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
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

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

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

```
    Fair  Helpful  Brutal
     |      |        |
   nice --- classy --- irrational
          |
          |
          |
```
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?

$$\text{PMI}(X,Y) = \log_2 \frac{P(x,y)}{P(x)P(y)}$$
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 (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.)

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

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

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

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

\[
= \log_2 \left( \frac{\text{hits}(\text{phrase NEAR } "\text{excellent}") \text{hits}("\text{poor})}{\text{hits}(\text{phrase NEAR } "\text{poor}) \text{hits}("\text{excellent}")} \right)
\]
## 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>
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<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>
</tbody>
</table>

Average: -1.2
Results of Turney algorithm

• 410 reviews from Epinions
  – 170 (41%) negative
  – 240 (59%) positive
• Majority class baseline: 59%
• Turney algorithm: 74%

• Phrases rather than words
• Learns domain-specific information
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 and Attitude

Behavior

Persuasion / Influence

RECEIVER

COMMUNICATOR

behavior change

determines

Attitude Object

messages
### 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:* *

<table>
<thead>
<tr>
<th>Very unlikely</th>
<th>Unlikely</th>
<th>Somewhat unlikely</th>
<th>Undecided</th>
<th>Somewhat likely</th>
<th>Likely</th>
<th>Very likely</th>
</tr>
</thead>
</table>

17. A harmful effect on environment is: *

<table>
<thead>
<tr>
<th>Very Bad</th>
<th>Bad</th>
<th>Poor</th>
<th>Neither Good nor Bad</th>
<th>Fair</th>
<th>Good</th>
<th>Very Good</th>
</tr>
</thead>
</table>
**Summative Model of Belief**

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

### Question 16

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

*Measures Belief strength ($b_i$)*

### Question 17

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 belief and sentiment to position/attitude

Belief + Sentiment

GMOs pollute the environment
AND
Polluting the environment is bad

Position / Attitude

Negative towards GMO
## From Beliefs & Sentiment to Attitude

<table>
<thead>
<tr>
<th>Genetically modified foods</th>
<th>belief $b_i$</th>
<th>sentiment $e_i$</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>
<tr>
<td>$\Sigma b_i e_i$</td>
<td></td>
<td></td>
<td>-8</td>
</tr>
</tbody>
</table>

$b_i$ 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
Assigned Reading – Paper 4

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

• Responses due: 3/6/2018 by 11:59 pm