Detecting Emotion in Text

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Introduction to Emotion Detection

Opposite reactions: Super Bowl 2012

Winning Team

"This is amazing, best time ever. Words cannot explain. I'm so excited, so happy I can't even talk now."

Losing Team

"I'm heartbroken. I've always been a Pats fan and I always will be, but there are no words to express how I am feeling."

Overview

- Background
- Parts of the emotion detection process
- An overview of one study
- Conclusions and future work

Subjectivity and Sentiment Analysis

Subjectivity

- Subjective sentence
  - The flower could not fold up its petals; it dropped sorrowfully.
- Objective sentence
  - The Earth revolves around the Sun.

Sentiment Analysis

- Positive versus negative

Emotion Detection

Emotion detection field

- New and growing
- Not standardized methods

Common parts of emotion detection process

- Annotation
- Emotional Lexicon

Annotation

Annotation Definition

Annotation is the process of manually labeling a text.

- Many variations
- Emotion labeled databases
- Used to check accuracy
- Multi-person process

Inter-Annotator Agreement

Example

Meredith: $[\text{The evil wolf ate}]_{fear}$ $[\text{the girl}]_{happiness}$.
Steve: The $[\text{evil wolf}]_{fear}$ ate the girl.

- Observed agreement (A_o):
  - $A_o = \frac{1}{I} \sum_{i \epsilon I} arg_i = \frac{2}{6} = 0.33$
- Expected agreement (A_e):
  - Addresses the probability of assigning random labels
  - $A_e = \frac{1}{I^2} \sum_{k \epsilon K} n_{c_1 k} n_{c_2 k} = \frac{8+0}{36} = 0.22$
- Kappa value (k):
  - $k = \frac{A_o - A_e}{1 - A_e} = \frac{0.33 - 0.22}{1 - 0.22} = \frac{0.11}{0.78} = 0.14$

Emotional Lexicon

Emotional Lexicon Definition

An emotional lexicon is a list of emotions and words that express each emotion.

- Many examples
- Different forms of emotional classification
- Categorical
  - Distinct emotional labels
  - Represented as words
- Dimensional
  - General emotional states
  - Represents as positions

Vector Space Model

- Categorical classification
- Matrix of co-occurrence frequency vectors
- Rows are terms and columns are documents
- Vectors are calculated *tf-idf* score

$$\begin{array}{cc} & \begin{array}{ccc} \phantom{x_{1,1}} & \mathbf{d} & \phantom{x_{1,n}} \\ & \downarrow & \end{array} \\ \mathbf{t} \longrightarrow & \begin{bmatrix} x_{1,1} & \cdots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{m,1} & \cdots & x_{m,n} \end{bmatrix} \end{array}$$

tf-idf Score Example

Dataset

- 10,000,000 documents
- *Badger* appears in 1,000
- A document of 100 words
- *Badger* appears 3 times

Term frequency (tf)

- Document level
- Percentage of words are *badger*
- $\text{tf} = \frac{3}{100} = 0.03$

Example Cont.

Inverse document frequency (idf)

- Dataset level
- Is the word common or rare?
- $\text{idf} = \log_{10} \frac{10{,}000{,}000}{1{,}000} = 4$

tf-idf score

- $\text{tf-idf} = 0.03 * 4 = 0.12$
- Weighs importance
- Prevents bias

Reduction Methods

- Matrix includes
  - Relevant data
  - Zeros and unimportant data
- Extraction of the dataset
- Dimension reduction methods
  - Latent Sentiment Analysis
  - Probabilistic Latent Sentiment Analysis
  - Non-Negative Matrix Factorization

Non-Negative Matrix Factorization

$X \approx TD$

- X = original matrix
- T = matrix of term vectors
- D = matrix of document vectors

Frobenius Norm

Minimize the Frobenius norm:

$$||A|| = \sqrt{\sum_{x=1}^{n}\sum_{y=1}^{m} a_{x,y}^2}$$

Key

- A = X - TD
- x = row (terms)
- y = column (documents)
- n = total number of terms
- m = total number of vectors
- $a_{x,y}$ = position in the matrix

Categorical Classification Result

- Assign emotion
- Emotional synset
  - Vocabulary list of emotion and its synonyms
- Cosine similarity
  - Emotion vector
  - Input text vector
  - Number between 0 and 1

Valence-Arousal-Dominance

Dimensional classification with three dimensions

- Valence, arousal, dominance
- Represented as a number between 0 and 10.
- w = (valence, arousal, dominance)
- neutral = (5, 5, 5)

VAD Values

- Sentence
- Emotion

VAD Example

Sentence Example

The flower dropped sorrowfully.

Words

- Flower = (6.64, 4.00, 4.98)
- Dropped = (4.09, 4.70, 4.00)
- Sorrowfully = (3.15, 4.56, 4.00)

Sentence = (5.20, 4.42, 4.32)

VAD Example cont.

Emotions

- Anger = (2.55, 6.60, 5.05)
- Fear = (3.20, 5.92, 3.60)
- Joy = (7.40, 5.73, 6.20)
- Sadness = (3.15, 4.56, 4.00)

Difference between sentence and emotion

- Sentence - Anger = 5.56
- Sentence - Fear = 4.22
- Sentence - Joy = 5.39
- Sentence - Sadness = 2.51

The sentence is labeled Sadness.

Results

Standard measures to present results:

- $\text{Precision} = \dfrac{\text{sentences correctly labeled by algorithm}}{\text{all sentences retrieved by algorithm}}$
- $\text{Recall} = \dfrac{\text{sentences correctly labeled by algorithm}}{\text{all sentences supposedly correct}}$
- $\text{f-score} = 2 * \dfrac{\text{Precision * Recall}}{\text{Precision} + \text{Recall}}$

Example

Sadness Sentences in a Fairy Tales Dataset

- 264 labeled sadness
- NMF labeled 305 sadness
- 216 of them were correctly labeled

- Precision $= \frac{216}{305} = 0.70$
- Recall $= \frac{216}{264} = 0.82$
- f-score $= 2 * \frac{0.70 * 0.82}{0.70 + 0.82} = 0.75$

Overall Results

Methods	SemEval (Headlines)			ISEAR (Personal)			Fairy Tales (Stories)		
	Prec.	Rec.	F1	Prec.	Rec	F1	Prec.	Rec	F1
Base	0.07	0.25	0.11	0.10	0.25	0.14	0.10	0.25	0.14
LSA	0.36	0.34	0.34	0.48	0.28	0.22	0.66	0.64	0.63
PLSA	0.18	0.28	0.21	0.26	0.31	0.27	0.28	0.30	0.28
NMF	**0.52**	**0.50**	**0.50**	0.46	0.25	0.16	**0.74**	**0.73**	**0.73**
VAD	0.46	0.42	0.38	**0.52**	**0.41**	**0.37**	0.53	0.40	0.41

Table: Four methods and a baseline algorithm tested on three datasets

- NMF did the best, but not over all three datasets
- Highest scores were in the fairy tales dataset

Conclusion

Conclusions

- Working methods out there
- Dataset specific

Future work

- Standardization
- Creating an algorithm for a general dataset

References

References

1 R. Artstein and M. Poesio: Inter-coder agreement for computational linguistics, 2008.

2 F. Keshtkar and D. Inkpen: A corpus-based method for extracting paraphrases of emotion terms, 2010.

3 S. M. Kim, A. Valitutti, and R. A. Calvo: Evaluation of unsupervised emotion models to textual affect recognition, 2010.

4 E.P. Volkova, B. J. Mohler, D. Meaurers, D. Gerdemann, and H. H. Bulthoff: Emotional perception of fairy tales: achieving agreement in emotion annotation of text, 2010.

5 J. Wiebe and E. Riloff: Finding mutual benefit between subjectivity analysis and information extraction, 2011.