Big Data and Automated Content Analysis

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Contents

Introduction: What and why?

"Big Data" is one of those often misused catchall terms. It sounds sexy, and people use it for all kind of data. As scientists, we want a clear definition, but it is hard to tell what the term Big Data actually entails. This document is not about *really* Big Data requiring a whole server farm, but it is about data that is too big to handle manually—think of one million tweets for example. It is about data sets that are small enough to be handled by an ordinary desktop computer, but too big to be processed by ordinary programs. Excel does not have an unlimited number of rows, and SPSS and STATA start complaining (or simply stop working) once you have too many cases and variables. If you know R, you are better off, but for some of the tasks we will discuss in this document, Python has much more to offer.[1]

This document introduces you to automated content analysis of data that typically comes in amounts that are too voluminous for traditional point-and-click applications: Tweets, blogposts, articles from RSS-feeds, etc. We will use the programming language Python, which is very flexible and highly suitable for this end. It also scales very nicely—meaning that you can use it now for some smaller projects, but it can also be used on immense data sets. So, if you will find yourself working on some really Big Data that cannot be handled on a single computer any more, the principles are not too different from what we do in this document (yes, I'm simplifying a bit).

You will be guided through the first steps towards automated content analysis with Python. This document is not necessarily self-contained. I wrote it for use in the course *Big Data and Automated Content Analysis*, which I teach at the Department of Communication Science at the University of Amsterdam, and it builds on and relates to lectures and tutorials of that course. Also note that I wrote it for an audience of students in the social sciences, communication science in particular. From a computer science point of view, much more would have to be said, and some things we do in this course might actually be considered bad programming style. But that's

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[1] I do not want to go into the R-vs-Python-for-data-analysis debate here, I use both tools a lot, but for completely different tasks. Google for it if you want some comparison.

not our objective here: This course should enable students of the social science to make some first steps with Python, in order to solve their analytical questions.

This also means that this manual is far from complete. It rather serves as a starting point—and from that point onwards, it's up to you. Once you got the basic ideas and concepts, there are enough resources out there to help you further.

Have fun! And, join me in thanking those who contributed with great ideas or served as guinea pig for earlier versions of this document: Björn, Anne, Guus, and others.

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Chapter 1

Preparing your computer

This chapter describes how to prepare your computer for use within the course Big Data and Automated Content Analysis. We work with so-called virtual machines, which means that we install a program within which you can install an own operating system. This means that

(a) you can play around without the danger of damaging your own system;

(b) you can make use of a lot of cool tools that might not be available for your own system;

(c) everyone in this course has exactly the same environment running.

Specifically, we are using Oracle VirtualBox, within which we will install Lubuntu (a lightweight version of Ubuntu, a user-friendly Linux distribution). Before you start, make sure that you have plenty of space available on your laptop, preferably more than 10 GB. (You'd better put your music and photos on an external drive for the duration of this course...)

Ready to go?

1.1   Install VirtualBox

Download and install VirtualBox from `https://www.virtualbox.org/`. Depending on your computer, download the binary for Windows, MacOS, or Linux.

1.2   Download a Lubuntu-image

Download the Lubuntu image from `http://lubuntu.net`. If you have a relatively new computer, download `lubuntu 64-bit (AMD64) desktop CD`,

only if you encounter problems later on or have an old computer (up to around 2007), download `lubuntu (Intel x86) desktop CD`. So, in most cases, select the 64-bit version. Save it at a place of your convenience.

> ! At the time of writing, the most recent version is 15.10, and that's what you download. If you should be using an older Apple computer that still has a PowerPC rather than an Intel processor (the white iBooks, for example, produced until 2006), than you will have to use version 12.04 instead (`http://cdimages.ubuntu.com/lubuntu/releases/precise/release/lubuntu -12.04-desktop-powerpc.iso`). Note that in that case, all following steps might be slightly different.

1.3   Create a virtual machine

Open VirtualBox, click on "New", give your image a name, and select first Linux, then Ubuntu 64bit from the list (or 32 bit, if that's what you downloaded). On the following screens, just leave the default settings and agree to everything—with one exception: When you are asked how much "base memory" you want to allocate to your machine, you should choose a value of at least around 1000 MB. More is better, if you you have 4,096 MB of RAM in total, you can safely choose 2,048 MB. The examples in this tutorial are tested on a VM with 2,048 MB RAM.

On the next screens, you are asked about a virtual hard disk to create. You can basically accept the suggested settings, but I strongly recommend you to use a bit more than the 8 GB that are suggested. If you choose more (say, 12 GB or so), chances are lower that you will run out of space later during the course.

> ! The virtual machine you just created should show up in the main window now. If it doesn't (I had that on one computer once), restart VirtualBox.

Now click on the name of the virtual machine and on "Settings" (Figure 1.1. Under "System"/"Processors", you should see a check box "Enable PAE/NX". If you can enable this, enable it. Confirm with OK.

When you are done, start the virtual machine by clicking on the green arrow in the main window. You will be asked for a location from which to boot. Click on the icon to select a file and select the Lubuntu-image you downloaded.

1.4   Install Lubuntu on your virtual machine

Once your virtual machine is running, you can select whether you want to try out Lubuntu without installing or install it. If you feel like, you can now
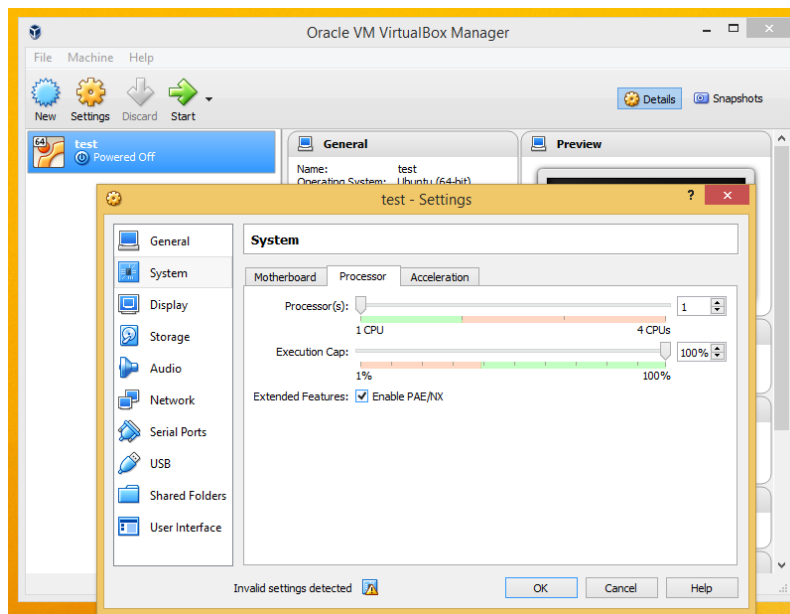
Figure 1.1: Enabling PAE/NX in the settings dialogue

just play around a bit in the try-out mode, but eventually, you'll need to go for installing as we need some specific tools for our course. So you can as well just select Install now, using the arrow keys. When you select "install", just follow the instructions. At one point in time, you will be asked whether you want to erase all data from your hard drive (yes, seriously). You can safely agree (remember, that's just the point of the VirtualBox, you have a fenced room in which you cannot damage anything. Only your *virtual* hard drive will be erased, not your real one). After finishing the installation, your virtual machine will reboot. After clicking on reboot, it might happen that you see only some lines of text saying something like "Unmounting crypto disks". If this takes longer than a minute or so, try pressing Enter twice.

1.5 Install necessary packages

Once you have installed and rebooted your virtual machine, you will have to install a couple of packages. It might be that your system is running now in a very low resulution, but that will change after the following step. Click on the button on the bottom left (where the Windows start button would be), then on System Tools/LXTerminal. Enter the following command:

```
sudo apt-get install virtualbox-guest-dkms
```

You will be asked for your password (the one you defined during the install process). Just type it and confirm with Enter (no, you do not see anything while you type, that's correct). If you reboot your virtual machine (by clicking on the Start button/logout/reboot or by typing

```
1  sudo reboot
```

it will display in a higher resolution and you can even run it full screen if you want to (by clicking on View/Switch to Full Screen in the VirtualBox menu).

We will now install some other programs we will use with the following commands (if you are running the 32bit version, leave away the _64). Just type them into the LX Terminal, which you already know:

```
1  sudo apt-get install gedit spyder3
```

You will be asked for your password and some questions which have to be answered with yes (by typing the letter y) followed by Enter. And another two commands to type for installing additional Python modules:

```
1  sudo easy_install3 -U pip
2  sudo pip3 install nltk
```

In the start menu under "Education" you now find a new program, Spyder 3. This is the tool we will be using for doing some Python programming. But of course, you can also start it from the command line by just typing:

```
1  spyder3 &
```

Chapter 2

The command line

2.1 Getting to know it

This chapter provides you with some basic knowledge about how to use the command line of your operating system. Chances are very high that you will need this later, so before diving into Python, I recommend doing this first.

Figure 2.1: The old MS-DOS command line prompt

Let's get started with a generational divide. It greatly helps if you are of the age of the author (32) or older, as you probably remember the thing in Figure 2.1. The Linux command line (which is basically the same as what you get when you start the Terminal on MacOS, so Mac users, you can use this on your own computer as well!), however, is much, much, much, much, much more powerful than the old MS-DOS thing. If you look on YouTube for "bash" (that's the specific one we are using) or "linux command line", you'll probably get some good tutorials, but let's explore the most basic things together.

- Open a Terminal by clicking on the Start button/System Tools/LX-Terminal.

- Type the following commands and watch what is happening:

```
1  pwd
2  mkdir test
3  cd test
4  pwd
5  ls
6  echo Hello world > test.txt
7  ls
8  cat test.txt
9  rm test.txt
10 cd ..
```

What happend? Let's discuss it line by line:

1. `pwd` means "print working directory". It asks the computer to tell you where you are, and you probably got some answer like `/home/damian`, which is your so-called home-directory. Directory is just another word for what you might know as a folder.

2. `mkdir` means "make directory" and creates a subdirectory.

3. `cd` means "change directory" and let you go to the directory in question.

4. . . . which, if you don't believe that you have really gone there, can confirm again with `pwd`.

5. `ls` stands for "list" and shows you all files in the directory. Obviously, there isn't a file yet, so. . .

6. . . . let's simply create one. The >-sign basically means that the output of a specific command should be saved under the following filename.

7. Now it's there.

8. Let's have a look at the file,

9. remove it again,

10. and finally go the parent directory (i.e., one level up), so that we are back at where we started.

2.2 Some useful commands for inspecting data

You now already learned how to create and change directories, list the files in a given directory, and how to delete them again. And, of course, in Chapter 1, you used it to install and start programs. One of the really useful things you can do in the command line is inspecting (also very large) files. Imagine you have millions of tweets, then you do not want to load all of them in a program, but maybe only see the first few to get a general idea.

Let's do a small exercise. Lets create a new directory for this exercise, download a training dataset, and have a look at it. I assume that you are in your home directory, you can check that with `pwd`.

```
1  mkdir exercise1
2  cd exercise1
3  wget datacollection.followthenews-uva.vm.surfsara.nl/bdaca/mytweets.csv --
      user=USERNAME --password=PASSWORD
```

(Of course, you replace USERNAME and PASSWORD by the username and password you received from your instructor to access all class materials. Also note that they are entered in the same line as the rest of the `wget`-command. **And note the space before the --!**).

You could as well just have downloaded this file by typing exactly the same URL in your browser, but `wget` allows you to do the same trick from the command line. If you have a really huge file, you'll appreciate this! Later on, you will learn some really cool stuff you can do with wget.

The general scheme of all following commands is that you type the command followed by the file name that you want to view.

You have four tools at your disposal: `head` (which gives you the first lines of a file), `tail` (last lines), `cat` (all lines), `less` (all lines, but with scrolling). By the way, if something goes wrong, you can always cancel by pressing CTRL-C. If you want to learn more about a command like `tail`, just type `man tail`. By default, `head` and `tail` give you 10 lines, but you can specify a different number, thus, you can produce the output below with `head -3 mytweets.csv`.

```
1  text,to_user_id,from_user,id,from_user_id,iso_language_code,source,
      profile_image_url,geo_type,geo_coordinates_0,geo_coordinates_1,
      created_at,time
2  :-) #Lectrr #wereldleiders #uitspraken #Wikileaks #klimaattop http://t.co/
      Udjpk48EIB,,henklbr,407085917011079169,118374840,nl,web,http://pbs.
      twimg.com/profile_images/378800000673845195/
      b47785b1595e6a1c63b93e463f3d0ccc_normal.jpeg,,0,0,Sun Dec 01 09:57:00
      +0000 2013,1385891820
3  Wat zijn de resulaten vd #klimaattop in #Warschau waard? @EP_Environment
      ontmoet voorzitter klimaattop @MarcinKorolec http://t.co/4Lmiaopf60,,
```

```
Europarl_NL,406058792573730816,37623918,en,<a href="http://www.
hootsuite.com" rel="nofollow">HootSuite</a>,http://pbs.twimg.com/
profile_images/2943831271/b6631b23a86502fae808ca3efde23d0d_normal.png
,,0,0,Thu Nov 28 13:55:35 +0000 2013,1385646935
```

This is a so-called CSV file, a table in which each column is separated by a comma. The first column contains the tweet, the second the user that the tweet is directed at (which obviously can be empty), the third the sender and so on.

But it gets even cooler: You can also just display a specific column (e.g., only the tweets): cut -f1 -d, mytweets.csv. See man cut for more details. And you can combine these kind of commands through a technique called "pipe", indicated by the |-sign. The command

```
1  cut -f1 -d, mytweets.csv | tail -5
```

for example sends the output of the cut-command to the tail-command. If you want to send output to a file instead of the screen, this is done with the >-sign (remember?). For example, try this cool pipe:

```
1  cut -f1 -d, mytweets.csv > mytweetsonlyfirstcolumn.csv
```

Now, play a bit around with the commands you learned!

2.3   Recap

In this chapter, you learned some basic command line commands. You should understand how the following commands work:

- pwd

- ls

- cd

- mkdir

- man

- rm

- cat

- head

- tail

- wget

You will encounter these over and over again, so you should have understood the general concept (`cut` was a pretty cool one, but probably too complicated to learn by heart—and hey, that's where `man` is for: you don't have to know all details!).

Chapter 3

The very, very basics of programming

Before we start writing our first own program, we need to clarify a few concepts. Luckily, they are pretty simple—but nevertheless, it is crucial to completely understand them.

> **!** Of course, what I present here is far from complete. I'll mention only the most essential parts that you need to understand to get started. Everything that is not strictly necessary right now or that is pretty intuitive (I guess I don't have to say that mathematical operators like $+$, $-$, $*$, or $/$ work exactly as you'd expect?) will be left out, and a lot is pretty much simplified. That's because our main objective is to get started as soon as possible with some real life data, not to get every detail right as you would do in a computer science course. After all, we are no computer scientists.

If you just type `python3` somewhere in the command line, you can actually also do the following examples (otherwise, you have to trust me that this is how it works). When you are finished with the exercises, just type `quit()`.

Alternatively, and to enjoy more comfort, you can use a graphical interface called: just type `spyder3` instead of `python3`.

Another way that is often used is to write a Python program in an arbitrary text editor, save it, and then start the program you wrote from the command line. The fact that there are so many ways to issue Python commands is actually a first important lesson: Python is not a program (like SPSS, or Word or Excel are programs), but a language — and there are a bunch of programs one can talk to in this language. Because of this, it is so flexible and can be used in so many contexts.
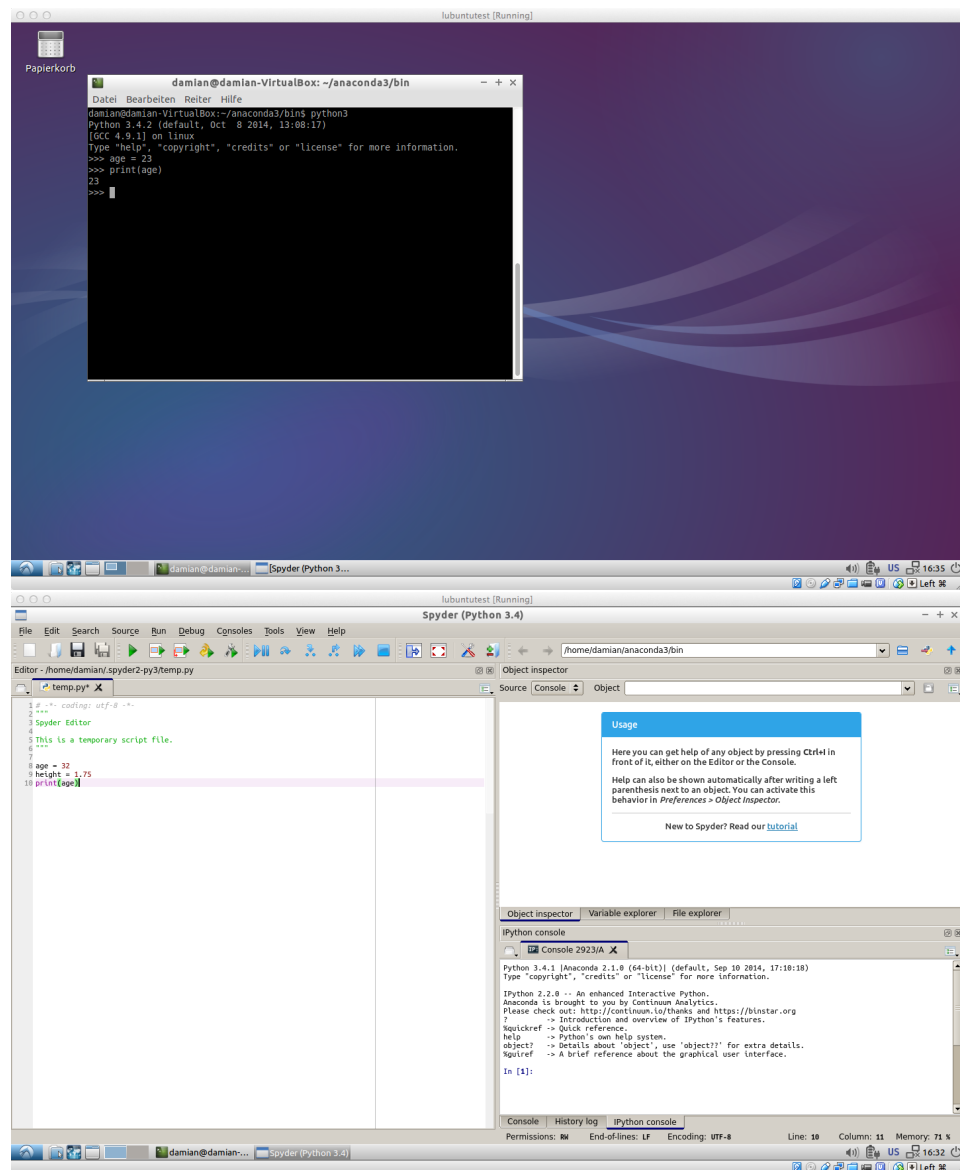
Figure 3.1: Different ways to issue Python commands: By starting the interpreter `python3` in the terminal (top) or by using an integrated development environment (IDE) like spyder (bottom).

3.1 Datatypes

3.1.1 Basic types

When thinking of a *variable*, most social scientists immediately think along the lines of how the term 'variable' is understood in SPSS or STATA datasets (or in methods sections in social science papers, for that matter): Something like age that has one value for each case (each person, each newspaper article, each unit of analysis). That's *not* how we define a variable here. (R users probably don't suffer from this misunderstanding.)

Instead, we distinguish several types of variables (datatypes), and the basic ones take—in contrast to what you might expect from the SPSS/STATA world—*one and only one* value:

```
1  age = 32
2  height = 1.75
3  male = True
4  name = "Damian"
```

It is of crucial importance to understand that each of these four variables is of a different type. The first one, age, is an *integer*, or, shorter, an *int*: A whole number without anything behind the comma. If age is an int, then someone cannot be aged 32.3.

The second one, height, is a *floating point number*, or, shorter, a *float*. In contrast to an int, a float can have something behind the comma. Unlike in SPSS, you do not have to specify a number of decimal places, $height = 1.7527647326573265743648$ would be perfectly acceptable.

The third one, a *Boolean value*, or, shorter, a *bool*, can only take two values: True or False. Note that there are no " " around True and that True starts with a capital latter. This is how Python recognizes it is not a . . .

. . . *string*, the fourth variable. A string contains some arbitrary text, which is indicated by surrounding " " or ' '.

3.1.2 Type conversion

Python automatically converts some types for you (for example, luckily, you can divide a float by an int without thinking about their types). But still, you have to be very careful in using the right datatype. For example, you cannot write code like this:

```
1  numberofguests = "20"
2  bottlesofbeer = 100
3  bottlesperperson = bottlesofbeer / numberofguests
```

This does not work, because you cannot divide an int by a string. However, one can convert a string to an int (if the string contains a number):

```
1  bottlesperperson = bottlesofbeer / int(numberofguests)
2  print(bottlesperperson)
```

This code would work! By the way, if you want to have it the other way around and make a string from an int, the function is called `str()`.

> You might wonder why one would have to convert types at all. Couldn't one just use the right type from the start? That's because a lot of data that we will analyze does not come in the right format. For example, if we have a file with some tweets followed by the number of retweets they received, then data that we read from the file in principle is text, thus, a string. If we want to do some calculations with the number of retweets, we have to convert it to an int.

3.1.3   Lists and dicitonaries

Imagine we want to calculate the mean age of a group. It would be very inefficient to have a variable for every single person:

```
1  age1 = 22
2  age2 = 25
3  age3 = 23
4  age4 = 28
5  age5 = 26
6  meanage = (age1 + age2 + age3 + age4 + age5) /5
7  print(meanage)
```

In fact, we could almost do it more efficiently by hand. Thus, we might want to have something that is more like what is called a variable in SPSS or STATA: something named age that can contain multiple values. Such a datatype is called a *list*. You can have lists of strings, lists of floats, lists of ints, and even lists of lists (and lists of lists of lists...). A list is denoted by `[ ]`, and the entries are seperated by commas. Let's create a list of ints:

```
1  age = [22, 25, 23, 28, 26]
```

To calculate the mean age, we could now divide the sum of the elements by the number of elements (or, technically speaking, by the *length* of the list). We'll discuss such functions in the next section, but for those who cannot wait, this is how it works:

```
1  age = [22, 25, 23, 28, 26]
2  meanage = sum(age)/len(age)
3  print(meanage)
```

> ? What do you think, of what type are `age`, `sum(age)`, `len(age)`, and
> `meanage`? If you want to know if you got it right, you can get the
> answer with `type(meanage)`, `type(sum(age))` and so on.

We can also access a specific item from a list: If we want to know the age of
the third person, then we can get it with

```
age[2]
```

Yes, 2, because we start counting with 0! The drawback of our current
approach is that you have no idea who the person is that is 23 years old.
You could have a second list in the same order:

```
name=["John","Bas","Anne","Sheila","Mark"]
```

Note that this is a list of strings, as we can see from the "-signs. Having
multiple lists in a corresponding order is actually a strategy we will work
with pretty often, and it is pretty much the same as having a dataset with
multiple variables in SPSS or STATA. If we are interested in the name and
age of the i$^{\text{th}}$ person, we could now find out:

```
i=3
print(name[i])
print(age[i])
```

Another option would be the last data type that we will discuss: a *dic-
tionary*. As the name says, a dictionary is something where you can look
something up——in Python terms, you search for a *key* and get its *value*. A
dictionary is denoted by { }, with entries separated by commas, and keys
and values by a colon:

```
nameage={"John": 22, "Bas": 25, "Anne": 23,"Sheila": 28 ,"Mark": 26}
```

Note that in this examples, the keys are strings and the values are ints, but
they could also have any other data type. If we want to know how old Sheila
is, we can retrieve that information:

```
print(nameage["Sheila"])
```

3.2 Functions

We have played around a bit with variables. To do some useful things with
them, however, we need something called *functions*. In fact, we already
used some: `print()` for example, or `len()` and `int()`. You can imagine a
function as a command that in most cases takes some input (or, as we will
call it, one or more *arguments*) and does something with it. The argument is
supplied between `()`. For example, the function `print()` takes some variable

as argument and show its content on the screen. This works for all types you know until now:

```
1  answer = 42
2  question = "What's the answer?"
3  print(question)
4  print(answer)
```

Note that you can use single quotes inside a string if you use double quotes outside the string (or vice versa!), but don't mix them up, otherwise it is unclear where the string ends. Of course, you do not have to define the variable in advance but also can do so on the fly:

```
1  print("Hello world")
```

Pay attention to the " ", which indicate that you do not supply a variable name that refers to a string, but the string itself. You could as well write:

```
1  hi="Hello world"
2  print(hi)
```

This gives exactly the same result. Another function that we already used is `len()`. It gives the length of an object, for example, the number of elements in a list or the number of characters in a string. You can actually also use functions within a function:

```
1  hi="Hello world"
2  print("The string",hi,"has",len(hi),"characters")
3  opdetap=["Estaminet","Steenbrugge Blond","Palm"]
4  print("They serve",len(opdetap),"different beers")
```

Make sure you understand where a " is placed and why!

3.2.1   Writing your own functions

There are a lot of useful functions available, either directly or from one of the numerous additional modules that can be loaded into Python. However, you can also write your own functions. This is something you might not need right now, but it can come in very handy later on. Imagine you would want to write a function to calculate the mean age, given a list of integers with ages. Then you could define a function to do this:

```
1  def averageage(agelist):
2      y = sum(agelist)/len(agelist)
3      return y
```

We basically define that our function takes some list as input (we called it `agelist`, but we could have chosen any other name). Then, it calculates some variable `y` (again, an arbitrary name) and returns that value.

So, if we have a list

```
1  ages = [22, 25, 23, 28, 26]
```

we can now simply write

```
1  averageage(ages)
```

to get the mean age, because we have defined the new function `averageage` before.

Obviously, for such a simple thing, this is not really necessary, because we could have just calculated

```
1  sum(ages)/len(ages)
```

directly. But if the calculation is more complicated and if we have to do it repeatedly, this can save us a lot of copy-pasting and makes our code more readable.

3.3   Methods

We have learned that a function is called[1] by simply writing its name and passing some variables as an argument between `()`. Another way of doing something with variables is using a *method*[2]. In contrast to a function, a method is directly associated with a variable. For example, each string has a built-in method with the name `.lower()`. If you want to change all Capital Letters to lowercase, you can simply call the method by attaching it to the string. See these examples:

```
1  hi="Hello world OUT THERE"
2  print(hi.lower())
3  print("TESTtttt".lower())
```

As you see, methods are very similar to functions, but the way they are called is different. If `lower()` was a function, you would write `lower("TEST")` — but it is a built-in method of each string rather than a function, so you have to call it by writing `"TEST".lower()` instead. Obviously, `.lower()` does not need an additional argument to convert the string to lowercase, as it a method *of the very string it is supposed to work on*, so there is simply nothing between the `()`. Nevertheless, you cannot leave away the`()`, because every function and every method has to end with `()`, otherwise, it would not be recognized as such.

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[1]To 'call a function' means to execute it.

[2]Strictly speaking, a method is also a function, but hey, this is no computer science course, so we'll allow ourselves to be a bit sloppy (and it relieves me from the burden to explain to you what a *class* is, what I would have to do to tell you the complete story).

For now, it is not important to know why some things are a method and some are a function.[3] It is important to know, however, that both ways of doing something with your variables exist and how you use them. One can actually also write ones own function, something that we might do later on as well.

> **!** Once I was teaching this course, a student had the great idea of writing a function she named `translatetoenglish()`. It took a Dutch string as argument, passed that one to to Google Translate, and returned the English translation. So, once the function was defined, you could write something like `print(translatetoenglish("Wat een mooie dag!"))`, which would produce the following output: `What a beautiful day!`. She used it for more serious business, namely to loop over a dataset of multilingual tweets to produce a new dataset in English. What a loop is, is explained in the next section.

3.4   Loops

All these functions and methods are mainly interesting if you do not apply them one time, to one string, but hundreds, thousands, or millions of times. In fact, this is the very essence of what we are doing in this course: Splitting up a task in small functions or methods that we then apply repeatedly.

To tell the computer to repeat something, we use a construction called a loop, or more specifically, a *for-loop*. Lets start with an example (when typing it over, start line 3 by pressing SPACE four times):

```
1  alltweets = ["Great lecture at the UvA", "I HATE YOU!", "I want BEER"]
2  for tweet in alltweets:
3      print(tweet.lower())
```

> **!** After a line ending with a colon, Python expects an indented block. If you do not do this in a consequent way (for example, you sometimes press TAB, sometimes use 4 spaces, sometimes 3, or none at all, Python will complain and give you an "indention error".

What happens? In line 1, we define the list `alltweets`. In line 2, we instruct the computer to take the first element of the list `alltweets` and give that element the name `tweet`. This is done by using the `for`-command. In human language, it might read as "Please repeat the task I will explain in the following indented lines `for` each element `in` the given list. In the task description given in the following block of indented lines, I will refer to the element that you are working on at that time as `tweet`".

---

[3]In fact, sometimes this is kind of an arbitrary choice made by those who invented Python. Some operations have even been implemented as both function and method.

Note that the name `tweet` is completely arbitrary chosen, while `for` and `in` are mandatory statements.

The indented line, line 3, is now executed. `tweet` now has the value of the first tweet of the first element of `alltweets`. After the indented block is finished, the program goes back to line 2, takes the next element from the list, assigns the name `tweet` to that next element, executes the indented block, and repeats until all elements have been used.

We could extend our code to produce output that looks a bit more fancy (and do not forget to indent lines 4 to 7 by using four spaces at the beginning of each line):

```
1  i=0
2  alltweets = ["Great lecture at the UvA", "I HATE YOU!", "I want BEER"]
3  for tweet in alltweets:
4      print("Printing tweet number",i,"in lowercase:")
5      print(tweet.lower())
6      print("\n")
7      i = i +1
```

`\n` denotes a line ending, so we get an empty line. In the last line, we add one to our counter variable `i`. A short form of doing this is `i+=1`, and it's pretty likely that I'll use that shorthand in the lectures.

> **?** Can you write your own loop based on the functions and data structures you learned until now?

3.5 If

Another important way of structuring your code is to define that it only has to be executed under specific conditions. Again, the block of code that has to be executed under a condition is indented and introduced by a colon.

```
1  age = 23
2  if age > 25:
3          print("Older than 25")
```

Of course, this does not print anything, as 23 is less than 25. You can also specify different conditions using the `elif` statement:

```
1  age = 23
2  if age >23:
3          print("Older than 23")
4  elif age <23:
5          print("Younger than 23")
6  elif age==23:
7          print("Exactly 23")
```

If you want to have a condition that is met if none of all others are met, you can use `else:`. Note the double `==` in line 6. This is very important: a single `=` assigns a value to a variable, a double `==` compares two variables. Maybe it is obvious, but also note that you can nest such structures and have a condition within a for-loop (and maybe have another loop within the condition).

> Can you write a program that takes each element from a list (using a for-loop), and then prints it if it if satisfies a specific condition?

3.6   Recap

You should have no problems explaining what the following datatypes are:

- int

- float

- bool

- string

- list

- dictionary

You should know what functions and methods are and how to use some basic ones like `print()`, `len()` or `.lower()`.

And, very importantly, you have to understand for-loops and if-conditions, including the role of indentation to structure your code.

Chapter 4

Basic ways to retrieve and store data

We already learned in section 3.1 (Datatypes) how we can internally create some data structures that we can use to further do some analyses. For example, if we wanted to do some analyses with names, ages, and height, we could create three lists like this:

```
1  age = [22, 25, 23, 28, 26]
2  name = ["John","Bas","Anne","Sheila","Mark"]
3  height = [1.83, 1.77, 1.55, 1.76, 1.74]
```

But of course, if we had such a limited amount of data, we wouldn't need to write a program to analyze it. So, we probably want to import the data from an external source. In this chapter, we will describe some ways to to this.

4.1 CSV files

In the easiest secenario, we already have a *table* in which each row contains a case and each column the value for age, name, and height, respectively. The universally acceptable format for such a table are CSV files: Text files in which columns are seperated by commas. Sometimes, a semicolon is used instead, conventions differ. Others use a TAB character instead, which is essentially the same, although one usually calls it a TAB-seperated file then.

You actually already saw a CSV file on page 7. Have a look back there if you forgot. Virtually all programs (including SPSS, Stata, Excel, ...) can read and write CSV files, that's why we will use them very frequently. When creating data with such a program, make sure that you know how they are formatted exactly (e.g., are columns separated by **,** or **;**, are strings

encapsulated by "" or not, ... You can use the tools described on 7 to inspect the files.

Lets create a text file with the following content:

```
1  John,22,1.83
2  Bas,25,1.77
3  Anne,23,1.55
4  Sheila,28,1.76
5  Mark,26,1.74
```

You can use gedit for this, an editor you find somewhere in the menu, but which you can—surprise, surprise!—also start from the command line with `gedit &`. Let's assume we saved this file as `/home/damian/mensen.csv`.

Now we can write a simple Python program to read this data:

```
1  import csv
2  name=[]
3  age=[]
4  height=[]
5  with open('/home/damian/mensen.csv', encoding='utf-8',mode='r',newline='')
       as csvfile:
6      reader = csv.reader(csvfile, delimiter=',')
7      for row in reader:
8          name.append(row[0])
9          age.append(row[1])
10         height.append(row[2])
11 print("Done!")
```

We see a lot of familiar structures: for example, the construction of (empty) lists in lines 2 to 4, the `for`-loop in line 7 to 10. So, let's first focus on the new parts:

- The `import` statement. It simply says that we want to load an external module, in this case one that knows how to read csv files. Import statements are usually written in the very first lines of a python scripts.

- The `with open(...) as:` construction. It indicates that we want to open a file and assigns a name to that so-called *file object*, indicated by `as` (in this case, we decided to call it `csvfile`, which is a completely arbitrary name). The statement ends with a colon, so an indented block has to follow (remember?). When the indented block is over (thus, after line 10), the file is automatically closed again. That's exactly what we want, because by then, we have read all the information and stored it in lists; we don't need the file any more. The arguments passed to the `open()` function specify the file name, but also some other details of how to open it. We'll skip the details for now.

- The `csv.reader()` function. It returns an object (which I decided to call, not very creatively, `reader`) that we can use to actually read the file. Note that in line 5, we only *opened* the file, we have not *read* a single byte from it yet. In line 5, we actually could have opened any arbitrary file—the `open()` command does not imply a specific data structure. Therefore now, in line 6, we define how to read from the file: Namely, by using the `csv` module. As an argument, we can give more specific information, for example, as done here, that the columns are separated by a `,`.

- The `.append()` method. It adds a new element to a list.

With your knowledge gained so far, you probably already can explain what in the for-loop in line 7–10 exactly happens. Think about it for a moment before reading further.

OK, the solution.

In line 7, we take the first row from the csv table, as provided by the `reader` object. We call it row. `row` simply is a list of all columns in that specific row. So, when we start, it is the list `["John",22,1.83]`. This means that we can get the value in the first column, `"John"`, by asking for the first element of the list, namely `row[0]`. That's what we do in line 8, where we put this value into the (until now empty) list of `name`s. The same is done with age and height, before we return to line 7 and get the next row from the `reader`.

Now, `row` has the value `"Bas",25,1.77`, and we again append `row[0]` to the list `name`, `row[1]` to the list `age`, and `row[2]` to the list `height`. We continue with this procedure until nothing is left to read from the file.

Let's also check if the data actually looks like what we expected:

```
1  print(name)
2  print(age)
3  print(height)
4  i=2
5  print(name[i],'is',age[i],'years old and',height[i],'meter tall')
```

Great!

Let's now save these columns in to a new file, `test.csv`, but in a different order. To this end, we use the `zip` command that basically clues several lists together. It goes like this:

```
1  output=zip(age,height,name)
2  with open("test.csv",mode="w",encoding="utf-8") as fo:
3      writer=csv.writer(fo)
4      writer.writerows(output)
```

That's all! Have a look at the file you just created and check if everything went right.

4.2   JSON files

OK, let's do this quickly, because what we will do in the next section is way cooler: We will retrieve JSON-data directly from an Google or Twitter. JSON is a data structure that is very similar to (if not identical to the one of) a Python dict, You already learned on page 15 what a dict is. Have a look back if you do not recall exactly.

Because a JSON file has the same data structure, we can open a JSON file and directly import it into a dict. This is really handy, as a lot of online data is available in that format.

Lets again with an editor like gedit and create a file with the following content and call it `/home/damian/mensen.json`.

```
1  {"Sheila": 28, "Anne": 23, "John": 22, "Bas": 25, "Mark": 26}
```

To read this file into a Python dict, we only need to do the following:

```
1  import json
2  with open("/home/damian/mensen.json", mode="r", encoding="utf-8") as fi:
3      mydict = json.load(fi)
4  print(mydict)
5  print("Sheila is",mydict["Sheila"])
```

Note that both the dictionary name `mydict` and the name of the file object `fi` are completely arbitrary. I often use `fi` (file in) for files I read from and `fo` (file out) for files I want to write to, so that I don't confuse the two.

As you might expect, saving is as easy as opening: we only need to do call the function `json.dump()`, which takes two arguments: the dictionary that we want to save and a file object:

```
1  import json
2  ages = {"Sheila": 28, "Anne": 23, "John": 22, "Bas": 25, "Mark": 26}
3  with open("/home/damian/mensen.json", mode="w", encoding="utf-8") as fo:
4      json.dump(ages,fo)
```

Note that in the `open()` function, we now specify `mode="w"` instead of `"r"` — we open a file for writing, not for reading.

> **!** Note that opening a file for writing (i.e., with `mode="w"`) creates a new file if it does not exist, **but if it already exists, it immediately deletes all content** that might have been in there.

But as I promised, it get's cooler, because in the next section, we will retrieve JSON objects not from a file, but directly via an API.

4.3 APIs

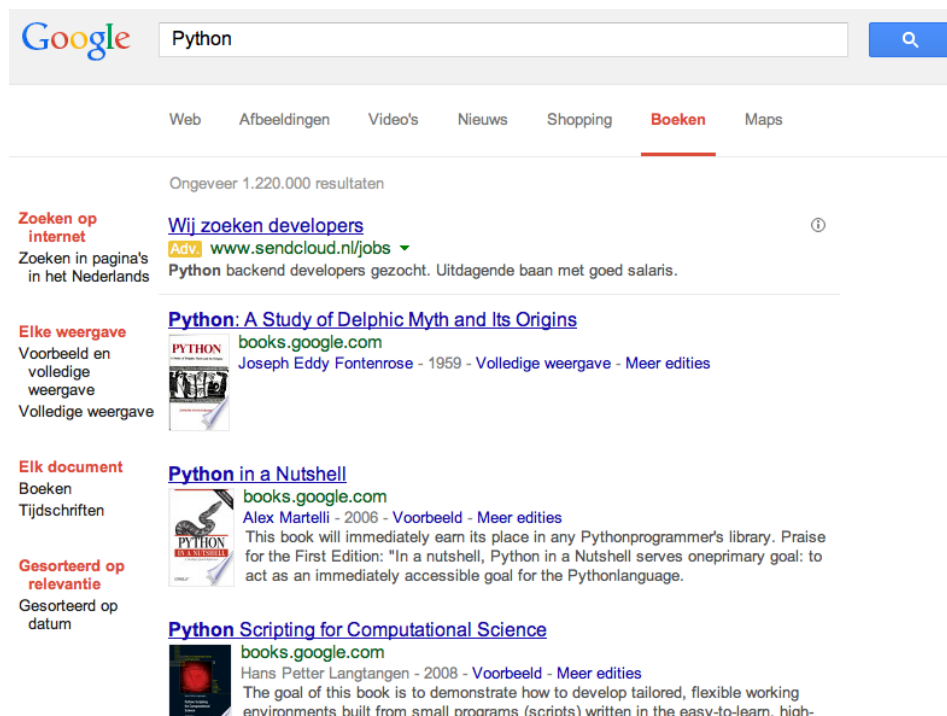### 4.3.1 How does it work?——A first example

Figure 4.1: The GoogleBooks web interface

Let's assume we want to retrieve data from some online service, for example book descriptions from GoogleBooks. Of course, we could surf to their website, enter a search query, and somehow save the result. This would result in a lot of impracticalities, most notably that the website is perfectly readable and understandable for humans, but may have no meaning for a computer program. As humans, we have no problem understanding which parts of Figure 4.1 refer to the author of a book, what the numbers "2006" and "2008" mean, and on. But it is not trivial to think of a way to explain to a computer program how to identify variables like `author`, `title`, or `year` in the output.

> ! We will learn how to do exactly that in Section 7 (Web scraping). Writing such a parser can be really useful, but it is also error-prone and some kind of a detour, as we are trying to bring some information that has been optimized for human reading *back* to a more structured data structure. Thus, if an API exists, it saves *a lot* of work.

Luckily, however, many online services do not only have web interfaces, but also offer another possibility to access the data they provide: an API (Application Programming Interface). In our example, we submit our request to GoogleBooks, and the API returns a JSON object with all the relevant data in it, in a neat and organized structure.

Consider the case of GoogleBooks. It offers an extremely simple API, as you do not have to log on (everyone can just use it), and because you call it in a very straightforward way: Assiming that you want to retrieve books that match the search string "python", you simply open the url `https://www.googleapis.com/books/v1/volumes?q=python` — and get a JSON object with all relevant information.

```
1  from urllib.request import urlopen
2  import json
3  from pprint import pprint
4  antwoord=urlopen("https://www.googleapis.com/books/v1/volumes?q=python").
       read()
5  data=json.loads(antwoord.decode("utf-8"))
6  pprint(data)
```

What does the code do? In lines 1 to 3, we import a module to download data from a URL, a module to read JSON data, and (to have some luxury) a module that prints json objects in a more readable way. Nothing spectacular so far.

In line 4, we access the GoogleBooks API and store the response in a variable we gave the arbitrary name `antwoord`. The function `urlopen` opens the URL, and its `.read()` method actually reads the content one gets when accessing the URL. Note that this is very much the same like opening a file and subsequently reading its content.

Until now, `antwoord` is just a bunch of bytes, and we have not made any attempt to somehow interpret it. That's what we do in line 5: `antwoord.decode("utf-8")` transforms the bunch of bytes into a string. However, a string is not really what we want, because we know that the string contains in fact JSON data[1]. And, as we saw in Section 4.2 (JSON files), a JSON string can be directly translated to a Python dict. This is done by the function `json.loads()`. Thus, `data` contains a Python dict with all information provided by the GoogleBooks API based on our search query. In line 6, we simply print that information.

Why `json.loads()` in line 5 and not `json.load()`, as we did in Section

---

[1]We know these things (that the bytes are a UTF-8 encoded string and that the string contains JSON data) because it is defined like that somewhere in the documentation of the GoogleBooks API. Nevertheless, both things are very common for many APIs, and one could therefore just try it out as well.

4.2 (JSON files)? Because `json.load()` takes a file object (which we don't have here) as argument, and `json.loads()` a string.

Let's have a look at the output `pprint(data)` produced to see what is actually stored in our dict `data`. As you can see, it is a lot, which is why I removed some lines from the following listing to make the picture clearer.

```
1  {'items': [{'accessInfo': {'accessViewStatus': 'SAMPLE',
2
3  <<I REMOVED SOME LINES HERE>>
4
5     'volumeInfo': {'authors': ['Niklas Luhmann'],
6         'canonicalVolumeLink': 'http://books.google.nl/books/about/Love.
            html?hl=&id=Hh-kncGf4QkC',
7         'categories': ['Social Science'],
8         'contentVersion': '0.0.2.0.preview.3',
9         'description': 'This short text, originally '
10
11 <<I REMOVED SOME LINES HERE>>
12
13        'language': 'en',
14        'pageCount': 96,
15        'previewLink': 'http://books.google.nl/books?id=Hh-kncGf4QkC&
              printsec=frontcover&dq=inauthor:%22Niklas+Luhmann%22&hl=&cd=1&
              source=gbs_api',
16        'printType': 'BOOK',
17        'publishedDate': '2010-12-06',
18        'publisher': 'Polity',
19        'readingModes': {'image': True, 'text': True},
20        'subtitle': 'A Sketch',
21        'title': 'Love'}},
```

First of all, we see at the very beginning that `data` contains an entry `items`, which is is probably what we need. We could access this part of the dict by typing `data["items"]`.

Now let's see what `data["items"]` consists of. First of all, it seems to be a list of different items (book records, in our case), as [denotes the beginning of a list here (in contrast to {, which would imply a dict, see Section 3.1 (Datatypes)). This implies that we could get the ith book by typing `data["items"][i]`.

What information is provided for each item? First of all, we find another dict called `'accessViewStatus'`. This doesn't look very interesting, so let's skip it. Some lines later, however, we see that our first book (and presumably also all the following books) have a dictionary called `'volumeInfo'`. That looks promising!

Now we're there! The dict `data['items'][i]['volumeInfo']` consists of several key-value pairs, so that we could get the language in which the 3rd

book was written by typing: `data['items'][2]['volumeInfo']['language']`
(remember, we start counting at 0).

Let's put all this into practice and write a small program that gives us
some information on books written by a specific author. What about some
information on books written by Niklas Luhmann, one of the most important
social theorists of the 20[2] century? We just saw how to access the data we
retrieve from the API, but we still have to see how we can transmit a more
complicated search string (namely, one specifying that we are interested in
one author only).

Let's do some reverse engineering. By playing around with the Google-
Books web interface and paying attention to the URLs that appear in your
browser's address bar, you can actually infer how the part after `?q=` is con-
structed for more complicated search strings. I basically surfed to `http://
books.google.com`, entered Luhmann as search string, got some results,
clicked on the link of one of the results that were actually indeed written
by Luhmann, which then gave me the page showed in Figure 4.2. In fact, I
saw that entering `inauthor:"Niklas Luhmann"` would have been the correct
search string for what I intended, and I also saw that this indeed becomes
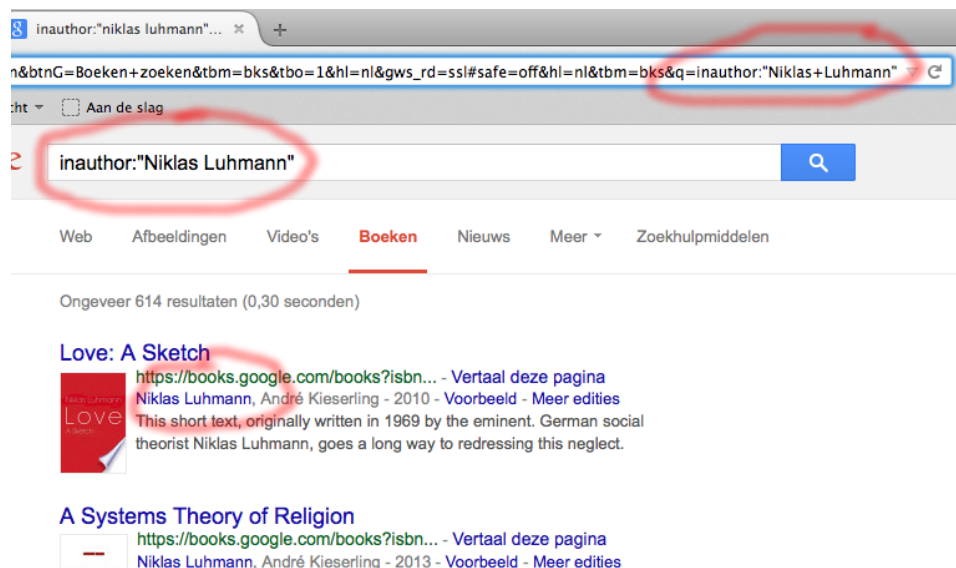part of the URL.

Figure 4.2: Reverse-engineering the GoogleBooks API

---

[2]Accoring to Wikipedia. Actually, we could also access Wikipedia's API as well to
directly retrieve this information. But, to be honest, I just used their web interface. But if
I were to collect biographical information on more than 20 sociologists, it would probably
already worth learning how to use Wikipedia's API.

Putting all this information together makes it possible to write the following code to retrieve information on some books written by Luhmann:

```
1  luhmann=urlopen('https://www.googleapis.com/books/v1/volumes?q=inauthor:"
       Niklas+Luhmann"').read()
2  niklas=json.loads(luhmann.decode("utf-8"))
3  for boek in niklas["items"]:
4      print (boek["volumeInfo"]["authors"],": ",boek["volumeInfo"]["title"])
```

And why not calculate how long they actually are?

```
1  totalpages=0
2  numberofbooks=0
3  for boek in niklas["items"]:
4      pages=int(boek["volumeInfo"]["pageCount"])
5      print(pages)
6      totalpages=totalpages+pages
7      numberofbooks=numberofbooks+1
8  print ("The average length of a book by Luhmann is", totalpages/
       numberofbooks, "pages")
```

> ? An alternative way of solving the same problem would be the following program. Can you see advantages and disadvantages of both approaches? Which approach would you choose?

```
1  pagelist=[]
2  for boek in niklas["items"]:
3      pagelist.append(int(boek["volumeInfo"]["pageCount"]))
4  print ("The average length of a book by Luhmann is", sum(
       pagelist)/len(pagelist), "pages")
```

4.3.2   The Twitter API

For this exercise, we need to import a module named `twitter`. You can easily install it from the command line with

```
1  sudo pip3 install twitter
```

Do this before you read any further.

There is a lot of information on the Web, an extensive documentation on `https://dev.twitter.com/`, and we will have a number of exercises on the Twitter API in class, so there is no need to go too much into detail here. There are two main differences with the GoogleBooks-example: (1) You do not have to access the API directly via `urlopen()`, but some nice person already wrote a so-called wrapper which does that for you; and (2) you need an account and log on.

To create an account, go to `https://apps.twitter.com/app/new`, register as a developer, create a new app and note down your consumer key,

consumer secret, access key and access secret (the latter two are also referred to as access token). See Figure 4.3 for screenshots. Most things should be rather self-explanatory. You can leave the field for a "callback URL" empty, and for "website", just make something up like `idontknowyet.com`.

In the following example, replace ACCESS_KEY etc. with your data (don't forget to put them between `" "`). If you want to retrieve my last 20 tweets as a JSON object (who wouldn't want to do that?), you can simpy do so with a three-line program:

```
1  from twitter import *
2  twitter = Twitter(auth = OAuth(ACCESS_KEY, ACCESS_SECRET, CONSUMER_KEY,
       CONSUMER_SECRET))
3  posts=twitter.statuses.user_timeline(screen_name="damian0604", count=20)
```

If you do not care about my tweets, but rather about more general information about me (like my bio statement or the number of followers I have), you can do so as well:

```
1  tweep="damian0604"
2  info=twitter.users.show(screen_name=tweep)
3  print(tweep,"has",info["followers_count"],"followers.")
4  print("He is following",info["friends_count"], "people.")
5  print("This means that his follower-to-following-ratio is",int(info["
       followers_count"])/int(info["friends_count"]))
6  print("\nThis is what he says about himself:\n")
7  print(info["description"])
```

To see what type of elements `info` contains, you can either read the documentation on `https://dev.twitter.com/` or use `print` or `pprint` to inspect its structure.

4.4   Saving the retrieved data

Once you have retrieved the data from an API, there are several ways to go. You could directly analyze them in some way, but maybe you just want to save them first (in fact, it might be a good idea to sve them anyway for archiving purposes). Combining our knowledge we gained up til know, we can conceive of multiple ways of storing the data. The first possibility, as we have learned, would be to simply dump the Twitter dataset we aquired into a JSON file.

```
1  with open("/home/damian/someone.json", mode="w", encoding="utf-8") as fo:
2        json.dump(info,fo)
```

We could also think of writing a CSV table, in which we store only the relevant information. This is especially useful if we want to further anayze

the data using a different program later on. To this end, we could first store all relevant information in lists and then save these lists to a CSV file.

```
1  import csv
2  tweets=[]
3  dates=[]
4  for i in posts:
5      tweets.append(posts[i]["text"])
6      dates.append(posts[i]["created_at"])
7  output=zip(dates,tweets)
8  with open("tweetswithdate.csv",mode="w",encoding="utf-8") as fo:
9      writer=csv.writer(fo)
10     writer.writerows(output)
```

4.5   Another example: The AmCAT API

Some of you might use AmCAT (Van Atteveldt, 2008), a framework for content analysis. If you have no idea what AmCAT is, just skip this section. If you do, however, you will be delighted to hear that you can access your AmCAT projects via an API and retrieve all your data for further analysis with Python.

There are several ways of installing the AmCAT Client (see `https://github.com/amcat/amcatclient`), but you do not need to do so: Just install the additional goodies in Chapter 5, then the AmCAT client is already included.

You need your username, your password, the project number, and the article set number. Then, you can simply adapt the following sample script to your own needs.

```
1  import json
2  import csv
3  from amcatclient import AmcatAPI
4
5  api = AmcatAPI('https://amcat.nl', 'USERNAME','PASSWORD')
6  articles = api.list_articles(project='XXXX', articleset='XXXX')
7
8  # articles is a generator, meaning you can read it only once
9  # that's impractical for us, so we turn it into a list:
10 articles = [art for art in articles]
11
12 #get an idea about the data by printing info about the first item
13 print(articles[0].keys())
14 print(articles[0])
15
16 #%% save as json
17 with open("articles.json",mode="w",encoding="utf-8") as fo:
```

```
18          json.dump(articles,fo)
19
20  #%% additionally, make a csv table with some of the data fields
21  with open("articles.csv",mode="w",encoding="utf-8") as fo:
22      writer=csv.writer(fo)
23      for art in articles:
24          # while saving, make sure that the text does not contain
25          # linebreaks ("\n" or "\r")
26          writer.writerow([art["medium"],art["date"],art["text"].replace("\n
                "," ").replace("\r"," ")])
```

4.6   Recap

You should have understood

- how a CSV file looks like and how it can be read;

- how a JSON file looks like and how it can be read;

- how JSON data can be retrieved via an API;

- how to write the retrieved data to a JSON file;
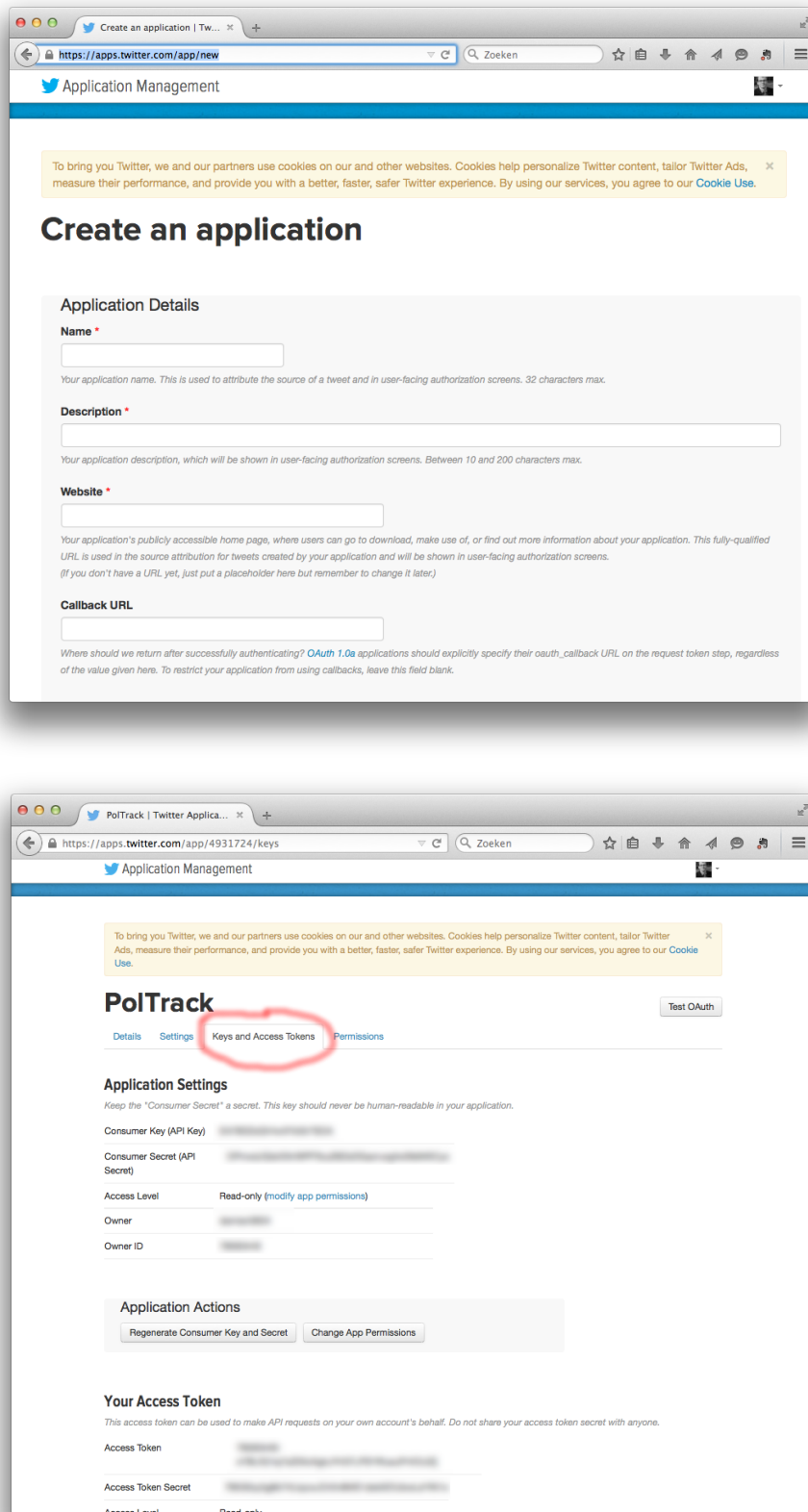
- how to write the retrieved data to a CSV file.

Figure 4.3: Creating a Twitter app and requesting tokens

Chapter 5

Sentiment Analysis

5.1 Preparation

In this chapter, we are going to conduct a sentiment analysis. You can use your own data for this, you only have to modify the proposed code accordingly. For instance, you can use the examples from earlier chapters about how to use CSV files, JSON files, or APIs and add the sentiment analysis code from the examples below to them.

Before you start, however, make sure you have all the necessary modules and data we need for this. To save you some work, I put a file together which contains an advanced sentiment analysis algorithm, but also two simple lists with positive and negative words. Download it using the following bash-commands:

```
1  cd /home/damian
2  wget datacollection.followthenews-uva.vm.surfsara.nl/bdaca/goodies.tar.gz
      --user=USERNAME --password=PASSWORD
3  tar -xzf goodies.tar.gz
4  rm goodies.tar.gz
```

In addition, you have to install Java:

```
1  sudo apt-get install default-jre
```

When finished, you have to tell Spyder where to find the new modules. You can do this via the menu Tools/PYTHONPATH Manager (see Figure 5.1 for the two necessary entries). After that, you have to select "Update module names list" from the same menu, and close the Python consoles that are still open (or restart Spyder).

Now you only need data to play with. You can download the following datasets for doing the exercises, but you are also free to use other datasets.
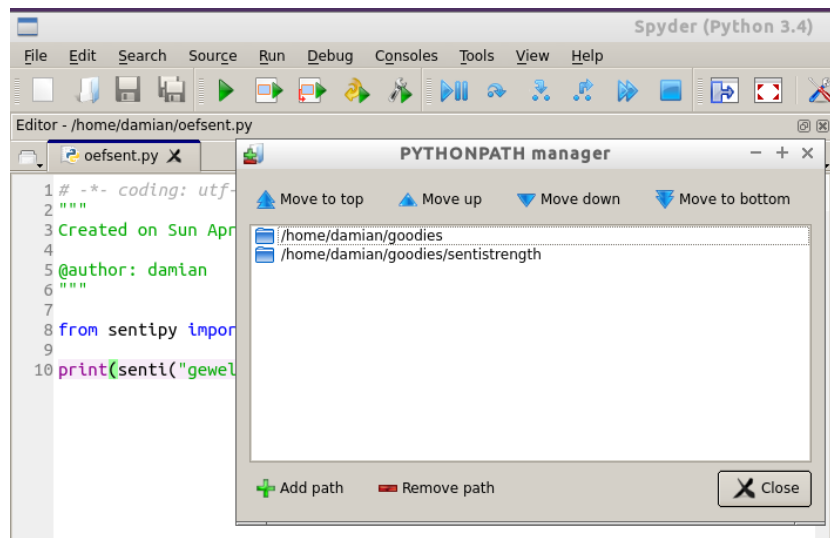
```
1  cd /home/damian
```

Figure 5.1: Telling spyder where to find additional modules

```
2  mkdir week4
3  cd week4
4  wget datacollection.followthenews-uva.vm.surfsara.nl/bdaca/hillary.csv --
       user=USERNAME --password=PASSWORD
5  wget datacollection.followthenews-uva.vm.surfsara.nl/bdaca/stateoftheunion
       .json --user=USERNAME --password=PASSWORD
```

You can also download the solutions for the following exercises:

```
1  wget datacollection.followthenews-uva.vm.surfsara.nl/bdaca/ex-senti-simple
       .py --user=USERNAME --password=PASSWORD
2  wget datacollection.followthenews-uva.vm.surfsara.nl/bdaca/ex-senti-
       sentistrength.py --user=USERNAME --password=PASSWORD
3  wget datacollection.followthenews-uva.vm.surfsara.nl/bdaca/ex-senti-
       sentistrength-file.py --user=USERNAME --password=PASSWORD
```

5.2   A simple dictionary-based approach

The data used in this example consist of a sample of 1 000 tweets related to the Democratic Party in the US, collected on the day when Hillary Clinton announced her candidacy. They were collected using DMI-TCAT (Borra & Rieder, 2014). Before you go any further, get an idea of the data. For example, you could use the `head` command on the bash command line (see Chapter 2.2). Which columns are interesting? Is there a header line (with column names), or do all lines contain data?

Once we have this information, we can make a plan on how to proceed.

1. We can skip the header row with the `next()` function (you didn't know that yet, but now you do).

2. We need a `list` of all tweets. As we know we can get this by starting with an empty list, followed by looping over all rows in the file and appending the value of the appropriate column to that list.

3. We are only interested in the words, not in punctuation. So, we could make a second list where we replace them by a space. This can be done using the `.replace()` method.

```python
import csv
tweetlist=[]
processedlist=[]
with open("/home/damian/week4/hillary.csv") as fi:
    reader=csv.reader(fi)
    next(reader)
    for row in reader:
        tweet=row[6]
        tweet_processed=tweet.lower().replace("!"," ").replace("."," ").
            replace("?"," ").replace(u"\u201A"," ").replace("'"," ").
            replace('"'," ").replace('#'," ").replace(':'," ")
        tweetlist.append(tweet)
        processedlist.append(tweet_processed)
```

Ok, we have the data and already did the necessary preprocessing (removing unnecessary characters in this case). BTW: You see why we access the element with the index 6 of the list `row` in line 7?

You might actually want to have a look at how the data look like to see that you did not make any mistakes. You can do so with some `print()` functions, or by clicking on the values in the variable explorer (Figure 5.2).

We can now plan our next steps:

4. We need to have a list of positive words

5. We need to have a list of negative words

In the goodies-folder, you have such a lists, `positive.txt` and `negative.txt`. Use the bash commands `head` or `cat` to find out how they look like!

Luckily, Python makes it very easy to read a text file in which each line should be treated as a single string into a list of strings:

```python
positivelist=open("/home/damian/goodies/positive.txt").read().splitlines()
negativelist=open("/home/damian/goodies/negative.txt").read().splitlines()
```
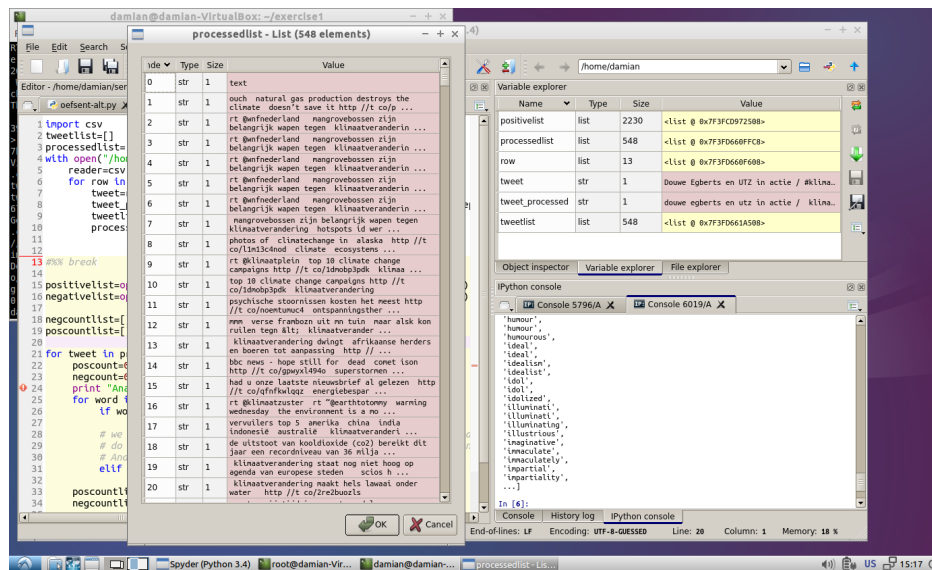
Figure 5.2: Inspecting the data with Spyder's variable explorer

Print the lists and check if they look like you would expect them to look like!

Now we can start with the real analysis. The algorithm is straightforward:

6. Loop over `processedlist`.

7. Within the loop: Set a variable `poscount` that indicates the number of positive words in this specific tweet is 0.

8. Within the loop: Set a variable `negcount` that indicates the number of negative words in this specific tweet is 0.

9. Within the loop: Split each element from that list (thus, each processed tweet) into words and loop over these words

10. Within this inner loop: check wether the word is an element of `positivelist`, and if so, increase `poscount` by one

11. Same for negative words

12. Add counts to some lists

13. Optionally: weigh by the length of the tweet

Translated to Python code, it looks like this:

```
1  negcountlist=[]
2  poscountlist=[]
3  sentilist=[]
4
5  for tweet in processedlist:
6      poscount=0
7      negcount=0
8      print ("Analyzing this one:",tweet)
9      for word in tweet.split():
10         if word in positivelist:
11             poscount+=1
12         elif word in negativelist:
13             negcount+=1
14     print("It contains",poscount,"positive words and",negcount,"negative
           words.")
15     poscountlist.append(poscount)
16     negcountlist.append(negcount)
17     sentilist.append((poscount-negcount)/len(tweet))
18
19 print("Average sentiment:",sum(sentilist)/len(sentilist))
```

The only thing we still want to do is to save a dataset for further analysis — maybe with Python, maybe with some statistics package:

```
1  output=zip(tweetlist,processedlist,negcountlist,poscountlist,sentilist)
2  with open("/home/damian/week4/hillary-analyzed.csv",mode="w",encoding="utf
       -8", newline="") as fo:
3      writer=csv.writer(fo)
4      writer.writerows(output)
```

5.3   Sentistrength

There are several nice things to the simple approach demonstrated above: First, it is insightful from a didactical point of view, as it illustrates the basic principles of bag-of-words analyses. Second, it is very flexible in that it can be modified to measure a lot of other things, not only positivity or negativity. Third, it is transparent—everyone can understand the basic algorithm.

However, in a real-world setting, it might be too simplistic. Instead of writing a sentiment analysis algorithm yourself, you can therefore invoke some third-party algorithm like SentiStrength Thelwall, Buckley, and Paltoglou (2012). SentiStrength is free for academic use, but you have to pay for it if you want to use it commercially. To link it to Python, I wrote a module called `sentipy`, which you already installed. You can test wether everything works:

```
1  from sentipy import senti
```

```
2  print(senti("geweldig nieuws","dutch"))
```

You see that it returns a list with two values, the first one being the positivity (on a scale from 1 to 5), the second one being the negativity (on a scale from −1 to −5).

So, let's run it on a real dataset. Why not open a JSON file with some paragraphs from State-of-the-Union speeches (which I exported from Am-CAT (Van Atteveldt, 2008)) and write the text, the positivity score, and the negativity score to a csv file?

```
1   from sentipy import senti
2   import csv
3   import json
4   with open("stateoftheunion.json",mode="r",encoding="utf-8") as fi:
5        articles=json.load(fi)
6   with open("articles.csv",mode="w",encoding="utf-8") as fo:
7      writer=csv.writer(fo)
8      for art in articles:
9         s=senti(art["text"],"english")
10        print(s)
11        writer.writerow([art["medium"],art["date"],art["text"],s[0],s[1]])
```

You will surely see that there is a problem, though: It takes almost a second to call `senti()`. This is because of the not-so-good implementation in this case (we call an external java program each time we want to get the sentiment). We wouldn't have to care about time, but as we have > 20 000 paragraphs to analyze, we can either wait six hours or interrupt with CTRL-C. You might have noticed that this time, we did not first create lists that we combined with `zip`, but that we write each line immediately to the file. This has two advantages: It saves memory, and if we abort, everything we did until that moment has already been written to the output file.

> ? Can you extend the algorithm in Chapter 5.2, so that additional columns
>   based on the Sentistrength-algorithm are saved?
>   Can you also implement some way of comparing the outcomes of both
>   approaches?

The reason why the above approach is so slow, however, is not the sentiment analysis *itself*, it is the the fact that the external Java program has to be *started* 20 000 times. It would be more efficient to do this only once (MUUUUUCH more efficient, in fact). The approach below takes *less than a minute* to run. It saves the 20 000 texts to analyze in *one* text file, one per row (thus, all line breaks within each text are removed before) and then tells sentistrength to calculate the sentiment per line. I wrote a function `sentifile` to achieve this. The `sentifile` takes two or three arguments: the name of an input file, the language, and optionally a boolean value that

indicates wether you want the full text to be returned or not. If False (or ommitted), the function returns a list of (positive, negative)-tuples, if True, it returns (postive, negative, text).

The following sample code illustrates its working¿

```python
from sentipy import sentifile
import csv
import json

with open("stateoftheunion.json",mode="r",encoding="utf-8") as fi:
    articles=json.load(fi)

with open("textonly.txt",mode="w",encoding="utf-8") as fo:
    for art in articles:
        fo.write(art["text"].replace("\n"," ").replace("\r"," ").replace("\
            t", " ") + "\n")

# without text:
with open("scoresonly.csv",mode="w",encoding="utf-8") as fo:
    writer=csv.writer(fo)
    sents=sentifile("textonly.txt","english")
    for s in sents:
        writer.writerow([s[0],s[1]])

# with text:
with open("scoreswithtext.csv",mode="w",encoding="utf-8") as fo:
    writer=csv.writer(fo)
    sents=sentifile("textonly.txt","english",True)
    for s in sents:
        writer.writerow([s[2],s[0],s[1]])
```

Chapter 6

Automated Content Analysis

Automated content analysis covers a wide range of techiques, and not all of them can be covered within this tutorial (for an overview and more background information, see Boumans and Trilling (2016)). We will start with a first, powerful yet easy deductive approach, in which we basically count how often a pre-defined pattern (a search string, for example) occurs. This technique is known as using *regular expressions*. We will then learn how to take characteristics of human language into account to get closer to the real meaning. The technique we use for this is called *Natural Language Processing (NLP)*. The other approaches to automated content analysis mentioned by Boumans and Trilling (2016) are discussed in Chapters 8 and 9.

6.1 Regular expressions

A regular expression is a *very* widespread way to describe patterns in strings. You probably know wildcats like * or operators like OR, AND or NOT that you can use in search strings in a lot of applications. But of course this is rather limited: Maybe you want to say somethhing like "I want all words starting with a letter or a number (but no special character), then a -sign, then again some letters, and after the last dot two or three letters (but not more!) letters. You probably saw that this would be some way of describing an email-adress.

A universal language to formulate such patterns is *regular expressions*. There are some dialects (but the differences are minimal), and you can use them in many editors (!), in the Terminal, in STATA . . . and in Python.

In its most simple form, a regular expression is just an ordinary search string:

```
1  python
```

finds ("matches") every occurance of the word "python". But we can also indicate that two different characters are allowed:

```
1  [pP]ython
```

matches both "python" and "Python". Some other useful things:

- `.` matches *any* character

- `[0-9]` matches a digit

- `[a-z]` matches all lowercase letters

- `[a-zA-Z]` matches all upper- and lowercase letters

- `([tT]witter|[fF]acebook)` matches both Twitter and Facebook and is OK with misspelling them as twitter or facebook.

You probably got the idea. You can also specify how often sth has to occur:
The item *before* has to occur

- `?` 0 or 1 times

- `*` 0 or more times

- `+` 1 or more times

- `?` 0 or 1 times

For example,

```
1  personali[zs]ed-?communication
```

matches

```
1  personalizedcommunication
2  personalized-communication
3  personalisedcommunication
4  personalised-communication
```

There are actually much more possibilities, so download a regular expression cheat sheet (google or try this one: `http://www.cheatography.com/davechild/cheat-sheets/regular-expressions/`) to build your own one. Also the wikipedia page on regular expressions is pretty good. You can also play around at `http://www.pyregex.com/`.

So, let's try to use regular expressions in Python. There is a whole module for this (its called `re`) that provides a lot of interesting functions for finding and replacing stuff based on regular expressions.

- `re.findall("[Tt]witter|[Ff]acebook",testo)` returns a list with all occurances of Twitter or Facebook in the string called `testo`

- `re.findall("[0-9]+[a-zA-Z]+",testo)` returns a list with all words that start with one or more numbers followed by one or more letters in the string called `testo`

- `re.sub("[Tt]witter|[Ff]acebook","a social medium",testo)` returns a string in which all all occurances of Twitter or Facebook are replaced by "a social medium"

- `re.match(" +([0-9]+) of ([0-9]+) points",line)` returns `None` unless it *exactly* matches the string `line`. If it does, you can access the part between () with the `.group()` method.

The difference between `findall` and `match` is thus that `findall` does not care about what it finds before and after the pattern, while `match` requires the whole line to be matched.

An example to illustrate the use:

```
line="            2 of 25 points"
result=re.match(" +([0-9]+) of ([0-9]+) points",line)
if result:
    print ("Your points:",result.group(1))
    print ("Maximum points:",result.group(2))
```

would produce the following output:

```
Your points: 2
Maximum points: 25
```

This is cool, isn't it? We now know how to extract information from a semi-structured string so that we can store it in variables for further analysis!

On page 52, you can find some additional information about some regular expression features, especially about the difference between lazy matching and greedy matching, which basically specifies where to "stop" when a regular expression contains something like `.*` (thus, matching an arbitrary number of arbitrary characters, which is in fact much more useful than it sounds).

? Can you write a program (a so-called parser) that takes a semi-structured input file of your choice (maybe something you downloaded somewhere) as input and uses regular expressions to store the data in a structured way in a CSV table?

6.2 Natural language processing

To prepare, we have to install some more ressources. Run the following Python lines:

```
1  import nltk
2  nltk.download()
```

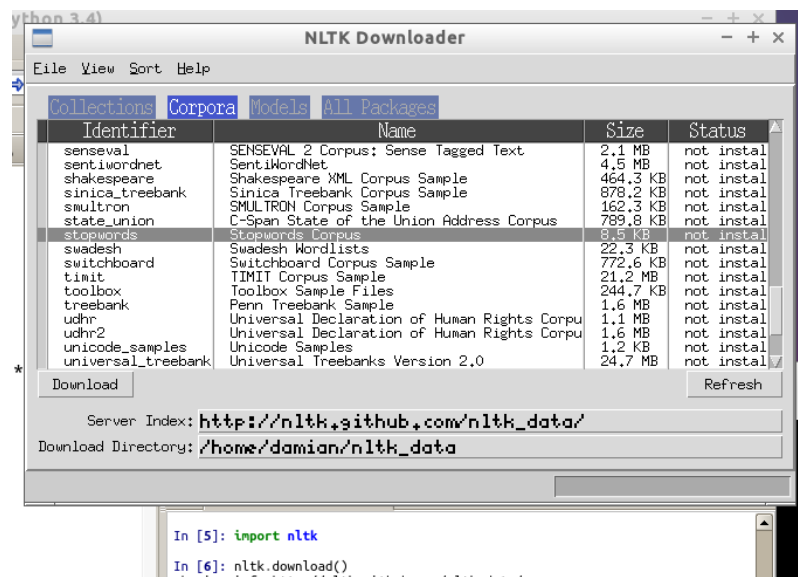A graphical interface is opened (Figure 6.1).

Figure 6.1: Loading additional NLTK-packages

Do *not* download all packages, that will take too much space and you do not need it. Instead, download only the packages "stopwords" , "punkt", and "maxent_treebank_pos_tagger" from the "all packages" tab. Close the window when done.

6.2.1 Stopword removal

Natural language processing is a term that is used to describe a set of techniques used to analyze language written by humans. This comprises simple tasks like the removal of stopwords in order to identify "relevant" words, but also much more complicated things like parsing of a sentence – which means to automatically identify, for instance, subject, verb and object in a sentence. The book by Bird, Loper, and Klein (2009) gives a comprehensive introduction into NLP with Python. The author also probide the Python package `nltk`, which we will use as well.

To find out all the possibilities, have a look at `nltk.org`, but here are some examples.

Let us first consider stopword removal. These are words without a meaning that is specific to a text, such as "a", "the", ... They are usually more disturbing than useful, because they hinder us from seeing the really interesting words. Keeping them in can lead to misleading results if we want to identify key terms (e.g., by means of a word count), if we want to calculate document similarities, or if we want to make a word co-occurance graphs. A very straightforward way to do so would be the following algorithm, which you – with the knowledge you gained so far – actually could have written yoursefl:

```
1  t = 'let us clean this up for her'
2  tn = ""
3  stopwords=['and','the','this','a','or','he','she','him','her','us']
4  for w in t.split():
5      if w not in stopwords:
6          tn=tn+w+" "
```

Instead of defining the list in the script itself, we could also read them from a file. Imagine we have a file called `stopwords.txt` in which we put one stopword per line (we could easily create such a file in `gedit` or Leafpad or any other text editor):

```
1  he
2  she
3  it
4  we
5  they
```

We could read this file to a list with

```
1  stopwords=[w.strip() for w in open("stopwords.txt",encoding="utf-8").
      readlines()]
```

Especially if we have a very long list, this makes our code much easier to read and to maintain. We could also use one of the pre-defined lists provided by `nltk`, but often, we might want to tweak it to our research interests anyway.

6.2.2 Stemming

Another interesting step is *stemming*. When interpreting text, we usually do not want to distinguish between smoke, smoked, smoking. Stemming reduces all of these forms to their stem `smoke`. Therefore, it is a typical preprocessing step (like stopword removal).

So, we could split a given string into words, then stem each word, and combine them again.

```
1  from nltk.stem.snowball import SnowballStemmer
2  stemmer=SnowballStemmer("english")
3  s="I am running while generously greeting my neighbors"
4  stems=""
5  for w in s.split():
6      stems=stems + stemmer.stem(w) + " "
```

We can now `print(stems)` to see how the stemmed string looks like.

> ⚠️ The last three lines can be replaced by a single line:
> `stems=" ".join([stemmer.stem(w) for w in s.split()])`
> The technique used for it is called *list comprehension* and a really cool feature, google it if you want to know more. In addition, the `.join()` method allows to join elements from a list to a single string. These two things are considered very pythonic and good coding style, so if you do this kind of stuff more often, it is useful to understand the working (but you can as well use the more elaborate way used in the example). In fact, also the stopword removal could be done in this way: Assuming we have a list with stopwords called `stopwords` and a sentence `s` from which we want to remove all stopwords, we can do so with
> `s2=" ".join([w for w in s.split() if w not in stopwords])`
> In doing so, we can create a new string `s2` with one single line of Python code in which we first split s into a list of words, then make a new list out of these words in which only those words are included that are not in the stopword list, and finally join this list into a single string seperated by spaces.

6.2.3   Parsing

With parsing, we can find out what grammatical function words have. To this end, NLTK splits a word into sentences (it is called *tokenizing*). But, in contrast to what we have done before with the `.split()` method, it attaches a label to each token that identifies the grammatical characteristics of each token.

```
1  import nltk
2  sentence = "At eight o'clock on Thursday morning, Arthur didn't feel very
       good."
3  tokens = nltk.word_tokenize(sentence)
4  print (tokens)
5  tagged = nltk.pos_tag(tokens)
6  print(tagged)
```

We see that we get a list of tuples (pairs of two values):

```
1  [('At', 'IN'), ('eight', 'CD'), ("o'clock", 'JJ'), ('on', 'IN'), ('
       Thursday', 'NNP'), ('morning', 'NN')]
```

This is pretty useful, because we can address the items with *slicing*. For example, to get the fifth tuple, we can write `tagged[5]`. Of course, we can also slice the tuple. So, to get only the grammatical function of the word "morning", we can use `tagged[5][1]`.

6.3 Recap

You should have understood

- How to remove stopwords

- How to stem a sentence

- How to parse a sentence

- How to use NLTK

Chapter 7

Web scraping

7.1 Overview

When scraping data from the web, we can distinguish two different stages:

1. Downloading a large number of webpages

2. Parsing the content of the webpages

Let us start with the first point. Sometimes, we have a list with all URLs of all Dutch news items of the last year, for example, from because we retrieved them from a RSS feed. In this case, downloading the data is trivial. We could for exampe use a for-loop in Python, or use the command `wget` from the bash command line. If we have a file `urls.txt` that contains one URL per row, we can download all urls with the command

```
1  wget -i urls.txt
```

We could use a number of additional options, in particular waiting between the URLs to avoid gettig blocked, or pretend that we use a specific web browser. `wget --help` or Google give you more information.

If we do not have such a list, but rather want to start from one page (e.g., the homepage of a specific website) and simply follow all links that we find on that page, we have to resort to a technique called *crawling*. If we for example want to download the page `http://gsc.uva.nl/`, including all links, plus all links encountered on the pages linked to (but stop after this second level of recursion), we can simply type

```
1  wget -l2 http://gsc.uva.nl/
```

The internet is full of examples (like here: `http://www.thegeekstuff.com/2009/09/the-ultimate-wget-download-guide-with-15-awesome-examples/`)

At the end of this chapter, I will point you to a framework that allows crawling with Python.

But first, let us turn to the second point: Parsing the content of the pages we downloaded. In virtually all cases, we do not care about the webpage as we downloaded it, but we rather want to extract *some* information in a meaningful way. For example, on a page with product reviews, we want to get rid of all advertisements, navigation elements, . . . — in fact, everything except the reviews themselves, which we probably want to store in a list or a similar data structure.

In the next section, we will do so with an approach you are already familiar with: regular expressions. This is useful to show the general idea, and you could use a similar approach a wide range of input data, not only web pages (think of the LexisNexis example). However, especially with complicated HTML pages, this approach can become cumbersome. We will therefore learn how to use XPath descriptions to parse a webpage in another section.

7.2   A simple regular-expression based approach

FIrst of all, have a look again at the materials about regular expressions. In particular, have another loot at how the `re.findall()` function can be used to get a list of all strings that match a regular expression within another string.

Then, open Firefox and go to `http://www.geenstijl.nl/mt/archieven/` `2014/05/das_toch_niet_normaal.html`. Even if you do not understand a word (which actually might help you to look at the structure rather than the content!), you will see that the article is followed by a whole bunch of comments. Already think about a way how one could identify the comments

Click on Tools/Web Developer/Page source (or press $\boxed{\text{CTRL-U}}$) to inspect the source code (Figure 7.1).

You should see that the whole block of comments starts with the tag `<div class="commentlist">` (and, much later, ends with `</div>`). Also, you should see that each comment starts with a tag `<article id="xxxxxxxx">` and ens with `</article>`.

This looks like a regular pattern, therefore, we can match it with a regular expression. Assuming that the whole page is called `tekst`, we can get the whole comment section with:

```
1  commentsection=re.findall(r'<div class="commentlist">.*?</div>',tekst)
```

Pay attention that we write `.*?` instead of `.*` only. The `.` matches every character, and `*` means an arbitrary number of times, therefore `.*` *also*

Figure 7.1: Examining the source code of a HTML page

matches `</div>`. This means that our regular expression would never stop, and we would get the whole rest of `tekst` — rather the part *until* `</div>` *is reached.* This is referred to as *greedy matching.* Using `.*?` instead of `.*` means that we want to perform *lazy matching* instead, where we do stop as soon as the next part of the regular expression is matched.

As `re.findall()` returns a list of all matches, `commentssection` is a list of all commentssections. As there is only one comment section (which we can verify by calculating `len(commentssection)`, we can get the whole chunk of HTML-code of the comment section by accessing the first and only element of the list, `commentssection[0]`.

Now, we can do the same for each comment ("article") within the comment section:

```
comments=re.findall(r'<article.*?>(.*?)</article>',commentsection[0])
```

Voilà! We got a list of all comments!

But wait, why did we write the `()` around`(.*?)`? This simply means that only the part between `()` is returned. In other words, `comments` contains only what is *between* `<article.*?>` and `</article>`.

If we now but all this together, add some code to actually download the data (and to also parse the metadata, like author and time of writing), we get the following script:

```
from urllib import request
import re
import csv

onlycommentslist=[]
metalist=[]
```

```
 7
 8  req = request.Request('http://www.geenstijl.nl/mt/archieven/2014/05/
        das_toch_niet_normaal.html', headers={'User-Agent' : "Mozilla/5.0"})
 9  tekst=request.urlopen(req).read()
10  tekst=tekst.decode(encoding="utf-8",errors="ignore").replace("\n"," ").
        replace("\t"," ")
11
12  commentsection=re.findall(r'<div class="commentlist">.*?</div>',tekst)
13  print (commentsection)
14  comments=re.findall(r'<article.*?>(.*?)</article>',commentsection[0])
15  print (comments)
16  print ("There are",len(comments),"comments")
17  for co in comments:
18      metalist.append(re.findall(r'<footer>(.*?)</footer>',co))
19      onlycommentslist.append(re.findall(r'<p>(.*?)</p>',co))
20  writer=csv.writer(open("geenstijlcomments.csv",mode="w",encoding="utf-8"))
21  output=zip(onlycommentslist,metalist)
22  writer.writerows(output)
```

Of course, rather than just saving it to a csv file, we could also add one or two lines to the for-loop and immediately perform a sentiment analysis!

> **!** What happens exactly in line 8 to 10? In line 8, we form a HTTP-request
> to specify what we want to download. We could skip this and just specify
> the URL, but we want to perform a little trick to fool the other side. As
> they do not like people scraping their content, we have to conceal that we
> actually do not use a web browser like normal people. Therefore, we let our
> program just pretend to be Firefox ("Mozilla"). In line 9, we download the
> web page. However, what we get is just a number of bytes, and Python does
> not know which byte corresponds to which character. This is why we use
> the `.decode()` method in line 10, which changes the sequence of bytes to a
> string as we know it. Furthermore, we remove all newlines and tabs from the
> string, because we want one long, uninterrupted string for further processing
> (especially, we do not want to care about this when designing our regular
> expressions).

Now, you should be ready to write your own parser for some content you are interested in!

7.3   XPath-parsing with lxml

One does not always have to reinvent the weel, though. It is incredibly useful to understand how parsing with regular expression works, and it is very likely to come into a situation where this knowledge can be applied. Especially in the case of HTML pages, though, several parsers exist that can make life easier.

In the example in the last section, we saw that an element in a HTML page can be nested in another element. In other words, a HTML page can be represented as a tree: For example, the page branches into an article, a navigation section, and a comment sections; the latter than branches into several comments. Each element in this tree can be identified by a so-called XPath. You can compare it with the path of a given file (`/home/damian/week6/slides.pdf`), where the leftmost element is the "highest" level, and where after each `/`, it indicates to which lower level one has to turn before finally arriving at the file (`slides.pdf`).

The good news is that you can look up the XPath of an element with your web browser (the bad news, though, is that on some pages it can be a bit tricky to get it *exactly* right). In Firefox, you have to install a plugin for that. It is called XPath Checker and you can get it by googling it or from `https://addons.mozilla.org/nl/firefox/addon/xpath-checker/`. Install it and restart Firefox.

Now, go to a website of your choice, select the part of content that you want to scrape, right-click on it, and select "View XPath". XPath Checker opens (Figure 7.2) and suggests an XPath. It also displays the content that would be selected if one used this XPath.
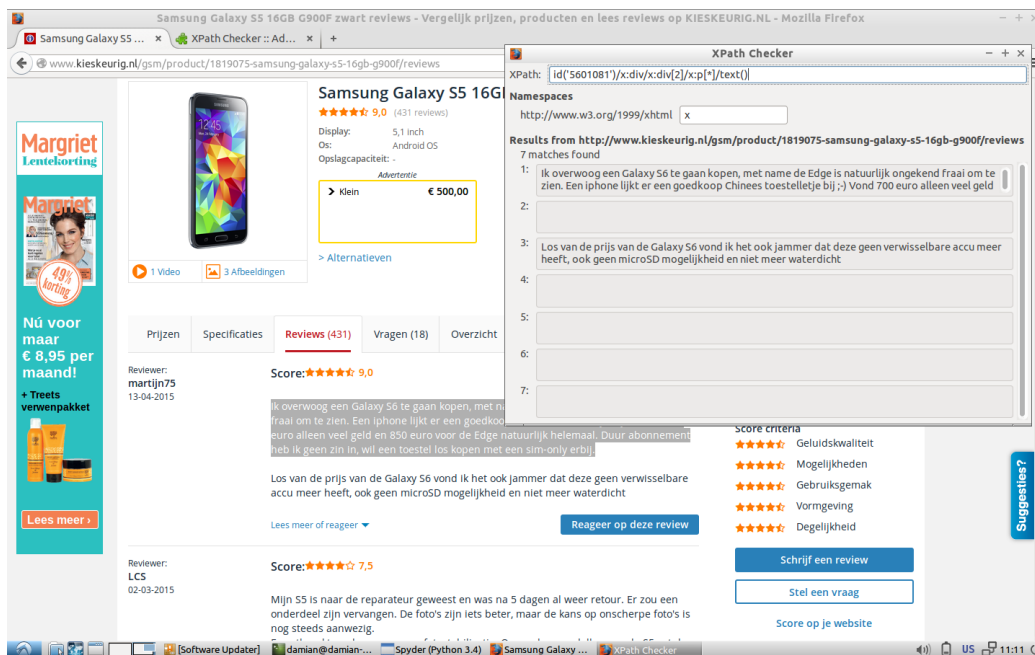

Figure 7.2: Identifying a correct XPath with XPath Checker

Often, you do not only want that *one* comment you selected, but *all*

comments. Nevertheless, select just one, and then try to modify the XPath until it fits your needs. The XPath Checker immediately shows you the results, so you can engage in a lot of trial- and error. Some rules for modifying the XPath:

- `//` (thus, a double slash rather than a single slash) means 'arbitrary depth' (=may be nested in many higher levels, there may be an arbitrary number of higher levels which are not further specified)

- `*` means 'anything' (if `p[2]` is the second paragraph, `p[*]` are all paragraphs)

- Let the XPath end with `/text()` to get all text

In addition, you can also have a look at alternative XPath specifications. Again, select the text you are interested in, right-click, and choose "Inspect element".[1] You can now see how the HTML tags referring to that element are nested, which should correspond to the construction of your XPath. In particular,

- If you want to refer to a specific attribute of a HTML tag, you can use `@`. For example, every `*[@id="reviews-container"]` in an XPath would grap what is within a tag like `<div id="reviews-container" class="user-content">`

An example that scrapes all reviews of a specific telephone using one single XPath expression:

```
1  from lxml import html
2  from urllib import request
3
4  req=request.Request("http://www.kieskeurig.nl/tablet/samsung/
       galaxy_tab_3_101_wifi_16gb/reviews/1344691")
5  tree = html.fromstring(request.urlopen(req).read().decode(encoding="utf
       -8",errors="ignore"))
6
7  reviews = tree.xpath('//*[@id="reviews-container"]//*[@class="text margin-
       mobile-bottom-large"]/text()')
8
9  print (len(reviews),"reviews scraped. Showing the first 60 characters of
       each:")
10 i=0
```

---

[1]If you use the Chrome browser, you can directly copy an XPath from the "Inspect element" window, but you have no way of interactively checking the XPath like with XPath Checker

```
11  for review in reviews:
12      print("Review",i,":",review[:60])
13      i+=1
```

This produces the following output:

```
1  34 reviews scraped. Showing the first 60 characters of each:
2  Review 0 : Ideaal in combinatie met onze Samsung curved tv en onze mobi
3  Review 1 : Gewoon een goed ding!!!!Ligt goed in de hand. Is duidelijk e
4  Review 2 : Prachtig mooi levendig beeld, hoever of kort bij zit maakt n
5  Review 3 : Opstartsnelheid is zeer snel.
```

Now it's your turn!

7.4 Alternatives

You can get very far with the approaches sketched in this paper: regular expressions, the lxml-package, and wget for automated downloading tasks. BeautifulSoup is a python package that lies somewhere in between, as it resembles lxml, but internally uses regular expressions rather than an XPath to parse the HTML.

If you want to write an implication that integrates crawling and parsing, you might have a look at the scrapy framework (`http://scrapy.org/`)

Chapter 8

Network visualization

We are often used to representation of data in forms of two-dimensional tables (an Excel or SPSS file, a CSV file). We have already seen that this is not always the most appropriate way to conceptualize data: Hierarchical data, for example, can often be much better represented in JSON format. Another way of representing data is in form of a *network* (Figure 8.1).
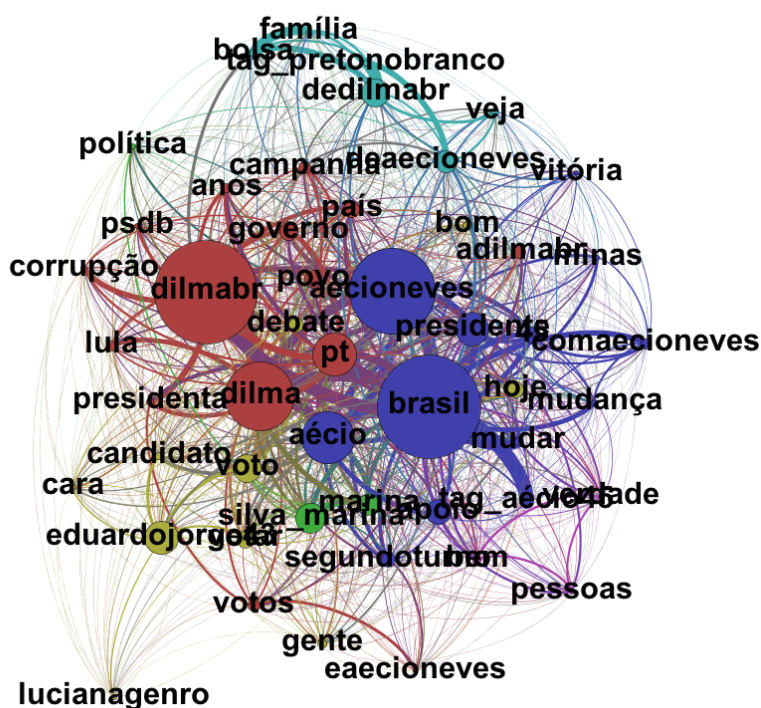

Figure 8.1: A network of co-occuring words

We call the elements in a network *nodes* and the connections between them *edges*. A node can be anything: a word, a person, whatever. Edges van be directed (like an arrow) or undirected. For example, a nework of Twitter users (the edges) could have edges that represent -mentions. These edges would be directed: if A mentions B, that does not imply that B mentions A as well. On a Facebook friendship network, this would be different: Here, we would have undirected edges.

Giving an introduction to network analysis falls outside of the scope of this tutorial, but you will learn how to save your data in a format that can be used to analyze or visualize them.

In particular, we will look how we can construct a network of words that co-occur together in texts, which can be a nice way to conduct some inductive framing analysis (see Boumans & Trilling, 2016).

8.1   Producing a file for analysis with Gephi

Let us considering the following case: We have a list of strings (e.g., a list of tweets) and want to know which words often occur together in the same string (tweet). We could model our data in such a way that each word is a node. We could also attach a weight to each node, so that the node can be displayed bigger the more often the word is mentioned. We could now say that if two words co-occur together, they are connected with a node. Again, we could say that the more often this happens, the thicker the edge should become.

Thus, we basically need

- a list with all words (the nodes) with their frequency (the weight/size of the nodes)

- a list with all connections (the edges, thus, a list of pairs of nodes that are co-occuring in the same string/tweet) with the number of strings/tweets in which they co-occur.

The GDF file format is a format that allows us to store exactly this information. Have a look at the following example. In lines 1, it is defined how the following node definitions are formated: a variable called `name`, which is a string (that's what they mean with VARCHAR), followed by a variable `width` which has the format double (a type of number, we would call it a float). And indeed, you see that the following lines contain strings (the words which are the nodes) followed by the size of the node (the frequency of the words). In line 12, it is defined that the following lines contain the edge definitions: two strings (node1 and node 2, followed by the edge weight.

For example, we see that the words "coffee" occurs three times in total (line 2), and one time together with the word "beer" (line 13).

```
1  nodedef>name VARCHAR, width DOUBLE
2  coffee,3
3  beer,2
4  i,4
5  and,1
6  with,1
7  friend,1
8  having,1
9  like,3
10 am,1
11 my,1
12 edgedef>node1 VARCHAR,node2 VARCHAR, weight DOUBLE
13 coffee,beer,1
14 i,beer,2
15 and,beer,1
16 with,friend,1
17 coffee,with,1
18 i,and,1
19 having,friend,1
20 like,beer,2
21 am,friend,1
22 i,am,1
23 i,coffee,3
24 i,with,1
25 am,having,1
26 i,having,1
27 coffee,and,1
28 like,coffee,2
29 am,coffee,1
30 with,my,1
31 i,friend,1
32 like,and,1
33 am,with,1
34 having,with,1
35 i,my,1
36 having,coffee,1
37 i,like,3
38 coffee,friend,1
39 having,my,1
40 am,my,1
41 coffee,my,1
42 my,friend,1
```

As the format is so simple, we can write a program that produces such a file. In fact, we have already done so for the first part: it is in fact nothing else than a CSV file with frequency counts.

For the second part, we need a module that tells us wich words co-occur together. In other words, we want to know all *combinations* of words in a given string. Not very surprisingly, this method is called `combinations`. See the example below:

```
1  from itertools import combinations
2  words="Let's combine stuff!".split()
3  print ([e for e in combinations(words,2)])
```

produces:

```
1  [("Let's", 'combine'), ("Let's", 'stuff!'), ('combine', 'stuff!')]
```

We already see that it is probably wise to do some preprocessing (to remove the punctuation for example, but you can also think of stopword removal, stemming, or converting to lowercase. We will leave that for know, you already know how to do this and can add that yourself.

There is one thing we still have to consider: We have an undirected network and do not want to distinguish between (`'combine', 'stuff!'`) and (`'stuff!', 'combine'`). We can construct the following minimal example, where we print a list of edges, based on co-occurrances of words in a set of three tweets. Do you see how we use lines 8 and 9 to turn around (`'stuff!', 'combine'`) if we already have (`'combine', 'stuff!'`) in our dict of edges that we construct? Also look at line 10, where we specify that a combination is only added to the dict (in line 11) if both nodes are not identical.

```
1  from collections import defaultdict
2  from itertools import combinations
3  tweets=["i am having coffee with my friend","i like coffee","i like coffee
       and beer","beer i like"]
4  cooc=defaultdict(int)
5  for tweet in tweets:
6      words=tweet.split()
7      for a,b in set(combinations(words,2)):
8          if (b,a) in cooc:
9              a,b = b,a
10         if a!=b:
11             cooc[(a,b)]+=1
12 for combi in sorted(cooc,key=cooc.get,reverse=True):
13     print (cooc[combi],"\t",combi)
```

This gives you:

```
1  3       ('i', 'coffee')
2  3       ('i', 'like')
3  2       ('like', 'coffee')
4  2       ('i', 'beer')
5  2       ('like', 'beer')
6  1       ('i', 'am')
7  1       ('am', 'friend')
```

You know have all building blocks you need to write a program that produces a GDF file. You would need to add

- something that reads your input from a file (e.g., a CSV file of tweets or a JSON file of speeches or a set of individual TXT files with newspaper articles)

- some preprocessing

- maybe some filter to filter out nodes and edges that occur very few times

- something to write the output to a file rather than printing to the screen.

The GDF file your program produces can be opened in Gephi (or some other network visualization or analysis tool). I will provide you with one solution, but of course you can also try yourself!

> ! Rather than producing a GDF file and opening it in Gephi, you can also do network analysis in Python itself, for example with the module `networkx`. This can be very interesting, especially for really large networks (which you maybe cannot open with a graphical tool like Gephi).

Chapter 9

Machine Learning and Topic Modelling

The vastness of the topic makes it impossible to cover it extensively in this course. Nevertheless, as last part, we will take a very small and superficial glimpse in the world of supervised and unsupervised machine learning. The lecture slides should give you a bit more context, but here you find two examples to illustrate the general principle — and to give you a starting point for your own investigations.

9.1 Supervised Machine Learning

For this demonstration, we use a dataset from the Internet Movie Database (Maas et al., 2011). It contains in total 50000 reviews, separated into a test dataset and a training datasset (25000 each), half of them positive, half of them negative.

Download and unpack the dataset:

```
1  cd /home/damian
2  wget http://ai.stanford.edu/~amaas/data/sentiment/aclImdb_v1.tar.gz
3  tar -xzf aclImdb_v1.tar.gz
4  rm aclImdb_v1.tar.gz
```

You now have a folder `aclImdb` in your home directory. Take a look at the structure of the dataset, maybe read the documentation that is included.

You should probably see rather quickly that there are two folders with an identical structure, `train` and `test`. Within each of them, there are two folders `pos` and `neg`, with a lot of plain text files within them. Have a look at them.

First of all, we need the training dataset and the test dataset. Lets

conceptualize them as a list of tuples where all positive reviews get a 1, and all negative ones a −1:

```
reviews=[("This is a great movie",1),("Bad movie",-1), ... ...]
test=[("Not that good",-1),("Nice film",1), ... ...]
```

Of course, we do not want to insert our 50000 reviews by hand, but read them from the files we downloaded. We did something similar already with for example the LexisNexis articles or the lists of positive or negative words. Let's do it using the package `glob` that makes our live easier here:

```
from glob import glob

reviews=[]

for file in glob ("/home/damian/aclImdb/train/pos/*.txt"):
    with open(file) as fi:
        reviews.append((fi.read(),1))

for file in glob ("/home/damian/aclImdb/train/neg/*.txt"):
    with open(file) as fi:
        reviews.append((fi.read(),-1))
```

After that, we do exactly the same for the test dataset. You only have to replace `reviews` with `test` in the code above, and `train` with `test`.

Once we have done this, and thus have two lists, `reviews` and `test`, each of them with a length of 25000, we can train and test the classifier — after importing the necessary modules from the package scikit-learn (Pedregosa et al., 2011), of course:

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.feature_extraction.text import CountVectorizer
from sklearn import metrics
```

We use a Bag-of-Word representation of all reviews rather than the whole reviews. We only want to know the frequency of each word in each review. While we could calculate this ourselves, scikit-learn integrates this nicely in the workflow (they even remove stopwords for us):

```
vectorizer = CountVectorizer(stop_words='english')
train_features = vectorizer.fit_transform([r[0] for r in reviews])
test_features = vectorizer.transform([r[0] for r in test])
```

> **!** Note that `[r[0] for r in reviews]` is a short form of writing something like the following (it is called "list comprehension"):

```
newlist=[]
for r in reviews:
    newlist.append[r[0]]
```

> It gives us a list of the reviews themselves, without the scores – and `r[1]` would give us only the scores.

Training the machine learning algorithm (we chose the Multinomial Naïve Bayes variant here, there are others as well – read the docs and check out which one is best!) takes only two lines:

```
1  # Fit a naive bayes model to the training data.
2  nb = MultinomialNB()
3  nb.fit(train_features, [r[1] for r in reviews])
```

Let's now use the classifier we just trained to predict the classification of our test dataset:

```
1  predictions = nb.predict(test_features)
2  actual=[r[1] for r in test]
```

(of course, we already know the actual, real classes, we just put them in a list in the second line for easier comparison)

We could compare the two lists `predictions` and `actual` by hand to find out in where our classifier is right or wrong. But we can also just calculate the AUC, a measure of accuracy:

```
1  fpr, tpr, thresholds = metrics.roc_curve(actual, predictions, pos_label=1)
2  print("Multinomal naive bayes AUC: {0}".format(metrics.auc(fpr, tpr)))
```

We can now play around and see how the classifier classifiers some new data:

```
1  newreviews=["What a crappy movie! It sucks!",
2          "This is awsome. I liked this movie a lot, fantastic actors",
3          "I would not recomment it to anyone.",
4          "Enjoyed it a lot"]
5
6  new_features=vectorizer.transform(newreviews)
7  predictions = nb.predict(new_features)
8  print(predictions)
```

9.2   Latent Dirichlet Allocation (LDA)

Topic Modelling is one form of unsupervised machine learning.

You can use gensim Řehůřek and Sojka (2010) for this. Install the module from the bash terminal:

```
1  sudo pip3 install gensim
```

You might need to restart the Python console you are using (or just restart Spyder).

Furthermore, let us assume you have a list of lists of words (!) called `texts`:

```
articles=['The tax deficit is higher than expected. This said xxx ...', '
    Germany won the World Cup. After a']
texts=[art.split() for art in articles]
```

which looks like this:

```
[['The', 'tax', 'deficit', 'is', 'higher', 'than', 'expected.', 'This', '
    said', 'xxx', '...'], ['Germany', 'won', 'the', 'World', 'Cup.', '
    After', 'a']]
```

I'll take the movie reviews from the last section as a test case (without the ratings, which are irrelevant now), but of course you can use any collection of text files.

```
from glob import glob
texts=[]
for file in glob ("/home/damian/aclImdb/train/pos/*.txt"):
    with open(file) as fi:
        texts.append(fi.read().split())
```

Pay attention to the `.split()` method, which makes that we now have a list of lists of words, just as we wanted.

We now let gensim create a BOW representation of the texts — just as in earlier examples, but each packages has a slightly different syntax for that. Luckily, you don't have to remember that, that's where the documentation and example scripts that come with each package are for.

```
from gensim import corpora, models
# Create a BOW represenation of the texts
id2word = corpora.Dictionary(texts)
mm =[id2word.doc2bow(text) for text in texts]
```

We can now train the LDA models:

```
lda = models.ldamodel.LdaModel(corpus=mm, id2word=id2word, num_topics=100,
     alpha="auto")
```

Of course, you can specify any other number of topics. Most people use something like 50 or 100 topics, though. Let's print the most characteristic words for each topic:

```
for top in lda.print_topics(num_topics=NTOPICS, num_words=5):
    print ("\n",top)
```

Only one thing left to do: Calculate the scores for each topic per document and save them to a file. I chose a tab-separated one:

```
scoresperdoc=lda.inference(mm)
with open("topicscores.tsv","w",encoding="utf-8") as fo:
```

```
3    for row in scoresperdoc[0]:
4        fo.write("\t".join(["{:0.3f}".format(score) for score in row]))
5        fo.write("\n")
```

This is the general principle, but of course, there are a lot of ways of tuning it. To start with, some stopword removal would be advisable - and we did not even remove punctuation or all the weird HTML tags, or bother about converting it to lower case. However, you already learned all this and should be able to write a good script by integrating the structure from above with other techniques.

For some suggestions, see the documentation of gensim and also the example script I send you.

Chapter 10

Statistics with Python

One of the things you have learned so far is how to output data in a format that suits your needs. For example, no matter what your input data are, you can always save the results of your program in a CSV file that you can open with R, Stata or SPSS for further analysis. And indeed, often it makes sense to use different tools in different stages of a project.

However, if you only want to calculate a mean and a standard deviation or even conduct a regression, this is actually not neccessary – and, let's face it, is pretty cool if your program just does *everything* in a single run. In this chapter, I'll briefly mention some modules that are useful for this, so that you know where to look further.

10.1   numpy & scipy

Numpy (der Walt, Colbert, & Varoquaux, 2011) is a package that provides a lot of mathematical functions. It can, for example, be used to calculate means (ok, that's boring, you could do that yourself), standard deviations, correlations, and much, much more. It also offers some specific data types that are more efficient for some calculations than the build-in lists. It goes a long with the similar package SciPy (Jones, Oliphant, Peterson, et al., 2001).

```
1  import numpy as np
2  >>> x = [1,2,3,4,3,2]
3  >>> y = [2,2,4,3,4,2]
4  >>> np.mean(x)
5  2.5
6  >>> np.std(x)
7  0.9574271077563381
8  >>> np.corrcoef(x,y)
9  array([[ 1.        ,  0.67883359],
10        [ 0.67883359, 1.        ]])
```

```
11
12 from scipy import stats
13 >>> stats.skew(x)
14 0.0
15 >>> stats.kurtosis(x)
16 -0.942148760330578
```

10.2   pandas

Pandas (McKinney et al., 2010) is a framework that allows statistical modelling in Python. Those of you who know R will see a lot of similarities. Within pandas, data are stored in a table, very much like a Stata or SPSS dataset – and yes, it is indeed called exactly as it is called in R: a *dataframe*. As you see below, a dataframe basically consists of different columns with a name, which consist of a list of data. Pandas can read directly fromm a CSV file, but as you can see below, you can also construct a dataframe yourself. To run an OLS regression, for example you then only have to specify which columns are the dependent and the independent variables.

```
1 import pandas as pd
2 from pandas.stats.api import ols
3 df = pd.DataFrame({"y": [10,20,30,40,50], "x1": [20, 30, 10, 40, 50], "x2
      ": [32, 234, 23, 23, 42523]})
4 result = ols(y=df['y'], x=df[['x1','x2']])
5 print(result)
```

prints a regression table like you would expect from any statistics program:

```
1 Formula: Y ~ <x1> + <x2> + <intercept>
2
3 Number of Observations:       5
4 Number of Degrees of Freedom: 3
5
6 R-squared:       0.5789
7 Adj R-squared:   0.1577
8
9 Rmse:            14.5108
10
11 F-stat (2, 2):   1.3746, p-value:   0.4211
12
13 Degrees of Freedom: model 2, resid 2
14
15 ----------------------Summary of Estimated Coefficients------------------
16        Variable     Coef    Std Err    t-stat    p-value   CI 2.5%  CI 97.5%
17 -----------------------------------------------------------------------
18            x1     0.4012    0.6497      0.62     0.5999   -0.8723    1.6746
19            x2     0.0004    0.0005      0.65     0.5826   -0.0007    0.0014
```

```
20      intercept   14.9525   17.7643      0.84    0.4886  -19.8655   49.7705
21 -------------------------------End of Summary-------------------------
```

Of course, you might want to give your variables more meaningful names than `x1` and `x2`.

A nice extra is that you can get much more than this regression table. You can access the estimates directly to do further calculations on them. Or, pretty cool, you easily get a list of predicted values with (`result.y_predict`).
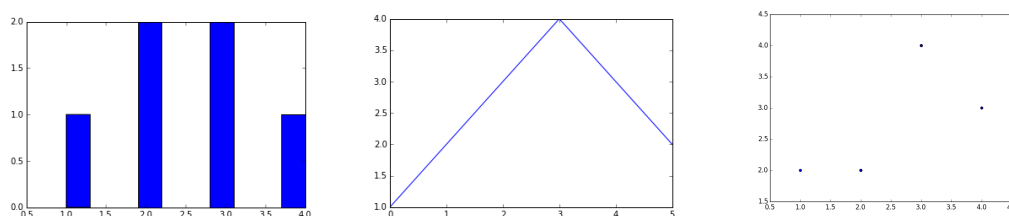
10.3   matplotlib

Figure 10.1: Examples of plots generated with `matplotlib`

While there are tools that make fancier graphics (take a look at the Python module `seaborn`; or use `ggplot2` in R), `matplotlib` (Hunter, 2007) is really useful if you just want to make a quick histogram, line graph, or scatter plot (Fig. 10.1).

```
1 import matplotlib.pyplot as plt
2 x = [1,2,3,4,3,2]
3 y = [2,2,4,3,4,2]
4 plt.hist(x)
5 plt.plot(x,y)
6 plt.scatter(x,y)
```

Chapter 11

Further reading

The following books provide the interested student with more and deeper information. They are intended for the advanced reader and might be useful for individual projects:

- Russel, 2013. Gives a lot of examples about how to analyze a variety of online data, including Facebook and Twitter, but going much beyond that.

- Bird et al., 2009. This is the official documentation of the NLTK package that we are using. A newer version of the book can be read for free at `http://nltk.org`

- McKinney, 2012: Another book with a lot of examples. A PDF of the book can be downloaded for free on `http://it-ebooks.info/book/1041/`.

In the last years, some other tutorials, partly similar to this one, have been published. See for exampe:

- Jürgens & Jungherr, 2016. Provides examples and code for non-pogrammers to analyze Twitter data using Python and R.

Appendix A

Exercise 1: Describing an existing structured dataset

A.1 Downloading the data

In this exercise, you will do some basic descriptive analyses of an existing dataset. Mazières, Trachman, Cointet, Coulmont, and Prieur (2014) scraped data from online porn sites, resulting in two datasets with metadata about almost two million amateur porn videos. We will work with one of these datasets, consisting of all metadata on all videos posted on `http://xhamster.com` from its creation in 2007 until February 2013. The authors made the dataset available on on `http://sexualitics.github.io`, and you can find a description of it in Figure A.1.

We do the exercise together in class, but make sure you have downloaded the dataset before class. You can do so as follows (but, of course, replace "damian" with your own user name):

```
1  cd /home/damian
2  mkdir pornexercise
3  cd pornexercise
4  wget pornstudies.sexualitics.org/data/xhamster.json.tar.gz
5  tar -xzf xhamster.json.tar.gz
```

The `wget` command downloads the dataset. It is compressed, so we have to uncompress it, which is done by the `tar` command (most of you probably are used to having `.zip` files for compressed or archived data, which is essentially the same; `.tar.gz` is more common among the nerdier part of the population). Lets check if everything went right:

```
1  ls -lh
```

should give you an output like this:

```
1  damian@damian-VirtualBox:~/pornexercise$ ls -lh
2  total 284M
3  -rw-r--r-- 1 damian damian 229M feb 8 2014 xhamster.json
4  -rw-rw-r-- 1 damian damian 55M feb 8 2014 xhamster.json.tar.gz
```
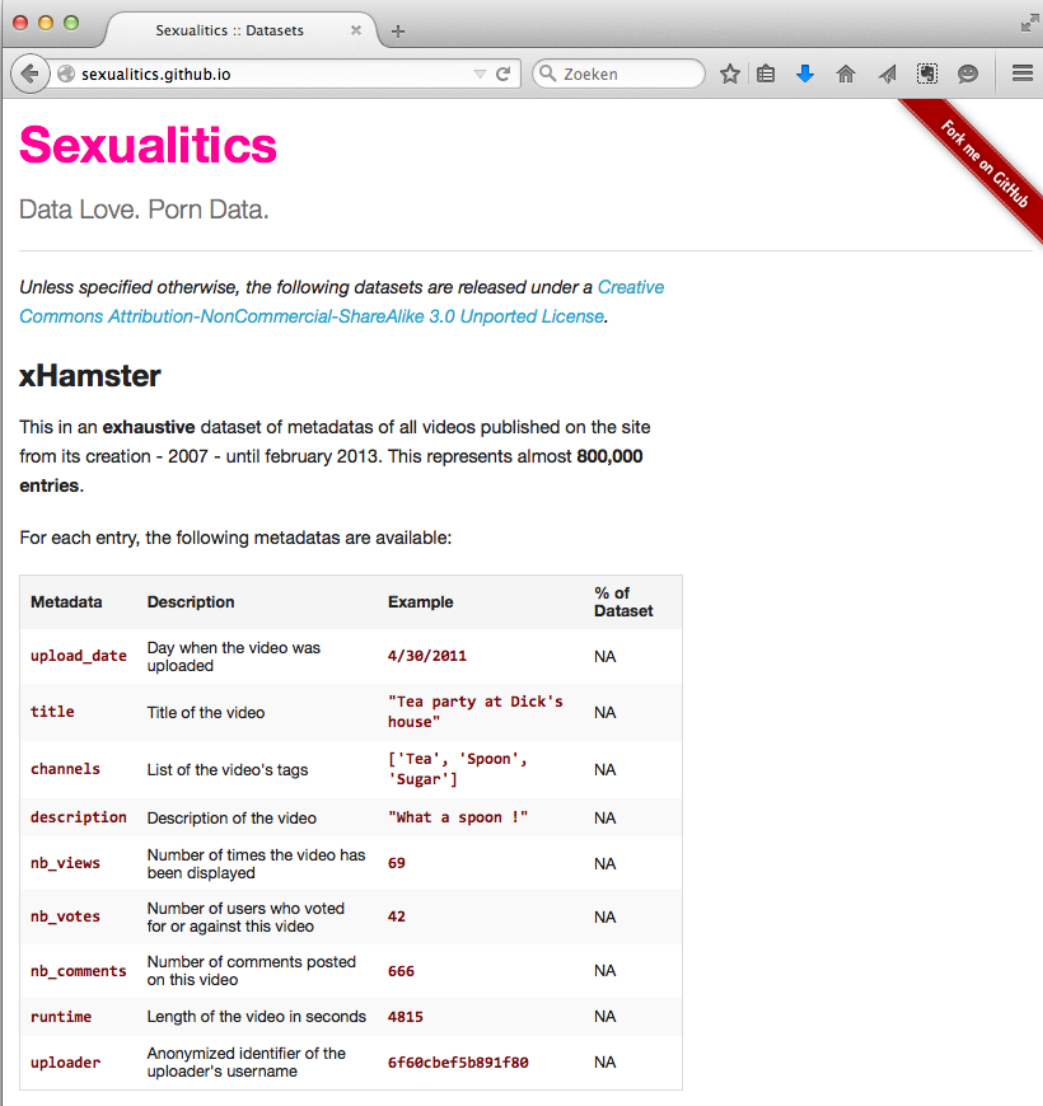
You see that the compressed file is 55MB large, but the uncompressed one is more than four times as large. Let's delete the compressed one, we don't need it any more:

```
1  rm xhamster.json.tar.gz
```

A.2   The tasks

Start with having a look at Figure A.1. It is important to understand the structure of the data: Which fields are there, how are they named, and what do they contain? For example, we see that the field "channels" contains a *list* of different tags, while "nb_votes" seems to contain an *integer*. Ready to go? Let's do some work:

1. Print the title of each video.

2. (a) What are the 100 most frequently used tags?
   (b) What is the average number of tags per video?

3. What tags generate the most comments/votes/views?

4. What is the average length of a video description?

5. What are the most frequently used words in the descriptions?

Figure A.1: The discription of the dataset.

References

Bird, S., Loper, E., & Klein, E. (2009). *Natural language processing with Python.* Sebastopol, CA: O'Reilly.

Borra, E., & Rieder, B. (2014). Programmed method: Developing a toolset for capturing and analyzing tweets. *Aslib Journal of Information Management*, *66*(3), 262–278. doi: 10.1108/AJIM-09-2013-0094

Boumans, J. W., & Trilling, D. (2016). Taking stock of the toolkit: An overview of relevant autmated content analysis approaches and techniques for digital journalism scholars. *Digital Journalism*, *4*(1), 8–23. doi: 10.1080/21670811.2015.1096598

der Walt, S. V., Colbert, S. C., & Varoquaux, G. (2011, mar). The NumPy array: A structure for efficient numerical computation. *Computing in Science & Engineering*, *13*(2), 22–30. doi: 10.1109/mcse.2011.37

Hunter, J. D. (2007). Matplotlib: A 2d graphics environment. *Computing in Science & Engineering*, *9*(3), 90–95. doi: 10.1109/mcse.2007.55

Jones, E., Oliphant, T., Peterson, P., et al. (2001). *SciPy: Open source scientific tools for Python.* Retrieved from `http://www.scipy.org/` ([Online; accessed 2016-02-25])

Jürgens, P., & Jungherr, A. (2016). A tutorial for using Twitter data in the social sciences: Data collection,. preparation, and analysis. *SSRN*. doi: 10.2139/ssrn.2710146

Maas, A. L., Daly, R. E., Pham, P. T., Huang, D., Ng, A. Y., & Potts, C. (2011). Learning word vectors for sentiment analysis. In *Proceedings of the 49th annual meeting of the association for computational linguistics: Human language technologies* (pp. 142–150). Portland, Oregon, USA: Association for Computational Linguistics. Retrieved from `http://www.aclweb.org/anthology/P11-1015`

Mazières, A., Trachman, M., Cointet, J.-P., Coulmont, B., & Prieur, C. (2014). Deep tags: toward a quantitative analysis of online pornography. *Porn Studies*, *1*(1-2), 80-95. doi: 10.1080/23268743.2014.888214

McKinney, W. (2012). *Python for data analysis.* Sebastopol, CA: O'Reilly.

McKinney, W., et al. (2010). Data structures for statistical computing

in Python. In *Proceedings of the 9th python in science conference* (Vol. 445, pp. 51–56).

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., . . . Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Řehůřek, R., & Sojka, P. (2010). Software framework for topic modelling with large corpora. In *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks* (pp. 45–50). Valletta, Malta: ELRA. (`http://is.muni.cz/publication/884893/en`)

Russel, M. (2013). *Mining the social web. Data mining Facebook, Twitter, LinkedIn, Google+, GitHub, and more* (2nd ed.). Sebastopol, CA: O'Reilly.

Thelwall, M., Buckley, K., & Paltoglou, G. (2012). Sentiment strength detection for the social web. *Journal of the American Society for Information Science and Technology*, *63*(1), 163–173. doi: 10.1002/asi.21662

Van Atteveldt, W. (2008). *Semantic network analysis: Techniques for extracting, representing, and querying media content.* Charleston, SC: BookSurge.