Unit 6: Handling data with pandas

Richard Foltyn
University of Glasgow

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Contents

6 Handling data with pandas

6.1 Motivation

So far, we have encountered NumPy arrays as the only way to store numerical data (we mostly ignored the built-in containers provided directly in Python). However, while NumPy arrays are great for storing *homogenous* data without any particular structure, they are somewhat limited when we want to use them for high-level data analysis.

For example, we usually want to process data sets with

1. several variables;
2. multiple observations, which need not be identical across variables (some values may be missing);
3. non-homogenous data types: for examples, names need to be stored as strings, birthdays as dates and income as a floating-point number.

While NumPy can in principle handle such situations, it puts all the burden on the user. Most users would prefer to not have to deal with such low-level details.

Imagine we want to store names, birth dates and annual income for two people:

Name	Date of birth	Income
Alice	1985-01-01	30,000
Bob	1997-05-12	-

No income was reported for Bob, so it's missing. With NumPy, we could do this as follows:

[1]:
```
import numpy as np
from datetime import date
```

```python
date1 = date(1985, 1, 1)            # birth date for Alice
date2 = date(1997, 5, 12)           # birth date for Bob

data = np.array([
    ['Alice', date1, 30000.0],
    ['Bob', date2, None]
])

data
```

[1]:
```
array([['Alice', datetime.date(1985, 1, 1), 30000.0],
       ['Bob', datetime.date(1997, 5, 12), None]], dtype=object)
```

[2]:
```python
data.dtype          # print array data type
```

[2]:
```
dtype('O')
```

While we can create such arrays, they are almost useless for data analysis, in particular since everything is stored as a generic `object`.

Pandas was created to offer more versatile data structures that are straightforward to use for storing, manipulating and analysing heterogeneous data:

1. Data is clearly organised in *variables* and *observations*, similar to econometrics programs such as Stata.
2. Each variable is permitted to have a different data type.
3. We can use *labels* to select observations instead of having to use a linear numerical index as with NumPy.

   We could, for example, index a data set using National Insurance Numbers.
4. Pandas offers many convenient data aggregation and reduction routines that can be applied to subsets of data.

   For example, we can easily group observations by city and compute average incomes.
5. Pandas also offers many convenient data import / export functions that go beyond what's in NumPy.

Should we be using pandas at all times, then? No!

- For low-level tasks where performance is essential, use NumPy.
- For homogenous data without any particular data structure, use NumPy.
- On the other hand, if data is heterogeneous, needs to be imported from an external data source and cleaned or transformed before performing computations, use pandas.

There are numerous tutorials on pandas on the internet, so we will keep this unit short and illustrate only the main concepts. Useful references to additional material include:

- The official user guide.
- The official pandas cheat sheet which nicely illustrates the most frequently used operations.
- The official API reference with details on every pandas object and function.
- There are numerous tutorials (including videos) available on the internet. See here for a list.

6.2 Creating pandas data structures

Pandas has two main data structures:

1. `Series` represents observations of a single variable.
2. `DataFrame` is a container for several variables. You can think of each individual column of a `DataFrame` as a `Series`, and each row represents one observation.

The easiest way to create a `Series` or `DataFrame` is to create them from pre-existing data.

To access pandas data structures and routines, we need to import them first. The near-universal convention is to make pandas available using the name `pd`:

```
import pandas as pd
```

Example: Create Series from 1-dimensional NumPy array

[3]:
```
import numpy as np
import pandas as pd             # universal convention: import using pd

data = np.arange(5, 10)

# Create pandas Series from 1d array
pd.Series(data)
```

[3]:
```
0    5
1    6
2    7
3    8
4    9
dtype: int64
```

Example: Create DataFrame from NumPy array

We can create a `DataFrame` from a NumPy array:

[4]:
```
# Create matrix of data
data = np.arange(15).reshape((-1, 3))

# Define variable (or column) names
varnames = ['A', 'B', 'C']

# Create pandas DataFrame from matrix
pd.DataFrame(data, columns=varnames)
```

[4]:
```
    A   B   C
0   0   1   2
1   3   4   5
2   6   7   8
3   9  10  11
4  12  13  14
```

This code creates a `DataFrame` of three variables called `A`, `B` and `C` with 5 observations each.

Example: Create from dictionary

Alternatively, we can create a `DataFrame` from non-homogenous data as follows:

[5]:
```
# Names (strings)
names = ['Alice', 'Bob']

# Birth dates (datetime objects)
```

```
bdates = pd.to_datetime(['1985-01-01', '1997-05-12'])

# Incomes (floats)
incomes = np.array([35000, np.nan])          # code missing income as NaN

# create DataFrame from dictionary
pd.DataFrame({'Name': names, 'Birthdate': bdates, 'Income': incomes})
```

[5]:

	Name	Birthdate	Income
0	Alice	1985-01-01	35000.0
1	Bob	1997-05-12	NaN

If data types differ across columns, as in the above example, it is often convenient to create the `DataFrame` by passing a dictionary as an argument. Each key represents a column name and each corresponding value contains the data for that variable.

6.3 Viewing data

With large data sets, you hardly ever want to print the entire `DataFrame`. Pandas by default limits the amount of data shown. You can use the `head()` and `tail()` methods to explicitly display a specific number of rows from the top or the end of a `DataFrame`.

To illustrate, we use a data set of 23 UK universities that contains the following variables:

- `Instititution`: Name of the institution
- `Country`: Country/nation within the UK (England, Scotland, . . .)
- `Founded`: Year in which university (or a predecessor institution) was founded
- `Students`: Total number of students
- `Staff`: Number of academic staff
- `Admin`: Number of administrative staff
- `Budget`: Budget in million pounds
- `Russell`: Binary indicator whether university is a member of the Russell Group, an association of the UK's top research universities.

The data was compiled based on information from Wikipedia.

Before we read in any data, it is convenient to define a variable pointing to the directory where the data resides. We can either use a relative local path `../data`, which, however, will not work when running the notebook in some cloud environments such as Google Colab. Alternatively, we can use the full URL to the data file in the GitHub repository.

[6]:
```
# Uncomment this to use files in the local data/ directory
DATA_PATH = '../data'

# Uncomment this to load data directly from GitHub
# DATA_PATH = 'https://raw.githubusercontent.com/richardfoltyn/python-intro-PGR/main/data'
```

We can now read in the data stored in the file `universities.csv` like this:

[7]:
```
import pandas as pd

# URL to CSV file in GitHub repository
file = f'{DATA_PATH}/universities.csv'

# Load sample data set of UK universities. Individual fields are separated
# using ; so we need to pass sep=';' as an argument.
df = pd.read_csv(file, sep=';')
```

We can now display the first and last three rows:

[8]:
```
df.head(3)      # show first three rows
```

```
[8]:                    Institution   Country  Founded  Students   Staff   Admin  \
     0      University of Glasgow  Scotland     1451     30805  2942.0  4003.0
     1    University of Edinburgh  Scotland     1583     34275  4589.0  6107.0
     2  University of St Andrews  Scotland     1413      8984  1137.0  1576.0

        Budget  Russell
     0   626.5        1
     1  1102.0        1
     2   251.2        0
```

```
[9]: df.tail(3)       # show last three rows
```

```
[9]:                     Institution           Country  Founded  Students   Staff  \
     20       University of Stirling          Scotland     1967      9548     NaN
     21  Queen's University Belfast  Northern Ireland     1810     18438  2414.0
     22           Swansea University             Wales     1920     20620     NaN

          Admin  Budget  Russell
     20  1872.0   113.3        0
     21  1489.0   369.2        1
     22  3290.0     NaN        0
```

To quickly compute some descriptive statistics for the *numerical* variables in the `DataFrame`, we use `describe()`:

```
[10]: df.describe()
```

```
[10]:           Founded      Students        Staff        Admin       Budget  \
      count    23.000000     23.000000    20.000000    19.000000    22.000000
      mean   1745.652174  24106.782609  3664.250000  3556.736842   768.609091
      std     256.992149   9093.000735  2025.638038  1550.434342   608.234948
      min    1096.000000   8984.000000  1086.000000  1489.000000   113.300000
      25%    1589.000000  18776.500000  2294.250000  2193.500000   340.850000
      50%    1826.000000  23247.000000  3307.500000  3485.000000   643.750000
      75%    1941.500000  30801.500000  4439.750000  4347.500000  1023.500000
      max    2004.000000  41180.000000  7913.000000  6199.000000  2450.000000

               Russell
      count  23.000000
      mean    0.739130
      std     0.448978
      min     0.000000
      25%     0.500000
      50%     1.000000
      75%     1.000000
      max     1.000000
```

Note that this automatically ignores the columns `Institution` and `Country` as they contain strings, and computing the mean, standard deviation, etc. of a string variable does not make sense.

For categorical data, we can use `value_counts()` to tabulate the number of unique values of a variable. For example, the following code shows the number of institutions by the Russell Group membership:

```
[11]: df['Russell'].value_counts()
```

```
[11]: 1    17
      0     6
      Name: Russell, dtype: int64
```

Lastly, to see low-level information about the data type used in each column and the number of non-missing observations, we call `info()`:

[12]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23 entries, 0 to 22
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Institution  23 non-null     object
 1   Country      23 non-null     object
 2   Founded      23 non-null     int64
 3   Students     23 non-null     int64
 4   Staff        20 non-null     float64
 5   Admin        19 non-null     float64
 6   Budget       22 non-null     float64
 7   Russell      23 non-null     int64
dtypes: float64(3), int64(3), object(2)
memory usage: 1.6+ KB
```

Pandas automatically discards missing information in computations. For example, the number of academic staff is missing for several universities, so the number of *non-null* entries reported in the table above is less than 23, the overall sample size.

6.4 Indexing

Pandas supports two types of indexing:

1. Indexing by position. This is basically identical to the indexing of other Python and NumPy containers.
2. Indexing by label, i.e., by the values assigned to the row or column index. These labels need not be integers in increasing order, as is the case for NumPy. We will see how to assign labels below.

Pandas indexing is performed either by using brackets `[]`, or by using `.loc[]` for label indexing, or `.iloc[]` for positional indexing.

Indexing via `[]` can be somewhat confusing:

- specifying `df['name']` returns the column `name` as a `Series` object.
- On the other hand, specifying a range such as `df[5:10]` returns the *rows* associated with the *positions* 5,...,9.

Example: Selecting columns

[13]:
```
import pandas as pd

# Load sample data set of UK universities
df = pd.read_csv(f'{DATA_PATH}/universities.csv', sep=';')
df['Institution']                # select a single column
```

[13]:
```
0               University of Glasgow
1             University of Edinburgh
2            University of St Andrews
3              University of Aberdeen
4           University of Strathclyde
5                                 LSE
6                                 UCL
7             University of Cambridge
8                University of Oxford
9               University of Warwick
10            Imperial College London
11              King’s College London
12           University of Manchester
```

```
13              University of Bristol
14           University of Birmingham
15    Queen Mary University of London
16                 University of York
17           University of Nottingham
18               University of Dundee
19                 Cardiff University
20             University of Stirling
21          Queen’s University Belfast
22                  Swansea University
Name: Institution, dtype: object
```

[14]:
```
df[['Institution', 'Students']]     # select multiple columns using a list
```

[14]:
```
                        Institution  Students
0             University of Glasgow     30805
1           University of Edinburgh     34275
2          University of St Andrews      8984
3            University of Aberdeen     14775
4          University of Strathclyde     22640
5                               LSE     11850
6                               UCL     41180
7           University of Cambridge     23247
8              University of Oxford     24515
9             University of Warwick     27278
10          Imperial College London     19115
11            King’s College London     32895
12         University of Manchester     40250
13            University of Bristol     25955
14         University of Birmingham     35445
15  Queen Mary University of London     20560
16               University of York     19470
17         University of Nottingham     30798
18             University of Dundee     15915
19               Cardiff University     25898
20           University of Stirling      9548
21        Queen’s University Belfast     18438
22               Swansea University     20620
```

Example: Selecting rows by position

To return the rows at positions 1, 2 and 3 we use

[15]:
```
df[1:4]
```

[15]:
```
                Institution   Country  Founded  Students   Staff   Admin  \
1   University of Edinburgh  Scotland     1583     34275  4589.0  6107.0
2  University of St Andrews  Scotland     1413      8984  1137.0  1576.0
3    University of Aberdeen  Scotland     1495     14775  1086.0  1489.0

   Budget  Russell
1  1102.0        1
2   251.2        0
3   219.5        0
```

Pandas follows the Python convention that indices are 0-based, and the endpoint of a slice is not included.

6.4.1 Creating and manipulating indices

Pandas uses *labels* to index and align data. These can be integer values starting at 0 with increments of 1 for each additional element, which is the default, but they need not be. The three main methods to create/manipulate indices are:

- Create a new `Series` or `DataFrame` object with a custom index using the `index=` argument.
- `set_index(keys=['column1', ...])` uses the values of `column1` and optionally additional columns as indices, discarding the current index.
- `reset_index()` resets the index to its default value, a sequence of increasing integers starting at 0.

Creating custom indices

First, consider the following code with creates a `Series` with three elements `[10, 20, 30]` using the default index `[0,1,2]`:

[16]:
```python
import pandas as pd

# Create Series with default integer index
pd.Series([10, 20, 30])
```

[16]:
```
0    10
1    20
2    30
dtype: int64
```

We can use the `index=` argument to specify a custom index, for example one containing the lower-case characters `a`, `b`, `c` as follows:

[17]:
```python
# Create Series with custom index [a, b, c]
pd.Series([10, 20, 30], index=['a', 'b', 'c'])
```

[17]:
```
a    10
b    20
c    30
dtype: int64
```

Manipulating indices

To modify the index of an *existing* `Series` or `DataFrame` object, we use the methods `set_index()` and `reset_index()`. Note that these return a new object and leave the original `Series` or `DataFrame` unchanged. If we want to change the existing object, we need to pass the argument `inplace=True`.

For example, we can replace the row index and use the Roman lower-case characters `a`, `b`, `c`, ... as labels instead of integers:

[18]:
```python
import pandas as pd

# Read in university data
df = pd.read_csv(f'{DATA_PATH}/universities.csv', sep=';')

# Create list of lower-case letters which has same
# length as the number of observations.
index = [chr(97+i) for i in range(len(df))]     # len(df) returns number of obs.
index
```

[18]:
```
['a',
 'b',
 'c',
```

```
 'd',
 'e',
 'f',
 'g',
 'h',
 'i',
 'j',
 'k',
 'l',
 'm',
 'n',
 'o',
 'p',
 'q',
 'r',
 's',
 't',
 'u',
 'v',
 'w']
```

[19]:
```
df['index'] = index                          # create new column 'index'
df.set_index(keys=['index'], inplace=True)   # set letters as index!

# print first 3 rows using labels
df['a':'c']              # This is the same as df[:3]
```

[19]:
```
                     Institution   Country  Founded  Students   Staff   Admin  \
index
a          University of Glasgow  Scotland     1451     30805  2942.0  4003.0
b        University of Edinburgh  Scotland     1583     34275  4589.0  6107.0
c       University of St Andrews  Scotland     1413      8984  1137.0  1576.0

       Budget  Russell
index
a       626.5        1
b      1102.0        1
c       251.2        0
```

Note that when specifying a range in terms of labels, the last element *is* included! Hence the row with index `c` in the above example is shown.

We can reset the index to its default integer values using the `reset_index()` method:

[20]:
```
# Reset index labels to default value (integers 0, 1, 2, ...) and print
# first three rows
df.reset_index(drop=True).head(3)
```

[20]:
```
                Institution   Country  Founded  Students   Staff   Admin  \
0     University of Glasgow  Scotland     1451     30805  2942.0  4003.0
1   University of Edinburgh  Scotland     1583     34275  4589.0  6107.0
2  University of St Andrews  Scotland     1413      8984  1137.0  1576.0

   Budget  Russell
0   626.5        1
1  1102.0        1
2   251.2        0
```

The `drop=True` argument tells pandas to throw away the old index values instead of storing them as a column of the resulting `DataFrame`.

6.4.2 Selecting elements

To more clearly distinguish between selection by label and by position, pandas provides the `.loc[]` and `.iloc[]` methods of indexing. To make your intention obvious, you should therefore adhere to the following rules:

1. Use `df['name']` only to select *columns* and nothing else.
2. Use `.loc[]` to select by label.
3. Use `.iloc[]` to select by position.

Selection by label

To illustrate, using `.loc[]` unambiguously indexes by label:

[21]:
```
df.loc['d':'f', ['Institution', 'Students']]
```

[21]:
```
                      Institution  Students
index
d          University of Aberdeen     14775
e       University of Strathclyde     22640
f                             LSE     11850
```

With `.loc[]` we can even perform slicing on column names, which is not possible with the simpler `df[]` syntax:

[22]:
```
df.loc['d':'f', 'Institution':'Founded']
```

[22]:
```
                      Institution   Country  Founded
index
d          University of Aberdeen  Scotland     1495
e       University of Strathclyde  Scotland     1964
f                             LSE   England     1895
```

This includes all the columns between `Institution` and `Founded`, where the latter is included since we are slicing by label.

Trying to pass in positional arguments will return an error for the given `DataFrame` since the index labels are a, b, c,... and not 0, 1, 2...

[23]:
```
df.loc[0:4]
```

```
TypeError: cannot do slice indexing on Index with these indexers [0] of type int
```

However, we can reset the index to its default value. Then the index labels are integers and coincide with their position, so that `.loc[]` works:

[24]:
```
df.reset_index(inplace=True, drop=True)     # reset index labels to integers,
                                            # drop original index
df.loc[0:4]
```

[24]:
```
                  Institution   Country  Founded  Students   Staff   Admin  \
0      University of Glasgow  Scotland     1451     30805  2942.0  4003.0
1    University of Edinburgh  Scotland     1583     34275  4589.0  6107.0
2   University of St Andrews  Scotland     1413      8984  1137.0  1576.0
3     University of Aberdeen  Scotland     1495     14775  1086.0  1489.0
4  University of Strathclyde  Scotland     1964     22640     NaN  3200.0

   Budget  Russell
0   626.5        1
1  1102.0        1
```

```
2    251.2        0
3    219.5        0
4    304.4        0
```

Again, the end point with label 4 is included because we are selecting by label.

Somewhat surprisingly, we can also pass boolean arrays to `.loc[]` even though these are clearly not labels:

[25]:
```
df.loc[df['Country'] == 'Scotland']
```

[25]:
```
                  Institution   Country  Founded  Students   Staff   Admin  \
0       University of Glasgow  Scotland     1451     30805  2942.0  4003.0
1     University of Edinburgh  Scotland     1583     34275  4589.0  6107.0
2    University of St Andrews  Scotland     1413      8984  1137.0  1576.0
3      University of Aberdeen  Scotland     1495     14775  1086.0  1489.0
4   University of Strathclyde  Scotland     1964     22640     NaN  3200.0
18       University of Dundee  Scotland     1967     15915  1410.0  1805.0
20     University of Stirling  Scotland     1967      9548     NaN  1872.0

    Budget  Russell
0    626.5        1
1   1102.0        1
2    251.2        0
3    219.5        0
4    304.4        0
18   256.4        0
20   113.3        0
```

Indexing via `.loc[]` supports a few more types of arguments, see the official documentation for details.

Selection by position

Conversely, if we want to select items exclusively by their position and ignore their labels, we use `.iloc[]`:

[26]:
```
df.iloc[0:4, 0:2]            # select first 4 rows, first 2 columns
```

[26]:
```
                 Institution   Country
0      University of Glasgow  Scotland
1    University of Edinburgh  Scotland
2   University of St Andrews  Scotland
3     University of Aberdeen  Scotland
```

Again, `.iloc[]` supports a multitude of other arguments, including boolean arrays. See the official documentation for details.

Boolean indexing

Similar to NumPy, pandas allows us to select a subset of rows in a `Series` or `DataFrame` if they satisfy some condition. The simplest use case is to create a column of boolean values, as shown earlier. This even works without explicitly using the `.loc[]` attribute:

[27]:
```
# Read in university data
df = pd.read_csv(f'{DATA_PATH}/universities.csv', sep=';')

# Select universities NOT in Russell Group
# (equivalent to df.loc[df['Russell'] != 1])
df[df['Russell'] != 1]
```

[27]:
```
                  Institution   Country  Founded  Students   Staff   Admin  \
2    University of St Andrews  Scotland     1413      8984  1137.0  1576.0
3      University of Aberdeen  Scotland     1495     14775  1086.0  1489.0
4   University of Strathclyde  Scotland     1964     22640     NaN  3200.0
```

```
18       University of Dundee  Scotland     1967     15915  1410.0  1805.0
20      University of Stirling  Scotland     1967      9548     NaN  1872.0
22          Swansea University     Wales     1920     20620     NaN  3290.0

    Budget  Russell
2    251.2        0
3    219.5        0
4    304.4        0
18   256.4        0
20   113.3        0
22     NaN        0
```

Multiple conditions can be combined using the & (logical and) or | (logical or) operators:

[28]:
```
# Select universities NOT In Russell Group located in Wales
df[(df['Russell'] != 1) & (df['Country'] == 'Wales')]
```

[28]:
```
           Institution Country  Founded  Students  Staff   Admin  Budget  \
22  Swansea University   Wales     1920     20620    NaN  3290.0     NaN

    Russell
22        0
```

If we want to include rows where an observation takes on one of multiple values, the `isin()` method can be used:

[29]:
```
# Select institutions located in Wales or Scotland
df[df['Country'].isin(('Wales', 'Scotland'))]
```

[29]:
```
                   Institution   Country  Founded  Students   Staff   Admin  \
0       University of Glasgow  Scotland     1451     30805  2942.0  4003.0
1     University of Edinburgh  Scotland     1583     34275  4589.0  6107.0
2    University of St Andrews  Scotland     1413      8984  1137.0  1576.0
3      University of Aberdeen  Scotland     1495     14775  1086.0  1489.0
4   University of Strathclyde  Scotland     1964     22640     NaN  3200.0
18       University of Dundee  Scotland     1967     15915  1410.0  1805.0
19          Cardiff University     Wales     1883     25898  3330.0  5739.0
20      University of Stirling  Scotland     1967      9548     NaN  1872.0
22          Swansea University     Wales     1920     20620     NaN  3290.0

    Budget  Russell
0    626.5        1
1   1102.0        1
2    251.2        0
3    219.5        0
4    304.4        0
18   256.4        0
19   644.8        1
20   113.3        0
22     NaN        0
```

Finally, `DataFrame` implements a `query()` method which allows us to combine multiple conditions in a single string in an intuitive fashion. Column names can be used directly within this string to put restrictions on their values.

[30]:
```
# Select institutions in England with more than 30000 students
df.query('Country == "England" & Students > 30000')
```

[30]:
```
                  Institution  Country  Founded  Students   Staff   Admin  \
6                         UCL  England     1826     41180  7700.0  5375.0
11      King's College London  England     1829     32895  5220.0  3485.0
12  University of Manchester  England     2004     40250  3849.0     NaN
```

```
14  University of Birmingham  England     1825     35445  4020.0      NaN
17  University of Nottingham  England     1798     30798  3495.0      NaN

    Budget  Russell
6   1451.1        1
11   902.0        1
12  1095.4        1
14   673.8        1
17   656.5        1
```

6.5 Aggregation, reduction and transformation

Similar to NumPy, pandas supports data aggregation and reduction functions such as computing sums or averages. Unlike NumPy, these operations can be applied to subsets of the data which have been grouped according to some criterion. For example, for the university data set we used earlier, it is straightforward to compute the average number of students *by country*.

6.5.1 Working with entire DataFrames

The simplest way to perform data reduction is to invoke the desired routine on the entire `DataFrame`:

[31]:
```python
import pandas as pd

df = pd.read_csv(f'{DATA_PATH}/universities.csv', sep=';')
df.mean(numeric_only=True)
```

[31]:
```
Founded      1745.652174
Students    24106.782609
Staff        3664.250000
Admin        3556.736842
Budget        768.609091
Russell         0.739130
dtype: float64
```

Methods such as `mean()` are by default applied column-wise to each column. The `numeric_only=True` argument is used to discard all non-numeric columns (depending on the version of pandas, `mean()` will issue a warning otherwise).

One big advantage over NumPy is that missing values (represented by `np.nan`) are automatically ignored:

[32]:
```python
# mean() automatically drops 3 missing observations
df['Staff'].mean()
```

[32]:
```
3664.25
```

6.5.2 Splitting and grouping

Applying aggregation functions to the entire `DataFrame` is similar to what we can do with NumPy. The added flexibility of pandas becomes obvious once we want to apply these functions to subsets of data, i.e., groups which we can define based on values or index labels.

For example, we can easily group our universities by country using `groupby()`:

[33]:
```python
import pandas as pd

df = pd.read_csv(f'{DATA_PATH}/universities.csv', sep=';')
```

```
# Group observations by country (Scotland, England, etc.)
groups = df.groupby(['Country'])
```

Here `groups` is a special pandas objects which can subsequently be used to process group-specific data. To compute the group-wise averages, we can simply run

[34]:
```
groups.mean(numeric_only=True)
```

[34]:
```
                     Founded      Students        Staff        Admin  \
Country
England          1745.923077  27119.846154  4336.692308  4112.000000
Northern Ireland 1810.000000  18438.000000  2414.000000  1489.000000
Scotland         1691.428571  19563.142857  2232.800000  2864.571429
Wales            1901.500000  23259.000000  3330.000000  4514.500000

                      Budget   Russell
Country
England          1001.700000  1.000000
Northern Ireland  369.200000  1.000000
Scotland          410.471429  0.285714
Wales             644.800000  0.500000
```

Groups support column indexing: if we want to only compute the total number of students for each country in our sample, we can do this as follows:

[35]:
```
groups['Students'].sum()
```

[35]:
```
Country
England             352558
Northern Ireland     18438
Scotland            136942
Wales                46518
Name: Students, dtype: int64
```

There are numerous routines to aggregate grouped data, for example:

- `mean()`: averages within each group
- `sum()`: sum values within each group
- `std()`, `var()`: within-group standard deviation and variances
- `size()`: number of observations in each group
- `first()`, `last()`: first and last elements in each group
- `min()`, `max()`: minimum and maximum elements within a group

Example: Number of elements within each group

[36]:
```
groups.size()       # return number of elements in each group
```

[36]:
```
Country
England             13
Northern Ireland     1
Scotland             7
Wales                2
dtype: int64
```

Example: Return first element of each group

[37]:
```
groups.first()      # return first element in each group
```

[37]:
```
                                     Institution  Founded  Students   Staff  \
Country
England                                      LSE     1895     11850  1725.0
Northern Ireland  Queen's University Belfast     1810     18438  2414.0
Scotland               University of Glasgow     1451     30805  2942.0
Wales                       Cardiff University     1883     25898  3330.0

                   Admin  Budget  Russell
Country
England           2515.0   415.1        1
Northern Ireland  1489.0   369.2        1
Scotland          4003.0   626.5        1
Wales             5739.0   644.8        1
```

We can create custom aggregation routines by calling `agg()` on the grouped object. To illustrate, we count the number of universities in each country that have more than 20,000 students:

[38]:
```python
import numpy as np

groups['Students'].agg(lambda x: np.sum(x >= 20000))
```

[38]:
```
Country
England             10
Northern Ireland     0
Scotland             3
Wales                2
Name: Students, dtype: int64
```

Note that we called `agg()` only on the column `Students`, otherwise the function would be applied to every column separately, which is not what we want.

The most flexible aggregation method is `apply()` which calls a given function, passing the entire group-specific subset of data (including all columns) as an argument, and glues together the results.

Example: Aggregation with custom functions

If we want to compute the average budget per student (in pounds), we can do this as follows:

[39]:
```python
# Budget is in millions of pounds, rescale by 1.0e6 to get
# pounds per student
groups.apply(lambda x: x['Budget'].sum() / x['Students'].sum() * 1.0e6)
```

[39]:
```
Country
England             36936.050239
Northern Ireland    20023.863760
Scotland            20981.875539
Wales               13861.301002
dtype: float64
```

We couldn't have done this with `agg()`, since `agg()` never gets to see the entire chunk of data but only one column at a time.

It is possible to apply multiple functions in a single call by passing a list of functions. These can be passed as strings or as callables.

Example: Applying multiple functions at once

If we want to compute the mean and median number of students by country, we proceed as follows:

[40]:
```python
groups['Students'].agg(['mean', 'median'])
```

[40]:
```
                      mean   median
Country
England           27119.846154  25955.0
Northern Ireland  18438.000000  18438.0
Scotland          19563.142857  15915.0
Wales             23259.000000  23259.0
```

Note that we could have also specified these function by passing references to the corresponding NumPy functions instead:

[41]:
```
groups['Students'].agg([np.mean, np.median])
```

[41]:
```
                      mean   median
Country
England           27119.846154  25955.0
Northern Ireland  18438.000000  18438.0
Scotland          19563.142857  15915.0
Wales             23259.000000  23259.0
```

Finally, a the following more advanced syntax allows us to create new column names using existing columns and some operation:

```
groups.agg(
    new_column_name1=('column_name1', 'operation1'),
    new_column_name2=('column_name2', 'operation2'),
    ...
)
```

Example: Applying multiple functions to multiple columns

The following code computes the average student numbers and the earliest year a university was founded in a single aggregation:

[42]:
```
groups.agg(
    average_students=('Students', 'mean'),
    first_founded=('Founded', 'first')
)
```

[42]:
```
                  average_students  first_founded
Country
England               27119.846154           1895
Northern Ireland      18438.000000           1810
Scotland              19563.142857           1451
Wales                 23259.000000           1883
```

This section provided only a first look at pandas's "split-apply-combine" functionality implemented via `groupby`. See the official documentation for more details.

6.5.3 Transformations

In the previous section, we combined grouping and reduction, i.e., data at the group level was reduced to a single statistic such as the mean. However, we can combine grouping with the `transform()` function which assigns the result of a computation to each observation within a group and consequently leaves the number of observations unchanged.

For example, for each observation we could compute the average number of students by the corresponding country:

[43]:
```
df['Avg_Student'] = df.groupby('Country')[['Students']].transform('mean')
```

```
# Print results for each institution
df[['Institution', 'Country', 'Avg_Student']].head(10)
```

```
[43]:                  Institution   Country    Avg_Student
      0        University of Glasgow  Scotland  19563.142857
      1      University of Edinburgh  Scotland  19563.142857
      2     University of St Andrews  Scotland  19563.142857
      3       University of Aberdeen  Scotland  19563.142857
      4    University of Strathclyde  Scotland  19563.142857
      5                          LSE   England  27119.846154
      6                          UCL   England  27119.846154
      7      University of Cambridge   England  27119.846154
      8         University of Oxford   England  27119.846154
      9        University of Warwick   England  27119.846154
```

As you can see, instead of collapsing the `DataFrame` to only 4 observations (one for each country), the number of observations remains the same, and the number of average students is constant within each country.

When would we want to use `transform()` instead of aggregation? Such use cases arise whenever we want to perform computations that include the individual value as well as an aggregate statistic.

Example: Deviation from average budget per student

Assume that we want to compute how much each university's budget per student differs from the average budget per student in the corresponding country. We could compute this using `transform()` as follows:

```
[44]: # Compute budget per student (multiply by 1e6 to get budget in pounds)
df['Budget_Student'] = df['Budget'] / df['Students'] * 1.0e6

# Compute deviation from country-average budget per student
df['Budget_Diff'] = df.groupby('Country')['Budget_Student'].transform(lambda x: x - np.
  ↪mean(x))

# Print relevant columns
df[['Institution', 'Country', 'Budget_Diff']].head()
```

```
[44]:                  Institution   Country   Budget_Diff
      0        University of Glasgow  Scotland    804.965611
      1      University of Edinburgh  Scotland  12619.072157
      2     University of St Andrews  Scotland   8428.177314
      3       University of Aberdeen  Scotland  -4676.465947
      4    University of Strathclyde  Scotland  -6087.412238
```

From the first row you see that the University of Glasgow has approximately 800 pounds per student more at its disposal than the average Scottish university.

6.6 Working with time series data

In economics and finance, we frequently work with time series data, i.e., observations that are associated with a particular point in time (time stamp) or a time period. pandas offers comprehensive support for such data, in particular if the time stamp or time period is used as the index of a `Series` or `DataFrame`. This section presents a few of the most important concepts, see the official documentation for a comprehensive guide.

To illustrate, let's construct a set of daily data for the first three months of 2022, i.e., the period 2022-01-01 to 2022-03-31 using the `date_range()` function (we use the data format `YYYY-MM-DD` in this section, but pandas also supports other date formats).

```
[45]: import pandas as pd
import numpy as  np

# Create sequence of dates from 2022-01-01 to 2022-03-31
# at daily frequency
index = pd.date_range(start='2022-01-01', end='2022-03-31', freq='D')

# Use date range as index for Series with some artificial data
data = pd.Series(np.arange(1, 1+len(index)), index=index)

# Print first 5 observations
data.head(5)
```

```
[45]: 2022-01-01    1
2022-01-02    2
2022-01-03    3
2022-01-04    4
2022-01-05    5
Freq: D, dtype: int64
```

6.6.1 Indexing with date/time indices

pandas implements several convenient ways to select observations associated with a particular date or a set of dates. For example, if we want to select one specific date, we can pass it as a string to `.loc[]`:

```
[46]: # Select single observation by date
data.loc['2022-01-01']
```

```
[46]: 1
```

It is also possible to select a time period by passing a start and end point (where the end point is included, as usual with label-based indexing in pandas):

```
[47]: # Select first 5 days
data.loc['2022-01-01':'2022-01-05']
```

```
[47]: 2022-01-01    1
2022-01-02    2
2022-01-03    3
2022-01-04    4
2022-01-05    5
Freq: D, dtype: int64
```

A particularly useful way to index time periods is a to pass a partial index. For example, if we want to select all observations from January 2022, we could use the range `'2022-01-01':'2022-01-31'`, but it is much easier to specify the partial index `'2022-01'` instead which includes all observations from January since no days were specified.

```
[48]: # Select all observations from January 2022
data.loc['2022-01']
```

```
[48]: 2022-01-01     1
2022-01-02     2
2022-01-03     3
2022-01-04     4
2022-01-05     5
2022-01-06     6
2022-01-07     7
2022-01-08     8
2022-01-09     9
```

```
2022-01-10    10
2022-01-11    11
2022-01-12    12
2022-01-13    13
2022-01-14    14
2022-01-15    15
2022-01-16    16
2022-01-17    17
2022-01-18    18
2022-01-19    19
2022-01-20    20
2022-01-21    21
2022-01-22    22
2022-01-23    23
2022-01-24    24
2022-01-25    25
2022-01-26    26
2022-01-27    27
2022-01-28    28
2022-01-29    29
2022-01-30    30
2022-01-31    31
Freq: D, dtype: int64
```

6.6.2 Lags, differences, and other useful transformations

When working with time series data, we often need to create lags or leads of a variable (e.g., if we want to include lagged values in a regression model). In pandas, this is done using `shift()` which shifts the index by the desired number of periods (default: 1). For example, invoking `shift(1)` creates lagged observations of each column in the `DataFrame`:

[49]:
```python
# Lag observations by 1 period
data.shift(1)
```

[49]:
```
2022-01-01     NaN
2022-01-02     1.0
2022-01-03     2.0
2022-01-04     3.0
2022-01-05     4.0
              ...
2022-03-27    85.0
2022-03-28    86.0
2022-03-29    87.0
2022-03-30    88.0
2022-03-31    89.0
Freq: D, Length: 90, dtype: float64
```

Note that the first observation is now missing since there is no preceding observation which could have provided the lagged value.

Another useful method is `diff()` which computes the difference between adjacent observations (the period over which the difference is taken can be passed as a parameter).

[50]:
```python
# Compute 1-period difference
data.diff()
```

[50]:
```
2022-01-01    NaN
2022-01-02    1.0
2022-01-03    1.0
2022-01-04    1.0
2022-01-05    1.0
```

```
                 ...
2022-03-27    1.0
2022-03-28    1.0
2022-03-29    1.0
2022-03-30    1.0
2022-03-31    1.0
Freq: D, Length: 90, dtype: float64
```

Note that `diff()` is identical to manually computing the difference with the lagged value like this:

```
data - data.shift()
```

Additionally, we can use `pct_change()` which computes the percentage change (the relative difference) over a given number of periods (default: 1).

[51]:
```
# Compute percentage change vs. previous period
data.pct_change()
```

[51]:
```
2022-01-01         NaN
2022-01-02    1.000000
2022-01-03    0.500000
2022-01-04    0.333333
2022-01-05    0.250000
                 ...
2022-03-27    0.011765
2022-03-28    0.011628
2022-03-29    0.011494
2022-03-30    0.011364
2022-03-31    0.011236
Freq: D, Length: 90, dtype: float64
```

Again, this is just a convenience method that is a short-cut for manually computing the percentage change:

```
(data - data.shift()) / data.shift()
```

6.6.3 Resampling and aggregation

Another useful feature of the time series support in pandas is *resampling* which is used to group observations by time period and apply some aggregation function. This can be accomplished using the `resample()` method which in its simplest form takes a string argument that describes how observations should be grouped (`'A'` or `'Y'` for aggregation to years, `'Q'` for quarters, `'M'` for months, `'W'` for weeks, etc.).

For example, if we want to aggregate our 3 months of artificial daily data to monthly frequency, we would use `resample('M')`. This returns an object which is very similar to the one returned by `groupby()` we studied previously, and we can call various aggregation methods such as `mean()`:

[52]:
```
# Resample to monthly frequency, aggregate to mean of daily observations
# within each month
data.resample('M').mean()
```

[52]:
```
2022-01-31    16.0
2022-02-28    45.5
2022-03-31    75.0
Freq: M, dtype: float64
```

Similarly, we can use `resample('W')` to resample to weekly frequency. Below, we combine this with the aggregator `last()` to return the last observation of each week (weeks by default start on Sundays):

[53]:
```
# Return last observation of each week
data.resample('W').last()
```

[53]:
```
2022-01-02     2
2022-01-09     9
2022-01-16    16
2022-01-23    23
2022-01-30    30
2022-02-06    37
2022-02-13    44
2022-02-20    51
2022-02-27    58
2022-03-06    65
2022-03-13    72
2022-03-20    79
2022-03-27    86
2022-04-03    90
Freq: W-SUN, dtype: int64
```

6.7 Visualisation

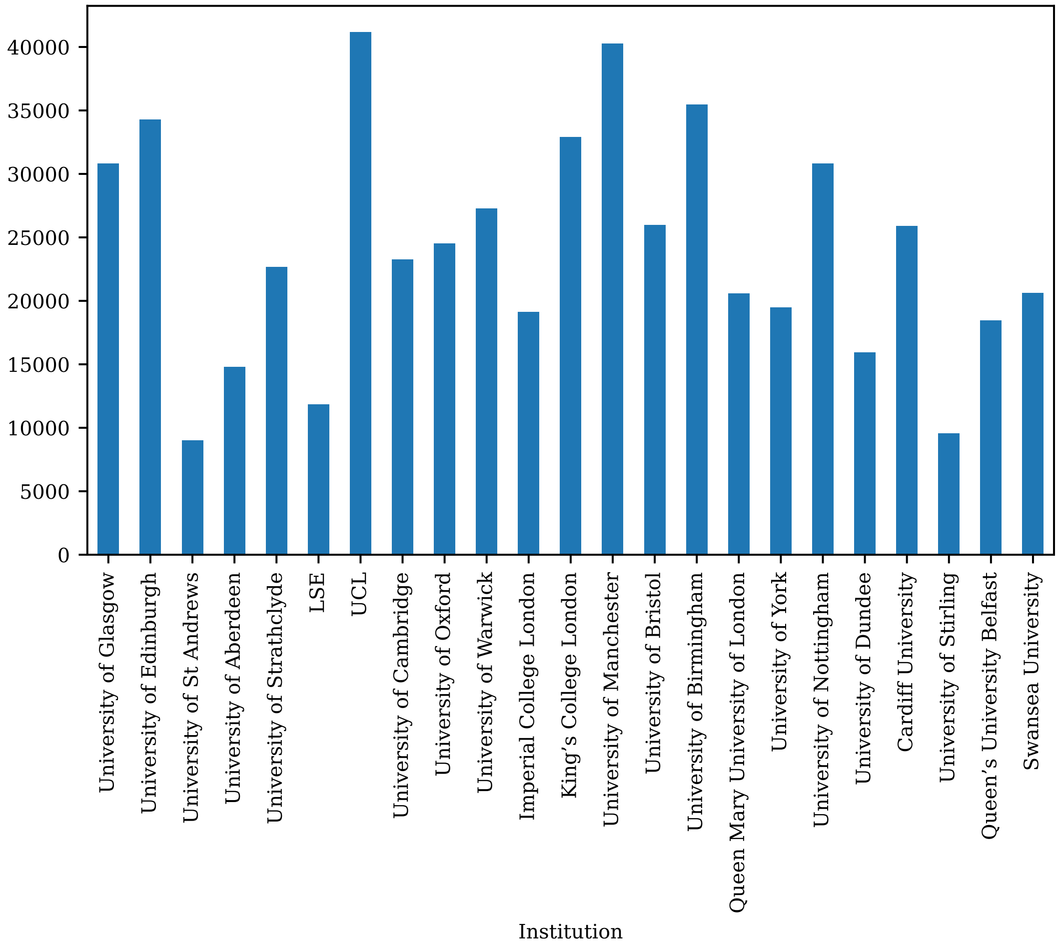
We covered plotting with Matplotlib in earlier units. Pandas itself implements some convenience wrappers around Matplotlib plotting routines which allow us to quickly inspect data stored in `DataFrames`. Alternatively, we can extract the numerical data and pass it to Matplotlib's routines manually.

Example: Creating bar charts

Let's return to our UK universities data. To plot student numbers as a bar chart, we can directly use pandas's `plot.bar()`:

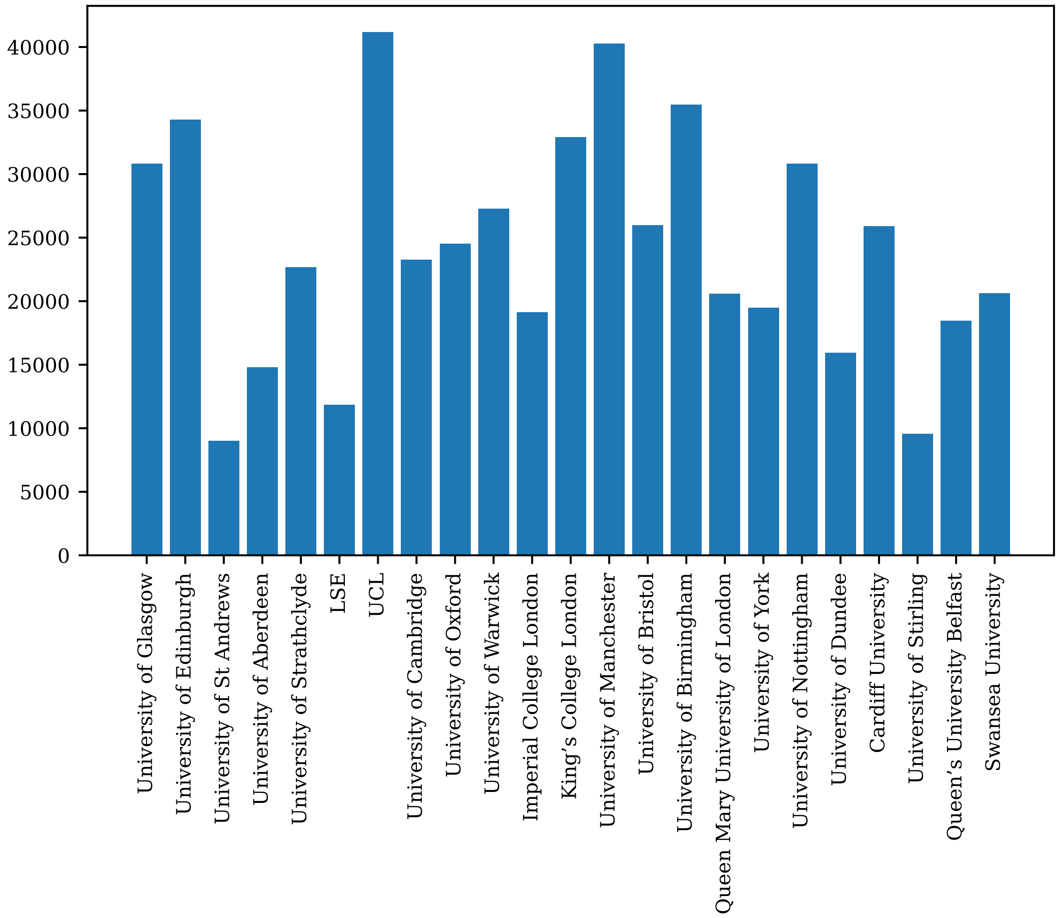
[54]:
```
import pandas as pd

# Uncomment this to use files in the local data/ directory
DATA_PATH = '../data'

# Uncomment this to load data directly from GitHub
# DATA_PATH = 'https://raw.githubusercontent.com/richardfoltyn/python-intro-PGR/main/data'

# Read universities data from CSV
df = pd.read_csv(f'{DATA_PATH}/universities.csv', sep=';')

# set institution as label so they automatically show up in plot
df2 = df.set_index(keys=['Institution'])

# Create bar chart. Alternatively, use df2['Students'].plot(kind='bar)
df2['Students'].plot.bar(figsize=(7, 4))
```

[54]:
```
<Axes: xlabel='Institution'>
```



Alternatively, we can construct the graph using Matplotlib ourselves:

[55]:
```
import matplotlib.pyplot as plt

labels = df['Institution'].to_list()        # labels as list
values = df['Students'].to_numpy()          # data as NumPy array

# Create new figure with desired size
plt.figure(figsize=(7, 4))

# Create bar chart
plt.bar(labels, values)

# Rotate ticks
plt.tick_params(axis='x', labelrotation=90)
```



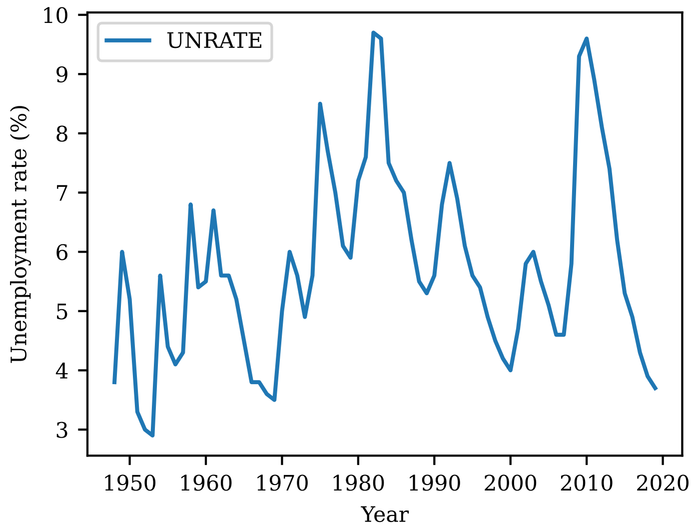
Sometimes Matplotlib's routines directly work with pandas's data structures, sometimes they don't. In cases where they don't, we can convert a `DataFrame` or `Series` object to a NumPy array using the `to_numpy()` method, or convert a `Series` to a Python list using `to_list()`, as illustrated in the example above.

Example: Plotting timeseries data

To plot timeseries-like data, we can use the `plot()` method which optionally accepts arguments to specify which columns should be used for the x-axis and which for the y-axis. We illustrate this using the US unemployment rate at annual frequency.

[56]:
```
import numpy as np
import pandas as pd

# Path to FRED.csv; DATA_PATH variable was defined above!
filepath = f'{DATA_PATH}/FRED.csv'

# Read CSV data
df = pd.read_csv(filepath, sep=',')

# Plot unemployment rate by year
df.plot(x='Year', y='UNRATE', ylabel='Unemployment rate (%)')
```

[56]:
```
<Axes: xlabel='Year', ylabel='Unemployment rate (%)'>
```

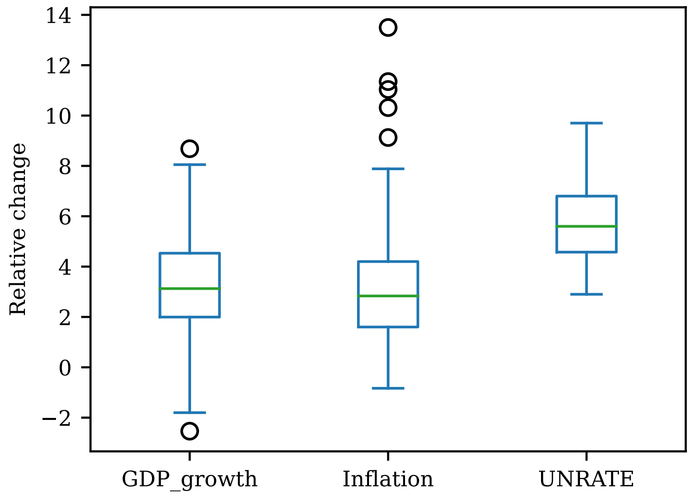


Example: Creating box plots

To quickly plot some descriptive statistics, we can use the `plot.box()` provided by pandas. We demonstrate this by plotting the distribution of post-ware GDP growth, inflation and the unemployment rate in the US:

[57]:
```python
import numpy as np
import pandas as pd

# Path to FRED.csv; DATA_PATH variable was defined above!
filepath = f'{DATA_PATH}/FRED.csv'

# Read CSV data
df = pd.read_csv(filepath, sep=',')

# Compute annual growth rates (in percent)
df['GDP_growth'] = df['GDP'].pct_change() * 100.0
df['Inflation'] = df['CPI'].pct_change() * 100.0

# Include only the following columns in plot
columns = ['GDP_growth', 'Inflation', 'UNRATE']

# Create box plot. Alternatively, use df.plot(kind='box')
df[columns].plot.box(ylabel='Relative change')
```

[57]:
```
<Axes: ylabel='Relative change'>
```

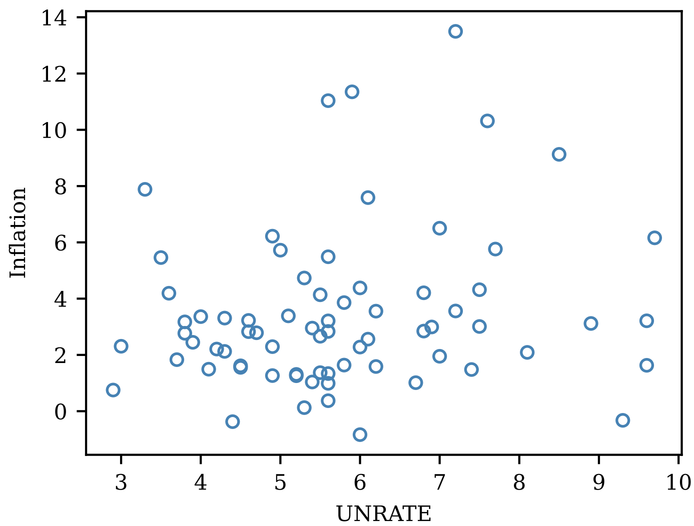


Example: Creating scatter plots

Similarly, we can generate scatter plots, plotting one column against another. To illustrate, we plot the US unemployment rate against inflation in any given year over the post-war period.

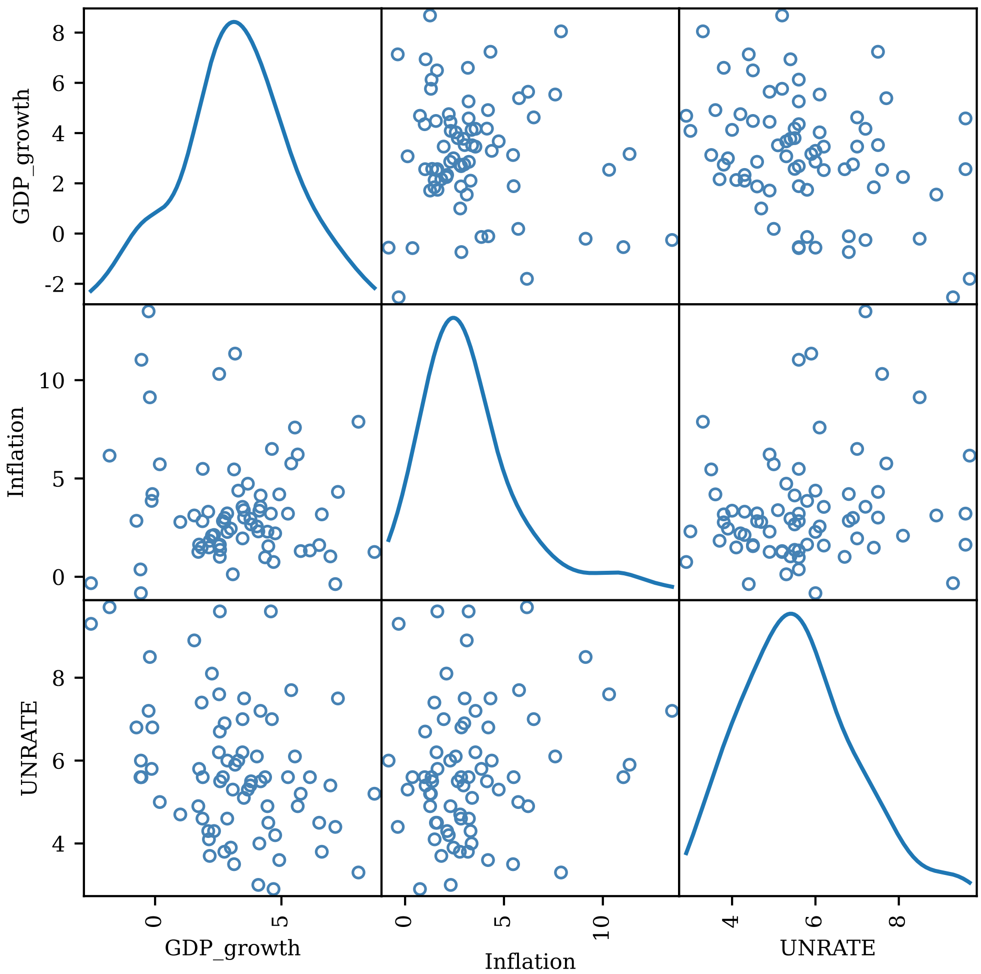
[58]:
```
# Path to FRED.csv; DATA_PATH variable was defined above!
filepath = f'{DATA_PATH}/FRED.csv'

# Read CSV data
df = pd.read_csv(filepath, sep=',')

# Compute annual inflation as growth rate of CPI
df['Inflation'] = df['CPI'].pct_change() * 100.0

df.plot.scatter(
    x='UNRATE', y='Inflation',
    color='none', edgecolor='steelblue'
)
```

[58]:
```
<Axes: xlabel='UNRATE', ylabel='Inflation'>
```



Pandas also offers the convenience function `scatter_matrix()` which lets us easily create pairwise scatter plots for more than two variables:

[59]:
```
from pandas.plotting import scatter_matrix

# Continue with DataFrame from previous example, compute GDP growth
df['GDP_growth'] = df['GDP'].pct_change() * 100.0

# Columns to include in plot
columns = ['GDP_growth', 'Inflation', 'UNRATE']

# Use argument diagonal='kde' to plot kernel density estimate
# in diagonal panels
axes = scatter_matrix(
    df[columns],
    figsize=(6, 6),
    diagonal='kde',              # plot kernel density along diagonal
    s=70,                        # marker size
    color='none',
    edgecolor='steelblue',
    alpha=1.0,
)
```



In general, the wrappers implemented in pandas are useful to get an idea how the data looks like. For reusable code or more complex graphs, we'll usually want to directly use Matplotlib and pass the data converted to NumPy arrays.

6.8 Optional exercises

The following exercises use data files from the `data/` folder.

6.8.1 Exercise 1: Basic data manipulations

In this exercise, we will perform some basic data manipulation and plot the results.

1. Load the CSV file `FRED_QTR.csv` (using `sep=','`). Set the columns `Year` and `Quarter` as (joint) indices.

   Hint: You can do this by specifying these column names in the `index_col` argument of `read_csv()`. Alternatively, you can cell `set_index()` once you have loaded the data.

2. This data comes at a quarterly frequency. Convert it to annual values by computing the average values for each year.

   Hint: Group the data by `Year` using the `groupby()` function and compute the mean on the grouped data.

3. Compute two new variables from the annualised data and add them to the `DataFrame`:

   - `Inflation`, defined as the growth rate of `CPI` (consumer price index)
   - `GDP_growth`, defined as the growth rate of `GDP`

4. Drop all rows with missing values (these show up as `NaN`).

   Hint: There is no need to manually filter out `NaN` values, you can use the `dropna()` method instead.

5. Plot the columns `GDP_growth`, `Inflation`, `UNRATE` (unemployment rate) and `LFPART` (labour force participation) using the pandas plotting routines. Use the option `subplots=True` and `layout=(2,2)` to create a 2×2 grid. See the documentation for `plot()` for details.

6.8.2 Exercise 2: Decade averages

Load the FRED data from the CSV file `FRED_QTR.csv` (using `sep=','`) and perform the following tasks:

1. Compute the quarterly GDP growth rate and inflation, similar to what you did in the previous exercise.
2. Add the column `Decade` which contains the decade for every observation. Use 1940 to code the 40s, 1950 for the 50s, etc.
3. We want to retain only observations for decades for which all 40 quarters are present:

   1. Group the data by `Decade` and count the number of observations using `count()`.
   2. A decade should be kept in the data set only if *all* variables have the full 40 observations.
   3. Drop all observations for which this is not the case.

4. With the remaining observations, compute the decade averages for quarterly GDP growth, inflation and the unemployment rate (`UNRATE`). Annualise the GDP growth and inflation figures by multiplying them by 4.
5. Create a bar chart that plots these three variables by decade.

6.8.3 Exercise 3: Group averages

Load the universities data from the CSV file `universities.csv` (using `sep=';'`) and perform the following tasks:

1. Group the data by Russell Group membership using the indicator variable `Russell`. For each group, compute the averages of the following ratios using `apply()`:

    - The ratio of academic staff (`Staff`) to students (`Students`)
    - The ratio of administrative staff (`Admin`) to students.
    - The budget (`Budget`) per student in pounds.

    Additionally, compute the number of universities is each group.

2. Repeat the task using a different approach:

    1. Compute the above ratios and add them as new columns to the initial `DataFrame`.
    2. Group the data by Russell Group membership.
    3. Compute the mean of each ratio using `mean()`.
    4. Compute the number of universities in each group using `count()`, and store the result in the column `Count` in the `DataFrame` you obtained in the previous step.

3. Create a bar chart, plotting the value for universities in and outside of the Russell Group for each of the four statistics computed above.

6.8.4 Exercise 4: Grouping by multiple dimensions

Load the universities data from the CSV file `universities.csv` (using `sep=';'`) and perform the following tasks:

1. Create an indicator `Pre1800` which is `True` for universities founded before the year 1800.

2. Group the data by `Country` and the value of `Pre1800`.

    Hint: You need to pass a list of column names to `groupby()`.

3. Compute the number of universities for each combination of `(Country, Pre1800)`.

4. Create a bar chart showing the number of pre- and post-1800 universities by country (i.e., create four groups of bars, each group showing one bar for pre- and one for post-1800).

5. Create a bar chart showing the number of universities by country by pre- and post-1800 period (i.e., create two groups of bars, each group showing four bars, one for each country.)

6.8.5 Exercise 5: Okun's law (advanced)

In this exercise, we will estimate Okun's law on quarterly data for each of the last eight decades.

Okun's law relates unemployment to the output gap. One version (see Jones: Macroeconomics, 2019) is stated as follows:

$$u_t - \overline{u}_t = \alpha + \beta \left(\frac{Y_t - \overline{Y}_t}{\overline{Y}_t} \right)$$

where u_t is the unemployment rate, $\overline{u}_t$ is the natural rate of unemployment, Y_t is output (GDP) and $\overline{Y}_t$ is potential output. We will refer to $u_t - \overline{u}_t$ as "cyclical unemployment" and to the term in parenthesis on the right-hand side as the "output gap." Okun's law says that the coefficient β is negative, i.e., cyclical unemployment is higher when the output gap is low (negative) because the economy is in a recession.

Load the FRED data from the CSV file `FRED_QTR.csv` (using `sep=','`) and perform the following tasks:

1. Compute the output gap and cyclical unemployment rate as defined above and add them as columns to the `DataFrame`.

2. Assign each observation to a decade as you did in previous exercises.
3. Write a function `regress_okun()` which accepts a `DataFrame` containing a decade-spefic subsample as the only argument, and estimates the coefficients α (the intercept) and β (the slope) of the above regression equation.

   This function should return a `DataFrame` of a single row and two columns which store the intercept and slope.

   Hint: Use NumPy's `lstsq()` to perform the regression. To regress the dependent variable `y` on regressors `X`, you need to call `lstsq(X, y)`. To include the intercept, you will manually have to create `X` such that the first column contains only ones.
4. Group the data by decade and call the `apply()` method, passing `regress_okun` you wrote as the argument.
5. Plot your results: for each decade, create a scatter plot of the raw data and overlay it with the regression line you estimated.

6.9 Solutions

These solutions illustrate *one* possible way to solve the exercises. Pandas is extremely flexible (maybe too flexible) and allows us to perform these tasks in many different ways, so your implementation might look very different.

The solutions are also provided as Python scripts in the lectures/solutions/unit06/ folder.

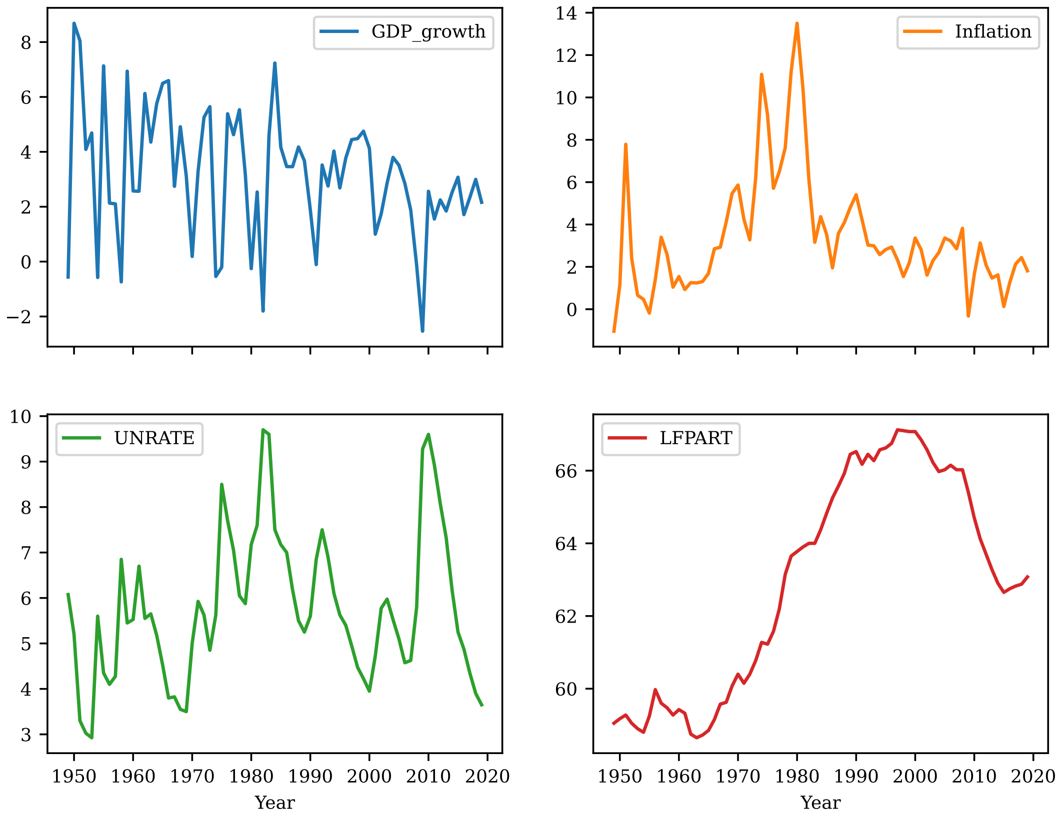
6.9.1 Solution for exercise 1

One possible implementation looks as follows:

[60]:
```
import pandas as pd

# Use either local or remote path to data/ directory
# DATA_PATH = '../data'
DATA_PATH = 'https://raw.githubusercontent.com/richardfoltyn/python-intro-PGR/main/data'
filepath = f'{DATA_PATH}/FRED_QTR.csv'

df = pd.read_csv(filepath, sep=',', index_col=['Year', 'Quarter'])
# Alternatively, set index columns later
# df = pd.read_csv(filepath, sep=',')
# df.set_index(keys=['Year', 'Quarter'], inplace=True)

# Convert to annual frequency
# Group by year
grp = df.groupby(['Year'])
# Compute annual data as mean of quarterly values
df_year = grp.mean()

# Alternative ways to perform the same aggregation:
# df_year = grp.agg('mean')
# df_year = grp.agg(np.mean)

# Compute CPI and GDP growth rates (in percent)
df_year['Inflation'] = df_year['CPI'].diff() / df_year['CPI'].shift() * 100.0
df_year['GDP_growth'] = df_year['GDP'].diff() / df_year['GDP'].shift() * 100.0

# Drop all rows that contain any NaNs
df_year = df_year.dropna(axis=0)

# Columns to plot
varnames = ['GDP_growth', 'Inflation', 'UNRATE', 'LFPART']
```

```python
df_year.plot.line(y=varnames, subplots=True, layout=(2, 2),
                  sharex=True, figsize=(8, 6))

# Alternatively, we can call plot() directly, which
# defaults to generating a line plot:
#
# df_year.plot(y=varnames, subplots=True, layout=(2, 2),
#              sharex=True, figsize=(10, 10))
```

[60]:
```
array([[<Axes: xlabel='Year'>, <Axes: xlabel='Year'>],
       [<Axes: xlabel='Year'>, <Axes: xlabel='Year'>]], dtype=object)
```



A few comments:

1. We can set the index column when loading a CSV file by passing the column names as `index_col`:

   ```
   df = pd.read_csv(filepath, sep=',', index_col=['Year', 'Quarter'])
   ```

   Alternatively, we can first load the CSV file and set the index later:

   ```
   df = pd.read_csv(filepath, sep=',')
   df.set_index(keys=['Year', 'Quarter'], inplace=True)
   ```

2. There are several ways to compute the means of grouped data:

   1. We can call `mean()` on the group object directly:

      ```
      df_year = grp.mean()
      ```

   2. Alternatively, we can call `agg()` and pass it the aggregation routine that should be applied:

      ```
      df_year = grp.agg('mean')
      df_year = grp.agg(np.mean)
      ```

Here we again have multiple options: pandas understands `'mean'` if passed as a string (which might not be the case for some other functions), or we pass an actual function such as `np.mean`.

3. The easiest way to compute differences between adjacent rows is to use the `diff()` method, which returns $x_t - x_{t-1}$. Pandas then automatically matches the correct values and sets the first observation to `NaN` as there is no preceding value to compute the difference.

   To compute a growth rate $(x_t - x_{t-1})/x_{t-1}$, we additionally need to lag a variable to get the correct period in the denominator. In pandas this is achieved using the `shift()` method (which defaults to shifting by 1 period).

6.9.2 Solution for exercise 2

This time we do not specify `index_cols` when reading in the CSV data since we need `Year` as a regular variable, not as the index.

We then compute the decade for each year, using the fact that // performs division with integer truncation. As an example, 1951 // 10 is 195, and (1951 // 10) * 10 = 1950, which we use to represent the 1950s.

[61]:
```
import pandas as pd

# Use either local or remote path to data/ directory
# DATA_PATH = '../data'
DATA_PATH = 'https://raw.githubusercontent.com/richardfoltyn/python-intro-PGR/main/data'
filepath = f'{DATA_PATH}/FRED_QTR.csv'

df = pd.read_csv(filepath, sep=',')

# Compute GDP growth rates, inflation (in percent)
df['GDP_growth'] = df['GDP'].diff() / df['GDP'].shift() * 100.0
df['Inflation'] = df['CPI'].diff() / df['CPI'].shift() * 100.0

# Assign decade using // to truncate division to
# integer part. So we have 194x // 10 = 194 for any x.
df['Decade'] = (df['Year'] // 10) * 10

grp = df.groupby(['Decade'])

# Print number of obs. by decade
print(grp.count())

# Create series that contains True for each
# decade if all variables have 40 observations.
use_decade = (grp.count() == 40).all(axis=1)
# Convert series to DataFrame, assign column name 'Keep'
df_decade = use_decade.to_frame('Keep')
# merge into original DataFrame, matching rows on value
# of column 'Decade'
df = df.merge(df_decade, on='Decade')
# Restrict data only to rows which are part of complete decade
df = df.loc[df['Keep'], :].copy()
# Drop 'Keep' column
del df['Keep']

# Compute average growth rates and unemployment rate by decade
grp = df.groupby(['Decade'])

df_avg = grp[['GDP_growth', 'Inflation', 'UNRATE']].mean()
# Convert to (approximate) annualised growth rates
df_avg['GDP_growth'] *= 4.0
df_avg['Inflation'] *= 4.0
```

```
        Year  Quarter  GDP  CPI  UNRATE  LFPART  GDPPOT  NROU  GDP_growth  \
Decade
1940       8        8    8    8       8       8       4     4           7
1950      40       40   40   40      40      40      40    40          40
1960      40       40   40   40      40      40      40    40          40
1970      40       40   40   40      40      40      40    40          40
1980      40       40   40   40      40      40      40    40          40
1990      40       40   40   40      40      40      40    40          40
2000      40       40   40   40      40      40      40    40          40
2010      40       40   40   40      40      40      40    40          40

        Inflation
Decade
1940            7
1950           40
1960           40
1970           40
1980           40
1990           40
2000           40
2010           40
```

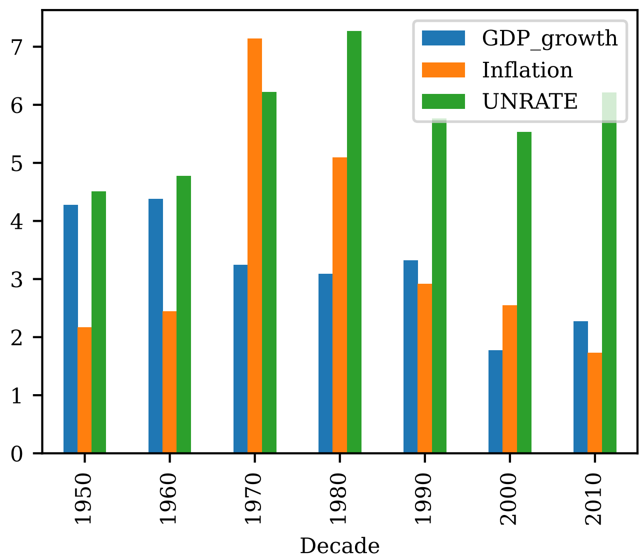
The tricky part is to keep only observations for "complete" decades that have 40 quarters of data. We see that this is not the case for the 1940s:

1. We group by `Decade` and use `count()` to determine the number of non-missing observations for each variable.
2. `count() == 40` evaluates to `True` for some variable if it has 40 observations.
3. We then use `all()` to aggregate across all variables, i.e., we require 40 observations for every variable to keep the decade.
4. Finally, we merge the indicator whether a decade should be kept in the data set using `merge()`, where we match on the value of the column `Decade`. Note that the argument to `merge()` must be a `DataFrame`, so we first have to convert our indicator data.
5. Finally, we keep only those observations which have a flag that is `True`.

The rest of the exercise is straightforward as it just repeats what we have done previously. You can create the bar chart directly with pandas as follows:

[62]:
```python
df_avg.plot.bar(y=['GDP_growth', 'Inflation', 'UNRATE'])
```

[62]: `<Axes: xlabel='Decade'>`



6.9.3 Solution for exercise 3

We first read in the CSV file, specifying `';'` as the field separator:

[63]:
```python
import pandas as pd

# Use either local or remote path to data/ directory
# DATA_PATH = '../data'
DATA_PATH = 'https://raw.githubusercontent.com/richardfoltyn/python-intro-PGR/main/data'

# Load CSV file
filepath = f'{DATA_PATH}/universities.csv'
df = pd.read_csv(filepath, sep=';')
```

For the first task we use `apply()` to create a new `Series` object for each ratio of interest.

We compute the ratios for each institution which will result in NaNs if either the numerator of denominator is missing. We thus use `np.nanmean()` to compute averages, ignoring any NaNs.

Finally, we combine all `Series` into a `DataFrame`. We do this by specifying the data passed to `DataFrame()` as a dictionary, since then we can specify the column names as keys.

[64]:
```python
# Variant 1
# Compute means using apply()

grp = df.groupby(['Russell'])

# Create Series objects with the desired means
staff = grp.apply(lambda x: np.nanmean(x['Staff'] / x['Students']))
admin = grp.apply(lambda x: np.nanmean(x['Admin'] / x['Students']))
# Budget in millions of pounds
budget = grp.apply(lambda x: np.nanmean(x['Budget'] / x['Students']))
# Convert to pounds
budget *= 1.0e6
# Count number of institutions in each group.
# We can accomplish this by calling size() on the group object.
count = grp.size()

# Create a new DataFrame. Each column is a Series object.
df_all = pd.DataFrame({'Staff_Student': staff,
                       'Admin_Student': admin,
                       'Budget_Student': budget,
                       'Count': count})

df_all
```

[64]:

	Staff_Student	Admin_Student	Budget_Student	Count
Russell				
0	0.096219	0.147762	16847.834366	6
1	0.155131	0.169079	35406.453649	17

For the second task, we first insert additional columns which contain the ratios of interest for each university.

We then drop all unused columns, group by the `Russell` indicator and compute the means by directly calling `mean()` on the group object.

[65]:
```python
# Variant 2:
# Compute ratios first, apply aggregation later

# Create new variables directly in original DataFrame
df['Staff_Student'] = df['Staff'] / df['Students']
df['Admin_Student'] = df['Admin'] / df['Students']
```

```python
# Budget in pounds (original Budget is in million pounds)
df['Budget_Student'] = df['Budget'] / df['Students'] * 1.0e6

# Keep only newly constructed ratios
columns_keep = [name for name in df.columns
                if name.endswith('_Student')]
# Also keep Russell indicator
columns_keep += ['Russell']
df = df[columns_keep].copy()

# Aggregate by Russell indicator
grp = df.groupby(['Russell'])
# Count number of institutions in each group.
# We can accomplish this by calling size() on the group object.
count = grp.size()

df_all = grp.mean()
# Add counter
df_all['Count'] = count

df_all
```

[65]:

Russell	Staff_Student	Admin_Student	Budget_Student	Count
0	0.096219	0.147762	16847.834366	6
1	0.155131	0.169079	35406.453649	17

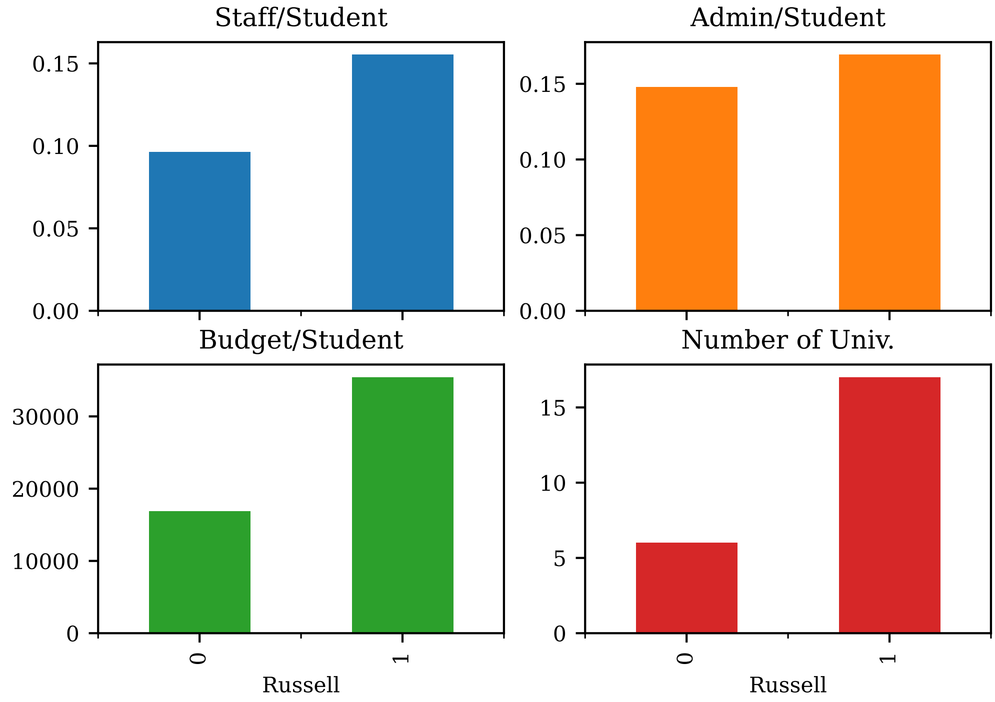
We plot the results using pandas's `bar()` function. Since the data is of vastly different magnitudes, we specify `sharey=False` so that each panel will have its own scaling on the y-axis.

[66]:

```python
# Plot results as bar charts, one panel for each variable

# Pretty titles
title = ['Staff/Student', 'Admin/Student', 'Budget/Student', 'Number of Univ.']
# Create bar chart using pandas's bar() function
df_all.plot.bar(sharey=False, subplots=True, layout=(2, 2), legend=False,
                title=title, figsize=(6, 4))
```

[66]:

```
array([[<Axes: title={'center': 'Staff/Student'}, xlabel='Russell'>,
        <Axes: title={'center': 'Admin/Student'}, xlabel='Russell'>],
       [<Axes: title={'center': 'Budget/Student'}, xlabel='Russell'>,
        <Axes: title={'center': 'Number of Univ.'}, xlabel='Russell'>]],
      dtype=object)
```



6.9.4 Solution for exercise 4

We create an indicator variable called `Pre1800` which is set to `True` whenever the founding year in column `Founded` is lower than 1800.

We then group the data by `Country` and `Pre1800` and count the number of universities in each group using `count()`.

[67]:
```
import pandas as pd

# Use either local or remote path to data/ directory
# DATA_PATH = '../data'
DATA_PATH = 'https://raw.githubusercontent.com/richardfoltyn/python-intro-PGR/main/data'

# Load CSV file
filepath = f'{DATA_PATH}/universities.csv'
df = pd.read_csv(filepath, sep=';')

# Create mask for founding period
df['Pre1800'] = (df['Founded'] < 1800)

# Create group by country and founding period;
grp = df.groupby(['Country', 'Pre1800'])

# Number of universities by country and founding period.
# Since we are grouping by two attributes, this will create a
# Series with a multi-level (hierarchical) index
count = grp.size()

count
```

[67]:
```
Country           Pre1800
England           False      8
                  True       5
Northern Ireland  False      1
Scotland          False      3
```

```
                    True       4
Wales               False      2
dtype: int64
```

The resulting `Series` only contains values for those combinations that are actually present in the data. For example, the combination `(Wales, True)` does not show up because there are no Welsh universities founded before 1800 in our sample. We will have to "complete" the data and add zero entries in all such cases.

First, we create a `DataFrame` with countries in rows and the number of universities for the pre- and post-1800 periods in columns. To accomplish this, we need to pivot the second row index using the `unstack()` method. The `level=-1` argument tells it to use the last row index, and `fill_value=0` will assign zeros to all elements that were not present in the initial `DataFrame`, such as the combination `(Wales, True)`.

[68]:
```
# DataFrame with countries in rows, Pre-1800 indicator in columns

# Pivot inner index level to create separate columns for True/False
# values of Pre1800 indicator
df_count = count.unstack(level=-1, fill_value=0)

# Set name of column index to something pretty: this will
# be used as the legend title
df_count.columns.rename('Founding year', inplace=True)
# Rename columns to get pretty labels in legend
df_count.rename(columns={True: 'Before 1800', False: 'After 1800'},
                inplace=True)

df_count
```

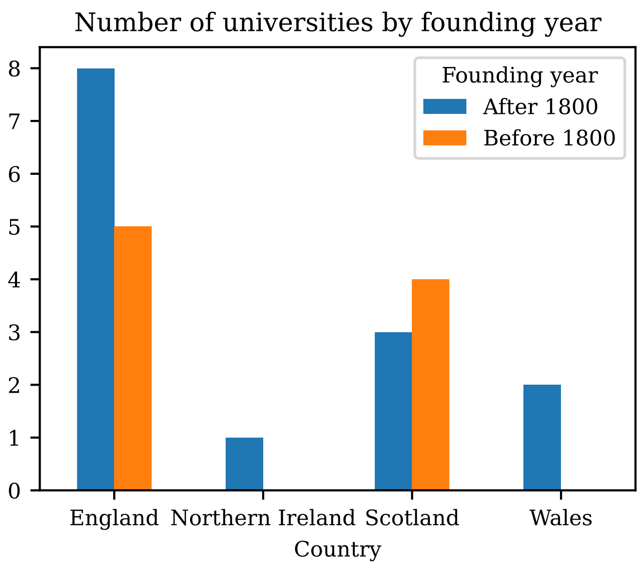
[68]:
```
Founding year     After 1800  Before 1800
Country
England                    8            5
Northern Ireland           1            0
Scotland                   3            4
Wales                      2            0
```

Whenever we use pandas's built-in plotting functions, these use index names and labels to automatically label the graph. We therefore first have to assign these objects "pretty" names.

We can then generate the bar chart as follows:

[69]:
```
# Create bar chart by country
title = 'Number of universities by founding year'
# pass rot=0 to undo the rotation of x-tick labels
# which pandas applies by default
df_count.plot.bar(xlabel='Country', rot=0, title=title)
```

[69]:
```
<Axes: title={'center': 'Number of universities by founding year'},
xlabel='Country'>
```



Note how the legend title is automatically set to the column index name and the legend labels use the column index labels.

We create the second `DataFrame` with the founding period in rows and country names in columns in exactly the same way, but now call `unstack(level=0)` so that the first index level will be pivoted.

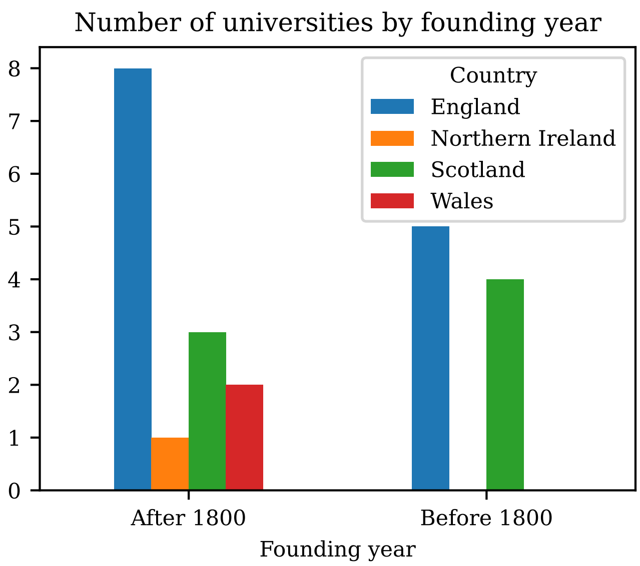
[70]:
```
# Pivot first row index level to create separate columns for each country
df_count = count.unstack(level=0, fill_value=0)

# Set index name to something pretty
df_count.index.rename('Founding year', inplace=True)
# Rename index labels to get pretty text in legend
df_count.rename(index={True: 'Before 1800', False: 'After 1800'},
                inplace=True)

df_count
```

[70]:

Country	England	Northern Ireland	Scotland	Wales
Founding year				
After 1800	8	1	3	2
Before 1800	5	0	4	0

[71]:
```
# Create bar chart by founding year
# pass rot=0 to undo the rotation of x-tick labels
# which pandas applies by default
df_count.plot.bar(rot=0, title=title)
```

[71]:
```
<Axes: title={'center': 'Number of universities by founding year'},
xlabel='Founding year'>
```



6.9.5 Solution for exercise 5

This exercise is quite involved, so we will discuss it in parts. First, we write the function that will be called by `apply()` to process sub-sets of the data which belong to a single decade:

[72]:
```
def regress_okun(x):
    # x is a DataFrame, restricted to rows for the current decade

    # Extract dependent and regressor variables
    outcome = x['unempl_gap'].to_numpy()
    GDP_gap = x['GDP_gap'].to_numpy()

    # Regressor matrix including intercept
    regr = np.ones((len(GDP_gap), 2))
    # overwrite second column with output gap
    regr[:,1] = GDP_gap

    # Solve least-squares problem (pass rcond=None to avoid a warning)
    coefs, *rest = np.linalg.lstsq(regr, outcome, rcond=None)

    # Construct DataFrame which will be returned to apply()
    # Convert data to 1 x 2 matrix
    data = coefs[None]
    columns = ['Const', 'GDP_gap']
    df_out = pd.DataFrame(data, columns=columns)

    return df_out
```

This function is passed in a single argument which is a `DataFrame` restricted to the sub-sample that is currently being processed.

- Our task is to perform the required calculations and to return the result as a `DataFrame`. `apply()` then glues together all decade-specific DataFrames to form the result of the operation.
- We first extract the relevant variables as NumPy arrays, and we create a regressor matrix which has ones in the first column. This column represents the intercept.
- We invoke `lstsq()` to run the regression. `lstsq()` returns several arguments which we mop up in the tuple `*rest` since we are only interested in the regression coefficients.

  Note that we wouldn't be using `lstsq()` to run OLS on a regular basis, but it's sufficient for this use case.

- Finally, we build the `DataFrame` to be returned by this function. It has only one row (since we ran only one regression) and two columns, one for each regression coefficient.

This was the hard part. We now need to perform some standard manipulations to prepare the data:

1. We construct the output gap (in percent), which we store in the column `GDP_gap`.
2. We construct the cyclical unemployment rate and store it in the column `unempl_gap`.
3. We determine the decade each observation belongs to using the same code as in previous exercises.
4. We then drop all unused variables from the `DataFrame` and also all observations which contain missing values.

Lastly, we can call `apply()` to run the regression for each decade.

[73]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Use either local or remote path to data/ directory
# DATA_PATH = '../data'
DATA_PATH = 'https://raw.githubusercontent.com/richardfoltyn/python-intro-PGR/main/data'

# Load CSV file
filepath = f'{DATA_PATH}/FRED_QTR.csv'
df = pd.read_csv(filepath, sep=',')

# Generate output gap (in percent)
df['GDP_gap'] = (df['GDP'] - df['GDPPOT']) / df['GDPPOT'] * 100.0

# Generate deviations of unempl. rate from natural unempl. rate
df['unempl_gap'] = df['UNRATE'] - df['NROU']

# Assign decade using // to truncate division to
# integer part. So we have 194x // 10 = 194 for any x.
df['Decade'] = (df['Year'] // 10) * 10

# Keep only variables of interest
df = df[['Decade', 'GDP_gap', 'unempl_gap']]
# Drop rows with any missing obs.
df = df.dropna(axis=0)

# Group by decade
grp = df.groupby(['Decade'])

# Apply regression routine to sub-set of data for each decade
df_reg = grp.apply(regress_okun)
# Get rid of second row index introduced by apply()
df_reg = df_reg.reset_index(level=-1, drop=True)

# Display intercept and slope coefficients
# estimated for each decade.
df_reg
```

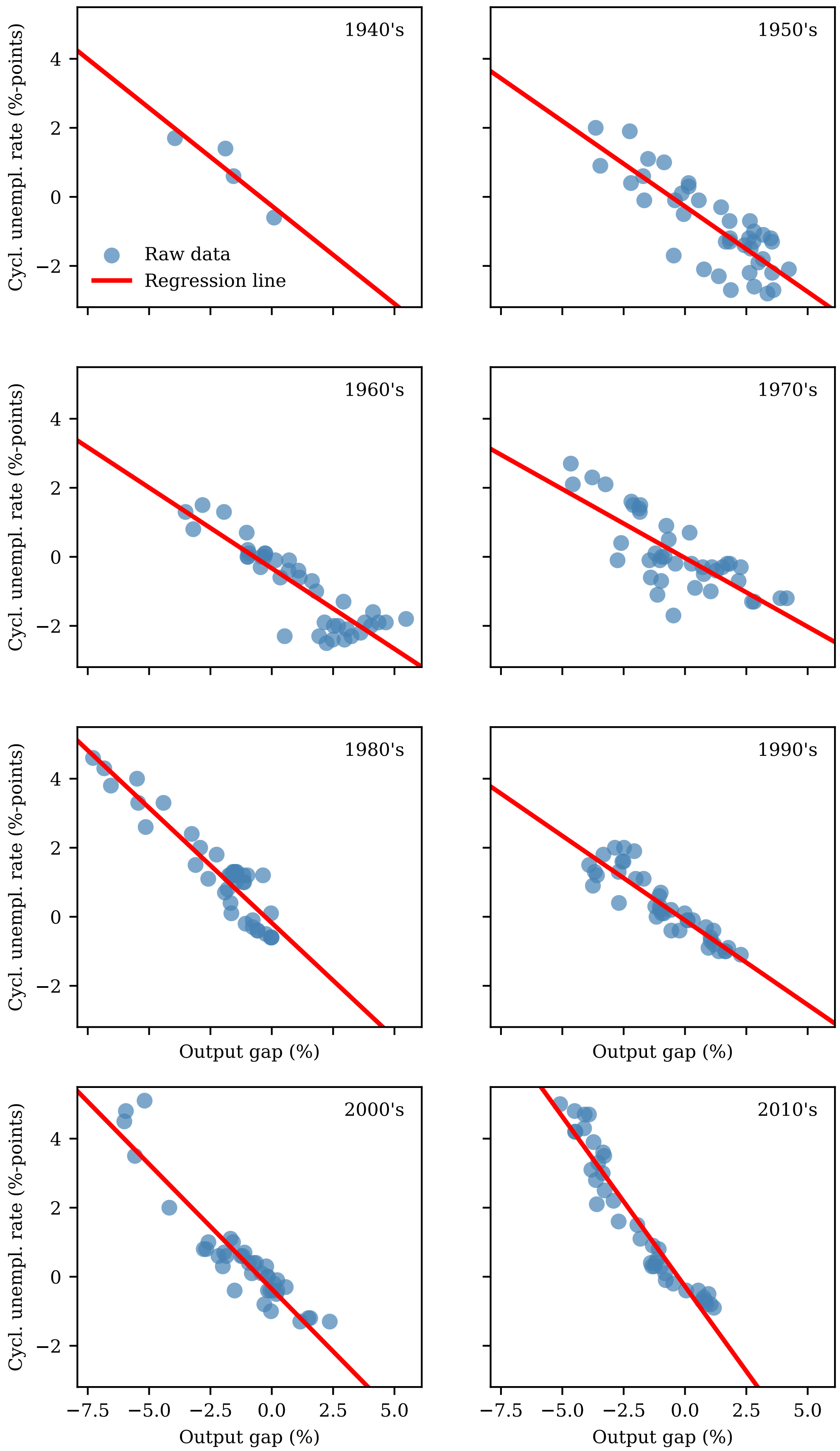
[73]:
```
           Const   GDP_gap
Decade
1940   -0.259986 -0.567257
1950   -0.277104 -0.494637
1960   -0.331665 -0.467206
1970   -0.032063 -0.398751
1980   -0.178001 -0.666688
1990   -0.102465 -0.489427
2000   -0.355138 -0.723567
2010   -0.279333 -0.983768
```

The following code creates 8 panels of scatter plots showing the raw data and overlays a regression line for each decade.

[74]:
```
# Number of plots (= number of decades)
Nplots = len(df_reg)

# Fix number of columns, determine rows as needed
ncol = 2
nrow = int(np.ceil(Nplots / ncol))

fig, axes = plt.subplots(nrow, ncol, sharey=True, sharex=True,
                         figsize=(6, 11))

for i, ax in enumerate(axes.flatten()):

    # decade in current iteration
    decade = df_reg.index.values[i]
    # restrict DataFrame to decade-specific data
    dfi = df.loc[df['Decade'] == decade]
    # Scatter plot of raw data
    ax.scatter(dfi['GDP_gap'], dfi['unempl_gap'], color='steelblue',
               alpha=0.7, label='Raw data')
    # Extract regression coefficients
    const = df_reg.loc[decade, 'Const']
    slope = df_reg.loc[decade, 'GDP_gap']

    # plot regression line:
    # We need to provide one point and a slope to define the line to be plotted.
    ax.axline((0.0, const), slope=slope, color='red',
              lw=2.0, label='Regression line')

    # Add label containing the current decade
    ax.text(0.95, 0.95, f"{decade}'s", transform=ax.transAxes,
            va='top', ha='right')

    # Add legend in the first panel only
    if i == 0:
        ax.legend(loc='lower left', frameon=False)

    # Add x- and y-labels, but only for those panels
    # that are on the left/lower boundary of the figure
    if i >= nrow * (ncol - 1):
        ax.set_xlabel('Output gap (%)')
    if (i % ncol) == 0:
        ax.set_ylabel('Cycl. unempl. rate (%-points)')

fig.suptitle("Okun's law")
```

[74]:
```
Text(0.5, 0.98, "Okun's law")
```

Okun's law


1940's
1950's
1960's
1970's
1980's
1990's
2000's
2010's
Raw data
Regression line
Cycl. unempl. rate (%-points)
Output gap (%)
4
2
0
−2
−7.5
−5.0
−2.5
0.0
2.5
5.0