

Class 10: Sentiment Analysis

MAST5953: Web Scraping and Text Mining

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Outline of Today's Class

Sentiment Analysis: Definitions & Examples

Dictionaries

The Naive Bayes Algorithm

Sentiment Analysis in R

Sentiment Analysis: Definitions & Examples

Sentiment Analysis

What for?

- ▶ Detecting the *attitude* of a text
 - ▶ positive/negative ...
 - ▶ left/right ...
 - ▶ anti-EU/pro-EU ...
- ▶ A classification exercise, but sentiment analysis can also be continuum/scale

Sentiment Analysis

Methods

1. Dictionaries

- ▶ Generating lists of words for each sentiment category

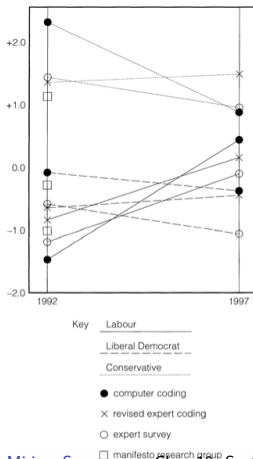
2. Machine Learning

- ▶ Training an algorithm via pre-labeled documents (e.g. Naive Bayes)

Sentiment Analysis

Example 1: Laver, M., Garry, J. (2000) "Estimating Policy Positions from Political Texts"
American Journal of Political Science

FIGURE 1 Standardized Expert Survey, Computer Coded and Expert Coded Estimates of Party Policy Positions in Britain 1992–97



Sentiment Analysis

Example 1: Laver, M., Garry, J. (2000) "Estimating Policy Positions from Political Texts"
American Journal of Political Science

- ▶ **Economy**
- ▶ **Institutions**
- ▶ **Values**
- ▶ **Law and Order**
- ▶ **Environment**
- ▶ **Culture**
- ▶ **Groups**
- ▶ **Rural**
- ▶ **Urban**

Sentiment Analysis

Example 1: Laver, M., Garry, J. (2000) "Estimating Policy Positions from Political Texts"
American Journal of Political Science

▶ Economy

- ▶ $+ State$
- ▶ $= State$
- ▶ $- State$

▶ Institutions

▶ Values

▶ Law and Order

▶ Environment

▶ Culture

▶ Groups

▶ Rural

▶ Urban

Sentiment Analysis

Example 1: Laver, M., Garry, J. (2000) "Estimating Policy Positions from Political Texts"
American Journal of Political Science

► Economy

► + State

- accommodation; age; ambulance; assist; benefit; care; class; clinics; deprivation; disabilities; disadvantaged; elderly; establish; hardship; hunger; invest; patients; pensions; poor; poverty; school; child; collective; contribution ...

► = State

► - State

► Institutions

► Values

► Law and Order

► Environment

► Culture

► Groups

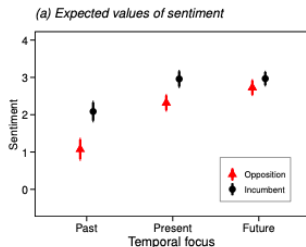
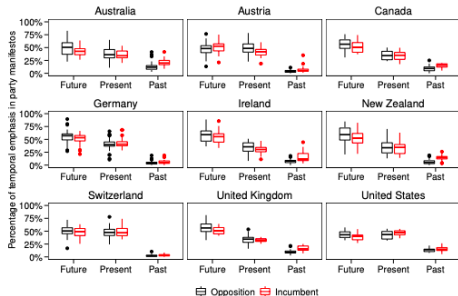
► Rural

► Urban

Sentiment Analysis

Example 3: Müller, S (forthcoming) "The Temporal Focus of Campaign Communication"
Journal of Politics

Figure 1: The emphasis on the past, present, and future, conditional on incumbency status



Sentiment Analysis

Engage with the Examples

1. Explore the Laver/Garry Dictionary yourself at:
<http://yoshikoder.sourceforge.net/code/yoshikoder/dictionaries/LaverGarryAJPS.ykd>
2. Watch Ken Benoit's presentation of the Brexit project here
<https://www.youtube.com/watch?v=IVayXmtI2VM>

Dictionaries

Dictionary Analysis

How it Works

- ▶ Both qualitative and quantitative
 - ▶ Contextual knowledge needed: validation crucial
 - ▶ Once defined, the dictionary will be automated: perfectly reliable
- ▶ Identify key concepts/categories (or “keys”)
- ▶ Identify words/n-grams (the “values”) associated with each key
 - ▶ From Laver & Garry:
 - ▶ **more state**: assist, benefit, care, disabilities, educat*,invest, pension
 - ▶ **less state**: autonomy, bidders, choice*, controls, market

Dictionary Analysis

How to build one

1. Order your concepts/keys **hierarchically**
 - 1.1 Domain - *Economy*
 - 1.2 Sub-Domain - *Labour Law*
 - 1.3 Sentiment Categories/Poles - *Pro-Business/Neutral/Pro-Worker*
2. Identify extreme texts among the texts with known positions: the “archetypes”
3. Identify words/n-grams that are statistically associated with the various archetypes
 - ▶ Chi-square tests
4. Examine these words/n-grams for their specificity: are they polysemes?
5. Examine these words to decide whether stemming is necessary
6. Create word/n-grams lists for the relevant dictionary key
7. Investigate whether the dictionary is sensitive enough: will it capture all instances of [key]?

Dictionary Analysis

Advantages

- Allows for detailed contextual knowledge to be reliably applied to large-scale text analysis

Dictionary Analysis

Disadvantages

- ▶ Time-consuming
- ▶ Non-generalisable: often dictionaries do not travel well to new corpuses
 - ▶ E.g. `freez*` is positive in the context of refrigeration appliances but negative in the context of computing
 - ▶ E.g. `revolut*` is positive in the context of technology, negative in the context of interior policy
- ▶ Difficult to know with certainty how comprehensive/valid the dictionary is

The Naive Bayes Algorithm

Naive Bayes

How it Works

- Bayes' Rule:

$$P(C_j|W_i) = \frac{P(W_i|C_j)P(C_j)}{P(W_i)}$$

- which can be transformed to:

$$P(C|D) = P(C) \prod \frac{P(W_i|C)}{P(W_i)}$$

Naive Bayes

How it Works: Example

► Training Set:

Document	Words	Class
1	like love fantastic perfect	<i>Positive</i>
2	love love great mean	<i>Positive</i>
3	awful terrible worse mean	<i>Negative</i>
4	like fantastic great like	<i>Positive</i>
5	terrible awful love mean	??

- What is the likelihood that the new document 5 is of class *Positive* vs. the likelihood that it is of class *Negative*?

Naive Bayes

How it Works: Example

Document	Words	Class
1	like love fantastic perfect	<i>Positive</i>
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3	awful terrible worse mean	<i>Negative</i>
4	like fantastic great like	<i>Positive</i>
5	terrible awful love mean	??

$$\begin{aligned}P(C_{pos}|D_5) &= P(C_{pos}) \frac{\prod P(W_{i5}|C_{pos})}{P(W_{i5})} \\&= 0.75 \frac{(0.04 * 0.04 * 0.29 * 0.13)}{(0.09 + 0.09 + 0.22 + 0.16)} \\&= 0.00008\end{aligned}$$

Naive Bayes

How it Works: Example

Document	Words	Class
1	like love fantastic perfect	<i>Positive</i>
2	love love great mean	<i>Positive</i>
3	awful terrible worse mean	<i>Negative</i>
4	like fantastic great like	<i>Positive</i>
5	terrible awful love mean	??

$$\begin{aligned}P(C_{neg}|D_5) &= P(C_{neg}) \frac{\prod P(W_{i5}|C_{neg})}{P(W_{i5})} \\&= 0.25 \frac{(0.38 * 0.38 * 0.13 * 0.38)}{(0.09 + 0.09 + 0.22 + 0.16)} \\&= 0.003\end{aligned}$$

Naive Bayes

Steps

1. Obtain a valid and reliable labeled set
 - ▶ Expert-coded
 - ▶ Label from meta-data - e.g. party
 - ▶ Crowd-sourced
2. Run the Naive Bayes classifier algorithm
3. Test the performance via cross-validation
 - ▶ Accuracy, Recall, Precision, F-Measure

Naive Bayes

Advantages

- ▶ Outperforms dictionaries in the sensitivity of classification - as long as the training sample is big enough
- ▶ Flexible and quick: it can be easily re-applied to new corpuses, provided satisfactory identification of archetypal training texts

Naive Bayes

Disadvantages

- ▶ Naive: word order does not count + probability of words/n-grams assumed independent from the class
 - ▶ formula might not correctly model the data-generation process!
- ▶ Very reliant on the training set: select a good one!
 - ▶ Make sure this is representative of the extreme points
 - ▶ Make sure it is large enough so that language styles/rhetoric does not influence classification
 - ▶ Make sure to appropriately pre-process the texts!
- ▶ Requires a lot of validation ex post (cross-validation steps).

Naive Bayes

Performance Metrics

- ▶ **Accuracy:** correctly classified texts divided by the total number of texts
- ▶ **Precision:** How many texts that were *predicted* as class A were *actual* class A texts?
- ▶ **Recall:** How many texts that *actually* are of class A were also *predicted* to be of class A?
- ▶ **F-Measure:** composite measure of precision and recall. Good recall can lead to low precision, so a mix measure is needed.

Naive Bayes

The Confusion Matrix

Predictive Model: Evaluation

Accuracy = $\frac{tp + tn}{tp + tn + fp + fn}$

		actual result / classification	
		yes	no
predictive result / classification	yes	tp (true positive)	fp (false positive) ← Type 1 error
	no	fn (false negative)	tn (true negative)

$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$

$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

$$\text{True Negative Rate} = \frac{tn}{tn + fp}$$

TP : The number of samples of class c are correctly classified into class c
FP: The number of samples not belonging to class c misclassified into class c
TN: The number of samples not belonging to class c is classified (correctly)
FN: The number of samples of class c misclassified (in other classes c)

Example from:

<https://stats.stackexchange.com/questions/116585/>

Sentiment Analysis in R

Sentiment Analysis: R code demonstration

- ▶ R Code
- ▶ Use your scraped tweets!

Naive Bayes Analysis in R

- ▶ For a tutorial check out:
- ▶ `https://tutorials.quanteda.io/machine-learning/nb/`