

# Introduction to Text Mining with R

## Dictionary Methods



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

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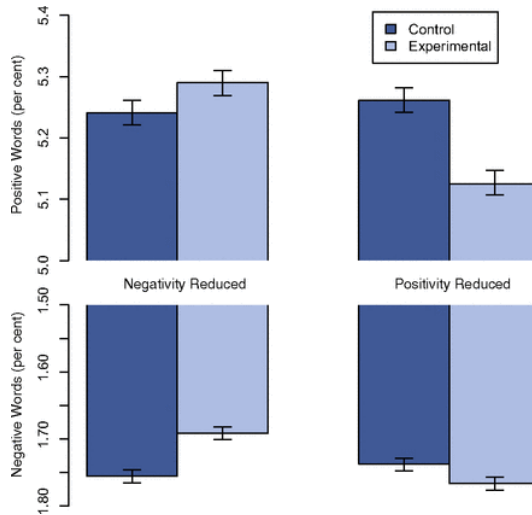
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- You can **buy** it here: <http://www.liwc.net/descriptiontable1.php>

# Example: Emotional Contagion on Facebook



**Source:** Kramer et al. 2014

# Potential advantage: Multi-lingual

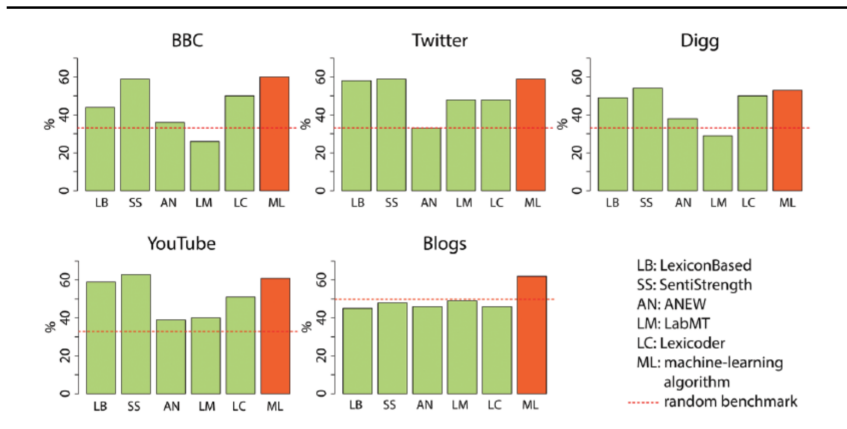
APPENDIX B  
DICTIONARY OF THE COMPUTER-BASED CONTENT ANALYSIS

	NL	UK	GE	IT
<b>Core</b>	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*
<b>Context</b>			schäm*	
	schand*	scandal*	skandal*	scandal*
	waarheid*	truth*	wahrheit*	verità
	oneerlijk*	dishonest*	unfair*	disonest*
			unehrlich*	
	establishm*	establishm*	establishm*	partitocrazia
	heersend*	ruling*	*hersch*	
	capitul*			
	kapitul*			
	kaste*			
	leugen*		lüge*	menzogn*
	lieg*			mentir*

**Source:** Rooduijn and Pauwels 2011

# Potential disadvantage: Context specific

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



**Source:** González-Bailón and Paltoglou (2015)

# How to build a dictionary



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