CS 6120/CS4120: Natural Language Processing

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College of Computer and Information Science
Northeastern University
Webpage: www.ccs.neu.edu/home/luwang
Presentation and report

• Problem Description (10 point)
  What is the task?
  System input and output
  Examples will be helpful

• Reference/Related work (20 points)
  Put your work in context: what has been done before? You need to have reference!
  What’s new in your work?

• Methodology: What you have done (30 points)
  Preprocessing of the data
  What are your data? Features used? What are effective, and what are not?
  What methods do you experiment with? And why do you think they’re reasonable and suitable for the task?

• Experiments (40 points)
  Datasets size, train/test/development
  Evaluation metrics: what are used and are they proper to calibrate system performance?
  Baselines: what are they?
  Results, tables, figures, etc
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 sheets

Reviews

Summary - Based on 377 reviews

<table>
<thead>
<tr>
<th></th>
<th>1 star</th>
<th>2</th>
<th>3</th>
<th>4 stars</th>
<th>5 stars</th>
</tr>
</thead>
<tbody>
<tr>
<td>ease of use</td>
<td></td>
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<tr>
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<tr>
<td>colors</td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

What people are saying

- "This was very easy to setup to four computers."
- "Appreciate good quality at a fair price."
- "Overall pretty easy setup."
- "I DO like honest tech support people."
- "Pretty Paper weight."
- "Photos were fair on the high quality mode."
- "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)

[Image of printer]

Average rating ★★★★★ (144)
★★★★☆ (55)
★★★★☆ (54)
★★★★☆ (10)
★★★★☆ (6)
★★★★☆ (23)
★★★★☆ (0)

Most mentioned
Performance (57)
Ease of Use (43)
Print Speed (39)
Connectivity (31)

Show reviews by source
Best Buy (140)
CNET (5)
Amazon.com (3)
Twitter sentiment versus Gallup Poll of Consumer Confidence


window = 15, $r = 0.804$

Sept. 15, 2008: Lehman collapse, AIG bailout
Feb 2009: Stock market bottoms out, begins recovery

Gallup Poll
Twitter Sentiment
Twitter sentiment:

Target Sentiment on Twitter

- **Twitter Sentiment App**
- Alec Go, Richa Bhayani, Lei Huang. 2009. Twitter Sentiment Classification using Distant Supervision
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, elated
- **Mood**: diffuse non-caused low-intensity long-duration change in subjective feeling
  - cheerful, gloomy, irritable, listless, depressed, buoyant
- **Interpersonal stances**: affective stance toward another person in a specific interaction
  - friendly, flirtatious, distant, cold, warm, supportive, contemptuous
- **Attitudes**: enduring, affectively colored beliefs, dispositions towards objects or persons
  - liking, loving, hating, valuing, desiring
- **Personality traits**: stable personality dispositions and typical behavior tendencies
  - nervous, anxious, reckless, morose, hostile, jealous
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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 Classification in Movie Reviews


- 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](http://www.cs.cornell.edu/people/pabo/movie-review-data)
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

Useful code:
- Christopher Potts sentiment tokenizer
- Brendan O’Connor twitter tokenizer
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

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

Reminder: Naïve Bayes

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

\[
\hat{P}(w | c) = \frac{\text{count}(w, c) + 1}{\text{count}(c) + |V|}
\]
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 $= c_j$

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

- 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 $w$
  - $Text_j \leftarrow$ single doc containing all $docs_j$
  - For each word $w_k$ in *Vocabulary*
    
    $n_k \leftarrow$ # of occurrences of $w_k$ in $Text_j$

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

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

$$c_{NB} = \arg\max_{c_j \in C} P(c_j) \prod_{i \in \text{positions}} P(w_i \mid c_j)$$
## 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>
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<td></td>
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<td>Chinese Macao</td>
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</tr>
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<td></td>
<td>4</td>
<td>Tokyo Japan Chinese</td>
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</tr>
<tr>
<td>Test</td>
<td>5</td>
<td>Chinese Chinese Chinese Tokyo Japan</td>
<td>?</td>
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</table>

<table>
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</tr>
<tr>
<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 5 folds**
  • (Equal positive and negative inside each fold?)

• **For each fold**
  • Choose the fold as a temporary test set
  • Train on 4 folds, compute performance on the test fold

• **Report average performance of the 4 runs**
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”
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


- 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, Virtue, Vice, Motivation, Cognitive Orientation, etc
- Free for Research Use
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*)

• Not free though!
MPQA Subjectivity Cues Lexicon


- 6885 words from 8221 lemmas
  - 2718 positive
  - 4912 negative
- Each word annotated for intensity (strong, weak)
- GNU GPL
Bing Liu Opinion Lexicon


• [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/](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”
  - Pos 0  Neg 0  Obj 1
- \[\text{estimable}(J,1)\] “deserving of respect or high regard”
  - Pos .75  Neg 0  Obj .25
Disagreements between polarity lexicons

Christopher Potts, *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></td>
<td>32/2411 (1%)</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>
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</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:
  \[ P(w \mid c) = \frac{f(w,c)}{\sum_{w \in c} f(w,c)} \]
• Make them comparable between words
  • Scaled likelihood:
  \[ \frac{P(w \mid c)}{P(w)} \]
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)
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
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

```
Google
"was nice and"
```

- Nice location in Porto and the front desk staff was nice and helpful...
- If a girl was nice and classy, but had some vibrant purple dye in...

- nice, helpful
- nice, classy
Hatzivassiloglou & McKeown 1997
Step 3

• Supervised classifier assigns “polarity similarity” to each word pair, resulting in graph:

```
                    brutal
                    /\     \
               helpful       corrupt
            /     \              /     \
        nice            unfair     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>
<td>Nor NN nor NNS</td>
</tr>
<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?

\[ PMI(X,Y) = \log_2 \frac{P(x,y)}{P(x)P(y)} \]
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 $\frac{\text{hits(\text{word}_1 \ \text{NEAR} \ \text{word}_2)}}{N}$
    • (More correctly the bigram denominator should be $kN$, because there are a total of $N$ consecutive bigrams $(\text{word}_1, \text{word}_2)$, but $kN$ bigrams that are $k$ words apart, but we just use $N$ on the rest of this slide and the next.)

$$\text{PMI(\text{word}_1, \text{word}_2)} = \log_2 \frac{\frac{1}{N} \text{hits(\text{word}_1 \ \text{NEAR} \ \text{word}_2)}}{\frac{1}{N} \text{hits(\text{word}_1)} \frac{1}{N} \text{hits(\text{word}_2)}}$$
Does phrase appear more with “poor” or “excellent”?

\[
\text{Polarity}(\text{phrase}) = \text{PMI}(\text{phrase}, "excellent") - \text{PMI}(\text{phrase}, "poor") \\
= \log_2 \frac{\frac{1}{N} \text{hits}(\text{phrase NEAR "excellent"})}{\frac{1}{N} \text{hits}(\text{phrase}) \frac{1}{N} \text{hits("excellent")}} - \log_2 \frac{\frac{1}{N} \text{hits}(\text{phrase NEAR "poor"})}{\frac{1}{N} \text{hits}(\text{phrase}) \frac{1}{N} \text{hits("poor")}} \\
= \log_2 \frac{\text{hits}(\text{phrase NEAR "excellent"})}{\text{hits}(\text{phrase}) \text{hits("excellent")}} \frac{\text{hits}(\text{phrase}) \text{hits("poor")}}{\text{hits}(\text{phrase NEAR "poor"})} \\
= \log_2 \left( \frac{\text{hits}(\text{phrase NEAR "excellent"}) \text{hits("poor")}}{\text{hits}(\text{phrase NEAR "poor"}) \text{hits("excellent")}} \right)
\]
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>low fees</td>
<td>JJ NNS</td>
<td>0.33</td>
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<tr>
<td>true service</td>
<td>JJ NN</td>
<td>-0.73</td>
</tr>
<tr>
<td>other bank</td>
<td>JJ NN</td>
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</tr>
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<td>inconveniently located</td>
<td>JJ NN</td>
<td>-1.5</td>
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<tr>
<td><strong>Average</strong></td>
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<td><strong>0.32</strong></td>
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Phrases from a thumbs-down review

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<th>Phrase</th>
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</tr>
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<td>JJ NN</td>
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<tr>
<td>very handy</td>
<td>RB JJ</td>
<td>1.4</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 (covered in later lecture).
- 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

• Use seeds and semi-supervised learning to induce lexicons
Other Sentiment Tasks
• 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>Casino</th>
<th>casino, 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
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
Emotions
Scherer’s typology of affective states

**Emotion**: relatively brief episode of synchronized response of all or most organismic subsystems in response to the evaluation of an event as being of major significance

- angry, sad, joyful, fearful, ashamed, proud, desperate

**Mood**: diffuse affect state ...change in subjective feeling, of low intensity but relatively long duration, often without apparent cause

- cheerful, gloomy, irritable, listless, depressed, buoyant

**Interpersonal stance**: affective stance taken toward another person in a specific interaction, coloring the interpersonal exchange

- distant, cold, warm, supportive, contemptuous

**Attitudes**: relatively enduring, affectively colored beliefs, preferences predispositions towards objects or persons

- liking, loving, hating, valuing, desiring

**Personality traits**: emotionally laden, stable personality dispositions and behavior tendencies, typical for a person

- nervous, anxious, reckless, morose, hostile, envious, jealous
Two families of theories of emotion

• Atomic basic emotions
  • A finite list of 6 or 8, from which others are generated

• Dimensions of emotion
  • Valence (positive negative)
  • Arousal (strong, weak)
  • Control
Ekman’s 6 basic emotions: 
Surprise, happiness, anger, fear, disgust, sadness
Valence/Arousal Dimensions

- High arousal, low pleasure: anger
- Low arousal, low pleasure: sadness
- High arousal, high pleasure: excitement
- Low arousal, high pleasure: relaxation
## Atomic units vs. Dimensions

### Distinctive
- Emotions are units.
- Limited number of basic emotions.
- Basic emotions are innate and universal

### Dimensional
- Emotions are dimensions.
- Limited # of labels but unlimited number of emotions.
- Emotions are culturally learned.

*Adapted from Julia Braverman*
One emotion lexicon from each paradigm!

1. 8 basic emotions:
   • NRC Word-Emotion Association Lexicon (Mohammad and Turney 2011)
2. Dimensions of valence/arousal/dominance
   • Warriner, A. B., Kuperman, V., and Brysbaert, M. (2013)

• Both built using Amazon Mechanical Turk
Plutchick’s wheel of emotion

- 8 basic emotions
- in four opposing pairs:
  - joy–sadness
  - anger–fear
  - trust–disgust
  - anticipation–surprise
NRC Word-Emotion Association Lexicon
Mohammad and Turney 2011

- 10,000 words chosen mainly from earlier lexicons
- Labeled by Amazon Mechanical Turk
- 5 Turkers per hit
- Give Turkers an idea of the relevant sense of the word
- Result:

<table>
<thead>
<tr>
<th>Word</th>
<th>Emotion</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>amazingly anger</td>
<td></td>
<td>0</td>
</tr>
</tbody>
</table>
  | amazingly ...
  | amazingly ...
  | amazingly ...
  | amazingly ...
  | amazingly ...
  | amazingly ...
  | amazingly ...
  | amazingly ...
  | amazingly ...
  | amazingly ...
  | amazingly ...
  | amazingly ...

<table>
<thead>
<tr>
<th>EmoLex</th>
<th># of terms</th>
</tr>
</thead>
<tbody>
<tr>
<td>EmoLex-Uni:</td>
<td></td>
</tr>
<tr>
<td>Unigrams from Macquarie Thesaurus:</td>
<td></td>
</tr>
<tr>
<td>adjectives</td>
<td>200</td>
</tr>
<tr>
<td>adverbs</td>
<td>200</td>
</tr>
<tr>
<td>nouns</td>
<td>200</td>
</tr>
<tr>
<td>verbs</td>
<td>200</td>
</tr>
<tr>
<td>EmoLex-Bi:</td>
<td></td>
</tr>
<tr>
<td>Bigrams from Macquarie Thesaurus</td>
<td></td>
</tr>
<tr>
<td>adjectives</td>
<td>200</td>
</tr>
<tr>
<td>adverbs</td>
<td>187</td>
</tr>
<tr>
<td>nouns</td>
<td>200</td>
</tr>
<tr>
<td>verbs</td>
<td>200</td>
</tr>
<tr>
<td>EmoLex-GI:</td>
<td></td>
</tr>
<tr>
<td>Terms from General Inquirer</td>
<td></td>
</tr>
<tr>
<td>negative terms</td>
<td>2119</td>
</tr>
<tr>
<td>neutral terms</td>
<td>4226</td>
</tr>
<tr>
<td>positive terms</td>
<td>1787</td>
</tr>
<tr>
<td>EmoLex-WAL:</td>
<td></td>
</tr>
<tr>
<td>Terms from WordNet Affect Lexicon</td>
<td></td>
</tr>
<tr>
<td>anger terms</td>
<td>165</td>
</tr>
<tr>
<td>disgust terms</td>
<td>37</td>
</tr>
<tr>
<td>fear terms</td>
<td>100</td>
</tr>
<tr>
<td>joy terms</td>
<td>165</td>
</tr>
<tr>
<td>sadness terms</td>
<td>120</td>
</tr>
<tr>
<td>surprise terms</td>
<td>53</td>
</tr>
<tr>
<td>Union</td>
<td>10170</td>
</tr>
</tbody>
</table>
The AMT Hit

Prompt word: startle

Q1. Which word is closest in meaning (most related) to startle?
- automobile
- shake
- honesty
- entertain

Q2. How positive (good, praising) is the word startle?
- startle is not positive
- startle is weakly positive
- startle is moderately positive
- startle is strongly positive

Q3. How negative (bad, criticizing) is the word startle?
- startle is not negative
- startle is weakly negative
- startle is moderately negative
- startle is strongly negative

Q4. How much is startle associated with the emotion joy? (For example, happy and fun are strongly associated with joy.)
- startle is not associated with joy
- startle is weakly associated with joy
- startle is moderately associated with joy
- startle is strongly associated with joy

Q5. How much is startle associated with the emotion sadness? (For example, failure and heartbreak 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

...
Lexicon of valence, arousal, and dominance


- Supplementary data: This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivs 3.0 Unported License.

- Ratings for 14,000 words for emotional dimensions:
  - **valence** (the pleasantness of the stimulus)
  - **arousal** (the intensity of emotion provoked by the stimulus)
  - **dominance** (the degree of control exerted by the stimulus)
Lexicon of valence, arousal, and dominance

• **valence** (the pleasantness of the stimulus)
  9: happy, pleased, satisfied, contented, hopeful
  1: unhappy, annoyed, unsatisfied, melancholic, despaired, or bored

• **arousal** (the intensity of emotion provoked by the stimulus)
  9: stimulated, excited, frenzied, jittery, wide-awake, or aroused
  1: relaxed, calm, sluggish, dull, sleepy, or unaroused;

• **dominance** (the degree of control exerted by the stimulus)
  9: in control, influential, important, dominant, autonomous, or controlling
  1: controlled, influenced, cared-for, awed, submissive, or guided

• Again produced by AMT
Lexicon of valence, arousal, and dominance: Examples

<table>
<thead>
<tr>
<th>Valence</th>
<th>Arousal</th>
<th>Dominance</th>
</tr>
</thead>
<tbody>
<tr>
<td>vacation</td>
<td>8.53</td>
<td>rampage</td>
</tr>
<tr>
<td>happy</td>
<td>8.47</td>
<td>tornado</td>
</tr>
<tr>
<td>whistle</td>
<td>5.7</td>
<td>zucchini</td>
</tr>
<tr>
<td>conscious</td>
<td>5.53</td>
<td>dressy</td>
</tr>
<tr>
<td>torture</td>
<td>1.4</td>
<td>dull</td>
</tr>
</tbody>
</table>
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

• **Emotion:**
  • Do the same for each emotion lexicon
Lexicons for detecting document affect: Simplest supervised method

• Build a classifier
  • Predict sentiment (or emotion, or personality) given features
  • Use “counts of lexicon categories” as a features
  • Sample features:
    • LIWC category “cognition” had count of 7
    • NRC Emotion category “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
Personality
Scherer’s typology of affective states

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  - angry, sad, joyful, fearful, ashamed, proud, desperate

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**Personality traits**: emotionally laden, stable personality dispositions and behavior tendencies, typical for a person
  - nervous, anxious, reckless, morose, hostile, envious, jealous
Personality

• The internal structures and propensities that explain a person’s characteristic patterns of thought, emotion, and behavior.
• Personality captures what people are like.
The Big Five Dimensions of Personality

**Extraversion vs. Introversion**
- sociable, assertive, playful vs. aloof, reserved, shy

**Emotional stability vs. Neuroticism**
- calm, unemotional vs. insecure, anxious

**Agreeableness vs. Disagreeable**
- friendly, cooperative vs. antagonistic, faultfinding

**Conscientiousness vs. Unconscientious**
- self-disciplined, organised vs. inefficient, careless

**Openness to experience**
- intellectual, insightful vs. shallow, unimaginative
Big Five Personality: Agreeableness

warm, kind, cooperative, sympathetic, helpful, and courteous.

- Strong desire to obtain acceptance in personal relationships as a means of expressing personality.
- Agreeable people focus on “getting along,” not necessarily “getting ahead.”
Big Five Personality: Extraversion

talkative, sociable, passionate, assertive, bold, and dominant

• Easiest to judge immediately on first meeting
• Prioritize desire to obtain power and influence within a social structure as a means of expressing personality.
• High in positive affectivity — a tendency to experience pleasant, engaging moods such as enthusiasm, excitement, and elation.

McGraw-Hill/Irwin Chapter 9
Big Five Personality: Neuroticism

- experience unpleasant moods: hostility, nervousness, and annoyance.
- more likely to appraise day-to-day situations as stressful.
- less likely to believe they can cope with the stressors that they experience.
- related to locus of control (attribute causes of events to themselves or to the external environment)
  - Neurotics: external locus of control: believe that the events that occur around them are driven by luck, chance, or fate.
  - less neurotic people hold internal locus of control: believe that their own behavior dictates events.
External and Internal Locus of Control

<table>
<thead>
<tr>
<th>People with an External Locus of Control Tend to Believe:</th>
<th>People with an Internal Locus of Control Tend to Believe:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Many of the unhappy things in people's lives are partly due to bad luck.</td>
<td>People's misfortunes result from the mistakes they make.</td>
</tr>
<tr>
<td>Getting a good job depends mainly on being in the right place at the right time.</td>
<td>Becoming a success is a matter of hard work; luck has little or nothing to do with it.</td>
</tr>
<tr>
<td>Many times exam questions tend to be so unrelated to course work that studying is really useless.</td>
<td>In the case of the well-prepared student, there is rarely if ever such a thing as an unfair test.</td>
</tr>
<tr>
<td>This world is run by the few people in power, and there is not much the little guy can do about it.</td>
<td>The average citizen can have an influence in government decisions.</td>
</tr>
<tr>
<td>There's not much use in trying too hard to please people; if they like you, they like you.</td>
<td>People are lonely because they don't try to be friendly.</td>
</tr>
</tbody>
</table>

McGraw-Hill/Irwin Chapter 9
Big Five Personality: Openness to Experience

curious, imaginative, creative, complex, sophisticated

• Also called “Inquisitiveness” or “Intellectualness”

• high levels of creativity, the capacity to generate novel and useful ideas and solutions.

• Highly open individuals are more likely to migrate into artistic and scientific fields.
Changes in Big Five Dimensions Over the Life Span

McGraw-Hill/Irwin Chapter
Aside: Do Animals Have Personalities?

- 4 human observers rated 44 personality traits of hyenas.
- Ran PCA on the ratings.
- Five dimensions: Assertiveness, Excitability, Human-Directed Agreeableness, Sociability, and Curiosity.
- Related to 3 human dimensions: neuroticism (excitability), openness (curiosity), agreeableness (sociability+agree).
Various text corpora labeled for personality of author


• 2,479 essays from psychology students (1.9 million words), “write whatever comes into your mind” for 20 minutes


• Speech from Electronically Activated Recorder (EAR)
• Random snippets of conversation recorded, transcribed
• 96 participants, total of 97,468 words and 15,269 utterances

Schwartz, H. Andrew, Johannes C. Eichstaedt, Margaret L. Kern, Lukasz Dziurzynski, Stephanie M. Ramones, Megha Agrawal, Achal Shah et al. 2013. "Personality, gender, and age in the language of social media: The open-vocabulary approach." PloS one 8, no. 9

• Facebook
• 75,000 volunteers
• 309 million words
• All took a personality test
## Ears (speech) corpus (Mehl et al.)

<table>
<thead>
<tr>
<th>Introvert</th>
<th>Extravert</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Yeah you would do kilograms. Yeah I see what you’re saying.</td>
<td>- That’s my first yogurt experience here.</td>
</tr>
<tr>
<td>- On Tuesday I have class. I don’t know.</td>
<td>Really watery. Why?</td>
</tr>
<tr>
<td>- I don’t know. A16. Yeah, that is kind of cool.</td>
<td>- Damn. New game.</td>
</tr>
<tr>
<td>- I don’t know. I just can’t wait to be with you and not have to do this every night, you know?</td>
<td>- Oh.</td>
</tr>
<tr>
<td>- Yeah. You don’t know. Is there a bed in there? Well ok just...</td>
<td>- That’s so rude. That.</td>
</tr>
<tr>
<td></td>
<td>- Yeah, but he, they like each other.</td>
</tr>
<tr>
<td></td>
<td>He likes her.</td>
</tr>
<tr>
<td></td>
<td>- They are going to end up breaking up and he’s going to be like.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Unconscientious</th>
<th>Conscientious</th>
</tr>
</thead>
<tbody>
<tr>
<td>- With the Chinese. Get it together.</td>
<td>- I don’t, I don’t know for a fact but I would imagine that historically women who have entered prostitution have done so, not everyone, but for the majority out of extreme desperation and I think. I don’t know, i think people understand that desperation and they don’t see [...]</td>
</tr>
<tr>
<td>- I tried to yell at you through the window.</td>
<td></td>
</tr>
<tr>
<td>Oh. xxx’s fucking a dumb ass. Look at him. Look at him. I wish we had a camera. He’s fucking brushing his t-shirt with a tooth brush. Get a kick of it. Don’t steal nothing.</td>
<td></td>
</tr>
</tbody>
</table>
## Essays corpus (Pennebaker and King)

<table>
<thead>
<tr>
<th>Introvert</th>
<th>Extravert</th>
</tr>
</thead>
<tbody>
<tr>
<td>I’ve been waking up on time so far. What has it been, 5 days? Dear me, I’ll never keep it up, being such not a morning person and all. But maybe I’ll adjust, or not. I want internet access in my room, I don’t have it yet, but I will on Wed??? I think. But that ain’t soon enough, cause I got calculus homework [...]</td>
<td>I have some really random thoughts. I want the best things out of life. But I fear that I want too much! What if I fall flat on my face and don’t amount to anything. But I feel like I was born to do BIG things on this earth. But who knows... There is this Persian party today.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Neurotic</th>
<th>Emotionally stable</th>
</tr>
</thead>
<tbody>
<tr>
<td>One of my friends just barged in, and I jumped in my seat. This is crazy. I should tell him not to do that again. I’m not that fastidious actually. But certain things annoy me. The things that would annoy me would actually annoy any normal human being, so I know I’m not a freak.</td>
<td>I should excel in this sport because I know how to push my body harder than anyone I know, no matter what the test I always push my body harder than everyone else. I want to be the best no matter what the sport or event. I should also be good at this because I love to ride my bike.</td>
</tr>
</tbody>
</table>
Classifiers

  • Various classifiers, lexicon-based and prosodic features

  • regression and SVM, lexicon-based and all-words
Sample LIWC Features

LIWC (Linguistic Inquiry and Word Count)


<table>
<thead>
<tr>
<th>Feature</th>
<th>Type</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anger words</td>
<td>LIWC</td>
<td>hate, kill, pissed</td>
</tr>
<tr>
<td>Metaphysical issues</td>
<td>LIWC</td>
<td>God, heaven, coffin</td>
</tr>
<tr>
<td>Physical state/function</td>
<td>LIWC</td>
<td>ache, breast, sleep</td>
</tr>
<tr>
<td>Inclusive words</td>
<td>LIWC</td>
<td>with, and, include</td>
</tr>
<tr>
<td>Social processes</td>
<td>LIWC</td>
<td>talk, us, friend</td>
</tr>
<tr>
<td>Family members</td>
<td>LIWC</td>
<td>mom, brother, cousin</td>
</tr>
<tr>
<td>Past tense verbs</td>
<td>LIWC</td>
<td>walked, were, had</td>
</tr>
<tr>
<td>References to friends</td>
<td>LIWC</td>
<td>pal, buddy, coworker</td>
</tr>
<tr>
<td>Imagery of words</td>
<td>MRC</td>
<td>Low: future, peace - High: table, car</td>
</tr>
<tr>
<td>Syllables per word</td>
<td>MRC</td>
<td>Low: a - High: uncompromisingly</td>
</tr>
<tr>
<td>Concreteness</td>
<td>MRC</td>
<td>Low: patience, candor - High: ship</td>
</tr>
<tr>
<td>Frequency of use</td>
<td>MRC</td>
<td>Low: duly, nudity - High: he, the</td>
</tr>
</tbody>
</table>
Facebook study, Learned words, Extraversion versus Introversion
Facebook study, Learned words
Neuroticism versus Emotional Stability