Refugees

June 24, 2019

1 Pandas

- https://pandas.pydata.org
- very high-level data containers with corresponding functionality
- many useful tools to work with time-series (look at `Series.rolling`)
- many SQL-like data operations (group, join, merge)
- Interface to a large variety of file formats (see `pd.read_[...]` functions)
- additional package with data-interface/API to many data repositories (https://pandas-datareader.readthedocs.io/en/latest/remote_data.html)

```
In [1]: import pandas as pd
```

1.1 Basic Data Structures

1.1.1 Series

One-dimensional ndarray with axis labels (called index).

Series can be created like an array

```
In [2]: pd.Series([11,13,17,19,23])
```

```
Out[2]: 0    11
        1    13
        2    17
        3    19
        4    23
        dtype: int64
```

or, if you want a special index

```
In [3]: series = pd.Series([11,13,17,19,23], index=['a', 'b', 'c', 'd', 'e'])
        print(series)
```

```
a    11
b    13
c    17
d    19
e    23
dtype: int64
```

to get the content back you can use

```
In [4]: series.index

Out[4]: Index(['a', 'b', 'c', 'd', 'e'], dtype='object')

In [5]: series.values

Out[5]: array([11, 13, 17, 19, 23])
```

but the power of pandas lies in all the other attributes

```
In [6]: #series. [TAB]
```

1.1.2 DataFrame

The primary pandas data structure.

Two-dimensional size-mutable, potentially heterogeneous tabular data structure with labeled axes. (index: row labels, columns: column labels) Can be thought of as a dict-like container for Series objects.

The easiest way to create a DataFrame is to read it from an input file (see later)

In addition there are many ways to create DataFrames manually. Most straight forward probably is to use a dict of iterables. (Series, Lists, Arrays). Pandas tries to choose sensible indexes.

```
In [7]: frame = pd.DataFrame({"primes": series, "fibo": [1,1,2,3,5], "0-4": range(5)})

In [8]: print(frame)

   primes  fibo  0-4
a      11     1    0
b      13     1    1
c      17     2    2
d      19     3    3
e      23     5    4
```

2 Refugee Example

We now want to use pandas to work with data from the World Bank. My goal is to create a plot showing the burden refugees put on different countries. For this we will plot the fraction of refugee in a give countries population versus that countries GDP.

I downloaded and extracted the following data-sets from the Worldbank website manually: * Refugee population by country or territory of asylum: https://data.worldbank.org/indicator/SM.POP.REFG * Population, total: https://data.worldbank.org/indicator/SP.POP.TOTL * GDP per capita (current US$): https://data.worldbank.org/indicator/NY.GDP.PCAP.CD

```
In [9]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
```

2.1 Loading and Accessing Data

loading a data file with pandas is trivial

```
In [10]: refugees = pd.read_csv("data/refugee-population.csv", skiprows=4)

In [11]: refugees.head()
```

```
Out[11]:   Country Name Country Code  \
         0        Aruba          ABW
         1  Afghanistan          AFG
         2       Angola          AGO
         3      Albania          ALB
         4      Andorra          AND

                                            Indicator Name Indicator Code  1960  \
         0  Refugee population by country or territory of ...    SM.POP.REFG   NaN
         1  Refugee population by country or territory of ...    SM.POP.REFG   NaN
         2  Refugee population by country or territory of ...    SM.POP.REFG   NaN
         3  Refugee population by country or territory of ...    SM.POP.REFG   NaN
         4  Refugee population by country or territory of ...    SM.POP.REFG   NaN

            1961  1962  1963  1964  1965     ...          2009     2010     2011  \
         0   NaN   NaN   NaN   NaN   NaN     ...           NaN      NaN      NaN
         1   NaN   NaN   NaN   NaN   NaN     ...          37.0   6434.0   3009.0
         2   NaN   NaN   NaN   NaN   NaN     ...       14734.0  15155.0  16223.0
         3   NaN   NaN   NaN   NaN   NaN     ...          70.0     76.0     82.0
         4   NaN   NaN   NaN   NaN   NaN     ...           NaN      NaN      NaN

               2012     2013      2014      2015     2016  2017  Unnamed: 62
         0      NaN      1.0       NaN       2.0      NaN   NaN          NaN
         1  16187.0  16863.0  300423.0  257554.0  59770.0   NaN          NaN
         2  23413.0  23783.0   15474.0   15555.0  15537.0   NaN          NaN
         3     86.0     93.0     104.0     104.0    111.0   NaN          NaN
         4      NaN      NaN       NaN       NaN      NaN   NaN          NaN

         [5 rows x 63 columns]
```

As you can see pandas choose the right column labels and numbered the rows continously. We can easily change the row labels (the index) to one of the columns.

```
In [12]: refugees.set_index(["Country Code"], inplace=True)

In [13]: refugees.head()
```

```
Out[13]:              Country Name                                     Indicator Name  \
         Country Code
         ABW                 Aruba  Refugee population by country or territory of ...
         AFG           Afghanistan  Refugee population by country or territory of ...
```

```
AGO                Angola  Refugee population by country or territory of ...
ALB               Albania  Refugee population by country or territory of ...
AND               Andorra  Refugee population by country or territory of ...

              Indicator Code  1960  1961  1962  1963  1964  1965  1966  \
Country Code
ABW              SM.POP.REFG   NaN   NaN   NaN   NaN   NaN   NaN   NaN
AFG              SM.POP.REFG   NaN   NaN   NaN   NaN   NaN   NaN   NaN
AGO              SM.POP.REFG   NaN   NaN   NaN   NaN   NaN   NaN   NaN
ALB              SM.POP.REFG   NaN   NaN   NaN   NaN   NaN   NaN   NaN
AND              SM.POP.REFG   NaN   NaN   NaN   NaN   NaN   NaN   NaN

                     ...          2009     2010     2011     2012     2013  \
Country Code         ...
ABW                  ...           NaN      NaN      NaN      NaN      1.0
AFG                  ...          37.0   6434.0   3009.0  16187.0  16863.0
AGO                  ...       14734.0  15155.0  16223.0  23413.0  23783.0
ALB                  ...          70.0     76.0     82.0     86.0     93.0
AND                  ...           NaN      NaN      NaN      NaN      NaN

                      2014      2015     2016  2017  Unnamed: 62
Country Code
ABW                    NaN       2.0      NaN   NaN          NaN
AFG               300423.0  257554.0  59770.0   NaN          NaN
AGO                15474.0   15555.0  15537.0   NaN          NaN
ALB                  104.0     104.0    111.0   NaN          NaN
AND                    NaN       NaN      NaN   NaN          NaN

[5 rows x 62 columns]
```

Now it's easy to select rows or columns

```
In [14]: refugees.loc[["CHE","DEU"]]
```

```
Out[14]:              Country Name                                    Indicator Name  \
Country Code
CHE              Switzerland  Refugee population by country or territory of ...
DEU                  Germany  Refugee population by country or territory of ...

              Indicator Code  1960  1961  1962  1963  1964  1965  1966  \
Country Code
CHE              SM.POP.REFG   NaN   NaN   NaN   NaN   NaN   NaN   NaN
DEU              SM.POP.REFG   NaN   NaN   NaN   NaN   NaN   NaN   NaN

                     ...          2009      2010      2011      2012      2013  \
Country Code         ...
CHE                  ...       46203.0   48813.0   50416.0   50747.0   52464.0
DEU                  ...      593799.0  594269.0  571684.0  589737.0  187567.0
```

```
                        2014      2015      2016  2017  Unnamed: 62
Country Code
CHE              62620.0   73336.0   82608.0   NaN          NaN
DEU             216973.0  316115.0  669408.0   NaN          NaN

[2 rows x 62 columns]
```

```
In [15]: refugees[["1990","2000"]].head()
```

```
Out[15]:                  1990     2000
         Country Code
         ABW               NaN      NaN
         AFG              50.0      NaN
         AGO           11557.0  12086.0
         ALB               NaN    523.0
         AND               NaN      NaN
```

```
In [16]: refugees.get(["1990","2000"]).head()
```

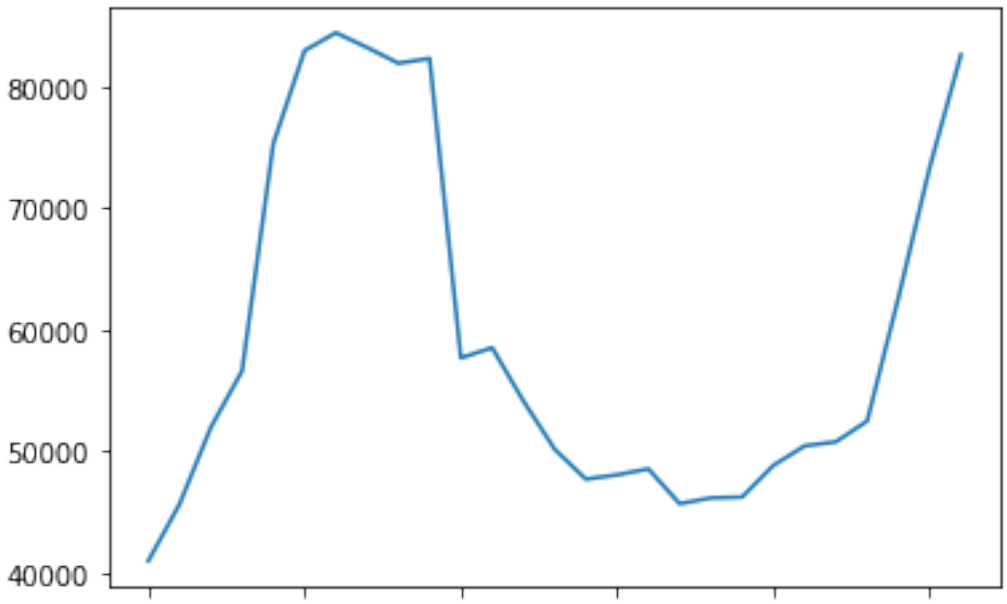
```
Out[16]:                  1990     2000
         Country Code
         ABW               NaN      NaN
         AFG              50.0      NaN
         AGO           11557.0  12086.0
         ALB               NaN    523.0
         AND               NaN      NaN
```

2.2 Working with a Single Country

With this we now choose the data for one country, remove all missing values and then create a plot:

```
In [17]: che = refugees.loc["CHE"][[str(year) for year in range(1990,2018)]]
```

```
In [18]: che.dropna().plot()
         plt.show()
```

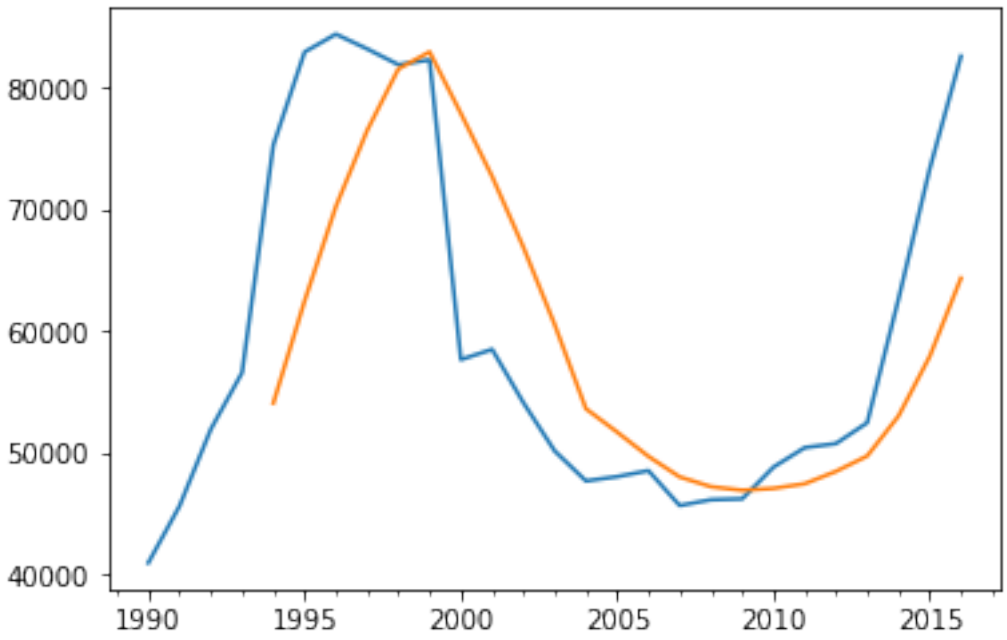


Usually it is easier to work with real datetime objects instead of strings. So we convert the index to datetime

```
In [19]: che.index.values

Out[19]: array(['1990', '1991', '1992', '1993', '1994', '1995', '1996', '1997',
                '1998', '1999', '2000', '2001', '2002', '2003', '2004', '2005',
                '2006', '2007', '2008', '2009', '2010', '2011', '2012', '2013',
                '2014', '2015', '2016', '2017'], dtype=object)

In [20]: che.index = pd.to_datetime(che.index, format="%Y")
         print(che.index)

DatetimeIndex(['1990-01-01', '1991-01-01', '1992-01-01', '1993-01-01',
               '1994-01-01', '1995-01-01', '1996-01-01', '1997-01-01',
               '1998-01-01', '1999-01-01', '2000-01-01', '2001-01-01',
               '2002-01-01', '2003-01-01', '2004-01-01', '2005-01-01',
               '2006-01-01', '2007-01-01', '2008-01-01', '2009-01-01',
               '2010-01-01', '2011-01-01', '2012-01-01', '2013-01-01',
               '2014-01-01', '2015-01-01', '2016-01-01', '2017-01-01'],
              dtype='datetime64[ns]', freq=None)
```

As mentioned in the introduction, `pandas` offers a very usefull `rolling` method

```
In [21]: che.plot()
         che.rolling(center=False,window=5).mean().plot()
         plt.show()
```



2.3 Removing Unwanted Data

We now want to create a scatter plot with refugees divided by gdp vs. gdp-per-captita. For each data set we will use the mean of the last 7 years.

Some of the rows and columns in the World-Bank Files are of no interest for this. We can remove these easily.

2.3.1 Excluding Non-Countries

The World-Bank provides meta-data for each country, where we can identify rows with non-countries (e.g. regional aggregates)

```
In [22]: !head data/metadata-countries_population.csv
```

```
"ARG","Latin America & Caribbean","Upper middle income","National Institute of Statistics and C
```

We load this file and extract the two relevant columns

```
In [23]: meta = pd.read_csv("data/metadata-countries_population.csv")

In [24]: meta.columns

Out[24]: Index(['Country Code', 'Region', 'IncomeGroup', 'SpecialNotes', 'TableName',
                'Unnamed: 5'],
               dtype='object')

In [25]: meta = meta[['Country Code', 'Region']]

In [26]: meta.head()

Out[26]:   Country Code                     Region
         0          ABW  Latin America & Caribbean
         1          AFG                 South Asia
         2          AGO         Sub-Saharan Africa
         3          ALB      Europe & Central Asia
         4          AND      Europe & Central Asia

In [27]: meta.set_index("Country Code", inplace=True)
```

From this we create a list of non-countries

```
In [28]: non_countries = meta.loc[meta.Region.isnull()].index
         print(non_countries)

Index(['ARB', 'CEB', 'CSS', 'EAP', 'EAR', 'EAS', 'ECA', 'ECS', 'EMU', 'EUU',
       'FCS', 'HIC', 'HPC', 'IBD', 'IBT', 'IDA', 'IDB', 'IDX', 'LAC', 'LCN',
       'LDC', 'LIC', 'LMC', 'LMY', 'LTE', 'MEA', 'MIC', 'MNA', 'NAC', 'OED',
       'OSS', 'PRE', 'PSS', 'PST', 'SAS', 'SSA', 'SSF', 'SST', 'TEA', 'TEC',
       'TLA', 'TMN', 'TSA', 'TSS', 'UMC', 'WLD'],
      dtype='object', name='Country Code')
```

and finally exclude the relevant rows

```
In [29]: refugees = refugees.drop(non_countries)
```

2.3.2 Excluding Columns

The data contains a few rows with unneeded text

```
In [30]: refugees.columns

Out[30]: Index(['Country Name', 'Indicator Name', 'Indicator Code', '1960', '1961',
                '1962', '1963', '1964', '1965', '1966', '1967', '1968', '1969', '1970',
                '1971', '1972', '1973', '1974', '1975', '1976', '1977', '1978', '1979',
                '1980', '1981', '1982', '1983', '1984', '1985', '1986', '1987', '1988',
```

```
       '1989', '1990', '1991', '1992', '1993', '1994', '1995', '1996', '1997',
       '1998', '1999', '2000', '2001', '2002', '2003', '2004', '2005', '2006',
       '2007', '2008', '2009', '2010', '2011', '2012', '2013', '2014', '2015',
       '2016', '2017', 'Unnamed: 62'],
      dtype='object')
```

In addition, the 2017 column is empty

```
In [31]: np.any(refugees["2017"].notnull())
```

```
Out[31]: False
```

so we can create a list of all interesting columns

```
In [32]: useful_cols = []
         for year in range(2010,2017):
             useful_cols.append(str(year))
```

```
In [33]: useful_cols
```

```
Out[33]: ['2010', '2011', '2012', '2013', '2014', '2015', '2016']
```

with this, we:

- select the reduced datase
- switch the index to Country Code
- calculate the mean for each country

```
In [34]: refugees = refugees[useful_cols]
```

```
In [35]: refugee_means = refugees.mean(axis=1)
```

2.4 Loading Additional Files

Of course we could execute these commands again manually for the two remaining data-files. However, the proper way to solve this is to create a function for this. Especially since all files have the exact same structure.

```
In [36]: def load_file(file):
             """Load and process a Worldbank File"""
             data = pd.read_csv(file, skiprows=4)
             data.set_index("Country Code", inplace=True)
             data.drop(non_countries, inplace=True)
             data = data[[str(year) for year in range(2010,2017)]]
             return data.mean(axis=1), data
```

```
In [37]: gdp_means, gdp = load_file("data/gdp-per-capita.csv")
```

```
In [38]: gdp_means.head()
```

```
Out[38]: Country Code
         ABW    24798.330391
         AFG      603.594404
         AGO     4134.962750
         ALB     4261.539631
         AND    39309.685362
         dtype: float64
```

```
In [39]: gdp.head()
```

```
Out[39]:                        2010          2011          2012          2013  \
         Country Code
         ABW           24271.940421  25324.720362           NaN           NaN
         AFG             553.300289    603.537023    669.009051    638.612543
         AGO            3529.053482   4299.012889   4598.249988   4804.616884
         ALB            4094.358832   4437.178068   4247.614308   4413.081697
         AND           39736.354063  41098.766942  38391.080867  40619.711298

                               2014          2015          2016
         Country Code
         ABW                    NaN           NaN           NaN
         AFG             629.345250    569.577923    561.778746
         AGO            4709.312024   3695.793748   3308.700233
         ALB            4578.666728   3934.895394   4124.982390
         AND           42294.994727  36038.267604  36988.622030
```

```
In [40]: population_means, population = load_file("data/population.csv")
```

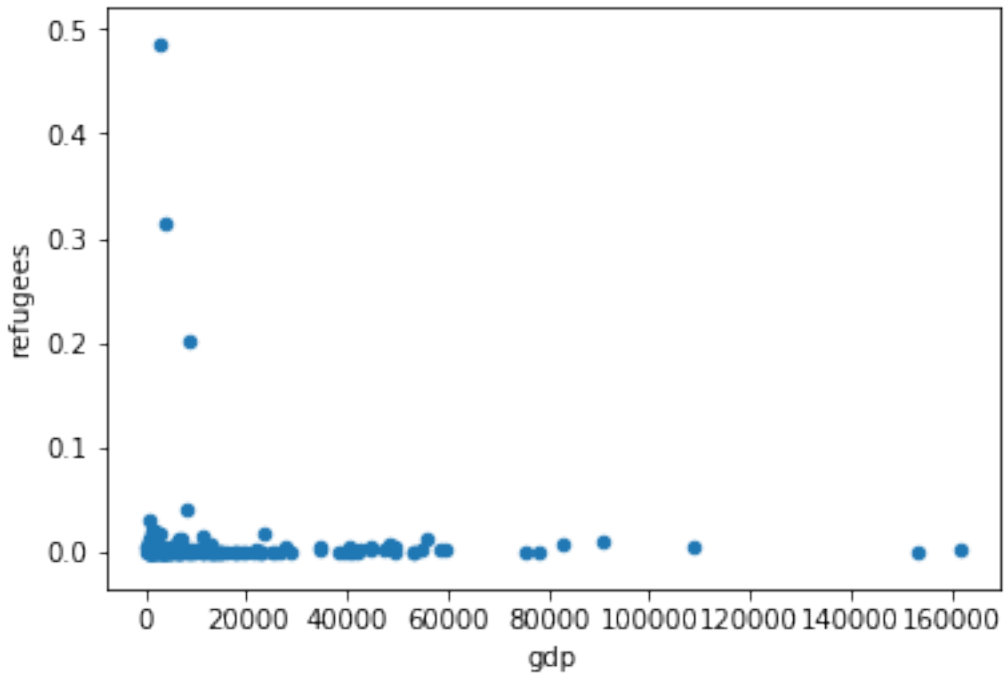
2.5 Creating the Plot

We now combine our three Series with means into one DataFrame and create our plot.

```
In [41]: data = pd.DataFrame({"gdp": gdp_means, "refugees": refugee_means/population_means}).d
```

(Here we loose some countries with missing data.)

```
In [42]: data.plot.scatter("gdp", "refugees")
         plt.show()
```



We can quickly find out who the three top countries are:

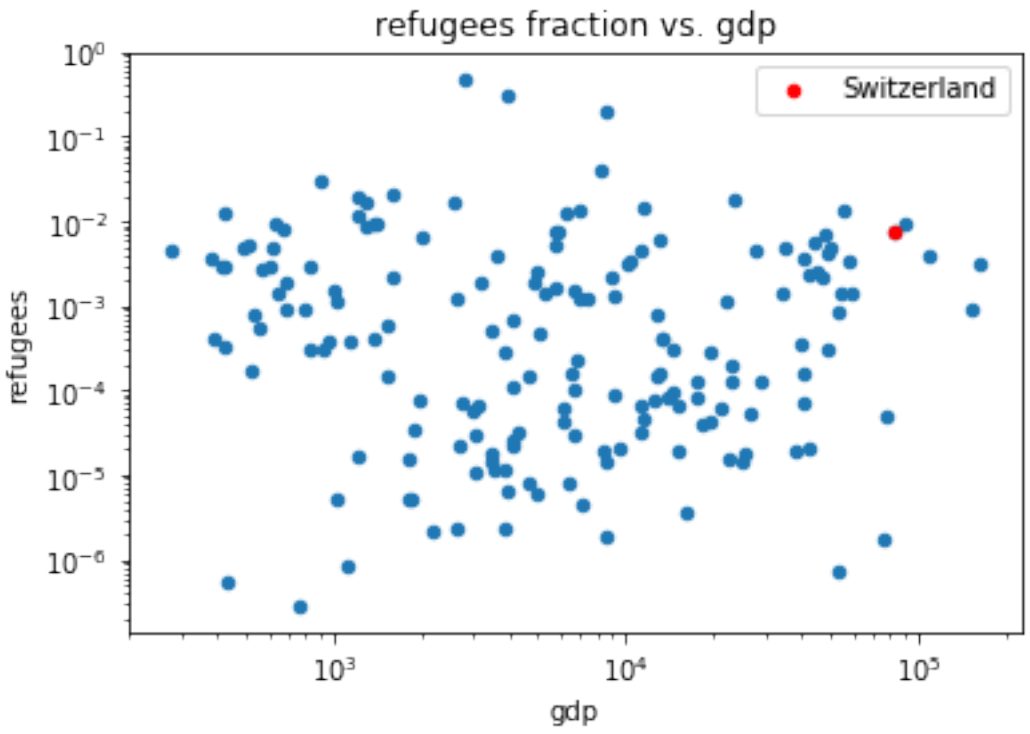
```
In [43]: data.where(data["refugees"]>0.1).dropna()
```

```
Out[43]:                      gdp  refugees
         Country Code
         JOR          3943.016044  0.313576
         LBN          8640.434951  0.202313
         PSE          2793.289949  0.484664
```

To improve readability:

- we switch to a log-log axis (we need to exclude countries with too small refugee numbers)
- we highlight one selected country
- We add a title

```
In [44]: ax = data[data["refugees"] > 1e-10].plot.scatter(y="refugees", x="gdp", loglog=True)
         ax = data.loc[["CHE"]].plot.scatter(y="refugees", x="gdp", ax=ax, color="r", label="Sw
         plt.title("refugees fraction vs. gdp")
         plt.show()
```



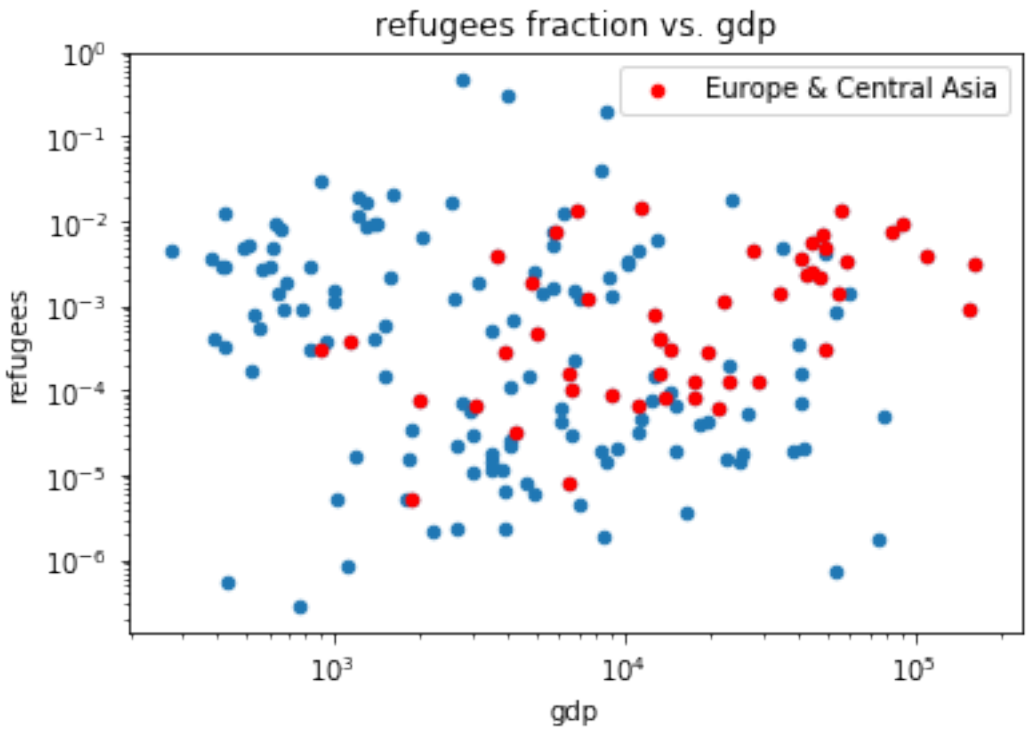
again we can print the info for one country

```
In [45]: data.loc["CHE"]

Out[45]: gdp         82883.020927
         refugees        0.007429
         Name: CHE, dtype: float64
```

2.5.1 Highlighting a Full Region

Based on th meta data provided by the World Bank, we can highlight a region

```
In [46]: europe = meta.loc[meta.Region == "Europe & Central Asia"].index

In [47]: europe[:10]

Out[47]: Index(['ALB', 'AND', 'ARM', 'AUT', 'AZE', 'BEL', 'BGR', 'BIH', 'BLR', 'CHE'], dtype='

In [48]: ax = data[data["refugees"] > 1e-10].plot.scatter(y="refugees", x="gdp", loglog=True)
         ax = data.loc[data.index.intersection(europe)].plot.scatter(y="refugees", x="gdp", ax=
         plt.title("refugees fraction vs. gdp")
         plt.show()
```



(As we lost some countries with missing data when we called `dropna` above, we need the `data.index.intersection`-call to select only country codes really contained in our data.)

2.6 Fitting

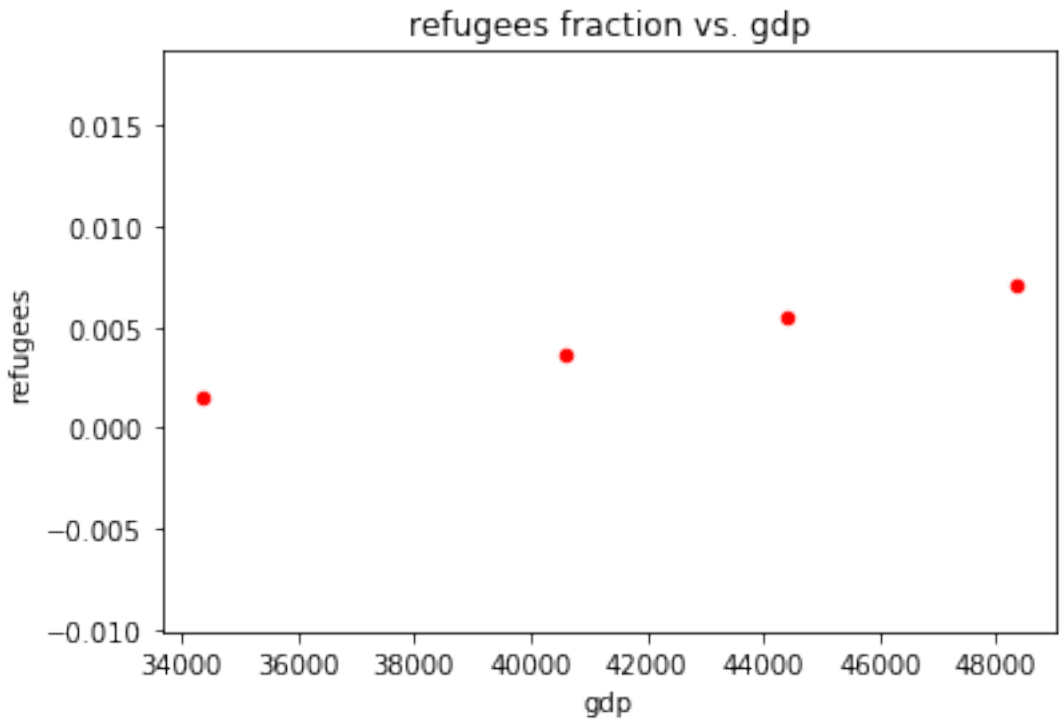
We now look at a tiny subset of this data and look at ways to fit a function to it.

Scipy preparse a huge number of options, we will look at three options of increasing complexity and flexibility.

2.6.1 Preparations

first we select our subset

```
In [49]: europe_small = ['AUT',
          'DEU',
          'FRA',
          'ITA',
         ]

In [50]: data_eu = data.loc[europe_small].dropna()

In [51]: ax = data_eu.plot.scatter(y="refugees", x="gdp", color="r")
         plt.title("refugees fraction vs. gdp")
         plt.show()
```



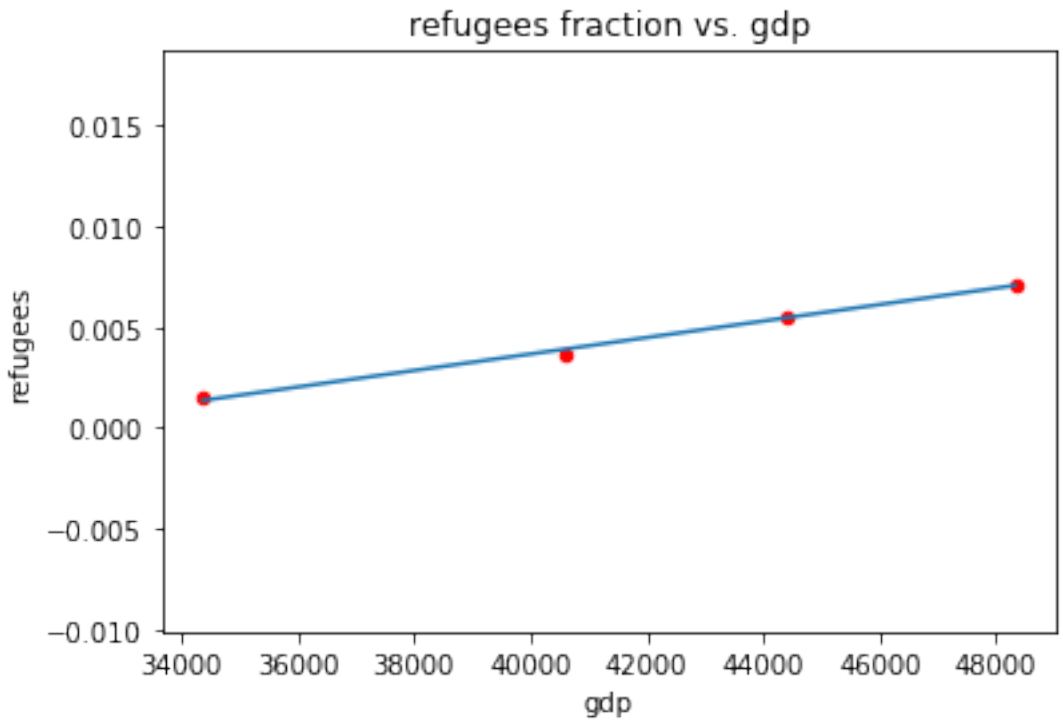
and we create a vector with all the x values we will need to plot our fit result

```
In [52]: x = np.linspace(data_eu["gdp"].min(), data_eu["gdp"].max(), 100)
```

2.6.2 polyfit

Polyfit is probably the easiest way to fit a polynome to given data.

```
In [53]: from scipy import polyfit, polyval

In [54]: res = polyfit(data_eu["gdp"], data_eu["refugees"],1)
         print(res)

[ 4.09014159e-07 -1.27066203e-02]


In [55]: ax = data_eu.plot.scatter(y="refugees", x="gdp", color="r")
         ax.plot(x, polyval(res, x))
         plt.title("refugees fraction vs. gdp")
         plt.show()
```



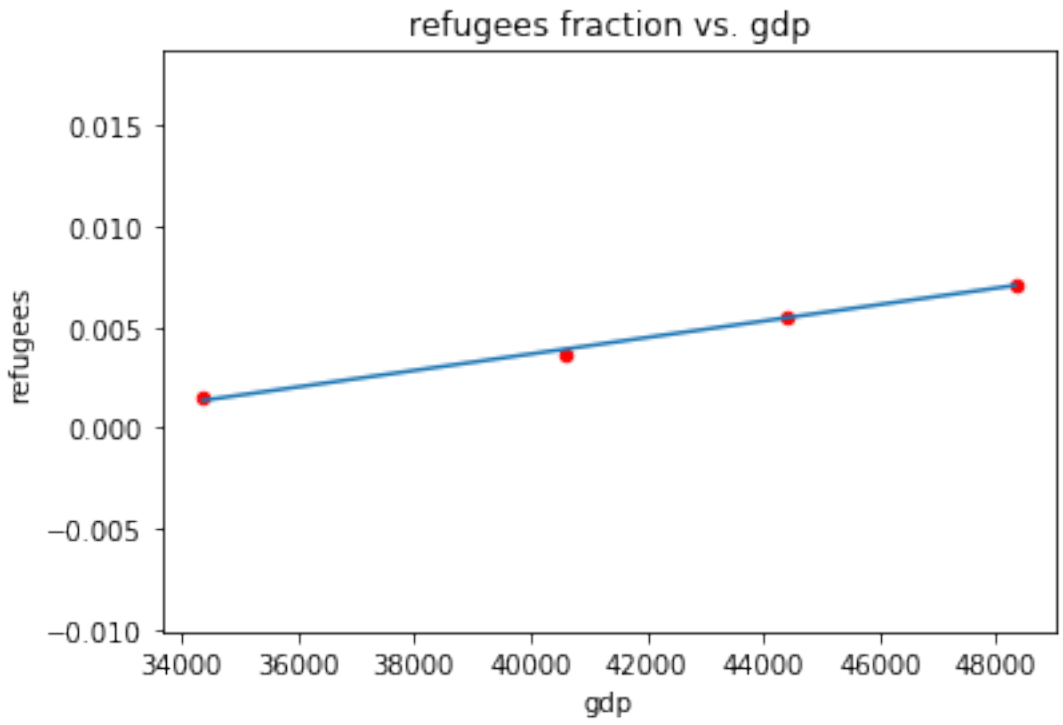
2.6.3 curve_fit

With `curve_fit` you can define a complex fit function.

```
In [56]: from scipy.optimize import curve_fit

In [57]: def fit_function(x,b,c):
             return b*x+c

In [58]: res = curve_fit(fit_function, data_eu["gdp"], data_eu["refugees"])
         print(res)
```

```
(array([ 4.09014159e-07, -1.27066203e-02]), array([[ 3.74367147e-16, -1.56946192e-11],
       [-1.56946192e-11,  6.67866539e-07]]))
```

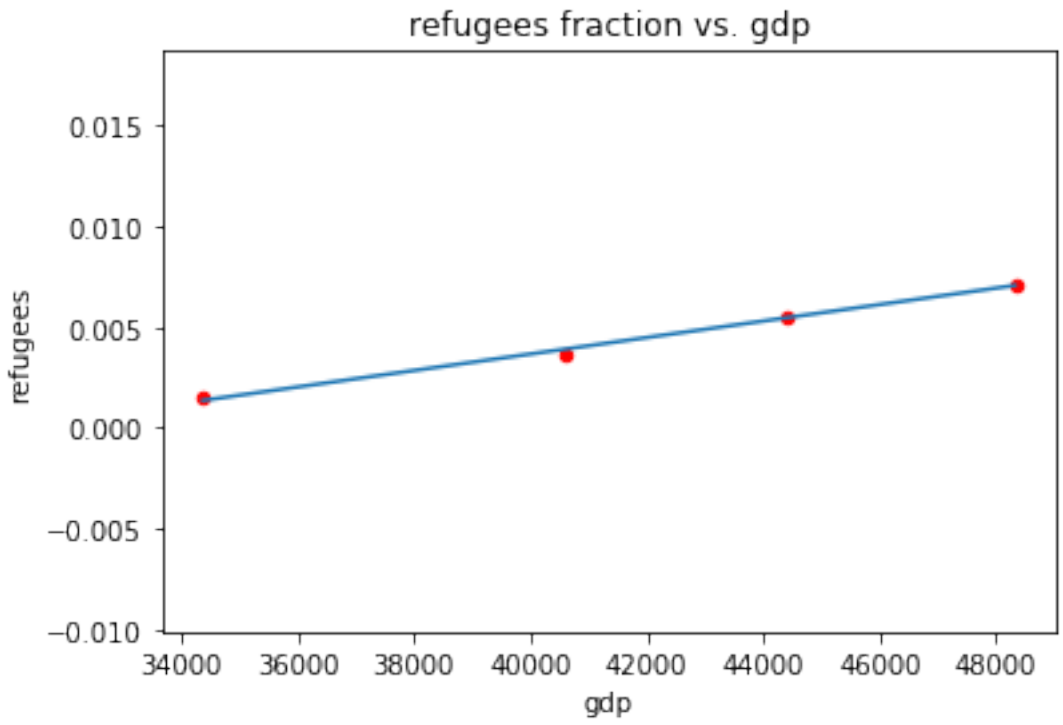
```
In [59]: ax = data_eu.plot.scatter(y="refugees", x="gdp", color="r")
         ax.plot(x, fit_function(x, *(res[0])))
         plt.title("refugees fraction vs. gdp")
         plt.show()
```



2.6.4 leastsq

Finally, least-squares allows you to even specify the cost function. With this you can factor in uncertainties or weights for your data points.

```
In [60]: from scipy.optimize import leastsq

In [61]: def fit_function(x, p):
             return x*p[0]+p[1]

In [62]: def error_function(params):
             return data_eu["refugees"] - fit_function(data_eu["gdp"], params)

In [63]: res = leastsq(error_function, [0,0])
         print(res)

(array([ 4.09014159e-07, -1.27066203e-02]), 2)


In [64]: ax = data_eu.plot.scatter(y="refugees", x="gdp", color="r")
         ax.plot(x, fit_function(x, res[0]))
         plt.title("refugees fraction vs. gdp")
         plt.show()
```



2.6.5 statsmodels

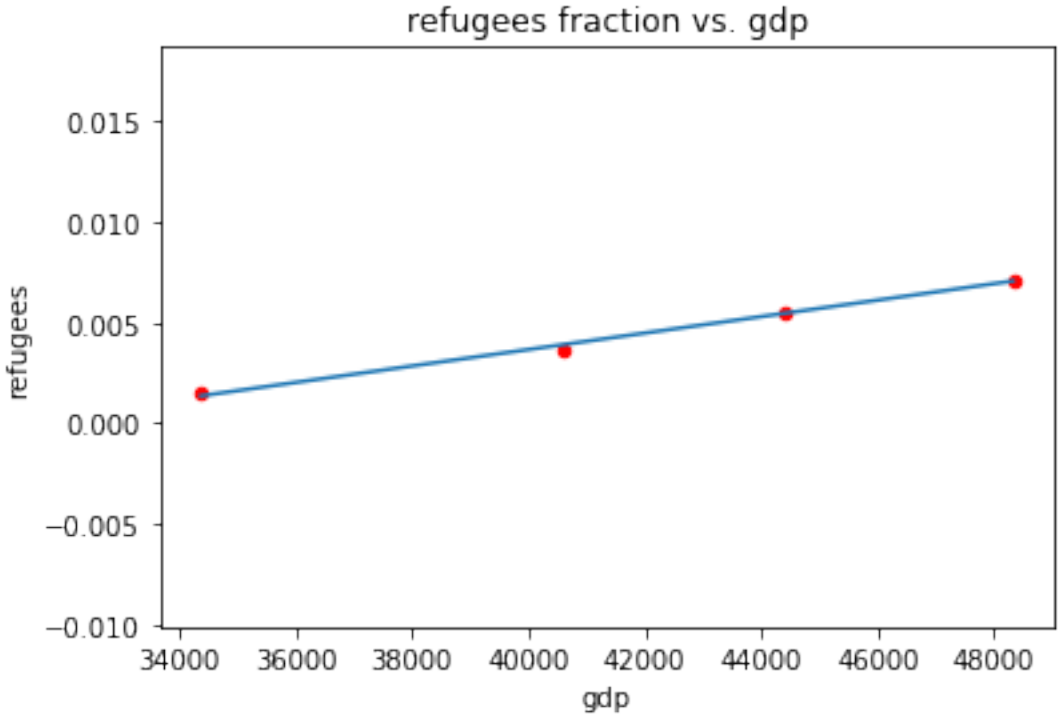
```
In [65]: import statsmodels.formula.api as smf

In [66]: res = smf.ols("refugees ~ gdp", data=data_eu).fit()

In [67]: print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                refugees   R-squared:                       0.996
Model:                            OLS   Adj. R-squared:                  0.993
Method:                 Least Squares   F-statistic:                     446.9
Date:                Mon, 24 Jun 2019   Prob (F-statistic):            0.00223
Time:                        16:24:53   Log-Likelihood:                 29.799
No. Observations:                   4   AIC:                            -55.60
Df Residuals:                       2   BIC:                            -56.83
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -0.0127      0.001    -15.548      0.004      -0.016      -0.009
gdp         4.09e-07   1.93e-08     21.139      0.002    3.26e-07    4.92e-07
```

```
==============================================================================
Omnibus:                        nan   Durbin-Watson:                   2.912
Prob(Omnibus):                  nan   Jarque-Bera (JB):                0.850
Skew:                        -1.067   Prob(JB):                        0.654
Kurtosis:                     2.261   Cond. No.                     3.47e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.47e+05. This might indicate that there are
strong multicollinearity or other numerical problems.


/usr/lib/python3/dist-packages/statsmodels/stats/stattools.py:72: ValueWarning: omni_normtest i
  "samples were given." % int(n), ValueWarning)
```

```
In [68]: print(res.params)

Intercept   -1.270662e-02
gdp          4.090142e-07
dtype: float64
```

```
In [69]: ax = data_eu.plot.scatter(y="refugees", x="gdp", color="r")
         ax.plot(x, res.params[1]*x+res.params[0])
         plt.title("refugees fraction vs. gdp")
         plt.show()
```



2.7 Appendix: Selecting from DataFrames

2.7.1 Accessing Rows

Passing a single value to `loc` returns a `Series`

```
In [70]: frame.loc["a"]

Out[70]: primes    11
         fibo       1
         0-4        0
         Name: a, dtype: int64
```

Passing a list to `loc` returns a `DataFrame` (even if the list contains a single a single value)

```
In [71]: frame.loc[["a"]]

Out[71]:    primes  fibo  0-4
         a      11     1    0

In [72]: frame.loc[["a","c"]]

Out[72]:    primes  fibo  0-4
         a      11     1    0
         c      17     2    2
```

Also slicing works (but includes the upper boundary)

```
In [73]: frame.loc["b":"d"]

Out[73]:    primes  fibo  0-4
         b      13     1    1
         c      17     2    2
         d      19     3    3
```

A list of boolean values with n-Rows entries, is considered a mask to select rows

```
In [74]: frame.loc[[True,False,True,False,True]]

Out[74]:    primes  fibo  0-4
         a      11     1    0
         c      17     2    2
         e      23     5    4
```

Instead of a list, a boolean-series can be used. Rows are matched on the index. (`frame[["primes"]] > 20` would not work as this returns a frame instead of a series.)

```
In [75]: frame.loc[frame["primes"] > 20]
```

```
Out[75]:    primes  fibo  0-4
         e      23     5    4
```

When using a mask, `.loc` is optional (but recommended to avoid confusion with columns).

```
In [76]: frame[frame["primes"] > 20]

Out[76]:    primes  fibo  0-4
         e      23     5    4
```

Using `iloc` it is possible to access rows by position as well. (without using the index)

```
In [77]: frame.iloc[2:-1]

Out[77]:    primes  fibo  0-4
         c      17     2    2
         d      19     3    3
```

2.7.2 Accessing Columns

The frame is subscripted directly. Again, passing a singel value returns a series.

```
In [78]: frame["primes"]

Out[78]: a    11
         b    13
         c    17
         d    19
         e    23
         Name: primes, dtype: int64
```

While a list returns a `DataFrame`

```
In [79]: frame[["primes"]]

Out[79]:    primes
         a      11
         b      13
         c      17
         d      19
         e      23

In [80]: frame[["primes","0-4"]]

Out[80]:    primes  0-4
         a      11    0
         b      13    1
         c      17    2
         d      19    3
         e      23    4
```

Instead of subscripting, the `get`-method can be used.

```
In [81]: frame.get(["primes","0-4"])
```

```
Out[81]:    primes  0-4
         a      11    0
         b      13    1
         c      17    2
         d      19    3
         e      23    4
```

For single columns, an attribute with the same name exists

```
In [82]: frame.primes
```

```
Out[82]: a    11
         b    13
         c    17
         d    19
         e    23
         Name: primes, dtype: int64
```

But this fails, if the column-name is not a valid attribute-name

```
In [83]: # Raises SyntaxError
         #frame.0-4
```

For even more options have a look at the pandas-website: https://pandas.pydata.org/pandas-docs/stable/indexing.html