# Support for Understanding Others by Visualizing Sentiment of Social Media Posts


Harumi Murakami
*Graduate School of Informatics*
*Osaka Metropolitan University*
Osaka, Japan
harumi@omu.ac.jp

Reo Saitoh
*Graduate School of Engineering*
*Osaka City University*
Osaka, Japan
reo.1016.02@gmail.com



***Abstract*—Understanding people is critical in various aspects of our daily lives. We believe that extracting and visualizing the emotions included in social media posts will facilitate the understanding of people. Based on this idea, we developed a tool for understanding others using sentiment analysis of a user's Twitter and Instagram posts. We experimentally evaluated our approach and the tool to understand professional baseball players as examples of others.**

***Index Terms*—Twitter, Instagram, emotion, sentiment analysis**


## I. Introduction

Understanding people is important in such aspects as decision-making and planning in our daily lives. Although doing an internet search is useful to learn more about people, the information provided by such searches is generally superficial, including occupation and organization. We want more information about what he/she likes and what he/she does both at work and during his/her private times. To obtain such personal information about people, we turn to their SNS posts, which often mention activities and describe them with emotions. We believe that extracting and visualizing emotions included in such posts will increase our understanding of people. Based on this idea, we developed a tool for self-understanding using sentiment analysis of a user's Twitter posts [1]. In this paper, we extend this idea and develop a tool for understanding others using sentiment analysis of both Twitter and Instagram posts.

Below we explain our approach's overview in Section 2 and describe our new tool for understanding others and report the experimental results in Section 3.

## II. Approach

We visualize the emotions included in user social media posts using the Google Natural Language API sentiment analysis to get a score and a magnitude for each post. We display the following: several types of bar graphs that show the transition of emotions, a list of posts with emotional scores, a pie chart showing the proportion of emotions, and the word lists included in positive and negative posts.

We developed two bar graphs with different units: posts and periods (day and month). A bar graph by post displays post scores. We summarize the period scores by developing three bar graphs with different values: A) maximal values of the scores (both positive and negative); B) their average values; and C) a modified average value using the scores and magnitudes. A score varies from -1 to 1, and a score less than 0 is negative, 0 is neutral, and greater than 0 is positive.

Graphs A and B have individual advantages and disadvantages. Graph A emphasizes the highest valued posts, although it hides other posts in the designated period. Graph B summarizes the values in one value, although it offsets the plusses and minuses and the values tend to be small, complicating the detection of posts with high emotion content. To overcome the disadvantage of graph B, we designed graph C, which emphasizes stronger emotions with a modified average value (an $E\text{-}score$):

$$E\text{-}score = \begin{cases} \frac{\sum_{i=1}^{n} |Score_i \times Magnitude_i|}{\sum_{i=1}^{n} Magnitude_i} & \text{if } \sum_{i=1}^{n} Score_i \geq 0, \\ -\frac{\sum_{i=1}^{n} |Score_i \times Magnitude_i|}{\sum_{i=1}^{n} Magnitude_i} & \text{otherwise,} \end{cases}$$

where $Score_i$ is a Google score for post $p_i$, $Magnitude_i$ is its magnitude, and $n$ is the number of posts except for those whose scores are 0.

Posts can be sorted by date or by score in a list of posts. A pie chart shows the ratio of the positive/negative/neutral scores of the posts. Our tool displays the top five frequent word lists extracted from the positive and negative posts. First, we performed morphological analysis and assigned the score of one post to the words contained in it. For each positive and negative category, the summation of the word's score is divided by its frequency.

We developed a tool for understanding others by modifying our previous tool [1]. The main difference is that we added Instagram posts to Twitter posts. Fig. 1 shows an example for a professional baseball player. After selecting a person, a user inputs the periods (one month in this example) and selects "Per day: graph A" and "Mixed," bar graph A, a log list, and a pie chart; positive/negative word lists are displayed using both Twitter and Instagram posts.

## III. Experiments

We experimentally evaluated our approach and the tool. As examples of "others," we selected 51 Japanese professional

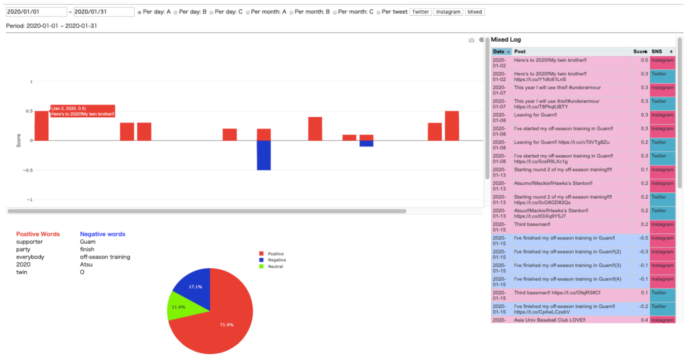

Fig. 1. Screen example

baseball players who have both Twitter and Instagram accounts. Our ten subjects (nine Japanese males and one female, ages 22-24) used the tool and answered questions about their experiences with it.

### A. Experiment 1: Google Scores

We verified the validity of the Google scores for the posts by randomly selecting one post from one player. The subjects evaluated the emotions of the 51 player's posts by five values (1: very negative; 5: very positive). Two types of correlation analysis (Kendall and Spearman) were performed between the Google and manual scores. The average values exceeded 0.3 in both types of analysis (0.349 in Kendall and 0.416 in Spearman). We believe Google scores for posts are promising.

### B. Experiment 2: Bar Graphs

We next evaluated the usefulness of the daily and monthly bar graphs. Our subjects answered the following three questions that evaluated the graphs of one month for daily bar graphs and those of six months for monthly bar graphs. Q1: "Which graph was useful for understanding his emotions: A, B, or C?" Q2: "Which graph was useful for understanding his emotions: Twitter only, Instagram only, or mixed?" Q3: "Which graph was the most useful for understanding his emotions among the nine (combination of 3 (A, B, C) $\times$ 3 (Twitter only, Instagram only, mixed)) graphs?

For Q1, all the subjects ranked graph A the best for both the daily and monthly graphs. For the daily graphs, nine subjects ranked C second, and for the monthly graphs, seven subjects ranked C second. For Q2, all subjects ranked the mixed graph the best for both the daily and monthly graphs. Six subjects ranked Twitter second in both daily and monthly graphs. For Q3, all the subjects answered that graph-A-mixed was the best in both the daily and monthly graphs.

We identified the daily and monthly usefulness of bar graph A. Since graph C is superior to graph B, it compensates for the latter's disadvantage. These results are identical to our previous research. We also found that mixed graphs are superior and that a graph-A-mixed was best among the nine graphs because it provides more information than the other graphs.

### C. Experiment 3: Tool

We evaluated our tool utility. Our subjects used it for a player, described his most positive and negative events for three months, and answered the questions in Table I. The average values were equal to or over 4.0, except for Q1, Q3, and Q4. Although the bar graphs and the log lists were useful, the words were less useful.

TABLE I
EXPERIMENTAL RESULTS FOR THE TOOL

| | Questions | Mean | SD |
|---|---|---|---|
| Q1 | Was the bar graph useful for understanding him? | 3.90 | 0.54 |
| Q2 | Was the log useful for understanding him? | 4.40 | 0.49 |
| Q3 | Were the words useful for understanding him? | 2.70 | 0.64 |
| Q4 | Was the pie chart useful for understanding him? | 3.10 | 0.70 |
| Q5 | Was the system useful for understanding him? | 4.00 | 0.45 |
| Q6 | Was using the system fun? | 4.00 | 0.45 |
| Q7 | Do you want to use the system in the future? | 4.00 | 0.45 |

We believe that our approach and tool are promising for understanding others. Instagram is another useful source as well as Twitter for understanding others.

## IV. Related Work

Numerous studies have addressed sentiment analysis on social media, most of which are analyses of user groups or communities, not individuals. One exception, Kumamoto et al. [2], proposed a web application system for visualizing Twitter users based on the temporal changes in impressions from tweets. We used not only Twitter but also Instagram posts and summarized and displayed the emotion scores contained in multiple posts. Several articles (e.g., [3] and [4]) surveyed sentiment analysis on social media and discussed fields related to it without addressing our task: understanding people.

The following are the three main contributions of this paper: (1) We presented an approach to support the understanding of others; (2) we developed a prototype tool using Twitter and Instagram posts; (3) we evaluated its usefulness.

## V. Summary

We developed a tool for understanding others using sentiment analysis of a user's Twitter and Instagram posts. We evaluated its usefulness for understanding professional baseball players as examples of others.

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