Text as Data: Computational Text Analysis

Week 1: Introduction to Computational Text Analysis and NLP

Ashrakat Elshehawy

Department of Politics and International Relations, University of Oxford

April 26, 2021

Organizational

- All course material will be posted on GitHub.
- For our coding sessions we will use Google Colab Notebooks, coding sheets and their solutions are hosted on the GitHub Page of the class.
- You can easily open any sheet from within GitHub by clicking on "Open in Colab" button, remember to always save a copy of your work.
- You should have a Google Drive account to easily work with Colab and load data.
- The Teams Website will serve our needs for communication.
- The Syllabus will be hosted on Canvas.

Class Times and Office Hours

We will meet on the following days on Zoom:

- Week 1: Monday the 26th of April 14.00-16.00
- Week 2: Tuesday the 4th of May 14.00-16.00
- Week 3: Monday the 10th of May 14.00-16.00
- Week 4: Monday the 17th of May 14.00 16.00

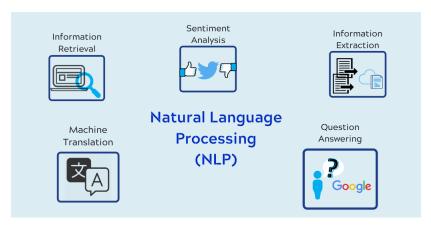
Office hours take place from week 1 to 4 on Fridays 4-6 pm. You need to book a slot beforehand (link in the Syllabus). Please come in the zoom room to attend the office hour sessions in the time you have booked.

Class Assessment

You will receive a coding assignment on the last session of the class, due by the Friday of the 5th week 24.00 - via email to the instructor (ashrakat.elshehawy@politics.ox.ac.uk).

What is Natural Language Processing?¹

The application of computational techniques for the the analysis of human language.



Source: Cybiant

¹Some of the slides are partly based on Federico Nanni's course of Computational Text Analysis at U Mannheim 📑

That is what we are learning in this class.

Most of data sets we use are already derived from Text

Examples:

Understanding Political Behavior

That is what we are learning in this class.

Most of data sets we use are already derived from Text

Examples:

- Understanding Political Behavior
- Coding Sentiment

That is what we are learning in this class.

Most of data sets we use are already derived from Text

Examples:

- Understanding Political Behavior
- Coding Sentiment
- Frequency of Conflict

That is what we are learning in this class.

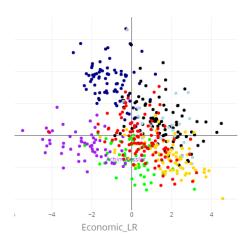
Most of data sets we use are already derived from Text

Examples:

- Understanding Political Behavior
- Coding Sentiment
- Frequency of Conflict
- Coding Topic Areas

Example: Infer from Twitter Text Ideological Positions of German Politicians

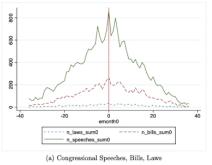
Marius Sälzer PhD Project, Universität Mannheim

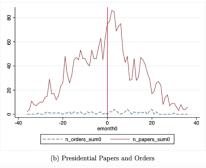


Source: Marius Sälzer Shiny app birdfish
Saeltzer, Marius (2020): Finding the Bird's Wings: Dimensions of Factional Conflict on Twitter. Party Politics (forthcoming).
DOI: 10.1177/1354068820957960

Example: How the US Electoral Cycle affects Elections Around the World?²

Documents Critical of a Country's Election: months -/+ election date





²Source: Bubeck, J, Elshehawy, Ashrakat, Marinov, Nikolay, and Federico Nanni, 2021. How the US Electoral Cycle Affects Elections Around the World. Working Paper

Example: Women's Authority in Patriarchal Movements

TABLE 1 Men Use Hadith-Related Phrases More Than Women

Term	% of Documents Using Term		% of All Words	
	Men	Women	Men	Women
allāh	95	85	3.02	1.60
şalā allāh	67	32	0.50	0.21
raḍī allāh	50	20	0.18	0.10
hadīth	64	39	0.30	0.14
qāl/yaqūl (al-)rasūl	30	10	0.047	0.026
Ibn Taymiyya	23	3	0.030	0.006
al-Bukhari	41	10	0.098	0.030
al-Bayhaqi	17	1	0.013	0.001
Abu Hurayra	29	4	0.048	0.008
al-Tabarani	16	1	0.014	0.002
Abu Dawud	29	4	0.043	0.006

Note: This table counts the use of hadith-related phrases in 3,470 documents (1,306,641 words) by women and 17,854 documents (74,991,711 words) by men on said.net. The left two columns show the percentage of men's and women's documents that contain each phrase. The right two columns show the percentage of men's and women's words devoted to each phrase. All gender differences are statistically significant at the .05 percent level.

Source: Nielsen, R.A., 2020. Women's Authority in Patriarchal Social Movements: The Case of Female Salafi Preachers. American Journal of Political Science, 64(1), pp.52-66.

 All quantitative models of language are wrong - but some are useful (Language is complex, "Time flies like an arrow. Fruit flies like a banana.")

- All quantitative models of language are wrong but some are useful (Language is complex, "Time flies like an arrow. Fruit flies like a banana.")
- The importance of "the human in the loop" (Deep understanding of text is necessary)

- All quantitative models of language are wrong but some are useful (Language is complex, "Time flies like an arrow. Fruit flies like a banana.")
- The importance of "the human in the loop" (Deep understanding of text is necessary)
- No-free-lunch theorem (There is no single best algorithm)

- All quantitative models of language are wrong but some are useful (Language is complex, "Time flies like an arrow. Fruit flies like a banana.")
- The importance of "the human in the loop" (Deep understanding of text is necessary)
- No-free-lunch theorem (There is no single best algorithm)
- Always validate!

Corpus Creation

- Corpus Creation
- Text-Processing and Cleaning

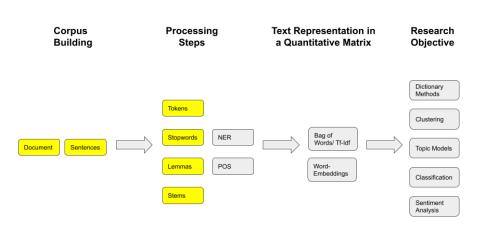
- Corpus Creation
- Text-Processing and Cleaning
- Dictionaries and Keyword-lists

- Corpus Creation
- Text-Processing and Cleaning
- Dictionaries and Keyword-lists
- Term-doc Matrices, Vector Space Representation

- Corpus Creation
- Text-Processing and Cleaning
- Dictionaries and Keyword-lists
- Term-doc Matrices, Vector Space Representation
- Unsupervised Techniques (e.g Topic-Models and Clustering)

- Corpus Creation
- Text-Processing and Cleaning
- Dictionaries and Keyword-lists
- Term-doc Matrices, Vector Space Representation
- Unsupervised Techniques (e.g Topic-Models and Clustering)
- Supervised Machine-Learning Techniques (e.g Classification)

From Text to Data



Newspaper Collections

New York Times Corpus (1987-2007, 1.8 million articles)

Newspaper Collections

- New York Times Corpus (1987-2007, 1.8 million articles)
- Die Zeit

Newspaper Collections

- New York Times Corpus (1987-2007, 1.8 million articles)
- Die Zeit
- Historical Corpus of German Newspaper (1650-1800)
 https://ota.bodleian.ox.ac.uk/repository/xmlui/handle/ 20.500.12024/2544

Newspaper Collections

- New York Times Corpus (1987-2007, 1.8 million articles)
- Die Zeit
- Historical Corpus of German Newspaper (1650-1800)
 https://ota.bodleian.ox.ac.uk/repository/xmlui/handle/ 20.500.12024/2544
- Lexis Nexis usually hard to scrape from

Political Speeches

• EuroParl: http://www.talkofeurope.eu/data/

- EuroParl: http://www.talkofeurope.eu/data/
- UK: https://www.hansard-corpus.org/

- EuroParl: http://www.talkofeurope.eu/data/
- UK: https://www.hansard-corpus.org/
- US Congress: https://www.congress.gov/

- EuroParl: http://www.talkofeurope.eu/data/
- UK: https://www.hansard-corpus.org/
- US Congress: https://www.congress.gov/
- German Officials Political Speeches: https://politische-reden.eu/#data

- EuroParl: http://www.talkofeurope.eu/data/
- UK: https://www.hansard-corpus.org/
- US Congress: https://www.congress.gov/
- German Officials Political Speeches: https://politische-reden.eu/#data
- United Nations General Debate Corpus https://dataverse.harvard.edu/dataset.xhtml? persistentId=doi:10.7910/DVN/OTJX8Y

 Party Manifestos via Manifesto Project https://manifestoproject.wzb.eu/

- Party Manifestos via Manifesto Project https://manifestoproject.wzb.eu/
- US Presidential Proclamations, Memoranda: http://www.presidency.ucsb.edu/

- Party Manifestos via Manifesto Project https://manifestoproject.wzb.eu/
- US Presidential Proclamations, Memoranda: http://www.presidency.ucsb.edu/
- Social Media Datasets

- Party Manifestos via Manifesto Project https://manifestoproject.wzb.eu/
- US Presidential Proclamations, Memoranda: http://www.presidency.ucsb.edu/
- Social Media Datasets
 - Brexit social media dataset https://aifb-ls3-kos.aifb.kit.edu/projects/BreXLiMe/

Overview of Data Collections Available to use as a Text Corpus

- Party Manifestos via Manifesto Project https://manifestoproject.wzb.eu/
- US Presidential Proclamations, Memoranda: http://www.presidency.ucsb.edu/
- Social Media Datasets
 - Brexit social media dataset https://aifb-ls3-kos.aifb.kit.edu/projects/BreXLiMe/
 - Reddit dataset https://www.reddit.com/r/datasets/comments/ 3bxlg7/i_have_every_publicly_available_reddit_comment/

Overview of Data Collections Available to use as a Text Corpus

- Party Manifestos via Manifesto Project https://manifestoproject.wzb.eu/
- US Presidential Proclamations, Memoranda: http://www.presidency.ucsb.edu/
- Social Media Datasets
 - Brexit social media dataset https://aifb-ls3-kos.aifb.kit.edu/projects/BreXLiMe/
 - Reddit dataset https://www.reddit.com/r/datasets/comments/ 3bxlg7/i_have_every_publicly_available_reddit_comment/
 - ▶ Trump Tweets Archive https://www.thetrumparchive.com/

Overview of Data Collections Available to use as a Text Corpus

Using an API:

An API is a tool that provides you with data, when querying a specific url. For example, you can "ask" Twitter for all the tweets with a certain hashtag. Important - always read the documentation and the limit of an API.

Usual first steps

Lower-case your words (Politics and politics)

Usual first steps

- Lower-case your words (Politics and politics)
- Remove punctuation

Usual first steps

- Lower-case your words (Politics and politics)
- Remove punctuation
- Remove numbers

Usual first steps

- Lower-case your words (Politics and politics)
- Remove punctuation
- Remove numbers
- Remove stopwords: function words that do not convey meaning but primarily serve grammatical function

Common Stopwords in English

i, me, my, myself, we, our, ours, ourselves, you, your, yours, yourself, yourselves, he, him, his, himself, she, her, hers, herself, it, its, itself, they, them, their, theirs, themselves, what, which, who, whom, this, that, these, those, am, is, are, was, were, be, been, being, have, has, had, having, do, does, did, doing, a, an, the, and, but, if, or, because, as, until, while, of, at, by, for, with, about, against, between, into, through, during, before, after, above, below, to, from, up, down, in, out, on, off, over, under, again, further, then, once, here, there, when, where, why, how, all, any, both, each, few, more, most, other, some, such, no, nor, not, only, own, same, so, than, too, very, s, t, can, will, just, don, should, now

Preparing Text for Text Analysis: **Adding to our NLP Pipeline - Tokenization**

NLP Pipeline:

- Lower-case your words (Politics and politics)
- Remove punctuation
- Remove numbers
- Remove stopwords
- Tokenization

Separating single words, starting from a string (which could be a document, a sentence, a tweet) \rightarrow they will become tokens.

Preparing Text for Text Analysis: **Adding to our NLP Pipeline - Tokenization**

"I don't know whether or not [the wall] is part of a D.A.C.A. equation"

```
1) Naive Approach: Split on White Spaces
I
don't ← dont? do not? don't?
know
...
```

 $\mathsf{D.A.C.A.} \leftarrow \mathsf{DACA?} \ \mathsf{D.A.C.A.?} \ \mathsf{Deferred} \ \mathsf{Action} \ \mathsf{for} \ \mathsf{Childhood} \ \mathsf{Arrivals}$

Tokenization

- Greys Anatomy one token or two?
- JAY Z one token or two?
- JLO one token or two?
- IPhone 12 one token or two?

Tokenization

- 1) Naive Approach: Split on White Spaces
- 2) Rule-based, language specific tools \rightarrow we will use the NLTK tokenizer.

• Lemmatization and Stemming

- Lemmatization and Stemming
- Stemming

- Lemmatization and Stemming
- Stemming
- Pos-Tagging

- Lemmatization and Stemming
- Stemming
- Pos-Tagging
- Named Enitity Recognition

- Lemmatization and Stemming
- Stemming
- Pos-Tagging
- Named Enitity Recognition
- Dictionaries

- Lemmatization and Stemming
- Stemming
- Pos-Tagging
- Named Enitity Recognition
- Dictionaries
- The Power of Counting Words

References

- Bubeck, J, Elshehawy, Ashrakat, Marinov, Nikolay, and Federico Nanni, 2021. How the US Electoral Cycle Affects Elections Around the World. Working Paper
- Grimmer, J. and Stewart, B.M., 2013. Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts. *Political Analysis*, 21(3), pp.267-297.
- Monroe, Burt and Phil Schrodt, 2008. Introduction to the Special Issue: The Statistical Analysis of Political Text. *Political Analysis* 16, 4, 351-355
- Saeltzer, Marius (2020): Finding the Bird's Wings: Dimensions of Factional Conflict on Twitter. Party Politics (forthcoming). DOI: 10.1177/1354068820957960
- Wilkerson, J. and Casas, A., 2017. Large-Scale Computerized Text Analysis in Political Science: Opportunities and Challenges. *Annual Review of Political Science*, 20, pp.529-544.