Computational Text Analysis for Legal Practice

(Class 3)

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github.com/cdcrabtree/uva-2022

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- Class 3: Measuring expressed sentiment in documents.
- Goal: Classify (measure) sentiment in texts.

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Dictionaries

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

Dictionaries

```
##    word       score
##    <chr>      <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
```

Dictionaries

```
##  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 abandonment anger
## 10 abandonment fear
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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 *what* parties say and *who* they say it about; campaign sentiment addresses *how* they say it.

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 use higher levels of positive sentiment in their campaign manifestos than their coalition partners.

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**.

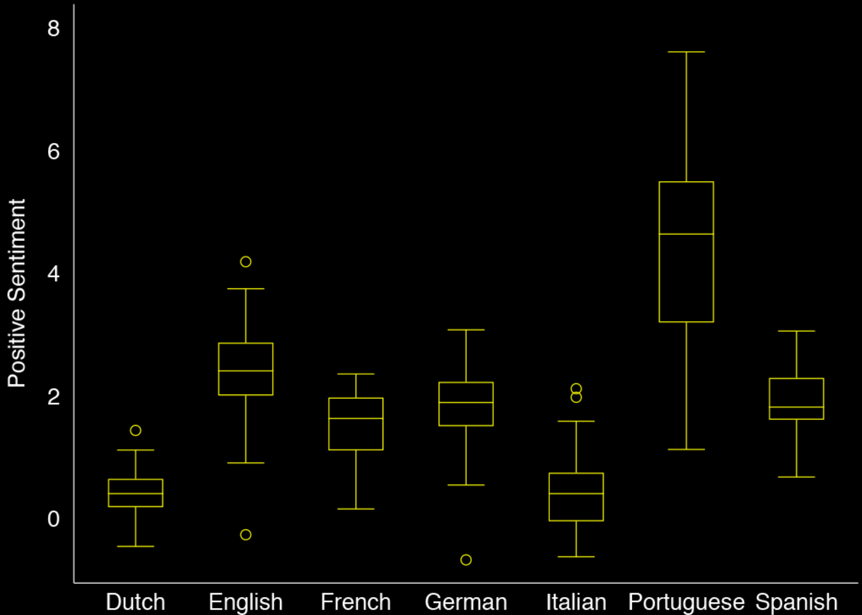
Positive words score = 1/13 = 7.69%.

UK Liberal Party's 1987 Manifesto

Too many elderly people suffer from **isolation** , **fear**, and **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)

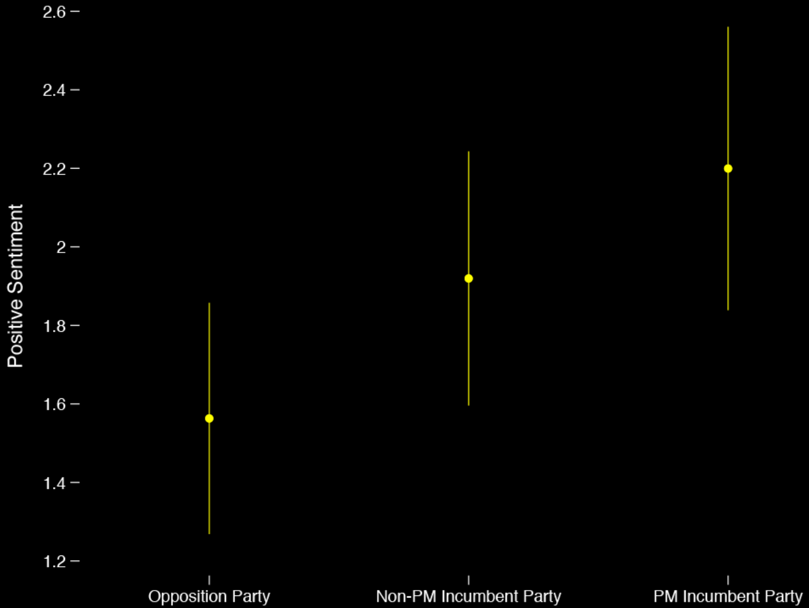
Model Specification

Unit of analysis: Election-party.

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

$$
\begin{aligned}
\text{Positive Sentiment} = \beta_0 & + \beta_1 \text{Incumbent Party} \\
& + \beta_2 \text{Incumbent Party} \times \text{PM Party} \\
& + \beta_3 \text{Left-Right} + \beta_4 \text{Left-Right}^2 \\
& + \beta_5 \text{Inflation} \\
& + \beta_6 \text{Incumbent Party} \times \text{Inflation} \\
& + \beta_7 \text{Unemployment} \\
& + \beta_8 \text{Incumbent Party} \times \text{Unemployment} \\
& + \beta_9 \text{Growth} \\
& + \beta_{10} \text{Incumbent Party} \times \text{Growth} \\
& + \epsilon
\end{aligned}
$$

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**.

Let's Program

Launch RStudio and we can get started programming.

crabtree@dartmouth.edu | charlescrabtree.com