Class 7: Dictionaries and Topic Modelling

Topic 2: Text

Computational Analysis of Text, Audio, and Images, Fall 2023

Aarhus University

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Aarhus University

Today’s Menu

Dictionaries

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Topic Models

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Lab

What Can We Do With Text?

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1. Prediction

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Methods

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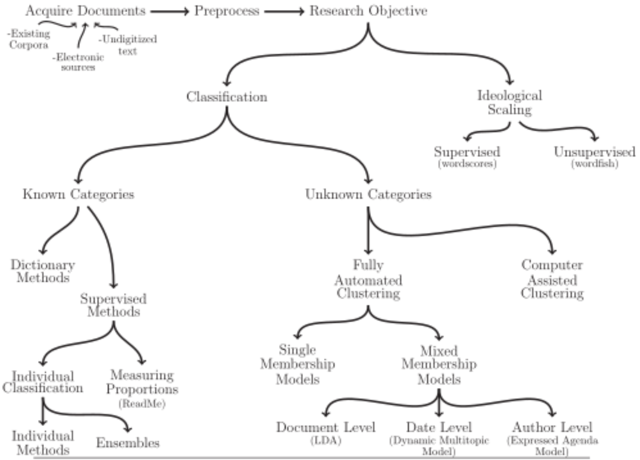

Acquire Documents
Preprocess
Research Objective
-Existing Corpora
-Electronic sources
-Undigitized text
Classification
Ideological Scaling
Supervised
(wordscores)
Unsupervised
(wordfish)
Known Categories
Unknown Categories
Dictionary Methods
Supervised Methods
Fully Automated Clustering
Computer Assisted Clustering
Individual Classification
Measuring Proportions
(ReadMe)
Single Membership Models
Mixed Membership Models
Individual Methods
Ensembles
Document Level
(LDA)
Date Level
(Dynamic Multitopic Model)
Author Level
(Expressed Agenda Model)

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    - Example: Use aggressive language
    - Words: [had, idiot, dum, fatsvag, dompap]

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⇝ Why do we normalize by n_i?

⇝ Note that we can also add a time-dimension. What does our score then look like?

Exercise

Assume the dictionary:

Key:	Aggression
Values:	stupid
	dishonest
	lier
	idiot
	ignorant
	hate
	fight
	battle

and the document $\mathcal{D}$: "That statement is as barbaric as it is downright stupid; it is nothing more than an ignorant, cruel, and deliberate misconception to hide behind."

1. Compute the dictionary score $\frac{\sum_{j=1}^{J} W_{ij}}{n_i}$ with $\boldsymbol{n_i}$ being the number of unique words (**14**)
2. What's the upper and lower bound of the aggressiveness scores?

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- Using a sentiment dictionary to compute a measure of positions of MPs expressed in tweets (X's?) about EU
- How do they measure sentiment about the EU in parliamentary speeches?

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⇝ How does this relates to questions about *recall* and *precision*?

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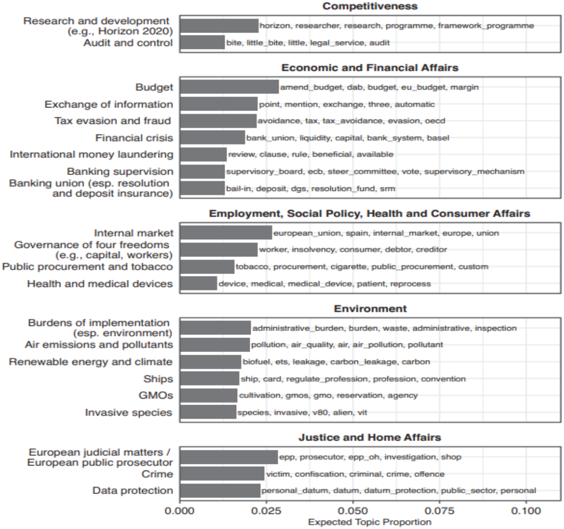

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- Seeded LDA (Watanabe and Baturo, 2023)
- BERTopic

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See you next week!

Topic 2: Text

Computational Analysis of Text, Audio, and Images, Fall 2023

Aarhus University

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