Linear regression - WHO data

September 22, 2021

1 Machine Learning Basics

Machine learning is a discipline that deals with the study of methods for pattern recognition in datasets undergoing data analysis. - learn from data - build model - make predictions

1.0.1 Supervised learning

The methods in which the training set contains additional attributes that you want to predict (*the target, or dependant variate*)
- **Classification**: the target belongs to two or more classes or categories. - **Regression**: the target to be predicted has continuous variate.

1.0.2 Unsupervised learning

the methods in which the training set consists of a series of input values x without any corresponding target value. - **Clustering**: discover groups of similar examples in a dataset - **Dimensionality** reduction: consider a dataset with n columns (variates) data, it can be treated as a n-dimensional feature space. dimensionality reduction is to find new data from original and then makes the higher dimension turns into lower dimension which is easier for training the model.

2 Linear regression, using WHO data

2.0.1 Data preparation

Visit WHO data web service and find all data provided at their web service site.
Click the first item 'Access the Global Health Observatory user interface', you can browse their data by category or special item, and download the data you wanted.
Click 'By Indicator' can find one specific indicator, view the definition and raw data, also can download the data.
Download the data in .csv format and we later process it.

[32]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

plt.style.use('seaborn')
plt.rcParams.update({'figure.figsize': (12,6),\
                     'figure.titlesize':16,\
                     'axes.titlesize':16,\
```

```
                           'axes.labelsize':14,\
                           'xtick.labelsize':14,\
                           'ytick.labelsize':14,
                          })
```

[33]:
```
import pathlib
file_path = pathlib.Path('D:/Edu/newcome/resource/data-who/age standardized␣
↪suicide rate.csv')

df = pd.read_csv(file_path, header=1)
df
```

[33]:
```
         Country         Sex              2019              2018  \
0    Afghanistan  Both sexes    6.0 [3.4-9.9]     5.9 [3.4-9.8]
1    Afghanistan        Male   6.2 [3.5-10.5]    6.2 [3.5-10.4]
2    Afghanistan      Female    5.7 [3.2-9.2]     5.6 [3.2-9.1]
3        Albania  Both sexes    3.7 [2.1-5.7]     3.9 [2.2-6.0]
4        Albania        Male    5.3 [2.7-8.3]     5.6 [2.9-8.7]
..           …           …               …               …
544       Zambia        Male  25.7 [16.0-39.0]  28.1 [17.7-42.4]
545       Zambia      Female    5.3 [3.1-8.4]     6.0 [3.5-9.6]
546     Zimbabwe  Both sexes  23.6 [12.6-37.5]  23.9 [12.7-37.8]
547     Zimbabwe        Male  37.8 [19.6-59.0]  38.6 [19.8-60.3]
548     Zimbabwe      Female   13.5 [7.5-22.0]   13.5 [7.6-21.9]

                 2017              2016              2015              2014  \
0       6.0 [3.4-9.9]     6.0 [3.5-9.9]     6.0 [3.5-9.9]     6.0 [3.5-9.9]
1      6.3 [3.7-10.7]    6.2 [3.6-10.3]    6.1 [3.6-10.2]    6.1 [3.6-10.2]
2       5.5 [3.1-9.0]     5.8 [3.3-9.5]     5.8 [3.3-9.4]     5.9 [3.4-9.5]
3       4.1 [2.3-6.3]     4.2 [2.3-6.3]     4.2 [2.3-6.4]     4.5 [2.5-6.7]
4       5.7 [2.9-9.0]     5.7 [2.9-8.8]     5.7 [2.9-8.7]     6.2 [3.1-9.3]
..                …                …                …                …
544  29.1 [18.4-43.7]  29.1 [18.5-43.5]  30.0 [19.2-44.6]  30.2 [19.5-44.5]
545    6.6 [3.9-10.6]    6.7 [3.9-10.7]    7.1 [4.2-11.2]    7.9 [4.7-12.4]
546  25.9 [13.8-40.9]  28.7 [15.4-45.3]  30.7 [16.6-48.3]  30.8 [16.7-48.4]
547  41.3 [21.2-64.6]  44.5 [22.8-69.2]  47.4 [24.5-73.4]  45.3 [23.5-70.1]
548   15.0 [8.5-24.3]  17.7 [10.0-28.6]  19.2 [11.0-30.9]  21.1 [12.1-33.9]

                 2013              2012  …              2009  \
0      6.2 [3.6-10.2]    6.2 [3.6-10.2]  …    6.8 [4.0-11.1]
1      6.3 [3.7-10.5]    6.4 [3.7-10.5]  …    7.0 [4.1-11.6]
2       6.0 [3.5-9.8]     6.1 [3.6-9.8]  …    6.6 [3.9-10.5]
3       4.8 [2.7-7.1]     4.8 [2.8-7.0]  …    8.0 [4.8-10.8]
4       6.5 [3.4-9.7]     6.6 [3.4-9.6]  …   10.2 [5.4-14.0]
..                …                …  …               …
544  30.0 [19.4-44.1]  31.1 [20.3-45.5]  …  32.6 [21.5-47.5]
545    8.5 [5.1-13.3]    8.7 [5.2-13.5]  …    8.4 [5.1-12.9]
```

```
546  31.4 [17.2-48.9]  33.1 [18.1-51.3]  …  35.2 [19.3-55.1]
547  46.4 [24.2-71.2]  50.7 [26.6-77.7]  …  48.3 [25.3-73.9]
548  21.3 [12.3-34.1]  20.9 [12.1-33.2]  …  26.9 [15.3-43.5]

                 2008              2007              2006              2005  \
0      7.2 [4.2-11.7]    7.4 [4.3-12.1]    7.6 [4.4-12.3]    7.6 [4.4-12.3]
1      7.4 [4.3-12.2]    7.7 [4.5-12.6]    7.8 [4.5-12.7]    7.8 [4.5-12.7]
2      6.9 [4.0-11.0]    7.1 [4.2-11.4]    7.3 [4.3-11.7]    7.4 [4.3-11.9]
3      8.1 [5.0-10.8]    8.1 [5.0-10.6]    7.8 [5.0-10.2]    7.7 [4.9-10.0]
4     10.5 [5.6-14.2]   10.5 [5.8-14.1]   10.1 [5.7-13.4]   10.2 [5.9-13.4]
..                 …                 …                 …                 …
544  32.8 [21.6-47.9]  33.4 [21.9-49.4]  35.6 [23.3-52.9]  35.8 [23.2-53.4]
545    8.2 [5.0-12.7]    9.2 [5.6-14.3]   11.0 [6.6-17.2]   11.4 [6.8-18.1]
546  31.7 [17.3-49.5]  27.2 [14.7-42.5]  22.0 [11.7-34.5]  22.0 [11.7-34.4]
547  42.0 [21.9-64.0]  36.3 [18.8-55.2]  28.5 [14.5-43.3]  32.1 [16.7-48.9]
548  25.5 [14.4-41.1]  21.8 [12.0-35.1]   18.2 [9.9-29.7]   15.2 [8.2-24.9]

                 2004              2003              2002              2001  \
0      7.8 [4.5-12.6]    7.7 [4.5-12.5]    7.9 [4.5-12.8]    7.9 [4.5-12.8]
1      7.9 [4.5-12.9]    7.8 [4.5-12.8]    8.0 [4.6-13.1]    7.9 [4.5-12.9]
2      7.6 [4.4-12.2]    7.6 [4.5-12.2]    7.7 [4.5-12.4]    7.9 [4.6-12.6]
3       4.9 [3.1-6.3]     4.9 [3.3-6.4]     4.8 [3.2-6.3]     4.7 [3.2-6.2]
4       6.7 [4.0-8.8]     6.6 [4.1-8.7]     6.6 [4.1-8.7]     6.5 [4.2-8.5]
..                 …                 …                 …                 …
544  35.8 [23.2-53.4]  34.2 [22.0-51.2]  34.5 [22.1-51.9]  34.3 [21.8-51.7]
545   11.9 [7.0-18.8]   11.4 [6.7-18.1]   12.6 [7.3-20.0]   13.4 [7.8-21.3]
546  21.5 [11.4-33.7]  20.2 [10.7-31.7]  20.3 [10.7-32.0]  19.5 [10.2-30.7]
547  30.1 [15.6-45.7]  29.4 [15.5-44.3]  29.8 [15.7-44.8]  28.6 [15.1-42.8]
548   15.7 [8.5-26.0]   13.7 [7.2-22.9]   13.5 [7.0-22.9]   13.0 [6.6-22.3]

                 2000
0      7.7 [4.4-12.5]
1      7.6 [4.4-12.5]
2      7.8 [4.5-12.4]
3       5.2 [3.6-6.9]
4      7.6 [5.1-10.1]
..                 …
544  35.9 [22.8-54.0]
545   14.5 [8.5-23.1]
546  20.0 [10.3-31.5]
547  28.2 [14.8-42.1]
548   14.2 [7.0-24.4]

[549 rows x 22 columns]
```

[34]:
```
df.dtypes
```

[34]:
```
Country    object
Sex        object
 2019      object
 2018      object
 2017      object
 2016      object
 2015      object
 2014      object
 2013      object
 2012      object
 2011      object
 2010      object
 2009      object
 2008      object
 2007      object
 2006      object
 2005      object
 2004      object
 2003      object
 2002      object
 2001      object
 2000      object
dtype: object
```

[35]:
```python
df.columns
```

[35]:
```
Index(['Country', 'Sex', ' 2019', ' 2018', ' 2017', ' 2016', ' 2015', ' 2014',
       ' 2013', ' 2012', ' 2011', ' 2010', ' 2009', ' 2008', ' 2007', ' 2006',
       ' 2005', ' 2004', ' 2003', ' 2002', ' 2001', ' 2000'],
      dtype='object')
```

[36]:
```python
df.columns = df.columns.map(lambda x: x.strip())
df
```

[36]:
```
         Country         Sex               2019               2018  \
0    Afghanistan  Both sexes     6.0 [3.4-9.9]      5.9 [3.4-9.8]
1    Afghanistan        Male    6.2 [3.5-10.5]     6.2 [3.5-10.4]
2    Afghanistan      Female     5.7 [3.2-9.2]      5.6 [3.2-9.1]
3        Albania  Both sexes     3.7 [2.1-5.7]      3.9 [2.2-6.0]
4        Albania        Male     5.3 [2.7-8.3]      5.6 [2.9-8.7]
..           …           …                 …                  …
544       Zambia        Male  25.7 [16.0-39.0]   28.1 [17.7-42.4]
545       Zambia      Female     5.3 [3.1-8.4]      6.0 [3.5-9.6]
546     Zimbabwe  Both sexes  23.6 [12.6-37.5]   23.9 [12.7-37.8]
547     Zimbabwe        Male  37.8 [19.6-59.0]   38.6 [19.8-60.3]
548     Zimbabwe      Female   13.5 [7.5-22.0]    13.5 [7.6-21.9]
```

```
                2017              2016              2015              2014  \
0       6.0 [3.4-9.9]     6.0 [3.5-9.9]     6.0 [3.5-9.9]     6.0 [3.5-9.9]
1      6.3 [3.7-10.7]    6.2 [3.6-10.3]    6.1 [3.6-10.2]    6.1 [3.6-10.2]
2       5.5 [3.1-9.0]     5.8 [3.3-9.5]     5.8 [3.3-9.4]     5.9 [3.4-9.5]
3       4.1 [2.3-6.3]     4.2 [2.3-6.3]     4.2 [2.3-6.4]     4.5 [2.5-6.7]
4       5.7 [2.9-9.0]     5.7 [2.9-8.8]     5.7 [2.9-8.7]     6.2 [3.1-9.3]
..                …                 …                 …                 …
544  29.1 [18.4-43.7]  29.1 [18.5-43.5]  30.0 [19.2-44.6]  30.2 [19.5-44.5]
545    6.6 [3.9-10.6]    6.7 [3.9-10.7]    7.1 [4.2-11.2]    7.9 [4.7-12.4]
546  25.9 [13.8-40.9]  28.7 [15.4-45.3]  30.7 [16.6-48.3]  30.8 [16.7-48.4]
547  41.3 [21.2-64.6]  44.5 [22.8-69.2]  47.4 [24.5-73.4]  45.3 [23.5-70.1]
548   15.0 [8.5-24.3]  17.7 [10.0-28.6]  19.2 [11.0-30.9]  21.1 [12.1-33.9]

                2013              2012  …              2009  \
0      6.2 [3.6-10.2]    6.2 [3.6-10.2]  …    6.8 [4.0-11.1]
1      6.3 [3.7-10.5]    6.4 [3.7-10.5]  …    7.0 [4.1-11.6]
2       6.0 [3.5-9.8]     6.1 [3.6-9.8]  …    6.6 [3.9-10.5]
3       4.8 [2.7-7.1]     4.8 [2.8-7.0]  …    8.0 [4.8-10.8]
4       6.5 [3.4-9.7]     6.6 [3.4-9.6]  …   10.2 [5.4-14.0]
..                …                 …  …                 …
544  30.0 [19.4-44.1]  31.1 [20.3-45.5]  …  32.6 [21.5-47.5]
545    8.5 [5.1-13.3]    8.7 [5.2-13.5]  …    8.4 [5.1-12.9]
546  31.4 [17.2-48.9]  33.1 [18.1-51.3]  …  35.2 [19.3-55.1]
547  46.4 [24.2-71.2]  50.7 [26.6-77.7]  …  48.3 [25.3-73.9]
548  21.3 [12.3-34.1]  20.9 [12.1-33.2]  …  26.9 [15.3-43.5]

                2008              2007              2006              2005  \
0      7.2 [4.2-11.7]    7.4 [4.3-12.1]    7.6 [4.4-12.3]    7.6 [4.4-12.3]
1      7.4 [4.3-12.2]    7.7 [4.5-12.6]    7.8 [4.5-12.7]    7.8 [4.5-12.7]
2      6.9 [4.0-11.0]    7.1 [4.2-11.4]    7.3 [4.3-11.7]    7.4 [4.3-11.9]
3      8.1 [5.0-10.8]    8.1 [5.0-10.6]    7.8 [5.0-10.2]    7.7 [4.9-10.0]
4     10.5 [5.6-14.2]   10.5 [5.8-14.1]   10.1 [5.7-13.4]   10.2 [5.9-13.4]
..                …                 …                 …                 …
544  32.8 [21.6-47.9]  33.4 [21.9-49.4]  35.6 [23.3-52.9]  35.8 [23.2-53.4]
545    8.2 [5.0-12.7]    9.2 [5.6-14.3]   11.0 [6.6-17.2]   11.4 [6.8-18.1]
546  31.7 [17.3-49.5]  27.2 [14.7-42.5]  22.0 [11.7-34.5]  22.0 [11.7-34.4]
547  42.0 [21.9-64.0]  36.3 [18.8-55.2]  28.5 [14.5-43.3]  32.1 [16.7-48.9]
548  25.5 [14.4-41.1]  21.8 [12.0-35.1]   18.2 [9.9-29.7]   15.2 [8.2-24.9]

                2004              2003              2002              2001  \
0      7.8 [4.5-12.6]    7.7 [4.5-12.5]    7.9 [4.5-12.8]    7.9 [4.5-12.8]
1      7.9 [4.5-12.9]    7.8 [4.5-12.8]    8.0 [4.6-13.1]    7.9 [4.5-12.9]
2      7.6 [4.4-12.2]    7.6 [4.5-12.2]    7.7 [4.5-12.4]    7.9 [4.6-12.6]
3       4.9 [3.1-6.3]     4.9 [3.3-6.4]     4.8 [3.2-6.3]     4.7 [3.2-6.2]
4       6.7 [4.0-8.8]     6.6 [4.1-8.7]     6.6 [4.1-8.7]     6.5 [4.2-8.5]
..                …                 …                 …                 …
544  35.8 [23.2-53.4]  34.2 [22.0-51.2]  34.5 [22.1-51.9]  34.3 [21.8-51.7]
```

```
545   11.9 [7.0-18.8]   11.4 [6.7-18.1]   12.6 [7.3-20.0]   13.4 [7.8-21.3]
546  21.5 [11.4-33.7]  20.2 [10.7-31.7]  20.3 [10.7-32.0]  19.5 [10.2-30.7]
547  30.1 [15.6-45.7]  29.4 [15.5-44.3]  29.8 [15.7-44.8]  28.6 [15.1-42.8]
548   15.7 [8.5-26.0]   13.7 [7.2-22.9]   13.5 [7.0-22.9]   13.0 [6.6-22.3]

                 2000
0      7.7 [4.4-12.5]
1      7.6 [4.4-12.5]
2      7.8 [4.5-12.4]
3       5.2 [3.6-6.9]
4      7.6 [5.1-10.1]
..                ...
544  35.9 [22.8-54.0]
545   14.5 [8.5-23.1]
546  20.0 [10.3-31.5]
547  28.2 [14.8-42.1]
548   14.2 [7.0-24.4]

[549 rows x 22 columns]
```

[37]:
```
df.columns
```

[37]:
```
Index(['Country', 'Sex', '2019', '2018', '2017', '2016', '2015', '2014',
       '2013', '2012', '2011', '2010', '2009', '2008', '2007', '2006', '2005',
       '2004', '2003', '2002', '2001', '2000'],
      dtype='object')
```

[38]:
```
df.loc[:,'2019':'2000'] = (df.loc[:, '2019':'2000'].applymap(lambda x: x.
 ↪split()[0])).to_numpy()
df
```

[38]:
```
         Country          Sex  2019  2018  2017  2016  2015  2014  2013  2012  \
0    Afghanistan  Both sexes   6.0   5.9   6.0   6.0   6.0   6.0   6.2   6.2
1    Afghanistan        Male   6.2   6.2   6.3   6.2   6.1   6.1   6.3   6.4
2    Afghanistan      Female   5.7   5.6   5.5   5.8   5.8   5.9   6.0   6.1
3        Albania  Both sexes   3.7   3.9   4.1   4.2   4.2   4.5   4.8   4.8
4        Albania        Male   5.3   5.6   5.7   5.7   5.7   6.2   6.5   6.6
..           ...         ...   ...   ...   ...   ...   ...   ...   ...   ...
544       Zambia        Male  25.7  28.1  29.1  29.1  30.0  30.2  30.0  31.1
545       Zambia      Female   5.3   6.0   6.6   6.7   7.1   7.9   8.5   8.7
546     Zimbabwe  Both sexes  23.6  23.9  25.9  28.7  30.7  30.8  31.4  33.1
547     Zimbabwe        Male  37.8  38.6  41.3  44.5  47.4  45.3  46.4  50.7
548     Zimbabwe      Female  13.5  13.5  15.0  17.7  19.2  21.1  21.3  20.9

     ...  2009  2008  2007  2006  2005  2004  2003  2002  2001  2000
0    ...   6.8   7.2   7.4   7.6   7.6   7.8   7.7   7.9   7.9   7.7
1    ...   7.0   7.4   7.7   7.8   7.8   7.9   7.8   8.0   7.9   7.6
```

```
2    …   6.6   6.9   7.1   7.3   7.4   7.6   7.6   7.7   7.9   7.8
3    …   8.0   8.1   8.1   7.8   7.7   4.9   4.9   4.8   4.7   5.2
4    …  10.2  10.5  10.5  10.1  10.2   6.7   6.6   6.6   6.5   7.6
..   …   …    …    …    …    …    …    …    …    …    …
544  …  32.6  32.8  33.4  35.6  35.8  35.8  34.2  34.5  34.3  35.9
545  …   8.4   8.2   9.2  11.0  11.4  11.9  11.4  12.6  13.4  14.5
546  …  35.2  31.7  27.2  22.0  22.0  21.5  20.2  20.3  19.5  20.0
547  …  48.3  42.0  36.3  28.5  32.1  30.1  29.4  29.8  28.6  28.2
548  …  26.9  25.5  21.8  18.2  15.2  15.7  13.7  13.5  13.0  14.2

[549 rows x 22 columns]
```

[39]:
```python
print('-'+df['Sex'][0]+'-')
```

```
- Both sexes-
```

[40]:
```python
df['Sex'] = df['Sex'].map(lambda x: x.strip())
df
```

[40]:
```
         Country         Sex  2019  2018  2017  2016  2015  2014  2013  2012  \
0    Afghanistan  Both sexes   6.0   5.9   6.0   6.0   6.0   6.0   6.2   6.2
1    Afghanistan        Male   6.2   6.2   6.3   6.2   6.1   6.1   6.3   6.4
2    Afghanistan      Female   5.7   5.6   5.5   5.8   5.8   5.9   6.0   6.1
3        Albania  Both sexes   3.7   3.9   4.1   4.2   4.2   4.5   4.8   4.8
4        Albania        Male   5.3   5.6   5.7   5.7   5.7   6.2   6.5   6.6
..           …          …   …    …    …    …    …    …    …    …
544       Zambia        Male  25.7  28.1  29.1  29.1  30.0  30.2  30.0  31.1
545       Zambia      Female   5.3   6.0   6.6   6.7   7.1   7.9   8.5   8.7
546     Zimbabwe  Both sexes  23.6  23.9  25.9  28.7  30.7  30.8  31.4  33.1
547     Zimbabwe        Male  37.8  38.6  41.3  44.5  47.4  45.3  46.4  50.7
548     Zimbabwe      Female  13.5  13.5  15.0  17.7  19.2  21.1  21.3  20.9

     …  2009  2008  2007  2006  2005  2004  2003  2002  2001  2000
0    …   6.8   7.2   7.4   7.6   7.6   7.8   7.7   7.9   7.9   7.7
1    …   7.0   7.4   7.7   7.8   7.8   7.9   7.8   8.0   7.9   7.6
2    …   6.6   6.9   7.1   7.3   7.4   7.6   7.6   7.7   7.9   7.8
3    …   8.0   8.1   8.1   7.8   7.7   4.9   4.9   4.8   4.7   5.2
4    …  10.2  10.5  10.5  10.1  10.2   6.7   6.6   6.6   6.5   7.6
..   …   …    …    …    …    …    …    …    …    …    …
544  …  32.6  32.8  33.4  35.6  35.8  35.8  34.2  34.5  34.3  35.9
545  …   8.4   8.2   9.2  11.0  11.4  11.9  11.4  12.6  13.4  14.5
546  …  35.2  31.7  27.2  22.0  22.0  21.5  20.2  20.3  19.5  20.0
547  …  48.3  42.0  36.3  28.5  32.1  30.1  29.4  29.8  28.6  28.2
548  …  26.9  25.5  21.8  18.2  15.2  15.7  13.7  13.5  13.0  14.2

[549 rows x 22 columns]
```

[41]:
```
type_convert = {'Country': 'string', 'Sex': 'category', '2019': float, '2018':␣
↪float, '2017': float, '2016': float, '2015': float,
                '2014': float, '2013': float, '2012': float, '2011': float,␣
↪'2010': float, '2009': float, '2008': float, '2007': float,
                '2006': float, '2005': float, '2004': float, '2003': float,␣
↪'2002': float, '2001': float, '2000': float,}
df = df.astype(type_convert)
df
```

[41]:
```
         Country         Sex  2019  2018  2017  2016  2015  2014  2013  2012  \
0    Afghanistan  Both sexes   6.0   5.9   6.0   6.0   6.0   6.0   6.2   6.2
1    Afghanistan        Male   6.2   6.2   6.3   6.2   6.1   6.1   6.3   6.4
2    Afghanistan      Female   5.7   5.6   5.5   5.8   5.8   5.9   6.0   6.1
3        Albania  Both sexes   3.7   3.9   4.1   4.2   4.2   4.5   4.8   4.8
4        Albania        Male   5.3   5.6   5.7   5.7   5.7   6.2   6.5   6.6
..           …           …    …    …    …    …    …    …    …    …
544       Zambia        Male  25.7  28.1  29.1  29.1  30.0  30.2  30.0  31.1
545       Zambia      Female   5.3   6.0   6.6   6.7   7.1   7.9   8.5   8.7
546     Zimbabwe  Both sexes  23.6  23.9  25.9  28.7  30.7  30.8  31.4  33.1
547     Zimbabwe        Male  37.8  38.6  41.3  44.5  47.4  45.3  46.4  50.7
548     Zimbabwe      Female  13.5  13.5  15.0  17.7  19.2  21.1  21.3  20.9

     …  2009  2008  2007  2006  2005  2004  2003  2002  2001  2000
0    …   6.8   7.2   7.4   7.6   7.6   7.8   7.7   7.9   7.9   7.7
1    …   7.0   7.4   7.7   7.8   7.8   7.9   7.8   8.0   7.9   7.6
2    …   6.6   6.9   7.1   7.3   7.4   7.6   7.6   7.7   7.9   7.8
3    …   8.0   8.1   8.1   7.8   7.7   4.9   4.9   4.8   4.7   5.2
4    …  10.2  10.5  10.5  10.1  10.2   6.7   6.6   6.6   6.5   7.6
..   …    …    …    …    …    …    …    …    …    …    …
544  …  32.6  32.8  33.4  35.6  35.8  35.8  34.2  34.5  34.3  35.9
545  …   8.4   8.2   9.2  11.0  11.4  11.9  11.4  12.6  13.4  14.5
546  …  35.2  31.7  27.2  22.0  22.0  21.5  20.2  20.3  19.5  20.0
547  …  48.3  42.0  36.3  28.5  32.1  30.1  29.4  29.8  28.6  28.2
548  …  26.9  25.5  21.8  18.2  15.2  15.7  13.7  13.5  13.0  14.2

[549 rows x 22 columns]
```

[42]:
```
df.dtypes
```

[42]:
```
Country       string
Sex         category
2019         float64
2018         float64
2017         float64
2016         float64
2015         float64
2014         float64
```

```
2013        float64
2012        float64
2011        float64
2010        float64
2009        float64
2008        float64
2007        float64
2006        float64
2005        float64
2004        float64
2003        float64
2002        float64
2001        float64
2000        float64
dtype: object
```

[43]:
```
country_2019 = pd.pivot_table(df, index=['Country'], columns=['Sex'],␣
↪values=['2019'])
country_2019
```

[43]:
```
                                          2019
Sex                                 Both sexes Female  Male
Country
Afghanistan                                6.0    5.7   6.2
Albania                                    3.7    2.2   5.3
Algeria                                    2.6    1.9   3.3
Angola                                    12.6    4.7  21.7
Antigua and Barbuda                        0.3    0.6   0.0
…                                            …     …     …
Venezuela (Bolivarian Republic of)         2.1    0.7   3.7
Viet Nam                                   7.2    4.2  10.6
Yemen                                      7.1    5.3   9.0
Zambia                                    14.4    5.3  25.7
Zimbabwe                                  23.6   13.5  37.8

[183 rows x 3 columns]
```

[44]:
```
country_2019.shape
```

[44]: (183, 3)

[45]:
```
country_2019.dtypes
```

[45]:
```
      Sex
2019  Both sexes    float64
      Female        float64
      Male          float64
```

```
dtype: object
```

[46]:
```
country_2019.columns
```

[46]:
```
MultiIndex([('2019', 'Both sexes'),
            ('2019',     'Female'),
            ('2019',       'Male')],
           names=[None, 'Sex'])
```

[47]:
```
country_2019.index
```

[47]:
```
Index(['Afghanistan', 'Albania', 'Algeria', 'Angola', 'Antigua and Barbuda',
       'Argentina', 'Armenia', 'Australia', 'Austria', 'Azerbaijan',
       …
       'United Republic of Tanzania', 'United States of America', 'Uruguay',
       'Uzbekistan', 'Vanuatu', 'Venezuela (Bolivarian Republic of)',
       'Viet Nam', 'Yemen', 'Zambia', 'Zimbabwe'],
      dtype='object', name='Country', length=183)
```

[48]:
```
country_2019[('2019', 'Male')]  # notice the columns using MultiIndex, need use␣
↪tuple.
```

[48]:
```
Country
Afghanistan                            6.2
Albania                                5.3
Algeria                                3.3
Angola                                21.7
Antigua and Barbuda                    0.0
                                      …
Venezuela (Bolivarian Republic of)     3.7
Viet Nam                              10.6
Yemen                                  9.0
Zambia                                25.7
Zimbabwe                              37.8
Name: (2019, Male), Length: 183, dtype: float64
```

[49]:
```
country_2019 = country_2019.droplevel(level=0,axis=1)
#country_2019.set_axis(country_2019.columns.map(lambda x: x[1]), axis=1,␣
↪inplace=True)  # remove MultiIndex and keep only one index for columns
country_2019
```

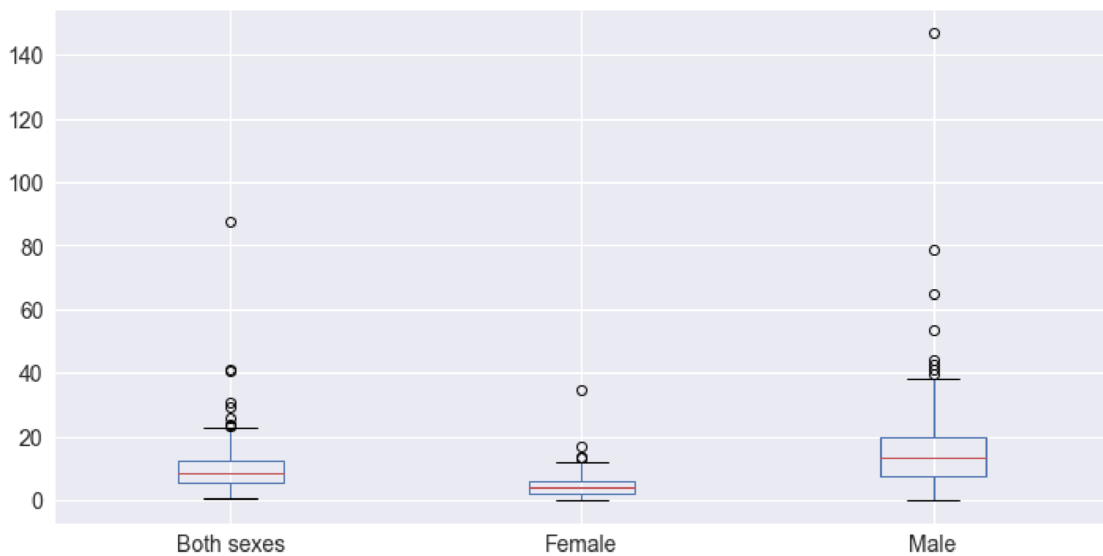
[49]:
```
Sex                                 Both sexes  Female  Male
Country
Afghanistan                                6.0     5.7   6.2
Albania                                    3.7     2.2   5.3
Algeria                                    2.6     1.9   3.3
Angola                                    12.6     4.7  21.7
Antigua and Barbuda                        0.3     0.6   0.0
```

```
…                                           …      …     …
Venezuela (Bolivarian Republic of)        2.1    0.7   3.7
Viet Nam                                  7.2    4.2  10.6
Yemen                                     7.1    5.3   9.0
Zambia                                   14.4    5.3  25.7
Zimbabwe                                 23.6   13.5  37.8

[183 rows x 3 columns]
```

2.0.2 explore the data

One of the ways to look at the data roughly is use box plot.

[50]:
```
country_2019.boxplot()
plt.show()
```



[51]:
```
country_2019.mean()
```

[51]:
```
Sex
Both sexes    10.086885
Female         4.535519
Male          16.139344
dtype: float64
```

there are many data which looks exteme, not a normal data, was at outside of the boxplot at the top.

Also we observe that there is one extraordinaryly high. We can filter that country by selecting the `Both` rate larger than 80, or the `Male` rate higher than 140.

[52]:
```
country_2019[country_2019['Male']>140]
```

[52]:
```
Sex      Both sexes  Female   Male
Country
Lesotho        87.5    34.6  146.9
```

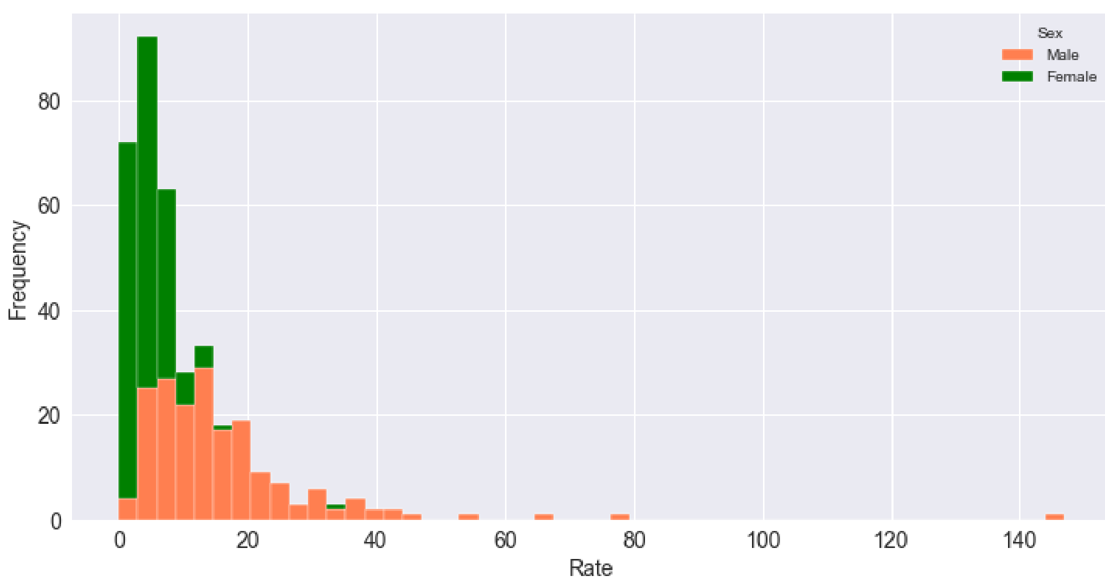
We can also order the record and then check the top

[53]:
```
country_2019.sort_values('Both sexes', axis=0, ascending=False, inplace=True)
country_2019.head()
```

[53]:
```
Sex                                 Both sexes  Female   Male
Country
Lesotho                                   87.5    34.6  146.9
Guyana                                    40.9    17.0   65.0
Eswatini                                  40.5     6.4   78.7
Kiribati                                  30.6     9.5   53.6
Micronesia (Federated States of)          29.0    13.2   44.3
```

Now let's look at the pmf (histogram) and cdf (through hist cumulative).

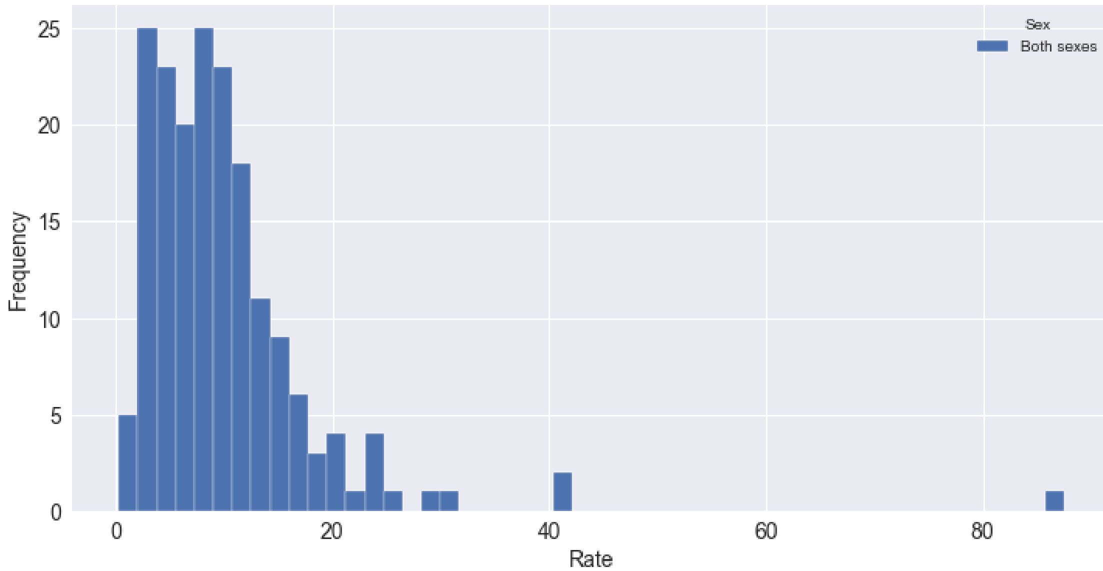
[54]:
```
ax = country_2019.plot.hist(stacked=True, y=['Male', 'Female'], bins=50,␣
 ↪color=['Coral', 'Green'], ec='white')
ax.set_xlabel('Rate')
plt.show()
```



the rate of male is much higher than femal.

[55]:

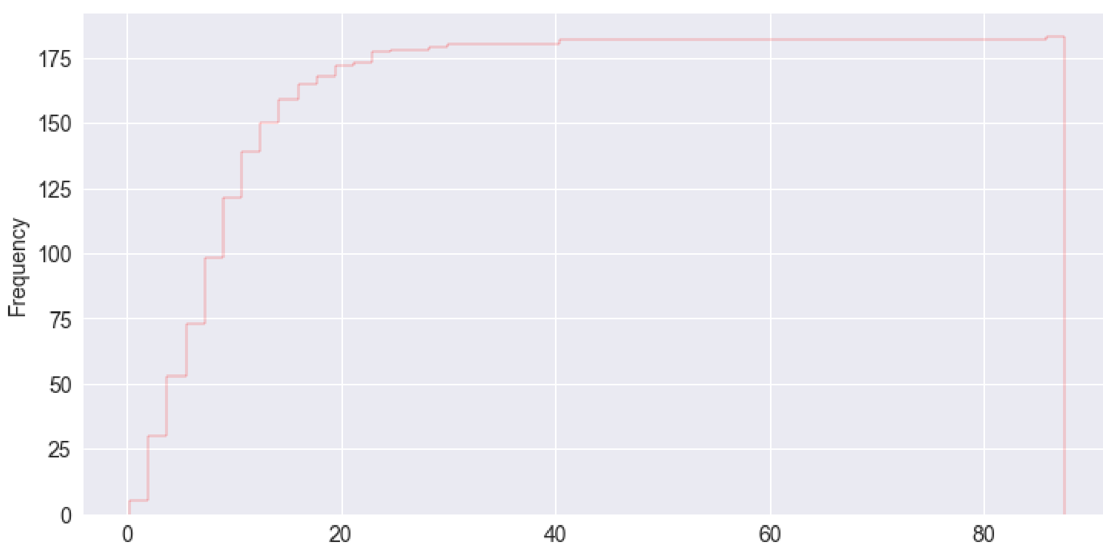
```
ax = country_2019.plot.hist(y=['Both sexes'], bins=50,ec='white')
ax.set_xlabel('Rate')
plt.show()
```



It shows that male is much higher in suicide rate than female.

[56]:

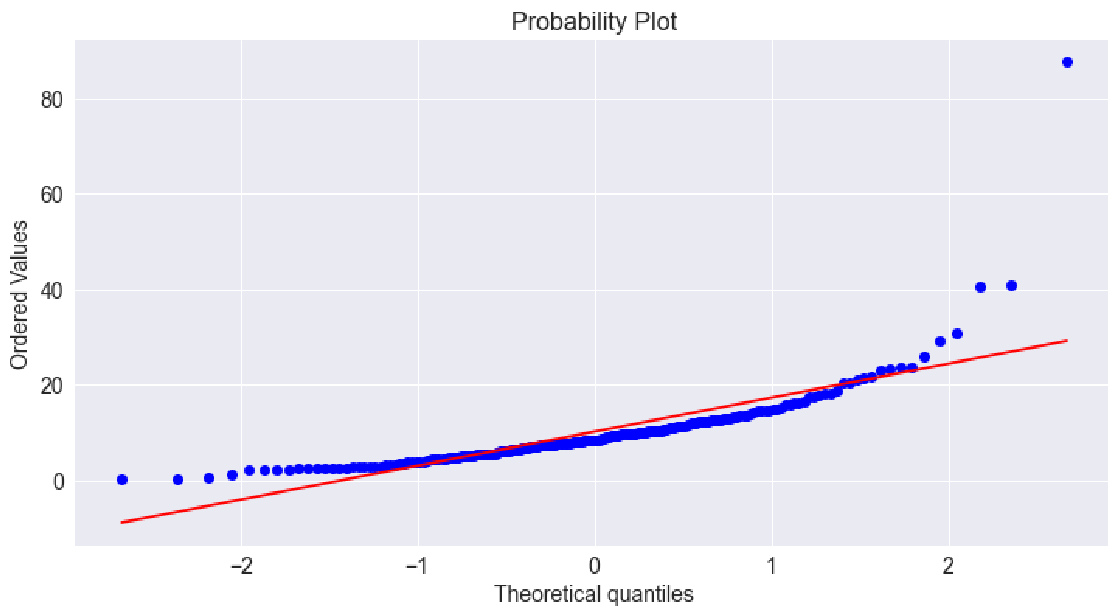
```
country_2019['Both sexes'].plot.hist(grid=True, cumulative=True, bins=50,
    histtype='step',ec='red')
plt.show()
```



It does not look like a normal distribution, because below the mean value (which is 10) is not showing any decrease trend towards left side (<10 side).

2.1 Probability plot

[57]:
```
import scipy.stats as st

ax = st.probplot(country_2019['Both sexes'], dist='norm', plot=plt)
plt.show()
```

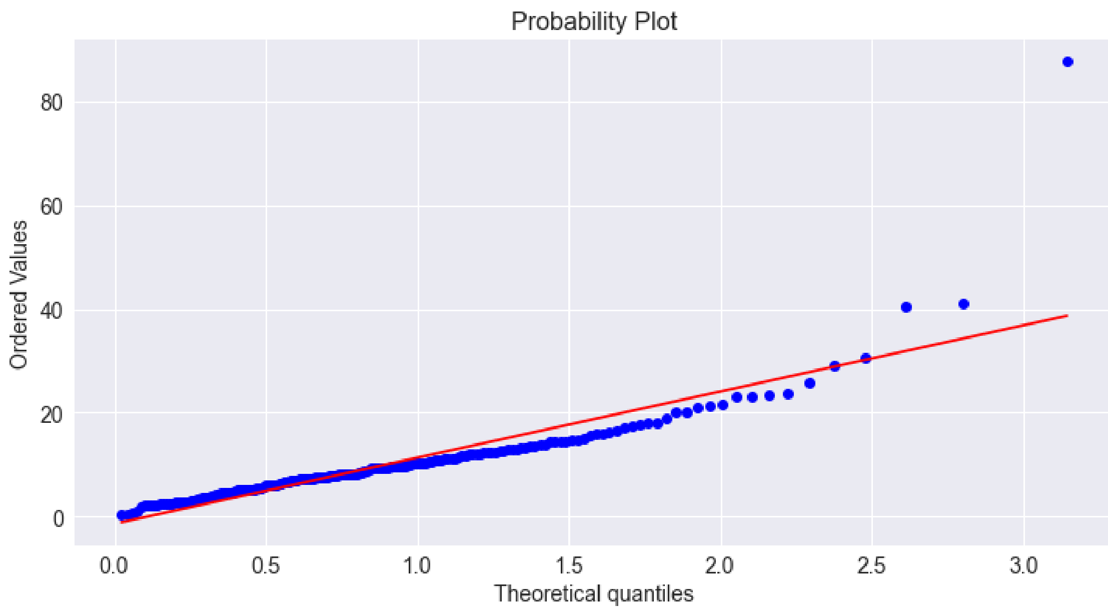


the probability plot show that normal distribution is not a good fit

[58]:
```
rvweib = st.weibull_min(c=1.5)
st.probplot(country_2019['Both sexes'], dist=rvweib, plot=plt)
```

[58]:
```
((array([0.02429869, 0.04396353, 0.06010995, 0.07438456, 0.08746701,
         0.09969973, 0.1112857 , 0.1223577 , 0.13300854, 0.14330632,
         0.15330285, 0.16303872, 0.17254649, 0.18185277, 0.19097968,
         0.19994584, 0.20876716, 0.21745733, 0.22602826, 0.23449041,
         0.24285301, 0.25112429, 0.2593116 , 0.26742157, 0.27546018,
         0.2834329 , 0.29134468, 0.29920011, 0.30700337, 0.31475835,
         0.32246866, 0.33013764, 0.33776841, 0.3453639 , 0.35292686,
         0.36045986, 0.36796534, 0.37544561, 0.38290286, 0.39033916,
         0.39775649, 0.40515674, 0.41254173, 0.41991318, 0.42727276,
         0.43462207, 0.44196266, 0.44929604, 0.45662363, 0.46394686,
         0.47126708, 0.47858563, 0.48590379, 0.49322285, 0.50054402,
         0.50786854, 0.51519759, 0.52253235, 0.52987396, 0.53722357,
```

```
       0.54458231, 0.55195129, 0.5593316 , 0.56672434, 0.57413061,
       0.58155148, 0.58898803, 0.59644133, 0.60391245, 0.61140248,
       0.61891247, 0.62644352, 0.6339967 , 0.64157309, 0.6491738 ,
       0.65679991, 0.66445254, 0.67213281, 0.67984184, 0.68758078,
       0.69535078, 0.70315303, 0.71098869, 0.71885899, 0.72676514,
       0.7347084 , 0.74269002, 0.7507113 , 0.75877356, 0.76687814,
       0.77502641, 0.78321977, 0.79145965, 0.79974752, 0.80808489,
       0.81647328, 0.82491429, 0.83340952, 0.84196065, 0.85056938,
       0.85923748, 0.86796676, 0.87675908, 0.88561638, 0.89454062,
       0.90353388, 0.91259825, 0.92173593, 0.93094918, 0.94024035,
       0.94961187, 0.95906624, 0.96860609, 0.97823412, 0.98795316,
       0.99776612, 1.00767606, 1.01768615, 1.02779969, 1.03802014,
       1.0483511 , 1.05879633, 1.06935976, 1.0800455 , 1.09085788,
       1.10180139, 1.1128808 , 1.12410107, 1.13546744, 1.14698543,
       1.15866083, 1.17049978, 1.18250872, 1.19469449, 1.20706433,
       1.21962588, 1.23238727, 1.24535714, 1.25854466, 1.27195961,
       1.28561241, 1.29951422, 1.31367696, 1.32811342, 1.34283732,
       1.35786343, 1.37320767, 1.38888724, 1.40492075, 1.42132839,
       1.43813214, 1.45535593, 1.47302594, 1.49117087, 1.50982229,
       1.52901503, 1.54878762, 1.56918293, 1.59024874, 1.61203864,
       1.63461291, 1.65803981, 1.68239697, 1.70777324, 1.73427104,
       1.7620092 , 1.79112678, 1.82178796, 1.85418852, 1.88856465,
       1.92520493, 1.96446732, 2.00680351, 2.05279521, 2.10320992,
       2.15909041, 2.22190614, 2.29382613, 2.37825445, 2.48100698,
       2.6133602 , 2.80235083, 3.14518902]),
 array([ 0.3,  0.3,  0.6,  1. ,  2. ,  2.1,  2.1,  2.2,  2.3,  2.3,  2.5,
         2.5,  2.6,  2.6,  2.6,  2.7,  2.7,  2.7,  2.8,  2.8,  2.9,  3. ,
         3.2,  3.2,  3.4,  3.4,  3.6,  3.6,  3.7,  3.7,  3.9,  4. ,  4.3,
         4.4,  4.5,  4.5,  4.5,  4.7,  4.7,  4.7,  4.8,  5.1,  5.1,  5.1,
         5.2,  5.2,  5.3,  5.3,  5.3,  5.3,  5.4,  5.5,  5.5,  5.8,  6. ,
         6. ,  6.1,  6.1,  6.2,  6.2,  6.4,  6.5,  6.7,  6.7,  6.8,  6.9,
         6.9,  6.9,  7.1,  7.2,  7.2,  7.2,  7.2,  7.3,  7.3,  7.4,  7.6,
         7.6,  7.7,  7.7,  7.7,  7.7,  7.9,  8. ,  8. ,  8. ,  8.1,  8.2,
         8.2,  8.3,  8.3,  8.3,  8.3,  8.3,  8.5,  8.6,  8.8,  8.9,  9.2,
         9.3,  9.3,  9.3,  9.5,  9.5,  9.5,  9.5,  9.6,  9.7,  9.7,  9.8,
         9.8,  9.8,  9.9, 10.1, 10.2, 10.3, 10.3, 10.4, 10.4, 10.5, 10.6,
        11. , 11. , 11. , 11.2, 11.2, 11.3, 11.3, 11.6, 11.8, 11.9, 12. ,
        12.1, 12.2, 12.2, 12.3, 12.4, 12.4, 12.4, 12.6, 12.7, 12.9, 12.9,
        13.1, 13.2, 13.4, 13.5, 13.5, 13.9, 14. , 14.4, 14.4, 14.5, 14.6,
        14.7, 14.8, 15.2, 15.7, 15.9, 16.1, 16.2, 16.5, 17.3, 17.4, 17.7,
        18. , 18.1, 18.8, 20.2, 20.2, 21. , 21.2, 21.6, 23. , 23.2, 23.5,
        23.6, 25.9, 29. , 30.6, 40.5, 40.9, 87.5])),
(12.722364797146128, -1.366822221363794, 0.8855277135515445))
```

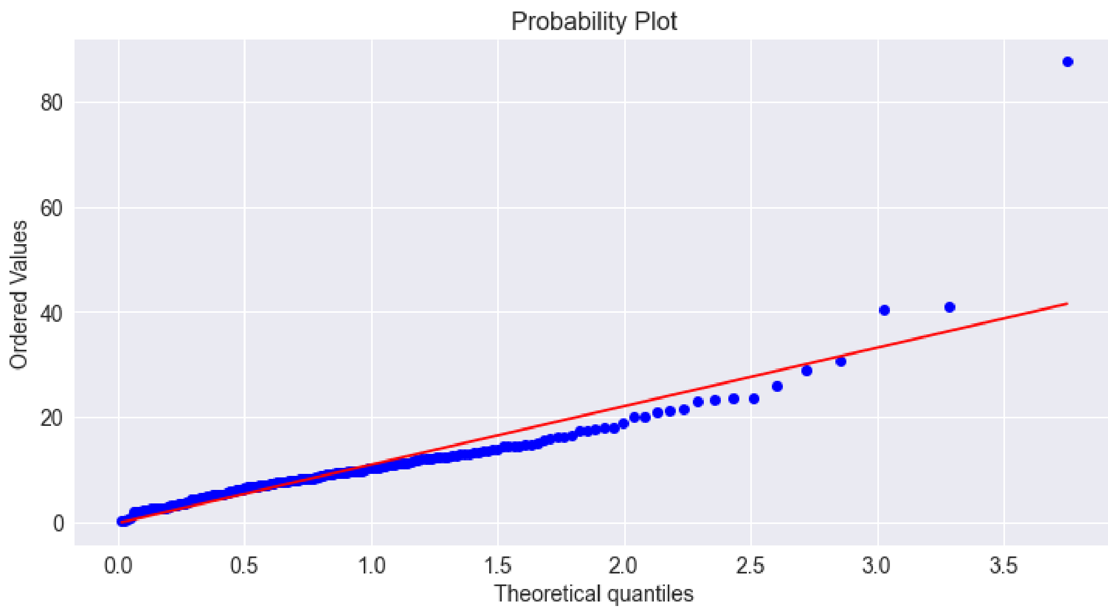


Weibull distribution seems a better one comapre with the normal distribution probability plot. But at the large end still not fit well.

[59]:
```
rvweib = st.weibull_min(c=1.3)
st.probplot(country_2019['Both sexes'], dist=rvweib, plot=plt)
```

[59]:
```
((array([0.01371548, 0.02718551, 0.03900246, 0.04987292, 0.06012445,
        0.06992732, 0.07938487, 0.08856597, 0.09751957, 0.10628207,
        0.11488154, 0.12334022, 0.13167614, 0.13990418, 0.14803684,
        0.15608474, 0.16405702, 0.17196164, 0.17980558, 0.18759499,
        0.1953354 , 0.20303173, 0.21068844, 0.21830959, 0.22589886,
        0.23345965, 0.24099509, 0.24850806, 0.25600125, 0.26347718,
        0.27093818, 0.27838647, 0.28582412, 0.29325311, 0.30067529,
        0.30809244, 0.31550626, 0.32291835, 0.33033029, 0.33774355,
        0.34515958, 0.35257977, 0.36000547, 0.36743798, 0.37487857,
        0.38232849, 0.38978895, 0.39726112, 0.40474617, 0.41224525,
        0.41975947, 0.42728995, 0.43483777, 0.44240401, 0.44998976,
        0.45759607, 0.46522399, 0.47287459, 0.4805489 , 0.48824798,
        0.49597287, 0.50372461, 0.51150426, 0.51931286, 0.52715148,
        0.53502116, 0.54292299, 0.55085803, 0.55882738, 0.56683212,
        0.57487337, 0.58295226, 0.5910699 , 0.59922746, 0.60742609,
        0.61566699, 0.62395135, 0.63228041, 0.64065539, 0.64907758,
        0.65754826, 0.66606875, 0.67464039, 0.68326456, 0.69194266,
        0.70067611, 0.7094664 , 0.71831502, 0.72722351, 0.73619346,
        0.74522647, 0.75432421, 0.76348839, 0.77272076, 0.78202313,
        0.79139735, 0.80084532, 0.81036903, 0.81997049, 0.8296518 ,
        0.83941511, 0.84926266, 0.85919675, 0.86921975, 0.87933412,
```

```
        0.88954242, 0.89984727, 0.91025142, 0.92075769, 0.93136903,
        0.94208848, 0.95291921, 0.96386452, 0.97492784, 0.98611272,
        0.99742289, 1.00886221, 1.02043472, 1.03214463, 1.04399635,
        1.05599447, 1.0681438 , 1.08044939, 1.0929165 , 1.10555069,
        1.11835775, 1.13134378, 1.14451521, 1.15787879, 1.17144163,
        1.18521124, 1.19919553, 1.21340288, 1.22784214, 1.24252268,
        1.25745446, 1.27264804, 1.28811464, 1.30386623, 1.31991553,
        1.33627616, 1.35296267, 1.36999063, 1.38737678, 1.40513907,
        1.42329685, 1.441871  , 1.46088407, 1.48036051, 1.50032685,
        1.52081199, 1.54184745, 1.56346771, 1.58571063, 1.60861786,
        1.6322354 , 1.65661423, 1.68181105, 1.70788917, 1.73491963,
        1.76298246, 1.79216831, 1.82258043, 1.85433714, 1.88757492,
        1.92245234, 1.95915519, 1.99790308, 2.03895825, 2.08263748,
        2.12932843, 2.17951265, 2.23379883, 2.29297225, 2.35807096,
        2.43050831, 2.51228048, 2.60634163, 2.71734144, 2.85325104,
        3.02958942, 3.28376538, 3.75152452]),
 array([ 0.3,  0.3,  0.6,  1. ,  2. ,  2.1,  2.1,  2.2,  2.3,  2.3,  2.5,
         2.5,  2.6,  2.6,  2.6,  2.7,  2.7,  2.7,  2.8,  2.8,  2.9,  3. ,
         3.2,  3.2,  3.4,  3.4,  3.6,  3.6,  3.7,  3.7,  3.9,  4. ,  4.3,
         4.4,  4.5,  4.5,  4.5,  4.7,  4.7,  4.7,  4.8,  5.1,  5.1,  5.1,
         5.2,  5.2,  5.3,  5.3,  5.3,  5.3,  5.4,  5.5,  5.5,  5.8,  6. ,
         6. ,  6.1,  6.1,  6.2,  6.2,  6.4,  6.5,  6.7,  6.7,  6.8,  6.9,
         6.9,  6.9,  7.1,  7.2,  7.2,  7.2,  7.2,  7.3,  7.3,  7.4,  7.6,
         7.6,  7.7,  7.7,  7.7,  7.7,  7.9,  8. ,  8. ,  8. ,  8.1,  8.2,
         8.2,  8.3,  8.3,  8.3,  8.3,  8.3,  8.5,  8.6,  8.8,  8.9,  9.2,
         9.3,  9.3,  9.3,  9.5,  9.5,  9.5,  9.5,  9.6,  9.7,  9.7,  9.8,
         9.8,  9.8,  9.9, 10.1, 10.2, 10.3, 10.3, 10.4, 10.4, 10.5, 10.6,
        11. , 11. , 11. , 11.2, 11.2, 11.3, 11.3, 11.6, 11.8, 11.9, 12. ,
        12.1, 12.2, 12.2, 12.3, 12.4, 12.4, 12.4, 12.6, 12.7, 12.9, 12.9,
        13.1, 13.2, 13.4, 13.5, 13.5, 13.9, 14. , 14.4, 14.4, 14.5, 14.6,
        14.7, 14.8, 15.2, 15.7, 15.9, 16.1, 16.2, 16.5, 17.3, 17.4, 17.7,
        18. , 18.1, 18.8, 20.2, 20.2, 21. , 21.2, 21.6, 23. , 23.2, 23.5,
        23.6, 25.9, 29. , 30.6, 40.5, 40.9, 87.5])),
(11.10078929875388, -0.1268930621191835, 0.8999734151762656))
```



2.2 Linear Regression

In statistical modeling, regression analysis is a set of statistical processes for estimating the **relationships between a dependent variable (often called the 'outcome variable') and one or more independent variables (often called 'predictors', 'covariates', or 'features')**.

Linear regression means try to find if the relation of them are linear or not. so if it is 2 variables, then should be like:

$$y = ax + b$$

At wikipedia website we can find a data table regarding sunshine duration of world different countyies and different cities. We can try to check the suicide rate and sunshine duration data and see if there possible any kind of correlation between them.

[60]:
```
import os
sunshine_data_path = pathlib.Path(os.getcwd())/'..'/'unitA2'/'sunshine_data.
↪html'
```

[61]:
```
data_sunshine = pd.read_html(sunshine_data_path, index_col=[0,1])
data_sunshine
```

[61]:
```
[                         Country          City    Jan    Feb    Mar    Apr    May  \
 Africa    0          Ivory Coast        Gagnoa  183.0  180.0  196.0  188.0  181.0
           1          Ivory Coast       BouakÃ©  242.0  224.0  219.0  194.0  208.0
           2          Ivory Coast       Abidjan  223.0  223.0  239.0  214.0  205.0
           3          Ivory Coast      OdiennÃ©  242.0  220.2  217.3  214.7  248.8
```

```
        4        Ivory Coast        FerkÃ©  279.0  249.0  253.0  229.0  251.0
...                      ...          ...   ...    ...    ...    ...    ...
Oceania 11        New Zealand  Christchurch  224.4  190.5  177.4  155.6  133.3
        12        New Zealand    Wellington  240.3  205.0  194.7  153.8  126.0
        13        New Zealand       Dunedin  179.6  158.0  146.1  125.9  108.4
        14   Papua New Guinea  Port Moresby  182.0  158.0  184.0  200.0  211.0
        15    Solomon Islands       Honiara  186.0  155.4  198.4  192.0  210.8

              Jun    Jul    Aug    Sep    Oct    Nov    Dec    Year   Ref.
Africa  0   118.0   97.0   80.0  110.0  155.0  171.0  164.0  1823.0    [2]
        1   145.0  104.0   82.0  115.0  170.0  191.0  198.0  2092.0    [2]
        2   128.0  137.0  125.0  139.0  215.0  224.0  224.0  2296.0    [2]
        3   221.8  183.5  174.5  185.4  235.8  252.0  242.6  2638.6    [3]
        4   221.0  183.0  151.0  173.0  245.0  261.0  262.0  2757.0    [2]
...           ...    ...    ...    ...    ...    ...    ...     ...    ...
Oceania 11  117.7  124.8  149.0  166.6  201.3  215.3  214.3  2070.2      ?
        12  102.3  111.4  137.2  163.2  191.1  210.8  222.9  2058.7      ?
        13   95.3  110.6  122.2  136.8  165.5  166.9  168.3  1683.7  [185]
        14  200.0  203.0  222.0  213.0  231.0  243.0  216.0  2463.0    NaN
        15  198.0  186.0  204.6  192.0  226.3  216.0  164.3  2330.0    NaN

[379 rows x 16 columns]]
```

[63]:
```python
type(data_sunshine)
```

[63]:
```
list
```

[64]:
```python
df_sunshine=data_sunshine[0]
df_sunshine
```

[64]:
```
                       Country          City    Jan    Feb    Mar    Apr    May  \
Africa  0          Ivory Coast        Gagnoa  183.0  180.0  196.0  188.0  181.0
        1          Ivory Coast        BouakÃ©  242.0  224.0  219.0  194.0  208.0
        2          Ivory Coast       Abidjan  223.0  223.0  239.0  214.0  205.0
        3          Ivory Coast       OdiennÃ©  242.0  220.2  217.3  214.7  248.8
        4          Ivory Coast        FerkÃ©  279.0  249.0  253.0  229.0  251.0
...                        ...           ...    ...    ...    ...    ...    ...
Oceania 11         New Zealand  Christchurch  224.4  190.5  177.4  155.6  133.3
        12         New Zealand    Wellington  240.3  205.0  194.7  153.8  126.0
        13         New Zealand       Dunedin  179.6  158.0  146.1  125.9  108.4
        14    Papua New Guinea  Port Moresby  182.0  158.0  184.0  200.0  211.0
        15     Solomon Islands       Honiara  186.0  155.4  198.4  192.0  210.8

              Jun    Jul    Aug    Sep    Oct    Nov    Dec    Year   Ref.
Africa  0   118.0   97.0   80.0  110.0  155.0  171.0  164.0  1823.0    [2]
        1   145.0  104.0   82.0  115.0  170.0  191.0  198.0  2092.0    [2]
        2   128.0  137.0  125.0  139.0  215.0  224.0  224.0  2296.0    [2]
```

```
        3   221.8  183.5  174.5  185.4  235.8  252.0  242.6  2638.6    [3]
        4   221.0  183.0  151.0  173.0  245.0  261.0  262.0  2757.0    [2]
…           …    …    …    …    …    …    …     …    …
Oceania 11  117.7  124.8  149.0  166.6  201.3  215.3  214.3  2070.2      ?
        12  102.3  111.4  137.2  163.2  191.1  210.8  222.9  2058.7      ?
        13   95.3  110.6  122.2  136.8  165.5  166.9  168.3  1683.7  [185]
        14  200.0  203.0  222.0  213.0  231.0  243.0  216.0  2463.0    NaN
        15  198.0  186.0  204.6  192.0  226.3  216.0  164.3  2330.0    NaN

[379 rows x 16 columns]
```

[65]:
```python
df_ss_country = df_sunshine.groupby(df_sunshine['Country']).agg('mean')
df_ss_country
```

[65]:
```
                    Jan         Feb         Mar         Apr         May  \
Country
Afghanistan  177.200000  178.600000  204.500000  232.500000  310.300000
Albania      124.000000  125.000000  165.000000  191.000000  263.000000
Algeria      223.300000  220.250000  262.200000  292.500000  323.800000
Angola       219.000000  208.000000  213.000000  199.000000  233.000000
Argentina    238.250000  207.066667  185.050000  170.616667  151.466667
…                 …           …           …           …           …
Uzbekistan   117.800000  127.100000  164.300000  216.000000  303.800000
Venezuela    259.133333  243.900000  261.700000  224.666667  217.400000
Vietnam      178.250000  168.000000  190.500000  185.000000  203.500000
Zambia       180.833333  168.933333  221.133333  254.000000  286.233333
Zimbabwe     230.950000  201.600000  241.800000  250.500000  274.350000

                    Jun         Jul     Aug         Sep         Oct  \
Country
Afghanistan  353.400000  356.800000  339.70  303.900000  282.600000
Albania      298.000000  354.000000  327.00  264.000000  218.000000
Algeria      312.000000  353.250000  325.35  262.500000  269.500000
Angola       223.000000  175.000000  150.00  145.000000  164.000000
Argentina    123.383333  138.616667  170.40  174.600000  208.566667
…                 …           …       …           …           …
Uzbekistan   363.000000  384.400000  365.80  300.000000  226.300000
Venezuela    212.333333  248.100000  248.00  245.833333  251.400000
Vietnam      182.250000  196.250000  175.00  161.750000  158.500000
Zambia       278.000000  300.700000  306.90  289.000000  273.833333
Zimbabwe     265.500000  283.650000  300.70  291.000000  279.000000

                    Nov         Dec         Year
Country
Afghanistan  253.200000  182.400000  3175.100000
Albania      127.000000   88.000000  2544.000000
Algeria      225.000000  204.400000  3266.500000
```

```
Angola        199.000000  212.000000  2341.000000
Argentina     222.833333  229.450000  2220.300000
…                  …           …            …
Uzbekistan    150.000000  105.400000  2823.900000
Venezuela     239.000000  243.933333  2895.300000
Vietnam       157.250000  167.000000  2123.500000
Zambia        223.000000  182.900000  2965.466667
Zimbabwe      234.000000  212.350000  3065.400000

[140 rows x 13 columns]
```

[66]:
```
df_sunshine[df_sunshine['Country']=='Albania']
```

[66]:
```
          Country    City    Jan    Feb    Mar    Apr    May    Jun    Jul  \
Europe 0  Albania  Tirana  124.0  125.0  165.0  191.0  263.0  298.0  354.0

            Aug    Sep    Oct    Nov   Dec    Year Ref.
Europe 0  327.0  264.0  218.0  127.0  88.0  2544.0  NaN
```

[67]:
```
df_ss_country.loc['Albania']
```

[67]:
```
Jan      124.0
Feb      125.0
Mar      165.0
Apr      191.0
May      263.0
Jun      298.0
Jul      354.0
Aug      327.0
Sep      264.0
Oct      218.0
Nov      127.0
Dec       88.0
Year    2544.0
Name: Albania, dtype: float64
```

[68]:
```
df_sunshine[df_sunshine['Country']=='China']
```

[68]:
```
        Country       City    Jan    Feb    Mar    Apr    May    Jun    Jul  \
Asia 3    China    Beijing  194.1  194.7  231.8  251.9  283.4  261.4  212.4
     4    China  Chongqing   48.0   56.0   81.0  111.0  139.0  128.0  221.0
     5    China     Fuzhou  101.6   79.2   89.1  111.0  114.4  141.9  225.6
     6    China  Guangzhou  118.5   71.6   62.4   65.1  104.0  140.2  202.0
     7    China  Hong Kong  143.0   94.2   90.8  101.7  140.4  146.1  212.0
     8    China      Lhasa  250.9  226.7  246.1  248.9  276.6  257.3  227.4
     9    China      Macau  127.4   79.4   71.5   85.3  136.4  155.3  223.2
     10   China    Nanjing  124.7  120.3  144.7  169.2  194.2  162.8  196.7
```

```
       11   China     Ningbo  123.7  108.4  121.7  142.4  156.7  147.8  243.8
       12   China    Qingdao  186.0  180.8  220.1  222.0  244.9  219.0  182.9
       13   China   Shanghai  114.3  119.9  128.5  148.5  169.8  130.9  190.8
       14   China    Tianjin  170.1  170.2  202.4  223.8  249.0  226.9  206.4
       15   China   Ã rÃ¼mqi  101.6  128.8  180.5  248.0  283.3  282.7  298.7
       16   China      Wuhan  101.9   97.0  121.8  152.8  181.0  170.9  220.2
       17   China     Xiamen  133.3   88.3   89.6  105.6  132.6  163.8  234.6

             Aug    Sep    Oct    Nov    Dec    Year  Ref.
Asia 3     220.9  232.1  222.1  185.3  180.7  2670.8     ?
     4     222.0  123.0   63.0   47.0   54.0  1293.0     ?
     5     199.2  153.7  144.2  120.3  126.9  1607.1     ?
     6     173.5  170.2  181.8  172.7  166.0  1628.0     ?
     7     188.9  172.3  193.9  180.1  172.2  1835.6  [75]
     8     219.6  229.0  281.7  267.4  258.6  2990.2  [76]
     9     195.4  176.5  192.3  172.2  159.1  1773.9  [77]
     10    201.6  164.0  164.2  147.4  137.1  1926.9  [77]
     11    238.0  171.5  166.5  143.4  146.1  1910.0     ?
     12    223.2  219.0  220.1  189.0  182.9  2489.9     ?
     13    185.7  167.5  161.4  131.1  127.4  1775.8     ?
     14    204.4  205.3  196.1  163.0  157.6  2375.2     ?
     15    301.0  262.6  224.4  127.4   84.3  2523.3  [78]
     16    226.4  175.8  151.9  139.3  126.5  1775.8     ?
     17    211.6  178.9  188.4  163.0  163.5  1853.2     ?
```

[69]:
```
df_ss_country.loc['China']
```

[69]:
```
Jan       135.940000
Feb       121.033333
Mar       138.800000
Apr       159.146667
May       187.046667
Jun       182.333333
Jul       219.846667
Aug       214.093333
Sep       186.760000
Oct       183.466667
Nov       156.573333
Dec       149.526667
Year     2028.580000
Name: China, dtype: float64
```

[70]:
```
df_new = pd.merge(country_2019, df_ss_country, left_index=True,␣
 ↪right_index=True, how='outer')
df_new
```

[70]:

```
                     Both sexes  Female  Male         Jan         Feb  \
Country
Afghanistan                 6.0     5.7   6.2  177.200000  178.600000
Albania                     3.7     2.2   5.3  124.000000  125.000000
Algeria                     2.6     1.9   3.3  223.300000  220.250000
Angola                     12.6     4.7  21.7  219.000000  208.000000
Antigua and Barbuda         0.3     0.6   0.0         NaN         NaN
…                          …     …     …      …       …
Viet Nam                    7.2     4.2  10.6         NaN         NaN
Vietnam                     NaN     NaN   NaN  178.250000  168.000000
Yemen                       7.1     5.3   9.0         NaN         NaN
Zambia                     14.4     5.3  25.7  180.833333  168.933333
Zimbabwe                   23.6    13.5  37.8  230.950000  201.600000

                            Mar    Apr         May     Jun     Jul     Aug  \
Country
Afghanistan          204.500000  232.5  310.300000  353.40  356.80  339.70
Albania              165.000000  191.0  263.000000  298.00  354.00  327.00
Algeria              262.200000  292.5  323.800000  312.00  353.25  325.35
Angola               213.000000  199.0  233.000000  223.00  175.00  150.00
Antigua and Barbuda         NaN    NaN         NaN     NaN     NaN     NaN
…                          …    …         …     …     …     …
Viet Nam                    NaN    NaN         NaN     NaN     NaN     NaN
Vietnam              190.500000  185.0  203.500000  182.25  196.25  175.00
Yemen                       NaN    NaN         NaN     NaN     NaN     NaN
Zambia               221.133333  254.0  286.233333  278.00  300.70  306.90
Zimbabwe             241.800000  250.5  274.350000  265.50  283.65  300.70

                        Sep         Oct     Nov     Dec         Year
Country
Afghanistan          303.90  282.600000  253.20  182.40  3175.100000
Albania              264.00  218.000000  127.00   88.00  2544.000000
Algeria              262.50  269.500000  225.00  204.40  3266.500000
Angola               145.00  164.000000  199.00  212.00  2341.000000
Antigua and Barbuda     NaN         NaN     NaN     NaN          NaN
…                    …        …     …     …          …
Viet Nam                NaN         NaN     NaN     NaN          NaN
Vietnam              161.75  158.500000  157.25  167.00  2123.500000
Yemen                   NaN         NaN     NaN     NaN          NaN
Zambia               289.00  273.833333  223.00  182.90  2965.466667
Zimbabwe             291.00  279.000000  234.00  212.35  3065.400000

[204 rows x 16 columns]
```

[71]:

```
df_new.index
```

[71]:
```
Index(['Afghanistan', 'Albania', 'Algeria', 'Angola', 'Antigua and Barbuda',
       'Argentina', 'Armenia', 'Australia', 'Austria', 'Azerbaijan',
       …
       'Uruguay', 'Uzbekistan', 'Vanuatu', 'Venezuela',
       'Venezuela (Bolivarian Republic of)', 'Viet Nam', 'Vietnam', 'Yemen',
       'Zambia', 'Zimbabwe'],
      dtype='object', name='Country', length=204)
```

We can find that for come countries, the two table are using different names, for example 'Venezuela' and 'Venezuela (Bolivarian Republic of)', also 'Viet Nam' and 'Vietnam'. Because we can not find a standard country code which is common to both table, this becomes the diffuculties we have to check.

[72]:
```
df_new.to_csv('check country name.csv')
```

[73]:
```
country_name_map  = {'Iran (Islamic Republic of)': 'Iran',
                     'United Kingdom of Great Britain and Northern Ireland':␣
 ↪'United Kingdom',
                     'United States of America':'United States',
                     'Venezuela (Bolivarian Republic of)': 'Venezuela',
                     'Viet Nam': 'Vietnam'}
country_2019['New country'] = country_2019.index.to_series().
 ↪replace(country_name_map)
```

[74]:
```
country_2019.set_index('New country', drop=True, inplace=True)
country_2019
```

[74]:
```
Sex                                 Both sexes  Female   Male
New country
Lesotho                                   87.5    34.6  146.9
Guyana                                    40.9    17.0   65.0
Eswatini                                  40.5     6.4   78.7
Kiribati                                  30.6     9.5   53.6
Micronesia (Federated States of)          29.0    13.2   44.3
…                                          …      …      …
Jordan                                     2.0     0.9    3.0
Saint Vincent and the Grenadines           1.0     0.7    1.3
Grenada                                    0.6     0.7    0.5
Antigua and Barbuda                        0.3     0.6    0.0
Barbados                                   0.3     0.2    0.5

[183 rows x 3 columns]
```

[75]:
```
df_new = pd.merge(country_2019, df_ss_country, left_index=True,␣
 ↪right_index=True, how='outer')
df_new
```

[75]:
```
                     Both sexes  Female  Male         Jan         Feb  \
Afghanistan                 6.0     5.7   6.2  177.200000  178.600000
Albania                     3.7     2.2   5.3  124.000000  125.000000
Algeria                     2.6     1.9   3.3  223.300000  220.250000
Angola                     12.6     4.7  21.7  219.000000  208.000000
Antigua and Barbuda         0.3     0.6   0.0         NaN         NaN
…                             …     …     …           …           …
Venezuela                   2.1     0.7   3.7  259.133333  243.900000
Vietnam                     7.2     4.2  10.6  178.250000  168.000000
Yemen                       7.1     5.3   9.0         NaN         NaN
Zambia                     14.4     5.3  25.7  180.833333  168.933333
Zimbabwe                   23.6    13.5  37.8  230.950000  201.600000

                            Mar         Apr         May         Jun     Jul  \
Afghanistan          204.500000  232.500000  310.300000  353.400000  356.80
Albania              165.000000  191.000000  263.000000  298.000000  354.00
Algeria              262.200000  292.500000  323.800000  312.000000  353.25
Angola               213.000000  199.000000  233.000000  223.000000  175.00
Antigua and Barbuda         NaN         NaN         NaN         NaN     NaN
…                             …           …           …           …       …
Venezuela            261.700000  224.666667  217.400000  212.333333  248.10
Vietnam              190.500000  185.000000  203.500000  182.250000  196.25
Yemen                       NaN         NaN         NaN         NaN     NaN
Zambia               221.133333  254.000000  286.233333  278.000000  300.70
Zimbabwe             241.800000  250.500000  274.350000  265.500000  283.65

                        Aug         Sep         Oct     Nov         Dec  \
Afghanistan          339.70  303.900000  282.600000  253.20  182.400000
Albania              327.00  264.000000  218.000000  127.00   88.000000
Algeria              325.35  262.500000  269.500000  225.00  204.400000
Angola               150.00  145.000000  164.000000  199.00  212.000000
Antigua and Barbuda     NaN         NaN         NaN     NaN         NaN
…                       …           …           …       …           …
Venezuela            248.00  245.833333  251.400000  239.00  243.933333
Vietnam              175.00  161.750000  158.500000  157.25  167.000000
Yemen                   NaN         NaN         NaN     NaN         NaN
Zambia               306.90  289.000000  273.833333  223.00  182.900000
Zimbabwe             300.70  291.000000  279.000000  234.00  212.350000

                            Year
Afghanistan          3175.100000
Albania              2544.000000
Algeria              3266.500000
Angola               2341.000000
Antigua and Barbuda          NaN
…                              …
Venezuela            2895.300000
```

```
Vietnam                2123.500000
Yemen                          NaN
Zambia                 2965.466667
Zimbabwe               3065.400000

[199 rows x 16 columns]
```

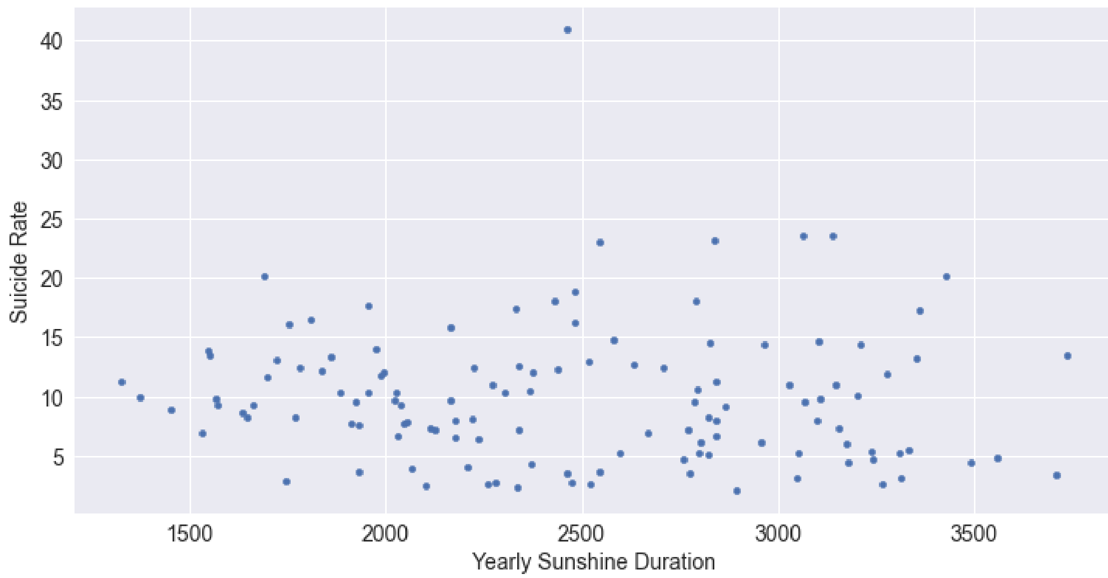
Now the new dataframe country name issue resolved.

[76]:
```
df_new.dropna(inplace=True)
df_new
```

[76]:
```
             Both sexes  Female  Male         Jan         Feb         Mar  \
Afghanistan         6.0     5.7   6.2  177.200000  178.600000  204.500000
Albania             3.7     2.2   5.3  124.000000  125.000000  165.000000
Algeria             2.6     1.9   3.3  223.300000  220.250000  262.200000
Angola             12.6     4.7  21.7  219.000000  208.000000  213.000000
Argentina           8.1     3.3  13.5  238.250000  207.066667  185.050000
…                     …     …     …           …           …           …
Uzbekistan          8.3     4.9  11.8  117.800000  127.100000  164.300000
Venezuela           2.1     0.7   3.7  259.133333  243.900000  261.700000
Vietnam             7.2     4.2  10.6  178.250000  168.000000  190.500000
Zambia             14.4     5.3  25.7  180.833333  168.933333  221.133333
Zimbabwe           23.6    13.5  37.8  230.950000  201.600000  241.800000

                    Apr         May         Jun         Jul     Aug  \
Afghanistan  232.500000  310.300000  353.400000  356.800000  339.70
Albania      191.000000  263.000000  298.000000  354.000000  327.00
Algeria      292.500000  323.800000  312.000000  353.250000  325.35
Angola       199.000000  233.000000  223.000000  175.000000  150.00
Argentina    170.616667  151.466667  123.383333  138.616667  170.40
…                     …           …           …           …       …
Uzbekistan   216.000000  303.800000  363.000000  384.400000  365.80
Venezuela    224.666667  217.400000  212.333333  248.100000  248.00
Vietnam      185.000000  203.500000  182.250000  196.250000  175.00
Zambia       254.000000  286.233333  278.000000  300.700000  306.90
Zimbabwe     250.500000  274.350000  265.500000  283.650000  300.70

                    Sep         Oct         Nov         Dec         Year
Afghanistan  303.900000  282.600000  253.200000  182.400000  3175.100000
Albania      264.000000  218.000000  127.000000   88.000000  2544.000000
Algeria      262.500000  269.500000  225.000000  204.400000  3266.500000
Angola       145.000000  164.000000  199.000000  212.000000  2341.000000
Argentina    174.600000  208.566667  222.833333  229.450000  2220.300000
…                     …           …           …           …            …
Uzbekistan   300.000000  226.300000  150.000000  105.400000  2823.900000
Venezuela    245.833333  251.400000  239.000000  243.933333  2895.300000
Vietnam      161.750000  158.500000  157.250000  167.000000  2123.500000
```

```
Zambia        289.000000  273.833333  223.000000  182.900000  2965.466667
Zimbabwe      291.000000  279.000000  234.000000  212.350000  3065.400000

[124 rows x 16 columns]
```

[77]:
```
ax = df_new.plot(kind='scatter', x='Year', y='Both sexes')
ax.set_xlabel('Yearly Sunshine Duration')
ax.set_ylabel('Suicide Rate')
plt.show()
```



2.2.1 using SciPy for linear regression

Linear regression, is basically for a set of data (x_i, y_i), find a line which best fit all those data:

$$y = ax + b$$

[78]:
```
rv = df_new[['Year', 'Both sexes']].to_numpy()
rv
```

[78]:
```
array([[3.17510000e+03, 6.00000000e+00],
       [2.54400000e+03, 3.70000000e+00],
       [3.26650000e+03, 2.60000000e+00],
       [2.34100000e+03, 1.26000000e+01],
       [2.22030000e+03, 8.10000000e+00],
       [2.47400000e+03, 2.70000000e+00],
       [2.84356667e+03, 1.13000000e+01],
       [1.88400000e+03, 1.04000000e+01],
       [2.20740000e+03, 4.00000000e+00],
```

```
[2.06600000e+03, 3.90000000e+00],
[1.80700000e+03, 1.65000000e+01],
[1.54600000e+03, 1.39000000e+01],
[2.63046667e+03, 1.27000000e+01],
[1.76900000e+03, 8.30000000e+00],
[3.42666667e+03, 2.02000000e+01],
[2.23758182e+03, 6.40000000e+00],
[2.17700000e+03, 6.50000000e+00],
[3.20900000e+03, 1.44000000e+01],
[2.37340000e+03, 1.21000000e+01],
[2.16512500e+03, 1.59000000e+01],
[2.02804444e+03, 1.03000000e+01],
[2.54650000e+03, 2.30000000e+01],
[3.35320000e+03, 1.32000000e+01],
[2.84178000e+03, 8.00000000e+00],
[2.02858000e+03, 6.70000000e+00],
[1.93077500e+03, 3.70000000e+00],
[1.69866667e+03, 1.16000000e+01],
[2.27200000e+03, 1.10000000e+01],
[3.31410000e+03, 3.20000000e+00],
[2.22500000e+03, 1.24000000e+01],
[1.93200000e+03, 7.60000000e+00],
[3.27900000e+03, 1.19000000e+01],
[1.90955000e+03, 7.70000000e+00],
[3.71068000e+03, 3.40000000e+00],
[2.95700000e+03, 6.10000000e+00],
[1.54895000e+03, 1.35000000e+01],
[3.36100000e+03, 1.73000000e+01],
[1.99450000e+03, 1.20000000e+01],
[2.78485000e+03, 9.50000000e+00],
[1.92200000e+03, 9.50000000e+00],
[1.85800000e+03, 1.34000000e+01],
[2.16666667e+03, 9.70000000e+00],
[1.72020000e+03, 1.31000000e+01],
[3.07000000e+03, 9.60000000e+00],
[2.04600000e+03, 7.70000000e+00],
[1.64400000e+03, 8.30000000e+00],
[2.36750000e+03, 1.05000000e+01],
[2.77300000e+03, 3.60000000e+00],
[2.44000000e+03, 1.23000000e+01],
[2.70700000e+03, 1.24000000e+01],
[2.46060000e+03, 4.09000000e+01],
[2.25980000e+03, 2.60000000e+00],
[1.98800000e+03, 1.18000000e+01],
[1.32600000e+03, 1.12000000e+01],
[2.51702000e+03, 1.29000000e+01],
[2.52165000e+03, 2.60000000e+00],
```

```
[2.82170000e+03, 5.10000000e+00],
[3.24080000e+03, 4.70000000e+00],
[1.45300000e+03, 8.90000000e+00],
[3.31100000e+03, 5.20000000e+00],
[2.37225000e+03, 4.30000000e+00],
[1.83712000e+03, 1.22000000e+01],
[2.43150000e+03, 1.81000000e+01],
[3.03002500e+03, 1.10000000e+01],
[1.75400000e+03, 1.61000000e+01],
[3.17810000e+03, 4.50000000e+00],
[1.69100000e+03, 2.02000000e+01],
[1.63400000e+03, 8.60000000e+00],
[2.86443333e+03, 9.20000000e+00],
[2.79586667e+03, 1.06000000e+01],
[3.09986667e+03, 8.00000000e+00],
[3.05400000e+03, 5.30000000e+00],
[3.33250000e+03, 5.50000000e+00],
[2.59625000e+03, 5.30000000e+00],
[2.79150000e+03, 1.80000000e+01],
[2.48100000e+03, 1.62000000e+01],
[3.15546667e+03, 7.30000000e+00],
[2.83800000e+03, 2.32000000e+01],
[3.73750000e+03, 1.35000000e+01],
[1.66200000e+03, 9.30000000e+00],
[1.95392500e+03, 1.03000000e+01],
[2.75990000e+03, 4.70000000e+00],
[3.20320000e+03, 1.01000000e+01],
[2.66908000e+03, 6.90000000e+00],
[2.33900000e+03, 7.20000000e+00],
[1.37333333e+03, 9.90000000e+00],
[3.49330000e+03, 4.50000000e+00],
[3.10851667e+03, 9.80000000e+00],
[1.74350000e+03, 2.90000000e+00],
[2.46300000e+03, 3.60000000e+00],
[2.80300000e+03, 6.20000000e+00],
[2.28165000e+03, 2.70000000e+00],
[2.10310000e+03, 2.50000000e+00],
[1.57100000e+03, 9.30000000e+00],
[2.77000000e+03, 7.20000000e+00],
[2.11500000e+03, 7.30000000e+00],
[3.23650000e+03, 5.40000000e+00],
[3.14600000e+03, 1.10000000e+01],
[2.05500000e+03, 7.90000000e+00],
[2.02240000e+03, 9.70000000e+00],
[2.03800000e+03, 9.30000000e+00],
[1.97400000e+03, 1.40000000e+01],
[2.33000000e+03, 1.74000000e+01],
```

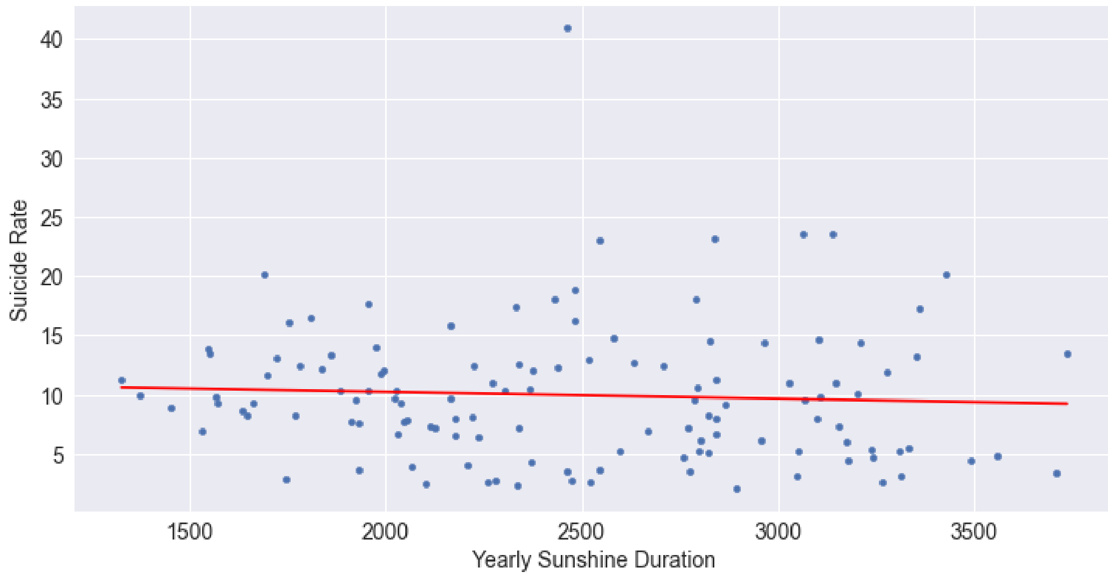
```
       [3.10300000e+03, 1.47000000e+01],
       [3.14131667e+03, 2.35000000e+01],
       [2.84130000e+03, 6.70000000e+00],
       [2.80020000e+03, 5.30000000e+00],
       [3.55955000e+03, 4.80000000e+00],
       [1.78250000e+03, 1.24000000e+01],
       [1.56600000e+03, 9.80000000e+00],
       [2.17502500e+03, 8.00000000e+00],
       [2.57995000e+03, 1.48000000e+01],
       [3.04995000e+03, 3.20000000e+00],
       [2.33380000e+03, 2.30000000e+00],
       [2.30400000e+03, 1.04000000e+01],
       [1.95500000e+03, 1.77000000e+01],
       [1.53000000e+03, 6.90000000e+00],
       [2.82761852e+03, 1.45000000e+01],
       [2.48140000e+03, 1.88000000e+01],
       [2.82390000e+03, 8.30000000e+00],
       [2.89530000e+03, 2.10000000e+00],
       [2.12350000e+03, 7.20000000e+00],
       [2.96546667e+03, 1.44000000e+01],
       [3.06540000e+03, 2.36000000e+01]])
```

[79]:
```python
result = st.linregress(rv.T)
print(result)
```

```
LinregressResult(slope=-0.0005738120093998853, intercept=11.38520524736704,
rvalue=-0.05806254629691001, pvalue=0.5218152700333842,
stderr=0.0008932239186459852, intercept_stderr=2.2676366374965635)
```

We check the slope result value, and also check the pvalue, the result tells that quite sure the slope should be 0. which means there is **no reslation** between sunshine time and suicide rate.

[80]:
```python
a, b = result.slope, result.intercept
x = np.linspace(df_new['Year'].min(), df_new['Year'].max(), endpoint=True)
y = a*x+b
ax = df_new.plot(kind='scatter', x='Year', y='Both sexes')
ax.set_xlabel('Yearly Sunshine Duration')
ax.set_ylabel('Suicide Rate')
ax.plot(x,y,color='red')
plt.show()
```



Simulation shows a decline trend, when sunshine duration increase, the suicide rate tends to decrease. The correlation is not strong.

2.3 Multivariate linear regression

When has multiple random variables, the linear formula becomes:

$$y = k_2x_2 + k_1x_1 + k_0$$

Here has 2 independant random variables x_2 and x_1, the dependant random variable is y.

Pandas has a data webservice, which gives DataFrame interface for many famous data source, for example world bank. to use those data just need import the package, find the indicators, and create the dataframe object and download the data needed.
Use `pip install padas_datareader` to install the package. (If has Anaconda, use `conda install pandas-datareader`)

[101]:
```
from pandas_datareader import wb
matches = wb.search('gdp.*capita.*const')
matches
```

[101]:
```
                          id                                               name  \
716     6.0.GDPpc_constant  GDP per capita, PPP (constant 2011 internation…
9296         NY.GDP.PCAP.KD                  GDP per capita (constant 2010 US$)
9298         NY.GDP.PCAP.KN                       GDP per capita (constant LCU)
9300      NY.GDP.PCAP.PP.KD  GDP per capita, PPP (constant 2017 internation…
9301   NY.GDP.PCAP.PP.KD.87  GDP per capita, PPP (constant 1987 internation…

     unit                           source  \
```

```
716                        LAC Equity Lab
9296        World Development Indicators
9298        World Development Indicators
9300        World Development Indicators
9301               WDI Database Archives

                                           sourceNote  \
716   GDP per capita based on purchasing power parit…
9296  GDP per capita is gross domestic product divid…
9298  GDP per capita is gross domestic product divid…
9300  GDP per capita based on purchasing power parit…
9301

                                   sourceOrganization            topics
716        b'World Development Indicators (World Bank)'  Economy & Growth
9296  b'World Bank national accounts data, and OECD …  Economy & Growth
9298  b'World Bank national accounts data, and OECD …  Economy & Growth
9300  b'International Comparison Program, World Bank…  Economy & Growth
9301                                               b''
```

[82]:
```
dat = wb.download(indicator='NY.GDP.PCAP.PP.KD', country='all', start=2000,␣
 ↪end=2020)
dat
```

[82]:
```
                                 NY.GDP.PCAP.PP.KD
country                     year
Africa Eastern and Southern 2020        3387.594670
                            2019        3568.597017
                            2018        3579.271917
                            2017        3569.667028
                            2016        3546.711250
…                                               …
Zimbabwe                    2004        2682.783000
                            2003        2857.152336
                            2002        3450.189031
                            2001        3796.657107
                            2000        3756.139483

[5586 rows x 1 columns]
```

[83]:
```
dat.index
```

[83]:
```
MultiIndex([('Africa Eastern and Southern', '2020'),
            ('Africa Eastern and Southern', '2019'),
            ('Africa Eastern and Southern', '2018'),
            ('Africa Eastern and Southern', '2017'),
            ('Africa Eastern and Southern', '2016'),
```

```
            ('Africa Eastern and Southern', '2015'),
            ('Africa Eastern and Southern', '2014'),
            ('Africa Eastern and Southern', '2013'),
            ('Africa Eastern and Southern', '2012'),
            ('Africa Eastern and Southern', '2011'),
            …
            (                    'Zimbabwe', '2009'),
            (                    'Zimbabwe', '2008'),
            (                    'Zimbabwe', '2007'),
            (                    'Zimbabwe', '2006'),
            (                    'Zimbabwe', '2005'),
            (                    'Zimbabwe', '2004'),
            (                    'Zimbabwe', '2003'),
            (                    'Zimbabwe', '2002'),
            (                    'Zimbabwe', '2001'),
            (                    'Zimbabwe', '2000')],
           names=['country', 'year'], length=5586)
```

[84]:
```
gdp_latest = dat.xs('2019', level=1, axis=0)
gdp_latest = gdp_latest.dropna()
gdp_latest
```

[84]:
```
                                NY.GDP.PCAP.PP.KD
country
Africa Eastern and Southern           3568.597017
Africa Western and Central            4142.398382
Arab World                           14599.707893
Caribbean small states               15994.260460
Central Europe and the Baltics       32553.732435
…                                               …
Vanuatu                               3117.678832
Vietnam                               8041.178384
West Bank and Gaza                    6245.448697
Zambia                                3470.448024
Zimbabwe                              3027.656038

[238 rows x 1 columns]
```

[85]:
```
df_3_rv = pd.merge(df_new, gdp_latest, left_index=True, right_index=True,␣
 ↪how='outer')
df_3_rv
```

[85]:
```
                             Both sexes  Female  Male         Jan         Feb  \
Afghanistan                         6.0     5.7   6.2  177.200000  178.600000
Africa Eastern and Southern         NaN     NaN   NaN         NaN         NaN
Africa Western and Central          NaN     NaN   NaN         NaN         NaN
Albania                             3.7     2.2   5.3  124.000000  125.000000
```

```
Algeria                            2.6      1.9   3.3  223.300000  220.250000
…                                  …     …    …          …           …
Vietnam                            7.2      4.2  10.6  178.250000  168.000000
West Bank and Gaza                 NaN      NaN   NaN         NaN         NaN
World                              NaN      NaN   NaN         NaN         NaN
Zambia                            14.4      5.3  25.7  180.833333  168.933333
Zimbabwe                          23.6     13.5  37.8  230.950000  201.600000

                                   Mar    Apr         May     Jun     Jul  \
Afghanistan                 204.500000  232.5  310.300000  353.40  356.80
Africa Eastern and Southern        NaN    NaN         NaN     NaN     NaN
Africa Western and Central         NaN    NaN         NaN     NaN     NaN
Albania                     165.000000  191.0  263.000000  298.00  354.00
Algeria                     262.200000  292.5  323.800000  312.00  353.25
…                                    …     …          …       …       …
Vietnam                     190.500000  185.0  203.500000  182.25  196.25
West Bank and Gaza                 NaN    NaN         NaN     NaN     NaN
World                              NaN    NaN         NaN     NaN     NaN
Zambia                      221.133333  254.0  286.233333  278.00  300.70
Zimbabwe                    241.800000  250.5  274.350000  265.50  283.65

                               Aug     Sep         Oct     Nov     Dec  \
Afghanistan                 339.70  303.90  282.600000  253.20  182.40
Africa Eastern and Southern    NaN     NaN         NaN     NaN     NaN
Africa Western and Central     NaN     NaN         NaN     NaN     NaN
Albania                     327.00  264.00  218.000000  127.00   88.00
Algeria                     325.35  262.50  269.500000  225.00  204.40
…                                …       …           …       …       …
Vietnam                     175.00  161.75  158.500000  157.25  167.00
West Bank and Gaza             NaN     NaN         NaN     NaN     NaN
World                          NaN     NaN         NaN     NaN     NaN
Zambia                      306.90  289.00  273.833333  223.00  182.90
Zimbabwe                    300.70  291.00  279.000000  234.00  212.35

                                   Year  NY.GDP.PCAP.PP.KD
Afghanistan                 3175.100000        2065.036235
Africa Eastern and Southern         NaN        3568.597017
Africa Western and Central          NaN        4142.398382
Albania                     2544.000000       13671.488422
Algeria                     3266.500000       11510.557088
…                                     …                  …
Vietnam                     2123.500000        8041.178384
West Bank and Gaza                  NaN        6245.448697
World                               NaN       16915.287846
Zambia                      2965.466667        3470.448024
Zimbabwe                    3065.400000        3027.656038
```

```
[247 rows x 17 columns]
```

[86]:
```
df_3_rv.to_csv('check_3_rv.csv')
```

Again we found few country name issue, need map the names.

[87]:
```
country_name_map2  = {'Congo, Rep.': 'Congo',
                      'Egypt, Arab Rep.': 'Egypt',
                      'Gambia, The': 'Gambia',
                      'Iran, Islamic Rep.': 'Iran'}
gdp_latest['new country'] = gdp_latest.index.to_series().
 ↪replace(country_name_map2)
gdp_latest
```

[87]:
```
                                NY.GDP.PCAP.PP.KD  \
country
Africa Eastern and Southern           3568.597017
Africa Western and Central            4142.398382
Arab World                           14599.707893
Caribbean small states               15994.260460
Central Europe and the Baltics       32553.732435
…                                             …
Vanuatu                               3117.678832
Vietnam                               8041.178384
West Bank and Gaza                    6245.448697
Zambia                                3470.448024
Zimbabwe                              3027.656038

                                                   new country
country
Africa Eastern and Southern        Africa Eastern and Southern
Africa Western and Central          Africa Western and Central
Arab World                                          Arab World
Caribbean small states                  Caribbean small states
Central Europe and the Baltics  Central Europe and the Baltics
…                                                          …
Vanuatu                                                Vanuatu
Vietnam                                                Vietnam
West Bank and Gaza                          West Bank and Gaza
Zambia                                                  Zambia
Zimbabwe                                              Zimbabwe

[238 rows x 2 columns]
```

[88]:
```
gdp_latest.set_index('new country', drop=True, inplace=True)
gdp_latest
```

[88]:
```
                                 NY.GDP.PCAP.PP.KD
new country
Africa Eastern and Southern            3568.597017
Africa Western and Central             4142.398382
Arab World                            14599.707893
Caribbean small states                15994.260460
Central Europe and the Baltics        32553.732435
…                                              …
Vanuatu                                3117.678832
Vietnam                                8041.178384
West Bank and Gaza                     6245.448697
Zambia                                 3470.448024
Zimbabwe                               3027.656038

[238 rows x 1 columns]
```

[89]:
```python
df_3_rv = pd.merge(df_new, gdp_latest, left_index=True, right_index=True, how='outer')
df_3_rv
```

[89]:
```
                             Both sexes  Female  Male         Jan         Feb  \
Afghanistan                         6.0     5.7   6.2  177.200000  178.600000
Africa Eastern and Southern         NaN     NaN   NaN         NaN         NaN
Africa Western and Central          NaN     NaN   NaN         NaN         NaN
Albania                             3.7     2.2   5.3  124.000000  125.000000
Algeria                             2.6     1.9   3.3  223.300000  220.250000
…                                     …     …     …           …         …
Vietnam                             7.2     4.2  10.6  178.250000  168.000000
West Bank and Gaza                  NaN     NaN   NaN         NaN         NaN
World                               NaN     NaN   NaN         NaN         NaN
Zambia                             14.4     5.3  25.7  180.833333  168.933333
Zimbabwe                           23.6    13.5  37.8  230.950000  201.600000

                                    Mar    Apr         May     Jun     Jul  \
Afghanistan                  204.500000  232.5  310.300000  353.40  356.80
Africa Eastern and Southern         NaN    NaN         NaN     NaN     NaN
Africa Western and Central          NaN    NaN         NaN     NaN     NaN
Albania                      165.000000  191.0  263.000000  298.00  354.00
Algeria                      262.200000  292.5  323.800000  312.00  353.25
…                                     …      …           …       …       …
Vietnam                      190.500000  185.0  203.500000  182.25  196.25
West Bank and Gaza                  NaN    NaN         NaN     NaN     NaN
World                               NaN    NaN         NaN     NaN     NaN
Zambia                       221.133333  254.0  286.233333  278.00  300.70
Zimbabwe                     241.800000  250.5  274.350000  265.50  283.65

                                Aug     Sep         Oct     Nov     Dec  \
```

```
Afghanistan                    339.70  303.90  282.600000  253.20  182.40
Africa Eastern and Southern       NaN     NaN         NaN     NaN     NaN
Africa Western and Central        NaN     NaN         NaN     NaN     NaN
Albania                        327.00  264.00  218.000000  127.00   88.00
Algeria                        325.35  262.50  269.500000  225.00  204.40
…                                 …       …         …        …       …
Vietnam                        175.00  161.75  158.500000  157.25  167.00
West Bank and Gaza                NaN     NaN         NaN     NaN     NaN
World                             NaN     NaN         NaN     NaN     NaN
Zambia                         306.90  289.00  273.833333  223.00  182.90
Zimbabwe                       300.70  291.00  279.000000  234.00  212.35

                                      Year  NY.GDP.PCAP.PP.KD
Afghanistan                    3175.100000        2065.036235
Africa Eastern and Southern            NaN        3568.597017
Africa Western and Central             NaN        4142.398382
Albania                        2544.000000       13671.488422
Algeria                        3266.500000       11510.557088
…                                      …                  …
Vietnam                        2123.500000        8041.178384
West Bank and Gaza                     NaN        6245.448697
World                                  NaN       16915.287846
Zambia                         2965.466667        3470.448024
Zimbabwe                       3065.400000        3027.656038

[243 rows x 17 columns]
```

[90]:
```python
df_3_rv.dropna(inplace=True)
df_3_rv
```

[90]:
```
             Both sexes  Female  Male         Jan         Feb         Mar  \
Afghanistan         6.0     5.7   6.2  177.200000  178.600000  204.500000
Albania             3.7     2.2   5.3  124.000000  125.000000  165.000000
Algeria             2.6     1.9   3.3  223.300000  220.250000  262.200000
Angola             12.6     4.7  21.7  219.000000  208.000000  213.000000
Argentina           8.1     3.3  13.5  238.250000  207.066667  185.050000
…                     …      …     …          …           …           …
Uruguay            18.8     7.7  31.1  294.900000  230.600000  222.800000
Uzbekistan          8.3     4.9  11.8  117.800000  127.100000  164.300000
Vietnam             7.2     4.2  10.6  178.250000  168.000000  190.500000
Zambia             14.4     5.3  25.7  180.833333  168.933333  221.133333
Zimbabwe           23.6    13.5  37.8  230.950000  201.600000  241.800000

                    Apr         May         Jun         Jul     Aug     Sep  \
Afghanistan  232.500000  310.300000  353.400000  356.800000  339.70  303.90
Albania      191.000000  263.000000  298.000000  354.000000  327.00  264.00
Algeria      292.500000  323.800000  312.000000  353.250000  325.35  262.50
```

```
Angola        199.000000  233.000000  223.000000  175.000000  150.00  145.00
Argentina     170.616667  151.466667  123.383333  138.616667  170.40  174.60
…                  …           …           …           …       …       …
Uruguay       179.600000  164.200000  129.700000  139.700000  164.40  182.30
Uzbekistan    216.000000  303.800000  363.000000  384.400000  365.80  300.00
Vietnam       185.000000  203.500000  182.250000  196.250000  175.00  161.75
Zambia        254.000000  286.233333  278.000000  300.700000  306.90  289.00
Zimbabwe      250.500000  274.350000  265.500000  283.650000  300.70  291.00

                     Oct         Nov     Dec         Year  NY.GDP.PCAP.PP.KD
Afghanistan   282.600000  253.200000  182.40  3175.100000        2065.036235
Albania       218.000000  127.000000   88.00  2544.000000       13671.488422
Algeria       269.500000  225.000000  204.40  3266.500000       11510.557088
Angola        164.000000  199.000000  212.00  2341.000000        6670.331458
Argentina     208.566667  222.833333  229.45  2220.300000       22063.904372
…                  …           …       …           …                 …
Uruguay       239.000000  248.900000  285.30  2481.400000       23032.734044
Uzbekistan    226.300000  150.000000  105.40  2823.900000        7014.324699
Vietnam       158.500000  157.250000  167.00  2123.500000        8041.178384
Zambia        273.833333  223.000000  182.90  2965.466667        3470.448024
Zimbabwe      279.000000  234.000000  212.35  3065.400000        3027.656038

[119 rows x 17 columns]
```

We first check the suicide rate and GDP these 2 variates.

[91]:
```python
rv = df_3_rv[['NY.GDP.PCAP.PP.KD', 'Both sexes']].to_numpy()
rv
```

[91]:
```
array([[2.06503624e+03, 6.00000000e+00],
       [1.36714884e+04, 3.70000000e+00],
       [1.15105571e+04, 2.60000000e+00],
       [6.67033146e+03, 1.26000000e+01],
       [2.20639044e+04, 8.10000000e+00],
       [1.36537634e+04, 2.70000000e+00],
       [4.94555385e+04, 1.13000000e+01],
       [5.58333157e+04, 1.04000000e+01],
       [1.44393014e+04, 4.00000000e+00],
       [4.75372660e+03, 3.90000000e+00],
       [1.92831171e+04, 1.65000000e+01],
       [5.17427264e+04, 1.39000000e+01],
       [3.28730954e+03, 1.27000000e+01],
       [1.48967900e+04, 8.30000000e+00],
       [1.77768083e+04, 2.02000000e+01],
       [1.47638717e+04, 6.40000000e+00],
       [2.31915746e+04, 6.50000000e+00],
       [2.17832288e+03, 1.44000000e+01],
       [7.51664153e+02, 1.21000000e+01],
```

```
[3.64227627e+03, 1.59000000e+01],
[4.90067431e+04, 1.03000000e+01],
[9.45142043e+02, 2.30000000e+01],
[1.57962610e+03, 1.32000000e+01],
[2.49675802e+04, 8.00000000e+00],
[1.60923008e+04, 6.70000000e+00],
[1.45853025e+04, 3.70000000e+00],
[3.84279886e+03, 1.16000000e+01],
[2.87535163e+04, 1.10000000e+01],
[4.02268095e+04, 3.20000000e+00],
[5.76780989e+04, 7.60000000e+00],
[5.53476617e+03, 1.19000000e+01],
[1.13706033e+04, 7.70000000e+00],
[1.17632533e+04, 3.40000000e+00],
[8.79606206e+03, 6.10000000e+00],
[1.85025640e+04, 1.35000000e+01],
[3.68300748e+04, 1.20000000e+01],
[2.22140466e+03, 9.50000000e+00],
[1.36843608e+04, 9.50000000e+00],
[4.86892342e+04, 1.34000000e+01],
[4.58341669e+04, 9.70000000e+00],
[1.49500771e+04, 1.31000000e+01],
[2.22287959e+03, 9.60000000e+00],
[1.49892582e+04, 7.70000000e+00],
[5.36392607e+04, 8.30000000e+00],
[5.39686609e+03, 1.05000000e+01],
[2.97232220e+04, 3.60000000e+00],
[2.56703399e+03, 1.23000000e+01],
[1.93928951e+03, 1.24000000e+01],
[1.30822026e+04, 4.09000000e+01],
[5.73618163e+03, 2.60000000e+00],
[3.25535237e+04, 1.18000000e+01],
[5.69139568e+04, 1.12000000e+01],
[6.71393221e+03, 1.29000000e+01],
[1.18119756e+04, 2.60000000e+00],
[1.23892234e+04, 5.10000000e+00],
[1.05652474e+04, 4.70000000e+00],
[8.77861569e+04, 8.90000000e+00],
[4.00073192e+04, 5.20000000e+00],
[4.26625224e+04, 4.30000000e+00],
[4.13800936e+04, 1.22000000e+01],
[2.63518044e+04, 1.81000000e+01],
[4.32987188e+03, 1.10000000e+01],
[3.08587501e+04, 1.61000000e+01],
[1.51741625e+04, 4.50000000e+00],
[3.70625868e+04, 2.02000000e+01],
[1.13940237e+05, 8.60000000e+00],
```

```
[1.61853231e+03, 9.20000000e+00],
[1.51466268e+03, 1.06000000e+01],
[2.32191717e+03, 8.00000000e+00],
[4.39505881e+04, 5.30000000e+00],
[5.19707225e+03, 5.50000000e+00],
[1.97013377e+04, 5.30000000e+00],
[1.23167914e+04, 1.80000000e+01],
[2.15339492e+04, 1.62000000e+01],
[7.53748527e+03, 7.30000000e+00],
[1.28150604e+03, 2.32000000e+01],
[9.84521307e+03, 1.35000000e+01],
[5.66291108e+04, 9.30000000e+00],
[4.28779429e+04, 1.03000000e+01],
[5.45170783e+03, 4.70000000e+00],
[1.22451026e+03, 1.01000000e+01],
[5.13549947e+03, 6.90000000e+00],
[1.66001436e+04, 7.20000000e+00],
[6.44528126e+04, 9.90000000e+00],
[2.72945730e+04, 4.50000000e+00],
[4.69048478e+03, 9.80000000e+00],
[3.14321133e+04, 2.90000000e+00],
[4.34980805e+03, 3.60000000e+00],
[1.26155286e+04, 6.20000000e+00],
[1.28536921e+04, 2.70000000e+00],
[8.91472380e+03, 2.50000000e+00],
[3.31205178e+04, 9.30000000e+00],
[3.48797060e+04, 7.20000000e+00],
[2.98576465e+04, 7.30000000e+00],
[4.69621477e+04, 5.40000000e+00],
[3.36146155e+03, 1.10000000e+01],
[1.82921750e+04, 7.90000000e+00],
[9.84115821e+04, 9.70000000e+00],
[3.89055479e+04, 1.40000000e+01],
[2.66097970e+03, 1.74000000e+01],
[8.66762290e+02, 1.47000000e+01],
[1.24818135e+04, 2.35000000e+01],
[4.08059170e+04, 5.30000000e+00],
[4.18560064e+03, 4.80000000e+00],
[5.25311744e+04, 1.24000000e+01],
[7.09203247e+04, 9.80000000e+00],
[1.84534698e+04, 8.00000000e+00],
[2.12189992e+03, 1.48000000e+01],
[1.07555727e+04, 3.20000000e+00],
[2.81990516e+04, 2.30000000e+00],
[2.18746523e+03, 1.04000000e+01],
[1.28087990e+04, 1.77000000e+01],
[4.64064617e+04, 6.90000000e+00],
```

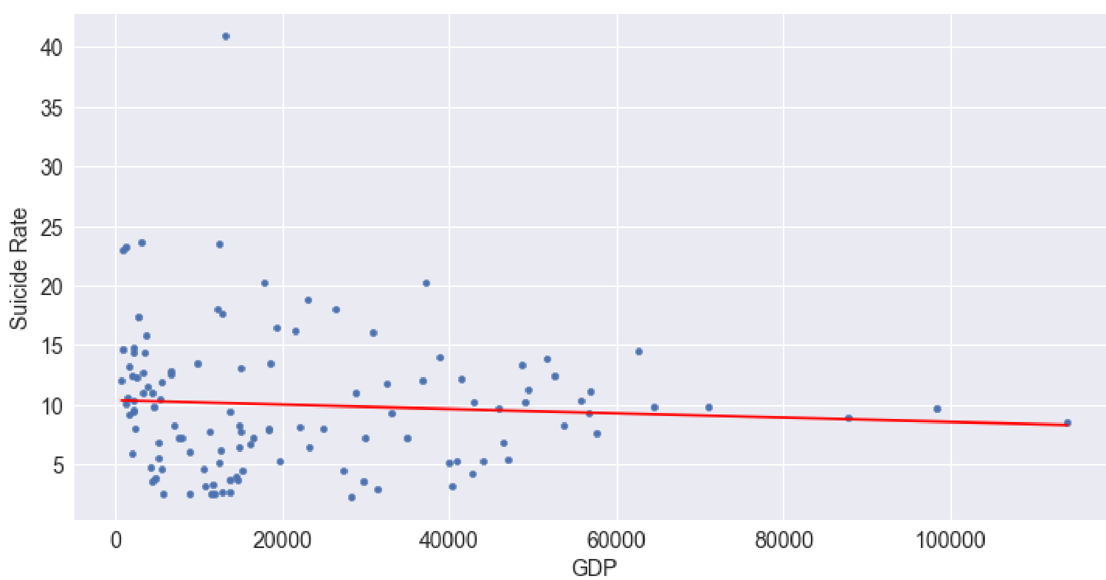
```
       [6.26308733e+04, 1.45000000e+01],
       [2.30327340e+04, 1.88000000e+01],
       [7.01432470e+03, 8.30000000e+00],
       [8.04117838e+03, 7.20000000e+00],
       [3.47044802e+03, 1.44000000e+01],
       [3.02765604e+03, 2.36000000e+01]])
```

[92]:
```python
result = st.linregress(rv.T)
print(result)
```

```
LinregressResult(slope=-1.817417434285351e-05, intercept=10.387075476344924,
rvalue=-0.0689218226362609, pvalue=0.4563934745927297,
stderr=2.4320418886822514e-05, intercept_stderr=0.7564535046242353)
```

again, the slope value, also the pvalue, tells that GDP has **no relation** with suicide rate.

[93]:
```python
a, b = result.slope, result.intercept
x = np.linspace(df_3_rv['NY.GDP.PCAP.PP.KD'].min(), df_3_rv['NY.GDP.PCAP.PP.
 ↪KD'].max(), endpoint=True)
y = a*x+b
ax = df_3_rv.plot.scatter(x='NY.GDP.PCAP.PP.KD', y='Both sexes')
ax.set_xlabel('GDP')
ax.set_ylabel('Suicide Rate')
ax.plot(x,y,color='red')
plt.show()
```



So we can see that maybe with the increase of GDP, it is showing a trend of decrease in suicide rate. The correlation is not strong.
Maybe a more noticable observation is with the GDP increase, the variation of different country

tends to become narrower.
The linregress() function from scipy.stats, only can do one random variable and one dependant variable. It we want work on multi variates regress then need to use other packages.

2.3.1 Using scikit learn, and statsmodels (supports multi-variables linear regression)

[94]:
```
from sklearn import linear_model
regr = linear_model.LinearRegression()
x = df_3_rv[['Year', 'NY.GDP.PCAP.PP.KD']]
y = df_3_rv['Both sexes']
regr.fit(x,y)
print(regr.coef_)
print(regr.intercept_)
```

```
[-1.26912103e-03 -3.47018295e-05]
13.879752998804774
```

The coefficient for both features are very small. which gives suggestion that the feature and the result (suicide rate) has no relation.

[95]:
```
from sklearn.metrics import mean_squared_error
y_predict = regr.predict(x.to_numpy())
stderr = np.sqrt(mean_squared_error(y_predict, y.to_numpy()))
stderr
```

[95]:
```
5.700884352804593
```

The error is so big, so the linear model is not a good model for those variates we studied.

The above we using scikit learn package. We can also use other regression package like statsmodels.

[96]:
```
import statsmodels.api as sm
x = x.to_numpy()
sm_x = sm.add_constant(x)
est = sm.OLS(y.to_numpy(), sm_x).fit()
est.summary()
```

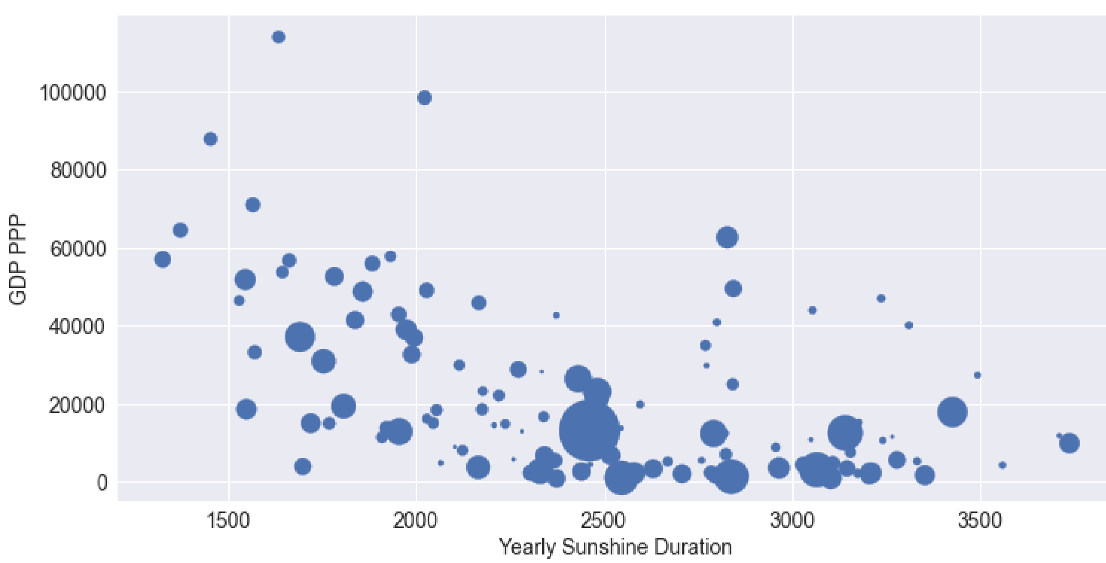
[96]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.017
Model:                            OLS   Adj. R-squared:                  0.000
Method:                 Least Squares   F-statistic:                     1.022
Date:                Mon, 20 Sep 2021   Prob (F-statistic):              0.363
Time:                        17:42:13   Log-Likelihood:                -375.99
No. Observations:                 119   AIC:                             758.0
Df Residuals:                     116   BIC:                             766.3
Df Model:                           2
Covariance Type:            nonrobust
```

```
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         13.8798      2.966      4.680      0.000       8.005      19.754
x1            -0.0013      0.001     -1.218      0.226      -0.003       0.001
x2          -3.47e-05   2.78e-05     -1.248      0.215   -8.98e-05    2.04e-05
==============================================================================
Omnibus:                       56.990   Durbin-Watson:                   1.777
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              222.544
Skew:                           1.666   Prob(JB):                     4.73e-49
Kurtosis:                       8.813   Cond. No.                     1.75e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.75e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

Two package are giving the same result. Here also we can see the pvalues, which same gives suggestion that the coefficients are 0, thus feature does not show relation with the result.

[97]:
```
df_last = df_3_rv[['Both sexes', 'Year', 'NY.GDP.PCAP.PP.KD']]
```

[98]:
```
ax = df_last.plot(kind='scatter', x='Year', y='NY.GDP.PCAP.PP.KD',␣
 ↪s=df_last['Both sexes']**2)
ax.set_xlabel('Yearly Sunshine Duration')
ax.set_ylabel('GDP PPP')
plt.show()
```



[99]:
```
df_last.to_csv('final_data.csv')
```

[ ]:
```
```