

# Community Interaction Optimization on Twitter for People with Mood Disorders

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### Resume



## Yuichi Okada

- Ph.D. student in Informatics
  - Optimization Algorithms
  - Software Development
  - Research on SNS(Twitter)
- President of a tutoring school in Japan
- Freelance programmer

## Agenda



Outline of our study and previous works

Overview of the current study

**Details of the Proposed System** 

**Computational Experiments and Result** 

Limitation and Future work

## Introduction

#### Purpose: Optimize Interactions of Twitter Users

- Maximize users' benefits (e.g. knowledge, encouragement, relief)
- Reduce the negative impact on users

#### **Challenging:** Solving Combinatorial Problem

- Quantification of user information and tweets
- Mathematical programming model using the knapsack problem

## The basis of our system

#### **Obtain optimal interactions using the knapsack problem**



## The previous work

## Optimal Community-Generation Methods for Acquiring Extensive Knowledge on Twitter.

- Optimized the volume and the spread of knowledge
- Verified the effectiveness of our method

Yuichi Okada, Naoya Ito, and Tomoko Yonezawa.

International Conference on Human-Computer Interaction. Springer, Cham, 2021.

# Define a feature of each users(Prev. work)



## Clustering users (Prev. work)



## Scoring the knowledge volume (Prev. work)

$$f_k: \text{Frequency of word[k]}$$

Word Frequency List of a User

Vector of Words

$$Score = \sum_{k=1}^{n} s_k \cdot \log(f_k + 1)$$
(n: size of the word frequency list)

## The current work: mental effect

# Optimizing SNS connection based on **psychological characteristics**

- Especially for the people with mood disorders
- The method defines the variables
  - Positivity Users based on SNS comments
  - Mood Disorder Level

# Define a feature of each users(Cur. work)



http://www.lr.pi.titech.ac.jp/~takamura/pndic\_en.html

Negative emotional value

# Classification of mood disorder levels(Cur. work)



# Scoring users' emotional polarity(Cur. work)

$$Pos(k,m) = \frac{pos_k}{neg_k} \{1.0 + \alpha(n_k - m)\}$$

#### **Our Tentative Emotional Score**

- k: index of user
- $pos_k$ : positive value of  $user_k$
- $neg_k$ : negative value of  $user_k$
- $n_k$ : mood disorder level of  $user_k$
- *m*: mood disorder level of the target user
- $\alpha$ : positive constant

### Construct a knapsack problem



subject to 
$$g_j(x) = \sum_{i \in N} g_1(x_i) \le b_j \quad j = \{1, 2\}$$

$$g_1(x_k) = \begin{cases} 1, member selected in Group k \\ 0, nobody selected \end{cases}$$

 $g_2(x_k) = days \ per \ tweet \ of \ user \ x_k$ 

## Computational experiment

# How does the optimal interaction change depending on the features of the user?

- Compared between users who tweet frequently(heavy users) and those who do not(casual users)
- Simulated users with the highest level of mood disorder as the target
- 500 users each for each level of mood disorder, for a total of 2000 users

## Result

#### Heavy Users

| -       |    | Lv.0  | Lv.1   | Lv.2   | Lv.3   |
|---------|----|-------|--------|--------|--------|
| n-users | 20 | 0.00% | 10.00% | 10.00% | 80.00% |
|         | 40 | 0.00% | 5.00%  | 20.00% | 75.00% |
|         | 60 | 0.00% | 5.00%  | 28.33% | 66.67% |
|         | 80 | 0.00% | 3.75%  | 37.50% | 58.75% |

#### **Casual Users**

|         |    | Lv.0  | Lv.1   | Lv.2   | Lv.3   |
|---------|----|-------|--------|--------|--------|
| n-users | 20 | 5.00% | 10.00% | 35.00% | 50.00% |
|         | 40 | 5.00% | 20.00% | 37.50% | 37.50% |
|         | 60 | 8.33% | 30.00% | 31.67% | 30.00% |
|         | 80 | 7.14% | 31.43% | 31.43% | 30.00% |

- Heavy users prefer to interact with users with higher mood disorder levels than casual users.
- A similar trend was observed when the  $\alpha$  (the weight of the difference in mood disorder levels) was varied.

## Discussions

#### • In case of interactions with heavy users

Do users with high levels of mood disorders prefer to have interactions with users who have similar levels to them?

#### • In case of interactions with casual users

When having interactions with casual users, is it less influenced by mood disorder level?

#### • Are these estimations likely to be correct?

Careful consideration needs to be given to whether issues exist in how the data is generated and the hypotheses formulated.

## Limitations

#### Classification of Mood Disorder Levels

More accurate classification should be conducted based on the content of profiles and tweets rather than the value of emotional polarity.

#### • Evaluation of emotional polarity

Emotional polarity data should be generated for Twitter-specific abbreviations and new words.

#### Justification of Hypothesis

Does the difference in mood disorder levels between users affect the optimality of interactions?



## Can the proposed method have a positive impact on the quality of communication?

- Large-scale investigation of actual data
- Methods for evaluating users' emotional features