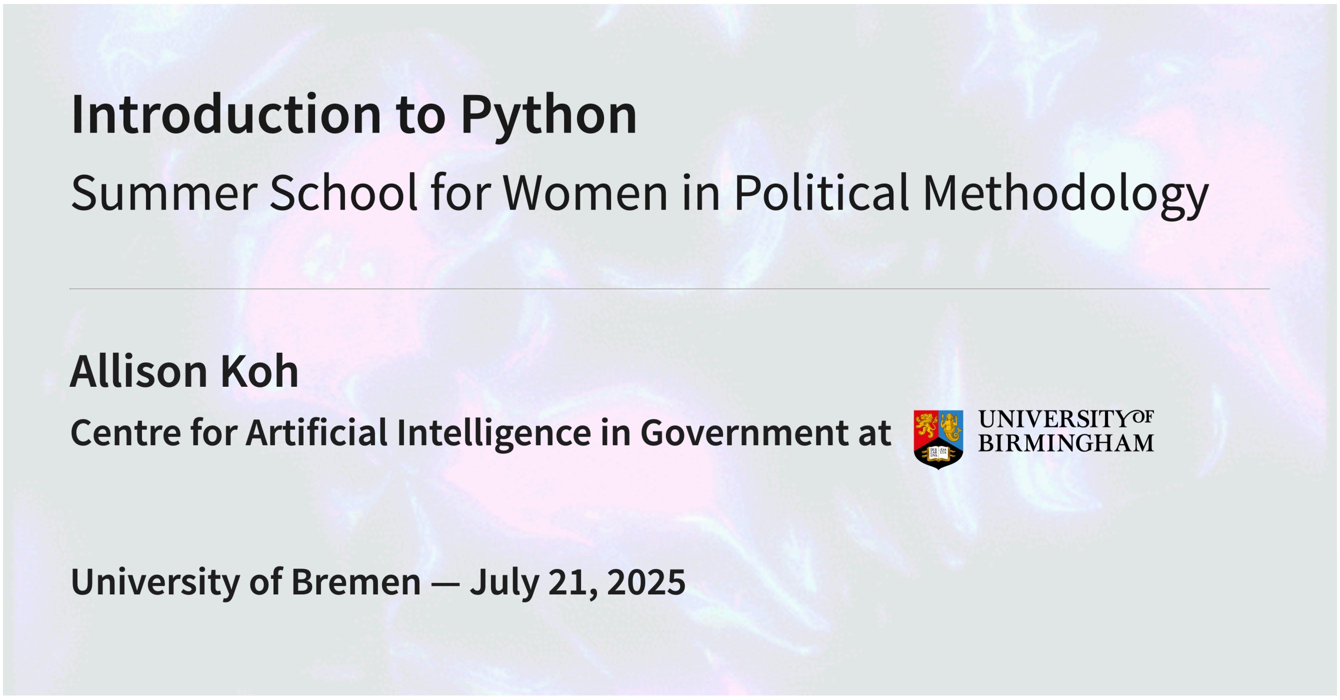
Welcome!



Introduction to Python

Summer School for Women in Political Methodology

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Course Description

While R is widely used by political scientists for data analysis, most of the cutting-edge work in machine learning and natural language processing happens in Python. This course offers an introduction to programming and data management in Python, designed with R users in mind. Participants will learn the building blocks needed to navigate Python syntax, adapt existing code, and begin integrating Python into their workflows for data management and analysis.

Overview

This afternoon, we will be going over:

- The basics of coding in Python
- Data management with `pandas` 🐼

Getting Started in Python

Python is a general-purpose programming language widely used for tasks like data analysis, machine learning, and natural language processing. Compared to `R`, which is designed for statistical computing with resources tailored for academic research, many Python tools are designed to be production-grade. This means that they are built not just for researchers and statisticians, but also for deployment, automation, and integration into broader systems.

For researchers who primarily use `R`, Python is a powerful complement that can expand what they're able to build, analyze, and automate in their workflows.

Using Google Colab

For this workshop, we will be using Google Colab. If you have used `.Rmd` or `.qmd` files in your `R` workflow, using Google Colab will feel familiar as a medium that combines code, narrative text, and outputs into one document. Colab is also built on the Jupyter notebook format, which is one of the most widely used notebook environments in the Python ecosystem.

The best part of using Colab for our purposes: *no installation of any software or dependencies needed to execute code!* In contrast, editors like Microsoft's [Visual Studio Code (VSCode)] usually require setting up your own Python environment. While that setup is fairly straightforward, we won't be covering it in today's session.

Another feature of Colab is integration into Gemini/generative code; would recommend for the purposes of this workshop to refrain from using it to really gain the intuition of Python syntax. Although for everyday use it seems decent if you end up using Colab as your editor

Keyboard Shortcuts

Google Colab has a variety of keyboard shortcuts that can speed up your workflow--these will become more intuitive as you begin actively using it yourself. Here are some useful ones to start with:

Action	Shortcut
Open command palette	`Ctrl/Cmd + Shift + P`
Show all shortcuts (cheatsheet)	`Ctrl/Cmd + M H`
Run current cell	`Shift + Enter`
Convert to code cell	`Ctrl/Cmd + M Y`
Convert to text/Markdown cell	`Ctrl/Cmd + M M`
Insert code cell above	`Ctrl/Cmd + M A`
Insert text cell below	`Ctrl/Cmd + M B`.
Delete current cell	`Ctrl/Cmd + M D`
Undo deleted cell	`Ctrl/Cmd + M Z`
Exit editing mode	`Esc`

Another way to discover keyboard shortcuts is by manually performing tasks in the editor. In Google Colab, when you complete an action using your mouse, a small popup will appear showing the keyboard shortcut for that action.

Language support

Another advantage of Google Colabs is that there is language support in Python, `R`, and Julia! So if you end up liking Colab, you can also use it for your R notebooks.

Working with external files

One of the more tedious aspects of using Google Colab is dealing with importing and exporting external files. While we won't dive too deep into that rabbit hole today, we do need to touch on it because we'll be working with data stored outside of Colab (and you will likely also do this throughout the week).

Today, we will upload data from our local machines. I will walk you through that process when we get to it.

If you are curious and want to explore more advanced file-handling options, you can check out this Colab notebook: https://colab.research.google.com/notebooks/io.ipynb#scrollTo=u22w3BFiOveA

Data

Speaking of external files, we will use the Parties‘ Immigration and Integration Positions (PImPo) dataset (Lehmann and Zobel 2018) to practice data management. As stated in the codebook for the dataset:

> The Parties' Immigration and Integration Positions Dataset (PImPo) includes data on parties' immigration and integration positions and saliency in 14 countries (Australia, Austria, Canada, Sweden, Denmark, Finland, Germany, Ireland, Netherlands, New Zealand, Norway, Spain, Switzerland, USA) between 1998 and 2013 based on crowd coding of parties' election manifestos.

To follow along, you'll need to upload the dataset from your local machine into Google Colab. Here's how to do it:

1. Download the **PImPo Party-Level DS** CSV file from here: https://manifesto-project.wzb.eu/information/documents/pimpo
2. Run the following code chunk to upload the file from your local system.

Note: Using this method, you will have to re-upload the file for every session. This method is convenient enough for our purposes (allocating more time for the coding over setup), but you probably wouldn't handle files this way for research projects.

```
from google.colab import files

uploaded = files.upload()
```

The following block of code will provide the file path.

```
for fn in uploaded.keys():
  print('User uploaded file "{name}" with length {length} bytes'.format(
      name=fn, length=len(uploaded[fn])))
```

Key Concepts

Shifting paradigms: functional programming in `R` vs. object-oriented programming in Python

Before jumping into the code, let's take a moment to unpack some big-picture things that will help us frame our approach for using Python.

We spent the first half of today focusing on functional programming (FP) in `R`. Overall, functional programming is a great paradigm for understanding how to organize what we want to do with our code and data.

While Python also supports FP, its dominant programming paradigm is **object-oriented programming (OOP)**. OOP focuses more on what an object *does*, rather than what to do with an object.

For example, a data frame in Python (`pandas.DataFrame`) is an object that contains methods like `.head()`, `.groupby()`, `.min()`, `.max()`, and `.mean()`. This is different from how `dplyr` works in `R`, where similarly named functions are applied to objects but exist outside of them. In other words, functions are not built into the data frame itself.

In this course, we won't be delving into the conceptual logics behind FP and OOP. However, as we work through applied examples, you'll start to notice how this difference shapes the way we write and organize code in Python compared to `R`.

Data types: R vs. Python

Similar to `R`, we can use integers, floating point numbers, boolean values, and strings in Python. Here's what each data type represents:

- Integers: numbers without a decimal
- Floating point numbers: numbers with a decimal
- Booleans: `True` or `False` values
- Strings: Typically a representation of plain text. *However*, anything that is wrapped in quotes (single or double) is treated as a string.

Here's an overview of the different variable types between `R` and Python:

Data type	R	Python
Integers	`numeric`	`int`
Floating point numbers	`numeric`	`float`
`True` or `False` values*	`logical`	`bool`
Strings	`character`	`str`

Functions vs. Methods vs. Attributes

Functions work similarly in both `R` and Python. However, while `R` relies heavily on functions, Python relies on functions, methods, *and* attributes.

Functions, methods, and attributes behave similarly, but they are not the same. This distinction reflects the underlying design philosophies of the languages: R is inherently a functional programming language, while Python is object-oriented.

As discussed earlier, in Python, **everything is an object** — variables, lists, strings, and even functions themselves. Each object can have its own **attributes** (stored properties) and **methods** (built-in actions it can perform).

The key difference between functions, methods, and attributes is how they're called:

- A **function** takes an object as an input (e.g., `len(my_list)`).
- A **method** is called *by* the object itself (e.g., `my_list.append(42)`).
- An **attribute** is accessed directly from the object without parentheses (e.g.: `my_list.size`)

Because methods are defined inside an object's class, they are specific to that type of object. In other words, a list has list-specific methods, a string has string-specific methods, and so on.

So far, we have only been applying built-in functions to objects. Now all that's about to change! Let's treat objects the way they're meant to be treated in Python.

A note on syntax: `.`

In Python, periods (.) cannot be used in variable or function names because they have specific, reserved meanings in Python. The dot notation is used for:

- Calling methods on objects (e.g., `my_string.upper()`)
- Accessing attributes of objects (e.g., `person.name`)
- Navigating modules and submodules (e.g., `math.sqrt`, `pandas.read_csv`)

You will encounter this notation often, and we will see how it works in each of these contexts as we move through the applied examples that follow.

Python 101

Before we start writing programs in Python, let's first walk through some foundational concepts that explain how Python works under the hood: the core data types and built-in data structures that you'll use all the time.

- Data types
- Assignment
- Strings
- Lists
- Dictionaries

Data types

There are four data types:

- Integers (`int`): numbers without a decimal
- Floating point numbers (`float`): numbers with a decimal
- Booleans (`bool`): `True` or `False` values
- Strings (`str`): Typically a representation of plain text. *However*, anything that is wrapped in quotes (single or double) is treated as a string.

The built-in function to check data types in Python is `type()` . This behaves the same as the `class()` function in `R` .

```
# Integers and floats
x = 5           # int
y = 3.14        # float

# Boolean
z = True        # bool

# String
name = "Alice"  # str
```

And here is how to check the data type of an object:

```
# Check types
type(z)
```

You can convert an object to a different type by calling the type as a function:

```
xx = str(5)
print(xx)
print(type(xx))
```

Assignment

In `R` , we typically use `<-` to assign values to objects. However, in Python, you can only use `=` for assigning values in Python.

Because there is no directional indicator with the equal sign, the values are always on the right hand side while the variable/object will always be on the left-hand side.

```
x = 3

y = 0.5

z = True
```

Printing

Use the `print` function if you want an object to be shown:

```
'Hello!'
'Hello world!'
```

```
print('Hello!')
print('Hello world!')
```

Working with strings

Knowing data types is important because you will get different behavior from different operations depending on the type of objects you're working with.

This is especially important for Python because, unlike `R`, you can perform mathematical operations across data types.

Mathematical operations with character strings are referred to as *string operations*. String operations are particularly useful for things like text analysis.

The examples below demonstrate how string operations work.

```
type(1)
```

```
type('1')
```

```
1 + 1
```

When you add two strings using the `+` operator, the two strings are concatenated:

```
'1' + '1'
```

A string multiplied by an integer *n* will repeat the string *n* times:

```
'1' * 5
```

Strings that are placed next to each other are automatically concatenated:

```
'1' '1'
```

```
print("3" + "4")
print("3" * 2)
print(3 + 4)
print(type("3" + "4"))
```

Exercise 1

- Assign the string "5" to a variable called `num_string`.
- Assign the integer `5` to a variable called `num_int`.
- Try printing `num_string + num_int`. What happens?
- Convert one of the variables to fix the error, and write an expression that produces the integer 55.

```
____ = ____
____ = ____
```

```
num_string + num_int
```

```
num_int = ___(num_int)
___(num_string + num_int)
```

Lists

Lists are a very common data structure in Python that can hold heterogenous information. They are created with a pair of square brackets. Each element in a list is separated by a comma. e.g.:

```
l = [1, True, "3"]
```

Python is a **0-indexed language**. This means counting starts at 0, and not 1.

If you're accustomed to coding in `R`, this can feel a bit unintuitive at first. This is because R uses 1-based indexing, so the first item in a vector or list is at position 1. In Python, the first item is at position 0, the second at 1, and so on.

This difference is especially important when you're accessing elements in lists or dictionaries, and it's a common stumbling block when switching between the two languages. With practice, though, 0-based indexing becomes second nature!

Subsetting lists

To extract an element from a Python list, you can use one pair of square brackets:

```
l[0]
```

Negative indices

You can select an element from the end of a list using **negative indices**:

```
l[-1]
```

-1 selects the last element in a list, -2 selects the penultimate element, and so on...

Slicing

Slicing refers to the extraction of multiple list elements.

To simultaneously select multiple elements you use the colon notation. The first value represents the beginning index, and the second value represents the last index:

```
l = [0, 1, 2, 3, 4, 5]
l[0:3]
```

You can also have an additional third value to specify a step size:

```
l[0:5:2]
```

The indices you pass into the colon notation can be optional.

If you leave the first value blank, Python will slice from the beginning to the second specified index:

```
l[:3]
```

If you leave the second value missing, Python will slice from the first specified index until the end:

```
l[1:]
```

If you leave the first two values blank, and just specify a step size, Python will go through the entire list and return the elements depending on the specified step size:

```
l[::2]
```

Dictionaries

While Python lists are great for storing information, they don't support named elements like R's named lists.

Instead, Python uses **dictionaries** for labeled data, where each item is stored as a key–value pair.

Python dictionaries are created with a pair of curly-brackets. Each key-value pair includes a colon, with the key to the left, and the value to the right of the colon. Multiple key-value pairs are separated by commas:

```
d = {'int_value':1, 'bool_value':True, 'str_value':'three'}
```

You can extract a "value" from the dictionary is by placing the "key" of the dictionary inside the square brackets:

```
d['str_value']
```

Note: Always access a value using its key, not by assuming where it appears in the dictionary.

You can find the number of elements in a list or dictionary by using the `len()` function:

```
print(len(d))
print(len(l))
```

Exercise 2

- Create a list called `characteristics` that contains the following strings: 'first_name', 'last_name', 'age', 'education', and 'employed'.
- Create a dictionary called `person` that assigns values to each of the characteristics.
- Print the full name of your person based on the values assigned in your person dictionary.

```
characteristics = []
person = {}
print(person['first_name'], person['last_name'])
```

Functions, methods, and attributes

As previously discussed, functions work similarly in both `R` and Python. However, while `R` relies heavily on functions, Python relies on functions, methods, *and* attributes.

Appending lists

You can add elements to a list using the `append()` method:

```
l = [0, 1, 2, 3, 4, 5]
l.append(6)
l
```

Note the use of the dot notation to call the `append` method from the `list` object.

Updating dictionaries

For dictionaries, you can call the `update()` method:

```
d = {'lol':'laugh out loud', 'idk':'i dont know', 'fml':'f my life'}
d.update({'dm': 'dont mind', 'afaik': 'as far as i know'},)
d
```

If the key already exists, the dictionary will be updated with the new value. Otherwise, new keys will be added to the dictionary (as above).

```
d.update({'dm': 'direct message'})
d
```

Exercise 3

- What happens when you try to run the following code chunk? Why?
- Edit the code to address this error.

```
d.append({'rofl': 'rolling on the floor laughing'})
```

Answer: Fill in your answer here

```
# Write the correct code here
d._____({'rofl': 'rolling on the floor laughing'})

# Check that it works
d
```

Libraries

Libraries in Python are similar to packages in `R`: they extend the base language with specialized tools and data structures.

Many of the objects that are widely used in data science are not built into Python by default. To use them, you'll need to import external libraries.

Two libraries you'll likely use in nearly every data analysis script are:

- `numpy`: Provides support for **numeric arrays and matrix operations**
- `pandas`: Offers the `DataFrame` object for working with tabular data (similar to `dplyr` in `R`)

When you load a package in `R`, you can use any of the functions from that package directly. However, things work a little differently with Python.

To load in a Python library, you use the `import` keyword, e.g.:

```
import numpy
```

It is also useful to have information on the versions of libraries you use in your code; this is helpful information for both replicability and troubleshooting:

```
numpy.__version__
```

Once you import the library, you have to access functions from the library using the dot notation: `library_name.function_name`, e.g.:

```
numpy.array([1, 2, 3])
```

Typing the full library name each time can get tedious. Since you *have* to use library names to call the functions attached to them, Python allows you to create a shortcut called an *alias*.

It's common practice to import NumPy as `np` and Pandas as `pd`:

```
import numpy as np
import pandas as pd
```

Now, instead of writing `numpy.array`, you can write:

```
np.array([1, 2, 3])
```

Data management with `pandas` 🐼

As previously mentioned, we'll be using the **Parties' Immigration and Integration Positions Dataset (PImPo)** for our applied examples. The dataset, which is an expansion of the data resources offered by the Manifesto Research on Political Representation (MARPOR), includes information on the following variables:

- `country`: MARPOR country id
- `party`: MARPOR party id
- `date`: election date
- `totals`: total quasi-sentences (QSs) coded
- `totals_immi`: total QSs on immigration
- `totals_inti`: total QSs on integration
- `saliency`: the proportion of QSs related to immigration and integration relative to the total QSs coded
- `saliency_immi`: proportion of immigration-related QSs relative to total QSs coded
- `saliency_inti`: proportion of integration-related QSs relative to total QSs coded
- `immi_pos`: a score that indicates how positively or negatively a party talks about immigration
- `immi_pos_saliency`: the percentage of directional (non-neutral stance) QSs about immigration
- `inti_pos`: a score that indicates how positively or negatively a party talks about integration
- `inti_pos_saliency`: the percentage of directional (non-neutral stance) QSs about integration

Loading datasets

Now that we've got everything we need, let's play around with data! First, let's import the `pandas` library under the alias `pd`:

```
import pandas as pd
```

Now let's load in our data using the `pandas.read_csv` function:

```
df = pd.read_csv("PImPo_party.csv")
```

Note: See the above section on data if you need to first upload the dataset from your local files.

Data frame at a glance

Let's inspect the data.

```
df.head()
```

Here you'll see that there are three components to a `Pandas` data frame:

- Column names on the top
- Index on the left
- Body of the data frame

Each of these components are *attributes* that can be accessed independently of one another, e.g.:

```
df.columns
```

Note that `()` is not necessary for this call since `columns` is not a function or method.

Calling a data frames *index* may be helpful when working with time series data; you can replace the original index with date-time information. This is how you access it:

```
df.index
```

The `shape` attributes store the dimensions of the data frame.

```
df.shape
```

The `values` attribute returns the body of the data frame:

```
df.values
```

If you don't have too many columns, `info()` is useful for summarizing what's in the data.

```
df.info()
```

Exercise 4

What do we now know about the data from this information, that we didn't know from looking at the `index`, `shape`, and `values` attributes?

Answer: Fill in your answer here

Subsetting data

Now that we've had a look at the data, let's do something with it!

Selecting a single column

If you want to extract a single column from a pandas DataFrame, you can use the square bracket notation:

```
df['country']
```

These numbers aren't the most useful for us; even with a key, it would be easier/more readable for the country names to be included in the data. We'll get to that in a bit.

We can take this column and save it to its own variable:

```
country_df = df['country']
```

Then we can preview only the first few rows using the `.head()` method:

```
country_df.head()
```

Let's check out the type of `country_df`:

```
type(country_df)
```

This tells us that a single column of a DataFrame is a Series, *not* a DataFrame. While they are very similar and interrelated, this also means that each of these object types have their own set of methods and attributes.

Selecting multiple columns

Let's say you want to select multiple columns from the dataset—specifically, information about the country, political party, and the total number of quasi-sentences coded.

Here's how you can do that and store it in a list:

```
subset = df[['country', 'party', 'totals']]
subset.head()
```

The double square brackets indicate that you are both taking the subset of the data frame and storing it as a list.

Filtering rows with `.loc[]` and `.iloc[]`

In pandas, there are two ways to access specific rows from a DataFrame: `.loc[]` and `.iloc[]`.

`.loc[]` (location) retrieves rows based on the row label, which is what we saw in our initial glance of the data. It's not about the row's numeric position, but what the index is *named*:

```
df.loc[2]
```

Note that, if you end up combining datasets, you may end up with two rows that have the same index number if the index labels correspond to the respective original datasets. So `.loc[]` can be a bit tricky in that way.

On the other hand, `.iloc[]` (index location) identifies rows based on their position. Recall that Python is 0-indexed. This means that, for example, `iloc[2]` will always return the third row, which is indexed at position 2.

```
df.iloc[2]
```

If you want to access multiple rows, you can put that set in a python list (like we did with columns), e.g.:

```
df.iloc[[5, 2]]
```

Extracting multiple rows and columns based on location

We use `.loc[]` to subset both rows and columns in a `DataFrame`. The syntax is similar to how subsetting works in `R`: **rows go on the left, columns go on the right, separated by a comma** inside the brackets.

```
df.iloc[0:5, 0:4]
```

As we reviewed with slicing elements of a list, we can use shortcuts to indicate ranges of rows and/or columns:

```
df.iloc[:5, :4]
```

Filtering rows with boolean subsetting

Sometimes, instead of selecting rows by their position or label, it makes more sense to filter them based on the values in one or more columns. This is known as *boolean subsetting*.

In pandas, you can create a condition that--under the hood--returns `True` or `False` for each row, and use that to filter the DataFrame.

Let's say we are only interested in looking at parties from Germany (country code `41`), and their positions on immigration (`immi_pos`). This is how we would subset the data to get this information:

```
df.loc[df['country'] == 41, ['date', 'country', 'party', 'immi_pos']]
```

Filtering rows with multiple boolean subsetting

Let's say we now want to filter based on two criteria:

- Germany (`country` = 41)
- anti-immigrant positions (`immi_pos` < 0)

To do this, we wrap each condition in its own set of parentheses and connect them using a logical operator (`&` for "and", `|` for "or"):

```
df.loc[(df['country'] == 41) & (df['immi_pos'] < 0), ['date', 'country', 'party', 'immi_pos']]
```

Exercise 5a

Run the two code chunks below. What do you notice about the similarities and differences in their outputs? Why are they behaving this way?

Hint: Have another glance at the `.head()` of the data frame to inspect how the rows are labeled.

```
df.loc[3]
```

```
df.iloc[3]
```

```
df.head()
```

Answer: Fill in your answer here

Exercise 5b

Use boolean filtering to create a data frame with information on the immigration and integration positions of political parties from the U.S. and Canada.

Hint: Have a look at the codebook: https://manifesto-project.wzb.eu/down/datasets/pimpo/PImPo_codebook.pdf#page=9.60

```
df.loc[(df['country'] == ___) ___ (df['country'] == ___), ['country', 'date', 'party', 'immi_pos', 'inti_pos']]
```

Tidy data management

Let's transform this data for analysis. We will select the variables we are interested in, reshape the data, and compute grouped summaries. If you have used `dplyr` or `tidyr` in R, some of the Python syntax will feel similar.

For your reference, here are some of the more common data wrangling tasks and their implementation in Python/ R:

Task	Description	Python (`pandas`)	R (`tidyverse`)
Recoding variables	Map values using a dictionary/lookup	`df['column'].map(dictionary)`	`dplyr::recode()` or `case_when()`
Selecting columns	Keep only specified columns	`df[['col1', 'col2', 'col3']]`	`dplyr::select(col1, col2, col3)`
Reshaping wide to long	Convert wide format to long format	`pd.melt()`	`tidyr::pivot_longer()`
Dropping missing values	Remove rows with missing values	`df.dropna()`	`tidyr::drop_na()`
Converting data types	Change column data types	`df['col'].astype()`	`dplyr::mutate()` with type conversion
Date parsing	Convert strings/integers to datetime	`pd.to_datetime()`	`lubridate::ymd()`, `as_date()`
Extracting date parts	Extract year, month, etc. from dates	`df['date'].dt.year`	`lubridate::year()`, `month()`
Grouping data	Group data by specified variables	`df.groupby(['col1', 'col2'])`	`dplyr::group_by(col1, col2)`
Summarizing grouped data	Calculate summary statistics by group	`.groupby().mean()`, `.sum()`, `.count()`	`dplyr::summarize(mean(), sum(), n())`
Resetting index	Convert grouped result back to regular DataFrame	`df.reset_index()`	`dplyr::ungroup()`

Let's say we want to **compare the average immigration and integration positions of political parties across countries and over time**. With this goal in mind, we need to:

1. Make the dataset more interpretable by mapping country codes to meaningful names.
2. Only keep the columns we care about.
3. Reshape the data from wide to long.
4. Drop missing values.
5. Convert the date variable to `datetime` format
6. Group and summarize the data by country and year.

Mutating/recoding variables

Based on the codebook, we can create a dictionary that maps `country` codes onto country names:

```
country_labels = {
    11: 'Sweden',
    12: 'Norway',
    13: 'Denmark',
    14: 'Finland',
    22: 'Netherlands',
    33: 'Spain',
    41: 'Germany',
    42: 'Austria',
    43: 'Switzerland',
    53: 'Ireland',
    61: 'USA',
    62: 'Canada',
    63: 'Australia',
    64: 'New Zealand'
}
```

We can then `map` this dictionary onto the dataset:

```
df['country'] = df['country'].map(country_labels)
```

Great, let's check to see that this worked:

```
df.head()
```

Select columns of interest

What are the relevant variables that we need to select for this exercise?

Let's have a look at what the variables are:

```
df.columns
```

Based on this information, we see that we only need 5 variables:

- `country`
- `party`
- `date`
- `immi_pos`
- `inti_pos`

```
df_subset = df[['country', 'party', 'date', 'immi_pos', 'inti_pos']]
```

Great, let's have another look at the data:

```
df_subset.head()
```

Reshaping the data from wide to long

Right now, immigration and integration positions are stored in separate columns — this means our data is in wide format. To make it easier to summarize, reshape, or visualize, we'll use `pd.melt()` to convert the dataset into long format:

```
df_long = pd.melt(
    df_subset,
    id_vars=['country', 'party', 'date'],
    var_name='position_type',
    value_name='position_score'
)
```

Great, let's have a look at the resulting data frame:

```
df_long
```

Dropping rows with missing values

We see that there are some `NaN` values under the `position_score` variable. This is going to impede on our goal of grouping and summarizing information from this variable.

Let's deal with these missing values. To do this, we drop any rows where `position_value` is missing using Panda's `.dropna` method:

```
df_complete = df_long.dropna(subset=['position_score'])
```

Great, let's check to see if this removed anything. We can do this using a combination of two methods:

- `.isna()` : returns `True` for missing values, `False` otherwise
- `.any()` : checks for the presence of something; returns `True` if it is found and `False` otherwise

Let's look at these one by one. This is what happens if you just use `.isna()` :

```
df_long['position_score'].isna()
```

It does the job, but we can present this information more cleanly. This is where `.any()` comes in:

```
df_long['position_score'].isna().any()
```

Now let's check for any missing values in `df_complete` :

```
df_complete['position_score'].isna().any()
```

Working with dates 📅

Dates in raw datasets are often stored as integers or strings. However, to work with them meaningfully (e.g. group by year, extract months, compare time periods), we need to convert them to a `datetime` format.

If you've used `lubridate` in `R`, this is similar to using functions like `ymd()` or `as_date()` to unlock date-aware functionality.

Pandas has a method called `to_datetime` that converts a variable into `datetime` format.

To get an idea of how this works, let's first inspect the type of variable we're starting out with. Let's try applyin the `type()` function from before:

```
type(df_complete['date'])
```

Did this give us the information we wanted? **Nope!** We instead got the type of the entire column, which is a `Series` as previously discussed.

In `pandas`, when we are interested in inspecting a variable's type, we call the `.dtype` method:

```
df_complete['date'].dtype
```

Okay, so we're starting out with an integer. We're going to need to convert this to a string variable if we want to then parse it to `datetime` format:

```
df_complete['date'] = df_complete['date'].astype(str)
```

Let's create a new variable `year_month`, which is a `datetime` object based on the existing `date` variable:

```
df_complete['year_month'] = pd.to_datetime(df_complete['date'], format='%Y%m')
```

We can use the `datetime` Python library to further parse our `year_month` variable:

```
import datetime as dt

df_complete['year'] = df_complete['year_month'].dt.year
df_complete['month'] = df_complete['year_month'].dt.month

df_complete.info()
```

Grouping and summarizing the data

Now that we have prepared our data, let's get to computing the average party positions regarding immigration and integration, disaggregated by country-years.

As with before, the syntax we use to group and summarize pandas data frames should seem familiar to similar functions if you are used to working with `dplyr`'s `group_by()` and `summarize()`.

The `.groupby()` method groups the data based on specified variable(s):

```
df_complete.groupby(['country', 'year'])
```

However, nothing happens with the data until you combine `.groupby()` with an aggregation method such as:

- `.mean()`
- `.count()`
- `.sum()`

```
df_avg_scores = df_complete.groupby(['country', 'year', 'position_type'])['position_score'].mean()
df_avg_scores.head()
```

Great, looks like we're getting somewhere! Let's just check one thing:

```
type(df_avg_scores)
```

Uh oh, that's not a data frame! Sometimes, when you're subsetting data frames to create new data frames, you should check if Python has recognized the new data frame as its own data frame.

We can remedy this with the `.reset_index()` method:

```
df_final = df_avg_scores.reset_index()
```

Nearly there; now that the calculations have been made, this data frame would probably be a little easier to read/more interpretable in its wide format. That said, time for another exercise!

Exercise 6

1. Reshape the data back to wide format
    - Create a new DataFrame called `df_wide` where immigration and integration scores are stored in separate columns.
    - *Hint:* Use the `.pivot_table()` method.
2. Inspect divergences between integration and immigration positions at the country level
    - Using your new `df_wide` DataFrame, create a new variable `gap` which computes the difference between `immi` and `inti` scores.
    - Which country has the largest *positive* divergence between their positions on immigration and integration?
    - Which country has the largest *negative* divergence between their positions on immigration and integration?

Hint: Use the pandas documentation if you are unsure how to apply the suggested methods.

```
df_wide = df_final.pivot_table(______)

df_wide

df_wide['gap'] = ______
```

```
df_wide.head()
```

```
# Find the country/year with the largest positive gap (immi > inti)
largest_positive_gap = df_wide['gap'].___()
country_largest_positive_gap = df_wide[df_wide['gap'] == largest_positive_gap]

# Find the country/year with the largest negative gap (inti > immi)
largest_negative_gap = df_wide['gap'].___()
country_largest_negative_gap = df_wide[df_wide['gap'] == largest_negative_gap]

print("Country/Year with the largest positive gap:")
print(country_largest_positive_gap)

print("\nCountry/Year with the largest negative gap:")
print(country_largest_negative_gap)
```

Bonus Exercise (if time permits)

Write a script that wrangles data in Python based on an `R` script and/or dataset from your research.

References

Lehmann, P., & Zobel, M. (2018). Positions and saliency of immigration in party manifestos: A novel dataset using crowd coding. *European Journal of Political Research*, 57(4), 1056-1083. https://doi.org/10.1111/1475-6765.12295