

# Combinatorial Pair Testing: Distinguishing Workers from Slackers

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**Abstract.** We formalize a problem we call *combinatorial pair testing* (CPT), which has applications to the identification of uncooperative or unproductive participants in pair programming, massively distributed computing, and crowdsourcing environments. We give efficient adaptive and nonadaptive CPT algorithms and we show that our methods use an optimal number of testing rounds to within constant factors. We also provide an empirical evaluation of some of our methods.

## 1 Introduction

*Pair programming* [19] is a software development paradigm where programmers are teamed in pairs and write software together using a single workstation. This paradigm is said to produce fewer software bugs and shorter programs than when programmers work alone [20]. Consequently, it is often used to teach software design in introductory programming courses [15], including courses at the authors' institution [13], the University of California, Irvine. This design paradigm presents an additional challenge, however, for evaluative purposes. Namely, if programmers are always working in pairs, how can a manager or instructor evaluate the performance of programmers as individuals?

For instance, suppose 100 students enroll in an introductory programming course, among whom 80 are conscientious and 20 are lazy. We will call the conscientious students *workers* and the lazy ones *slackers*. In order to assign final grades to these students, the instructor would like to distinguish the workers from the slackers, but whenever she pairs a worker and a slacker on a project, the worker will do the assignment individually and the project will be completed successfully in spite of the slacker's laziness. Based on their performances, the instructor can only detect slackers when two slackers are paired together. Therefore, it would be useful for her to have systematic and effective strategies for pairing the students in order to distinguish workers from slackers.

Motivated by this evaluation problem, we are interested in this paper in the design of efficient algorithms for generating testing schemes that can distinguish workers from slackers. We formulate such problems in a general framework, which we call *combinatorial pair testing* (CPT), and we consider a number of different assessment settings, such as whether all tests must be specified in advance or whether tests may be determined adaptively. This approach allows us to focus on natural performance characteristics of such problems and provides a general framework that unifies other diagnosis problems under the CPT heading.

**Combinatorial Pair Testing.** Suppose we are given a set  $X$  of  $n$  individuals,  $\epsilon n$  of whom are *slackers* and  $(1 - \epsilon)n$  of whom are *workers*, where  $\epsilon$  may or may not be known in advance. A *pairwise test* is a function  $T(x, y)$  that takes as its arguments two members  $x$  and  $y$  of  $X$ , and produces as output a Boolean value, the result of a test performed for  $x$  and  $y$  based solely on the worker/slacker status of  $x$  and  $y$ . Naturally, although this framework allows for  $T$  to be any Boolean function, some Boolean functions will be more interesting than others. In this paper, we are particularly interested in the following type of test:

- *Performance-based testing:* In a performance-based test, we pair two individuals,  $x$  and  $y$ , and evaluate their output performance as a team. Thus, if both  $x$  and  $y$  are slackers, then  $T(x, y) = \mathbf{false}$ , indicating that the two slackers,  $x$  and  $y$ , have been paired together and didn't complete the assigned project. If, on the other hand,  $x$ ,  $y$ , or both, are workers, then  $T(x, y) = \mathbf{true}$ , indicating that the project was completed.

Performance-based testing is symmetric, so  $T(x, y) = T(y, x)$ , and, indeed, this test is equivalent to a Boolean OR of  $x$  and  $y$ , where a slacker corresponds to a 0 and a worker corresponds to a 1. Moreover, by De Morgan's laws, any CPT algorithm that uses OR for  $T(x, y)$  can be easily modified to produce a CPT algorithm that uses AND for  $T(x, y)$ .

In *combinatorial pair testing* (CPT), only pairwise tests are allowed. The tests are organized in a sequence of *rounds*, in which each member of  $X$  may be tested at most once, so up to  $\lfloor n/2 \rfloor$  pairwise tests can be performed in a single round. The choices made by CPT algorithms can be determined adaptively or non-adaptively and may be based on decisions that are either deterministic or randomized. In some cases we will also require some prior knowledge of the relative numbers of slackers and workers; for instance, using only performance-based tests, it is not possible to distinguish the case of there being only one slacker in  $X$  from that of there being none. Moreover, the efficiency of a given testing scheme may depend on assumptions about the number of slackers.

Because our intended applications may involve sensitive information about individual misbehavior, we may also desire CPT algorithms to have additional security or privacy guarantees. For instance, we may want our algorithms to be implementable in a way that allows an instructor to outsource the evaluation of the tests without revealing the input data [1]. Such an approach is common in privacy-preserving computations (e.g., see [21]).

One additional security condition that we study in this paper, which appears to be novel, is that of a detection algorithm that is *participant oblivious*. A detection algorithm is participant oblivious if an individual cannot detect whether he has been identified by the evaluator as a worker or slacker based only on the pairings to which he has been assigned (without knowing the status of his or her partners or the outcome of their tests). A nonadaptive algorithm must be participant oblivious, but we show that some adaptive algorithms can also be participant oblivious. The advantage of a participant-oblivious algorithm is that it allows the evaluator to impose penalties to slackers or rewards to workers after

the completion of the tests without tipping off a participant during the testing process that the evaluator might already know his or her status.

**Prior Related Work.** Combinatorial pair testing is related to *combinatorial group testing* [6]. In combinatorial group testing, we are given a set,  $S$ , of  $n$  items, at most  $d$  of which are “defective.” A test consists of selecting a subset,  $T$ , and determining whether  $T$  contains any defective items. Thus, combinatorial pair testing with performance-based testing is a restricted type of combinatorial group test in which every subset is a pair. There are many known results and applications for algorithmic problems in combinatorial group testing (e.g., see [6, 9, 11]), but we are not aware of any results for the case where every subset must be a pair and in which tests are issued in groups of  $O(n)$  independent tests. The closest previous analysis is by Hwang [12], who analyzes random size- $k$  tests that are issued independently (that is, not in groups). Instead, insisting that every test to be a pair and that the pairs are issued in groups, as is required in combinatorial pair testing, goes against a standard approach in combinatorial group testing, according to which one performs tests to limit the defective items to a subset of size at most  $O(d \log n)$  and then tests each such item individually.

Combinatorial pair testing is also a generalization of *processor fault diagnosis*. In this problem, we are given a set of  $n$  processors, each of which can be either faulty or good. One processor can check another, but the result of this check can only be trusted if the processor doing the testing is good. Often, in fact, one assumes that faulty processors deliberately misidentify the ones they are testing [5, 17]. Beigel *et al.* [2–4] show that if the number of faulty processors is sufficiently far below  $n/2$ , then  $O(n)$  tests can be organized into a sequence of  $O(1)$  parallel testing rounds, where each processor tests at most one other in each round, so as to identify all faulty processors. Thus, processor fault diagnosis forms a type of combinatorial pair testing problem where the tests are based on queries and, in the case when faulty processors deliberately misidentify the ones they are testing, the Boolean function that determines the outcome of a test is the exclusive-or function.

In addition, combinatorial pair testing can be applied to cheater detection in *massively distributed computations* [10], such as SETI@home and distributed.net. These systems break very large computations into independent tasks, which are then sent out to be executed to participants of the system (typically by using the idle time of individual personal computers). The problem is that some participants cheat: instead of performing the requested tasks, they rig their computers to return false or partial results, often merely for the sake of appearing on a leader board of top participants. To deal with this problem, these distributed systems often will send out the same task to two participants at the same time, and if they both return the same answer, then the output is accepted and the participants are labeled as being honest (e.g., see [7]). One challenge is that when two answers don’t agree, the system doesn’t immediately know which participant(s) cheated. The problem of identifying all the honest participants (and, hence, all the cheaters) in a distributed computing environment can be formulated using the approach of this paper, and solved, using combinatorial pair

testing with performance-based tests based on the AND function. Previous work on cheater-detection in distributed computations does not take this approach, however, and is instead based on ad hoc solutions or reductions to processor fault diagnosis (e.g., see [7, 8, 10]).

Along these same lines, combinatorial pair testing also has applications to *crowdsourcing*, where complex, independent tasks, such as labeling images, is farmed out to a large set of individuals to perform. One challenge in this case is that the group of individuals contains both “experts,” who are competent and diligent with their work, and “spammers,” whose performance is no better than a random oracle [14]. Combinatorial pair testing can be applied in this context to weed out the spammers, much in the same way as it applies to cheater detection for massively distributed computations.

**Our Results.** Given a set,  $X$ , of  $n$  individuals such that  $\epsilon n$  of them are slackers, we formalize the combinatorial pair testing (CPT) problem, and we present and analyze several efficient CPT algorithms for identifying the slackers in  $X$ . For the adaptive case, we give an algorithm that uses  $O(1/\epsilon)$  testing rounds, and we show this to be optimal to within constant factors. Moreover, we show that our algorithm is participant oblivious and we extend our algorithm to work in  $O(1/\epsilon)$  testing rounds even if we don’t know the value of  $\epsilon$  in advance. We also give both deterministic and randomized nonadaptive CPT algorithms, and we show that the performance of these algorithms is optimal to within constant factors. For example, our randomized nonadaptive CPT algorithm uses  $O((1/\epsilon) \log n)$  testing rounds and succeeds in identifying all slackers with high probability. Our analysis of this algorithm is based on an extension to the coupon collectors problem, which we call the coupon packet collectors problem. In addition, we give an empirical study of our randomized CPT algorithm that provides experimental bounds for the number of tests needed to identify various percentages of the slackers in  $X$ .

## 2 Adaptive Algorithms

In this section, we describe an adaptive participant-oblivious algorithm for identifying all the slackers in a performance-based testing problem.

**The Two-Phase Algorithm.** Assume that we know there are  $\epsilon n$  slackers.

In phase one, we perform the following computation:

- *Phase One:* We group the individuals into  $\lfloor \epsilon n/2 \rfloor$  “bins” of size at most  $\lceil 2/\epsilon \rceil$  each. We then do  $\lceil 2/\epsilon \rceil$  “round-robin” rounds of testing to compare all pairs of items in the same bin as each other, across all bins in parallel.

This completes phase one, and gives us the following.

**Lemma 1.** *After phase one completes, we will have identified all the slackers in each bin that has at least 2 slackers.*

**Proof:** If a bin contains 0 or 1 slackers, then each pairing of two individuals in that bin will contain a worker. Thus, every test for that bin has the same outcome (true). If, on the other hand, a bin contains 2 or more slackers, then each slacker in that bin will eventually be paired with another slacker; hence, we discover each slacker in that bin. ■

More importantly, we also have the following.

**Lemma 2.** *After phase one completes, we will have identified at least  $\lceil \epsilon n/2 \rceil$  slackers.*

**Proof:** By the previous lemma, a slacker can go undiscovered only if he is the sole slacker assigned to a given bin. Since there are  $\lfloor \epsilon n/2 \rfloor$  bins, then, by a generalized pigeonhole argument, there has to be at least  $\epsilon n - \lfloor \epsilon n/2 \rfloor = \lceil \epsilon n/2 \rceil$  slackers that are assigned to bins that each contain at least two slackers. ■

Given that we now have identified at least  $\lceil \epsilon n/2 \rceil$  slackers, in phase two we perform the following computation.

- *Phase Two:* We choose  $\lceil \epsilon n/2 \rceil$  known slackers and assign one of them to each bin randomly. We assign the remaining individuals to bins, while keeping the bins to be of size at most  $\lceil 2/\epsilon \rceil$ . Moreover, we choose these assignments uniformly at random, subject to the rule that each bin contains a slacker and that no two individuals who were paired in round one are assigned to the same bin as each other. We then do  $\lceil 2/\epsilon \rceil$  “round-robin” rounds of testing to compare all pairs of items in the same bin as each other, across all bins in parallel.

This completes phase two.

From the perspective of any individual, their bin assignment is done at random, with every bin being equally likely, and the people they are paired with are equally likely to come from any other bin from phase one. Moreover, the only nonadaptive step is the assignment of known slackers to bins in phase two, which is done via a random permutation, similar to how elements not known to be slackers are assigned. Thus, so long as individuals in our group do not collude, this algorithm is participant oblivious. Note, in addition, that any bin that now contains a previously undiscovered slacker, will necessarily contain at least two slackers. Thus, by Lemma 1, we will discover this (and all other) remaining slackers in phase two.

**Theorem 1.** *Given a set,  $X$ , of  $n$  workers and slackers, such that  $\epsilon n$  of the individuals in  $X$  are known to be slackers, we can identify all the slackers in  $X$  in  $O(1/\epsilon)$  rounds of disjoint pairwise tests, in a participant-oblivious adaptive fashion.*

This bound is optimal, to within constant factors, as the following theorem establishes.

**Theorem 2.** *Given a set,  $X$ , of  $n$  workers and slackers, such that  $\epsilon n$  of the individuals in  $X$  are slackers, then identifying all the slackers in  $X$  (either deterministically in the worst case or randomly with success probability  $\geq 1/2$ ) requires at least  $\Omega(1/\epsilon)$  rounds of disjoint pairwise tests.*

**Proof:** We consider the randomized case first, and we assume a randomized input distribution in which all permutations of workers and slackers are equally likely. Let  $x$  be a random variable whose value is one of the slackers in the input, chosen uniformly at random among the slackers. In the first  $1/(2\epsilon)$  rounds of testing, at most  $n/2$  of the members of  $X$  may become identified. In any given round of testing in which  $x$  has not already been identified as a slacker, at most  $\epsilon n - 1$  of the unidentified members of  $X$  can be paired with (identified or unidentified) slackers other than  $x$ , and  $x$  is equally likely to be any one of the  $\geq n/2$  unidentified members, so the probability that  $x$  becomes identified by being paired with a slacker is at most  $(\epsilon n - 1)/(n/2) < \epsilon/2$ . By the union bound, after  $1/(4\epsilon) = \Omega(1/\epsilon)$  rounds,  $x$  will remain unidentified with probability greater than  $1/2$ , so the probability that all slackers are identified is less than  $1/2$ .

Since this randomized input distribution fools even a randomized algorithm with probability at least  $1/2$ , after  $\Omega(1/\epsilon)$  rounds, it follows that for every deterministic algorithm there exists an input in this distribution that is certain to fool the algorithm with the same number of rounds. ■

**Estimating Epsilon.** Suppose now that there are  $\epsilon n$  slackers, but we do not know the value of  $\epsilon$ . Instead, let us assume we have an estimate,  $\epsilon'$ , and our goal is to use  $O(1/\epsilon')$  rounds, and either find all  $\epsilon n$  slackers, with  $\epsilon' \leq 2\epsilon$ , or determine that  $\epsilon' > \epsilon$ .

Consider again the above two-phase algorithm, but now assume that it is calibrated for  $\epsilon'$  instead of  $\epsilon$ . One possible outcome of phase one, is that we discover at least  $\lceil \epsilon' n/2 \rceil$  slackers, which then allows us to discover all the slackers in phase two. In this case,

$$\epsilon n \geq \epsilon' n/2,$$

hence,  $\epsilon' \leq 2\epsilon$ .

Alternatively, phase one may discover fewer than  $\lceil \epsilon' n/2 \rceil$  slackers. Since a bin that appears to hold no slackers can hold at most one, this implies that

$$\epsilon < \epsilon'/2 + \epsilon'/2 = \epsilon'.$$

Thus, our two-phase algorithm achieves our goal.

We can therefore now use our two-phase algorithm in an iterative fashion. We start with  $\epsilon' = 1/2$ , and use the two-phase algorithm with this estimate for  $\epsilon$ . If we discover all the slackers, then we are done. Otherwise, we determine that  $\epsilon < \epsilon'$ . In this case, we set  $\epsilon' \leftarrow \epsilon'/2$  and we repeat the process with this estimate. Eventually, we will reach a point where we discover all the slackers, with  $\epsilon' \leq 2\epsilon$ . Moreover, since the previous iteration, if there is one, would have failed, we also

know that  $\epsilon < 2\epsilon'$ , that is,  $\epsilon' > \epsilon/2$ . The number of testing rounds is therefore proportional to

$$2 + 4 + 8 + \dots + 1/\epsilon' \leq 2 + 4 + 8 + \dots + 2/\epsilon \leq 4/\epsilon.$$

Therefore, even without knowing the value of  $\epsilon$ , the number of rounds is  $O(1/\epsilon)$ , which implies the following.

**Theorem 3.** *Given a set,  $X$ , of  $n$  workers and slackers, such that  $\epsilon n$  of the individuals in  $X$  are slackers, we can identify all the slackers in  $X$  in  $O(1/\epsilon)$  rounds of  $O(n)$  pairwise tests per round, in a participant-oblivious adaptive algorithm, without knowing  $\epsilon$  in advance.*

In the full version of this paper, we explore optimizations to the constant factors in the above bounds, in adaptive CPT algorithms for the case when  $\delta = 1 - \epsilon \leq 1/2$ , that is, when at least half of the individuals are slackers. Such instances of the combinatorial pair testing problem arise naturally in massively distributed and crowdsourcing applications, for example, where the roles of slackers and workers are reversed and the testing function,  $T$ , is Boolean AND instead of OR.

### 3 Nonadaptive Pair Testing

In this section, we study nonadaptive algorithms for combinatorial pair testing, to identify  $\epsilon n$  slackers in a group of  $n$  individuals. In this case, if we assume that we do not know the value of  $\epsilon$ , then the only valid algorithm is the trivial brute-force algorithm that compares every pair of individuals, since a nonadaptive algorithm must specify all its tests in advance and it is possible that  $\epsilon = 2/n$ . Therefore, we assume that we know in advance that there are  $\epsilon n$  slackers.

**Deterministic Nonadaptive Pair Testing.** Unfortunately, nonadaptive deterministic pair testing is not very interesting, because it requires a linear number of rounds. The argument is simple: suppose a deterministic nonadaptive pair testing algorithm could use at most  $(1 - \epsilon)n/2$  rounds. Then, in the graph of pairs that are tested by the algorithm, each vertex would have at most  $(1 - \epsilon)n/2$  neighbors. An adversary could choose one edge of the graph, make one of its two endpoints a slacker and the other endpoint a worker, set all neighbors of these two vertices to be workers, and fill out the rest of the graph arbitrarily to fit whatever number of slackers and workers is desired. From the set of tests that are performed, there is no way to distinguish which of the two endpoints of the chosen edge is the slacker and which is the worker. Therefore, there must be at least  $\Omega((1 - \epsilon)n)$  rounds in a deterministic nonadaptive CPT algorithm, which, for any fixed  $\epsilon < 1$ , is asymptotically not any better than the brute-force algorithm that tests every pair.

This bound can be achieved as an upper bound, as well, using an algorithm that pairs each individual,  $x$ , with at least  $(1 - \epsilon)n + 1$  other distinct individuals, using  $O((1 - \epsilon)n)$  rounds. For this algorithm, at least one of the individuals paired with each such  $x$  must be a slacker.

**Randomized Nonadaptive Pair Testing.** Despite the nonexistence of efficient deterministic nonadaptive pair testing algorithms, there is a simple randomized algorithm for nonadaptive randomized testing, which succeeds with high probability using many fewer tests than the deterministic nonadaptive solution. In particular, let us repeatedly choose a random matching of all the members of the set,  $X$ , for some value,  $k$ , number of rounds. Each matching corresponds to a round of testing. For instance, for  $k = (c/\epsilon) \log n$ , for a sufficiently large constant,  $c \geq 1$ , then this scheme uses  $O((1/\epsilon) \log n)$  rounds and  $O((n/\epsilon) \log n)$  tests in total.

**Relation to the Coupon Collector's Problem.** The expected performance of the nonadaptive randomized algorithm described above can be analyzed precisely using a variant of the classical *coupon collector's problem*.

In the coupon collector's problem, a collector wishes to collect a set of  $n$  trading cards, by randomly acquiring one card at a time, and the problem is to calculate the number of steps that are required until, with high probability, all cards have been collected. Now consider a slight variation, which we call the *coupon packet collector's problem*: instead of buying one card at a time, the collector buys the cards in packets of  $m$  cards [18]. Each packet of trading cards is guaranteed to have no duplicates, and is uniformly random among all  $m$ -card samples of the whole set of cards. How does this affect the total time required for the collector? If  $m$  is much smaller than  $n$ , the difference between this problem and the standard coupon collector's problem is very small: a random sample of  $m$  cards, each independently and uniformly randomly sampled, is very likely to be duplicate-free. But if  $m$  is a constant fraction of  $n$ , then the avoidance of duplicates in each packet is very likely to cause the number of packets that the collector needs to collect to be smaller by a constant fraction than the number that a one-at-a-time collector would need. But what is the fraction?

In the coupon packet collector's problem, the probability that a card remains uncollected after  $k$  rounds is  $(1 - m/n)^k$ . So, after  $k$  rounds, by the linearity of expectation, the expected number of uncollected cards is  $n(1 - m/n)^k$ . Thus, for  $k = (1 + \alpha) \log_{1/(1-m/n)} n$  rounds, the expected number of uncollected cards is  $1/n^\alpha$ ; hence, by Markov's inequality, with very high probability,  $1 - 1/n^\alpha$ , all the cards are collected.

In the pair testing problem, observe that a slacker's status is identified whenever the slacker is paired with another slacker, and a student's status is identified whenever that student is paired with a known slacker. If we allow these identifications to be made retroactively (*i.e.*, once we find a known slacker we use that identity to confirm as workers all the other students the slacker has already been paired with) then there is a very simple criterion for whether we have identified everybody: we have done so if and only if all students have been paired at least once with a slacker. More weakly, we have identified all slackers whenever the slackers have all been paired with another slacker in some round of testing. Suppose that there are  $m$  slackers and  $n$  total students. In each round, exactly  $m$  students will be paired with slackers, so it is very much like the coupon



packet collector’s problem, where the trading cards in a packet correspond to the students that are paired with slackers. There is a small complication, however: in the pair testing problem the sets of students that are identified are not quite uniformly random over all  $m$ -element subsets of students. In particular, the slackers are slightly less likely to be paired with other slackers than the workers, because there are fewer other slackers for them to be paired with.

To be precise, in the case that there are an even number of students, a slacker has probability exactly  $(n - m)/(n - 1)$  of remaining unidentified after one round, because there are  $n - 1$  students the slacker could be paired with, each of which is equally likely, and  $n - m$  of which (the workers) fail to identify the slacker. The probability that a specific student is identified in any one round is independent of the same probability for the same student in a different round, so after

$$k = (1 + \alpha) \log_{\frac{n-1}{n-m}} m$$

rounds, the probability that an individual slacker remains unidentified is  $1/m^{1+\alpha}$ . Similarly, a worker has probability exactly  $(n - m - 1)/(n - 1)$  of not having been paired with a slacker after one round, and probability  $1/(n - m)^{1+\alpha}$  of never having been paired with a slacker after

$$k = (1 + \alpha) \log_{\frac{n-1}{n-m-1}} (n - m)$$

rounds. Different students have probabilities that are not independent of each other, but by linearity of expectation after

$$k = (1 + \alpha) \max \left\{ \log_{\frac{n-1}{n-m}} m, \log_{\frac{n-1}{n-m-1}} (n - m) \right\}$$

rounds the expected number of students who have not been paired with a slacker is  $\min\{1/m^\alpha, 1/(n - m)^\alpha\}$ , so by Markov’s inequality, with high probability all students will be identified. In the case that there are an odd number of students, there are  $n$  alternatives for each student in each round rather than  $n - 1$ , so the number of rounds needed is instead

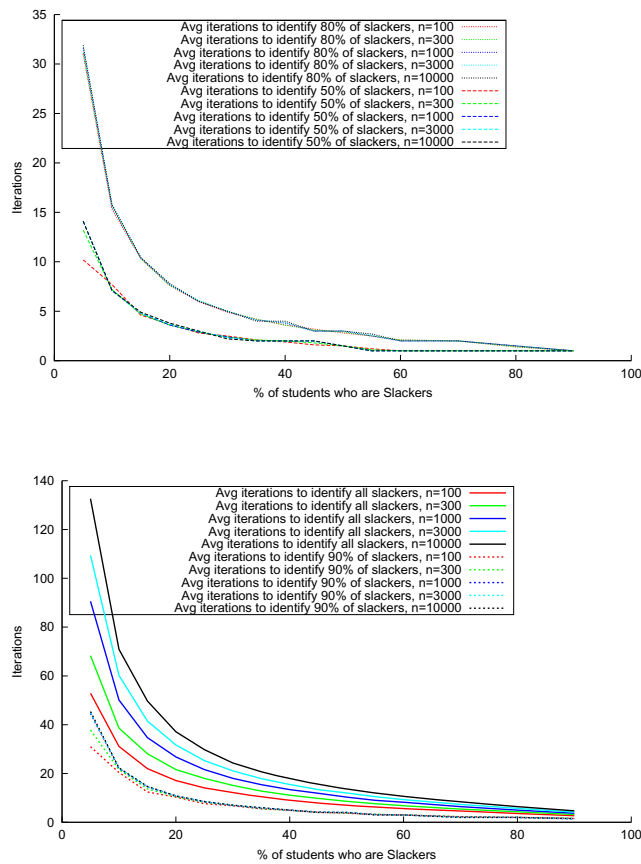
$$k = (1 + \alpha) (\log_{\frac{n}{n-m+1}} m + \log_{\frac{n}{n-m}} (n - m)).$$

In either case, for  $m = \epsilon n$  slackers, if we extend the above two bounds so that the number of rounds is increased to

$$k = (1 + \alpha) \log_{1/(1-\epsilon)} n,$$

then the expected number of unclassified students is  $1/n^\alpha$ . Thus, by Markov’s inequality, there are no unclassified students with high probability,  $1 - 1/n^\alpha$ . Choosing  $\alpha \geq 1$  to be a fixed constant, and using the inequality,  $x < -\ln(1 - x)$ , for  $0 < x < 1$ , we get the following result.

**Theorem 4.** *Given a set,  $X$ , of  $n$  individuals, such that  $\epsilon n \geq 2$  of them are slackers and the rest are workers, we can distinguish the workers and slackers using  $O((1/\epsilon) \log n)$  rounds of random performance-based tests, with  $O(n)$  tests per round, with high probability,  $1 - 1/n^c$ , in a nonadaptive fashion, for any fixed constant  $c \geq 1$ .*



**Fig. 1.** Results for number of random tests needed to identify various percentages of slackers, for various values of the set size,  $n$ , and slacker percentage,  $\epsilon$

In a nonadaptive randomized strategy, the most information is gathered by randomly matching of the members of  $X$  and testing each matched pair. Thus, for any slacker,  $s$ , the probability  $s$  is not paired with another slacker is at least  $(1 - \epsilon)$ . So, after  $k$  independent rounds of testing, the probability  $s$  has not been discovered to be a slacker is at least  $(1 - \epsilon)^k$ , which we can bound as

$$(1 - \epsilon)^k \geq \left(\frac{1 - \epsilon}{e}\right)^{ek},$$

by an inequality due to Niculescu and Vernescu [16]. Thus, we have the following.

**Theorem 5.** *For  $2/n \leq \epsilon \leq 1/2$ , we require  $\Omega((1/\epsilon) \log n)$  rounds of testing for each slacker to be identified, with probability at least  $1 - 1/n$ , in a nonadaptive randomized testing scheme for a set of  $n$  members having  $\epsilon n$  slackers.*

Therefore, the above analysis is tight to within constant factors.

**Experimental Results.** To get a better handle on the expected number of tests needed to identify various percentages of slackers, we performed an experimental study of the above nonadaptive randomized CPT algorithm. We performed tests for values of  $n$  ranging from 100 to 10000, with percentage of slackers ranging from 5% to 90%. We then performed tests to determine the average number of tests required in order to identify 50%, 80%, 90%, and 100% of the slackers. We show the results in Figure 1.

## 4 Conclusion

In this paper, we have given efficient algorithms for solving combinatorial pair testing problems, along with lower bounds showing that our algorithms are optimal to within constant factors. All of our algorithms assume we are using performance-based tests. Therefore, one possible direction for future work would be to explore CPT algorithms and applications for other kinds of tests (other than the exclusive-or tests used in processor fault diagnosis [2–5, 17]). Another direction would be to enlarge the size of tested groups beyond two and explore the effect of different group sizes on the numbers of rounds needed for testing.

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