Personalized Feedback Emails: A Case Study on Online Introductory Computer Science Courses

Sahar Voghoei*
University of Georgia
Athens, GA, USA
voghoei@uga.edu

Navid Hashemi Tonekaboni*
Emory University
Atlanta, GA, USA
navid.ht@emory.edu

Delaram Yazdansepas
University of Georgia
Athens, GA, USA
delaram@uga.edu

Saber Soleymani
University of Georgia
Athens, GA, USA
saber.s@uga.edu

Abolfazl Farahani
University of Georgia
Athens, GA, USA
a.farahani@uga.edu

Hamid R. Arabnia
University of Georgia
Athens, GA, USA
hra@uga.edu

ABSTRACT

The absence of face-to-face interaction between instructors and students in online courses has been the focus of discussion in many research papers. To compensate for this defect, the concept of Personalized Feedback Email (PFE) was introduced in two undergraduate online courses at the University of Georgia. A distinct component of PFE is a grade forecast for each individual student projected visually in graphs. The quantitative and qualitative data collected from students made it possible to claim that PFE contributes to students' engagement in online courses and encourages the majority of them to do better in class. Given that the rate of contribution of each student in course activities is correlated with student's performance, we were able to show that students who find PFE motivating make higher contributions in class activities. PFE is especially capable of targeting students who stand in the middle of the grade-range and improves their contribution and performance. In this respect, PFE also has a considerable short-term effect. The extensive applications of this effect should be limited by the optimization of the number of PFEs. All this machinery is expected to enable the complex of decision-makers associated with students to adopt the most effective learning strategies. This study shows a drastic and positive change in the performance of students who alter their learning strategy after being exposed to their forecasted grades, which enhances the potential of supervised improvement. The accuracy of forecasting model will be crucial when forecast grades are expected early in the semester to identify at-risk students. Applying machine learning methods, particularly the Greedy Linear Regression, satisfies this expectation and increases the correlation coefficient of the forecasts to 0.98.

*Both authors contributed equally to this research.

ACMSE 2020, April 2–4, 2020, Tampa, FL, USA

ACM ISBN 978-1-4503-7105-6/20/03…$15.00
https://doi.org/10.1145/3374135.3385274

CCS CONCEPTS

• **Applied computing** → **Interactive learning environments**; **Distance learning**; *E-learning*; • **Computing methodologies** → *Machine learning*.

KEYWORDS

Feedback System, Personalized Monitoring, Class Participation, Online Course, Student Success, Data Analysis

ACM Reference Format:
Sahar Voghoei, Navid Hashemi Tonekaboni, Delaram Yazdansepas, Saber Soleymani, Abolfazl Farahani, and Hamid R. Arabnia. 2020. Personalized Feedback Emails: A Case Study on Online Introductory Computer Science Courses. In *2020 ACM Southeast Conference (ACMSE 2020), April 2–4, 2020, Tampa, FL, USA*. ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3374135.3385274

1 INTRODUCTION

Compared to conventional classes, online classes offer some significant advantages both to the instructors and the students, including the efficiency in time, cost, and accessibility. However, many believe that online classes cannot substitute for conventional ones, mainly due to the lack of proper interactions between instructors and students, which results in a lower level of satisfaction in virtual learning environments [12].

Due to the considerable increase in the number of fully online and asynchronous courses offered by various institutions [9], most of these online platforms use discussion forums as one of their primary components. In order to efficiently leverage this interactive environment between instructors, teaching assistants, and students, a clear guideline is required. All the parties need to know their role and how they can effectively use these tools [10].

In particular, one of the significant shortcomings of these online platforms is the lack of an active observer similar to that of the conventional classes to motivate students to participate in various class activities. To address this problem, we performed a case study to see how a personalized monitoring and feedback mechanism can add the human element to online classes and consequently enhance the participation rate of students. Furthermore, we analyzed our data to understand the group of students who receive the most benefit from our monitoring and feedback approach.

Furthermore, we explored different forecasting techniques to target at-risk students, as early as possible, during each semester. The importance of providing timely feedback to students has been well studied [6]. It is of crucial importance to have an accurate forecasting model to specifically locate, motivate, and engage students who are at the risk of failure or dropping out of the course to improve their learning performance. This urged us to apply several machine learning methods to improve the accuracy of forecasts.

In this paper, we first review related work in this domain. Then, we provide the details of our research, including the data collection and the study setting. This section will be then followed by the experimental results, which include both the quantitative and qualitative data on the effectiveness of our approach with respect to students' performance. In the discussion section, we discuss our ideas to improve our current methodology to serve all groups of students in a more effective manner. Finally, we conclude the paper and summarize the contributions of this study.

2 BACKGROUND AND RELATED WORK

There are different research studies on the positive effect of contribution rate in online courses [3, 4, 16]. They analyze how being more active in the class affects students' motivation, attitude, and, consequently, their performance. For instance, Anderson et al. [1] show that this correlation is categorically strong and positive. Therefore, students who contribute to class activities are very unlikely to drop out of the course [15].

On the other hand, some studies focused on methods that motivate students to contribute more. For instance, grouping students and asking them to work on collaborative projects is shown to be very useful in this regard [8]. However, the role of instructors as the primary motivators who influence students' approach to a subject can not be ignored [2]. As an example, Wu et al. [19] measured the perceived learning data of online discussion forums collected from a post-course questionnaire to show the high correlation between instructors' involvement in online discussions and students' contribution rate.

Furthermore, some studies show that the consistency of contributions is a more important factor compared to the contribution rate itself. Two different studies [2, 20] show that although the majority of students who have a high rate of contribution in the first few weeks of the semester, start contributing less during the following weeks, consistency is the most important feature leading to a higher final grade. Some other studies [5, 14, 18, 21] suggest that for temporal contribution analysis, event-based participation plays the primary role. In other words, they believe that the key to keeping students engaged is to design frequent events (e.g., quizzes, assignments, and projects) that make students remain active throughout the semester.

Another effective mechanism to keep students involved is to provide them with feedback about their progress in the course, which is considered as a double-edged sword. Onah et al. [11] explain that although peer review feedback (such as the occasions on which students evaluate the contributions of one another) evaluations can be very influential in increasing the contribution rate of students, it may increase the dropout rate too. Students, even the ones who are not doing well in the course, need to feel valued and involved. Therefore, the feedback should be personalized such that it conveys the sense of inclusion to all groups of students. Another study [13] elaborates on the crucial role of instructors in providing support and showing empathy to students as the most effective approach to keeping students involved and active in the class environment.

In this paper, we discuss our case study on an online introductory computer science course in which we integrated personalized feedback, including visualized progress forecasting, to enhance students' performance. In particular, we identified and targeted at-risk students to provide them with additional levels of support.

3 RESEARCH METHODS

3.1 Data Collection

For this study, we have focused on a fully online and asynchronous course titled "Foundations for Informatics". It was an introductory online course offered by the Department of Computer Science at the University of Georgia during Summer and Fall 2019. The Summer class had 25 students, and the Fall class had 30 students. Our data was collected through opinion surveys and online learning management tools.

3.1.1 Surveys. We prepared two questionnaires on students' backgrounds, their academic standings, and their opinion about receiving regular feedback during the semester. The first questionnaire was given to students before performing our case study at the start of each semester, and the second one was given in the last week of the semester. To create these surveys, we used Qualtrics and a web-based survey tool. More than 76% of students in each section (Summer and Fall semesters) participated in our surveys.

3.1.2 Online Learning Management Tools. We leveraged three different online learning tools, namely, ELC, Mimir, and Piazza. ELC or eLearning Commons at the University of Georgia is an online learning management system containing all class material including instructor-made videos paired with lecture slides. Mimir provides online tools for instructors to efficiently teach Computer Science course material. It is specifically designed to create coding assignments and exams. Piazza is an online Q&A discussion board that was used for course announcements, questions, and discussions. Using these tools, we collected various data such as the amount of time each student spent on the course materials, the assignments' submission times, the number of questions asked, the number of answers given to the questions of other students, and the voting information for the quality of questions asked. The frequency of activities of these sorts comprise what we call in this paper "the rate of contribution".

3.2 Study Setting

During the semester, we regularly provided students with feedback about their progress and performance. These reports can be classified into three main categories:

3.2.1 Intelligent Agents. The Learning Management System (LMS) provides Intelligent Agents (IA) that automatically scan the LMS for any instructor-defined criteria. The IA would trigger an email to alert students who have not accessed at least one of the course materials from the previous week. The email could be constructed using a template that calls the system database to automatically replace the name or the email of a student. In this way, IA emails sent to students will be personalized and address them by their first and last name to remind them that they have missed some specific material or content from the past week. This template enables the instructors to create personalized messages to students without creating several individually targeted emails.

3.2.2 Quantitative Feedback Reports. The quantitative feedback emails provide students with their cumulative grades for each class item, along with their contribution score up to that specific point of time (i.e., the first, second, and third quarter of the semester). In the rest of this paper, we refer to students' contributions with the quarter number of the semester. For instance, "contribution 3" would refer to online contributions during the third quarter of the semester.

In particular, we asked students whose performance was lower than average to participate further in online discussions and ask for help from the instructor and other students. On the other hand, we also targeted the students with good performance who had declared their willingness to help their classmates in the first survey. Reminder emails were sent to this group of students, notifying them about the potential bonus points for answering questions on Piazza. Figure 1 shows a sample feedback email sent to students. Furthermore, by using such reports, we provided a mediator for students to encourage their social acts that is one of the goals of computer-supported collaborative learning [17].

So far, your performance has been **exceptional**:

- On your first three assignment, you earned **17.69** points out of **18** points of your final course grade. (Average class point: **14.41**)
- You've had **8** contributions in Piazza. You asked **2** question and helped your classmates by answering **1** question(s).

Please actively participate in class discussions on Piazza.

Based on the survey, you showed interest to help your classmates out. I highly recommend that you actively help other peers by answering their questions through Piazza. This way you would earn bonus points too.

- You had **2** contributions on Piazza until July 6th, and now you have **13** contributions. Good Job!

Figure 1: A Sample Quantitative Feedback Email

3.2.3 Progress and Forecasting Charts. To show the current standing of each student, we designed progress and forecasting charts which provided a visualized estimated projection of the final grade of each student based on the totality of the student's so-far performance. A sample chart is shown in Figure 2. We used the forecasting method, Exponential Triple Smoothing (ETS), with confidence level of 95%, to estimate the progress of individual students based on their previous series of data (including their grades and contribution rate so far). We generated and sent these forecasting charts after the second and the third quarter of the semester when sufficient data were available in order to make accurate predictions.

4 EXPERIMENTAL RESULTS

In this section, we analyze the effectiveness of our personalized feedback sent to students, the precision of our forecasts, and how

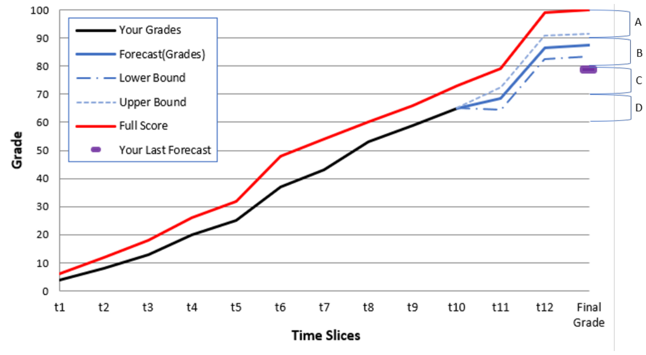

Figure 2: A Sample Progress and Forecasting Chart

machine learning approaches can help us identify the at-risk students early in the semester.

Due to the absence of the human factor in online courses, students may believe that these courses are less engaging. This opinion was reflected in the class surveys conducted at the beginning of each semester (indicated by the shaded columns in Figure 3). In similar surveys that were conducted at the end of each semester, after the personalized feedback method was fully applied, the negative opinion about the engaging capacity of online courses was remarkably lower than the first surveys (the checkered columns indicate the result of the second survey in Figure 3). It gives a hint to the achievement of the method in this regard. This achievement was also stressed in the non-quantitative feedback we received from the students, in which the effect of personalized feedback on filling the lack of human factor was explicitly addressed. Figure 4 gives an instance of this feedback.

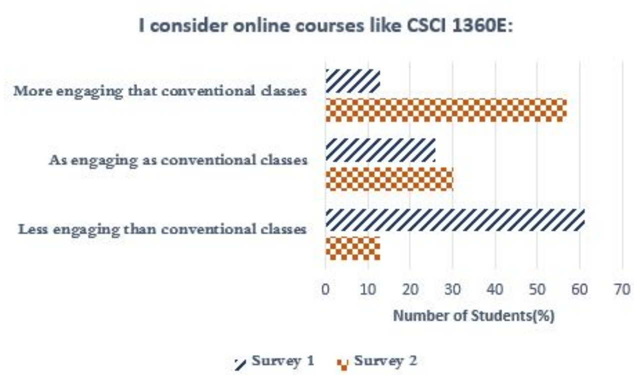

Figure 3: Students' Opinion about Class Engagement in Online Courses

I'm mainly writing to thank you. That message gave a very human element to an online class. It helped me know that a teacher was keeping track and cared about my progress. This is not my first online class and they can often feel very formulaic and distant, so it was a breath of fresh air.

Figure 4: A Sample Qualitative Feedback from Students

4.1 The Effect of Personalized Feedback on Educational Performance

The first task we would like to undertake is to figure out whether personalized feedback emails improve the performance of students or not. For this purpose, we consider two indicators for improvement: 1) the enhancement of students' online activities and contributions; 2) students' planned reorientation in terms of learning strategy. In other words, we aim to measure how personalized feedback affects students in terms of improving their online activities and also in adjusting their learning methods. In the following sections, our findings regarding these two indicators will be elaborated.

4.1.1 The Effect of PFE on Contribution Rate. As discussed in the previous sections, some studies suggest that the correlation between students' contribution rate and performance is categorically strong and positive. However, there are studies claiming that only event-based contribution rate should be taken into account. In this section, we show that personalized feedback emails improve students' contribution rates on both bases.

Figure 5 shows a considerable increase in the contribution rate of the students who found the feedback emails motivating, in contrast with the remarkable decrease in the contribution rate of those who found the feedback emails demotivating (the blue line indicates the ratio of the first two contributions of each group to that of the whole class and the red line does the same regarding the last two contributions). Postulating that the rise of contribution rate is associated with the improvement of performance, it can be suggested that students feeling motivated by the PFE are the ones who improved their performance during the semester. Note that it is merely an improvement and doesn't necessarily mean a top grade.

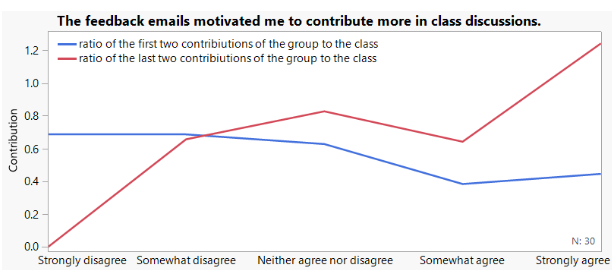

Figure 5: Distribution of Contributions by Degree of Motivation

Furthermore, as shown in Figure 6, the group of students who found the feedback emails encouraging ended up earning the highest final grades (averagely 89.4%). This group is followed by the students who found the emails and forecasts discouraging (grade average 81.8%), and then, the group who believed they were neither encouraged nor discouraged by the emails and forecasts (grade average 62.0%). In other words, students who earned the highest final grades are the ones who felt more affected (positively of negatively) by the PFE. However, remembering what we found in the preceding paragraph, we will be led to conclude that the students whose feelings were positively affected by the PFE, not only improved their contributions but also gained the best final grades. Nevertheless, it is to note that no strong causative relationship has been claimed so far.

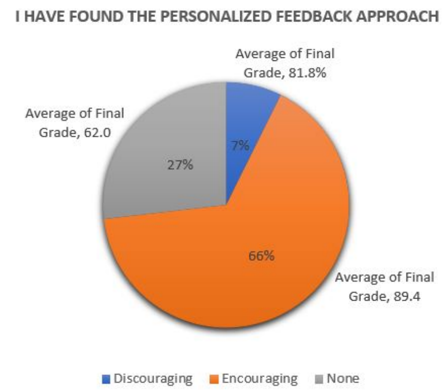

Figure 6: Students' Opinion about the Impact of PFE

In order to understand the immediate effect of the feedback emails on the contribution rate of the students (which is called "event-based contribution rate" by [14]), we analyzed the number of contributions (posts, responses, edits, follow-ups, and comments on follow-ups) per each forum discussion and also the number of students who contributed to each forum (the latter indicates the rate of students' engagement). Figure 7 shows the normalized distribution of these two variables in the Summer and Fall semesters, respectively.

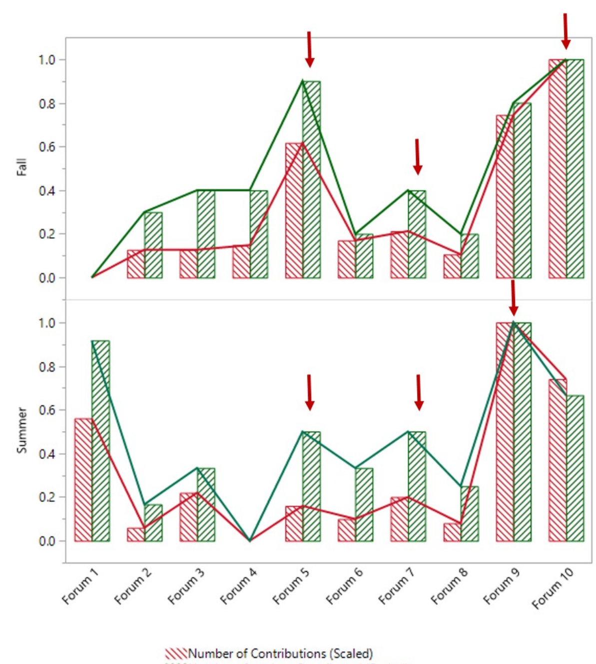

Figure 7: Quantity of Contributions and Contributors for Each Forum

In the Summer semester, our three feedback emails were sent right before forums 5, 7, and 9. As clearly shown in Figure 7, we can see an immediate increase in the number of students contributed in forum discussion, as well as the total number of questions and answers posted in those specific forums (i.e., the number of contributors, illustrated in green, and the number of contributions, illustrated in red,).

In the Fall semester, we came up with a different emailing schedule to verify the effect of the emails as the primary incentive for students to enhance their contribution. For this purpose, we sent the first two feedback emails right before forums 5 and 7 (as we did in the Summer), but the third email was sent when the assignment and class activities associated with forum 9 were over. Despite this time alteration, in both semesters the columns indicating forums 9 and 10 display a high rate of contribution. However, it should be noted that in the design of the assignments associated with forums 9 and 10, a higher amount of interaction had been required from students, which explains the distinct height of the respective columns in the graphs of Figure 7. On the other hand, the fact that in Fall a personalized feedback email was sent immediately before forum 10, while in Summer it was sent immediately before forum 9, explains the relatively high rate of contributions in forum 10 in Summer, which is comparable with the relatively high rate of contributions in forum 9 in Fall. This observation highlights the temporal effect of feedback emails as the primary factor on enhancing the contribution rate of students.

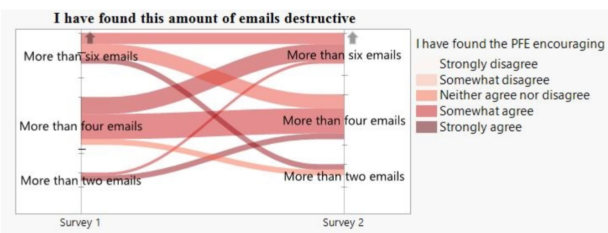

Figure 8: Change of Opinion Regarding Maxim Effective Number of PFEs (Intensity of Color Indicates Feeling Encouraged by PFEs)

The naive indication of this result might be that the more frequent the emails are sent, the higher the rate of contribution will be maintained throughout the semester. However, this optimism will be limited by fixing the maximum possible number of effective emails in a semester (i.e., the threshold of quantity crossing which emails will not be positively effective). In other words, it may be the case that besides finding the best times in a semester to send the emails, it is of crucial importance to determine the optimized number of emails to be sent in each semester. Figure 8 represents the students' opinions about the optimal number of feedback emails to receive during each semester. Although most of the students believed four is an ideal number in this respect, more than one third of the students were inclined to receive more emails of this nature.

4.1.2 Planned Alteration of Strategies. At the beginning of this section, it was suggested that the planned alteration of learning strategy can be considered as a contributor to learning improvement. To support this suggestion and to demonstrate that this alteration has been affected by the feedback emails the students received, we measured the absolute difference between the forecast grade of each student released shortly after the beginning of the semesters and the one released close to the end of the semesters (i.e., |Forecast 2 - Forecast 1|). This difference indicates the change in students' performance in the interval between the two forecasts. The height of each bar in Figure 9 represents the change in the performance of distinct groups of students. These groups have been characterized by their opinions regarding the influence of the forecasts on their learning strategies.

The ascending distribution of the heights of the bars (from left to right) Figure 9 shows that the more the students believed that the emails motivated them to change their learning strategy, the more their performance changed (indicated by the absolute difference between the forecasts). In other words, the students' report was an honest report that was correlated with the changes in their performance during the semester. For example, the rightmost column, which represents the students who felt strongly motivated by the first forecast to change their learning strategies, is also the reddest column, which indicates the highest improvement in performance. Moreover, the colors assigned to the columns indicate that the best improvement in students' performance, which is indicated by the non-absolute difference between Forecast 2 and Forecast 1, also belongs to the students who strongly believed the feedback emails motivated them to change their learning strategy. The claim suggested by this study is that where emails motivate students to change their learning strategy, this change is likely to take place and leads to better performance.

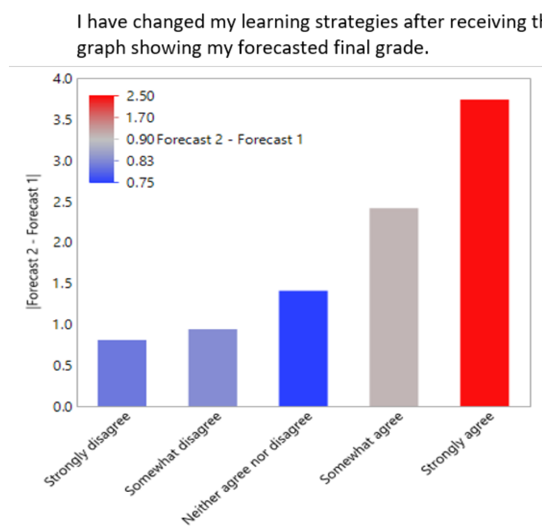

Figure 9: The Effect of FEP on Planned Alteration of Learning Strategy

4.2 Forecast Accuracy

Another interesting aspect of this case study deals with the accuracy of the forecasting graphs, which are distinct components of personalized feedback emails. An ideal forecasting method is expected to predict the final grade of students accurately. It is primarily expected to detect the students who are at the risk of failure (at-risk students). This prediction should provide a perspective of the success of students for all agents who may influence students' performance, including instructors, teaching assistants, coordinators, mentors, advisers, parents, and students themselves. In addition, this perspective should be presented early enough to provide decision-makers and advisors with an adequate time window to make appropriate modifications in learning strategy, or at least, to decide about the fundamental measures such as withdrawal. Here, the accuracy of forecasts significantly matters.

In order to figure out the forecast accuracy, we measured the absolute error of the initial forecast compared with the actual final grades (i.e., |Final - Forecast 1|). This measure is expected to indicate the accuracy of the initial forecast grade. We found a correlation of -0.67 (significance: 0.0001*) between the accuracy of the initial forecasts (|Final - Forecast 1|) and students' final grades. This means, roughly speaking, the lower the final grade of a student was, the less accurately it had been forecasted at the beginning of the semester (see Figure 10). As a complement to this finding, Figure 11 shows that students whose forecasts were very accurate (the blue zone), would highly contribute to class activities and/or would obtain the best final grades. Indeed, students with low contribution rates are more likely to end up receiving final grades far from the forecasted ones. If the most useful function expected from forecasting is to precisely detect students at risk at an early stage of the semester, our forecasting method has not served this cause. In the following section, we devise a machine learning approach to remedy the inaccuracy of the forecasts.

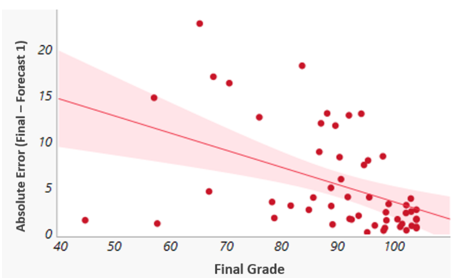

Figure 10: Correlation Between Final Grades and Forecast Accuracy

4.3 Forecast Improvement through Machine Learning

The inefficiency of forecast method at the edges, which we addressed in the preceding section, is clearly illustrated in Figure11, where it is shown that the forecast has a high error in the case of at-risk students with lower grades (lower than 70%). This encouraged us to leverage different machine learning techniques to improve the precision of our forecasting model.

As a diagnostic attempt, we looked at Figure 12, which represents the accuracy of the two forecasts. The size of each spot denotes the total magnitude of students' contributions. This figure shows

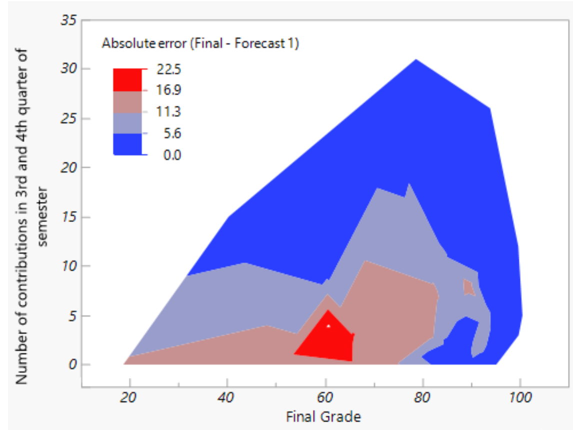

Figure 11: Distribution of Forecast Accuracy (Color-Coded) by Rate of Contribution and Final Grade

that both forecasts have a reasonable general accuracy (0.69 and 0.88, respectively). On the other hand, the highest magnitude and density of contributions appear at the segments of the curves that bear the maximum accuracy. Furthermore, it is interesting that in the first forecast, a strong majority of large spots (which mean significant contributions) are located at points for which the forecast is lower than the actual final grade (spots below the line). This observation naively suggests that there must be a model in which, by emphasizing on contributions, the accuracy of forecasts can be improved.

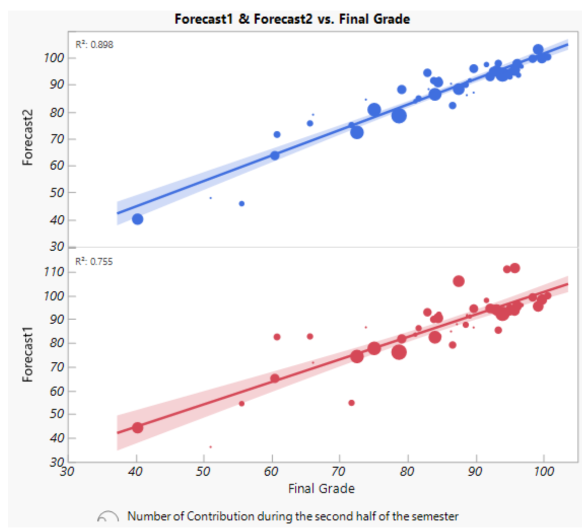

Figure 12: The Accuracy of First and Second Forecasts, and Rate of Contribution

In order to enhance the accuracy of the model, we tried various machine learning techniques with all the information we gathered from students' backgrounds, including the current GPA, grade details, contributions, and our initial forecasts. Table 1 shows the list of the top well-performed machine learning algorithms along with their correlation coefficient, mean absolute error, and root means squared error. The Greedy Linear Regression resulted in the correlation coefficient of 0.98, which is the best among all.

Table 1: Result of Machine Learning Models

Model	Correlation Coefficient	Mean Absolute Error	Root Mean Squared Error
Greedy Linear Regression	0.9858	2.0762	2.7263
Linear Regression	0.984	2.2871	2.9115
M5Rules	0.9752	2.4308	3.6135
Multilayer Perceptron	0.9659	3.2996	4.2346
Random Forest	0.9339	3.7979	6.3216
Decision Table	0.6152	8.7758	12.7693
Random Tree	0.7374	7.6238	11.9853

Looking at the effect of each feature in the created model (based on their P-Value), the features that play the primary role in our regression model are:

- Midterm Exam's Grade
- $(Contribution1)^2$
- $(Contribution1) * (Contribution2)$
- The multiplication of all first 6 assignment grades

Having applied the Greedy Linear Regression, Figure 13 shows how the updated model resulted in a lower error rate, specifically for at-risk students, which, as a result, enables us to identify and target the students who are at the risk of failure, early enough in the semester.

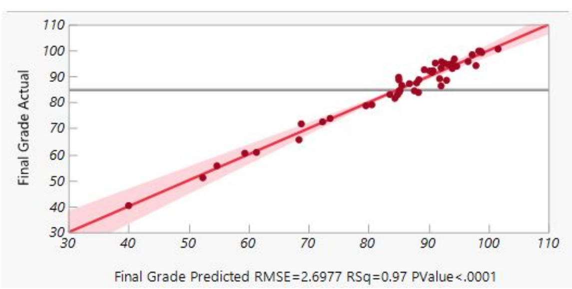

Figure 13: The Accuracy of Forecasting Model Improved by Greedy Regression

5 DISCUSSION AND FUTURE WORK

In this study, we analyzed the data collected from two different sections of the same online course taught during Summer and Fall semesters, respectively. Although some control variables such as the number of assignments and exams, course material, instructor, and teaching assistant were the same in these two sections, some potentially significant features of the Summer semester were different from those of the Fall semester. For example, as Figure 14 shows, the mean of the GPA of the students who took this course in Summer was higher than that of the students of the Fall semester.

Furthermore, another difference between the semesters that needs to be considered lies in the fact that Summer courses are shorter than those of regular semesters. This makes a Summer

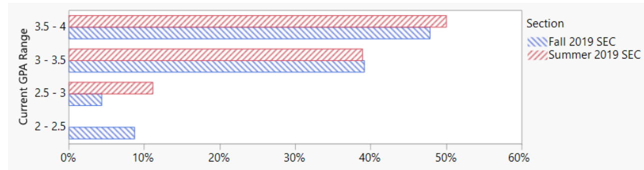

Figure 14: GPA Comparison in the Summer and Fall Semesters

course denser than a regular one in terms of events, including the frequency of PFEs. Consequently, the short-time effect of feedback emails covers a larger proportion of a summer semester in comparison with that of regular semesters. If, as we discussed in section 4.1.1, the short-time effect of PFEs has resulted in the rise of the rate of contribution, the fact that in summer more contribution opportunities could fall in the scope of the short-time effect of PFEs, may explain the higher contribution rates in summer (see Figure 15).

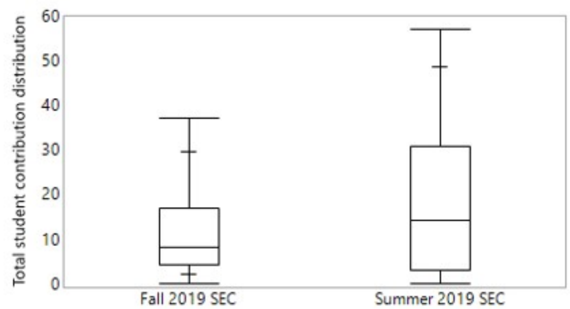

Figure 15: Distribution of Contribution in Fall and Summer

With all these remarks in mind, creating two separate models, one for a regular semester (Fall or Spring) and the other one for a short semester (Summer), would help us increase the accuracy of our models. Enforcing such a separation, the accuracy of the models will increase to RMSE=2.9724, RSq=0.99, PValue<.0001 for the Fall semester, and RMSE=3.9696, RSq=0.99, PValue=0.0002 for the Summer semester.

On the other hand, despite the effect of feedback emails on the contribution rate and learning strategy of students, Figure 16 shows how the progress monitoring emails helped most students to relieve their stress during the semester. However, considering that most of the students who did not earn high final grades found these emails stressful, we are thinking of creating different email themes for students with different levels of performance.

In particular, there are three main areas on which we are planning to focus in order to improve our research. First, we would like to use more data points gathered from different semesters, different courses, and other schools to make a more generalized conclusion. Besides, we would also like to look into the quality of the contributions made by students. Most discussion platforms, such as Piazza, allow the students and instructors to rate the responses based on

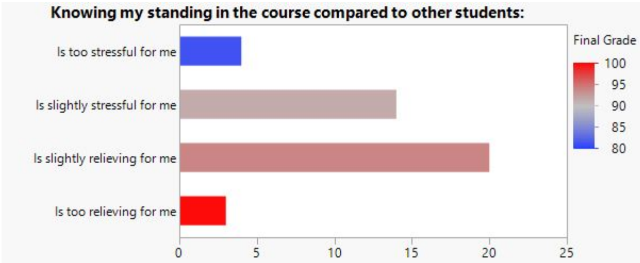

Figure 16: Distribution of Final Grades by Intensity of Stress Caused by PFE

their quality and relevance. This could also be considered as a data point in our future analysis.

Second, we are planning to develop a more practical, personalized, and sophisticated method for the feedback delivery system. We have realized that finding the best point of time to send feedback to students and its effect on students' feelings and behaviors are challenging aspect in teaching, as it is discussed in [6]. Also, students' mindsets affect the way students respond to the feedback they receive [7]. Therefore time, frequency, and content of feedback emails should be studied further in order to be able to provide more personalized and efficient emails.

We also aim to study the effect of placebo feedback emails to see if wit is possible to motivate a bigger group of students to get more involved in class discussions and to posit better questions to get proper assistance.

6 CONCLUSION

The quantitative and qualitative analysis of the effect of Personalized Feedback Emails (PFE) shows that they were remarkably successful at engaging students. The strong correlation between the improvement of students' contributions and the improvement of their performance suggests that PFE is an effective tool for the majority of students and equips educators to assist students to improve their class contributions and performance. PFE's short-time effect on students' performance is even stronger and has a significant impact on students' performance in assignments and exams. Besides, this method can aid students in finding better learning strategies, which also results in the enhancement of their performance. The majority of students report that having been exposed to PEF, their stress level significantly declined in the course of the semester. Finally, machine learning techniques enable us to accurately identify the students who are at the risk of dropping the course, who usually need special assistance to become more involved in class activities.

REFERENCES

[1] A. Anderson, D. Huttenlocher, J. Kleinberg, and J. Leskovec. 2014. *Engaging with Massive Online Courses.* ACM, -. 687–698 pages.
[2] C. G. Brinton, M. Chiang, S. Jain, H. Lam, Z. Liu, and F. M. F. Wong. 2014. Learning about Social Learning in MOOCs: From Statistical Analysis to Generative Model. *IEEE transactions on Learning Technologies* 7, 4 (2014), 346–359.
[3] M. Bullen. 2007. Participation and Critical Thinking in Online University Distance Education. *International Journal of E-Learning & Distance Education/Revue internationale du e-learning et la formation à distance* 13, 2 (2007), 1–32.
[4] R.A. Croxton. 2014. The Role of Interactivity in Student Satisfaction and Persistence in Online Learning. *Journal of Online Learning and Teaching* 10, 2 (2014), 314.
[5] D. Engle, C. Mankoff, and J. Carbrey. 2015. Coursera's Introductory Human Physiology Course: Factors that Characterize Successful Completion of a MOOC. *The International Review of Research in Open and Distributed Learning* 16, 2 (2015).
[6] J. Fluckiger, Y. T. Y. Vigil, R. Pasco, and K. Danielson. 2010. Formative Feedback: Involving Students as Partners in Assessment to Enhance Learning. *College teaching* 58, 4 (2010), 136–140.
[7] A. Forsythe and S. Johnson. 2017. Thanks, but no-Thanks for the Feedback. *Assessment & Evaluation in Higher Education* 42, 6 (2017), 850–859.
[8] S. Goggins and W. Xing. 2016. Building Models Explaining Student Participation Behavior in Asynchronous Online Discussion. *Computers & Education* 94 (2016), 241–251.
[9] S. Kurkovsky, C. C. Whitehead, et al. 2005. *Using Asynchronous Discussions to Enhance Student Participation in CS Courses.* Vol. 37. ACM, na. 111–115 pages.
[10] Y. Ma, C. Friel, and W. Xing. 2014. *Instructional Activities in a Discussion Board forum of an e-Learning Management Ssystem.* Springer, na. 112–116 pages.
[11] D. FO. Onah, J. Sinclair, and R. Boyatt. 2014. Dropout Rates of Massive Open Online Courses: Behavioural Patterns. *EDULEARN14 proceedings* 1 (2014), 5825–5834.
[12] G. Piccoli, R. Ahmad, and B. Ives. 2001. Web-based Virtual Learning Environments: A research Framework and a Preliminary Assessment of Effectiveness in Basic IT Skills Training. *MIS quarterly* na, na (2001), 401–426.
[13] J. Reeve and H. Jang. 2006. What Teachers Say and Do to Support Students' Autonomy During a Learning Activity. *Journal of educational psychology* 98, 1 (2006), 209.
[14] P. Reimann. 2009. Time is Precious: Variable-and Event-Centred Approaches to Process Analysis in CSCL Research. *International Journal of Computer-Supported Collaborative Learning* 4, 3 (2009), 239–257.
[15] C. P. Rosé, R. Carlson, D. Yang, M. Wen, L. Resnick, P. Goldman, and J. Sherer. 2014. *Social factors that contribute to attrition in MOOCs.* ACM, na. 197–198 pages.
[16] J. L. Shackelford and M. Maxwell. 2012. Sense of Community in Graduate Online Education: Contribution of Learner to Learner Interaction. *The International Review of Research in Open and Distributed Learning* 13, 4 (2012), 228–249.
[17] G. Stahl, T.D. Koschmann, and D.D. Suthers. 2006. *Computer-Supported Collaborative Learning.* na, na.
[18] S. Voghoei, N. Hashemi Tonekaboni, D. Yazdansepas, and H. R. Arabnia. 2019. University Online Courses: Correlation between Students' Participation Rate and Academic Performance. *6th Annual Conf. on Computational Science & Computational Intelligence, CSCI-ISED* na, na (2019), na.
[19] D. Wu and S. R. Hiltz. 2003. Online Discussions and Perceived Learning. *AMCIS 2003 Proceedings* na, na (2003), 86.
[20] D. Yang, T. Sinha, D. Adamson, and C. P. Rosé. 2013. *Turn on, Tune in, Drop out: Anticipating Student Dropouts in Massive Open Online Ccourses.* Vol. 11. NIPS, Boston. 14 pages.
[21] M. Zhu, Y. Bergner, Y. Zhang, R. Baker, Y. Wang, and L. Paquette. 2016. *Longitudinal Engagement, Performance, and Social Connectivity: a MOOC Case Study using Exponential Random Graph Models.* ACM, na. 223–230 pages.