Community Interaction Optimization on Twitter for People with Mood Disorders

Yuichi Okada
Graduate School of Informatics
Kansai University
Osaka, Japan
email: k393424@kansai-u.ac.jp

Naoya Ito
Graduate School of Informatics
Kansai University
Osaka, Japan

Tomoko Yonezawa
Faculty of Informatics
Kansai University
Osaka, Japan
email: yone@kansai-u.ac.jp

***Abstract*—This paper proposes our designed system to estimate the optimal social networking connections for people with mood disorders, such as depression. We collected data from Twitter and analyzed users' characteristics by adopting an emotional polarity value index. Based on these data analyses, we defined each user's positivity level and estimated the level of mood disorder from the content of their tweets. We also simulated the system's use by people with severe mood disorders. A computational model based on a knapsack problem, a combinatorial problem to solve using an optimization method, was created based on the hypothesis that people likely to have mood disorders will more likely connect with people who have similarly severe mood disorders. The proposed system solved it using an approximate solution method that can be computed in a practical amount of time. As a result, (1) the user preferred a user with the same mood disorder severity when a user connected to a user with frequent tweets and (2) the difference in mood disorder severity was not as important when the user connected to a user with infrequent tweets.**

Keywords-Twitter; SNS; data mining; combinatorial optimization.

I. Introduction

We will present an outline of our research in this section.

A. SNS and Depression

Social Networking Services (SNSs) have attracted attention as a communication platform less affected by time and space constraints compared to face-to-face communication. However, the cost of SNSs' convenience is that many people suffer from physical and mental fatigue. Fatigue caused by information overload has been studied in large social networks [1].

Depression can be caused by diverse factors, including problems with health, family, economics, and employment and labor, but a relationship between social network use and depression has also been recently identified [2]. In other words, information overload emotional overload must both be addressed.

Depressed people tend to underestimate their social skills and avoid communicating with others [3]. A relationship between loneliness and depression has been suggested, and appropriate communication may help alleviate depressive symptoms [4]. Bessiere et al. [5] also pointed out the importance of considering the psychological impact of communicating on the Internet.

B. Motivation

One negative effect of social networking sites is people's inevitable unpleasant experiences with anonymous communication. In the real world, more people suffer from depression for various reasons, and SNSs' ease of use greatly benefits society and should be utilized to solve these problems. If we can improve relationships through SNS, we can alleviate mood disorders, such as depression.

C. Optimization Problem

The number of people an individual can connect with is very small compared to the number of people who use an SNS, so it is important to know who to connect with. Finding the best connections among users is essentially a combinatorial optimization problem.

Although combinatorial optimization problems are solvable in computational theory, solving them in practical computing time is difficult when their scale becomes large. However, many solutions to restrictive problems have been studied, and the solution to the knapsack problem is practical. Optimization methods based on mathematical programming make it easier to estimate the calculation accuracy and time required compared to learning algorithms such as neural networks.

Therefore, these optimization methods are suitable for building elaborate computational models. In this study, we use the surrogate constraint method for the multi-constraint nonlinear knapsack problem to optimize connections among Twitter users.

D. Research Subject

1) Language: Considering the author's language-dependent environment and the possibility of future experiments on subjects, we targeted SNS users who use Japanese. Notably, Japanese has no explicit word separators, so a morphological analysis is needed to generate word list data from sentence data for analyses.

2) Types of SNS: Several types of SNSs exist, and we chose Twitter for its wide usage rate among Japanese people and its easy-to-use an Application Programming Interface(API). The most popular SNS in Japan is LINE, but LINE is mainly used for private purposes, so it was excluded from the study.

E. Proposed System

We devised a system that suggests optimal connections for Japanese Twitter users likely to have mood disorders. Based on a user's tweet data, we defined the user's characteristics, created a computational model of the knapsack problem by clustering the characteristics, and calculated a sub-optimal solution using an approximate solution method.

In general, mood disorders refer to conditions such as depression and bipolar disorder, which are characterized by emotional ups and downs so severe or unstable that they interfere with daily life. This study concerned situations ranging from weak to severe tendencies but did not use a clinical diagnosis.

Instead, we defined "mood disorder" broadly to cover mild conditions, such as lethargy and depression to severe conditions with a high possibility of depression. These states were estimated via statements posted on SNS.

F. Structure of The Paper

The paper is organized as follows: Section2 gives related works corresponding to our study. In Section 3, we show the overview of proposed system. In Section 4, the features of the Twitter users targeted for research are explained. Section 5 describes how to quantify the features of Twitter users and how to evaluate them. In Section 6, we present our method for finding the optimal interactions of Twitter users based on evaluation method we defined. In Section 7, we show the results of computer simulations using the method set up in Section 6. In Section 8, we provide a discussion of the simulation results, and in Section 9, we conclude and discuss future work.

II. Related Works

In this section, we will present the effects on the mind and the Twitter-based recommendation system as they relate to our research.

A. Effects on the mind

Tsukawa et al. [6] studied data from remarks on Twitter to diagnose depression. They used the Zung score [7], a depression evaluation index obtained using an advance questionnaire, and performed a multiple-regression analysis using the frequency of words detected by a morphological analysis of tweets from 50 subjects. Among detected words, negative words showed a high correlation with the Zung score. A moderate correlation (correlation coefficient $R = 0.45$) appeared between the score obtained by the regression equation and the Zung score. Considering the number of samples, this result seems valid, so it should be possible to diagnose depression symptoms using tweets.

One study of college students indicated that a long usage history or a high degree of dependence made people seem unhappier than others [8]. Researchers also stated this tendency would be strong among unacquainted people. On the other hand, almost no relationship exists between SNS usage duration and stress or depression when targeting SNSs while excluding Instagram [9]. The stress load depends on the quality of communication with other people.

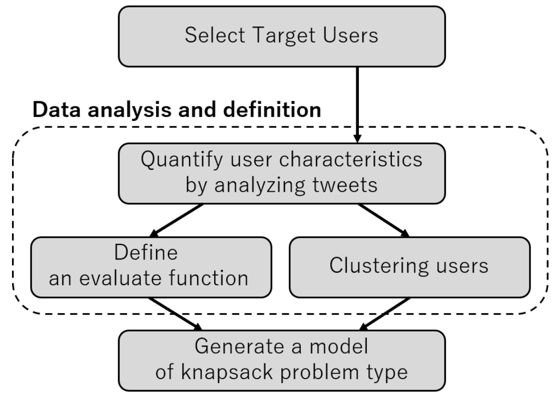

Fig. 1. System flow.

B. Twitter-based recommendation systems

Chen et al. [10] proposed a system that recommends useful tweets to Twitter users. The system provides collaborative-filtering-based recommendations via tweet content, social relationships, and other explicitly defined user data generally used as indicators of a tweet's usefulness. This system provided better recommendations than previous methods.

Research focused on followers has also indicated that follower-adding patterns can help predict who the user will follow next [11]. Another system considered users' emotions in recommendations focused on users' interests [12]. The researchers implemented better recommendations for the user by including functions with positive, negative, and neutral parameters in the evaluation axis.

All these studies aimed to efficiently select useful information for users from the large amount of information flooding the SNS.

III. System overview

In the proposed system, we obtain information from target users whose tweets contain keywords related to depression. The tweets are then analyzed and mood disorder levels are assigned to individual users in three phases. The first phase is conducting a morphological analysis of the tweets to determine the emotional polarity value. The second is quantifying the user's characteristics based on the emotional polarity value. The third is clustering users to improve the optimization by grouping users with similar characteristics. The second and third phases depend on the first phase's results, but they are not mutually dependent. Finally, these data are formulated as a knapsack problem, and the optimal solution is computed. Figure 1 shows the flow of our method.

IV. Target users

Target users include the following words in their tweets:

1) "languid" or "melancholic"
2) medicine names related to depression

The number of users who included the keywords "languid" ('da-ru-i' in Japanese) or "melancholic" ('yu-u-tsu' in Japanese) in their tweets was insufficient, so the names of 27 drugs related to mood disorder treatment, such as antidepressants, mood stabilizers, and anxiolytics, were added to the keywords to collect data. Twitter API was used for data collection, and a maximum of 3200 tweets per user (upper limit) were obtained. For each level of mood disorder, 500 user accounts were collected. Data were collected in February 2019.

V. Data analysis and definition

In this section, we will present a method for quantifying and evaluating the features of Twitter users.

A. Emotional polarity of tweets

The tweets were split into word data for each noun of a sentence using MeCab [13], a morphological analyzer. Japanese tweets must be morphologically analyzed because Japanese sentences have no explicit separators, such as spaces in English. Word data are quantified using the emotion polarity table [14], a database generated by a system that estimates a word's emotional polarity (desirability or non-desirability), with a floating number from -1 to +1 associated with the word. Values close to +1 are generally more desirable, and values close to -1 are less desirable; values close to 0 are neutral. Words not included in this database are considered 0.

B. Evaluation function of user's emotional polarity

1) Classification of mood disorder level: Based on the emotional polarity values, a user's mood disorder level was set from 0 to 3, and the user was classified into one of four classes. Research on mood disorders, especially depression, is active and many diagnostic scales exist for them. However, most scales are subjective, use questionnaires, and are not appropriate for objective assessments based on tweet data.

Non-anonymous computer mediated communication (CMC) has less effect on users than does face-to-face communication because CMC has fewer channels compared to communication in real spaces [15]. However, people with mood disorders are influenced by others' remarks, especially negative remarks. Thus, positivity should be transmitted differently depending on users' symptom levels. We therefore classified the mood disorder states according to the rules in Figure 1.

The classification involved the following steps. First, target users were divided into two groups. Group A's tweets contained names of medications for mood disorders, and Group B's tweets did not. Then, each group was further divided into two groups. In Group A, users whose tweets contained two or more names of medications for mood disorders were classified as Level 3, the highest level. The remaining Group A users were classified as Level 2, the second highest level of mood disorder. Among the members of Group B, users whose tweets contained the words "languid" and "melancholic" less than 3% of the total tweets were classified as Level 0, the lowest level of mood disorder. The remaining Group B users were classified as Level 1, the second lowest level. Figure 2 shows the flow of users.

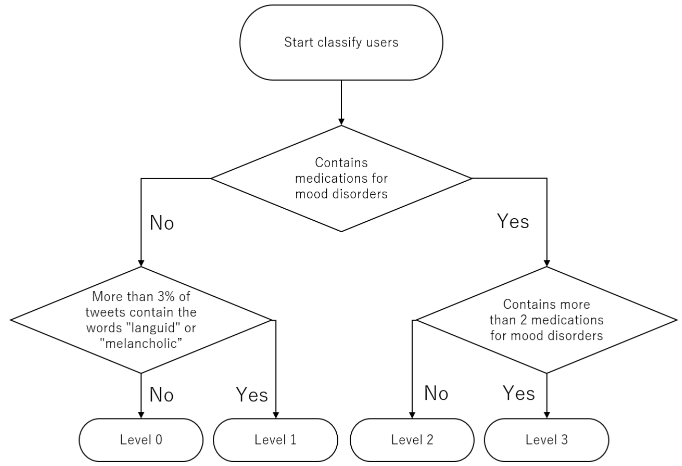

Fig. 2. The classification of users.

2) Defining the evaluation function: We defined the following evaluation function based on the hypothesis that a user with a tendency toward a mood disorder would be suitable for communicating with a user who has a similar mood disorder level and who offers many positive comments.

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

where

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 main user

This evaluation function is named the positive function, which quantifies the degree of individual positivity and considers differences in mood disorder levels. α is a constant and is specified, so the function's value becomes positive. The values of the function $1.0 + \alpha(n - m)$ for $\alpha = 1/4$ and for $1/6$ appear in Figure 3.

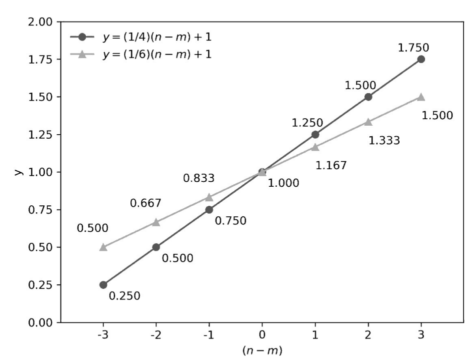

Fig. 3. Effect of level difference on positive values.

VI. Optimization

In this section, we will present a method for optimizing Twitter users' interactions using the knapsack problem.

A. Combinatorial Optimization Problems

Combinatorial optimization cannot be solved in a practical amount of computation time for a large-scale problem. This is especially critical for huge social networking sites like Twitter. For the knapsack problem among combinatorial optimization problems, however, a method to quickly obtain an approximate solution using the surrogate constraint method has been developed [16]. The surrogate constraint method generates a single constraint function by weighting multiple constraint functions, and a method for calculating the optimal weights has also been established [17]. We used this calculation method to quickly obtain an approximate solution to the single constrained knapsack problem via the algorithm [18].

B. Nonlinear knapsack problem

The multi-constraint nonlinear knapsack problem is formulated as follows.

$$\text{maximize} \sum_{i \in N} f_i(x_i)$$

subject to

$$g_j(x) = \sum_{i \in N} g_{ji}(x_i) \leq \ b_j (j = 1, 2, \cdots, m),$$

$$x_j \in A_j (j = 1, 2, \cdots, m),$$

where $N = \{1, 2, \ldots, n\}$ is a set of variable numbers, $x = \{x_1, x_2, \ldots, x_n\}$ and $A_i = \{1, 2, \ldots, a_i\}(i \in N)$ is the alternative item set for each variable.

C. Knapsack computation model

To calculate the optimal connections for a user, we defined a nonlinear knapsack-type computational model of Twitter user data. Each user has an emotional polarity value, and users with similar values were grouped into the same class, as shown in Figure 4.

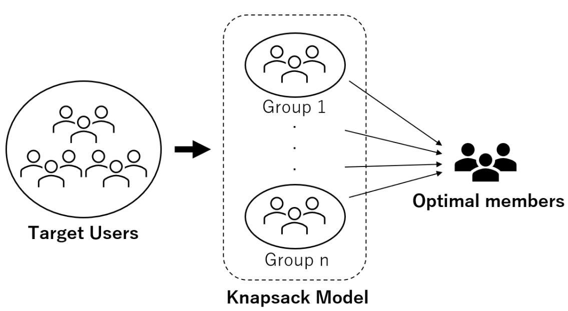

Fig. 4. Make a knapsack model.

The objective function and the inequalities for constraint function are as follows:

$$\text{maximize} \sum_{i \in N} Pos(x_i, m)$$

subject to

$$g_1(x) = \sum_{i \in N} g_1(x_i) \leq b_1$$

$$g_2(x) = \sum_{i \in N} g_2(x_i) \leq b_2$$

where

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

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

The function $Pos()$ is defined at V-B2. $N = \{1, 2, \ldots, n\}$ is a set of group numbers, $x = \{x_1, x_2, \ldots, x_n\}$ is a set of members of the group.b_1 is the upper limit for the number of connected users. $b2$ is the upper limit for the tweet frequency, which depends on $b1$. Thus, $b2 = (days\, per\, tweet) \times b1$.

VII. Computational experiment

In this section, we will present a computational simulation of our proposed method.

A. Creating problem data

1) Setting the positive function: As a parameter of the positivity function, the user's mood disorder level (m) was set to 3. For α, which represents the weight of the mood disorder level on the positivity level, we set $\alpha = \frac{1}{4}$ and $= \frac{1}{6}$.

2) Setting the knapsack problem: We created the problem data according to the model defined in the previous section. A total of 2000 target users were selected, with 500 for each of the four mood disorder levels. At each level, the 500 users were sorted by the magnitude of their emotional polarity values and then divided into 50 groups of 10 users each in a descending order. It is possible to choose one person from each group or no one from any group. In other words, we created a nonlinear knapsack problem with 50 (=500/10) variables and with 11 choices in each group: 10 ways to choose a member plus a way to choose no one. The whole problem comprises 50 groups with 4 levels, for a total of 200 groups.

The first constraint ($b1$) is the number of users with connections, and we created four types: 20, 40, 60, and 80. The second constraint($b2$) is the number of days per tweet(dpr)$\times b1$, where dpr is $\frac{1}{2}$ or $\frac{1}{5}$. We assume that users who tweet twice a day are casual users, and users who tweet five times a day are heavy users.

3) Total number of problems: There were 2 types of parameters for the positive function and 4($b1$)×2($b2$) combinations regarding the knapsack problem's constraints, yielding 16 total types of problems.

B. Computation results

The calculations for each problem appear in tables I to table IV. * 1: not mood disorder, * 2: early mood disorder, * 3: mild mood disorder, and * 4 severe mood disorder.

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TABLE I
CONNECTING HEAVY USERS($m = 3\ \alpha = 1/4$).

20	level0*1	level1*2	level2*3	level3*4	total
	0	1	2	16	19
40	level0*1	level1*2	level2*3	level3*4	total
	0	2	4	33	39
60	level0*1	level1*2	level2*3	level3*4	total
	0	2	8	50	60
80	level0*1	level1*2	level2*3	level3*4	total
	0	2	27	51	80

TABLE II
CONNECTING HEAVY USERS($m = 3\ \alpha = 1/6$).

20	level0*1	level1*2	level2*3	level3*4	total
	0	2	2	16	20
40	level0*1	level1*2	level2*3	level3*4	total
	0	2	8	30	40
60	level0*1	level1*2	level2*3	level3*4	total
	0	3	17	40	60
80	level0*1	level1*2	level2*3	level3*4	total
	0	3	30	47	80

TABLE III
CONNECTING CASUAL USERS($m = 3\ \alpha = 1/4$).

20	level0*1	level1*2	level2*3	level3*4	total
	1	1	5	13	20
40	level0*1	level1*2	level2*3	level3*4	total
	2	6	16	16	40
60	level0*1	level1*2	level2*3	level3*4	total
	1	20	19	20	60
80	level0*1	level1*2	level2*3	level3*4	total
	2	24	22	23	71

TABLE IV
CONNECTING CASUAL USERS($m = 3\ \alpha = 1/6$).

20	level0*1	level1*2	level2*3	level3*4	total
	1	2	7	10	20
40	level0*1	level1*2	level2*3	level3*4	total
	2	8	15	15	40
60	level0*1	level1*2	level2*3	level3*4	total
	5	18	19	18	60
80	level0*1	level1*2	level2*3	level3*4	total
	5	22	22	21	70

VIII. DISCUSSION

In this section, we will discuss the results of computational simulations.

A. Computational results

We proposed a method for optimizing a user's connections with other users according to the mood disorder level. Based on the optimization results, the optimal solution is 1) to connect users with a similar mood disorder level when a user desires connections with heavy users, and 2) to connect with others at various levels from 1 (early mood disorder) to 3 (severe mood disorder) when the user desires connections with casual users.

In connecting with heavy users, we anticipate that the amount a user communicates with a particular person will increase and that the user will spend much time browsing Twitter to see what they are up to. In other words, if users want to communicate deeply for a long time, they should engage with people at a similar mood disorder level. In the case of $\alpha = \frac{1}{6}$, the above characteristics appeared in users preferring to connect with casual users and with heavy users. In the case of a larger $\alpha (= \frac{1}{4})$, however, these characteristics appeared stronger.

A comparison between heavy users and casual users shows that users with severe mood disorders (Level 3) often tweet frequently, and many Level-0 users had fewer tweets per day than Level-3 users. On the other hand, users who connect with casual users have shorter visits to Twitter. Therefore, connecting with people of various mood disorder levels is considered optimal. This observation aligns with the difference between using Twitter for communication and using it for information gathering.

When we want to get to know other people deeply, we gain a sense of security by connecting with people in situations similar to ours. When we want a shallow relationship with people, we gain diverse ideas by connecting with people who have diverse situations and personalities.

B. About the system

1) Knapsack problematization: Although combinatorial optimization problems are generally hard to compute, we quickly obtained a solution using an approximate solution method in the knapsack problem. This should be sufficient for developing applications that run at a practical speed. In this study, we used the positive function value to group the users. Various clustering methods can be used to group users via indicators such as personality and knowledge traits, which will increase the scope of the analysis.

2) Evaluation function: In this study, we defined a positive function as an evaluation function. The difference in the computational results between heavy users and casual users suggests the positive function worked well.

However, the sentiment polarity dictionary required for the positive function was created based on WordNet [19] words, so the performance of the dictionary may not be sufficient in the SNS world, where abbreviations and new words are created every day (such as on Twitter).

Developing a sentiment polarity dictionary based on word variance information on Twitter should be considered to improve evaluation function. Because of the wide variety of user characteristics and purposes of use in practice, multiple evaluation axes [20] should be considered instead of using a single polarity of positive/negative.

C. Limitation

We used the Twitter API's keyword search to obtain users' data. The first search did not provide sufficient information, so search words were appended later. In this regard, the data collection method is somewhat inconsistent.

We conducted an additional study to estimate users with depressive tendencies and obtained data from 1,008,618 profiles from the followers and friends of 100 tweeters. The data were obtained from a keyword search for "depression" ('u-tsu' in Japanese Kanji). The number of users who had sentences in their profiles that could indicate they were depressed was 882.

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By more carefully observing their tweets and their interaction relationships, we should make more accurate estimates of mood disorder levels. Correlations between mood disorder levels and positive functions, as well as other statistical analyses, must be studied to show a valid estimation method.

D. Summary

Using this study's proposed system, we show the possibility of designing an optimal way for users to connect with other users. This system reveals to users the best way to interact with other people.

If this approach can be realized, the system could reduce mood disorders and provide support for healthy reintegration into society by using the online resource of SNS.

IX. Conclusion And Future Work

In this paper, we analyzed tweet data from about 2,000 Twitter accounts and calculated positive and negative values for individual users using an emotional polarity dictionary. We also estimated the mood disorder degree using the vocabulary in the tweets and classified the users into four mood disorder levels. A positive function was also defined based on the assumption that statements from other users with similar or more severe mood disorders would positively affect the user.

Next, we created a computational model of the knapsack-problem type using these characteristics. We then simulated the optimal community environment for users with mood disorders by solving the problem. From the results, we assumed that a user with a high-level mood disorder who wanted to interact with users who tweeted frequently should optimally follow people with the same level of mood disorder as the user. On the other hand, we inferred that a user with a high-level mood disorder who wanted to interact with casual users who tweeted infrequently should optimally connect with people who have various levels of mood disorder.

These estimations can be made in a practical computation time, suggesting the possibility of developing an interactive user-recommendation system. Considering actual use, however, a unified evaluation function is inappropriate because individual users have different purposes for using SNS. Therefore, a system that dynamically generates an evaluation function according to a user's purpose and values is necessary.

For future work, we want to examine our proposed system's validity and consider systems that can help people with mood disorders. For users without mood disorders, we should also research SNS uses that allow them to enjoy their social networking life to the fullest while maintaining their mental health. Slandering behavior, flaming, and polarization are major social issues in modern SNS use. SNSs are a powerful tool for knowledge acquisition and communication, and it is important to use SNSs well instead of running from them.

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