Natural Language Processing

Sentiment Analysis

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What is Sentiment Analysis?

Positive or negative movie review?







 Full of zany characters and richly applied satire, and some great plot twists

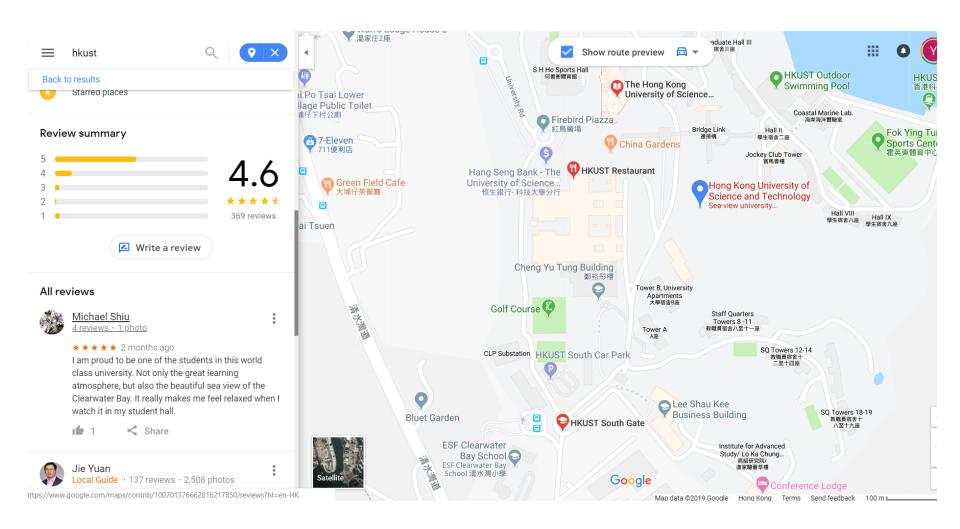


this is the greatest screwball comedy ever filmed



 It was pathetic. The worst part about it was the boxing scenes.

Google Map



Amazon

Apple iPhone 7 (32GB) - Black - [Locked to Simple Mobile Prepaid]

31 customer reviews



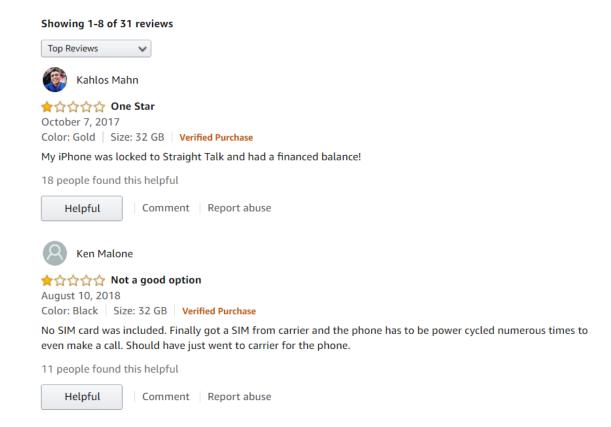
By feature

Durability	★★★★★ 5.0
Battery life	★★★★☆ 4.3
Material quality	★★★☆☆ 4.0

Review this product

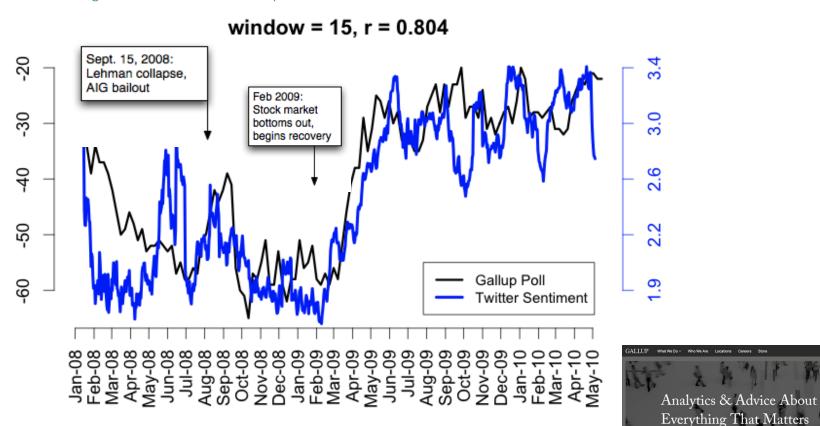
Share your thoughts with other customers

Write a customer review



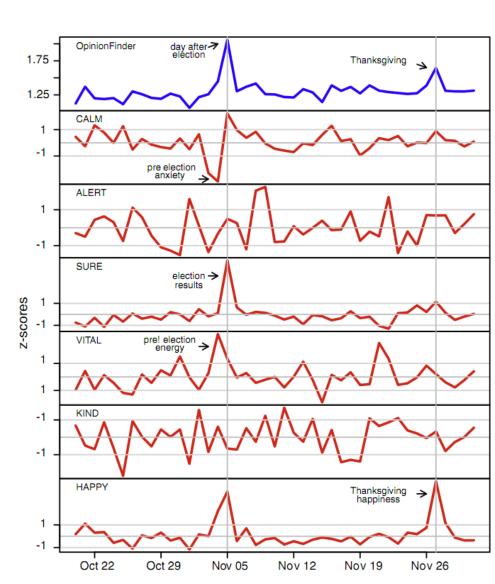
Twitter sentiment versus Gallup Poll of Consumer Confidence

Brendan O'Connor, Ramnath Balasubramanyan, Bryan R. Routledge, and Noah A. Smith. 2010. From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series. In ICWSM-2010



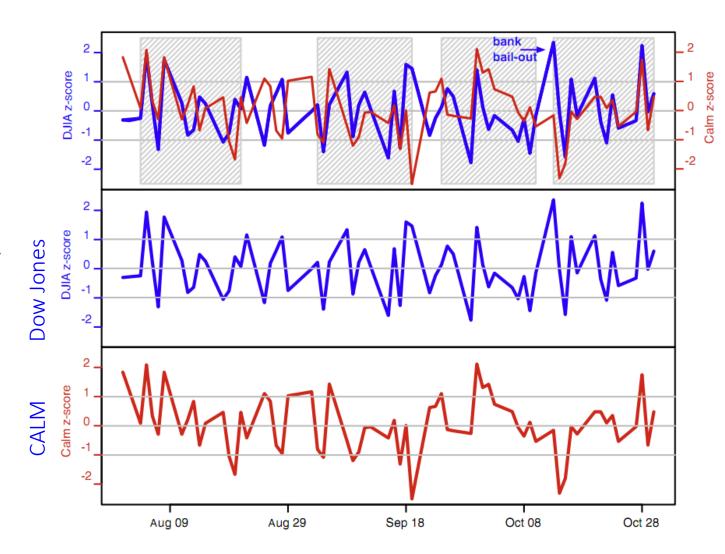
Twitter sentiment:

Johan Bollen, Huina Mao, Xiaojun Zeng. 2011. Twitter mood predicts the stock market, Journal of Computational Science 2:1, 1-8. 10.1016/j.jocs.2010.12.007.



Bollen et al. (2011)

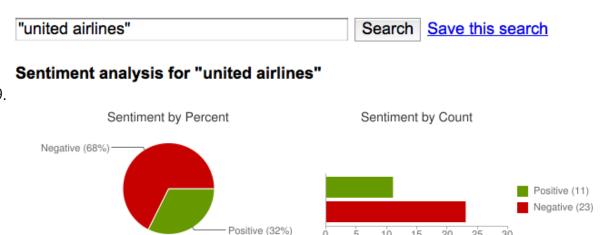
- CALM predicts
 DJIA 3 days later
- At least one current hedge fund uses this algorithm



Target Sentiment on Twitter

Type in a word and we'll highlight the good and the bad

- Twitter SentimentApp
- Alec Go, Richa Bhayani, Lei Huang. 2009.
 Twitter Sentiment Classification using Distant Supervision



<u>iljacobson</u>: OMG... Could @**United airlines** have worse customer service? W8g now 15 minutes on hold 4 questions about a flight 2DAY that need a human.

12345clumsy6789: I hate **United Airlines** Ceiling!!! Fukn impossible to get my conduit in this damn mess! ?

EMLandPRGbelgiu: EML/PRG fly with Q8 united airlines and 24seven to an exotic destination. http://t.co/Z9QloAjF
Posted 2 hours ago

CountAdam: FANTASTIC customer service from **United Airlines** at XNA today. Is tweet more, but cell phones off now! Posted 4 hours ago

Sentiment analysis has many other names

- Opinion extraction
- Opinion mining
- Sentiment mining
- Subjectivity analysis

Why sentiment analysis?

- *Movie*: is this review positive or negative?
- Products: what do people think about the new iPhone?
- Public sentiment: how is consumer confidence?
- Politics: what do people think about this candidate or issue?
- Prediction: predict election outcomes or market trends from sentiment

Scherer Typology of Affective States

- **Emotion**: brief organically synchronized ... evaluation of a major event
 - angry, sad, joyful, fearful, ashamed, proud, elated
- Mood: diffuse non-caused low-intensity long-duration change in subjective feeling
 - cheerful, gloomy, irritable, listless, depressed, buoyant
- Interpersonal stances: affective stance toward another person in a specific interaction
 - friendly, flirtatious, distant, cold, warm, supportive, contemptuous
- Attitudes: enduring, affectively colored beliefs, dispositions towards objects or persons
 - liking, loving, hating, valuing, desiring
- Personality traits: stable personality dispositions and typical behavior tendencies
 - nervous, anxious, reckless, morose, hostile, jealous

Sentiment analysis is the detection of attitudes

"enduring, affectively colored beliefs, dispositions towards objects or persons"

- 1. Holder (source) of attitude
- 2. Target (aspect) of attitude
- 3. Type of attitude
 - From a set of types
 - Like, love, hate, value, desire, etc.
 - Or (more commonly) simple weighted **polarity**:
 - positive, negative, neutral, together with strength
- **4. Text** containing the attitude
 - Sentence or entire document

2

"The paper is like a rubbish. It's written very badly!"

- 1. What is the sentiment of the sentence?
- 2. What would be the sentiment of the holder (source) of attitude?
- 3. What would be the sentiment of the target (aspect) of attitude?
- 4. What would be the emotion of the listener of the sentence?

Here's the analysis of your questions:

1. What is the sentiment of the sentence?

The sentiment of the sentence "The paper is like a rubbish. It's written very badly!" is negative. The terms "rubbish" and "written very badly" convey strong criticism and dissatisfaction.

2. What would be the sentiment of the holder (source) of attitude?

The holder (source) of the attitude is the speaker or writer expressing this view. Their sentiment is negative, as they are the ones voicing disapproval and a critical opinion about the paper.

3. What would be the sentiment of the target (aspect) of attitude?

The target (aspect) of the attitude is "the paper," the object being judged. The sentiment directed toward the target is negative, as the sentence explicitly denigrates its quality. (Note: The target itself doesn't have sentiment; this refers to the sentiment *about* it from the holder's perspective.)

4. What would be the emotion of the listener of the sentence?

The emotion of the listener depends on their context and relationship to the paper, which isn't provided. Possible emotions include:

- Neutral listener (unrelated to the paper): They might feel indifference, mild surprise, or curiosity.
- Author of the paper: They could feel hurt, defensive, or angry due to the harsh critique.
- Someone who agrees with the speaker: They might feel amusement, satisfaction, or vindication.

Without specific context, the listener's emotion is speculative, but the negative tone might generally provoke unease or empathy in someone hearing it.

- Simplest task:
 - Is the attitude of this text positive or negative?
- More complex:
 - Rank the attitude of this text from 1 to 5
- Advanced:
 - Detect the target, source, or complex attitude types

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A Baseline Algorithm

Sentiment Classification in Movie Reviews

- Polarity detection:
 - Is an IMDB movie review positive or negative?
- Data: Polarity Data 2.0:
 - http://www.cs.cornell.edu/people/pabo/movie-reviewdata

Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79—86.
Bo Pang and Lillian Lee. 2004. A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts. ACL, 271-278

IMDB data in the Pang and Lee database



when _star wars_ came out some twenty years ago , the image of traveling throughout the stars has become a commonplace image . [...]

when han solo goes light speed, the stars change to bright lines, going towards the viewer in lines that converge at an invisible point.

cool.

october sky offers a much simpler image—that of a single white dot, traveling horizontally across the night sky. [...]



"snake eyes" is the most aggravating kind of movie: the kind that shows so much potential then becomes unbelievably disappointing.

it's not just because this is a brian depalma film, and since he's a great director and one who's films are always greeted with at least some fanfare.

and it's not even because this was a film starring nicolas cage and since he gives a brauvara performance, this film is hardly worth his talents.

Baseline Algorithm (adapted from Pang and Lee)

- Tokenization: Split document into words (tokens)
- Feature Extraction: Find useful features
- Classification using different classifiers
 - Naïve Bayes
 - Logistic Regression
 - Support Vector Machine

Sentiment Tokenization Issues

- Deal with HTML and XML markup
- Twitter mark-up (names, hash tags)
- Capitalization (preserve for

words in all caps)

- Phone numbers, dates
- Emoticons
- Useful code:

Potts emoticons

```
# optional hat/brow
[<>]?
[:;=8]
                             # eyes
[\-0\*\']?
                              # optional nose
[\)\]\(\[dDpP/\:\}\{@\|\\]
                              # mouth
                             #### reverse orientation
[\)\]\(\[dDpP/\:\}\{@\|\\]
                             # mouth
                             # optional nose
[\-0\*\']?
[:;=8]
                             # eyes
                             # optional hat/brow
[<>]?
```

- Christopher Potts sentiment tokenizer
- Brendan O'Connor twitter tokenizer
- http://www.ark.cs.cmu.edu/TweetNLP

Extracting Features for Sentiment Classification

- How to handle negation
 - I didn't like this movie
 vs
 - I really like this movie
- Which words to use?
 - Only adjectives
 - All words
 - All words turns out to work better, at least on this data

Negation

Das, Sanjiv and Mike Chen. 2001. Yahoo! for Amazon: Extracting market sentiment from stock message boards. In Proceedings of the Asia Pacific Finance Association Annual Conference (APFA). Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79—86.

Add NOT_ to every word between negation and following punctuation:

didn't like this movie , but I



didn't NOT like NOT this NOT movie but I

Binarized (Boolean feature)

Intuition:

- For sentiment (and probably for other text classification domains)
- Word occurrence may matter more than word frequency
 - The occurrence of the word *fantastic* tells us a lot
 - The fact that it occurs 5 times may not tell us much more.
- Boolean Multinomial Naïve Bayes
 - Clips all the word counts in each document at 1

Problems:

Thwarted Expectations and Ordering Effects

- "This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it can't hold up."
- Well as usual Keanu Reeves is nothing special, but surprisingly, the very talented Laurence Fishbourne is not so good either, I was surprised.

- Sentiment Lexicons
 - Expert annotation
 - Data mining
 - Machine learning

The General Inquirer

Philip J. Stone, Dexter C Dunphy, Marshall S. Smith, Daniel M. Ogilvie. 1966. The General Inquirer: A Computer Approach to Content Analysis. MIT Press

- Home page: http://www.wjh.harvard.edu/~inquirer
- List of Categories:
 http://www.wjh.harvard.edu/~inquirer/homecat.htm
- Spreadsheet: http://www.wjh.harvard.edu/~inquirer/inquirerbasic.xls
- Categories:
 - Positiv (1915 words) and Negativ (2291 words)
 - Strong vs Weak, Active vs Passive, Overstated versus Understated
 - Pleasure, Pain, Virtue, Vice, Motivation, Cognitive Orientation, etc.
- Free for Research Use

LIWC (Linguistic Inquiry and Word Count)

Pennebaker, J.W., Booth, R.J., & Francis, M.E. (2007). Linguistic Inquiry and Word Count: LIWC 2007. Austin, TX

- Home page: http://www.liwc.net/
- 2300 words, >70 classes
- Affective Processes
 - negative emotion (bad, weird, hate, problem, tough)
 - positive emotion (love, nice, sweet)
- Cognitive Processes
 - Tentative (maybe, perhaps, guess), Inhibition (block, constraint)
- Pronouns, Negation (no, never), Quantifiers (few, many)
- \$30 or \$90 fee

MPQA Subjectivity Cues Lexicon

Theresa Wilson, Janyce Wiebe, and Paul Hoffmann (2005). Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis. Proc. of HLT-EMNLP-2005.

Riloff and Wiebe (2003). Learning extraction patterns for subjective expressions. EMNLP-2003.

- Home page:
 - http://www.cs.pitt.edu/mpga/subj lexicon.html
- 6885 words from 8221 lemmas
 - 2718 positive
 - 4912 negative
- Each word annotated for intensity (strong, weak)
- GNU GPL

Bing Liu Opinion Lexicon

Minqing Hu and Bing Liu. Mining and Summarizing Customer Reviews. ACM SIGKDD-2004.

- Bing Liu's Page on Opinion Mining
- http://www.cs.uic.edu/~liub/FBS/opinion-lexicon-English.rar

- 6786 words
 - 2006 positive
 - 4783 negative

SentiWordNet

Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani. 2010 SENTIWORDNET 3.0: An Enhanced Lexical Resource for Sentiment Analysis and Opinion Mining. LREC-2010

- Home page: http://sentiwordnet.isti.cnr.it/
- All WordNet synsets automatically annotated for degrees of positivity, negativity, and neutrality/objectiveness
- [estimable(J,3)] "may be computed or estimated"

Pos 0 Neg 0 Obj 1

[estimable(J,1)] "deserving of respect or high regard"

Pos .75 Neg 0 Obj .25

Disagreements between polarity lexicons

Christopher Potts, Sentiment Tutorial, 2011

	Opinion Lexicon	General Inquirer	SentiWordNet	LIWC
MPQA	33/5402 (0.6%)	49/2867 (2%)	1127/4214 (27%)	12/363 (3%)
Opinion Lexicon		32/2411 (1%)	1004/3994 (25%)	9/403 (2%)
General Inquirer			520/2306 (23%)	1/204 (0.5%)
SentiWordNet				174/694 (25%)
LIWC				

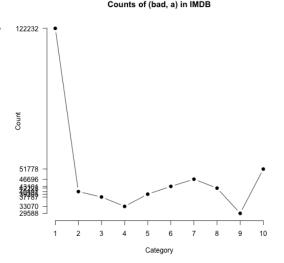
Disagreed words/Overlapped words

- Sentiment Lexicons
 - Expert annotation
 - Data mining
 - Machine learning

Analyzing the polarity of each word in IMDB

Potts, Christopher. 2011. On the negativity of negation. SALT 20, 636-659.

- How likely is each word to appear in each sentiment class?
- Count("bad") in 1-star, 2-star, 3-star, etc. 12232]
- But can't use raw counts:
- Instead, likelihood: $P(w|c) = \frac{f(w,c)}{\mathring{a}_{wl} f(w,c)}$

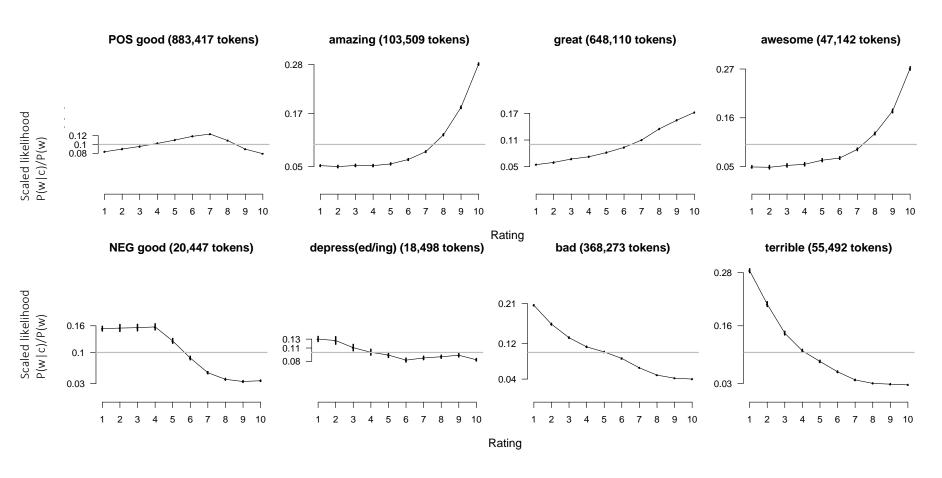


- Make them comparable between words
 - Scaled likelihood:

$$\frac{P(w \mid c)}{P(w)}$$

Analyzing the polarity of each word in IMDB

Potts, Christopher. 2011. On the negativity of negation. SALT 20, 636-659.



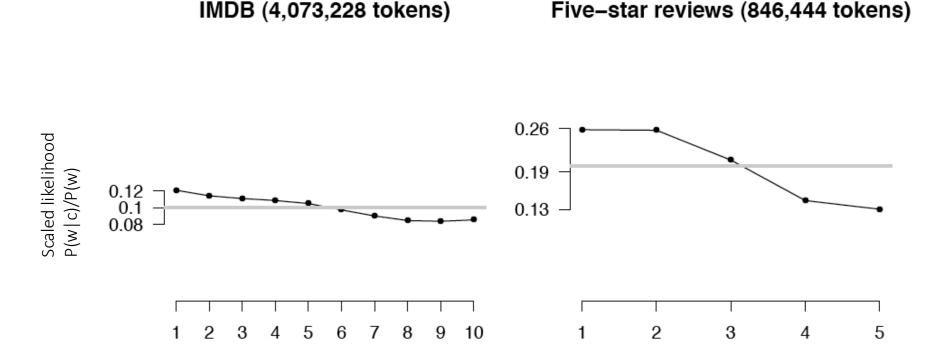
POS good plots involve good outside the scope of negation, and the NEG good plots involve good in the scope of a negative morpheme (not, n't, never, and forms of no)

Other sentiment feature: Logical negation

Potts, Christopher. 2011. On the negativity of negation. SALT 20, 636-659.

- Is logical negation (no, not) associated with negative sentiment?
- Potts experiment:
 - Count negation (not, n't, no, never) in online reviews
 - Regress against the review rating

Potts 2011 Results: More negation in negative sentiment



Sentiment Analysis

- Sentiment Lexicons
 - Expert annotation
 - Data mining
 - Machine learning

Semi-supervised learning of lexicons

- Use a small amount of information
 - A few labeled examples
 - A few hand-built patterns
- To bootstrap a lexicon

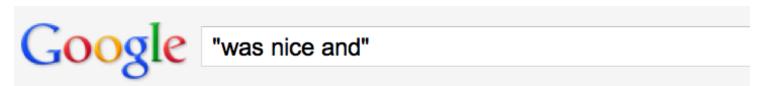
Hatzivassiloglou and McKeown intuition for identifying word polarity

Vasileios Hatzivassiloglou and Kathleen R. McKeown. 1997. Predicting the Semantic Orientation of Adjectives. ACL, 174–181

- Adjectives conjoined by "and" have same polarity
 - Fair and legitimate, corrupt and brutal
 - *fair and brutal, *corrupt and legitimate
- Adjectives conjoined by "but" do not
 - fair but brutal

- Label seed set of 1336 adjectives (all >20 in 21 million word WSJ corpus)
 - 657 positive
 - adequate central clever famous intelligent remarkable reputed sensitive slender thriving...
 - 679 negative
 - contagious drunken ignorant lanky listless primitive strident troublesome unresolved unsuspecting...

Expand seed set to conjoined adjectives



Nice location in Porto and the front desk staff was nice and helpful... www.tripadvisor.com/ShowUserReviews-g189180-d206904-r12068...

Mercure Porto Centro: Nice location in Porto and the front desk staff was nice and helpful - See traveler reviews, 77 candid photos, and great deals for Porto, ...

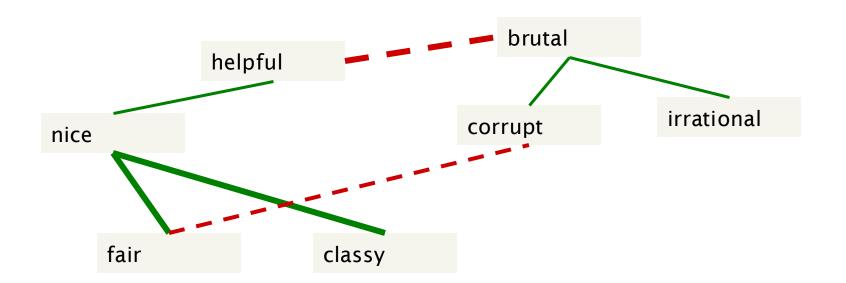
nice, helpful

If a girl was nice and classy, but had some vibrant purple dye in ... answers.yahoo.com > Home > All Categories > Beauty & Style > Hair 4 answers - Sep 21

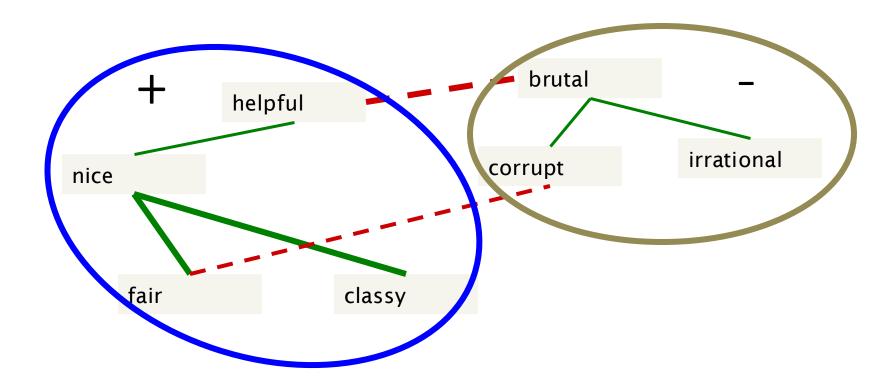
nice, classy

Question: Your personal opinion or what you think other people's opinions might ... Top answer: I think she would be cool and confident like katy perry:)

 Supervised classifier assigns "polarity similarity" to each word pair, resulting in graph:



Clustering for partitioning the graph into two



Output polarity lexicon

Positive

 bold decisive disturbing generous good honest important large mature patient peaceful positive proud sound stimulating straightforward strange talented vigorous witty...

Negative

 ambiguous cautious cynical evasive harmful hypocritical inefficient insecure irrational irresponsible minor outspoken pleasant reckless risky selfish tedious unsupported vulnerable wasteful...

Output polarity lexicon

Positive

 bold decisive disturbing generous good honest important large mature patient peaceful positive proud sound stimulating straightforward strange talented vigorous witty...

Negative

 ambiguous cautious cynical evasive harmful hypocritical inefficient insecure irrational irresponsible minor outspoken pleasant reckless risky selfish tedious unsupported vulnerable wasteful...

Sentiment Analysis

Other Sentiment Tasks

Finding sentiment of a sentence

- Important for finding aspects or attributes
 - Target of sentiment
- The food was great but the service was awful

Finding aspect/attribute/target of sentiment

M. Hu and B. Liu. 2004. Mining and summarizing customer reviews. In Proceedings of KDD. S. Blair-Goldensohn, K. Hannan, R. McDonald, T. Neylon, G. Reis, and J. Reynar. 2008. Building a Sentiment Summarizer for Local Service Reviews. WWW Workshop.

Frequent phrases + rules

Find all highly frequent phrases across reviews ("fish tacos")

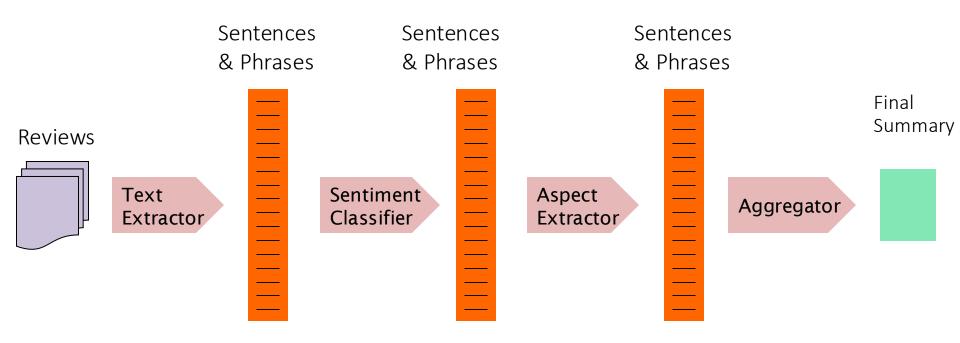
Casino	casino, buffet, pool, resort, beds
Children's Barber	haircut, job, experience, kids
Greek Restaurant	food, wine, service, appetizer, lamb
Department Store	selection, department, sales, shop, clothing

Finding aspect/attribute/target of sentiment

- The aspect name may not be in the sentence
- For restaurants/hotels, aspects are well-understood
- Supervised classification
 - Hand-label a small corpus of restaurant review sentences with aspect
 - food, service, value, NONE
 - Train a classifier to assign an aspect to a sentence
 - "Given this sentence, is the aspect food, décor, service, value, or NONE"

Putting it all together: Finding sentiment for aspects

S. Blair-Goldensohn, K. Hannan, R. McDonald, T. Neylon, G. Reis, and J. Reynar. 2008. Building a Sentiment Summarizer for Local Service Reviews. WWW Workshop



Results of Blair-Goldensohn et al. method

Rooms (3/5 stars, 41 comments)

- (+) The room was clean and everything worked fine even the water pressure ...
- (+) We went because of the free room and was pleasantly pleased ...
- (-) ...the worst hotel I had ever stayed at ...

Service (3/5 stars, 31 comments)

- (+) Upon checking out another couple was checking early due to a problem ...
- (+) Every single hotel staff member treated us great and answered every ...
- (-) The food is cold and the service gives new meaning to SLOW.

Dining (3/5 stars, 18 comments)

- (+) our favorite place to stay in biloxi.the food is great also the service ...
- (+) Offer of free buffet for joining the Play

What would be the LLM solution to this global statistics?

Summary on Sentiment

- Generally modeled as classification or regression task
 - predict a binary or ordinal label
- Features:
 - Negation is important
 - Using all words (in naïve bayes) works well for some tasks
 - Finding subsets of words may help in other tasks
 - Hand-built polarity lexicons
 - Use seeds and semi-supervised learning to induce lexicons