

In [1]:

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

DataSet1

In [2]:

```
df=pd.read_csv(r'C:\Users\user\Downloads\2015.csv')
```

In [3]:

```
print(df.mean())
```

Happiness Rank	79.493671
Happiness Score	5.375734
Standard Error	0.047885
Economy (GDP per Capita)	0.846137
Family	0.991046
Health (Life Expectancy)	0.630259
Freedom	0.428615
Trust (Government Corruption)	0.143422
Generosity	0.236917
Dystopia Residual	2.098977
dtype: float64	

In [4]:

```
print(df.median())
```

Happiness Rank	79.500000
Happiness Score	5.232500
Standard Error	0.043940
Economy (GDP per Capita)	0.910245
Family	1.029510
Health (Life Expectancy)	0.696705
Freedom	0.435515
Trust (Government Corruption)	0.107220
Generosity	0.215420
Dystopia Residual	2.095415
dtype: float64	

In [5]:

```
print(df.mode())
```

	Country	Region	Happiness	Rank	Happiness Score \
0	Afghanistan	Sub-Saharan Africa		82.0	5.192
1	Albania	NaN		NaN	NaN
2	Algeria	NaN		NaN	NaN
3	Angola	NaN		NaN	NaN
4	Argentina	NaN		NaN	NaN
..
153	Venezuela	NaN		NaN	NaN
154	Vietnam	NaN		NaN	NaN
155	Yemen	NaN		NaN	NaN
156	Zambia	NaN		NaN	NaN
157	Zimbabwe	NaN		NaN	NaN

	Standard Error	Economy (GDP per Capita)	Family \
0	0.03751	0.00000	0.00000
1	0.03780	0.01530	0.13995
2	0.04394	0.01604	0.30285
3	0.04934	0.06940	0.35386
4	0.05051	0.07120	0.38174
..
153	NaN	1.45900	1.34043
154	NaN	1.52186	1.34951
155	NaN	1.55422	1.36058
156	NaN	1.56391	1.36948
157	NaN	1.69042	1.40223

	Health (Life Expectancy)	Freedom	Trust (Government Corruption) \
0	0.92356	0.00000	0.32524
1	NaN	0.07699	NaN
2	NaN	0.09245	NaN
3	NaN	0.10081	NaN
4	NaN	0.10384	NaN
..
153	NaN	0.65821	NaN
154	NaN	0.65980	NaN
155	NaN	0.66246	NaN
156	NaN	0.66557	NaN
157	NaN	0.66973	NaN

	Generosity	Dystopia	Residual
0	0.00000		0.32858
1	0.00199		0.65429
2	0.02641		0.67042
3	0.05444		0.67108
4	0.05547		0.89991
..
153	0.51752		3.10712
154	0.51912		3.17728
155	0.57630		3.19131
156	0.79588		3.26001
157	NaN		3.60214

[158 rows x 12 columns]

In [6]:

```
df.describe()
```

Out[6]:

	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom
count	158.000000	158.000000	158.000000	158.000000	158.000000	158.000000	158.000000
mean	79.493671	5.375734	0.047885	0.846137	0.991046	0.630259	0.428615
std	45.754363	1.145010	0.017146	0.403121	0.272369	0.247078	0.150693
min	1.000000	2.839000	0.018480	0.000000	0.000000	0.000000	0.000000
25%	40.250000	4.526000	0.037268	0.545808	0.856823	0.439185	0.328330
50%	79.500000	5.232500	0.043940	0.910245	1.029510	0.696705	0.435515
75%	118.750000	6.243750	0.052300	1.158448	1.214405	0.811013	0.549092
max	158.000000	7.587000	0.136930	1.690420	1.402230	1.025250	0.669730

In [7]:

```
print(df.sum())
```

Country SwitzerlandIcelandDenmarkNorwayCanadaFinl
andNe...
Region Western EuropeWestern EuropeWestern Europ
eWest...
Happiness Rank
12560
Happiness Score
849.366
Standard Error
7.56579
Economy (GDP per Capita) 1
33.68968
Family 1
56.58526
Health (Life Expectancy)
99.58098
Freedom
67.72116
Trust (Government Corruption)
22.66065
Generosity
37.19591
Dystopia Residual 3
31.63833
dtype: object

In [8]:

```
print(df.cumsum())
```

	Country \
0	Switzerland
1	SwitzerlandIceland
2	SwitzerlandIcelandDenmark
3	SwitzerlandIcelandDenmarkNorway
4	SwitzerlandIcelandDenmarkNorwayCanada
..	...
153	SwitzerlandIcelandDenmarkNorwayCanadaFinlandNe...
154	SwitzerlandIcelandDenmarkNorwayCanadaFinlandNe...
155	SwitzerlandIcelandDenmarkNorwayCanadaFinlandNe...
156	SwitzerlandIcelandDenmarkNorwayCanadaFinlandNe...
157	SwitzerlandIcelandDenmarkNorwayCanadaFinlandNe...

	Region	Happiness Rank \
0	Western Europe	1
1	Western EuropeWestern Europe	3
2	Western EuropeWestern EuropeWestern Europe	6
3	Western EuropeWestern EuropeWestern EuropeWest...	10
4	Western EuropeWestern EuropeWestern EuropeWest...	15
..
153	Western EuropeWestern EuropeWestern EuropeWest...	11934
154	Western EuropeWestern EuropeWestern EuropeWest...	12089
155	Western EuropeWestern EuropeWestern EuropeWest...	12245
156	Western EuropeWestern EuropeWestern EuropeWest...	12402
157	Western EuropeWestern EuropeWestern EuropeWest...	12560

	Happiness Score	Standard Error	Economy (GDP per Capita)	Family
0	7.587	0.03411	1.39651	1.34951
1	15.148	0.08295	2.69883	2.75174
2	22.675	0.11623	4.02431	4.11232
3	30.197	0.15503	5.48331	5.44327
4	37.624	0.19056	6.80960	6.76588
..
153	837.276	7.32523	132.51585	155.20069
154	840.616	7.36179	132.80250	155.55455
155	843.622	7.41194	133.46570	156.02944
156	846.527	7.49852	133.48100	156.44531
157	849.366	7.56579	133.68968	156.58526

	Health (Life Expectancy)	Freedom	Trust (Government Corruption) \
0	0.94143	0.66557	0.41978
1	1.88927	1.29434	0.56123
2	2.76391	1.94372	1.04480
3	3.64912	2.61345	1.40983
4	4.55475	3.24642	1.73940
..
153	98.03156	66.59679	22.18356
154	98.35066	67.08129	22.26366
155	99.07259	67.23813	22.45272
156	99.29655	67.35663	22.55334
157	99.58098	67.72116	22.66065

	Generosity	Dystopia	Residual
0	NaN		2.51738
1	0.43630		5.21939
2	0.77769		7.71143
3	1.12468		10.17674
4	1.58279		12.62850
..
153	36.17744		326.27619

154	36.36004	327.90947
155	36.83183	328.23805
156	37.02910	330.07107
157	37.19591	331.63833

[158 rows x 12 columns]

In [9]:

```
print(df.count())
```

Country	158
Region	158
Happiness Rank	158
Happiness Score	158
Standard Error	158
Economy (GDP per Capita)	158
Family	158
Health (Life Expectancy)	158
Freedom	158
Trust (Government Corruption)	158
Generosity	157
Dystopia Residual	158

dtype: int64

In [10]:

```
df.min()
```

Out[10]:

Country	Afghanistan
Region	Australia and New Zealand
Happiness Rank	1
Happiness Score	2.839
Standard Error	0.01848
Economy (GDP per Capita)	0.0
Family	0.0
Health (Life Expectancy)	0.0
Freedom	0.0
Trust (Government Corruption)	0.0
Generosity	0.0
Dystopia Residual	0.32858

dtype: object

In [11]:

```
df.max()
```

Out[11]:

Country	Zimbabwe
Region	Western Europe
Happiness Rank	158
Happiness Score	7.587
Standard Error	0.13693
Economy (GDP per Capita)	1.69042
Family	1.40223
Health (Life Expectancy)	1.02525
Freedom	0.66973
Trust (Government Corruption)	0.55191
Generosity	0.79588
Dystopia Residual	3.60214

dtype: object

In [12]:

```
from numpy import cov
from scipy.stats import spearmanr
from scipy.stats import pearsonr
```

In [13]:

```
cov(df['Family'],df['Freedom'])
```

Out[13]:

```
array([[0.07418492, 0.0181217 ],
       [0.0181217 , 0.02270832]])
```

In [14]:

```
spearmanr(df['Family'],df['Freedom'])
```

Out[14]:

```
SpearmanrResult(correlation=0.5281391142435108, pvalue=9.937786974199143e-13)
```

In [15]:

```
pearsonr(df['Family'],df['Freedom'])
```

Out[15]:

```
(0.44151821062286056, 6.363670360267173e-09)
```

DataSet2

In [16]:

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

In [17]:

```
df2=pd.read_csv(r'C:\Users\user\Downloads\4_drug200.csv')
```

In [18]:

```
df2.mean()
```

Out[18]:

```
Age      44.315000
Value    16.084485
dtype: float64
```

In [19]:

```
df2.median()
```

Out[19]:

```
Age      45.00000
Value    13.9365
dtype: float64
```

In [20]:

```
df2.mode()
```

Out[20]:

	Age	Sex	BP	Cholesterol	Value	Drug
0	47.0	M	HIGH	HIGH	12.006	drugY
1	NaN	NaN	NaN	NaN	18.295	NaN

In [21]:

```
df2.describe()
```

Out[21]:

	Age	Value
count	200.000000	200.000000
mean	44.315000	16.084485
std	16.544315	7.223956
min	15.000000	6.269000
25%	31.000000	10.445500
50%	45.000000	13.936500
75%	58.000000	19.380000
max	74.000000	38.247000

In [22]:

```
df2.sum()
```

Out[22]:

Age	8863
Sex	FMMFFFFMMFFMFFFMMFMMFFFMFFMFMMFMMMFMMFFMFF...
BP	HIGHLOWLOWNORMALLOWNORMALNORMALLOWNORMALLOWLOW...
Cholesterol	HIGHHIGHHIGHHIGHHIGHHIGHHIGHHIGHHIGHHIGHNORMALHIGH...
Value	3216.897
Drug	drugYdrugCdrugCdrugXdrugYdrugXdrugYdrugCdrugYd...
dtype:	object

In [26]:

```
df2.max()
```

Out[26]:

```
Age          74
Sex          M
BP          NORMAL
Cholesterol  NORMAL
Value       38.247
Drug        drugY
dtype: object
```

DataSet3

In [27]:

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

In [28]:

```
df3=pd.read_csv(r'C:\Users\user\Downloads\5_Instagram data.csv')
```

In [29]:

```
df3.mean()
```

Out[29]:

```
Impressions      5703.991597
From Home        2475.789916
From Hashtags    1887.512605
From Explore     1078.100840
From Other       171.092437
Saves            153.310924
Comments         6.663866
Shares           9.361345
Likes            173.781513
Profile Visits   50.621849
Follows          20.756303
dtype: float64
```

In [30]:

```
df3.median()
```

Out[30]:

Impressions	4289.0
From Home	2207.0
From Hashtags	1278.0
From Explore	326.0
From Other	74.0
Saves	109.0
Comments	6.0
Shares	6.0
Likes	151.0
Profile Visits	23.0
Follows	8.0
dtype:	float64

In [31]:

```
df3.mode()
```

Out[31]:

	Impressions	From Home	From Hashtags	From Explore	From Other	Saves	Comments	Shares	Likes	Profile Visits
0	5394.0	1975.0	116	45.0	34.0	40.0	6.0	3.0	114.0	19.0
1	NaN	NaN	201	84.0	NaN	135.0	NaN	NaN	151.0	21.0
2	NaN	NaN	278	NaN	NaN	144.0	NaN	NaN	NaN	NaN
3	NaN	NaN	362	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	411	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5	NaN	NaN	583	NaN	NaN	NaN	NaN	NaN	NaN	NaN
6	NaN	NaN	655	NaN	NaN	NaN	NaN	NaN	NaN	NaN
7	NaN	NaN	707	NaN	NaN	NaN	NaN	NaN	NaN	NaN
8	NaN	NaN	771	NaN	NaN	NaN	NaN	NaN	NaN	NaN
9	NaN	NaN	794	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10	NaN	NaN	1248	NaN	NaN	NaN	NaN	NaN	NaN	NaN
11	NaN	NaN	1260	NaN	NaN	NaN	NaN	NaN	NaN	NaN
12	NaN	NaN	1278	NaN	NaN	NaN	NaN	NaN	NaN	NaN
13	NaN	NaN	1693	NaN	NaN	NaN	NaN	NaN	NaN	NaN
14	NaN	NaN	1938	NaN	NaN	NaN	NaN	NaN	NaN	NaN
15	NaN	NaN	2351	NaN	NaN	NaN	NaN	NaN	NaN	NaN
16	NaN	NaN	2975	NaN	NaN	NaN	NaN	NaN	NaN	NaN
17	NaN	NaN	3450	NaN	NaN	NaN	NaN	NaN	NaN	NaN
18	NaN	NaN	3551	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [32]:

```
df3.describe()
```

Out[32]:

	Impressions	From Home	From Hashtags	From Explore	From Other	Saves	Comments
count	119.000000	119.000000	119.000000	119.000000	119.000000	119.000000	119.000000
mean	5703.991597	2475.789916	1887.512605	1078.100840	171.092437	153.310924	11.000000
std	4843.780105	1489.386348	1884.361443	2613.026132	289.431031	156.317731	11.000000
min	1941.000000	1133.000000	116.000000	0.000000	9.000000	22.000000	0.000000
25%	3467.000000	1945.000000	726.000000	157.500000	38.000000	65.000000	0.000000
50%	4289.000000	2207.000000	1278.000000	326.000000	74.000000	109.000000	0.000000
75%	6138.000000	2602.500000	2363.500000	689.500000	196.000000	169.000000	0.000000
max	36919.000000	13473.000000	11817.000000	17414.000000	2547.000000	1095.000000	11.000000

In [33]:

```
df3.sum()
```

Out[33]:

Impressions	678775
From Home	294619
From Hashtags	224614
From Explore	128294
From Other	20360
Saves	18244
Comments	793
Shares	1114
Likes	20680
Profile Visits	6024
Follows	2470
Caption	Here are some of the most important data visua...
Hashtags	#finance💎#money💎#business💎#investing💎#investme...
dtype: object	

In [34]:

```
df3.cumsum()
```

Out[34]:

	Impressions	From Home	From Hashtags	From Explore	From Other	Saves	Comments	Shares	Likes	Prof Vis
0	3920	2586	1028	619	56	98	9	5	162	
1	9314	5313	2866	1793	134	292	16	19	386	
2	13335	7398	4054	1793	667	333	27	20	517	1
3	17863	10098	4675	2725	740	505	37	27	730	1
4	20381	11802	4930	3004	777	601	42	31	853	1
...
114	599291	266275	214385	90803	17545	16325	782	1011	19448	52
115	605022	268198	215753	93069	17610	16460	786	1012	19596	52
116	609161	269331	217291	94436	17643	16496	786	1013	19688	52
117	641856	281146	220438	111850	17813	17591	788	1088	20237	54

	Impressions	From Home	From Hashtags	From Explore	From Other	Saves	Comments	Shares	Likes	Prof Vis
118	678775	294619	224614	128294	20360	18244	793	1114	20680	60

In [35]:

```
df3.count()
```

119 rows × 13 columns

Out[35]:

Impressions 119
From Home 119
From Hashtags 119
From Explore 119
From Other 119
Saves 119
Comments 119
Shares 119
Likes 119
Profile Visits 119
Follows 119
Caption 119
Hashtags 119
dtype: int64

In [36]:

```
df3.min()
```

Out[36]:

Impressions 1941
From Home 1133
From Hashtags 116
From Explore 0
From Other 9
Saves 22
Comments 0
Shares 0
Likes 72
Profile Visits 4
Follows 0
Caption 170 Python Projects with Source Code solved an...
Hashtags #career🔎#job🔎#jobs🔎#jobsearch🔎#education🔎#busi...
dtype: object

In [37]:

```
df3.max()
```

Out[37]:

```
Impressions          36919
From Home            13473
From Hashtags        11817
From Explore         17414
From Other           2547
Saves                1095
Comments              19
Shares                75
Likes                549
Profile Visits        611
Follows               260
Caption              You must have seen the news divided into categ...
Hashtags              #timeseries #time #statistics #datascience #bi...
dtype: object
```

In [38]:

```
from numpy import cov
from scipy.stats import spearmanr
from scipy.stats import pearsonr
```

In [39]:

```
cov(df3['Shares'],df3['Likes'])
```

Out[39]:

```
array([[ 101.79205241,  588.27453354],
       [ 588.27453354, 6786.29084176]])
```

In [40]:

```
spearmanr(df3['Shares'],df3['Likes'])
```

Out[40]:

```
SpearmanrResult(correlation=0.5692666973936509, pvalue=1.42478204825654e-11)
```

In [41]:

```
pearsonr(df3['Shares'],df3['Likes'])
```

Out[41]:

```
(0.7077940026881047, 2.258074786066927e-19)
```

DataSet4

In [42]:

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

In [43]:

```
df4=pd.read_csv(r'C:\Users\user\Downloads\6_Salesworkload1.csv')
```

In [44]:

```
df4.mean()
```

Out[44]:

```
Time index      5.000000e+00
StoreID         6.199522e+04
Dept_ID         9.470588e+00
HoursLease      2.203608e+01
Sales units     1.076471e+06
Turnover        3.721393e+06
Customer              NaN
dtype: float64
```

In [45]:

```
df4.median()
```

Out[45]:

```
Time index      5.0
StoreID         75400.5
Dept_ID         9.0
HoursLease      0.0
Sales units     293230.0
Turnover        931957.5
Customer              NaN
dtype: float64
```

In [46]:

```
df4.mode()
```

Out[46]:

	MonthYear	Time index	Country	StoreID	City	Dept_ID	Dept. Name	HoursOwn	Hours
0	01.2017	1.0	France	12227.0	Aalborg (I)	1.0	Admin	47.205	
1	02.2017	2.0	Germany	15552.0	Aalborg (II)	2.0	Checkout	NaN	
2	03.2017	3.0	United Kingdom	16927.0	Amsterdam	3.0	Clothing	NaN	
3	04.2017	4.0	NaN	17647.0	Antwerp	4.0	Customer Services	NaN	
4	05.2017	5.0	NaN	18808.0	Barcelona (I)	5.0	Delivery	NaN	
5	06.2017	6.0	NaN	19000.0	Barcelona (II)	6.0	Dry	NaN	
6	10.2016	7.0	NaN	19340.0	Berlin (I)	7.0	Fish	NaN	
7	11.2016	8.0	NaN	19769.0	Berlin (II)	8.0	Food	NaN	
8	12.2016	9.0	NaN	20166.0	Bilbao	9.0	Frozen	NaN	
9	NaN	NaN	NaN	20891.0	Birmingham	11.0	Fruits & Vegetables	NaN	
10	NaN	NaN	NaN	22117.0	Bologna	12.0	Hardware	NaN	
11	NaN	NaN	NaN	23623.0	Bordeaux	13.0	Household	NaN	
12	NaN	NaN	NaN	29650.0	Brno	14.0	Meat	NaN	
13	NaN	NaN	NaN	32949.0	Brussels (I)	15.0	Non Food	NaN	
14	NaN	NaN	NaN	34378.0	Brussels (II)	16.0	all	NaN	
15	NaN	NaN	NaN	38560.0	Cologne	17.0	other	NaN	
16	NaN	NaN	NaN	38976.0	Copenhagen (I)	18.0	others	NaN	
17	NaN	NaN	NaN	42367.0	Copenhagen (II)	NaN	NaN	NaN	
18	NaN	NaN	NaN	45583.0	Den Haag	NaN	NaN	NaN	
19	NaN	NaN	NaN	63354.0	Frankfurt	NaN	NaN	NaN	
20	NaN	NaN	NaN	64983.0	Gothenburg	NaN	NaN	NaN	
21	NaN	NaN	NaN	71991.0	Groningen	NaN	NaN	NaN	
22	NaN	NaN	NaN	73422.0	Hamburg	NaN	NaN	NaN	
23	NaN	NaN	NaN	73762.0	Krakow	NaN	NaN	NaN	
24	NaN	NaN	NaN	73949.0	Leicester	NaN	NaN	NaN	
25	NaN	NaN	NaN	76852.0	Liverpool	NaN	NaN	NaN	
26	NaN	NaN	NaN	77348.0	London (I)	NaN	NaN	NaN	
27	NaN	NaN	NaN	78325.0	London (II)	NaN	NaN	NaN	
28	NaN	NaN	NaN	78450.0	Lyon	NaN	NaN	NaN	
29	NaN	NaN	NaN	79785.0	Madrid (I)	NaN	NaN	NaN	
30	NaN	NaN	NaN	81473.0	Madrid (II)	NaN	NaN	NaN	
31	NaN	NaN	NaN	83160.0	Malmö	NaN	NaN	NaN	
32	NaN	NaN	NaN	85124.0	Manchester	NaN	NaN	NaN	

	MonthYear	Time index	Country	StoreID	City	Dept_ID	Dept. Name	HoursOwn	Hours
33	NaN	NaN	NaN	85321.0	Marseille	NaN	NaN	NaN	
34	NaN	NaN	NaN	85696.0	Milano	NaN	NaN	NaN	
35	NaN	NaN	NaN	86089.0	Munich	NaN	NaN	NaN	
36	NaN	NaN	NaN	86208.0	Nantes	NaN	NaN	NaN	
37	NaN	NaN	NaN	87703.0	Napoli	NaN	NaN	NaN	
38	NaN	NaN	NaN	88253.0	Ostrava	NaN	NaN	NaN	
39	NaN	NaN	NaN	88750.0	Paris (I)	NaN	NaN	NaN	
40	NaN	NaN	NaN	88994.0	Paris (II)	NaN	NaN	NaN	
41	NaN	NaN	NaN	90992.0	Poznan	NaN	NaN	NaN	
42	NaN	NaN	NaN	91973.0	Prague (I)	NaN	NaN	NaN	
43	NaN	NaN	NaN	93033.0	Prague (II)	NaN	NaN	NaN	
44	NaN	NaN	NaN	94153.0	Rome (I)	NaN	NaN	NaN	
45	NaN	NaN	NaN	94882.0	Rome (II)	NaN	NaN	NaN	
46	NaN	NaN	NaN	95434.0	Rotterdam	NaN	NaN	NaN	
47	NaN	NaN	NaN	96493.0	Stockholm	NaN	NaN	NaN	
48	NaN	NaN	NaN	96857.0	Warsaw (I)	NaN	NaN	NaN	
In [47]:	NaN	NaN	NaN	98422.0	Warsaw (II)	NaN	NaN	NaN	

```
df4.describe()
```

Out[47]:

	Time index	StoreID	Dept_ID	HoursLease	Sales units	Turnover	Cu
count	7650.000000	7650.000000	7650.000000	7650.000000	7.650000e+03	7.650000e+03	
mean	5.000000	61995.220000	9.470588	22.036078	1.076471e+06	3.721393e+06	
std	2.582158	29924.581631	5.337429	133.299513	1.728113e+06	6.003380e+06	
min	1.000000	12227.000000	1.000000	0.000000	0.000000e+00	0.000000e+00	
25%	3.000000	29650.000000	5.000000	0.000000	5.457125e+04	2.726798e+05	
50%	5.000000	75400.500000	9.000000	0.000000	2.932300e+05	9.319575e+05	
75%	7.000000	87703.000000	14.000000	0.000000	9.175075e+05	3.264432e+06	
max	9.000000	98422.000000	18.000000	3984.000000	1.124296e+07	4.271739e+07	

In [48]:

```
df4.sum()
```

Out[48]:

```
MonthYear      10.201610.201610.201610.201610.201610.201610.2...
Time index                                38250.0
StoreID                                474263433.0
Dept_ID                                72450.0
HoursLease                                168576.0
Sales units                                8235000965.0
Turnover                                28468656015.0
Customer                                              0.0
dtype: object
```

In [49]:

```
cumsum(df4['Country'],df4['City'])
```

```
-----
-
NameError                                Traceback (most recent call las
t)
<ipython-input-49-02b57bd1b938> in <module>
----> 1 cumsum(df4['Country'],df4['City'])

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

In [50]:

```
df4.count()
```

Out[50]:

```
MonthYear      7658
Time index      7650
Country         7650
StoreID         7650
City           7650
Dept_ID        7650
Dept. Name     7650
HoursOwn       7650
HoursLease     7650
Sales units    7650
Turnover      7650
Customer       0
Area (m2)     7650
Opening hours  7650
dtype: int64
```

In [51]:

```
df4.min()
```

Out[51]:

```
MonthYear      - - - -  
Time index      1.0  
StoreID        12227.0  
Dept_ID         1.0  
HoursLease       0.0  
Sales units     0.0  
Turnover        0.0  
Customer        NaN  
dtype: object
```

In [52]:

```
df4.max()
```

Out[52]:

```
MonthYear      12.2016  
Time index      9.0  
StoreID        98422.0  
Dept_ID        18.0  
HoursLease     3984.0  
Sales units    11242955.0  
Turnover       42717390.0  
Customer        NaN  
dtype: object
```

In [53]:

```
from numpy import cov  
from scipy.stats import spearmanr  
from scipy.stats import pearsonr
```

In [54]:

```
cov(df4['Dept_ID'],df4['Turnover'])
```

Out[54]:

```
array([[nan, nan],  
       [nan, nan]])
```

In [55]:

```
spearmanr(df4['Dept_ID'],df4['Turnover'])
```

Out[55]:

```
SpearmanrResult(correlation=nan, pvalue=nan)
```

DataSet5

In [56]:

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

In [57]:

```
df5=pd.read_csv(r'C:\Users\user\Downloads\8_BreastCancerPrediction.csv')
```

In [58]:

```
df5.mean()
```

Out[58]:

```
id                3.037183e+07
radius_mean       1.412729e+01
texture_mean      1.928965e+01
perimeter_mean    9.196903e+01
area_mean         6.548891e+02
smoothness_mean   9.636028e-02
compactness_mean  1.043410e-01
concavity_mean    8.879932e-02
concave points_mean 4.891915e-02
symmetry_mean     1.811619e-01
fractal_dimension_mean 6.279761e-02
radius_se         4.051721e-01
texture_se        1.216853e+00
perimeter_se      2.866059e+00
area_se           4.033708e+01
smoothness_se     7.040979e-03
compactness_se    2.547814e-02
concavity_se      3.189372e-02
concave points_se 1.179614e-02
symmetry_se       2.054230e-02
fractal_dimension_se 3.794904e-03
radius_worst      1.626919e+01
texture_worst     2.567722e+01
perimeter_worst   1.072612e+02
area_worst        8.805831e+02
smoothness_worst  1.323686e-01
compactness_worst 2.542650e-01
concavity_worst   2.721885e-01
concave points_worst 1.146062e-01
symmetry_worst    2.900756e-01
fractal_dimension_worst 8.394582e-02
Unnamed: 32              NaN
dtype: float64
```

In [59]:

```
df5.median()
```

Out[59]:

id	906024.000000
radius_mean	13.370000
texture_mean	18.840000
perimeter_mean	86.240000
area_mean	551.100000
smoothness_mean	0.095870
compactness_mean	0.092630
concavity_mean	0.061540
concave points_mean	0.033500
symmetry_mean	0.179200
fractal_dimension_mean	0.061540
radius_se	0.324200
texture_se	1.108000
perimeter_se	2.287000
area_se	24.530000
smoothness_se	0.006380
compactness_se	0.020450
concavity_se	0.025890
concave points_se	0.010930
symmetry_se	0.018730
fractal_dimension_se	0.003187
radius_worst	14.970000
texture_worst	25.410000
perimeter_worst	97.660000
area_worst	686.500000
smoothness_worst	0.131300
compactness_worst	0.211900
concavity_worst	0.226700
concave points_worst	0.099930
symmetry_worst	0.282200
fractal_dimension_worst	0.080040
Unnamed: 32	NaN

dtype: float64

In [60]:

```
df5.mode()
```

Out[60]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothr
0	8670	B	12.34	14.93	82.61	512.2	
1	8913	NaN	NaN	15.70	87.76	NaN	
2	8915	NaN	NaN	16.84	134.70	NaN	
3	9047	NaN	NaN	16.85	NaN	NaN	
4	85715	NaN	NaN	17.46	NaN	NaN	
...	
564	911157302	NaN	NaN	NaN	NaN	NaN	
565	911296201	NaN	NaN	NaN	NaN	NaN	
566	911296202	NaN	NaN	NaN	NaN	NaN	
567	911320501	NaN	NaN	NaN	NaN	NaN	
568	911320502	NaN	NaN	NaN	NaN	NaN	

569 rows × 33 columns

In [61]:

```
df5.describe()
```

Out[61]:

	id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_
count	5.690000e+02	569.000000	569.000000	569.000000	569.000000	569.000000
mean	3.037183e+07	14.127292	19.289649	91.969033	654.889104	0.054579
std	1.250206e+08	3.524049	4.301036	24.298981	351.914129	0.014619
min	8.670000e+03	6.981000	9.710000	43.790000	143.500000	0.049981
25%	8.692180e+05	11.700000	16.170000	75.170000	420.300000	0.051784
50%	9.060240e+05	13.370000	18.840000	86.240000	551.100000	0.055457
75%	8.813129e+06	15.780000	21.800000	104.100000	782.700000	0.100272
max	9.113205e+08	28.110000	39.280000	188.500000	2501.000000	0.163457

8 rows × 32 columns

In [62]:

```
df5.sum()
```

Out[62]:

id	172815720
85	
diagnosis	MMMMMMMMMMMMMMMMMMMMBBBBMMMMMMMMMMMMMMMMBMMMMMM
M...	
radius_mean	8038.4
29	
texture_mean	10975.
81	
perimeter_mean	52330.
10 [63]:	
area_mean	37263
1.9	
smoothness_mean	54.8
29	
compactness_mean	59.370
02 id	diagnosis
concavity_mean	50.5268
11 0 842302	M
concave points_mean	27.8349
94 1 1684819	MM
symmetry_mean	103.00
11	MM
fractal_dimension_mean	35.731
84 4 254692425	MMMM
radius_se	230.54
29...	..
texture_se	692.38
564 17278698457	MMMMMMMMMMMMMMMMMMMMBBBBMMMMMMMMMMMMMMMMBMMMMMM..
96	
perimeter_se	1630.78
565 17279625139	MMMMMMMMMMMMMMMMMMMMBBBBMMMMMMMMMMMMMMMMBMMMMMM..
77	
area_se	22951.7
566 17280552093	MMMMMMMMMMMMMMMMMMMMBBBBMMMMMMMMMMMMMMMMBMMMMMM..
98	
smoothness_se	4.0063
568 17281572085	MMMMMMMMMMMMMMMMMMMMBBBBMMMMMMMMMMMMMMMMBMMMMMM..
17	
compactness_se	14.4970
569 rows x 33 columns	
<div><div></div></div>	
25	
concave points_se	6.7120
02	
symmetry_se	11.6885
68	
fractal_dimension_se	2.15
93	
radius_worst	9257.1
69	
texture_worst	14610.
34	
perimeter_worst	61031.
63	
area_worst	50105
1.8	
smoothness_worst	75.317
73	
compactness_worst	144.676
81	
concavity_worst	154.8752
47	
concave points_worst	65.2109
41	
symmetry_worst	165.0

```
53
Fractal_dimension_worst 47.765
17
df5.count()
Unnamed: 32
0.0
In [64]:
dtype: object
id 569
diagnosis 569
radius_mean 569
texture_mean 569
perimeter_mean 569
area_mean 569
smoothness_mean 569
compactness_mean 569
concavity_mean 569
concave points_mean 569
symmetry_mean 569
fractal_dimension_mean 569
radius_se 569
texture_se 569
perimeter_se 569
area_se 569
smoothness_se 569
compactness_se 569
concavity_se 569
concave points_se 569
symmetry_se 569
fractal_dimension_se 569
radius_worst 569
texture_worst 569
perimeter_worst 569
area_worst 569
smoothness_worst 569
compactness_worst 569
concavity_worst 569
concave points_worst 569
symmetry_worst 569
fractal_dimension_worst 569
Unnamed: 32 0
dtype: int64
```

In [65]:

```
df5.min()
```

Out[65]:

id	8670
diagnosis	B
radius_mean	6.981
texture_mean	9.71
perimeter_mean	43.79
area_mean	143.5
smoothness_mean	0.05263
compactness_mean	0.01938
concavity_mean	0.0
concave points_mean	0.0
symmetry_mean	0.106
fractal_dimension_mean	0.04996
radius_se	0.1115
texture_se	0.3602
perimeter_se	0.757
area_se	6.802
smoothness_se	0.001713
compactness_se	0.002252
concavity_se	0.0
concave points_se	0.0
symmetry_se	0.007882
fractal_dimension_se	0.000895
radius_worst	7.93
texture_worst	12.02
perimeter_worst	50.41
area_worst	185.2
smoothness_worst	0.07117
compactness_worst	0.02729
concavity_worst	0.0
concave points_worst	0.0
symmetry_worst	0.1565
fractal_dimension_worst	0.05504
Unnamed: 32	NaN
dtype:	object

In [66]:

```
df5.max()
```

Out[66]:

```
id          911320502
diagnosis    M
radius_mean   28.11
texture_mean  39.28
perimeter_mean 188.5
area_mean    2501.0
smoothness_mean 0.1634
compactness_mean 0.3454
concavity_mean 0.4268
concave points_mean 0.2012
symmetry_mean 0.304
fractal_dimension_mean 0.09744
radius_se     2.873
texture_se     4.885
perimeter_se   21.98
area_se        542.2
smoothness_se 0.03113
compactness_se 0.1354
concavity_se   0.396
concave points_se 0.05279
symmetry_se    0.07895
fractal_dimension_se 0.02984
radius_worst   36.04
texture_worst  49.54
perimeter_worst 251.2
area_worst     4254.0
smoothness_worst 0.2226
compactness_worst 1.058
concavity_worst 1.252
concave points_worst 0.291
symmetry_worst 0.6638
fractal_dimension_worst 0.2075
Unnamed: 32    NaN
dtype: object
```

In [67]:

```
from numpy import cov
from scipy.stats import spearmanr
from scipy.stats import pearsonr
```

In [68]:

```
cov(df5['perimeter_worst'],df5['area_worst'])
```

Out[68]:

```
array([[ 1129.13084694, 18702.86999057],
       [18702.86999057, 324167.38510217]])
```

In [69]:

```
spearmanr(df5['perimeter_worst'],df5['area_worst'])
```

Out[69]:

```
SpearmanrResult(correlation=0.992432709857714, pvalue=0.0)
```

In [70]:

```
pearsonr(df5['perimeter_worst'],df5['area_worst'])
```

Out[70]:

```
(0.9775780914063879, 0.0)
```