ANTI-COLLUSION DISTANCED ONLINE TESTING

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INTRODUCTION

Testing plays an important role in education by helping reinforce lessons, measure student outcomes and drive improvements. However, cheating poses a major challenge to effective testing, and is prevalent at all levels (Diekhoff et al., 1996; Galante, 2012), as a long-term study by The International Center for Academic Integrity (McCabe et al., 2012) conducted between 2002 and 2015 found: 43%, 68% and 95% of students admitted to cheating in assignments or exams at graduate, undergraduate, and high school level respectively. Indeed, a 2010 survey based on self-reports (Watson and Sottile, 2010), later validated by direct measurements (Corrigan-Gibbs et al., 2015) shows that 80% of cheating events involve collusion among students, significantly more than cheating from Internet websites at 42%, while 21% of cheating events fell in both categories. Recent shifts towards online delivery of education in response to the COVID-19 pandemic (Toquero, 2020; Vlachopoulos, 2020) have only exacerbated these serious concerns around cheating. Unfortunately, traditional forms of anti-collusion such as proctoring are often ineffective (Chin, 2020), or raise serious concerns regarding privacy (Harwell, 2020; Lilley et al., 2016; Sullivan, 2016).

We address this problem by developing a DOT platform which implements novel anti-collusion techniques developed in (Li et al., 2020) to minimize total collusion gain, given students' competencies and a collusion network to represent relationships between pairs of students who can possibly collude. Here, the expected gain a student may experience by colluding to answer a question is proportional to the difference between her competency and the competency of the student they are colluding with. A key challenge to the practical use of the anti-collusion techniques developed in (Li et al., 2020) is estimating the collusion network. Our work addresses this by integrating deep learning techniques into our DOT platform to estimate the collusion network, thus enabling the practical realization and application of our DOT platform to run real online exams for the first time. Our approach of minimizing collusion is independent from and complementary to proctoring, and conserves privacy.

DOT PLATFORM

(1) Framework: Our framework assigns questions to students to be answered sequentially within designated time slots during which students cannot navigate to another question. The length of a time slot is carefully chosen to allow sufficient time for a student to answer one question, while being insufficient to answer more than one, based on past data. Therefore, a student involved in collusion can only share the answer to a question they have already answered. More details about our framework can be found in (Li et al., 2020). A demonstration of our DOT platform is available at: `https://www.distancedot.ml/visitors/visitor_demo`. Our DOT platform allows educators to create an exam by specifying a roster of students, a pool of questions, number of questions each student must be assigned, and

historical data on student performance and behaviors, and optionally, each question's time slot length and difficulty. Our algorithms (shown below) estimate student competencies and collusion and compute an assignment with minimum collusion gain w.r.t. these estimates. Our DOT platform ensures fairness by allowing instructors to specify whether every student should receive an exam with equal average difficulty, length, number, and total length of questions, and can be naturally extended to ensure more sophisticated objective notions of fairness such as bounding the maximum collusion gain any student can experience, irrespective of competence or other attributes.

(2) Two phase approach to minimizing collusion gain: (i) Phase 1: Learn Competency and Collusion Behavior. We estimate student competencies based on past performance and use deep learning techniques to predict the collusion network of students. Our models can be trained on both real-world data of collusion behavior and large synthetic data generated using probabilistic generative models of collusion behavior and response dynamics. (ii) Phase 2: Compute Collusion Gain Minimizing Assignment. We compute a collusion gain minimizing assignment using optimal and approximate heuristic algorithms presented in (Li et al., 2020).

EMPIRICAL VALIDATION

We conducted midterm and final exams for a course on Medical Imaging with Machine Intelligence at the Rensselaer Polytechnic Institute involving 17 students.

(1) Student Outcomes: Our results show that the distribution of the scores of students from the midterm exams, and the final exam are similar as are the mean and mode of the scores. This suggests that collusion gain minimizing assignments do not skew class performance overall. More details and figures will be made available in a full version online.

(2) Student Feedback: Students were surveyed at the end of the final exam to rate their satisfaction with the convenience of using our DOT platform, and perceptions of similarity with other online testing platforms, on a five-point Likert scale, ranging from very satisfied to very unsatisfied and from very similar to very different respectively. We observe that greater than 75% of students found the platform to be convenient or very convenient and that the length of time slots to be generally acceptable and not stressful, while more than 61% students found the DOT platform similar or very similar to other platforms.

CONCLUSION

The results from real world online tests demonstrate the effectiveness of our DOT platform. While the intuitively natural approach to prevent collusion by assigning questions randomly in fixed time slots is well known, it is demonstrably sub-optimal in lowering collusion in online testing. Our collusion gain minimizing approach provides a low-cost, and privacy-preserving solution to the problem of cheating in online exams during social distancing and compliments other methods to prevent cheating such as proctoring, and methods to prevent contract cheating such as ID authentication and behavioral biometrics analysis (Amigud et al., 2017). The deep learning techniques we develop to estimate collusion networks enable the practical realization of our DOT platform to real world online tests. In the long term, we believe that our methods will help improve the quality of online courses and contribute to the future of education by democratizing it globally.

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