Computing with Affective Lexicons

Affective, Sentimental, and Connotative Meaning in the Lexicon
Affective meaning

• Drawing on literatures in
  • affective computing (Picard 95)
  • linguistic subjectivity (Wiebe and colleagues)
  • social psychology (Pennebaker and colleagues)

• Can we model the lexical semantics relevant to:
  • sentiment
  • emotion
  • personality
  • mood
  • attitudes
Why compute affective meaning?

- Detecting:
  - sentiment towards politicians, products, countries, ideas
  - frustration of callers to a help line
  - stress in drivers or pilots
  - depression and other medical conditions
  - confusion in students talking to e-tutors
  - emotions in novels (e.g., for studying groups that are feared over time)

- Could we generate:
  - emotions or moods for literacy tutors in the children’s storybook domain
  - emotions or moods for computer games
  - personalities for dialogue systems to match the user
Connotation in the lexicon

• Words have connotation as well as sense
• Can we build lexical resources that represent these connotations?
• And use them in these computational tasks?
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
Computing with Affective Lexicons

Sentiment Lexicons
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**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

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   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

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   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
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)


- 2300 words, >70 classes
- **Affective Processes**
  - negative emotion (*bad, weird, hate, problem, tough*)
  - positive emotion (*love, nice, sweet*)
- **Cognitive Processes**
  - Tentative (*maybe, perhaps, guess*), Inhibition (*block, constraint*)
- **Pronouns, Negation** (*no, never*), **Quantifiers** (*few, many*)
- $30 or $90 fee
MPQA Subjectivity Cues Lexicon


- 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


- 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”
  \[
  \begin{array}{ccc}
  \text{Pos} & \text{Neg} & \text{Obj} \\
  0 & 0 & 1 \\
  \end{array}
  \]
- \([\text{estimable}(J,1)]\) “deserving of respect or high regard”
  \[
  \begin{array}{ccc}
  \text{Pos} & \text{Neg} & \text{Obj} \\
  .75 & 0 & .25 \\
  \end{array}
  \]
Computing with Affective Lexicons

Sentiment Lexicons
Computing with Affective Lexicons

Other Affective Lexicons
Scherer’s typology of affective states

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

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  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
- Low arousal, high pleasure: relaxation
- High arousal, high pleasure: excitement
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>Value</th>
</tr>
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<tbody>
<tr>
<td>amazingly</td>
<td>anger</td>
<td>0</td>
</tr>
<tr>
<td>amazingly</td>
<td>anticipation</td>
<td>0</td>
</tr>
<tr>
<td>amazingly</td>
<td>disgust</td>
<td>0</td>
</tr>
<tr>
<td>amazingly</td>
<td>fear</td>
<td>0</td>
</tr>
<tr>
<td>amazingly</td>
<td>joy</td>
<td>1</td>
</tr>
<tr>
<td>amazingly</td>
<td>sadness</td>
<td>0</td>
</tr>
<tr>
<td>amazingly</td>
<td>surprise</td>
<td>1</td>
</tr>
<tr>
<td>amazingly</td>
<td>trust</td>
<td>0</td>
</tr>
<tr>
<td>amazingly</td>
<td>negative</td>
<td>0</td>
</tr>
<tr>
<td>amazingly</td>
<td>positive</td>
<td>1</td>
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</tbody>
</table>

<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>
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<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>
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</tr>
<tr>
<td>Bigrams from Macquarie Thesaurus</td>
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</tr>
<tr>
<td>adjectives</td>
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<tr>
<td>adverbs</td>
<td>187</td>
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<tr>
<td>nouns</td>
<td>200</td>
</tr>
<tr>
<td>verbs</td>
<td>200</td>
</tr>
<tr>
<td>EmoLex-GI:</td>
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</tr>
<tr>
<td>Terms from General Inquirer</td>
<td></td>
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<tr>
<td>negative terms</td>
<td>2119</td>
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<tr>
<td>neutral terms</td>
<td>4226</td>
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<tr>
<td>positive terms</td>
<td>1787</td>
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<tr>
<td>EmoLex-WAL:</td>
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<tr>
<td>Terms from WordNet Affect Lexicon</td>
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<tr>
<td>anger terms</td>
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<tr>
<td>disgust terms</td>
<td>37</td>
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<tr>
<td>fear terms</td>
<td>100</td>
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<tr>
<td>joy terms</td>
<td>165</td>
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<tr>
<td>sadness terms</td>
<td>120</td>
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<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>self</td>
</tr>
<tr>
<td>happy</td>
<td>8.47</td>
<td>incredible</td>
</tr>
<tr>
<td>whistle</td>
<td>5.7</td>
<td>skillet</td>
</tr>
<tr>
<td>conscious</td>
<td>5.53</td>
<td>concur</td>
</tr>
<tr>
<td>torture</td>
<td>1.4</td>
<td>earthquake</td>
</tr>
</tbody>
</table>
Concreteness versus abstractness

• The degree to which the concept denoted by a word refers to a perceptible entity.
  • Do concrete and abstract words differ in connotation?
  • Storage and retrieval?
  • Bilingual processing?
  • Relevant for embodied view of cognition (Barsalou 1999 inter alia)
    • Do concrete words activate brain regions involved in relevant perception

• Brysbaert, M., Warriner, A. B., and Kuperman, V. (2014) Concreteness ratings for 40 thousand generally known English word lemmas Behavior Research Methods 46, 904-911.
  • Supplementary data: This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivs 3.0 Unported License.

• 37,058 English words and 2,896 two-word expressions ("zebra crossing" and "zoom in"),
• Rating from 1 (abstract) to 5 (concrete)
• Calibrator words:
  • shirt, infinity, gas, grasshopper, marriage, kick, polite, whistle, theory, and sugar
Concreteness versus abstractness

- Supplementary data: This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivs 3.0 Unported License.
- Some example ratings from the final dataset of 40,000 words and phrases
  - banana 5
  - bathrobe 5
  - bagel 5
  - brisk 2.5
  - badass 2.5
  - basically 1.32
  - belief 1.19
  - although 1.07
# Perceptual Strength Norms

## Connell and Lynott norms

<table>
<thead>
<tr>
<th>Word</th>
<th>Perceptual strength</th>
<th>Concreteness</th>
<th>Imageability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Auditory</td>
<td>Gustatory</td>
<td>Haptic</td>
</tr>
<tr>
<td>soap</td>
<td>0.35</td>
<td>1.29</td>
<td>4.12</td>
</tr>
<tr>
<td>noisy</td>
<td>4.95</td>
<td>0.05</td>
<td>0.29</td>
</tr>
<tr>
<td>atom</td>
<td>1.00</td>
<td>0.63</td>
<td>0.94</td>
</tr>
<tr>
<td>republic</td>
<td>0.53</td>
<td>0.67</td>
<td>0.27</td>
</tr>
</tbody>
</table>
Computing with Affective Lexicons

Semi-supervised algorithms for 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...
Step 2

- Expand seed set to conjoined adjectives

Google search: "was nice and"

nice, helpful

nice, classy
Step 3

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

\[
\text{PMI}(X, Y) = \log_2 \frac{P(x, y)}{P(x)P(y)}
\]
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 $\frac{\text{hits(}\text{word}_1 \text{ NEAR } \text{word}_2)}{N}$
    • (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”?

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

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

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

\[
= \log_2 \left( \frac{\text{hits}(\text{phrase NEAR "excellent"}) \text{hits("poor")}}{\text{hits}(\text{phrase NEAR "poor"}) \text{hits("excellent")}} \right)
\]
## 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>...</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>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td><strong>0.32</strong></td>
</tr>
</tbody>
</table>
**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 semi-supervised lexicon learning

• 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
Computing with Affective Lexicons

Supervised Learning of Sentiment Lexicons
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)
• Just count how many times each word occurs with each score
  • (and normalize)
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**:  
  \[ \frac{P(w \mid c)}{P(w)} \]
“Potts diagrams”

Positive scalars
- good
- great
- excellent

Negative scalars
- disappointing
- bad
- terrible

Emphatics
- totally
- absolutely
- fairly
- utterly
- pretty

Attenuators
- somewhat

Potts, Christopher. 2011. NSF workshop on restructuring adjectives.
Or use regression coefficients to weight words

- Train a classifier based on supervised data
  - Predict: human-labeled connotation of a document
  - From: all the words and bigrams in it
- Use the regression coefficients as the weights
- We’ll return to an example of this in the next section.
Computing with Affective Lexicons

Using the lexicons to detect affect
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
Computing with Affective Lexicons

Sample affective task: personality detection
Sample affective task: personality detection
**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
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
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


- 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></td>
</tr>
<tr>
<td>- On Tuesday I have class. I don’t know.</td>
<td></td>
</tr>
<tr>
<td>- I don’t know. A16. Yeah, that is kind of cool.</td>
<td></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></td>
</tr>
<tr>
<td>- Yeah. You don’t know. Is there a bed in there? Well ok just...</td>
<td></td>
</tr>
<tr>
<td>- That’s my first yogurt experience here. Really watery. Why?</td>
<td></td>
</tr>
<tr>
<td>- Damn. New game.</td>
<td></td>
</tr>
<tr>
<td>- Oh.</td>
<td></td>
</tr>
<tr>
<td>- That’s so rude. That.</td>
<td></td>
</tr>
<tr>
<td>- Yeah, but he, they like each other. He likes her.</td>
<td></td>
</tr>
<tr>
<td>- They are going to end up breaking up and he’s going to be like.</td>
<td></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></td>
</tr>
<tr>
<td>- I tried to yell at you through the window. Oh. xxxx’s fucking a dumb ass. Look at him. Look at him, dude. 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>
<tr>
<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 don’t see [...]</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>
<tr>
<td><strong>Neurotic</strong></td>
<td><strong>Emotionally stable</strong></td>
</tr>
<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>
Normalizing LIWC category features
(Schwartz et al. 2013, Facebook study)

- Mairesse:
  Raw LIWC counts
- Schwartz et al:
  Normalized per writer:

\[ p(\text{category} | \text{subject}) = \frac{\sum_{\text{word} \in \text{category}} \text{freq (word, subject)}}{\sum_{\text{word} \in \text{vocab (subject)}} \text{freq (word, subject)}} \]
Sample results

- **Agreeable:**
  - +Family, +Home, -Anger, -Swear

- **Extravert**
  - +Friend, +Religion, +Self

- **Conscientiousness:**
  - -Swear, -Anger, -NegEmotion,

- **Emotional Stability:**
  - -NegEmotion, +Sports,

- **Openness**
  - -Cause, -Space
Decision tree for predicting extraversion in essay corpus (Mairesse et al)

Remarkably, we can see that the LIWC features outperform the MRC features for every trait, and the LIWC features on their own always perform slightly better than the full feature set. This clearly suggests that MRC features aren't as helpful as the LIWC features for classifying personality from written text, however Table 13 shows that they can still outperform the baseline for four traits out of five.

Concerning the algorithms, we find that AdaboostM1 performs the best for extraversion (56.3% correct classifications), while SMO produces the best models for all other traits. It suggests that support vector machines are promising for modelling personality in general.

The easiest trait to model is still openness to experience, with 62.5% accuracy using LIWC features only.

4.2 EAR Corpus

Classification accuracies for the EAR corpus are in Table 14. We find that extraversion is the easiest trait to model using observer reports, with both Naive Bayes and AdaboostM1
Using all words instead of lexicons
Facebook study

Schwartz et al. (2013)

• Choosing phrases with $\text{pmi} > 2 \times \text{length}$ [in words]

$$\text{pmi (phrase)} = \log \frac{p(\text{phrase})}{\prod_{w \in \text{phrase}} p(w)}$$

• Only use words/phrases used by at least 1% of writers

• Normalize counts of words and phrases by writer

$$p(\text{phrase} \mid \text{subject}) = \frac{\text{freq (phrase, subject)}}{\sum_{\text{phrase}'} \text{freq (phrase', subject)}}$$
Facebook study, Learned words, Extraversion versus Introversion
Facebook study, Learned words
Neuroticism versus Emotional Stability
Evaluating Schwartz et al (2013) Facebook Classifier

- Train on labeled training data
  - LIWC category counts
  - words and phrases (n-grams of size 1 to 3, passing a collocation filter)
- Tested on a held-out set
- Correlations with human labels
  - LIWC .21-.29
  - All Words .29-.41
Affect extraction: of course it’s not just the lexicon


- Detecting interpersonal stance in conversation
- Speed dating study, 1000 4-minute speed dates
- Subjects labeled selves and each other for
  - friendly (each on a scale of 1-10)
  - awkward
  - flirtatious
  - assertive
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
Affect extraction: of course it’s not just the lexicon

Logistic regression classifier with

- LIWC lexicons
- Other lexical features
  - Lists of hedges
- Prosody (pitch and energy means and variance)
- Discourse features
  - Interruptions
  - Dialog acts/Adjacency pairs
    - sympathy (“Oh, that’s terrible”)
    - clarification question (“What?”)
    - appreciations (“That’s awesom!”)
Results on affect extraction

• Friendliness
  • -negEmotion
  • -hedge
  • higher pitch
• Awkwardness
  • +negation
  • +hedges
  • +questions
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- nervous, anxious, reckless, morose, hostile, envious, jealous
Summary: Connotation in the lexicon

• Words have various connotational aspects
• Methods for building connotation lexicons
  Based on theoretical models of emotion, sentiment
  • By hand (mainly using crowdsourcing)
  • Semi-supervised learning from seed words
  • Fully supervised (when you can find a convenient signal in the world)
• Applying lexicons to detect affect and sentiment
  • Unsupervised: pick simple majority sentiment (positive/negative words)
  • Supervised: learn weights for each lexical category