SENTIMENT ANALYSIS

Mausam

(With slides from Jan Wiebe, Kavita Ganesan, Heng Ji, Dan Jurafsky, Chris Manning)

Motivation

"What people think?"

What others think has always been an important piece of information

"Which car should I buy?"

"Which schools should I apply to?"

"Which Professor to work for?"

"Whom should I vote for?"

“So whom shall I ask?”

Pre Web

- Friends and relatives
- Acquaintances
- Consumer Reports

Post Web

“…I don’t know who..but apparently it’s a good phone. It has good battery life and…”

- Blogs (google blogs, livejournal)
- E-commerce sites (amazon, ebay)
- Review sites (CNET, PC Magazine)
- Discussion forums (*forums.craigslist.org, forums.macrumors.com*)
- Friends and Relatives (occasionally)

“Whoala! I have the reviews I need”

Now that I have “too much” information on one topic…I could easily form my opinion and make decisions…

Is this true?

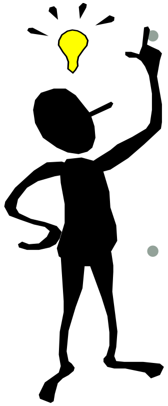
…Not Quite

Searching for reviews may be difficult

- Can you <u>search</u> for opinions as conveniently as general Web search?
- eg: is it easy to search for *“iPhone vs Google Phone”*?

“Let me look at reviews on one site only…”

Problems?

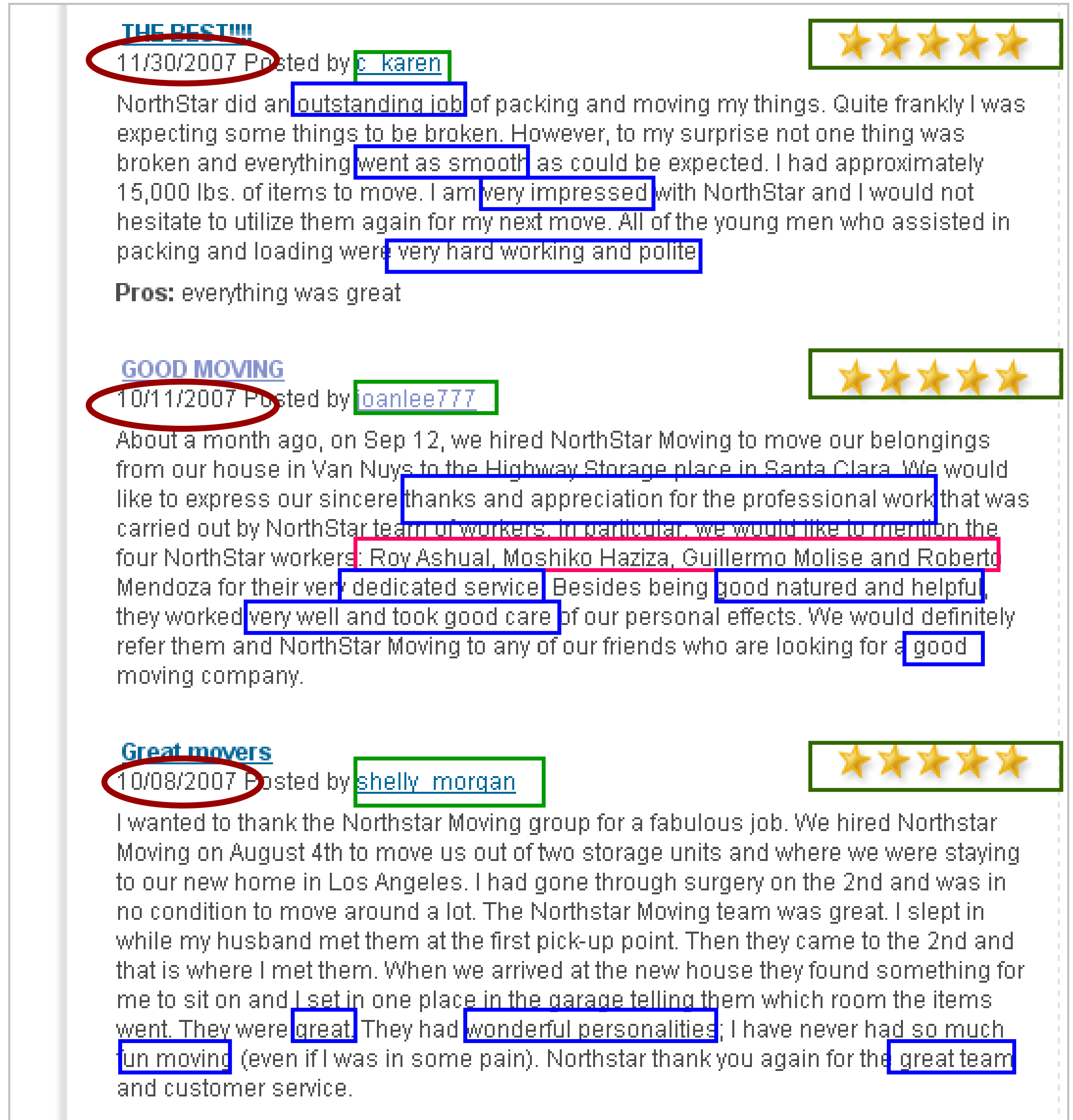


- Biased views
  - all reviewers on one site may have the same opinion
- Fake reviews/Spam (sites like YellowPages, CitySearch are prone to this)
  - people post good reviews about their own product OR services
  - some posts are plain spams

Coincidence or Fake?

Reviews for a moving company from YellowPages

- # of merchants reviewed by the each of these reviewers ➔ 1
- Review dates close to one another
- All rated 5 star
- Reviewers seem to know exact names of people working in the company and TOO many positive mentions



THE BEST!!!!
11/30/2007 Posted by c_karen
NorthStar did an outstanding job of packing and moving my things. Quite frankly I was expecting some things to be broken. However, to my surprise not one thing was broken and everything went as smooth as could be expected. I had approximately 15,000 lbs. of items to move. I am very impressed with NorthStar and I would not hesitate to utilize them again for my next move. All of the young men who assisted in packing and loading were very hard working and polite
Pros: everything was great

GOOD MOVING
10/11/2007 Posted by joanlee777
About a month ago, on Sep 12, we hired NorthStar Moving to move our belongings from our house in Van Nuys to the Highway Storage place in Santa Clara. We would like to express our sincere thanks and appreciation for the professional work that was carried out by NorthStar team of workers. In particular, we would like to mention the four NorthStar workers: Roy Ashual, Moshiko Haziza, Guillermo Molise and Roberto Mendoza for their very dedicated service. Besides being good natured and helpful, they worked very well and took good care of our personal effects. We would definitely refer them and NorthStar Moving to any of our friends who are looking for a good moving company.

Great movers
10/08/2007 Posted by shelly_morgan
I wanted to thank the Northstar Moving group for a fabulous job. We hired Northstar Moving on August 4th to move us out of two storage units and where we were staying to our new home in Los Angeles. I had gone through surgery on the 2nd and was in no condition to move around a lot. The Northstar Moving team was great. I slept in while my husband met them at the first pick-up point. Then they came to the 2nd and that is where I met them. When we arrived at the new house they found something for me to sit on and I set in one place in the garage telling them which room the items went. They were great. They had wonderful personalities; I have never had so much fun moving (even if I was in some pain). Northstar thank you again for the great team and customer service.

Problem Names

Subjectivity Analysis

Sentiment Analysis

Review Mining

Opinion Mining

Appraisal Extraction

Synonymous
&
Interchangeably Used!

So, what is Subjectivity?

- The linguistic expression of somebody's opinions, sentiments, emotions…..(private states)
- private state: state that is not open to objective verification *(Quirk, Greenbaum, Leech, Svartvik (1985). A Comprehensive Grammar of the English Language.)*
- Subjectivity analysis - is the computational study of affect, opinions, and sentiments expressed in text
  - blogs
  - editorials
  - reviews (of products, movies, books, etc.)
  - newspaper articles

Example: iPhone review

InfoWorld
- summary is structured
- everything else is plain text
- mixture of objective and subjective information
- no separation between positives and negatives

Review on InfoWorld - tech news site

CNET
- nice structure
- positives and negatives separated

CNET review

Review posted on a tech blog

Tech BLOG
- everything is plain text
- no separation between positives and negatives

Example: iPhone review

Lab test: Apple gets iPhone 3G right for business

An abundance of new features carries iPhone 3G and iPhone 2.0 into the enterprise

By Tom Yager
July 24, 2008

Talkback | E-mail | Printer Friendly | Reprints | Text Size A A

With the iPhone 3G's banner opening weekend and newsstands looking like a rack of brochures for the device, a review of the iPhone 3G at this point might be pro forma, except for one thing: Much of the iPhone 3G and the new iPhone 2.0 software remains an enigma to professionals and enterprises, users set apart by, among other things, their tendency to use punctuation in their e-mail. These users demand more from a handset than a cellular browser and YouTube.

Related Stories

New MacBook Air: now with extra SSD goodness

AT&T says iPhone 3G tethering coming 'soon'

Popular Tags
apple, iphone-3g

See Also

iPhone delivers more misses than hits

iPhone: The $1,975 iPod

» **Back to special report: Apple launches the iPhone 3G**

The Bottom Line

Apple iPhone 3G
Apple, apple.com/iphone

Very Good 8.5

criteria	score	weight
Extensibility	7	20%
Messaging	8	20%
Networking	9	20%
Usability	9	20%
Multimedia	10	10%
Value		

With mature and well-established QWERTY devices fr
and Research in Motion known to be capable of handli
the iPhone 3G needs to be weighed against alternative
and enterprise-targeted handsets to set the bar. As yo
2007 iPhone to fall far short of professional standards
to be missing so much.

[Not everyone thinks the iPhone is enterprise-class
argues Apple must fix 13 iPhone flaws before it's a B

This time around, there are two new products under di
Apple's pair of new 8GB and 16GB phone models (whi
respectively, for AT&T customers who agree to a two-ye
ActiveSync, Assisted GPS (A-GPS), and 1Mbps 3G cell
the iPhone 2.0 software, Apple's new iPhone firmware
later will update existing iPhones and iPod Touches to
you'll end up with a device that is, except for GPS and 3
iPhone 3G. The iPod Touch is also upgradable to iPho

I've taken to referring to first-gen iPhone and iPhone 3G
iPhone, which now identifies a consistently implement
that *Mac* covers all Apple client computers. Wherever I
that I'm making specific reference to Apple's new hand

Second time's the charm

Apple has turned iPhone into a mobile platform that I c
and enterprise users. I make that recommendation wit
testing of the iPhone 3G against Apple's claims. Those
some time. It's my opinion that final judgment about th
can't be rendered until you've trusted your digital identit

Clearly, I haven't had time to carry it that far, but the iPh
software meet the expectations set by Apple, and Apple
produced a mobile device and platform that hold their
E-Series, RIM BlackBerry, and Windows Mobile 6. In ar
its innovation, the iPhone 3G exceeds the capabilities
makes it hard to imagine competitors closing the gap.

Review on InfoWorld - tech news site

Product summary

The good:
The Apple iPhone has a stunning display, a sleek design, and an innovative multitouch user interface. Its Safari browser makes for a superb Web surfing experience, and it offers easy-to-use apps. As an iPod, it shines.

CNET editors' rating:
Excellent
Detailed editors' rating

Average user rating:
out of 755 reviews
See all user reviews

The bad:
The Apple iPhone has variable call quality and lacks some basic features found in many cell phones, including stereo Bluetooth support and 3G compatibility. Integrated memory is stingy for an iPod, and you have to sync the iPhone to manage music content.

The bottom line:
Despite some important missing features, a slow data network, and call quality that doesn't always deliver, the Apple iPhone sets a new benchmark for an integrated cell phone and MP3 player.

Specifications:
OS provided: Apple MacOS X; Band / mode: GSM 850/900/1800/1900 (Quadband); Wireless connectivity: IEEE 802.11b, IEEE 802.11g, Bluetooth 2.0 EDR; **See full specs**

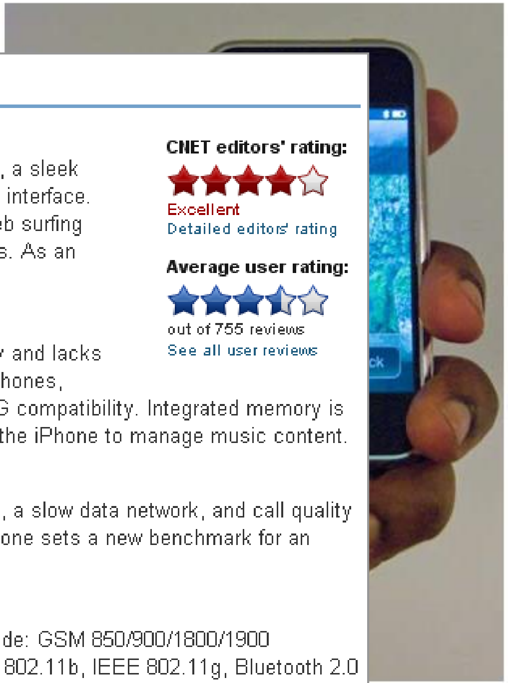
See all products in the Apple iPhone series

CNET editors' review

Reviewed by: Kent Ger
Edited by: Lindsey Turr
Reviewed on: 06/30/20
Updated on: 07/11/2008

CNET review

Review posted on a tech blog



See my NEW iPhone 3g review

Let me start off by saying that while I'm a fan of Apple's success and products, I'm not one of those people that blindly apologizes for their products no matter what. I'll be the first to say that something works or it doesn't. My friends and many of you come to me all the time because they want my HONEST assessment. So I wanted a couple of days with the iPhone to really take it through its paces and see if this new phone is what it's hyped up to be. You must also understand that there isn't a smartphone out there that I think is perfect. As a matter of fact before the iPhone there were basically 4 smartphone OS's, Palm, Blackberry, Symbian and Windows Mobile. I stuck with Palm because it was the lessor of the 4 evils or the one that sucks least. Palm has a UI (user interface) that
lly zero innovation. However, there are thousands of
OS. Blackberry doesn't have a touch screen or tap
ypad/thumb wheel. Also the Blackberry's I considered
etc.) Symbian looked very promising, but I was
how slooooow it was and that there were very few
ed up on him just last week right in front of me.

Subjectivity Analysis on iPhone Reviews

Individual's Perspective

- Highlight of what is good and bad about iPhone
  - Ex. Tech blog may contain mixture of information
- Combination of good and bad from the different sites *(tech blog, InfoWorld and CNET)*
  - Complementing information
  - Contrasting opinions
    Ex.

CNET: *The iPhone lacks some basic features*

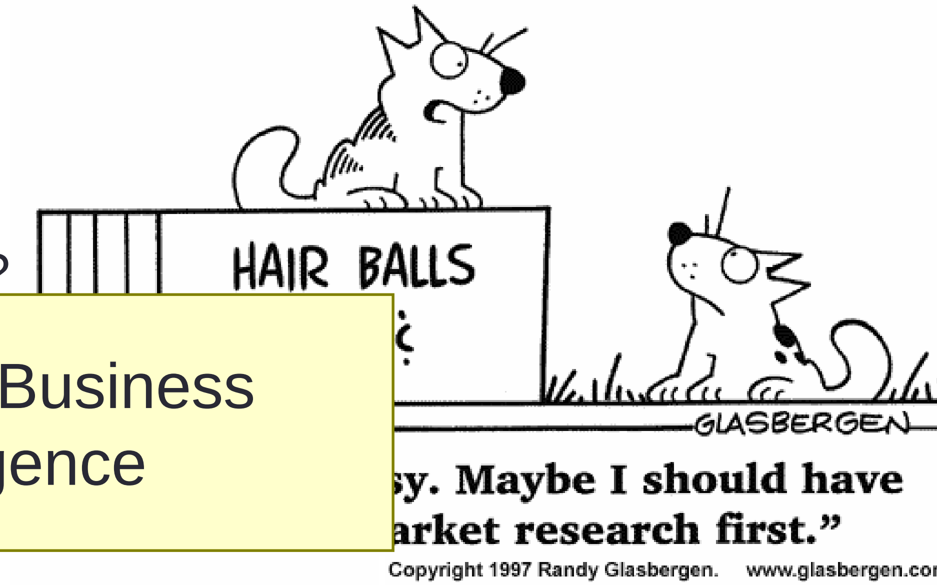
Tech Blog: *The iPhone has a complete set of features*

Subjectivity Analysis on iPhone Reviews

Business’ Perspective

- Apple: What do consumers think about iPhone?
  - Do they like it?
  - What do they dislike?
  - What are the major complaints?
  - What features should we add?

- Apple’s competitor:
  - What are iPhone’s weaknesses?
  - How can we compete with them?
  - Do people like



Known as Business Intelligence

Bing Shopping

HP Officejet 6500A E710N Multifunction Printer

Product summary   Find best price   **Customer reviews**   Specifications   Related items

$121.53 - $242.39 (14 stores)

☐ Compare

Average rating ★★★½☆ (144)

★★★★★	(55)
★★★★☆	(54)
★★★☆☆	(10)
★★☆☆☆	(6)
★☆☆☆☆	(23)
☆☆☆☆☆	(0)

Most mentioned

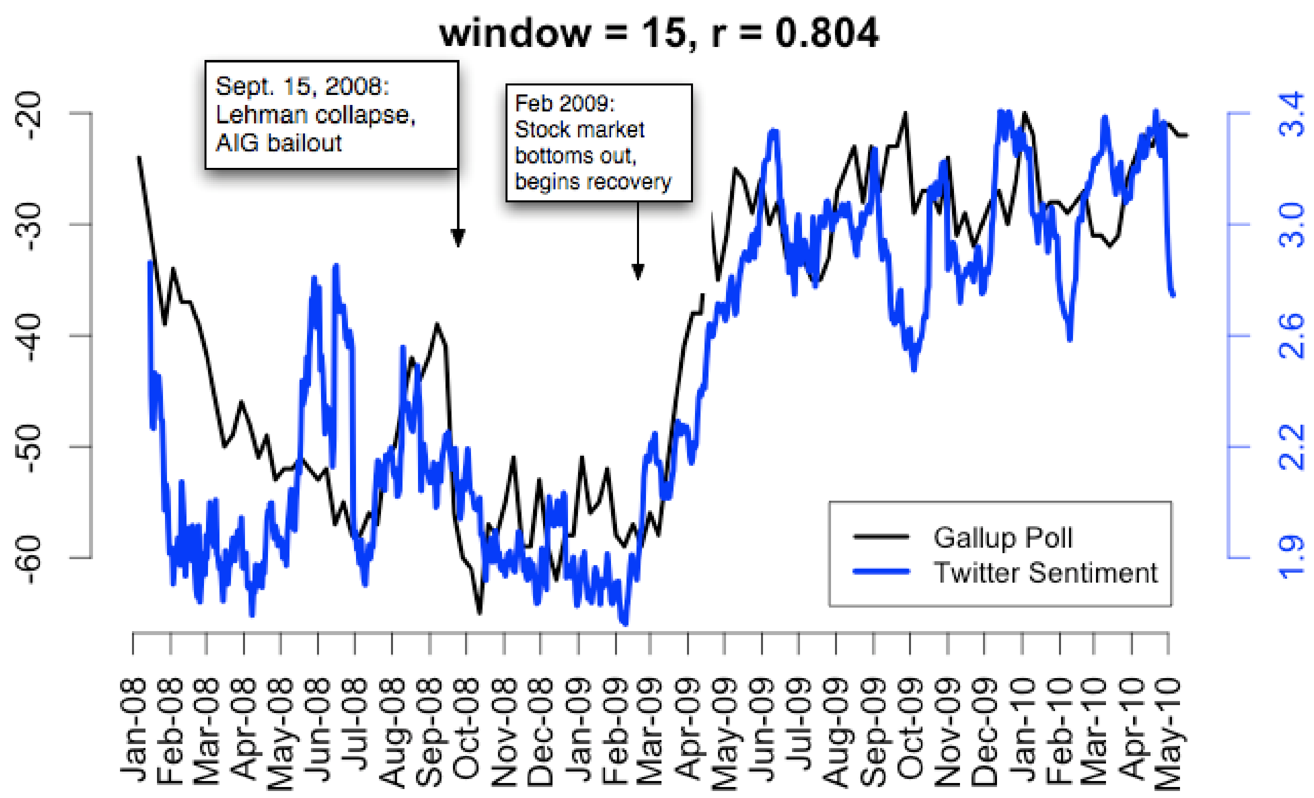
Performance	(57)
Ease of Use	(43)
Print Speed	(39)
Connectivity	(31)
More ▼	

Show reviews by source

- Best Buy (140)
- CNET (5)
- Amazon.com (3)

Twitter sentiment versus Gallup Poll of Consumer Confidence

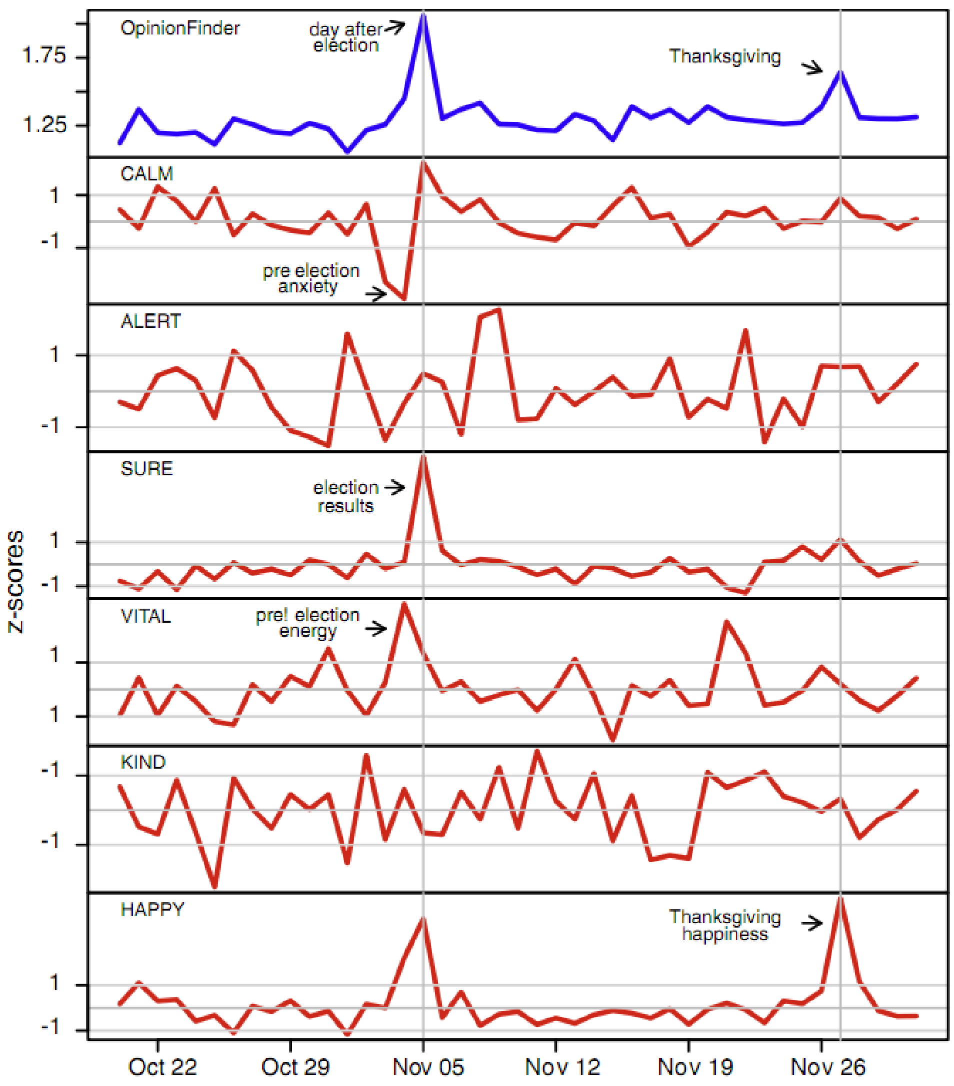
Brendan O'Connor, Ramnath Balasubramanyan, Bryan R. Routledge, and Noah A. Smith. 2010. From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series. In ICWSM-2010



Twitter sentiment:

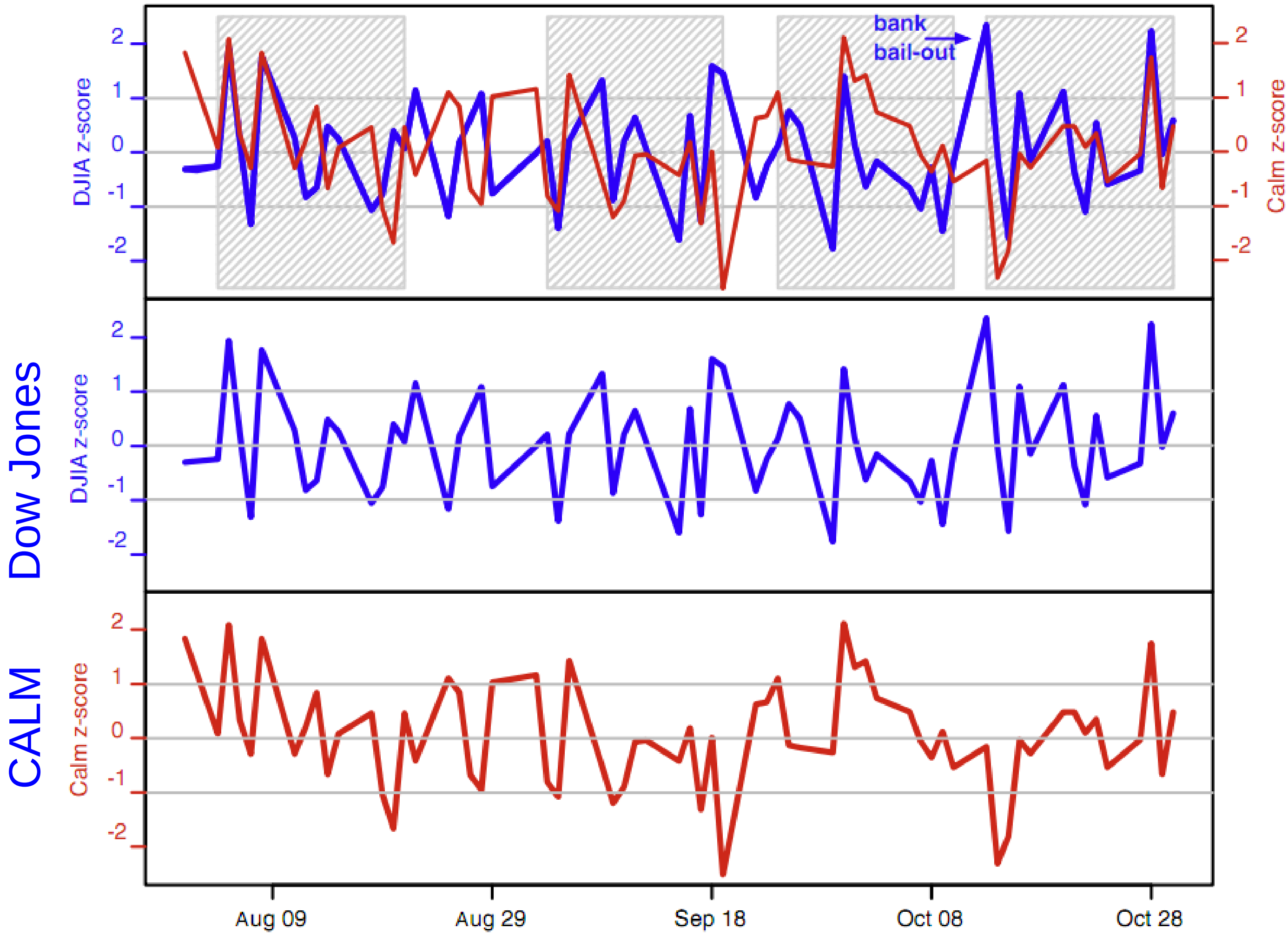
Johan Bollen, Huina Mao, Xiaojun Zeng. 2011. [Twitter mood predicts the stock market,]()

Journal of Computational Science 2:1, 1-8. 10.1016/j.jocs.2010.12.007.



Bollen et al. (2011)

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



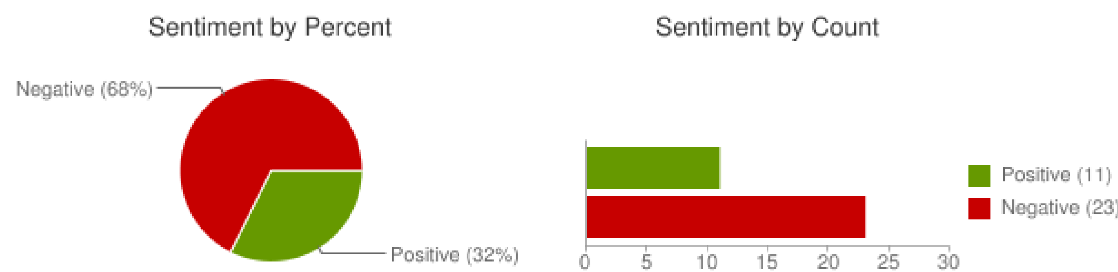
Target Sentiment on Twitter

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

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

"united airlines" | Search | Save this search

Sentiment analysis for "united airlines"



jljacobson: OMG... Could **@United airlines** have worse customer service? W8g now 15 minutes on hold 4 questions about a flight 2DAY that need a human.
Posted 2 hours ago

12345clumsy6789: I hate **United Airlines** Ceiling!!! Fukn impossible to get my conduit in this damn mess! ?
Posted 2 hours ago

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

Definition

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*

Scherer Typology of Affective States

Type of affective state: brief definition (*examples*)	Intensity	Duration	Syn-chroni-zation	Event focus	Appraisal elicita-tion	Rapid-ity of change	Behav-ioral impact
Emotion: relatively brief episode of synchronized response of all or most organismic subsystems in response to the evaluation of an external or internal event as being of major significance (*angry*, *sad*, *joyful*, *fearful*, *ashamed*, *proud*, *elated*, *desperate*)	+ +–+ ++	+	+ + +	+ + +	+ + +	+ + +	+ + +
Mood: diffuse affect state, most pronounced as change in subjective feeling, of low intensity but relatively long duration, often without apparent cause (*cheerful*, *gloomy*, *irritable*, *listless*, *depressed*, *buoyant*)	+–+ +	++	+	+	+	++	+
Interpersonal stances: affective stance taken toward another person in a specific interaction, colouring the interpersonal exchange in that situation (*distant*, *cold*, *warm*, *supportive*, *contemptuous*)	+–+ +	+–+ +	+	++	+	+ + +	++
Attitudes: relatively enduring, affectively coloured beliefs, preferences, and predispositions towards objects or persons (*liking*, *loving*, *hating*, *valueing*, *desiring*)	0–+ +	+ +–+ ++	0	0	+	0–+	+
Personality traits: emotionally laden, stable personality dispositions and behavior tendencies, typical for a person (*nervous*, *anxious*, *reckless*, *morose*, *hostile*, *envious*, *jealous*)	0–+	+ + +	0	0	0	0	+

0: low, +: medium, ++: high, + + +: very high, –: indicates a range.

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

- 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

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

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

Baseline Algorithms

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

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

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

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
```

38

Accounting for Negation

- Let us consider the following positive sentence:
  - Example: *Luckily, the smelly poo did not leave awfully nasty stains on my favorite shoes!*
- Rest of Sentence (RoS):
  - Following: *Luckily, the smelly poo did not leave awfully nasty stains on my favorite shoes!*
  - Around: *Luckily, the smelly poo did not leave awfully nasty stains on my favorite shoes!*
- First Sentiment-Carrying Word (FSW):
  - Following: *Luckily, the smelly poo did not leave awfully nasty stains on my favorite shoes!*
  - Around: *Luckily, the smelly poo did not leave awfully nasty stains on my favorite shoes!*

Determining Negation Scope and Strength in Sentiment Analysis, Hogenboom et al SMC 2011.

39

Accounting for Negation

- Let us consider the following positive sentence:
  - Example: *Luckily, the smelly poo did* not *leave awfully nasty stains on my favorite shoes!*
- Next Non-Adverb (NNA):
  - Following: *Luckily, the smelly poo did* not *leave awfully <u>nasty</u> stains on my favorite shoes!*
- Fixed Window Length (FWL):
  - Following (3): *Luckily, the smelly poo did* not *leave <u>awfully</u> <u>nasty</u> stains on my favorite shoes!*
  - Around (3): *Luckily, the <u>smelly</u> <u>poo</u> did* not *leave <u>awfully</u> <u>nasty</u> stains on my favorite shoes!*

KEYWORDS SELECTION FROM TEXT

- Pang et. al. (2002)
  - Binary Classification of unigrams
    - Positive
    - Negative
  - Unigram method reached 80% accuracy.

N-GRAM BASED CLASSIFICATION

- Learn N-Grams (frequencies) from pre-annotated training data.
- Use this model to classify new incoming sample.

PART-OF-SPEECH BASED PATTERNS

- Extract POS patterns from training data.
- Usually used for subjective vs objective classification.
- Adjectives and Adverbs contain sentiments
- Example patterns
  - *-JJ-NN : trigram pattern
  - JJ-NNP : bigram pattern
  - *-JJ : bigram pattern

Reminder: Naïve Bayes

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}} P(c_j) \prod_{i \in positions} P(w_i \mid c_j)$$

$$\hat{P}(w \mid c) = \frac{count(w,c)+1}{count(c)+|V|}$$

Binarized (Boolean feature) Multinomial Naïve Bayes

- 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

Boolean Multinomial Naïve Bayes: Learning

- From training corpus, extract *Vocabulary*

- Calculate $P(c_j)$ terms
  - For each c_j in C do

    $docs_j \leftarrow$ all docs with class $=c_j$

$$P(c_j) \neg \frac{|docs_j|}{|\text{total \# documents}|}$$

- Calculate $P(w_k \mid c_j)$ terms
  - Remove duplicates in each doc:
    - For each word type w in doc_j
      - Retain only a single instance of w
  - $Text_j \leftarrow$ single doc containing all $docs_j$
  - For each word w_k in *Vocabulary*

    $n_k \leftarrow$ # of occurrences of w_k in $Text_j$

$$P(w_k \mid c_j) \neg \frac{n_k + a}{n + a\,|Vocabulary|}$$

Boolean Multinomial Naïve Bayes on a test document *d*

- First remove all duplicate words from *d*
- Then compute NB using the same equation:

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}} P(c_j) \prod_{i \in positions} P(w_i \mid c_j)$$

Other issues in Classification

- MaxEnt and SVM tend to do better than Naïve Bayes

Problems: What makes reviews hard to classify?

- 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”

CHALLENGES

- Ambiguous words
  - This music cd is literal waste of time. (negative)
  - Please throw your waste material here. (neutral)
- Sarcasm detection and handling
  - “All the features you want - too bad they don’t work. :-P”
- (Almost) No resources and tools for low/scarce resource languages like Indian languages.

User written: grammar, spellings…

Hi,

I have Haier phone.. It was good when i was buing this phone.. But I invented A lot of bad features by this phone those are It's cost is low but Software is not good and Battery is very bad..,,Ther are no signals at out side of the city..,, People can't understand this type of software..,, There aren't features in this phone, Design is better not good..,, Sound also bad..So I'm not intrest this side They are giving heare phones it is good. They ar… ty these are also good.They are gi… e it is also good because other phones … so low wait.

Lack of punctuation marks, Grammatical errors

Wait.. err.. Come again

From: www.mouthshut.com

Alternating Sentiment

I suggest that instead of fillings songs in tunes you should [illegible] tunes (not made of songs) only. The phone has good popularity in old age people. Third I had tried much for its data cable but i find it nowhere. It should be supplied with set with some extra cost.

Good features of this phone are its cheapest price and durability . It should have some features more than nokia 1200. it is easily available in market and repair is also available

From: www.mouthshut.com

Subject Centrality

- I have this personal experience of using this cell phone. I bought it one and half years back. It had modern features that a normal cell phone has, and the look is excellent. I was very impressed by the design. I bought it for Rs. 8000. It was a gift for someone. It worked fine for first one month, and then started the series of multiple faults it has. First the speaker didnt work, I took it to the service centre (which is like a govt. office with no work). It took 15 days to repair the handset, moreover they ch~~arged me Rs. 500. Then after 15~~ days again the mike didnt work, then again same set of time was consumed for the repairs and it continued. Later the camera didnt work, the speakes were rubbish, it used to hang. It started restarting automatically. And the govt. office had staff which I doubt have any knoledge of cell phones??
  These multiple faults continued for as long as one year, when the warranty period ended. In this period of time ~~I spent a considerable amount on the petrol, a lot of time (as~~ the service centre is a govt. office). And at last the phone is still working, but now it works as a paper weight. The company who produces such items must be sacked. I understand that it might be fault with one prticular handset, but the company itself never bothered for replacement and I have never seen such miserable cust service. For a comman man like me, Rs. 8000 is a big amount. And I spent almost the same amount to get it work, if any ~~has a good suggestion and can gude me how to sue such~~ companies, please guide.
  For this the quality team is faulty, the cust service is really miserable and the worst condition of any organisation I have ever seen i~~s with the service centre for Fly and Sony Errisson, (it's near~~ Sancheti hospital, Pune). I dont have any thing else to say.

From: www.mouthshut.com

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.

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

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:
  - Positive (1915 words) and Negative (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/mpqa/subj_lexicon.html
- 6885 words
  - 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
```

ADVANTAGES AND DISADVANTAGES

- Advantages
  - Fast
  - No Training data necessary
  - Good initial accuracy
- Disadvantages
  - Does not deal with multiple word senses
  - Does not work for multiple word phrases

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				

Analyzing the polarity of each word in IMDB

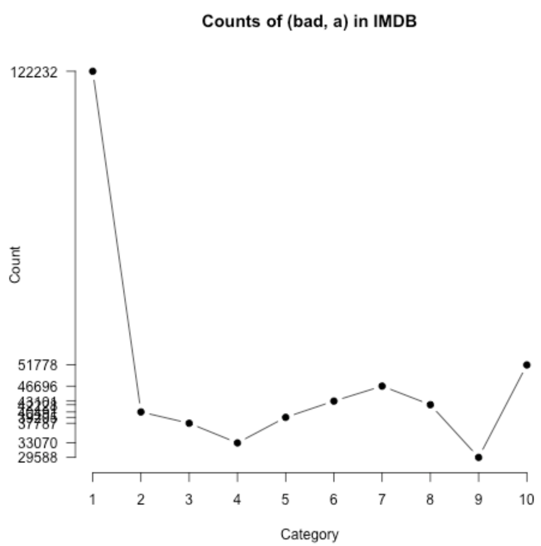
Potts, Christopher. 2011. On the negativity of negation. SALT 20, 636-659.

- 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:**

$$P(w|c) = \frac{f(w,c)}{\sum_{w \in c} f(w,c)}$$

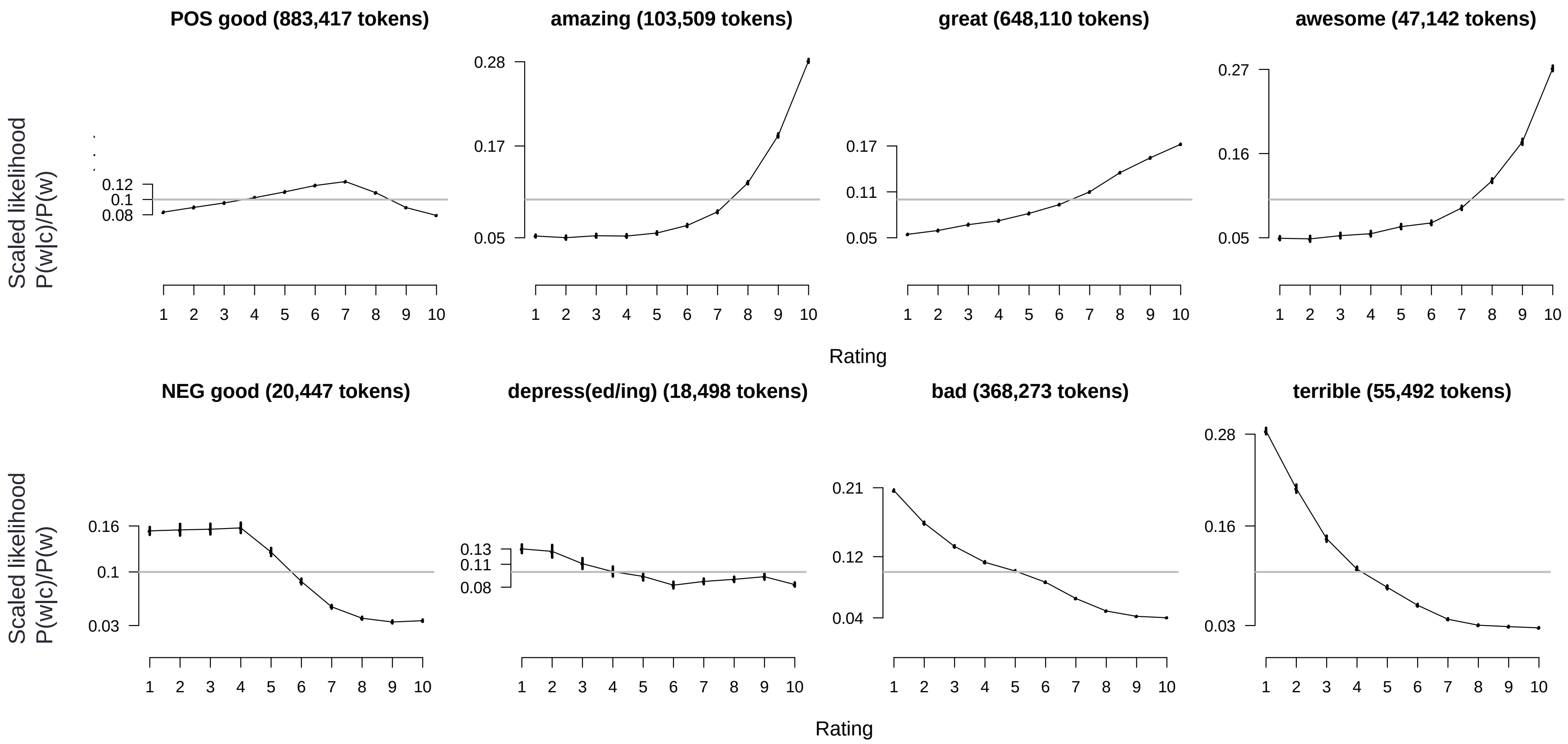
- Make them comparable between words
  - **Scaled likelihood:**

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



Analyzing the polarity of each word in IMDB

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

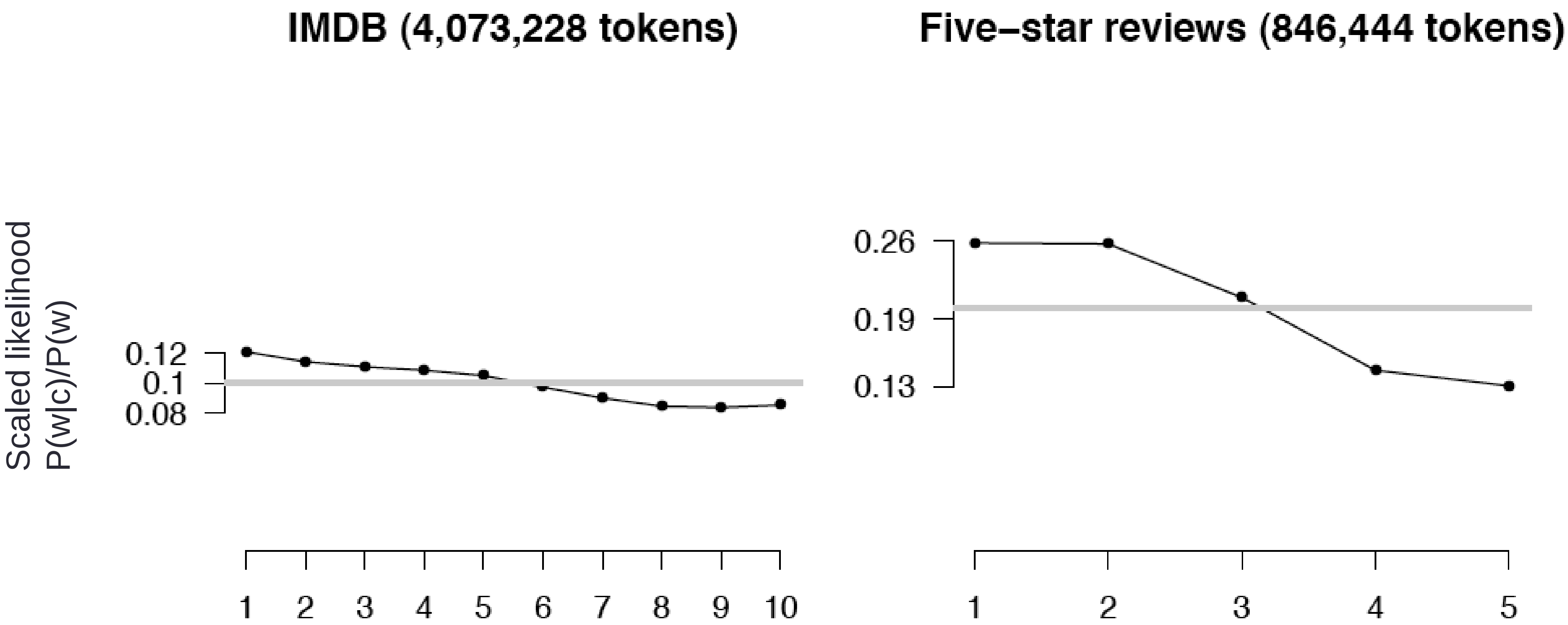


Other sentiment feature: Logical negation

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



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

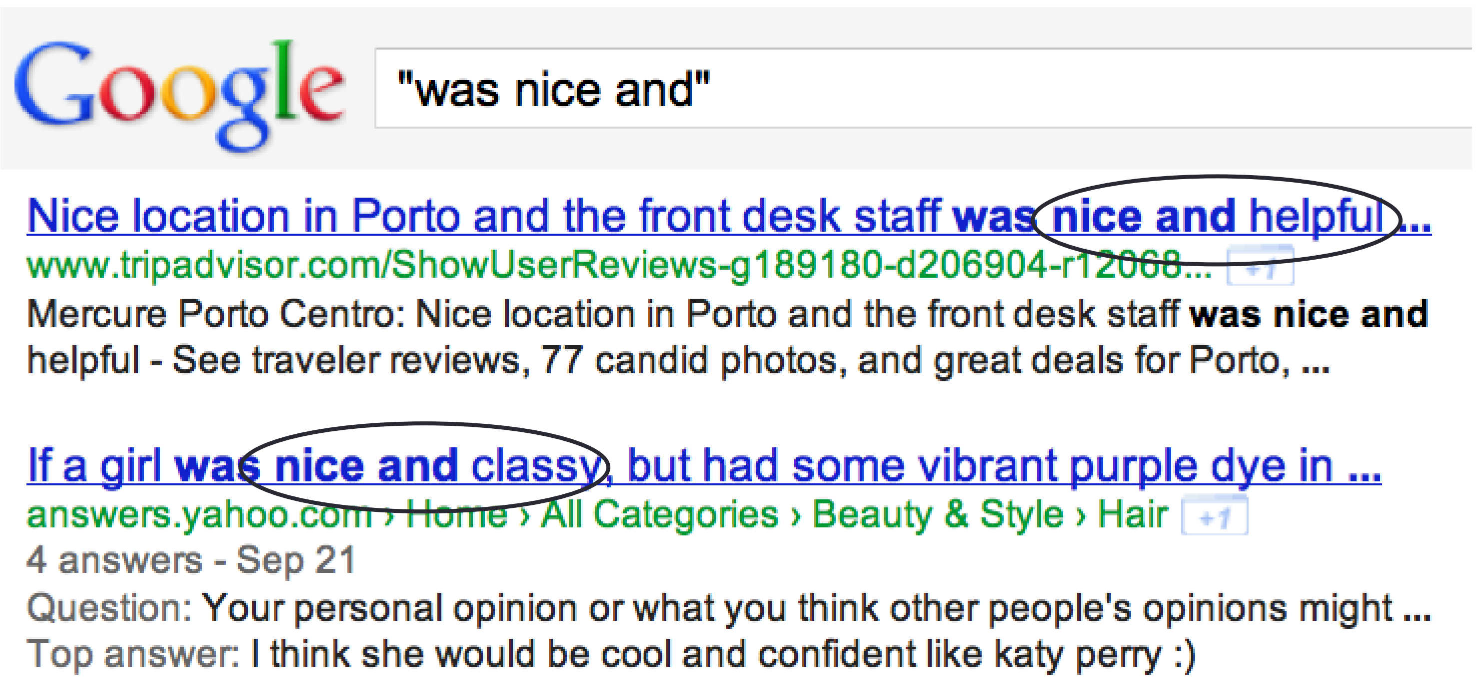
- Adjectives conjoined by "*and*" have same polarity
  - Fair **and** legitimate, corrupt **and** brutal
  - *fair **and** brutal, *corrupt **and** legitimate
- Adjectives conjoined by "*but*" do not
  - fair **but** brutal

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

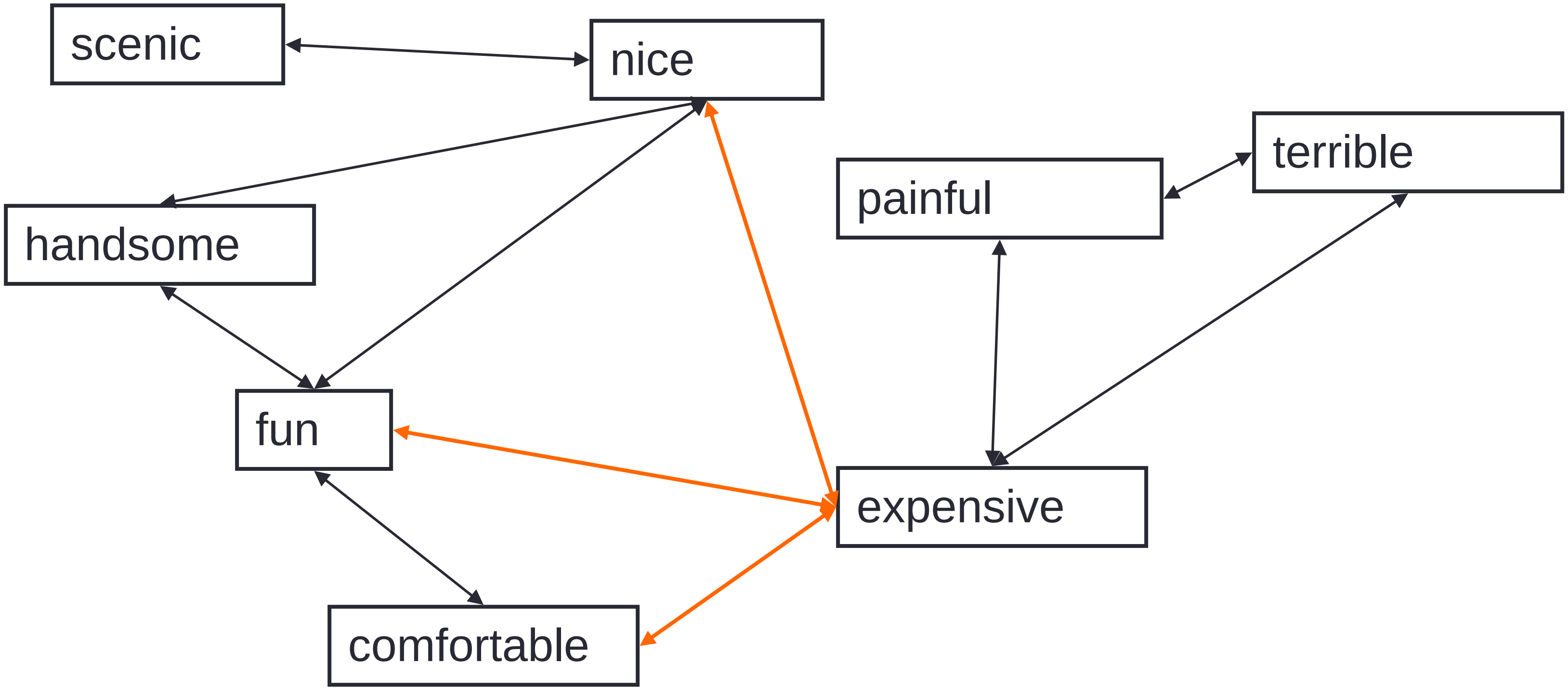


nice, helpful

nice, classy

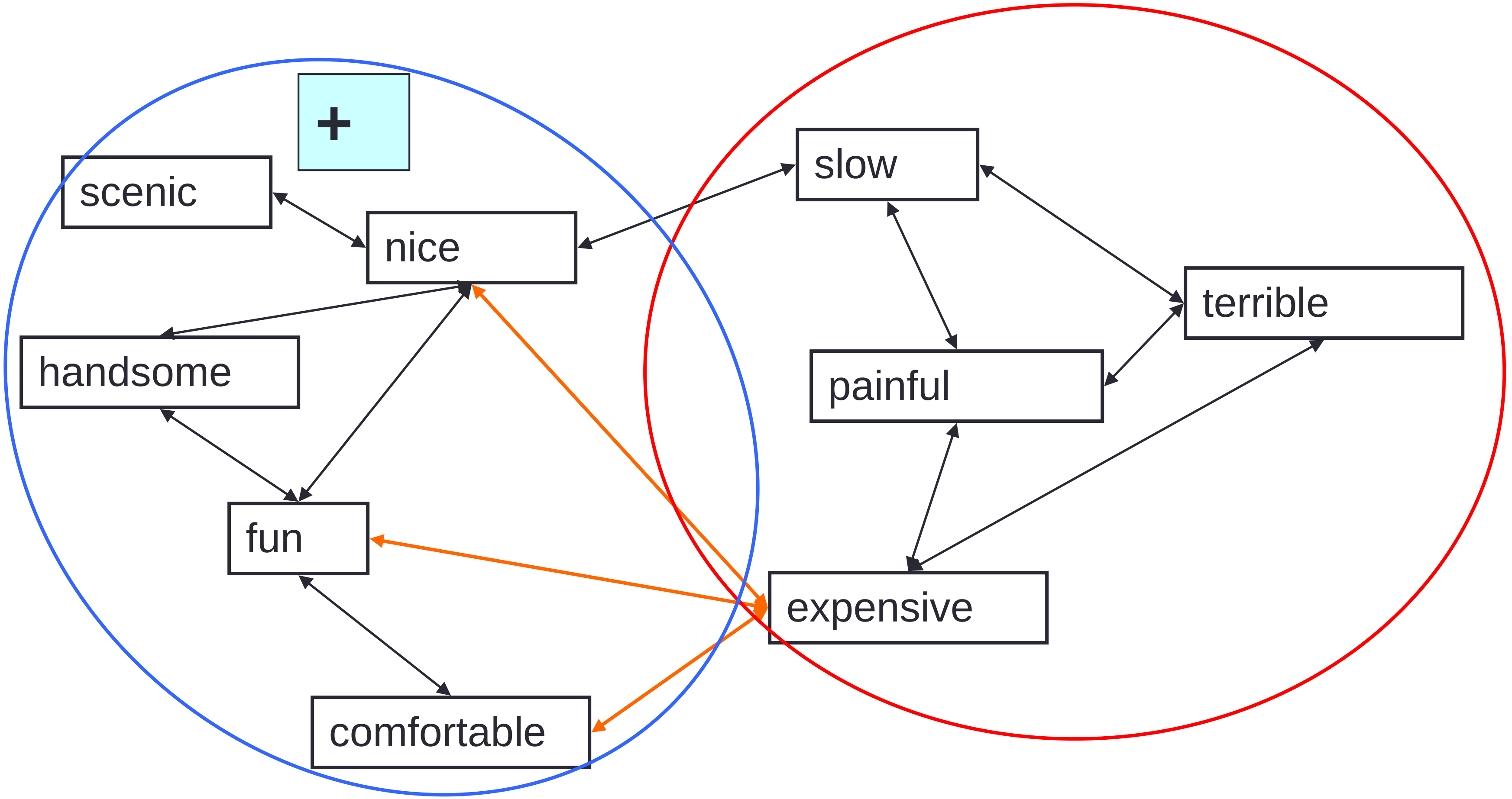
Hatzivassiloglou & McKeown 1997 Step 3

3. A supervised learning algorithm builds a graph of adjectives linked by the same or different semantic orientation



Hatzivassiloglou & McKeown 1997 Step 4

4. A clustering algorithm partitions the adjectives into two subsets



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…

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

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

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?

Pointwise Mutual Information

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

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

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

$$\mathrm{PMI}(x,y)=\log_2 \frac{P(x,y)}{P(x)P(y)}$$

Pointwise Mutual Information

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

$$\mathrm{PMI}(x, y) = \log_2 \frac{P(x,y)}{P(x)P(y)}$$

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

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

How to Estimate Pointwise Mutual Information

- Query search engine
  - P(word) estimated by `hits(word)/N`
  - P(word_1,word_2) by `hits(word1 NEAR word2)/N`
    - (More correctly the bigram denominator should be kN, because there are a total of N consecutive bigrams (word1,word2), but kN bigrams that are k words apart, but we just use N on the rest of this slide and the next.)

$$\mathrm{PMI}(word_1, word_2) = \log_2 \frac{\frac{1}{N} hits(word_1\ \mathrm{NEAR}\ word_2)}{\frac{1}{N} hits(word_1) \frac{1}{N} hits(word_2)}$$

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

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

$$= \log_2 \frac{\frac{1}{N}\text{hits}(\textit{phrase}\ \text{NEAR "excellent"})}{\frac{1}{N}\text{hits}(\textit{phrase})\frac{1}{N}\text{hits}(\text{"excellent"})} - \log_2 \frac{\frac{1}{N}\text{hits}(\textit{phrase}\ \text{NEAR "poor"})}{\frac{1}{N}\text{hits}(\textit{phrase})\frac{1}{N}\text{hits}(\text{"poor"})}$$

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

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

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

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

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

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

    - Use seeds and semi-supervised learning to induce lexicons

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

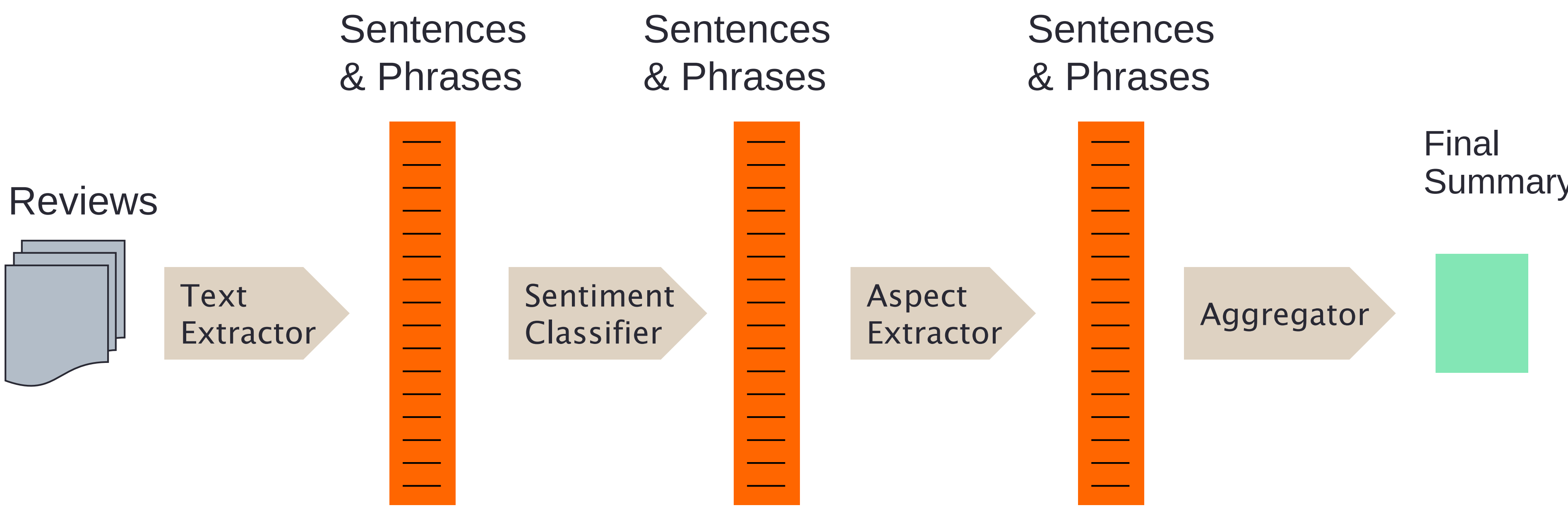
Casino	casino, buffet, pool, resort, beds
Children’s Barber	haircut, job, experience, kids
Greek Restaurant	food, wine, service, appetizer, lamb
Department Store	selection, department, sales, shop, clothing

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*"

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

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

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