Natural Language Processing: Sentiment Analysis

16 February 2022

https://tinyurl.com/NLP2022part4

Sentiment Analysis

Background

"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)

Too Much Data

- Searching for reviews may be however difficult
  - Can we search for opinions as conveniently as in general Web search?
  - Eg.: is it easy to search for *“iPhone vs Google Phone”*?

“Look at reviews on one site only…?”

Problems?

- Biased views
  - all reviewers on one site may have the same opinion

- Fake reviews/Spam
  - 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 each of these reviewers more than 1?
- Review dates close to one another
- All rated 5 stars
- 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.

Research Task's Names

Subjectivity Analysis

Review Mining

Appraisal Extraction

Sentiment Analysis

Opinion Mining/Analysis

They are synonyms and are interchangeably used

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/simply) simple weighted **polarity**:
       - *positive, negative, neutral,* together with their *strengths*
  4. **Text** containing the attitude
     - Sentence or entire document
       - blogs
       - editorials
       - reviews (of products, movies, books, etc.)
       - newspaper articles
       - etc.

Sentiment Analysis

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

Why sentiment analysis?

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

Political opinion mining

emilia @PoliticalEmilia · 43m
As somebody whose immediate family are **immigrants** from Iran, I want to remind that this isn't the fault of Iranian Americans. Most of us want no more war in the Middle East.

Take your anger out at your government leaders, not at us. We have nothing to do with it. #IranAttacks

81 239 1.9K

Nithya Raman @nithyavraman · Jan 6
LA is one of the most **immigrant**-rich cities in the US.

Almost 50% of residents are foreign-born. 10% are undocumented.

As Trump works to implement his racist agenda, what are our elected officials doing to defend **immigrant** Angelenos?

The answer: infuriatingly little. (thread)

55 138 606

Brigitte Gabriel @ACTBrigitte · 3m
Thank Goodness there were ZERO U.S. casualties from the attacks Iran made tonight.

President **Trump** is monitoring the situation with his top leaders right now.

I've never felt more comfortable with a leader at the helm, than I do tonight with President **Trump** in office.

21 145 413

Palmer Report @PalmerReport · 1m
So a foreign nation fired missiles at U.S. troops tonight, and the President of the United States ISN'T addressing the nation? How far gone is Donald **Trump**? His handlers don't even trust him to read a speech off a teleprompter anymore.

15 74 225

Andrea Chalupa @AndreaChalupa · 7m
Trump is betting on Iran doing something so horrific to Americans that we rally around the flag, and the 2020 election becomes a mindless debate of who's "patriotic" vs. who's anti-war ("weak" on Iran).

47 147 425

Entity
Also called (target) objects, which can be a product, a service, an organization, an event, etc.

Time
Time when opinions has been expressed

Attributes/Aspects
Characteristics or components of an entity (e.g. the size of a camera, the price of a product, etc.)

Opinion Holder
The person who expresses opinions on an entity in the form of a review, a rating, a twitter message, etc.

Google Product Search

HP Officejet 6500A Plus e-All-in-One Color Ink-jet - Fax / copier / printer / scanner

$89 online, **$100** nearby ★★★★☆ 377 reviews

September 2010 - Printer - HP - Inkjet - Office - Copier - Color - Scanner - Fax - 250 sh

Reviews

Summary - Based on 377 reviews

1 star | 2 | 3 | 4 stars | 5 stars

What people are saying

ease of use	"This was very easy to setup to four computers."
value	"Appreciate good quality at a fair price."
setup	"Overall pretty easy setup."
customer service	"I DO like honest tech support people."
size	"Pretty Paper weight."
mode	"Photos were fair on the high quality mode."
colors	"Full color prints came out with great quality."

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)

Subjectivity Analysis on iPhone Reviews

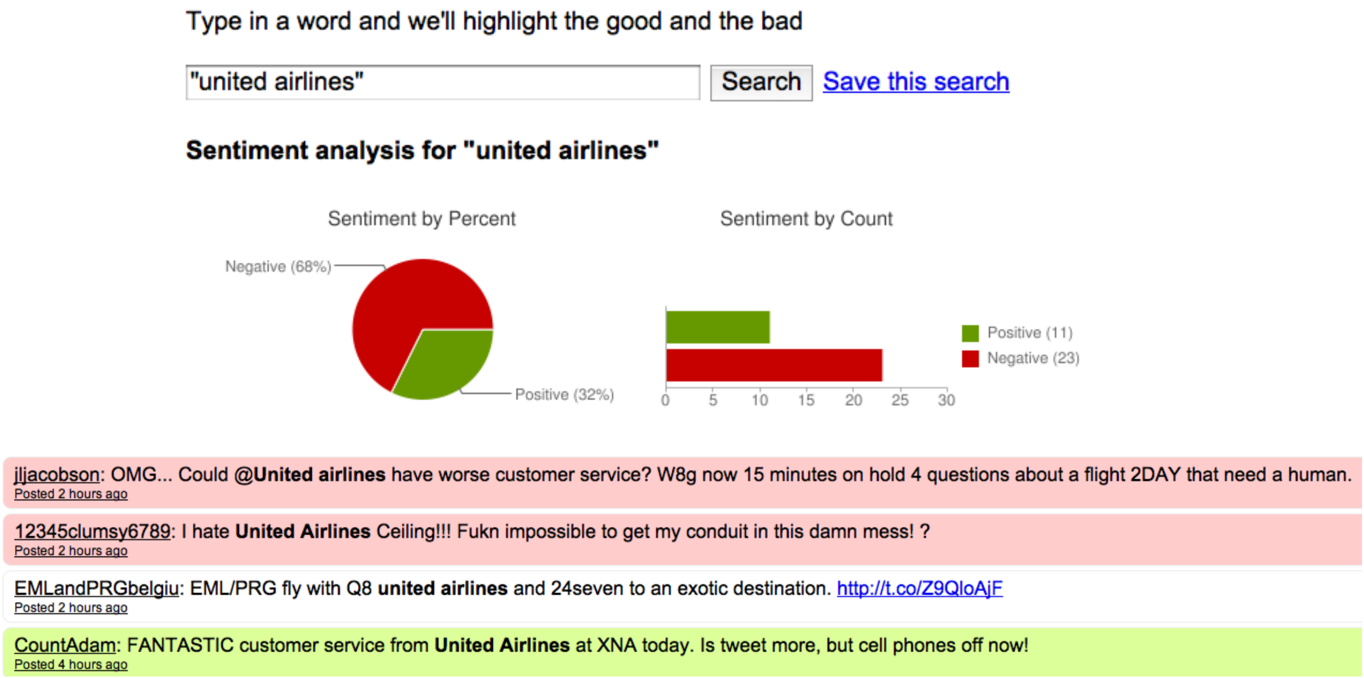
Business' Perspective (e.g.:)

- 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?

Business intelligence

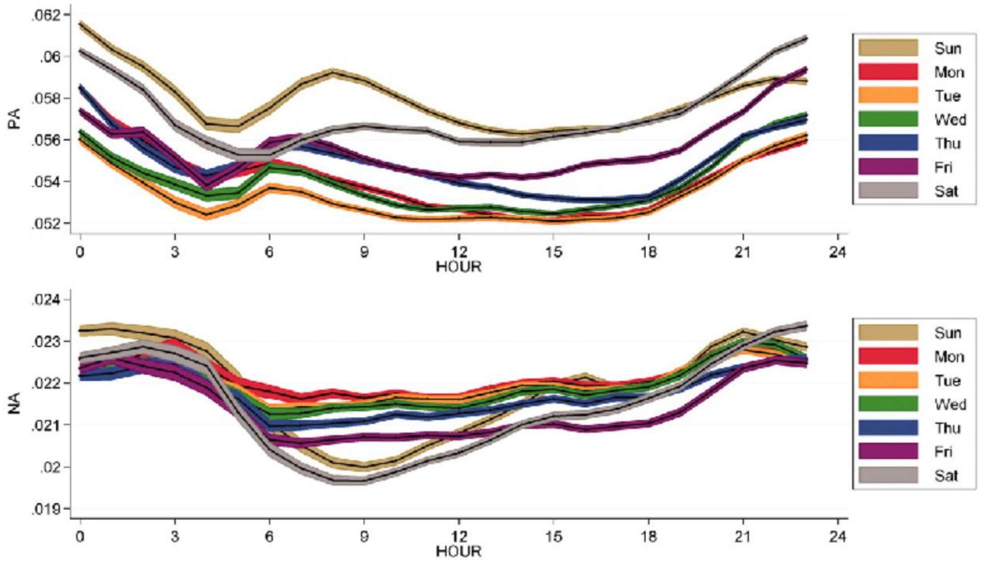
- Apple's competitor:
  - What are iPhone's weaknesses?
  - How can we compete with them?
    - Do people like everything about it?

Target Sentiment on Twitter



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

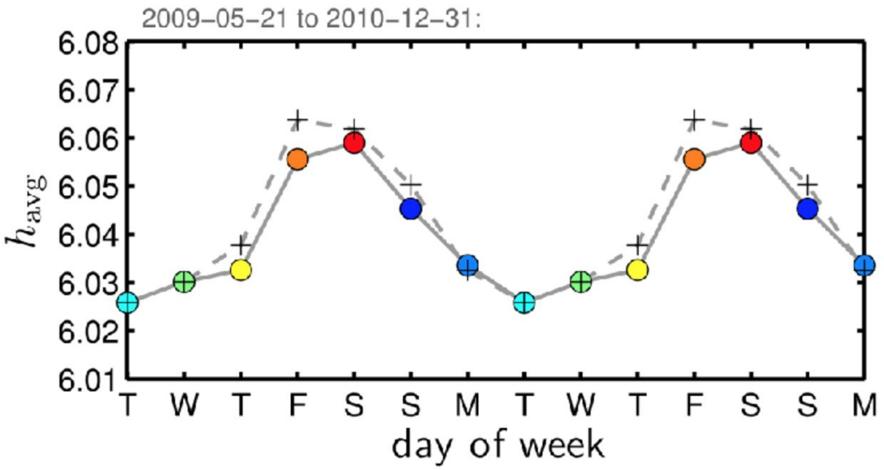
Positive/negative tone during a day (Twitter study across globe)



Positive affect (PA) and negative affect (NA) measured with LIWC

Golder and Macy (2011), “Diurnal and Seasonal Mood Vary with Work, Sleep, and Daylength Across Diverse Cultures,” Science.

Patterns of Happiness vs. Days of Week



Analysis of 46 billion words contained in nearly 4.6 billion expressions
posted over a 33 month span by over 63 million unique users

Dodds et al. (2011), "Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter" (PLoS One)

Sentiment Analysis

Difficulaties & Challenges

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*."

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.

Alternating Sentiments

- I suggest that instead of fillings songs in tunes you should fill 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

Sentiment Classification: Dealing with Negations

I really like this movie

I really **don't** like this movie

Negation changes the meaning of "like" to negative

Negation can also change negative to positive

- **Don't** dismiss this film
- **Doesn't** let us get bored

Sentiment Classification: Dealing with Negation

Simple baseline method: 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
```

Das, Sanjiv and Mike Chen. 2001. Yahoo! for Amazon: Extracting market sentiment from stock message boards. 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.

Similar Ways of 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.

Similar Ways of Accounting for Negation

The best performing method is considering two words following a negation keyword to be negated by that keyword. Overall accuracy of sentiment classification significantly increases with 5.5% and macro-level F1 significantly increases with 6.2%, compared to not accounting for negation (2k English movie review sentences).

- 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!*

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

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 are … these are also good.They are givi… it is also good because other phones a… low wait.

Lack of punctuation marks, grammatical errors

From: www.mouthshut.com

Direct vs. Comparative Opinions

Direct opinion

Sentiment is directly expressed, for example, on one or more attributes of an object, such as a product, a service or an event:

- "*The television has a clear screen with very high contrast*."

Comparative opinion

Relations expressing similarities or differences between two or more objects based on some of the shared attributes of the objects, e.g.

- "*The picture quality of camera x is **better than** that of y*"

Two types of comparatives and superlatives: by adding –er, -est suffix or by words like "more", "less", "better", "least"

Explicit vs. Implicit Opinions

Explicit opinion: an opinion (e.g., on an attribute of an entity) expressed explicitly in a subjective sentence, e.g.

- ‘*The screen of this smartphone is difficult to read*.’
- ‘*The story of this book is very interesting*.’

Implicit opinion: an opinion (e.g., on an attribute of an entity) implied in an objective sentence, e.g.

- ‘*The shop charges much more than I expected*.’
- ‘*This laptop computer is not suitable for people who want to bring it along with them to different places*.’

More challenges

- Ambiguous words
  - This music cd is literal waste of time (negative)
  - Please throw your waste material here (neutral)

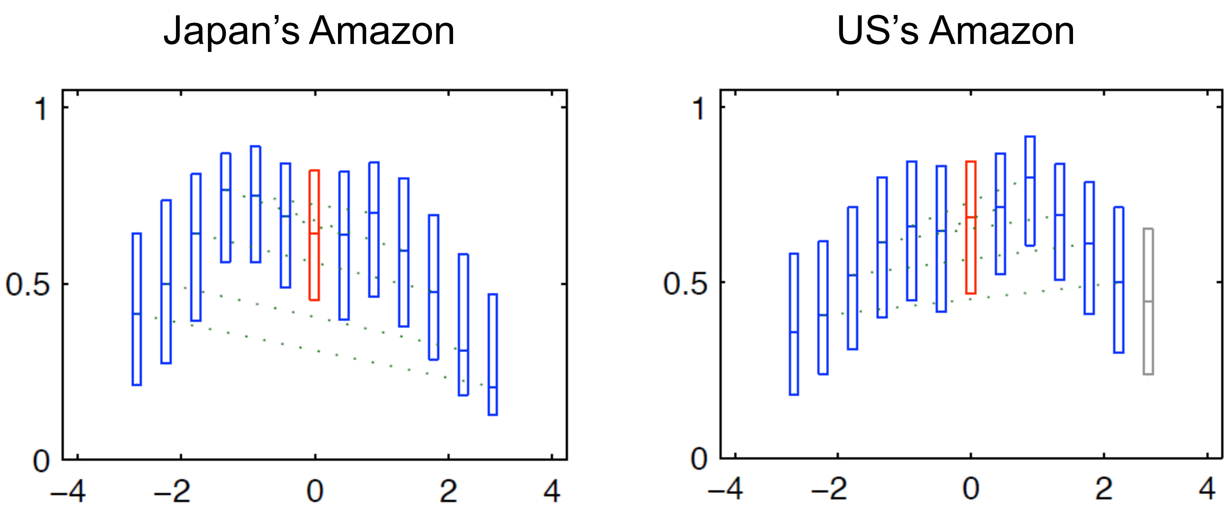
- Sarcasm detection and handling
  - “All the features you want - too bad they don’t work. :-P”

- (Almost) no or few resources and tools for low/scarce resource languages like Indian/African languages

Difficulty depending on Data Type

- **Difficulty depending on the data type**:
  - Tweets from Twitter are the easiest as being short and straight to the point
  - Reviews are next: entities are given and there is little noise
  - Discussions, comments, and blogs are most difficult as they contain multiple entities, comparisons, noise, sarcasm, etc.

Cultural Difference in Product Reviews?



Helpfulness vs. Deviation of a rating from the mean

Danescu-Niculescu-Mizil et al. How opinions are received by online communities: a case study on Amazon.com helpfulness votes. WWW 2008.

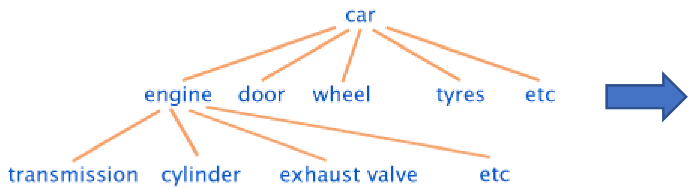
Sentiment Analysis

Closer Look into Issues in Detailed Product Sentiment Analysis

Product Sentiment Analysis Scenario: Entity, Attributes and Aspects

- Entity: object, product, service, person, event, etc.
  - Can have components or subcomponents: e.g., iPhone → battery, screen
  - These can form a tree
- Entity can have different entity expressions: e.g., Motorola, Moto, Mot
- Entity can have some attributes → e.g., size, weight, voice quality
  - So can its components

- Opinions can refer to the entity or to its components:
  - e.g., “I dislike iPhone”, “The voice quality of iPhone is poor”, “The battery is too weak”
- Aspect: components and their attributes (e.g., voice quality)
- Aspect expression: word of phrase in text indicating aspect (e.g., “sound”, “voice”, “voice quality”)
  - Explicit vs. implicit aspect expressions (e.g., “large” or “phone cannot easily fit to pocket” refer to the aspect “size”)



car, engine, door, wheel, tyres, transmission, cylinder, exhaust valve, etc.

Formal Model of Opinion

- Opinion is quintuple (e_i, a_{ij}, oo_{ijkl}, h_k, t_l):
  - e_i: name of entity
  - a_{ij}: an aspect of e_i (could be “general”)
  - oo_{ijkl}: opinion orientation or intensity
  - h_k: opinion holder
  - t_l: time when opinion is expressed

The components must correspond to each other

Without some of these components understanding of the opinion can be hindered…

Additional Details about the Model

- (e_i, a_{ij}) is called the opinion target
- Value of an aspect may indicate the opinion: “This drug causes my blood pressure to reach 200”.
- Reader’s viewpoint – different readers may feel differently
  - E.g., “*I am happy that Facebook stock price increased so much today*.”
  - Often neglected issue in the current state-of-the-art systems

Example

Mary W., 5 Nov 2009

"After discussing with my friends, I made up my mind and bought a MacBook Air a few days ago. It is really a cool machine. The screen is quite amazing. The battery is powerful, too. It is then much better than my old Dell notebook, which was a terrible laptop. However, my boss was disappointed with me as I did not tell him about this expense before. He also thought the laptop was too expensive, …"

- In quintuples:
  - (MacBook Air, GENERAL, +, Mary W., 5-11-2009)
  - (MacBook Air, screen, +, Mary W., 5-11-2009)
  - (MacBook Air, battery, +, Mary W., 5-11-2009)
  - (DELL XPS, GENERAL, -, Mary W., 5-11-2009)
  - (MacBook Air, price, -, Mary W.'s boss, 5-11-2009)

Need for entity finding and co-reference resolution

Tasks

1. Entity extraction and grouping to entity clusters
2. Aspect extraction and grouping into clusters (each aspect of entity e)
3. Opinion holder and time extraction
4. Aspect sentiment classification
5. Opinion quinduple generation

Sentiment Analysis touches many (most?) aspects of NLP

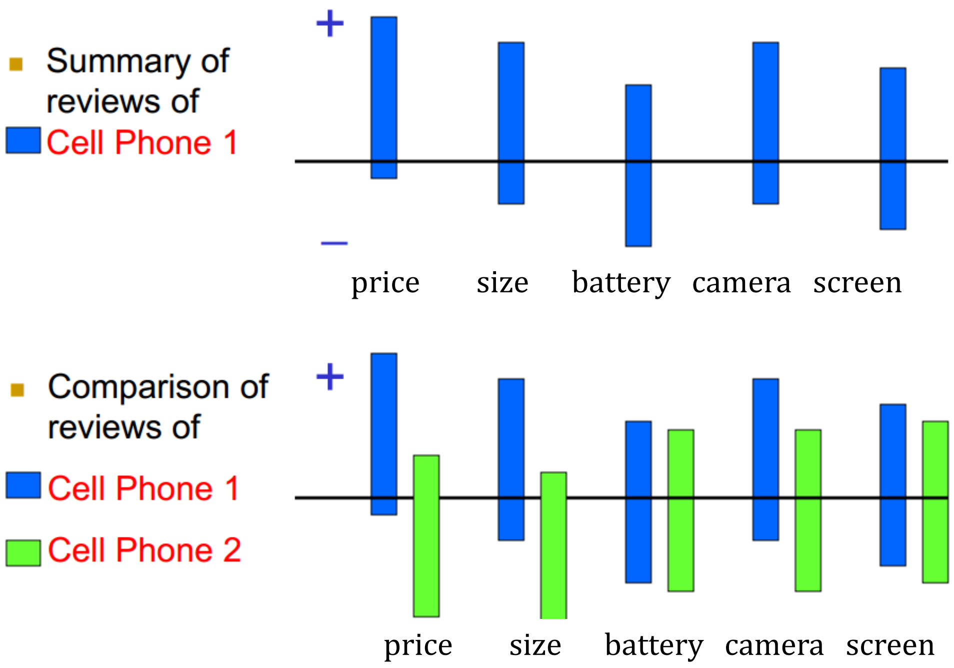
Objective

- Goal: From an opinionated document, discover all quintuples or, solve some simpler forms of the problem
  - E.g., sentiment classification at the document or sentence level
- Quintuples allow to move from unstructured text to structured data
- Traditional data and visualization tools can be used

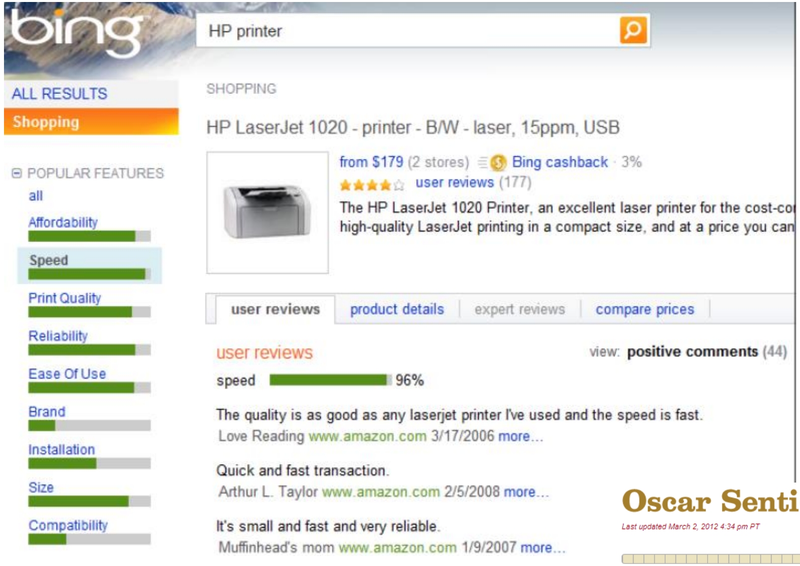
Summarizing Sentiment

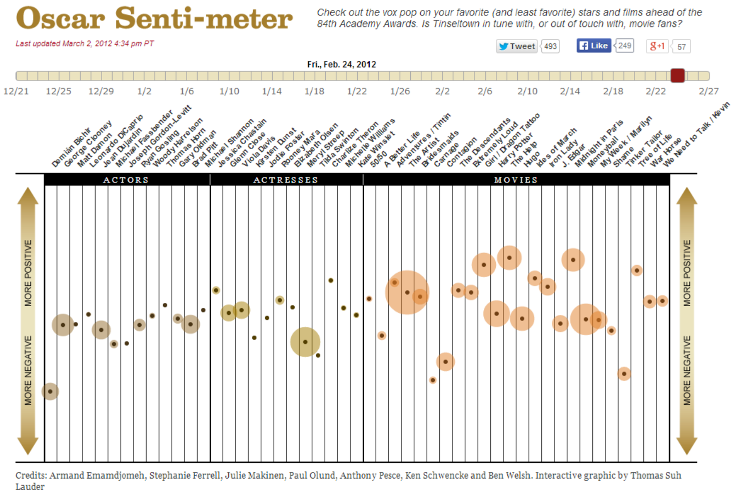
- One opinion is of limited use
- Necessary to capture some form of summary of many opinions
- Multi-document summarization variant
    - Documents are reviews, forums, news articles, comments, etc.

Opinion Visualization Examples



Bing Liu, Minqing Hu, and Junsheng Cheng. 2005. Opinion observer: analyzing and comparing opinions on the Web.
In Proceedings of the 14th international conference on World Wide Web (WWW '05). ACM, New York, NY, USA, 342-351





http://graphics.latimes.com/senti-meter/

Sentiment Analysis

Sentiment Lexicons

Sentiment Classification: Lexicons

- Sometimes we do not have enough labeled training data
- In that case, we can make use of pre-built word lists called **lexicons**
- Many types of publicly available lexicons

What is a Lexicon?

- A (usually hand-built) list of words that correspond to some meaning or class
- Possibly with numeric values
- The simplest sentiment lexicons just mark sentiment (positive or negative)

The General Inquirer

- 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
  - Also: Pleasure, Pain, Virtue, Vice, Motivation, Cognitive Orientation, etc.
  - Also: Academic, legal, military, politics, religion, etc.
- Free for research use

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

The General Inquirer

1	Entry	Source	Positiv	Negativ
2586	DAKOTA	Lvd		
2587	DAMAGE#1	H4Lvd		Negativ
2588	DAMAGE#2	H4Lvd		Negativ
2589	DAMN	H4Lvd		Negativ
2590	DAMNABLE	H4		Negativ
2591	DAMNED	H4		Negativ
2592	DAMP	H4Lvd		
2593	DANCE#1	H4Lvd	Positiv	
2594	DANCE#2	H4Lvd	Positiv	
2595	DANCE#3	H4Lvd	Positiv	
2596	DANCER	H4Lvd		
2597	DANGER	H4Lvd		Negativ
2598	DANGEROUS	H4Lvd		Negativ
2599	DANISH	Lvd		
2600	DARE	H4Lvd	Positiv	
2601	DARING	H4Lvd	Positiv	
2602	DARK	H4Lvd		Negativ
2603	DARKEN	H4Lvd		Negativ
2604	DARKNESS	H4Lvd		Negativ
2605	DARLING	H4Lvd	Positiv	

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

MPQA Subjectivity Cues Lexicon

- Home page: http://www.cs.pitt.edu/mpqa/subj_lexicon.html
- 6885 words from 8221 lemmas, annotated for intensity (strong/weak)
  - 2718 positive
  - 4912 negative

+ : *admirable, beautiful, confident, dazzling, ecstatic, favor, glee, great*

− : *awful, bad, bias, catastrophe, cheat, deny, envious, foul, harsh, hate*

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.

LIWC (Linguistic Inquiry and Word Count)

- 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*)

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

LIWC

- Over 70 lexicons for applications from social psychology etc.

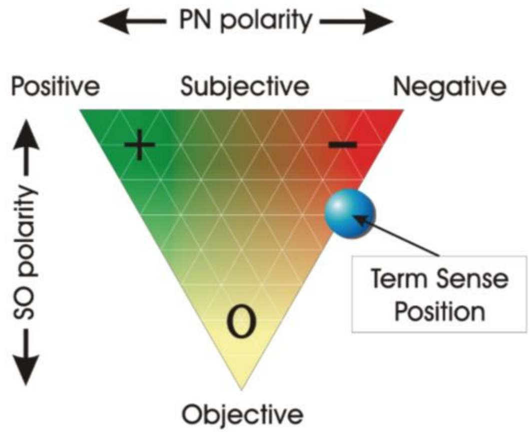
Positive Emotion	Negative Emotion	Insight	Inhibition	Family	Negate
appreciat*	anger*	aware*	avoid*	brother*	aren't
comfort*	bore*	believe	careful*	cousin*	cannot
great	cry	decid*	hesitat*	daughter*	didn't
happy	despair*	feel	limit*	family	neither
interest	fail*	figur*	oppos*	father*	never
joy*	fear	know	prevent*	grandf*	no
perfect*	griev*	knew	reluctan*	grandm*	nobod*
please*	hate*	means	safe*	husband	none
safe*	panic*	notice*	stop	mom	nor
terrific	suffers	recogni*	stubborn*	mother	nothing
value	terrify	sense	wait	niece*	nowhere
wow*	violent*	think	wary	wife	without

SentiWordNet

- https://github.com/aesuli/SentiWordNet
  http://www.nltk.org/howto/sentiwordnet.html
- 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



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

Disagreements between polarity lexicons

	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%)**

Christopher Potts, Sentiment Tutorial, 2011: http://sentiment.christopherpotts.net/lexicons.html

Words with consistent sentiment across lexicons

Positive	admire, amazing, assure, celebration, charm, eager, enthusiastic, excellent, fancy, fantastic, frolic, graceful, happy, joy, luck, majesty, mercy, nice, patience, perfect, proud, rejoice, relief, respect, satisfactorily, sensational, super, terrific, thank, vivid, wise, wonderful, zest
Negative	abominable, anger, anxious, bad, catastrophe, cheap, complaint, condescending, deceit, defective, disappointment, embarrass, fake, fear, filthy, fool, guilt, hate, idiot, inflict, lazy, miserable, mourn, nervous, objection, pest, plot, reject, scream, silly, terrible, unfriendly, vile, wicked

Advantages and Disadvantages of using Lexicons

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

Sentiment Analysis

Constructing Lexicons

Where do lexicons can come from?

- One "simple" method: crowdsourcing
- E.g., 10,000 words collected from earlier lexicons
- Labeled by workers on Amazon Mechanical Turk
  - "Turkers"
- 5 Turkers per hit

Mohammad, S. M. (2018a). Obtaining reliable human ratings of valence, arousal, and dominance for 20,000 english words. ACL

The AMT Hit

Q5. How much is *startle* associated with the emotion sadness? (For example, *failure* and *heart-break* are strongly associated with sadness.)

- *startle* is not associated with sadness
- *startle* is weakly associated with sadness
- *startle* is moderately associated with sadness
- *startle* is strongly associated with sadness

Q6. How much is *startle* associated with the emotion fear? (For example, *horror* and *scary* are strongly associated with fear.)

- Similar choices as in 4 and 5 above

Q7. How much is *startle* associated with the emotion anger? (For example, *rage* and *shouting* are strongly associated with anger.)

- Similar choices as in 4 and 5 above

Q8. How much is *startle* associated with the emotion trust? (For example, *faith* and *integrity* are strongly associated with trust.)

- Similar choices as in 4 and 5 above

Q9. How much is *startle* associated with the emotion disgust? (For example, *gross* and *cruelty* are strongly associated with disgust.)

- Similar choices as in 4 and 5 above

…

Issues to keep in mind with crowdsourcing lexicons

- Native (or very fluent) speakers
- Making the task clear for non-linguists or non computer scientists
- Paying minimum wage
- Eliminating poor quality results (or workers)

Learn word sentiment supervised by online review scores

- Review datasets
  - IMDB, Goodreads, Open Table, Amazon, Trip Advisor
- Each review has a score (1-5, 1-10, etc.)
- Count how many times each word occurs with each score
  - (and normalize)

Using review scores as supervision

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

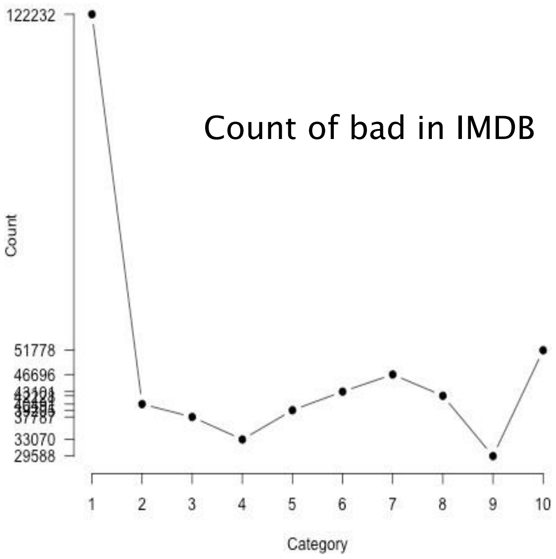
Online review data examples

	Movie review excerpts (IMDb)
10	A great movie. This film is just a wonderful experience. It's surreal, zany, witty and slapstick all at the same time. And terrific performances too.
1	This was probably the worst movie I have ever seen. The story went nowhere even though they could have done some interesting stuff with it.
	Restaurant review excerpts (Yelp)
5	The service was impeccable. The food was cooked and seasoned perfectly... The watermelon was perfectly square ... The grilled octopus was ... mouthwatering...
2	...it took a while to get our waters, we got our entree before our starter, and we never received silverware or napkins until we requested them...
	Book review excerpts (GoodReads)
1	I am going to try and stop being deceived by eye-catching titles. I so wanted to like this book and was so disappointed by it.
5	This book is hilarious. I would recommend it to anyone looking for a satirical read with a romantic twist and a narrator that keeps butting in
	Product review excerpts (Amazon)
5	The lid on this blender though is probably what I like the best about it... enables you to pour into something without even taking the lid off! ... the perfect pitcher! ... works fantastic.
1	I hate this blender... It is nearly impossible to get frozen fruit and ice to turn into a smoothie... You have to add a TON of liquid. I also wish it had a spout ...

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 we can not use raw counts
- Instead, **likelihood**:

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

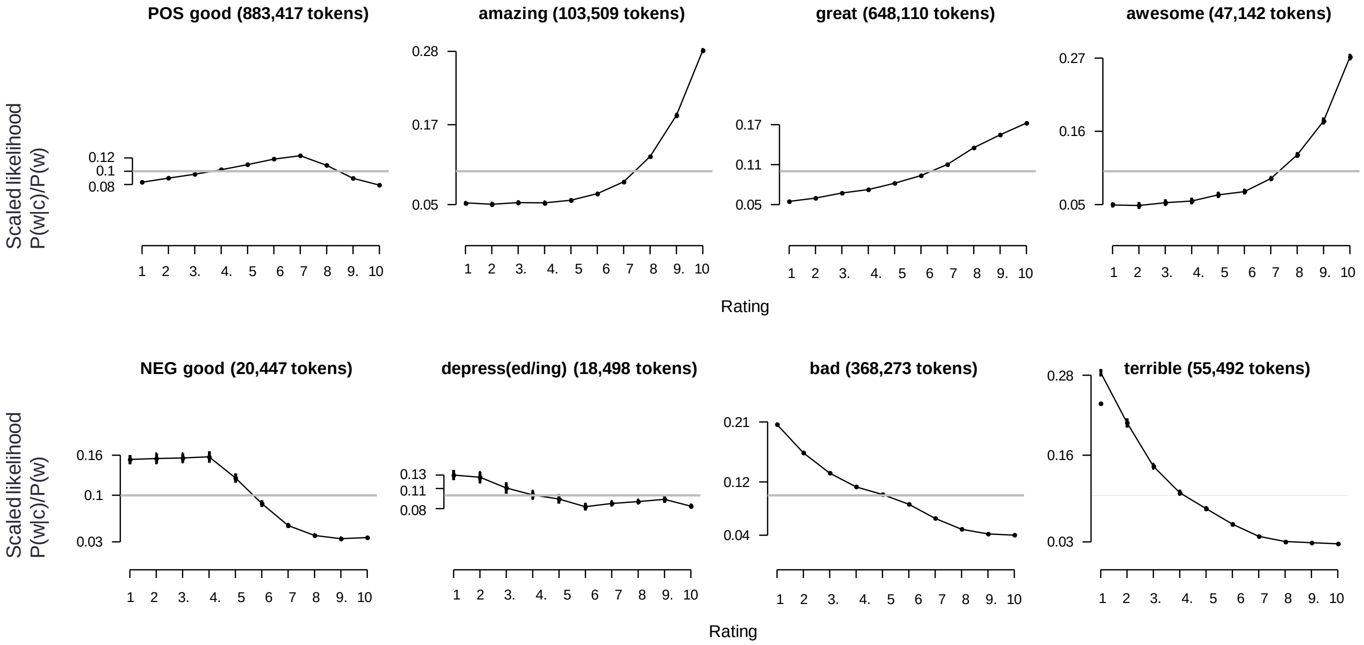


- Make them comparable between words
  - **Scaled likelihood**:

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

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

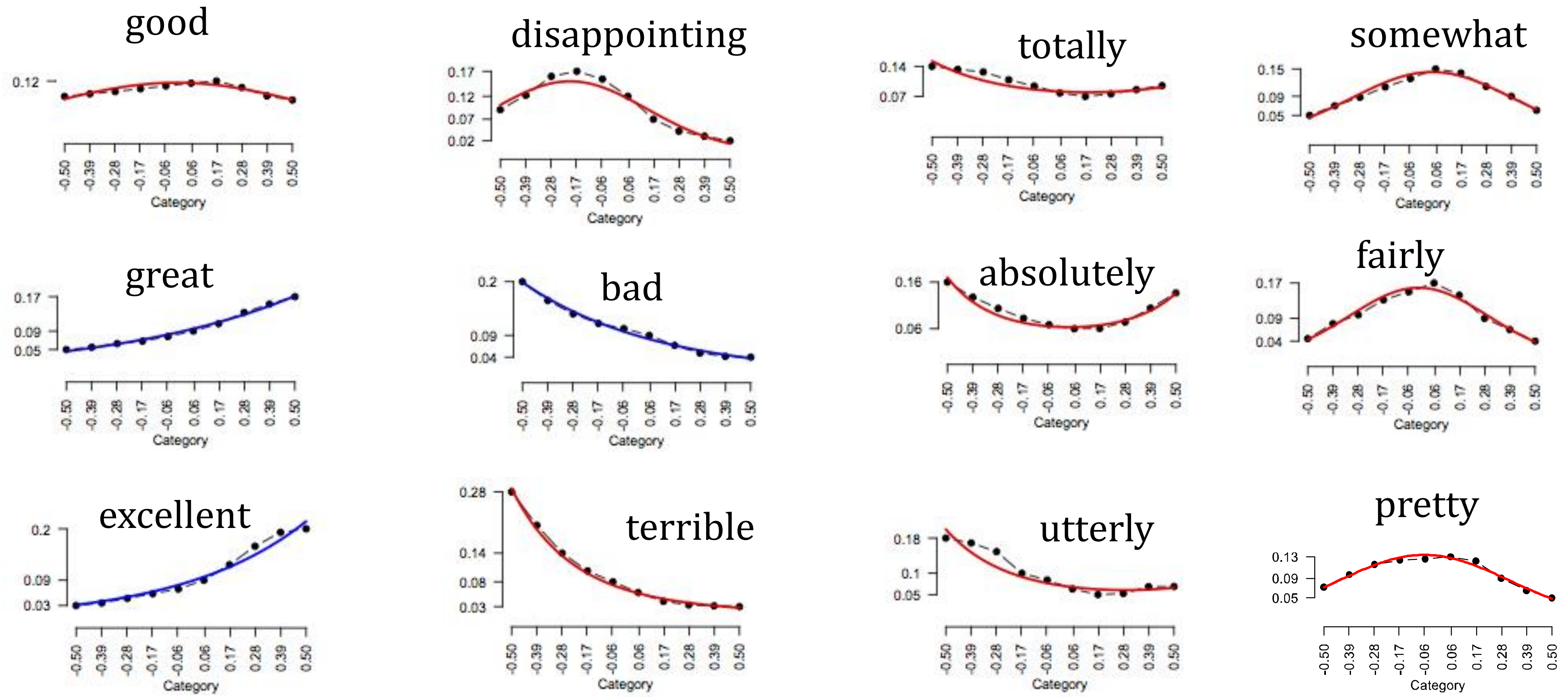
Analyzing the polarity of each word in IMDB



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

“Potts diagrams”

Positive scalars | **Negative scalars** | **Emphatics** | **Attenuators**

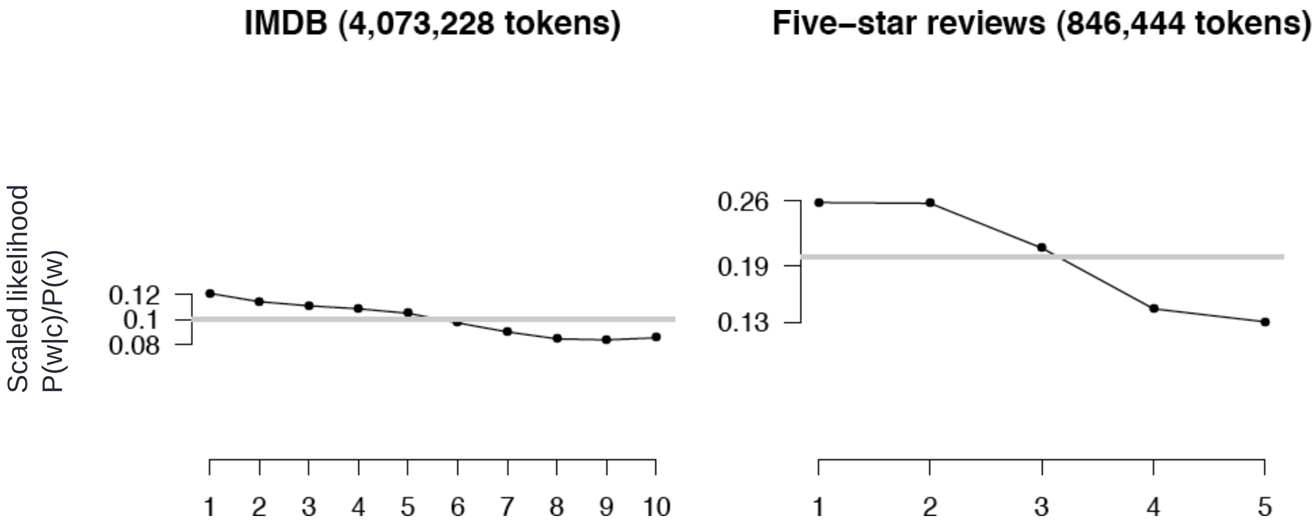


On important sentiment feature: Logical negation

- 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

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

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
- And **bootstrap** a lexicon

Hatzivassiloglou and McKeown intuition for identifying word polarity

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

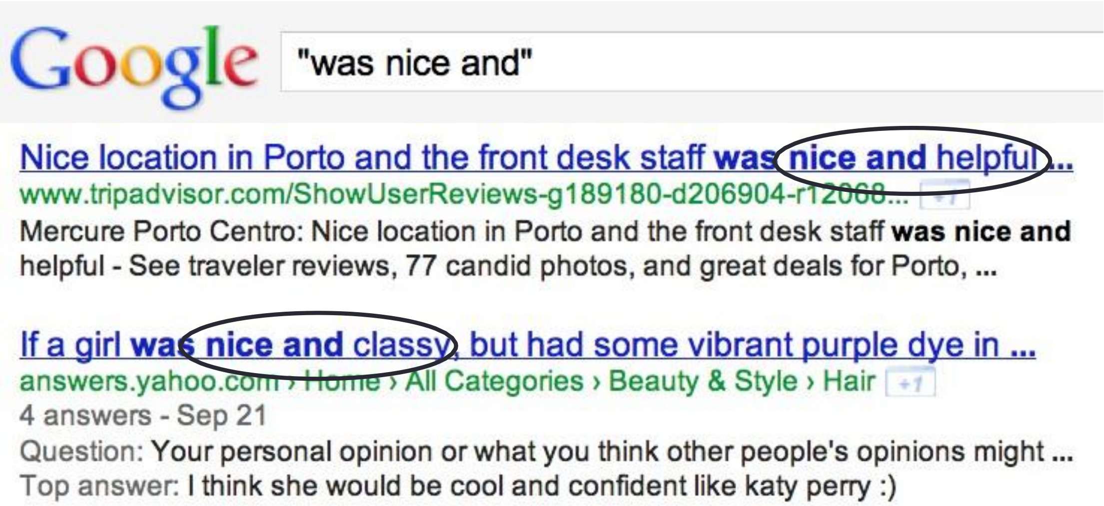
Vasileios Hatzivassiloglou and Kathleen R. McKeown. 1997. Predicting the Semantic Orientation of Adjectives. ACL, 174–181

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

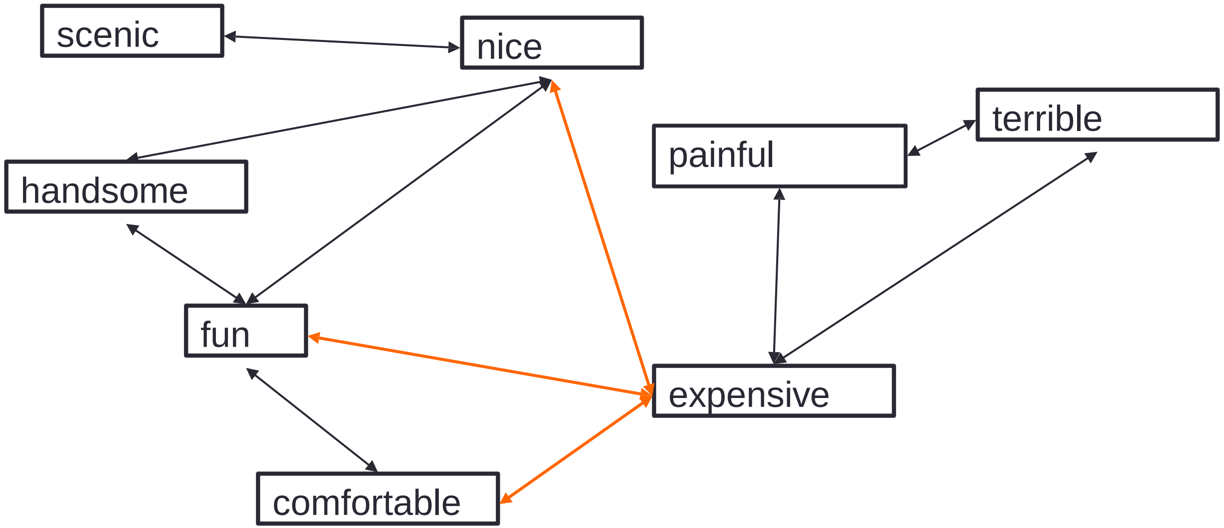


nice, helpful

nice, classy

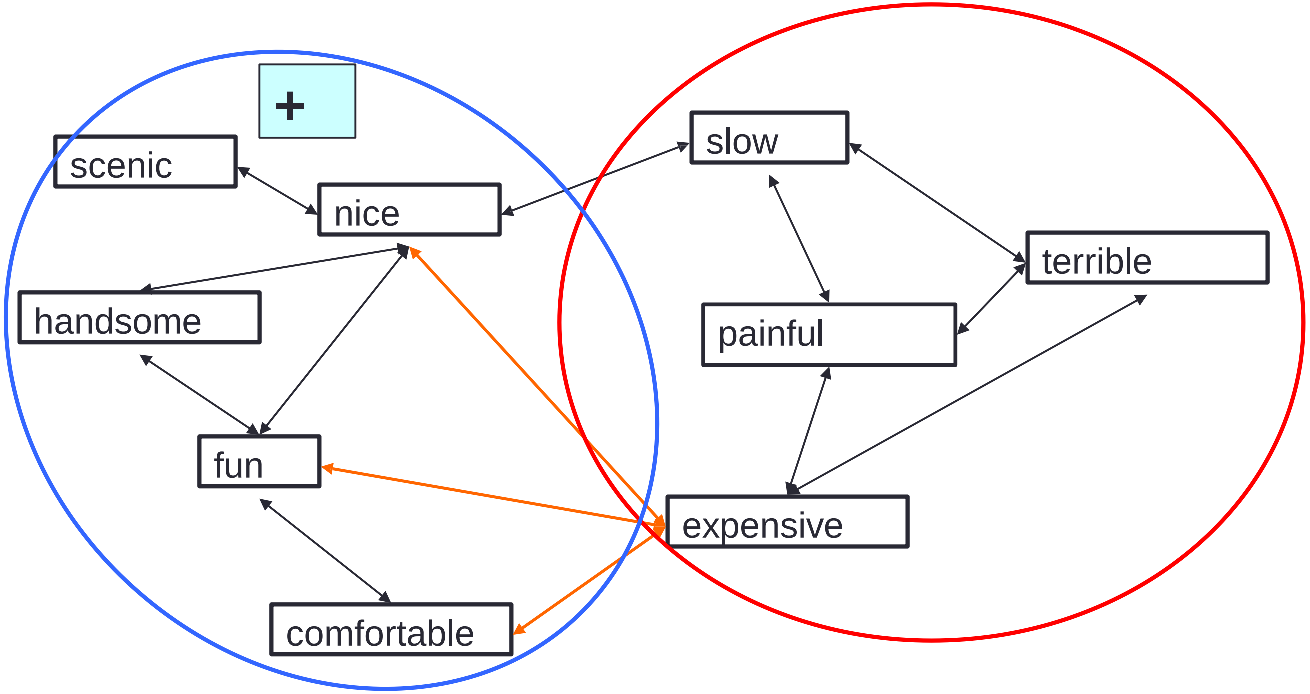
Hatzivassiloglou & McKeown 1997 Step 3

- A supervised learning algorithm builds a graph of adjectives linked by the same or different semantic orientation (polarity similarity)



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…

Turney Algorithm

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

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

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?

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

Estimating Pointwise Mutual Information

- Query search engine
  - P(word) estimated by `hits(word)/N`
  - P(word$_1$,word$_2$) by `hits(word1 NEAR word2)/N`

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

Does phrase appear more with "poor" or "excellent"?

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

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

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

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

Example 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

Example 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

Sentiment Analysis

Using Lexicons for Sentiment Analysis

Lexicons for detecting document affect: Simplest unsupervised method

- Sentiment:
  - Sum the weights of each positive word in the document
  - Sum the weights of each negative word in the document
  - Choose whichever value (positive or negative) has higher sum

Lexicons for detecting document affect: Simplest unsupervised method

$$f^{+} = \sum_{w \text{ s.t. } w \in positivelexicon} \theta_w^{+} count(w)$$

$$f^{-} = \sum_{w \text{ s.t. } w \in negativelexicon} \theta_w^{-} count(w)$$

```
Sentiment = +   if   f+ > f-
```

Lexicons for detecting document affect: Slightly more "complex" unsupervised method

$$f^+ = \sum_{w \text{ s.t. } w \in positivelexicon} \theta_w^+ count(w)$$

$$f^- = \sum_{w \text{ s.t. } w \in negativelexicon} \theta_w^- count(w)$$

$$sentiment = \begin{cases} + & \text{if } \frac{f^+}{f^-} > \lambda \\ - & \text{if } \frac{f^-}{f^+} > \lambda \\ 0 & \text{otherwise.} \end{cases}$$

Lexicons for detecting document affect: Simple supervised method

- Build a classifier
  - Predict sentiment (or emotion, or personality) given features
  - Use "counts of lexicon categories" as a features
  - Sample features, eg.:
    - LIWC category "cognition" had count of 7
    - NRC Emotion category [1] "anticipation" had count of 2
- Baseline
  - Instead use counts of **all** the words and bigrams in the training set
  - This is hard to beat but only works if the training and test sets are very similar
  - In real life, sometimes the test set is very different
    - Lexicons are useful in that situation

[1] https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm

Using Lexicons in Sentiment Classification

Add a feature that gets a count whenever a word from the lexicon occurs

- E.g., a feature called "this word occurs in the positive lexicon" or "this word occurs in the negative lexicon"

All positive words (*good, great, beautiful, wonderful*) or negative words count for that feature

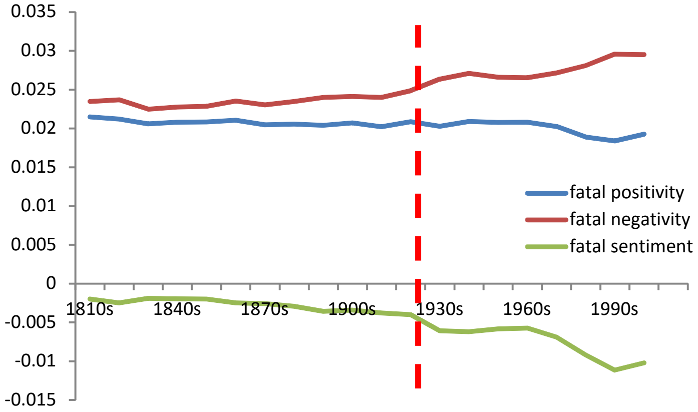
Using 1-2 features isn't as good as using all the words

- But when training data is sparse or is not representative of the test set, dense lexicon features can help

Example of using Lexicons: Tracking Changes in Word Sentiment over Time

- Studying evolution of word sentiment based on Google Book ngrams
- *Google Ngram (>5% books ever published, 0.3 trillion words)*
- Using sentiwordnet

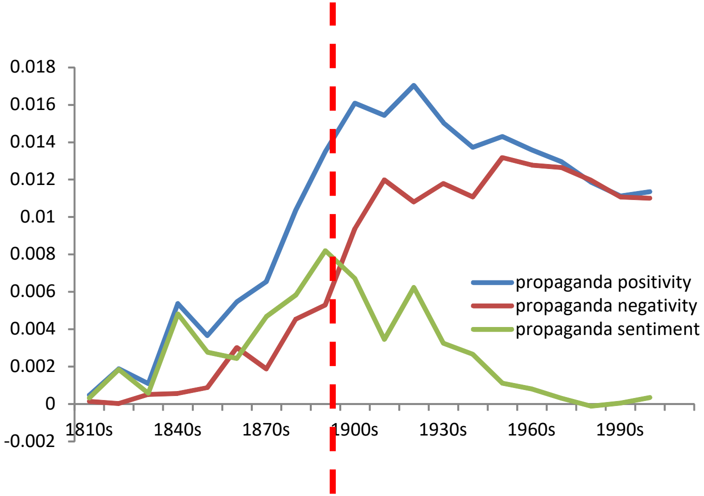
Adam Jatowt, Kevin Duh: A framework for analyzing semantic change of words across time. JCDL 2014: 229-238



“Fatal”

1820s	proved	consequences	blow
1830s	proved	consequences	prove
1840s	proved	consequences	blow
1850s	proved	consequences	prove
1860s	proved	blow	prove
1870s	proved	prove	blow
1880s	proved	prove	blow
1890s	proved	prove	blow
1900s	proved	prove	blow
1910s	cases	prove	proved
1920s	prove	proved	mistake
1930s	prove	proved	mistake
1940s	prove	cases	mistake
1950s	prove	cases	proved
1960s	prove	cases	blow
1970s	prove	disease	blow
1980s	disease	prove	blow
1990s	disease	blow	mistake
2000s	blow	mistake	proved

“Propaganda”



1820s	fide	congregation	rome
1830s	rome	fide	college
1840s	fide	congregation	rome
1850s	fide	college	congregation
1860s	fide	college	congregation
1870s	congregation	college	fide
1880s	fide	congregation	college
1890s	congregation	fide	rome
1900s	congregation	fide	active
1910s	german	austria	anti
1920s	anti	carried	purposes
1930s	anti	religious	purposes
1940s	anti	ministry	the
1950s	anti	purposes	agitation
1960s	anti	department	purposes
1970s	anti	campaign	agitation
1980s	anti	campaign	department
1990s	anti	department	campaign
2000s	anti	campaign	purposes

Note: “Congregatio de Propaganda **Fide**” (**Congregation for Propagation of the Faith**) set up by Pope Gregory XV in 1622 in order to spread the world of Christianity