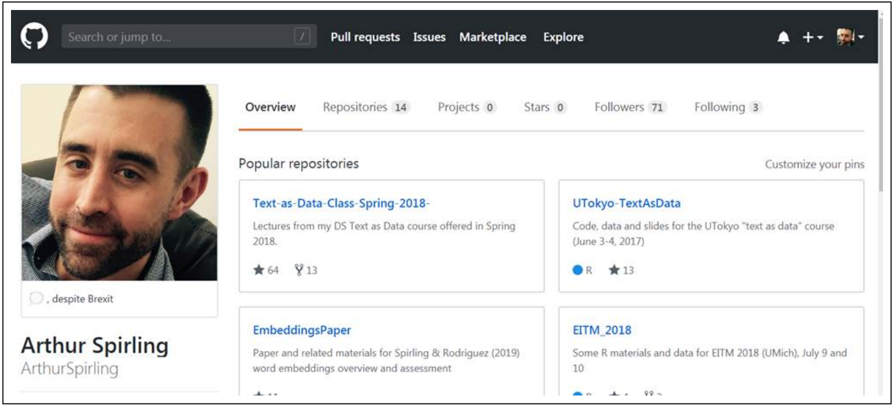

https://github.com/ArthurSpirling/EITM_2019

Unsupervised Learning and Its Vagaries

Theory, Feature Selection, Discovery

Arthur Spirling

New York University

July 11, 2018

1. The Basics

Goal of Text Analysis

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author ‘what does this Senator prioritize?’,

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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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Get Texts

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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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→ Operate

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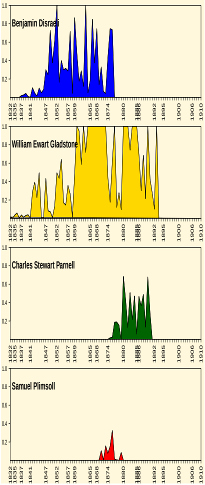

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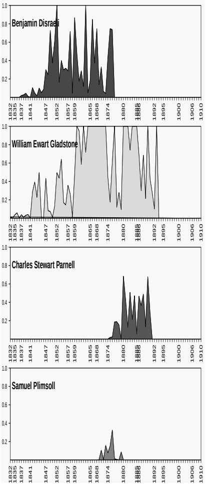

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Theoretical Model(s)? $\longrightarrow$ Empirical Implications

Get Texts $\rightarrow$ Document Term Matrix $\rightarrow$ Operate $\rightarrow$ Inference

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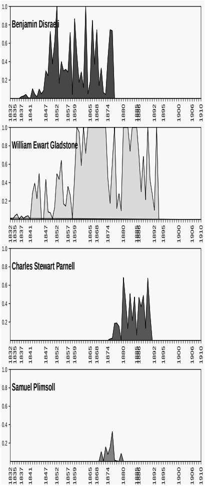

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"PREPROCESSING"

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$\rightarrow$ convert everything to whitespace (?)

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but may not be as important as you think.

‘superfluous’ material: capitalization

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Federalist 1

`The subject speaks its own importance; comprehending in its consequences nothing less than the existence of the UNION, the safety and welfare of the parts of which it is composed, the fate of an empire in many respects the most interesting in the world.`

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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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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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$\rightarrow$ 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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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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2. Record Scratch

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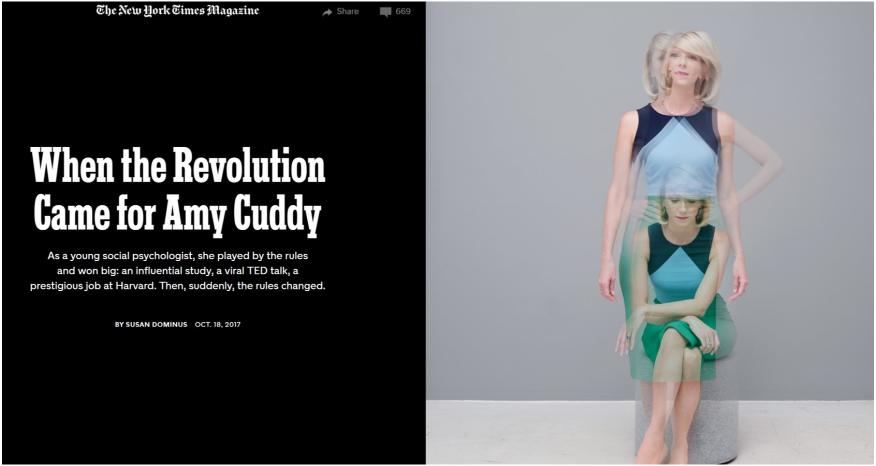

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→ huh. Seems we're making *a lot* of decisions when we preprocess.

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

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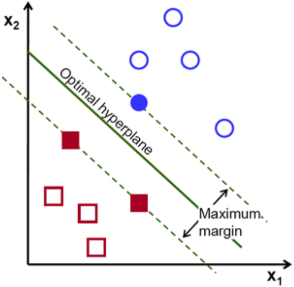

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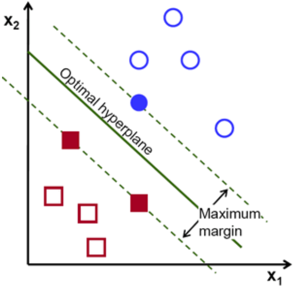

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Actual Class	P	True Positives (TP)	False Negatives (FN)
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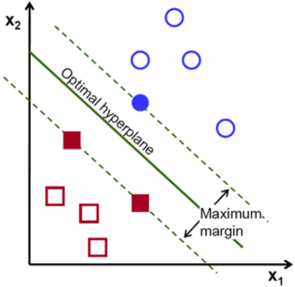

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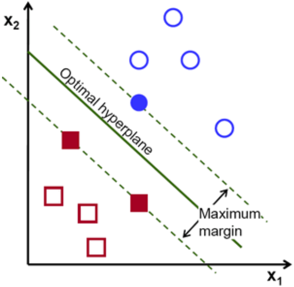

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Well-defined: either step improves ability to predict target, or it doesn't.

Does it Matter? Unsupervised Learning Edition

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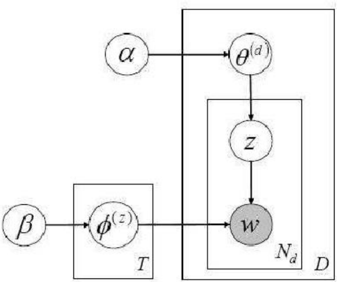

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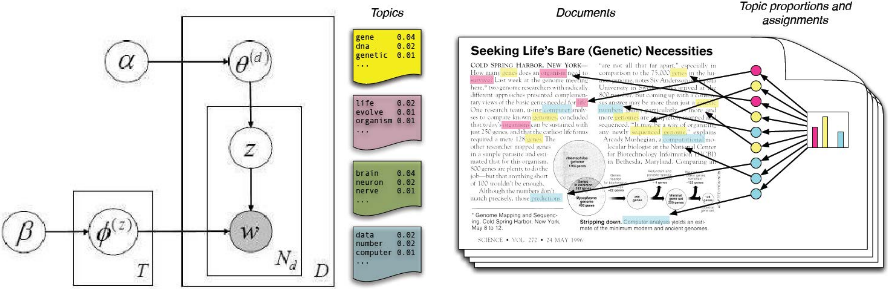

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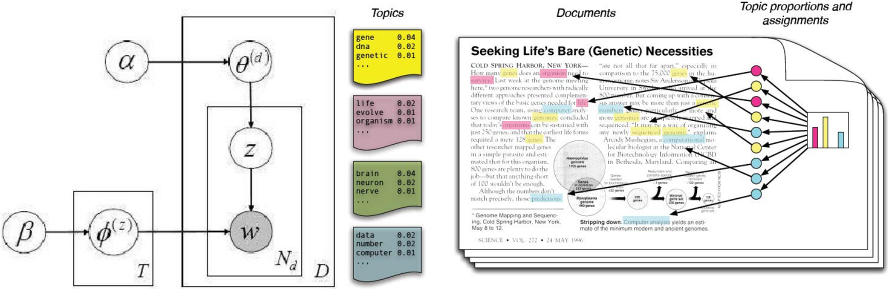

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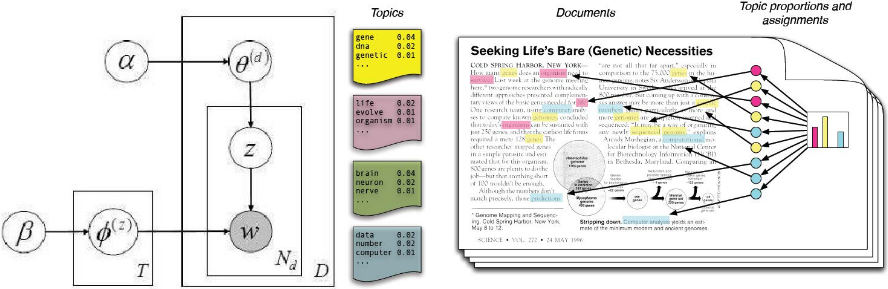

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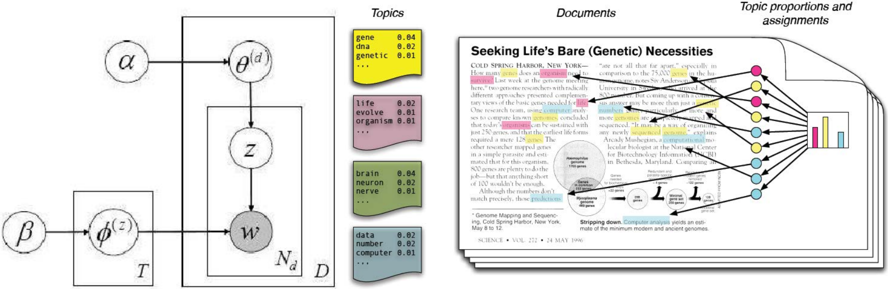

No well-defined/general performance measure: what matters is 'discovery' and 'description'. So, it might.

Aside: The 'discovery' problem

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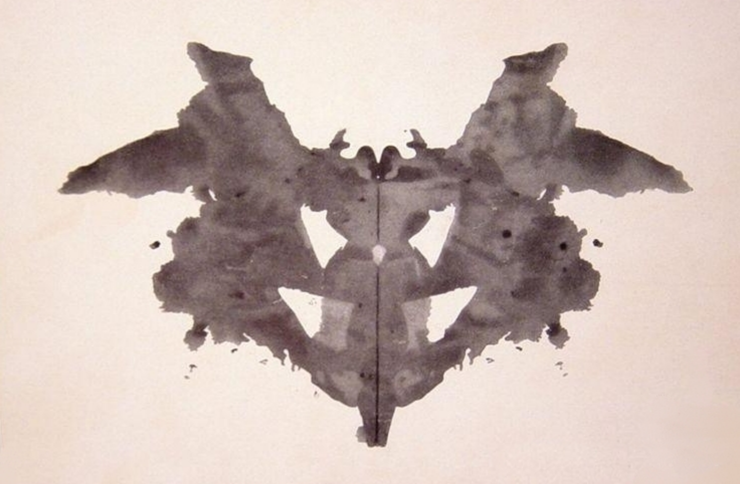
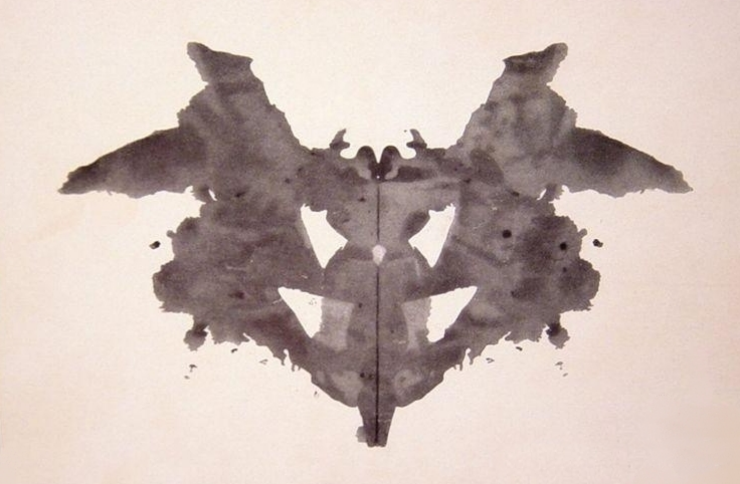


Aside: The 'discovery' problem



→ what do you see?

The ‘discovery’ problem: what do you see?

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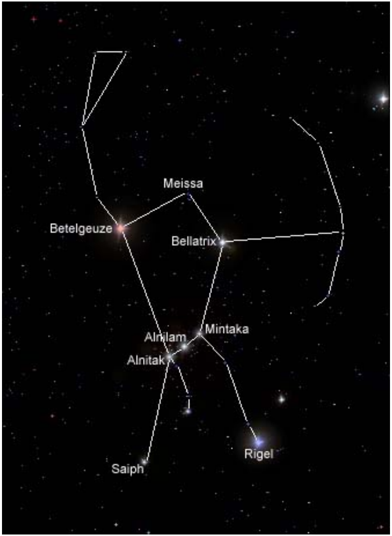

The 'discovery' problem

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Very unclear how to make ‘discovery’ unfalsifiable as a criteria of research. Could we preregister what would count as a discovery?

Advice from the field. . .

Advice from the field...

Citation	Steps	Cites
Slapin & Proksch, 2008	P-S-L-N-W	427
Grimmer, 2010	L-P-S-I-W	258
Quinn et al, 2012	P-L-S-I	275
Grimmer & King, 2011	L-P-S-I	109
Roberts et al, 2014	P-L-S-W	117

Related advice from a related field (?)

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3. What Could Possibly Go Wrong?

Motivating Example

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UK Manifesto Corpus
(1918–2001)

Motivating Example




UK Manifesto Corpus (1918–2001): Labour, Liberal, Conservatives.

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Exercise, through the Bank of England, much closer direct control over bank lending. Agreed development plans will be concluded with the banks and other financial institutions. Create a public bank operating through post offices, by merging the National Girobank, National Savings Bank and the Paymaster General's Office.

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For all these reasons, British withdrawal from the Community is the right policy for Britain

Fixing Ideas: *a priori* rankings

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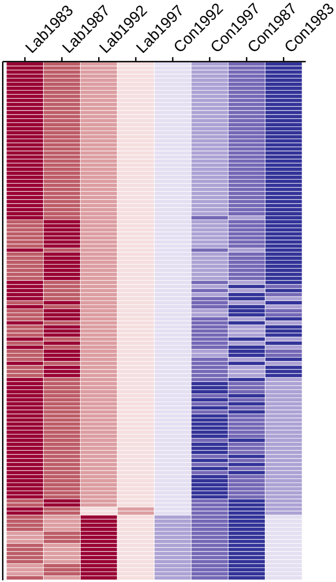
$$\text{Lab}_{1983} < \text{Lab}_{1987} < \text{Lab}_{1992} < \text{Lab}_{1997} <$$
$$\text{Con}_{1992} < \text{Con}_{1997} < \text{Con}_{1987} < \text{Con}_{1983}$$

Wordfish Rankings

Wordfish Rankings



Forking Paths

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Specification	Most Left	Most Right

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Specification	Most Left	Most Right
P-N-S-W-I-3	Lab $_{1983}$	Cons $_{1983}$
N-S-W-3	Lab $_{1987}$	Cons $_{1987}$
N-L-3	Lab $_{1992}$	Cons $_{1987}$
N-L-S	Lab $_{1983}$	Cons $_{1992}$

4. A Solution

A ‘Solution’: `preText`

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1. Assess consequences of preprocessing choices,

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A 'Solution': preText

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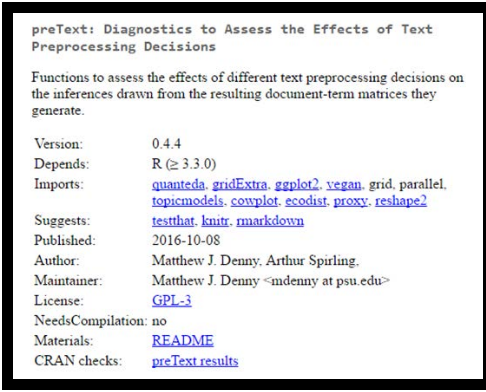

preText: Diagnostics to Assess the Effects of Text Preprocessing Decisions

Functions to assess the effects of different text preprocessing decisions on the inferences drawn from the resulting document-term matrices they generate.

Version:	0.4.4
Depends:	R (≥ 3.3.0)
Imports:	quanteda, gridExtra, ggplot2, vegan, grid, parallel, topicmodels, cowplot, ecodist, proxy, reshape2
Suggests:	testthat, knitr, rmarkdown
Published:	2016-10-08
Author:	Matthew J. Denny, Arthur Spirling.
Maintainer:	Matthew J. Denny <mdenny at psu.edu>
License:	GPL-3
NeedsCompilation:	no
Materials:	README
CRAN checks:	preText results

Fundamental Idea

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Start with (no preprocessing) base case

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Measure how 'unusual' these changes are:

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Compare how pairwise document distances change with different preprocessing decisions

Measure how 'unusual' these changes are: more unusual $\Rightarrow$ be more cautious

Toy Example

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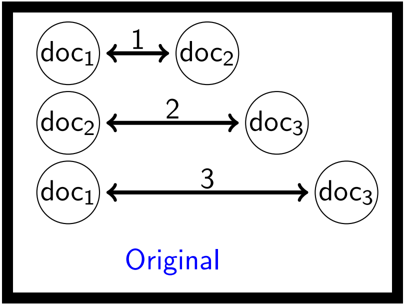

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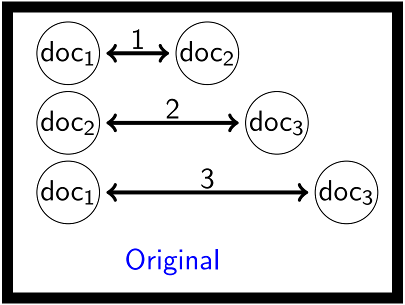
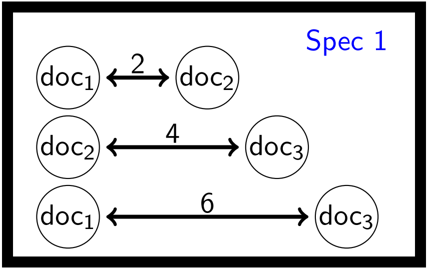
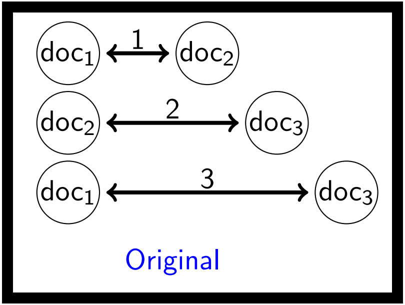


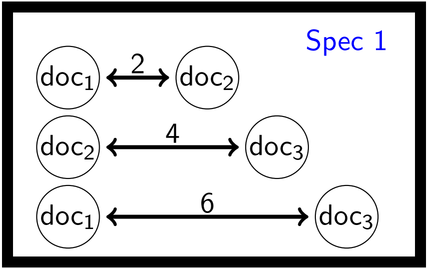
doc$_1$ $\xleftrightarrow{1}$ doc$_2$
doc$_2$ $\xleftrightarrow{2}$ doc$_3$
doc$_1$ $\xleftrightarrow{3}$ doc$_3$
Original

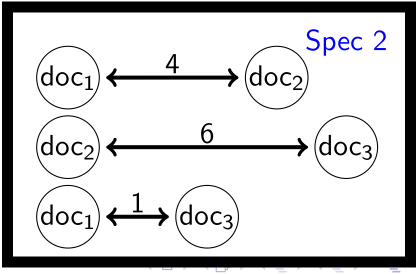


Spec 1
doc$_1$ $\xleftrightarrow{2}$ doc$_2$
doc$_2$ $\xleftrightarrow{4}$ doc$_3$
doc$_1$ $\xleftrightarrow{6}$ doc$_3$

Toy Example


doc_1 1 doc_2
doc_2 2 doc_3
doc_1 3 doc_3
Original


Spec 1
doc_1 2 doc_2
doc_2 4 doc_3
doc_1 6 doc_3


Spec 2
doc_1 4 doc_2
doc_2 6 doc_3
doc_1 1 doc_3

Ranking Distance Changes

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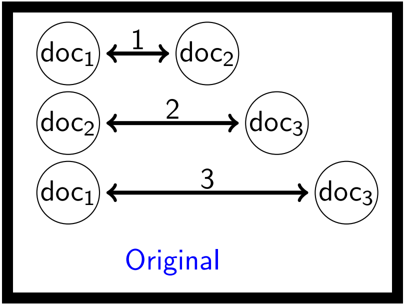
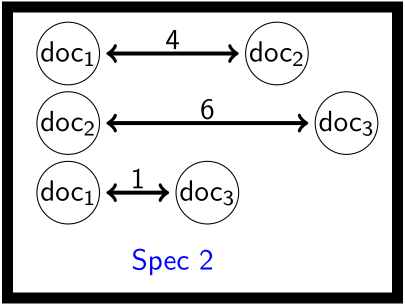
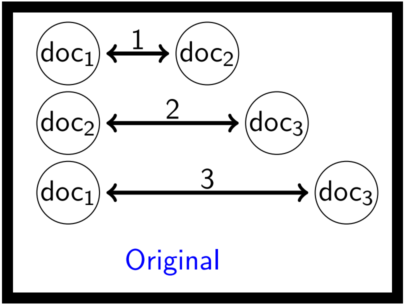
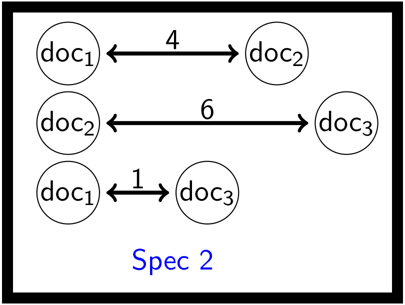




Ranking Distance Changes





Original	Specification 2	Abs Rank Difference
$d(1,3) = 3$	$d(2,3) = 6$	$\Delta d(1,3) = 2$
$d(2,3) = 2$	$d(1,2) = 4$	$\Delta d(2,3) = 1$
$d(1,2) = 1$	$d(1,3) = 1$	$\Delta d(1,2) = 1$

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Generalizing: `preText` score (of *i*th specification)

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Now, consider top k largest moving document pairs

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Normalize by $\frac{n(n-1)}{2}$ (n = number of documents)

$$\boxed{\texttt{preText}\ \text{score}_i = \frac{2{\mathbf{v}_{\mathbf{M_i}}}^{(k)}}{n(n-1)}}$$

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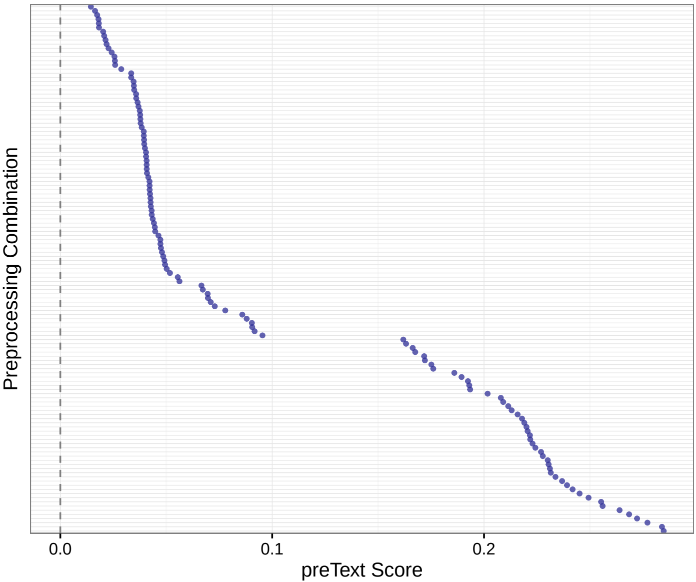
preText Scores for Press Releases



Regression Analysis Results

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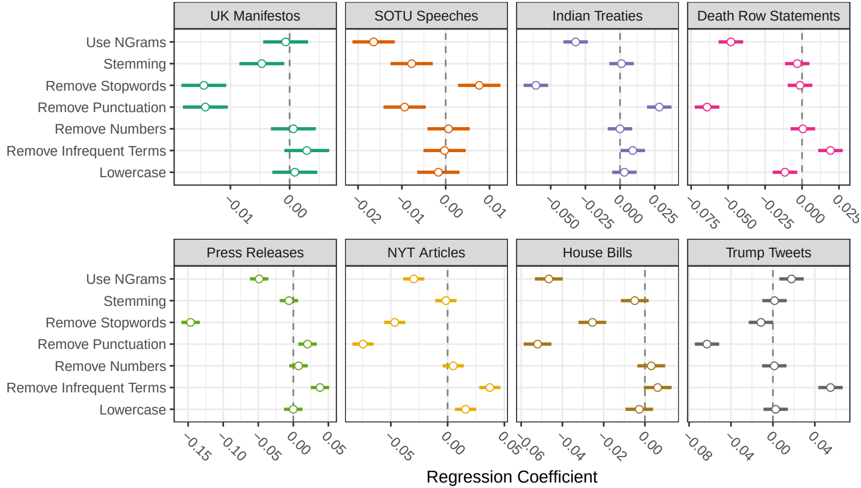

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4. *A priori* reasons for selecting a particular specification.

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3. Weak theory, some parameter estimates are significantly different from zero.

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→ moderate panic. Reconsider 'theory' of preprocessing, check robustness.

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→ curl up in ball, cry. Reconsider life choices. Replicate across all combinations: aggregate over results.

Returning To The UK Wordfish Example

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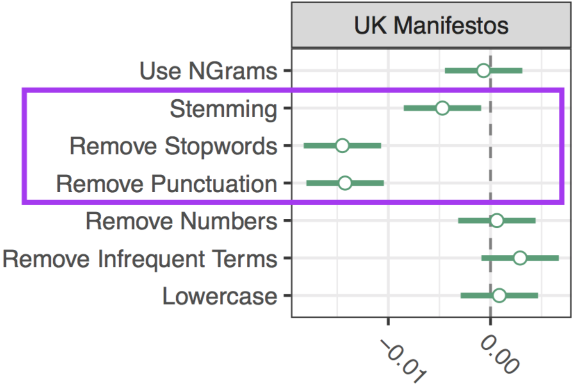

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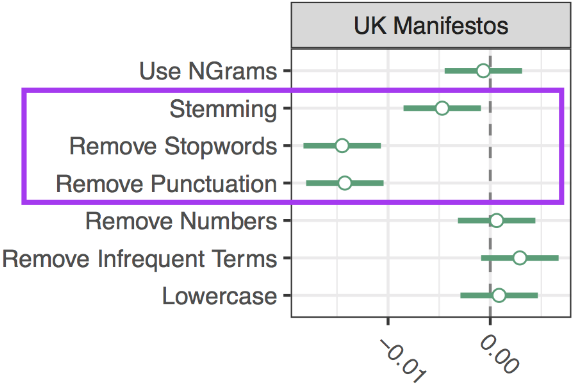
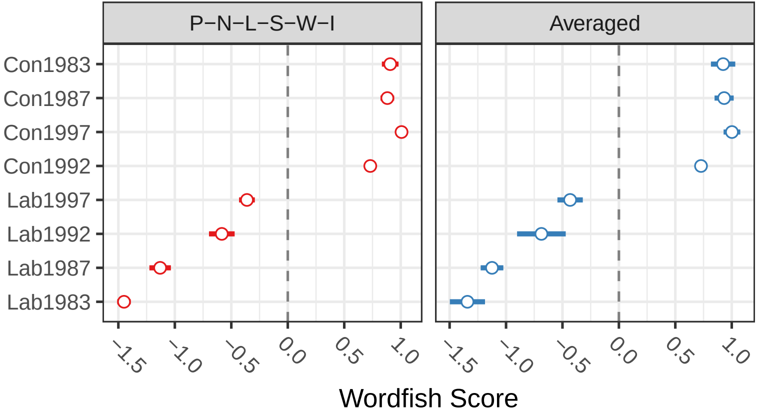


$2^3 = 8$ combinations of choices to average over.

Model Averaging



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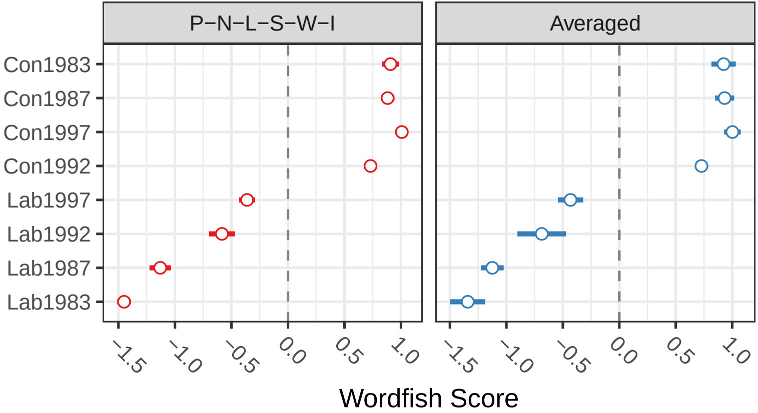

Theoretical Specification: “Wrong”

Averaged: Less “Wrong”

So. . . Does it Work?

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In theory:

So. . . Does it Work?

In theory: probably.

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In practice:

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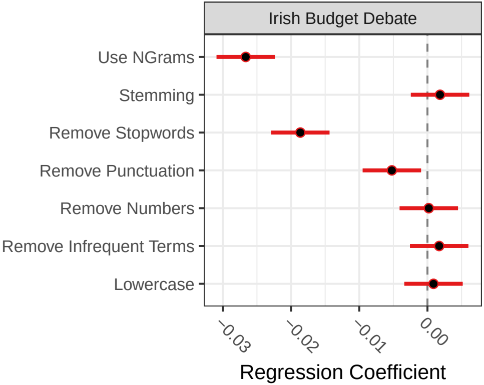

Software and Paper

```
install.packages("preText")
```

Denny, Matthew J., and Arthur Spirling. "Text preprocessing for unsupervised learning: why it matters, when it misleads, and what to do about it." Political Analysis 26.2 (2018): 168-189.

github.com/matthewjdenny/preText