

1. Representing Text

DS-GA 3001-004, Text as Data
Arthur Spirling

January 31, 2017

Housekeeping

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- 1 Section have began! Make sure you know where relevant github is etc.

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- 2 Speaker series Thursday: Chris Callison-Burch (UPenn) on public health

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

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 - comparing, **testing**, **validating**.

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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...

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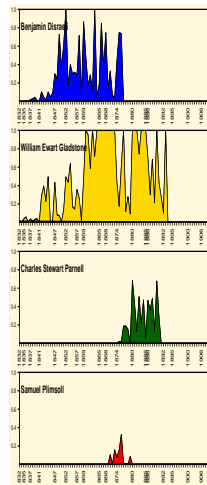
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- Excluding any technical issues with the scraping, give three concerns about the validity of inferences from such a project.



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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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a	about	above	after	again	against	all
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.

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Number	Tag	Description			
1.	CC	Coordinating conjunction	18.	PRP	Personal pronoun
2.	CD	Cardinal number	19.	PRP\$	Possessive pronoun
3.	DT	Determiner	20.	RB	Adverb
4.	EX	Existential <i>there</i>	21.	RBR	Adverb, comparative
5.	FW	Foreign word	22.	RBS	Adverb, superlative
6.	IN	Preposition or subordinating conjunction	23.	RP	Particle
7.	JJ	Adjective	24.	SYM	Symbol
8.	JJR	Adjective, comparative	25.	TO	<i>to</i>
9.	JJS	Adjective, superlative	26.	UH	Interjection
10.	LS	List item marker	27.	VB	Verb, base form
11.	MD	Modal	28.	VBD	Verb, past tense
12.	NN	Noun, singular or mass	29.	VBG	Verb, gerund or present participle
13.	NNS	Noun, plural	30.	VBN	Verb, past participle
14.	NNP	Proper noun, singular	31.	VBP	Verb, non-3rd person singular present
15.	NNPS	Proper noun, plural	32.	VBZ	Verb, 3rd person singular present
16.	PDT	Predeterminer	33.	WDT	Wh-determiner
17.	POS	Possessive ending	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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abolished	\mapsto	abolish
abolishing	\mapsto	abolish
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treasure	↦	treasure
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treasures	↦	treasure
treasuring	↦	treasure
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- 1 The mountains are beautiful in Ore. and Wash.
- 2 <http://www.wsj.com/articles/son-of-saul-not-about-the-survivors-1449590175>
- 3 I can't go with him to Beijing.

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

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Very similar documents may not share short n -grams

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The screenshot shows a Google search interface. The search bar contains the text "is obama a citizen of kenya". Below the search bar, the "All" tab is selected. The search results show "About 1,180,000 results (0.75 seconds)". The first result is titled "Obama's Kenyan Citizenship? - FactCheck.org" and includes a URL: www.factcheck.org/2008/08/obamas-kenyan-citizenship/. The snippet below the title reads: "Aug 29, 2008 - Q: Does Barack Obama have Kenyan citizenship? A: No. He held both U.S. and Kenyan citizenship as a child, but lost his Kenyan citizenship ...". At the bottom of the page, there are navigation icons for back, forward, and other search functions.

Google

is obama a citizen of kenya

All News Images Videos Shopping More Search tools

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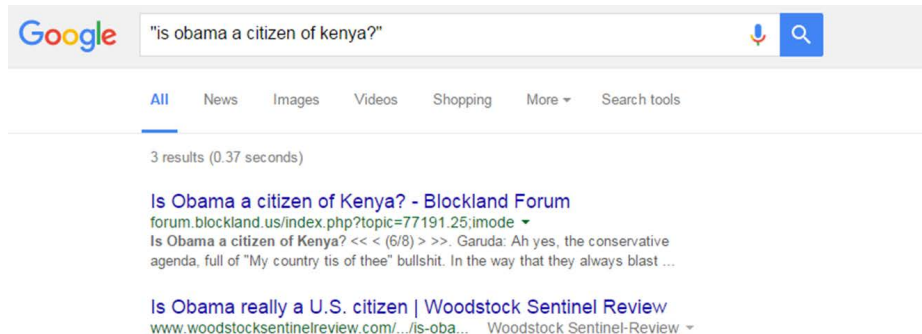
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Text Preprocessing For Unsupervised Learning: Why It Matters, When It Misleads, And What To Do About It

[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". [\[ssrn.com/abstract=2849145\]](https://ssrn.com/abstract=2849145)

Installation

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

If preprocessing makes no difference to 'results', it shouldn't matter which we do—punctuation, numbers, lowercase, stem, stops, infrequent terms, n -grams—in terms of manifesto estimated to be most left (or right).

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→ more variance than we would like!

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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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→ 'expect' helps us discriminate better than 'will'.

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

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

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