Modeling Sentiment Association in Discourse for Humor Recognition

Lizhen Liu, Donghai Zhang, Wei Song
Information Engineering, Capital Normal University, Beijing 100048, China
wsong@cnu.edu.cn

Introduction

Sentiment should be important for humor understanding.

- Considering superiority theory (Gruner, 1997), sentiment should be common in humorous texts to express comparisons between *good* and *bad*.
- Considering relief theory (Rutter, 1997), sentiment can be used to indicate emotion changes.
- Existing work mainly considers statistical sentiment information such as counting the number of emotional words.
- **We propose to model sentiment association at discourse unit level for humor recognition.** Sentiment association in some extent can be used to describe the expectedness or unexpectedness, which is the idea of incongruity theory (Suls, 1972).

Sentiment Association in Discourse

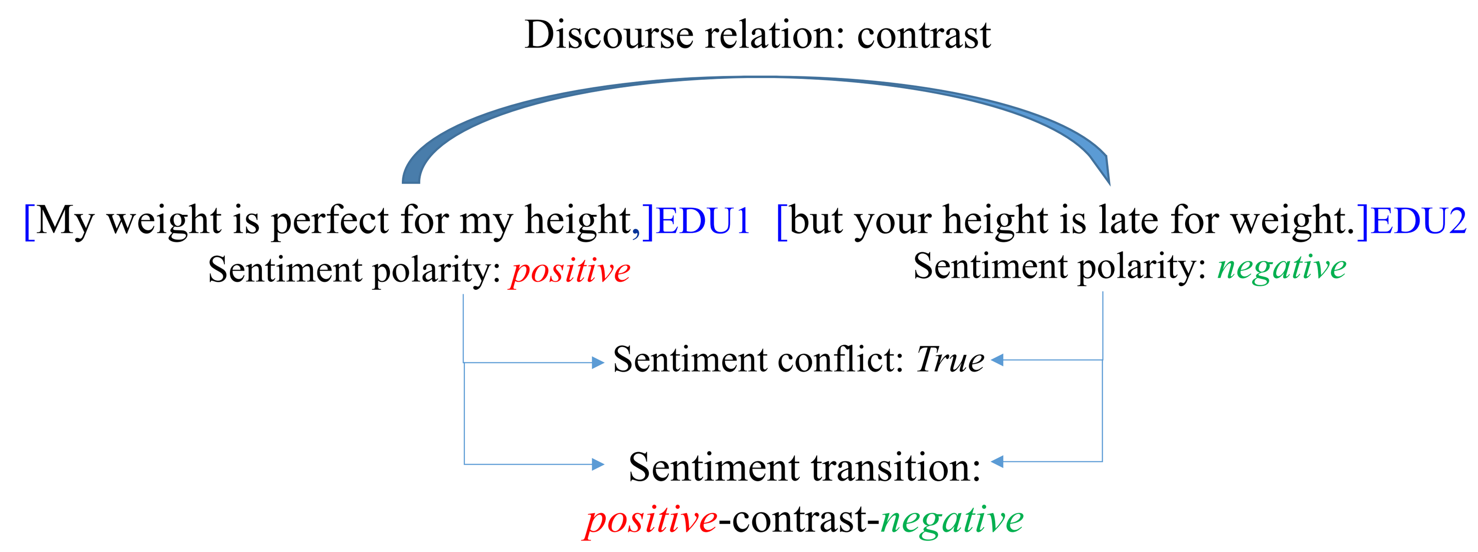

Figure 1: An example of RST style discourse parsing, sentiment polarity analysis and the features we consider in this paper

We first exploit a RST style discourse parser (Feng and Hirst 2012) to get discourse units (EDUs) and their relations; then, we use the TextBlob toolkit to get the sentiment polarity of EDUs.

☐ Three types of features are derived

- **Discourse Relation (DR)**. We design Boolean features to indicate the occurrence of discourse relations
- **Sentiment Conflict (SC)**. If there are at least two EDUs and their polarity are opposite (positive vs. negative), the feature is set as True
- **Sentiment Transition (ST)**. For two EDUs with a discourse relation R, we get their sentiment polarity respectively, namely E1 and E2. We design a feature E1∘R∘E2, where ∘ indicates a concatenation operation and E1 and E2 are ordered according to the order in which they appear in the instance

Previous Features

We mainly follow the recent work of Yang et al. (2015) to build baseline features.

☐ Humor theory motivated features

- **Incongruity Structure.** We describe inconsistency through the largest and smallest semantic distance between word pairs in a sentence
- **Ambiguity.** We use WordNet to obtain all senses of each word *w* in an instance and measure the possibility of ambiguity by computing $\log \prod_{w \in s} num\_of\_sense(w)$. We also compute the sense farmost and sense closest features
- **Interpersonal Effect.** The number of subjective words and the number of words with positive and negative polarity
- **Phonetic Style.** The number of alliteration chains and rhyme chains. The length of the longest alliteration chain and rhyme chain

☐ Content related features (may overfit the data rather than capture the nature of humor)

- **KNN.** The KNN feature set contains the labels of the top 5 instances in the training data, which are closest to the target instance
- **Word2Vec Features.** Averaged word embeddings are used as sentence representations

Results

The experimental results on the dataset provided in (Mihalcea and Strapparava, 2005) , 5-fold cross validation.

☐ **System Comparisons.**

- Base1: HCF. Include the incongruity structure, ambiguity, interpersonal effect, phonetic style features and KNN features.
- Base2: HCF w/o KNN. Remove KNN features from HCF, purely humor theory motivated features.
- Base3: Word2Vec. Only the Word2Vec features.
- Base4: Base1+Base3. Combine all features.
- SA: Sentiment association features.

	Acc.	P	R	F_1
Base1: HCF	0.787	0.779	0.815	0.797
KNN	0.756	0.733	0.821	0.775
Base2: HCF w/o KNN	0.710	0.706	0.745	0.725
Base3: Word2Vec	0.770	0.775	0.774	0.775
Base4: Base1+Base3	**0.808**	0.810	0.816	**0.813**
Base1+SA	0.799	0.789	0.828	0.808
Base2+SA	0.750	0.747	0.774	0.760
Base3+SA	0.783	0.788	0.787	0.788
Base4+SA	**0.814**	0.812	0.828	**0.820**

☐ **Comparing with Emotional Word Count(EWC).** Base2 and Base4 are used as the baseline systems. Base2 doesn't consider content information; Base4 combine all features.

	Acc.	P	R	F_1
Base2	0.710	0.706	0.745	0.725
Base2-EWC	0.709	0.705	0.742	0.723
Base2-EWC+SA	**0.748**	0.744	0.773	**0.758**
Base4	0.808	0.810	0.816	0.813
Base4-EWC	0.808	0.808	0.818	0.813
Base3-EWC+SA	**0.812**	0.812	0.823	**0.817**

☐ **Improvements of Individual Sentiment Association Features** on the basis of Base2 and Base4.

	Acc.	P	R	F_1
Base2	0.710	0.706	0.745	0.725
Base2+DR	0.741	0.737	0.768	0.752
Base2+SC	0.738	0.734	0.764	0.749
Base2+ST	**0.748**	0.743	0.775	**0.759**
Base4	0.808	0.810	0.816	0.813
Base4+DR	**0.813**	0.813	0.824	**0.818**
Base4+SC	0.811	0.812	0.820	0.816
Base4+ST	**0.813**	0.814	0.823	**0.818**

Conclusions

We have studied humor recognition from a novel perspective: modeling sentiment association in discourse. We integrate discourse parsing and sentiment analysis to get sentiment association patterns as features. We found that

- Sentiment association features can improve humor recognition, especially on the basis of humor theory motivated features
- Sentiment association features are more effective than statistical sentiment features such as emotional word count

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