# RECSM Summer School: Social Media and Big Data Research

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# Dictionary Methods Applied

to Social Media Text

### Dictionary methods

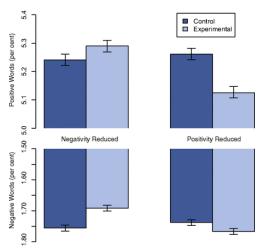
#### Classifying documents when categories are known:

- Lists of words that correspond to each category:
  - Positive or negative, for sentiment
  - Sad, happy, angry, anxious... for emotions
  - Insight, causation, discrepancy, tentative... for cognitive processes
  - Sexism, homophobia, xenophobia, racism... for hate speech many others: see LIWC, VADER, SentiStrength, LexiCoder...
- Count number of times they appear in each document
- Normalize by document length (optional)
- Validate, validate, validate.
  - Check sensitivity of results to exclusion of specific words
  - Code a few documents manually and see if dictionary prediction aligns with human coding of document

#### Linquistic Inquiry and Word Count

- Created by Pennebaker et al see http://www.liwc.net
- uses a dictionary to calculate the percentage of words in the text that match each of up to 82 language dimensions
- Consists of about 4,500 words and word stems, each defining one or more word categories or subdictionaries
- For example, the word *cried* is part of five word categories: sadness, negative emotion, overall affect, verb, and past tense verb. So observing the token *cried* causes each of these five subdictionary scale scores to be incremented
- Hierarchical: so "anger" are part of an emotion category and a negative emotion subcategory
- You can buy it here: http://www.liwc.net/descriptiontable1.php

## Example: Emotional Contagion on Facebook



Source: Kramer et al, PNAS 2014

### Potential advantage: Multi-lingual

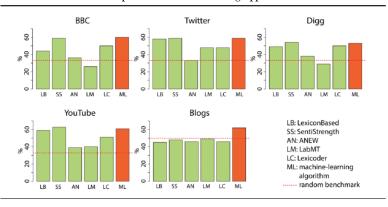
APPENDIX B
DICTIONARY OF THE COMPUTER-BASED CONTENT ANALYSIS

	NL	UK	GE	IT
Core	elit*	elit*	elit*	elit*
	consensus*	consensus*	konsens*	consens*
	ondemocratisch* ondemokratisch*	undemocratic*	undemokratisch*	antidemocratic*
	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* schäm*	vergogn*
	schand*	scandal*	skandal*	scandal*
	waarheid*	truth*	wahrheit*	verità
	oneerlijk*	dishonest*	unfair* unehrlich*	disonest*
Context	establishm* heersend*	establishm* ruling*	establishm* *herrsch*	partitocrazia
	capitul* kapitul* kaste*	C		
	leugen* lieg*		lüge*	menzogn* mentir*

(from Rooduijn and Pauwels 2011)

#### Potential disadvantage: Context specific

Lexicons' Accuracy in Document Classification Compared to Machine-Learning Approach



Source: González-Bailón and Paltoglou (2015)

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

```
Validity Is the dictionary's category scheme valid?
Recall Does this dictionary identify all my content?
Precision Does it identify only my content?
```

Imagine two logical extremes of including all words (too sensitive), or just one word (too specific)

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- Use regular expressions to see whether stemming or wildcarding is required