University of Tokyo: Text-as-Data
Day 1, Part I

Arthur Spirling

June 3, 2017

Boring but important sanity check

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What this class is about. . .

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Text as the new frontier of. . .

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Introduction to quantitative 'text-as-data' approaches as strategies to learn more about social scientific phenomena of interest.

Overview

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since
race
stand
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We will use `quanteda` and other packages.

Writing R: RStudio

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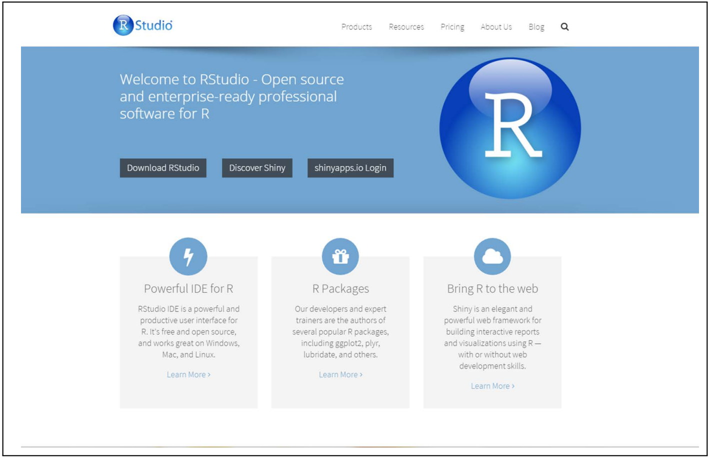

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both 'how does the way Japanese politicians talk about national defence change in response to electoral system shift?'

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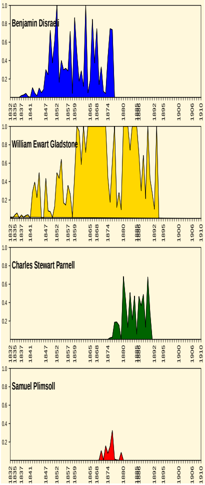

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Often, authors claim to have the universe of cases in their corpus: *all* press releases,

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but may not be as important as you think.

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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
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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`.

Snowball examples

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Original Word		Stemmed Word
abolish	$\mapsto$	`abolish`
abolished	$\mapsto$	`abolish`
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treasuring	$\mapsto$	`treasure`
treasury	$\mapsto$	`treasuri`

NYT

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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.

Using String Kernels instead...

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1. `peace not war between`
2. `brothers not warfare now`
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documents are similar in word use terms...

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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`

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
```

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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trigrams

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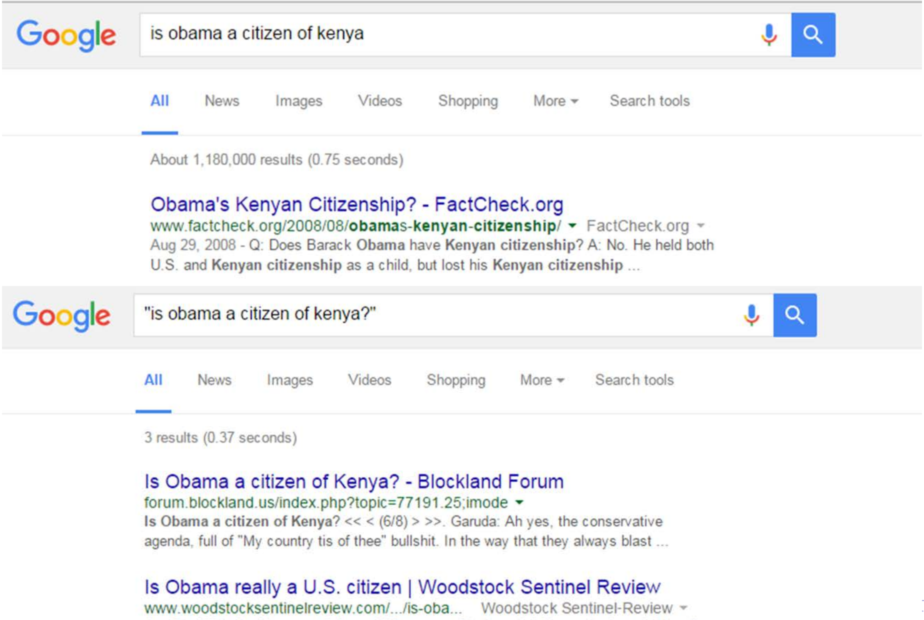

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Denny & Spirling look at (Wordfish) scaling of four sets of UK election manifestos (1983, 1987, 1992, 1997).

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$\rightarrow$ more variance than we would like!

III. Vector Space Model

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  1933-Roosevelt            2      1      1      1   12
  1937-Roosevelt            4      0      0      2   16
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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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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.

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