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Evaluating Humor Features on Web Comments

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1. Preliminaries

Humor

- Multidimensional phenomenon
  - Cultural and social information
  - Linguistic competence
  - Cognitive stimuli
- Personal and subjective

Automatic Humor Processing

- Approaches
  - Generation
  - Recognition
  - *Retrieval*
- Focus on verbal humor

Goal

- Humor retrieval
  - Funny comments on Web items
- Distinguish between an implicit funny comment from a not funny one
- New challenge: different characteristics compared to other text types

2. Humor Model & Evaluation Corpus

Features

- Sexual-content
- Semantic ambiguity terms
- Negative polarity
- Emotions
- Slang and emoticons, e.g., "LOL" or ": -)"

Learning Transfer

- One-liners corpus
- Features representativeness
  - Frequency threshold > 50

Evaluation Corpus

- 1.068,953 comments from the Slashdot news Web site
- Comments are categorized in a community-driven process
- Four classes
  - *Funny*
  - Informative
  - Insightful
  - Negative
- Avoiding class imbalance, 150,000 comments from each class, i.e., 600,000 comments in total.

3. Experiments & Results

Classifier technologies

- Bayes, Decision tree, and Support Vector Machines
- Training sets contain 100,000 comments per class
- Test sets contain 50,000 comments per class

Feature Evaluation

s_1 sexual-content and semantic ambiguity
s_2 sexual-content, semantic ambiguity, and polarity
s_3 sexual-content, semantic ambiguity, polarity, and emotions
s_4 all features

Results

- Classification accuracy
  - A: Funny *vs.* Informative
  - B: Funny *vs.* Insightful
  - C: Funny *vs.* Negative

Exp.	Bayes	SVM	REPTree	
s_1	57.15%	57.16%	57.16%	A
s_2	57.35%	57.38%	57.36%	
s_3	58.03%	57.38%	57.29%	
s_4	58.26%	57.94%	58.31%	
s_1	62.19%	62.25%	62.25%	B
s_2	62.66%	62.43%	62.74%	
s_3	62.39%	62.52%	62.94%	
s_4	63.08%	62.97%	63.52%	
s_1	60.37%	60.36%	60.37%	C
s_2	60.54%	60.41%	60.54%	
s_3	60.13%	60.37%	60.54%	
s_4	60.48%	60.89%	61.33%	

4. Observations & Final Remarks

Discussion

- Features are not very useful for comments
- *Hypothesis*
  - (1) Negative data (similar structures, significant differences)
  - (2) Linguistic strategies (verbal *vs.* situational humor)

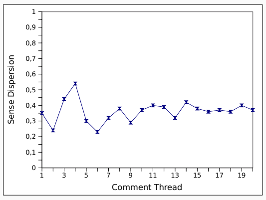
Assessing hypothesis

1. New negative data (10,000 hotel reviews)
   Funny *vs.* TripAdvisor

Exp.	Bayes	SVM	REPTree
s_4	**73.43%**	**74.06%**	**73.17%**

2. Linguistic strategies
   (-) Sense Dispersion
   (-) 20 threads

$$\delta(w_s) = \frac{1}{P(|S|,2)} \sum_{s_i,s_j \in S} d(s_i,s_j) \quad (1)$$



New Results

- Different negative data improved significantly accuracy
- Comments share more similarities than differences
- Low dispersion among the threads senses

Conclusions & Future Work

- Features have a limited performance in distinguishing the classes
- Last experiments supported our hypothesis
- Corroborate results and investigate new features (Irony detection)

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