1. Representing Text

DS-GA 1015, Text as Data
Arthur Spirling

February 9, 2021

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author 'what does this Senator prioritize?', 'where is this party in ideological space?'

doc 'does this treaty represent a fair deal for American Indians?', 'how did the discussion of lasers change over time?'

both 'how does the way Japanese politicians talk about national defence change in response to electoral system shift?'

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$\rightarrow$ comparing, testing, validating.

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An expert hospital consultant has written to my hon. Friend…

Order. The Minister must be allowed to reply without interruption.

I am grateful to my hon. Friend for her question. I pay tribute to her work with the International Myeloma Foundation…

My constituent, Brian Jago, was fortunate enough to receive a course of Velcade, as a result of which he does not have to…

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\\
MP_{001} \\
MP_{002} \\
\\
MP_i \\
\\
MP_{654} \\
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\end{array}
\begin{array}{c}
\begin{array}{cccc} a & an & \ldots & ze \end{array} \\
\begin{pmatrix}
2 & 0 & \ldots & 1 \\
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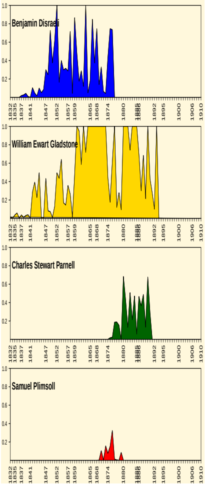
→ Inference



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"PREPROCESSING"

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→ convert everything to whitespace (?)

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e.g. stemmed word like '`treasuri`', which doesn't appear in the document itself.

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e.g. "`Brown vs Board of Education`" may not be usefully tokenized as '`Brown`', '`vs`', '`Board`', '`of`', '`Education`'

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NB these words mean something ‘special’ (and slightly opaque) when combined. Related to idea of collocations: words that appear together more often than we’d predict based on random sampling.

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am	an	and	any	are	aren't	as
at	be	because	been	before	being	below
between	both	but	by	can't	cannot	could
couldn't	did	didn't	do	does	doesn't	doing
don't	down	during	each	few	for	from
further	had	hadn't	has	hasn't	have	haven't
having	he	he'd	he'll	he's	her	here
here's	hers	herself	him	himself	his	how
how's	i	i'd	i'll	i'm	i've	if
in	into	is	isn't	it	it's	its
itself	let's	me	more	most	mustn't	my
myself	no	nor	not	of	off	on
once	only	or	other	ought	our	ours
ourselves	out	over	own	same	shan't	she
she'd	she'll	she's	should	shouldn't	so	some
such	than	that	that's	the	their	theirs
them	themselves	then	there	there's	these	they
they'd	they'll	they're	they've	this	those	through
to	too	under	until	up	very	was
wasn't	we	we'd	we'll	we're	we've	were
weren't	what	what's	when	when's	where	where's
which	while	who	who's	whom	why	why's
with	won't	would	wouldn't	you	you'd	you'll
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→ annotating in this way is called parts-of-speech tagging.

Penn POS Tagger

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Number	Tag	Description
1.	CC	Coordinating conjunction
2.	CD	Cardinal number
3.	DT	Determiner
4.	EX	Existential *there*
5.	FW	Foreign word
6.	IN	Preposition or subordinating conjunction
7.	JJ	Adjective
8.	JJR	Adjective, comparative
9.	JJS	Adjective, superlative
10.	LS	List item marker
11.	MD	Modal
12.	NN	Noun, singular or mass
13.	NNS	Noun, plural
14.	NNP	Proper noun, singular
15.	NNPS	Proper noun, plural
16.	PDT	Predeterminer
17.	POS	Possessive ending
18.	PRP	Personal pronoun
19.	PRP$	Possessive pronoun
20.	RB	Adverb
21.	RBR	Adverb, comparative
22.	RBS	Adverb, superlative
23.	RP	Particle
24.	SYM	Symbol
25.	TO	*to*
26.	UH	Interjection
27.	VB	Verb, base form
28.	VBD	Verb, past tense
29.	VBG	Verb, gerund or present participle
30.	VBN	Verb, past participle
31.	VBP	Verb, non-3rd person singular present
32.	VBZ	Verb, 3rd person singular present
33.	WDT	Wh-determiner
34.	WP	Wh-pronoun
35.	WP$	Possessive wh-pronoun
36.	WRB	Wh-adverb

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In practice, need something faster (and cruder), so software implements the Porter Stemmer using algorithms like `Snowball`.

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NYT

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also can use *substrings* which are groups of *n* contiguous characters.

original/some pre-processing

`a military patrol boat rescued three of the kayakers on general carrera lake and a helicopter lifted out the other three the chilean army said`

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```
a military patrol boat rescued three of the kayakers on general carrera
lake and a helicopter lifted out the other three the chilean army said
```

bigrams

```
"a military" "military patrol" "patrol boat" "boat rescued" "rescued
three" "three of" "of the" "the kayakers" "kayakers on" "on general"
"general carrera" "carrera lake" "lake and" "and a" "a helicopter"
"helicopter lifted" "lifted out" "out the" "the other" "other three"
"three the" "the chilean" "chilean army" "army said"
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A Well, 7 binary steps $\Rightarrow 2^7 = 128$ possible combinations. Good luck.

Q What *can* we do?

A Check how pairwise distances move between texts as we make choices, esp important when 'theory' is weak. See `preText`.

Denny & Spirling, 2017

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Text Preprocessing For Unsupervised Learning: Why It Matters, When It Misleads, And What To Do About It

Matthew James Denny
Pennsylvania State University

Arthur Spirling
New York University

January 25, 2017

Abstract:
Despite the popularity of unsupervised techniques for political science text-as-data research, the importance and implications of preprocessing decisions in this domain have received scant systematic attention. Yet, as we show, such decisions have profound effects on the results of real models for real data. We argue that substantive theory is typically too vague to be of use for feature selection, and that the supervised literature is not necessarily a helpful source of advice. To aid researchers working in unsupervised settings, we introduce a statistical procedure that examines the sensitivity of findings under alternate preprocessing regimes. This approach complements a researcher's substantive understanding of a problem by providing a characterization of the variability changes in preprocessing choices may induce when analyzing a particular dataset. In making scholars aware of the degree to which their results are likely to be sensitive to their preprocessing decisions, it aids replication efforts. We make easy-to-use software available for this purpose.

Number of Pages in PDF File: 44

Keywords: text-as-data, preprocessing, forking paths

preText -- Master: build passing

An R package to assess the consequences of text preprocessing decisions.

[getting started with preText vignette].

The paper detailing the procedure can be found at the link below:

- Matthew J. Denny, and Arthur Spirling (2017). "Text Preprocessing For Unsupervised Learning: Why It Matters, When It Misleads, And What To Do About It". [ssrn.com/abstract=2849145]

Installation

The easiest way to do this is to install the package from CRAN via the standard `install.packages` command:

Denny & Spirling, 2017

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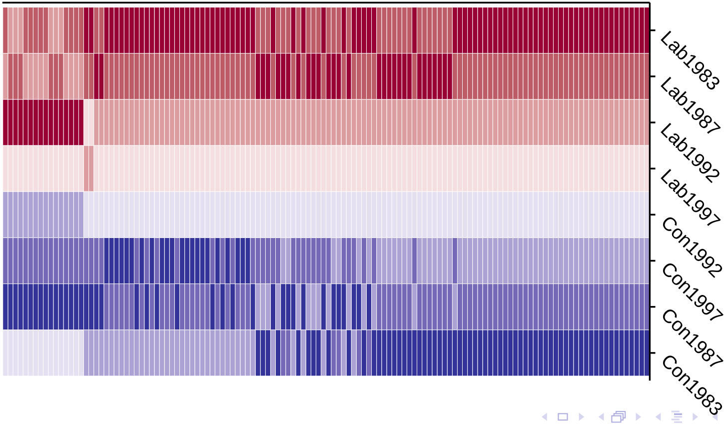

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e.g. '`the cat sat on the mat`' becomes `(2,1,1,1,1)` if we define the dimensions as `(the, cat, sat, on, mat)` and use simple counts.

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                  features
docs                  american expect induct presid will
  1933-Roosevelt             2      1      1      1   12
  1937-Roosevelt             4      0      0      2   16
  1941-Roosevelt             4      0      0      1    4
  1945-Roosevelt             1      0      0      1    7
```

partial TDM from Roosevelt's Inaugural Addresses

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along with term frequency, we may want to consider document frequency: the number of documents in which this word appears.

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- $\ln \frac{|D|}{df_w}$, inverse document frequency: (natural) log of the total size of the corpus $|D|$ divided by the number of documents in the collection of documents that contain word w. When the word is common in the corpus, this will be a small number. When the word is rare, this will be a large number.

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$\rightarrow$ '`expect`' helps us discriminate better than '`will`'.

Animals at the Zoo

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Term frequency		Document frequency	
n (natural)	$\mathrm{tf}_{t,d}$	n (no)	1
l (logarithm)	$1 + \log(\mathrm{tf}_{t,d})$	t (idf)	$\log \frac{N}{\mathrm{df}_t}$
a (augmented)	$0.5 + \frac{0.5 \times \mathrm{tf}_{t,d}}{\max_t(\mathrm{tf}_{t,d})}$	p (prob idf)	$\max\{0, \log \frac{N-\mathrm{df}_t}{\mathrm{df}_t}\}$
b (boolean)	$\begin{cases} 1 & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$		
L (log ave)	$\frac{1+\log(\mathrm{tf}_{t,d})}{1+\log(\mathrm{ave}_{t\in d}(\mathrm{tf}_{t,d}))}$		

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NB there are efficient ways to store and manipulate sparse matrices.