

# Sentiment Analysis: An overview from Linguistics

## Problems

### 2.1 Which words and phrases

	Subjectivity dictionary	SO-CAL	SentWordNet	Macquarie dictionary
good	Positive (weak)	3	Positive	Positive
excellent	Positive (strong)	5	Positive	Positive
masterpiece	Positive (strong)	5	Positive	Positive
bad	Negative (strong)	-3	Negative	Negative
terrible	Negative (strong)	-5	Negative	Negative
disaster	Negative (strong)	-4	Negative	Negative

2.1.4. Other dictionaries have a more fine-grained scale. The dictionary in our system, the Semantic Orientation Calculator (SO-CAL) has a 10-point scale, from -5 to +5, which has been shown to be consistent with the judgements of human subjects (Taboada et al 2011).

2.1.5. If the presence of a negative word is more indicative of a negative review, then negative words should maybe carry more weight in the final aggregation.

2.2.1The general term intensifier is used for devices that change the intensity of an individual word, whether by bringing it up or down.

2.2.2Within the context of downtoning are typically discussed a host of phenomena that indicate that individual words and phrases may not be reliable for the purposes of sentiment analysis.

2.2.3 A general consensus in sentiment analysis is that nonveridicality and irrealis result in the unreliability of any expression of sentiment in the sentences containing it ( Benamara et al 2012, Denis et al 2014, Morante & Sporleder 2012, Taboada et al 2011, Wilson et al 2009), but not enough research has explored exactly how evaluation is affected.

### 2.2 Intensification and downtoning; irrealis and nonveridicality

As with the asymmetry in frequency between positive and negative terms, it turns out that negation in general shows interesting asymmetries, with important consequences for sentiment analysis.

### 2.3 Negation

Assuming that negation and its scope have been adequately identified, the next problem is to decide how negation affects dictionary values for sentiment words. A straightforward strategy is to reverse the polarity of the lexical item in the scope of a negative item.

### 2.4 Sentence and clause patterns

Evaluation and subjectivity are not only expressed by individual words and phrases, but often conveyed through entire sentences, and particular patterns in sentences.

### 2.5 Relevant sentences

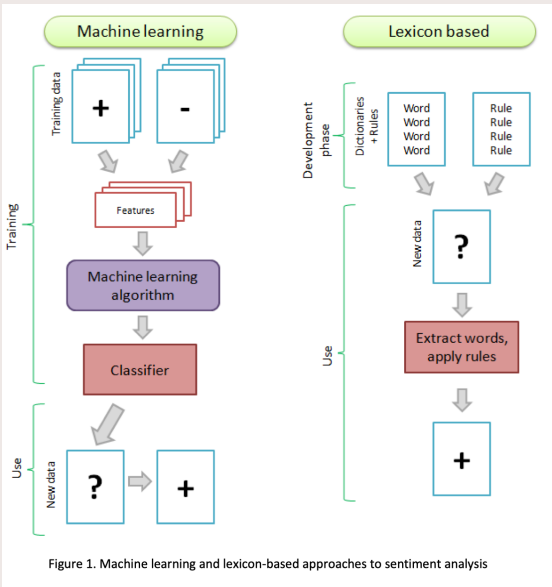
It is obvious that not all parts of a text contribute equally to the possible overall opinion expressed therein.

### 2.6 Discourse patterns

Once we have extracted words and phrases from a text, with or without having used a pruning method for sentences, the next step is to aggregate the semantic orientation, or evaluative value, of those individual words.

## 1. Sentiment, subjectivity, opinion, appraisal, affect, emotion

In this paper, I briefly summarize the different approaches to extracting sentiment and opinion automatically, and present the state of the art. In particular, I will discuss the aspects of sentiment analysis most relevant to linguistics, and where interaction would be beneficial.



## 2. The ‘analysis’ part: Computational methods

### machine learning

In the machine learning approach, a classifier is built that can determine the polarity of new texts. The classifier is built thanks to labelled instances of other items (sentences, documents, etc.).

### lexicon-based

These are often also referred to as rule-based, because the dictionaries are applied following certain rules. On this approach, sentiment values of text are derived from the sentiment orientation of the individual words in the text, and using an existing dictionary.

## 3. A small sample of interesting projects in sentiment analysis

Tumasjan et al (2010) exploit the potential of tweets about political parties to determine how well tweets align with the parties’ stated values.

Most interesting is their finding that the volume of messages may be a good indicator of election results, although this has been criticized as an artifact of the data collection (Jungheer et al 2012).

New work is being produced in this area, and current approaches make use not only of the text, but of characteristics of the author, and their online interactions (Qiu et al 2015).

As with other forms of social media, researchers have found that sarcasm poses a particularly difficult problem (Bakliwal et al 2013).

One interesting recent study by Stewart (2015) analyzes students’ written comments in course evaluations, from a quantitative point of view, and using the Appraisal framework (Martin & White 2005).

Of an even more sensitive nature are the suicide notes that Pestian et al ( 2012) made available as part of a shared task. One important outcome of such analysis is determining who among those who attempt suicide are likely to try again.

Both Borth et al (2013) and Wang et al (2015) use a combination of characteristics of images posted online and text (comments and tags) about the image, to identify the sentiment conveyed by images.

The practice has led to court cases and settlements, with companies being found guilty of paying for positive reviews, or of writing them themselves ( Streitfeld 2013).

TripAdvisor was recently fined €500,000 for failing to prevent fake reviews on their site (Scott 2013).

Fake review detection employs many features that prove very useful for the task, but are linguistically not so interesting, such as user IDs, user activity, URLs, and temporal patterns (Li et al 2014).

Some of the research, however, relies on the same principles that are deployed in authorship attribution: genre identification through part of speech distribution, similarity of linguistic patterns, and style characteristics of the text (Feng et al 2012, Ott et al 2011).