Report-Sensitive Spot-Checking in Peer-Grading Systems

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Abstract

Peer grading systems make large courses more scalable, provide students with faster and more detailed feedback, and help students to learn by thinking critically about the work of others. A key obstacle to the broader adoption of peer grading is motivating students to provide accurate grades. To incentivize accurate grading, previous work has considered mechanisms that spot-check each submission (i.e., randomly compare it to a TA grade) with a fixed probability. In this work, we introduce a mechanism that spot checks students in a way that depends on the grades they report, providing the same incentives at lower costs than the fixed-probability mechanism. We also show, surprisingly, that TA workload is reduced by choosing not to spot check some students even when TA assessments are available.

1 Introduction

Peer grading has the potential to improve educational outcomes in three main ways: (i) making classes more scalable by offloading some grading work to students, (ii) providing students with faster and more detailed feedback, and (iii) improving student learning by providing opportunities to think critically about the work of others. Various recent implementations of peer grading mechanisms make such systems relatively easy to deploy in practice (Wright \textit{et al.}, 2015; De Alfaro and Shavlovsky, 2014; Merrifield and Saari, 2009). The broader adoption of such systems faces a common, critical obstacle: motivating students to provide accurate grades. A natural solution is asking multiple students to grade the same assignment and rewarding them based on their behavior (e.g., based on the extent to which their grades agree with the grades given by other students). Such solutions have been explored in detail in a large literature on \textit{peer prediction}, which considers how to incentivize agents to truthfully disclose unverifiable private information (Faltings \textit{et al.}, 2012; Prele, 2004; Radanovic and Faltings, 2014; Riley, 2014; Witkowski and Parkes, 2012; Witkowski \textit{et al.}, 2013; Jurca and Faltings, 2009; Kong \textit{et al.}, 2016; Jurca and Faltings, 2005; Kamble \textit{et al.}, 2015; Radanovic and Faltings, 2013; Shnayer et al., 2016).

Miller \textit{et al.} (2005) were the first to introduce peer prediction mechanisms in which truthful declarations constitute a Nash equilibrium. Unfortunately, these mechanisms (and, indeed, many others that were subsequently proposed) also give rise to uninformative equilibria in which agents do not reveal their private information; e.g., all students grading an assignment favorably regardless of its quality (Jurca and Faltings, 2009; Witkowski \textit{et al.}, 2013; Kong \textit{et al.}, 2016; Shnayer \textit{et al.}, 2016; Dasgupta and Ghosh, 2013). Human experiments show that such strategic behavior does arise in practice (Gao \textit{et al.}, 2014).

Much subsequent work has attempted to identify peer prediction mechanisms in which either no uninformative equilibrium exists or the truthful equilibrium is always preferred by agents (Jurca and Faltings, 2009; Witkowski \textit{et al.}, 2013; Kong \textit{et al.}, 2016; Shnayer \textit{et al.}, 2016). Two examples are particularly notable. First, Dasgupta and Ghosh (2013) considered a model in which agents make a binary decision about whether or not to invest costly effort, in the former case observing a noisy signal about the assignment’s true value. Agents are paid according to a function that rewards agreement between graders on the same assignment and penalizes correlations in the grades assigned across different assignments. Under this mechanism, truthful reporting yields payoffs that exceed those of any other equilibrium for every agent. Furthermore, if the system contains a small fraction of agents (e.g., TAs) who are always truthful, the truthful equilibrium becomes unique. Second, De Alfaro \textit{et al.} (2016) showed how to achieve unique, truthful equilibria by combining peer prediction with trusted reports in a hierarchical mechanism. One drawback of all such approaches is that they cannot do better than Nash equilibrium implementations. This is because agents’ payoffs depend on other agents’ actions, and so agents must reason about each other’s behavior. In a classroom setting, where some students will almost surely fail to invest effort, students may need stronger incentives; we thus seek dominant strategy mechanisms. Such mechanisms can be obtained by incorporating trusted graders (TAs) more fundamentally into the mechanism: guaranteeing that each student report is compared to a trusted evaluation (which we will call a spot check) rather than to other student evaluations with some sufficiently large probability. The idea of combining such “spot checking” with peer grading mechanisms to incentivize accurate grading has been explored in some re-
recent past work (Jurca and Faltings, 2005; Wright et al., 2015; Gao et al., 2016; Wang et al., 2018). Because spot checking is expensive (e.g., TAs need to be paid in proportion to the amount of work they do), it is natural to seek to minimize the amount of spot checking required to obtain dominant strategies. This minimization problem was first attacked by Gao et al. (2016), who proposed a very simple mechanism that makes truthfulness a dominant strategy by unconditionally rewarding students when they are not spot checked and penalizing them to the extent that they disagree with the TA otherwise. They compared this mechanism with various alternatives based on peer prediction, showing that the latter require strictly more spot checking than the former, even despite the fact that peer-prediction-based mechanisms do not offer dominant strategies.

Gao et al.’s model always performs spot checks with some fixed probability. It is intuitive to think that report-sensitive spot checking—that is, varying the spot checking probability based on the students’ reports—could lower the expected amount of spot checking required overall. For example, imagine that an instructor already knows that a given problem set is extremely difficult. If the reported grades for a given submission are all very high, the instructor might believe that there is an increased likelihood that students have reported dishonestly, and so might want to spot check with a higher probability. It turns out to be nontrivial to confirm or refute this intuition, for two key reasons. First, more complex ways of computing spot check probabilities opens the door to new ways for students to manipulate a mechanism. Second, students’ interests become intertwined in a new way, since spot checking probabilities now depend on other agents’ strategies.

Despite these obstacles, this paper identifies the optimal dominant-strategy incentive-compatible report-sensitive spot-checking mechanism, and shows that it requires less spot checking than the previous state of the art, the simple mechanism of Gao et al. Like much other work in the literature (e.g., Dasgupta and Ghosh, 2013; Wang et al., 2018), our analysis is limited to the case where students are asked to report only positive or negative grades about each assignment. Our new mechanism is general in several important senses: it allows for arbitrary numbers of graders per assignment and nearly arbitrary\(^1\) prior probability distributions over both the true grades and the noise models describing the probabilities that students and TAs will observe each signal given the ground truth.

One final and very recent related paper is worth mentioning here. Wang et al. (2018) propose a different approach for designing peer grading systems that also varies spot check probabilities. Their model is substantially different from ours, and hence their mechanism is not directly applicable to our setting. Like us, they study strategic students who make a binary decision about whether to invest effort. However, they also assume that TAs can directly observe whether a student invested effort, making it simple to ensure that a spot-checked student who invested no effort gets no reward. In contrast, we assume that the TA noisily observes the assignment’s grade and is only able to compare this observation to the student’s own report, which is either a noisy signal or a misreport; thus, students who invest no effort cannot reliably be identified.

In the remainder of this paper, we first define our model and formalize the different mechanisms that we study throughout the paper in Section 2. We prove that our proposed mechanism is optimal in Section 3 and show that it outperforms alternatives in Section 4. Finally, we conclude in Section 5.

2 Model

A single assignment needs to be graded by a set \(N\) of students (with \(|N| = n\) and has an unobservable binary quality \(q \in Q = \{a, b\}\) drawn from a commonly known distribution \(P(q)\). Each student \(i\), by exerting effort at cost \(c\), can examine the submission and observe a signal \(s_i \in Q\) that is informative about the assignment’s quality. More formally, in a way that depends on the true quality \(q\), the signals observed by different students are independently drawn from a commonly known distribution \(P(s|q)\). The ex ante signal distribution is then

\[
Pr[s = t] = \sum_{t \in Q} Pr[|s = l|q = t] Pr[q = t].
\]

We denote by \(P_{i}\) the ex ante probability of each agent receiving the signal corresponding to its index in vector \(\vec{l}\). By our assumption of conditional independence, this is

\[
P_{i} := Pr[s_1 = l_1, \ldots, s_n = l_n] = \prod_{j \in N} Pr[s = l_j|q = t].
\]

Because of conditional independence, any two vectors of reports \(\vec{l}\) and \(\vec{l}'\) containing the same numbers of \(a\’s\) and \(b\’s\) occur with the same probability: \(P_i = P_{i}'\). For this reason, we often drop the ordering in the subscript, writing, e.g., \(P_{(a,b)} = P_{(b,a)} = P_{ab}\), and similarly for longer vectors. Also, we name the signals so that \(P_a \geq P_b\).

Besides the students, a teaching assistant (TA) may also receive a signal. Formally, signal \(s_{TA}\) is drawn from \(P(s|q)\) independently from the students’ signals and again depends on the assignment’s quality \(q\).

Strategy space In our model, each student faces two strategic choices: whether to expend effort grading the assignment and what grade to report. Three actions are thus possible: the student (i) may be truthful, investing effort to examine the assignment, observing her signal, and reporting this signal; (ii) may invest effort but report a different signal than the one she observed; or (iii) may choose not to invest effort and report an arbitrary signal. In contrast, the TA is not a strategic agent. When asked to grade the assignment, the TA always reports an independently observed signal.

2.1 Spot-checking Mechanisms

A focus of our work is on minimizing the need for the TA’s input via spot-checking mechanisms. A spot-checking mechanism takes in students’ reported signals and decides both whether a TA signal is needed and how much to reward the students.

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\(^1\)We restrict these distributions only via the assumption that deterministically spot checking yields dominant strategies for the mechanism of Gao et al; see Assumption 2.8.
Definition 2.1 (Spot-checking mechanism). A spot-checking mechanism is defined by a tuple \((x_a, x_b, Y)\), where:

1. \(x_a : \mathbb{N} \times \mathbb{N} \to [0, 1]\) denotes the probability of spot checking an agent who reports \(a\). Given two natural numbers \((k, n)\) specifying the number of \(a\)’s reported by the agents and the total number of agents, \(x_a\) returns the probability that the mechanism will spot check agents reporting \(a\).
2. \(x_b : \mathbb{N} \times \mathbb{N} \to [0, 1]\) is an analogous function for computing the probability of spot checking an agent who reports \(b\). The first argument remains the total number of agents who report \(a\), not \(b\).
3. \(Y : \mathbb{Q} \times \mathbb{Q} \to \mathbb{R}^+\) denotes the reward given to a student who is spot checked. \(Y(r, s_{TA})\) is the reward given to a spot-checked student who made report \(r\) when the TA reported signal \(s_{TA}\). When a student is not spot checked, she receives no reward.

The \(x\) functions are defined for every \(n\) because we require peer grading mechanisms to work for any number of agents. However, when \(n\) is obvious from context, we will overload notation and write simply \(x_a(k)\) and \(x_b(k)\).

Throughout this paper we focus on mechanisms where the reward function \(Y\) is the simplest identity function:

\[
Y(r, s_{TA}) = \begin{cases} 1 & \text{if } r = s_{TA} \\ 0 & \text{otherwise.} \end{cases}
\]

This function is called the output agreement reward function; it has been widely studied in the peer prediction literature (Witkowski et al., 2013; Waggerer and Chen, 2014).

We model students as having quasilinear utility: i.e., when investing effort (at cost \(c\)) and being rewarded \(Y\), a student’s utility is \(Y - c\).

Definition 2.2 (DSIC). A spot-checking mechanism is dominant strategy incentive compatible (DSIC) if, for each student \(i\) and for any strategies that the other students choose, \(i\)’s expected utility-maximizing strategy over TA signal is to be truthful, i.e., to invest effort to observe her signal and to report what she observes.

The mechanism we will later show to be optimal is DSIC; however, we also define a weaker solution concept (“ICCP”), to allow us to compare our preferred mechanism to a broader set. ICCP corresponds to requiring that it be a dominant strategy for students to invest effort under the assumption that every student who does observe a signal reports it honestly.

Definition 2.3 (ICCP). A spot-checking mechanism is Incentive Compatible with Conscientious Plays (ICCP) if, for each student and for any strategy that other students choose, as long as each student that examines the assignment always reports the observed signal, the truthful strategy, i.e., to invest effort to examine the assignment and report her observed signal, is expected utility maximizing over TA signal.

Definition 2.4 (TA workload). For a DSIC or ICCP spot-checking mechanism, the TA workload (or simply the workload) is the probability with which the TA needs to provide a signal, assuming all students are truthful:

\[
\sum_{r \in Q} \Pr[q = t] \sum_{j=0}^{n-1} \left( \Pr[s = a(q = t)] \right)^j 
\cdot \left( \Pr[s = b(q = t)] \right)^{n-j} \max\{x_a(j), x_b(j)\}. \tag{2}
\]

The expression \(\max\{x_a(j), x_b(j)\}\) in (2) is the probability with which the TA needs to be consulted, given that \(j\) students report \(a\), in order to require that every student reporting signal \(a\) is spot checked with probability \(x_a(j)\) and every student reporting \(b\) is spot checked with probability \(x_b(j)\). We say that a mechanism is optimal for some class if it minimizes TA workload among all mechanisms in that class.

2.2 ROS, RSS, and RSUS Mechanisms

We now introduce three families of mechanisms, beginning with one studied by Gao et al. (2016).

Definition 2.5 (ROS Mechanism). A Report-Oblivious Spot-checking (ROS) mechanism spot checks every student with fixed probability \(x\), regardless of the students’ reports.

The focus of this paper is on report-sensitive spot-checking.

Definition 2.6 (RSS Mechanism). A Report-Sensitive Spot-checking (RSS) mechanism spot checks every student with probability that can depend on all the students’ reports.

Once the TA spot checks one student, there is no additional workload imposed for using the observed signal to spot check other students too. We now define a class of mechanisms that leverages this fact.

Definition 2.7 (RSUS Mechanism). A Report-Sensitive, Uniform Spot-checking (RSUS) mechanism ensures that whenever one student is spot checked, all are spot checked.

In RSUS mechanisms, \(\forall j \in \{0, \ldots, n\}, x_a(j) = x_b(j)\); of course, it still allows for \(j \neq j’\) that \(x_a(j) \neq x_a(j’)\).

A main result of this paper is that RSUS mechanisms can require strictly larger spot-checking budgets than a DSIC RSS mechanism, and are hence strictly suboptimal, not just under the DSIC solution concept but even if they only need to satisfy the weaker ICCP solution concept. In other words, paradoxically, in order to minimize the overall TA workload, it is necessary to commit sometimes not to use the TA’s signal to spot check some students.

2.3 Assumptions

We now set up assumptions to ensure that the ROS mechanism is DSIC at least with checking probability 1; if not, the setting is ill conditioned. We make these assumptions throughout the paper, including our consideration of mechanisms other than ROS.

Our first assumption is that a student, upon observing a signal, expects any other grader (the TA or another student) to be strictly more likely to observe the same signal than the opposite. This assumption is needed to ensure that students are strictly incentivized to report honestly in ROS mechanisms.
We therefore should have that, for $k \in \{0, \ldots, n - 1\}$,
\[
P_a \cdot \Pr[s_{TA} = a | s_i = a] x_a(k + 1) + P_b \cdot \Pr[s_{TA} = b | s_i = b] x_b(k) - \Pr[s_{TA} = a] x_a(k + 1) \geq c. 
\]
Similarly we should have for $k \in \{0, \ldots, n - 1\}$ that
\[
P_a \cdot \Pr[s_{TA} = a | s_i = a] x_a(k + 1) + P_b \cdot \Pr[s_{TA} = b | s_i = b] x_b(k) - \Pr[s_{TA} = b] x_b(k) \geq c.
\]
Simplifying (6) and (7), we have
\[ -P_{ab}r_a(k + 1) + P_{bb}r_b(k) \geq c. \quad (8) \]
\[ P_{aa}r_a(k + 1) - P_{ab}r_b(k) \geq c. \quad (9) \]

Consider minimizing the TA workload subject to (8) and (9):
\[
\min_{x_a, x_b} \sum_{t \in Q} \Pr[q = t] \sum_{j=0}^{n} \left( \Pr[s = a|q = t] \right)^j \cdot \left( \Pr[s = b|q = t] \right)^{n-j} \max\{x_a(j), x_b(j)\}
\]
with \(0 \leq x_a(k), x_b(k) \leq 1\) for all \(k \in \{0, \ldots, n - 1\}\). The value of this optimization problem is an upper bound to the workload of any DSIC mechanism, since it relaxed all DSIC constraints except (6) and (7). Note also that the objective function is convex in the variables, due to the presence of the \(\max\) function, and its feasible region is a convex polytope since all constraints are linear. There are \(2n\) variables: \(x_a(0), x_a(1), x_b(1), x_a(2), \ldots, x_a(n - 1), x_b(n - 1), x_a(n)\). (Note that \(x_a(0)\) and \(x_b(0)\) are undefined.) These variables can be grouped into \(n\) pairs, with \(x_a(k)\) and \(x_a(k + 1)\) as a pair for each \(k\). Each pair is subject to a pair of constraints from (8) and (9) with the corresponding \(k\), and there is no constraint governing variables from different pairs. This means the optimization problem is separated into \(n\) subproblems, one for each pair of variables. We now claim that the optimal solution for each subproblem is given by (8) and (9) to be tight, which gives us the expressions in (4) and (5). We first check that these solutions are feasible: by Assumptions 2.8 and 2.9, \(P_{bb} - P_{ab} \geq c\) and \(P_{aa} \geq P_{ab}\), which implies that the spot-checking probabilities in (4) and (5) are indeed between 0 and 1. To see that these solutions are optimal, we invoke the convexity of the problem, which means we only need to argue that the solutions are locally optimal. At the point where (8) and (9) are tight for a given \(k\), increasing \(x_a(k + 1)\) forces \(x_b(k)\) to increase, and vice versa, in order for the pair to keep being feasible — this is a consequence of the coefficients’ signs in (8) and (9) — but it is not feasible to decrease both variables. Therefore the local move within the feasible region is to increase both variables. However, both variables have positive coefficients in the objective function. Therefore the solution in (4) and (5) is both locally optimal and globally optimal for our convex program.

**Step 2.** We now show that the spot-checking probabilities given in (4) and (5) in fact give rise to a DSIC mechanism. We only need to check the validity of the DSIC constraints not included in the convex program above.

We first check the condition that a student having spent the effort to get a signal should be incentivized to report the observation faithfully. We need for \(k \in \{0, \ldots, n - 1\},\)
\[
\Pr[s_{TA} = a | s_i = a] x_a(k + 1) \geq \Pr[s_{TA} = b | s_i = a] x_b(k), \quad (10)
\]
and
\[
\Pr[s_{TA} = b | s_i = b] x_b(k) \geq \Pr[s_{TA} = a | s_i = b] x_a(k + 1), \quad (11)
\]

which simplify to
\[
P_{aa}x_a(k + 1) - P_{ab}x_b(k) \geq 0. \quad (12)
\]
\[
P_{ab}x_a(k + 1) + P_{bb}x_b(k) \geq 0. \quad (13)
\]

Note that (12) and (13) are in fact implied by (8) and (9).

For the other DSIC constraints that concern a student’s utility when some other students may spend effort to observe a signal, note that the spot-checking probabilities given by (4) and (5) are independent of \(k\), i.e., they are independent from what the other students report, and therefore the corresponding mechanism is PRSS. In such a mechanism, a student’s utility is independent from the other students’ strategies. If the truthful strategy maximizes a student’s utility when no other student spends any effort, it still does when other students spend effort. Therefore the mechanism obtained from Step 1 is indeed DSIC, and this completes the proof.

### 4 Comparing ROS, RSS, and RSUS

Drawing on our characterization from Section 3, we can now compare the workloads required by each of the different mechanisms discussed in Section 2.1. We begin by comparing the TA workload of the optimal DSIC RSS mechanism with that of the optimal DSIC ROS Mechanism.

**Corollary 4.1.** When \(P_a > P_b\), the TA workload of the optimal DSIC ROS mechanism exceeds that of the optimal DSIC RSS mechanism by at least
\[
\frac{cP_b}{P_{bb} - (P_{ab})^2}.
\]

**Proof.** By Theorem 3.1, the optimal DSIC ROS solution is
\[
s_T = \frac{c}{P_{bb} - P_{ab}}.
\]

Therefore, from (4) and (5), the TA workload saved by the RSS mechanism is:
\[
c \left( P_a \left( x^* - \frac{cP_b}{P_{aa}P_{bb} - (P_{ab})^2} \right) + (1 - P_a) \left( x^* - \frac{cP_a}{P_{aa}P_{bb} - (P_{ab})^2} \right) \right) \geq c \left( x^* - \frac{cP_a}{P_{bb} - (P_{ab})^2} \right) = c \left( \frac{1}{P_{bb} - (P_{ab})^2} \right) \geq \frac{cP_b}{P_{aa}P_{bb} - (P_{ab})^2},
\]

where the first and second inequalities are due to the facts that \(P_a \geq P_b\) and \(P_{aa} \geq P_{ab}\).

**Corollary 4.2.** When \(P_a = P_b\), the TA workload of the optimal DSIC RSS mechanism is equal to that of the optimal DSIC ROS mechanism.

**Proof.** The optimal DSIC ROS solution is \(s_T = \frac{c}{P_{bb} - P_{ab}}\). Also, when \(P_a = P_b\), \(P_a - P_{ab} = P_{aa} = P_b - P_{ab} = P_{bb}\), and
We start from the optimal DSIC ROS solution \(x^*\) and decrease \(x(n)\) by
\[
\Delta x(n) = \frac{P_a - P_b}{P_{bb} - P_{ab}} \cdot \frac{P_{bb}}{P_{ab}} \Delta x(k - 1), \quad \forall k \in \{0, \ldots, n\}. 
\]

At \(x^*\), Constraint (15) becomes tight, following directly from our construction of the step size given by (20). Constraint (16) is tight when \(k = n - 1\); the rest of the constraints are easily satisfied. Hence, we only need to show that Constraint (16) will not be violated by the specified decrease in the decision variables. However, by (20) we get that for \(k \in \{0, \ldots, n-1\}\), the ratios by which the gap between the left and right hand sides of Constraints (16) decreases is
\[
\left(\frac{P_{aa}}{P_{ab}}\right)^{n-k} \leq 1 \times \text{the ratio by which the gap for the constraint corresponding to } n = k - 1 \text{ is decreasing. Therefore, the constraint corresponding to } n = k - 1 \text{ binds faster.}
\]

As a result, since Constraint (15) and (16) when \(k = n - 1\) are all binding, we can not decrease any of the decision variables anymore without increasing another. Since every objective coefficient is positive, increasing \(x(k)\) for any \(k \in \{0, \ldots, n\}\) could be beneficial only if it resulted in decreasing the value of the rest of the decision variables, achieving an overall objective function improvement. However, if \(x(k+1)\) is increased then \(x(k)\) needs to increase as well to preserve feasibility; if \(x(k)\) increases then \(x(k-1)\) needs to increase as well; and so on. Thus, overall, there exist no local, objective-improving changes to the current values of \(x(k)\), and so we have identified an optimal solution to our linear program. Finding the intersection point of the binding constraints shows that \(x_n = x^a \leq x_{n-1} = x^b < x_{n-2}, \ldots, < x_0\), which leads to the result of the theorem statement.2 □

### 5 Conclusion

We have investigated peer grading mechanisms that achieve dominant-strategy incentive compatibility by using TAs to spot check students, and have focused on minimizing the required TA workload. We have explored mechanisms for report-sensitive spot checking: varying spot-checking probabilities based on the profile of grades that all students report for a given assignment. We proposed a simple optimal DSIC “PRSS” mechanism, and showed that it minimizes the required spot-checking budget (across both the “RSS” mechanisms and the more constrained “RSUS” mechanisms even under a weaker solution concept) and outperforms the (“ROS”) mechanisms that spot checks all students with a fixed, report-oblivious probability.

We consider the most important direction for future work to be generalizing our results beyond two signals. We note that we actually prove more than claimed in the theorem statement: our result holds not only for the ICCP solution concept, but also for any strategies in which none of the students invest the grading effort.
that this would require a fundamentally different proof technique, as our convex programming formulation depends critically on the problem’s two-signal structure. We expect that the multi-signal setting would also require other variations in the model. Notably, in such domains it becomes natural to impose an ordering over the signals and to reward agents according to the distance between their reports and that of the TA, rather than rewarding all “correct” reports equally. Another limitation of our work is the assumption that the prior distribution over signals is known to the mechanism designer. The derivation of prior-independent report-sensitive mechanisms is a second, worthwhile direction for future work. One possible strategy for building such mechanisms could be learning the prior in a repeated setting.

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