

Introduction to Computational Text Analysis

BigSurv Text Analysis

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Instructors

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Core Learning Objectives

Ultimate Goal: Introduce students to modern computational text analysis techniques and provide an orientation for those wishing to go further with text analysis in their own research.

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Proximate Goals

- 1) Learn about the main methods and techniques involved in modern computational text analysis.
- 2) Be able to load, preprocess, and conduct simple analysis on text data.
- 3) Know where to go next in their pursuit of more advanced computational text methods..

Course Outline

Together

- Overview of Computational Text Analysis
- Preprocessing Texts
- Dictionary methods / Sentiment Analysis (Supervised)

On Your Own

- Topic Modeling (Unsupervised)
- Distinctive Words
- Text similarity / distances
- K-means Clustering

This Course Will Not

- Go into the technical details behind text analysis methods, such as optimization algorithms and theoretical properties.
- Cover all text analysis tools, or even most of them.
- Teach you how to scraping or acquiring texts.

Format of the Course

Semi flipped classroom

- 1/2 lecture, 1/2 coding in R.
- Bring your laptop, prepare to close it.
- Work with a friend, especially if you're computer isn't working.

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- There are costs to large-scale text analysis.
- Computers can lower these costs.

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- Newspapers \rightsquigarrow media attention and political events.
- Blogs and social media \rightsquigarrow public opinion and communication.

Acquiring texts: Sources

Where to get texts:

- Online databases, e.g. LexisNexis, Comparative Manifesto Project
- Websites (Scraping, APIs)
- Archives (High-quality scanner + optical character recognition)

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Sources we'll be analyzing:

- Monographs (Machiavelli's Prince, British Fiction)
- News Articles (about women around the world)
- Song Lyrics (Michael Jackson's Thriller)
- Press Releases (by U.S. congressperson)

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- Directory of .txt's or a “tidy” dataset
- Preprocessing to extract the most important information. (We'll cover this in-depth.)

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- Validate, Validate, Validate.

An Overview of Methods

Two broad approaches to computational text analysis:

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- 1 **Supervised methods:** We identify what we're interested in first, and then use computers to extend our insights to a larger population of unseen documents.
- 2 **Unsupervised methods:** We do not specify the conceptual structure of the texts beforehand. Instead, we use the model to discover a structure that best explains the documents.

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- 5) **Validate** by comparing *predicted* label to actual (hand-coded) *label*.

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- 2) Method to **discover** categories and then classify documents into those categories (k-means clustering, topic models)
- 3) **Interpretation** skills to assign labels to categories and understand what they mean

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Methods we won't be covering

- Text scaling
- Complex supervised methods
- Information retrieval
- Natural Language Processing

Let's Get Started!

- 1 Download the Class Repo as a zip file:
<https://github.com/rochelleterman/BigSurvText>
- 2 Unzip the file in a location of your choice.
- 3 Find the path of the repo and write it down.
- 4 Download the R packages listed in B-Tech-Requirements.md.