

# Cross-discourse development of supervised sentiment analysis

Phil Smith

`pxs697@cs.bham.ac.uk`

Supervisor: Dr. Mark Lee

February 17, 2012

- 1 Introducing my research
- 2 NHS Choices datasets
- 3 Sentiment and Advice Corpus
- 4 Analysing the Corpus
- 5 Supervised Machine Learning Experiments

# What is Sentiment Analysis?

- Sentiment Analysis is the computational classification of qualitative and emotional language that is expressed through written discourse.
- Detail in classification can vary:
  - ▶ Polarity based classification - Positive or Negative
  - ▶ Finer-grained combinations of emotional states: Joy, anger, surprise, fear, sadness..
- Occasionally referred to as Opinion Mining - focuses on product reviews
- Applies knowledge from a number of fields:
  - ▶ Natural Language Processing
  - ▶ Corpus Linguistics
  - ▶ Information Retrieval

# Why is Sentiment Analysis important?

*"Emotion is one of the most central and pervasive aspects of human experience"*

*Ortony, Clore & Collins (1988)*

- Decisions are not always motivated by logic alone, and can often be overpowered by emotion.
- The consequences of not understanding or misunderstanding emotion can be costly.

# Practical Applications

- Customer-facing industries
- Advertising campaigns
- Augmenting search capabilities
- Personal decision making

# Where can it be applied?

- Social media: Facebook, Twitter, blogs, forums, reviews.
- Customer Feedback: Call centres, emails, text messages, web surveys.
- Traditional Media: News headlines and articles

# Examples from SemEval 2007 Headline Corpus

*“Bombers kill shoppers”*

- Clearly negative.

*“PS3 pricey but impressive”*

- Comparative statement, weight put on final word.
- Lexical order is important to understanding the sentiment here.

*“Nigeria hostage feared dead is freed ”*

- Again, interpretation depends on final word.
- The majority of the statement suggests a negative statement.

# Sentiment Analysis Corpora

- Pang & Lee (2002) Movie Review Corpora ( $\sim 2,000$ ).
- Semeval 2013 SMS and Tweet Corpora ( $\sim 12,000$ ).
- Lin and Hauptmann (2006) Political Perspective Corpora.
- CMC Suicide Note Corpora.



- Making Public Data Public
- ~5,400 Datasets available from central government departments.
  - ▶ Department for Transport.
  - ▶ Department for Communities and Local Government.
  - ▶ Office for National Statistics.
  - ▶ Department of Health.
- Make clear results of policy changes.
- Can be used to analyse trends over time.

# NHS Choices Patient Feedback

- Public given the opportunity to submit feedback online regarding the NHS.
- Post about experiences with individual hospitals and GP surgeries.
- Responses from the relevant organizations are also able to be given.
- Currently there are 3 main datasets:
  - 1 Overall hospital ratings.
  - 2 Individual comments about hospitals and responses.
  - 3 Individual comments about GPs and responses.

# Individual Comments About Hospitals and Responses

- Two sub-datasets within this:
  - ① Feedback from the period 1<sup>st</sup> January 2008 to 31<sup>st</sup> July 2011.
  - ② Feedback from 1<sup>st</sup> August to today.
- Available as comma-separated value files.
- The most recent dataset was chosen to derive corpora for preliminary experiments.

# Structure of the Dataset

- Hospital Name -  $\sim$ 450 Unique Hospitals and Treatment Centres.
- Relative trust and organisation codes.
- Comment ID
- Comment Title
- Liked
- Disliked
- Advice
- Date of comment
- Date of patient admission
- Response
- Date of Response

# Creating the Corpus

- Extract relevant data for preliminary experimentation.
- Liked, Disliked and Advice Data

Corpus	# of Docs	# of words	Doc <sub>avglength</sub>	# of unique words
<i>Expressive</i>				
Positive	1152	75052	65.15	6107
Negative	1108	76062	68.65	6791
<i>Persuasive</i>				
Positive	768	46642	60.73	4679
Negative	864	113632	131.52	7943

- NB. Advice data was manually annotated.

# Annotating the Persuasive Corpus

- 1702 unique documents were annotated.
- Annotations were placed at the document level.
- Overall sentiment of the recommendation taken into account.
  - ▶ In the cases of comparative phrases being used to express sentimental information, the predominant sentiment was chosen.
- 70 were annotated as not containing any emotion due to the content.
  - ▶ e.g “N/A”
- Neutrally annotated data was removed from the corpus.

# Examples from the Corpus

*Liked: "The honesty of the Consultants PA's."*

*Disliked: "The attitude of the nursing staff."*

*Positive Advice: "Please just do what you do, you are all so good."*

*Negative Advice: "It's very well spending all this money on a new hospital building, however what is the point when people are being wrongly diagnosed."*

## Keyword List: Positively Annotated Sections of Corpus: Unusually Frequent

Comparing the Positive section of the Persuasive Corpus with the Positive section of the Expressive Corpus (reference corpus)

Rank	Keyword	Keyness	Frequency
1	thank	46.631	190
2	tameside	27.496	14
3	scan	19.602	42
4	week	18.520	41
5	musgrove	17.676	9
6	wife	16.411	41
7	hospital	16.102	387
8	thanks	14.584	72
9	rotheram	13.876	10
10	cannock	13.748	7



## Keyword List: Positively Annotated Sections of Corpora: Unusually Infrequent

Rank	Keyword	-Keyness	Frequency
1	friendly	44.210	57
2	professional	26.628	40
3	polite	24.586	9
4	environment	16.675	5
5	helpful	14.116	59
6	staff	13.723	466
7	including	13.200	3
8	caring	12.912	51
9	treated	12.610	70
10	exceptional	12.400	6

## Keyword List: Negatively Annotated Sections of Corpus: Unusually Frequent

Rank	Keyword	Keyness	Frequency
1	hospital	54.296	659
2	now	24.210	165
3	hip	23.245	37
4	catheter	22.266	32
5	wrightington	19.084	18
6	days	18.406	162
7	weeks	17.933	157
8	daughter	17.447	66
9	doctor	16.803	307
10	admitted	16.233	95

## Keyword List: Negatively Annotated Sections of Corpus: Unusually Infrequent

Rank	Keyword	-Keyness	Frequency
1	patients	56.453	232
2	improved	50.314	18
3	staff	46.085	444
4	food	39.336	52
5	communication	37.649	32
6	room	34.476	97
7	improvement	28.515	3
8	waiting	25.936	208
9	little	19.653	54
10	training	17.706	10

## Concordance Data: Experience

Rank	Keyword	-Keyness	Frequency
24	experience	11.388	107

- Positive expressive corpus.

! Helpful in my experience. Very nice nursing  
this a pleasant experience! nice and relaxed t  
staff made the experience bearable and the bi  
y other peoples Experience with midwives in ot  
nd she made the experience very happy for me a  
uld to make the experience go as smoothly as i  
Throughout the experience all the staff I enc  
happy with the experience. I would recommend  
! they made the experience easy to cope with.

# Concordance Data: Experience

- Positive persuasive corpus.

... me. My recent experience gave me a very positive  
...ing the overall experience a little negative. The  
... for making this experience as easy as it could be.  
...are my positive experience of excellent care recei  
...ly say that our experience as a family of the care  
... A truly great experience! The LGI is a superb ho  
...: that the whole experience had been very positive.  
... .. Very good experience. Very welcoming departm

## Concordance Data: Negative Experience

Rank	Keyword	-Keyness	Frequency
22	experience	13.558	131

- Negative expressive corpus.

rembling at this experience and I have now  
n it. The whole experience is proving a ni  
e improved in my experience at this hospita  
d that the whole experience was a waste of  
rd. We know from experience that we can exp  
pinion--my whole experience can only be des  
a terrible birth experience which left me w  
Based on my own experience I cannot think  
based on my own experience. However, one

# Concordance Data: Negative Experience

Negative Persuasive corpus.

posted about my experience trying to book an  
weeks ago of my experience and still haven't  
have had a bad experience today in that I  
about the whole experience. After being ad  
patient. My experience in 2010 and since  
ach, this whole experience totally knocked  
yacerbated my experience. I can't speak fo  
ves Nurses, my experience was so traumatis  
e waits, in my experience some poor staff c

# Applying Supervised Machine Learning Methods

- Treats sentiment analysis as a text classification problem.
- Three machine learning methods were used:
  - ▶ Naive Bayes
  - ▶ Multinomial Naive Bayes
  - ▶ Support Vector Machines
- Various features were used:
  - ▶ Unigrams
  - ▶ Bigrams
  - ▶ Bigrams + Part of Speech information



# Validation of training models

- 10-fold cross-validation performed to check model accuracy:

Features	NB	Multinomial NB	SVM
Unigrams	<b>79.65</b>	<b>78.14</b>	<b>76.11</b>
Bigrams	57.79	60.84	63.36
Bigrams + POS	74.25	75.71	72.83

# Testing on Persuasive Section

- Testing produces the following accuracy results:

Features	NB	Multinomial NB	SVM
Unigrams	76.60	<b>83.39</b>	68.12
Bigrams	50.10	62.13	57.6
Bigrams + POS	66.73	70.42	64.00

# Shortcomings of Machine Learning Methods

- A statistical approach to language
- Does not observe nuances of a language
  - ▶ Negation is ignored.
  - ▶ Emphasis is ignored.
- Repetition often doesn't imply a particular sentiment.

# Discussion

- It would appear that training on a corpus whose discourse function differs to that of the training corpus still enables machine learning algorithms to create suitable models.
- Word frequency should be taken into account when training the models.
- Multinomial Naive Bayes is a machine learning technique well suited to this.

# Future Work

- Current Corpus: Experiment with other machine learning approaches and features.
- Annotate the larger dataset:  $\sim 10,000$  rows of data which could be used as the basis for further experimentation.
- Annotate the corpus with fine-grained emotions
- Investigate and present results from suicide note corpus.

# Summary

- Sentiment Analysis
- NHS Choices
- Creating the Expressive and Persuasive Corpus
- Analysing the Corpus
- Training and testing supervised machine learning methods