

Game Theory based Peer Grading Mechanisms for MOOCS

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ABSTRACT

An efficient peer grading mechanism is proposed for grading the multitude of assignments in online courses. This novel approach is based on game theory and mechanism design. A set of assumptions and a mathematical model is ratified to simulate the dominant strategy behavior of students in a given mechanism. A benchmark function accounting for grade accuracy and workload is established to quantitatively compare effectiveness and scalability of various mechanisms. After iteration of mechanisms under increasingly realistic assumptions, three are proposed: Calibration, Improved Calibration, and Deduction. The Calibration mechanism performs as predicted by game theory when tested in an online crowd-sourced experiment. The Deduction mechanism performs relatively well in the benchmark, outperforming traditional automated and peer grading systems. The mathematical model and benchmark opens the way for future derivative works to be performed and compared.

Author Keywords

MOOC; game theory; mechanism design; peer grading; learning at scale;

ACM Classification Keywords

K.3.m. Computers and Education: Miscellaneous

INTRODUCTION

Over the past few years, there has been a tremendous increase in the popularity of MOOCs (Massive Open Online Courses) and their importance to education as a whole. Popular MOOC systems such as Coursera or EdX are well funded, which explains their rapid growth: 60 million dollars were invested in EdX when it started in May of 2012 [9]. However, the main importance of MOOCs come from their scalability. MOOCs are able to educate massive numbers of students from anywhere in the world [4]: by the end of 2012, 1.7 million students had attended a course through Coursera [7]. The sheer number of students leads to high student-professor ratios that can reach 150,000:1 in some courses.

High student-professor ratios lead to problems for professors. Professors are simply unable to grade hundreds of thousands of submissions. Currently, two types of solutions are used to remedy the problem: automated grading and peer grading [8]. Automated grading relies on machines to grade assignments. Machines can only check certain types of answers (i.e. multiple choice), severely limiting the depth of the questions asked [2]. Even though automated grading for written essays is an active area of research with much recent progress, the quality and accuracy of such systems is under heavy debate [5]. Students who know the machine's grading criteria can fool the system [10], yielding inconsistent grades. On the other hand, peer grading can grade any type of question, a system utilizing it could easily be "hacked" by the students [4]. Additionally, lack of feedback from peer grading is an area of complaint in systems such as Coursera [11]. These limitations render the students unable to effectively evaluate the mastery of the course material.

We propose several peer grading mechanisms based on game theory and our student model - a set of assumptions we believe students abide by. We also create a benchmark to compare between our and existing mechanisms. Although a theoretical model cannot predict exactly what will happen in practice, game theory and mechanism design have a history of generally determining mechanisms that work in practice from ones that do not [6]. Mechanisms that do not follow game theoretic constraints may work in the short-term, but they will be exploited if possible in the long term [3].

MODEL AND ASSUMPTIONS

Our student model consists of assumptions we believed students abide by, as follows:

1. Let H be a function of a student's grade, returning a student's happiness, such that $H(0)=0$.
Happiness is an arbitrary numerical unit.
2. Students want to maximize their happiness.
3. Grading an assignment costs 1 happiness.
4. Happiness is not affected by external factors, such as the grades of peers.
5. Students can communicate with their peers.
6. Students are not perfect graders.
7. There is no such thing as partial-grading.

8. Students can report their level of uncertainty when they grade. Let this factor be equal to U .
9. More effort spent in grading lowers uncertainty.
10. When a student assigns a grade G , the chance of the grade being N off from the actual grade is proportional to U .

BENCHMARK

To compare mechanisms, we created a numerical benchmark (objective function) where a lower score is better. The score is computed by adding the most work done by any person to the highest possible error in grading. Mathematically:

$$\max_{i \geq 1} \{|H(g_i) - H(o_i)|\} + \max_{i \geq 0} \{w_i\}$$

Mechanisms

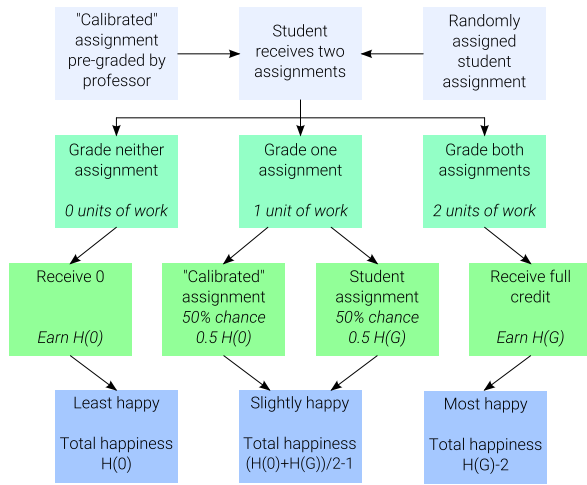


Figure 1. A flowchart of the Calibration Mechanism from the student perspective.

The Calibration mechanism is described visually in Figure 1. It achieves a low benchmark score of 4, of a 2 in max work done and 2 in max error in grade. The Calibration mechanism can break when students communicate to reveal the calibrated assignment to circumvent grading. The Improved Calibration mechanism mitigates this issue by introducing multiple calibrated papers at the expense of more work, raising the objective score.

We tested and verified the Calibration mechanism through an anonymous crowdsourced experiment. In this case, “grading” involved counting two sets of objects. Initially unknown to the participant, one set is “calibrated” and will be used to reward the participant based on the accuracy of the grading.

The Calibration mechanism rewards students for accurately grading the Calibrated set in order to reduce the grading error for the uncalibrated set, as shown in Figure 2. This is also evident in Figure 3, where less error in grading the Calibrated set correlates to a lower maximum grading error. An accurate grade for the uncalibrated set is the goal for the Calibration mechanism, and the data suggests that the mechanism works in practice.

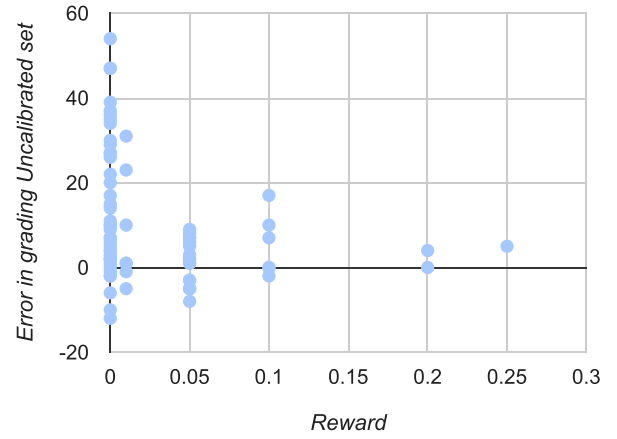


Figure 2. Uncalibrated Error vs Reward

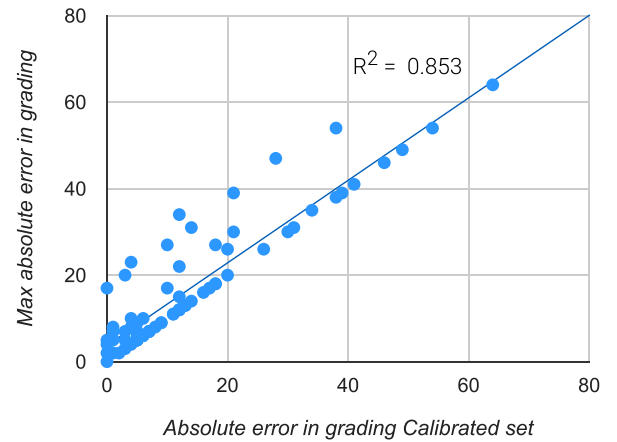


Figure 3. Max error vs Calibrated error

Deduction Mechanism

The Deduction mechanism (Figure 4) achieves a very low benchmark score of 2, consisting of a 2 in max work done and a 0 in max error in grade. Incapable graders will raise the benchmark score, as they issue refutations that add work to the professor.

RESULTS

The comparison of existing solutions and those proposed in this work can be seen in Figure 5. Each mechanism will be explained below.

Traditional Professor Grading involves one professor grading all assignments. In a class of 1000 students, this method is extremely inefficient.

In Traditional Peer Grading, each student grades another’s assignment without any supervision. However, as in this mechanism, the objective score is high due to the potential error caused by lack of motivation to grade properly.

Although without requiring effort from either professor or student, Traditional Automated Grading of open-ended responses are still under heavy research. Current solutions are quite preliminary, though can arrive at a grade within approximately 25 percent [5].

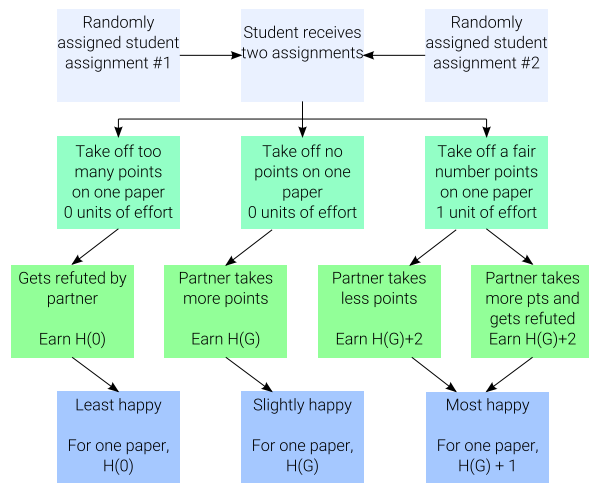


Figure 4. A flowchart of the Deduction Mechanism from the student perspective.

The Calibration Mechanism requires one calibrated paper from the professor and two papers graded by each student. The objective score is raised to 4 instead of 2 because students are incentivized by increasing their grade, thus sacrificing accuracy.

The Improved Calibration Mechanism requires each student to grade a subset of the other student's assignments, and the teacher to grade another subset. This mechanism addresses the flaw in the Calibration Mechanism that occurs when students can communicate, at the expense of more work. Thus, leading to poor scalability.

The Deduction Mechanism rewards graders for grading more harshly than their peers, and relies on a voting system to reject grades that are below the expected grade to be reviewed by the professor. In the dominant strategy behavior of the system, no grades should be rejected, leading to no work for the professor. Again, incentive given to the students comes at the cost of accuracy, raising the objective score by two points.

Overall, our Calibration and Deduction mechanisms vastly outperform existing solutions with the exception of Improved Calibration.

CONCLUSION

An efficient and accurate solution is needed to grade the large number of assignments in MOOCs.

We began by creating a student model - a set of assumptions that approximate the realistic behavior of students. We then developed various grading mechanisms based on our student model and mechanism design. These mechanisms would incentivize students to grade accurately and efficiently as proven by game theory.

We tested our Calibration mechanism using a crowdsourced experiment, finding that it could work in practice. A mechanism based on a more realistic model would achieve better results.

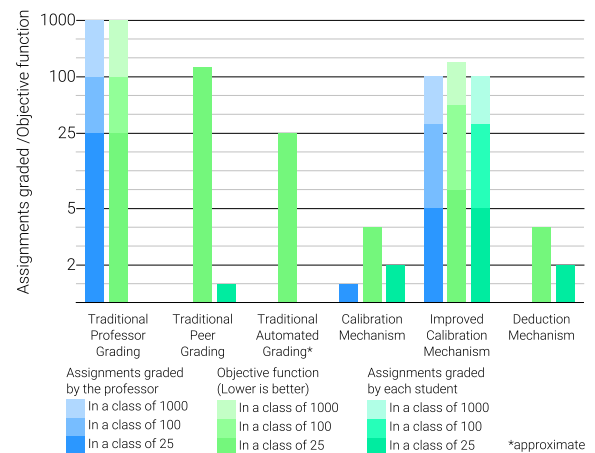


Figure 5. A comparison of mechanisms in terms of effectiveness and scalability.

Our model can easily be reused and improved upon by future researchers who wish to develop more efficient solutions. Efficiency is measured in terms of the benchmark we created, a numerical score encompassing both the accuracy of grades and the effort spent by any one person. To the best of our knowledge, this is the first game-

FUTURE WORK

As we consider how to generate accurate grades from incompetent graders, our model will require more realistic assumptions, which in turn may create more complex mechanisms. Eventually, we would like to see new mechanisms based off of our model or our existing mechanisms implemented in MOOCs such as EdX or Coursera.

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