Refugees

July 11, 2023

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)

[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

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

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

or, if you want a special index

[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

[4]:
```
series.index
```

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

[5]:
```
series.values
```

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

but the power of pandas lies in all the other attributes

[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.

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

[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

[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

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

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

[11]:

	Country Name	Country Code	Indicator Name	Indicator Code	1960	1961	1962	1963	1964	1965	…	2014	2015	2016	2017	2018	2019	2020	2021	2022	Unnamed: 67
0	Aruba	ABW	Refugee population by country or territory of …	SM.POP.REFG	NaN	NaN	NaN	NaN	NaN	NaN	…	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	Africa Eastern and Southern	AFE	Refugee population by country or territory of …	SM.POP.REFG	NaN	NaN	NaN	NaN	NaN	NaN	…	2637640.0	3333273.0	3990478.0	5155400.0	5114399.0	5087755.0	5183533.0	5436720.0	5412266.0	NaN
2	Afghanistan	AFG	Refugee population by country or territory of …	SM.POP.REFG	NaN	NaN	NaN	NaN	NaN	NaN	…	300421.0	257553.0	59770.0	75927.0	72228.0	72227.0	72278.0	66949.0	52159.0	NaN
3	Africa Western and Central	AFW	Refugee population by country or territory of …	SM.POP.REFG	NaN	NaN	NaN	NaN	NaN	NaN	…	1108169.0	1138010.0	1200854.0	1172523.0	1285773.0	1315229.0	1474135.0	1631057.0	1705777.0	NaN
4	Angola	AGO	Refugee population by country or territory of …	SM.POP.REFG	NaN	NaN	NaN	NaN	NaN	NaN	…	15468.0	15547.0	15547.0	41119.0	39856.0	25793.0	25791.0	26045.0	25514.0	NaN

[5 rows x 68 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.

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

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

[13]:

Country Code	Country Name	Indicator Name	Indicator Code	1960	1961	1962	1963	1964	1965	1966	…
ABW	Aruba	Refugee population by country or territory of …	SM.POP.REFG	NaN	NaN	NaN	NaN	NaN	NaN	NaN	…
AFE	Africa Eastern and Southern	Refugee population by country or territory of …	SM.POP.REFG	NaN	NaN	NaN	NaN	NaN	NaN	NaN	…
AFG	Afghanistan	Refugee population by country or territory of …	SM.POP.REFG	NaN	NaN	NaN	NaN	NaN	NaN	NaN	…
AFW	Africa Western and Central	Refugee population by country or territory of …	SM.POP.REFG	NaN	NaN	NaN	NaN	NaN	NaN	NaN	…
AGO	Angola	Refugee population by country or territory of …	SM.POP.REFG	NaN	NaN	NaN	NaN	NaN	NaN	NaN	…

Country Code	2014	2015	2016	2017	2018
ABW	NaN	NaN	NaN	NaN	NaN
AFE	2637640.0	3333273.0	3990478.0	5155400.0	5114399.0
AFG	300421.0	257553.0	59770.0	75927.0	72228.0
AFW	1108169.0	1138010.0	1200854.0	1172523.0	1285773.0
AGO	15468.0	15547.0	15547.0	41119.0	39856.0

Country Code	2019	2020	2021	2022	Unnamed: 67
ABW	NaN	NaN	NaN	NaN	NaN
AFE	5087755.0	5183533.0	5436720.0	5412266.0	NaN
AFG	72227.0	72278.0	66949.0	52159.0	NaN
AFW	1315229.0	1474135.0	1631057.0	1705777.0	NaN
AGO	25793.0	25791.0	26045.0	25514.0	NaN

```
[5 rows x 67 columns]
```

Now it's easy to select rows or columns

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

[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  \
Country Code
CHE              SM.POP.REFG   20000.0   20000.0   20000.0   20000.0   20000.0
DEU              SM.POP.REFG  197000.0  190000.0  185000.0  182000.0  180000.0

                    1965      1966  …      2014      2015      2016      2017  \
Country Code                        …
CHE              20000.0   20500.0  …   62596.0   73326.0   82668.0   93030.0
DEU             180000.0  140000.0  …  216956.0  316098.0  669468.0  970357.0

                     2018       2019       2020       2021       2022  \
Country Code
CHE               104011.0   110162.0   115798.0   118829.0   182474.0
DEU              1063835.0  1146682.0  1210596.0  1255694.0  2075445.0

                Unnamed: 67
Country Code
CHE                     NaN
DEU                     NaN

[2 rows x 67 columns]
```

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

[15]:
```
                    1990       2000
Country Code
ABW                  NaN        NaN
AFE            4709569.0  2444941.0
AFG                 50.0        NaN
AFW             932052.0   968325.0
AGO              11557.0    12086.0
```

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

[16]:
```
                    1990       2000
Country Code
ABW                  NaN        NaN
```

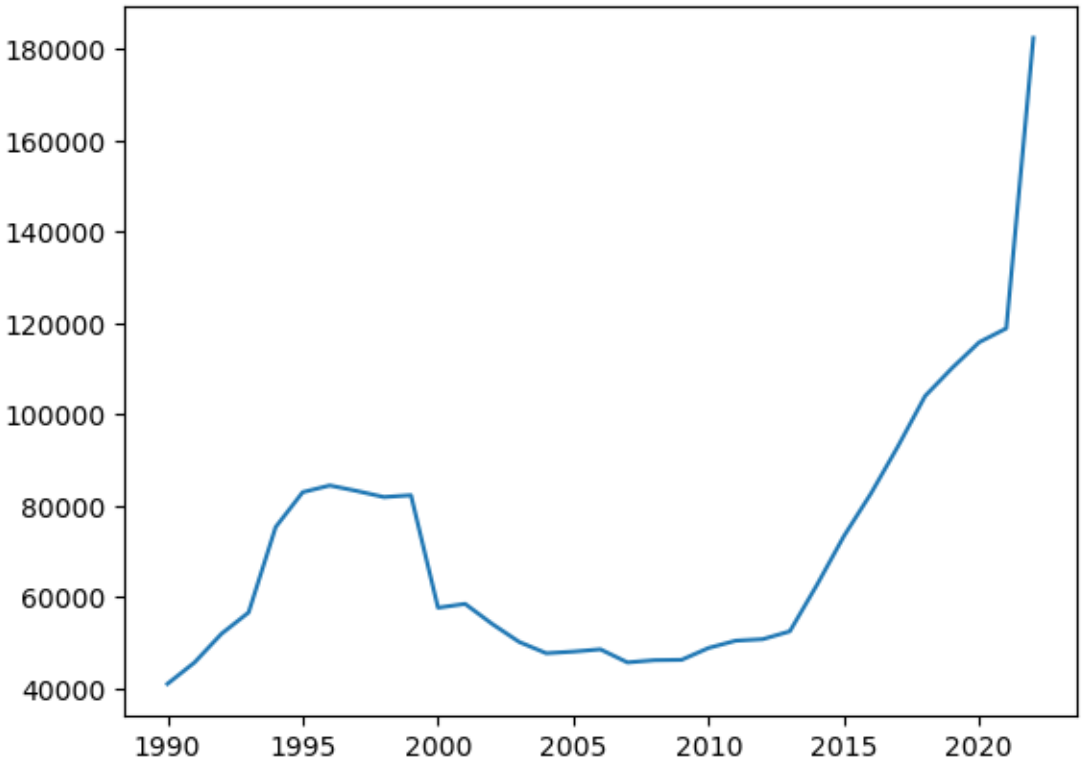
```
AFE          4709569.0  2444941.0
AFG               50.0        NaN
AFW           932052.0   968325.0
AGO            11557.0    12086.0
```

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:

[17]:
```
che = refugees.loc["CHE"][[str(year) for year in range(1990,2023)]]
```

[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

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

[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', '2018', '2019', '2020', '2021',
```

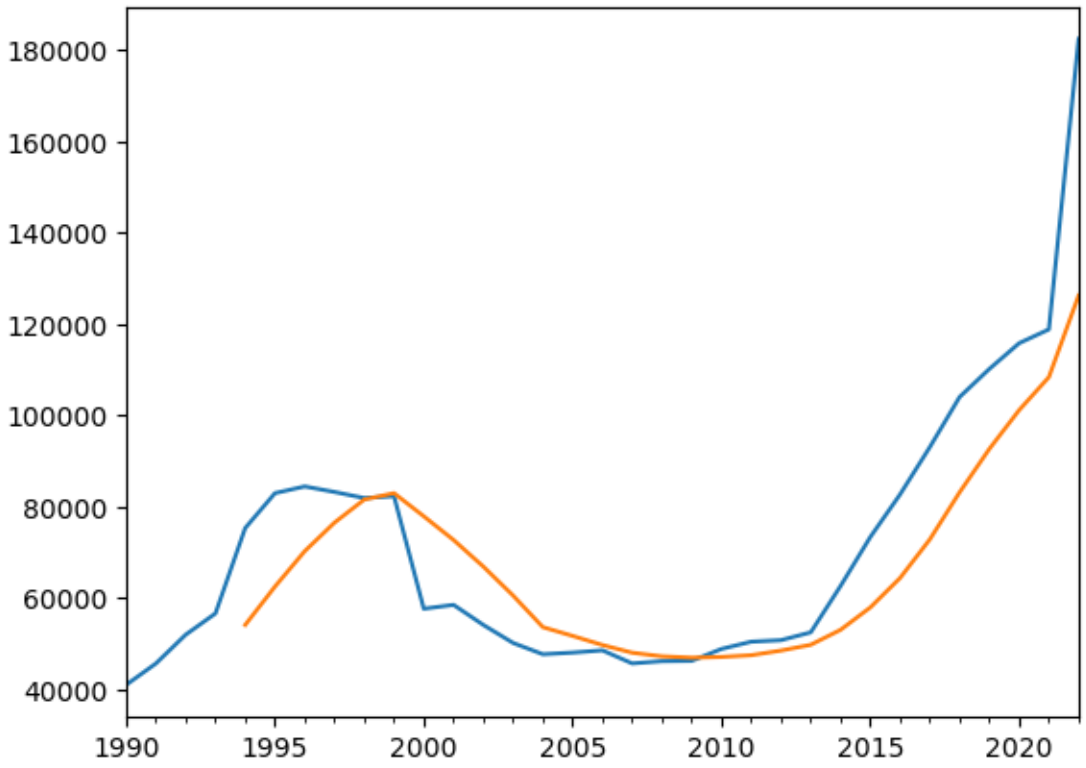
```
       '2022'], dtype=object)
```

[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',
               '2018-01-01', '2019-01-01', '2020-01-01', '2021-01-01',
               '2022-01-01'],
              dtype='datetime64[ns]', freq=None)
```

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

[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 population vs. gdp-per-captita. For each data set we will use the mean of the last 5 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)

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

```
"AFG","South Asia","Low income","The reporting period for national accounts data
is designated as either calendar year basis (CY) or fiscal year basis (FY). For
this country, it is fiscal year-based (fiscal year-end: March 20). Also, an
estimate (PA.NUS.ATLS) of the exchange rate covers the same period and thus
differs from the official exchange rate (CY).
```

We load this file and extract the two relevant columns

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

[24]:
```
meta.columns
```

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

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

[26]:
```
meta.head()
```

[26]:

	Country Code	Region
0	ABW	Latin America & Caribbean
1	AFE	NaN
2	AFG	South Asia
3	AFW	NaN
4	AGO	Sub-Saharan Africa

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

From this we create a list of non-countries

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

```
Index(['AFE', 'AFW', '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

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

2.3.2 Excluding Columns

The data contains a few rows with unneeded text

[30]:
```
refugees.columns
```

[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', '2018', '2019', '2020', '2021', '2022', 'Unnamed: 67'],
      dtype='object')
```

In addition, the last column might be missig a lot of data

[31]:
```
np.sum(refugees["2022"].notnull())
```

[31]:
```
163
```

so we can create a list of all interesting columns

[32]:
```
useful_cols = []
last_year = 2022 # depending on output above
for year in range(last_year-5,last_year+1):
    useful_cols.append(str(year))
```

[33]:
```
useful_cols
```

[33]:
```
['2017', '2018', '2019', '2020', '2021', '2022']
```

with this, we:

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

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

[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.

[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[useful_cols]
    return data.mean(axis=1), data
```

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

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

[38]:
```
Country Code
ABW    29195.590031
AFG      482.654165
AGO     2219.687217
ALB     5622.992095
AND    41023.002828
dtype: float64
```

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

[39]:
```
                    2017          2018          2019          2020  \
Country Code
ABW          29326.708058  30918.515218  31902.762582  24487.863569
AFG            530.149863    502.057099    500.522981    516.866797
AGO           2283.214233   2487.500996   2142.238757   1502.950754
ALB           4531.032207   5287.660817   5396.214227   5343.037704
AND          40632.231554  42904.828456  41328.600499  37207.222000

                    2021          2022
Country Code
ABW          29342.100730           NaN
```

```
AFG             363.674087           NaN
AGO            1903.717405   2998.501158
ALB            6377.203096   6802.804519
AND           42072.341103  41992.793358
```

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

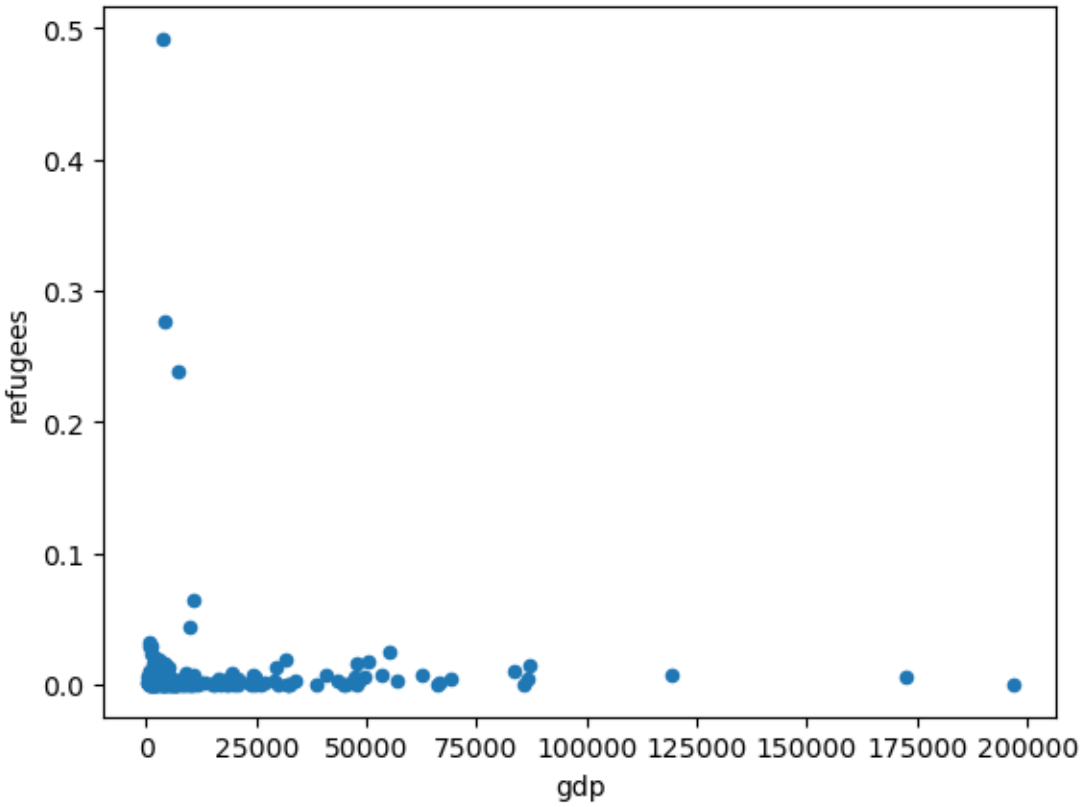
2.5 Creating the Plot

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

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

(Here we loose some countries with missing data.)

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



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

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

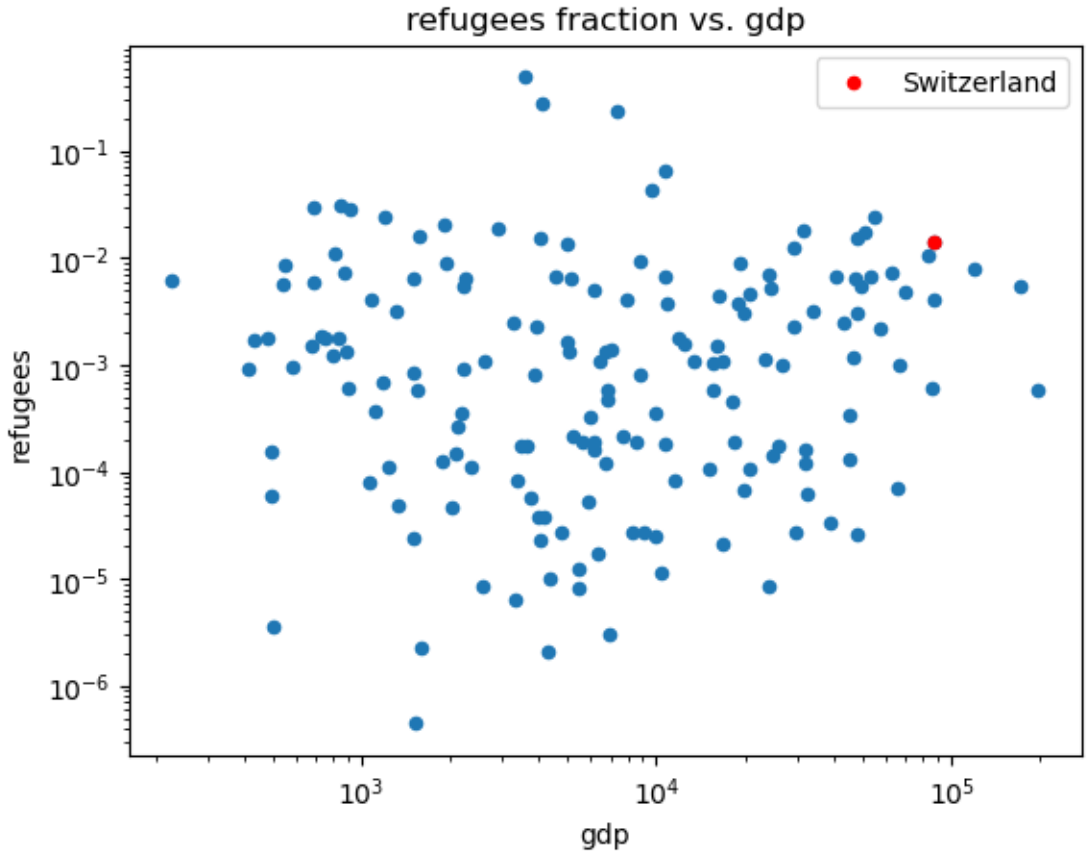
[43]:

Country Code	gdp	refugees
JOR	4103.047067	0.277147
LBN	7313.453707	0.239103
PSE	3590.180327	0.491745

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

[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="Switzerland")
plt.title("refugees fraction vs. gdp")
plt.show()
```



again we can print the info for one country

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

[45]:
```
gdp          86890.390629
refugees         0.014023
Name: CHE, dtype: float64
```

2.5.1 Highlighting a Full Region

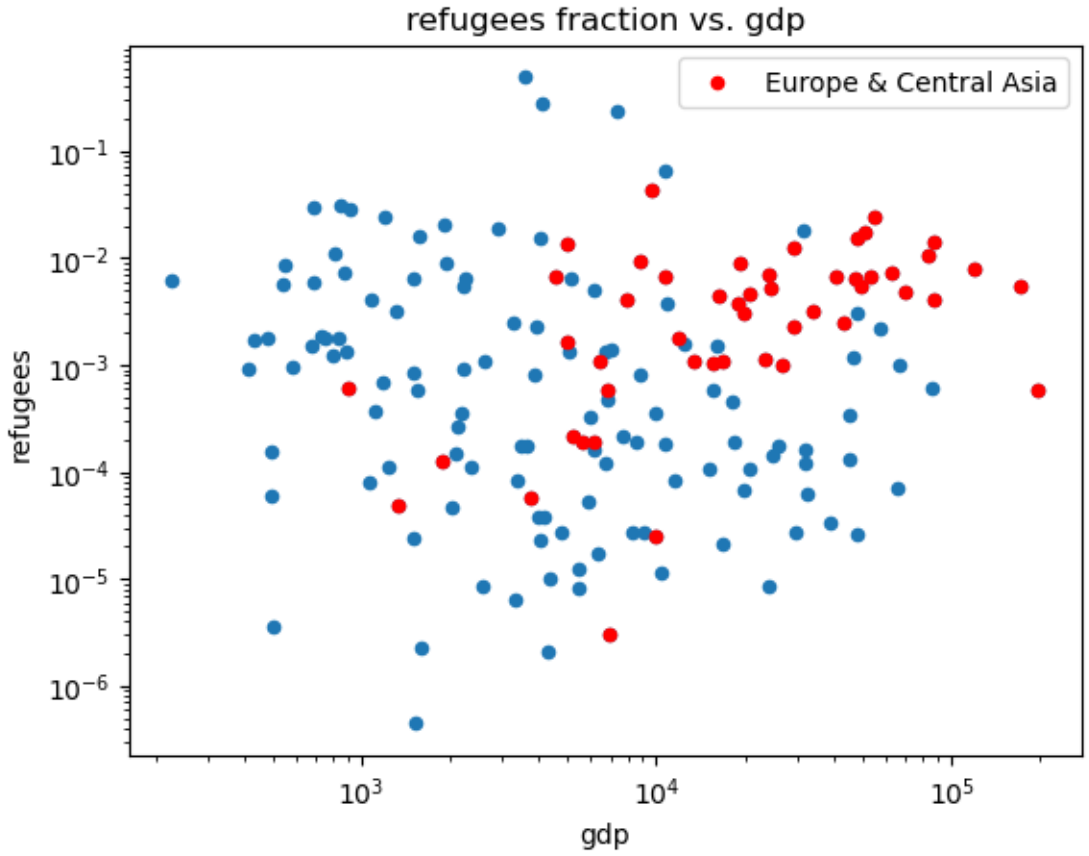
Based on the meta data provided by the World Bank, we can highlight a region

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

[47]:
```
europe[:10]
```

[47]:
```
Index(['ALB', 'AND', 'ARM', 'AUT', 'AZE', 'BEL', 'BGR', 'BIH', 'BLR', 'CHE'],
dtype='object', name='Country Code')
```

[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=ax, color="r", label="Europe & Central Asia")
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

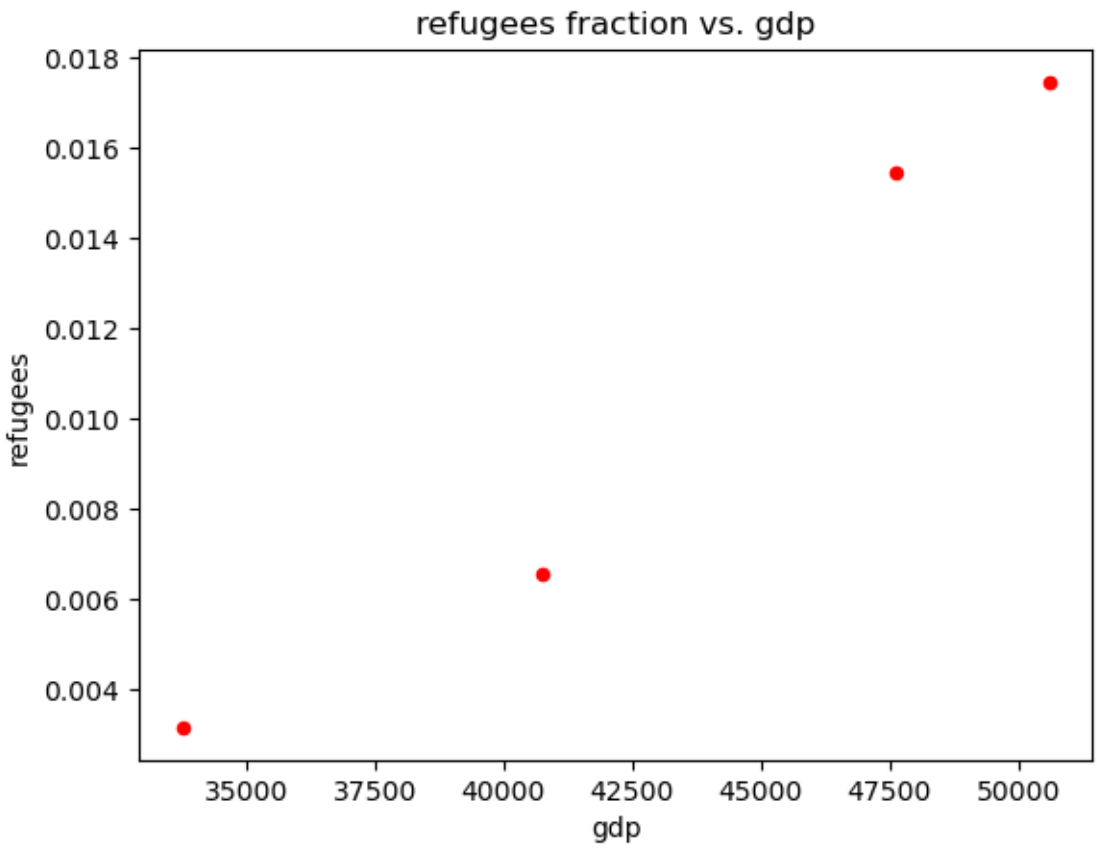
[49]:
```
europe_small = ['AUT',
 'DEU',
 'FRA',
 'ITA',
]
```

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

[50]:

Country Code	gdp	refugees
AUT	50590.749602	0.017460
DEU	47632.398320	0.015473
FRA	40751.983647	0.006578
ITA	33758.229029	0.003165

[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

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

2.6.2 polyfit

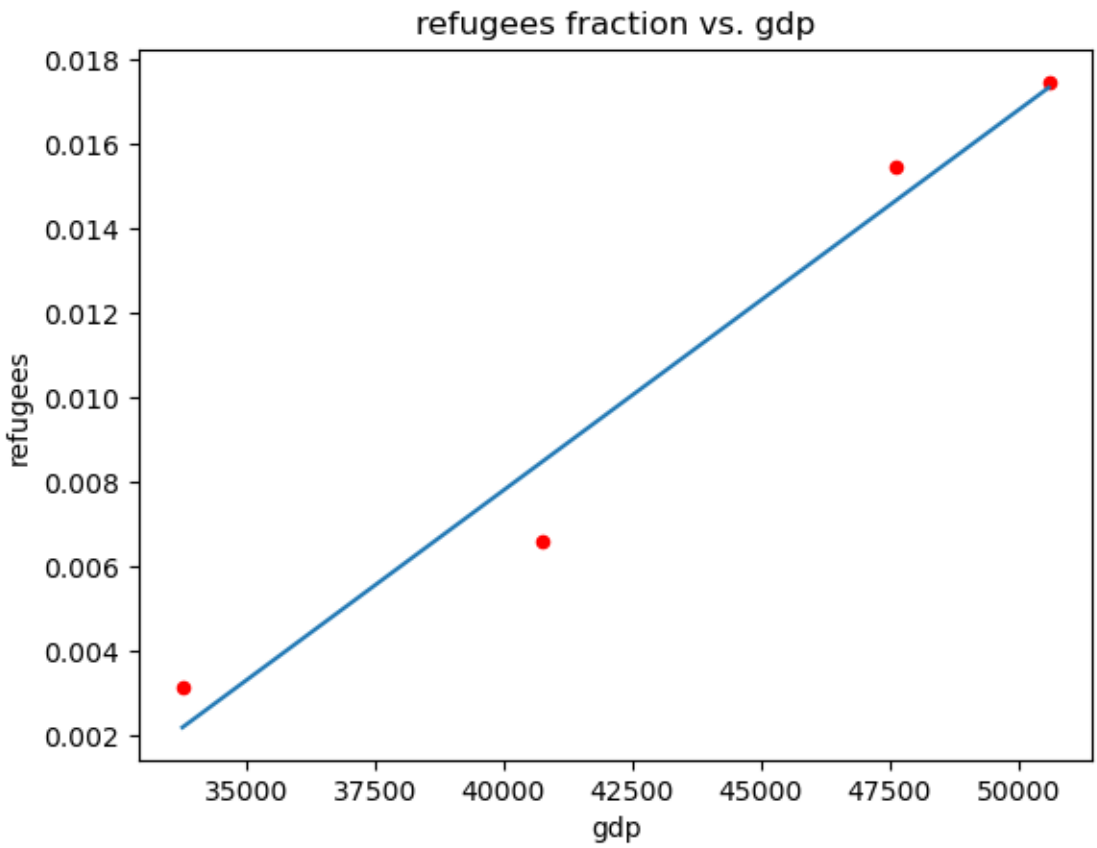
Polyfit is probably the easiest way to fit a polynome to given data.

[53]:
```
from numpy import polyfit, polyval
```

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

```
[ 8.99316549e-07 -2.81665523e-02]
```

[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.

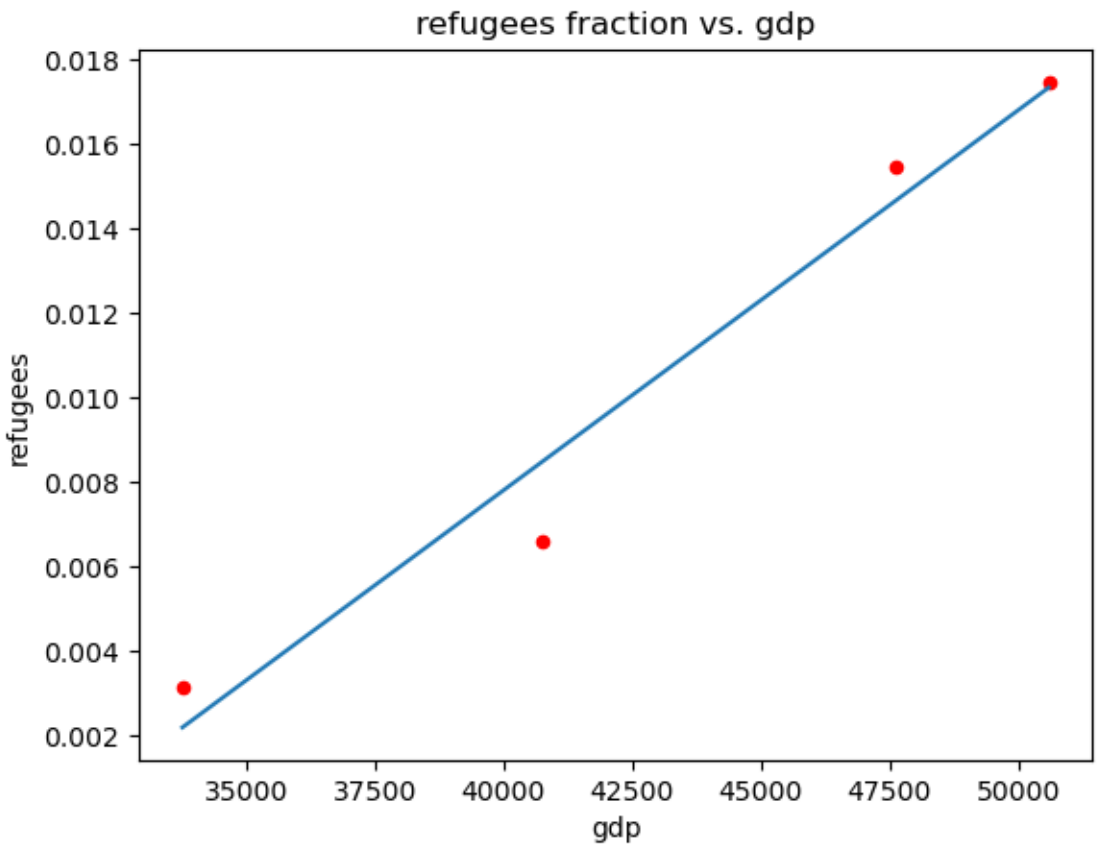
[56]:
```
from scipy.optimize import curve_fit
```

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

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

```
(array([ 8.99316549e-07, -2.81665522e-02]), array([[ 1.54432316e-14,
-6.66890325e-10],
       [-6.66890325e-10,  2.94526038e-05]]))
```

[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.

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

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

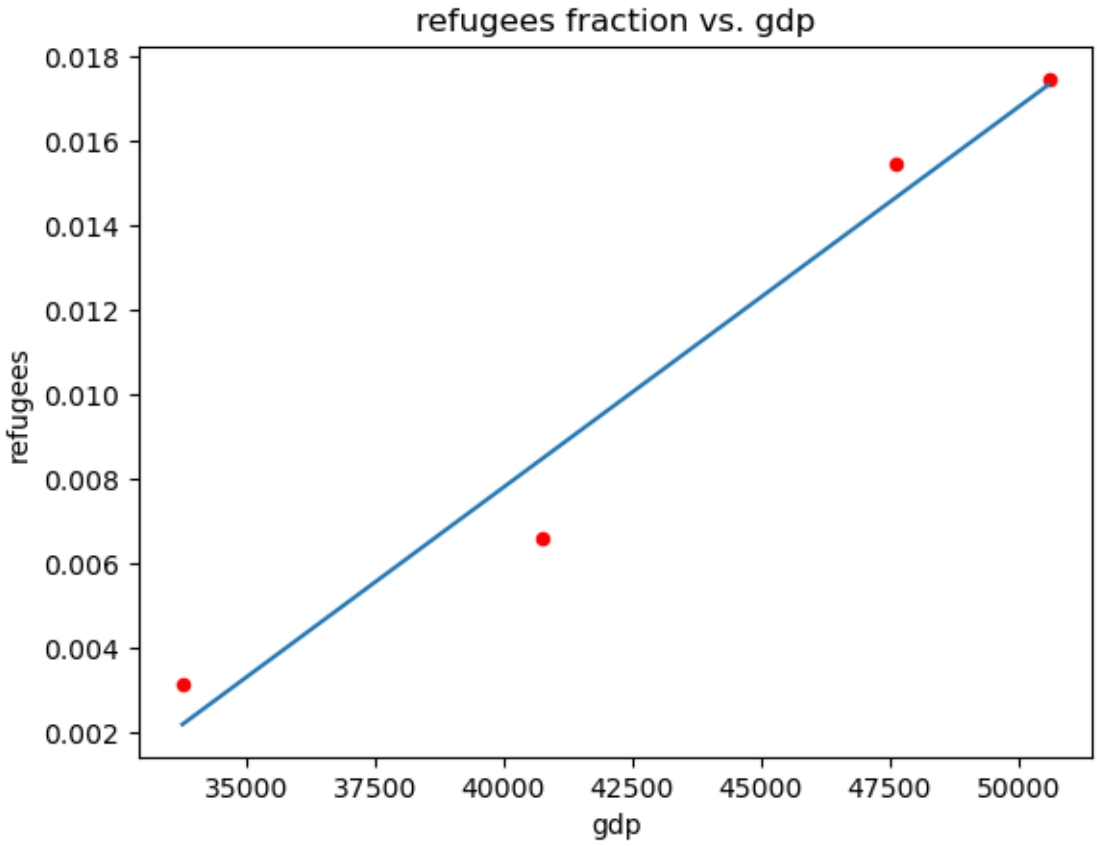
[62]:
```
def error_function(params):
    return data_eu["refugees"] - fit_function(data_eu["gdp"], params)
```

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

```
(array([ 8.99316549e-07, -2.81665523e-02]), 3)
```

[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

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

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

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

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                refugees   R-squared:                       0.963
Model:                            OLS   Adj. R-squared:                  0.945
Method:                 Least Squares   F-statistic:                     52.37
Date:                Tue, 11 Jul 2023   Prob (F-statistic):             0.0186
Time:                        12:17:35   Log-Likelihood:                 21.418
No. Observations:                   4   AIC:                            -38.84
Df Residuals:                       2   BIC:                            -40.06
Df Model:                           1
```

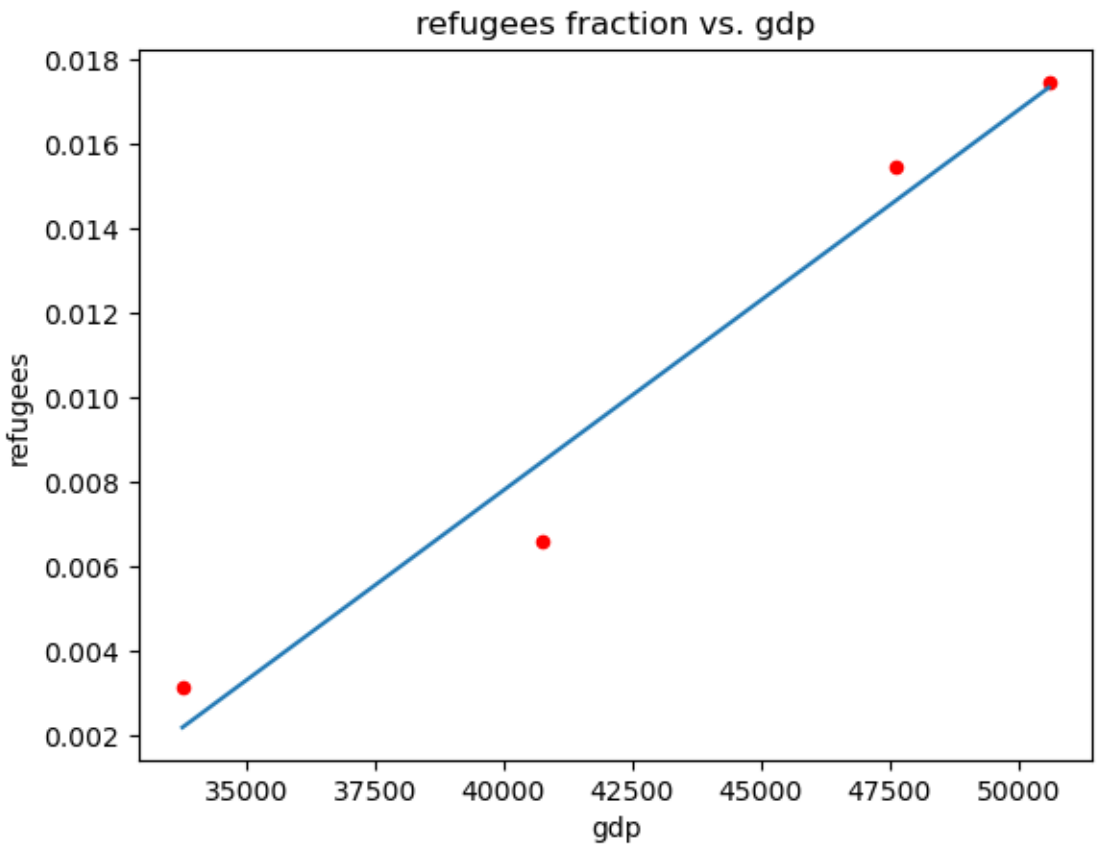
```
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -0.0282      0.005     -5.190      0.035      -0.052      -0.005
gdp         8.993e-07   1.24e-07      7.237      0.019    3.65e-07    1.43e-06
==============================================================================
Omnibus:                        nan   Durbin-Watson:                   3.069
Prob(Omnibus):                  nan   Jarque-Bera (JB):                0.688
Skew:                        -0.913   Prob(JB):                        0.709
Kurtosis:                     2.112   Cond. No.                     2.93e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.93e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
/usr/lib/python3/dist-packages/statsmodels/stats/stattools.py:74: ValueWarning:
omni_normtest is not valid with less than 8 observations; 4 samples were given.
  warn("omni_normtest is not valid with less than 8 observations; %i "
```

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

```
Intercept   -2.816655e-02
gdp          8.993165e-07
dtype: float64
```

[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`

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

[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)

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

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

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

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

Also slicing works (but includes the upper boundary)

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

[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

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

[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.)

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

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

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

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

[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)

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

[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.

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

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

While a list returns a `DataFrame`

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

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

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

[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.

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

[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

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

[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

[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