Information Engineering Express
International Institute of Applied Informatics
2019, Vol. 5, No. 1, 59 – 72

Key Factor Not to Drop Out is to Attend Lectures

Hideo Hirose * †

Abstract

To find key factors not to drop out using learning analytics, we have added accumulated data such as the number of successes in learning check testing, the number of attendances to follow-up program classes, and etc., in addition to learning check testing ability scores performed at each lecture. Then, we have found key factors strongly related to the students at risk. They are the following. 1) Badly failed students (score range is 0-39 in the term ex-amination) tend to be absent for the regular classes and fail in learning check testing even if they attended, and they are very reluctant to attend follow-up program classes. 2) Success-ful students (score range is 60-100 in the term examination) attend classes and obtain good scores in every learning check testing. 3) Failed students but not so badly (score range is 40-59 in the term examination) reveal both sides of features appeared in score range of 0-39 and score range of 60-100. Therefore, it is crucial to attend lectures in order not to drop out. Students who failed in learning check testing more than half out of all testing times almost absolutely failed in the term examination, which could cause the drop out. Also, students who were successful to learning check testing more than two third out of all testing times took better score in the term examination.

Keywords: learning check testing, placement test, follow-up program, item response theory, multiple linear regression, term examination.

1 Introduction

It is crucial to identify students at risk of failing courses and/or dropping out as early as pos-sible because students of widely varying abilities are now enrolled in universities and we teachers have to educate them together. This circumstance prohibits us to use conventional methods such as a mass education method. However, the number of staffs and classes are limited. New assisting systems using ICTs shall be introduced to solve such a difficulty. To overcome this, we have established an online testing system aimed at helping students who want to improve their mathematical skills. Such a system include 1) learning check testing (LCT) for every class to check if students comprehend the contents of lectures or not, 2) collaborative working testing (CWT) for training skills with supporters and teachers, and 3) follow-up program testing (FPT) to check if the follow-up program class members un-derstand the standard level of the lectures. A brief introduction to this online testing system

* Hiroshima Institute of Technology, Hiroshima, Japan
† This work was supported by JSPS KAKENHI Grant Number 17H01842.

applied to more than 1,000 freshman students is illustrated in the appendix. The system has been successfully operating (see [5], [6]), and some computational results were reported [8], [10], where, importance of initial habituation for learning using LCT are shown. In addition, other relevant cases have been investigated (see [7], [9], [11], [13], [15]).

Using accumulated data in the database, we may find some key factors strongly related to the students at risk, as indicated in [2], [3], [14], and [16], if we pay attention to learning analytics. Then, we may be able to actively make an appropriate decision for better learning methods. As indicated in [17], it is also important to analyze the data theoretically.

Thus, this paper is aimed at obtaining effective learning strategies for students at risk of failing courses and/or dropping out, using a large-scale of learning data accumulated from the online testing system. They consist of, in addition to every LCT scores, the placement test scores, FPT success/failure times, FPC attendances, etc. In considering the learning skills of students, we use the ability values obtained from the item response theory (IRT, e.g., see [1], [4], [12]). IRT scheme is briefly introduced in the appendix. Although the subjects we deal with are analysis basic (similar to calculus) and linear algebra, we show the case of linear algebra as a typical case.

2 Success/Failure Responses and the LCT Ability Values

To evaluate the LCT results numerically, we have adopted the IRT scheme in the risk analysis in [8], [10] as seen in the appendix. In LCT, the number of questions in one testing is so small such as five or seven because of the limited testing time. Therefore, as easily imagined, due to the small number of questions, the estimated ability values tend to have biases and variances are large (see [13], [15]). It would be difficult to classify the students into a successful group and a failed group in the term examination using each LCT result. Then, we have used all the LCT results together in classifying.

Figure 1 shows the histogram of estimated abilities of LCT to successful students over-laid the histogram of estimated abilities of LCT to failed students in the case of linear algebra, using all the LCT results together in the first semester in 2017. We can see that it would be difficult to find the optimal discriminating threshold to success/failure students. The numbers of successful students is 898, and failed students is 145; the ratio of failed students to all the students is 0.14. Except for very low values of estimates for ability, the histograms indicate the normal distributions with different mean values (around 0.63 for successful students and −0.17 for failed students); the lowest estimates around −3.0 in both groups were resulting from the absence for testing. However, it seems also very difficult to discriminate students into two groups by using certain ability threshold value, even if we used all the LCT results together.

When we adopt the decision tree method, the most appropriate ability threshold values becomes to be −0.1065. The confusion matrix using this threshold is illustrated in table 1. The misclassification rate for this confusion matrix is 0.11. Limited to failed students, the decision tree predicted that 107 students may fail, and that 70 students actually failed; the hitting ratio was 65%.

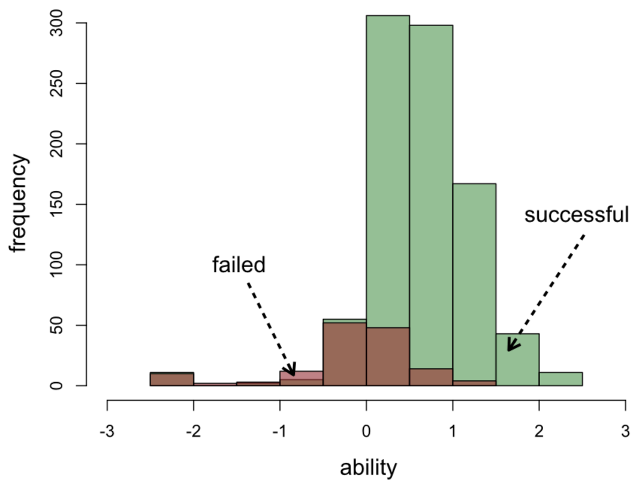

Figure 1: Histograms of estimated abilities of LCT to successful students and to failed students (linear algebra in the first semester in 2017).

Table 1: Confusion matrix determined by decision tree using full response matrix.

		predicted		
		successful	failed	total
	successful	861	37	898
observed	failed	75	70	145
	total	936	107	1043

threshold $= -0.1065$

For risk analysis, in addition to the LCT results, we have incorporated the placement test (PT) results taken at the very beginning of the first semester. As for PT, we provided two kinds of tests: one is rather fundamental test and the other is advanced test in high school level. By using the fundamental PT and the LCT results, we plotted the correlations for these two tests in three groups in Figure 2 in the case of linear algebra in the first semester in 2017; first group is the successful in the term examination, where score range is 60-100 expressed by green dots in the figure, second group is the badly failed group, where score range is 0-39 expressed by red dots, and the rest is the group, where score range is 40-59 expressed by yellow dots. The horizontal axis means the LCT ability value standardized to the standard normal distribution, and the vertical axis means the fundamental PT score value. Even if the additional information is added, it is still hard to find the boundaries to classify students into three groups or two successful/failed groups. In order to discriminate the successful/failed students much more clearly, it would be recommended to include other kind of information.

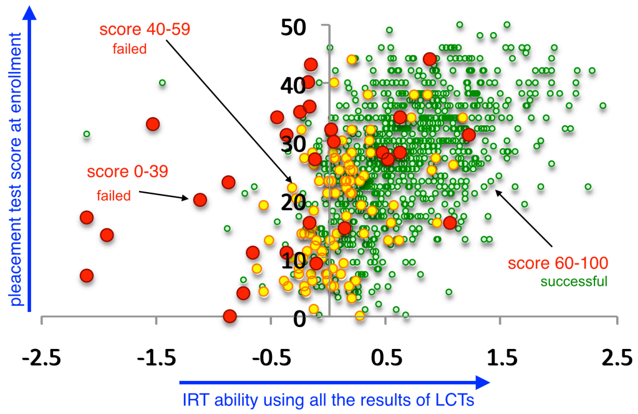

Figure 2: Correlations for the LCT results and the placement test results in three successful/failed groups (linear algebra in the first semester in 2017).

3 Attendance to the Lectures and the Follow-up Program Classes

Attendance/absence to classes is the discrete type information different from continuous data such as LCT ability values. Intuitively, we feel that the more frequently attend the classes, the higher the scores of the term examination. Recently, it is often seen that attendance/absence information is memorized to the database automatically using the electric card attendance check system. However, the system is not perfectly working; some students may disappear just after exposing their cards.

On the contrary, LCT compensate this defect. The attendance information cannot be guaranteed unless the testing is completed. Figure 3 shows that the attendance/absence information are classified into three groups: the first is for score range is 60-100 seen on the right in the figure, the second is for score range is 40-59 seen in the middle, and third is for score range is 0-39 seen on the left. In these matrices, row means the student id, and column means the question id. Using two kinds of attendance/absence information by electric cards (expressed by y shown in Figure 4) and LCT results (expressed by x shown in Figure 4), the value of each element, s, is determined and is colored by the formula of $s = 10x+y$, where meanings of s, x, and y are indicated in Figure 4. s means a magnitude to express the heat-map of risks to students. To unify two different factors from 1) the online testing system (x) and 2) the electric card attendant system (y) in one number, we have used an equation of $s = 10x + y$. The meaning of "10" is merely derived from decimal notation.

Coloring weight is much on x, which means that we rely on the online testing system much more than electric cards. Thus, the figure shows the scheme of the attendance/absence information and LCT successful/failed information, simultaneously. For example, s = 55 means that a student was absolutely absent for the class, and s = 11 means that a student is absolutely attended the class; they are also indicated in Figure 3.

Since each element is colored by green to red according to s value from lower to higher, red and orange colors indicate the absence or failed in the LCT, and green color indicate the success in the LCT. Obviously, three groups can be classified clearly by these colors by looking at the figure. This indicates that the attendance/absence information may play a key role in determining the risk of a student in addition to the LCT results.

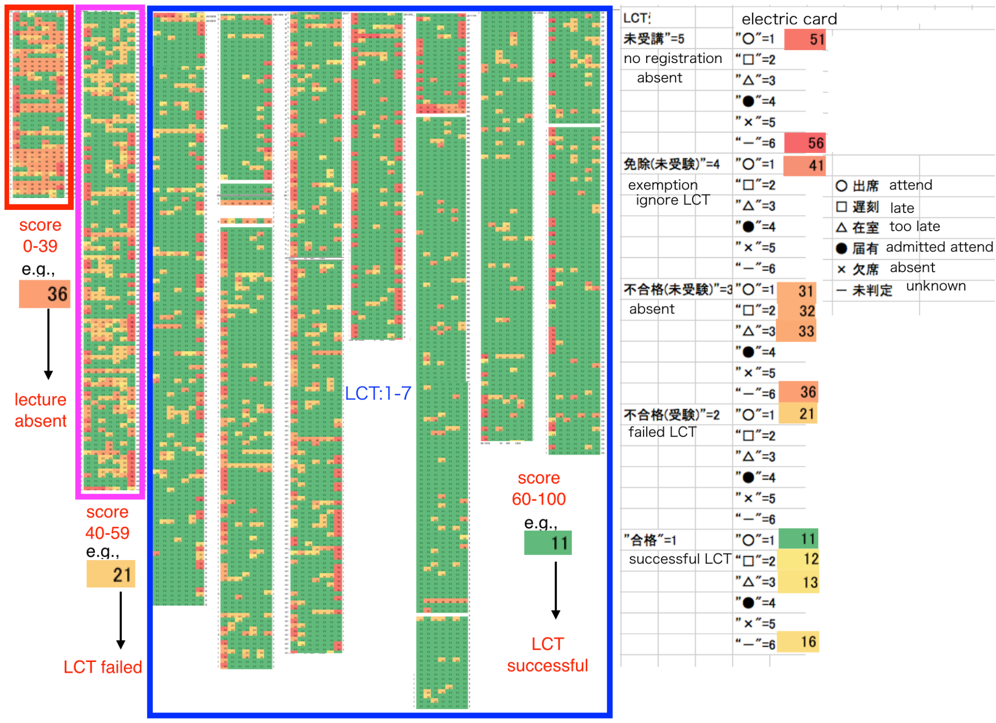

Figure 3: Three groups classified by using the attendance/absence information and LCT successful/failed information.

4 Finding the Important Factors for Risk

We first show the relationships among the factors we are concerned with in Figures 5 and 6. These factors are the number of successful LCT, the number of failed LCT, the number of absent for LCT, the number of exempted LCT, the number of LCT unavailable, the number of FPT not required, the number of FPT for LCT failed students, the number of FPT absence for LCT failed students, and the number of unnecessary FPT. The scores of LCT, PTA, and PTB are not presented in the figures. The computational results for coefficient of correlation and their relevant figures are obtained using R system [18], the statistical computing and graphics language and environment. In the upper side of the matrices, numbers for correlation coefficient are shown. In the diagonal boxes in the figures, we see notations, such as "LCTsuccess", "LCT.fail.took", "LCT.fail.absent",

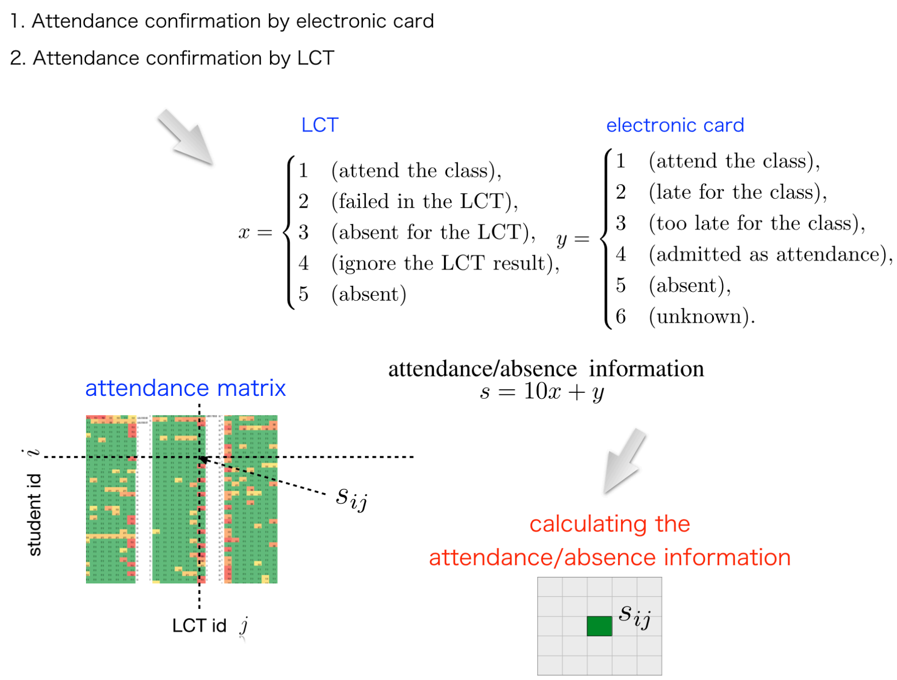

Figure 4: Scheme of the attendance/absence information and LCT successful/failed information.

"LCTexempt", "LCTu-navailable", "FPTnotrequired", "FPTtook", "FPTabsent", and "Necessary.unavailbale". As shown in Figure 7, the meaning of them are the same as mentioned as above. Also, in the diagonal boxes, histograms and fitted density distribution functions are seen.

In these figures, for example, we see that there is a strong relationship between the number of LCT successes and the number of no-requirement for FPT (see first column and sixth row in the figures), but it seems unclear which factors are key factors in classifying the successful/failed groups. In this paper, however, we will not deeply discuss the dimension reduction problem. We are only interested in finding the key factors related to the risky students in the term examination. Thus, a much easier method will be taken in the following.

Since we have known that the attendance/absence information may be effective for classifying the students groups into successful/failed students in the term examination, we apply the multiple regression analysis of $Y = X\beta + \varepsilon$ in finding the key factors, where, X are the explanation variables, Y are the target variables, β are the regression coefficients, and ε express the noise terms following the normal distributions. The meaning of the regression factors are also shown in Figure 7. For example, to a student having id of i,

$$y_i = \beta_0 + x_{i,1}\beta_1 + \cdots + x_{i,11}\beta_{11} + \varepsilon_i, \tag{1}$$

expresses the multiple linear regression, where, β_1 is the PTA score, ..., β_{11} is the number of FPT absence for student i as indicated in Figure 7.

Applying the multiple linear regression using the accumulated learning data, e.g., estimated LCT ability values, placement scores, class attendance/absence, follow-up class attendance/absence, and etc., we obtained the result shown in Figure 8 using R environment. In the figure, "intercept" means the constant value β_0, and other β_j values are presented;

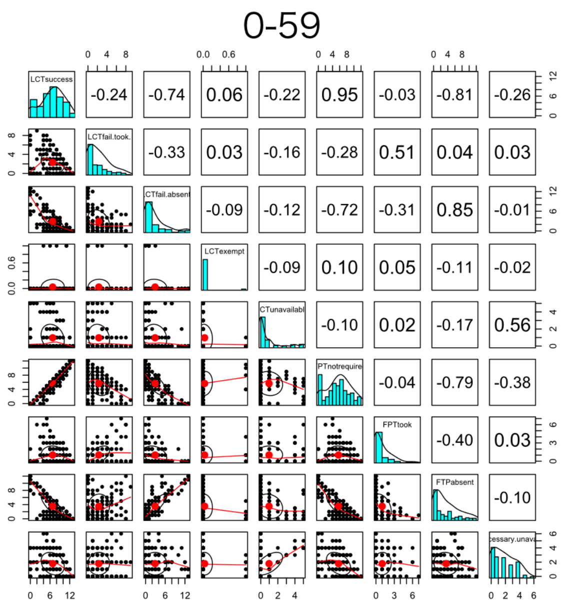

Figure 5: Relationships among the factors when the score range is 0-59.

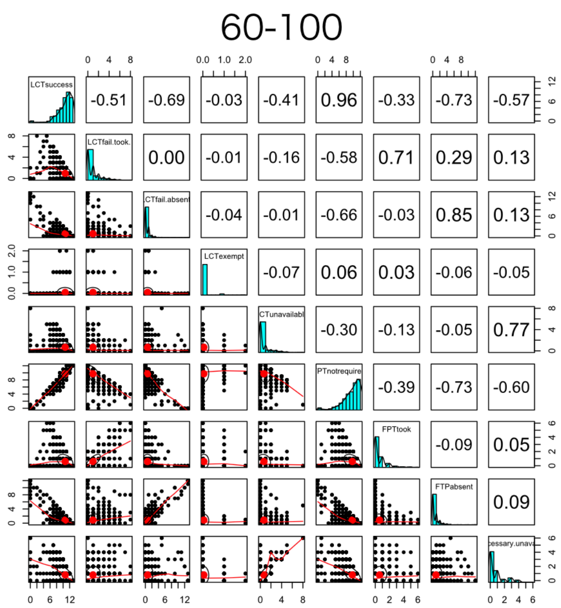

Figure 6: Relationships among the factors when the score range is 60-100.

$$Y = X\beta + \varepsilon$$

name of the explanation variable		meaning of the explanation variable
PTA	:	fundamental PT score,
PTB	:	advanced PT score,
$LCTability$	:	LCT ability score,
$LCTsuccess$	:	LCT successful,
β $LCTfail.took$ and	:	LCT took and failed,
$LCTfail.absent$	:	LCT absent,
$LCTexempt$	:	LCT exempted,
$LCTunavailable$	:	LCT unavailable and failed,
$FPTnotrequired$	:	FPT not required,
$FPTtook$	:	FPT absent,
$FPTabsent$	:	FPT absent

Figure 7: Factors in the multiple regression analysis.

estimates are located in the left, standard deviations and t-values are in the middle, and probabilities for significance are in the right. Marked symbols by asterisks indicate that these factors are significant with given p-values; p-values corresponding to symbols are indicated on the bottom in the figure. The symbol of three asterisks marked “FPTnotrequired” means that students took the LCT and successful, resulting no requirement for follow-up class attendance. That is, attendance/absence for FPT is the most significant information in deciding successful/failed students.

```
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)              -1.087e-05  2.622e-02   0.000 0.999669
PTA                      -7.327e-02  4.323e-02  -1.695 0.090388 .
PTB                      -2.413e-03  4.927e-02  -0.049 0.960954
LCTability                9.609e-02  6.803e-02   1.412 0.158138
LCTsuccess                4.574e-01  3.229e-01   1.417 0.156881
LCTfail.took              1.170e-01  1.908e-01   0.613 0.539930
LCTfail.absent            3.746e-01  2.542e-01   1.473 0.140986
LCTexempt                 6.509e-02  3.582e-02   1.817 0.069490 .
LCTunavalilable           3.793e-02  3.069e-02   1.236 0.216658
FPTnotrequired           -4.470e-01  1.210e-01  -3.695 0.000232 ***
FPTtook                   4.582e-02  7.231e-02   0.634 0.526433
FPTabsent                 1.985e-01  1.367e-01   1.452 0.146709
Notnecessarrily.unavailable      NA         NA      NA       NA
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 8: Multiple linear regression analysis result.

Therefore, we next focus on this factor. Figure 9 shows the relationships between the number of successes in the LCT and the number of absents for the follow-up classes for the three groups, score ranges are 60-100, 40-59, and 0-39 in the term examination. At a first glance, we can see that a clear linear relationship between the number of successes in the LCT and the number of absents for the FPC when score range is 0-39. We also see some similarity between the cases score range 40-59 and the cases score range 60-100.

By looking at the figure, we find the following: 1) When score range is 60-100, almost all the students show successful results in the LCT and very small number of absences for the FPC (almost all are not required the attendance for the FPC). 2) When score range is 0-39, we see a clear linear relationship between the number of successes in the LCT and the number of absents for the FPC, which means that almost all the failed students in the LCT or students absent for the classes ignore the attendance for the FPC. 3) When score range is 40-59, students reveal both sides of features appeared in score range of 0-39 and score range of 60-100. Some students tried to make effort to be successful, and some were successful but unfortunately some were not. Therefore, we have found that failed students in the term examination were reluctant to attend the classes and showed failed LCT results, and they were unwilling to attend the FPC in addition. As intuition suggests, the most crucial factor for the success in the term examination is attendance to the class.

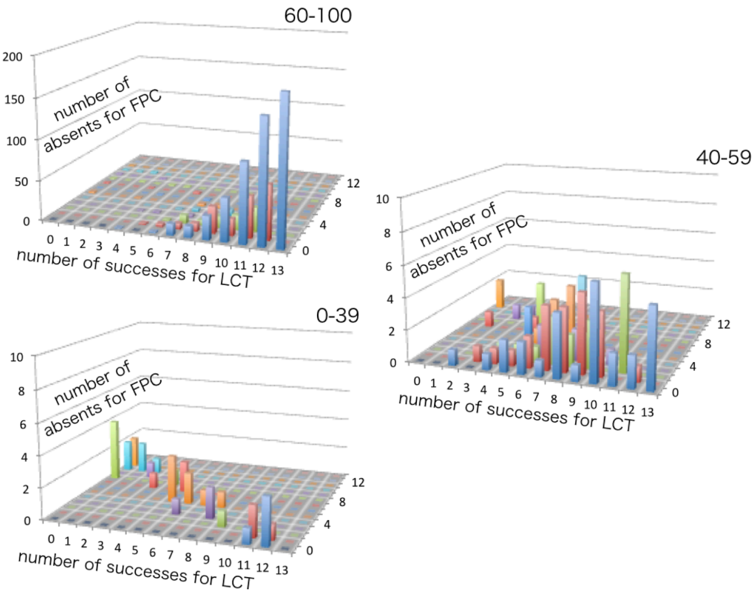

Figure 9: 3-dimensional bar charts representing the relationship between the number of successes in the LCT and the number of absents for the FPC.

5 Discussions

We have been looking at some factors to classify successes and failures in the term examination. To investigate such factors much more precisely, more detailed information may be required. Thus, we have classified the successful group into four groups such as A+, A, B, C, where scores in these groups are distributed to be 90-100, 80-89, 70-79, 60-69. The possible factor to discriminate these groups is considered to be the number of successful LCT.

Figure 10 shows the frequency bar charts for the number of successful LCT to each group. Taking a look at the figure, we can see that students who failed in LCT more than seven times almost absolutely failed in the term examination, which could cause the drop out. Also, students who were successful to LCT more than ten times took better score in the term examination. Since all the testing times were 13 in this case, this means that students who failed in LCT more than half out of all testing times almost absolutely failed in the term examination, and students who were successful to LCT more than two third out of all testing times took better score in the term examination.

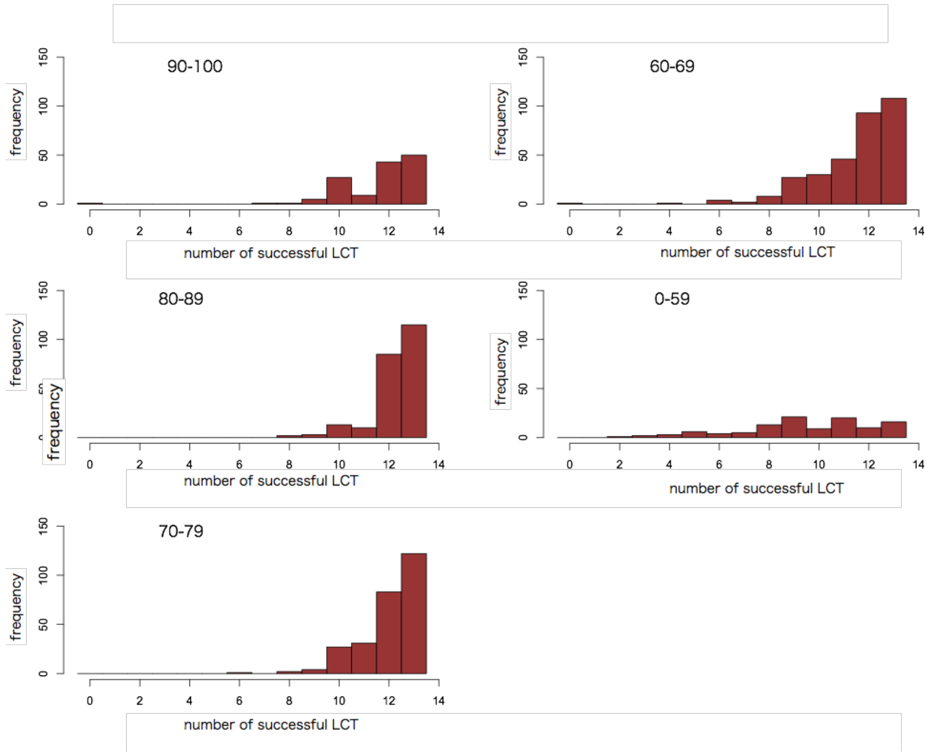

Figure 10: Histograms of estimated abilities of LCT to successful students and to failed students (linear algebra in the first semester in 2017).

6 Concluding Remarks

It is crucial to identify students at risk of failing courses and/or dropping out as early as possible because students of widely varying abilities are now enrolled in universities and we teachers have to educate them together. To overcome this, we established the online testing system aimed at helping students who want to improve their mathematical skills. The system includes the learning check testing, the collaborative working testing, and the follow-up program testing. Using the accumulated data from these testings in the database, we aimed at obtaining effective learning strategies for students at risk of failing courses and/or dropping out. Although the subjects we deal with are analysis basic (similar to calculus) and linear algebra, we focused on linear algebra case as a typical one.

In this paper, we have found some key factors strongly related to the students at risk. The findings are the following. 1) Badly failed students (score range is 0-39 in the term examination) tend to be absent for the regular classes and fail in the learning check testing even if they attended, and they are very reluctant to attend the follow-up program classes. 2) Successful students (score range is 60-100 in the term examination) attend classes and get good scores in every learning check testing. 3) Failed students but not so badly (score range is 40-59 in the term examination) reveal both sides of features appeared in score range of 0-39 and score range of 60-100. Therefore, it is crucial to attend lectures in order not to drop out. Students who failed in learning check testing more than half out of all testing times almost absolutely failed in the term examination, which could cause the drop out. Also, students who were successful to learning check testing more than two third out of all testing times took better score in the term examination.

Acknowledgment

The author would like to thank mathematical staffs at Hiroshima Institute of Technology.

Appendix: A brief introduction to the online testing system

The online testing system consists of three parts: 1) Learning Check Testing (LCT), 2) Collaborative Work Testing (CWT), and 3) Follow-up Program Testing (FPT). Figure 11 shows the configuration of the follow-up program testing system. All the students take LCT in regular classes to check if they comprehend the content of the lecture. If a student showed insufficient comprehension, he/she will be enrolled to the follow-up program classes (FP class). At each FP class, all the students take examinations to check if the class work can compensate the insufficient part of their knowledges and skills. In the FP class, the class work is to take the adaptive online IRT testing system collaborated with peer supporters. Figure 12 shows the procedure for the follow-up program testing system.

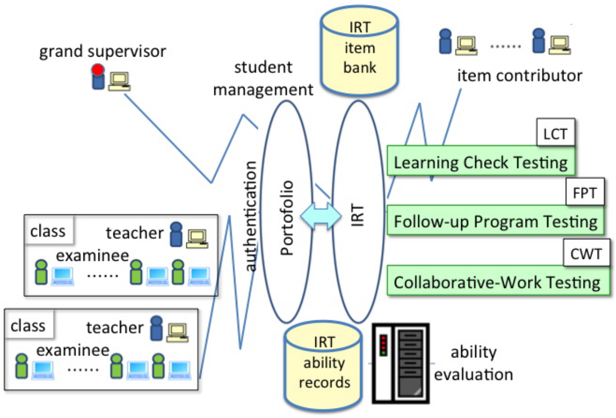

Figure 11: Configuration of the online testing system [5].

Learning Check Testing, LCT

The learning check testing, LCT, is a kind of mini test, but the evaluation method for the LCT adopts the IRT partially in which the difficulty values are provided in advance, unlikely to the common IRT method where difficulty values and ability values are unknown simultaneously. All the students in regular classes take LCT using their own personal computers via online Wi-fi system. All the questions are the same to each student, but sorted in different order. The levels of the questions are distributed from difficult one to easy one to cover all the levels. After a teacher in a class admits accesses to LCT to all the attendees in the class, students are able to begin the examination. After the examination is performed,

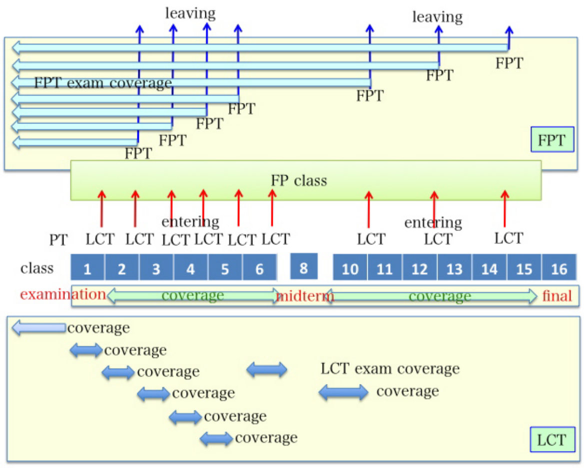

Figure 12: Procedure of the online testing system [5].

the system computes the students' abilities by using the IRT. The system also sends students their scores transformed from the ability values, and upload results to the portfolio system. The questions and answers for LCT are not open, and are different from the questions used to CWT (explained below). One LCT in a lecture has own unit name to be easily understood by teachers who admit access to the system, such as "special functions". Units are consisting of several sections such that "exponential, logarithmic, and trigonometric functions".

Follow-up Program Testing, FPT

The follow-up program testing, FPT, is also a kind of mini test. Students who unfortunately failed to LCT are automatically enrolled to the FP class, and take CWT and FPT. The examination covers contents previously learnt or before. Unlikely to LCT, FPT adopts adaptive online IRT testing system, and thus, students take different questions each other. After FP class ends, the system send results to students, and upload results to the portfolio system. The questions and answers for FPT are closed, and are different from the questions used to CWT.

Collaborative Work Testing, CWT

The collaborative work testing, CWT, is used everywhere including the FP class, where, more than forty peer supporters are arranged to support students failed in LCT examination unfortunately. The questions in CWT is chosen from some certain section, and the examination focused on questions in the targeted section. Thus, students first select the sections to be taken. CWT adopts the adaptive online IRT testing system. Therefore, the aim of testing is not evaluation of the exact students' skills. Rather, CWT is aimed at eagerness and fun in taking examinations. CWT is open to all the students for self-learning and self-study. Students can access to the system from anywhere and at anytime.

Item Response Theory, IRT

In this paper, the IRT method uses the two-parameter logistic function $P(\theta_i; a_j, b_j)$ shown below instead of the three-parameter logistic function including pseudo-guessing parameter.

$$P_{i,j} = P(\theta_i; a_j, b_j) = \frac{1}{1 + \exp\{-1.7a_j(\theta_i - b_j)\}} = 1 - Q_{i,j}, \tag{2}$$

where θ_i expresses the ability for student i, and a_j, b_j are constants in the logistic function for item j, and they are called the discrimination parameter and the difficulty parameter, respectively. Then, the likelihood for all the examinees, $i = 1, 2, \ldots, N$, and all the items, $j = 1, 2, \ldots, n$, will become

$$L = \prod_{i=1}^{N} \prod_{j=1}^{n} \left(P_{i,j}^{\delta_{i,j}} \times Q_{i,j}^{1-\delta_{i,j}} \right), \tag{3}$$

where $\delta_{i,j}$ denotes the indicator function such that $\delta = 1$ for success and $\delta = 0$ for failure. Since a_j, b_j, and θ_i are all unknown here, we have to obtain the maximum likelihood estimates for a_j and b_j, and θ_i simultaneously by maximizing L in Equation (2). We use the estimated values of θ_i for learning analytics.

References

[1] R. de Ayala, The Theory and Practice of Item Response Theory. Guilford Press, 2009.

[2] N. Elouazizi, Critical Factors in Data Governance for Learning Analytics, Journal of Learning Analytics, 1, 2014, pp. 211-222.

[3] D. Gasevic, S. Dawson, and G. Siemens, Let's not forget: Learning analytics are about learning, TechTrends, 59, 2015, pp. 64-71.

[4] R. Hambleton, H. Swaminathan, and H. J. Rogers, Fundamentals of Item Response Theory. Sage Publications, 1991.

[5] H. Hirose, Meticulous Learning Follow-up Systems for Undergraduate Students Using the Online Item Response Theory, 5th International Conference on Learning Technologies and Learning Environments, 2016, pp.427-432.

[6] H. Hirose, M. Takatou, Y. Yamauchi, T. Taniguchi, T. Honda, F. Kubo, M. Imaoka, T. Koyama, Questions and Answers Database Construction for Adaptive Online IRT Testing Systems: Analysis Course and Linear Algebra Course, 5th International Conference on Learning Technologies and Learning Environments, 2016, pp.433-438.

[7] H. Hirose, Learning Analytics to Adaptive Online IRT Testing Systems "Ai Arutte" Harmonized with University Textbooks, 5th International Conference on Learning Technologies and Learning Environments, 2016, pp.439-444.

[8] H. Hirose, M. Takatou, Y. Yamauchi, T. Taniguchi, F. Kubo, M. Imaoka, T. Koyama, Rediscovery of Initial Habituation Importance Learned from Analytics of Learning Check Testing in Mathematics for Undergraduate Students, 6th International Conference on Learning Technologies and Learning Environments, 2017, pp.482-486.

[9] H. Hirose, Dually Adaptive Online IRT Testing System, Bulletin of Informatics and Cybernetics Research Association of Statistical Sciences, 48, 2016, pp.1-17.

[10] H. Hirose, Difference Between Successful and Failed Students Learned from Analytics of Weekly Learning Check Testing, Information Engineering Express, Vol 4, No 1, 2018, pp.11-21.

[11] H. Hirose, A Large Scale Testing System for Learning Assistance and Its Learning Analytics, Proceedings of the Institute of Statistical Mathematics, Vol.66, No.1, 2018, pp.79-96.

[12] W. J. D. Linden and R. K. Hambleton, Handbook of Modern Item Response Theory. Springer, 1996.

[13] T. Sakumura, H. Hirose, Bias Reduction of Abilities for Adaptive Online IRT Testing Systems, International Journal of Smart Computing and Artificial Intelligence (IJSCAI), 1, 2017, pp.57-70.

[14] G. Siemens and D. Gasevic, Guest Editorial - Learning and Knowledge Analytics, Educational Technology & Society, 15, 2012, pp.1-2.

[15] Y. Tokusada, H. Hirose, Evaluation of Abilities by Grouping for Small IRT Testing Systems, 5th International Conference on Learning Technologies and Learning Environments, 2016, pp.445-449.

[16] R. J. Waddington, S. Nam, S. Lonn, S.D. Teasley, , Improving Early Warning Systems with Categorized Course Resource Usage, Journal of Learning Analytics, 3, 2016, 263-290.

[17] A.F. Wise and D.W. Shaffer, Why Theory Matters More than Ever in the Age of Big Data, Journal of Learning Analytics, 2, pp. 5-13, 2015.

[18] `https://www.r-project.org/about.html`