Text Cleaning: An Introduction with R

Social Science Data Analytics Workshop

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Michigan State University

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    - Understand why text cleaning matters
    - Clean messy text using R
    - Process/prepare text for analysis using R
    - Plan to attend the workshop tomorrow (same time, same place) that covers the next step- text analysis!

Text Analysis- what is it?

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    - Make inferences about things we can't directly observe like ideology
- Or to categorize texts into different classes

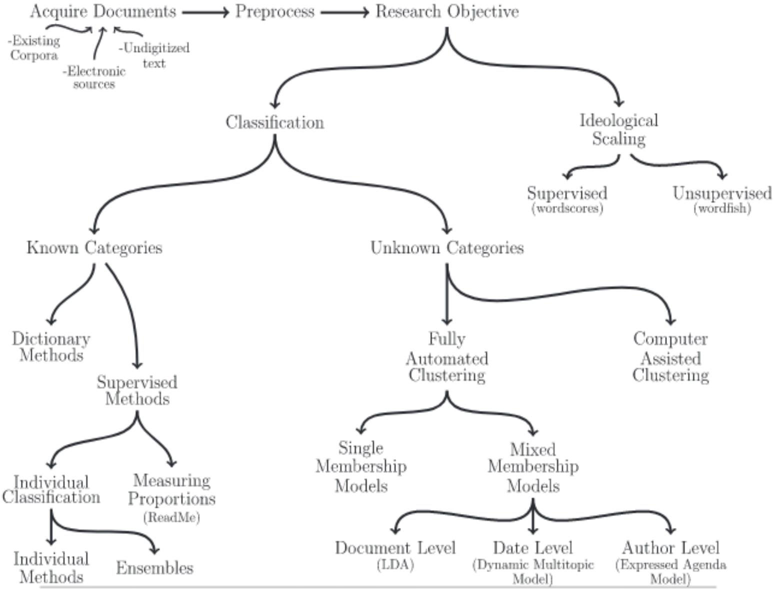

Fig. 1 An overview of text as data methods.

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  - ... but it can affect results/findings and is hard!

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  ↪ Need to clean and prepare for statistical modeling

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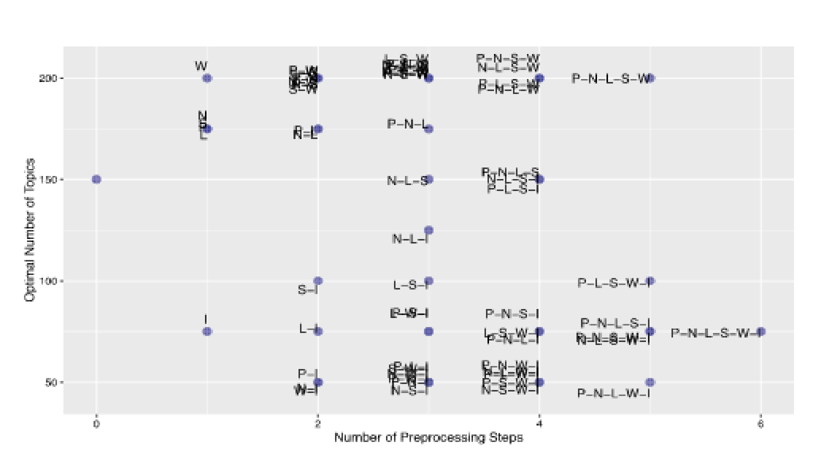
  - 7 binary preprocessing steps = 128 possible models

Denny and Spirling (2018)



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   - Researchers typically 'fall into' these steps as they analyze - leads to important point...

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  - Limits chance of weird data/results, which is easy to spot with text data

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Text Processing

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Ok, you cleaned the text up... now what?

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- Acknowledges "run" and "runs" are different versions of the same word

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- More computationally expensive
- Not available in every language

Data Format

- We typically format text data as a document term matrix
  - Rows = documents, columns = terms
- *Terms* are typically single words, but can be other things that we *tokenize* the text into
  - *Tokens* are just units of the text used in the analysis
  - We can tokenize text into sentences, paragraphs, n-grams (collections of words or sentences), etc.

	Token_1	Token_2	…	Token_n
Doc_1	0	0	.	0
Doc_2	5	0	.	3
…	.	.	.	.
Doc_n	1	0	.	0

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    - A great deal of ad hoc decisions
    - Not obvious object type conversions, etc.

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R sesh!

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https://github.com/caleblucas/text_cleaning