POIR 613: Computational Social Science

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Today

1. Zoom discussion sessions (for now):
   - September 21st – **today**
   - October 5th
2. Describing and comparing documents
3. Solutions to challenge 3
4. Code: descriptive text analysis

Comparing documents

- Describing a single document
  - Lexical diversity
  - Readability
- Comparing documents
  - Similarity metrics: cosine, Euclidean, edit distance
  - Keyness statistics

Quantities for describing a document

Length
: in characters, words, lines, sentences, paragraphs, pages, sections, chapters, etc.

Word (relative) frequency
: counts or proportions of words

Lexical diversity
: (At its simplest) involves measuring a *type-to-token ratio* (TTR) where unique words are types and the total words are tokens

Readability statistics
: Use a combination of syllables and sentence length to indicate “readability” in terms of complexity

Lexical Diversity

- Basic measure is the TTR: Type-to-Token ratio
- Problem: This is very sensitive to overall document length, as shorter texts may exhibit fewer word repetitions
- Another problem: length may relate to the introduction of additional subjects, which will also increase richness

Lexical Diversity: Alternatives to TTRs

TTR $\frac{\text{total types}}{\text{total tokens}}$

Guiraud $\frac{\text{total types}}{\sqrt{\text{total tokens}}}$

S Summer's Index: $\frac{\log(\log(\text{total types}))}{log(log(\text{total tokens}))}$

MATTR the Moving-Average Type-Token Ratio (Covington and McFall, 2010) calculates TTRs for a moving window of tokens from first to last token. MATTR is the mean of the TTRs of each window.

Readability

- Use a combination of syllables and sentence length to indicate “readability” in terms of complexity
- Common in educational research, but could also be used to describe textual complexity
- No natural scale, so most are calibrated in terms of some interpretable metric

Flesch-Kincaid readability index

- Based on the Flesch Reading Ease Index:

  $$206.835 - 1.015\left(\frac{\text{total words}}{\text{total sentences}}\right) - 84.6\left(\frac{\text{total syllables}}{\text{total words}}\right)$$

  Interpretation: 0-30: university level; 60-70: understandable by 13-15 year olds; and 90-100 easily understood by an 11-year old student.

- Flesch-Kincaid rescales to the US educational grade levels (1–12):

  $$0.39\left(\frac{\text{total words}}{\text{total sentences}}\right) + 11.8\left(\frac{\text{total syllables}}{\text{total words}}\right) - 15.59$$

Application: readability scores

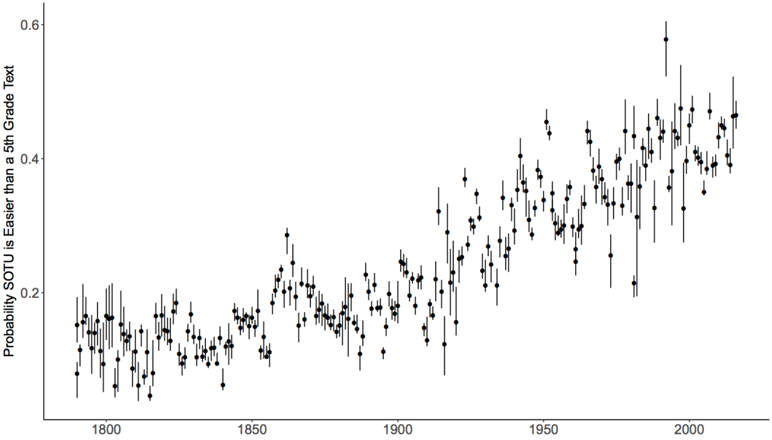

Figure 2: The probability that a State of the Union address is easier to understand than a fifth grade text baseline.

Benoit, Munger & Spirling (2017)

- Describing a single document
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Comparing documents

- The idea is that (weighted) features form a vector for each document, and that these vectors can be judged using metrics of similarity
- A document's vector for us is simply (for us) the row of the document-feature matrix
- The question is: how do we measure distance or similarity between the vector representation of two (or more) different documents?

Euclidean distance

Between document A and B where j indexes their features, where y_{ij} is the value for feature j of document i

- Euclidean distance is based on the Pythagorean theorem
- Formula

$$\sqrt{\sum_{j=1}^{j} (y_{Aj} - y_{Bj})^2} \tag{1}$$

- In vector notation:

$$\|\mathbf{y}_A - \mathbf{y}_B\| \tag{2}$$

- Can be performed for any number of features J (where J is the number of columns in of the dfm, same as the number of feature types in the corpus)

Cosine similarity

- Cosine distance is based on the size of the angle between the vectors
- Formula

$$\frac{\mathbf{y}_A \cdot \mathbf{y}_B}{\|\mathbf{y}_A\|\|\mathbf{y}_B\|} \tag{3}$$

- The $\cdot$ operator is the dot product, or $\sum_j y_{Aj} y_{Bj}$
- The $\|\mathbf{y}_A\|$ is the vector norm of the (vector of) features vector $\mathbf{y}$ for document A, such that $\|\mathbf{y}_A\| = \sqrt{\sum_j y_{Aj}^2}$
- Nice property: independent of document length, because it deals only with the angle of the vectors
- Ranges from -1.0 to 1.0 for term frequencies

Edit distances

- Edit distance refers to the number of operations required to transform one string into another for strings of equal length
- Common edit distance: the Levenshtein distance
- Example: the Levenshtein distance between ”kitten” and ”sitting” is 3
  - kitten $\rightarrow$ sitten (substitution of ”s” for ”k”)
  - sitten $\rightarrow$ sittin (substitution of ”i” for ”e”)
  - sittin $\rightarrow$ sitting (insertion of ”g” at the end).

Application: text reuse in legislative bills

PSJ Policy Studies Journal

Text as Policy: Measuring Policy Similarity through Bill Text Reuse

Fridolin Linder, Bruce Desmarais, Matthew Burgess, and Eugenia Giraudy

The identification of substantively similar policy proposals in legislation is important to scholars of public policy and legislative politics. Manual approaches are prohibitively costly in constructing datasets that accurately represent policymaking across policy domains, jurisdictions, or time. We propose the use of an algorithm that identifies similar sequences of text (i.e., text reuse), applied to legislative text, to measure the similarity of the policy proposals advanced by two bills. We study bills from U.S. state legislatures. We present three ground truth tests, applied to a corpus of 500,000 bills. First, we show that bills introduced by ideologically similar sponsors exhibit a high degree of text reuse, that bills classified by the National Conference of State Legislatures as covering the same policies exhibit a high degree of text reuse, and that rates of text reuse between states correlate with policy diffusion network ties between states. In an empirical application of our similarity measure, we find that Republican state legislators introduce legislation that is more similar to legislation introduced by Republicans in other states, than is legislation introduced by Democratic state legislators to legislation introduced by Democrats in other states.

KEY WORDS: policy diffusion, text analysis, state legislatures, asymmetric politics

Linder et al (2018)

Outline

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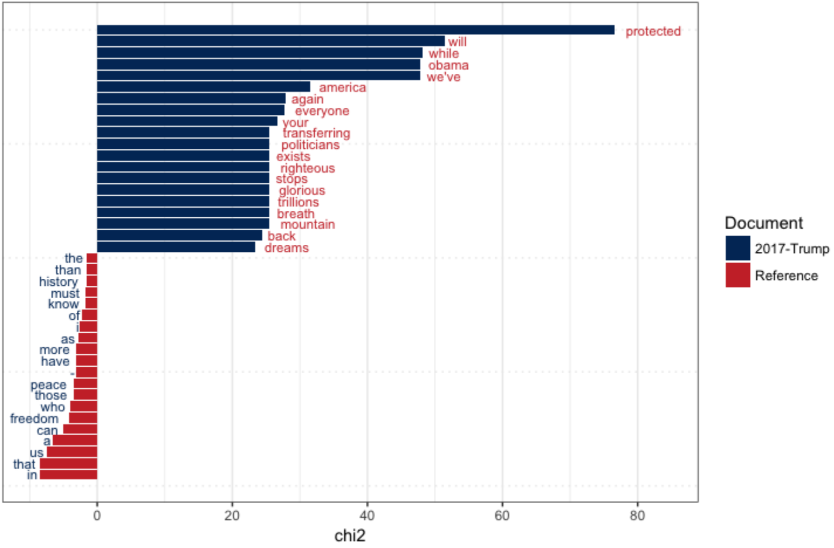
Keyness statistics

	Target	~ Target	
Word 1	n_{11}	n_{12}	$n_{1.}$
~ (Word 1)	n_{21}	n_{22}	$n_{2.}$
	$n_{.1}$	$n_{.2}$	n

χ^2 Pearson's χ^2 statistic, computed as:

$$\sum_i \sum_j \frac{(n_{ij} - m_{ij})^2}{m_{ij}}$$

where m_{ij} represents the cell frequency expected according to independence; i.e. $m_{ij} = n \times (\frac{n_i}{n} \times \frac{n_j}{n})$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