

Today

- Working with textual data
 - Top down vs bottom up
 - Enriching (textual) datasets
- Ingesting textual data

Beyond numbers

Working with textual data



Bottom-up

VS

top-down

- What are the texts about?
- What language is used?
- We have no 'hypothesis', no a priori
 list of words we are interested in
- Counting the most frequently used words
- [clustering, topic modeling]

- How often is party X mentioned?
- How many texts are about the economy?
- We know what we are looking for, we have an a priori list of words we are interested in
- ☐ Search terms, regular expressions
- ☐ [supervised machine learning]

A simple bottom-up approach

- We count the most frequently occuring words
 - (probably after cleaning up a bit: stopword and punctuation removal, lowercasing)
- Variations:
 - Word clouds
 - bigrams

A simple bottom-up approach

```
>>> from collections import Counter
>>> text = 'This is some text with more text and text. Yes it is.'
>>> text_clean = text.replace('.','').lower()
>>> Counter(text_clean.split()).most_common(5)
[('text', 3), ('is', 2), ('and', 1), ('this', 1), ('some', 1)]
```

A simple bottom-up approach

Discuss:

When do we do this? Think of journalistic use cases!

Advantages/disadvantages?

A simple top-down approach

- We make a list of words we are interested in and count how often (or whether) they occur
- Or we select only documents in which these words occur
- Variations
 - Regular expressions, e.g. "ABN.? Amro" (google for more info),

Another top-down approach: Sentiment analysis

- Essentially, we have lists of words with associated valence scores
- Using some math, we calculate an overall measure per text.

We can get it for an individual string:

```
from nltk.sentiment import vader

classifier = vader.SentimentIntensityAnalyzer()

classifier.polarity_scores('This is crappy shit')
{'neg': 0.783, 'neu': 0.217, 'pos': 0.0, 'compound': -0.802}
```

Or add columns to a dataset (and choose what you care about):

```
df['sentiment'] = df['text'].map(classifier.polarity_scores)

df['neg'] = df['sentiment'].map(lambda x: x.get('neg'))
```

A simple top-down approach

Discuss:

When do we do this? Think of journalistic use cases!

Advantages/disadvantages?

Towards a complete workflow

Enriching data

But first: Our workflow

(1) retrieval --> (2) preprocessing --> (3) enrichment --> (4) analysis

- We talked about retrieval (file formats, APIs)
- We talked about (simple) analyses (descriptive statistics, [first] visualizations)
- We now learn how to preprocess and enrich our data



Recap: (1) Data retrieval

APIs and files (CSV, JSON)

• Files:

- direct via, e.g., pd.Dataframe.read_csv()
- to extracts part from a deeply nested JSON-file: via json-module and for-loops



Recap: (4) Analysis

- .describe() for numerical data
- .value_counts() for frequency tables (especially nominal data)
- First .groupby() if you want to distinguish between groups
- Possibly .plot(), .hist() etc.



(2) Preprocessing

- Cleaning up, e.g. renaming columns
- Applying a function to a column (and create a new one):
 - df['numbers'] = df['comlumnwithnumbersasstrings'].map(int)
 - df['mytextlower'] = df['sometext'].map(lambda x: x.lower())
 - Stopword removal ('the', 'and', 'a', ...)
 - Punctuation removal

•

Let's try something...

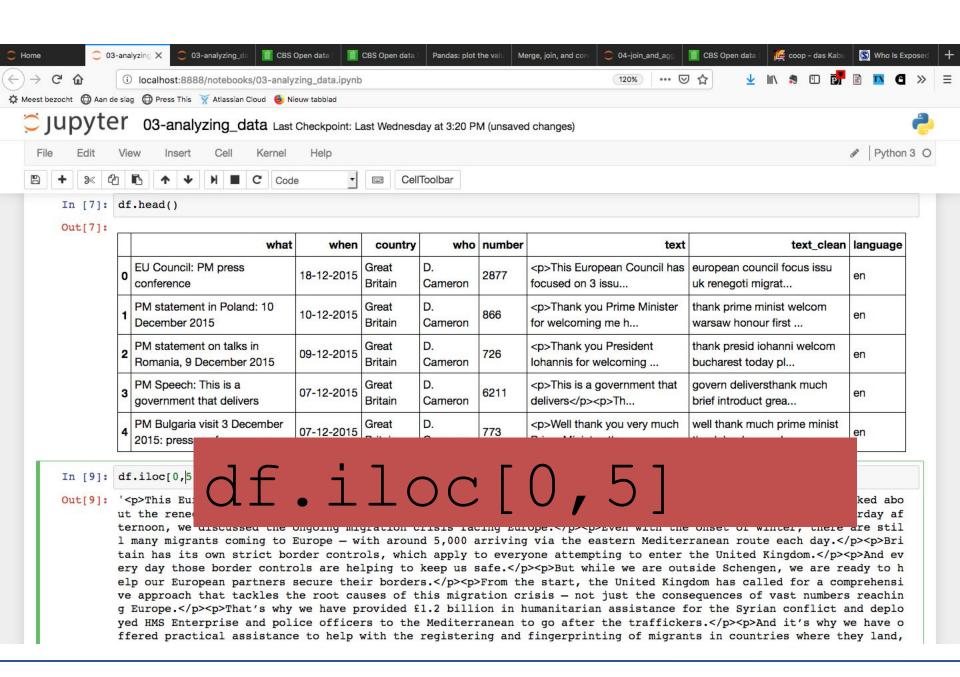
• In a dataset of all speeches in the EU parliament, let's check out who talks most about terror and then read that speech.

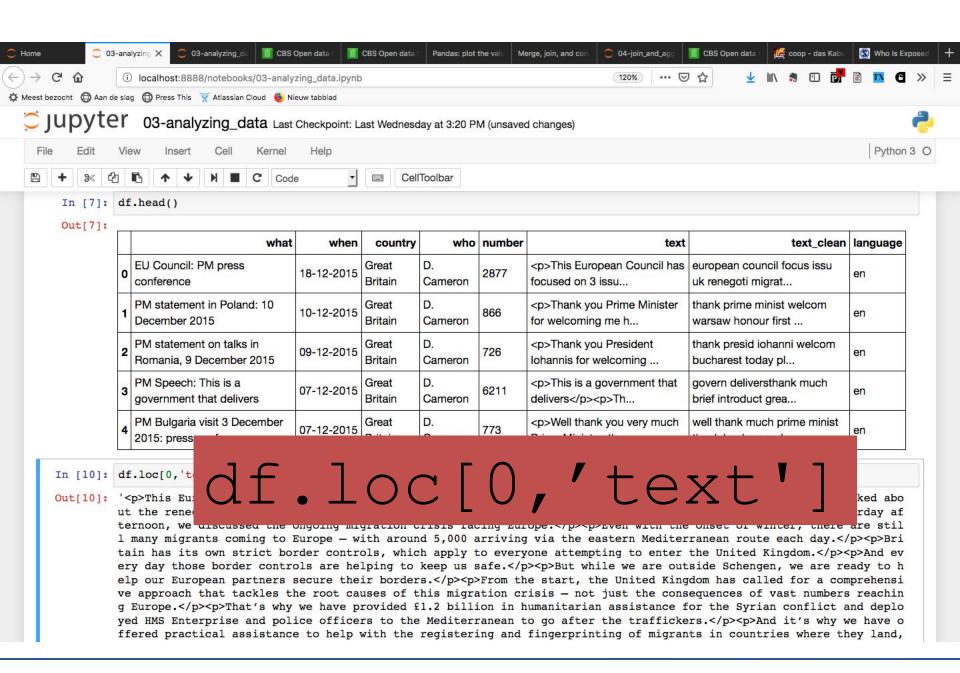
[This example will come back]

(3) Enrichment

 Create new columns by, for example, counting mentions of a term/regular expression

- df['terror'] = df['speech'].str.count('[tT]error')
- → and here comes back our example from last week!





More subsetting and slicing

- Advanced example: Get the whole row where the column 'terrorrefs' has the highest value in the whole dataset:
 - df.iloc[df['terrorrefs'].idxmax()]
- That works because df.iloc[] expects an integer to identify the row number, and df['terrorrefs'].idxmax() returns an integer (687 in our case)
- We could also do it in two steps:

df.iloc[df['terrorrefs'].idxmax()] is the same as:

```
df['terrorrefs'].idxmax()
687
df.iloc[687]
                Permanent Link to Press conference in Islamabad
what
when
                                                       14-12-2008
                                                    Great Britain
country
who
                                                         G. Brown
number
                                                             2954
text
              Transcript of a press conference given by t...
              transcript press confer given prime minist mr ...
text clean
language
                                                               en
terrorrefs
                                                               44
Name: 687, dtype: object
```



From files to Pandas (or not)

Ingesting textual data



tabular file vs text files*

- You have a table where one column contains text (e.g., speeches), and the other columns metadata (e.g., who gave it, when, ...)
 - → pd.read_csv(), as always

df['speech'].str.count('[tT]error'

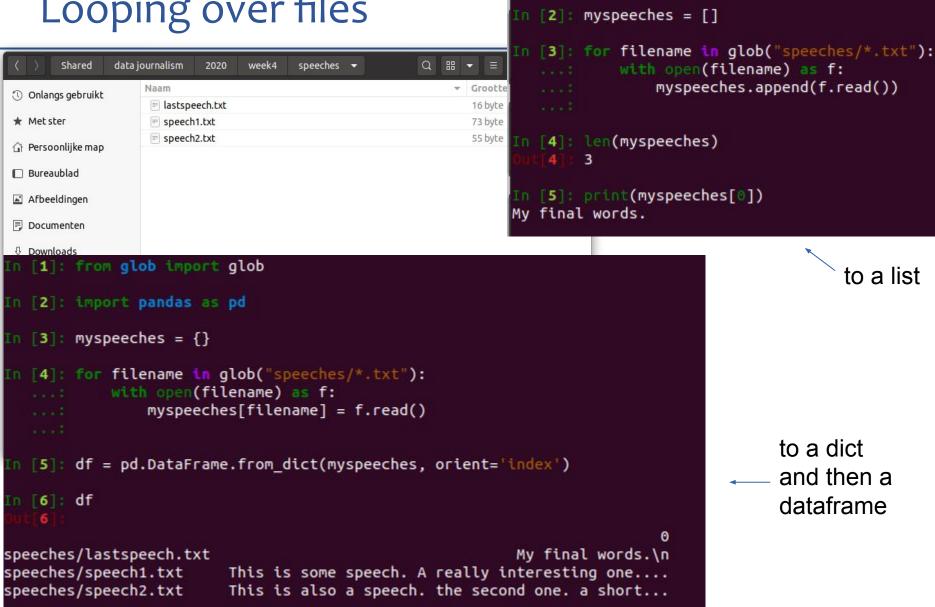
 → Pandas string functions on that column
 e.g., df['terror'] =

- You have one long file
 - → you need to parse it (e.g., using regular expressions)
 - → the less clearly structured, the harder (discuss individually)
- You have one file per text (speech, article,...)
 - → for loop to read files and add to a list or dict
 - → potentially transform to dataframe (partly matter of preference)

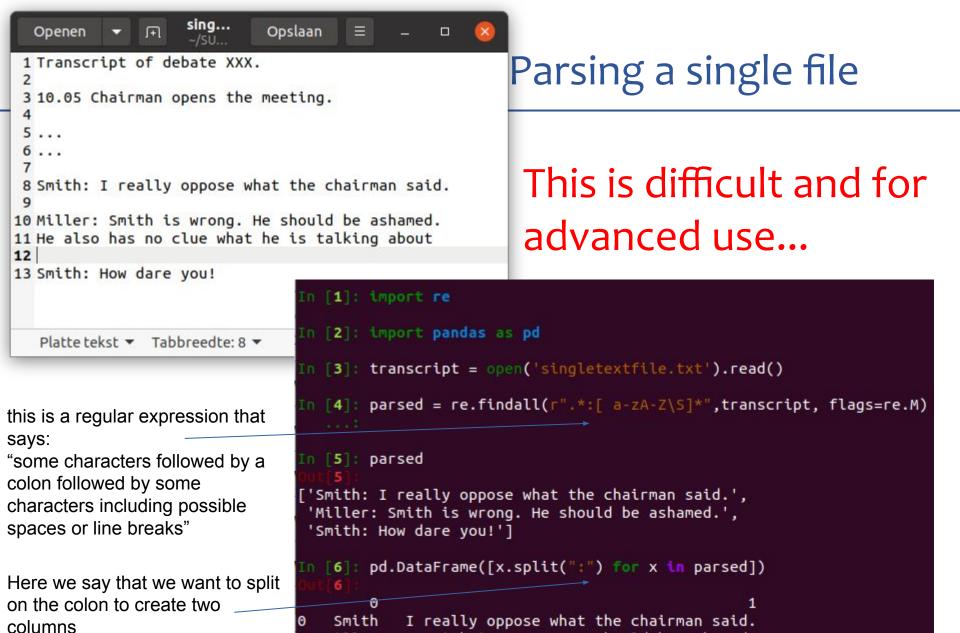
^{*} we assume plain text files (often called *.txt). There are Python modules for extracting plain text from other file formats (such as PDF).



Looping over files



[1]: from glob import glob



Smith is wrong. He should be ashamed.

How dare you!

Miller

Smith

Think about your data

• 1. How do my data look like?

- Ready-to-use table vs semi-structured vs unstructured
- Plain text files versus Word, PDF, HTML

• 2. What do I want to do with it?

- Bottom-up: most likely you just need a (list of) string(s)
- Top-Down: maybe pandas (but not always)

A range of possibilities

- Working with text can range from almost trivial (you have a dataframe already, you only need to apply .str.count(), .map() or similar and you are done) to very complicated (parsing badly structured text)
- Device a workflow and discuss the bottlenecks (with each other or us): e.g. "I can do A and C to achieve D, but don't know how to do B to get from A to C"

Summing up

Important modules, methods, functions



For reading files beyond using pandas

- glob to get a list of all files (with certain name pattern) in a folder
- •with open(filename) as f: f.read() to read plain text files

For matching patterns in strings

- Google "regular expression" and/or read the recommended reading in the syllabus for this week!
- re, in particular re.findall()

For working with text in pandas

- .map() to map some input value onto some output value using a function
 - e.g., df['lengthofspeech'] = df['speech'].map(len)
 - Or, more complex, with a user defined function (to get length in words):
 df['lengthofspeech'] = df['speech'].map(lambda x: len(x.split()))
 - Or, by using a function supplied by a tool such as Vader
- .str.count() to count how often a pattern (in fact, a regular expression) occurs in a string

For bottom-up text analysis

- Counter, in particular Counter.most_common() for getting the most common elements.
 - e.g. Counter.most_common(mystring.split()) to get the most common words by splitting a string into a list of words

How further?

Have a look at notebook 06-analyzing_text.ipynb and today's slides to try out some text analysis techniques.

Thursday: OPEN LAB (= time to work on your own projects)

Good luck!

