

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

Data Collection

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

```
In [155]: #import the dataset
data=pd.read_csv(r"C:\Users\user\Desktop\Vicky\18_world-data-2023.csv")[0:50]
```

```
In [156]: #to display top 10 rows
data.head()
```

Out[156]:

	Country	Density\n(P/Km2)	Abbreviation	Agricultural Land(%)	Land Area(Km2)	Armed Forces size	Birth Rate	Calling Code	Capital/Major City	Co2 Emission:
0	Afghanistan	60	AF	58.10%	652,230	323,000	32.49	93.0	Kabul	8,67:
1	Albania	105	AL	43.10%	28,748	9,000	11.78	355.0	Tirana	4,53:
2	Algeria	18	DZ	17.40%	2,381,741	317,000	24.28	213.0	Algiers	150,00:
3	Andorra	164	AD	40.00%	468	NaN	7.20	376.0	Andorra la Vella	46:
4	Angola	26	AO	47.50%	1,246,700	117,000	40.73	244.0	Luanda	34,69:

5 rows × 35 columns



```
In [157]: #to display null values
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 35 columns):
 #   Column                                                                 Non-Null Count  Dtype
---  -
 0   Country                                                                50 non-null    object
 1   Density                                                                50 non-null    object
    (P/Km2)
 2   Abbreviation                                                            49 non-null    object
 3   Agricultural Land( %)                                                  50 non-null    object
 4   Land Area(Km2)                                                         50 non-null    object
 5   Armed Forces size                                                      47 non-null    object
 6   Birth Rate                                                             50 non-null    float64
 7   Calling Code                                                           50 non-null    float64
 8   Capital/Major City                                                    50 non-null    object
 9   Co2-Emissions                                                         50 non-null    object
10   CPI                                                                    47 non-null    object
11   CPI Change (%)                                                         48 non-null    object
12   Currency-Code                                                          46 non-null    object
13   Fertility Rate                                                         50 non-null    float64
14   Forested Area (%)                                                     50 non-null    object
15   Gasoline Price                                                         48 non-null    object
16   GDP                                                                    50 non-null    object
17   Gross primary education enrollment (%) 49 non-null    object
18   Gross tertiary education enrollment (%) 48 non-null    object
19   Infant mortality                                                       50 non-null    float64
20   Largest city                                                            49 non-null    object
21   Life expectancy                                                        49 non-null    float64
22   Maternal mortality ratio                                               48 non-null    float64
23   Minimum wage                                                           42 non-null    object
24   Official language                                                      50 non-null    object
25   Out of pocket health expenditure 49 non-null    object
26   Physicians per thousand                                                50 non-null    float64
27   Population                                                             50 non-null    object
28   Population: Labor force participation (%) 47 non-null    object
29   Tax revenue (%)                                                        44 non-null    object
30   Total tax rate                                                         48 non-null    object
31   Unemployment rate                                                      47 non-null    object
32   Urban_population                                                       50 non-null    object
33   Latitude                                                               50 non-null    float64
34   Longitude                                                              50 non-null    float64
dtypes: float64(9), object(26)
memory usage: 13.8+ KB
```

```
In [158]: data.shape
```

```
Out[158]: (50, 35)
```

```
In [159]: #to display summary of statistics
data.describe()
```

Out[159]:

	Birth Rate	Calling Code	Fertility Rate	Infant mortality	Life expectancy	Maternal mortality ratio	Physicians per thousand	Latitude	Longitude
count	50.000000	50.000000	50.000000	50.000000	49.000000	48.000000	50.000000	50.000000	50.000000
mean	19.64860	291.820000	2.62600	22.618000	72.312245	174.041667	1.929800	17.670807	4.900287
std	10.67511	272.353663	1.41232	22.042368	7.988498	248.707549	1.782451	24.015082	58.380156
min	7.20000	1.000000	1.27000	1.900000	52.800000	2.000000	0.040000	-38.416097	-106.346771
25%	10.75000	56.250000	1.66000	5.225000	66.600000	13.750000	0.272500	5.080929	-57.638718
50%	14.89000	240.000000	1.94000	11.750000	74.900000	50.000000	1.665000	16.799808	15.336481
75%	24.68500	375.750000	2.98250	35.375000	78.100000	242.750000	2.972500	39.017239	32.552116
max	42.17000	994.000000	5.92000	84.500000	82.700000	1140.000000	8.420000	56.263920	133.775136

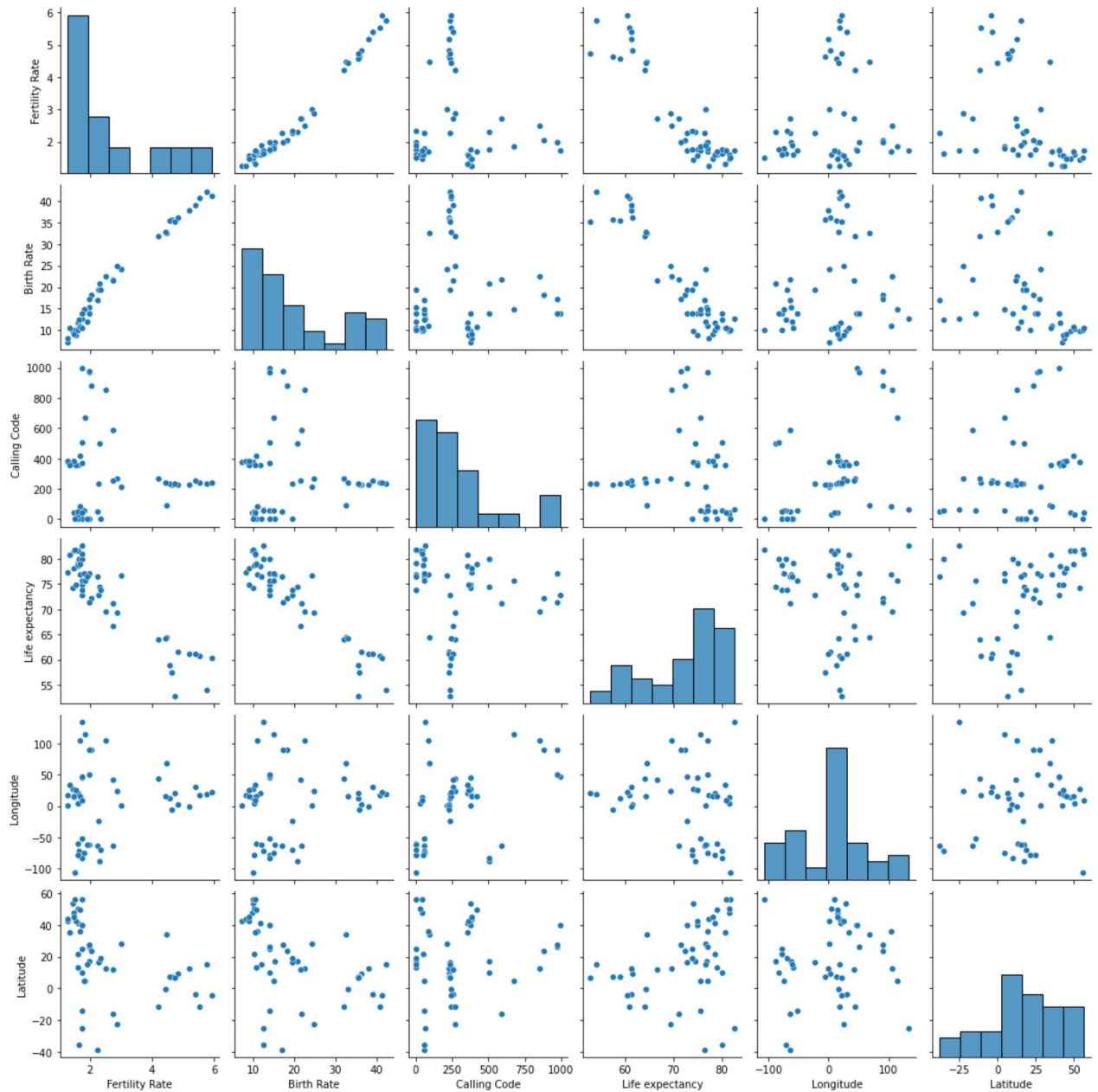
```
In [160]: #to display columns name
data.columns
```

Out[160]: 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 [161]: data1=data[['Fertility Rate','Birth Rate','Calling Code','Life expectancy','Longitude','Latitude
```

```
In [162]: sns.pairplot(data1)
```

```
Out[162]: <seaborn.axisgrid.PairGrid at 0x2389a4c3eb0>
```

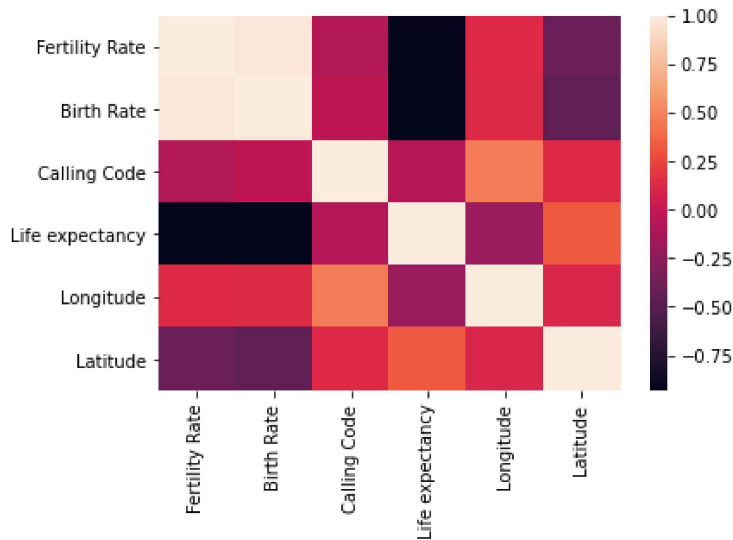


EDA and Visualization

```
In [163]: #sns.distplot(data['Co2-Emissions'])
```

```
In [164]: sns.heatmap(data1.corr())
```

```
Out[164]: <AxesSubplot:>
```



To train the model

we are going to train the linear regression model ;We need to split the two variable x and y where x in independent variable (input) and y is dependent of x(output) so we could ignore address columns as it is not requires for our model

```
In [165]: x=data[['Fertility Rate','Birth Rate','Calling Code','Life expectancy','Longitude','Latitude']]
          y=data1['Birth Rate']
```

```
In [166]: #To split test and train data
          from sklearn.model_selection import train_test_split
          x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.6)
```

```
In [167]: from sklearn.linear_model import LinearRegression
          lr=LinearRegression()
          lr.fit(x_train,y_train)
```

```
Out[167]: LinearRegression()
```

```
In [168]: lr.intercept_
```

```
Out[168]: -1.8829382497642655e-13
```

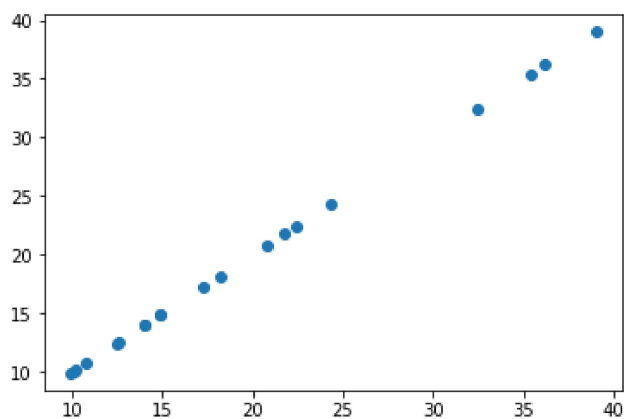
```
In [169]: coeff = pd.DataFrame(lr.coef_,x.columns,columns=["Co-efficient"])
          coeff
```

```
Out[169]:
```

	Co-efficient
Fertility Rate	-6.809439e-14
Birth Rate	1.000000e+00
Calling Code	1.248655e-16
Life expectancy	1.512232e-15
Longitude	-1.506115e-16
Latitude	1.800967e-16

```
In [170]: prediction = lr.predict(x_train)
plt.scatter(y_train, prediction)
```

```
Out[170]: <matplotlib.collections.PathCollection at 0x23899d56cd0>
```



In [171]: lr.score(x_test,y_test)

```
-----
ValueError                                Traceback (most recent call last)
<ipython-input-171-1785cf3deb61> in <module>
----> 1 lr.score(x_test,y_test)

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\base.py in score(self, X, y, sample_weight)
    551
    552     from .metrics import r2_score
--> 553     y_pred = self.predict(X)
    554     return r2_score(y, y_pred, sample_weight=sample_weight)
    555

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\base.py in predict(self, X)
    236     Returns predicted values.
    237     """
--> 238     return self._decision_function(X)
    239
    240     _preprocess_data = staticmethod(_preprocess_data)

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\base.py in _decision_function
(self, X)
    218     check_is_fitted(self)
    219
--> 220     X = check_array(X, accept_sparse=['csr', 'csc', 'coo'])
    221     return safe_sparse_dot(X, self.coef_.T,
    222                           dense_output=True) + self.intercept_

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py in inner_f(*args, **kwargs)
    61     extra_args = len(args) - len(all_args)
    62     if extra_args <= 0:
--> 63         return f(*args, **kwargs)
    64
    65     # extra_args > 0

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py in check_array(array, accept_sparse, accept_large_sparse, dtype, order, copy, force_all_finite, ensure_2d, allow_nd, ensure_min_samples, ensure_min_features, estimator)
    661
    662     if force_all_finite:
--> 663         _assert_all_finite(array,
    664                             allow_nan=force_all_finite == 'allow-nan')
    665

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py in _assert_all_finite(X, allow_nan, msg_dtype)
    101     not allow_nan and not np.isfinite(X).all()):
    102     type_err = 'infinity' if allow_nan else 'NaN, infinity'
--> 103     raise ValueError(
    104         msg_err.format
    105         (type_err,

ValueError: Input contains NaN, infinity or a value too large for dtype('float64').
```

In [172]: lr.score(x_train,y_train)

Out[172]: 1.0

In [176]: *#from sklearn.linear_model import Ridge,Lasso*

```
In [177]: """rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
rr.score(x_test,y_test)"""
```

File "<ipython-input-177-7221d7f5e5ba>", line 1

```
"""rr=Ridge(alpha=10)
    ^
```

SyntaxError: invalid syntax


```
In [175]: la=Lasso(alpha=10)
          la.fit(x_train,y_train)
          la.score(x_test,y_test)
```

```

-----
ValueError                                Traceback (most recent call last)
<ipython-input-175-3bb63ba76728> in <module>
      1 la=Lasso(alpha=10)
      2 la.fit(x_train,y_train)
----> 3 la.score(x_test,y_test)

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\base.py in score(self, X, y, sample_weight)
    551
    552     from .metrics import r2_score
--> 553     y_pred = self.predict(X)
    554     return r2_score(y, y_pred, sample_weight=sample_weight)
    555

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\base.py in predict(self, X)
    236     Returns predicted values.
    237     """
--> 238     return self._decision_function(X)
    239
    240     _preprocess_data = staticmethod(_preprocess_data)

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\coordinate_descent.py in _decision_function(self, X)
    896                                     dense_output=True) + self.intercept_
    897     else:
--> 898     return super()._decision_function(X)
    899
    900

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\base.py in _decision_function(self, X)
    218     check_is_fitted(self)
    219
--> 220     X = check_array(X, accept_sparse=['csr', 'csc', 'coo'])
    221     return safe_sparse_dot(X, self.coef_.T,
    222                           dense_output=True) + self.intercept_

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py in inner_f(*args, **kwargs)
    61     extra_args = len(args) - len(all_args)
    62     if extra_args <= 0:
--> 63         return f(*args, **kwargs)
    64
    65     # extra_args > 0

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py in check_array(array, accept_sparse, accept_large_sparse, dtype, order, copy, force_all_finite, ensure_2d, allow_nd, ensure_min_samples, ensure_min_features, estimator)
    661
    662     if force_all_finite:
--> 663         _assert_all_finite(array,
    664                             allow_nan=force_all_finite == 'allow-nan')
    665

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py in _assert_all_finite(X, allow_nan, msg_dtype)
    101     not allow_nan and not np.isfinite(X).all()):
    102     type_err = 'infinity' if allow_nan else 'NaN, infinity'
--> 103     raise ValueError(
    104         msg_err.format
    105         (type_err,

ValueError: Input contains NaN, infinity or a value too large for dtype('float64').

```

In []:

In []:

In []: