or [generate](#) with AI.

```
mymodel=list(map(myfunc,x))
```

draw the original scatter plot

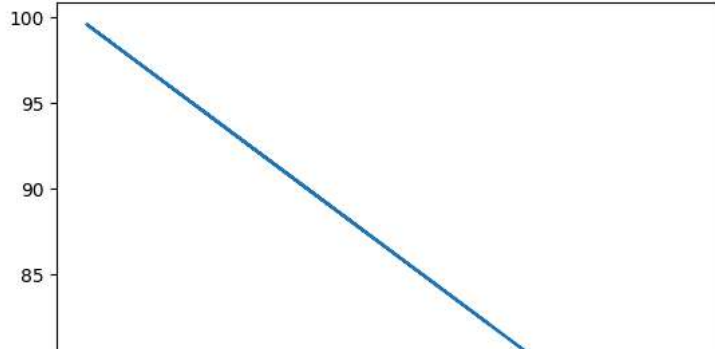
```
plt.scatter(x,y)
```

```
<matplotlib.collections.PathCollection at 0x7b817bdadd20>
```



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

[&lt;matplotlib.lines.Line2D at 0x7b817c0fdb0&gt;]



```
def estimator_coeff(p,q):
    #here we will estimate the total number of points or observation
    n1=np.size(p)
    #now we will calculate the mean of a and b vector
    m_p=np.mean(p)
    m_q=np.mean(q)
    #here we will calculate the cross deviation and deviation
    SS_pq=np.sum(q*p)-n1*m_q*m_p
    SS_pp=np.sum(p*p)-n1*m_q*m_p
    #here we will calculate the regression coefficient
    b_1=SS_pq/SS_pp
    b_0=m_q-b_1*m_p
    return(b_0,b_1)
```

```
def plot_regression_line(p,q,b):
    #now we will plot actual points or observation as scatter plot
    plt.scatter(p,q,color="m",marker="o",s=30)
    #Here we will calculate the predicted response vector
    q_pred=b[0]+b[1]*p
    #here we will plot regression line
    plt.plot(p,q_pred,color="g")
    plt.xlabel('p')
    plt.ylabel('q')
    plt.show()
```

```
def main():
    #entering the observation points and data
    p=np.array([10,11,12,13,14,15,16,17,18,19])
    p=np.array([11,13,12,15,17,18,18,19,20,22])
    #now we will plot the regression line
    plot_regression_line(p,q,b)
if __name__=="__main__":
    main()
```

Start coding or [generate](#) with AI.