Semantic Orientation of Adjectives Automatic Detection of Sem. Orientation: Hatzivassiloglou Turnev (PMI Method)

Automatic Detection of Sem. Orientation: Hatzivassilogiou Turney (PMI Method)

Lecture 5: Semantic Orientation

Lexical Semantics and Discourse Processing MPhil in Advanced Computer Science

Simone Teufel

Natural Language and Information Processing (NLIP) Group UNIVERSITY OF CAMBRIDGE

Simone.Teufel@cl.cam.ac.uk

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Semantic Orientation of Adjectives

- Antonymy
- Linguistic tests for complementaries and antonymy type
- Linguistic vs. natural polarity

2 Automatic Detection of Sem. Orientation: Hatzivassiloglou

- Idea
- Algorithm
- Results

Turney (PMI Method)

- Idea
- Algorithm
- Results

Reading: Cruse (1986), chapters 9 and 11.3; Hatzivassiloglou and McKeown (1997); Turney (2002).



- There are different kinds of opposites: complementaries and antonyms
- Semantic orientation: degree of positiveness/negativeness.
- Many antonyms have opposite semantic orientation. Exceptions: verbose—terse



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tomatic Detection of Sem. Orientation: Hatzivassili

Linguistic tests for complementaries and antonymy type Linguistic vs. natural polarity

Complementaries

Complementaries between them exhaustively divide some conceptual domain into mutually exclusive compartments. Antonyms don't. *neither-not* test:

? Mary is neither married nor is she single.

It's neither hot nor cold today.

They are also not gradable:

- extremely true extremely safe
- ? more pregnant than most longer than some
- ? moderately female moderately clean

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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? hot seems to mean hot, and to a larger degree, whereas heavier seems to mean of greater weight.

- · hotter is a true comparative of hot
- heavier is a pseudo-comparative of heavy/1, and a true comparative of heavy/2



Are they 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?

Does one of the questions imply something about your presuppositions?

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

clean-dirty:

- How clean was the room? → impartial
- How dirty was the room? → committed

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Antonyms: Three types

- 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.
- Iong-short is an example of a polar antonym.

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 Polar antonyms show the greatest level of abstraction, but are neutral/descriptive. Linguistic tests for complementaries and antonymy type Linguistic vs. natural polarity

Linguistic polarity vs. natural polarity

- Can we predict from the linguistic form which one of the antonyms is more 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.
- clean and safe are exceptions in that
 - Something is clean when there is no dirt present.
 - Something is dirty when there is no cleanness present.

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Linguistic tests for complementaries and antonymy type Linguistic vs. natural polarity

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Linguistic polarity vs. natural polarity, II



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Automatic Detection of Semantic Orientation of Adjectives

- Test 3: The more salient antonym yields the impartial interpretation in the how-adj question.
- In the case of verbs:
 - Antonymy in verbs often concerns directional actions, and reversive actions (Cruse, chapter 10)
 - The salient antonym is the one that results in "increased entropy" (undress, dismount, disarrange, unscrew, unpack...)

Hatzivassiloglou and McKeown's (1997) algorithm classifies adjectives into those with positive or negative semantic orientation:

- Semantic Polarity of an adjective:
 - Direction: In which direction does the referent deviate from the norm in its semantic field?
 - · Evaluative: Is this good or bad?
- If we know that two adjectives relate to the same property (e.g., *hot* and *cold*) but have different orientations they are usually antonyms



Idea

- In coordinations, these facts result in constraints on the semantic orientation:
 - (1)
- The tax proposal was simple and well-received a. by the public.

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Algorithm

- 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

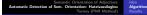
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Coordinated adjectives

This indirect information can be exploited using a corpus.



Algorithm

- Extract all coordinated adjectives from corpus
- Classify each extracted adjective pair as same or different orientation
- This results in graph with same or different links between adjectives
- Cluster into two orientations, placing as many words of the same orientation as possible into the same subset
- Cluster with higher overall frequency is labelled positive
- Evaluate against independently orientation-annotated gold standard set (1336 most frequent adjectives: 657 positive, 679 negative)

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Automatic Detection of Sem. Orientation: Hatzivassiloglou Algorithm

Classifier

- Eestures:
 - Type of coordination
 - Type of modification (attributive, predicative, appositive, resultative ("Bill laughed himself hoarse")
 - Number of modified noun (singular or plural)
- Simple derivational morphological analysis suggests additional different orientations: Out of the labelled adjectives, 97% of morphologically related pairs (102) have different orientation
- Log-linear regression model with linear predictor; best classifier achieves 82%
- Baseline: always predict same-orientation: 79%
- But-rule: different if seen with but, same-orientation otherwise: 82%

Extract from POS tagged WSJ (21 million words) adjective pairs coordinated by and, or, but, either-or, neither-nor

- This results in 15048 adjective pairs (token); 9296 (type)
- Number of those where orientation of both partners is known (via gold standard): 4024 (token); 2748 (type)
 - and is most reliable same-orientation predictor, particularly in predicative position (85%), this drops to 70% in appositive nosition
 - a but has 31% same orientation

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Semantic Orientation of Adjectives Idea Automatic Detection of Sem. Orientation: Hatzivassilogiou Turney (PMI Method) Results

Clustering adjectives with same orientation

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

$$\frac{1}{|\mathcal{C}|-1}\sum_{y\in\mathcal{C},x\neq y}d(x,y)<\frac{1}{|\mathcal{C}|}\sum_{y\in\mathcal{C}}d(x,y)$$

Semantic Orientation of Adjectives	Idea
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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.

Semantic Orientation of Adjectives	Idea
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Labelling Clusters as Positive or Negative

- In antonym pairs, the one which is semantically unmarked is also in most cases the positive one.
- \bullet Semantically unmarked ones should occur overall more frequently \to group with overall higher frequency count gets labelled as positive.



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Strengths:

- · Fully unsupervised, algorithm starts from nothing
- 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)

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Algorithm

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

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-2.050

-0.850

-0.286

5.771

1.936

0.395

1.349

-2.288

Use IR to quantify effect

· 66% accuracy on movie reviews

little difference

programs such

possible moment

unetical practices

probably wondering

Total: -1.218. Rating: Not recommended

other problems

clever tricks

old man

An example:

Measure success indirectly via classification of entire reviews

74% accuracy on classifying 410 reviews from Epinions

-1.615

-0.040

0.117

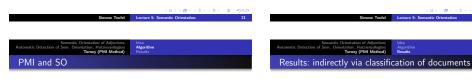
-0.668

-8 484

-2.566

-2.748

-1.830



$$PMI(word_1, word_2) = log_2(\frac{P(word_1, word_2)}{P(word_1)P(word_2)})$$

Semantic Orientation:

SO(phrase) = PMI(phrase, excellent) - PMI (phrase, poor)

- · Counts are calculated via search engine hits
- Altavista's NEAR operator window of 10 words

Therefore:

$$SO(phrase) = log_2(\frac{hits(phrase NEAR excellent)hits(poor)}{hits(phrase NEAR poor)hits(excellent)})$$

virtual monopoly

direct deposits

other bank

online web

cool thing

very handy

lesser evil

extra day

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

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References

Hatzivassiloglou and McKeown (1997): Predicting the Semantic Orientation of Adjectives. Proceedings of the ACL.

Algorithm Results

 $\label{eq:constraint} \begin{array}{l} \textbf{Turney} \mbox{ (2002): Thumbs up or down? Semantic Orientation} \\ \mbox{ Applied to Unsupervised Classification of Reviews. Proceedings of ACL.} \end{array}$

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Homework					
Homework					

- Familiarize yourself with the organisation of WordNet (e.g., www.wordnet-online.com)
- Explore lexical neighbourhood in WordNet of some of the examples given in either of the two papers discussed today
- Are they part of an antonym pair, and if so, which type of antonymy is it? Support your answer with linguistic tests.