

Recognizing Emotions in Text

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Agenda

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



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



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)

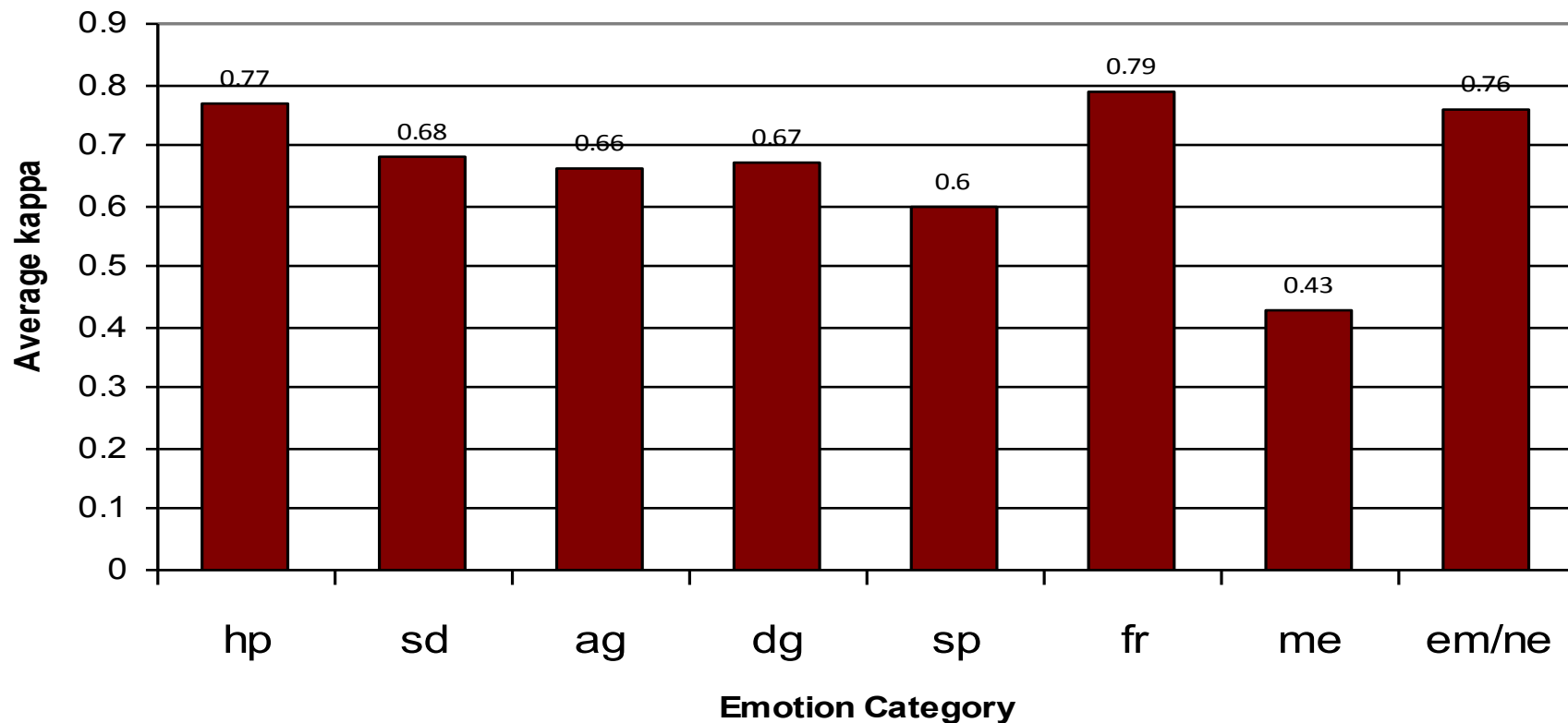


Annotation Agreement Measurement

Emotion Category

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

Pairwise agreement in emotion categories

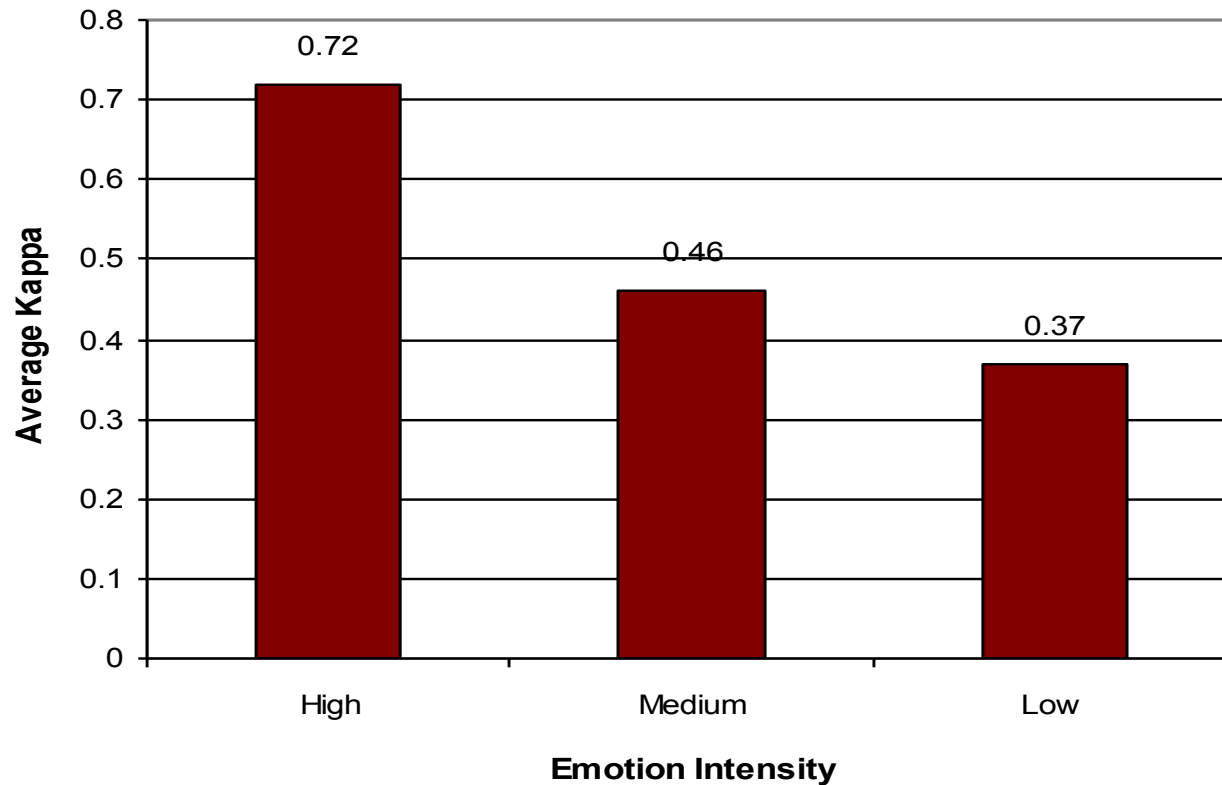


Annotation Agreement Measurement

Emotion Intensity

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

Pairwise agreement in emotion intensity



Annotation Agreement Measurement

Emotion Indicators

- **MASI** (Passonneau, 2006)

A/B = set of emotion indicators identified by Judge1/Judge2

$$\text{MASI} = J * M$$

$$J = |A \cap B| / |A \cup B|$$

$$M = \begin{cases} 1, & \text{if } A = B \\ 2 / 3, & \text{if } A \subset B \text{ or } B \subset A \\ 1 / 3, & \text{if } A \cap B \neq \phi, A - B \neq \phi, \text{ and } B - A \neq \phi \\ 0, & \text{if } A \cap B = \phi \end{cases}$$

- **I/O Method**

each word labeled (**I**n) or (**O**utside) an emotion indicator

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

- Avg. MASI = 0.61 ; Avg. kappa = 0.66



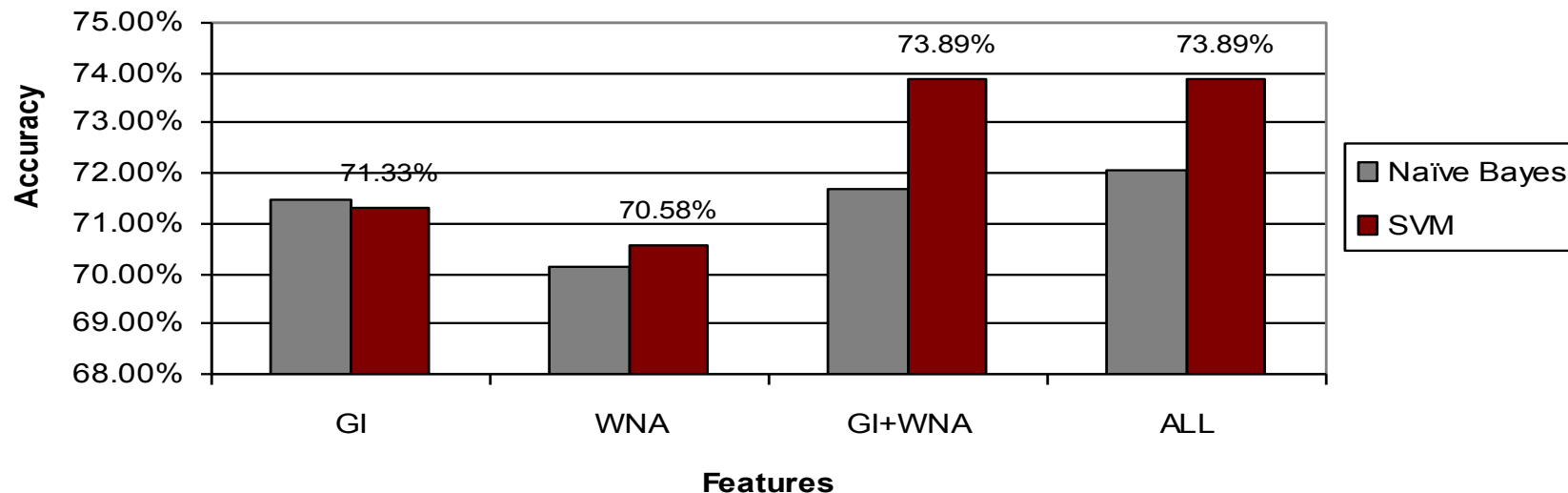
Experiments – Emotion/Non Emotion Classification

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



Experiments – Fine-grained Emotion Classification

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

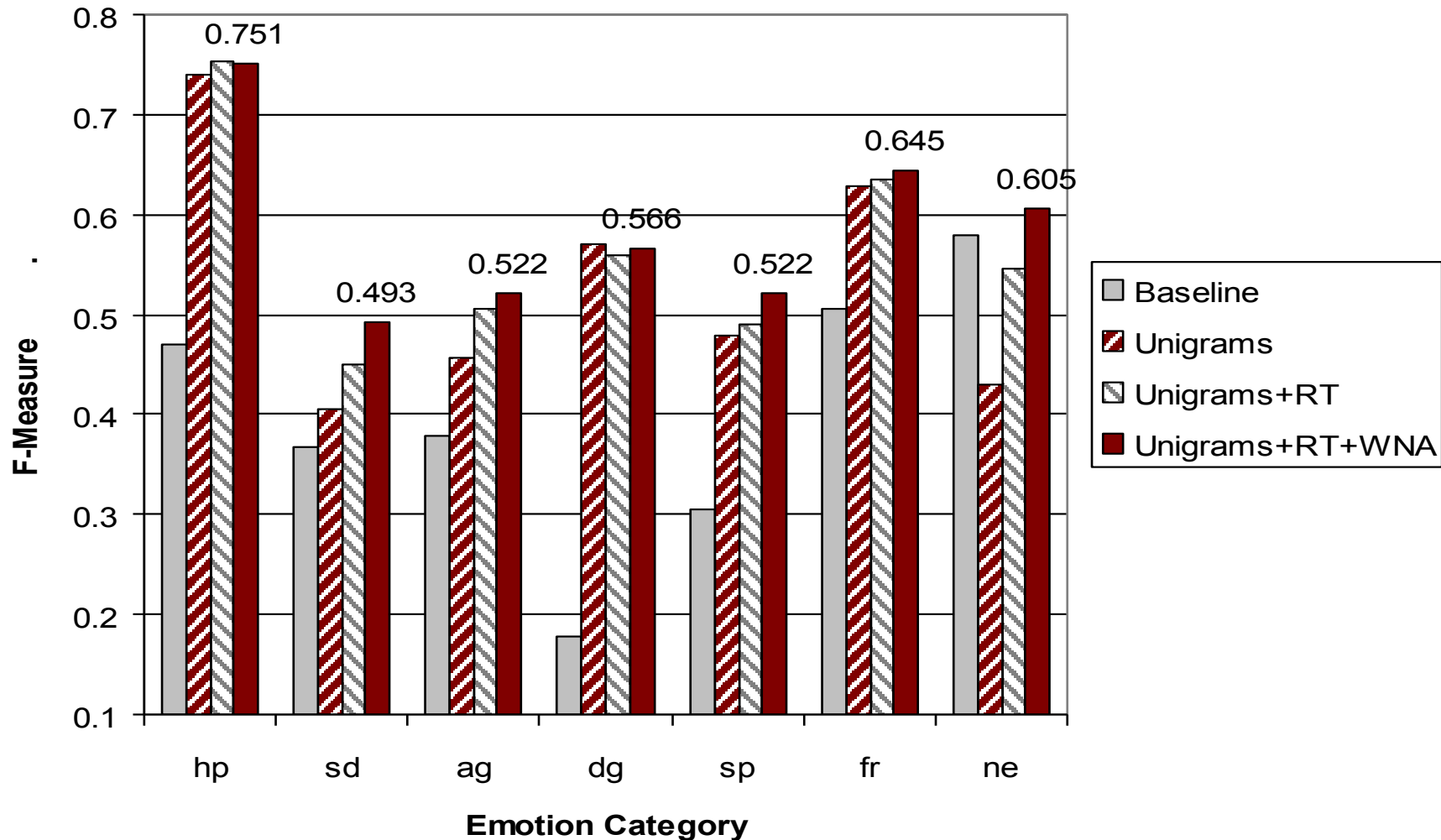
Lexicon from *Roget's* Thesaurus

- 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



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.

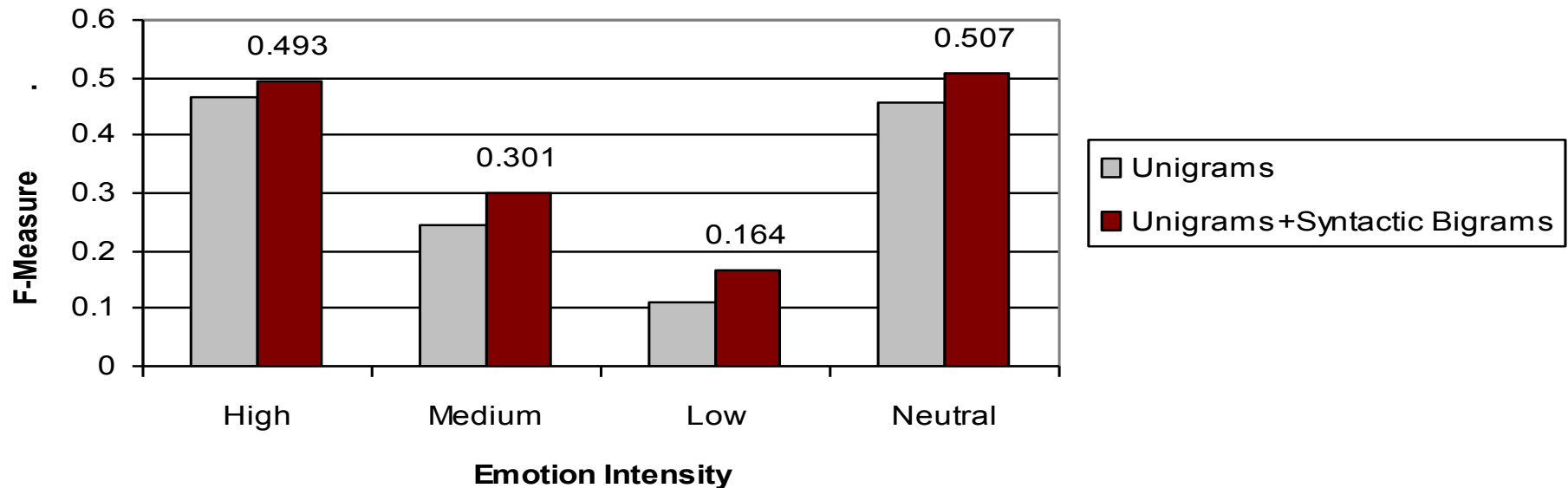


Experiments – Emotion Intensity Recognition

Features

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

Emotion intensity classification results



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



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Thank you!

