What is Sentiment Analysis?
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.
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 shi

Reviews

Summary - Based on 377 reviews

<table>
<thead>
<tr>
<th>1 star</th>
<th>2</th>
<th>3</th>
<th>4 stars</th>
<th>5 stars</th>
</tr>
</thead>
</table>

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)

Average rating  ★★★★★ (144)

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

From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series. In ICWSM-2010
Twitter sentiment:

Bollen et al. (2011)

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

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

"united airlines" Search Save this search

Twitter Sentiment App

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

Sentiment analysis for "united airlines"

Sentiment by Percent

Sentiment by Count

jaljacobson: OMG... Could @United_airlines have worse customer service? W8g now 15 minutes
Posted 2 hours ago

12345clumsy6789: I hate United Airlines Ceiling!!! FuKn impossible to get my conduit in this dept
Posted 2 hours ago

EMLandPRGbelgium: EML/PRG fly with Q8 united airlines and 24seven to an exotic destination
Posted 2 hours ago

CountAdam: FANTASTIC customer service from United Airlines at XNA today. Is tweet more
Sentiment analysis has many other names

• Opinion extraction
• Opinion mining
• Sentiment mining
• Subjectivity analysis
Why sentiment analysis?

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

- **Emotion**: brief organically synchronized ... evaluation of a major event
  - angry, sad, joyful, fearful, ashamed, proud, ...
- **Mood**: diffuse non-caused low-intensity long-duration change in subjective feeling
  - cheerful, gloomy, irritable, depressed, ...
- **Interpersonal stances**: affective stance toward another person in a specific interaction
  - friendly, distant, cold, warm, supportive, ...
- **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, 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
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
Sentiment Analysis

A Baseline Algorithm
Sentiment Classification in Movie Reviews


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

• Data: *Polarity Data 2.0:*
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
  • 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
• Useful code:
  • [Christopher Potts sentiment tokenizer](https://example.com)
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
Add NOT_ to every word between negation and following punctuation:

didn’t NOT_like NOT_this NOT_movie but I
Reminder: Naïve Bayes

\[ c_{NB} = \arg\max_{c_j \in C} P(c_j) \prod_{i \in \text{positions}} P(w_i \mid c_j) \]

\[ \hat{P}(w \mid c) = \frac{\text{count}(w, c) + 1}{\text{count}(c) + |V|} \]
• 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
    
    $docs_j \leftarrow \text{all docs with class } = c_j$

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

• Calculate $P(w_k \mid c_j)$ terms
  • $Text_j \leftarrow \text{single doc containing all } docs_j$
  • For each word $w_k$ in *Vocabulary*
    
    $n_k \leftarrow \text{# of occurrences of } w_k \text{ in } Text_j$

    $P(w_k \mid c_j) \leftarrow \frac{n_k + \alpha}{N + \alpha|\text{Vocabulary}|}$
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 $= c_j$

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

- 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 $w$
  - $\text{Text}_j \leftarrow$ single doc containing all $docs_j$
  - For each word $w_k$ in *Vocabulary*
    
    $n_k \leftarrow$ # of occurrences of $w_k$ in $\text{Text}_j$

    $$P(w_k \mid c_j) \leftarrow \frac{n_k + \alpha}{N + \alpha |\text{Vocabulary}|}$$
Boolean Multinomial Naïve Bayes on a test document $d$

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

$$c_{NB} = \arg\max_{c_j \in C} P(c_j) \prod_{i \in \text{positions}} P(w_i | c_j)$$
## Normal vs. Boolean Multinomial NB

<table>
<thead>
<tr>
<th>Normal</th>
<th>Doc</th>
<th>Words</th>
<th>Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>1</td>
<td>Chinese Beijing Chinese</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Chinese Chinese Shanghai</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Chinese Macao</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>Tokyo Japan Chinese</td>
<td>j</td>
</tr>
<tr>
<td>Test</td>
<td>5</td>
<td>Chinese Chinese Chinese Tokyo Japan</td>
<td>?</td>
</tr>
</tbody>
</table>

<table>
<thead>
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<td>Test</td>
<td>5</td>
<td>Chinese Tokyo Japan</td>
<td>?</td>
</tr>
</tbody>
</table>
Binarized (Boolean feature)
Multinomial Naïve Bayes


• Binary seems to work better than full word counts

• Other possibility: \( \log(\text{freq}(w)) \)
Cross-Validation

- Break up data into 10 folds
  - (Equal positive and negative inside each fold?)
- For each fold
  - Choose the fold as a temporary test set
  - Train on 9 folds, compute performance on the test fold
- Report average performance of the 10 runs
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”
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 Analysis

Sentiment Lexicons
The General Inquirer


- Home page: [http://www.wjh.harvard.edu/~inquirer](http://www.wjh.harvard.edu/~inquirer)
- List of Categories: [http://www.wjh.harvard.edu/~inquirer/homecat.htm](http://www.wjh.harvard.edu/~inquirer/homecat.htm)
- Spreadsheet: [http://www.wjh.harvard.edu/~inquirer/inquirerbasic.xls](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, Motivation, etc.
- Free for Research Use
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
- \([\text{estimable}(J,3)]\) “may be computed or estimated”
  \[
  \text{Pos} \ 0 \quad \text{Neg} \ 0 \quad \text{Obj} \ 1
  \]
- \([\text{estimable}(J,1)]\) “deserving of respect or high regard”
  \[
  \text{Pos} \ .75 \quad \text{Neg} \ 0 \quad \text{Obj} \ .25
  \]
## Disagreements between polarity lexicons

Christopher Potts, [Sentiment Tutorial](https://www.fas.harvard.edu/~chrisp/sentiment/tutorial/), 2011

<table>
<thead>
<tr>
<th></th>
<th>Opinion Lexicon</th>
<th>General Inquirer</th>
<th>SentiWordNet</th>
<th>LIWC</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MPQA</strong></td>
<td>33/5402 (0.6%)</td>
<td>49/2867 (2%)</td>
<td>1127/4214 (27%)</td>
<td>12/363 (3%)</td>
</tr>
<tr>
<td><strong>Opinion Lexicon</strong></td>
<td>32/2411 (1%)</td>
<td></td>
<td>1004/3994 (25%)</td>
<td>9/403 (2%)</td>
</tr>
<tr>
<td><strong>General Inquirer</strong></td>
<td></td>
<td></td>
<td>520/2306 (23%)</td>
<td>1/204 (0.5%)</td>
</tr>
<tr>
<td><strong>SentiWordNet</strong></td>
<td></td>
<td></td>
<td></td>
<td>174/694 (25%)</td>
</tr>
<tr>
<td><strong>LIWC</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Analyzing the polarity of each word in IMDB


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

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

- Make them comparable between words
  - Scaled likelihood:

\[ \frac{P(w | c)}{P(w)} \]
Analyzing the polarity of each word in IMDB

Other sentiment feature: Logical negation


• Is logical negation (*no, not*) associated with negative sentiment?

• Potts experiment:
  • Count negation (*not, n’t, no, never*) in online reviews
  • Regress against the review rating
Potts 2011 Results:
More negation in negative sentiment

IMDB (4,073,228 tokens)  
Five–star reviews (846,444 tokens)

Scaled likelihood
$P(w|c)/P(w)$
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


• 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
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...
Step 2

- Expand seed set to conjoined adjectives

predicate example: nice, helpful

Google search: "was nice and"

nice, classy

Predicate example:

- "was nice and classy, but had some vibrant purple dye in"
- "nice, classy"
Supervised classifier assigns “polarity similarity” to each word pair, resulting in a graph:

- nice
- fair
- classy
- helpful
- brutal
- corrupt
- irrational
Hatzivassiloglou & McKeown 1997

Step 4

- Clustering for partitioning the graph into two
Output polarity lexicon

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

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

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

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

Extract two-word phrases with adjectives

<table>
<thead>
<tr>
<th>First Word</th>
<th>Second Word</th>
<th>Third Word (not extracted)</th>
</tr>
</thead>
<tbody>
<tr>
<td>JJ</td>
<td>NN or NNS</td>
<td>anything</td>
</tr>
<tr>
<td>RB, RBR, RBS</td>
<td>JJ</td>
<td>Not NN nor NNS</td>
</tr>
<tr>
<td>JJ</td>
<td>JJ</td>
<td>Not NN or NNS</td>
</tr>
<tr>
<td>NN or NNS</td>
<td>JJ</td>
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<tr>
<td>RB, RBR, or RBS</td>
<td>VB, VBD, VBN, VBG</td>
<td>anything</td>
</tr>
</tbody>
</table>
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

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

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

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

\[
\text{PMI}(\text{word}_1, \text{word}_2) = \log_2 \frac{P(\text{word}_1, \text{word}_2)}{P(\text{word}_1)P(\text{word}_2)}
\]
How to Estimate Pointwise Mutual Information

- Query search engine (Altavista)
  - \( P(\text{word}) \) estimated by \( \frac{\text{hits(\text{word})}}{N} \)
  - \( P(\text{word}_1, \text{word}_2) \) by \( \frac{\text{hits(\text{word}_1 \ \text{NEAR} \ \text{word}_2)}}{N^2} \)

\[
\text{PMI}(\text{word}_1, \text{word}_2) = \log_2 \frac{\text{hits}(\text{word}_1 \ \text{NEAR} \ \text{word}_2)}{\text{hits}(\text{word}_1) \times \text{hits}(\text{word}_2)}
\]
Does phrase appear more with “poor” or “excellent”? 

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

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

\[ = \log_2 \left( \frac{\text{hits}(\text{phrase NEAR } "excellent")}{\text{hits}(\text{phrase})\text{hits}("excellent")} \cdot \frac{\text{hits}(\text{phrase NEAR } "poor")}{\text{hits}(\text{phrase})\text{hits}("poor")} \right) \]
# Phrases from a thumbs-up review

<table>
<thead>
<tr>
<th>Phrase</th>
<th>POS tags</th>
<th>Polarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>online service</td>
<td>JJ NN</td>
<td>2.8</td>
</tr>
<tr>
<td>online experience</td>
<td>JJ NN</td>
<td>2.3</td>
</tr>
<tr>
<td>direct deposit</td>
<td>JJ NN</td>
<td>1.3</td>
</tr>
<tr>
<td>local branch</td>
<td>JJ NN</td>
<td>0.42</td>
</tr>
<tr>
<td>...</td>
<td></td>
<td></td>
</tr>
<tr>
<td>low fees</td>
<td>JJ NNS</td>
<td>0.33</td>
</tr>
<tr>
<td>true service</td>
<td>JJ NN</td>
<td>-0.73</td>
</tr>
<tr>
<td>other bank</td>
<td>JJ NN</td>
<td>-0.85</td>
</tr>
<tr>
<td>inconveniently located</td>
<td>JJ NN</td>
<td>-1.5</td>
</tr>
</tbody>
</table>

**Average** 0.32
### Phrases from a thumbs-down review

<table>
<thead>
<tr>
<th>Phrase</th>
<th>POS tags</th>
<th>Polarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>direct deposits</td>
<td>JJ NNS</td>
<td>5.8</td>
</tr>
<tr>
<td>online web</td>
<td>JJ NN</td>
<td>1.9</td>
</tr>
<tr>
<td>very handy</td>
<td>RB JJ</td>
<td>1.4</td>
</tr>
<tr>
<td>...</td>
<td></td>
<td></td>
</tr>
<tr>
<td>virtual monopoly</td>
<td>JJ NN</td>
<td>-2.0</td>
</tr>
<tr>
<td>lesser evil</td>
<td>RBR JJ</td>
<td>-2.3</td>
</tr>
<tr>
<td>other problems</td>
<td>JJ NNS</td>
<td>-2.8</td>
</tr>
<tr>
<td>low funds</td>
<td>JJ NNS</td>
<td>-6.8</td>
</tr>
<tr>
<td>unethical practices</td>
<td>JJ NNS</td>
<td>-8.5</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td><strong>-1.2</strong></td>
</tr>
</tbody>
</table>
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
Using WordNet to learn polarity


- WordNet: online thesaurus.
- Create positive (“good”) and negative seed-words (“terrible”)
- Find Synonyms and Antonyms
  - Positive Set: Add synonyms of positive words (“well”) and antonyms of negative words
  - Negative Set: Add synonyms of negative words (“awful”) and antonyms of positive words (“evil”)
- Repeat, following chains of synonyms
- Filter
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
Sentiment Analysis

Other Sentiment Tasks
Finding sentiment of a sentence

- Important for finding aspects or attributes
  - Target of sentiment

- The food was great but the service was awful
Finding aspect/attribute/target of sentiment


- 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

<table>
<thead>
<tr>
<th>Hotel</th>
<th>hotel, buffet, pool, resort, beds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Children’s Barber</td>
<td>haircut, job, experience, kids</td>
</tr>
<tr>
<td>Greek Restaurant</td>
<td>food, wine, service, appetizer, lamb</td>
</tr>
<tr>
<td>Department Store</td>
<td>selection, department, sales, shop, clothing</td>
</tr>
</tbody>
</table>
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

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
Baseline methods assume 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 unbalancing 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
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 Ordinal regression
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
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*
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
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  …