Sentiment and Belief Extraction (Part 2)

Lecture #7
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...
Hatzivassiloglou & McKeown 1997
Step 2

- Expand seed set to conjoined adjectives

Google search for "was nice and" shows examples:

- 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 ...
Hatzivassiloglou & McKeown 1997

Step 3

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

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  – 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 (Google)
  • \( P(\text{word}) \) estimated by \( \frac{\text{hits(\text{word})}}{N} \)
  • \( P(\text{word}_1, \text{word}_2) \) by \( \frac{\text{hits(\text{word}_1 \text{ NEAR word}_2)}}{N} \)

  – (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.)

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

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

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

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

\[ = \log_2 \left( \frac{\text{hits}(\textit{phrase} \text{ NEAR } "excellent") \text{hits("poor")}}{\text{hits}(\textit{phrase} \text{ NEAR } "poor") \text{hits("excellent")}} \right) \]
## 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>0.32</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>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
Automatic Expansion of ANEW


• Affective Norms of Words Lexicon
• Using Wordnet
  – Assign score of word in ANEW to all synonyms of that word
  – Use the most frequent synset
ANEW Expansion: Multiple words

• What if multiple original words expand to the same word?
  – Assign average score
Automatic Expansion of ANEW

• Validating the expansion is key!
• Two methods of validation
  – Validate against existing manually created lexicons
  – Validate by asking humans to rate the polarity of expanded word

• Expansion is valid only if the correlation of expansion scores and human scores is sufficiently high
Validating expansion: Against existing lexicon

Statistically significant!

\[ N = 1,013; r = .661 \]
Validating expansion: Against human judgement from mturk

Statistically significant!

\[ N = 235; r = .759 \]
Expansion in foreign languages

Figure 6. Scatterplot of affect ratings of Russian (left) and Farsi (right) words from our expansion method compared to values from turkers.
• Beliefs and Attitudes
What is belief?

• Belief is the state of mind in which a person thinks something to be the case, with or without there being empirical evidence to prove that something is the case with factual certainty
Beliefs in AI

• From a programmer’s point of view, belief is a piece of data that has a truth value (either true or false)

• From a logician’s point of view, beliefs can be propositions
Why are beliefs important in AI?

• One may argue that intelligence involves the process of forming beliefs and behaving in accordance to them

• If an agent believes that it may rain soon
  – Agent will attempt to bring an umbrella
Implicit and Explicit beliefs

• If an agent believes
  – \( a \)
  – \( a \rightarrow b \)

• Then the agent implicitly believes \( b \)

• \( b \) is said to be deduced by the agent
• How are beliefs, sentiment/attitude and behavior related?
Behavior and Attitude

Behavior change

Behavior

Attitude Object

determines

RECEIVER

COMMUNICATOR

Persuasion / Influence

messages
Summative Model of Belief

**RECEIVER**

- Behavior change
- Behavior determines

**COMMUNICATOR**

- Persuasion / Influence
- Tailored messages

Summative Model of Belief

\[ A_o = \sum b_i e_i \]

- \( A_o \) is the attitude towards the object
- \( b_i \) is the strength of a given belief
- \( e_i \) is the evaluation of given belief
Summative Model of Belief

- Topic: Genetically Modified Foods
- Survey questions on a 7-point Likert scale

16. How likely do you feel the following statement to be true?

*Genetically modified foods have a harmful effect on environment:*

- Very unlikely
- Unlikely
- Somewhat unlikely
- Undecided
- Somewhat likely
- Likely
- Very likely

17. A harmful effect on environment is:

- Very Bad
- Bad
- Poor
- Neither Good nor Bad
- Fair
- Good
- Very Good

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Summative Model of Belief

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Measures Belief strength ($b_i$)

17. A harmful effect on environment is:

- Very Bad
- Bad
- Poor
- Neither Good nor Bad
- Fair
- Good
- Very Good

Measures Belief evaluation ($e_i$)
# From Beliefs to Attitude

## Genetically modified foods

<table>
<thead>
<tr>
<th>Genetically modified foods</th>
<th>belief strength $b_i$</th>
<th>belief evaluation $e_i$</th>
<th>$b_i * e_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Harmful to environment</td>
<td>2</td>
<td>-3</td>
<td>-6</td>
</tr>
<tr>
<td>Adaptable to many climates</td>
<td>-2</td>
<td>1</td>
<td>-2</td>
</tr>
<tr>
<td>More affordable</td>
<td>1</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Lead to less starvation</td>
<td>-1</td>
<td>2</td>
<td>-2</td>
</tr>
</tbody>
</table>

$\Sigma b_i e_i = -8$

$b_i$ and $e_i$ range from -3 to +3
• Extracting beliefs from text
Beliefs in text

• Components of belief
  – Source (who believes?)
  – Relation (what do they believe?)
  – Target (about what/whom is the belief?)
An example

• Mary: I ate the cheese.
• Source: Mary
• Belief Relation: ate the cheese
• Target: N/A
Another example

• *Mary*: *John ate the cheese.*
• Source: Mary
• Belief Relation: ate the cheese
• Target: John (agent of belief relation)
Extracting beliefs automatically

- One way to do it is using syntactic information from a parse tree:

  - nsubj(ate-2, John-1)
  - root(ROOT-0, ate-2)
  - det(cheese-4, the-3)
  - dobj(ate-2, cheese-4)

- We discussed this in affect calculus lecture.
How beliefs and sentiment can be related to each other?

| Relation type | Type 1 (proportive)  
|               |  
|               |  
|               | Rel(Target) | Type 2 (agentive)  
|               |  
|               |  
|               | Rel (Target, X) | Type 3 (patientive)  
|               |  
|               |  
|               | Rel(X, Target) |
| Relation/X    |                | $X \geq \text{neutral}$ | $X < \text{neutral}$ | $X \geq \text{neutral}$ | $X < \text{neutral}$ |
| Positive      | POSITIVE       | POSITIVE                     | $\leq \text{UNSYMP}$ | POSITIVE                     | $\leq \text{SYMPAT}$ |
| Negative      | NEGATIVE       | $\leq \text{UNSYMP}$         | $\geq \text{SYMPAT}$ | $\leq \text{SYMPAT}$         | $\geq \text{SYMPAT}$ |
| Neutral       | NEUTRAL        | NEUTRAL                      | $\leq \text{NEUTRAL}$ | NEUTRAL                      | $\leq \text{NEUTRAL}$ |
Assigned Reading – Paper 4

• Semi-Supervised Recognition of Sarcastic Sentences in Twitter and Amazon
  – Davidov, Tsur, Rappoport
  – ACL 2010

• Responses due: 3/7/2017 by 11:59 pm