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## Comparison of Different Algorithms for Sentiment Analysis: Psychological Stress Notes

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### Abstract

To visualize and compare three text analysis algorithms of sentiment (AFINN, Bing, Syuzhet), applied to 1549 ecologically assessed self-report stress notes obtained by smartphone, in order to gain insights about stress measurement and management.

### Keywords

natural language processing

### Introduction

Psychological stress is linked to all six of the most common causes of death in the U.S. In psychology, content analysis methods derived from paper-and-pencil surveys have been applied to patient records to improve mental health outcomes. With the advance of technology, there is an increasing volume of patient generated free-text data reporting mental health symptoms and context. As a result, natural language processing-computer linguistics has been successfully applied to patient-generated free-text to gain insights from symptom and emotion management. A sentiment analysis package, 'Syuzhet', for processing free-text data has recently become publicly available. However, few studies have applied this package to free-text stress notes or diaries extracted from smartphone-based ecological momentary assessments [1].

This study aims to visualize and compare three algorithms for sentiment analysis (Syuzhet, AFINN, Bing) applied to 1549 ecologically assessed self-report stress notes using smartphones to gain insights into how the analysis of large volumes of stress diaries might inform emotion management.

## Methods

We extracted 1549 free-text notes describing self-reported momentary stressful occurrences, which were collected daily from Jan 2014 to April 2015 from sixty participants. Natural language processing was applied using three sentiment analysis algorithms (Syuzhet, AFINN, Bing) [1]. Pearson correlations were calculated between each algorithm and the participant's concurrently self-reported stress rating (0–10 scale).

## Results

Figure 1 displays the pooled emotion scores from 1549 stress notes, each applying a different sentiment analysis. Pearson correlation coefficients among the three algorithms and self-rated stress scores are shown in Table 1. The correlations among the three algorithms are moderately high, but the correlations of algorithm scores with self-ratings are low. Positive emotion (lack of negative feeling) was detected from half of the corpora of stress notes. (e.g., “Excitement!” Syuzhet emotion score +1, Self-report stress score −4).

## Conclusion

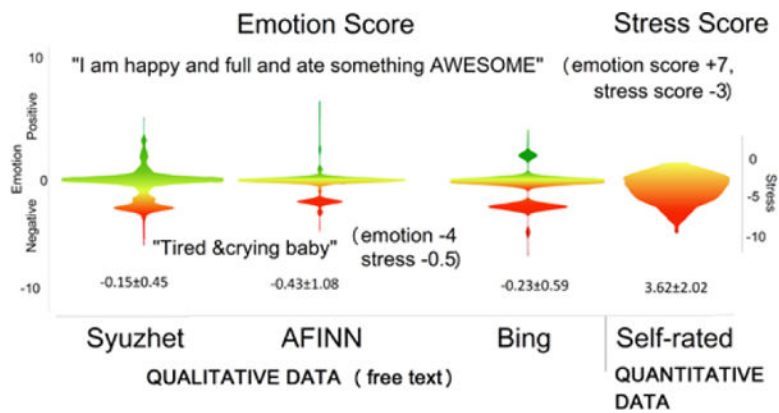
Application of sentiment analysis natural language processing and visualization techniques provide insights for research teams regarding large volumes of daily self-report stress notes. The positive emotion scores detected by sentiment analysis algorithms from qualitative data (free text) provide quantified descriptive contextual information on low level self-rated stress scores.

## Acknowledgments

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## References

1. Jockers M. Package Syuzhet. 2016 V 1.0.



**Figure 1.** Visualization of Distribution of Emotion Scores of Daily Stress Notes applying Different Algorithms

**Table 1**

Correlations among Three Sentiment Algorithms

Algorithms	Syuzhet	AFINN	Bing
Syuzhet	1		
AFINN	0.73 **	1	
Bing	0.83 **	0.67 **	1
Self-Report Score	0.04	0.03	0.03

\*\*  
p< 0.01, N=1549 notes