Unsupervised Learning and Its Vagaries

Theory, Feature Selection, Discovery

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1. The Basics

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author ‘what does this Senator prioritize?’,

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

In general, we will. . .

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Get Texts

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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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Get Texts → Document Term Matrix → Operate

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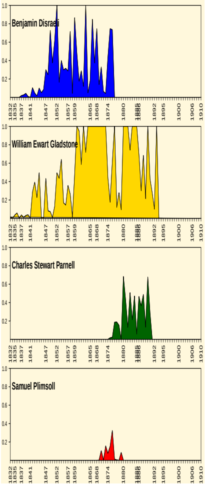

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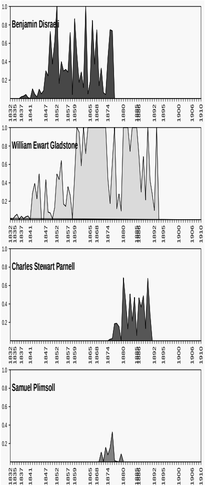

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Theoretical Model(s)? $\longrightarrow$ Empirical Implications

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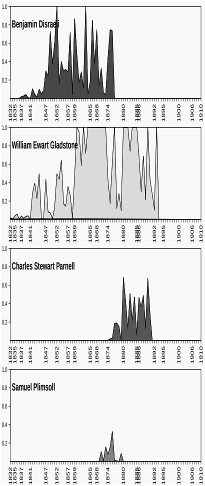

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→ comparing, testing, validating.

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"PREPROCESSING"

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→ convert everything to whitespace (?)

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but may not be as important as you think.

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a token is a particular *instance* of type.

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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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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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2. Record Scratch

Recent Happenings...

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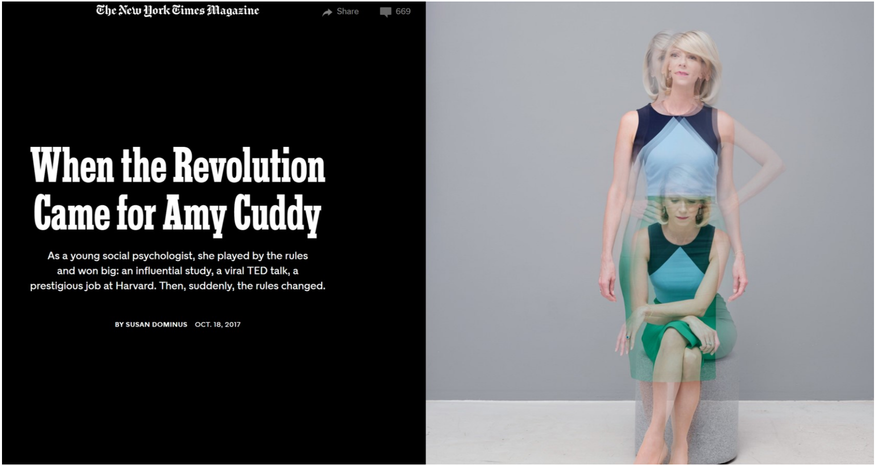

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→ huh. Seems we're making *a lot* of decisions when we preprocess.

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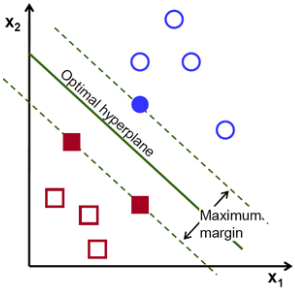

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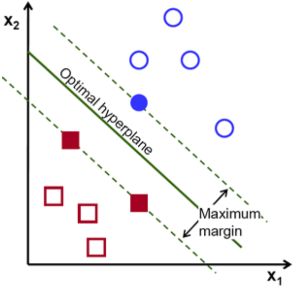

Predicted class

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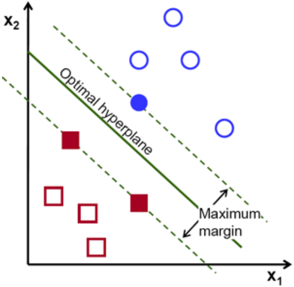

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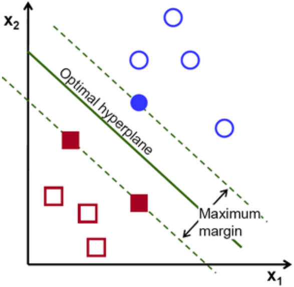

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Actual Class	P	True Positives (TP)	False Negatives (FN)
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Well-defined: either step improves ability to predict target, or it doesn't.

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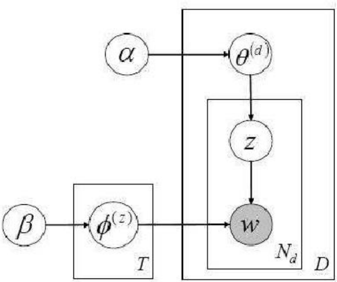

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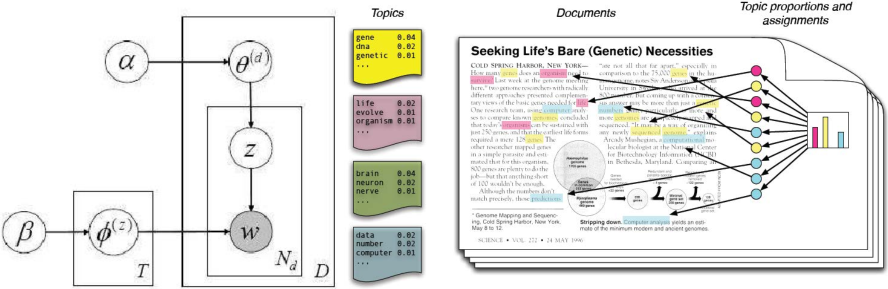

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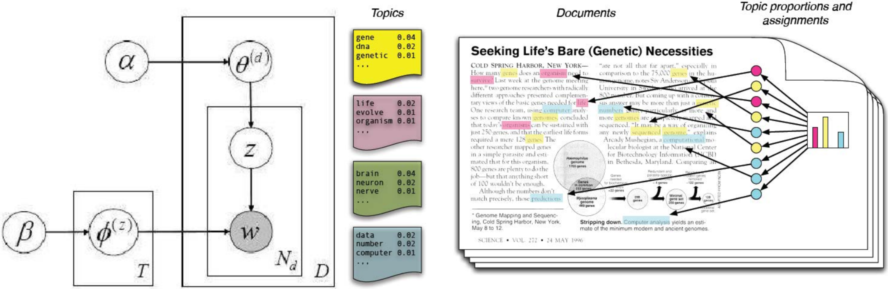

No well-defined/general performance measure:

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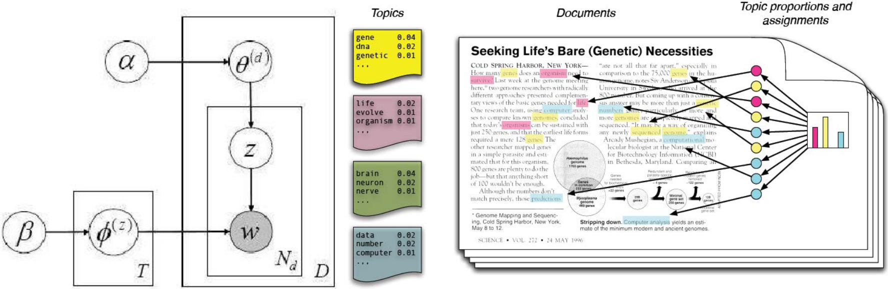

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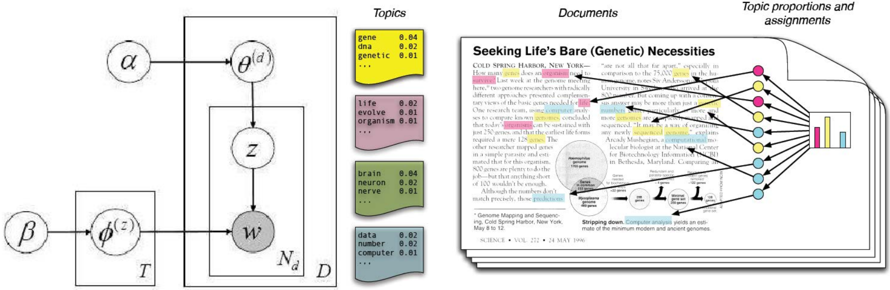

No well-defined/general performance measure: what matters is 'discovery' and 'description'. So, it might.

Aside: The 'discovery' problem

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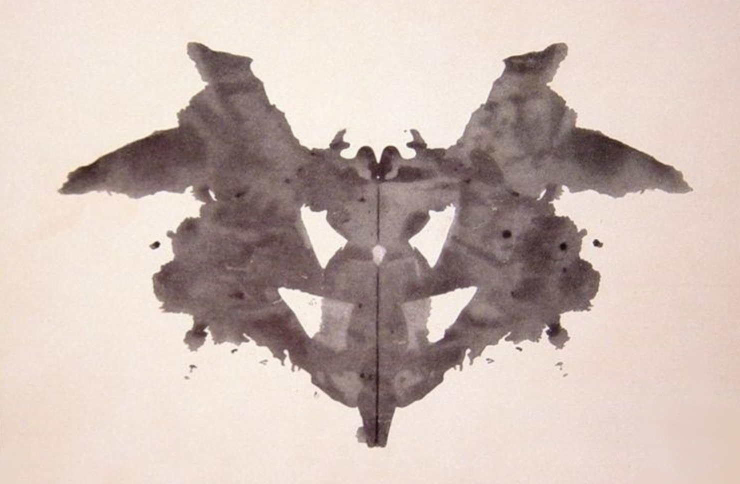
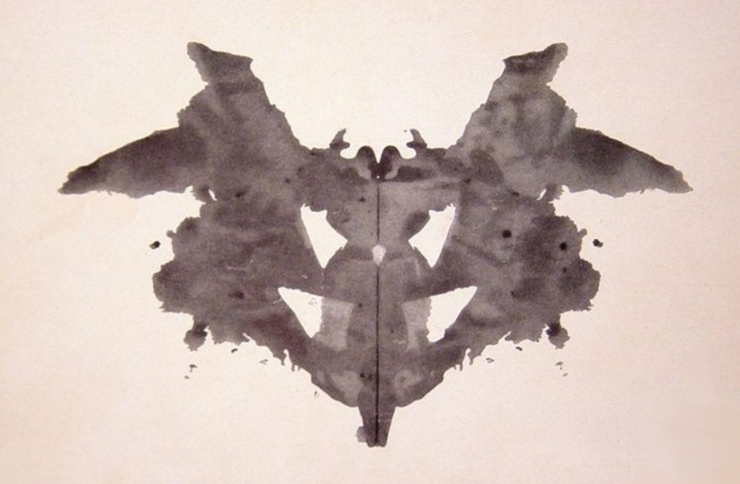


Aside: The ‘discovery’ problem



$\rightarrow$ what do you see?

The 'discovery' problem: what do you see?

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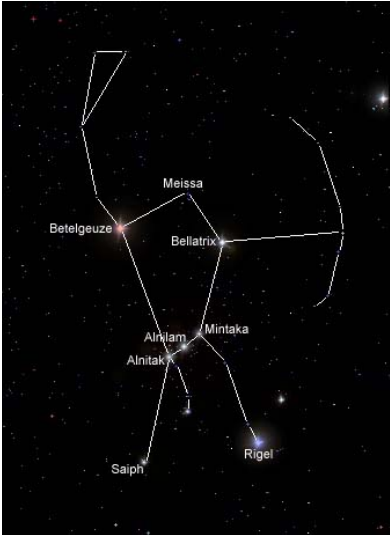

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Very unclear how to make 'discovery' unfalsifiable as a criteria of research. Could we preregister what would count as a discovery?

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

Motivating Example




Motivating Example




UK Manifesto Corpus
(1918–2001)

Motivating Example




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

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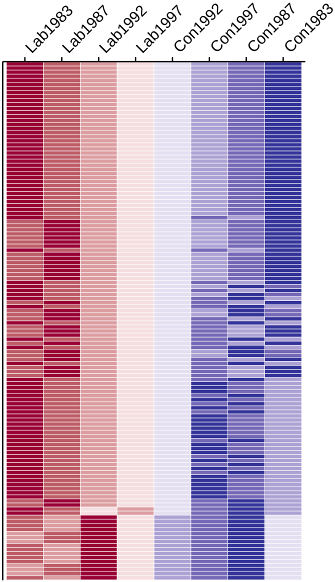
$$\text{Lab}_{1983} < \text{Lab}_{1987} < \text{Lab}_{1992} < \text{Lab}_{1997} <$$

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

Wordfish Rankings

Wordfish Rankings



Forking Paths

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and substantially different conclusions.

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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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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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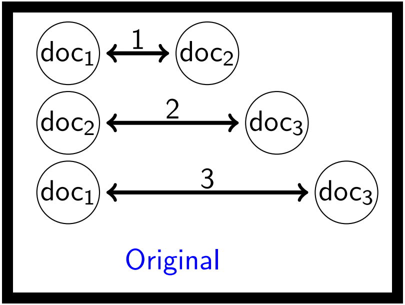

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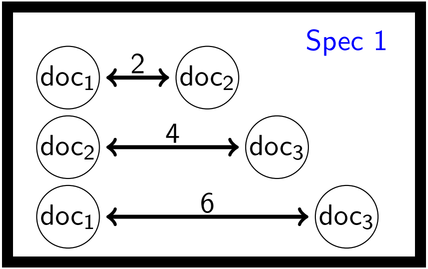
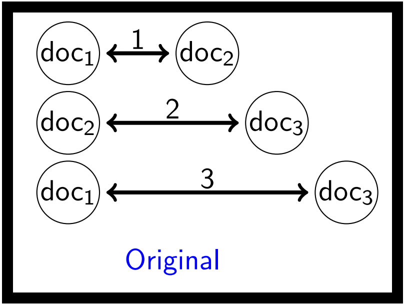

Spec 1
doc1 2 doc2
doc2 4 doc3
doc1 6 doc3


doc1 1 doc2
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Original

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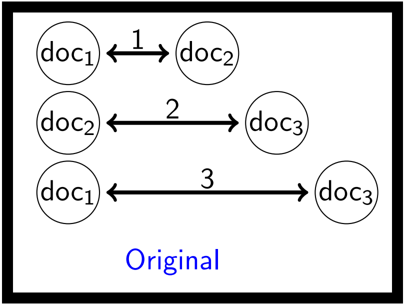
doc$_1$ 1 doc$_2$
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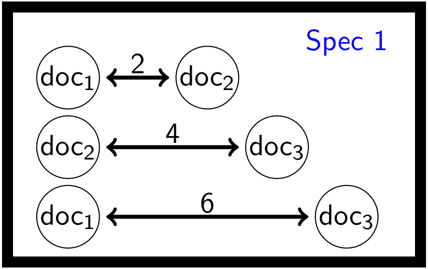
Original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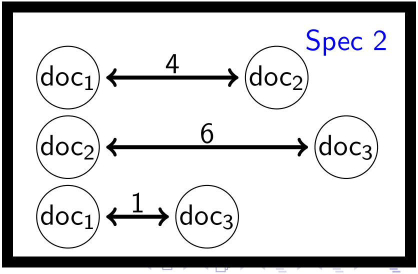
Spec 2
doc$_1$ 4 doc$_2$
doc$_2$ 6 doc$_3$
doc$_1$ 1 doc$_3$

Ranking Distance Changes

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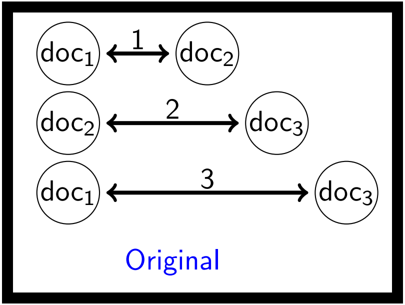
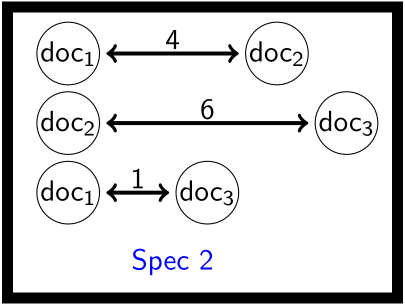
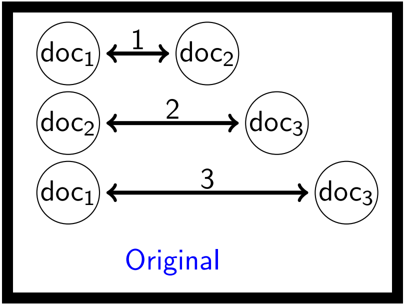
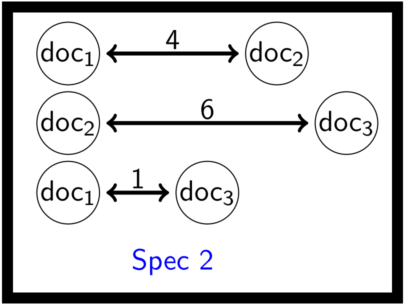




Ranking Distance Changes





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 ith specification)

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

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

Interpreting preText scores

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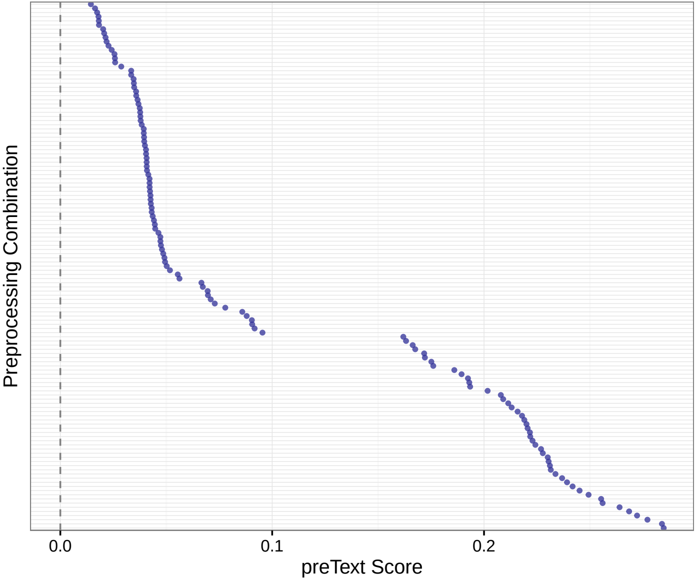
preText Scores for Press Releases



Regression Analysis Results

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1. Significant parameter estimates serve as an "early warning".
2. Conservative approach: average results over all specifications.
3. Depends on how good your "theory" is.
4. *A priori* reasons for selecting a particular specification.

Three Cases

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   $\rightarrow$ curl up in ball, cry.

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Returning To The UK Wordfish Example

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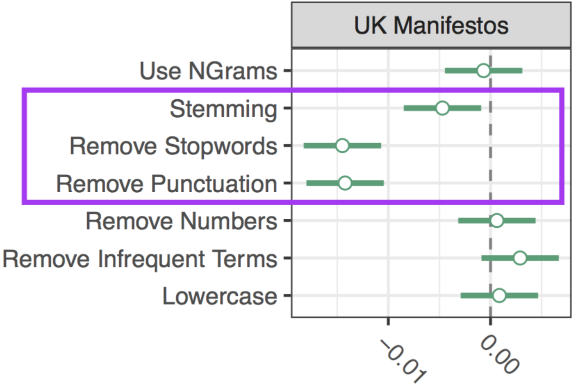

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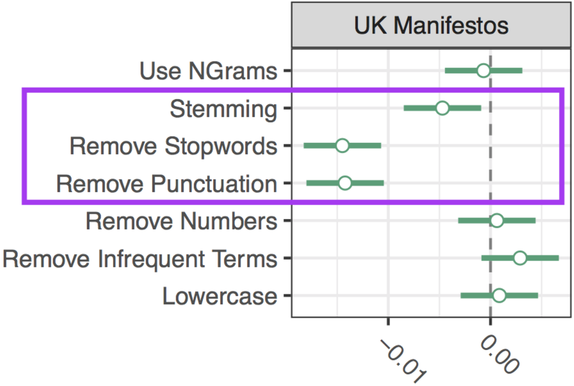
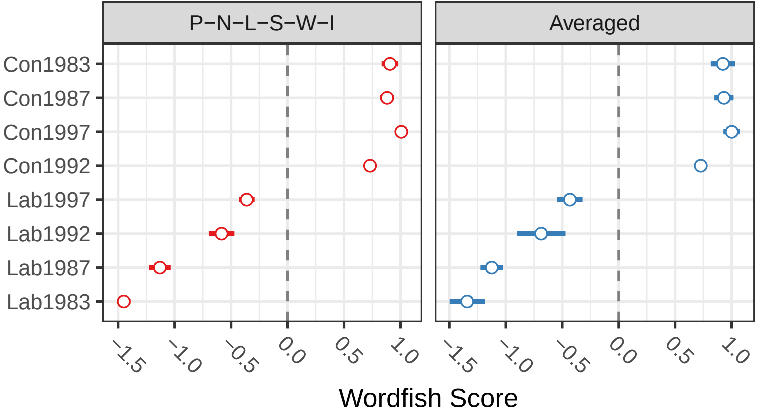


$2^3 = 8$ combinations of choices to average over.

Model Averaging



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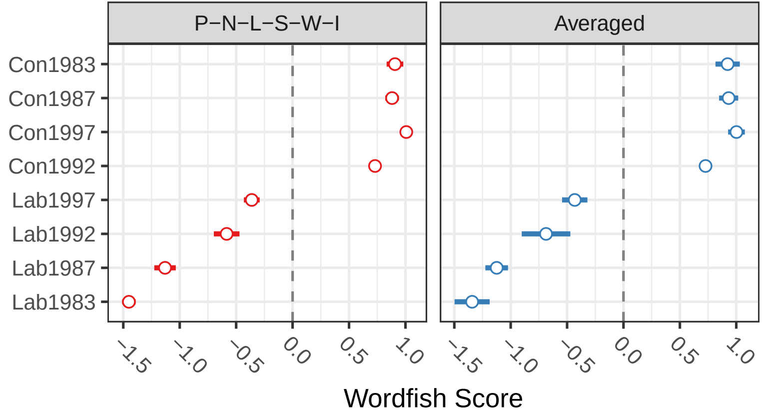

Theoretical Specification: "Wrong"

Averaged: Less "Wrong"

So. . . Does it Work?

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In theory:

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In theory: probably.

So. . . Does it Work?

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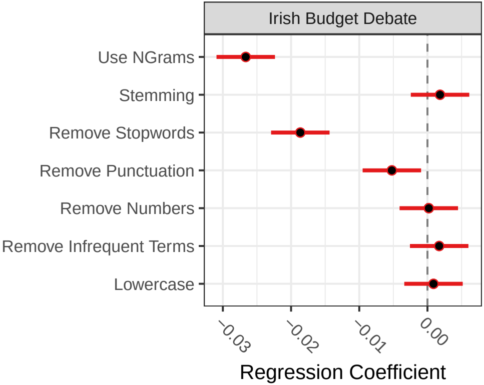

Software and Paper

```
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