Problem Statement

A real estate agent want help to predict the house price for regions in USA.He gave us the dataset to work on to use linear regression model.Create a model that helps him to estimate of what the house would sell for

Import libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# To import dataset
df=pd.read_csv('18 world csv')
df
```

Out[2]:

	Country	Density\n(P/Km2)	Abbreviation	Agricultural Land(%)	Land Area(Km2)	Armed Forces size	Birth Rate	Calling Code	Capital/Ma C
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	Tira
2	Algeria	18	DZ	17.40%	2,381,741	317,000	24.28	213.0	Algi
3	Andorra	164	AD	40.00%	468	NaN	7.20	376.0	Andorra Ve
4	Angola	26	AO	47.50%	1,246,700	117,000	40.73	244.0	Luan
...	...	...	...	...	...	...	...	...	
190	Venezuela	32	VE	24.50%	912,050	343,000	17.88	58.0	Carac
191	Vietnam	314	VN	39.30%	331,210	522,000	16.75	84.0	Ha
192	Yemen	56	YE	44.60%	527,968	40,000	30.45	967.0	San
193	Zambia	25	ZM	32.10%	752,618	16,000	36.19	260.0	Lusa
194	Zimbabwe	38	ZW	41.90%	390,757	51,000	30.68	263.0	Hara

195 rows × 35 columns

In [3]:
```
# To display top 10 rows
df.head(10)
```

Out[3]:

	Country	Density\n(P/Km2)	Abbreviation	Agricultural Land(%)	Land Area(Km2)	Armed Forces size	Birth Rate	Calling Code	Capital/Major City
0	Afghanistan	60	AF	58.10%	652,230	323,000	32.49	93.0	Kabu
1	Albania	105	AL	43.10%	28,748	9,000	11.78	355.0	Tirana
2	Algeria	18	DZ	17.40%	2,381,741	317,000	24.28	213.0	Algiers
3	Andorra	164	AD	40.00%	468	NaN	7.20	376.0	Andorra la Vella
4	Angola	26	AO	47.50%	1,246,700	117,000	40.73	244.0	Luanda
5	Antigua and Barbuda	223	AG	20.50%	443	0	15.33	1.0	St. John's, Saint John
6	Argentina	17	AR	54.30%	2,780,400	105,000	17.02	54.0	Buenos Aires
7	Armenia	104	AM	58.90%	29,743	49,000	13.99	374.0	Yerevan
8	Australia	3	AU	48.20%	7,741,220	58,000	12.60	61.0	Canberra
9	Austria	109	AT	32.40%	83,871	21,000	9.70	43.0	Vienna

10 rows × 35 columns

Data Cleaning and Pre-Processing

In [4]:
```
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
```

In [5]:
```
df.describe()
```

Out[5]:

	Birth Rate	Calling Code	Fertility Rate	Infant mortality	Life expectancy	Maternal mortality ratio	Physicians per thousand	Latitude
count	189.000000	194.000000	188.000000	189.000000	187.000000	181.000000	188.000000	194.000000
mean	20.214974	360.546392	2.698138	21.332804	72.279679	160.392265	1.839840	19.092351
std	9.945774	323.236419	1.282267	19.548058	7.483661	233.502024	1.684261	23.961779
min	5.900000	1.000000	0.980000	1.400000	52.800000	2.000000	0.010000	-40.900557
25%	11.300000	82.500000	1.705000	6.000000	67.000000	13.000000	0.332500	4.544175
50%	17.950000	255.500000	2.245000	14.000000	73.200000	53.000000	1.460000	17.273849
75%	28.750000	506.750000	3.597500	32.700000	77.500000	186.000000	2.935000	40.124603
max	46.080000	1876.000000	6.910000	84.500000	85.400000	1150.000000	8.420000	64.963051

In [6]:
```
df.columns
```

Out[6]:
```
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')
```

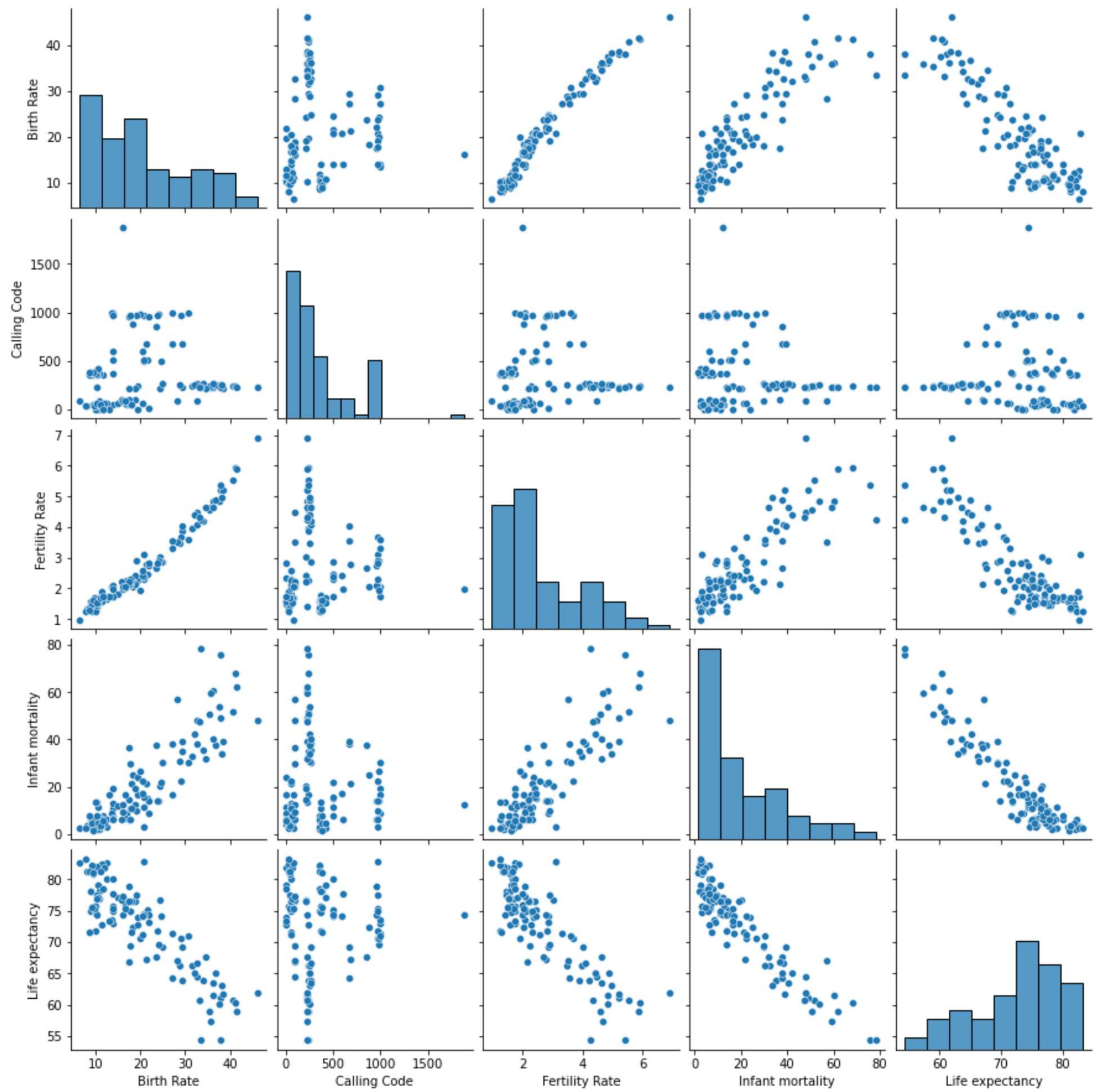
In [7]:
```
a = df.dropna()
a.columns
```

Out[7]:
```
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')
```

EDA and Visualization

In [8]:
```
sns.pairplot(a[['Birth Rate', 'Calling Code', 'Fertility Rate', 'Infant mortality',
        'Life expectancy']])
```

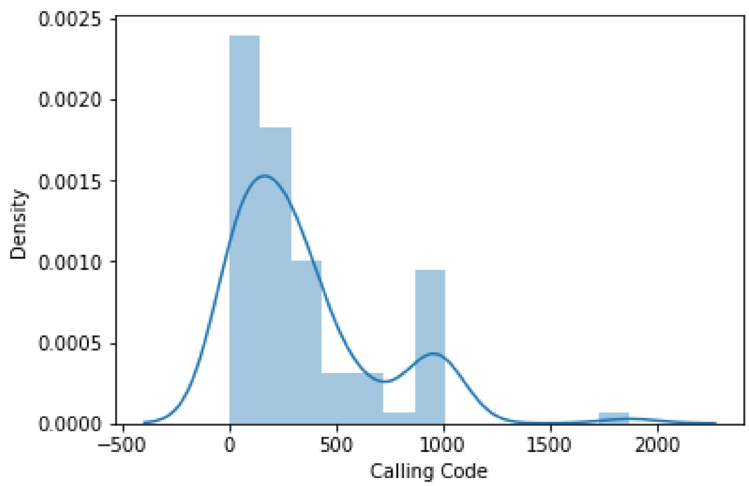
Out[8]: <seaborn.axisgrid.PairGrid at 0x1283e2d4160>



In [9]:
```
sns.distplot(a['Calling Code'])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarnin
g: `distplot` is a deprecated function and will be removed in a future version. Please
adapt your code to use either `displot` (a figure-level function with similar flexibil
ity) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

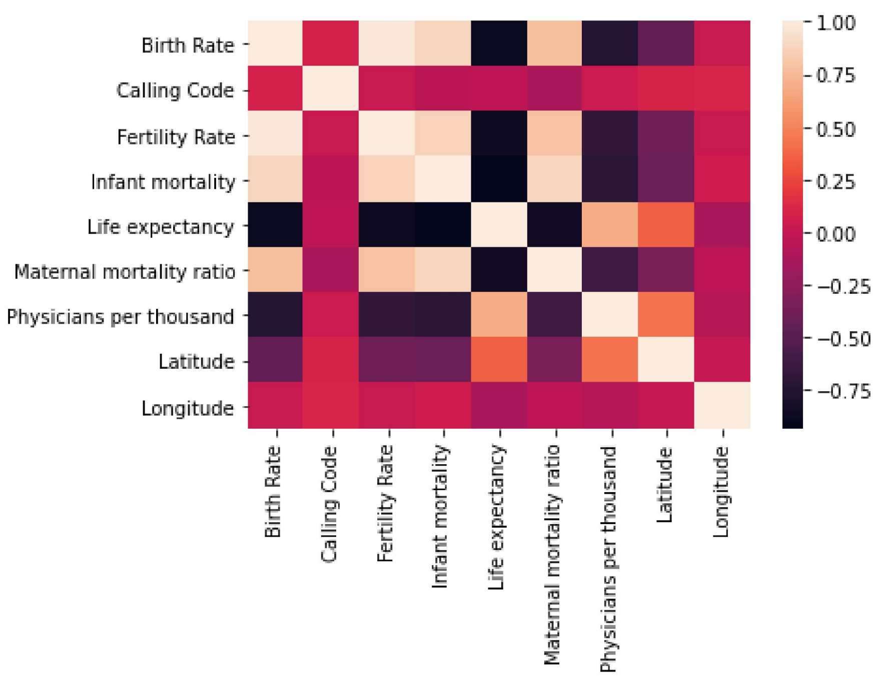
Out[9]: <AxesSubplot:xlabel='Calling Code', ylabel='Density'>



In [10]:
```
a1=a[[ 'Birth Rate', 'Calling Code', 'Fertility Rate', 'Infant mortality',
       'Life expectancy', 'Maternal mortality ratio','Physicians per thousand',
       'Latitude',  'Longitude']]
```

In [11]:
```
sns.heatmap(a1.corr())
```

Out[11]: <AxesSubplot:>



To Train the Model - Model Building

We are going to train Linear Regression model;We need to split out data into two variables x and y where x is independent variable (input) and y is dependent on x(output). We could ignore address column as it is not required for our model.

In [12]:
```
x=a1[['Birth Rate', 'Calling Code', 'Fertility Rate', 'Infant mortality',
       'Life expectancy', 'Maternal mortality ratio','Physicians per thousand',
       'Latitude',  'Longitude']]
y=a1['Calling Code']
```

To split my dataset into training and test data

In [13]:
```
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)
```

In [14]:
```
from sklearn.linear_model import LinearRegression

lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[14]:
```
LinearRegression()
```

In [15]:
```
print(lr.intercept_)
```

```
-9.094947017729282e-13
```

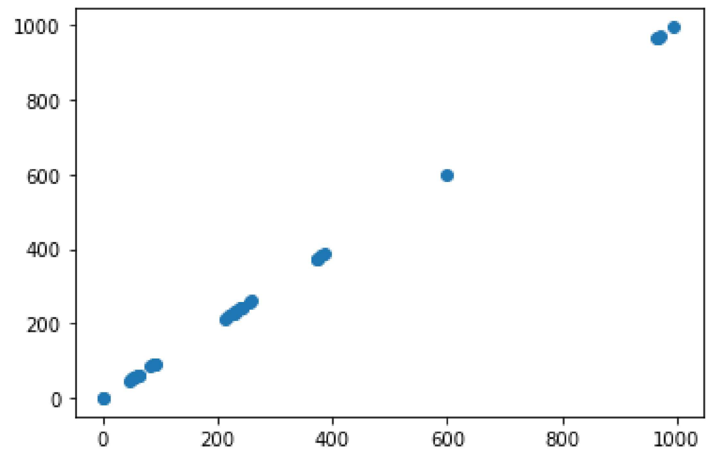
In [16]:
```
coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

Out[16]:

	Co-efficient
Birth Rate	5.721086e-14
Calling Code	1.000000e+00
Fertility Rate	-4.327835e-13
Infant mortality	9.598178e-15
Life expectancy	1.427610e-14
Maternal mortality ratio	-7.384279e-18
Physicians per thousand	-1.313557e-15
Latitude	4.254127e-16
Longitude	1.933811e-16

In [17]:
```
prediction=lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[17]: <matplotlib.collections.PathCollection at 0x12840321250>



In [18]:
```
print(lr.score(x_test,y_test))
```

1.0

ACCURACY

In [19]:
```
from sklearn.linear_model import Ridge,Lasso
```

In [20]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
rr.score(x_test,y_test)
rr.score(x_train,y_train)
```

Out[20]: 0.9999999999987259

In [21]:
```
rr.score(x_test,y_test)
```

Out[21]: 0.9999999999975898

In [22]:
```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[22]: Lasso(alpha=10)

In [23]:
```
la.score(x_test,y_test)
```

Out[23]: 0.9999999932306496

In [24]:
```
from sklearn.linear_model import ElasticNet
en = ElasticNet()
en.fit(x_train,y_train)
```

Out[24]: ElasticNet()

In [25]:
```
print(en.coef_)
```

```
[ 0.          0.99999212  0.          0.         -0.         -0.
 -0.          0.          0.        ]
```

In [26]:
```
print(en.intercept_)
```

```
0.002917744443323045
```

In [27]:
```
print(en.predict(x_test))
```

```
[371.99998659 597.99820584  84.00225587 385.99987628 372.99997872
 994.99507771  48.00253953  55.00248438 241.0010188    1.00290987
   1.00290987 243.00100304 238.00104244  62.00242922 230.00110547
 971.99525893 221.00117639  91.00220072 963.99532197 229.00111335
 967.99529045 244.00099516  63.00242134  92.00219284  60.00244498
  90.0022086   56.0024765  380.99991568 260.00086909 212.0012473
  49.00253165 255.00090849 225.00114487]
```

In [28]:
```
print(en.score(x_test,y_test))
```

```
0.999999999932307
```

In [29]:
```
from sklearn import metrics
print("Mean Absolytre Error:",metrics.mean_absolute_error(y_test,prediction))
print("Mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
print("Root Mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
Mean Absolytre Error: 2.90878432451791e-13
Mean Squared Error: 1.107136190215131e-25
Root Mean Squared Error: 3.3273656099309724e-13
```