# 1 Lecture 5: Advanced Pandas

Data Visualization · 1-DAV-105

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As usual, we start by importing libraries. We also import the country data set from World Bank https://databank.worldbank.org/home under CC BY 4.0 license (see Lecture 03b).

[1]:
```
import numpy as np
import pandas as pd
from IPython.display import Markdown
import matplotlib.pyplot as plt
import seaborn as sns
pd.options.display.float_format = '{:,.2f}'.format
```

[2]:
```
url = 'https://bbrejova.github.io/viz/data/World_bank.csv'
countries = pd.read_csv(url).set_index('Country')
```

## 1.1 Hierarchical index (MultiIndex)

### 1.1.1 A small example table

To illustrate a hierarchical index, we first create a very small table consisting of two countries and their population in two years, and convert this table from wide to long format.

[3]:
```
example_countries = countries.loc[["Slovak Republic", "Austria"],
                                  ["Population2010", "Population2018"]]
display(Markdown("**A small subset of countries table:**"), example_countries)
# change to long format
example_long = (example_countries.reset_index()
                                 .melt(id_vars=['Country'],
                                       var_name='Year',
                                       value_name='Population'))
# change year from string such as "Population2010" to int 2010
example_long.Year = example_long.Year.apply(lambda x : int(x[-4:]))
display(Markdown("**Changed to long format:**"), example_long)
```

**A small subset of countries table:**

| | Population2010 | Population2018 |
|---|---|---|
| Country | | |
| Slovak Republic | 5,391,428.00 | 5,446,771.00 |
| Austria | 8,363,404.00 | 8,840,521.00 |

**Changed to long format:**

| | Country | Year | Population |
|---|---|---|---|
| 0 | Slovak Republic | 2010 | 5,391,428.00 |
| 1 | Austria | 2010 | 8,363,404.00 |

```
2  Slovak Republic  2018 5,446,771.00
3          Austria  2018 8,840,521.00
```

### 1.1.2 An index with duplicate labels

The original wide table had country as index, but in the long table, each country can have multiple rows. Pandas still allows us to use country as index with duplicate values. Selecting the name of the country then gives us multiple rows.

[4]:
```
# set country name as index in a copy of the table
example_long_indexed = example_long.set_index('Country')
# display table with index
display(Markdown("**Table with country as index:**"), example_long_indexed)
# select Slovakia from this table
display(Markdown("**Selecting multiple rows using `example_long_indexed.
↪loc['Slovak Republic']`:**"))
display(example_long_indexed.loc['Slovak Republic'])
```

**Table with country as index:**

```
                 Year   Population
Country
Slovak Republic  2010 5,391,428.00
Austria          2010 8,363,404.00
Slovak Republic  2018 5,446,771.00
Austria          2018 8,840,521.00
```

**Selecting multiple rows using `example_long_indexed.loc['Slovak Republic']`:**

```
                 Year   Population
Country
Slovak Republic  2010 5,391,428.00
Slovak Republic  2018 5,446,771.00
```

### 1.1.3 Finally the hierarchical index

Our table can be more naturally indexed by a pair (country, year), which uniquely specifies a row. An index consisting of two or more levels is called hierarchical or multi-level.

- MultiIndex can be created by `set_index` with a list of columns to use as index.
- For faster operations, it is a good idea to sort the table by the index using `sort_index`.
- In `loc` use a tuple with one value per level, or only several initial levels.
- To specify other levels, use `xs`.

[5]:
```
# create MultiIndex by choosing a list of columns
example_multiindexed = example_long.set_index(['Country', 'Year']).sort_index()
display(Markdown("**Table with a multiindex:**"), example_multiindexed)
```

**Table with a multiindex:**

```
                    Population
Country        Year
Austria        2010 8,363,404.00
               2018 8,840,521.00
Slovak Republic 2010 5,391,428.00
               2018 5,446,771.00
```

[6]:
```
display(Markdown("**Selecting a row by using a tuple in `loc`:**"))
display(example_multiindexed.loc[('Slovak Republic', 2010)])
```

**Selecting a row by using a tuple in `loc`:**

```
Population   5,391,428.00
Name: (Slovak Republic, 2010), dtype: float64
```

[7]:
```
display(Markdown("**Selecting all rows for a country using a shorter tuple in␣
↪`loc`:**"))
display(example_multiindexed.loc[('Slovak Republic',)])
```

**Selecting all rows for a country using a shorter tuple in `loc`:**

```
       Population
Year
2010 5,391,428.00
2018 5,446,771.00
```

[8]:
```
display(Markdown("**Selecting all rows for a year using `xs`:**"))
display(example_multiindexed.xs(2010, level='Year'))
```

**Selecting all rows for a year using `xs`:**

```
                  Population
Country
Austria         8,363,404.00
Slovak Republic 5,391,428.00
```

[9]:
```
display(Markdown("**Names of index levels can be used in `query`:**"))
display(example_multiindexed.query('Year > 2015'))
```

**Names of index levels can be used in `query`:**

```
                       Population
Country         Year
Austria         2018 8,840,521.00
Slovak Republic 2018 5,446,771.00
```

## 1.2 Combining tables

### 1.2.1 Concatenating tables using `concat`

- Function `concat` can be used to concatenate several tables.

- At the default settings, it combines along axis 0, meaning that the rows of second table are added after the rows of the first table.
- We will also use it for `axis=1`, in which case it finds rows with the same index in both tables and combines their columns.
- By default, the result has union of rows of the two tables, but intersection can be obtained by `join='inner'`.

**Example** Create a second small table of countries and display both tables. Then illustrate various concatenation modes using these tables.

[10]:
```
example_countries2 = countries.loc[["Slovak Republic", "Austria", "Hungary"],
                                   ["Area", "Region"]]
display(Markdown("**The first small table:**"), example_countries)
display(Markdown("**The second small table:**"), example_countries2)
```

**The first small table:**

```
                 Population2010  Population2018
Country
Slovak Republic    5,391,428.00    5,446,771.00
Austria            8,363,404.00    8,840,521.00
```

**The second small table:**

```
                     Area                 Region
Country
Slovak Republic 49,030.00  Europe & Central Asia
Austria         83,879.00  Europe & Central Asia
Hungary         93,030.00  Europe & Central Asia
```

[11]:
```
display(Markdown("**Tables concatenated along axis 0:**"))
display(pd.concat([example_countries, example_countries2]))
```

**Tables concatenated along axis 0:**

```
                 Population2010  Population2018      Area  \
Country
Slovak Republic    5,391,428.00    5,446,771.00       NaN
Austria            8,363,404.00    8,840,521.00       NaN
Slovak Republic             NaN             NaN 49,030.00
Austria                     NaN             NaN 83,879.00
Hungary                     NaN             NaN 93,030.00

                                Region
Country
Slovak Republic                    NaN
Austria                            NaN
Slovak Republic  Europe & Central Asia
Austria          Europe & Central Asia
Hungary          Europe & Central Asia
```

[12]:
```
display(Markdown("**Tables concatenated along axis 1:**"))
display(pd.concat([example_countries, example_countries2], axis=1))
```

**Tables concatenated along axis 1:**

```
                 Population2010  Population2018      Area  \
Country
Slovak Republic    5,391,428.00    5,446,771.00 49,030.00
Austria            8,363,404.00    8,840,521.00 83,879.00
Hungary                     NaN             NaN 93,030.00

                                Region
Country
Slovak Republic  Europe & Central Asia
Austria          Europe & Central Asia
Hungary          Europe & Central Asia
```

[13]:
```
display(Markdown("**Tables concatenated along axis 1 with inner join:**"))
display(pd.concat([example_countries, example_countries2], axis=1,␣
 ↪join='inner'))
```

**Tables concatenated along axis 1 with inner join:**

```
                 Population2010  Population2018      Area  \
Country
Slovak Republic    5,391,428.00    5,446,771.00 49,030.00
Austria            8,363,404.00    8,840,521.00 83,879.00

                                Region
Country
Slovak Republic  Europe & Central Asia
Austria          Europe & Central Asia
```

### 1.2.2 Merging tables with `merge`

- Function `merge` works similarly as `concat` with `axis=1`, but it will match lines of two tables using any specified columns, not necessarily index.
- If values in these columns repeat, it combines all matching pairs of rows.
- Setting `how` in `merge` allows us to include rows that do not have a matching row in the other table.

#### Example

- Countries belong to various international organizations and a single country can belong to many. We will represent this as a table having one row for each pair of country and an organization it belongs to.
- To combine this with other country data, we apply `merge` to get a table in which each country is copied for each organization it is in.
- Then we can for example aggregate value for individual organizations.

[14]:
```python
# we create a small membership table by parsing a CSV-format string
import io
membership_str = io.StringIO("""Country,Member
Slovak Republic,NATO
Slovak Republic,EU
Slovak Republic,UN
Austria,UN
Austria,EU
""")
membership = pd.read_csv(membership_str)
display(Markdown("**A small country membership table:**"), membership)
```

**A small country membership table:**

```
           Country Member
0  Slovak Republic   NATO
1  Slovak Republic     EU
2  Slovak Republic     UN
3          Austria     UN
4          Austria     EU
```

[15]:
```python
# merging tables using column Country in both
example_membership = pd.merge(example_countries, membership, on='Country')
display(Markdown("**Merged table:**"), example_membership)
```

**Merged table:**

```
           Country  Population2010  Population2018 Member
0  Slovak Republic    5,391,428.00    5,446,771.00   NATO
1  Slovak Republic    5,391,428.00    5,446,771.00     EU
2  Slovak Republic    5,391,428.00    5,446,771.00     UN
3          Austria    8,363,404.00    8,840,521.00     UN
4          Austria    8,363,404.00    8,840,521.00     EU
```

[16]:
```python
#aggregating organisations
display(Markdown("**The sum of country populations for each organization**␣
↪(only for our two countries)"))
display(example_membership.groupby('Member')['Population2018'].sum())
```

**The sum of country populations for each organization** (only for our two countries)

```
Member
EU      14,287,292.00
NATO     5,446,771.00
UN      14,287,292.00
Name: Population2018, dtype: float64
```

Similar operations are often done in relational databases, where `merge` is called join. Aggregation is also frequently used. More in a specialized database course in the third year.

### 1.3 Aggregation, split-apply-combine (groupby)

We have already seen simple examples of aggregation by `groupby` in Lecture 04. Here we discuss it in more detail.

Pandas follow the split-apply-combine strategy introduced in R by Hadley Wickham.

**Split**: split data into groups, often by values in some column, e.g. `Region` in the `countries` table

**Apply**: apply some computation on each group, obtaining some result (single value, Series, DataFrame)

**Combine**: concatenate results for all groups together to a new table

**Typical operations in the apply step:**

- **aggregation**: e.g. compute group size, mean, median etc.
- **transformation**: e.g. compute percentage or rank of each item within group
- **filtering**: e.g. include only groups that are large enough

In Pandas, this is done by combination of `groupby` for the split step and additional functions for the apply step. The combine step is done implicitly. Pandas library provides many options, we will cover only basics.

#### 1.3.1 Simple aggregation in the apply step

Apply functions such as `sum`, `mean`, `median`, `min`, `max`, `size`, `count`, `describe` after `groupby`.

- `size` gives the number of rows in the group.
- `count` gives the number of non-missing values in each column.

[42]:
```
display(Markdown("**The number of countries in each region:**"))
display(countries.groupby('Region').size())
```

**The number of countries in each region:**

```
Region
East Asia & Pacific           37
Europe & Central Asia         58
Latin America & Caribbean     42
Middle East & North Africa    21
North America                  3
South Asia                     8
Sub-Saharan Africa            48
dtype: int64
```

[43]:
```
display(Markdown("**Sums of country indicators in each region**"))
display(Markdown(" (including nonsense sums such as life expectation or GDP per␣
 ↪capita"))
display(countries.groupby('Region').sum(numeric_only=True))
```

**Sums of country indicators in each region**

(including nonsense sums such as life expectation or GDP per capita

```
                            Population2000   Population2010   Population2018  \
Region
East Asia & Pacific         2,025,467,590.00 2,183,746,243.00 2,304,563,792.00
Europe & Central Asia         861,278,548.00   887,926,820.00   917,922,618.50
Latin America & Caribbean     520,903,450.00   589,932,554.00   640,467,174.00
Middle East & North Africa    315,326,801.00   385,917,886.00   448,912,962.00
North America                 312,909,974.00   343,391,679.00   363,809,186.00
South Asia                  1,390,946,064.00 1,638,792,934.00 1,814,388,744.00
Sub-Saharan Africa            665,327,581.00   869,025,106.00 1,074,853,734.00

                                   Area    GDP2000      GDP2010      GDP2018  \
Region
East Asia & Pacific         24,791,783.40 230,490.22   450,761.32   587,887.86
Europe & Central Asia       28,691,030.98 880,359.02 1,726,243.88 1,991,497.58
Latin America & Caribbean   20,425,545.98 195,238.12   454,889.22   511,688.30
Middle East & North Africa  11,370,619.99 170,287.55   305,224.50   332,228.47
North America               19,820,470.00 116,809.33   197,790.81   222,331.06
South Asia                   5,135,333.06   5,489.53    16,396.33    24,319.91
Sub-Saharan Africa          21,754,456.00  43,129.49   109,876.37   115,339.80

                             Expectancy2000  Expectancy2010  Expectancy2018  \
Region
East Asia & Pacific                2,297.62        2,256.05        2,311.10
Europe & Central Asia              3,892.03        4,034.44        4,057.23
Latin America & Caribbean          2,513.09        2,667.81        2,633.67
Middle East & North Africa         1,500.65        1,549.98        1,581.12
North America                        233.66          239.08          242.14
South Asia                           511.29          550.20          570.71
Sub-Saharan Africa                 2,521.07        2,783.95        3,002.43

                             Fertility2000  Fertility2010  Fertility2018
Region
East Asia & Pacific                  91.76          80.27          74.22
Europe & Central Asia                91.23          95.88          92.16
Latin America & Caribbean            94.52          82.26          74.70
Middle East & North Africa           71.23          59.39          53.70
North America                         5.28           5.32           4.83
South Asia                           31.48          24.13          20.20
Sub-Saharan Africa                  261.73         235.17         209.67
```

[45]:
```
display(Markdown("**Specifically sum only population in 2018 per region:**"))
display(countries.groupby('Region')['Population2018'].sum())
```

**Specifically sum only population in 2018 per region:**

```
Region
East Asia & Pacific           2,304,563,792.00
Europe & Central Asia           917,922,618.50
```

```
Latin America & Caribbean      640,467,174.00
Middle East & North Africa     448,912,962.00
North America                  363,809,186.00
South Asia                   1,814,388,744.00
Sub-Saharan Africa           1,074,853,734.00
Name: Population2018, dtype: float64
```

### 1.3.2 Transformation in the apply step

Function groupby can be followed by function apply which gets a function (e.g. lambda expression) and runs it on each group, producing a transformed version of the group. These are finally combined together.

Here we compute for each country what percentage is its population from the population of the region.

[47]:
```
# apply gets a single column with population sizes within a group
# and divides each number by the sum of the group
pop_within_group = (countries.groupby('Region',␣
 ↪group_keys=False)['Population2018']
                     .apply(lambda x : x / x.sum()))
display(Markdown("**For each country, what fraction is its population within␣
 ↪region:**"))
display(pop_within_group.head())
```

**For each country, what fraction is its population within region:**

```
Country
Afghanistan      0.02
Albania          0.00
Algeria          0.09
American Samoa   0.00
Andorra          0.00
Name: Population2018, dtype: float64
```

[51]:
```
display(Markdown("**Add back region name using concat:**"))
pop_within_group2 = pd.concat([pop_within_group, countries['Region']], axis=1)
display(pop_within_group2.head())

display(Markdown("**Look up value for Slovakia:**"))
display(pop_within_group2.loc["Slovak Republic"])
```

**Add back region name using concat:**

```
                Population2018                      Region
Country
Afghanistan               0.02                  South Asia
Albania                   0.00       Europe & Central Asia
Algeria                   0.09  Middle East & North Africa
```

```
American Samoa             0.00         East Asia & Pacific
Andorra                    0.00       Europe & Central Asia
```

**Look up value for Slovakia:**

```
Population2018                           0.01
Region                 Europe & Central Asia
Name: Slovak Republic, dtype: object
```

[52]:
```
display(Markdown("**Check that the sum of each region is 1:**"))
display(pop_within_group2.groupby('Region').sum())
```

**Check that the sum of each region is 1:**

```
                            Population2018
Region
East Asia & Pacific                   1.00
Europe & Central Asia                 1.00
Latin America & Caribbean             1.00
Middle East & North Africa            1.00
North America                         1.00
South Asia                            1.00
Sub-Saharan Africa                    1.00
```

### 1.3.3 Filtering in the apply step

Finally, `groupby` can be followed by `filter`to use only some of the groups in the result.

Here we report all countries in regions that have at least billion inhabitants.

[53]:
```
# filter gets a function returning a boolean value for each group
filtered = (countries.groupby("Region")
            .filter(lambda x : x['Population2018'].sum() > 1e9))
display(Markdown("**Filtered data:**"))
display(filtered.head())
display(Markdown("**Check sums in regions for selected countries:**"))
display(filtered.groupby('Region')['Population2018'].sum())
```

**Filtered data:**

```
                             Region         Income Group  Population2000  \
Country
Afghanistan              South Asia           Low income   20,779,953.00
American Samoa  East Asia & Pacific  Upper middle income       57,821.00
Angola           Sub-Saharan Africa  Lower middle income   16,395,473.00
Australia       East Asia & Pacific          High income   19,153,000.00
Bangladesh               South Asia  Lower middle income  127,657,854.00

                Population2010  Population2018         Area    GDP2000  \
Country
Afghanistan      29,185,507.00   37,172,386.00   652,860.00        NaN
```

```
American Samoa       56,079.00       55,465.00       200.00       NaN
Angola            23,356,246.00   30,809,762.00 1,246,700.00    556.84
Australia         22,031,750.00   24,982,688.00 7,741,220.00 21,679.25
Bangladesh       147,575,430.00  161,356,039.00   147,630.00    418.07

                  GDP2010   GDP2018  Expectancy2000  Expectancy2010  \
Country
Afghanistan         543.30    493.75           55.84           61.03
American Samoa 10,271.22 11,466.69             NaN             NaN
Angola            3,587.88  3,289.65           46.52           55.35
Australia        52,022.13 57,354.96           79.23           81.70
Bangladesh          781.15  1,698.35           65.45           69.88

                Expectancy2018  Fertility2000  Fertility2010  Fertility2018
Country
Afghanistan              64.49           7.49           5.98           4.47
American Samoa             NaN            NaN            NaN            NaN
Angola                   60.78           6.64           6.19           5.52
Australia                82.75           1.76           1.93           1.74
Bangladesh               72.32           3.17           2.32           2.04
```

**Check sums in regions for selected countries:**

```
Region
East Asia & Pacific   2,304,563,792.00
South Asia            1,814,388,744.00
Sub-Saharan Africa    1,074,853,734.00
Name: Population2018, dtype: float64
```

### 1.3.4 Grouping by multiple values

Function groupby can get a single column, but also a list of columns or a Series which will be used as if it was a column of the table.

[54]:
```
display(Markdown("**Populations split by both region and income group**"))
display(countries.groupby(['Region', "Income Group"])['Population2018'].sum())
```

**Populations split by both region and income group**

```
Region                      Income Group
East Asia & Pacific         High income              222,924,695.00
                            Low income                25,549,819.00
                            Lower middle income      293,430,538.00
                            Upper middle income    1,762,658,740.00
Europe & Central Asia       High income              520,487,513.00
                            Low income                 9,100,837.00
                            Lower middle income       86,607,467.00
                            Upper middle income      301,726,801.50
Latin America & Caribbean   High income               32,341,730.00
                            Low income                11,123,176.00
```

```
                               Lower middle income      33,826,921.00
                               Upper middle income     563,175,347.00
Middle East & North Africa     High income              66,016,247.00
                               Low income               45,404,970.00
                               Lower middle income     193,774,373.00
                               Upper middle income     143,717,372.00
North America                  High income             363,809,186.00
South Asia                     Low income               37,172,386.00
                               Lower middle income   1,776,700,662.00
                               Upper middle income         515,696.00
Sub-Saharan Africa             High income               1,362,065.00
                               Low income              519,523,613.00
                               Lower middle income     488,057,804.00
                               Upper middle income      65,910,252.00
Name: Population2018, dtype: float64
```

- Now we create a Series classifying each countries as small, medium and large using cutoff 1 million for small and 100 million for medium.
- We then use this series in `groupby`.
- The classification is created by `pd.cut` function.

[60]:
```
bin_ends = [0, 1e6, 1e8, 1e10]
bin_labels = ["small", "medium", "large"]
size_groups = pd.cut(countries['Population2018'],
                     bins=bin_ends, labels=bin_labels).rename("SizeCategory")
display(Markdown("**Country size classification:**"))
display(size_groups.head())
```

**Country size classification:**

```
Country
Afghanistan       medium
Albania           medium
Algeria           medium
American Samoa     small
Andorra            small
Name: SizeCategory, dtype: category
Categories (3, object): ['small' < 'medium' < 'large']
```

[63]:
```
# now use size_groups in groupby
display(Markdown("**The number of countries in each size group:**"))
display(countries.groupby(size_groups).size())
display(Markdown("**The number of countries in each size group and region:**"))
display(countries.groupby(['Region', size_groups]).size())
```

**The number of countries in each size group:**

```
SizeCategory
small      58
```

```
medium    145
large      13
dtype: int64
```

**The number of countries in each size group and region:**

```
Region                      SizeCategory
East Asia & Pacific         small           18
                            medium          15
                            large            4
Europe & Central Asia       small           12
                            medium          45
                            large            1
Latin America & Caribbean   small           19
                            medium          21
                            large            2
Middle East & North Africa  small            2
                            medium          19
                            large            0
North America               small            1
                            medium           1
                            large            1
South Asia                  small            2
                            medium           3
                            large            3
Sub-Saharan Africa          small            4
                            medium          41
                            large            2
dtype: int64
```

### 1.4 Categorical variables

Categorical variables have values from a small set, such as region and income group in the table of countries. So far we have represented them only as strings, but we can explicitly convert them to a categorical data type in Pandas.

This has several advantages: * Strings are internally replaced by numerical IDs within the table, potentially saving memory. * Categories can be ordered and then sorting, minimum, maximum etc works as desired, not alphabetically. * Pandas is aware of the full set of possib;e values. For example categories without members can appear in the `groupby` results.

**Example** Income groups in our table are strings, we will convert them to an ordered categorical variable.

[68]:

```
# creating a categorical type
cat_type = pd.api.types.CategoricalDtype(categories=["Low income",
                                                     "Lower middle income",
                                                     "Upper middle income",
                                                     "High income"],
```

```
                                                ordered=True)
# converting Income Group column to cat_type in a new DataFrame
countries_cat = countries.astype({'Income Group': cat_type})

display(Markdown("**Income Group column in the old table:**"),
        countries['Income Group'].head(3))
display(Markdown("**Income Group column in the new table:**"),
        countries_cat['Income Group'].head(3))
```

**Income Group column in the old table:**

```
Country
Afghanistan            Low income
Albania       Upper middle income
Algeria       Lower middle income
Name: Income Group, dtype: object
```

**Income Group column in the new table:**

```
Country
Afghanistan            Low income
Albania       Upper middle income
Algeria       Lower middle income
Name: Income Group, dtype: category
Categories (4, object): ['Low income' < 'Lower middle income' < 'Upper middle␣
 ↪income' < 'High income']
```

[73]:
```
display(Markdown("**Minimum and maximum income group in the table with␣
 ↪categorical values:**"
                 "  (manually fixed order):"))
display(countries_cat['Income Group'].min())
display(countries_cat['Income Group'].max())

display(Markdown("**Minimum and maximum income group in the table with␣
 ↪strings**"
                 "  (alphabetical order):"))
display(countries['Income Group'].min())
display(countries['Income Group'].max())
```

**Minimum and maximum income group in the table with categorical values:** (manually fixed order):

```
'Low income'
```

```
'High income'
```

**Minimum and maximum income group in the table with strings** (alphabetical order):

```
'High income'
```

```
'Upper middle income'
```

- Note that if categories do not need a fixed order, they can be created directly in the astype function as in the code below.
- Notice that groupby creates even empty groups which would not happen with strings.

[74]:
```
# convert region to an unordered category
countries_cat2 = countries_cat.astype({'Region': 'category'})
# count the number of countries for each combination of income group and region
countries_cat2.groupby(['Income Group', 'Region']).size()
```

[74]:
```
Income Group         Region
Low income           East Asia & Pacific           1
                     Europe & Central Asia         1
                     Latin America & Caribbean     1
                     Middle East & North Africa    2
                     North America                 0
                     South Asia                    1
                     Sub-Saharan Africa           23
Lower middle income  East Asia & Pacific          12
                     Europe & Central Asia         4
                     Latin America & Caribbean     4
                     Middle East & North Africa    6
                     North America                 0
                     South Asia                    6
                     Sub-Saharan Africa           18
Upper middle income  East Asia & Pacific          10
                     Europe & Central Asia        15
                     Latin America & Caribbean    20
                     Middle East & North Africa    5
                     North America                 0
                     South Asia                    1
                     Sub-Saharan Africa            5
High income          East Asia & Pacific          14
                     Europe & Central Asia        38
                     Latin America & Caribbean    17
                     Middle East & North Africa    8
                     North America                 3
                     South Asia                    0
                     Sub-Saharan Africa            2
dtype: int64
```

### 1.5 Dates and times

An important type of data sets are time series, where some variables are measured repeatedly over time. Pandas has an extensive support for work with times and dates. Here we show only a small example.

- We illustrate this on the movie dataset from Kaggle (see lecture 04).
- The column labeled release_date is recognized as date by passing parse_dates parameter

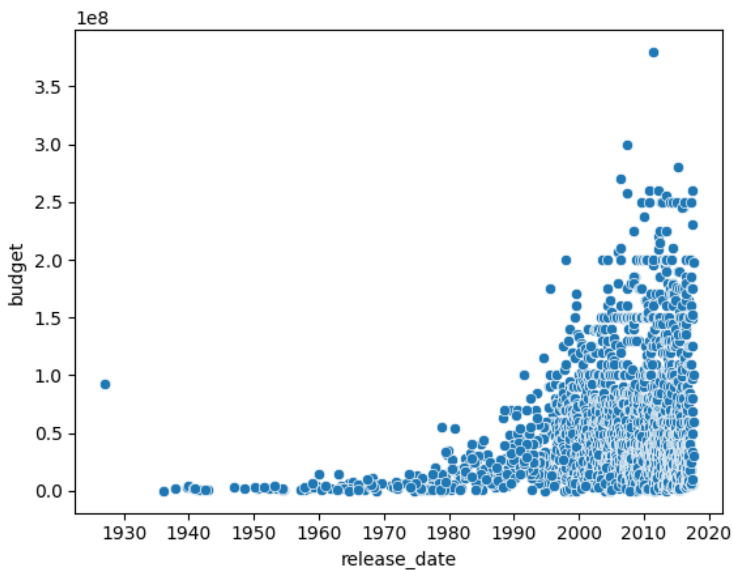
to `read_csv`.

- Then we call function `day_name()` to get the day of week for each release day and use `value_counts` to see which days are most frequent as movie release dates.
- We also use the release date as the x-coordinate in a scatterplot.

[77]:
```
# import data, including parsing of dates
url = 'https://bbrejova.github.io/viz/data/Movies_small.csv'
movies = pd.read_csv(url, parse_dates=['release_date'])
# get days of week for realse dates
days = movies['release_date'].apply(lambda x : x.day_name())
days.value_counts()
```

[77]:
```
Friday       639
Thursday     515
Wednesday    474
Tuesday      175
Saturday      94
Monday        87
Sunday        65
Name: release_date, dtype: int64
```

[78]:
```
# use release date is x-coordinate
sns.scatterplot(data=movies, x='release_date', y='budget')
pass
```




### 1.6 Missing values

Data sets are often incomplete, and Pandas provides techniques for working with missing data.

- Missing data are typically imported as `np.nan` (not-a-number).
- These cannot occur in int-type columns, so ints are converted to floats, but can be handled in a special way.

Bellow we show a small example what happens when working with missing data, including functions `isna`, `dropna`, `fillna`.

[86]:
```
# create a small series with one missing value
a = pd.Series([1, 2, np.nan, 3])
display(Markdown("**`a.sum()` skips missing values:**"),
        a.sum())
display(Markdown("**`a.count()` counts non-missing values:**"),
        a.count())
display(Markdown("**`a.mean()` also considers only non-missing:**"),
        a.mean())
display(Markdown("**`a > 2` evaluates missing values as `False`, similarly `<`,␣
 ↪`==`:**"),
        a > 2)
display(Markdown("**`a == np.nan` also evaluates as `False`:**"),
        a == np.nan)
display(Markdown("**`a.isna()` can be used to detect missing values:**"),
        a.isna())
display(Markdown("**`a.dropna()` omits missing values:**"),
        a.dropna())
display(Markdown("**`a.fillna(-1)` replaces them with a specified value:**"),
        a.fillna(-1))
```

**`a.sum()` skips missing values:**

```
6.0
```

**`a.count()` counts non-missing values:**

```
3
```

**`a.mean()` also considers only non-missing:**

```
2.0
```

**`a > 2` evaluates missing values as `False`, similarly `<`, `==`:**

```
0    False
1    False
2    False
3     True
dtype: bool
```

**`a == np.nan` also evaluates as `False`:**

```
0    False
1    False
2    False
```

```
3    False
dtype: bool
```

**a.isna() can be used to detect missing values:**

```
0    False
1    False
2     True
3    False
dtype: bool
```

**a.dropna() omits missing values:**

```
0   1.00
1   2.00
3   3.00
dtype: float64
```

**a.fillna(-1) replaces them with a specified value:**

```
0    1.00
1    2.00
2   -1.00
3    3.00
dtype: float64
```

## 1.7 Pandas efficiency

Below we show several examples how different ways of implementing the same operation can have very different running time on large data. Pandas functions are usually much faster than manual iteration. However, if you do not work on huge data sets, the difference is not so important.

To measure time, we use a special Jupyter command `%timeit`. * It runs the code several times to estimate the time per one repeat.

[87]:
```
# generate a Series of million random numbers and also convert it to Python list
length = int(1e6)
xs = pd.Series(np.random.uniform(0,100, length))
xl = list(xs)
```

Below we see that method `sum()` on Series is faster than built-in `sum` on a Python list, but built-in `sum` on Series is much slower, because it iterates over elements of Series.

[90]:
```
display(Markdown("**Method `sum` on `Series` `xs.sum()`:**"))
%timeit result = xs.sum()
display(Markdown("**Python `sum` on Python list `sum(xl)`:**"))
%timeit result = sum(xl)
display(Markdown("**Python `sum` on Series `sum(xs)`:**"))
%timeit result = sum(xs)
```

**Method sum on Series xs.sum():**

```
473 µs ± 26.3 µs per loop (mean ± std. dev. of 7 runs, 1,000 loops each)
```

**Python sum on Python list sum(xl):**

4.33 ms ± 68.4 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

**Python sum on Series sum(xs):**

36.5 ms ± 1.07 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

Below we compare three ways of generating a sequence of squared values. Multiplying Series with * is the fastest, Python list comprehension is much slower and `apply` function from Pandas is even slower.

[92]:
```
display(Markdown("**Pandas `Series` multiplication `x2s = xs * xs`**:"))
%timeit x2s = xs * xs
display(Markdown("**Python list comprehension on a list `x2l = [x * x for x in␣
↪xl]`:**"))
%timeit x2l = [x * x for x in xl]
display(Markdown("**Pandas `apply` function `x2s = xs.apply(lambda x : x *␣
↪x)`**"))
%timeit x2s = xs.apply(lambda x : x * x)
```

**Pandas `Series` multiplication `x2s = xs * xs`:**

621 µs ± 27.9 µs per loop (mean ± std. dev. of 7 runs, 1,000 loops each)

**Python list comprehension on a list `x2l = [x * x for x in xl]`:**

34.5 ms ± 200 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

**Pandas `apply` function `x2s = xs.apply(lambda x : x * x)`**

123 ms ± 1.29 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

The code below creates the Series of squares by creating a Series filled with zeroes and then assigning individual values using for-loop. This is again much slower than all methods above, so to make the code reasonably fast, we run it on data which is 100 times smaller than above.

[36]:
```
length2 = 10000
xs_small = xs.iloc[0:length2]
def assignments(len, x):
  x2 = pd.Series([0] * len)
  for i in range(len):
    x2[i] = x[i] * x[i]
  return x2
%timeit x2s_small = assignments(length2, xs_small)
```

79.8 ms ± 418 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

Finally the code below is even worse. It appends individual squares to a Series which starts with size 1. We run it on even smaller list of size 1000.

[40]:
```
length3 = 1000
xs_tiny = xs.iloc[0:length3]
def assignments(len, x):
```

```
  x2 = pd.Series([0])
  for i in range(len):
    x2[i] = x[i] * x[i]
  return x2
%timeit x2s_tiny = assignments(length3, xs_tiny)
```

```
203 ms ± 8.1 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```