A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts

Document-level Polarity Classification

- Determining whether an article is a good or bad movie review
- Resistant to data-driven methods (counting positive, negative words)
- A lot of the text is objective (plot summary, etc.)
Sentence-level Subjectivity Extraction

• Polarity classification would be easier if you could eliminate the plot summaries
• Classify sentences as objective or subjective, throw out the objective ones and then classify what's left
• How?
You could come up with some interesting features and train a classifier with those.

But this is a paper about graph-based models!
Pairwise interaction information

- You want individual feature vectors for each sentence $\text{ind}_j(x_i)$
- you also want to measure how important it is that two sentences belong to the same class, never mind which one. Call those $\text{assoc}(x_i, x_k)$
- Minimize this:

$$\sum_{x \in C_1} \text{ind}_2(x) + \sum_{x \in C_2} \text{ind}_1(x) + \sum_{x_i \in C_1, \atop x_k \in C_2} \text{assoc}(x_i, x_k).$$
The graph part

- Cut of a graph: a partition of the vertices of a graph into two disjoint subsets that are joined by at least one edge (wikipedia)

- Minimum cut: the cut such that the edges that separate the subsets have minimum weight

- If you set it up right, you can use it to minimize the equation
Setting up the graph

```

C_1          | Individual penalties | Association penalties | Cost
---          |---------------------|-----------------------|------
\{Y,M\}     | .2 + .5 + .1        | .1 + .2               | 1.1  
{none}       | .8 + .5 + .1        | 0                     | 1.4  
\{Y,M,N\}   | .2 + .5 + .9        | 0                     | 1.6  
\{Y\}       | .2 + .5 + .1        | 1.0 + .1              | 1.9  
\{N\}       | .8 + .5 + .9        | .1 + .2               | 2.5  
\{M\}       | .8 + .5 + .1        | 1.0 + .2              | 2.6  
\{Y,N\}     | .2 + .5 + .9        | 1.0 + .2              | 2.8  
\{M,N\}     | .8 + .5 + .9        | 1.0 + .1              | 3.3  
```
The data

- Polarity dataset: 2000 reviews, half positive and half negative, max 20 per author
- Subjectivity dataset: 5000 review snippets from rotten tomatoes, 5000 plot summary snippets from imdb, collected automatically
Experiments – no minimum cut

• Train a polarity classifier on the polarity dataset. Use unigram presence features, and do 10-fold cross-evaluation.

• Classify based on the full review, the first N, and the last N sentences with various values of N.

• Do subjectivity detection without also considering proximity (no graph models yet). Train classifiers on the subjectivity dataset. Extract the N most subjective sentences.

• Also try with the N least subjective sentences.
Results – no minimum cut
Results – no minimum cut
Experiments – minimum cut

- In addition to the individual subjectivity scores for sentences, give them proximity scores to the other sentences in the same document.
- Find the minimum cut, extract the N most subjective again.
Results – minimum cut

Accuracy for subjective abstracts (def = NB)

- Extract$_{NB}$
- Extract$_{SVM}$
- Extract$_{NB+Prox}$
- Extract$_{SVM+Prox}$

- Full Review

% of words extracted: 0.6 to 1.1

Average accuracy: 83 to 87

- Indicates statistically significant improvement in accuracy
- Difference in accuracy not statistically significant
Results – minimum cut
Learning General Connotations of Words using Graph-based Algorithms

- Song Feng, Ritwik Bose, Yejin Choi
Problem

- Sentiment Lexicons
- Connotation Lexicons
  - World knowledge?
  - Connotative predicates
Connotative Predicates

- Selectional preference of connotative predicates
- Example: prevent, congratulate
- Semantic prosody
Connotation

- Some words have polar connotation even though they are objective
- Predicates are not necessarily words with strong sentiment and inverse
- Ex's: save, illuminate, cause, abandon
Creating a Graph

- Predicates on left, words with connotative polarity on right, thickness of edges is strength of association
- Only look at THEME role of predicate
- Given seed predicates, learn connotation lexicon and new predicates via graph centrality
Graphs

- Two types: undirected (symmetric) and directed (asymmetric)
- Different edge weighting: PMI and conditional probability
- Start with seed of specifically connotative predicates
HITS

- Good hubs point to many good authorities, good authorities pointed to by many good hubs
- Authority and hub scores calculated recursively
  - \( h(A_i) = \sum_{P_j, A_j \in E} a(P_j) w(j,i) \)
  - \( a(A_i) = \sum_{P_i, A_j \in E} w(i,j) h(A_j) + \sum_{P_j, A_i \in E} h(P_j) w(j,i) \)
Based on edges leading into and out of nodes, which are either predicates or arguments

\[ S(i) = \alpha \sum_{j \in \text{In}(i)} S(j) \times w(i, j)/|\text{Out}(i)| + (1 - \alpha) \]
Tests

- Both symmetric and asymmetric graphs
- Both truncated and focused (teleportation)
- Data from Google Web 1T
- Co-occurrence pattern: \([p] [^*]^n-2 [a]\)
Comparison to Sentiment Lexicons

- Compare overlap with two sentiment lexicons: General Inquirer and Opinion Finder
- Best results
  - General Inquirer 73.6 vs 77.7
  - Opinion Finder 83.0 vs 86.3
Extrinsic Evaluation via Sentiment Analysis

- Evaluated on SemEval2007 and Sentiment Twitter
- BOW + Opinion Finder + connotation lexicon
- 78.0 vs 71.4 on Sentiment Twitter
Intrinsic Evaluation via Human Judgment

- Human judges give connotative polarity judgments for words (1-5)
- 97% on control, 94% on words without graph, 87.3 vs 79.8 for graph words
Critique

- Solution in search of problem?
- No discussion of low human evaluation score
- Comparison with sentiment lexicons may not be informative – idea is to find words NOT in lexicons
- Naive predicate/argument extraction - very confident that noise will be filtered out
Positives

- Connotation lexicon seems intuitively important
- Graph algorithms are great workarounds to world knowledge-heavy task
- Uses theoretically motivated linguistic knowledge and find results