

ti6doai3g

July 28, 2023

```
[42]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
[43]: df=pd.read_csv("/content/18_world-data-2023.csv")
df
```

```
[43]:
```

	Country	Density\n(P/Km2)	Abbreviation	Agricultural Land( %)	\
0	Afghanistan	60	AF	58.10%	
1	Albania	105	AL	43.10%	
2	Algeria	18	DZ	17.40%	
3	Andorra	164	AD	40.00%	
4	Angola	26	AO	47.50%	
..	...	...	...	...	
190	Venezuela	32	VE	24.50%	
191	Vietnam	314	VN	39.30%	
192	Yemen	56	YE	44.60%	
193	Zambia	25	ZM	32.10%	
194	Zimbabwe	38	ZW	41.90%	

	Land Area(Km2)	Armed Forces size	Birth Rate	Calling Code	\
0	652,230	323,000	32.49	93.0	
1	28,748	9,000	11.78	355.0	
2	2,381,741	317,000	24.28	213.0	
3	468	NaN	7.20	376.0	
4	1,246,700	117,000	40.73	244.0	
..	...	...	...	...	
190	912,050	343,000	17.88	58.0	
191	331,210	522,000	16.75	84.0	
192	527,968	40,000	30.45	967.0	
193	752,618	16,000	36.19	260.0	
194	390,757	51,000	30.68	263.0	

	Capital/Major City	Co2-Emissions	... Out of pocket health expenditure	\
0	Kabul	8,672	...	78.40%
1	Tirana	4,536	...	56.90%

2	Algiers	150,006	...	28.10%
3	Andorra la Vella	469	...	36.40%
4	Luanda	34,693	...	33.40%
..	...	...	...	...
190	Caracas	164,175	...	45.80%
191	Hanoi	192,668	...	43.50%
192	Sanaa	10,609	...	81.00%
193	Lusaka	5,141	...	27.50%
194	Harare	10,983	...	25.80%

	Physicians per thousand	Population \
0	0.28	38,041,754
1	1.20	2,854,191
2	1.72	43,053,054
3	3.33	77,142
4	0.21	31,825,295
..	...	...
190	1.92	28,515,829
191	0.82	96,462,106
192	0.31	29,161,922
193	1.19	17,861,030
194	0.21	14,645,468

	Population: Labor force participation (%)	Tax revenue (%)	Total tax rate \
0	48.90%	9.30%	71.40%
1	55.70%	18.60%	36.60%
2	41.20%	37.20%	66.10%
3	NaN	NaN	NaN
4	77.50%	9.20%	49.10%
..	...	...	...
190	59.70%	NaN	73.30%
191	77.40%	19.10%	37.60%
192	38.00%	NaN	26.60%
193	74.60%	16.20%	15.60%
194	83.10%	20.70%	31.60%

	Unemployment rate	Urban_population	Latitude	Longitude
0	11.12%	9,797,273	33.939110	67.709953
1	12.33%	1,747,593	41.153332	20.168331
2	11.70%	31,510,100	28.033886	1.659626
3	NaN	67,873	42.506285	1.521801
4	6.89%	21,061,025	-11.202692	17.873887
..	...	...	...	...
190	8.80%	25,162,368	6.423750	-66.589730
191	2.01%	35,332,140	14.058324	108.277199
192	12.91%	10,869,523	15.552727	48.516388
193	11.43%	7,871,713	-13.133897	27.849332

194                      4.95%                      4,717,305   -19.015438      29.154857

[195 rows x 35 columns]

[44]: df.head()

```
[44]:      Country Density\n(P/Km2)  Abbreviation  Agricultural Land( %)  \
0  Afghanistan          60          AF          58.10%
1    Albania          105          AL          43.10%
2    Algeria           18          DZ          17.40%
3    Andorra          164          AD          40.00%
4    Angola           26          AO          47.50%

      Land Area(Km2)  Armed Forces size  Birth Rate  Calling Code  \
0      652,230          323,000        32.49          93.0
1      28,748           9,000        11.78          355.0
2    2,381,741        317,000        24.28          213.0
3         468           NaN          7.20          376.0
4    1,246,700        117,000        40.73          244.0

      Capital/Major City  Co2-Emissions  ...  Out of pocket health expenditure  \
0          Kabul          8,672  ...          78.40%
1          Tirana          4,536  ...          56.90%
2          Algiers        150,006  ...          28.10%
3  Andorra la Vella          469  ...          36.40%
4          Luanda         34,693  ...          33.40%

      Physicians per thousand  Population  \
0              0.28  38,041,754
1              1.20   2,854,191
2              1.72  43,053,054
3              3.33    77,142
4              0.21  31,825,295

      Population: Labor force participation (%)  Tax revenue (%)  Total tax rate  \
0              48.90%          9.30%          71.40%
1              55.70%          18.60%          36.60%
2              41.20%          37.20%          66.10%
3              NaN          NaN          NaN
4              77.50%          9.20%          49.10%

      Unemployment rate  Urban_population  Latitude  Longitude
0          11.12%          9,797,273  33.939110  67.709953
1          12.33%          1,747,593  41.153332  20.168331
2          11.70%        31,510,100  28.033886   1.659626
3           NaN           67,873  42.506285   1.521801
4           6.89%        21,061,025 -11.202692  17.873887
```

[5 rows x 35 columns]

## 1 DATA CLEANING AND DATA PREPROCESSING

```
[45]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 195 entries, 0 to 194
```

```
Data columns (total 35 columns):
```

#	Column	Non-Null Count	Dtype
---	-----	-----	-----
0	Country	195 non-null	object
1	Density (P/Km2)	195 non-null	object
2	Abbreviation	188 non-null	object
3	Agricultural Land( %)	188 non-null	object
4	Land Area(Km2)	194 non-null	object
5	Armed Forces size	171 non-null	object
6	Birth Rate	189 non-null	float64
7	Calling Code	194 non-null	float64
8	Capital/Major City	192 non-null	object
9	Co2-Emissions	188 non-null	object
10	CPI	178 non-null	object
11	CPI Change (%)	179 non-null	object
12	Currency-Code	180 non-null	object
13	Fertility Rate	188 non-null	float64
14	Forested Area (%)	188 non-null	object
15	Gasoline Price	175 non-null	object
16	GDP	193 non-null	object
17	Gross primary education enrollment (%)	188 non-null	object
18	Gross tertiary education enrollment (%)	183 non-null	object
19	Infant mortality	189 non-null	float64
20	Largest city	189 non-null	object
21	Life expectancy	187 non-null	float64
22	Maternal mortality ratio	181 non-null	float64
23	Minimum wage	150 non-null	object
24	Official language	194 non-null	object
25	Out of pocket health expenditure	188 non-null	object
26	Physicians per thousand	188 non-null	float64
27	Population	194 non-null	object
28	Population: Labor force participation (%)	176 non-null	object
29	Tax revenue (%)	169 non-null	object
30	Total tax rate	183 non-null	object
31	Unemployment rate	176 non-null	object
32	Urban_population	190 non-null	object

```

33 Latitude 194 non-null float64
34 Longitude 194 non-null float64
dtypes: float64(9), object(26)
memory usage: 53.4+ KB

```

```
[46]: df.describe()
```

```

[46]:      Birth Rate  Calling Code  Fertility Rate  Infant mortality \
count  189.000000    194.000000    188.000000    189.000000
mean    20.214974    360.546392     2.698138     21.332804
std     9.945774    323.236419     1.282267    19.548058
min     5.900000     1.000000     0.980000     1.400000
25%    11.300000    82.500000     1.705000     6.000000
50%    17.950000    255.500000     2.245000    14.000000
75%    28.750000    506.750000     3.597500    32.700000
max    46.080000   1876.000000     6.910000    84.500000

      Life expectancy  Maternal mortality ratio  Physicians per thousand \
count    187.000000          181.000000          188.000000
mean     72.279679          160.392265           1.839840
std       7.483661          233.502024           1.684261
min      52.800000           2.000000           0.010000
25%      67.000000          13.000000           0.332500
50%      73.200000          53.000000           1.460000
75%      77.500000         186.000000           2.935000
max      85.400000        1150.000000           8.420000

      Latitude  Longitude
count  194.000000  194.000000
mean    19.092351   20.232434
std    23.961779   66.716110
min   -40.900557 -175.198242
25%     4.544175   -7.941496
50%    17.273849   20.972652
75%    40.124603   48.281523
max    64.963051  178.065032

```

```
[47]: df.columns
```

```

[47]: Index(['Country', 'Density\n(P/Km2)', 'Abbreviation', 'Agricultural Land( %)',
'Land Area(Km2)', 'Armed Forces size', 'Birth Rate', 'Calling Code',
'Capital/Major City', 'Co2-Emissions', 'CPI', 'CPI Change (%)',
'Currency-Code', 'Fertility Rate', 'Forested Area (%)',
'Gasoline Price', 'GDP', 'Gross primary education enrollment (%)',
'Gross tertiary education enrollment (%)', 'Infant mortality',
'Largest city', 'Life expectancy', 'Maternal mortality ratio',
'Minimum wage', 'Official language', 'Out of pocket health expenditure',

```

```

'Physicians per thousand', 'Population',
'Population: Labor force participation (%)', 'Tax revenue (%)',
'Total tax rate', 'Unemployment rate', 'Urban_population', 'Latitude',
'Longitude'],
dtype='object')

```

```

[48]: df1=df.dropna()
df1

```

```

[48]:
Country Density\n(P/Km2) Abbreviation Agricultural Land( %) \
0      Afghanistan          60          AF          58.10%
1      Albania             105          AL          43.10%
2      Algeria             18          DZ          17.40%
4      Angola              26          AO          47.50%
6      Argentina           17          AR          54.30%
..      ...
185    United Kingdom       281          GB          71.70%
186    United States        36          US          44.40%
187    Uruguay              20          UY          82.60%
191    Vietnam             314          VN          39.30%
193    Zambia              25          ZM          32.10%

Land Area(Km2) Armed Forces size Birth Rate Calling Code \
0      652,230      323,000      32.49      93.0
1      28,748       9,000      11.78      355.0
2      2,381,741    317,000      24.28      213.0
4      1,246,700    117,000      40.73      244.0
6      2,780,400    105,000      17.02      54.0
..      ...
185     243,610     148,000      11.00      44.0
186    9,833,517    1,359,000     11.60       1.0
187     176,215     22,000      13.86     598.0
191     331,210     522,000      16.75      84.0
193     752,618     16,000      36.19     260.0

Capital/Major City Co2-Emissions ... Out of pocket health expenditure \
0      Kabul          8,672 ...          78.40%
1      Tirana         4,536 ...          56.90%
2      Algiers       150,006 ...          28.10%
4      Luanda        34,693 ...          33.40%
6      Buenos Aires  201,348 ...          17.60%
..      ...
185    London        379,025 ...          14.80%
186    Washington, D.C. 5,006,302 ...          11.10%
187    Montevideo      6,766 ...          16.20%
191    Hanoi         192,668 ...          43.50%
193    Lusaka         5,141 ...          27.50%

```

	Physicians per thousand	Population \
0	0.28	38,041,754
1	1.20	2,854,191
2	1.72	43,053,054
4	0.21	31,825,295
6	3.96	44,938,712
..	...	...
185	2.81	66,834,405
186	2.61	328,239,523
187	5.05	3,461,734
191	0.82	96,462,106
193	1.19	17,861,030

	Population: Labor force participation (%)	Tax revenue (%)	Total tax rate \
0	48.90%	9.30%	71.40%
1	55.70%	18.60%	36.60%
2	41.20%	37.20%	66.10%
4	77.50%	9.20%	49.10%
6	61.30%	10.10%	106.30%
..	...	...	...
185	62.80%	25.50%	30.60%
186	62.00%	9.60%	36.60%
187	64.00%	20.10%	41.80%
191	77.40%	19.10%	37.60%
193	74.60%	16.20%	15.60%

	Unemployment rate	Urban_population	Latitude	Longitude
0	11.12%	9,797,273	33.939110	67.709953
1	12.33%	1,747,593	41.153332	20.168331
2	11.70%	31,510,100	28.033886	1.659626
4	6.89%	21,061,025	-11.202692	17.873887
6	9.79%	41,339,571	-38.416097	-63.616672
..	...	...	...	...
185	3.85%	55,908,316	55.378051	-3.435973
186	14.70%	270,663,028	37.090240	-95.712891
187	8.73%	3,303,394	-32.522779	-55.765835
191	2.01%	35,332,140	14.058324	108.277199
193	11.43%	7,871,713	-13.133897	27.849332

[110 rows x 35 columns]

```
[49]: df1.columns
```

```
[49]: Index(['Country', 'Density\n(P/Km2)', 'Abbreviation', 'Agricultural Land( %)',
        'Land Area(Km2)', 'Armed Forces size', 'Birth Rate', 'Calling Code',
        'Capital/Major City', 'Co2-Emissions', 'CPI', 'CPI Change (%)',
```

```
'Currency-Code', 'Fertility Rate', 'Forested Area (%)',
'Gasoline Price', 'GDP', 'Gross primary education enrollment (%)',
'Gross tertiary education enrollment (%)', 'Infant mortality',
'Largest city', 'Life expectancy', 'Maternal mortality ratio',
'Minimum wage', 'Official language', 'Out of pocket health expenditure',
'Physicians per thousand', 'Population',
'Population: Labor force participation (%)', 'Tax revenue (%)',
'Total tax rate', 'Unemployment rate', 'Urban_population', 'Latitude',
'Longitude'],
dtype='object')
```

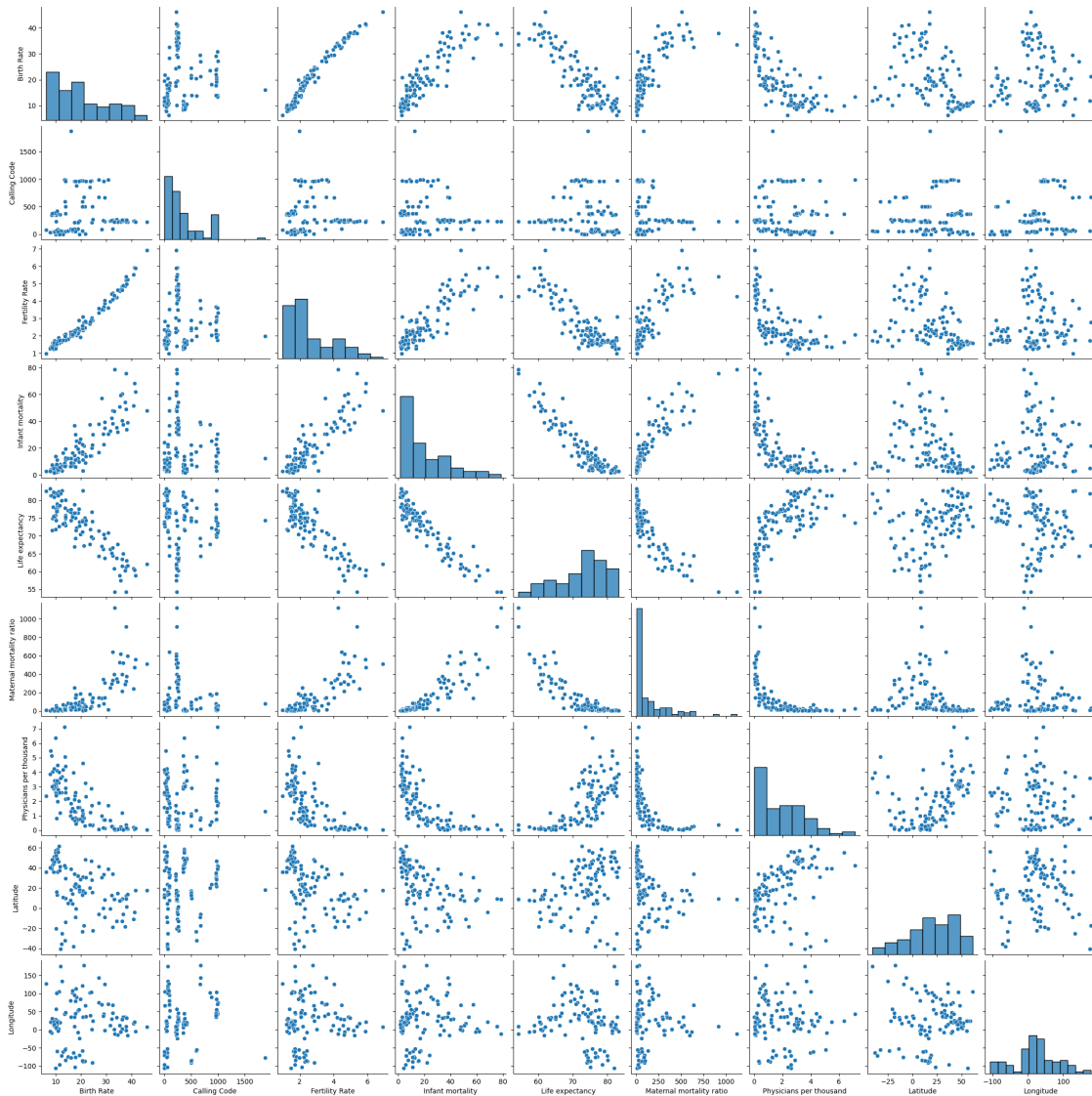
```
[50]: df1=df1[['Country', 'Density\n(P/Km2)', 'Abbreviation', 'Agricultural Land( %)',
'Land Area(Km2)', 'Armed Forces size', 'Birth Rate', 'Calling Code',
'Capital/Major City', 'Co2-Emissions', 'CPI', 'CPI Change (%)',
'Currency-Code', 'Fertility Rate', 'Forested Area (%)',
'Gasoline Price', 'GDP', 'Gross primary education enrollment (%)',
'Gross tertiary education enrollment (%)', 'Infant mortality',
'Largest city', 'Life expectancy', 'Maternal mortality ratio',
'Minimum wage', 'Official language', 'Out of pocket health expenditure',
'Physicians per thousand', 'Population',
'Population: Labor force participation (%)', 'Tax revenue (%)',
'Total tax rate', 'Unemployment rate', 'Urban_population', 'Latitude',
'Longitude']]
```

## 2 EDA AND VISUALIZATION

```
[51]: sns.pairplot(df1)
```

```
[51]: <seaborn.axisgrid.PairGrid at 0x7def98113d60>
```





```
[52]: sns.distplot(df1['Birth Rate'])
```

<ipython-input-52-a422519242bd>:1: UserWarning:

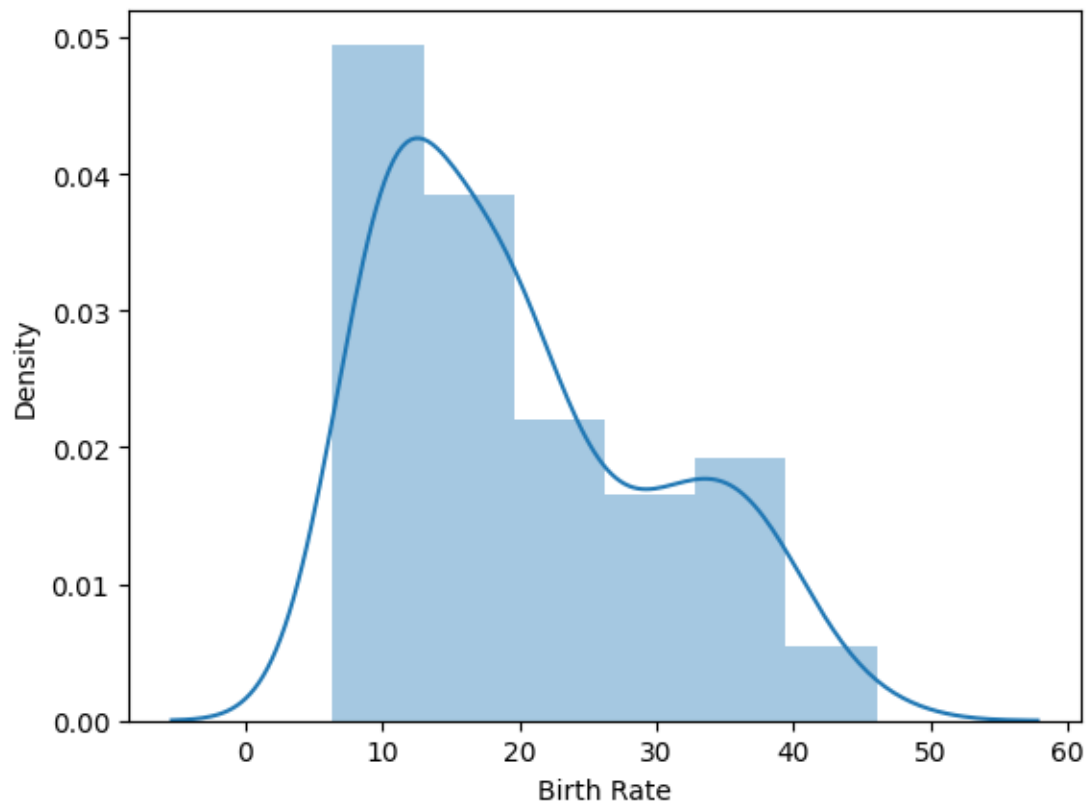
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

```
sns.distplot(df1['Birth Rate'])
```

[52]: <Axes: xlabel='Birth Rate', ylabel='Density'>



```
[53]: sns.heatmap(df1.corr())
```

<ipython-input-53-3ed1a1a51dc0>:1: FutureWarning: The default value of numeric\_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric\_only to silence this warning.

```
sns.heatmap(df1.corr())
```

[53]: <Axes: >



### 3 TO TRAIN THE MODEL AND MODEL BUILDING

```
[ ]: df2=df[['Calling Code','Fertility Rate', 'Infant mortality', 'Life expectancy',
↳ 'Maternal mortality ratio',
      'Physicians per thousand', 'Latitude',
      'Longitude', 'Birth Rate']].dropna()
df2=df2[df['Calling Code']!="NaN"]
df2=df2[df['Fertility Rate']!="NaN"]
df2=df2[df['Infant mortality']!="NaN"]
df2=df2[df['Life expectancy']!="NaN"]
df2=df2[df['Maternal mortality ratio']!="NaN"]
df2=df2[df['Physicians per thousand']!="NaN"]
df2=df2[df['Latitude']!="NaN"]
df2=df2[df['Longitude']!="NaN"]
df2=df2[df['Birth Rate']!="NaN"]
x=df2[['Calling Code','Fertility Rate', 'Infant mortality', 'Life expectancy',
↳ 'Maternal mortality ratio',
```

```

        'Physicians per thousand', 'Latitude',
        'Longitude']]
y=df2['Birth Rate']

```

```

[55]: from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)

```

```

[56]: from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(x_train,y_train)

```

```

[56]: LinearRegression()

```

```

[57]: lr.intercept_

```

```

[57]: 10.733758879073386

```

```

[58]: coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff

```

```

[58]:

```

	Co-efficient
Calling Code	0.001283
Fertility Rate	6.240502
Infant mortality	0.055379
Life expectancy	-0.097915
Maternal mortality ratio	-0.003079
Physicians per thousand	-0.520847
Latitude	-0.012308
Longitude	0.001092

```

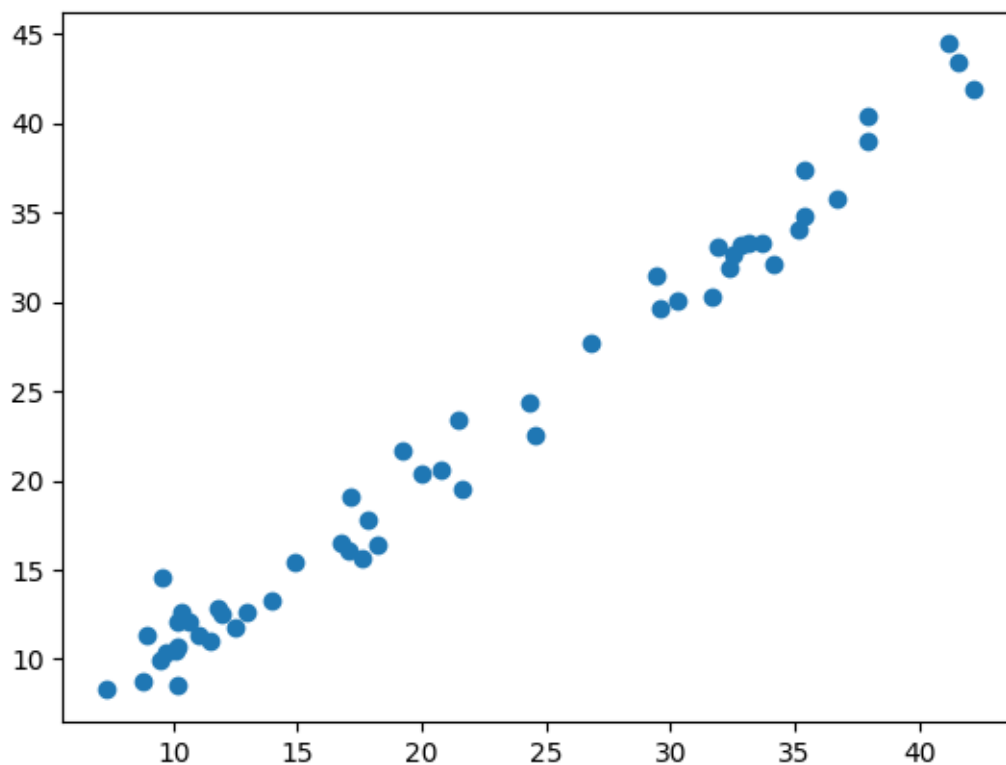
[59]: prediction =lr.predict(x_test)
plt.scatter(y_test,prediction)

```

```

[59]: <matplotlib.collections.PathCollection at 0x7def91e2d9f0>

```



## 4 ACCURACY

```
[60]: lr.score(x_test,y_test)
```

```
[60]: 0.9806877092024798
```

```
[61]: lr.score(x_train,y_train)
```

```
[61]: 0.9751603749732664
```

```
[62]: from sklearn.linear_model import Ridge,Lasso
```

```
[63]: rr=Ridge(alpha=10)  
rr.fit(x_train,y_train)
```

```
[63]: Ridge(alpha=10)
```

```
[64]: rr.score(x_test,y_test)
```

```
[64]: 0.9735184910913641
```

```
[65]: rr.score(x_train,y_train)
```

```
[65]: 0.9696892571133249
```

```
[66]: la=Lasso(alpha=10)  
      la.fit(x_train,y_train)
```

```
[66]: Lasso(alpha=10)
```

```
[67]: la.score(x_test,y_test)
```

```
[67]: 0.7957158842726227
```

```
[68]: la.score(x_train,y_train)
```

```
[68]: 0.7732472649044777
```