Sentiment Analysis

What is Sentiment Analysis?

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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.

2

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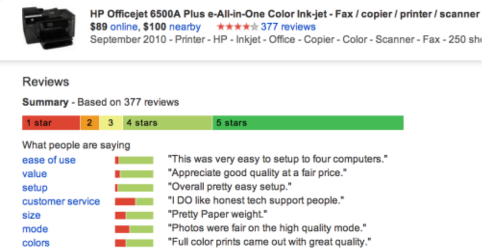
Google Product Search



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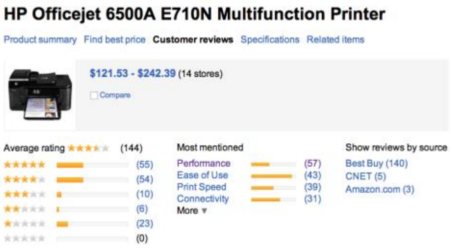
Bing Shopping



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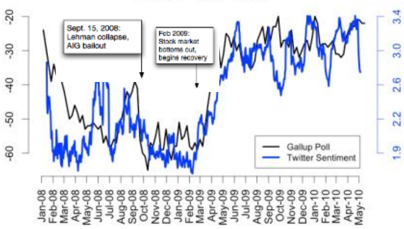
Twitter sentiment versus Gallup Poll of Consumer Confidence

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



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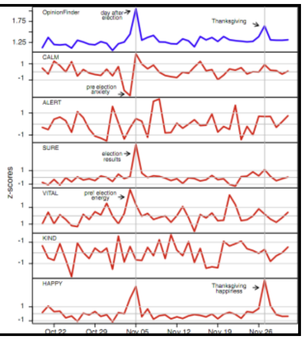
Twitter sentiment:

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.



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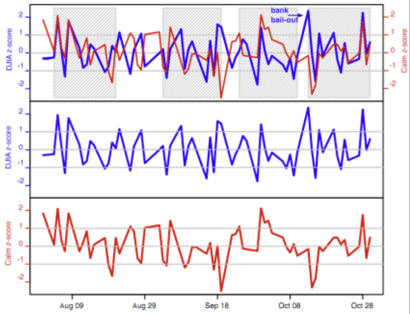
Bollen et al. (2011)

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



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Beware: Spurious Correlations

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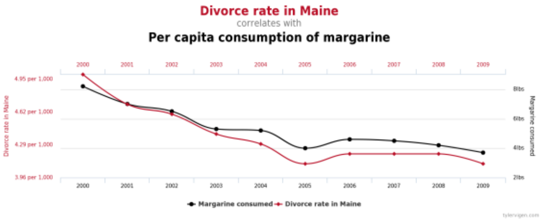
Beware: Spurious Correlations



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Target Sentiment on Twitter

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

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Sentiment analysis has many other names

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

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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

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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*

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Scherer Typology of Affective States

Recall that public mood said to predict stock market

- **Emotion**: brief organically synchronized … evaluation of a major event
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  - *friendly, flirtatious, distant, cold, warm, supportive, contemptuous*
- **Attitudes: enduring, affectively colored beliefs, dispositions towards objects or persons**
  - *liking, loving, hating, valuing, desiring* Majority of review sentiment focuses on this
- **Personality traits**: stable personality dispositions and typical behavior tendencies
  - *nervous, anxious, reckless, morose, hostile, jealous*

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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
     - Sentence or entire document

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Sentiment Analysis

- 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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Sentiment Analysis

- 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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Sentiment Analysis

A Baseline Algorithm

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Sentiment Classification in Movie Reviews

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

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

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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 .

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Baseline Algorithm (adapted from Pang and Lee)

- Tokenization
- Feature Extraction
- Classification using different classifiers
  - Naïve Bayes
  - MaxEnt
  - SVM

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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:
  - Christopher Potts sentiment tokenizer
  - Brendan O'Connor twitter tokenizer

Potts emoticons

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


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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

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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`

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Binarized (Boolean) features

- 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.

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Classification Results

- SVM Classifier achieves 92.1% accuracy on positive/negative!
- But need to train a classifier per domain
  - Scary movie = good!
  - Scary hotel = bad!
  - Hotel with "thin walls"?

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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."
  - Dorothy Parker on Katherine Hepburn
    - "She runs the gamut of emotions from A to B"

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Classifiers don't capture everything

- Word interactions:
  - Raising taxes = bad
  - Raising salaries = good
  - Lowering taxes = good
  - Lowering salaries = bad
- A solution? Adjective*Noun where…
  - Raising=+1, Lowering=-1, Taxes=-1, Salaries=+1
  - Also supports Adverb*Adjective: very(+2) happy (+1), very (+2) sad (-1)

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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.

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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.

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Sentiment Analysis

Sentiment Lexicons

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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

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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

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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/mpqa/subj_lexicon.html
- 6885 words from 8221 lemmas
  - 2718 positive
  - 4912 negative
- Each word annotated for intensity (strong, weak)
- GNU GPL

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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

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SentiWordNet (do not use!)

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`

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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				

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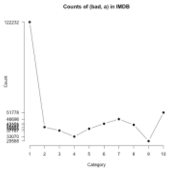
Analyzing the polarity of each word in IMDB

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.
- But can't use raw counts:
- Instead, **likelihood:** $P(w|c) = \frac{f(w,c)}{\sum_{w \in c} f(w,c)}$
- Make them comparable between words
  - **Scaled likelihood:** $\frac{P(w|c)}{P(w)}$

Actually what is this really?



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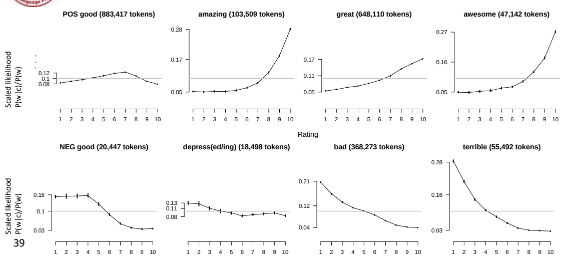
Analyzing the polarity of each word in IMDB

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



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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

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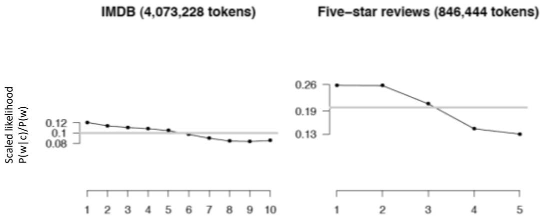
Potts 2011 Results: More negation in negative sentiment



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Sentiment Analysis

Sentiment Lexicons

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Sentiment Analysis

Learning Sentiment Lexicons

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

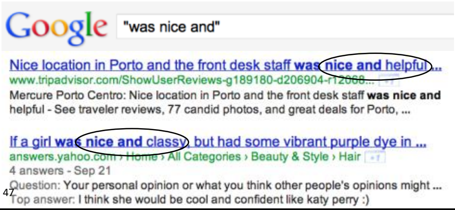
- Adjectives conjoined by "*and*" have same polarity
  - Fair **and** legitimate, corrupt **and** brutal
  - *fair **and** brutal, *corrupt **and** legitimate
- Adjectives conjoined by "*but*" do not
  - fair **but** brutal

Hatzivassiloglou & McKeown 1997 Step 1

- 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…

Hatzivassiloglou & McKeown 1997 Step 2

- Expand seed set to conjoined adjectives

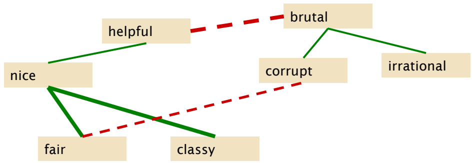


nice, helpful

nice, classy

Hatzivassiloglou & McKeown 1997 Step 3

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



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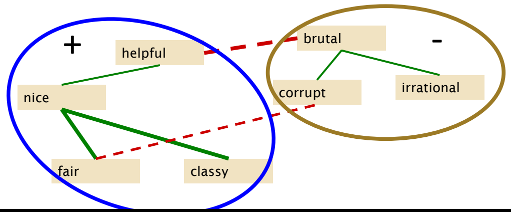
Hatzivassiloglou & McKeown 1997 Step 4

- Clustering for partitioning the graph into two



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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…

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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…

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Turney Algorithm

Turney (2002): Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews

1. Extract a *phrasal lexicon* from reviews
2. Learn polarity of each phrase
3. Rate a review by the average polarity of its phrases

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Extract two-word phrases with adjectives

First Word	Second Word	Third Word (not extracted)
JJ	NN or NNS	anything
RB, RBR, RBS	JJ	Not NN nor NNS
JJ	JJ	Not NN or NNS
NN or NNS	JJ	Nor NN nor NNS
RB, RBR, or RBS	VB, VBD, VBN, VBG	anything

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How to measure polarity of a phrase?

- Positive phrases co-occur more with *"excellent"*
- Negative phrases co-occur more with *"poor"*
- But how to measure co-occurrence?

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Pointwise Mutual Information

- **Mutual information** between 2 random variables X and Y

$$I(X,Y) = \sum_x \sum_y P(x,y)\log_2 \frac{P(x,y)}{P(x)P(y)}$$

- **Pointwise mutual information**:
  - How much more do events x and y co-occur than if they were independent?

$$\text{PMI}(X,Y) = \log_2 \frac{P(x,y)}{P(x)P(y)}$$

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Pointwise Mutual Information

- **Pointwise mutual information**:
  - How much more do events x and y co-occur than if they were independent?

$$\text{PMI}(X,Y) = \log_2 \frac{P(x,y)}{P(x)P(y)}$$

- **PMI between two words**:
  - How much more do two words co-occur than if they were independent?

$$\text{PMI}(word_1, word_2) = \log_2 \frac{P(word_1,word_2)}{P(word_1)P(word_2)}$$

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How to Estimate Pointwise Mutual Information

- Query search engine (Altavista)
  - P(word) estimated by `hits(word)/N`
  - P($word_1$,$word_2$) by `hits(word1 NEAR word2)/N`^{2}

$$\text{PMI}(word_1, word_2) = \log_2 \frac{hits(word_1 \text{ NEAR } word_2)}{hits(word_1)hits(word_2)}$$

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Does phrase appear more with “poor” or “excellent”?

$$\text{Polarity}(phrase) = \text{PMI}(phrase,\text{"excellent"}) - \text{PMI}(phrase,\text{"poor"})$$

$$= \log_2 \frac{\text{hits}(phrase \text{ NEAR "excellent"})}{\text{hits}(phrase)\text{hits}(\text{"excellent"})} - \log_2 \frac{\text{hits}(phrase \text{ NEAR "poor"})}{\text{hits}(phrase)\text{hits}(\text{"poor"})}$$

$$= \log_2 \frac{\text{hits}(phrase \text{ NEAR "excellent"})}{\text{hits}(phrase)\text{hits}(\text{"excellent"})} \frac{\text{hits}(phrase)\text{hits}(\text{"poor"})}{\text{hits}(phrase \text{ NEAR "poor"})}$$

$$= \log_2 \left(\frac{\text{hits}(phrase \text{ NEAR "excellent"})\text{hits}(\text{"poor"})}{\text{hits}(phrase \text{ NEAR "poor"})\text{hits}(\text{"excellent"})} \right)$$

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Phrases from a thumbs-up review

Phrase	POS tags	Polarity
online service	JJ NN	2.8
online experience	JJ NN	2.3
direct deposit	JJ NN	1.3
local branch	JJ NN	0.42
…		
low fees	JJ NNS	0.33
true service	JJ NN	-0.73
other bank	JJ NN	-0.85
inconveniently located	JJ NN	-1.5
Average		0.32

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Phrases from a thumbs-down review

Phrase	POS tags	Polarity
direct deposits	JJ NNS	5.8
online web	JJ NN	1.9
very handy	RB JJ	1.4
…		
virtual monopoly	JJ NN	-2.0
lesser evil	RBR JJ	-2.3
other problems	JJ NNS	-2.8
low funds	JJ NNS	-6.8
unethical practices	JJ NNS	-8.5
Average		-1.2

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Results of Turney algorithm

- 410 reviews from Epinions
  - 170 (41%) negative
  - 240 (59%) positive
- Majority class baseline: 59%
- Turney algorithm: 74%

- Phrases rather than words
- Learns domain-specific information

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Summary on Learning Lexicons

- Advantages:
  - Can be domain-specific
  - Can be more robust (more words)
- Intuition
  - Start with a seed set of words ('good', 'poor')
  - Find other words that have similar polarity:
    - Using "and" and "but"
    - Using words that occur nearby in the same document
    - Using WordNet synonyms and antonyms (be careful with senses)

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Other Sentiment Tasks

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Finding sentiment of a sentence

- Important for finding aspects or attributes
  - Target of sentiment

- `The food was great but the service was awful`

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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`")
  - Filter by rules like "occurs right after sentiment word"
    - "…`great fish tacos`" means `fish tacos` a likely aspect

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

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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, décor, 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*"

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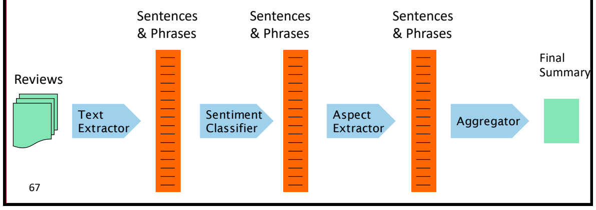
Putting it all together: Finding sentiment for aspects

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



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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

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Methods work best when classes have equal frequencies

- If not balanced (common in the real world)
  - can't use accuracies as an evaluation
  - need to use F-scores
- Severe imbalancing also can degrade classifier performance
- Two common solutions:
  1. Resampling in training
     - Random undersampling
  2. Cost-sensitive learning
     - Penalize SVM more for misclassification of the rare thing

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How to deal with 7 stars?

Bo Pang and Lillian Lee. 2005. Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales. ACL, 115–124

1. Map to binary
2. Use linear or ordinal regression
   - Or specialized models like metric labeling

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Summary on Sentiment

- Generally modeled as classification / 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 or automated polarity lexicons
- Aspect extraction

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Recall: 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*

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Computational work on other affective states

- **Emotion**:
  - Detecting annoyed callers to dialogue system
  - Detecting confused/frustrated versus confident students
- **Mood**:
  - Finding traumatized or depressed writers
- **Interpersonal stances**:
  - Detection of flirtation or friendliness in conversations
- **Personality traits**:
  - Detection of extroverts

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Detection of Friendliness

Ranganath, Jurafsky, McFarland

- Friendly speakers use collaborative conversational style
  - Laughter
  - Less use of negative emotional words
  - More sympathy
    - `That's too bad` `I'm sorry to hear that`
  - More agreement
    - `I think so too`
  - Less hedges
    - `kind of` `sort of` `a little …`

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