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

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression,Lasso,Ridge

df=pd.read_csv("/content/14_Iris.csv")
df

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Specie
0	1	5.1	3.5	1.4	0.2	Iri: setos
1	2	4.9	3.0	1.4	0.2	Iri: setos
2	3	4.7	3.2	1.3	0.2	Iri: setos
3	4	4.6	3.1	1.5	0.2	Iri: setos
4	5	5.0	3.6	1.4	0.2	Iri: setos
	146	6.7	3.0	5.2	2.3	lri: virginic
4						

df=df.drop(["Species"],axis=1)
df

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	1
0	1	5.1	3.5	1.4	0.2	
1	2	4.9	3.0	1.4	0.2	
2	3	4.7	3.2	1.3	0.2	
3	4	4.6	3.1	1.5	0.2	
4	5	5.0	3.6	1.4	0.2	
145	146	6.7	3.0	5.2	2.3	
146	147	6.3	2.5	5.0	1.9	
147	148	6.5	3.0	5.2	2.0	
148	149	6.2	3.4	5.4	2.3	
149	150	5.9	3.0	5.1	1.8	

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
```

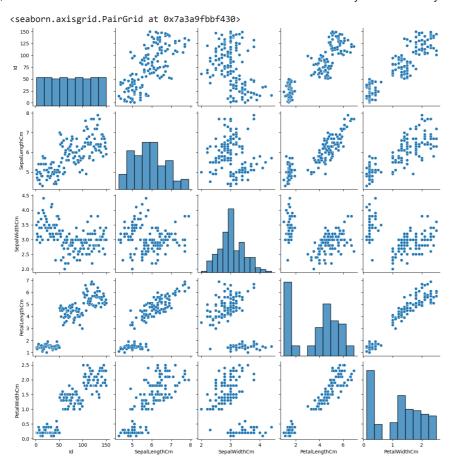
υаτа	columns (total	5 columns):	
#	Column	Non-Null Count	Dtype
0	Id	150 non-null	int64
1	SepalLengthCm	150 non-null	float64
2	SepalWidthCm	150 non-null	float64
3	PetalLengthCm	150 non-null	float64
4	PetalWidthCm	150 non-null	float64
4+,,,,,	sc. £100+64(4)	:n+C1(1)	

dtypes: float64(4), int64(1)
memory usage: 6.0 KB

ilicilior y dadge. 0.0 KE

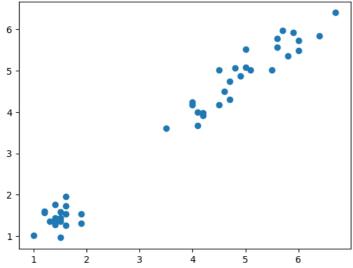
sns.pairplot(df)

 \Box



sns.heatmap(df.corr())

```
7/29/23, 12:27 PM
                                                                           Day 9 - Colaboratory
         <Axes: >
                                                                                     - 1.0
                       ld
                                                                                      - 0.8
                                                                                       0.6
          SepalLengthCm -
                                                                                       0.4
           SepalWidthCm
   y=df['PetalLengthCm']
   x=df.drop(['PetalLengthCm'],axis=1)
   x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
   model=LinearRegression()
   model.fit(x_train,y_train)
   model.intercept_
         0.05270943475182621
                                         £
                                                    무
                                                               문
   coeff=pd.DataFrame(model.coef_,x.columns,columns=["Coefficient"])
                          Coefficient
                             0.001202
          SepalLengthCm
                             0.704042
          SepalWidthCm
                             -0.714965
          PetalWidthCm
                             1.391341
   prediction=model.predict(x test)
   \verb"plt.scatter"(y_test, prediction")"
         <matplotlib.collections.PathCollection at 0x7a3a9efbd3c0>
          6
```



```
model.score(x_test,y_test)
```

0.9732057688319714

```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
la=Lasso(alpha=10)
la.fit(x_train,y_train)
print(rr.score(x_test,y_test))
la.score(x_test,y_test)
```

0.9679230025891463 0.8006190313275552

```
{\tt df1=pd.read\_csv("/content/16\_Sleep\_health\_and\_lifestyle\_dataset.csv")}
```

	Person ID	Gender	Age	Occupation	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	BMI Category	Blood Pressure	Heart Rate	Daily Steps	Sleep Disorder
0	1	Male	27	Software Engineer	6.1	6	42	6	Overweight	126/83	77	4200	None
1	2	Male	28	Doctor	6.2	6	60	8	Normal	125/80	75	10000	None
2	3	Male	28	Doctor	6.2	6	60	8	Normal	125/80	75	10000	None
3	4	Male	28	Sales Representative	5.9	4	30	8	Obese	140/90	85	3000	Sleep Apnea
4	5	Male	28	Sales Representative	5.9	4	30	8	Obese	140/90	85	3000	Sleep Apnea
								•••		•••			
369	370	Female	59	Nurse	8.1	9	75	3	Overweight	140/95	68	7000	Sleep Apnea
370	371	Female	59	Nurse	8.0	9	75	3	Overweight	140/95	68	7000	Sleep Apnea
371	372	Female	59	Nurse	8.1	9	75	3	Overweight	140/95	68	7000	Sleep Apnea
372	373	Female	59	Nurse	8.1	9	75	3	Overweight	140/95	68	7000	Sleep Apnea

df2=df1.drop(["Gender","Occupation","BMI Category","Sleep Disorder","Blood Pressure"],axis=1)
df2

	Person ID	Age	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	Heart Rate	Daily Steps	1	ıl.
0	1	27	6.1	6	42	6	77	4200		
1	2	28	6.2	6	60	8	75	10000		
2	3	28	6.2	6	60	8	75	10000		
3	4	28	5.9	4	30	8	85	3000		
4	5	28	5.9	4	30	8	85	3000		
369	370	59	8.1	9	75	3	68	7000		
370	371	59	8.0	9	75	3	68	7000		
371	372	59	8.1	9	75	3	68	7000		
372	373	59	8.1	9	75	3	68	7000		
373	374	59	8.1	9	75	3	68	7000		
374 rc	ows × 8 colum	ıns								

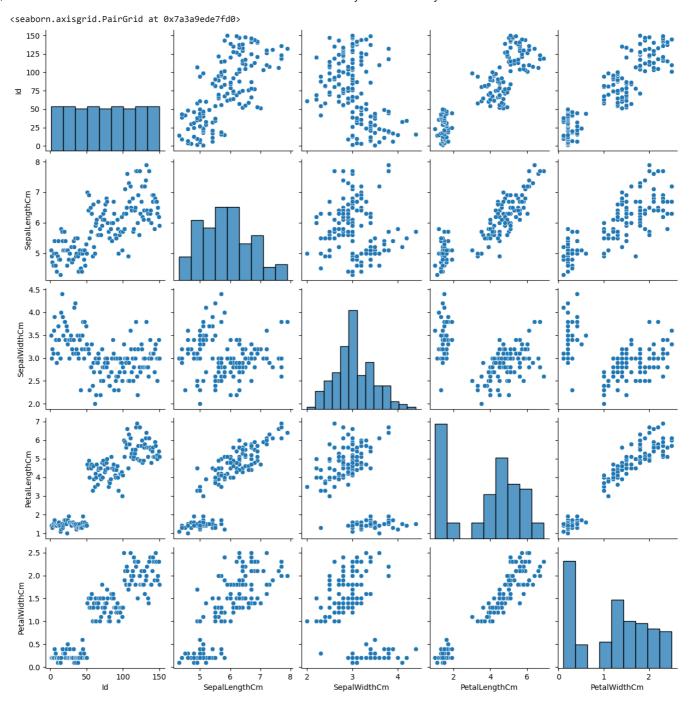
df2.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 374 entries, 0 to 373
Data columns (total 8 columns):

Data	COTUMNIS (COCAT & COTUMNIS)•	
#	Column	Non-Null Count	Dtype
0	Person ID	374 non-null	int64
1	Age	374 non-null	int64
2	Sleep Duration	374 non-null	float64
3	Quality of Sleep	374 non-null	int64
4	Physical Activity Level	374 non-null	int64
5	Stress Level	374 non-null	int64
6	Heart Rate	374 non-null	int64
7	Daily Steps	374 non-null	int64

dtypes: float64(1), int64(7)
memory usage: 23.5 KB

sns.pairplot(df)



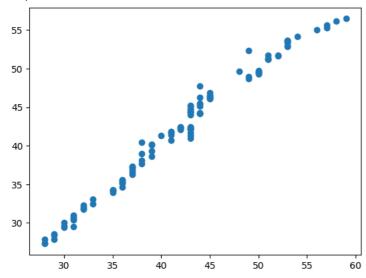
sns.heatmap(df1.corr())

```
<ipython-input-104-3ed1a1a51dc0>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future v
      sns.heatmap(df1.corr())
     <Axes: >
                                                                                       - 1.00
                  Person ID -
                                                                                       - 0.75
                       Age ·
                                                                                        0.50
             Sleep Duration -
                                                                                        0.25
            Quality of Sleen
y=df2['Age']
x=df2.drop(['Age'],axis=1)
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
                                                                                     - -0.25
model=LinearRegression()
model.fit(x_train,y_train)
model.intercept_
     9.70952758771648
coeff=pd.DataFrame(model.coef_,x.columns,columns=["Coefficient"])
coeff
```

	Coefficient	10-	ıl.
Person ID	0.077839		
Sleep Duration	0.271183		
Quality of Sleep	0.716281		
Physical Activity Level	-0.004037		
Stress Level	0.081725		
Heart Rate	0.141143		
Daily Steps	0.000094		

prediction=model.predict(x_test)
plt.scatter(y_test,prediction)

<matplotlib.collections.PathCollection at 0x7a3a9e2b8a30>



```
model.score(x_test,y_test)
```

0.9797045985318592

```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
la=Lasso(alpha=10)
la.fit(x_train,y_train)
print(rr.score(x_test,y_test))
la.score(x_test,y_test)
```

0.9799564320958067 0.9769271400204332

df3=pd.read_csv("/content/17_student_marks.csv")
df3

	Student_ID	Test_1	Test_2	Test_3	Test_4	Test_5	Test_6	Test_7	Test_8	Test_9	Test_10	Test_11	Test_12	1	ılı
0	22000	78	87	91	91	88	98	94	100	100	100	100	93		
1	22001	79	71	81	72	73	68	59	69	59	60	61	67		
2	22002	66	65	70	74	78	86	87	96	88	82	90	86		
3	22003	60	58	54	61	54	57	64	62	72	63	72	76		
4	22004	99	95	96	93	97	89	92	98	91	98	95	88		
5	22005	41	36	35	28	35	36	27	26	19	22	27	31		
6	22006	47	50	47	57	62	64	71	75	85	87	85	89		
7	22007	84	74	70	68	58	59	56	56	64	70	67	59		
8	22008	74	64	58	57	53	51	47	45	42	43	34	24		
9	22009	87	81	73	74	71	63	53	45	39	43	46	38		
10	22010	40	34	37	33	31	35	39	38	40	48	44	50		

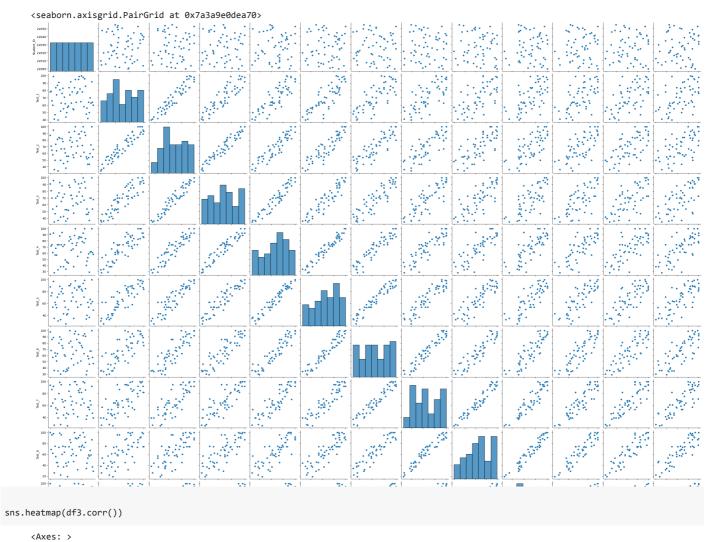
df3.info()

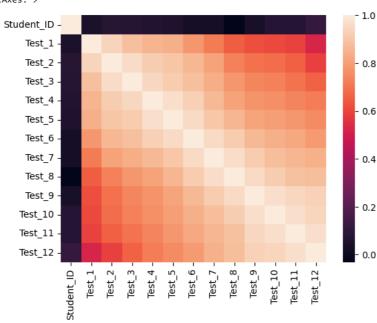
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56 entries, 0 to 55
Data columns (total 13 columns):
Column Non-Null Count Dtype

Ŧ	Column	Non-Null Count	υτуре
0	Student_ID	56 non-null	int64
1	Test_1	56 non-null	int64
2	Test_2	56 non-null	int64
3	Test_3	56 non-null	int64
4	Test_4	56 non-null	int64
5	Test_5	56 non-null	int64
6	Test_6	56 non-null	int64
7	Test_7	56 non-null	int64
8	Test_8	56 non-null	int64
9	Test_9	56 non-null	int64
10	Test_10	56 non-null	int64
11	Test_11	56 non-null	int64
12	Test_12	56 non-null	int64
dtvp	es: int64(13)	

dtypes: int64(13) memory usage: 5.8 KB

sns.pairplot(df3)





```
y=df3['Test_2']
x=df3.drop(['Student_ID',"Test_2"],axis=1)
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

```
model=LinearRegression()
model.fit(x_train,y_train)
model.intercept_
```

1.82330302617234

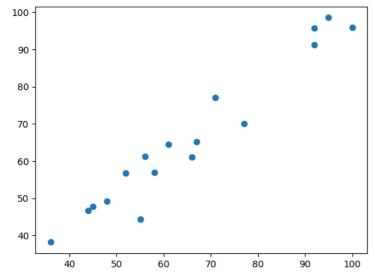
coeff=pd.DataFrame(model.coef_,x.columns,columns=["Coefficient"])
coeff

	Coefficient	7	ıl.
Test_1	0.407266		
Test_3	0.470980		
Test_4	0.022131		
Test_5	0.045375		
Test_6	-0.079965		
Test_7	0.252799		
Test_8	-0.003530		
Test_9	-0.183875		
Test_10	-0.035321		
Test_11	0.282963		
Test_12	-0.202148		

plt.scatter(y_test,prediction)

prediction=model.predict(x_test)

<matplotlib.collections.PathCollection at 0x7a3a94a32860>



 ${\tt model.score}(x_{\tt test}, y_{\tt test})$

0.9426166099503436

```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
la=Lasso(alpha=10)
```

 $\label{eq:df4} $$ df4=pd.read_csv("/content/18_world-data-2023.csv") $$ df4$

	Country	Density\n(P/Km2)	Abbreviation	Agricultural Land(%)	Land Area(Km2)	Armed Forces size	Birth Rate	Calling Code	Capital/Major City	Co2- Emissions	 exp
0	Afghanistan	60	AF	58.10%	652,230	323,000	32.49	93.0	Kabul	8,672	
1	Albania	105	AL	43.10%	28,748	9,000	11.78	355.0	Tirana	4,536	
2	Algeria	18	DZ	17.40%	2,381,741	317,000	24.28	213.0	Algiers	150,006	
3	Andorra	164	AD	40.00%	468	NaN	7.20	376.0	Andorra la Vella	469	
4	Angola	26	AO	47.50%	1,246,700	117,000	40.73	244.0	Luanda	34,693	
190	Venezuela	32	VE	24.50%	912,050	343,000	17.88	58.0	Caracas	164,175	
191	Vietnam	314	VN	39.30%	331,210	522,000	16.75	84.0	Hanoi	192,668	
192	Yemen	56	YE	44.60%	527,968	40,000	30.45	967.0	Sanaa	10,609	
193	Zambia	25	ZM	32.10%	752,618	16,000	36.19	260.0	Lusaka	5,141	
194	Zimbabwe	38	ZW	41.90%	390,757	51,000	30.68	263.0	Harare	10,983	
105 rc	× 25 oolum	200									

195 rows × 35 columns





df4.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 195 entries, 0 to 194

```
Data columns (total 35 columns):
                                              Non-Null Count Dtype
# Column
___
0
   Country
                                              195 non-null
                                                             object
    Density
1
(P/Km2)
                                  195 non-null
                                                object
                                              188 non-null
2 Abbreviation
                                                            object
    Agricultural Land( %)
                                              188 non-null
 3
                                                              object
    Land Area(Km2)
                                              194 non-null
                                                              object
                                                              object
 5
    Armed Forces size
                                              171 non-null
 6
    Birth Rate
                                              189 non-null
                                                              float64
    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
                                                              float64
 13 Fertility Rate
                                              188 non-null
14 Forested Area (%)
                                              188 non-null
                                                              object
 15 Gasoline Price
                                              175 non-null
                                                              obiect
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
                                              187 non-null
                                                              float64
 21 Life expectancy
 22 Maternal mortality ratio
                                              181 non-null
                                                              float64
23 Minimum wage
                                              150 non-null
                                                              obiect
 24 Official language
                                              194 non-null
                                                              obiect
 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
    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
                                              194 non-null
 34 Longitude
                                                              float64
```

dtypes: float64(9), object(26)
memory usage: 53.4+ KB

```
df4=df4.dropna()
df4
```

	Country	Density\n(P/Km2)	Abbreviation	Agricultural Land(%)	Land Area(Km2)	Armed Forces size	Birth Rate	Calling Code	Capital/Major City	Co2- Emissions	•••	ex
0	Afghanistan	60	AF	58.10%	652,230	323,000	32.49	93.0	Kabul	8,672		
1	Albania	105	AL	43.10%	28,748	9,000	11.78	355.0	Tirana	4,536		
2	Algeria	18	DZ	17.40%	2,381,741	317,000	24.28	213.0	Algiers	150,006		
4	Angola	26	AO	47.50%	1,246,700	117,000	40.73	244.0	Luanda	34,693		
6	Argentina	17	AR	54.30%	2,780,400	105,000	17.02	54.0	Buenos Aires	201,348		
185	United Kingdom	281	GB	71.70%	243,610	148,000	11.00	44.0	London	379,025		
186	United States	36	US	44.40%	9,833,517	1,359,000	11.60	1.0	Washington, D.C.	5,006,302		
187	Uruguay	20	UY	82.60%	176,215	22,000	13.86	598.0	Montevideo	6,766		
191	Vietnam	314	VN	39.30%	331,210	522,000	16.75	84.0	Hanoi	192,668		
193	Zambia	25	ZM	32.10%	752,618	16,000	36.19	260.0	Lusaka	5,141		

110 rows × 35 columns

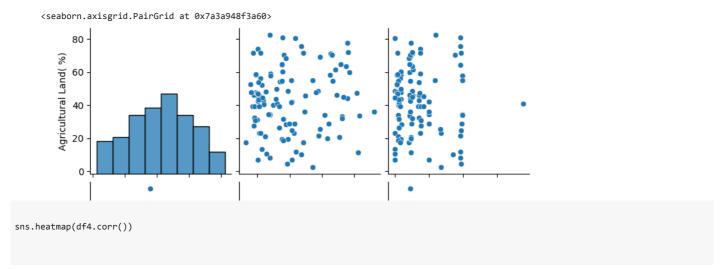




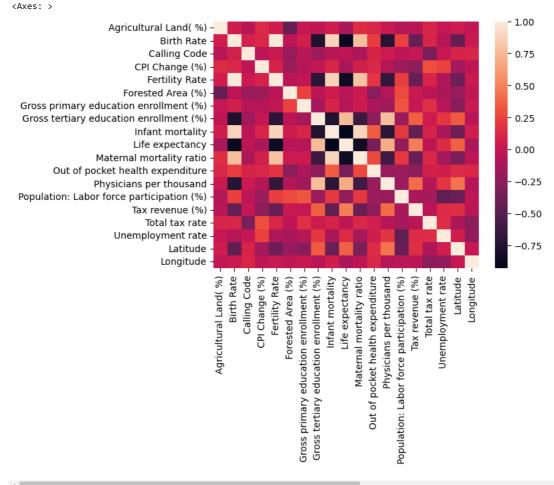
df4=df4.drop(["Country", "Abbreviation", "Capital/Major City", "Currency-Code", "Largest city", "Official language", "Minimum wage", "Gasoline F df4["Agricultural Land(%)"]=df4["Agricultural Land(%)"].replace("%","", regex=True).astype(float)
df4["CPI Change (%)"]=df4["Forested Area (%)"].replace("%","", regex=True).astype(float)
df4["Forested Area (%)"]=df4["Forested Area (%)"].replace("%","", regex=True).astype(float)
df4["Gross primary education enrollment (%)"]=df4["Gross primary education enrollment (%)"].replace("%","", regex=True).astype(float)
df4["Gross tertiary education enrollment (%)"]=df4["Gross tertiary education enrollment (%)"].replace("%","", regex=True).astype(float)
df4["Out of pocket health expenditure"]=df4["Out of pocket health expenditure"].replace("%", "", regex=True).astype(float)
df4["Population: Labor force participation (%)"]=df4["Population: Labor force participation (%)"].replace("%", "", regex=True).astype(float)
df4["Tax revenue (%)"]=df4["Tax revenue (%)"].replace("%", "", regex=True).astype(float)
df4["Total tax rate"]=df4["Unemployment rate"].replace("%", "", regex=True).astype(float)
df4["Unemployment rate"]=df4["Unemployment rate"].replace("%", "", regex=True).astype(float)

df4=df4.drop(["GDP"],axis=1)

sns.pairplot(df4.iloc[:,:8])



<ipython-input-127-16ec28ac65e5>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future v
 sns.heatmap(df4.corr())



```
df4=df4.replace(",",","",regex=True)
df4=df4.astype(float)

y=df4['Fertility Rate']
x=df4.drop(['Fertility Rate'],axis=1)
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)

model=LinearRegression()
model.fit(x_train,y_train)
model.intercept_
```

1.2208407111776067

coeff=pd.DataFrame(model.coef_,x.columns,columns=["Coefficient"])
coeff

	Coefficient	7	11.
Density\n(P/Km2)	1.166185e-05		
Agricultural Land(%)	-1.259609e-03		
Land Area(Km2)	-4.361556e-09		
Armed Forces size	-9.837214e-08		
Birth Rate	1.376233e-01		
Calling Code	-1.867638e-04		
Co2-Emissions	-1.275433e-09		
CPI	2.296431e-04		
CPI Change (%)	-5.367021e-03		
Forested Area (%)	-1.410413e-03		
Gross primary education enrollment (%)	-6.752963e-03		
Gross tertiary education enrollment (%)	1.980932e-03		
Infant mortality	-3.247107e-03		
Life expectancy	-9.387256e-03		
Maternal mortality ratio	4.303126e-04		
Out of pocket health expenditure	-3.783321e-03		
Physicians per thousand	7.280566e-02		
Population	2.246167e-10		
Population: Labor force participation (%)	2.028631e-03		
Tax revenue (%)	-2.334029e-03		
Total tax rate	5.861105e-04		
Unemployment rate	-6.325363e-03		
Urban_population	1.683495e-10		
Latitude	2.627209e-03		
Longitude	4.304176e-04		

 ${\tt prediction=model.predict(x_test)}$

plt.scatter(y_test,prediction)