L114 Lexical Semantics

Session 7: Antonymy and Sentiment Detection

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1. Semantic Orientation of Adjectives
   - Antonymy
   - Linguistic tests for complementaries and antonymy type
   - Linguistic vs. natural polarity

2. Automatic Detection of Sem. Orientation
   - Hatzivassiloglou and McKeown
   - Turney (PMI Method)
There are different kinds of opposites: complementaries and antonyms.

Antonyms are closely related to semantic orientation (degree of positiveness/negativeness).

If we know that two adjectives relate to the same property (e.g., *hot* and *cold*) but have different semantic orientations they are typically antonyms.

Exceptions: *verbose*—*terse* (same semantic orientation)
Oppositeness and Antonymy

Opposites

- gradable?
- neither–nor?

Complementaries

- married–single
- dead–alive

Antonyms

- how many pseudocomparatives exist?
- how–adj possible?
- how adj committed or impartial?

- polar
- overlapping
- equipollent

- long–short
- good–bad
- hot–cold
Complementaries

Complementaries between them exhaustively divide some conceptual domain into mutually exclusive compartments. Antonyms don’t.

**neither–nor test:**

- ? Mary is *neither married nor is she single*. (→ complementaries)
- *It’s neither hot nor cold today*. (→ antonyms)

**Gradability test:**

- ? *extremely true* – *extremely safe*
- ? *more pregnant than most* – *longer than some*
- ? *moderately female* – *moderately clean*
Antonyms 1: Pseudo comparatives and true comparatives

light–heavy and hot–cold do not behave in the same way:

- *This box is light, but it’s heavier than that one.*
- *Today it’s cold, but hotter than yesterday.*

What is going on?
light–heavy and hot–cold do not behave in the same way:

- *This box is light, but it’s heavier than that one.*
- *Today it’s cold, but hotter than yesterday.*

What is going on? Heavier seems to mean *of greater weight* here (relative property), whereas hot seems to express a more absolute property.

- *hotter* is a true comparative of *hot*
- *heavier* is a pseudo-comparative of *heavy/1*, and a true comparative of *heavy/2*
Antonyms 2: How-adj questions

Are how-adj questions possible for both antonyms? Compare *long–short*:

- *How long is it?*
- *How short is it?*

with *hot–cold*:

- *How cold is it?*
- *How hot is it?*
Antonyms 3: Impartiality of how-adj questions

Does one of the questions imply something about your presuppositions? (this is about neutrality)

*hot–cold:*

- *How cold is it?* → committed
- *How hot is it?* → committed

*clean–dirty:*

- *How clean was the room?* → impartial
- *How dirty was the room?* → committed
Excursion: presuppositions

- A presupposition is an implicit assumption about the world or background belief relating to an utterance whose truth is taken for granted in discourse.

Examples:

- Jane no longer writes fiction.
  Presupposition: Jane once wrote fiction.
- Have you stopped eating meat?
  Presupposition: you had once eaten meat.
- Have you talked to Hans?
  Presupposition: Hans exists.
- If the notice had only said 'mine-field' in Welsh as well as in English, we would never have lost poor Llewellyn.
  Presupposition: The notice didn’t say 'mine-field’ in Welsh.
Presupposition triggers

- Many words and constructions are presupposition triggers
- *regret, realise, manage, forget, try, again, since X happened, Carol is a better linguist than Mary...*
Presuppositions

- Negation of utterance does not cancel its presuppositions.
- This distinguishes it from entailment.
- A presupposition of a sentence must normally be part of the common ground of the utterance context (the shared knowledge of the interlocutors) in order for the sentence to be felicitous.
- If not, presupposition accommodation takes place unless this leads to inconsistency. (“My wife is a dentist”, said to somebody who does not know that you have a wife.)
Three types of antonyms

- *good–bad* is an example of an **overlapping** antonym.
  - Overlapping antonyms are evaluative, and thus carry semantic orientation in our sense.
- *hot–cold* is an example of an **equipollent** antonym.
  - Equipollent antonyms are often correlated with sensory perceptions.
- *long–short* is an example of a **polar** antonym.
  - Polar antonyms show the greatest level of abstraction, but are neutral/descriptive.
Linguistic polarity vs. natural polarity

- Can we predict which one of the antonyms is more “salient” (that is typically the one that is positive)?
- Prediction: the more salient antonym often has a positive polarity.

Test 1: The antonym that can be paraphrased as the other one plus a negative prefix is the less salient one.

Test 2: The more salient antonym is associated with “more” properties:
  - *Something is dead when there is no life present.*
  - *Something is alive when there is no deadness present.*

Test 3: The more salient antonym yields the impartial interpretation in the how-adj question.
That picture again

Opposites

gradable? neither–nor?

Complementaries

married–single
dead–alive

Antonyms

how many pseudocomparatives exist?
how–adj possible?
how adj committed or impartial?

deck: polar, overlapping, equipollent

polar
long–short

equipollent
hot–cold
Hatzivassiloglou and McKeown’s (1997) algorithm classifies adjectives into those with positive or negative semantic orientation.

- In coordinations, antonymy results in constraints on the semantic orientation:

(1)  
  a. The tax proposal was *simple and well-received* by the public.  
  b. The tax proposal was *simplistic but well-received* by the public.  
  c. ?The tax proposal was *simplistic and well-received* by the public.

- *but* combines adjectives of opposite orientation; *and* adjectives of the same orientation
- This indirect information can be exploited using a corpus.
Algorithm

- Extract all coordinated adjectives from 21 million word WSJ corpus (and, or, but, either-or, neither-nor)
- 15048 adj pairs (token), 9296 (type)
- Classify each extracted adjective pair as same or different orientation (82% accuracy)
- This results in graph with same or different links between adjectives
Classification

- features used: number of modified noun; type of coordination; type of modification (attributive, predicative, appositive, resultative (“Bill laughed himself hoarse”))
- *and* is most reliable same-orientation predictor, particularly in predicative position (85%), this drops to 70% in appositive position.
- *but* has 31% same-orientation.
- This information comes from an independently annotated gold standard (1336 most frequent adjectives; 657 positive, 679 negative)
- Additional different orientations comes from simple morphological analysis: Out of the labelled adjectives, 97% of morphologically related pairs (102) have different orientation
Clustering adjectives with same orientation

- Now cluster adjectives into two orientations, placing as many words of the same orientation as possible into the same subset.
- Interpret classifier’s P(same-orientation) as dissimilarity value.
- Perform non-hierarchical clustering via Exchange Method.
- Start from random partition, locate the adjective which reduces the cost $c$ most if moved.

$$c = \sum_{i=1}^{2} \left( \frac{1}{|C_i|} \sum_{x,y \in C_i, x \neq y} d(x, y) \right)$$

- Repeat until no movements can improve the cost; overall dissimilarity cost is now minimised.
Exchange method; final step

At final iteration, move any adjective which violates the following constraint:

\[
\frac{1}{|C| - 1} \sum_{y \in C, x \neq y} d(x, y) < \frac{1}{|\bar{C}|} \sum_{y \in \bar{C}} d(x, y)
\]
Labelling Clusters as Positive or Negative

- Hatzivassiloglou empirically find that the cluster with overall higher frequency tends to be the positive one; so this is the final step in their algorithm.
- Possible reason: In overlapping antonym pairs, the positive adjective tends to be semantically unmarked (as we heard earlier today).
- Semantically unmarked adjectives should occur more frequently in language (if only because of neutral questions etc).
Results

- Dependent on how sparse the test set is, results between 78% and 92% correct.
- Baselines: MFC 51% negative.
- Classified as positive: bold, decisive, disturbing, generous, good, honest, important, large, mature, patient, peaceful, positive, proud, sound, stimulating, straightforward, strange, talented, vigorous, witty.
- Classified as negative: ambiguous, cautious, cynical, evasive, harmful, hypocritical, inefficient, insecure, irrational, irresponsible, minor, outspoken, pleasant, reckless, risky, selfish, tedious, unsupported, vulnerable, wasteful.
Discussion

Strengths:
- Algorithm only needs gold standard list
- Convincing results

Weaknesses:
- Analysis of isolated adjectives, not phrases
- Needs large corpus in order to contain enough coordinated adjectives
- Clustering algorithm is not optimal (problem is NP-hard); it is a steepest-descending hill climbing method, which is at least guaranteed to converge (but might run algorithm repeatedly with different start partitions)
Turney’s 2002 method

- Determine semantic orientation of phrases, not just single adjectives
- Single adjectives do not always carry full orientation; context is needed. *unpredictable plot* vs. *unpredictable steering*
- Unsupervised method based on distributional semantics
- Assign a numerical ranking indicating strength of orientation
- Use search engine hits to estimate semantic orientation of a phrase
Idea

- If an adjectival phrase has a positive semantic orientation, it will appear more frequently in the intermediate vicinity of known positive adjectives, and vice versa.
- Measure an adjective’s tendency to appear in positive or negative vicinity via PMI-IR
  - Pointwise mutual information determines similarity of a pair of phrases
  - Use IR to quantify effect
- Measure success indirectly via classification of entire reviews
PMI and SO

\[
PMI(\text{word}_1, \text{word}_2) = \log_2 \left( \frac{P(\text{word}_1, \text{word}_2)}{P(\text{word}_1)P(\text{word}_2)} \right)
\]

- Semantic Orientation:
  \[
  \text{SO(phrase)} = \text{PMI(phrase, } \text{excellent}) - \text{PMI(phrase, poor)}
  \]
- Counts are calculated via search engine hits
- Altavista’s NEAR operator – window of 10 words

Therefore:

\[
\text{SO(phrase)} = \log_2 \left( \frac{\text{hits(phrase NEAR excellent)}\text{hits(poor)}}{\text{hits(phrase NEAR poor)}\text{hits(excellent)}} \right)
\]
Results: indirectly via classification of documents

- 74% accuracy on classifying 410 reviews from Epinions
- 66% accuracy on movie reviews

An example:

<table>
<thead>
<tr>
<th>Phrase</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>little difference</td>
<td>-1.615</td>
</tr>
<tr>
<td>clever tricks</td>
<td>-0.040</td>
</tr>
<tr>
<td>programs such</td>
<td>0.117</td>
</tr>
<tr>
<td>possible moment</td>
<td>-0.668</td>
</tr>
<tr>
<td>unethical practices</td>
<td>-8.484</td>
</tr>
<tr>
<td>old man</td>
<td>-2.566</td>
</tr>
<tr>
<td>other problems</td>
<td>-2.748</td>
</tr>
<tr>
<td>probably wondering</td>
<td>-1.830</td>
</tr>
<tr>
<td>virtual monopoly</td>
<td>-2.050</td>
</tr>
<tr>
<td>other bank</td>
<td>-0.850</td>
</tr>
<tr>
<td>extra day</td>
<td>-0.286</td>
</tr>
<tr>
<td>direct deposits</td>
<td>5.771</td>
</tr>
<tr>
<td>online web</td>
<td>1.936</td>
</tr>
<tr>
<td>cool thing</td>
<td>0.395</td>
</tr>
<tr>
<td>very handy</td>
<td>1.349</td>
</tr>
<tr>
<td>lesser evil</td>
<td>-2.288</td>
</tr>
</tbody>
</table>

Total: -1.218. Rating: Not recommended.
Discussion

Strengths:
- Fully unsupervised
- Nominal context makes adjective semantics more interpretable

Weaknesses:
- No direct evaluation of SO provided
- Very simple model
- Requires many searches (too many without API)
- NEAR no longer supported
- Results depend substantially on lexical items chosen, but choice largely unmotivated
- Cruse (1986), chapters 9 and 11.3;