Deadlocks as Runtime Exceptions

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Abstract. Concurrent programming is difficult as programs fail in non obvious ways. When deadlocks happen, there's no clear indication of error. This paper supports the idea that deadlocks are runtime errors and they should be signaled with exceptions. We leverage two insights to make this practical: (i) most deadlocks occurring in real systems involve only two threads acquiring two locks (TTTL deadlocks); and (ii) it's possible to detect TTTL deadlocks efficiently enough for most practical systems. We conducted a study on bug reports and found that more than 90% of identified deadlocks were indeed TTTL (i). We extended Java's `ReentrantLock` class to detect TTTL deadlocks and measured its performance impact with conservative benchmark. Its overhead ranges between 50% to 90% (ii). Empirical usability evaluation in two experiments showed that students finished tasks faster with our implementation. We conclude deadlock exceptions allows finding bugs more efficiently with sufficiently low overhead.

Keywords: deadlock, concurrency, exception handling, empirical studies

1 Introduction

Real-world applications use concurrency to do computation in parallel with multiple threads/processes taking more advantage of multicore processors. Unfortunately, concurrent code is difficult to write correctly, as it is well documented in [1], and a very common mistake when using locks is known as deadlock. Deadlocks manifest when threads are waiting each other in a cycle, where each thread is waiting for another thread to release its desired lock, in a never-ending wait. Although we have two types of deadlocks, resource deadlocks and communication deadlocks [2] [3], in this work, as other studies did before [9] [10], our focus is on resource deadlocks. From now on, whenever the term *deadlock* is used we implicitly mean resource deadlocks.

Different from previous deadlock detection studies, we believe deadlocks should not fail silently but instead they should be signaled as exceptions in programming languages. Rather than trying to detect them when explicitly requested for a deadlock analysis, programs should instead be written in such a way that they can either handle the deadlock when it happens or just show the error in the output in order to allow easy identification of bugs. Some programming languages such as Haskell and Go already contain some kind of deadlock exception for very particular cases, and for this study, our proposed deadlock algorithm have focused on what we found to be the most common type of deadlock: between two threads and two locks (TTTL deadlocks).

Our main goals in this study are: to show how to detect TTTL deadlocks without extra atomic operations, providing a lightweight implementation of *ReentrantLock* that dynamically detects TTTL deadlocks running seamlessly on top of Java OpenJDK; to evaluate the runtime overhead of such implementation; and, lastly, to understand the benefits of such exceptions in programming languages by evaluating how the speed and accuracy of bug identification are affected. We start this paper by describing our bug reports study where we found TTTL deadlocks were the most common type of deadlock. Then we move forward to describe how and why the deadlock algorithm works for TTTL deadlocks. Then we present our evaluation for both usability and performance.

2 Bug Reports Study

In Lu et al.'s study about concurrency bugs [1], they found that 30 out of 31 deadlock cases involved at most two resources. We decided to investigate this further, focusing on deadlock related bugs.

2.1 Data Collection

We selected three open source projects to investigate: Lucene, Eclipse and OpenJDK. Lucene[1] is a text search engine library. Eclipse[2] is one of the most popular IDE for java developers. OpenJDK[3] is an open-source implementation of the Java Platform. These three projects share some key similarities: they're mostly written in Java; they have immense bug report repositories with easy tools to search into them; and lastly, their bug reports were usually well discussed and contained enough context that allowed us to classify them with some high degree of confidence, which was very important in this study.

In total, we collected 541 bug reports containing the word *deadlock* on its title or on its description. In Lucene, we found 27 closed issues of type "bug" in module "lucene-core".[4] In Eclipse, we found 406 resolved issues with resolution "fixed".[5] In OpenJDK, we found 108 issues of type "bug" on module "JDK" with resolution "fixed" and status "resolved".[6] Then we've calculated the sample size that would allow us to have 95% of confidence level and 5% sampling error which

[1] Lucene: http://lucene.apache.org/
[2] Eclipse: https://eclipse.org/
[3] OpenJDK: http://openjdk.java.net/
[4] Lucene bug reports list: http://goo.gl/DhVI3t
[5] Eclipse bug reports: http://goo.gl/qQnrEm
[6] OpenJDK bug reports: http://goo.gl/xYFfsO

resulted in 225 bugs. Thus we created a random sample of that size to analyze further [7].

2.2 Data Labeling

We defined a set of fields to classify for each bug analyzed in the sample. First, we define a category. Then complete other fields based on how much we could understand of each bug report, like the number of threads involved, number of resources involved, type of locking mechanism used, and so on. Some extra information we collected were not used for this research.

We have four different values for category field. Category A represents we were confident this was a resource deadlock, then we should be able to provide the number of threads and locks that were involved. In contrast, category B represents the opposite: it was certainly not a resource deadlock, then we have found a clear evidence of lost notify/signal in the bug context or anything else that supports it wasn't a resource deadlock. Category C is for all false-positive results: the term *deadlock* was used as a synonym of "hang" or "infinite loop", or to just mention another deadlock bug as a reference, not as a cause of the current bug. Lastly, category D is set for all bugs that we could not understand clearly, thus we use it as a fallback if no other category was used, usually happening when bugs do not have enough evidence or discussion.

The labeling process had a set of guidelines which described each step of investigating a bug and where to look for the information we needed on each bug, like attachments, comments, duplicate bugs, and so on. We omit these guidelines here for brevity.

2.3 Results Analysis

Initially we will consider only bugs we clearly identified, that is, bugs that were not labeled as category D. On table below, we can see that from all resource deadlocks, 92.07% of them were indeed TTTL deadlocks. Another interesting finding is that 75.93% of all deadlocks were indeed resource deadlocks.

Table 1: Labeled Categories

Category	Number of Bugs
A	101
A+TTTL	93
B	32
C	23
D	69

[7] Bug reports sample: http://goo.gl/zNsIGz

If we now consider bugs we could not clearly classify, we can make some estimations of how many of them would be resource deadlocks and TTTL deadlocks. The first estimate is the worse case scenario, that is, all bugs in category D should be in category A but none of them would be TTTL deadlocks. In this case, only 54.7% of resource deadlocks would be TTTL deadlocks. If we look at the best case scenario, that is, all bugs in D would be TTTL deadlocks, then it would be 95.29% instead. However none of these two scenarios are realistic. Now we estimate the distribution of categories of bugs in D based on what we already found about the other categories.

Table 2: Estimated Labeled Categories Based On Distribution Found

Category	Number of Bugs
A	146
A+TTTL	134
B	46
C	33

In this case, out of all resource deadlocks, we estimate that 91.7% of them would also be TTTL deadlocks. Thus TTTL deadlocks are certainly the most popular type of resource deadlocks. Also, we saw that resource deadlocks were indeed more popular than communication deadlocks. Then if we focus on detecting TTTL deadlocks only, we would still cover most of the cases and at the same time optimize the code to detect it with as low overhead as possible.

2.4 Threats to Internal Validity

Although we've created a set of guidelines expecting to have many reviewers, only one reviewer labeled all bug reports due to constraints on time and lack of resources. In counterpart, having only one reviewer makes it easier to guarantee that all bug reports were reviewed following the exact same procedure, but we would have preferred to have at least one more reviewer to label each bug independently and use it as a way to double check the labels accuracy.

2.5 Threats to External Validity

One factor that might limit generalization of these findings is that we've looked at only three different open-source projects written mostly in Java, but different programming languages may also have a different distribution of deadlock bugs.

3 Deadlock Detection

We have modified the default implementation of Java's *ReentrantLock* to allow efficient runtime detection of TTTL deadlocks. We take advantage of *ReentrantLock* current algorithm and some of its guarantees to avoid the need to introduce extra synchronization mechanisms or costly atomic operations in this detection. It works as follows:

1. Each lock has a pointer for a thread which is the current owner or null when there's no thread owning that lock.
2. Each lock has an integer to represent its current state: 0 means the lock is free and no thread owning it (the *unlocked* state), 1 means there's a thread owning the lock (the *locked* state). For simplicity, we are only interested on these two states and its change holds the most complexity, but in the implementation of *ReentrantLock* each time the thread owner acquires the same lock, this state would be incremented, and decremented each time the thread releases it.
3. Each thread has a thread-local list of pointers of locks they are currently owning.
4. Each lock has a waiting queue of threads that are waiting to acquire it. Whenever a thread try to obtain a lock when it's already acquired, the thread will add itself on the waiting queue before parking. Upon the event of releasing the lock, the owner of that lock will look for the first thread in the waiting queue and unpark it.
5. When a thread wants to acquire a lock, it will swap the current state to *locked* if the current state is *unlocked* atomically.
   (a) If the thread fails, it must be because the lock is already owned by some other thread, then it will add itself on the waiting queue for that lock. Finally, the thread will park.
   (b) Otherwise, the thread will set itself as the current owner of that lock and also add this lock to its thread-local list of pointers of locks it owns.
6. When a thread is about to release a lock, the current owner pointer of that lock is set to null and that lock is also removed from the thread-local list of owned locks. Finally, the lock state is changed to *unlocked*.
7. Before parking, a thread will check whether there's deadlock. When the current thread is unable to acquire its desired lock, it must be because another thread is owning it already. It is possible to know who is the owner of any lock, so the current thread identifies the owner of its desired lock as the conflicting thread. Then the current thread will search on each lock of its thread-local list of owned locks if the conflicting thread is waiting on it.
   (a) If positive, then we have a circular dependency (current thread is stuck waiting its desired lock and the conflicting thread is stuck waiting for a lock the current thread owns) thus a deadlock exception will be raised.
   (b) Otherwise, the thread parks.

This protocol relies on a few guarantees that were already provided by *ReentrantLock* default implementation such as:

1. The operation of swapping the state of a lock from *unlocked* to *locked* must be done atomically by the thread, so only one thread can be successful at a time.

2. A thread will only park when it's guaranteed some other thread can unpark it. Missing notifications will never happen and concurrent uses of park and unpark on the same thread will be resolved gracefully.
3. Inserts on each lock's waiting queue must be done atomically. If multiple threads concurrently attempt to insert themselves in the waiting queue on the same lock, they will both succeed eventually but the exact order of insertions is not important.
4. Once the last element in the waiting queue of a lock is read, it should be safe to read all threads in the waiting queue that arrived before the last element. Since the thread who reads the waiting queues is also the one who blocks every thread waiting on the queues, we can guarantee the only updates that could happen concurrently is new insertions at the end of each queue. However insertions in the end of the queue are not important once a last element pointer is obtained.

Now we show why this algorithm works:

Lemma 1. *Protocol can always detect deadlock TTTL deadlocks as soon as they happen.*

Proof. Suppose not and a TTTL deadlock occurred without deadlock exception being raised. Let's assume that threads A and B have both acquired locks a and b respectively, as follows:

$$write_A(state_a = locked) \rightarrow write_A(owner_a = A) \tag{1}$$

$$write_B(state_b = locked) \rightarrow write_B(owner_b = B) \tag{2}$$

And now each thread will attempt to acquire the opposing lock: thread A is trying to acquire lock b and thread B is trying to acquire lock a, as follows:

$$read_A(state_b == locked) \rightarrow write_A(waiting\_queue_b.insert(A)) \tag{3}$$

$$read_B(state_a == locked) \rightarrow write_B(waiting\_queue_a.insert(B)) \tag{4}$$

If a TTTL deadlock happened, then both threads are now parked and all previous equations should be correct. But before parking, each thread must check for deadlock by inspecting each lock it owns if the opposing thread is on its waiting queue. As we initially assumed no deadlock exception has been raised, then both threads are parked and also the following equations must be correct:

$$read_A(owner_b == B) \rightarrow read_A(waiting\_queue_a.contains(B) == false) \tag{5}$$

$$read_B(owner_a == A) \rightarrow read_B(waiting\_queue_b.contains(A) == false) \tag{6}$$

The problem with the previous equations is that they both cannot be true simultaneously. Before checking for deadlock, each thread must add itself on the waiting queue of its desired lock. If it holds that the opposing thread is not in the waiting queue yet, then it must be because it did not start to check for deadlock yet, thus a contradiction. $\square$

Lemma 2. *Protocol never throw a deadlock exception for a non-existent TTTL deadlock.*

Proof. Suppose the opposite: a deadlock exception was raised and there's no real 2-deadlock. At least one of the following equations must be true in order to raise a deadlock exception:

$$read_A(owner_b == B) \rightarrow read_A(waiting\_queue_a.contains(B) == true) \quad (7)$$

$$read_B(owner_a == A) \rightarrow read_B(waiting\_queue_b.contains(A) == true) \quad (8)$$

Suppose without loss of generality the first equation is correct. It means thread B is waiting for lock a and it is also the owner of lock b. If it is on the waiting queue, that thread is either parked already or about to park and in both cases it means thread B is going to depend on the release of lock a to proceed. However, as we have seem previously, thread A at this point is also about to park and is checking for a deadlock. If this condition holds, we have a circular dependency between threads A and B, a real TTTL deadlock, thus we have a contradiction. □

We have further extended the protocol to also guarantee the exception being raised on both threads involved. This does not affect how deadlock is detected but what should be done after a deadlock is detected, adding the following steps:

1. Each lock has a list of tainted threads. This list should only be read or updated by the owner of that lock, allowing immunity from interference without any extra synchronization cost.
2. Once a deadlock is detected and the current thread is about to raise a deadlock exception, it already knows: which thread is conflicting with itself; and which lock that thread is desiring. Then the current thread (the owner of the desired lock) will add this conflicting thread in tainted threads list for that lock. After that, deadlock exception is raised.
3. When the conflicting thread is unparked and finally acquires its desired lock (it becomes the owner of that lock), then it is allowed to read the list of tainted threads. If this thread identifies itself into this list, then it must be because it was part of a deadlock before, so it removes its reference from the list and also raise a deadlock exception.
4. Every operation on the list of tainted threads of any locks (either reading or inserting values) should be followed up by some cleanup on all references of threads that are no longer running.

That is sufficient to force both threads to throw exceptions when only one of them would raise an exception in the initial protocol. Initial protocol would only throw exception on both if both threads simultaneously reach the point where they check for deadlock existence. However, for this particular case, this change introduces a different problem: dangling references: each thread would have added their conflicting thread on its owned locks's tainted threads list, but none of them would be able to acquire their respective desired locks (as in *item 3*), thus leaving their references behind for others to cleanup (as in *item 4*). We minimize this issue by asking other threads to clean these unneeded references as soon as they use any of the locks involved in the deadlock.

We modified OpenJDK *ReentrantLock* to implement this algorithm and its code can be found on our code repository[18]. We had to omit here details about that implementation for brevity, but our repository contains commits log history describing what changes we did and why we did them.

4 Evaluation

In this section we present an evaluation of our approach. Our evaluation comprises two parts: (i) a usability evaluation involving two experiments with two groups of students (Section 4.1); and (ii) a preliminary analysis of the performance overhead of our approach (Section 4.2).

4.1 Usability Evaluation

We ran empirical evaluation to measure the efficiency of deadlock exceptions with regards to problem solving speed and accuracy. We defined two research questions for this evaluation: **RQ1.** Is the time spent to identify the bug reduced using our implementation? **RQ2.** Is the accuracy of bug description improved for implementation with deadlock exception when compared to the default one? To answer the first question, we watched for the time (in seconds) to finish each task. For the second question, each answer was evaluated based on five criteria with three different values: 0 for absence, 0.5 for partially present and 1 for fully present. Whenever $(A-B)+C \geq 1.5$ was true, we defined it as a correct answer. It defines a correct answer whenever the bug was described as deadlock and at least one of the methods (out of two) involved in the deadlock were identified.

Table 3: Criteria evaluated for each answer

Type	Description
A	Correctly classified problem as deadlock.
B	Classified problem as different from deadlock.
C	Correctly identified method calls involved in the deadlock.

We wrote two programs with different complexity which were presented in the same order for all subjects. The first program, known as *Bank*, contained 4 classes spread in 4 files, 3 threads, 3 explicit locks, and 82 lines of code in average. The second program, known as *Eclipse* had 15 classes spread in 11 files, 4 threads, 5 explicit locks, and 40 lines of code in average. We expected the first program to be easier to identify the deadlock because it contained fewer classes and files. Each program could use either *LockA* or *LockB*, where *LockA* was our implementation with deadlock detection on at least one thread involved in a deadlock, while *LockB* was just the default *ReentrantLock* implementation. We randomly assigned a group to each student. In group A, student would start with *LockA* in the first question but change to *LockB* on the second one; meanwhile, in group B students would have the locks in opposite order. Finally, we randomly paired subjects in pairs composed of one subject in group A and another subject of group B and created latin squares for each pair.

All students started the experiment with the first question containing *Program 1*. When they finish to provide an answer, they should request for the second question. In this case, we collect the assignment, set a timestamp on it, and deliver second question with *Program 2*. The timestamp was written by supervisors of this experiment based on a chronometer we had visible to everyone on the laboratory. Sometimes when the subject wrote the timestamp themselves once they have finished, supervisors had to double check the value at the time the assignment was collected, overwriting the timestamp if needed. We wanted to have 60 min as time limit for each question on both days, but on the first day the students asked for more time, so we expanded to 90 min each.

We have repeated this experiment for two groups of students with different backgrounds. The first group consisted of undergraduate students attending Programming Language Paradigms course. They had classes about concurrent programming, including exercises in Java using *ReentrantLock* where deadlocks and other concurrent bugs should be avoided; however, these students were not experienced in this area. The second group consisted of graduate students enrolled in master's degree or PhD program attending Parallel Programming course where they had classes about advanced concepts of parallel programming and had a lot of practical exercises, including implementing their own lock; thus, they were expected to have a lot of experience. We run this experiment with each group on different days.

Time Analysis. We defined the following hypothesis to answer **RQ1**:

$$H_0 : \mu_{TimeLockA} \geq \mu_{TimeLockB} \tag{9}$$

$$H_1 : \mu_{TimeLockA} < \mu_{TimeLockB} \tag{10}$$

In order to prevent bias, we needed to control a few factors during the experiment execution. The first factor was the selection of subjects to participate on this experiment, as different background knowledge could potentially influence chosen metrics. The second factor we had to control was the complexity of each program. Complexity we define as the amount of files in the program, number of threads and number of locks to analyze. We wanted to have one program that we considered easy to identify the problem without exceptions and another that was more complex and composed by many files and classes, reflecting a more realistic case. We provided implementations of each program using either *LockA* or *LockB*: the two possible treatments that we want to compare.

We used Latin Square Design to control these two factors mentioned earlier: subjects and program complexity factors. Since we had N subjects, 2 programs and 2 possible treatments, we disposed subjects in rows and programs in columns of latin squares, randomly assigning in each cell of the square a treatment that could be *LockA* or *LockB*, but also guaranteeing that for any given row or column in this square, each treatment appears only once. Consequently, we have replication, local control and randomization which are the three principles of experiment design [25].

Time analysis was conducted with R Statistical Software using the inputs extracted from each day. We've used the linear model described in Figure 1 that considers the effect of different factors on the response variable similarly to Paola's work [21], but we've also added the effect between each replica and the treatment as explained by Sanchez [20].

$$Y_{lijk} = \mu + \tau_l + \tau\alpha_{li} + \beta_j + \gamma_k + \tau\gamma_{lk} + \epsilon_{lijk}$$

Y_{lijk} - response of l_{th} replica, i_{th} student, j_{th} program, k_{th} lock
τ_l - effect of l_{th} replica
$\tau\alpha_{li}$ - effect of interaction between l_{th} replica and i_{th} student
β_j - effect of j_{th} program
γ_k - effect of k_{th} lock
$\tau\gamma_{lk}$ - effect of interaction between l_{th} replica and k_{th} lock
ϵ_{lijk} - random error

Fig. 1: Regression model.

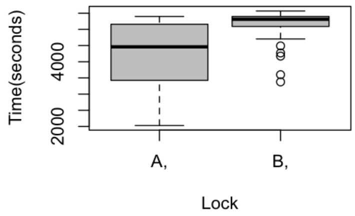
Initially, we've plotted the box-plot graphic shown in Figure 2 for both experiments. Then we've run the Box-Cox transformation - which is a power transformation - to reduce anomalies such as non-additivity and non-normality, and we found the value of λ at the maximum point in the curve was not approximately 1 ($\lambda = 5$), thus we should apply the transformation; that is, on our regression model, Y_{lijk} should be powered to λ we found. Similarly, we applied Box-Cox transformation for the second experiment as $\lambda = 1.3636$.

After applying Box-Cox transformation, we ran Tukey Test of Additivity that checks whether effect model is additive, so we can evaluate whether interaction between factors displayed on the rows and columns of each latin square won't affect significantly the response when the model is additive [25]; thus, considering the following hypothesis:

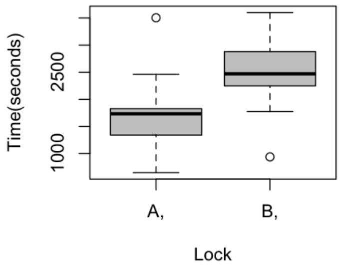
H_0 : The model is additive
H_1 : H_0 is $false$

In the first experiment, we obtained a p-value of 0.514, which is not lower than 0.05 thus we cannot reject H_0. That means the model was considered to be additive. We had the same conclusion for the second experiment where p-value was 0.914.

Finally, we ran the ANOVA (ANalysis Of VAriance) test which compares the effect of treatments on the response variable, providing an approximated p-value



(a) First experiment



(b) Second experiment

Fig. 2: Box-plot on both experiment days

for every associated factor. When a variable has *p-value* < 0.05, it means that factor was significant to the response. We can see from Table 4 and Table 5 the most important factor was indeed the type of *Lock* for both experiments, thus allowing us to reject our null hypothesis defined for **RQ1**.

Table 4: First experiment ANOVA results.

	Df	Sum Sq	Mean Sq	F value	*p-value*
Replica	14	3.8633e+37	2.7595e+36	1.6553	0.1784197
Program	1	4.1460e+36	4.1460e+36	2.4869	0.1371197
Lock	1	3.9489e+37	3.9489e+37	23.6873	0.0002492 ***
Replica:Student	15	4.1013e+37	2.7342e+36	1.6401	0.1808595
Replica:Lock	14	2.4033e+37	1.7166e+36	1.0297	0.4785520
Residuals	14	2.3340e+37	1.6671e+36		

Accuracy Analysis. We defined the following hypothesis to answer **RQ2**:

$$H_0 : \mu_{CorrectAnswersLockA} \leq \mu_{CorrectAnswersLockB} \tag{11}$$

$$H_1 : \mu_{CorrectAnswersLockA} > \mu_{CorrectAnswersLockB} \tag{12}$$

Since we were interested in the number of correct answers for each lock, we ran the equation defined previously to count how many of them were correct and obtained the following tables:

Applying Fisher's exact test we can see that undergraduate students results presented a two-tailed P value equals 0.0004: the association between rows (groups) and columns (outcomes) was considered to be extremely statistically significant; consequently, it's an evidence of improvement on accuracy. Meanwhile graduate students results presented a two-tailed P value equals 0.3259, which does not represent a statistically significant evidence.

Table 5: Second experiment ANOVA results.

	Df	Sum Sq	Mean Sq	F value	Pr(¿F)
replica	6	2576883250	429480542	14.1891	0.0025793 **
program	1	6875586	6875586	0.2272	0.6505035
lock	1	1958179433	1958179433	64.6938	0.0001975 ***
replica:student	7	2328154077	332593440	10.9881	0.0047601 **
replica:lock	6	823830276	137305046	4.5362	0.0441188 *
Residuals	6	181610625	30268438		

	Correct	Incorrect
LockA	29	2
LockB	16	15

Table 6: First group accuracy

	Correct	Incorrect
LockA	13	1
LockB	10	4

Table 7: Second group accuracy

Discussion We can see in our results that both groups of students have improved their time to solve the problem when they had the lock with deadlock exception. But only for the first group we found statistically significant evidence that it improved answers accuracy. Although we cannot draw conclusions regarding improved accuracy, we can share some relevant observation we had during the second experiment: some students in the second group were greatly experienced on concurrent programming and they knew how to efficiently find a deadlock using the tools available in Eclipse, thus being able to finish the tasks really quickly for both problems knowing exactly which points in the code were involved in the deadlock. Thus it's possible deadlock exceptions being more helpful for less experienced programmers in general. However we believe their benefits are beyond helping just inexperienced programmers. Experienced programmers would still benefit in many cases where the deadlock is not as obvious as in the exercise we presented. For example, in a more realistic situation, a deadlock can happen in a background thread that doesn't really affect the program execution overall but make the execution lack some expected behavior. Furthermore, in non-interactive systems where they are only running in background, is nearly impossible to know when there's a problem unless this software is monitored constantly which is very time consuming or the system produces output constantly that is affected by a potential deadlock. If we have a deadlock exception, we can either prepare and handle this exception on the code level, or just have this signal from output that would help developers to fix it later.

Threats to Validity In this usability evaluation, we collected evidence on how the presence of deadlock exception affects student ability to quickly identify deadlocks accurately, but we should make a few remarks regarding the validity of our results. First remark is about the way we collected the timestamps: when a student finished any question, we manually wrote their name with the timestamp on the whiteboard so we could track time limit individually later, but we could potentially reduce overhead and increase timestamps precision if we used an automated alternative. Secondly, the first group did this experiment in replacement of their actual exam might have impacted the time we measured. We noticed some students spent more time on each question by purpose. We believe that they were reluctant to ask for the next question because they still had plenty of time left and they wanted to make sure it was correct. We did not notice such behavior with the second group of students and we believe it is because they did not have the same pressure to deliver correct results as the first group had. Third remark is related to programs' complexity: the ones we used to evaluate the students are considerably easier to understand than most programs in real world, but unfortunately we could not use any real world scenario as students would not be able to finish each assignment in time; with that in mind, we created two questions based on real world bugs we found on our bug report studies. Forth remark is about different background over different subjects: we tried to minimize their background differences by selecting groups where students had at least basic experience in concurrent programming and they should be familiarized with the types of bugs such codes could have; the first group was composed by undergraduate students who attended the class *Paradigms of Computaional Languages* where deadlocks were covered in classes and exercises; meanwhile, the second group had graduate students who attended the class *Parallel Programming* which covered concurrent programming in low level detail including deadlock detection. Last remark is about whether we are able to draw conclusions based on students data: some studies suggest that using students as subjects is as good as using industry professionals [24]; Runes ran an experiment which shows that there's not much significant differences between undergraduate, graduate and industry professionals, with the exception that undergraduate students often take more time to complete the tasks [23].

4.2 Performance Overhead

We conducted a preliminary set of experiments to analyze the overhead of our approach. We compared our deadlock-safe implementation with the original `ReentrantLock` implementation available in the JDK and with Eclipse's deadlock-safe `OrderedLock` [19]. `OrderedLock` is similar our approach in the sense that it attempts to detect deadlocks at runtime. However, it aims to be general, detecting N-thread deadlocks without much concern for performance. OrderedLock deeply relies on Eclipse's code architecture. So, in order to use it in our evaluation, we had to perform some small code changes, removing only Eclipse-specific bits that did not affect the core functionality of `OrderedLock`. The source code for these lock implementations is available elsewhere[18].

We developed a synthetic benchmark that creates N threads that perform additions to ten integer counters where each increment in a counter is protected by explicit locks. Each thread would have to increment its corresponding counter 1000 times before finishing its execution and the counters were evenly distributed across the threads. Therefore, each counter will have exactly *(N / 10)* threads doing increments on it and higher values of N result in higher contention, that is, more threads will compete against each other for a particular counter. In this preliminary evaluation, we have conducted measurements for values of N equal to 10, 50, 100, and 200. Since each thread in the benchmark never acquires more than one lock at the same time, deadlocks cannot occur. We emphasize that this setup is very conservative, since every operation that each thread performs requires locking. Thus, the obtained overhead will be a worst-case estimate and thus much higher than one would encounter in a real-world application [26].

The measurements were made on an Intel CoreTM i7 3632QM Processor (6Mb Cache, 2.2GHz) running Linux and each cell in Table 8 is the average of 50 executions (preceded by 20 executions that served as a warm-up).

Table 8: Benchmark time measurements (in seconds)

# Threads	ReentrantLock	ReentrantLock Modified	OrderedLock
10	0.084184	0.105729	0.159503
50	0.089094	0.136507	1.094718
100	0.090978	0.159541	3.395974
200	0.131739	0.194075	11.258714

The difference of results between our implementation and the original ReentrantLock gives a range of increased time from about 50% to 90%. Meanwhile, OrderedLock performed a lot worse, reaching a 8446.3% increase in time for the worst case.

To get a rough estimate of the impact that this overhead would have on actual application execution time, we analyzed the results obtained by Lozi et al. [26]. The authors profiled 19 real-world applications and small benchmarks in order to measure the time these systems spend on their critical sections. Worst-case results ranged between 0.3% and 92.7%. If we consider the average time spent on the critical sections of 12 of these systems, the impact of our approach on the overall execution time would be **less than 6% in the worst case**. The remaining cases are extreme, in the sense that these systems spend more time in their critical sections than out of them [26].

5 Related Work

We have found recent studies with proposed techniques to either detect deadlock or avoid them, but they are not yet practical in real world as they have many limitations either performance wise or regarding difficulty to be deploy in already existing languages. Since deadlock detection algorithms can either be static analysis, dynamic analysis or a mix of both, we present some studies related to each type.

Static analysis techniques verify source code from a program and try to identify potential problems present in the code without even executing it. For deadlock detection, they generally attempt to detect cyclic relationships of resource acquisition between threads where each cycle represents a possible deadlock. Many static analysis approaches were proposed [4][6][7][8] but in general they suffer of signficant amount of false positives being reported as there may exist deadlock cycles that are just impossible to happen during execution.

Dynamic analysis [9][10] finds potential deadlock cycles from execution traces of programs which makes them often more scalable and precise than static analysis. However, due to the sizes of large-scale programs, the probability that a given run will show a thread acquiring a lock at the right time to trigger a deadlock for each potential deadlock present in the code is very low, which poses a challenge for dynamic deadlock detection tools. Other dynamic techniques [11] [14] offer dynamic detection and recovery of deadlocks using *rollback* operations which are usually very costly and not always possible [13].

Lastly, we have a hybrid analysis, they are often using program analysis and compile time instrumentation to guide runtime and achieve better performance [12] or to run expensive computations during compile time to use later used at runtime [17]. Even though they employ both techniques simultaneously, they generate slower compile times, also requiring recompiling code to be able to find new potential deadlocks later. They also share limitations runtime techniques does, the main difference is that they tend to perform better than dynamic analysis alone during runtime.

6 Conclusion

In this work, we investigated which kind of deadlock is the most popular by looking at actual bug reports in relevant open source projects and confirmed a previous study claim that TTTL deadlocks are the most frequent case of deadlock, that is, 92.07% of all resource deadlocks we identified. This claim allowed us to focus on it instead and proposed an algorithm that efficiently detects them without any extra lock operations. We modified Java's *ReentrantLock* and provided a lightweight version of it that detects TTTL deadlock in runtime. We measured its performance overhead with a very conservative benchmark and we estimate our cost to be less than 6% for worse case on real world applications. Finally, we did an empirical evaluation to measure its usability and we found that deadlock exceptions speeds up finding deadlock bugs in code, and we also found some non-conclusive evidence showing that it may also improve accuracy of deadlock bug reports, but we leave for future work to verify whether this last observation is actually true.

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