USING RHETORICAL STRUCTURE IN SENTIMENT ANALYSIS OF TEXT

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INTRODUCTION (1)

- Semantic information systems for decision support can benefit from a sense of people’s sentiment with respect to events, products, brands, etc.
- The Web offers an overwhelming amount of textual data, containing traces of sentiment.
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- Let us consider the following *negative* review:
  - Example: Although Brad Pitt’s *well-deserved* fall off a cliff was quite *entertaining*, this movie was *terrible*!
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Let us consider the following *negative* review:

- Example: *Although Brad Pitt’s well-deserved fall off a cliff was quite entertaining, this movie was terrible!*

How can the structure of natural language text be exploited when determining the text’s polarity?
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- Let us consider the following negative review:
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SENTIMENT ANALYSIS

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- Applications in summarizing reviews, determining a general mood (consumer confidence, politics)
- State-of-the-art approaches classify the polarity of natural language text by analyzing vector representations using, e.g., machine learning techniques
- Alternative approaches are lexicon-based, which renders them robust across domains and texts and enables linguistic analysis at a deeper level
STRUCTURE-GUIDED CLASSIFICATION (1)

- Early approaches involve accounting for segments’ positions in a text or their semantic cohesion.
- Recent work exploits discursive relations by applying the Rhetorical Structure Theory (RST).
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- Recent work exploits discursive relations by applying the Rhetorical Structure Theory (RST).
- RST can be used to split a text into a hierarchical structure of rhetorically related segments.
- Nucleus segments form the core of a text, whereas satellites support the nuclei.
- Many types of relations between segments exist, e.g., background, elaboration, explanation, contrast, etc.
STRUCTURE-GUIDED CLASSIFICATION (2)

- Rhetorical structure of an example sentence:
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While always complaining that he hates this type of movies, John bitterly confessed that he enjoyed this movie.
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- We propose to:
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  - Account for the full rhetorical structure
  - Guide polarity classification by sentence-, paragraph-, and document-level RST analysis
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**STRUCTURE-GUIDED CLASSIFICATION (4)**

- Top-level RST-guided sentiment analysis:

  ![Diagram showing attribution and background with text highlighted.]

While always complaining that he hates this type of movies, John bitterly confessed that he enjoyed this movie.
STRUCTURE-GUIDED CLASSIFICATION (5)

- Leaf-level RST-guided sentiment analysis:

```
BACKGROUND

ATTRIBUTION
While always complaining that
he hates this type of movies,

John bitterly confessed that
he enjoyed this movie.
```
STRUCTURE-GUIDED CLASSIFICATION (5)

- Leaf-level RST-guided sentiment analysis:

  While always complaining that he hates this type of movies,
  John bitterly confessed that he enjoyed this movie.
STRUCTURE-GUIDED CLASSIFICATION (5)

- Leaf-level RST-guided sentiment analysis:

  While always complaining that he *hates* this type of movies, John *bitterly* confessed that he *enjoyed* this movie.
STRUCTURE-GUIDED CLASSIFICATION (6)

- Hierarchical RST-guided sentiment analysis:

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FRAMEWORK (1)

- Lexicon-based document-level polarity classification
- Based on its lemma, Part-of-Speech (POS), and disambiguated word sense (Lesk-based), each individual word is scored in the range [-1,1]
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- Word scores are aggregated and corrected for a bias towards positivity in order to classify text as positive (corrected score $\geq 0$) or negative (corrected score $< 0$)
- Discourse parsing is applied in order to determine appropriate weights for word scores in this process
FRAMEWORK (2)

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- Simple discourse parsing: weights proportional to position of words in the full text

- RST-based discourse parsing:
  - Unit of analysis: sentence (S), paragraph (P), or document (D)
  - Rhetorical parsing: top-level (T), leaf-level (L), or hierarchical (H)
  - Weighting schemes:
    - I: nucleus weights of 1, satellite weights of 0
    - II: nucleus weights of 1.5, satellite weights of 0.5
    - X: optimized weights, differentiated by satellite type
    - F: optimized weights, differentiated by nucleus and satellite type
FRAMEWORK (3)

- Polarity classification framework:

Documents → Paragraph Splitter → Sentence Splitter → Word Tokenizer

Semantic Lexicon → Word Sense Disambiguator

Sentiment Lexicon → Word Scorer

Lemmatizer

POS Tagger

Rhetorical Structure Processor

Document Classifier

Weighting Schemes

Classified Documents
EVALUATION (1)

- Implementation in Java, Stanford tokenizer, OpenNLP POS tagger, Java WordNet Library (JWNL) API for lemmatization, SentiWordNet 3.0 sentiment lexicon

- RST parsers:
  - Sentence-level PArsing of DiscoursE (SPADE, for sentences)
  - HIgh-Level Discourse Analyzer (HILDA, for sentences, paragraphs, and documents)
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- Optimization of weights for weighting schemes X and F by means of a Particle Swarm Optimization approach

- For hierarchical RST-based sentiment analysis, a diminishing factor is optimized as well
EVALUATION (2)

- Performance evaluation by 10-fold cross-validation on a corpus of 1,000 positive and 1,000 negative manually classified English movie reviews
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- RST-guided alternatives are all 48 combinations of:
  - Unit of analysis S (for both SPADE and HILDA), P, and D
  - Parsing methods T, L, and H
  - Weighting schemes I, II, X, and F
EVALUATION (3)

- Performance of baselines and best methods for each level of analysis:

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<th>Rec.</th>
<th>F1</th>
<th>Prec.</th>
<th>Rec.</th>
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- Optimized diminishing factors result in the first 15 to 30 levels of an RST tree to be accounted for in the analysis.
- The best approaches enable a focused analysis.
EVALUATION (5)

We're back in blade runner territory with this one, conceptual artist Robert Longo's vision of a William Gibson-inspired future where information is the commodity to kill for. Front and center is Johnny (Keanu Reeves), a "cyber-courier" who smuggles data via a "wet-wired" implant. He's ready to quit the biz and get a portion of his long-term memory restored, but, first, he has to finish one last, dangerous job.

The pressing problem in Johnny mnemonic is that Keanu Reeves seems to have forgotten how to play an action hero since his stint on speed. He's walking wood in a forest of stiffs that includes Henry Rollins, Ice-T, and Dina Meyer. (Dolph Lundgren's street preacher is in an acting category all its own.) Without a believable performance between them, all we can do is sit back and watch the atmosphere, which is pretty good in places. The VR sequences are way cool, but the physical fx -- such as miniatures and mattes -- leave a lot to be desired. Watch out for those bad blue-screens.

We wouldn't mind a minute of Johnny mnemonic if the action played better. Too bad the debut director is n't very strong in this department. His big finale is a sloppy, silly mess that runs twenty minutes too long, which is way past the time that most of our "wet-wired" processors have already shut down.

Bottom line: yatf (yet another tortured future). Skip it.
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- RST-guided polarity classification works best when exploiting RST trees of smaller units of a text
- Both nuclei and satellites appear to play an important role in conveying sentiment, whereas satellites have until now been deemed predominantly irrelevant
- Significantly improved polarity classification performance w.r.t. not accounting for structural aspects of content comes at a cost of increased processing times
FUTURE WORK

- Explore other (faster) methods of identifying discourse structure in natural language text
- Investigate our findings’ applicability to vector-based machine learning approaches to sentiment analysis
- Evaluate our findings on different corpora
QUESTIONS?

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