1 Lecture 2: Data processing in Pandas library

Data Visualization · 1-DAV-105

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1.1 Tabular data

- We will often work with data in the form of tables.
- Columns represent different features / variables (príznaky, atribúty, veličiny, premenné).
- Rows represent different items / data points / observations (countries, people, dates of measurement, …).
- A small example:

Country	Region	Population	Area (km2)	Landlocked
Slovakia	Europe	5450421	49035	yes
Czech Republic	Europe	10649800	78866	yes
Hungary	Europe	9772756	93030	yes
Poland	Europe	38386000	312696	no

1.2 Pandas library

- Pandas is a Python library for data manipulation and analysis.
- It is fast and has many functions for data import and export in various formats.
- Documentation, overview, tutorial

Basic data structures

- `Series`: 1D table, all elements of the same type.
- `DataFrame`: 2D table, elements within each column of the same type.

NumPy library

- NumPy is a library of efficient multi-dimensional arrays used for numerical computations.
- We will mostly use Pandas, but some NumPy functions will be useful.
- Tutorial, reference

[1]:
```
import numpy as np
import pandas as pd
from IPython.display import Markdown
import matplotlib.pyplot as plt
```

1.2.1 Creating Series and DataFrames

- Bellow we show two manual ways of creating a DataFrame containing the small table of countries above.
- The first way gets a Series for each column, the second way gets a dictionary (or a tuple) for each row.
- We will usually read tabular data from files, see an example in the second half this lecture.

[2]:
```python
# create Series for each column
countries = pd.Series(['Slovakia', 'Czech Republic', 'Hungary', 'Poland'])
regions = pd.Series(['Europe', 'Europe', 'Europe', 'Europe'])
populations = pd.Series([5450421, 10649800, 9772756, 38386000])
areas = pd.Series([49035, 78866, 93030, 312696])
landlocked = pd.Series([True, True, True, False])
# combine columns into a DataFrame
table = pd.DataFrame({'country':countries,
                      'region':regions,
                      'population':populations,
                      'area':areas,
                      'landlocked':landlocked})
# display: special notebook command for pretty-printing data
display(table)
```

	country	region	population	area	landlocked
0	Slovakia	Europe	5450421	49035	True
1	Czech Republic	Europe	10649800	78866	True
2	Hungary	Europe	9772756	93030	True
3	Poland	Europe	38386000	312696	False

[3]:
```python
list_of_dicts = [
    {'country':'Slovakia', 'region':'Europe', 'population':5450421, 'area':
 ↪49035, 'landlocked':True},
    {'country':'Czech Republic', 'region':'Europe', 'population':10649800,␣
 ↪'area':78866, 'landlocked':True},
    {'country':'Hungary', 'region':'Europe', 'population':9772756, 'area':
 ↪93030, 'landlocked':True},
    {'country':'Poland', 'region':'Europe', 'population':38386000, 'area':
 ↪312696, 'landlocked':False},
]
table_from_list = pd.DataFrame.from_records(list_of_dicts)
display(table_from_list)
```

	country	region	population	area	landlocked
0	Slovakia	Europe	5450421	49035	True
1	Czech Republic	Europe	10649800	78866	True
2	Hungary	Europe	9772756	93030	True
3	Poland	Europe	38386000	312696	False

1.2.2 Accessing elements of Series and DataFrame by position

- Attribute `ndim` is the number of dimensions. E.g. `areas.ndim` is 1, `table.ndim` is 2.
- Attribute `shape` is a tuple holding the size in each dimension. E.g. `areas.shape` is `(4,)`, `table.shape` is `(4,5)`.
- Rows and columns are numbered 0, 1, …
- To access a particular column / row, use `some_series.iloc[row]` or `some_table.iloc[row, column]`.

- Rows and columns in `iloc` can be
  - a single number e.g. `0`,
  - a slice (range) e.g. `0:2` or `:` for everything,
  - a list of positions e.g. `[0, 2, 3]`
  - a list of boolean values `[True, False, True, True]`.
- The result is a single element or a Series / DataFrame of a smaller size.

```
[4]: display(Markdown("**table:**"), table)
     display(Markdown("**table.iloc[1, 2]:**"), table.iloc[1, 2])
     display(Markdown("**table.iloc[[0, 2, 3], 0:2]**"), table.iloc[[0, 2, 3],  0:2])
     display(Markdown("**table.iloc[[True, False, True, True], :]**"),
             table.iloc[[True, False, True, True], :])
```

table:

	country	region	population	area	landlocked
0	Slovakia	Europe	5450421	49035	True
1	Czech Republic	Europe	10649800	78866	True
2	Hungary	Europe	9772756	93030	True
3	Poland	Europe	38386000	312696	False

table.iloc[1, 2]:

```
np.int64(10649800)
```

table.iloc[[0, 2, 3], 0:2]

	country	region
0	Slovakia	Europe
2	Hungary	Europe
3	Poland	Europe

table.iloc[[True, False, True, True], :]

	country	region	population	area	landlocked
0	Slovakia	Europe	5450421	49035	True
2	Hungary	Europe	9772756	93030	True
3	Poland	Europe	38386000	312696	False

1.2.3 Views vs. copies

- Accessing parts of tables by `iloc` may return a partial copy or simply a "view".
- If we later modify this result, it is not clear if the original table is modified.
- Direct assignment of new values to a part of the table works: `some_table.iloc[row, column] = new_value` modifies `some_table`.
- To copy a table, use `other_table = some_table.copy(deep=True)`.

```
[ ]: table2 = table.copy(deep=True)
     # create a copy of the original table

     table2.iloc[0,0] = 'Slovensko'
     display(table2)
```

```
# table2 now has Slovensko instead of Slovakia

countries2 = table2.iloc[: , 0]
# countries2 is now a view or a copy of one column of table2
countries2.iloc[2] = 'Maďarsko'
display(table2)
# table2 now can have Hungary or Maďarsko
# we get a warning
```

```
          country  region  population    area  landlocked
0       Slovensko  Europe     5450421   49035        True
1  Czech Republic  Europe    10649800   78866        True
2         Hungary  Europe     9772756   93030        True
3          Poland  Europe    38386000  312696       False
```

```
/tmp/ipykernel_858765/2667016646.py:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  countries2.iloc[2] = 'Maďarsko'
```

```
          country  region  population    area  landlocked
0       Slovensko  Europe     5450421   49035        True
1  Czech Republic  Europe    10649800   78866        True
2        Maďarsko  Europe     9772756   93030        True
3          Poland  Europe    38386000  312696       False
```

1.2.4 Inplace operations

- Many operations return a new table.
- If you do not need the original table, you can specify option `inplace=True`.
- The example below sorts a table by a specified column, returning a new table or replacing the old one.

[6]:
```
# copy original table to table2
table2 = table.copy(deep=True)

# table3 is a copy of table2 sorted by population size
table3 = table2.sort_values(by="population")

# display both table2 and table3
display(Markdown("**Original table2:**"), table2)
display(Markdown("**Sorted table3:**"), table3)

# now change table2 to be sorted by name of the country
table2.sort_values(by="country", inplace=True)
display(Markdown("**Sorted table2:**"), table2)
```

Original table2:

	country	region	population	area	landlocked
0	Slovakia	Europe	5450421	49035	True
1	Czech Republic	Europe	10649800	78866	True
2	Hungary	Europe	9772756	93030	True
3	Poland	Europe	38386000	312696	False

Sorted table3:

	country	region	population	area	landlocked
0	Slovakia	Europe	5450421	49035	True
2	Hungary	Europe	9772756	93030	True
1	Czech Republic	Europe	10649800	78866	True
3	Poland	Europe	38386000	312696	False

Sorted table2:

	country	region	population	area	landlocked
1	Czech Republic	Europe	10649800	78866	True
2	Hungary	Europe	9772756	93030	True
3	Poland	Europe	38386000	312696	False
0	Slovakia	Europe	5450421	49035	True

1.2.5 Indexes

- Rows and columns have both an integer location (0,1,2,...) and an index (name).
- In our table, column names are `'country'`, `'region'` etc.
- We have not named rows, so a default location-based index was constructed.
  - See the sorted tables above—their index labels are kept from the original.
- Indexes can be obtained by attributes `index` and `columns`.
- We can set the country name as an index using `set_index`, the opposite is `reset_index` (in Series, use `set_axis` and `reset_index`).
- Index can be more complex (multiindex), we will see later.

[7]:
```
display(Markdown("**`table.columns` is an object of class `Index`:**"),
        table.columns)
display(Markdown("**`table.columns.values` is an array of column names:**"),
        table.columns.values)

display(Markdown("**`table.index.values` is an array of row names, "
                 + "here equal to location:**"),
        table.index.values)
display(Markdown("**`index` for Series `areas`:**"), areas.index.values)

display(Markdown("**`table` after setting country name as index:**"))
table2 = table.set_index('country')
display(table2)

display(Markdown("**`reset_index` will put the index back as a column:**"))
```

```
table3 = table2.reset_index()
display(table3)
```

`table.columns` is an object of class `Index`:

```
Index(['country', 'region', 'population', 'area', 'landlocked'], dtype='object')
```

`table.columns.values` is an array of column names:

```
array(['country', 'region', 'population', 'area', 'landlocked'],
      dtype=object)
```

`table.index.values` is an array of row names, here equal to location:

```
array([0, 1, 2, 3])
```

index for Series `areas`:

```
array([0, 1, 2, 3])
```

table after setting country name as index:

```
                region  population    area  landlocked
country
Slovakia        Europe     5450421   49035        True
Czech Republic  Europe    10649800   78866        True
Hungary         Europe     9772756   93030        True
Poland          Europe    38386000  312696       False
```

`reset_index` will put the index back as a column:

```
          country  region  population    area  landlocked
0        Slovakia  Europe     5450421   49035        True
1  Czech Republic  Europe    10649800   78866        True
2         Hungary  Europe     9772756   93030        True
3          Poland  Europe    38386000  312696       False
```

1.2.6 Accessing elements by index

- Method `some_table.loc[row, column]` is an analog of `iloc`, but using indexes rather than locations.
- You can use just `[]` instead of `loc`, but this is sometimes ambiguous whether you mean `iloc` or `loc`.
- Some examples for `Series`:

[8]:
```
populations2 = populations.set_axis(countries)
display(Markdown("**`populations2` Series with index:**"), populations2)
display(Markdown("**`populations2.loc['Slovakia']`**:"),
        populations2.loc['Slovakia'])
display(Markdown("**`populations2.loc[['Slovakia','Poland']]`**:"),
        populations2.loc[['Slovakia','Poland']])

display(Markdown("**`populations2['Czech Republic']`**:"),
```

```
        populations2['Czech Republic'])
```

populations2 Series with index:

```
Slovakia           5450421
Czech Republic    10649800
Hungary            9772756
Poland            38386000
dtype: int64
```

`populations2.loc['Slovakia']`:

```
np.int64(5450421)
```

`populations2.loc[['Slovakia','Poland']]`:

```
Slovakia     5450421
Poland      38386000
dtype: int64
```

`populations2['Czech Republic']`:

```
np.int64(10649800)
```

1.2.7 Operations and functions on Series

- Operations such as `+`, `*` can be applied on two Series, causing them to be used on each corresponding pair of elements.
- For example, `populations / areas` will compute population density for each country.
- You can also use a single number (scalar) as an operand, e.g. `populations / 1e6` will get population in millions.
- NumPy also contains functions that can be applied to each element of a series, e.g. `np.log(populations)`.
- Relational operators such as `populations < 10e6` produce Series of boolean values.
  - Those can be then used in `iloc`, `loc`, `[]`.

[9]:
```
# creating two Series with country as index
populations2 = populations.set_axis(countries)
areas2 = areas.set_axis(countries)
display(Markdown("**`populations2 / areas2`:**"), populations2 / areas2)
display(Markdown("**`populations2 / 1e6`:**"), populations2 / 1e6)
display(Markdown("**`populations2 > 10e6`:**"), populations2 > 10e6)
display(Markdown("**`areas2[populations2 > 10e6]`:**"),
        areas2.loc[populations2 > 10e6])
display(Markdown("**`np.log10(populations2)`:**"), np.log10(populations2))
```

`populations2 / areas2`:

```
Slovakia          111.153686
Czech Republic    135.036644
Hungary           105.049511
```

```
Poland            122.758206
dtype: float64
```

populations2 / 1e6:

```
Slovakia           5.450421
Czech Republic    10.649800
Hungary            9.772756
Poland            38.386000
dtype: float64
```

populations2 > 10e6:

```
Slovakia          False
Czech Republic     True
Hungary           False
Poland             True
dtype: bool
```

areas2[populations2 > 10e6]:

```
Czech Republic     78866
Poland            312696
dtype: int64
```

np.log10(populations2):

```
Slovakia          6.736430
Czech Republic    7.027341
Hungary           6.990017
Poland            7.584173
dtype: float64
```

Beware: when we combine two Series, e.g. by +, Pandas will use index, not position, to pair up elements.

[10]:
```
a = pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])
b = pd.Series([10, 20, 30], index=['c', 'a', 'e'])
c = pd.Series([100, 200])
display(Markdown("**Series a:**"), a)
display(Markdown("**Series b:**"), b)
display(Markdown("**Series c:**"), c)
display(Markdown("**Series a+b:**"), a + b)
display(Markdown("**Series a+c:**"), a + c)
```

Series a:

```
a    1
b    2
c    3
d    4
dtype: int64
```

Series b:

```
c    10
a    20
e    30
dtype: int64
```

Series c:

```
0    100
1    200
dtype: int64
```

Series a+b:

```
a    21.0
b     NaN
c    13.0
d     NaN
e     NaN
dtype: float64
```

Series a+c:

```
a   NaN
b   NaN
c   NaN
d   NaN
0   NaN
1   NaN
dtype: float64
```

1.2.8 Working with DataFrame columns

- `DataFrame` is similar to a dictionary of `Series` objects (columns).
- For example, `table['area']` or `table.area` is the **column** of country areas.
- New columns can be added to a DataFrame: `table['density'] = table['population'] / table['area']`
- By `table[table['population'] > 1e7]` we get countries with more that 10 million people (CZ, PL).

[11]:
```
display(Markdown("**`table['area']`:**"), table['area'])
display(Markdown("**`table.area`:**"), table.area)
display(Markdown("**Adding density:**"))
display(Markdown("`table['density'] = table['population'] / table['area']`"))
table['density'] = table['population'] / table['area']
display(Markdown("**`table[table['population'] > 1e7]`:**"),
        table[table['population'] > 1e7])
```

`table['area']`:

```
0     49035
1     78866
2     93030
3    312696
Name: area, dtype: int64
```

`table.area`:

```
0     49035
1     78866
2     93030
3    312696
Name: area, dtype: int64
```

Adding density:

`table['density'] = table['population'] / table['area']`

`table[table['population'] > 1e7]`:

	country	region	population	area	landlocked	density
1	Czech Republic	Europe	10649800	78866	True	135.036644
3	Poland	Europe	38386000	312696	False	122.758206

1.2.9 Selecting table rows with query

- Method query is very useful for selecting `DataFrame` rows satisfying some properties.
- In examples below, `@` substitutes variable value.
- While `loc[]` and `iloc[]` raise an exception if the requested value is not found, `query` can return an empty table.

[12]:
```python
display(Markdown("**`table.query(\"country=='Slovakia'\")`:**"),
        table.query("country=='Slovakia'"))

def get_country(table, country):
  """Get a given country from the table"""
  return table.query("country == @country")
display(Markdown("**The same but for Hungary and using a function:**"),
        get_country(table, 'Hungary'))

display(Markdown("**Query with an empty result:**"))
display(Markdown("`table.query(\"population < 10e6 and not landlocked\")`:"))
display(table.query("population < 10e6 and not landlocked"))
```

`table.query("country=='Slovakia'")`:

	country	region	population	area	landlocked	density
0	Slovakia	Europe	5450421	49035	True	111.153686

The same but for Hungary and using a function:

	country	region	population	area	landlocked	density
2	Hungary	Europe	9772756	93030	True	105.049511

Query with an empty result:

`table.query("population < 10e6 and not landlocked")`:

```
Empty DataFrame
Columns: [country, region, population, area, landlocked, density]
Index: []
```

1.2.10 Importing and exporting data

- Import and export is possible using many file formats (text-based CSV, JSON, HTML; binary Excel, HDF5 etc.).
- We will mostly use CSV (=comma separated values) format.
  - Each table row is one line of the file.
  - Columns are separated by commas.
  - Columns containing commas or end-of-line characters may be enclosed in quotation marks.
  - Sometimes a different column separator is used, e.g. tab `"\t"`.
  - We have used a CSV file in Homework 1: a table with life expectancies of different countries in different years.
- Writing our table to a csv file: `table.to_csv("countries.csv")`.
  - If run in Colab, this will create a temporary file, which you can save on your computer (see the right panel, tab Files).
- Conversely, `table2 = pd.read_csv("countries.csv", index_col=0)` will read data from the file to a new `DataFrame` called `table2`.
- Input and output functions allow you to set many optional arguments to tweak the format.

1.3 Example: a table of country populations from the United Nations

- Obtained from the UN webpage https://data.un.org/
- We will read the table in CSV format directly from a URL.
- We need to play a bit with settings:
  - We skip the top two lines.
  - We supply our own (simpler) column names.
  - We specify character encoding (default is UTF8) and that thousands are separted by a comma in numerical values, such as 1,000,000.
  - Note that empty fields (missing values) are imported as `np.NaN`.

[13]:
```python
# original source:
# url = 'https://data.un.org/_Docs/SYB/CSV/
↪SYB65_1_202209_Population,%20Surface%20Area%20and%20Density.csv'
# our local copy:
url = 'https://bbrejova.github.io/viz/data/Un_population.csv'
column_names = ['Region ID', 'Region', 'Year',
                'Series', 'Value', 'Footnotes', 'Source']
un_table = pd.read_csv(url, encoding='latin-1', names=column_names,
                       skiprows=2, thousands=",")
# print the first 5 rows to check the result
un_table.head()
```

[13]:
```
   Region ID                       Region  Year  \
0          1  Total, all countries or areas  2010
1          1  Total, all countries or areas  2010
2          1  Total, all countries or areas  2010
3          1  Total, all countries or areas  2010
4          1  Total, all countries or areas  2010

                                              Series    Value Footnotes  \
0         Population mid-year estimates (millions)  6985.60       NaN
1  Population mid-year estimates for males (milli…  3514.41       NaN
2  Population mid-year estimates for females (mil…  3471.20       NaN
3                Sex ratio (males per 100 females)   101.20       NaN
4     Population aged 0 to 14 years old (percentage)    27.10       NaN

                                              Source
0  United Nations Population Division, New York, …
1  United Nations Population Division, New York, …
2  United Nations Population Division, New York, …
3  United Nations Population Division, New York, …
4  United Nations Population Division, New York, …
```

[14]:
```
# print the last 5 rows, to see if the bottom looks ok
un_table.tail()
```

[14]:
```
      Region ID    Region  Year  \
7868        716  Zimbabwe  2022
7869        716  Zimbabwe  2022
7870        716  Zimbabwe  2022
7871        716  Zimbabwe  2022
7872        716  Zimbabwe  2022

                                              Series  Value  \
7868  Population mid-year estimates for females (mil…   8.61
7869                Sex ratio (males per 100 females)  89.40
7870     Population aged 0 to 14 years old (percentage)  40.60
7871         Population aged 60+ years old (percentage)   4.80
7872                              Population density  42.20

                                          Footnotes  \
7868  Projected estimate (medium fertility variant).
7869  Projected estimate (medium fertility variant).
7870  Projected estimate (medium fertility variant).
7871  Projected estimate (medium fertility variant).
7872  Projected estimate (medium fertility variant).

                                              Source
7868  United Nations Population Division, New York, …
```

```
7869  United Nations Population Division, New York, …
7870  United Nations Population Division, New York, …
7871  United Nations Population Division, New York, …
7872  United Nations Population Division, New York, …
```

[15]:
```
# check types of columns; strings are imported as object, which is expected
un_table.dtypes
```

[15]:
```
Region ID      int64
Region        object
Year           int64
Series        object
Value        float64
Footnotes     object
Source        object
dtype: object
```

- Each country has data for several years.
- There are several values per country and year, e.g. total population, the number of men and women, sizes of three age groups.
- The first part of the table contains various continents and regions, later individual countries arranged alphabetically from `'Afghanistan'` to `'Zimbabwe'`.

1.3.1 A simple table with total population across years

We will create a simpler table `country_pop`.

- It will contain only countries, not regions.
- It will contain only rows with total population, all available years.
- It will contain columns `Country` (originally `Region`) , `Year`, and `Population` (originally `Value`).

[16]:
```
# get all rows for Afghanistan, choose the label for the first of them
first_country = un_table.query('Region == "Afghanistan"').index[0]
# get all rows from the first Afghanistan onwards and all columns
un_countries = un_table.iloc[first_country:, :]
# get only rows with total population and select only some columns using loc
country_pop = (un_countries
               .query('Series=="Population mid-year estimates (millions)"')
               .loc[:, ['Region', 'Year', 'Value']]
               .rename(columns={'Value':'Population', 'Region':'Country'}))
# print the start of the result
country_pop.head()
```

[16]:

	Country	Year	Population
930	Afghanistan	2010	28.19
937	Afghanistan	2015	33.75
945	Afghanistan	2020	38.97

```
953  Afghanistan  2022       41.13
960      Albania  2010        2.91
```

1.4 Tidy data, wide and long tables

- The original UN table has in `Value` column various values, including population size, sex ratio, population density, etc.
- In general, one column of a table should contain values of the same type.
- This is true in our `country_pop` table with columns `Country`, `Year`, and `Population`.
- This type of table is called **long**, and it is usually preferable.
- For some analysis, we may want to have countries as rows and years as columns; this is called a **wide table**.
- Pandas has methods to convert between the two formats, e.g. `wide_to_long`, `melt`, `pivot`, `unstack` etc.
- See the article Tidy data by Hadley Wickham for a longer discussion.

1.5 Back to example: comparing populations in 2010 and 2022

- We select only two years from `country_pop`.
- Function pivot will use the column `Country` as the row index, values from column `Year` as new column names and values from column `Population` as values to populate the table itself.
- Finally we rename the columns so that they are strings starting with a letter; otherwise they are harder to be used in `query`.

[17]:
```
display(Markdown("**Original `country_pop` table:**"), country_pop.head())


pop = (country_pop.query("Year==2010 or Year==2022")
       .pivot(index='Country', columns=['Year'], values='Population')
       .rename(columns={2010:'pop2010', 2022:'pop2022'}))

display(Markdown("**New `pop` table:**"), pop.head())
```

Original `country_pop` table:

```
         Country  Year  Population
930  Afghanistan  2010       28.19
937  Afghanistan  2015       33.75
945  Afghanistan  2020       38.97
953  Afghanistan  2022       41.13
960      Albania  2010        2.91
```

New `pop` table:

```
Year                pop2010  pop2022
Country
```

```
Afghanistan       28.19    41.13
Albania            2.91     2.84
Algeria           35.86    44.90
American Samoa     0.05     0.04
Andorra            0.07     0.08
```

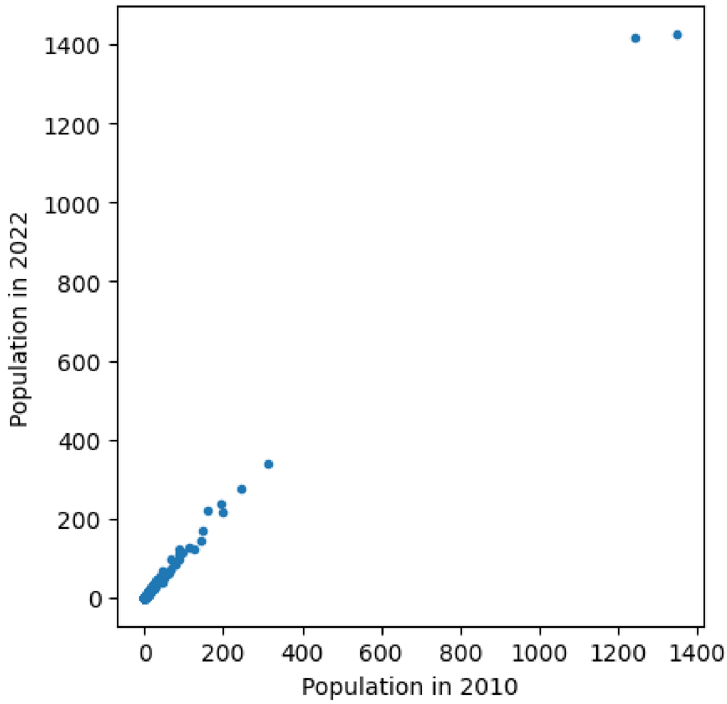
[18]:
```python
# compute the difference between years for each country (positive = increase)
pop['difference'] = pop['pop2022'] - pop['pop2010']
# relative difference, as a fraction of population in 2010
#  (value 1 means 100% increase)
pop['relDifference'] = pop['difference'] / pop['pop2010']
pop.head()
```

[18]:
```
Year            pop2010  pop2022  difference  relDifference
Country
Afghanistan       28.19    41.13       12.94       0.459028
Albania            2.91     2.84       -0.07      -0.024055
Algeria           35.86    44.90        9.04       0.252091
American Samoa     0.05     0.04       -0.01      -0.200000
Andorra            0.07     0.08        0.01       0.142857
```

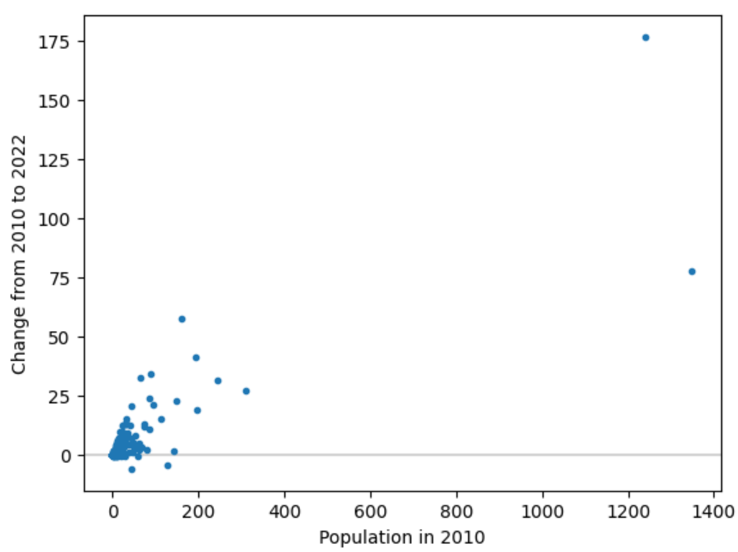
Now we will use this table to create some plots and tables.

- What can you observe from these data displays?
- Are some of these visualizations more useful than others or are they complementary? How could we improve them?
- What other questions you could ask about this table and how would you answer them using plots or tables?

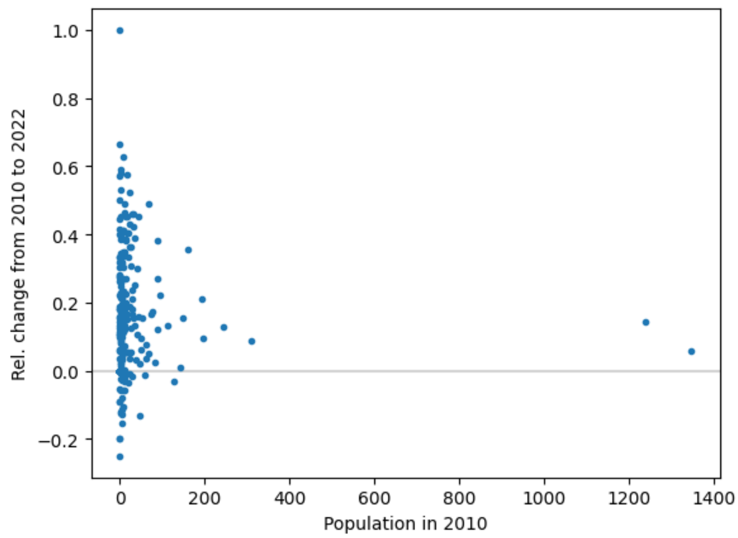
[19]:
```python
figure, axes = plt.subplots()
axes.plot(pop.pop2010, pop.pop2022, '.')
axes.set_aspect('equal')
axes.set_xlabel('Population in 2010')
axes.set_ylabel('Population in 2022')
pass
```



[20]:
```
figure, axes = plt.subplots()
axes.axhline(0, color="lightgrey")
axes.plot(pop.pop2010, pop.difference, '.')
axes.set_xlabel('Population in 2010')
axes.set_ylabel('Change from 2010 to 2022')
pass
```



[21]:
```
figure, axes = plt.subplots()
axes.axhline(0, color="lightgrey")
axes.plot(pop.pop2010, pop.relDifference, '.')
axes.set_xlabel('Population in 2010')
axes.set_ylabel('Rel. change from 2010 to 2022')
pass
```



[22]:
```
pop.sort_values('relDifference').head(10)
```

[22]:

Year	pop2010	pop2022	difference	relDifference
Country				
Saint Martin (French part)	0.04	0.03	-0.01	-0.250000
American Samoa	0.05	0.04	-0.01	-0.200000
Marshall Islands	0.05	0.04	-0.01	-0.200000
Bosnia and Herzegovina	3.81	3.23	-0.58	-0.152231
Ukraine	45.68	39.70	-5.98	-0.130911
Puerto Rico	3.72	3.25	-0.47	-0.126344
Lithuania	3.14	2.75	-0.39	-0.124204
Latvia	2.10	1.85	-0.25	-0.119048
Republic of Moldova	3.68	3.27	-0.41	-0.111413
Bulgaria	7.59	6.78	-0.81	-0.106719

[23]:
```
pop.sort_values('relDifference', ascending=False).head(10)
```

[23]:

Year	pop2010	pop2022	difference	relDifference
Country				
Anguilla	0.01	0.02	0.01	1.000000

Turks and Caicos Islands	0.03	0.05	0.02	0.666667
Jordan	6.93	11.29	4.36	0.629149
Oman	2.88	4.58	1.70	0.590278
Qatar	1.71	2.70	0.99	0.578947
Niger	16.65	26.21	9.56	0.574174
Mayotte	0.21	0.33	0.12	0.571429
Equatorial Guinea	1.09	1.67	0.58	0.532110
Angola	23.36	35.59	12.23	0.523545
Bonaire, St. Eustatius & Saba	0.02	0.03	0.01	0.500000

[24]:

```
neighbor_countries = ['Slovakia','Czechia','Hungary','Poland','Austria','Ukraine']
neighbors = pop.loc[neighbor_countries, : ]
display(neighbors)
```

Year	pop2010	pop2022	difference	relDifference
Country				
Slovakia	5.40	5.64	0.24	0.044444
Czechia	10.46	10.49	0.03	0.002868
Hungary	9.99	9.97	-0.02	-0.002002
Poland	38.60	39.86	1.26	0.032642
Austria	8.36	8.94	0.58	0.069378
Ukraine	45.68	39.70	-5.98	-0.130911

1.6 Summary and outlook

- We will work mostly with tabular data.
- We will store them in `DataFrame` from Pandas library.
- This is more convenient and more efficient than regular Python lists.
- We have seen several functions for basic manipulation:
  - `iloc[]`, `loc[]`, `query`, `head`, `set_index`, `reset_index`, `rename`, `pivot`, `copy`, `sort_values`, operations and functions on `Series`.
- Next lecture will be focused on examples of different chart types.
- More Pandas later.