Analyzing Sentiment while Accounting for Negation Scope and Strength

Introduction

- Decisions in, e.g., economics, politics, or reputation management require information monitoring tools for tracking sentiment.
- The Web offers an overwhelming amount of textual data (e.g., blogs, reviews, or tweets), containing traces of sentiment.
- Existing quantitative sentiment analysis approaches are typically based on word frequencies, yet one may want to consider a simple, computationally tractable way of accounting for negation by, e.g., exploiting negation keywords.
- How to model the influence of negation keywords on the sentiment conveyed by natural language text?

Accounting for Negation

- The challenge lies in finding the scope of influence of a negation keyword, which can be done by means of several methods:
  - Consider the following positive sentence with one negation keyword, some positive, and many negative words:
    - Example review sentence: This great product removed the nasty stain without badly damaging my shoe!
  - One way of accounting for negation is negating the sentiment of the Rest of the Sentence (RoS):
    - Following a negation keyword: This great product removed the nasty stain without badly damaging my shoe!
    - Around a negation keyword: This great product removed the nasty stain without badly damaging my shoe!
  - Another common method would negate the sentiment of the First Sentiment-carrying Word (FSW):
    - Following a negation keyword: This great product removed the nasty stain without badly damaging my shoe!
    - Around a negation keyword: This great product removed the nasty stain without badly damaging my shoe!
  - One may assume adverbs to simply modify sentiment-carrying words, and hence negate the Next Non-Adverb (NNA):
    - Following a negation keyword: This great product removed the nasty stain without badly damaging my shoe!
    - Alternatively, one could negate the sentiment of words within a Fixed Window Length (FWL), e.g., 2 words:
      - Following a negation keyword: This great product removed the nasty stain without badly damaging my shoe!
    - Around a negation keyword: This great product removed the nasty stain without badly damaging my shoe!
  - We propose to also optimize the negation strength, as negated sentiment is not necessarily exactly the opposite sentiment.

Assessing the Impact of Negation Handling Methods

- Framework for assessing the impact of our considered negation handling methods in sentence-level sentiment analysis.
- Evaluation based on sentiment classification performance on a test set of annotated sentences; for each sentence:
  - Extract all words (simple and compound) and retrieve their part-of-speech and lemma.
  - Disambiguate each word’s sense by means of a Lesk-based algorithm which iteratively selects the word sense that is semantically most similar to the already disambiguated words in the rest of the sentence.
  - Retrieve sentiment scores of words, ranging from -1 (negative) to 1 (positive), from the SentiWordNet sentiment lexicon.
  - Negate sentiment scores of negated words by multiplying these scores with an inversion factor (typically negative).
  - Calculate sentence score as sum of word scores and classify sentence as positive (score > 0) or negative (score < 0).
- The inversion factor can be optimized in a range of -2 to 0 by means of hill-climbing on a training set.

Evaluation

- Corpus of 930 positive and 1,355 negative manually annotated English movie review sentences (60% training, 40% test).
- Baseline: sentiment analysis without accounting for negation; alternatives: RoS, FSW, NNA, and FWL (window sizes 1 to 4).
- Most alternatives fail to improve the performance of the baseline on the test set, except for negating the FSW following a negation keyword or negating words within a FWL of 1 to 4 words following a negation keyword.
- The best performing method turns out to be negating words within a FWL of 2 words following a negation keyword, which yields a significant increase in both overall accuracy and macro-level F1 of approximately 6% on the test set.
- Optimizing this method’s sentiment inversion factor to a value of -1.27 rather than -1 on our training set yields a significant increase in accuracy and macro-level F1 of 7% and 8%, respectively, on the test set, compared to the baseline.

Conclusions

- Accounting for negation in automated sentiment analysis can help improve the performance of classifying text as carrying either positive or negative sentiment, when properly modeling scope and strength of negation keywords.
- In future work, we will explore the applicability of distinct sentiment inversion factors for negated positive and negative words.

Acknowledgement

- We would like to thank Teezir for their technical support and fruitful discussions.

Alexander Hogenboom, Paul van Iterson
Bas Heerschop, Flavius Frasincar, and Uzay Kaymak
hogenboom@ese.eur.nl, {basherschop, paulvaniterson}@gmail.com,
{frasincar, kaymak}@ese.eur.nl.

Econometric Institute
Erasmus School of Economics
Erasmus University Rotterdam
P.O. Box 1738, NL-3000 DR
Rotterdam, The Netherlands
+31 (0) 10 408 8907
+31 (0) 10 408 9031
http://www.eur.nl/ese/english/