Problem Statement

Linear Regression ¶

Import Libraries

In [1]:

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

In [2]:

```
a=pd.read_csv("world.csv")
a
```

Out[2]:

	Country	Density\n(P/Km2)	Abbreviation	Agricultural Land(%)	Land Area(Km2)	Armed Forces size	Birth Rate	Calling Code	Capital/M
0	Afghanistan	60	AF	58.10%	652,230	323,000	32.49	93.0	Ka
1	Albania	105	AL	43.10%	28,748	9,000	11.78	355.0	Tir
2	Algeria	18	DZ	17.40%	2,381,741	317,000	24.28	213.0	Alg
3	Andorra	164	AD	40.00%	468	NaN	7.20	376.0	Andorr V
4	Angola	26	AO	47.50%	1,246,700	117,000	40.73	244.0	Lua
...	...	...	...	...	...	...	...	...	
190	Venezuela	32	VE	24.50%	912,050	343,000	17.88	58.0	Cara
191	Vietnam	314	VN	39.30%	331,210	522,000	16.75	84.0	Ha

To display top 10 rows

In [3]:

```
c=a.head(15)
c
```

Out[3]:

	Country	Density\n(P/Km2)	Abbreviation	Agricultural Land(%)	Land Area(Km2)	Armed Forces size	Birth Rate	Calli Co
0	Afghanistan	60	AF	58.10%	652,230	323,000	32.49	93
1	Albania	105	AL	43.10%	28,748	9,000	11.78	355
2	Algeria	18	DZ	17.40%	2,381,741	317,000	24.28	213
3	Andorra	164	AD	40.00%	468	NaN	7.20	376
4	Angola	26	AO	47.50%	1,246,700	117,000	40.73	244
5	Antigua and Barbuda	223	AG	20.50%	443	0	15.33	1
6	Argentina	17	AR	54.30%	2,780,400	105,000	17.02	54
7	Armenia	104	AM	58.90%	29,743	49,000	13.99	374
8	Australia	3	AU	48.20%	7,741,220	58,000	12.60	61
9	Austria	109	AT	32.40%	83,871	21,000	9.70	43
10	Azerbaijan	123	AZ	57.70%	86,600	82,000	14.00	994
11	The Bahamas	39	BS	1.40%	13,880	1,000	13.97	1
12	Bahrain	2,239	BH	11.10%	765	19,000	13.99	973
13	Bangladesh	1,265	BD	70.60%	148,460	221,000	18.18	880
14	Barbados	668	BB	23.30%	430	1,000	10.65	1

15 rows × 35 columns

To find Missing values

In [4]:

```
c.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15 entries, 0 to 14
Data columns (total 35 columns):
 #   Column                                    Non-Null Count  Dtype  
---  ------                                    --------------  -----  
 0   Country                                   15 non-null     object 
 1   Density
(P/Km2)                          15 non-null     object 
 2   Abbreviation                              15 non-null     object 
 3   Agricultural Land( %)                     15 non-null     object 
 4   Land Area(Km2)                            15 non-null     object 
 5   Armed Forces size                         14 non-null     object 
 6   Birth Rate                                15 non-null     float64
 7   Calling Code                              15 non-null     float64
 8   Capital/Major City                        15 non-null     object 
 9   Co2-Emissions                             15 non-null     object 
 10  CPI                                       14 non-null     object 
 11  CPI Change (%)                            14 non-null     object 
 12  Currency-Code                             14 non-null     object 
 13  Fertility Rate                            15 non-null     float64
 14  Forested Area (%)                         15 non-null     object 
 15  Gasoline Price                            15 non-null     object 
 16  GDP                                       15 non-null     object 
 17  Gross primary education enrollment (%)    15 non-null     object 
 18  Gross tertiary education enrollment (%)   14 non-null     object 
 19  Infant mortality                          15 non-null     float64
 20  Largest city                              15 non-null     object 
 21  Life expectancy                           14 non-null     float64
 22  Maternal mortality ratio                  14 non-null     float64
 23  Minimum wage                              13 non-null     object 
 24  Official language                         15 non-null     object 
 25  Out of pocket health expenditure          15 non-null     object 
 26  Physicians per thousand                   15 non-null     float64
 27  Population                                15 non-null     object 
 28  Population: Labor force participation (%) 13 non-null     object 
 29  Tax revenue (%)                           14 non-null     object 
 30  Total tax rate                            14 non-null     object 
 31  Unemployment rate                         13 non-null     object 
 32  Urban_population                          15 non-null     object 
 33  Latitude                                  15 non-null     float64
 34  Longitude                                 15 non-null     float64
dtypes: float64(9), object(26)
memory usage: 4.2+ KB
```

To display summary of statistics

In [5]:

```
a.describe()
```

Out[5]:

	Birth Rate	Calling Code	Fertility Rate	Infant mortality	Life expectancy	Maternal mortality ratio	Physicians per thousand
count	189.000000	194.000000	188.000000	189.000000	187.000000	181.000000	188.000000
mean	20.214974	360.546392	2.698138	21.332804	72.279679	160.392265	1.839840
std	9.945774	323.236419	1.282267	19.548058	7.483661	233.502024	1.684261
min	5.900000	1.000000	0.980000	1.400000	52.800000	2.000000	0.010000
25%	11.300000	82.500000	1.705000	6.000000	67.000000	13.000000	0.332500
50%	17.950000	255.500000	2.245000	14.000000	73.200000	53.000000	1.460000
75%	28.750000	506.750000	3.597500	32.700000	77.500000	186.000000	2.935000
max	46.080000	1876.000000	6.910000	84.500000	85.400000	1150.000000	8.420000

To display column heading

In [6]:

```
a.columns
```

Out[6]:

```
Index(['Country', 'Density\n(P/Km2)', 'Abbreviation', 'Agricultural Land(
%)',
       'Land Area(Km2)', 'Armed Forces size', 'Birth Rate', 'Calling Cod
e',
       '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 expendit
ure',
       'Physicians per thousand', 'Population',
       'Population: Labor force participation (%)', 'Tax revenue (%)',
       'Total tax rate', 'Unemployment rate', 'Urban_population', 'Latitud
e',
       'Longitude'],
      dtype='object')
```

Pairplot

In [7]:

```
s=a.dropna(axis=1)
s
```

Out[7]:

	Country	Density\n(P/Km2)
0	Afghanistan	60
1	Albania	105
2	Algeria	18
3	Andorra	164
4	Angola	26
...	...	...
190	Venezuela	32
191	Vietnam	314
192	Yemen	56
193	Zambia	25
194	Zimbabwe	38

195 rows × 2 columns

In [8]:

```
s.columns
```

Out[8]:

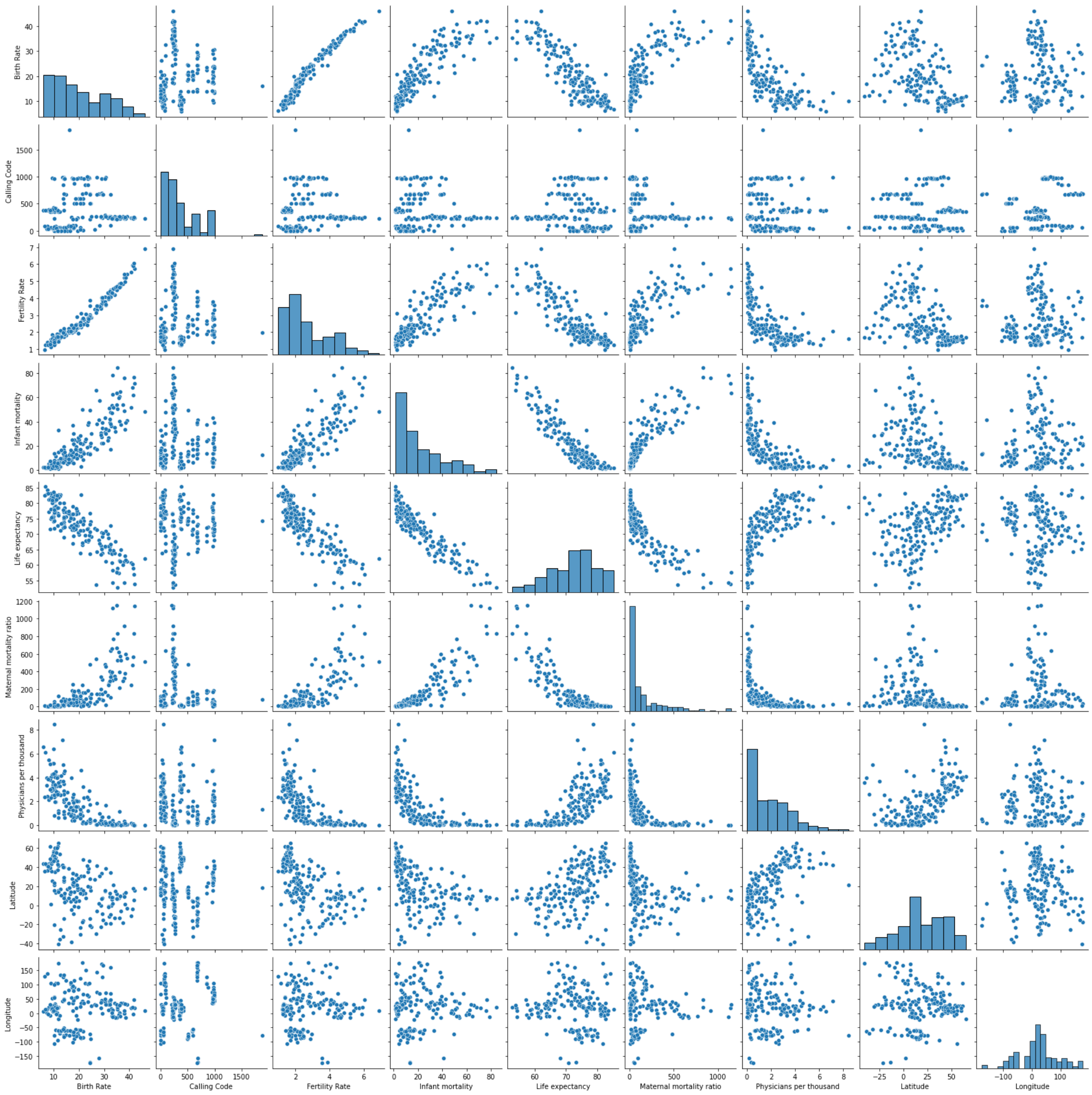
```
Index(['Country', 'Density\n(P/Km2)'], dtype='object')
```

In [9]:

```
sns.pairplot(a)
```

Out[9]:

```
<seaborn.axisgrid.PairGrid at 0x272f0cd5370>
```



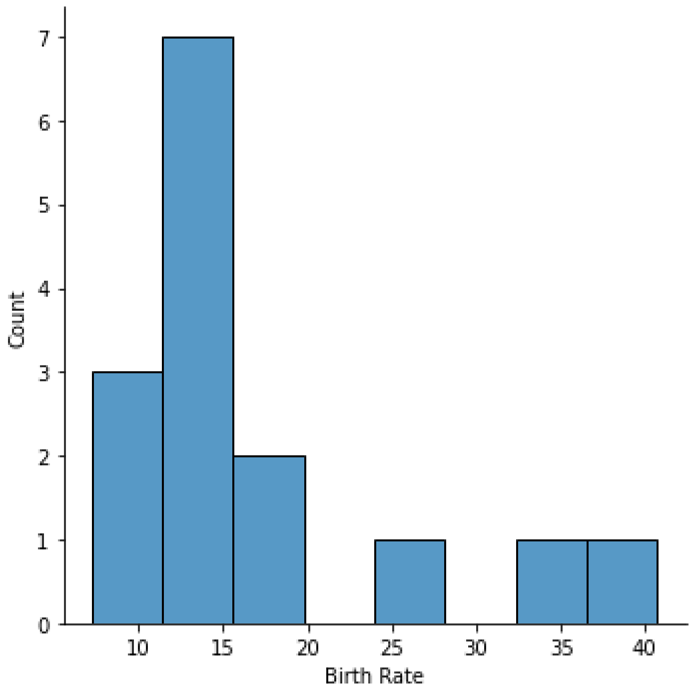
Distribution Plot

In [10]:

```
sns.displot(c['Birth Rate'])
```

Out[10]:

```
<seaborn.axisgrid.FacetGrid at 0x272f3544fd0>
```



Correlation

In [11]:

```
b=a[['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']]
sns.heatmap(b.corr())
```

Out[11]:

<AxesSubplot:>

Train the model - Model Building

In [12]:

```
g=c[['Birth Rate']]
h=c['Birth Rate']
```

To split dataset into training end test

In [13]:

```
from sklearn.model_selection import train_test_split
g_train,g_test,h_train,h_test=train_test_split(g,h,test_size=0.6)
```

To run the model

In [14]:

```
from sklearn.linear_model import LinearRegression
```

In [15]:

```
lr=LinearRegression()
lr.fit(g_train,h_train)
```

Out[15]:

```
LinearRegression()
```

In [16]:

```
print(lr.intercept_)
```

```
-1.0658141036401503e-14
```

Coeffecient

In [17]:

```
coeff=pd.DataFrame(lr.coef_,g.columns,columns=['Co-effecient'])
coeff
```

Out[17]:

	Co-effecient
Birth Rate	1.0

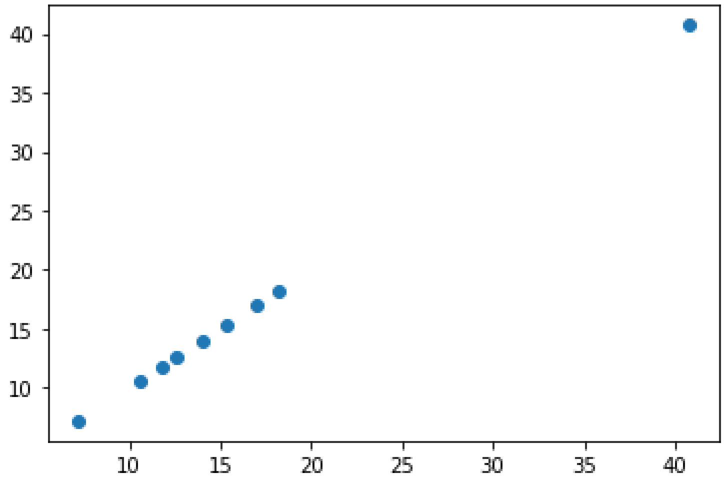
Best Fit line

In [18]:

```
prediction=lr.predict(g_test)
plt.scatter(h_test,prediction)
```

Out[18]:

```
<matplotlib.collections.PathCollection at 0x272f5bf67c0>
```



To find score

In [19]:

```
print(lr.score(g_test,h_test))
```

```
1.0
```

Import Lasso and ridge

In [20]:

```
from sklearn.linear_model import Ridge,Lasso
```

Ridge

In [21]:

```
ri=Ridge(alpha=5)
ri.fit(g_train,h_train)
```

Out[21]:

```
Ridge(alpha=5)
```

In [22]:

```
ri.score(g_test,h_test)
```

Out[22]:

```
0.9998128127752102
```

In [23]:

```
ri.score(g_train,h_train)
```

Out[23]:

```
0.999818933367054
```

Lasso

In [24]:

```
l=Lasso(alpha=6)
l.fit(g_train,h_train)
```

Out[24]:

```
Lasso(alpha=6)
```

In [25]:

```
l.score(g_test,h_test)
```

Out[25]:

```
0.9900296967569474
```

In [27]:

```
ri.score(g_train,h_train)
```

Out[27]:

```
0.999818933367054
```

ElasticNet

In [28]:

```
from sklearn.linear_model import ElasticNet
e=ElasticNet()
e.fit(g_train,h_train)
```

Out[28]:

```
ElasticNet()
```

Coeffecient,intercept

In [29]:

```
print(e.coef_)
```

```
[0.9837653]
```

In [30]:

```
print(e.intercept_)
```

```
0.29338813327121827
```

Prediction

In [31]:

```
d=e.predict(g_test)
d
```

Out[31]:

```
array([40.3621487 ,  7.37649827, 12.68883088, 10.77048855, 17.0370735 ,
       11.88214334, 14.05626464, 15.37451014, 18.17824124])
```

In [32]:

```
print(e.score(g_test,h_test))
```

```
0.999727525130763
```

Evaluation

In [33]:

```
from sklearn import metrics
print("Mean Absolute error:",metrics.mean_absolute_error(h_test,d))
```

```
Mean Absolute error: 0.10949104312669228
```

In [34]:

```
print("Mean Squared error:",metrics.mean_squared_error(h_test,d))
```

```
Mean Squared error: 0.02288607251677668
```

In [35]:

```
print("Mean Squared error:",np.sqrt(metrics.mean_squared_error(h_test,d)))
```

```
Mean Squared error: 0.15128143480538742
```

In [ ]:

```

```