ESANN 2015 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 22-24 April 2015, i6doc.com publ., ISBN 978-287587014-8. Available from http://www.i6doc.com/en/.

The prediction of learning performance using features of note taking activities

Minoru Nakayama[1], Kouichi Mutsuura[2] and Hiroh Yamamoto[3] *

1- Human System Science, Tokyo Institute of Technology
Ookayama, Meguro-ku, Tokyo 152-8552 Japan

2- School of Economics, Shinshu University
Asahi, Matsumoto, 390-8621 Japan

3- Shinshu University
Asahi, Matsumoto, 390-8621 Japan

Abstract. To promote effective learning in online learning environments, the prediction of learning performance is necessary, using various features of learning behaviour. In a blended learning course, participant's note taking activity reflects learning performance, and the possibility of predicting performance in final exams is examined using metrics of participant's characteristics and features of the contents of notes taken during the course. According to the results of this prediction performance, features of note-taking activities are a significant source of information to predict the score of final exams. Also, the accuracy of this prediction was evaluated using factors of the feature extraction procedure and the course instructions.

1 Introduction

The current learning environment uses information communication technology to promote learning activities in order to maximize the effectiveness of learning for participants. To promote the most preferred learning methods, learning situations are estimated using the disparate features recorded during learning events, and the effectiveness of this has often been discussed previously [1, 2].

Note-taking activity is an obvious behavioural action used throughout learning sessions. The activity has been evaluated conventionally in order to determine the understanding situations in any learning environments. As various metrics of participant's characteristics also reflect learning performance, the effectiveness can be illustrated as a causal relationship using a structural equation modelling technique [3, 4]. This suggests that these note-taking features reflect learning performance. If the appropriate features can be extracted to indicate learning situations during the course, they are key components of the process of the participant's learning. To confirm the hypothesis, the possibility of predicting overall learning performance using features of note-taking and other participants characteristics, such as test scores, should be determined. The following topics are addressed in this paper:

- A procedure for extracting features of note-taking content is quantitatively developed.

*This research was partially supported by the Japan Society for the Promotion of Science (JSPS), Grant-in-Aid for Scientific Research (B-26282046: 2014-2016).

ESANN 2015 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 22-24 April 2015, i6doc.com publ., ISBN 978-287587014-8. Available from http://www.i6doc.com/en/.

- The procedure for estimation of the final exam scores is proposed using the features of contents of notes taken and participants characteristics.
- The effectiveness of note-taking instructions is evaluated, to examine the performance of the estimations.

2 Method

2.1 Blended learning course and note-taking instructions

Surveys were conducted for two years during Blended Learning courses at a Japanese university. The subject was Information Networks. The courses were Bachelor level credit courses. The course consisted of weekly face-to-face sessions for 15 weeks [7]. Learning performance was evaluated using the scores of final exams (FE) at the end of the course.

All participants were required to present their notebooks in order to track the progress of their learning. To determine the possibility of improving note-taking activities by having the lecturer give instructions, two survey conditions were developed: with instructions and without instructions. The first year course was conducted without any instructions being given or feedback about notes provided, and this condition is defined as the "without instruction" condition. The second year course was conducted twice, with instructions concerning note-taking techniques and examples of good notes shown at the beginning and mid-points of the courses. This condition is defined as "with instruction".

The valid number of participants is 32 for without instruction and 24 for with instruction.

2.2 Characteristics of participants

Participant's characteristics were individually surveyed at the beginning of the course. The constructs are: Personality, Information Literacy [6] and Learning Experience [4]. In additional, an inventory of note-taking skills was surveyed to extract three factor scores. The total number of variables is 13. The causal relationships between these characteristics and overall learning performance were confirmed using these metrics [3, 4].

Personality: The personalities of participants were measured using the International Personality Item Pool (IPIP) inventory [1]. This questionnaire can produce a five factor personality model : "Extroversion" (IPIP-1), "Agreeableness" (IPIP-2), "Conscientiousness" (IPIP-3), "Neuroticism" (IPIP-4) and "Openness to Experience" (IPIP-5).

Information Literacy: Information literacy inventories were defined and developed by Fujii [6]. These 8 factors can be summarized as two secondary factors: Operational Skills (IL-1), and Attitudes toward Information Literacy (IL-2) [4].

Learning experience: Three factors are Factor 1 (LE-1): Overall Evaluation of the e-learning experience, Factor 2 (LE-2): Learning Habits, and Factor 3 (LE-3): Learning Strategies [4].

[1] http://ipip.ori.org

ESANN 2015 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 22-24 April 2015, i6doc.com publ., ISBN 978-287587014-8.
Available from http://www.i6doc.com/en/.

$$
\begin{array}{c c}
 & \begin{array}{ccccccc} T1 & T2 & T3 & T4 & T5 & T6 & T7 \end{array} \\
\begin{array}{c} T1 \\ T2 \\ T3 \\ T4 \\ T5 \\ T6 \\ T7 \end{array} &
\begin{pmatrix}
0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
$$

Fig. 1: An example of an adjacency matrix.

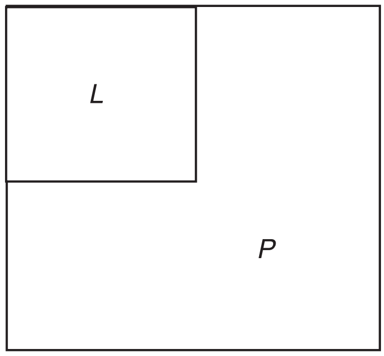

Fig. 2: Relationship between two adjacency matrices.

Note-taking skills: This construct consists of the following three factors: NT-1: Recognizing note taking functions, NT-2: Methodology of utilizing notes, and NT-3: Presentation of notes.

2.3 Lexical analysis for contents of notes taken

The contents of participant's notes, with the exception of figures and tables, were read and recorded manually as electronic text files. The lecturer's hand-written notes to be presented to participants during face-to-face sessions were also transformed into electronic text files.

Both notes of the participants and the lecturer were lexically analyzed using a Japanese morphological term analysis tool MeCab [2]. The term frequencies in the contents of notes of both participants and the lecturer were evaluated as follows [5, 3].

- Word ratio (wr): the ratio between the number of terms written and the number of terms given (the number of terms participants recorded vs. the number of terms the lecturer presented)
- Coverage (cv): the coverage ratio was calculated as a percentage of the number of terms recorded by participants.

As an additional lexical analysis, co-occurring noun terms were also surveyed. As well, concurrent frequencies of noun terms were calculated using the following procedure: For example, noun transitions of terms such as A-B and B-C were extracted from a text A-B-C. A pair of nouns appearing consecutively in a sentence is defined as a consequential noun. The transitions of terms are summarized in Figure 1 as consequential nouns, which are sometimes called 2-gram nouns [3, 5]. This is an example of a lecturer's presentation (Session 13). The

[2] http://mecab.sourceforge.net

ESANN 2015 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 22-24 April 2015, i6doc.com publ., ISBN 978-287587014-8. Available from http://www.i6doc.com/en/.

two noun term connections can be illustrated as an adjacency matrix. Therefore, the adjacency matrix indicates the contents of notes taken.

Generally, participants do not record all of the terms the lecturer presents, though they do record some related, original terms. To evaluate these two different note-taking activities, two adjacency matrices, such as the lecturer's notes (L) and notes of each participant (P), are compared in Figure 2. When participants made notes using terms which were not mentioned by the lecturer, the number of terms was greater than the number of terms in the lecturer's notes. These differences can be calculated mathematically, as edit distances, otherwise known as Levenshtein distances. As a result, the two indices are defined as follows:

- Additional distance (ad) means the sum of the number of additional nodes or edges in a matrix.
- Insufficient distance (id) means the sum of the number of reduced nodes or edges in a participant's matrix in comparison with the lecturer's matrix.

Both distances are influenced by the total number of terms in the lecturer's presentation, so that the relative distances are calculated using the number of terms the lecture presented in each session. As a result, four indices of note-taking were extracted from each session, then ground averages across all sessions were calculated, and partial averages for the first and the second halves of sessions were calculated, respectively.

3 Results and discussion

Regarding the surveys taken during course sessions, 17 variables ($\mathbf{x}$) mentioned above were measured and final exam scores were recorded. To determine the relationship between the 17 variables and test scores, multiple regression analysis with variable selection was conducted using a step wise method. In the results of linear regression analysis, the scores of the final exams were predicted, to a level of significance. Regarding the results, the sets of selected variables are different between analyzing data sets such as all data (All), data with note-taking instructions (with) and data without instruction (WO). Typical results of variable selections are indicated in the left hand column of Table 3. In most of the cases, the features of note-taking (NT) are included.

To evaluate accuracy of prediction, a support vector regression (SVR) technique with leave-one-out procedure has been introduced to the sets of variables which were created by the linear regression analysis mentioned in the above table. SVR with Gaussian kernel (G) can be noted as in the following equation, using the constant b.

$$\mathbf{x} \in \{wr, cv, ad, id, IPIP_{1-5}, IL_{1-2}, LE_{1-3}, NT_{1-3}\}$$
$$G(\mathbf{x}) = \ < \mathbf{w}, \mathbf{x} > \ + \ b$$

Here, G($\mathbf{x}$) can provide estimated scores of the final exam ($\tilde{FE}$) after optimization training. The actual calculation was conducted using a LIBSVM

	r			RMSE		
feature set	All	WO	with	All	WO	with
NT-f* + 13 variables[1]	0.08	-.08	0.27	5.7	6.6	4.4
NT-f** + 2 variables[2]	0.55	0.41	0.80	4.8	5.9	2.8
NT-f* + 2 variables[3]	0.56	0.42	0.85	4.8	5.9	2.5
NT-f(first half means)	0.32	0.19	0.60	5.6	6.7	3.6
NT-f(second half means)	0.02	-.13	0.13	6.1	6.9	4.9
3 variables[4]	0.14	0.21	0.09	6.0	6.6	5.1

"with" instructions, "WO" without instructions, All: with+without instructions

NT-f*: Means for four features of NT in the first half sessions (1-7)

1: Four features and other 13 features of characteristics.

2: selected features of NT-f, IPIP1, and NT3

3: NT-f, NT3, and a feature of NT in the second sessions (8-14)

4: IPIP2, LE-1, and a feature of NT in the first sessions

Table 1: Correlation coefficients and RMSE between final exam scores and predictions across sets of selected feature variables.

package [8]. The relationships between the scores and the predictions are evaluated using a correlation coefficient (r) and prediction error (RMSE: root mean square error). The results are summarized in Table 3, where the four features of note-taking activity in the first half of the course session contribute to accurate estimation of scores of FE. In comparing the performance of estimations between with and without note-taking instructions, the predictions are more accurate when instructions for note-taking were given. The giving of instructions may improve note-taking activity, and causes most features to shift to preferable values, and affect the relationship between those features and scores of the final exams.

Note-taking activities present cumulative learning behaviours across course sessions, though features of NT can be calculated for every session of this survey. To determine how to survey note-taking activity, the prediction performance was compared using features of course sessions. Prediction was conducted using four features of note-taking and note-taking factor score (NT3). The performance is displayed in Figure 3, where the horizontal axis indicates the course sessions, and the vertical axis indicates correlation coefficients and RMSE. The greatest accuracy can be obtained at the 11th session, while the accuracy is not significant in the first several sessions. At the 11th session, the correlation coefficient for all data is over 0.6, and the scores of final exams are nearly precisely estimated using those features. The scores are more accurately predicted across the 4th to 12th sessions ($r > 0.6$) when note-taking procedures were given.

On the other hand, the accuracy decreased after the 11th session. Regarding the survey of the number of terms the lecturer presented in sessions, the number of terms was small in the last several sessions [7]. Therefore, consideration of the number of terms the lecturer presented in the session should be given regards to using features of note-taking to evaluate prediction performances. Though

ESANN 2015 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 22-24 April 2015, i6doc.com publ., ISBN 978-287587014-8.
Available from http://www.i6doc.com/en/.

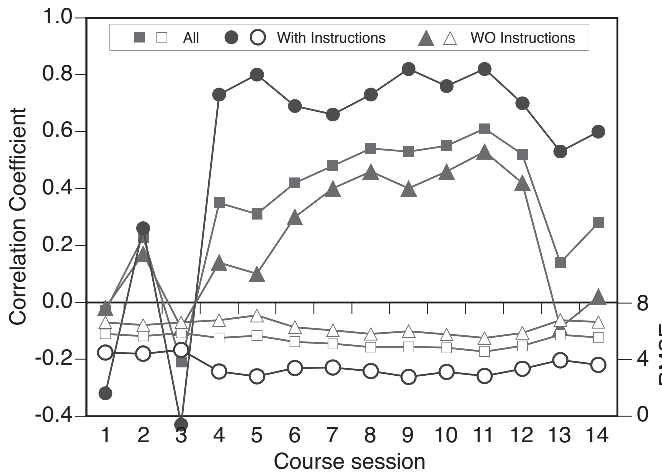

Fig. 3: Correlation coefficients and RMSE between final exam scores and predictions using mean NT features of course sessions.

the features of the contents of notes taken is significant for predicting learning performance, the collection of data is not easy, and so a more simplified procedure is required. These points will be subjects of our further study.

References

[1] M. Ueno, Online outlier detection for e-learning time data, *IEICE Trans.*, J90-D(1), pages 40–51, 2007.

[2] M. Nakayama, H. Kanazawa, and H. Yamamoto, Detecting incomplete learners in a blended learning environment among Japanese university students, *Int. J. Emerging Technology in Learning*, 4(1), pages 47–51, IAOE, 2009.

[3] M. Nakayama, K. Mutsuura and H. Yamamoto, Lexical Analysis of Student's Learning Activities during the Giving of Instructions for Note-Taking in a Blended Learning Environment, *IJIET*, 6(1), pages 1–6, IACSIT, 2016.

[4] M. Nakayama, K. Mutsuura and H. Yamamoto, Impact of Learner's Characteristics and Learning Behaviour on Learning Performance during a Fully Online Course, *Electronic J. e-Learning*, 12(4), pages 394–408, api, 2014.

[5] M. Nakayama, K. Mutsuura and H. Yamamoto, A note taking evaluation index using term networks in a blended learning environment, *Proc. Eighth Int. Conf. Complex, Intelligent and Software Intensive System*, pages 486–490, IEEE, 2014.

[6] Y. Fujii, Development of a scale to evaluate the information literacy level of young people, *Japan Journal of Educational Technology*, 30(4), pages 387–395, JSET, 2007.

[7] M. Nakayama, K. Mutsuura and H. Yamamoto, Evaluation of student's notes in a blended learning course, *Int. J. New Computer Architectures and their Applications*, 1(4), pages 1080–1089, 2011.

[8] C. Chang, C. Lin, LIBSVM: a library for support vector machines, *ACM Trans. Intelligent Systems and Technology*, 2:27:1–27:27, 2011. `Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm`