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Paper:

Data Mining for Discovering Effective Time-Series Transition of Learning Strategies on Mutual Viewing-Based Learning

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We aim to develop a real-time feedback system of learning strategies during lesson time to improve academic achievement. It has been known that mutual viewing-based learning is an effective educational method. However, even though mutual viewing is an effective lesson style, there are effective or ineffective learning strategies in the learners' individual activities. In general, the method of evaluating learning strategies is a questionnaire survey. However, the questionnaire cannot measure the learning strategies in real time. Thus, it is difficult to detect the students who use ineffective learning strategies during lesson time in real time. Recently, a system that can measure the learning strategies in real time has been developed. Using this system, it is possible to detect students who use ineffective learning strategies during lesson time on the mutual viewing-based learning. From this point of view, we aim to develop a recommendation system for real-time learning strategies for teachers and students to achieve a highly educational effect. For this purpose, we must know the features of effective or ineffective learning strategies via a system that can measure learning strategies. In this paper, we report the discovery of features of effective or ineffective learning strategies based on the data-mining approach using the *k*-means method, transition diagram, and random forest. We classified the time-series learning strategies over 40 min into 216 strategies and surveyed the improvement probability of academic achievement via a random-forest-based classification model. By embedding our results into the system, we may be able to automatically detect students who use ineffective learning strategies and recommend effective learning strategies.

Keywords: data mining, educational technology, *k*-means method, random forest, Markov chain

1. Introduction

Learning strategies refer to the students' activities (including psychological activities) to improve their own academic achievement [1]. The general method to measure the students' learning strategies is questionnaire made by educational researchers. There are many questionnaires to measure strategies, such as strategies of comprehension and repetition [2] and Self-Regulated Learning (SRL) [3].

Through these works, researchers and/or teachers can know the differences between effective and ineffective learning strategies based on the students' answers. However, to measure the learning strategies by using a questionnaire has some problems. The effectiveness cannot be measured continuously and in the short term. Students do not answer appropriately if teacher gives the same questionnaire everyday. In addition, we cannot measure the time-series transition of learning strategies during lesson time. Chamot has reviewed other methods to measure learning strategies: interviews, diaries, and so on [4].

Recently, the systems that can support the mutual viewing have been developed [5, 6]. There is a possibility that the lessons based on this system can be effective. In the lesson, learners perform the mutual viewing and try to improve their own academic achievement. We can regard the mutual viewing of content recorded by learners as learning strategies because they are the learners' activities to improve their own academic achievement. The lesson based on the mutual viewing (e.g., problem-based learning [7], information education [8], science education [9, 10]) has high effectiveness. However, there are effective or ineffective learning strategies in the learners' activities, even if the mutual viewing is an effective lesson style. Thus, if there were an algorithm that can detect learners who use ineffective mutual viewing for their learning strategies, the teacher could provide a more effective lesson.

Therefore, as the final objective of our research, we will develop a real-time feedback system for learning strategies during class for the teachers and students. To achieve this objective, we must know the features of effective and ineffective learning strategies from the educational data of the system.

We focus on the improvement of the summary-writing ability as the academic achievement. The summary-writing ability or summarization means a skill of summarizing content that students have already learned. This ability is a high-level skill compared with the skills of memorization of technical terms, simple calculations, and so on.

From this point of view, in this paper, we report on the features of effective and ineffective learning strategies based on a data-mining approach.

2. Previous Research

The final objective of our research is to develop a real-time feedback system of effective learning strategies during lesson time for the teacher and students. As the first step, in this paper, we report on the data-mining method to extract effective and ineffective learning strategies from an automatic educational data logging system during the lesson. To this end, we review previous research: (i) the relationship between the academic achievement and questionnaire-based learning strategies and (ii) the system of the learners' learning strategies.

Initially, we describe (i). Wolters and Hussain have surveyed Self-Regulated Learning (SRL) and the academic achievement [3]. SRL is a learning strategy that consists of planning, monitoring, and so on. They describe a relationship between SRL and academic achievement. Fang and Ahmed have surveyed the relationship between the Motivated Strategies for Learning Questionnaire (MSLQ) and the academic achievement [11, 12]. MSLQ is a questionnaire to measure the learning strategies and academic motivation [13]. They have explained their relationship from the correlation-based analysis. Omae et al. have surveyed the effect of the strategies of comprehension and repetition on academic achievement [14]. They have developed an estimation model based on the decision tree. Their method can estimate academic achievement based on learning strategies. Matsukawa et al. have developed the feedback system learning strategy [15]. It has a function of the feedback on effective learning strategy based on a questionnaire to the students. Golino et al. have developed a prediction method for academic achievement based on a random-forest classifier [16]. These works are effective for learning the tendency of students who have high academic achievement. However, in all cases, the questionnaire cannot measure learning strategies in real time, whereas the method presented in this paper can.

Next, we describe (ii). Ueno has developed an intelligent e-learning system. This system has functions to predict academic achievement from learning strategies, detect the students who need the teacher's help, and so on [17]. Moreover, there is the function to detect students who select anomalous learning strategies in e-learning. It is a very effective intelligent e-learning system. Budiyanto et al. have also developed an intelligent e-learning system [18]. Their system has the functions to detect the learning styles and ability levels of learners and to present learning materials in accordance with the learning style and ability level. Through these functions, the learners may select better learning strategies compared with the common e-learning system. This system will be able to improve the academic achievement. DelSignore et al. have investigated the relationship between the learning strategies of viewing videos and academic achievement [19]. From the result, they describe an optimized e-learning system. Michel et al. have developed the automatic activity trace system [20]. The system supports the self-regulation in the project-based learning. These systems are effective to improve students' academic achievement. In contrast, our research target is not e-learning that is asynchronous between the teacher and students, but synchronous learning of the teacher and students in a real classroom. Moreover, our target ability in many academic skills is the summarization ability. These are the differences in our research compared with the previous research.

3. Teaching Plan and Logging System

We explain our teaching plan to improve and measure the students' academic achievement (summarization ability).

The overview is shown in **Fig. 1**. First, the students write a pre-report to measure their initial summary-writing ability (the upper left in **Fig. 1**). Next, they attend n 40-min lesson units. During the lesson, the students record the content by handwriting or taking pictures in the form of a screenshot on their own tablet. Then, the screenshots are stored in database.

After finishing n times lessons, the students write the report in 40 min. The pictures are shown in **Fig. 1**. While writing the report, the students only refer the stored screenshots and textbook. They can see their own and other students' screenshots. After writing the report, the students attend the next unit. One loop took three to four

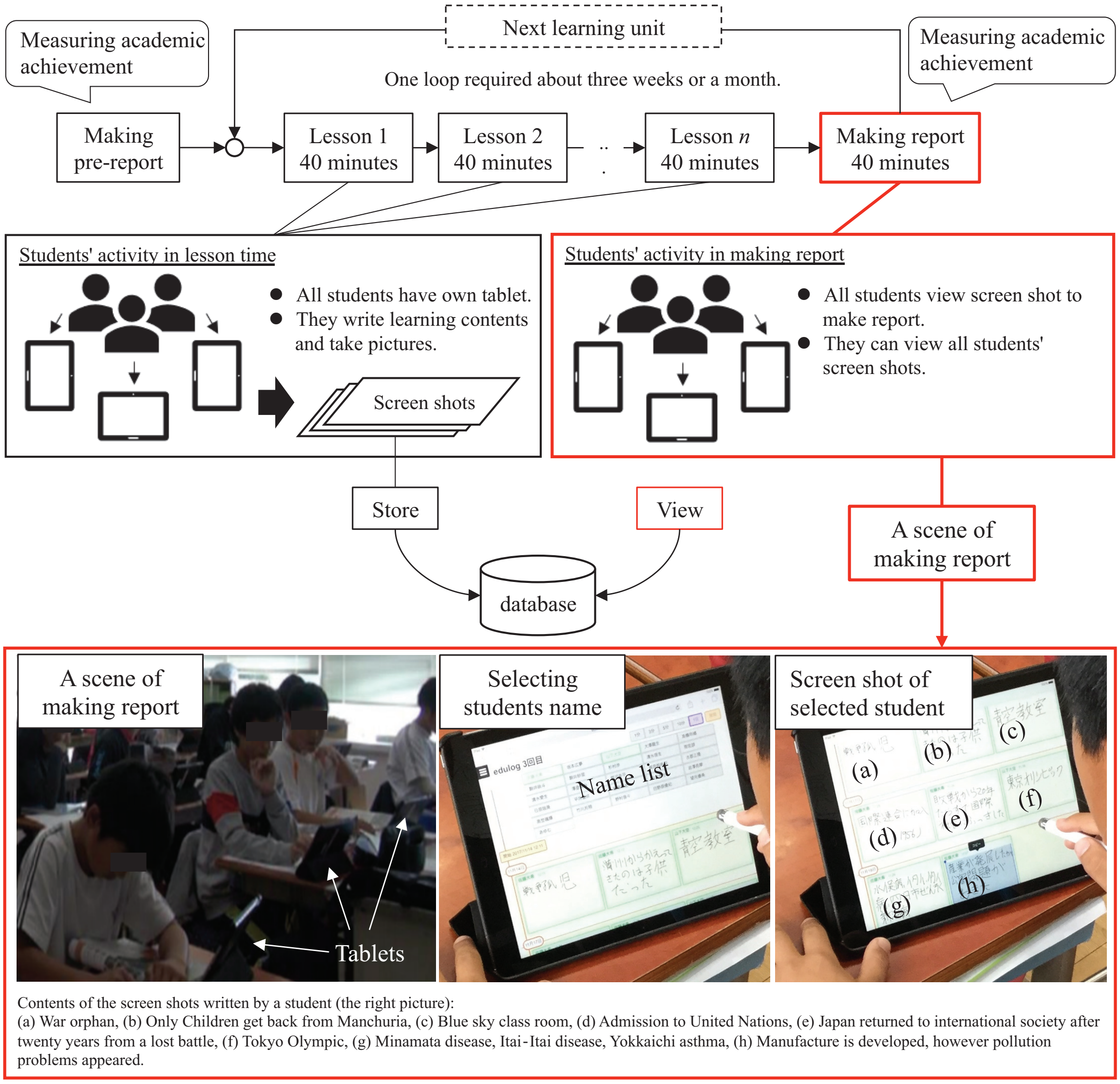

Fig. 1. Teaching plan, students' activity, and pictures of writing the report.

weeks. If a student's report score is an improvement from the previous report, then the student's academic achievement is improved.

Next, we describe the educational data logging system used in this paper, "edulog" [6], to measure mutual viewing as a learning strategy. The system can measure the viewing time of screenshots during the report writing (this system is not used from lesson 1 to lesson n). This image is shown in **Fig. 2**. Its output is a CSV file. "Subject name" means the target subject of the learning unit. "Internal time" is the time according to the clock on the student's tablet. "From" means the student who sees the screenshot. "To" means the student that is seen by other students. "On" and "off" indicate the opening and closing time of the screenshot. For example, Hanako starts her viewing of Taro's screenshot at 11:05. After that, Hanako ends her viewing of Taro's screenshot at 11:06. As a result, we can store the students' activity log as they are writing their reports. In this paper, we define this viewing log as the learning strategy.

	A	B	C	D	E	F
1	Internal time	Time	Subject name	From	To	Activity
2	1508465398914	2017/10/20 11:05	Social study	Taro	Saburo	on
3	1508465004991	2017/10/20 11:05	Social study	Taro	Saburo	off
4	1508465118224	2017/10/20 11:05	Social study	Hanako	Taro	on
5	1508465024435	2017/10/20 11:05	Social study	Saburo	Hanako	on
6	1508465209153	2017/10/20 11:06	Social study	Hanako	Taro	off
7	1508465209929	2017/10/20 11:06	Social study	Taro	Hanako	on
8	1508465054653	2017/10/20 11:06	Social study	Saburo	Hanako	off
9	1508465210374	2017/10/20 11:06	Social study	Taro	Hanako	off

Fig. 2. CSV output of our automatic educational data-logging system "edulog."

4. Experiment

4.1. Outline

We have the following research questions: (Q1) What kinds of learning strategies exist? (Q2) What strategies do the students select? (Q3) What is the learning strategy that leads improvements in the students' academic achievement? We carried out an experiment to find the answers to these research questions based on a data-mining approach.

The outline of experiment is as follows. The 6th-grade elementary school students performed 4 cycles of our teaching plan. The learning content is social studies in Japan (Japanese history and civics) and the number of students is 24. The days on which the students write their reports are Oct. 20, Nov. 9, Nov. 28, and Dec. 13, 2017. From this experiment, we obtained the 96 strategies and reports.

The discussions of (Q1), (Q2), and (Q3) are shown in Sections 4.3, 4.4, and 4.5, respectively.

4.2. Data Processing

We split the students' activity time during the lesson (40 min) and defined the phase set P:

$$P = \{\mathrm{P}_1, \mathrm{P}_2, \mathrm{P}_3\}, \qquad (1)$$

where P_1 means the period from the start time to 13 min, P_2 means the period from 13 min to 26 min, and P_3 means the period from 26 min to the end time. P_1, P_2, and P_3 are called the first, middle, and last phase, respectively.

As a result, we obtain the 288 learning strategies used during 13 min (the number of students, phases, and reports are 24, 3, and 4, respectively. Thus, $24 \times 3 \times 4 = 288$). We also obtain 96 time-series learning strategies for the set of all phases (the number of students and reports are 24 and 4, respectively. Thus, $24 \times 4 = 96$).

After that, we extract the students' log data from "edulog" and generate the data:

$$\boldsymbol{x}_p = [x_{\mathrm{Own},p},\ x_{\mathrm{HS},p},\ x_{\mathrm{LS},p}]^T, \qquad (2)$$

where p means the phase ID and $p \in P$. $x_{\mathrm{Own},p}$ means the viewing time of one's own screenshot in the phase $p \in P$. $x_{\mathrm{HS},p}$ means the viewing time of a screenshot from the student who has a high score in phase $p \in P$. $x_{\mathrm{LS},p}$ means the viewing time of a screenshot from the student who has a low score in phase $p \in P$. Before the experiment, all students were assigned a high score (HS) or low score (LS) by the pre-report. If the pre-report score was greater than the average, this student was assigned HS, and otherwise, LS. Note that there is an attention point when we see Eq. (2). A single-phase period is about 13 min. However, because the students can see multiple screenshots at the same time, $\boldsymbol{x}_p$ can exceed the 13-min viewing time.

Moreover, if we represent $\boldsymbol{x}_p$ as the viewing time of the single phase $p \in P$, the viewing time of all phases (40 min) can be expressed by:

$$\boldsymbol{x}_{\mathrm{ALL}} = [(\boldsymbol{x}_{\mathrm{P}_1})^T\ \ (\boldsymbol{x}_{\mathrm{P}_2})^T\ \ (\boldsymbol{x}_{\mathrm{P}_3})^T]^T. \qquad (3)$$

Equation (2) presents a students' learning strategies in the period of a single phase (13 min). Moreover, Eq. (3) presents a student learning strategies during the period of all phases (40 min). Thus, we represent $\boldsymbol{x}^i_p$ as the i-th student viewing data during single phase $p \in P$ and $\boldsymbol{x}^i_{\mathrm{ALL}}$ as the i-th student viewing data during all phases.

4.3. Pattern of the Learning Strategies

From the obtained data discussed in Section 4.2, we can obtain the learning-strategy set C, which has the $k_{\max}$ clusters by using the k-means method:

$$C = \{\mathrm{C}_i \mid i = 1, \ldots, k_{\max}\}. \qquad (4)$$

In this paper, we set $k_{\max} = 6$ based on the understandability of the centroid and sample size. The results are shown in **Fig. 3**. Each subplot corresponds to each cluster. The number at the upper right in each figure means the centroid value obtained by the k-means method. The filled circles mean the centroid and the non-filled circles mean the real learning strategies selected by each student.

Cluster C_1 has a feature that the viewing time of HS students' screenshots is long. In cluster C_2, the viewing time of own, HS, and LS students' screenshots are long. We find that it is a very active learning strategy. In cluster C_3, all viewing times are very short. It is a very inactive learning strategy. The viewing time of the students' own screenshots is long in cluster C_4. In cluster C_5, the viewing time of LS students' screenshots is long. Cluster C_6 has a feature that the viewing time of HS students and the students' own screenshots are long.

We summarize the these results: C_1, C_3, and C_5 are inactive strategies, and C_2, C_4, and C_6 are active strategies.

Using the results, we can understand the tendencies of learning strategies based on the k-means method.

4.4. Transition of the Learning Strategies

Next, we survey the time-series transition between the learning strategies during all phases (40 min). To achieve this, we calculate the transition probability p_{ij} from learning strategy C_i to C_j:

$$p_{ij} = \Pr(X_{n+1} = \mathrm{C}_j \mid X_n = \mathrm{C}_i), \qquad (5)$$

$$\mathrm{C}_j, \mathrm{C}_i \in C, \qquad (6)$$

where n means a phase and has the first phase P_1 or middle phase P_2. If n is the first phase P_1, then $n+1$ means the middle phase P_2. Otherwise, if n is the middle phase P_2, then $n+1$ means the last phase P_3. Moreover, we calculate the transition probability matrix $\boldsymbol{M}$ based on Laplace smoothing and the collected data:

$$\boldsymbol{M} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1k_{\max}} \\ p_{21} & p_{22} & \cdots & p_{2k_{\max}} \\ \vdots & \vdots & \ddots & \vdots \\ p_{k_{\max}1} & p_{k_{\max}2} & \cdots & p_{k_{\max}k_{\max}} \end{bmatrix}, \qquad (7)$$

where $k_{\max}$ means the number of clusters based on the k-means method ($k_{\max} = 6$ in this paper). Laplace smoothing means the addition of one to each count [21].

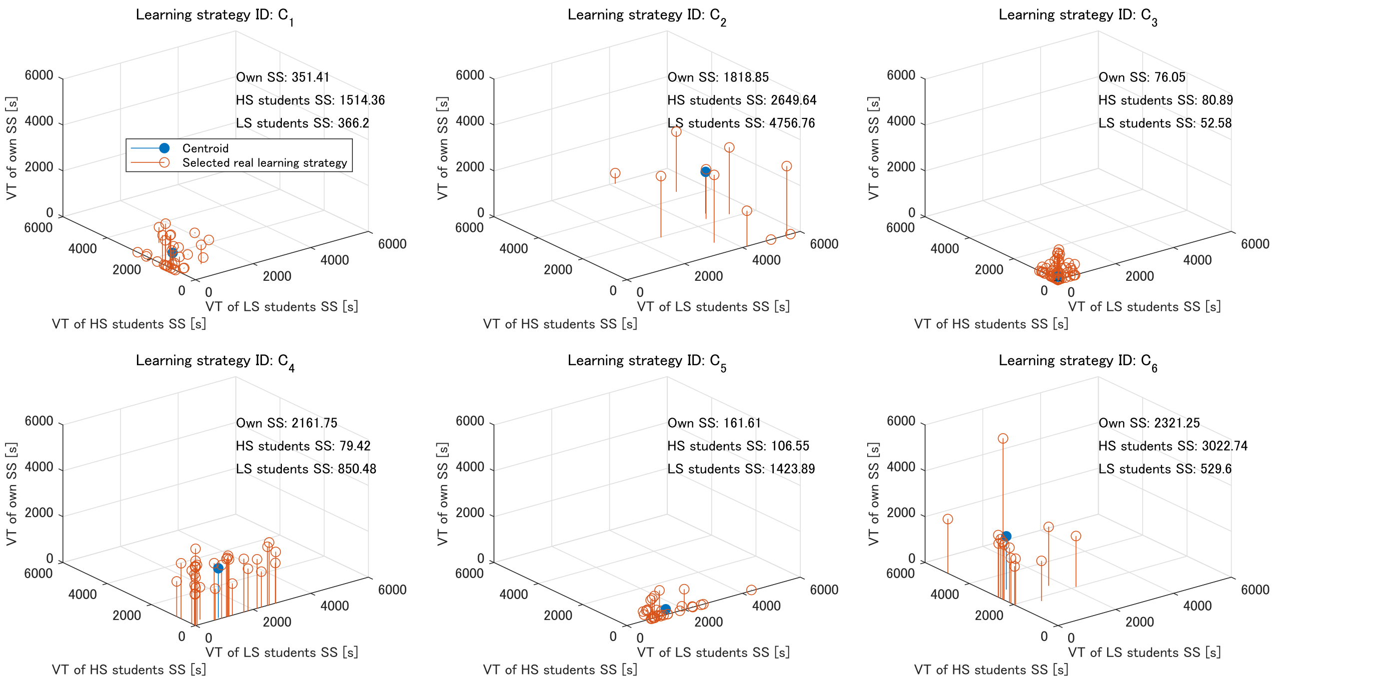

Fig. 3. Clustering of the learning strategies based on the k-means method. Numbers in each subplot mean the clusters' centroid values of the learning strategies of a single phase (13 min). VT means the summation of the viewing time. HS or LS are the HS or LS student's screenshot (SS) except for one's own SS. Note that students were only aware of their own academic achievement rating.

After that, we calculate the initial probability p_i selected in first phase P_1:

$$p_i = \Pr(X_1 = C_i),\ \ C_i \in C. \quad (8)$$

We also calculated the initial probability vector $\boldsymbol{M}_0$:

$$\boldsymbol{M}_0 = [p_1,\ p_2,\ \ldots,\ p_{k_{\max}}]^T. \quad (9)$$

As a result, we can find the probability of the selected first phase P_1.

The constructed graphical model of learning strategies transition based on the transition probability matrix $\boldsymbol{M}$ and the initial probability vector $\boldsymbol{M}_0$ is shown in **Fig. 4**. Initially, we consider the learning strategies selected in the first phase. The learning strategies are selected as follows: $C_4 (p_4 = 32.29\%)$, $C_5 (p_5 = 16.67\%)$, $C_6 (p_6 = 16.67\%)$, $C_3 (p_3 = 13.54\%)$, $C_2 (p_2 = 10.42\%)$, $C_1 (p_1 = 10.42\%)$. This means that the probability that the students obtain the information from their own screenshot and the LS students' screenshot (C_4) is the highest. However, there are many patterns in the first phase. In contrast, in the case of the middle or last phase, the transition probability to C_3 is high, which means the students do not obtain information from the screenshot in the middle and last phases.

If we set a simple Markov-chain process [22], we can determine the transition probability of the learning strategies from the first phase P_1 to the last phase P_3 through the middle phase P_2. Now, the student selects the m-th learning strategy C_m in the first phase P_1. Then, the probability of the i-th learning strategy C_i in middle phase P_2 and the probability of the j-th learning strategy C_j in last phase P_3 can expressed by:

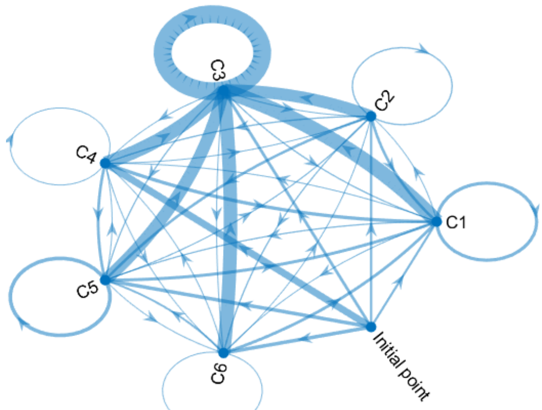

Fig. 4. Learning strategies transition diagram. The nodes indicate learning strategies clusters based on the k-means methods. The arrow width indicates the probability of transition based on Laplace smoothing and collected data.

$$\begin{aligned} O_{mij} &= \Pr(X_2 = C_i | X_1 = C_m) \times \Pr(X_3 = C_j | X_2 = C_i) \\ &= p_{mi} \times p_{ij}. \end{aligned} \quad (10)$$

Thus, we can calculate O_{mij} after the first phase (about

Table 1. The top 3 probabilities of time-series learning strategies transition based on Markov chain after the first phase P_1 is decided.

First P_1	Middle P_2	Last P_3	Probability
C_1	C_3	C_3	58.08 %
	C_1	C_3	10.56 %
	C_3	C_5	4.15 %
C_2	C_3	C_3	46.88 %
	C_1	C_3	8.71 %
	C_5	C_3	7.14 %
C_3	C_3	C_3	69.44 %
	C_3	C_1	4.96 %
	C_3	C_5	4.96 %
C_4	C_3	C_3	52.63 %
	C_1	C_3	11.00 %
	C_5	C_3	7.52 %
C_5	C_3	C_3	47.62 %
	C_1	C_3	9.96 %
	C_5	C_3	9.80 %
C_6	C_3	C_3	53.03 %
	C_1	C_3	9.50 %
	C_5	C_3	5.19 %

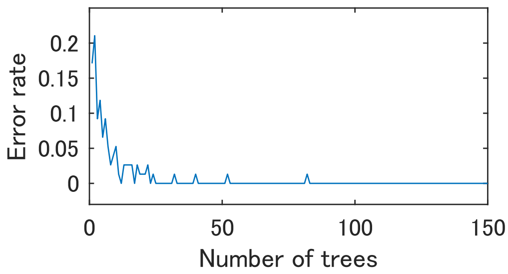

Fig. 5. The relationship between the number of trees and error rate based on the training data.

Table 2. Classification score of the random-forest classifier. $\hat{y}^i$ means the classification output for the i-th student.

Dataset	Observed class	Estimated class $\hat{y}^i = 0$	Estimated class $\hat{y}^i = 1$	Accuracy
Training data	$y^i = 0$	36	0	100.0%
	$y^i = 1$	0	40	
Test data	$y^i = 0$	6	2	75.0%
	$y^i = 1$	3	9	

13 min after the lesson's start). In other words, the teacher can know the time-series transition of learning strategies for all students by checking O_{mij}.

We show the top 3 probabilities after selecting the first phase's learning strategy in **Table 1**. In all cases for the first phase's learning strategy, the maximum probability transition is from C_3 to C_3. Moreover, in the case of the second and third grade, C_1, C_3, and C_5 are selected in the middle or last phase. From the results of the k-means method in **Fig. 3**, learning strategies C_1, C_3, and C_5 are inactive learning strategies compared to the other strategies (C_2, C_4, and C_6). These results show that the students do not select the active learning strategies to obtain information from screenshots. We guess that the students are focused on writing the report and do not check the screenshots. In other words, if the student selects ineffective learning strategies in first phase, the teacher must teach appropriate strategies to this student. To achieve this, we describe effective learning strategies in the next subsection.

4.5. Discovering the Effective Learning Strategies

To develop the prediction model for the improvement of academic achievement by the learning strategies, we make the following dataset:

$$D = \{(\boldsymbol{x}^i_{\mathrm{ALL}};\, y^i) \mid i \in I\}, \quad \ldots \ldots \ldots \quad (11)$$

where $\boldsymbol{x}^i_{\mathrm{ALL}}$ is the learning strategies in all phases defined by Eq. (3) of the i-th student. y^i means the class label of the i-th student for the supervised machine learning and it represents the state of academic achievement after the selected learning strategies $\boldsymbol{x}^i_{\mathrm{ALL}}$ of the i-th student. $y^i = 1$ means that there is improvement of the i-th student's academic achievement. $y^i = 0$ means that there is no improvement. In this paper, the number of classes labelled $y^i = 0$ is 44 and the number of classes labelled $y^i = 1$ is 52. If we can develop a high quality classifier, we can know the predict academic achievement by using learning strategies.

After that, we split the dataset D into the training dataset and test dataset. The training dataset is used to teach the the machine-learning algorithm and the test dataset is to evaluate the developed model. The size of the training and test dataset are 76 ($y^i = 0$ is 36, $y^i = 1$ is 40 samples) and 20 ($y^i = 0$ is 8, $y^i = 1$ is 12 samples), respectively. We develop the random forest-based classifier by using the training dataset. In the case of making the random forest, two model parameters must be set [23]. One is the number of weak learners B, and the other is the number of randomly selected features that branch each tree γ. We set $(B, \gamma) = (150, 5)$. γ is a half value of the dimension of the feature vector. B is given by searching the model parameters based on error rate. The relationship between the number of trees and error rate of a random-forest classifier based on training data is shown in **Fig. 5**. If the number of trees is 150, the error rate stably achieved 0.00%. For this reason, we adopted 150 as the number of trees B.

After developing the prediction model, we survey the classification score by using the training and test data. The results are shown in **Table 2**. $\hat{y}^i$ means the estimated class for the i-th student. In the case of training data, 100.0% accuracy has been achieved. In the case of test data, there are few misclassifications. For the overall result, the accuracy of the test data reached 75.0%.

By using the developed model, we survey the effective and ineffective learning strategies. Initially, we pre-

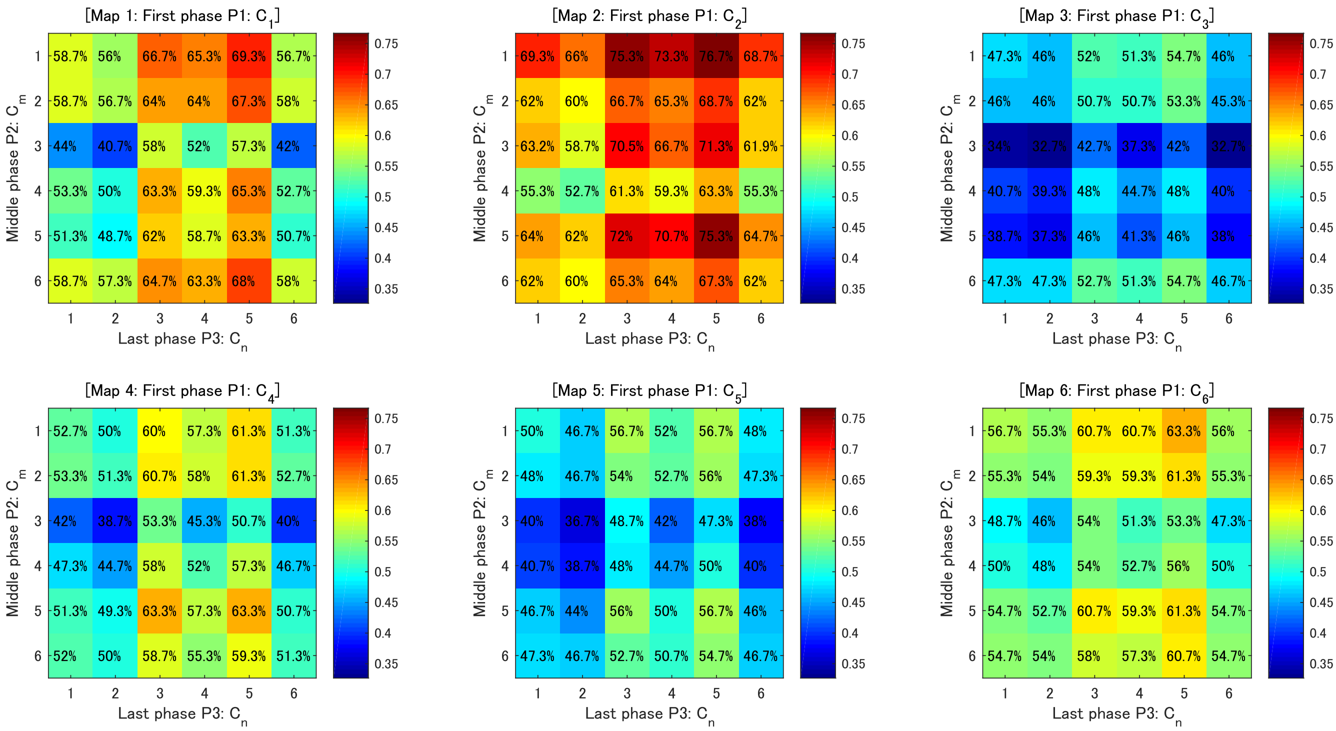

Fig. 6. The relationship between the learning strategies and improvement probability of academic achievement based on the k-means method and random-forest classifier. The six maps correspond to the results of the selected learning strategies of the first phase. The vertical and horizontal axes mean the selected learning strategies of the middle or last phase.

pare the representative feature vectors set in the form of Eq. (3):

$$X_{\text{cent}} = \{[(\boldsymbol{x}_{\text{P}_1} = \boldsymbol{N}_i)^T \ (\boldsymbol{x}_{\text{P}_2} = \boldsymbol{N}_j)^T \ (\boldsymbol{x}_{\text{P}_3} = \boldsymbol{N}_m)^T]^T | i, j, m \in C\}, \quad . \quad (12)$$

where $\boldsymbol{N}_i$ is the centroid value of cluster $\text{C}_i \in C$. In other words, the elements of set X_{cent} indicate representative learning strategies in all phases.

After that, we define the improvement probability of academic achievement $R(x)$ from the element $x \in X_{\text{cent}}$:

$$R(x) = \frac{1}{B}\sum_{b=1}^{B} Tr_b(x),\ x \in X_{\text{cent}}, \quad . \ . \ . \ . \ . \ . \ (13)$$

where Tr_b is the b-th weak learner of the developed random forest. $R(x)$ means the ratio of answering class 1 (increase) of the inputted feature x. If $R(x) = 1$, it means that all weak learners answer class 1. In other words, we can determine the improvement probability of academic achievement based on selected learning strategies. To discover effective learning strategies, we make 216 representative learning strategies by a combination of the clustering results (The number of a single phase's learning strategies is 6. Because there are the first, middle, and last phases, the number of all patterns is $6^3 = 216$). After that, the 216 obtained feature vectors are input to a random-forest classifier and the improvement probability of academic achievement $R(x)$ is calculated.

The results are shown in **Fig. 6**. These maps show the improvement probability of academic achievement as a function of the selected learning strategies. The six maps correspond to the results of the selected learning strategies of the first phase. The vertical and horizontal axes indicate the selected learning strategies of the middle or last phase.

From **Fig. 6**, we find that the improvement probability of academic achievement depends on the selected C_n. The improvement tendency of the selection of the first phase is roughly $\text{C}_2 > \text{C}_1 > \text{C}_6 > \text{C}_4 > \text{C}_5 > \text{C}_3$.

We discuss these results in combination with the results of the k-means method shown in **Fig. 3**.

In the case of selecting learning strategy C_2 in the first phase, the probability of improving academic achievement is very high. This means that selecting active learning strategies is important to improve the summary-writing ability for students. After that, in the case of C_1 and C_5 in the middle and last phases, the maximum value of improving academic achievement is obtained.

In the case of selecting learning strategy C_1 in the first phase, the probability of improving the academic score achieves a high value. This shows that it is important to view the HS students' screenshots.

In the case of selecting learning strategy C_6 in the first phase, the probability of improvement is high. This shows that it is important to view both the HS students' screenshots and one's own screenshots.

In contrast, in the case of C_4 and C_5 in the first phase, the maximum value of probability is low. The feature common to C_4 and C_5 is not viewing HS students' screenshots. Thus, we understand that viewing HS students' screenshots is important.

The worst case is the selection of C_3 in the first phase. In this cluster, the viewing times for all screenshots are very small. Thus, it is important to view some screenshots for students.

As a result, we could search the effective and ineffective time-series learning strategies. If the prediction result of the improvement probability for target students is poor, the teacher should teach them a better learning strategies. We can predict students' academic achievement before finishing the report by using only the information from the first phase if we integrate the algorithm proposed in this paper. It may be effective to support improvements in the students' academic achievement. We will develop this system in the future.

5. Conclusion

We have an objective to develop a real-time learning-strategy feedback system to detect ineffective learning strategies and recommend effective learning strategies. To achieve this, we ask the following research questions: (Q1) What does the kind of learning strategies exist? (Q2) What strategies do students select? (Q3) What is the learning strategy that lead to improve students' academic achievement?

To answer about these questions, we performed the experiment and data-mining-based analysis. We discussed (Q1), (Q2), and (Q3) in Sections 4.3, 4.4, and 4.5, respectively. As a result, we could learn the time-series transition of learning strategies and the probability of improving academic achievement based on the Markov chain and random-forest classifier.

In future works, we will develop the real-time learning-strategy feedback system to detect ineffective learning strategies and to recommend effective learning strategies based on the knowledge described in this paper. Moreover, we aim to improve the classification quality by using other machine-learning techniques (e.g., support vector machine, neural network) instead of the random-forest approach.

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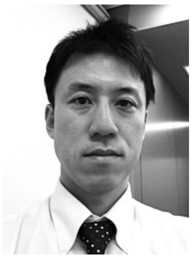

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