Recognizing Emotions in Text

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2007
Introduction
- Problem Definition
- Related Work

Data
- Emotion Annotation
- Annotation Agreement Measurement

Experiments
- Emotion/Non-emotion Classification
- Fine-grained Emotion Classification
- Emotion Intensity Recognition

Conclusions
Problem Definition

Objective
- Determine emotions expressed in text at the sentence level

Recognize Emotion Class
- happiness, sadness, anger, disgust, surprise, fear (Ekman, 1992)
- mixed emotion, no emotion

Determine Emotion Intensity
- high, medium, low, neutral

Data
- Drawn from blogs
- Manually annotated with emotion labels
Application Areas

Affective Interfaces
- make sense of emotional input
- provide emotional responses
- human-computer interaction (HCI)
- computer-mediated communication (CMC)
- e-learning systems

Text-to-Speech (TTS) Systems
- natural emotional rendering of text

Psychological Analysis of Text
- learn user preferences, inclinations, and biases
- personality modeling
- consumer review analysis
Related Work

**Sentiment Analysis**
- finding subjectivity, opinion, appraisal, orientation, affect, emotions
- finding polarity – positive/negative sentiment
- finding intensity – high, low, neutral

**Genres**
- news articles, editorials, opinion pieces (edited, professional)
- movie reviews, product reviews, blogs (unedited, informal)

**Sentiment Analysis Methods**
- Machine Learning methods
- Unsupervised methods
Related Work

**Knowledge Sources**
For identifying semantic orientation of words/phrases

- Specialized lexicons (e.g., GI, WN-Affect, SentiWordNet)

- Lexicons built using
  - domain-specific words/phrases (e.g., “great acting”)
  - syntactic patterns (e.g., adverb-adj as in “very happy”)
  - existing general-purpose lexicons (e.g., WordNet, Roget’s)

- Corpus-driven approaches
  - PMI-IR (based on co-occurrence with similar words)
  - probabilistic sentiment scores (based on relative frequency in labeled documents)

- Contextual valence shifters
  - intensifiers, diminishers, negations
Data Collection
- Used seed words for each emotion category
- 173 blog posts collected (5205 sentences)

Annotation Process
- four judges involved in the annotation process
- each sentence subjected to two decisions

Types of Annotations
- Emotion Category – {hp, sd, ag, dg, sp, fr, me, ne}
- Emotion Intensity – {h, m, l}
- Emotion Indicators (individual words / strings of words)

Example
But all of a sudden it’s hit me that I have all this work due. (sp, h)
**Emotion Category**

- Cohen’s kappa used for agreement measurement (Cohen, 1960)

**Pairwise agreement in emotion categories**

<table>
<thead>
<tr>
<th>Emotion Category</th>
<th>Average Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>hp</td>
<td>0.77</td>
</tr>
<tr>
<td>sd</td>
<td>0.68</td>
</tr>
<tr>
<td>ag</td>
<td>0.66</td>
</tr>
<tr>
<td>dg</td>
<td>0.67</td>
</tr>
<tr>
<td>sp</td>
<td>0.6</td>
</tr>
<tr>
<td>fr</td>
<td>0.79</td>
</tr>
<tr>
<td>me</td>
<td>0.43</td>
</tr>
<tr>
<td>em/ne</td>
<td>0.76</td>
</tr>
</tbody>
</table>
Emotion Intensity
- Cohen’s kappa used for agreement measurement (Cohen, 1960)
**Emotion Indicators**

- **MASI** (Passonneau, 2006)
  
  \[ A/B = \text{set of emotion indicators identified by Judge1/Judge2} \]
  
  \[ \text{MASI} = J \times M \]
  
  \[ J = \frac{|A \cap B|}{|A \cup B|} \]

\[ M = \begin{cases} 
1, & \text{if } A = B \\
2/3, & \text{if } A \subseteq B \text{ or } B \subseteq A \\
1/3, & \text{if } A \cap B \neq \emptyset, A - B \neq \emptyset, \text{ and } B - A \neq \emptyset \\
0, & \text{if } A \cap B = \emptyset 
\end{cases} \]

- **I/O Method**

  each word labeled (In) or (Outside) an emotion indicator

  Example – “I/O am/O very/I happy/I” (kappa can be used)

- Avg. MASI = 0.61 ; Avg. kappa = 0.66
Experiments – Emotion/Non Emotion Classification

Used ML methods – SVM and Naïve Bayes

Features
- GI – Emotion, Positive, Negative, Interjection Pleasure, Pain words
- WN-Affect – Happiness, Sadness, Anger, Disgust, Surprise, Fear words
- Special symbols – Emoticons, Punctuations (“?” and “!”)

Emotion/non-emotion classification results

<table>
<thead>
<tr>
<th>Features</th>
<th>Naïve Bayes</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>GI</td>
<td>71.33%</td>
<td>73.89%</td>
</tr>
<tr>
<td>WNA</td>
<td>70.58%</td>
<td>73.89%</td>
</tr>
<tr>
<td>GI+WNA</td>
<td>73.89%</td>
<td>73.89%</td>
</tr>
<tr>
<td>ALL</td>
<td>73.89%</td>
<td>73.89%</td>
</tr>
</tbody>
</table>
Baseline
Term counting method using emotion words from WordNet-Affect

Features
- Corpus-based unigram features (excluding low-freq words and stopwords)
- Features from emotion lexicons -
  - WordNet-Affect (existing emotion lists)
  - emotion lexicon automatically built from Roget’s Thesaurus

Lexicon from Roget’s Thesaurus
- Words in Roget’s classification hierarchy considered as nodes in a network
- Related words likely to be located close to each other in the network
- They can be found using Semantic Similarity Measure (Jarmasz and Szpakowicz, 2004)
- Emotion words for each emotion category acquired by selecting words similar to {happy, sad, anger, disgust, surprise, fear}
Experiments – Fine-grained Emotion Classification

Fine-grained emotion classification results

<table>
<thead>
<tr>
<th>Emotion Category</th>
<th>F-Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>hp</td>
<td>0.751</td>
</tr>
<tr>
<td>sd</td>
<td>0.493</td>
</tr>
<tr>
<td>ag</td>
<td>0.522</td>
</tr>
<tr>
<td>dg</td>
<td>0.566</td>
</tr>
<tr>
<td>sp</td>
<td>0.522</td>
</tr>
<tr>
<td>fr</td>
<td>0.645</td>
</tr>
<tr>
<td>ne</td>
<td>0.605</td>
</tr>
</tbody>
</table>

- Baseline
- Unigrams
- Unigrams+RT
- Unigrams+RT+WNA
Experiments – Emotion Intensity Recognition

Emotion Intensity Modifications
- relatively weak and strong words (e.g., “dislike” and “abhor”)
- intensifiers (e.g., “very happy”, “highly grateful”, “much disappointed”)
- diminishers (e.g., “little embarrassed”, “somewhat apprehensive”, “not pathetic”)
- comparative and superlative forms of adjectives (“happier”, “greatest”)

Syntactic Bigrams
- Represent English language constructs used to express and modify emotion
- Identified using the Link Parser
- Pairs of words connected by links output by the parser
- Link examples:
  - EA connects adverbs to adjectives (e.g., <more, happy>)
  - EE connects adverbs to other adverbs (e.g., <so, angrily>)
  - Other adjective and adverb related links (e.g., <awful, lot>, <much, more>)
  - Idiomatic expressions (e.g., <very, very>), etc.
**Features**

- Corpus-based unigram features (excluding low-freq words and stopwords)
- Syntactic bigrams

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**Emotion intensity classification results**

<table>
<thead>
<tr>
<th>Emotion Intensity</th>
<th>F-Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>0.493</td>
</tr>
<tr>
<td>Medium</td>
<td>0.301</td>
</tr>
<tr>
<td>Low</td>
<td>0.164</td>
</tr>
<tr>
<td>Neutral</td>
<td>0.507</td>
</tr>
</tbody>
</table>

- **Unigrams**
- **Unigrams + Syntactic Bigrams**
Conclusions

Summary

- Studied emotion expressions in text during manual annotation
- Investigated computational methods to identify the type and strength of the expressed emotion

Results

- Use of external knowledge resources helpful in determining emotion-related words
- Use of syntactic features along with the corpus-based unigram features helpful in recognizing emotion intensity

Contributions

- Prepared an emotion-labeled corpus
- Demonstrated the feasibility of applying computational methods for automatic emotion recognition
- Introduced a novel approach of automatically building Emotion Lexicon using Roget’s thesaurus
References


Resources


Thank you!