Predicting student performance using data from an Auto-grading system

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ABSTRACT
As online auto-grading systems appear, information obtained from those systems can potentially enable researchers to create predictive models to predict student behaviour and performances. In the University of Waterloo, the ECE 150 (Fundamentals of Programming) Instructional Team wants to get an insight into how to allocate the limited teaching resources better to achieve improved educational outcomes. Currently, the Instructional Team allocates tutoring time in a reactive basis. They help students “as-requested”. This approach serves those students with the wherewithal to request help; however, many of the students who are struggling do not reach out for assistance. Therefore, we, as the Research Team, want to explore if we can determine students which need help by looking into the data from our auto-grading system, Marmoset.

In this paper, we conducted experiments building decision-tree and linear-regression models with various features extracted from the Marmoset auto-grading system, including passing rate, testcase outcomes, number of submissions and submission time intervals (the time interval between the student’s first reasonable submission and the deadline). For each feature, we interpreted the result at the confusion matrix level. Specifically for poor-performance students, we show that the linear-regression model using submission time intervals performs the best among all models in terms of Precision and F-Measure. We also show that for students who are misclassified into poor-performance students, they have the lowest actual grades in the linear-regression model among all models. In addition, we show that for the midterm, the submission time interval of the last assignment before the midterm predicts the midterm performance the most. However, for the final exam, the midterm performance contributes the most on the final exam performance.

CCS CONCEPTS
• Theory of computation → Machine learning theory.

KEYWORDS
Data Mining, Exploratory Data Analysis, Linear regression, Decision Tree, Student Performance

1 INTRODUCTION
In programming courses, if students can get feedback in a short time after they submit their code, they might be able to improve quickly. However, it is not realistic for instructors or teaching assistants (TAs) to mark students’ code repeatedly and generate feedback if students can submit their code multiple times. The reason is that students may potentially have a large amount of submissions, and it may take much time for Instructional Team to mark before they can give feedback. Thus, an auto-grading system is needed. A sound auto-grading system can not only give out the testcase outcomes but also generate useful feedback for the students. Since the system can keep running in the background, the feedback can be quickly generated whenever students submit their code (within a few minutes, typically).

The auto-grading system, Marmoset, allows students to submit code multiple times for a coding assignment. Marmoset then will test the code and record the testcase outcomes into a MySQL database [17]. Students can keep modifying their code until they get an acceptable score, or until the deadline. Therefore, assignment marks or testcase outcomes may not necessarily be a valuable metric to judge if a student has learned the material well or not. However, their behaviour, such as how frequently they submit, how early they submit for the first time, and so on, might give valuable information.

In our study, we, as the Research Team, are focusing on investigating the following research themes.

(1) If we put students into categories according to their final exam and midterm performances, can we create a model over the Marmoset data to understand the students’ behaviour and predict those categories?
(2) Can we predict the students’ numerical midterm grades and the final exam grades using the Marmoset data?
(3) Can we find any interesting relations between the Marmoset data, grades and student categories?

2 RELATED WORK
Many studies were focusing on predicting the student’s overall performance. Nghe et al. [13] tried to predict the student’s actual GPA at the end of the year using the student’s information from the previous year. Dekker et al. [4] described case studies of electrical engineering students to predict if they will drop out program after the first semester of their studies, or even before they enter the study program. Khobragade and Mahadik [9] conducted several
experiments using students data to predict if a student will fail or not at the end of the semester. These studies usually use data from a wide range of years and a wide range of courses.

For programming courses, Koprinska et al. [10] tried to predict whether students will pass or fail their final exam with three different sources: progression in code writing and diagnostic from an auto-grading system (PASTA), interaction and engagement from online discussion boards and wikis (Piazza), and assessment marks. Gramoli et al. [6] studied the contribution of auto-grading and instant feedback using the PASTA system in various computer science courses. However, the only student performance prediction mentioned in their paper is that the students who start submitting their work early or finish submitting early (meaning that they finished the work) tend to get higher marks, but no complete evaluation provided. However, their data is not within one semester, and auto-grading data is not the primary data source.

The few studies in which the researchers only consider the data from an auto-grading system as the data source, however, were not trying to use the data for student performance prediction. For example, McBroom et al. [12] mined data from the PASTA system and cluster the students according to their submissions. However, rather than making a suggestive prediction on an individual student for the Instructional Teams, they focused on analyzing all students’ behaviour and the evolution of the behaviour over the semester.

Because of the easy-collecting nature of the data from auto-grading systems, predictive models using these data can be easily integrated into other educational systems. We believe such predictive models can further help the Instructional Teams to allocate their limited teaching resources on students.

3 STUDENT PERFORMANCE

In the University of Waterloo, student performance for one course is usually calculated based on a mixture of assignments’ marks, projects’ marks, midterm grades, and final exam grades. In terms of the course Fundamentals of Programming (ECE 150) in Electrical and Computer Engineering department, the midterm grades and final exam grades contribute from 60% to 90% to the final course grades. In other words, student performance highly depends on the midterm grades and final exam grades. In the year 2016, the maximum score for the midterm for ECE 150 was 110, and for the final exam, it was 120.

4 MARMOSET

Marmoset [16] is an auto-grading system for marking programming project submissions. It was built at and used for, computer science courses in the University of Maryland. In the year 2015, it was integrated as the auto-grading tool for ECE 150 (Fundamentals of Programming) and ECE 356 (Database systems) in the University of Waterloo.

In ECE 150, an assignment usually comes with multiple tasks. Each task corresponds to a project in Marmoset and contains several testcases. There are three types of testcases: public testcases, release testcases, and secret testcases.

The naming convention for the year 2016 of ECE 150 is "course number"-"assignment number"-"task name" for graded tasks. Figure 1 shows the graded tasks for assignment 1 of ECE 150. Notice that they have the same deadline. Figure 2 shows us the student view of the test results in Marmoset. In the year 2016, the Instructional Team only used public testcases (shown in the right part of the figure) but no release testcases nor secret testcases. Green colour means a submission passed a given testcase while red colour means it failed that testcase. There is also grey colour meaning the submission failed to compile. Points for testcases can be different. Each testcase may not always worth one point. Therefore, the top submission in figure 2 gets a result as "6/0/0/0" because testcases were worth different points. Figure 3 shows us the student view of the detailed test results and feedback for the second submission in figure 2. Students can pick any task to start, and they can switch between tasks even if they have not passed all testcases.

350-1.texviewCal  view  submit  26 Sep. 11:59 PM Assignment 1, Task 3
350-1-basicPNum view  submit  26 Sep. 11:59 PM Assignment 1, Task 1
350-1-basicAdd view  submit  26 Sep. 11:59 PM Assignment 1, Task 2
350-1-ASCII view  submit  26 Sep. 11:59 PM Assignment 1, Task 1

Figure 1: The graded tasks in Marmoset

Project 150-0-basicgraphics: Assignment 0, Graded Task 2

Deadline: Mon, 19 Sep at 11:59 PM (Late: Tue, 20 Sep at 01:59 AM)
Current Extension: 0
language: c
Submissions

| date submitted | Results | submit | test name | view source | download | Public |
|----------------|---------|--------|-----------|-------------|----------|--------|
| 9/19/16 8:00 AM | pass | yes | 350-1.BasicAdd | 100/100/100/100 | yes | yes |

Figure 2: Student view of a task in Marmoset

Project 150-0-basicgraphics: Assignment 0, Graded Task 2

Deadline: Mon, 19 Sep at 11:59 PM (Late: Tue, 20 Sep at 01:59 AM)
Current Extension: 0
language: c
Test Results

Note: For test outcomes, failed means wrong and error means crashed.

| type | test # | outcome | name | short result |
|------|--------|---------|------|-------------|
| public | 0 | failed | TopBottonWall.py | TestTopBottonWall.py failed |
| public | 1 | passed | 2 | TestTopBottonWall.py passed |
| public | 2 | passed | 2 | TestTopBottonWall.py passed |
| public | 3 | passed | 1 | TestOtherSideWall.py passed |

Figure 3: Test results of a task in Marmoset
5 MODELLING TECHNIQUES
This section describes the modelling techniques used in predicting student performance. We selected decision tree and linear regression in our experiments.

5.1 Decision Tree
Decision tree is a method for approximating discrete-valued target functions, in which the learned function is represented by a decision tree. Decision trees classify instances by sorting them down the tree from the root to a leaf node, which provides the classification of the instance. Each node in the tree specifies a test of some attribute of the instance, and each branch descending from that node corresponds to one of the possible values for this attribute. An instance is classified by starting at the root node of the tree, testing the attribute specified by this node, then moving down the tree branch corresponding to the value of the attribute. This process is then repeated for the subtree rooted at the new node.

C4.5 Decision Tree [15]. C4.5 builds decision trees from a set of training data by choosing the split that gives the maximum information gain ratio using the concept of information entropy. The attribute with the highest normalized information gain is chosen to make the decision. C4.5 is also able to handle both continuous and discrete attributes. In Weka [18], the class implements this is J48. Many researchers use this technique for exploring their data [1, 3, 4, 13], and this is the decision tree algorithm used in our experiments.

5.2 Linear Regression
Linear regression assumes that the relationship between a dependent variable and an independent variable can be described in a linear manner. The target is to find the best estimation of the value for the coefficient of the equation by using the values of the independent variable. A standard approach in finding the coefficient is applying the least-squares method.

The error between observation and the true value can be caused by measurement error, system error, etc. It can be thought of as the composite of a number of minor influences or errors. As the number of these minor influences gets large, the distribution of the error tends to approach the normal distribution (Central Limit Theorem [11]). Therefore, the error follows:

\[ e \sim N(0, \sigma^2) \]

It should be equal variance and normally distributed.

Multiple Linear Regression. The difference between linear regression and multiple linear regression is that in linear regression, we have only one independent variable; however, in multiple linear regression, we can have multiple independent variables. We will refer to linear regression as multiple linear regression in later sections.

5.2.1 Correlation Coefficient. The correlation coefficient measures the degree to which two variables are related in a linear relationship. A positive relationship between two variables means if there is a positive increase in one variable, there is also a positive increase in the second variable. A value of precisely 1.0 means a perfect positive relationship. In comparison, a value of precisely −1.0 means a perfect negative relationship, which means the two variables move in opposite directions. However, if the correlation is 0, it means no relationship exists between the two variables. The value of the correlation coefficient indicates the strength of the relationship. For example, a value of 0.3 indicates a very weak positive relationship.

5.2.2 Verify linear regression assumptions. In order to verify the linear regression assumptions that the error is equal variance and normally distributed, graphic techniques are often applied. A residual vs fitted plot is used for visually observing non-linearity, unequal error variances, and outliers [14]. A normal Q-Q plot is the plot to estimate if a dataset is from theoretical normal distribution [5]. A residuals vs leverage plot illustrates influential points. Not all outliers are influential in the linear regression analysis. Even though data have extreme values, they might not be influential in determining a regression line. However, some points could be very influential even if they appear to be within a reasonable range of values. They could be extreme points against a regression line and can alter the results if we exclude them from the analysis.

6 FEATURES
This section describes the features.

6.1 Passing Rate for each task
This feature reflects the passing rate of the best submission of a student for a given task. In the course ECE 150 during the year 2016, the total number of graded tasks for all students is 28. Among these tasks, the first 16 tasks are due before the midterm, and the other 12 tasks are released after midterm and due before the final exam. Note that multiple tasks can belong to one assignment, which means they have the same deadline.

The number of testcases differs from one task to another. We show the distribution of testcases in Figure 4. The larger the task number is, the closer towards the final exam.

6.2 Testcase Outcomes
This feature is similar to the passing rate feature. It reflects the testcase outcomes of the best submission of a student for a given task. However, different from the passing rate, this feature emphasizes on individual testcase. It provides us with an insight into the contribution of each testcase and might be able to tell us which testcases are important.
6.3 Submission Time Interval

The time interval between the time of submissions and the task deadline might be considered as a useful feature. In Gramoli et al. [6] study, they observe that students who start submitting early or stop (re)submitting early to the auto-grading system tend to get higher marks in their assignments.

In our experiments, we consider using the time interval between the time of the submission passing 75% testcases and the task deadline as the feature.

Figure 5: Time interval difference between a good-performance student and a poor-performance student

Figure 5 shows us an example of the feature, the time interval difference between a randomly selected poor-performance student (32/110 for the midterm and 45/120 for the final exam) and a randomly selected good-performance student (109/110 for the midterm and 103/120 for the final exam). Here the Y-axis shows us the number of hours before the deadline when the student makes a submission which passes at least 75% of the testcases for a given task. Note that the average hours of poor-performance students for all tasks reside mostly between 10 hours and 60 hours while the average hours of good-performance students reside mostly between 100 hours and 140 hours. The difference is quite significant.

6.4 Number of Submissions

The number of submission feature can be directly generated from the number of submission information stored in the MySQL database of Marmoset. Typically, the last submission is the best. The reason is that it is common that a student stops working on the task if he has already passed all the testcases; if he has not achieved that, he might keep working on it. It means the last submission will be the best. For a smart student, who may improve his/her code significantly from the feedbacks for his/her previous submission, the number of submissions should be relatively small. However, for a less smart student, he may need to make more submissions to get his code correct. Therefore, the number of submissions might be able to help us predict student performance.

Figure 6 gives us the maximum number of submissions. We refer to good-performance students as GP, satisfactory-performance students as SP, and poor-performance students as PP in the following tables.

7 EXPERIMENTS AND EVALUATION

This section describes the experiments and evaluation of our study. Weka [18] is a tool containing many machine learning algorithms for data mining tasks, and it is the tool we used in the experiments.

7.1 Methodology

We conduct two types of experiments: classification to predict student categories; regression to predict the grades of the midterm and the final exam.

The dataset in our experiments contains 428 instances which representing the students who have both the midterm grade and the final exam grade in ECE 150 for the Fall term in the year 2016. Students who missed either the midterm exam or the final exam are excluded.

We split the dataset into a training set and a testing set. We use the training set to build the model; then we apply the model to the testing set for evaluation. We use Weka to conduct the experiments, and the default parameter settings of the algorithms in Weka are used. For the classification method, we select the C4.5 decision-tree algorithm; for the regression method, we select the multiple linear regression algorithm.

We refer to good-performance students as GP, satisfactory-performance students as SP, and poor-performance students as PP in the following tables.

7.2 Classification for Predicting Student Categories

This section describes the classification experiments for predicting the student categories aiming to explore the answer of the first research question: If we put students into categories according to their midterm and final exam performances, can we create a model over the auto-grading data to understand the students’ behaviour and predict those categories?

In this section, we describe our experiments for predicting student categories using the C4.5 decision-tree classification algorithm and their results. We split the students into three categories according to their exam grades. We apply the same rule for both the midterm and the final exam: Students who get higher than 80 are categorized as good-performance students; students who get lower than 80 are categorized as poor-performance students; the remaining students are categorized as satisfactory-performance students. Note that students who are categorized in one category for the midterm can be in a different category for the final exam. Here, the number 80 is selected according to common sense, the
number 50 is the term average for not withdrawing the engineering program in University of Waterloo. For predicting the midterm performance, we only use the tasks assigned before the midterm (16 tasks). For predicting the final exam performance, we use all the tasks (28 tasks).

In the experiments, the training set to testing set ratio is 8:2 for both the midterm and the final exam. We apply the Synthetic Minority Over-sampling Technique (SMOTE) [2] to oversample the poor performance students in both training sets for building better predictive models.

7.2.1 Passing Rate as the Feature. For each submission, Marmoset tests the code against pre-set testcases, and stores the testcase outcomes. For each testcase, the test outcome will be either ‘passed’ or ‘failed’. The passing rate for a task is calculated by the number of testcases passed divided by the total number of testcases for that task. The experiment result for classifying students according to their midterm grades is shown in Table 1. The experiment result for classifying students according to their final exam grades is shown in Table 2.

| PP | SP | GP | ← classified as |
|----|----|----|----------------|
| 0  | 0  | 10 | PP             |
| 2  | 3  | 27 | SP             |
| 0  | 2  | 42 | GP             |

Table 1: Confusion Matrix for Passing Rate (midterm)

| PP | SP | GP | ← classified as |
|----|----|----|----------------|
| 2  | 2  | 9  | PP             |
| 3  | 6  | 18 | SP             |
| 0  | 9  | 37 | GP             |

Table 2: Confusion Matrix for Passing Rate (final)

From table 1 and table 2, we can tell in both models, most of the students are classified as good-performance students. In terms of the poor-performance students (whom we are more care about), the midterm model makes no correct prediction for them. Even worse, all poor-performance students are classified as good-performance students. However, it turns better when it comes to the final exam, which classifies some number of poor-performance students correctly. It might indicate the passing rate for tasks after midterm are able to reflect some variance among students since the tasks after midterm might be more difficult. We will discuss more the comparison in terms of poor-performance students in later sections.

7.2.2 Testcase Outcomes as the Feature. Different from the passing-rate feature, an individual testcase outcome from the best submissions might be useful. A poor-performance student might satisfy with the overall passing rate for the task, but not passing all the testcases. Therefore, the individual testcases might help us to build a useful model. Specifically, certain testcase may act as differentiation between students. The experiment result for classifying students according to their midterm grades is shown in Table 3. The experiment result for classifying students according to their final exam grades is shown in Table 4.

| PP | SP | GP | ← classified as |
|----|----|----|----------------|
| 0  | 1  | 9  | PP             |
| 0  | 5  | 27 | SP             |
| 0  | 6  | 40 | GP             |

Table 3: Confusion Matrix for Testcases Outcomes (midterm)

| PP | SP | GP | ← classified as |
|----|----|----|----------------|
| 1  | 4  | 8  | PP             |
| 2  | 11 | 14 | SP             |
| 1  | 8  | 37 | GP             |

Table 4: Confusion Matrix for Testcases Outcomes (final)

From table 3 and table 4, unexpectedly, the results are very similar to the results using passing-rate as the feature. The students are biased to be predicted as good-performance students. It indicates that there are no outstanding testcases which can be used to differentiate students. Since it is an introduction level programming course, the testcases are relatively straightforward, so it makes sense that there are no outstanding testcases.

7.2.3 Number of Submissions as the Feature. The experiment result for classifying students according to midterm grades is shown in Table 5. The experiment result for classifying students according to their final grades is shown in Table 6.

| PP | SP | GP | ← classified as |
|----|----|----|----------------|
| 3  | 3  | 4  | PP             |
| 6  | 13 | 13 | SP             |
| 6  | 17 | 21 | GP             |

Table 5: Confusion Matrix for Number of Submissions (midterm)

| PP | SP | GP | ← classified as |
|----|----|----|----------------|
| 7  | 5  | 1  | PP             |
| 1  | 10 | 16 | SP             |
| 6  | 14 | 26 | GP             |

Table 6: Confusion Matrix for Number of Submissions (final)

From table 5 and table 6, it seems both models manage to make some predictions of the poor-performance students. However, for the midterm, most of the predicted poor-performance students are satisfactory students and good-performance students (12 out of 15). For the final exam, most of the predicted poor-performance students are poor-performance students and good-performance students. Because there is more considerable variance in this feature after the midterm, as shown in figure 6, the result is expected. It might
indicate for the midterm, some satisfactory students and some good-performance students behave similarly as poor-performance students. However, for the final exam, only a small fraction of satisfactory students will behave like poor-performance students, while for good-performance students, there are still some good-performance students who behave similarly as poor-performance students, which indicates that the number of submissions feature itself cannot differentiate good-performance students from poor-performance students. Combination of some other features might be helpful.

### 7.2.4 Time Interval between certain Submission and Deadline as the Feature

We calculate how many hours before the deadline, a student submits as the feature (a submission time after the deadline or no submission, is deemed as 0 hour before the deadline). Then we try to build a decision tree using the submission time intervals to predict the students’ categories.

Instead of using the submission time of the last submission, we used the submission time of the submission when it gets 75% correct of all the test cases. The reason is that the last submission may be very close to the deadline and for a student who is cheating, his/her submission can jump over the submission which passes 75% and goes to 100% directly. By using the submission passing 75% test cases, we are able to create a more considerable variance in the feature.

The experiment result for classifying students according to midterm grades is shown in Table 7. The experiment result for classifying students according to their final exam grades is shown in Table 8.

| PP | SP | GP | classified as |
|----|----|----|--------------|
| 4  | 6  | 0  | PP           |
| 5  | 16 | 11 | SP           |
| 5  | 14 | 25 | GP           |

Table 7: Confusion Matrix for Submission Time Interval (midterm)

| PP | SP | GP | classified as |
|----|----|----|--------------|
| 5  | 6  | 2  | PP           |
| 6  | 8  | 13 | SP           |
| 2  | 15 | 29 | GP           |

Table 8: Confusion Matrix for Submission Time Interval (final)

From table 7 and table 8, both models make some prediction for the poor-performance students. However, we found that putting the submission time intervals into a linear-regression model can make better predictions, and we will discuss it in the next section.

### 7.3 Regression for Predicting the Grades

This section describes the regression experiments for predicting the grades aiming to explore the answer of the second research question: Can we predict the students’ numerical midterm grades and the final exam grades from the students’ behaviour?

#### 7.3.1 Time Interval between certain Submission and Deadline as the Feature

The linear-regression model is based on the time interval between the time of the submission that the student gets 75% percent testcases passed of a given task and the deadline.

**Training Regression Model for Predicting Transformed Midterm Grades.** The tasks we used for regression to predict midterm grades only includes the first 16 tasks (total 28 tasks) that were assigned before the midterm.

We used stats.\texttt{lm()} in R to build the linear-regression model and to stabilize the variance we applied \texttt{spreadLevelPlot()} function (It is a function for suggesting the numeric number for power transformation of a linear-regression model) to find suggested power transformation.

The p-value for the model is $<2.2 \times 10^{-16}$, which is much less than 0.05 ($H_0$ hypothesis: no relationship between the time intervals and the transformed midterm grades), which indicates there is a relationship between the time intervals and the transformed midterm grades.

![Figure 7: Histogram of Regression Difference between the Predicted grades and the Actual Grades](image)

Figure 7 shows us the histogram of the difference between the predicted grades and actual grades of the testing set. The predicted midterm grades were calculated by applying reversal power transformation. The mean of the difference between the predicted grades and the actual midterm grades (maximum is 110 points) is $-5.76$ points, and the standard deviation is 16.44 points.

**Training Regression Model for Predicting Transformed Final Exam Grades.** The tasks we used for this experiment include all 28 tasks. The midterm grades were not included. Similarly to transforming midterm grades, we also applied \texttt{spreadLevelPlot()} function to find suggested power transformation in order to stabilize the variance. The p-value for the model is $<2.2 \times 10^{-16}$, which indicates there is a relationship between the time intervals and the transformed final exam grades.

Figure 8 shows us the histogram of the difference between the predicted grades and actual grades of the testing set. The predicted final exam grades were calculated by applying reversal transformation. The mean of the difference between the predicted grades and the actual final exam grades (maximum is 120 points) is 0.92 points, and the standard deviation is 17.12 points.
Figure 8: Histogram of Regression Difference between the Predicted and the Actual Grades

In order to compare the performance of the regression model with the classification models, we used the predicted the midterm grade or the final exam grade from the regression models to generate the predicted categories and compared them with the actual categories of students. The confusion matrix for the midterm is shown in table 9, and the confusion matrix for the final exam is shown in table 10.

| PP | SP | GP | ← predicted as |
|----|----|----|----------------|
| 5  | 5  | 0  | PP             |
| 5  | 20 | 7  | SP             |
| 0  | 19 | 25 | GP             |

Table 9: Confusion Matrix from Predicted Midterm Grades

| PP | SP | GP | ← predicted as |
|----|----|----|----------------|
| 6  | 4  | 3  | PP             |
| 1  | 17 | 9  | SP             |
| 1  | 13 | 32 | GP             |

Table 10: Confusion Matrix from Predicted Final Exam Grades

From table 9 and table 10, we can observe that the most significant number of each row and each column resides on the diagonal line from the top-left corner to the bottom-right corner, meaning the model separates the students well. Impressively, from the left-bottom zero and top-right zero from table 9, it indicates the midterm model successfully distinguishes poor-performance students and good-performance students. Students from either category are not classified into the other category.

7.4 Comparison in terms of Poor-Performance Students

We always care more about the poor-performance students comparing to others because they are the students who need help urgently. Especially for 1st year engineering students, if they failed ECE 150, they are likely to have much difficulty in passing other courses. Therefore, we want to compare the results based on how models behave for poor-performance students (labelled as positive).

Table 11 shows us the results for poor-performance students on the midterm and table 12 shows us the results for poor-performance students on the final exam. Among them, what we care about is the precision for different models. In this case, if any students are classified as poor-performance students, they are likely to be in trouble. However, by focusing on increasing the precision, we might put the other poor-performance students who are not classified as poor-performance students aside (low recall). The reason we let this situation happens is that even if we cannot classify them, the worst case for them is that they remain in an unchanged learning environment where they have to ask for help by themselves. It is acceptable.

The importance of the values is Precision > F measure > Recall > FP_rate. F-measure is a good way to judge the balance between precision and recall, so we put it to the second place. FP rate comes the last because a model can easily achieve a perfect FP_rate by not making any positive instances. However, we want our models to be able to make positive instances. Among them, precision, F-measure and recall are the higher, the better while FP_rate is the lower, the better.

We refer to the passing rate feature as PR, testcase outcomes as TO, Number of submissions as NOS, and submission time interval as STI in the following tables.

| PP | SP | GP | ← predicted as |
|----|----|----|----------------|
| 5  | 5  | 0  | PP             |
| 5  | 20 | 7  | SP             |
| 0  | 19 | 25 | GP             |

Table 11: Results for Poor-Performance Students on the Midterm

From table 11, we can see for the midterm, linear regression with submission time interval gives us the best result for precision, F-measure and recall.

| PP | SP | GP | ← predicted as |
|----|----|----|----------------|
| 6  | 4  | 3  | PP             |
| 1  | 17 | 9  | SP             |
| 1  | 13 | 32 | GP             |

Table 10: Confusion Matrix from Predicted Final Exam Grades

| PR | Recall | F-Measure | FP_rate |
|----|--------|-----------|---------|
| 0.00 | 0.00   | 0.00      | 0.03    |

Table 11: Results for Poor-Performance Students on the Midterm

| PR | Recall | F-Measure | FP_rate |
|----|--------|-----------|---------|
| 0.40 | 0.15   | 0.22      | 0.04    |
| 0.25 | 0.07   | 0.12      | 0.04    |
| 0.50 | 0.54   | 0.52      | 0.10    |

Table 12: Results for Poor-Performance Students on the Final Exam

From table 12, we can see for the final exam, linear regression with submission time interval gives us the best result for precision, F-measure and recall.

| PR | Recall | F-Measure | FP_rate |
|----|--------|-----------|---------|
| 0.75 | 0.46   | 0.57      | 0.03    |

Table 12: Results for Poor-Performance Students on the Final Exam

From table 12, we can see for the final exam, linear regression with submission time interval gives us the best result for precision, F-measure and FP_rate. Only the recall comes the second place.

In addition to those values, we also interested in what the actual grades are for the predicted poor-performance students because
although some students are misclassified, their actual grades might be very close to poor-performance students. Figure 9 and figure 10 are showing the boxplots for the actual grades of predicted poor-performance students.

![Boxplot for Actual Midterm Grades of Predicted Poor Performance Students](image)

Figure 9: Boxplot for the Actual Midterm Grades of Predicted Poor Performance Students

![Boxplot for Actual Final Exam Grades of Predicted Poor Performance Students](image)

Figure 10: Boxplot for the Actual Final Exam Grades of Predicted Poor Performance Students

From figure 9, we can see for the midterm, the actual grades of predicted poor-performance students from submission time linear-regression model are mostly the lowest among all. Also, we have a similar result for the final exam, as shown in figure 10.

Therefore, it is reasonable to say that the linear-regression model using the submission time interval performs better than other models. However, for the final exam, it seems the highest point for submission time interval (linear regression) boxplot is an outlier. After we looked into the submission time interval information of that specific student, we found out he/she submit his/her code with an average of 23 hours before the deadline while the average hours of other good-performance students reside mostly between 100 hours and 140 hours. Therefore, that student is not behaving like a good-performance student in terms of the submission time interval feature, but rather a poor performance student of whom the average hours reside mostly between 10 and 60 hours. It makes sense that the student is predicted as poor performance student.

7.5 Correlation between The Time Interval Information of an Assignment and Exam Grades

This section is aiming to answer the third research question: Can we find any interesting relations between the features generated (reflecting students’ behaviour), grades and student categories? Currently, we have one finding that the time interval of different assignment contributes to the prediction on the midterm grades and the final exam grades differently.

We apply the linear-regression algorithm to different assignment (each assignment contains several tasks with the same deadline) and calculate the correlation coefficient for comparing the effect of the time interval information from each assignment in order to have an insight into the correlation between that and the exam grades. However, in all these experiments, no power transformation is applied because the suggested power might not be constant across the experiments. Thus, some underlying assumptions of the residuals of linear regression are not met. The model is as:

\[
grades = \beta_0 + \sum \beta_i x_i
\]

In the equation, the \(i\) is between 1 and the number of tasks of an assignment. For a task, \(x_i\) is the time interval between the submission time of a certain submission passing \(T\%\) testcases and the deadline. In our experiments, the \(T\%\) is set to 75%. The difference from previous experiments is that only part of the time interval information of all tasks before the midterm or the final exam is used. Specifically, we combined the time interval information of tasks of an assignment to do the regression. For example, in figure 1, assignment 1 contains 5 tasks. Then in our experiment, we will use the time interval information of those 5 tasks for prediction.

The dataset in the experiments is not split into a training set and a testing set, but cross validation is applied. The values are averaged (The exact values are lost from each split of the dataset during the cross validation. However, the average value would give us a sense of the relation between each assignment and midterm or the final exam grades).

| # assignment | 0 | 1 | 2 | 3 |
|--------------|---|---|---|---|
| number of sub tasks | 2 | 5 | 3 | 6 |
| Correlation coefficient | 0.37 | 0.46 | 0.51 | 0.61 |
| Mean absolute error | 17.09 | 16.02 | 15.53 | 14.03 |
| Root mean squared error | 20.94 | 19.99 | 19.35 | 17.94 |

Table 13: Correlation between assignments (STI) and midterm grades

Table 13 shows that for the midterm, the assignment immediately before the midterm has the most significant contribution to the midterm grades (the most considerable correlation). It makes sense since there can be a large portion of questions in the midterm asking about the content of that assignment, if a student fails to manage time well, he/she may fail to fully understand that assignment (they may still get a high score of that assignment since they can ask for help from other students or cheat), which, in return, makes him/her perform poorly in midterm.

Table 14 show that for the final exam, it turns out that the midterm grades has the most significant correlation with the final exam grades. Figure 11 shows us the scatter plot of the midterm grades and the final exam grades. A linear relation can be observed.
Predicting student performance using data from an Auto-grading system

### Table 14: Correlation between assignments (STI) or midterm grades and final exam grades

| # assignment or midterm | 0 | 1 | 2 | 3 | midterm | 4 | 5 | 6 | 7 |
|-------------------------|---|---|---|---|---------|---|---|---|---|
| number of sub tasks     | 2 | 5 | 3 | 6 |         | 3 | 3 | 4 | 2 |
| Correlation coefficient | 0.36 | 0.39 | 0.47 | 0.56 | 0.72 | 0.54 | 0.55 | 0.52 | 0.57 |
| Mean absolute error     | 15.22 | 15.09 | 14.61 | 13.36 | 11.25 | 13.57 | 13.58 | 13.78 | 13.23 |
| Root mean squared error | 18.93 | 18.73 | 17.98 | 16.81 | 14.20 | 17.10 | 16.97 | 17.35 | 16.67 |

Figure 11: Relation between the midterm grades and the final exam grades

8 CONCLUSION AND FUTURE WORK

This paper is a summary of our preliminary study in predicting student performance by using the data from the auto-grading system Marmoset. We carried out two types of experiments: classification and regression, aiming to explore the answer of three research questions.

1. If we put students into categories according to their final exam and midterm performances, can we create a model over the Marmoset data to understand the students’ behaviour and predict those categories?
2. Can we predict the students’ numerical midterm grades and the final exam grades using the Marmoset data?
3. Can we find any interesting relations between the Marmoset data, grades and student categories?

For classification, we put students into categories according to their midterm or final exam grades. The categories are good-performance students, satisfactory-performance students and poor-performance students. We apply C4.5 decision-tree algorithm to the passing rate, testcases outcomes, the number of submissions and submission time intervals, separately, and the results show that, for predicting midterm performance, the classification models of passing rate and testcases outcomes cannot label any poor-performance students correctly. A strong bias exists tending to put every student into satisfactory-performance students or good-performance students. For the final exam, no such bias exists, and all the features are able to make limited predictions.

For regression, we use linear regression algorithm on the time interval between a student’s first reasonable submission and the deadline (STI) to predict the exam grades of the student. The results show that for the midterm, the mean of the difference between predicted grades and actual midterm grades (maximum is 110 points) is -5.76 points, and the standard deviation is 16.44 points. For the final exam, the mean of the difference between predicted grades and actual final exam grades (maximum is 120 points) is 0.92 points, and the standard deviation is 17.12 points.

In order to compare the results in terms of poor-performance students, we have to convert the predicted grades from the linear-regression models into categories. We categorize students by setting threshold on their predicted grades. Then we calculate the FP_rate, Precision, Recall and F-measure of the poor-performance students for both cases. The importance of the values is Precision > F-measure > Recall > FP_rate. For both the midterm and the final exam, we find out the regression model using the STI gives us the best value for precision and F-measure. For students who are misclassified as poor-performance students, we compare the boxplots of their actual grades from each model. We find for both the midterm and the final exam, the linear-regression models using the STI give the best result.

To compare the correlation between an individual assignment and exam grades, we compared the contributions of the STI of different assignments, and it shows that for the midterm, the assignment assigned right before the midterm exam has the most significant contribution. For the final exam grades, the midterm grades contribute the most.

In summary, it is reasonable to say that the linear-regression model using submission time interval performs better than other models in terms of predicting poor-performance students and further researching on this might be the best next step.

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