Extracting Sentiments about a Given Topic using Natural Language Processing Techniques

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Paper

Sentiment Analyzer: Extracting Sentiments about a Given Topic using Natural Language Processing Techniques

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Abstract

Many sentiment analysis algorithms classify an entire review as positive/negative.

Many reviews contain more information than just an overall score.

- A negative review could have positive elements in it about a particular feature.
- A positive review could have negative elements in it.
- The positive/negative elements could refer to something different altogether.

Authors use information extraction and sentiment analysis techniques to provide a summary of the sentiment of the topics in web reviews.

Problems Being Addressed

A huge amount of information is available in web pages, newsgroup postings, and online databases.

- Often useful to understand the sentiment behind the article.
  - Company/product reputations
  - Stock market rise/fall

Companies can benefit by understand specific pain points

- If the motor is good, but the tires are bad
- Battery-life is good but size is bad

Sentiment Analyzer (SA)

Extracts topic-specific features

Extracts sentiment of each sentiment-bearing phrase

Makes (topic|feature, sentiment) association

Feature Extraction

- **Topic part-of relationship**
  - Lenses, battery or memory card
- **Topic attribute-of relationship**
  - Size or price
- **Feature attribute-of relationship**
  - Battery life

Example

Review for NR70

- As with every Sony PDA before it, the NR70 series is equipped with Sony's own Memory Stick expansion.
- Unlike the more recent T series CLIEs, the NR70 does not require an add-on adapter for MP3 playback, which is certainly a welcome change.
- The Memory Stick support in the NR70 series is well implemented and functional, although there is still a lack of non-memory Memory Sticks for consumer consumption.

Overall, positive or negative?

Result

Sentence	Topic	Result
1	Sony PDA	Positive
1	NR70	Positive
2	T Series CLIEs	Negative
2	NR70	Positive
3	NR70	Positive
3	NR70	Negative

Candidate Feature Term Selection

Extracting the noun phrases

Base Noun Phrases

- NN, NN NN, JJ NN, NN NN NN, JJ NN NN, JJ JJ NN

Definite Base Noun Phrases

- Same as BNP, but preceded by the word "the"

Beginning Definite Noun Phrases

- Same as dBNP but at the start of a sentence and followed by verb phrase

Feature Selection Algorithms

Mixture Model

- Query model (general web language)
- Corpus language model (topic)
- alpha/beta – background noise
- Fi - # of times word(i) appears

$$\theta_{T_i} = \begin{cases} \frac{f_i}{\lambda} - \frac{\alpha}{\beta}\theta_{W_i} & \text{if } 1 \leq i \leq t \\ 0 & \text{otherwise} \end{cases}$$

$$\lambda = \frac{\sum_{i=1}^{t} f_i}{1 + \frac{\alpha}{\beta}\sum_{i=1}^{t} \theta_{W_i}}$$

Likelihood Test

- D+ and D- documents
- L(p1,p2) is the likelihood of seeing bnp in both D+ and D-
- Compute for each bnp, take largest likelihood ratio

$$-2log\lambda = -2log\frac{\max_{p_1 \leq p_2} L(p_1,p_2)}{\max_{p_1,p_2} L(p_1,p_2)}$$

$$p_1 = p(d \in D_+ | bnp \in d)$$

$$p_2 = p(d \in D_+ | \overline{bnp} \in d)$$

Evaluation

Group bBNP-L was highest:

	$\|D_+\|$	$\|D_-\|$	source
digital camera	485	1838	www.cnet.com www.dpreview.com www.epinions.com, www.steves-digicams.com
music	250	2389	www.epinions.com

Table 2. The product review datasets

	digital camera (38)	music (31)
BNP-M	63%	61%
dBNP-M	68%	32%
bBNP-M	32%	29%
BNP-L	68%	92%
dBNP-L	81%	96%
bBNP-L	**97%**	**100%**

Table 3. Precision of feature term extraction algorithms

Sentiment Analysis

Sentiment Lexicon

- “excellent” JJ +

<lexical_entry> <POS> <sent_category>

- `lexical_entry` is a (possibly multi-word) term that has sentimental connotation.
- `POS` is the required POS tag of `lexical entry`.
- `sentiment_category`: + | -

Sentiment Analysis

Sentiment Pattern Database

- Predictate – verb
- Sent_category - +-~ source
  - SP|OP|CP|PP
  - Subject, object, complement, prepositional phrase
- Target SP|OP|PP (target of sentiment)
- Examples
  - Impress + PP(by;with)
    - I am impressed by the picture quality.
  - Be CP SP
    - The colors are vibrant
  - Offer OP SP
    - IBM offers high quality products

```
<predicate> <sent_category> <target>
```

Scope of Sentiment Analysis, Preprocessing

- positive or negative sentiment verbs:
  <target, verb, "">
- trans verbs:
  <target, verb, source>

<the camera, like, "">
 ex. I like the camera.
<the digital zoom, be, too grainy>
 ex. The digital zoom is too grainy.

Sentiment Phrases and Sentiment Assignment

Identifies adjective phrases and subject, object and prepositional phrases

- The colors are vibrant
- Excellent pictures (JJ NN), JJ is positive. Counts for negation by reversing.

SA example:

```
I am impressed by the flash capabilities.
pattern : "impress" + PP(by;with)
subject : flash

<flash capability, impress, "">

(flash capability, +)
```

Evaluation

	Precision	Recall	Accuracy
SA	87%	56%	85.6%
Collocation	18%	70%	N/A
ReviewSeer	N/A	N/A	88.4%

Table 5. Performance comparison of sentiment extraction alorithms on the product review datasets.

	Precision	Accuracy	Acc. w/o *I class*
SA(Petroleum, Web)	86%	90%	N/A
SA(Pharmaceutical, Web)	91%	93%	N/A
SA(Petroleum, News)	88%	91%	N/A
ReviewSeer (Web)	N/A	38%	68%

Table 6. The performance of *SA* and *ReviewSeer* on general web documents and news articles.

Main Things Learned

Algorithm was effective on non-domain specific articles

- Web and news
- Music
- Players

New approach that did not have a comparable baseline (ReviewSeer), innovative.

Critique

Baseline of ReviewSeer had to use a different data set than SA. Not direct comparison.

Seems like two research papers in one, information extraction and sentiment analysis.