Effectiveness of Comments on Self-reflection Sheet in Predicting Student Performance

Rumiko Azuma
College of Commerce, Nihon University, Setagaya-ku, Tokyo, Japan

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Abstract: In recent years, schools and universities have become more focused on how to allow learners to learn successfully, and it has become an expectation to design instruction in a way that takes into account the individual differences of learners. Accordingly, the purpose of this study is to predict, at an earlier stage in a course, which students are likely to fail, so that adequate support can be provided for them. We proposed a new approach to identify such students using free-response self-reflection sheets. This method uses the unrestricted comments from the students to create a comment vector that can be used to predict who are likely to fail the course. Subsequently, we conducted experiments to verify the effectiveness of this prediction. In comparison to methods used in existing research which predict potential failures using quiz scores and the students' subjective level of understanding, our proposed method was able to improve the prediction performance. In addition, when cumulative data after several sessions were used to predict which students were likely to fail, the predictions made by the support vector machine (SVM) algorithm showed a consistent prediction performance, and the prediction accuracy was higher than that of other algorithms.

1 INTRODUCTION

Recently, Learning Analytics (LA) that is a study of estimating or predicting learners' performance through Learning Management System (LMS) or e-learning system has been actively performed (Hirose, 2019a). The most common use of LA is to identify students who appear less likely to succeed academically and to enable targeted interventions to help them achieve better outcomes (Scapin, 2018). Providing some kind of feedback to the learners based on the analysis results in LA enable learners to take learning support tailored to each learner. It offers promise for predicting and improving learners success and retention (Uhler et al., 2013).

On the other hand, a decline in academic ability of university students has become a problem in Japan, and universities are required to find students who cannot keep up with classes at an early stage and follow them up. Therefore, it is important for educational institutions to predict the student's real understanding level or their grade from the student's learning data by LA.

In many Japanese universities, students' class evaluation questionnaire is adopted as one of the methods for measuring students' understanding level. The questionnaire is for students to evaluate their subjective understanding level, their attitude towards class, lecturer and class contents. However, student's subjective evaluations often do not reflect the student's real understanding level or learning conditions (Azuma, 2016). In addition, since the questionnaire is often conducted at the final lesson, it serves to improve the future offering of the class than to provide feedback to the student. For these reasons, in order to measure the level of understanding and satisfaction of students in a class, the lecturers increase the frequency of questionnaire conducting surveys with.

One of the methods for lecturers to grasp students' level understanding and satisfaction is "a minute paper" (Davis et al., 1983). "A minute paper" is defined as a very short comment of a student, in-class writing activity (taking one minute or less to complete). It prompts students to reflect on the day's lesson and provides the lecturer with useful feedback.

In this study, we propose a method to predict students who have a risk of failing course from their comments in self-reflection sheets like "a minute paper". The purpose of this study is to improve the student's learning behavior by predicting the student's grade and providing useful feedback to the student. In

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addition, lecturers could quickly find out students with low level understanding and provide personalized advice.

2 RELATED STUDIES

It is very important for both learner and lecturer to grasp learner's performance because feedback of the information obtained from these can help improve their learning.

Hirose (2018, 2019a) analyzed the accumulated weekly testing results to identify students who may fail in the final examination, using item response theory. He also proposed a method with high predictive accuracy which predicts the risk for failing courses and/or dropping out for students using the learning check testing scores, the follow-up program testing success/failure times, and attendance rate (Hirose, 2019b). Although the subjects dealt with in his paper are limited to mathematics, it describes this kind of system will easily be applied to other subjects.

On the other hand, there are several studies which predict student performance based on student comments in the lesson. Sorour et al., (2014, 2015) proposed the model to predict university students' grade from their comments written according to the PCN method. Their paper describes that they can clearly distinguish high score group, but the prediction accuracy of lower score group became lower. The PCN method (Goda et al., 2011) categorizes student comments into three items of P(previous), C(current) and N(next). Item P is learning activities for preparation of a lesson such as review of previous class. Item C is understanding of the lesson and learning attitudes to the lesson. Item N is the learning activity plan until the next lesson. Luo (Luo et al., 2015) discussed the prediction method of student grade based on the comments of item C using Word2Vec and Artificial Neural Network. Their study expressed the correlation between self-evaluation descriptive sentences and academic performance. Niiya and Mine (2017) also verified the accuracy of model which predicts junior high school students score from their comments based on the PCN method.

However, students' freestyle comments such as the minute paper used in universities often do not limit what is written because it is effective for increasing student satisfaction. It is different from student's comments using PCN with limited writing content. This study discusses a method that be able to predict students' final examination score (pass or fail) using the reflection sheets based on "a minute paper". An aim of this study is to quickly find students who may fail in the course and give them feedback. Therefore, we consider the method that does not predict their score or grade, but predicts the possibility of whether they will fail in the final examination.

3 OVERVIEW OF STUDENTS' DATA

In previous study (Azuma, 2017), we tried to predict student's final exam score by multiple regression analysis based on student's understanding level, background knowledge level, quiz scores, and reflection sheets. Regarding the reflection sheet, the number of characters and technical terms extracted from the reflection sheets were used quantitatively as independent variables. The final model had a coefficient of multiple determination, R^2, of 0.211 ($p<0.001$), and predictive accuracy was low.

In this study, we used 193 university students' data for 3 years (from 2012 to 2014) that is data from the previous study (Azuma, 2017) plus new data. Then, we discuss the prediction model using machine learning algorithms.

This study's data were collected from 13 lessons of "basic statistics" course in three years. The reflection sheet is a freestyle comment sheet that students can write freely about things they have learned, noticed, understood, did not understand, questions, requests, etc. Number of reflection sheets is 2501 and number of sentences is 6051. Mean of characters per sheet is 87.35, maximum of it 686, and minimum of it 6. This study uses the following data except student's background knowledge level because of very weak correlation with student's score.

- Score of final examination
- Score of quizzes
- Understanding level for a lesson (5-level evaluation based on student's subjectivity)
- Comments in reflection sheets (Japanese)

To predict failed student from these data, we classified final examination score to two categories such as "Passed" or "Failed". Table 1 shows a corresponding relation between the categories and the scores. Scores less than 60 were classified as the Failed group, and others were classified as the Passed group. Table 2 shows the summary statistics of examination score. The correlation coefficient between the final score and each features is shown in Table 3.

Table 1: The corresponding relation between the categories and the range of examination scores.

Category	Passed	Failed
Score	60~100	0~59
Grade	S, A, B, C	D
Number of students	129	64

Table 2: The summary statistics of examination scores.

Mean	63.63
Standard deviation	21.83
Max	100
Min	1
Rate of Failed students	0.33

Table 3: The correlation coefficient between the final score and each features (p<0.01).

Score of quizzes	0.35
Understanding level	0.24
Comments in reflection sheets	
Num. of characters	0.31
Num. of technical terms	0.33

4 PREDICTION METHODOLOGY OF FAILED STUDENT

4.1 Prediction Methodology using Four Features

In the previous study (Azuma, 2017), it was clarified that students with high score tend to have more comments and technical terms in the reflection sheet, although a weak positive correlation with students' score. Therefore, first of all, we selected the number of characters and technical terms in comments, the quiz scores and the understanding level as features to predict. Each value was the average of 13 lessons.

4.1.1 Performance Measures of Failed Student Prediction

The ML models used in the prediction are followings: Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), Generalized Linear Model (GLM), and Naive Bayes (NB).

We evaluated the performance of each machine learning (ML) models by 10-fold cross validation using four features. We randomly separated dataset to training and test data set, taking into account the balance of the categories so that they are the same as the original dataset. 80% of the data is randomly assigned to the training data and the remaining 20% is assigned to the test data.

Table 4: The confusion matrix.

		Actual value 1	Actual value 0
Predicted outcome	1	TP	FP
	0	FN	TN

Table 5: The prediction results of **"Failed"** by basic method.

ML Model	Precision	Recall	F-measure	Accuracy
DT	1.000	0.071	0.133	0.675
RF	0.500	0.285	0.333	0.650
SVM	0.400	0.285	0.333	0.600
LR	0.400	0.285	0.333	0.600
GLM	0.400	0.285	0.333	0.600
NB	0.571	0.571	**0.571**	**0.700**

The experiment results show the test accuracy and F-measure for each of the models. These values are defined using TP (True Positive), FP (False Positive), TN (True Negative), FN (False Negative) in Table 4 as follows:

$$precision = \frac{TP}{(TP + FP)} \tag{1}$$

$$recall = \frac{TP}{(TP + FN)} \tag{2}$$

$$F\ measure = 2 \times \frac{(precision \times recall)}{(precision + recall)} \tag{3}$$

$$Accuracy = \frac{TP + FN}{TP + TN + FP + FN} \tag{4}$$

Recall tells us how confident we can be that all the instances with the positive target level have been found by the model. Precision tells us how confident we can be that an instance predicted to have the positive target level actually has the positive target level (Kelleher et al., 2015). In this study, "Failed" students are the positive target. F-measure is the harmonic mean of precision and recall and offers a useful alternative to the simpler misclassification rate. It reaches its best value at 1 and worst score at 0.

4.1.2 Prediction Results using ML

The prediction results using four features are shown in Table 5. We call this method the basic method.

Precision, Recall, and *F*-measure in Table 5 are values when "Failed" is the positive target.

Although accuracies were over 60% in all models, all *F*-measure scores were low. As for accuracy and *F*-measure, the results of NB were the highest, which scores 70.0% and 57.1%.

4.2 Prediction Methodology by Quantification of Student Comments

We analyzed quantitatively student comments in reflection sheets using KHcoder (Higuchi, 2004). KH Coder is software for quantitative content analysis or text mining. KHcoder supports multilingual analysis. The number of analysis target words extracted by KHcoder was 123046 in this study. The average of words used per sheet was 43.9. In this section, we describe a method for treating student comments as features.

4.2.1 Creating a Comment Vector

We assigned some labels to sentences of student comment containing specific words that were extracted by correspondence analysis. Each label was defined as shown in Table 6.

"Positive Understanding" means whether or not a phrase indicating understanding is included in the student's comment. For example, if a student's comment contains the sentence "I understood today's lesson", the comment was labeled the PU-. On the other hand, if a technical term is included, such as "I understood about the Bayes' theorem", the comment was labeled the PU+.

Similarly, "Negative Understanding" means a comment with a phrase that expresses what student could not understand. For example, if a comment contains a technical term such as "I did not understand the conditional probability well", the comment was labeled NU+, and otherwise NU-. In addition, seven labels including "Negative Words", "Vagueness Words", and "phrase for Expressing Willingness" were assigned to each sentence.
Moreover, it was allowed to be assigned multiple labels to one sentence. A sentence like "I did not understand today's lesson because it was difficult" was labeled NU- and NW. Then we counted the number of sentences for each label and created a 7-dimensional comment vector that has the number of occurrences of each label as elements, for each student. The correlation coefficient between each element of comment vector and the number of characters or technical terms are shown in Table 7. In addition to 4 features of the previous section, the comment vector and the number of words were added as features to improve predictive accuracy.

Table 6: The kinds of label associated with specific words.

Meaning	Label	Specific words
Positive Understanding		
co-occurrence with technical terms	PU+	I understood xxxx, I got xxxx
no co-occurrence with technical terms	PU-	
Negative Understanding		
co-occurrence with technical terms	NU+	I could not understand xxx, I am not sure xxx
no co-occurrence with technical terms	NU-	
Negative Words	NW	difficult, many, poor, tough, anxiety, forget
Vagueness Words	VW	feel, to an extent, a little
phrase for Expressing Willingness	EW	I want to, I need to, I have to

Table 7: The correlation coefficient between each element of comment vector and the number of characters or technical terms ($p < 0.01$).

	PU+	PU-	NU+	NU-	NW	VW	EW
Characters	0.41	0.23	0.30	0.41	0.40	0.30	0.50
Technical terms	0.43	-0.01	0.19	0.25	0.12	0.02	0.33

4.2.2 Prediction Results using Comment Vector

The results predicted by the dataset including the comment vectors are shown in Table 8. For all models except DT and NB models, *F*-measure and accuracy were increased. In particular, the *F*-measure of RF model was the highest score and was improved from 33.3% to 58.3% compared to the basic method. The *F*-measure score of NB also improved slightly from 57.1% to 57.8% in this method, but accuracy, which was the highest in the basic method, was declined from 70.0% to 66.0%.

4.3 Prediction of Potential Students of Failed Examination

4.3.1 Category of Potential Students

Next, students with grades C or D, less than 70 score are regarded as a "problem" group. We calculated the prediction performance of "problem" students. Table

9 displays a corresponding relation between new categories and the range of scores.

Table 8: The prediction results of **"Failed"** by comment vector + basic method.

ML Model	Precision	Recall	*F*-measure	Accuracy
DT	0.500	0.062	0.111	0.600
RF	0.875	0.437	**0.583**	**0.750**
SVM	0.545	0.375	0.444	0.625
LR	0.666	0.375	0.480	0.675
GLM	0.714	0.312	0.434	0.675
NB	0.500	0.687	0.578	0.660

Table 9: The corresponding relation between new categories and the range of examination scores.

Category	No problem	Problem
Score	70~100	0~69
Grade	S, A, B	C, D
Number of students	88	105

Table 10: The prediction results of **"Problem"** students by comment vector + basic method.

ML Model	Precision	Recall	*F*-measure	Accuracy
DT	0.615	1.000	0.761	0.625
RF	0.700	0.875	0.777	0.700
SVM	0.724	0.875	**0.792**	**0.725**
LR	0.720	0.750	0.734	0.675
GLM	0.714	0.833	0.769	0.700
NB	0.700	0.875	0.777	0.700

Table 11: The prediction results of **"Problem"** students using only data of reflection sheets.

ML Model	Precision	Recall	*F*-measure	Accuracy
DT	0.615	1.000	0.761	0.625
RF	0.666	0.833	0.740	0.650
SVM	0.656	0.875	0.750	0.650
LR	0.740	0.833	**0.784**	**0.725**
GLM	0.714	0.833	0.769	0.700
NB	0.700	0.875	0.777	0.700

4.3.2 Prediction Results by New Category

Students of category "Problem" were predicted using features, which the understanding level, quiz score, number of characters, number of technical terms, the number of words, and comment vector, as well as in section 4.2. The prediction results are shown in Table 10.

As for *F*-measure and accuracy, the result of SVM model was the highest, which scores 79.2% and 72.5%. In all models, the *F*-measure scores were over 70%. RF, which had the highest predictive accuracy in the previous section (the prediction of "Failed" students), was the second highest accuracy in this case.

4.3.3 Prediction Results using Only Reflection Sheets

Since the purpose of this study is to predict the failure by using only the student's comments, we also checked performance for prediction of "Problem" students using only data of reflection sheets; those are the comment vector, the number of characters, and the number of technical terms, the number of words. Table 11 shows the results. In all models, its *F*-measure scores were more than 70%. The result of LR model was the highest, with *F*-measure score 78.4% and accuracy 72.5%. Secondly, the results of NB were better, with *F*-measure score 77.7% and accuracy 70.0%. Those scores in the DT model did not change.

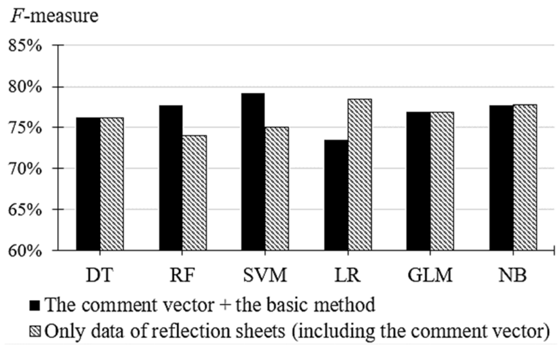
We compared this results with the results of the method added comment vector to the basic method in prediction of "Problem". As shown in Figure 1, in LR, GLM, and NB, prediction performances of the method using only data of reflection sheets were better or equal to the method with comment vector added to the basic method. In the other three algorithms, adding the comment vector to the basic method had higher accuracy and *F*-measure. Therefore, we can see that it is possible to predict potential students of failed examination only with the reflection sheets depending on the machine learning algorithm.

4.4 Prediction Results using Cumulative Data from Prior Weeks

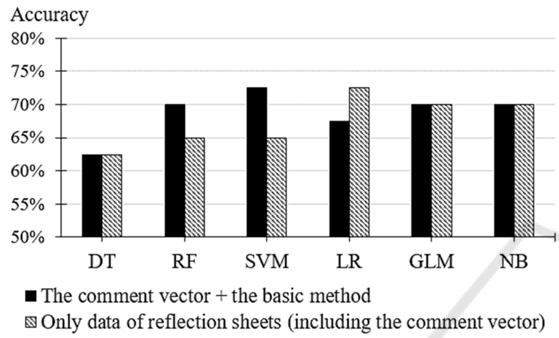
Finally, we examined the performance of the prediction of potential students who may fail using cumulative weekly data.

All weeks (1-13) training data was used to construct the SVM and LR models, which had higher predictive performance on the comment vector. Then, the model was evaluated on cumulative data from each weeks labeled as test data.

The results are shown in Figure 2 and 3. In both figures, the x-axis represents the cumulative test data from week 1 to n. For example, the 1-3 on x-axis shows the prediction result using average of students' data from week 1 to 3. Figure 2 displays the plot of results with the comment vector and basic method.

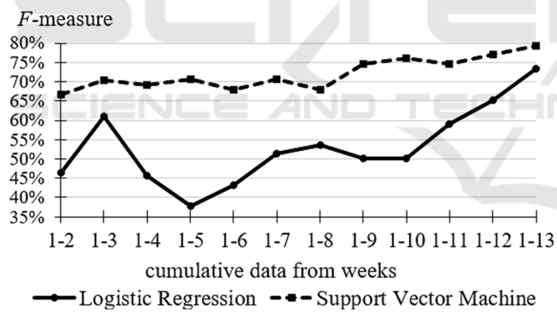


(a) Comparison of *F*-measure scores in prediction results.

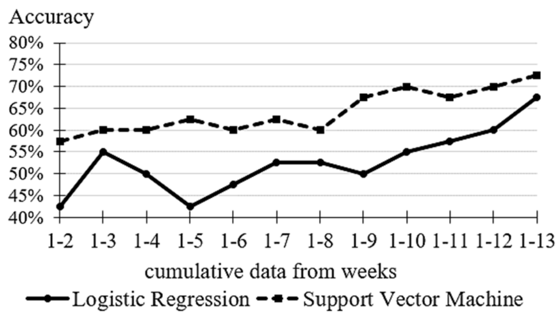


(b) Comparison of accuracies in prediction results.

Figure 1: Comparison of the results of Tab. 8 with Tab. 9.



(a) *F*-measure using the comment vector + basic method.

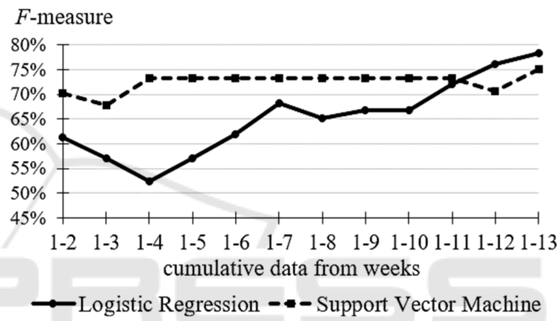


(b) Accuracy using the comment vector + basic method.

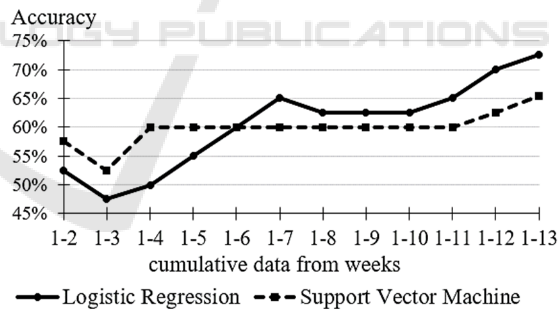
Figure 2: The prediction results of **"Problem"** students using the comment vector + basic method in each week. The used model is constructed from all weeks (1-13) data.

Similarly, Figure 3 shows the test accuracy based on reflection sheets including the comment vector.

As shown in Figure 2 and 3, SVM showed consistent prediction performance on both the test sets. Unlike SVM, LR had a higher variance in accuracy of the prediction results, for instance with comment vector and basic method the *F*-measure ranged from 37.8% to 73.4%. As the number of weeks progressed, the prediction accuracy improved. This is to be expected as the learning algorithm is given more data points which gives a better reflection of the level of student's understanding of concepts. It is worth highlighting that half way into the semester, SVM achieves at least 60% accuracy in identifying "problem" students. This is very useful in instituting remedial help for these at-risk students in the second half of the semester.



(a) *F*-measure using only the data of reflection sheets.



(b) Accuracy using only the data of reflection sheets.

Figure 3: The prediction results using of **"Problem"** students only the data of reflection sheets in each week. The used model is constructed from all weeks (1-13) data.

5 CONCLUSIONS AND FUTURE WORK

In this study, we proposed the method to predict students who may fail the examination using reflection sheets. In addition to conventional features of the previous study, adding the comment vector extracted from the reflection sheets to features improved the prediction performance. Moreover, the prediction using only the reflection sheets did not significantly reduce the accuracy. Therefore, we believe the comment vector is an effective feature to predict failing students.

Furthermore, we examined the performance using cumulative weekly students' data on the prediction of potential students who may fail. As the result based on models constructed from all data, the prediction by support vector machine (SVM) was relatively stable. The prediction with only the data of reflection sheets showed lower accuracy than one including basic method, but the F-measure, which is a predictive measure for "Problem" students, was around 70%. In order to predict "Problem" students with high accuracy at an early stage, improvements in the method are needed.

Another issue is whether this method can also be applied to other courses in the prediction of failed student. Also, it is necessary to examine a comment vector or factors (McKenzie et al., 2001) more strongly associated with predicting academic performance than the labels defined in this study, through data mining. Furthermore, we need to consider about predicting student performance from English comments using our proposed method. In the future, we will try to investigate these issues.

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