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Exploring Failure Transparency and the Limits of Generic Recovery

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Abstract: We explore the abstraction of failure transparency in which the operating system provides the illusion of failure-free operation. To provide failure transparency, an operating system must recover applications after hardware, operating system, and application failures, and must do so without help from the programmer or unduly slowing failure-free performance. We describe two invariants that must be upheld to provide failure transparency: one that ensures sufficient application state is saved to guarantee the user cannot discern failures, and another that ensures sufficient application state is lost to allow recovery from failures affecting application state. We find that several real applications get failure transparency in the presence of simple stop failures with overhead of 0-12%. Less encouragingly, we find that applications violate one invariant in the course of upholding the other for more than 90% of application faults and 3-15% of operating system faults, rendering transparent recovery impossible for these cases.

1. Introduction

One of the most important jobs of the operating system is to conceal the complexities and inadequacies of the underlying machine. Towards this end, modern operating systems provide a variety of abstractions. To conceal machines' limited memory, for example, operating systems provide the abstraction of practically boundless virtual memory. Similarly, operating systems give the abstraction of multithreading for those applications that might benefit from more processors than are present in hardware.

Failures by computer system components, be they hardware, software, or the application, are a shortcoming of modern systems that has not been abstracted away. Instead, computer programmers and users routinely have to deal with the effects of failures, even on machines running state-of-the-art operating systems.

With this paper we explore the abstraction of *failure transparency* in which the operating system generates the illusion of failure-free operation. To provide this illusion, the operating system must handle all hardware, software, and application failures to keep them from affecting what the user sees. Furthermore, the operating system must do so without help from the programmer and without unduly slowing down failure-free operation.

Fault-tolerance research has established many of the components of failure transparency, such as programmer-transparent recovery [4, 11, 25, 28], and recovery for general applications [4, 14]. Some researchers have even discussed handling application failures [13, 17, 31].

However, significant questions surrounding failure transparency remain. The focus of this paper is on delving into several of these unanswered questions. First, we will explore the question "how does one guarantee failure transparency in general?" The answer to this question comes in the form of two invariants. The first invariant is a reformulation of existing recovery theory, governing when an application must save its work to ensure that the user does not discern failures. In contrast, the second invariant governs how much work an application must lose to avoid forcing the same failure during recovery.

The Save-work invariant can require applications to commit their state frequently to stable storage. The question therefore arises "how expensive is it for general applications to uphold the Save-work invariant?" In answering this question we find, to our surprise, that even complex, general applications are able to efficiently uphold Save-work.

Given that the Save-work invariant forces applications to preserve work and the Lose-work invariant forces applications to throw work away, we conclude by investigating the question, "how often do these invariants conflict, making failure transparency impossible?" The unfortunate answer is that the invariants conflict all too often.

2. Guaranteeing Failure Transparency

We first delve into the question: *how does one guarantee failure transparency in general?* Our exploration begins with a synthesis of existing recovery theory that culminates in the Save-work invariant. In Section 2.4, we then extend recovery theory to point out a parameterization of the space of recovery protocols, as well as the relationship between protocols at different points in the space. Finally, we develop a new theory and second invariant for ensuring the possibility of recovery from failures that affect application state.

2.1. Primitives for general recovery

In attempting to provide failure transparency, the goal is to recover applications using only general techniques that

require no help from the application. There are several recovery primitives available to us in this domain: *commit events*, *rollback* of a process, and *reexecution* from a prior state.

A process can execute commit events to aid recovery after a failure. By executing a commit event, a process preserves its state at the time of the commit so that it can later restore that state and continue execution. Although how commit events are implemented is not important to our discussion, executing a commit event might involve writing out a full-process checkpoint to stable storage, ending a transaction, or sending a state-update message to a backup process.

When a failure occurs, the application undergoes rollback of its failed processes; each failed process is returned to its last committed state. From that state, the recovering process begins reexecution, possibly recomputing work lost in the failure.

Providing generic recovery requires that applications tolerate forced rollback and reexecution. As a result, all application operations must be either undoable or redoable.

Most application operations that simply modify process state are easily undone. However, some events, such as message sends, are hard to undo. Undoing a send can involve the added challenge of rolling back the recipient's state. Other events can be impossible to undo. For example, we cannot undo the effects on the user resulting from visible output. However, systems providing failure transparency ensure that these user-visible events will never be undone.

Similarly, since simple state changes by the application are idempotent, most application events can be safely redone. However, events like message sends and receives are more difficult to redo. For message send events to be redoable, the application must either tolerate or filter duplicate messages. For receive events to be redoable, messages must be saved at either the sender or receiver so they can be redelivered after a failure. Luckily, these reexecution requirements are very similar to the demands made of systems that transmit messages on unreliable channels (e.g. UDP). Such systems must already work correctly even with lost or duplicated messages. For many recovery systems, an application or protocol layer's natural filtering and retransmission mechanisms will be enough to support the needs of reexecution recovery. For others, messages may have to be held in a recovery buffer of some kind so they can be re-delivered should a receive event be redone.

2.2. Computation and failure model

We will informally present a recovery theory that will let us relate the challenge of guaranteeing failure transparency to the precise events executed by an application. For a more formal version of the theory, please see [22].

We begin by constructing a model of computing. One or more processes working together on a task is called a *computation*. We model each process as a finite state machine. That is, each process has state and computes by transitioning from state to state according to the inputs it receives. Each state transition executed by a process is an *event*. An event e_p^i is the i'th event executed by process p. Events can correspond in real programs to simple changes of application state, sending and receiving messages, and so on. We call events that have an effect on the user *visible events* (these events have traditionally been called "output events" [11]). Under our model, computation proceeds *asynchronously*, that is, without known bounds on message delivery time or the relative speeds of processes.

As needed, we will order events in our asynchronous computations with Lamport's *happens-before* relation [19]. We may also need to discuss the causal relationship between events. For example, we may need to ask, "did event e in some way *cause* event e'?" We will use *happens-before* as an approximation of causality. We will however distinguish between *happens-before*'s use as an ordering constraint and its use as an approximation of causality by using the expression *causally precedes* in this latter role. That is, we say event e *causally precedes* event e' if and only if e *happens-before* e' and we intend to convey that e causes event e'.

We will consider failures of two forms. A *stop failure* is one in which execution of one or more processes in the computation simply ceases. Stop failures do occur in real systems—the loss of power, the frying of a processor, or the abrupt halting of the operating system all appear to the recovery system as stop failures. Since stop failures instantaneously stop the execution of the application and do not corrupt application state, recovering from them is relatively easy.

Harder to handle are *propagation failures*. We define a propagation failure to be one in which a bug somewhere in the system causes the application to enter a state it would not enter in a failure-free execution. A propagation failure can begin with a bug in hardware, the operating system, or the application. Bugs in the application are always propagation failures, but bugs in hardware and the operating system are propagation failures only once they affect application state.

Recovering from propagation failures is hard because a process can execute for some time after the failure is triggered. During that time the process can propagate buggy data into larger portions of its state, to other processes, or onto stable storage.

We can imagine bugs that do not cause crashes, but that simply cause incorrect visible output by the application. However, our focus with this work is on recovering from failures. Therefore, we will assume that applications will detect faults and fail before generating incorrect output.

2.3. Failure transparency for stop failures

We start by examining how to ensure failure transparency in the presence of stop failures. We must first fix a precise notion of "correct" recovery from failures. We could

establish almost any standard: recovering the exact pre-failure state, losing less than 10 seconds of work, and so on. However, given that our end goal is to mask failures from the user, we will define correct recovery in terms of the application output seen by the user.

Given a computation in which processes have failed, recovered, and continued execution:

Definition: Consistent Recovery

Recovery is *consistent* if and only if there exists a complete, failure-free execution of the computation that would result in a sequence of visible events equivalent to the sequence of visible events actually output in the failed and recovered run.

Thus for an application's recovery to be consistent, the sum total of the application's visible output before and after a failure must be equivalent to the output from some failure-free execution of the application.

It is possible that many different modes of consistent recovery could be allowed depending on how one defines "equivalent". For our purposes, we will call a sequence of visible events V output by a recovered computation equivalent to sequence V' output by a failure-free run if the only events in V that differ from V' are repeats of earlier events from V.

We use equivalence in which duplicate visible events are allowed because guaranteeing no duplication is very hard (exactly once delivery problem). Furthermore, allowing duplicates provides some flexibility in how one attains consistent recovery. More importantly, users can probably overlook duplicated visible events. See [22] for a more detailed discussion of equivalence.

Our definition of consistent recovery places two constraints on recovering applications. First, computations must always execute visible events that extend a legal, failure-free sequence of visible events, even in the presence of failures. We will call this the *visible constraint*. Second, computations must always be able to execute to completion. This latter constraint follows from the fact that consistent recovery is defined in terms of *complete* sequences of visible events. If a failure prevents an application from running to completion, its sequence can never be complete. For reasons that will become clear later, we will call this second constraint on recovery the *no-orphan constraint*.

Although consistent recovery and failure transparency are closely related, they are not the same thing. Providing failure transparency amounts to guaranteeing consistent recovery without any help from the application, and without slowing the application's execution appreciably.

Our next task is to examine how to guarantee applications get consistent recovery. One particular class of events poses the greatest challenge: *non-deterministic events*. In a state-machine, a non-deterministic event is a transition from a state that has multiple possible next states. For example, in

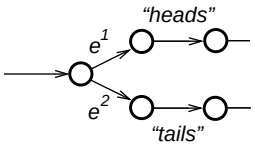


Figure 1: Coin-flip application. Depending on whether non-deterministic event e^1 or e^2 gets executed, the application executes one of two possible visible events.

Figure 1, events e^1 and e^2 are both non-deterministic. In real systems, non-deterministic events correspond to actions that can have different results before and after a failure, like checking the time-of-day clock, taking a signal, reading user input, or receiving a message.

Non-deterministic events are intimately related to consistent recovery. To see how, again consider the application shown in Figure 1. Imagine that the application executes non-deterministic event e^1, then the visible event *"heads"*, then fails. Then during recovery imagine that the application rolls back and this time executes e^2 followed by the visible event *"tails"*. Although this application can correctly output either *heads* or *tails*, in no correct execution does it output both *heads* and *tails*. Therefore, recovery in this example is not consistent and our sample application's non-deterministic events are the culprits.

As discussed in Section 2.1, applications can execute commit events to aid later rollback. We would like to use commit events to guarantee consistent recovery, avoiding the inconsistency non-deterministic events can cause. The following theorem provides the necessary and sufficient condition for doing exactly that under stop failures.

Save-work Theorem

A computation is guaranteed consistent recovery from stop failures if and only if for each executed non-deterministic event e_p^i that *causally precedes* a visible or commit event e, process p executes a commit event e_p^j such that e_p^j *happens-before* (or atomic with) e, and $i \leq j$.

This theorem dictates when processes must commit in order to ensure consistent recovery. At the heart of this theorem is the Save-work invariant, which informally states "each process has to commit all its non-deterministic events that causally precede visible or commit events". We can further divide this invariant into separate rules, one that enforces the visible constraint of consistent recovery, and one that enforces the no-orphan constraint. If we follow the rule "commit every non-deterministic event that causally precedes a visible event", we are assured that the application's visible output will always extend a legal sequence of visible events. We'll call this the Save-work-visible invariant. If we follow the rule "commit every non-deterministic event that causally precedes a commit event", we are assured that a finite number of stop failures cannot prevent the application from executing to completion. We'll call this the

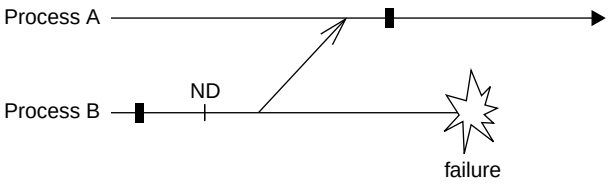


Figure 2: A problematic distributed computation. We see two processes' timelines. The arrow between the processes represents a message from B to A. Black boxes represents commits. The event marked "ND" is a non-deterministic event. Process A is an orphan after Process B's failure as A has committed a dependence on B's lost non-deterministic event.

Save-work-orphan invariant. To better understand this latter rule, consider the computation depicted in Figure 2.

A process is called an *orphan* if it has committed a dependence on another process's non-deterministic event that has been lost and may not be reexecuted. For example, Process A in Figure 2 is an orphan because it has committed its dependence on Process B's lost non-deterministic event.

An orphan can prevent an application from executing to completion when it is upholding Save-work-visible. Consider an orphan that has committed a dependence on a lost non-deterministic event e_p^{ND}. If the orphan attempts to execute a visible event *e*, Save-work-visible requires that process *p* commit e_p^{ND}. However, since process *p* has already failed and aborted e_p^{ND}, it cannot commit it. Furthermore, since the orphan cannot abort its dependence on e_p^{ND}, it can never execute *e* and the computation will not be able to complete.

The remedy for this scenario is to uphold Save-work-orphan, which ensures that any non-deterministic event that causally precedes a commit is committed.

We must make two assumptions for the Save-work Theorem to be necessary. We ensure the necessity of Save-work-visible by assuming that all non-deterministic events can cause inconsistency. We ensure the necessity of Save-work-orphan by assuming that all processes in the computation affect the computation's visible output. For the details of these assumptions as well as the proof of the Save-work Theorem, please see [22].

2.4. Upholding Save-work

There are many ways an application can uphold the Save-work invariant to ensure consistent recovery for stop failures. For example, an application can execute a commit event for every event executed by the application. Although such a protocol will cause a very large number of commits, it has the advantage of being trivial to implement: the protocol does not need to figure out which events are non-deterministic, or which events are visible. Even without knowing event types, it correctly upholds the Save-work invariant.

Consider a protocol in which each process executes a commit event immediately after each non-deterministic event. In committing all non-deterministic events, this protocol will certainly commit those non-deterministic events that causally precede visible or commit events. Therefore it upholds Save-work and will guarantee consistent recovery. We call this protocol Commit After Non-Deterministic, or CAND.

We can also uphold Save-work without knowing about the non-determinism in the computation. Under the Commit Prior to Visible or Send protocol (CPVS), each process commits just before doing a visible event or a send to another process. When a process commits before each of its visible events, it is assured that all its non-determinism that causally precedes the visible event is committed. If each process also commits before every send event, then it cannot pass a dependence on an uncommitted non-deterministic event to another process. Thus, CPVS also upholds Save-work.

The Commit Between Non-Deterministic and Visible or Send (CBNDVS) protocol takes advantage of knowledge of both non-determinism and visible and send events in order to uphold Save-work. Under this protocol, each process commits immediately before a visible or send event if the process has executed a non-deterministic event since its last commit.

Since commit events can involve writing lots of data to stable storage, they can be slow. Therefore, minimizing the number of commits executed can be important to failure-free performance. There exist several general techniques for minimizing commits.

Logging is a general technique for reducing an application's non-determinism [12]. If an application writes the result of a non-deterministic event to a persistent log, and then uses that log record during recovery to ensure the event executes with the same result, the event is effectively rendered deterministic. Logging some of an application's non-determinism can significantly reduce commit frequency. Logging *all* an application's non-determinism lets the application uphold Save-work without committing at all.

Tracking whether one process's non-determinism causally precedes events on another process can be complex. In fact, we can think of the CPVS protocol as pessimistically committing before send events rather than track causality between processes. However, applications can avoid committing before sends without tracking causality by employing a distributed commit, such as *two-phase commit* (2PC)—all processes would commit whenever any process does a visible event. Using two-phase commit can reduce commit frequency if visible events are less frequent than sends. Applications can further reduce commits by tracking causality between processes, involving in the coordinated commit only those processes with relevant non-deterministic events.

Not only can each of these protocols be viewed as a different technique for upholding Save-work, but so can all existing protocols from the recovery literature.

For example, pure message logging protocols make all message receive events deterministic, allowing applications

whose only non-deterministic events are receives to uphold Save-work without committing. The different message logging protocols differ in how the logging is carried out. For example, *Sender-based Logging* (SBL) protocols keep the log record for the receive event in the volatile memory of the sender [15], while *Family-based Logging* (FBL) keeps log entries in the memory of downstream processes [2].

In the *Manetho* system, each process maintains log records for all the non-deterministic events it depends on in an *antecedence graph*. When a process wants to execute a visible event, it upholds Save-work by writing the antecedence graph to stable storage [11]. In the *Optimistic Logging* protocol, processes write log records to stable storage asynchronously [28]. When a process wants to do a visible event, it upholds Save-work by first waiting for all relevant log records to make it to disk.

The *Targon/32* system attempts to handle more non-determinism than these other logging protocols [4]. All sources of non-determinism except signals are converted into messages that are logged in the memory of a backup process on another processor. Whenever a signal is delivered (an event that remains non-deterministic), Targon/32 forces a commit to uphold Save-work. The *Hypervisor* system logs *all* sources of non-determinism using a virtual machine under the operating system [5].

Under a Coordinated Checkpointing protocol, a process executing a visible event essentially assumes that all processes in the computation with which it has recently communicated have executed non-deterministic events that causally precede the visible event [18]. To uphold the Save-work invariant, the process executing the visible event initiates an agreement protocol to force all these other processes to commit.

Each of these recovery protocols represents a different technique for upholding Save-work. Each to varying degrees trades off programmer effort and system complexity for reduced commit frequency (and hopefully overhead).

Some protocols focus their effort to reduce commit frequency on the challenge of identifying and reducing non-determinism. Others endeavor to use knowledge of an application's visible events. Still others do some of each. Each protocol can be seen as representing a point in a two-dimensional space of protocols. One axis in the space represents effort made to identify and possibly convert application non-determinism. The other axis represents effort made to identify visible events and to commit as few non-visible events as possible.

Such a protocol space is useful because it helps us understand the relationships between historically disparate protocols and to identify new ones. Figure 3 shows how the protocols we have described in this section might appear in such a protocol space.

A protocol falling at the origin of the space would uphold Save-work by committing every event executed by each process, exerting no effort to determine which events are non-deterministic or visible. As protocols fall further out the horizontal axis, they make sufficient effort to recognize that some events are deterministic and therefore do not require commits. At the point occupied by CAND, the protocol makes sufficient effort to distinguish all of the application's deterministic and non-deterministic events, executing a commit only after non-deterministic ones. Beyond that point, the protocols begin to employ logging, exerting effort to convert more and more of the application's non-deterministic events into deterministic ones. A protocol in that portion of the space forces a commit only when the application executes some unlogged non-determinism. At the point occupied by Hypervisor, the protocol makes sufficient effort to log all non-determinism, never forcing a commit.

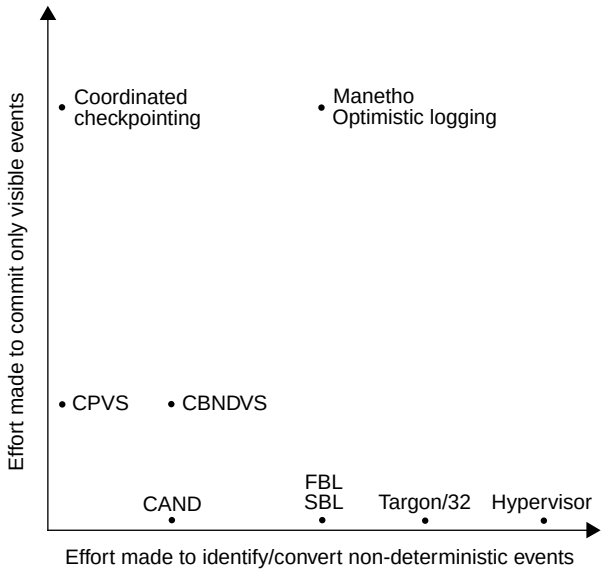


Figure 3: Protocol space. All consistent recovery protocols fall somewhere in this space. Some protocols focus on dealing with non-determinism, while others concern themselves with visible events. Some do a little of each.

For the vertical axis, we can think of the protocol at the origin as committing all events rather than exert the effort needed to determine which events are visible. Protocols falling further up the axis exert more effort to avoid committing events that are not visible. At the point occupied by CPVS, protocols commit only the true visible events and send events—committing before sends takes less effort than tracking whether that send leads to a visible event on another process. Protocols falling yet further up in the space (such as Coordinated Checkpointing) are able to ask remote processes to commit if needed. Under those protocols, applications are forced to commit before visible events only.

Some protocols fall in the middle of the space, applying techniques both for identifying and converting non-determinism, as well as for tracking the causal relationship

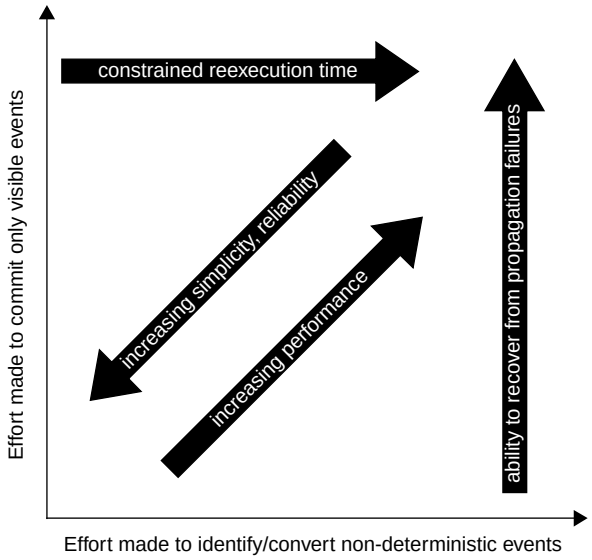


Figure 4: Protocol space with other design variables.

between non-deterministic events and the visible events they cause.

Although all protocols in the space are equivalent in terms of upholding Save-work, they do differ in terms of other design variables. As shown in Figure 4, we can map trends in several important design variables onto the protocol space.

The farther a protocol falls from the origin, the lower its commit frequency is likely to be, and therefore, the better its performance. However, this improved performance comes at the expense of simplicity and reliability. Protocols close to the origin are very simple to implement, and therefore are more likely to be implemented correctly.

For protocols that fall on the vertical axis, the recovery system needs only rollback failed processes and let them continue normally. Protocols further to the right in the protocol space have longer recovery times because after rollback, the recovery system must for some time constrain reexecution to follow the path taken before the failure.

The further a protocol falls from the horizontal axis, the more non-determinism it safely leaves in the application. As we will discuss in Section 2.6, the more non-determinism in an application, the better the chance it will survive propagation failures.

2.5. Failure transparency for stop and propagation failures

As mentioned in Section 2.2, failures can take two forms: stop failures and propagation failures. Upholding the Save-work invariant is enough to guarantee consistent recovery only in the presence of stop failures. To illustrate this observation, consider a protocol that commits all events a process executes. This protocol clearly upholds Save-work. However, if the process experiences a propagation failure

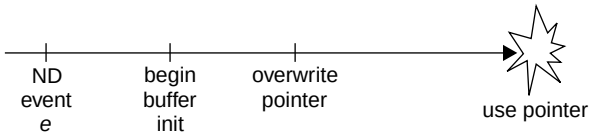


Figure 5: Sample propagation failure timeline. A non-deterministic event *e* causes buffer initialization to overflow and trash a pointer. A commit any time after *e* will prevent recovery from this failure.

(which by definition involves executing buggy events), this protocol is guaranteed to commit buggy state. As a result, the process will fail again during recovery, and the application will never be able to complete after the failure.

Thus, in order to guarantee consistent recovery in the presence of propagation failures, an application must not only commit to uphold Save-work, but when it commits it must avoid preserving the conditions of its failure. In this section we examine what exactly an application must do to guarantee consistent recovery in the presence of propagation failures.

As was the case in our discussion of consistent recovery, non-deterministic events are central to the issue of recovering from propagation failures. Imagine an application that, as a result of non-deterministic event *e*, overruns a buffer it is clearing and zeroes out a pointer down the stack (see Figure 5). Later, it attempts to dereference the pointer and crashes. Obviously if the application commits after zeroing the pointer, recovery is doomed. However, if the application commits any time *before* zeroing the pointer and after *e*, recovery will still be doomed if there are no other non-deterministic events after *e*. In this case, the pointer is not corrupted in the last committed state, but it is guaranteed to be *re-corrupted* during recovery.

Note that had the application committed just before *e* and not after, all could be well. During recovery, the application would redo the non-deterministic event which could execute with a different result and avoid this failure altogether.

Thus non-determinism helps our prospects for recovering from propagation failures by limiting the scope of what is preserved by a commit.

But, not all non-determinism is created equal in this regard. In building up the Save-work invariant, we conservatively treated as non-deterministic any event that could conceivably have a different result during recovery. However, some non-deterministic events are likely to have the same result before and after a failure, and the recovery system cannot depend on these events to change after recovery. We will called these events *fixed non-deterministic* events.

A common example of a fixed non-deterministic event is user input. We cannot depend on the user to aid recovery by entering different input values after a failure. Other examples of fixed non-deterministic events include non-deterministic events whose results are based on the fullness of the

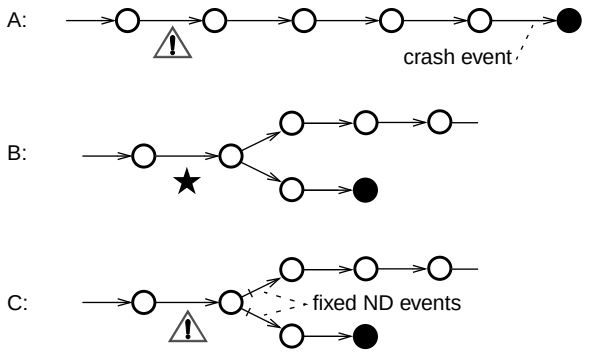


Figure 6: Three sample machines with crash events (events that end states filled black). It is okay to commit in case B at the point marked. Committing either A or C where marked could prevent recovery.

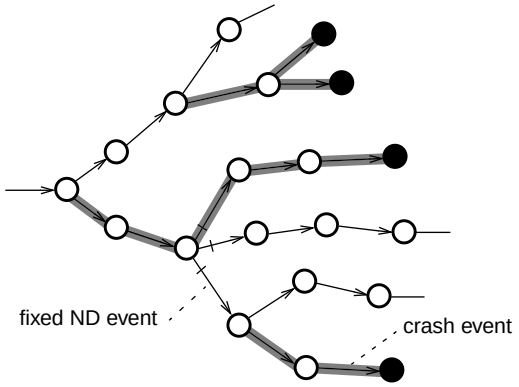


Figure 7: Portion of a state machine, its crash events, and corresponding dangerous paths. Crash events are those that end in states filled black. Fixed non-deterministic events are marked with a slash. The shaded paths are dangerous.

disk (such as the `write` system call), or that depend on the number of slots left in the operating system's open file table (such as the `open` system call).

Non-deterministic events that are not fixed we will call *transient non-deterministic* events. Scheduler decisions, signals, message ordering, the timing of user input, and system calls like `gettimeofday` are all transient non-deterministic events.

We need to incorporate into our computational model a way to represent the eventual crash of a process during a propagation failure. We will model a process's crash as the execution of a *crash event*. When a process executes a crash event, it transitions into a state from which it cannot continue execution. In the example in Figure 5, the crash event is the dereferencing of the null pointer.

As mentioned above, an untimely commit during a propagation failure can ensure that recovery fails. Let us examine in more detail when a process should not commit.

Clearly a process should not commit while executing a string of deterministic events that end in a crash event. Doing so is guaranteed to either commit the buggy state that leads to the crash, or to ensure that the faulty state is regenerated during recovery. This case is shown in Figure 6A.

However, a process can safely commit before a transient non-deterministic event as long as at least one of the possible results of that event does not lead to the execution of a crash event (see Figure 6B).

How about committing before a fixed non-deterministic event where one of the event's possible results leads to a crash? This case is shown in Figure 6C. If the application commits before the fixed non-deterministic event, recovery is possible only if the event executes with a result that leads down the path not including the crash event. If the application is unlucky and the fixed non-deterministic event sends the application down the path towards the crash, the commit will ensure recovery always fails. Since we cannot rely on fixed non-deterministic events having results conducive to recovery, we cannot commit before any fixed non-deterministic events that might lead to a crash.

We can infer that some paths through a portion of a state machine are problematic for handling propagation failures—committing anywhere along the paths could prevent recovery. We next present an algorithm for finding these paths. For this discussion, we assume perfect knowledge of each process's crash events. We recognize that this is not practical—if we knew all the crash events, we could likely fix all the bugs! However, making this assumption will help us to analyze when recovery is possible with the best possible knowledge.

Given a single process's state machine and its crash events:

Single-Process Dangerous Paths Algorithm

- Color all crash events in the state machine.
- Color an event *e* if all events out of *e*'s end state are colored.
- Color an event *e* if at least one event out of *e*'s end state is colored and is a fixed non-deterministic event.

We call all the paths in the state machine colored by this algorithm *dangerous paths*. A portion of a state machine with its dangerous paths highlighted is shown in Figure 7.

We now present without proof a theorem which governs when recovery is possible in the presence of propagation failures.

Lose-work Theorem

Application-generic recovery from propagation failures is guaranteed to be possible if and only if the application executes no commit event on a dangerous path.

This theorem provides an invariant for ensuring the possibility of recovery from propagation failures: processes must not commit on dangerous paths. It is interesting to note that the location of the initial bug that caused the crash is surprisingly irrelevant. In the end, all that matters is the eventual crash event (or events) that result from that bug and its location relative to the application's transient non-deterministic events.

How about for multi-process applications? The challenge for distributed applications is in computing their dangerous paths. Unlike the dangerous paths algorithm presented above, computing dangerous paths for a distributed application cannot be done statically: whether one process's path is dangerous can depend on the paths taken by the other processes in the computation and where they have committed.

Given a process P that wants to determine its dangerous paths (presumably so it can commit without violating Lose-work):

Multi-Process Dangerous Paths Algorithm

- Process P collects a snapshot of when each process in the computation last committed.
- For each non-deterministic receive event that P has executed, treat that receive as a transient non-deterministic event if the sender's last commit occurred before the send, and the sender executed a transient non-deterministic event between its last commit and the send. All other receives P has executed are fixed non-deterministic events.
- Run the single-process dangerous paths algorithm to compute P's dangerous paths.

2.6. Upholding Lose-work

The simplest way to uphold Lose-work is to ensure that no process ever commits. Although this solution has the advantage of requiring no application-specific knowledge to implement, it also prohibits guaranteeing consistent recovery.

Clearly, without perfect knowledge of the application's non-determinism and crash events it is impossible to guarantee a committing application upholds Lose-work. Despite the impossibility of directly upholding the invariant, we can use the Lose-work Theorem to draw some conclusions about recovering from propagation failures.

First, we observe that it is impossible to uphold both Save-work and Lose-work for some applications. Consider an application with a visible event on a dangerous path. The dangerous path will extend back at least to the last non-deterministic event. Upholding Save-work forces the application to commit between the last non-deterministic event and the visible event, which will violate Lose-work.

Second, some protocols designed to uphold Save-work for stop failures *guarantee* that applications will not recover from propagation failures. These protocols either commit or convert all non-determinism, ensuring a commit after the non-deterministic event that steers a process onto a dangerous path, thus violating Lose-work. CAND, Sender-based logging, Targon/32, and Hypervisor are all examples of protocols that prevent applications from surviving propagation failures. Indeed, any protocol that falls on the horizontal axis of the Save-work protocol space (see Figure 3) will prevent upholding Lose-work. The farther a protocol falls from the horizontal axis, the more it focuses its attention on handling visible events and the more non-determinism it leaves safely uncommitted, thus decreasing the chances of violating Lose-work (see Figure 4).

Although directly upholding Lose-work is impossible, some applications with mostly "non-repeatable" bugs (so called "Heisenbugs" [13]) may be able to commit with a low probability of violating the invariant. There are also a number of ways applications can deliberately endeavor to minimize the chance that one of their commits causes them to violate Lose-work.

First, applications should try to crash as soon as possible after their bugs get triggered. Doing so shortens dangerous paths and thus lowers the probability of the application committing while executing on one. In order to move crashes sooner, processes can try to catch erroneous state by performing consistency checks. For example, a process could traverse its data structures looking for corruption, it could compute a checksum over some data, or it could inspect guard bands at the ends of its buffers and malloc'ed data. Voting amongst independent replicas is a general but expensive way to detect erroneous execution [27]. When a process fails one of these checks, it simply terminates execution, effectively crashing.

Although it is a good idea for processes to perform these consistency checks frequently, performing them right before committing is particularly important.

Applications may also be able to reduce the likelihood they will violate Lose-work by not committing all their state. Applications may have knowledge of which data absolutely must be preserved, and which data can be recomputed from an earlier (hopefully bug-free) state. Should a bug corrupt state that is not written to stable storage during commit, recomputing that state after a failure leaves open the possibility of not retriggering the bug.

Applications can also try to commit as infrequently as possible. When upholding Save-work, applications should do so with a protocol that commits less often and that leaves as much non-determinism as possible. Some applications may be able to add non-determinism to their execution, or they may be able to choose a non-deterministic algorithm over a deterministic one.

The application or the operating system may also able to make some fixed non-deterministic events into transient

ones by increasing disk space or other application resource limits after a failure.

In Section 4 we will measure how often several applications violate Lose-work in the process of upholding Save-work.

3. Cost of Upholding Save-work

In Section 2.3, we presented the Save-work invariant, which applications can uphold to guarantee consistent recovery in the presence of stop failures. However, we have not talked about the performance penalty applications incur to uphold it. As mentioned above, executing commits can be expensive. It may be the case for real applications that adhering to Save-work may be prohibitively expensive. In this section we measure the performance penalty incurred for several real applications upholding Save-work.

For this experiment we have selected four real applications: *nvi*, *magic*, *xpilot* and *TreadMarks*. *nvi* is a public domain version of the well known Unix text editor *vi*. *magic* is a VLSI CAD tool. *xpilot* is a distributed, multi-user game. Finally, *TreadMarks* is a distributed shared memory system. Within *TreadMarks's* shared memory environment we run an N-body simulation called Barnes-Hut.

Of these applications, all but *TreadMarks* are interactive. We chose mainly interactive applications for several reasons. First, interactive applications are important recipients of failure transparency (when these applications fail there is always an annoyed user nearby). Second, interactive applications have been little studied in recovery literature. Finally, interactive applications can be hard to recover: they have copious system state, non-determinism, and visible output, all of which requiring an able recovery system.

TreadMarks and *xpilot* are both distributed applications, while the others are single-process.

To recover these applications we run them on top of *Discount Checking*, a system designed to provide failure transparency efficiently using lightweight, full-process checkpoints [24]. Discount Checking is built on top of reliable memory provided by the Rio File Cache [9], and lightweight transactions provided by the Vista transaction library [23].

In order to preserve the full user-level state of a process, Discount Checking maps the process's entire address space into a segment of reliable memory managed by Vista. Vista traps updates to the process's address space using copy-on-write, and logs the before-images of updated regions to its persistent undo log. To capture the application state in the register file (which cannot be mapped into persistent memory), Discount Checking copies the register file into a persistent buffer at commit time. Thus, taking a checkpoint amounts to copying the register file, atomically discarding the undo log, and resetting page protections.

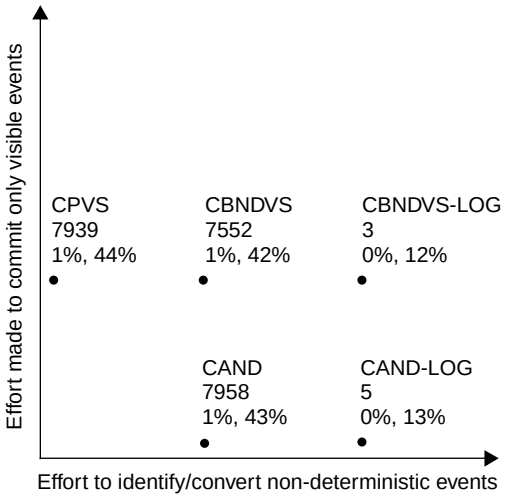
Although the steps outlined so far will allow Discount Checking to checkpoint and recover user-level state, Discount Checking must also preserve and recover the application's kernel state. To capture system state, the library implements a form of copy-on-write for kernel data: it traps system calls, copies their parameter values into persistent buffers, and then uses those parameter values to directly reconstruct relevant kernel state during recovery. For more on the inner workings of Discount Checking, please see [24].

As mentioned in Section 2.4, there exist a large variety of protocols for upholding Save-work. In order to get a sense of which work best for our suite of applications, we implemented seven different protocols within Discount Checking. Our core protocols are CAND, CPVS, and CBNDVS, which we described in Section 2.4. Recall that CAND upholds Save-work by committing immediately after every non-deterministic event. CPVS commits just before all visible and send events. CBNDVS commits before a visible or send event if the process has executed a non-deterministic event since its last commit. We also added to Discount Checking the ability to log non-deterministic user input and message receive events to render them deterministic, as well as the ability to use two-phase commit so one process can safely pass a dependency on an uncommitted non-deterministic event to another process. Adding these techniques to our core protocols yielded an additional four protocols: CAND-LOG, CBNDVS-LOG, CPV-2PC, and CBNDV-2PC. For example, CAND-LOG executes a commit immediately after any non-deterministic event that has not been logged. CPV-2PC commits all processes whenever any process executes a visible, but does not need to commit before a process does a send.

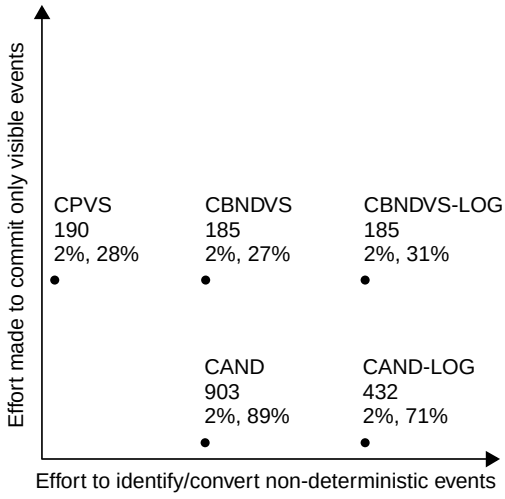
In order to implement these protocols, Discount Checking needs to get notification of an application's non-deterministic, visible, and send events. To learn of an application's non-deterministic events, Discount Checking intercepts a process's signals and non-deterministic system calls such as `gettimeofday`, `bind`, `select`, `read`, `recvmsg`, `recv`, and `recvfrom`. To learn of a process's visible and send events, Discount Checking intercepts calls to `write`, `send`, `sendto`, and `sendmsg`.

In addition to measuring the performance of our applications on Discount Checking on Rio, we wanted to get a sense of how our applications performed using a disk-based recovery system. We created a modified version of Discount Checking called DC-disk that wrote out a redo log synchronously to disk at checkpoint time. Although we did not add the code needed to let DC-disk truncate its redo log, or even properly recover applications, its overhead should be representative of what a lightweight disk-based recovery system can do.

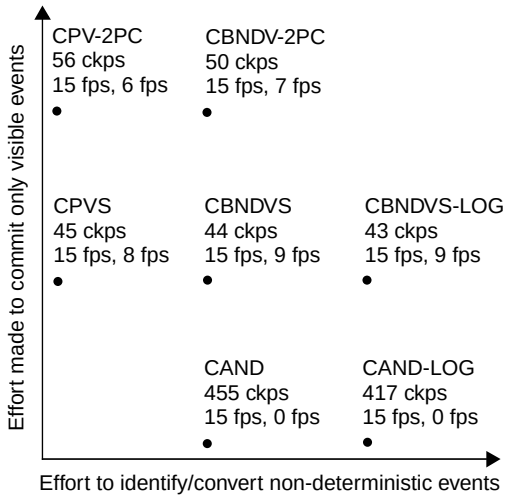
We ran our experiments on 400 MHz Pentium II computers each with 128 MB of memory (100 MHz SDRAM). Each machine runs FreeBSD 2.2.7 with Rio and is connected to a 100 Mb/s switched Ethernet. Rio was turned off when using DC-disk. Each computer has a single IBM Ultrastar



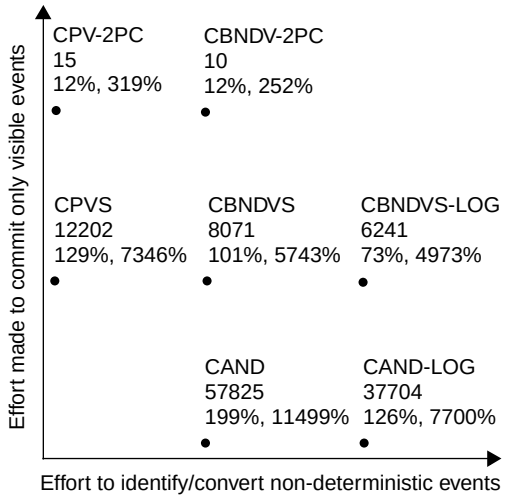
(a) nvi



(b) magic



(c) xpilot



(d) TreadMarks Barnes-Hut

Figure 8: Performance of several protocols for four applications. Each application has its own protocol space. At each point in each space, we list the protocol at that point, the number of checkpoints in the complete run of the application, and the runtime overhead for Discount Checking, and for DC-disk. For *xpilot* we list the protocol, number of checkpoints per second, followed by sustainable frame rate for Discount Checking and DC-disk. Full speed for *xpilot* is 15 frames per second.

DCAS-34330W ultra-wide SCSI disk. All points represent the average of five runs. The standard deviation for each data point was less than 1% of the mean for Discount Checking, and less than 4% of the mean for DC-disk. The distributed workloads (*TreadMarks* and *xpilot*) were both run on four computers. We simulate fast interactive rates by delaying 100 ms between each keystroke in *nvi* and by delaying 1 second between each mouse-generated command in *magic*.

We present the result of our runs in Figure 8. For each application we show the protocol space developed in Section 2.4. In each application's protocol space we plot the protocol used for each data point, and the number of checkpoints taken during the complete run of the application when running on that protocol. For each protocol's data point we also show the percent expansion in execution time that protocol caused compared to an unrecoverable version of the application, first for Discount Checking, then for DC-disk.

Because *xpilot* is a real-time, continuous program we report its performance as the frame rate it can sustain rather than runtime overhead. Higher frame rates indicate better interactivity, with full speed being 15 frames-per-second. *xpilot*'s number of checkpoints is given as the largest checkpointing frequency (in checkpoints per second) amongst its processes.

We can make a number of interesting observations based on these results. As expected, commit frequency generally decreases, and performance increases, with radial distance from the origin. The sole exception to this rule is *xpilot*, where having all processes commit whenever any one

of them wants to execute a visible event (as is done in protocols using two-phase commit) results in a net *increase* in commit frequency.

Despite the fact that several of these applications generate many commits, there is at least one protocol for each application with very low overhead for Discount Checking. We conclude that the cost of upholding Save-work using Discount Checking on these applications is low.

For all the interactive applications, the overhead of using DC-disk is not prohibitive. We see overhead of 12% and 27% for *nvi* and *magic* respectively. *xpilot* is able to sustain a usable 9 frames per second. On the other hand, no protocol for DC-disk was able to keep up with *TreadMarks*. From our experiments, we conclude that Save-work can be upheld with a disk-based recovery system for many interactive applications with reasonably low overhead.

We observe that the protocols that perform best for each application are the ones that exploit the infrequent class of events for that application in deciding when to commit. For example, *TreadMarks* has very few visible events, despite having copious non-deterministic and send events. For it, the 2PC protocols which let it commit only for the rare visible events are the big win.

While overhead is low for many applications, we can conceive of applications for which Save-work incurs a large performance overhead. These applications would have copious visible and non-deterministic events—that is, no rare class of events—and they would be compute bound rather than user bound. Applications that might fall into this category include interactive scientific or engineering simulation, online transaction processing, and medical visualization.

4. Measuring Conflict between the Save-work and Lose-work Invariants

Guaranteeing consistent recovery in the presence of stop and propagation failures requires upholding both the Save-work and Lose-work invariants. Unfortunately, some failure scenarios make it impossible to uphold both invariants simultaneously.

For example, consider the failure timeline shown in Figure 9. In this timeline, the application executes a transient non-deterministic event that causes it to execute down a code path containing a bug. The application eventually executes the buggy code (shown as "fault activation"), then correctly executes a visible event. After this visible event, the program crashes. Section 2.5's coloring algorithm shows that the entire execution path from the transient non-deterministic event to the crash forms a dangerous path, along which the Lose-work invariant prohibits a commit. Unfortunately, the Save-work invariant specifically requires a commit between the transient non-deterministic event and the visible event. For this application, both invariants cannot be upheld simultaneously.

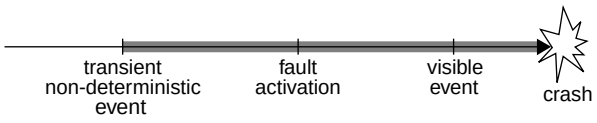


Figure 9: Failure timeline in which the Save-work invariant and the Lose-work invariant conflict. The shaded portion is the dangerous path.

Some applications may have bugs that prevent upholding Lose-work even without committing to uphold Save-work. For example, many applications contain repeatable bugs (so called, "Bohrbugs"[13]). With these faults it is possible to execute from the initial state of the program to the bug without ever executing a transient non-deterministic event. In other words, the dangerous path resulting from the bug extends all the way back to the initial state of the program. And since the initial state of any application is always committed, applications with Bohrbugs inherently violate Lose-work.

In this section, we endeavor to examine how often in practice faults cause a fundamental conflict between the Save-work and Lose-work invariants. Our focus is on software faults (both in the application and operating system), which field studies and everyday experience teach is the dominant cause of failures today [13].

4.1. Application faults

We would like to measure how often upholding Save-work forces an application to commit on a dangerous path, like the application depicted in Figure 9. We divide this problem into three subproblems. First, how often does an application bug create a dangerous path beginning at the start state of the application? As described above, this scenario arises from Bohrbugs in the application. Second, given an application fault that does depend on a transient non-deterministic event (a Heisenbug), how often is the application forced to commit between the transient non-deterministic event at the beginning of the dangerous path and the fault activation? Third, how often is the application forced to commit between the fault activation and the crash? We examine this third question first using a fault-injection study.

Our strategy is to force crashes of real applications, recover the applications, and measure after the fact whether any of their commits to uphold Save-work occurred between fault activation and the crash. We induce faults in the application by running a version of the application with changes in the source code to simulate a variety of programming errors. These errors include actions like overwriting random data in the stack or heap, changing the destination variable, neglecting to initialize a variable, deleting a branch, deleting a random line of source code, and off-by-one errors in conditions like >= and <. See [6] for more information on our fault model. We only consider runs where the program crashes.

Fault Type	*nvi* Lose-work violations	*postgres* Lose-work violations
Stack bit flip	0%	35%
Heap bit flip	83%	92%
Destination reg	18%	0%
Initialization	4%	6%
Delete branch	81%	86%
Delete instruction	51%	13%
Off by one	24%	0%
Average	37%	33%

Table 1: Fraction of application faults in *nvi* and *postgres* that violate Lose-work by committing after the fault is activated. For each fault type we list the percent of crashes by that fault that commit after the fault is activated. Over all fault types, *nvi* and *postgres* commit after the fault activation for 37% and 33% of all crashes respectively.

Checkpointing and recovery for the applications is provided by Discount Checking using the CPVS protocol. CPVS is the best protocol possible for not violating Lose-work for non-distributed applications. For our experiments, we use two applications: the Unix text editor *nvi*, and *postgres*, a large, publicly available relational database. These two applications differ greatly in their code size and amount of data they touch while executing.

We detect a run in which the application commits between fault activation and the crash by instrumenting Discount Checking to log each fault activation and commit event. If the program commits after activating the fault, it has violated the Lose-work invariant. We also conduct an end-to-end check of this criteria by suppressing the fault activation during recovery, recovering the process, and trying to complete the run. As expected, we found that runs recovered from crashes if and only if they did not commit after fault activation.

We collected data from approximately 50 crashes for each fault type. Table 1 shows the fraction of crashes that violated the Lose-work invariant by committing after fault activation. For both *nvi* and *postgres*, approximately 35% of faults caused the process to commit along this portion of the dangerous path. While not included in the table, 7-9% of the runs did not crash but resulted in incorrect program output.

We next turn our attention to question one, namely, for what fraction of bugs does the dangerous path extend back to the initial state of the program? That is, of the bugs users encounter, what portion are deterministic (Bohrbugs), and what portion depend on a transient non-deterministic event (Heisenbugs)? Although it is difficult to measure this fraction directly, several prior studies have attempted to shed light on this issue.

Chandra and Chen showed that for *Apache*, *GNOME*, and *MySQL*, three large, publicly available software packages, only 5-15% of the bugs in the developer's bug log were Heisenbugs (for shipping versions of the applications) [7]. The remaining bugs were Bohrbugs. Most of these deterministic bugs resulted from untested boundary conditions (e.g. an older version of *Apache* crashed when the URL was too long). Several other researchers have found a similarly low occurrence (5-29%) of application bugs that depend on transient non-deterministic events like timing [20, 29, 30]. Note that these results conflict with the conventional wisdom that mature code is populated mainly by Heisenbugs—it has been held that the easier-to-find Bohrbugs will be captured more often during development [13, 17]. It appears that for non-mission-critical applications, the current software culture tolerates a surprising number of deterministic bugs.

We have yet to tackle the second question, which asks how often an application is forced to commit on the dangerous path between the transient non-deterministic event and fault activation (see Figure 9). Unfortunately, we are unable to measure this frequency using our fault-injection technique because no realistic model exists for placing injected bugs relative to an application's transient non-deterministic events. However, as we will see, the case for generic recovery from application failures is already sufficiently discouraging, even optimistically assuming no commits on this portion of the dangerous path.

We would like to compose these separate experimental results in order to illuminate the overarching question of this section. Our fault-injection study shows that *nvi* and *postgres* violate Lose-work in at least 35% of crashes from non-deterministic faults. If we assume the same distribution of deterministic and non-deterministic bugs in *nvi* and *postgres* as found in *Apache*, *GNOME*, and *MySQL* by Chandra and Chen, these non-deterministic faults make up only 5-15% of crashes. Therefore, Lose-work is upheld in at most 65% of 15%, or 10% of application crashes. Lose-work and Save-work appear to conflict in the remaining 90% of failures by these applications. While extrapolating other applications' fault distributions to *nvi* and *postgres* is somewhat questionable, as is generalizing to all applications from the measurement of two, these preliminary results raise serious questions about the feasibility of generic recovery from propagation failures.

4.2. Operating systems faults

Although failures due to application faults appear to frequently violate Lose-work, we can hope for better news for faults in the operating system. In contrast to application faults, not all operating system faults cause propagation failures: some crash the system before they affect application state. Commits at any time by the application are okay in the presence of these stop failures. Thus if failures by the operat-

Fault Type	*nvi* failed recoveries	*postgres* failed recoveries
Stack bit flip	12%	10%
Heap bit flip	8%	6%
Destination reg	10%	0%
Initialization	16%	0%
Delete branch	26%	4%
Delete instruction	12%	4%
Off by one	22%	0%
Average	15%	3%

Table 2: Percent of OS faults in which *nvi* and *postgres* failed to recover. We list the percentage of crashes that led to failures during recovery for each fault type and over all failures.

ing system usually manifest as stop failures, we would rarely observe system failures causing Lose-work violations.

We wanted to measure the fraction of operating system failures for which applications are able to successfully recover. This fraction will include cases where the operating system experienced a stop failure, as well as cases in which the system failure was a propagation failure and the application did not violate Lose-work.

In order to perform this measurement, we again use a fault-injection study. This time we inject faults into the running kernel rather than into the application [9].

We again ran *nvi* and *postgres* with Discount Checking upholding Save-work using CPVS. For each run, we started the application and injected a particular type of fault into the kernel. We discarded runs in which neither the system nor the application crashed. If either the operating system or the application crashed, we rebooted the system and attempted to recover the application. We repeated this process until each fault type had induced approximately 50 crashes. The results of this experiment are shown in Table 2.

Of the 350 operating system crashes we induced for each application, we found that *nvi* failed to properly recover in 15% of crashes. *postgres* did better, only failing to recover 3% of the time. These numbers are encouraging: application-generic recovery is likely to work for operating systems failures, despite the challenge of upholding Lose-work.

If we assume that all propagation failures will violate Lose-work with the probabilities in Table 1 (regardless of whether the propagation failure began in the operating system or application), we can infer how often system failures manifest as propagation failures in our experiments. Combining our application crash results with our operating system crash results implies that for *nvi*, 41% of system failures were propagation failures. For *postgres*, 10% of system failures manifest as propagation failures. We hypothesize that the proportion of propagation failures differs for the two applications because of the different rate at which they communicate with the operating system: the non-interactive version of *nvi* used in our crash tests executes almost 10 times as many system calls per second as *postgres* executes.

5. Related Work

Many fault-tolerant systems are constructed using transactions to aid recovery. Transactions simplify recovery by grouping separate operations into atomic units, reducing the number of states from which an application must recover after a crash. However, the programmer must still bear the responsibility for building recoverability into his or her applications, a task that is difficult even with transactions. We have focused on higher-level application-generic techniques that absolve programmers from adding recovery abilities to their software. However, we use transactions to implement our abstraction.

A number of researchers have endeavored to build systems that provide some flavor of failure transparency for stop failures [3, 4, 5, 11, 14, 21, 25, 26]. Our work extends their work by analyzing propagation failures as well.

The theory of distributed recovery has been studied at length [10]. Prior work has established that committed states in distributed systems must form a consistent cut to prevent orphan processes [8], that recoverable systems must preserve a consistent cut before visible events [28], and that non-determinism bounds the states preserved by commits [11, 16]. Our Save-work invariant is equivalent to the confluence of these prior results.

The Save-work invariant contributes to recovery theory by expressing the established rules for recovery in a single, elemental invariant. Viewing consistent recovery through the lens of Save-work, we exposed the protocol space and the relationships between the disparate protocols on it, as well as several new protocols.

To the best of our knowledge, no prior work has proposed an invariant for surviving propagation failures that relates all relevant events in a process, nor has any prior work attempted to evaluate the fraction of propagation failures for which consistent recovery is not possible.

CAND, CPVS, and CBNDVS all bear a resemblance to simple communication-induced checkpointing protocols (CIC) [1]. However there are some important differences. First, all CIC protocols assume no knowledge of application non-determinism. As a result, they are forced to roll back any process that has received a message from an aborted sender. Commits under these protocols serve primarily to limit rollback distance, and to prevent the domino effect. In contrast, our protocols all to varying degrees make use of knowledge of application non-determinism. Rather than abort the receivers of lost messages, they allow senders to deterministically regenerate the messages. Under our protocols, only failed processes are forced to roll back.

Recovery systems often depend on the assumption that applications will not commit faulty state—a so called "fail-stop assumption" [27]. Our examination of propagation failures amounts to a fine parsing of the traditional fail-stop assumption in which we consider a single commit's ability to preserve not just past execution, but all future execution up to the next non-deterministic event. Making a fail-stop assumption in the presence of propagation failures is the same as assuming that applications can safely commit at any time without violating the Lose-work invariant.

6. Conclusion

The lure of operating systems that conceal failures is quite powerful. After all, what user or programmer wants to be burdened with the complexities of dealing with failures? Ideally, we could handle all those complexities once and for all in the operating system.

Our goal with this paper has been to explore the subject of failure transparency, looking at what it takes to provide it and exposing the circumstances where providing it is not possible. We find that providing failure transparency in general involves upholding two invariants, a Save-work invariant which constrains when an application must preserve its work before a failure, and a Lose-work invariant which constrains how much work the application has to throw away after a failure.

For stop failures, which do not require upholding Lose-work, the picture is quite rosy. We show that Save-work can be efficiently upheld for a variety of real applications. Using a transparent recovery system based on reliable memory, we find overheads of only 0-12% for our suite of real applications. We also find that disk-based recovery makes a credible go of it, with interactive applications experiencing only moderate overhead.

Unfortunately, the picture is somewhat bleaker for surviving propagation failures. Guaranteeing that an application can recover from a propagation failure requires upholding our Lose-work invariant, and Save-work and Lose-work can directly conflict for some fault scenarios. In our measurements of application faults in *nvi* and *postgres*, upholding Save-work causes them to violate Lose-work for at least 35% of crashes. Even worse, studies have suggested that 85-95% of application bugs today cause crashes that violate the Lose-work invariant by extending the dangerous path to the initial state.

We conclude that providing failure transparency for stop failures alone is feasible, but that recovering from propagation failures requires help from the application. Applications can help by performing better error detection, masking errors through N-version programming, reducing commit frequency by allowing the loss of some visible events, or reducing the comprehensiveness of the state saved by the recovery system. Our results point to interesting future work. Since pure application-generic recovery is not always possible, what is the proper balance between generic recovery services provided by the operating system and application-specific aids to recovery provided by the programmer?

7. Acknowledgements

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8. Software Availability

The Rio version of the FreeBSD 2.2.7 kernel, as well as Vista and Discount Checking are all available for download at http://www.eecs.umich.edu/Rio.

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