Quantitative text analysis: Automated Dictionary Methods

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MY 459: Quantitative Text Analysis

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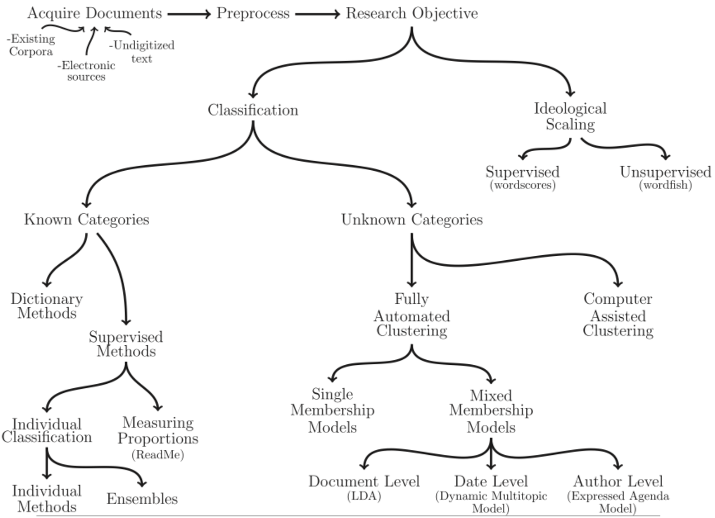
Course website: lse-my459.github.io

1. Overview and Fundamentals
2. Descriptive Statistical Methods for Text Analysis
3. Automated Dictionary Methods
4. Machine Learning for Texts
5. Supervised Scaling Models for Texts
6. *Reading Week*
7. Unsupervised Models for Scaling Texts
8. Similarity and Clustering Methods
9. Topic models
10. Word embeddings
11. Working with Social Media

Overview of text as data methods



Outline for today

- Dictionary methods: an overview
- Some well-known dictionaries
- Advantages and disadvantages
- Dictionary construction
- Keyword detection
- Practical demo with quanteda

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  - Code a few documents manually and see if dictionary prediction aligns with human coding of document

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- Perfect reliability because there is no human decision making as part of the text analysis procedure

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- Two components:
  - **key** the label for the equivalence class for the concept or canonical term
  - **values** (multiple) terms or patterns that are declared equivalent occurrences of the key class
- Frequently involves stemming/lemmatization: transformation of all inflected word forms to their "dictionary look-up form"

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  - interest = `engage, appeal, excite, attract, entertain`

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- Output example:
  `http://www.wjh.harvard.edu/~inquirer/Spreadsheet.html`

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- Categories were derived from the theoretical and empirical literature on regressive thought by Martindale (1975, 1990)

Regressive Imagery Dictionary categories

- Full listing of categories

1 orality	21 brink-passage	41 aggression	62 novelty
2 anality	22 narcissism	42 expressive behaviour	63 negation
3 sex	23 concreteness	43 glory	64 triviality
4 touch	24 ascend	44 female role	65 transmute
5 taste	25 height	45 male fole	
6 odour	26 descent	46 self	
7 general sensation	27 depth	47 related others	
8 sound	28 fire	48 diabolic	
9 vision	29 water	49 aspiration	
10 cold	30 abstract thought	50 angelic	
11 hard	31 social behaviour	51 flowers	
12 soft	32 instrumental behaviour	52 synthesize	
13 passivity	33 restraint	53 streight	
14 voyage	34 order	54 weakness	
15 random movement	35 temporal references	55 good	
16 diffusion	36 moral imperative	56 bad	
17 chaos	37 positive affect	57 activity	
18 unknown	38 anxiety	58 being	
19 timelessness	39 sadness	59 analogy	
20 counscious	40 affection	61 integrative con	

- More on categories:
`http://www.kovcomp.co.uk/wordstat/RID.html`

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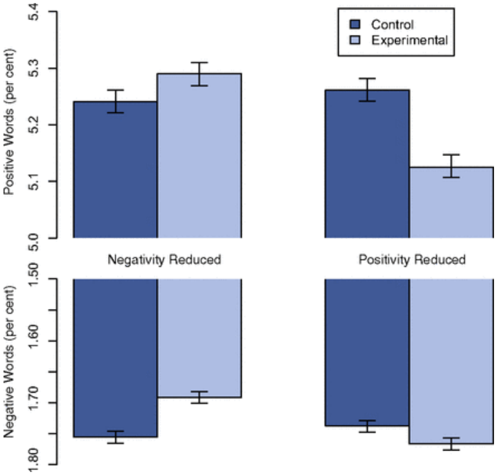
- You can buy it here: `http://www.liwc.net/descriptiontable1.php`

Example: Terrorist speech (Pennebaker, 2008)

	Bin Ladin (1988 to 2006) N = 28	Zawahiri (2003 to 2006) N = 15	Controls N = 17	p (two-tailed)
Word Count	2511.5	1996.4	4767.5	
Big words (greater than 6 letters)	21.2a	23.6b	21.1a	.05
Pronouns	9.15ab	9.83b	8.16a	.09
I (e.g. I, me, my)	0.61	0.90	0.83	
We (e.g. we, our, us)	1.94	1.79	1.95	
You (e.g. you, your, yours)	1.73	1.69	0.87	
He/she (e.g. he, hers, they)	1.42	1.42	1.37	
They (e.g., they, them)	2.17a	2.29a	1.43b	.03
Prepositions	14.8	14.7	15.0	
Articles (e.g. a, an, the)	9.07	8.53	9.19	
Exclusive Words (but, exclude)	2.72	2.62	3.17	
Affect	5.13a	5.12a	3.91b	.01
Positive emotion (happy, joy, love)	2.57a	2.83a	2.03b	.01
Negative emotion (awful, cry, hate)	2.52a	2.28ab	1.87b	.03
Anger words (hate, kill)	1.49a	1.32a	0.89b	.01
Cognitive Mechanisms	4.43	4.56	4.86	
Time (clock, hour)	2.40b	1.89a	2.69b	.01
Past tense verbs	2.21a	1.63a	2.94b	.01
Social Processes	11.4a	10.7ab	9.29b	.04
Humans (e.g. child, people, selves)	0.95ab	0.52a	1.12b	.05
Family (mother, father)	0.46ab	0.52a	0.25b	.08
Content				
Death (e.g. dead, killing, murder)	0.55	0.47	0.64	
Achievement	0.94	0.89	0.81	
Money (e.g. buy, economy, wealth)	0.34	0.38	0.58	
Religion (e.g. faith, Jew, sacred)	2.41	1.84	1.89	

Note. Numbers are mean percentages of total words per text file. Statistical tests are between Bin Ladin, Zawahiri, and Controls. Documents whose source indicates "Both" (n=3) or "Unknown" (n=2) were excluded due to their small sample sizes.

Example: Emotional Contagion on Facebook



Source: Kramer et al, PNAS 2014

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Other open-source sentiment dictionaries: LexiCoder (media text), SentiStrength (social media text)

Example: Laver and Garry (2000)

- A *hierarchical* set of categories to distinguish policy domains and policy positions – similar in spirit to the CMP
- Five domains at the top level of hierarchy
  - economy
  - political system
  - social system
  - external relations
  - a " 'general' domain that has to do with the cut and thurst of specific party competition as well as uncodable pap and waffle"
- Looked for word occurences within "word strings with an average length of ten words"
- Built the dictionary on a set of specific UK manifestos

Example: Laver and Garry (2000): Economy

TABLE 1 Abridged Section of Revised Manifesto Coding Scheme

1 ECONOMY
Role of state in economy

- 1 1 ECONOMY/+State+
  Increase role of state
  - 1 1 1 ECONOMY/+State+/Budget
    Budget
    - 1 1 1 1 ECONOMY/+State+/Budget/Spending
      Increase public spending
      - 1 1 1 1 1 ECONOMY/+State+/Budget/Spending/Health
      - 1 1 1 1 2 ECONOMY/+State+/Budget/Spending/Educ. and training
      - 1 1 1 1 3 ECONOMY/+State+/Budget/Spending/Housing
      - 1 1 1 1 4 ECONOMY/+State+/Budget/Spending/Transport
      - 1 1 1 1 5 ECONOMY/+State+/Budget/Spending/Infrastructure
      - 1 1 1 1 6 ECONOMY/+State+/Budget/Spending/Welfare
      - 1 1 1 1 7 ECONOMY/+State+/Budget/Spending/Police
      - 1 1 1 1 8 ECONOMY/+State+/Budget/Spending/Defense
      - 1 1 1 1 9 ECONOMY/+State+/Budget/Spending/Culture
    - 1 1 1 2 ECONOMY/+State+/Budget/Taxes
      Increase taxes
      - 1 1 1 2 1 ECONOMY/+State+/Budget/Taxes/Income
      - 1 1 1 2 2 ECONOMY/+State+/Budget/Taxes/Payroll
      - 1 1 1 2 3 ECONOMY/+State+/Budget/Taxes/Company
      - 1 1 1 2 4 ECONOMY/+State+/Budget/Taxes/Sales
      - 1 1 1 2 5 ECONOMY/+State+/Budget/Taxes/Capital
      - 1 1 1 2 6 ECONOMY/+State+/Budget/Taxes/Capital gains
    - 1 1 1 3 ECONOMY/+State+/Budget/Deficit
      Increase budget deficit
      - 1 1 1 3 1 ECONOMY/+State+/Budget/Deficit/Borrow
      - 1 1 1 3 2 ECONOMY/+State+/Budget/Deficit/Inflation

Example: Laver and Garry (2000)

```
ECONOMY / +STATE
    accommodation
    age
    ambulance
    assist
    ...

ECONOMY / -STATE
    choice*
    compet*
    constrain*
    ...
```

MFD (Graham and Haidt)

Moral Foundations dictionary:

- Moral foundations: dimensions of difference that explain human moral reasoning
- Measures the proportions of virtue and vice words for each foundation:
  1. Care/Harm
  2. Fairness/Cheating
  3. Loyalty/Betrayal
  4. Authority/Subversion
  5. Purity/Degradation
- Link: `https://www.moralfoundations.org/othermaterials`

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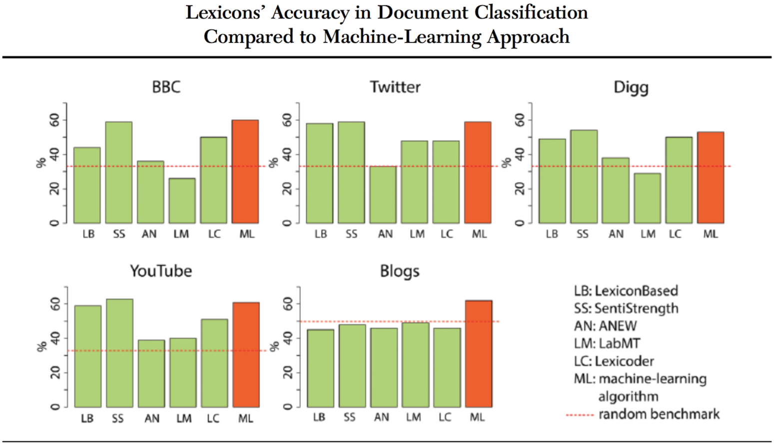
Potential advantage: Multi-lingual

APPENDIX B
DICTIONARY OF THE COMPUTER-BASED CONTENT ANALYSIS

	NL	UK	GE	IT
Core	elit*	elit*	elit*	elit*
	consensus*	consensus*	konsens*	consens*
	ondemocratisch*	undemocratic*	undemokratisch*	antidemocratic*
	ondemokratisch*			
	referend*	referend*	referend*	referend*
	corrupt*	corrupt*	korrupt*	corrot*
	propagand*	propagand*	propagand*	propagand*
	politici*	politici*	politiker*	politici*
	bedrog	*deceit*	täusch*	ingann*
	bedrieg	*deceiv*	betrüg*	
			betrug*	
	verraa	*betray*	*verrat*	tradi*
	verrad			
	schaam*	shame*	scham*	vergogn*
			schäm*	
	schand*	scandal*	skandal*	scandal*
	waarheid*	truth*	wahrheit*	verità
	oneerlijk*	dishonest*	unfair*	disonest*
			unehrlich*	
Context	establishm*	establishm*	establishm*	partitocrazia
	heersend*	ruling*	*herrsch*	
	capitul*			
	kapitul*			
	kaste*			
	leugen*		lüge*	menzogn*
	lieg*			mentir*

(from Rooduijn and Pauwels 2011)

Potential disadvantage: Context specific



Source: González-Bailón and Paltoglou (2015)

Disadvantage: Highly specific to context

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- Problem: polysemes – words that have multiple meanings
- Another problem: dictionary lacked important negative financial words, such as *felony*, *litigation*, *restated*, *misstatement*, and *unanticipated*

Potential disadvantage: sensitive to frequent words

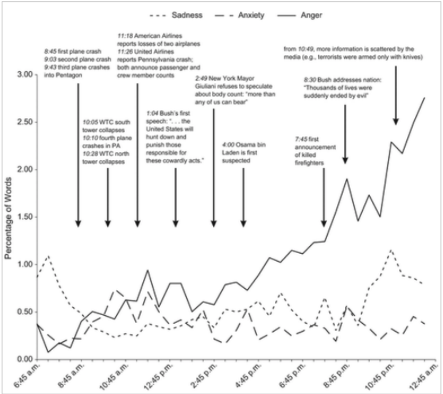

Fig. 1. The timeline of sadness, anxiety, and anger on September 11 as expressed in messages sent to text pagers. Each data point represents the mean percentage of words related to the specific negative emotion, averaged across 30 min. The time slots start at 6:45 a.m. to 7:14 a.m. on September 11, 2001, and end at 12:15 a.m. to 12:44 a.m. on September 12, 2001. Exact times and brief descriptions of the most important events of September 11 are included above the timelines. WTC = World Trade Center

(from Back et al, Psychological Science, 2010)

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Automation can lead to confounds in text analysis: Back, Küfner, and Egloff (2010) and the not-so-angry Americans.

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Pury, Cynthia L. S.

Citation

Pury, C. L. S. (2011). Automation can lead to confounds in text analysis: Back, Küfner, and Egloff (2010) and the not-so-angry Americans. *Psychological Science, 22*(6), 835-836.
http://dx.doi.org/10.1177/0956797611408735

Abstract

Comments on an article by Mitja D. Back et al. (see record 2010-25035-010). The authors used Linguistic Inquiry and Word Count (LIWC) to analyze pager messages sent to more than 85,000 American pagers on September 11, 2001. They found that anger, as indexed by the words contained in those messages, rose steadily throughout the day. The data contained many technical codes; thus, Back et al. counted only words recognized by LIWC. However, this procedure did not exclude automatically generated messages. Consequently, LIWC words in such messages were counted, even if the words lacked emotional meaning in context. Furthermore, computers can send messages with superhuman frequency, turning an otherwise minor measurement error into a serious confound. This confound can be detected by treating individual text messages as primary units, reading samples of each key word in context, and looking for repeating false positives. Thus, it appears that much of the dramatic rise in anger reported by Back et al. was due to a repeated and emotionally neutral technical message associated with a single pager. Because today's e-mail, social media, and text messages can include automatically generated messages, future researchers of linguistic archives should consider ways to prevent similar confounds.

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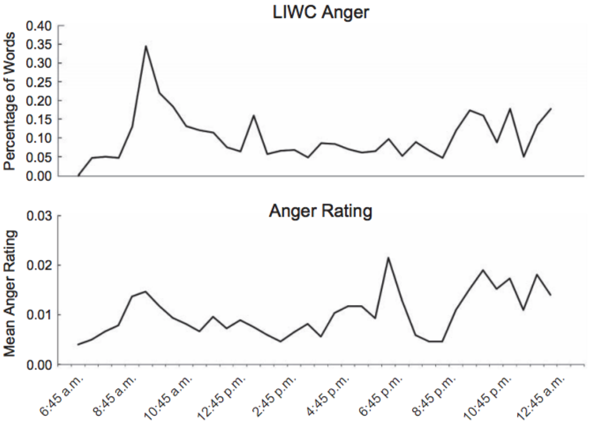

Fig. 1. A revised timeline of anger as expressed in 37,606 social messages sent to text pagers on September 11, 2001. The graphs show (a) the mean percentage of words related to anger (as classified by Linguistic Inquiry and Word Count; Pennebaker, Francis, & Booth, 2001) and (b) the mean anger rating (0 = *no anger*, 1 = *some anger*, 2 = *strong anger*; averaged across three raters for each message) across time slots starting at 6:45 a.m. to 7:14 a.m. on September 11, 2001, and ending at 12:15 a.m. to 12:44 a.m. on September 12, 2001.

(from Back et al, Psychological Science, 2011)

Outline for today

- Dictionary methods: an overview
- Some well-known dictionaries
- Advantages and disadvantages
- Dictionary construction
- Keyword detection
- Practical demo with quanteda

How to build a dictionary

- The ideal content analysis dictionary associates all and only the relevant words to each category in a perfectly valid scheme

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- Three key issues:

Validity	Is the dictionary's category scheme valid?
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- Imagine two logical extremes of including all words (too sensitive), or just one word (too specific)

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4. Use regular expressions to see whether stemming or wildcarding is required

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- For instance, we could partition the Irish budget speech corpus into "government" and "opposition" speeches, and look for words that occur in one partition with higher relative frequency in opposition than in government speeches
- This is done by constructing a 2×2 table for each word, and testing association between that word and the partition categories

Detecting "keywords": Constructing the association table

	Target	~ Target	
Word 1	n_{11}	n_{12}	$n_{1.}$
~ (Word 1)	n_{21}	n_{22}	$n_{2.}$
	$n_{.1}$	$n_{.2}$	n

- Once this is constructed, any standard measures of association (similar to those used to detect collocations) can be used to identify keyword associations with a class
- Same association measures are used as with collocation detection

statistical association measures

where m_{ij} represents the cell frequency expected according to independence:

G^2 likelihood ratio statistic, computed as:

$$2 * \sum_i \sum_j (n_{ij} * log \frac{n_{ij}}{m_{ij}})$$

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pmi point-wise mutual information score, computed as $\log n_{11}/m_{11}$

Examples

```
# compare Trump 2017 to other post-war presidents
period <- ifelse(docvars(data_corpus_inaugural, "Year") < 1945,
                 "pre-war", "post-war")
pwdfm <- dfm(corpus_subset(data_corpus_inaugural, period == "post-war"))

textstat_keyness(pwdfm, target = "2017-Trump") %>%
    head(n = 7)
#     feature      chi2            p n_target n_reference
# 1 protected 76.64466 0.000000e+00        5           1
# 2      will 51.44795 7.351897e-13       40         299
# 3     while 48.23022 3.790079e-12        6           7
# 4     obama 47.85727 4.584000e-12        3           0
# 5     we've 47.85727 4.584000e-12        3           0
# 6   america 31.45537 2.040775e-08       18         112
# 7     again 27.81145 1.337322e-07        9          33
```

Examples

```
# using the likelihood ratio method
textstat_keyness(dfm_smooth(pwdfm), measure = "lr", target = "2017-Trum
    head()
#     feature        G2            p n_target n_reference
# 1      will 24.604106 7.040156e-07       41         317
# 2  america 14.040255 1.789387e-04       19         130
# 3      your 10.435140 1.236402e-03       12          68
# 4     again  9.758516 1.784939e-03       10          51
# 5     while  9.504990 2.049139e-03        7          25
# 6 american  8.877690 2.886766e-03       12          76
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textstat_keyness(pwdfm, target = "2017-Trump") %>%
    textplot_keyness()
```

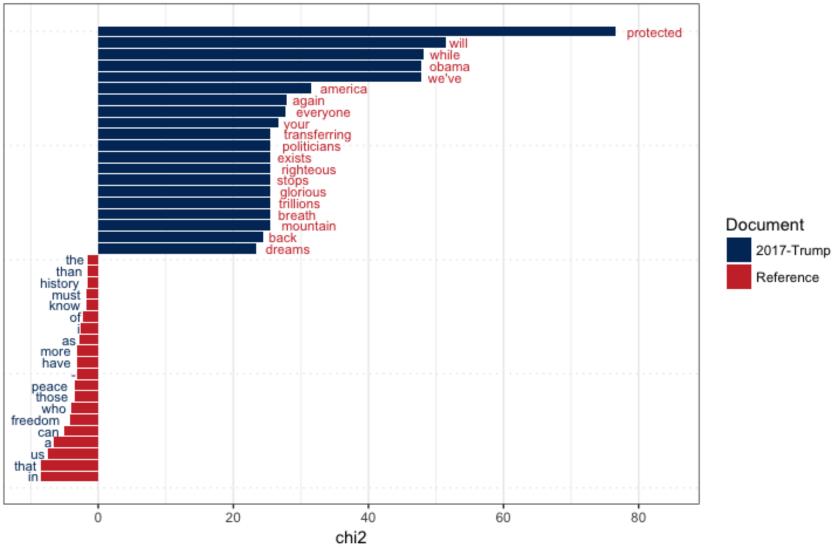

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