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ANALYZING STUDENTS' COURSE EVALUATIONS USING TEXT MINING: VISUALIZATION OF OPEN-ENDED RESPONSES IN A CO-OCCURRENCE NETWORK

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Abstract

Japan's Standards for Establishment of Universities states, "A university shall conduct organized training and research to improve the content and methodology used in courses at said university." Based on this, most of Japan's universities have recently implemented course evaluations by students. Student course evaluations are intended to quantify and provide an understanding of students' satisfaction with their courses, and all universities are implementing them as one way to objectively evaluate courses. These course evaluations often combine computer-graded multiple-choice items with open-ended items. Computer-graded multiple-choice items are easy to assess because the responses are quantifiable. However, open-ended items' responses are text data, and objectively grasping the students' general tendencies is challenging. Moreover, it is difficult to avoid risking arbitrary and subjective interpretations of the data by the analysts who summarize them. Therefore, to avoid these risks as much as possible, the so-called "text-mining" method or "quantitative content analysis" approach might be useful. This study shares our experiences using text mining to analyze students' course evaluations through visualization of their open-ended responses in a co-occurrence network, and we discuss the potential of this method.

Keywords

Course Evaluation by Students, Open-Ended Responses, Text Mining, Quantitative Content Analysis, Co-occurrence Network

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1. Introduction

1.1 History of Course Evaluation in Japan

Japan's Standards for Establishment of Universities states, "A university shall conduct organized training and research to improve the content and methodology used in the courses it offers." Accordingly, several Japanese universities have recently implemented course evaluations by students. Student course evaluations are intended to quantify and provide an understanding of students' satisfaction with the courses they study, and all universities are implementing them as a method to objectively evaluate courses.

In most Japanese universities in recent years, course evaluation has been conducted through administering a questionnaire survey to students. According to statistics, course evaluation was conducted only by 38 schools (7.3% of the total) in 1992, but by 574 schools

(83.7% of the total) in 2002 (R. Sato & Miura, 2005). Further, most Japanese universities performed course evaluation in 2009 (Yomiuri, 2009).

In most universities, course evaluation was conducted as part of self-assessment and self-evaluation. Since 2004, all universities are obliged by the law to be evaluated by an evaluation agency, which is certified by the Ministry of Education, Culture, Sports, Science and Technology (MEXT) every seven years. This is called the certification evaluation system. In the certification evaluation system, self-assessment and self-evaluation play important roles; and evaluation criteria in the certification evaluation include course evaluation.

During the initial years of course evaluation by students in universities, teachers only obtained the result of course evaluation as the averages of each item in the survey. In recent years, many universities have started using course evaluation by students for faculty development (FD) (H. Sato, 2008). However, there still remains the problem of analyzing course evaluations by students. (T. Sato, Matsuura, Kobayashi, Watanabe, & Sasahara, 2010).

1.2 Text-mining for Course Evaluation

These course evaluations by students often combine computer-graded multiple-choice items with open-ended items. Computer-graded multiple-choice items are easy to assess because the responses are quantifiable. However, the responses to open-ended items are text data, and objectively grasping the students' general tendencies is challenging. Moreover, it is difficult to avoid risking arbitrary and subjective interpretations of the data by the analysts who summarize them. Therefore, to avoid these risks as much as possible, the so-called "text-mining" or "quantitative content analysis" approach might be useful. This paper presents our experiences of using text mining to analyze students' course evaluations through visualization of their open-ended responses in a co-occurrence network; further, we discuss the potential of this method.

2. Research issue

Our research question is whether the quantitative content analysis of course evaluation by students is a useful method to improve the quality of courses. We will present a few samples in our university to establish that quantitative content analysis of course evaluation by students is a useful method to improve the quality of courses.

3. Methodology

3.1 Objective

We administered a questionnaire to students who had attended “Academic Skills & Deep Learning I.” course Our University uses a cloud-based education assistance service “Manaba,” which is provided by Asahi Net, Inc.

3.2 Analysis Method

3.2.1 Quantitative Content Analysis or Text Mining

We performed text analysis / text mining. In this article, we have defined text analysis / text mining as “a method of content analysis that modifies or analyzes text-style data by using quantitative analysis.” Further, we only extracted the frequency of words and co-occurrence networks, avoiding any arbitrary information.

Here, we mention background that use co-occurrence network to analysis. Through this analysis, we want to grasp the meanings that students were conveying subjectively. Meanings are invisible things; for example, an Apple is associated with words like “red,” “eatable,” “sweet,” “round,” etc. In addition, we also emphasize that meanings exist “in clusters and not individually.” According to Willard van Orman Quine, knowledge should be regarded as a network of structurally- linked clusters (Quine, 1980).

In a recent theory on complicated networks, it was revealed that a large cluster (connected networks) contained 96% of all the words from the entire data in a word-association experiment. In other words, knowledge and belief do not exist individually, but are linked with each other in a close relationship. Moreover, we live in a world where networks are created to generate meaning. Through this analysis, we want to reveal the complete meanings grasped by students while attending “Academic Skills & Deep Learning I” course.

On the co-occurrence networks that resulted from the analysis in this article, words that have high frequency appear on nodes (vertex) with several intersections, words that have high co-occurrence relationship are linked with thick lines, and blue words connected to dark pink words indicate that it is a node with a high degree of uncertainty.

3.2.2 Software of statistics analysis

We used KH Coder (Ver. 3. Alpha. 9), a free software for quantitative content analysis or text mining. It is also used in computational linguistics (Higuchi, 2016) (Higuchi, 2017).

This software was developed by Associate Professor Koichi Higuchi of Ritsumeikan University and one can perform text-mining or quantitative content analysis through the graphical user interface of the software. KH coder makes various weighing text analyses possible using R (statistical analysis software) (Ihaka & Gentleman, 1996), chasen (morphological analysis software) (Matsumoto, 1997), and mysql (free database search software) ("mysql," 2018). The advantage of using KH coder is that it allows you to do extensive text mining easily, even in the absence of a calculation formula. KH coder can analyze extracted words, hierarchical clusters, co-occurrence networks, multidimensional scaling, related words, correspondence, etc. In addition to Japanese and English data, KH coder also supports Dutch, French, German, Italian, Portuguese and Spanish data.

3.3 Ethical Consideration

We have already obtained the verbal and written consent from the students who attended the "Academic Skills & Deep Learning I" course for using recorded materials submitted in this course as research materials to improve courses. Further, the students were explained that they have the right to withdraw their consent, demand protection of personal information and anonymization of data, and that they will have no disadvantage if they do not give their consent.

4. Conclusion

First, we demonstrate an example of course evaluation using text mining to improve the quality of a course. Since 2017, Kobe Tokiwa university, publishes an annual report on its website. In Kobe Tokiwa university, all faculty members have to write a self-assessment and improvement report based on their course evaluation by students. Until 2016, these reports were summarized to write the annual report.

As briefly described in the introduction, there are a few methods to analyze open-ended responses in questionnaires. Here, we will describe them in more detail. There are two methods of text analysis. One method is the dictionary-based approach and the other is the correlational approach. The dictionary-based approach classifies words and documents according to coding standards created by analysts, while the correlational approach classifies words and documents by multivariate analysis. The advantage of the dictionary-based approach is that you can freely manipulate the theory and problem awareness of analysts and focus freely on various aspects of data. A disadvantage of the dictionary-based approach is that there is a danger that only the most convenient coding rules will be created and used.

The advantage of the correlational approach is that it summarizes and presents data in such a way that it remains largely uninfluenced by the analyst's theory or problem awareness. The drawback of the correlational approach is that it relies heavily on multivariate analysis, so there is a limit to manipulating and pursuing theory and problem awareness (Higuchi, 2004).

Therefore, Higuchi developed and published KH Coder as an analysis system for textual data that integrated these two approaches, the dictionary-based approach and the correlational approach, in a mutually complementing manner (Higuchi, 2016) (Higuchi, 2017). The main feature of KH Coder is that is does not do "manual work," which can lead to an arbitrary choice of word selection. KH Coder summarizes and presents the whole data by multivariate analysis instead of manual work. Next, KH Coder will disclose the coding rules. Therefore, KH Coder allows both freedom and objectivity in manipulation. In this paper, we show that by using KH Coder to analyze the open-ended responses of the course evaluation by students, it is possible to capture the overall tendency of those responses while ensuring objectivity.

In this paper, we illustrate two examples of the application of text mining to improve the quality of courses. First, we applied text mining to the response report by teachers on the open-ended responses of course evaluation by students in 2017 annual report of Kobe Tokiwa university (Kobe Tokiwa University, 2017). In this annual report, we could find improvements corresponding to each department. Using these data, we will perform faculty development next year.

Some articles and reports have already applied text mining to open-ended responses of course evaluation by students (Etchu et al., 2015) (Fushikida, Kitamura, & Yamauchi, 2012) (Matsukawa & Saito, 2011) (Mekuta, Nakaoka, & Etchu, 2013). However, while conducting our survey, we could not find such articles and reports. We propose that this method is very useful to improve the quality of courses.

As a part of university reforms (Kirimura et al., 2018), in 2017 Kobe Tokiwa university created a new first-year course titled "Academic Skills and Deep Learning I" (Mitsunari et al., 2018). In 2017, nineteen teachers taught this course to approximately 350 students in total, with 16-17 students per class. In these classes, the students formed groups of approximately six students. Further, in 2018, twenty teachers teach this course to approximately 350 students in total.

In the last lecture of "Academic Skills and Deep Learning I," we administered a questionnaire to students. The questionnaire includes an open-ended question. The question is "Please freely express your opinion on the content and form of this lesson (Please give us your opinion including harsh opinions to allow us to make use of this feedback next year)." We obtained 119 and 138 answers in 2017 and 2018, respectively. We apply text mining to open-ended responses.

Table 1 shows the extracted frequent words from 2017. Figure 1 uses these words to create a co-occurrence network. "Group" and "Department" are found to be the frequently occurring words (Table 1). In the co-occurrence network diagram, "tackle" is connected with "talk" and "communication." Further, "company" and "relationship" are connected (Figure 1).

Table 1: *Frequent Words in 2017 (Top 30 Words)*

Extracted word	Frequency	Extracted word	Frequency	Extracted word	Frequency
Suppose	66	Person	9	Team	5
Group	31	Other	9	meaning	5
Department	27	long	9	Differ	5
Class	21	Feel	8	Task	5
contents	19	involve	7	chance	5
time	18	Myself	7	mixed	5
good	16	slightly	7	growing	5
enjoyable	12	interesting	6	Know	5
much	12	little more	5	Course	4
Work	9	Communication	5	class	4

In "Academic Skills and Deep Learning I," in anticipation of students' careers, we intentionally made groups of hybrid departments. In addition, "Academic Skills and Deep Learning I" has promoted Team Based Learning (TBL) and Problem Based Learning (PBL). The above result shows that students are aware of the importance of working as a team "team."

In addition, it is evident from the co-occurrence network diagram that "working" has the highest center-mediate (Figure 1). Further, since "good" and "fun" are also ranked high in terms of frequent occurrence, it is understood that the students have a positive attitude toward "Academic Skills and Deep Learning I" course (Table 1).

Table 2: *Frequent Words in 2018 (Top 30 Words)*

Extracted word	Frequency	Extracted word	Frequency	Extracted word	Frequency
Suppose	62	good	12	change	7
Department	32	chance	11	involve	6
time	28	Work	10	classroom	6
Group	27	contents	10	last half	6
Class	24	exchange	9	Ability	6
much	18	enjoyable	8	Disclose	6
Person	17	little more	7	meaning	5
Communication	16	Differ	7	Learn	5
Team	15	Think	7	Feel	5
long	12	slightly	7	make	5

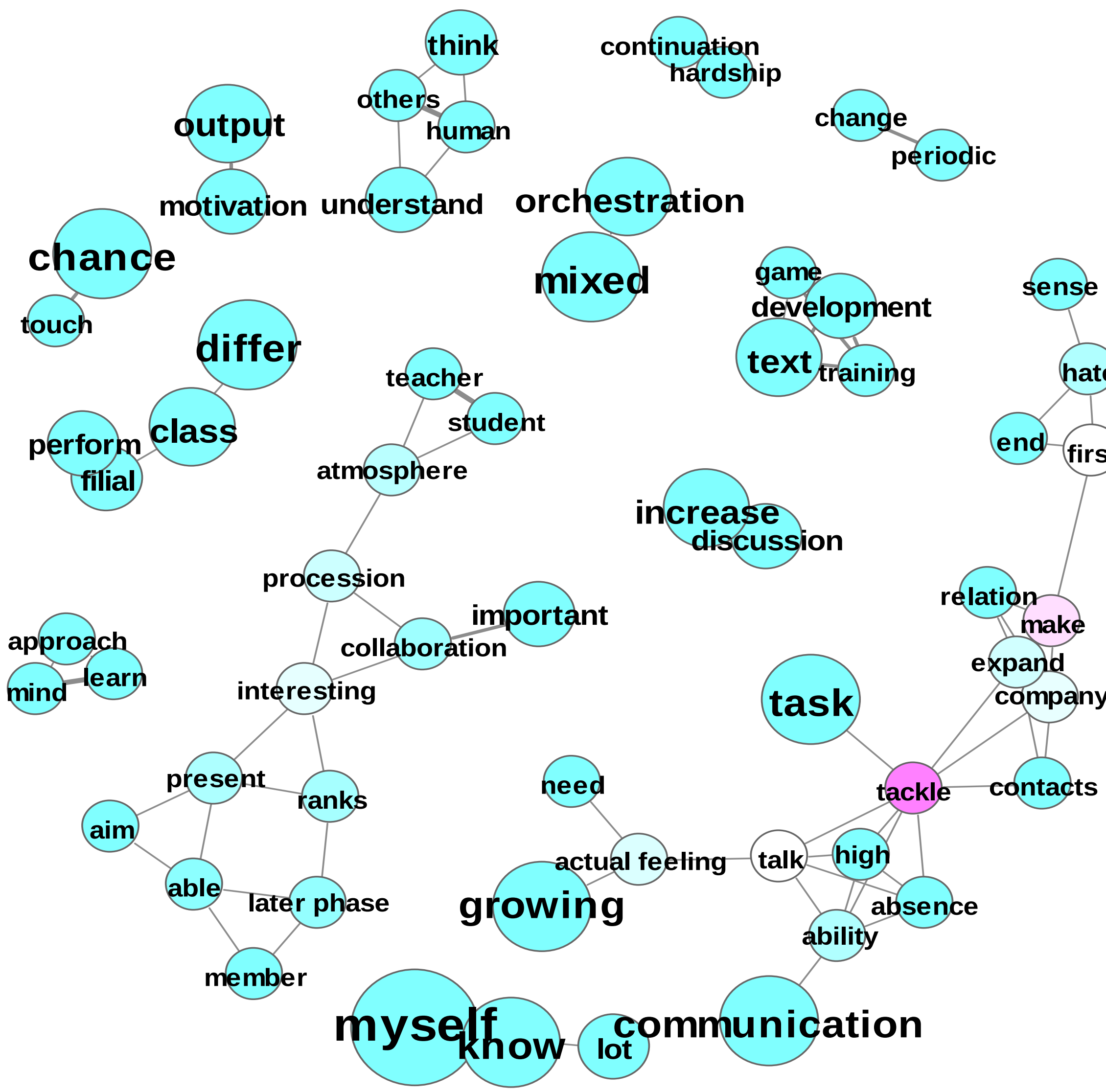

Figure 1: *Co-occurrence network in 2017*

Next, Table 2 shows the extracted frequent words from 2018. Figure 2 shows the co-occurrence network created using these words. In the co-occurrence network diagram, “partner” and “discussion” are connected, “build up” “discussion” and “partner” are connected (Figure 2), and “group” and “team” are at the top in terms of frequent occurrence (Table 2). This means that even in 2018, students are aware of the importance of “TBL” and “PBL,” which we had emphasized in “Academic Skills and Deep Learning I.”

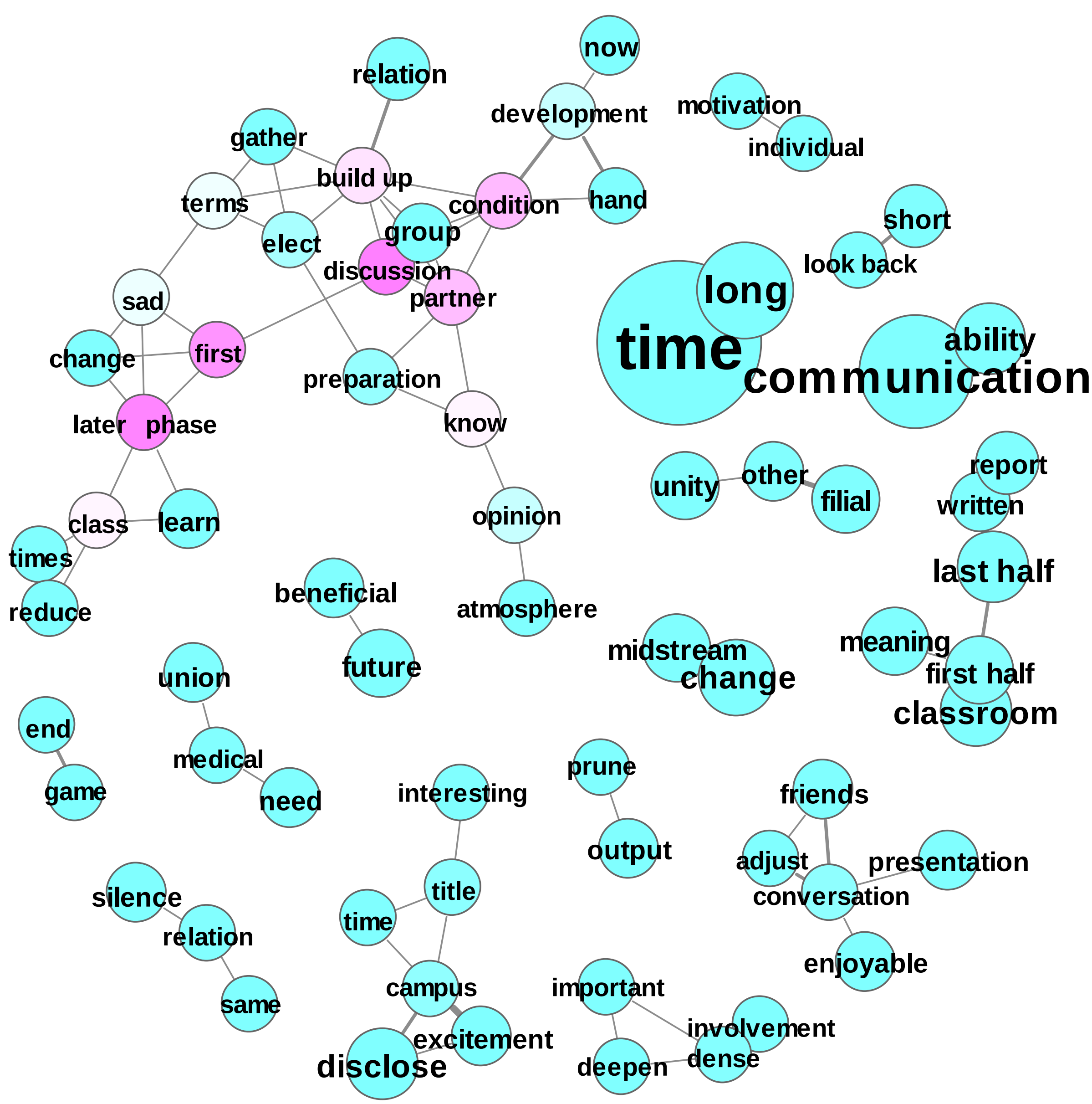

Figure 2: *Co-occurrence network in 2018*

The fact that "future" and "beneficial" are connected only in co-occurrence networks indicates that the students acknowledge that "Academic Skills and Deep Learning I" will be a useful course in the future (Figure 2). "Communication" and "ability" were connected with each other. This emphasizes the importance of TBL and shows that the students are conscious that the lesson is not effective without everyone's involvement. Furthermore, the fact that three words "medical," "union" and "need" are linked indicates that the students in team medicine understand that they will study medicine in future. On the other hand, since "time" and "long" are big circles, we understand that the students feel that the lesson time of three hours is long.

Our research question was whether quantitative content analysis (using text mining) of course evaluation by students is a useful method to improve the quality of a course. In this study, we demonstrate that text mining allows both freedom and objectivity for manipulation. Further, we establish that by using text mining to analyze open-ended responses of course evaluation by students, it is possible to capture the overall tendency of those responses while ensuring objectivity. Finally, we presented some samples in our university to demonstrate that quantitative content analysis (using text-mining) of course evaluation by students is a useful method to improve the quality of courses.

And we will describe our research limitations. There are many visualization methods by the text-mining method to analyze open-ended responses of course evaluation by students. In this article, we only show a visualization by network method. Network method is easy to understand. However, for example, visualization of multiple dimensional scaling (MDS) methods is better to understand relationship or distance between words than network methods. In the future, we will analyze using other methods by text-mining.

Finally, we describe the scope of future research. In this paper, we applied text mining to the response report by teachers on the open-ended responses of course evaluation by students in 2017 annual report of Kobe Tokiwa University (Kobe Tokiwa University, 2017). In this annual report, we could find improvements corresponding to each department. Using these data, we will perform faculty development next year.

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