# Text Analysis for Legal Practice (Class 3)

Charles Crabtree & Kevin L. Cope

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github.com/cdcrabtree/uvashortcourse

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```
negative
   1 2-faced
   2 2-faces
                  negative
                  positive
    4 abnormal
                  negative
    5 abolish
                  negative
    6 abominable
                  negative
    7 abominably
                  negative
    8 abominate
                  negative
    9 abomination negative
## 10 abort
                  negative
```

##		word	score
##		<chr></chr>	<int></int>
##	1	abandon	- 2
##	2	abandoned	-2
##	3	abandons	-2
##	4	abducted	- 2
##	5	abduction	- 2
##	6	abductions	-2
##	7	abhor	- 3
##	8	abhorred	- 3
##	9	abhorrent	- 3
##	10	abhors	- 3

##	1	abacus	trust
##	2	abandon	fear
##	3	abandon	negative
##	4	abandon	sadness
##	5	abandoned	anger
##	6	abandoned	fear
##	7	abandoned	negative
##	8	abandoned	sadness
##	9	${\it abandonment}$	anger
##	10	abandonment	fear

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#### CONTEXT MATTERS.

An Application

# The Strategic Use of Campaign Sentiment

## What explains the type of

electoral campaign run by

political parties?

# Campaign Sentiment refers to the emotive content of campaign messages.

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Campaign content and campaign focus address

campaign sentiment addresses how they say it.

### what parties say and who they say it about;

Language has emotive content.

It is language that evokes most of the political 'realities' people experience.

Edelman 1976, 3

Mental pictures are ways of seeing and comprehending something as evoked by words.

Hipt 1990, 209

Emotive content affects VOter behavior.

# Do parties use emotive language strategically?

Parties can try to change the Salience of the economic dimension.

Parties can use **emotive** language to frame the state of the economy.

"the economic outlook is positive, with employment increasing by 150,000"

'employment has increased by only 150,000"

"the economic outlook is positive, with employment increasing by 150,000"

"employment has increased by only 150,000"

**Incumbent Party Hypothesis:** Incumbent parties use higher levels of positive sentiment in their campaign manifestos than

opposition parties.

### Prime Ministerial Party Hypothesis: Prime ministerial parties

manifestos than their coalition partners.

use higher levels of positive sentiment in their campaign

### Why manifestos?

Unfiltered by the media

Overarching strategy

Common campaign message

Long period of time

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France, Germany, Ireland, Italy, Netherlands, Portugal, Spain, United Kingdom.

421 manifestos and 9,274,954 words.

70 legislative elections and 108 parties, 1980-2012.

Political Document Archive (Benoit, Bräuninger, & Debus 2009).

# Dependent Variable: Positive Sentiment

## Linguistic Inquiry and Word Count (LIWC) Pennebaker, Booth, and Francis (2007)

*Positive Sentiment* = positive words score – negative words score.

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UK Conservative Party's 1987 Manifesto

In the last eight years our country has changed — changed for the **better**.

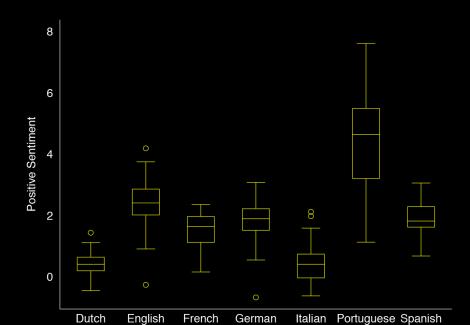
Positive words score = 1/13 = 7.69%.

UK Liberal Party's 1987 Manifesto

Too many elderly people suffer from  ${\bf isolation}$  ,  ${\bf fear},$  and  ${\bf cold}.$ 

Negative words score = 3/10 = 30.00%.

### Positive Sentiment by Language



Independent Variables

#### Incumbency

Incumbent Party (Glasgow and Golder 2015)

Prime Ministerial Party (Glasgow and Golder 2015)

#### Ideology

Left-Right (ParlGov 2015) Extremist Party (ParlGov 2015)

#### **Economic Context**

Unemployment (IMF 2015) Inflation (WB 2012) Growth (PWT 9.0) Model Specification

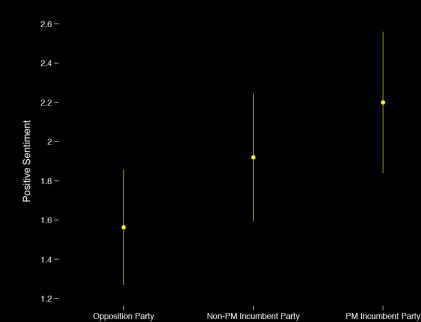
#### Unit of analysis: Election-party.

Method: OLS; language FE; bootstrap SE clustered by election.

Positive Sentiment =  $\beta_0 + \beta_1$ Incumbent Party

$$+$$
  $eta_2$ Incumbent Party  $imes$  PM Party  $+$   $eta_3$ Left-Right  $+$   $eta_4$ Left-Right<sup>2</sup>  $+$   $eta_5$ Inflation  $+$   $eta_6$ Incumbent Party  $imes$  Inflation  $+$   $eta_7$ Unemployment  $+$   $eta_8$ Incumbent Party  $imes$  Unemployment  $+$   $eta_9$ Growth  $+$   $eta_{10}$ Incumbent Party  $imes$  Growth  $+$   $\epsilon$ 

#### Positive Sentiment and a Party's Incumbency Status

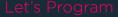


Positive Sentiment and a Party's Incumbency Status

**Non-PM incumbent parties** exhibit 23% [12.9%, 34.5%] more positive sentiment than **opposition parties**.

PM parties exhibit 41% [30%, 53.8%] more positive sentiment than opposition parties.

PM parties exhibit 18% [8.8%, 27.5%] more positive sentiment than non-PM incumbent parties.



Launch RStudio and we can get started programming.

crabtree@dartmouth.edu | charlescrabtree.com