Text Analysis: An Introduction with R

Social Science Data Analytics Workshop

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Michigan State University

Introduction

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Text Analysis- what is it?

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- But, new ways to use them in experiments, etc.!

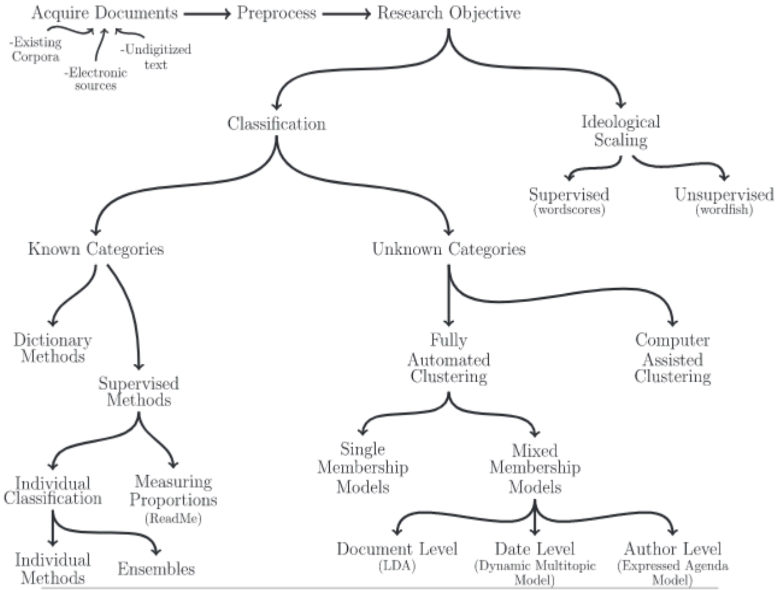

Fig. 1 An overview of text as data methods.

Supervised vs Unsupervised

- Supervised methods

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    - Explore the hidden or latent structure in unlabeled data

Assumption

Bag of Words

- We typically format text data as a document term matrix
    - Rows = documents, columns = terms
- Disregards grammar and word order
- *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.

	I	love	programming	in	R
Document1	0	2	3	0	3
Document2	1	1	1	1	1
Document3	1	1	0	3	0

Classifying Known Categories

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- Dictionary methods use sets of words that are associated with certain labels to do this

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- Dictionary models classify documents using the score of each word in the document, the number of word occurrences, and the number of total words

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  - Score = 0.3

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  - E.g. scoring the sentiment of Islamic State propaganda without a purpose-built dictionary
    - Words like *martyr* and *caliphate*
  - Easy to create custom dictionaries or add to existing dictionaries

Supervised Learning

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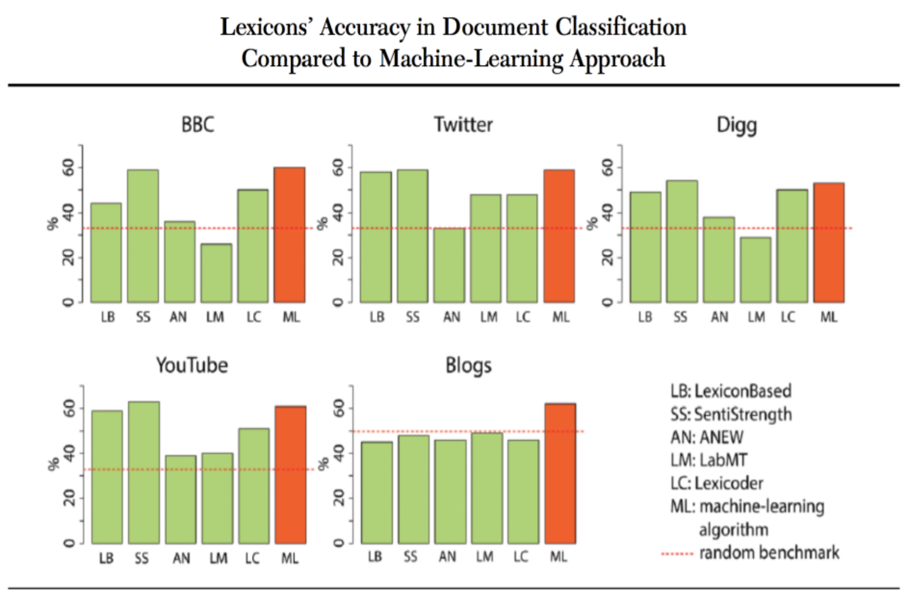
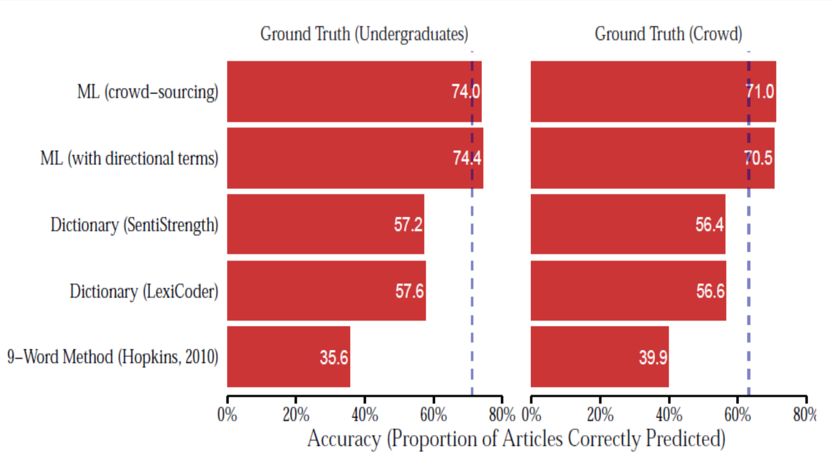
- Supervised learning will outperform dictionary methods in classification tasks given sufficient training set



Gonzalez-Bailon and Paltoglu (2015)



Barbera et al (2017)

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  - We do want to use a number of tools to assess the performance of the labels (percent agreement, correlation, etc.)

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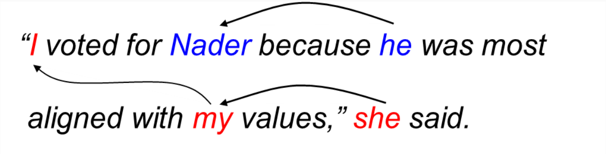

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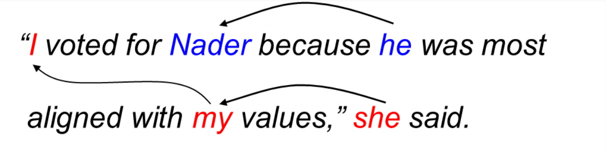

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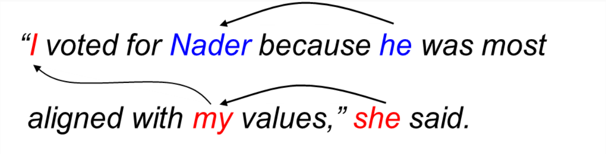

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  - Don't overfit and accept bias but reduce variance (allow noise in training set)

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    - Measure can be used in future observational studies

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    - Applications to experiments and observational studies

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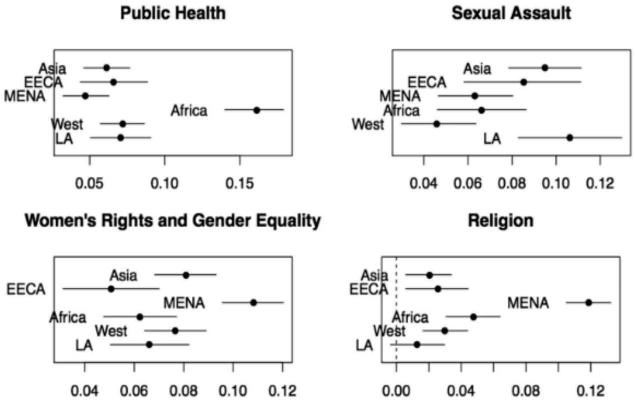

Figure 4. Expected document proportions for four topics

- Expected document proportion of an unseen document as a function of region and year
- Terman (2017)

R sesh!

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https://github.com/caleblucas/text_analysis