

# Sentiment Analysis

MIE223  
Winter 2025

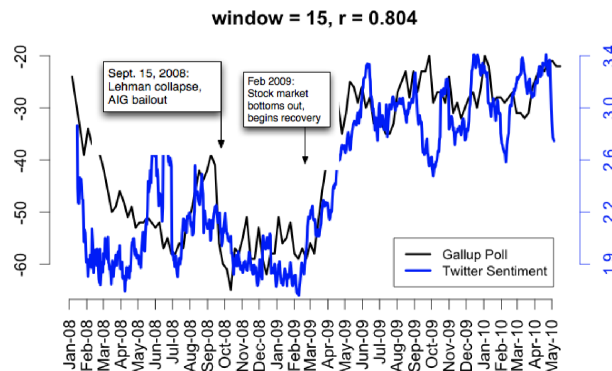
## 1 Sentiment Analysis

### 1.1 Positive or negative movie review?

- unbelievably disappointing
- 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.

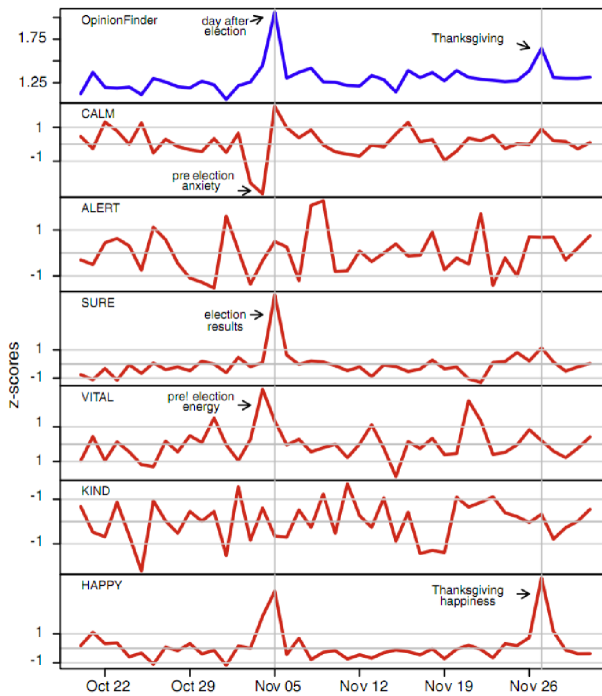
How do we find the sentiment of a review? you can automatically extract common tokens and phrases from the reviews and use them to determine the sentiment of the review. We use phrase chunking to get key phrases. use entailment to determine if a sentence is relevant to a specific key phrase. determine whether phrase is positive or negative called polarity analysis.

### 1.2 Twitter sentiment versus Gallup Poll of Consumer Confidence

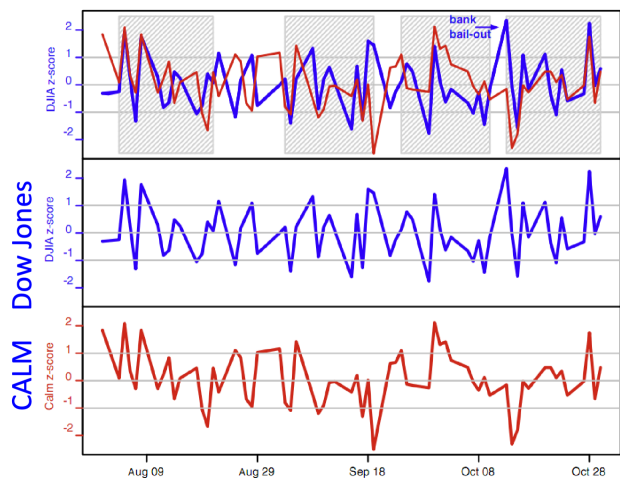


- gallup poll can be used to survey public opinion
- twitter sentiment can be used to predict public opinion

### 1.3 Twitter sentiment:



- CALM predicts DJIA 3 days later, Twitter predicts the stock market shifts 2-6 days later
- At least one current hedge fund uses this algorithm



- an efficient market makes use of information
- twitter sentiment can be used to predict stock prices
- the results are terrible
- ideas are good, nuanced emotions can influence the stock market
- different events give rise to different emotions which can be measured

## 1.4 Beware: Spurious Correlations

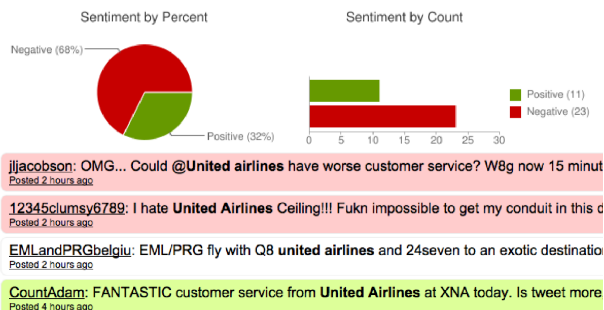
- data matching correlations are similar but not true

## 1.5 Target Sentiment on Twitter

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

"united airlines"  [Save this search](#)

Sentiment analysis for "united airlines"



## 1.6 Sentiment analysis has many other names

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

## 1.7 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? Is despair increasing?
- Politics: what do people think about this candidate or issue?
- Prediction: predict election outcomes or market trends from sentiment

## 1.8 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

**Note 1.** Majority of review sentiment focuses on attitudes. Public mood predicts stock market.

## 1.9 Sentiment Analysis

- 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 like sentence or entire document
  5. Coreference resolution: who is talking about what?
    - 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

## 2 Text Processing and Sentiment Classifier Limitations

### 2.1 Sentiment Classification in Movie Reviews

- Polarity detection:
  - Is an IMDB movie review positive or negative?

## 2.2 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 . [ . . . ]

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“ 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 .

## 2.3 Sentiment Analysis and Prediction

- Sentiment-aware tokenization
  - Important if text analysis should be sensitive to sentiment
- Prediction using different classifiers / regressors
  - Could learn with Naïve Bayes, Logistic Regression, SVM
  - Vader is an off-the-shelf tool for predicting sentiment
  - Actually a regressor, predicts strength of polarity [-1,+1]
  - +1 = Most positive, -1 = Most negative, 0 = Neutral

## 2.4 Sentiment Tokenization Issues

Let’s consider tokenization text analysis should be sensitive to sentiment

- Capitalization
  - Preserve capital letters
  - Why?
- Emoticons (useful to express emotion)
- Useful code Regex

### Christopher Potts emoticons

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

## 2.5 Classification Results

- Trained classifier achieves 92.1% accuracy on movies
  - Off-the-shelf Vader would do well: around 80-85% accuracy
- Need to train a classifier per domain for best results
  - Scary movie = good!
  - Scary hotel = bad!
  - Hotel with “thin walls”?
- Vader would deem scary bad even though it may be good for movies

## 2.6 Classifiers don’t capture everything

Subtlety:

- Perfume review in Perfumes: the Guide:
  - “If you are reading this because it is your darling fragrance, please wear it at home exclusively, and tape the windows shut.”
  - not a good review but has positive adjectives
- Dorothy Parker on Katherine Hepburn
  - “She runs the gamut of emotions from A to B”
  - bad statement but no negative words
- Word interactions:
  - Raising taxes = bad
  - Raising salaries = good
  - Lowering taxes = good
  - Lowering salaries = bad
- A solution? Adjective\*Noun where... word interactions
  - Raising=+1, Lowering=-1, Taxes=-1, Salaries=+1
  - Also supports Adverb\*Adjective: very(+2) happy (+1), very (+2) sad (-1)

**Note 2.** the holder and target matter as well. here the opinion holder is assumed to be an individual, but how would this change if the opinion holder was a government or organization?

## 2.7 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

**Note 3.** many good things but one bad thing turns the entire thing negative

## 2.8 Sarcasm

- Josef Stalin might enjoy this movie.
- As exciting as watching the grass grow.
- This movie should win flop of the year.
- I wondered whether I had checked into the Bates Motel.

## 3 Sentiment Lexicons

### 3.1 Disagreements between polarity lexicons

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

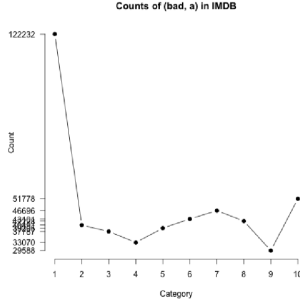
## 4 Automatic Polarity Analysis (with PMI)

### 4.1 Analyzing the polarity of each word in IMDB

- How likely is each word to appear in each sentiment class?
- Count(“bad”) in 1-star, 2-star, 3-star, etc.
- But can’t use raw counts:
- Instead, likelihood:
- Make them comparable between words
- Scaled likelihood:

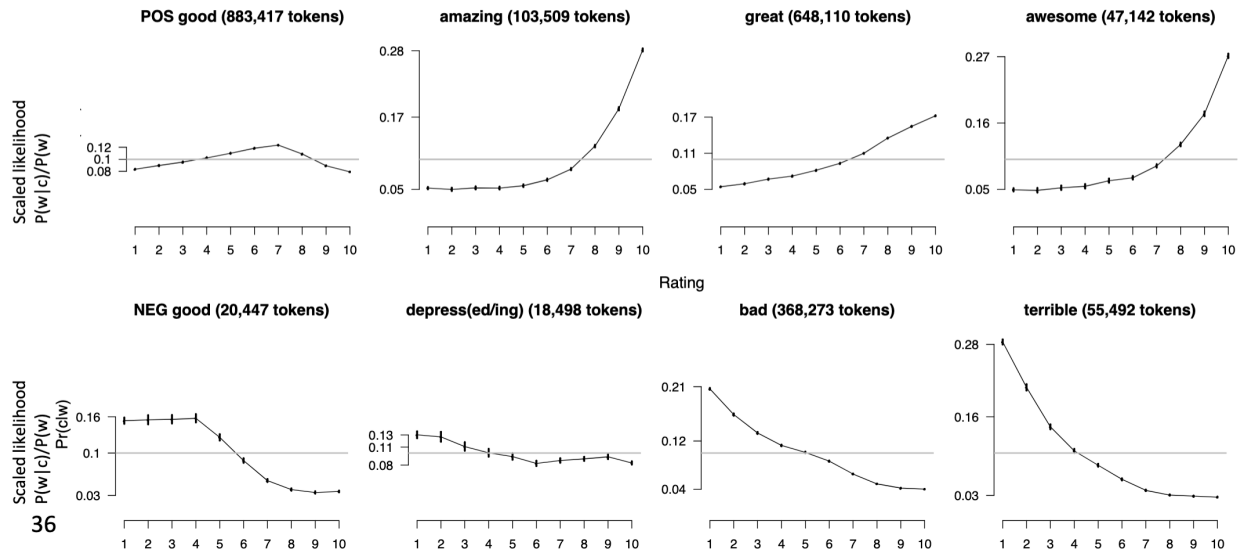
$$likelihood(P(w|c)) = \frac{f(w|c)}{\sum_{w \in c} f(w|c)} \quad (1)$$

$$\text{Scaled likelihood} = \frac{P(w|c)}{P(w)} \quad (2)$$



how often does "bad" show up when pertaining to ratings  
peak at 7 and 10 due to "its not bad" or sheer number of 7 and 10 ratings

## 4.2 Analyzing the polarity of each word in IMDB



## 4.3 Other sentiment feature: Logical negation

- 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



#### 4.4 Potts 2011 Results: More negation in negative sentiment

