SWEEPER: An Efficient Disaster Recovery Point Identification Mechanism

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Abstract

Data corruption is one of the key problems that is on top of the radar screen of most CIOs. Continuous Data Protection (CDP) technologies help enterprises deal with data corruption by maintaining multiple versions of data and facilitating recovery by allowing an administrator restore to an earlier clean version of data. The aim of the recovery process after data corruption is to quickly traverse through the backup copies (old versions), and retrieve a clean copy of data. Currently, data recovery is an ad-hoc, time consuming and frustrating process with sequential brute force approaches, where recovery time is proportional to the number of backup copies examined and the time to check a backup copy for data corruption.

In this paper, we present the design and implementation of $SWEEPER$ architecture and backup copy selection algorithms that specifically tackle the problem of quickly and systematically identifying a good recovery point. We monitor various system events and generate checkpoint records that help in quickly identifying a clean backup copy. The $SWEEPER$ methodology dynamically determines the selection algorithm based on user specified recovery time and recovery point objectives, and thus, allows system administrators to perform trade-offs between recovery time and data currentness. We have implemented our solution as part of a popular Storage Resource Manager product and evaluated $SWEEPER$ under many diverse settings. Our study clearly establishes the effectiveness of $SWEEPER$ as a robust strategy to significantly reduce recovery time.

1 Introduction

Data Resiliency is a very important concern for most organizations to ensure business continuity in the face of different types of failures and disasters, such as virus attacks, site failures, machine/firmware malfunction, accidental and malicious human/application errors [17, 2]. Resiliency is not only about being able to resurrect data after failures, but also about how quickly the data can be resurrected so that the business can be operational again. While in the case of total data loss failures, the recovery time is largely dominated by *Restoration Cost*, i.e., time to restore the data from backup systems at local or remote locations; in the case of data corruption failures, the time to identify a clean previous copy of data to revert to can be much larger. Often, data corruption is detected after the incidence of corruption itself. As a result, the administrator has a large number of candidate backup copies to select the recovery point from. The key to fast recovery in such cases is reducing the time required in the identification step. Much research and industrial attention have been devoted to protecting data from disasters. However, relatively little work has been done in the area of how to quickly retrieve the latest clean copy of uncorrupted data. The focus of this paper is on how to efficiently identify clean data.

Data resiliency is based on *Data Protection*: taking either continuous or periodic snapshots of the data as it is being updated. Block level [7] [15], file level [10], logical volume level [27] and database level [5] data replication/recovery mechanisms are the most prominent data protection mechanisms. The mechanisms vary with respect to their support for different data granularities, transactional support, replication site distance, backup latencies, recovery point and recovery time objectives [11]. Continuous data protection (CDP) [24] is a form of continuous data protection that allows one to go back in time after a failure and recover earlier versions of an object at the granularity of a single update.

The recovery process is preceded by *Error Detection*. Errors are usually found either by application users or by automated data integrity tools. Tools such as disk scrubbers and S.M.A.R.T. tools [23] can detect corruptions caused by hardware errors. Virus scanners, application specific data integrity checkers such as fsck for filesystem integrity, and storage level intrusion detection

tools [19, 3] can detect logical data corruptions caused by malicious software, improper system shutdown, and erroneous administrator actions. For complex Storage Area Network (SAN) environments, configuration validation tools [1] have been proposed that can be used in both proactive and reactive mode to identify configuration settings that could potentially lead to logical data corruptions.

Once system administrators are notified of a corruption, they need to solve the *Recovery Point Identification* problem, i.e., determine a recovery point that will provide a clean copy of their data. Typically, system administrators choose a recovery point by trading-off recovery speed (the number of versions that need to be checked to find a clean copy) versus data currentness (one might not want to lose valid data updates for the sake of fast recovery). Recovery point identification is currently a manual, error-prone and frustrating process for system administrators, due to the pressure to quickly bring organization's applications back on-line. Even though CDP technologies provide users with the ability to rollback every data update, they do not address the problem of identifying a clean copy of data. It is only after a good recovery point has been identified, that *Data Recovery* can begin by replacing the corrupt copy by the clean copy of data. The efficacy of a recovery process is characterized by a Recovery Time Objective (RTO) and a Recovery Point objective (RPO). RTO measures the downtime after detection of corruption, whereas RPO indicates the loss in data currency in terms of seconds of updates that are lost.

This paper describes and evaluates methods for efficient recovery point identification in CDP logs which reduce RTO, while not compromising on RPO. The basic idea behind our approach is to evaluate the events generated by various components such as applications, file systems, databases and other hardware/software resources and generate checkpoint records. Subsequently upon the detection of failure, we efficiently process these checkpoint records to start the recovery process from an appropriate CDP record. Since CDP mechanisms are typically used along with point-in-time snapshot (PIT) technologies, it is possible to create data copies selectively. Further, since the time it takes to test a copy of data for corruption dominates overall recovery time, selective testing of copies can drastically reduce recovery time. This selective identification of copies that one can target for quick recovery is the focus of this work.

Some existing CDP solutions [16, 21, 30] are based on the similar idea of checkpointing *interesting* events in CDP logs. While event checkpointing mechanisms help in narrowing down the search space, they do not guarantee that the most appropriate checkpoint record will be identified. Thus, the CDP log evaluation techniques presented in this paper compliment these checkpoint record generation mechanisms in quickly identifying the most suitable CDP record. The key *contributions* of this paper are:

- $SWEEPER$ **Recovery Point Identification Architecture:** We present the architecture of an extensible recovery point identification tool that consists of event monitoring, checkpoint generation, clean copy detection and CDP log processing components. The architectural framework is independent of specific applications and can easily be used with other application specific CDP solutions such as [16, 21].
- **Novel Event Checkpointing Mechanism:** Data corruptions are usually not silent but are accompanied by alerts and warning messages from applications, file systems, operating systems, SAN elements (e.g., switches, virtualization engines), storage controllers and disks. Table 2 lists some events that usually accompany data corruption caused by various components. We define a mechanism that identifies events from various application and system activities and uses a combination of a) expert provided knowledge base, b) resource dependency analysis, and c) a event correlation technique to correlate them with various types of corruption.
- **CDP Record Scanning Algorithms:** We present three different CDP record scanning algorithms that efficiently process the event checkpoints for identifying the appropriate CDP log record for data recovery. The scanning mechanisms isolate a recovery point quickly by using the observations that (a) pruning the space of timestamps into equal sized partitions reduces the search space exponentially and (b) checkpoint records that have high correlation with corruptions are more likely to be indicative of corruption. One of the novel features of the checkpoint record selection process is the acceptance of recovery time objective (RTO) and recovery point objective (RPO) as input parameters. Thus, the algorithms have the desirable property of providing a tradeoff between the total execution time and the data currency at the recovery point. The expected execution time of the algorithms is logarithmic in the number of checkpoint records examined and linear in the number of data versions tested for integrity. The proposed algorithms are robust with noise in the checkpoint record generation process, and can deal with errors in correlation probability estimation. Further, even though they are not designed to deal with silent errors, they still find a recovery point in logarithmic time for silent errors.

- **Performance Evaluation:** We present an implementation of the $SWEEPER$ architecture and algorithms in context of a popular Storage Resource Manager product (IBM Total Storage Productivity Center), and demonstrate the scalability of our design. We also present a comparative analysis of the various Record Scanning algorithms proposed by us under different operational parameters, which include failure correlation probability distribution for events, number of checkpoint records, and rate of false negatives. We identify the different scenarios for which each algorithm is most suited and conclusively establish the efficacy of the $SWEEPER$ methodology.

The rest of this paper is organized as follows. We formally define the *Recovery Point Identification* problem and model in Sec. 2.1 and 2.2. The $SWEEPER$ architecture is presented in Sec. 2.3. The CDP record scanning algorithms are described in Sec.3, and our implementation in Sec. 4. Sec. 5 describes our experimental evaluation. Sec. 6 discusses the strengths and weaknesses of $SWEEPER$ in the context of related work followed by a conclusion in Sec. 7.

2 Recovery-point Identification: Model and Architecture

We now provide a formal definition of the *Recovery Point Identification* problem and model parameters.

2.1 Problem Formulation

We investigate the problem of data recovery after a failure has resulted in data corruption. Data corruption is detected by an integrity checker (possibly with application support). The second step in this process is to identify the nature of corruption (e.g., virus corruption, hardware error). For isolating the problem, the components (e.g, controllers, disks, switches, applications) that may be the cause of error are identified by constructing a mapping from the corrupted data to the applications. Once the affected components are identified, the recovery module finds a time instance to go back to when the data was uncorrupted. Once the time instance is identified, CDP logs and point-in-time images are used to construct the uncorrupted data.

We now formally describe the *Recovery Point Identification* problem. The notations used in this paper are tabulated in Table. 1. The *Recovery Point Identification* problem is to minimize the total time taken to recover the data in order to get the most current uncorrupted data (i.e., find a timestamp T_i such that $T_i = T_e$ while minimizing D_{rec}). A constrained version of the problem is to minimize $T_e - T_i$ subject to a bound on D_{rec}. The identification of T_i proceeds by finding an ordered set S of timestamps, which is a subset of the set of all the timestamps $(T_0, ..., T_N)$ such that S_m $(m = |S|)$, the last element of the set S, is the same as the error point T_e. Further, the total cost of creating and testing the data images corresponding to the m timestamps in S, which equals D_{rec}, should be minimized. The cost of checking a data image at timestamp T_i for corruption is the sum of (a) the cost of making the first PIT image preceding the timestamp available for read/write (C_p) (b) the cost of applying the $T_i\%T_p$ (T_i modulo T_p) CDP logs ($C_l(T_i\%T_p)$) and (c) the cost of testing the copy (C_t). Hence, the total time spent in isolating the uncorrupted copy is the sum of the costs of all the timestamps checked in the sequence S.

T_0	Time at which data was last known to be clean
T_d	Time at which corruption was detected
T_i	Timestamp i
T_e	Error Timestamp
T_p	Number of CDP logs after which a PIT copy is taken
N	Number of CDP logs between T_0 and T_d
N_c	Number of checkpoints between T_0 and T_d
D_{rec}	Time taken for recovery
C_p	Cost of getting a PIT copy online and ready to read/write
C_l	Average Cost of applying one CDP log entry
C_t	Cost of testing one data image for corruption
$p_{i,j}$	probability that checkpoint j is correlated with corruption i

Table 1: Notations

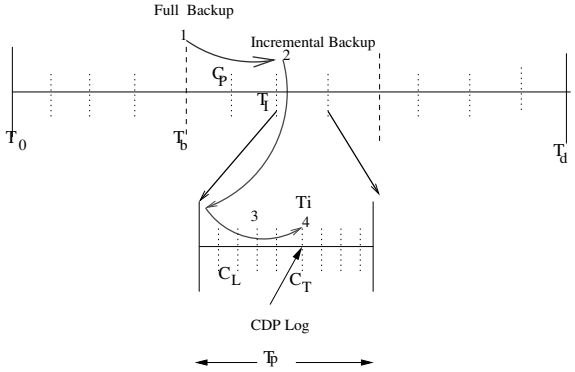


Figure 1: Timeline for testing the snapshot at time T_i: 1 Getting a full backup online. 2 Applying incremental backups over it. 3 Applying CDP logs to create the snapshot at time T_i. 4 Testing the data for integrity.

2.2 Recovery Point Parameters and Estimating Sequential Checking Time

We now elaborate on the recovery parameters like C_p, C_t etc and their typical values. For a typical example, consider Fig. 1, where a *Recovery Point Identification* strategy decided to check data image at T_i for corruption. The data protection (continuous and point-in-time) solution employed in the setting takes a total backup of the data at regular intervals. In between total backups, incremental backups are taken after every T_p writes (CDP logs). The number of incremental backups taken between two consecutive total backups is denoted by f_I. Hence, in order to construct the point-in-time snapshot of data at time T_i, we make the first total backup copy preceding T_i (labeled as T_b in the example) online. Then, we apply incremental backups over this data till we reach the timestamp T_I of the last incremental backup point before T_i. The total time taken in getting the PIT copy at T_I online is denoted by C_p. On this PIT copy, we now apply the CDP logs that capture all the data changes made between T_I and T_i, and incur a cost of C_l for each log. Finally, an integrity check is applied over this data, and the running time of the integrity checker is denoted by C_t.

For average metadata and data write sizes of $E(S_m)$ and $E(S_w)$ respectively, write coalescing factor W_{cf}, average filesize $E(S_f)$, read and write bandwidth of B_r and B_w respectively, a file corpus of N_f files, and a unit integrity test time I_t, the expected time taken for each of these three activities are given by the following equations. (C_p calculation is based on the assumption that constructing the PIT copy only requires metadata updates.)

$$C_p = \frac{(f_I/2)(T_p/W_{cf})E(S_m)}{B_w}, \quad C_l(T_i\%T_p) = \frac{(T_p/2)E(S_w)}{B_w} \tag{1}$$

$$C_t = \frac{N_f E(S_f)}{B_r} + N_f E(S_f) I_t \tag{2}$$

In a typical setup with 1000 files being are modified every second, update sizes of $4KB$, file sizes of $100KB$, metadata size of $64Bytes$, total backups every 12 hours, incremental backups every $1hr$, and disk transfer rate of $100Mbps$, the time taken to get a PIT image online C_p is approximately 50 seconds. The time taken to apply the CDP logs is of the order of 10 minutes, whereas the I/O time taken (not including any computations) by the integrity checker C_t comes to about 4 hours assuming that the integrity checker only needs to check the modified files. In a deployment with a CDP log window of 24 hrs, if one sequentially checks every 1000^{th} record, the expected time to find the point of corruption would be of the order of 100 days. Hence, sequential checking is infeasible and minimizing the time taken by the recovery process essentially boils down to minimizing the number of data images that are checked by recovery process.

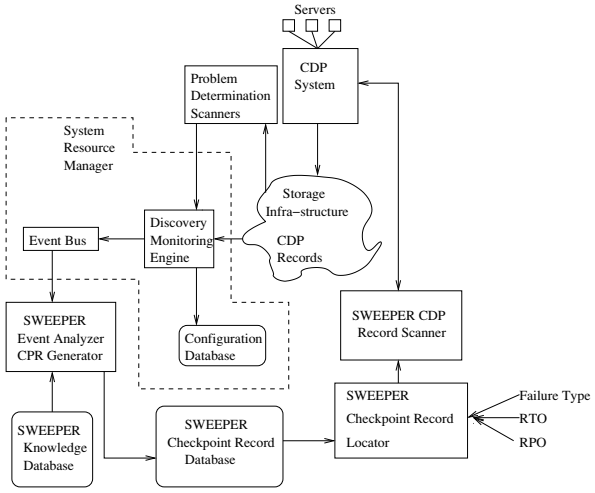


Figure 2: SWEEPER Recovery Point Indentification Architecture

2.3 SWEEPER Recovery Point Identification Architecture

The central *idea* of $SWEEPER$ is to automatically checkpoint important system events from various application-independent monitoring sources as indicators of corruption failures. In contrast to earlier work [16] that requires an administrator to manually define the events for each application that are correlated with various corruption types, we automate the process of creating these checkpoints and indexing them with the type and scope of corruption along with a number that indicates the probability of the event being correlated with the specific corruption type. We then use these checkpoints as hints to quickly pinpoint the most recent clean copy of data. The overall architecture of $SWEEPER$ is described in Fig. 2

The key design question while architecting a recovery mechanism like $SWEEPER$ is whether to build it a) as part of a CDP system, or b) as part of a Storage Resource Manager product like EMC Control Center, HP OpenView or IBM TotalStorage Productivity Centre, or c) as a standalone component. We have separated the design of algorithms and the architecture so that the algorithms can work with any architecture and vice versa. Implementing $SWEEPER$ outside the CDP system allows it to be leveraged by many different types of CDP systems. The disadvantage of this implementation is that some CDP systems might not completely expose all of the internal system state changes via an event mechanism. Most of this information is available from Stor-

age Resource Managers. Furthermore, most Storage Resource Managers have a comprehensive monitoring and resource discovery mechanism that can be leveraged by the Recovery module. Hence, we recommend the design choice (b) for $SWEEPER$ (Fig. 2), with the following key components.

- **CDP System:** CDP system is essentially a data versioning system that can generate either log records or snapshots during data updates. The Users can retrieve snapshots using temporal queries based on timestamps, or they can simply traverse the snapshots using a cursor returned by query. The CDP system also allows for restoring the data in a previous copy and make it the latest copy.

- **Storage Infra-Structure:** The storage infrastructure consists of servers (hosts), switches, storage controllers (contain disks), file systems, database systems, virtualization boxes, and security boxes. A CDP system is also part of the storage infra-structure but we are showing it separately in Fig. 2.

- **Storage Resource Manager:** Storage resource managers contain a discovery/monitoring engine for monitoring storage infra-structure using a combination of SNMP protocol, CIM/SMI-S protocol, proprietary agents, in-band protocol discovery/monitoring agents, operating system event registries, proc file systems and application generated events. Event bus is the module in the resource manager product that subscribes to all the events and it presents them in a consolidated manner to other event analyzer modules. The configuration database persistently stores the storage infrastructure configuration data, performance data, historical trends and also event data. The configuration database purges historical and event data based on user specified deletion policies.

- **SWEEPER Event Analyzer and Checkpoint Record Generator:** This module looks at the incoming stream of event data and filters out irrelevant events. For the relevant events, it determines the probability that the corruption may be correlated with this event and the scope (affected components) of the event. After the event analysis, this module generates a checkpoint record. The SWEEPER checkpoint record store is structured into two tiers of checkpoints. All checkpoint records generated by *Event Analyzer* are included in the lower tier and the records that have a high correlation probability with any type of corruption are promoted to the upper tier. The tier-ing notion can be extended from 2 tiers to n tiers. However, we observed in our experimental study that 2 tiers are usually sufficient for reducing recovery time.

- **SWEEPER Knowledgebase:** The knowledgebase consists of records with the following fields: a) List of event identifiers b) type or reason for data corruption c) probability of seeing an event (or a set of correlated events) in the case of data corruption. Corruption probability is represented as low, medium or high values because, in many cases, it is difficult for experts to specify exact probability values.

- **Problem Determination Scanners:** Failure detection can be done either manually or using an automated checking tool, $SWEEPER$ leverages existing failure detection systems towards this purpose. Failure detectors also help in determining the type of failure (e.g., virus corruption) without pinpointing the system events that caused it.

- **SWEEPER Checkpoint Record Locator:** The *Checkpoint Record Locator* module orchestrates the overall recovery point identification process using one of the algorithms implemented by the *CDP Record Scanner*. The first task of the *Checkpoint Record Locator* module is to identify a subset of the checkpoint records that pertain to the current data corruption it is investigating. Towards this purpose, it queries the *Problem Determination Scanner* for the type and scope of the current corruption, and identifies the components that may be the cause of corruption. It uses the information to query the checkpoint database (indexed by type and scope) for checkpoint records that relate to the type of corruption and pertain to the affected components and creates a *Checkpoint Record Cache* for use by the *CDP Record Scanner*. The *Checkpoint Record Locator* allows the user to specify Recovery Time Objective or RTO (how long the user is willing to wait for the recovery process to complete) and Recovery Point Objective or RPO (how stale the data can be, and this is measure as a unit of time) and uses them along with the properties of the *Checkpoint Cache* to select one of the scanning algorithms implemented by the *CDP Record Scanner*. It queries the *CDP Record Scanner* with the *Cache* and scanning algorithm as input and receives a timestamp as the answer. It then uses the *CDP Recovery Module* and the *Problem Determination Scanner* to create and test the data according to the timestamp and returns the answer (corrupt/clean) of the *Problem Determination Scanner* to the CDP Record Scanner and receives a new timestamp. In each iteration of the procedure, it computes the total time taken by

the *Recovery Flow* and if it exceeds the RTO objective, it terminates with the most recent clean copy of the data as the recovered data. Also, for each timestamp that is checked, it computes the RPO (distance between the most recent clean copy and the most stale corrupt copy) and terminates if the RPO objective is met with the most recent clean copy of the data.

- **SWEEPER CDP Record Scanner:** The *CDP Record Scanner* implements an interface that takes as input a scanning strategy, a Checkpoint record, cache, a cursor (timestamp), and the integrity (corrupt or clean) of the cursor and returns a new cursor (timestamp) to check for data integrity. The separation of the recovery point identification algorithms from the checkpoint database allows *SWEEPER* to be flexible enough to include new search strategies in future. Also, since the search strategies are independent of *SWEEPER*, they can be implemented in other recovery point identification architectures as well.

2.4 Overall System Flow

We now describe the *Checkpoint generation* flow and *Fault-isolation or Recovery* flow that capture the essence of the $SWEEPER$ architecture. The *Checkpoint Generation* flow captures the generation of checkpoint records during normal CDP system operation. The recovery process is initiated by system administrators when they determine that data corruption has occured and this is captured by the *Fault-Isolation* flow.

Checkpoint Generation Flow:

- The CDP system generates CDP records (either logs or data copies) based on user defined policies.
- The Storage Resource Manager product monitors and aggregates various types of system events (hardware and software failure triggers, user action triggers etc).
- In parallel with the CDP record generation process, the $SWEEPER$ event analyzer module analyzes the system events and generates a checkpoint record for each relevant event. The checkpoint records are logically co-related with the CDP records via timestamps.
- The checkpoint record generator a) leverages the information in the expert knowledge base b) correlates the information in the event stream and c) traverses the configuration resource graph, to index the checkpoint record with the scope of the event and its correlation probability with each type of corruption.

Fault-Isolation Flow:

- The Problem Determination Scanner or a human detects that data corruption has occured and identifies its scope and type (e.g., virus, hardware).
- A query is posed to the $SWEEPER$ *Checkpoint Record Locator* module by the system administrator with RTO and RPO as input. The reason or type of the data corruption and its scope is also an input to the *Checkpoint Record Locator*. The input information is used by the *Checkpoint Record Locator* to create a list of checkpoint records that should be examined, and the scanning algorithm to be employed.
- The $SWEEPER$ *CDP Record Scanner* is invoked with the list of checkpoint records and the scanning strategy as input. It determines the checkpoint record that should be examined next and returns the CDP record corresponding to it to the user.
- The user retrieves the CDP record from the CDP system and then either runs the appropriate diagnostics or manually examines the checkpoint record to see whether it is corrupted. This process is repeated by the user until a clean data copy is retrieved.

3 SWEEPER Checkpoint Log Processing Algorithms

The checkpoint log processing algorithms are implemented in the *Checkpoint Record Locator* and the *CDP Record Scanner* modules. The *Checkpoint Record Locator* iteratively queries the *CDP Record Scanner* for the next checkpoint that it should verify for correctness, whereas the *CDP Record Scanner* has the core intelligence for identifying the next eligible checkpoint. The iterative flow of *Checkpoint Record Locator* is presented in Fig. 3.

```
function locateCheckPoints
 start = 0,  end = currTime
 while (timeSpent < RTO) AND (RPO not met)
    currCopy = scanRecordsAlgoType(start, end)
    if currCopy is clean
       start = timestamp of currCopy
    else
       end = timestamp of currCopy
 end while
end locateCheckPoints
```

Figure 3: Checkpoint Record Locator Flow

3.1 CDP Record Scanning Algorithms

We now present the scanning algorithms that contain the core intelligence of $SWEEPER$. As in Sec. 2.1, N

denotes the number of CDP logs, C_t is the cost of testing a data image for corruption, C_p is the cost of getting a PIT copy online, C_l is the cost of applying one CDP log on a data image and T_p is the number of CDP logs after which a PIT image is taken. Further, we use N_c to denote the number of checkpoint records in the relevant history.

3.1.1 Sequential Checkpoint Strategy

The *Sequential Checkpoint Strategy* starts from the first clean copy of data (Fig. 4) and applies the CDP logs in a sequential manner. However, it creates data images only for timestamps corresponding to some checkpoint record. The implementation of the $scanRecords$ algorithm returns the first checkpoint record after the given start time. Hence, the number of integrity tests that *Checkpoint Record Locator* needs to perform using the *scanRecordsSequential* method is proportional to the number of checkpoint records N_c and not on the number of CDP logs N. The worst-case cost of creating the most current clean data image by the *Sequential Scanning Strategy* is $N_cC_t + C_p + NC_L$.

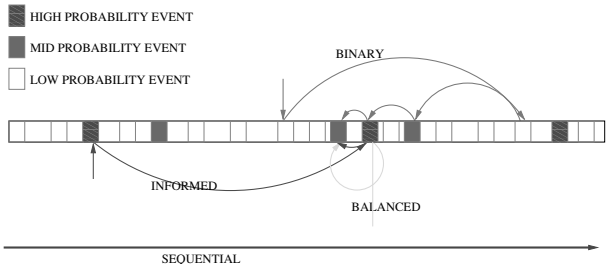


Figure 4: Search Strategies: Sequential follows a straight path. Binary Search reduces space by half in each step, Informed follows a strict order between probabilities, Balanced behaves in a probability-weighted Binary Search fashion.

3.1.2 Binary Search Strategy

We use the observation that corruption errors are not transient in nature and hence, if data is found to be corrupt at any time T_i, the data would remain corrupt for all timestamp $T_j > T_i$. This order preservation in corruption testing allows us to partition the search space quickly. We use the intuition of binary-search algorithms that partitioning a search space into two equal sized partitions leads one to converge to the required point in logarithmic time steps instead of linear number of steps. Hence, for a search space with $N_c(t)$ checkpoints at any given time t, $scanRecordsBinary$ returns the timestamp corresponding to the $(N_c(t)/2)^{th}$ checkpoint record for inspection. If the data corresponding to the timestamp is corrupt, we recursively search for corruption in the timestamps between the 0^{th} and $(N_c(t)/2)^{th}$ checkpoints. On the other hand, if the data is clean, our inspection window is now the timestamps between the $(N_c(t)/2)^{th}$ and the $N_c(t)^{th}$ checkpoint records. It is easy to see that since the inspection window reduces by a factor of 2 after every check, we would complete the search in $\log N_c$ steps and the total time (expected as well as worst case) spent in *recovery point identification* is given by $\log N_c(C_t + C_p + C_lT_p/2)$.

3.1.3 Informed Search Strategy

While identifying the next timestamp to test for corruption, the *Binary Search* strategy selects the next checkpoint without taking into account the probability that the particular checkpoint was correlated with corruption. Our next strategy, called the *Informed* strategy, uses the probabilities associated with the checkpoint records to decide the next timestamp to examine. At any given time, it figures out the checkpoint j that has the highest likelihood ($p_{i,j}$) of being correlated with the corruption c_i. Hence, for cases where data corruption is associated with a rare event, the search may terminate in a constant number of steps (constant number of timestamps are examined) or take upto N_c steps in the adversarial worst case. However, as long as the probability $p_{i,j}$ of a particular checkpoint being the cause of corruption is uncorrelated with the time of its occurrence, the search would still reduce the space exponentially and is expected to terminate in logarithmic steps. Formally, we have the following result for the expected running time of *Informed Search*.

Theorem 1 *The* Informed Search *Strategy identifies the most recent uncorrupted data in* $O(\log N_c(C_t + C_p + C_LT_p/2))$.

Proof: To prove the result, it is sufficient to prove that the search is expected to examine only $O(\log N_c)$ timestamps before it finds the most recent uncorrupted entry. It is easy to see that the average cost of testing a given timestamp is given by $C_t + C_p + C_LT_p/2$.

Observe that as the highest probability checkpoint is uncorrelated with its timestamp, each of the N_c checkpoint records are equally likely to be examined next. Further, if the i^{th} checkpoint is examined, it divides the search space into two partitions, and we need to examine only one of them after the check. Hence, the recurrence relation for the search algorithm is given by

$$\begin{aligned} T(N_c) \quad &\leq \tfrac{1}{N_c}(T(N_c-1) + T(1) + ... + T(i) + \\ &\quad T(N_c - i) + ... + T(1) + T(N_c - 1)) \end{aligned} \tag{3}$$

One may observe that $T(N_c) = \log N_c$ satisfies the recurrence relation. To verify, note that the right hand side of the equation reduces to $1/N_c \log N_c!^2$, if $T(N_c)$ is replaced by $\log N_c$. Hence, we only need to show that $T(N_c) < c \log N_c$ for some constant c

i.e., $\frac{\log(N_c!)^2}{N_c} < c \log N_c$
i.e., $\log(N_c!)^2 < cN_c \log N_c$
i.e., $\log(N_c!)^2 < c \log N_c^{N_c}$
which holds for $c = 2$ by using the fact that $N_c!^2 > N_c^{N_c} > N_c!$. This completes the proof. ■

3.1.4 Balanced Search Strategy

The *Informed Search* strategy attempts to find the corruption point quickly by giving greater weightage to checkpoints that have a higher correlation probability with the corruption. On the other hand, *Binary Search* strategy prunes the space quickly oblivious to the probabilities associated with the checkpoint records. We combine the key idea of both these heuristics to design the $scanRecordBalanced$ algorithm (Fig. 5). The algorithm computes the total search time in an inductive manner and selects the checkpoint record that minimizes the expected running time.

```
algorithm scanRecordsBalanced
 P(L) = 0; P(R) = 1; currMin = ∞
 for i in start to end
  T(i) = P(L) log(i-start) + P_{i,j} + P(R) log(end-i)
  P(L) = P(L) + P_{i,j}; P(R) = P(R) − P_{i,j}
  if T(i) < currMin
    currMin = T(i)
 end for
 return checkpoint of currMin
end scanRecordsBalanced
```

Figure 5: Balanced Scanning Algorithm

Intuitively speaking, the *Balanced* strategy picks the checkpoint records that (a) are likely to have caused the corruption and (b) partition the space into two roughly equal-sized partitions. The algorithm strikes the right balanced between partitioning the space quickly and selecting checkpoints that are correlated with the current corruption c_j. We have the following optimality result for the balanced strategy.

Theorem 2 *The balanced strategy miminizes the total expected search time required for recovery.*

Proof: In order to prove the result, we formulate precisely the expected running time of a strategy that picks a checkpoint record i for failure j. The expected running time of the strategy is then given in terms of the size and probabilities associated with the two partitions L and R.

$$T(N) = P(L)T(L) * C_{tot} + P_{i,j} * C_{tot} + P(R)T(|R|) * C_{tot} \quad (4)$$

where $P(L)$ and $P(R)$ are the accumulated probabilities of the left and right partitions respectively, and C_{tot} is the total cost of creating and testing data for any given timestamp. Using the fact that $T(L)$ can be as high as $O(\log |L|)$ in the case where all checkpoint records have equal probabilities, we modify Eqn. 4 by

$$T(N) = P(L) \log |L| * C_{tot} + P_{i,j} * C_{tot} + P(R) \log |R| * C_{tot} \quad (5)$$

Hence, the optimal strategy minimizes the term on the right hand side, which is precisely what our balanced strategy does (after taking the common term C_{tot} out from the right hand side). This completes the proof. ■

4 Implementation

We have implemented $SWEEPER$ as a pluggable module in a popular SRM (Storage Resource Manager) product, and it can use any CDP product. We use the SRM's *Event Bus* to drive the checkpoint record generation process in $SWEEPER$. The output of $SWEEPER$ is a timestamp T_e that is fed to the *CDP Recovery Module*, and the $CDP\ System$ rolls back all updates till time T_e. Since we can leverage many components from the SRM, the only components we needed to implement for $SWEEPER$ were *SWEEPER Event Analyzer and Checkpoint Generator*, *SWEEPER Knowledge Database*, *SWEEPER CDP Record Scanner*, and *SWEEPER Checkpoint Record Locator*. Details of the algorithms implemented by *SWEEPER CDP Record Scanner* and *SWEEPER Checkpoint Record Locator* have been presented in Sec. 3 and we restrict ourselves to describing the implementation of the remaining components in this section. We start with the checkpoint record structure and its implementation.

4.1 Checkpoint Record Structure and Database

In our implementation, we use a relational database to store the checkpoint records for each event or event-set. Each checkpoint record consists of (i) *Checkpoint Record ID* (ii) *Timestamp* (iii)*Scope* (iv) *Failure Type*, and (v) *Correlation Probability*. *Checkpoint Record Id* is an auto-generated primary key and *Timestamp* corresponds to the time the event-set occured (consists of year, month, day, hour, minute, second), and is synchronized with the CDP system clock. *Scope* describes whether the event-set is relevant for a particular physical device (e.g, switch, host, storage controller), or a software component (e.g., file system, database system), or a logical construct (e.g., file, table, zone, directory) and is used for quickly scoping the checkpoint records during recovery. *Failure Type* specifies the types of failure the checkpoint is relevant for is also used to scope the checkpoint records during recovery processing. The failure types (hardware failure, configuration error etc) are

listed in Table 2. *Correlation Probability* is computed as the probability that data corruption happened at the same time as the occurence of the event or a set of events.

4.2 SWEEPER Knowledge Database

Event (e)	Source	$E(e\|c)$
Zoning Changes	Event Bus	Medium
LUN Masking	Event Bus	Medium
Access control changes	Event Bus	High
De-activating service	Event Bus	Medium
OS Update	Event Bus	Medium
Application Update	Event Bus	Medium
Driver Update	Event Bus	Medium
Firmware Update	Event Bus	Medium
New app deployment	Event Bus	Medium

(a)

Event (e)	Source	$E(e\|c)$
Writes in System Directory	DIR	High
Update of Registry startup entries	regedit	High
Writes to Files of specific type	DIR	Medium
Abnormal Network Activity	Perfmon, Nmap	Medium
Terminating Anti-virus Services	Win Event Viewer	Medium
High CPU Activity	Perfmon	Medium
SAN Activity	Event Bus	Low
Writes in registry and sysdir	DIR, regedit	High

(b)

Event (e)	Source	$E(e\|c)$
RSE Threshold Violation	SMART	High
SKE Threshold Violation	SMART	High
Mechanical Shock	SMART	Low
Opening of Unit	Manual	Low
Temperature Increase	SMART	Medium
Disk Scrubbers	Event Bus	Medium

(c)

Event (e)	Source	$E(e\|c)$
fsck	SRM	High
Exchange edbutil	Event Bus	High
Exchange eseutil	Event Bus	High
App Specific file updates	Event Bus	High
App Specific registry updates	Event Bus	High

(d)

Table 2: Monitored Events e_i of failure types (c_j): (a) Misconfiguration (b) Virus (c) Hardware related and (d) Application, along with their monitoring source and expert information ($P(e_i|c_j)$)

The $SWEEPER$ checkpoint record generation centres around an expert information repository that we call the *SWEEPER Knowledge Database*. The *Knowledge Database* is structured as a table and a row in the table represents an event or a set of events e_i, and details the source of the event, the failure type(s) c_j relevant to the event and the correlation probability $E(e_i|c_j)$ of the event with each relevant failure type. A split-view of the *Knowledge Base* is presented in Table 1. We use expert information derived from literature to generate the *Knowledge Database*. We obtained common configuration related probabilities from the proprietary level two field support team problem database of a leading storage company for storage area networks. We obtained hardware failure information from proprietary storage controller failure database of the same company. We obtained the virus failure information by looking at virus behavior for many common viruses at the virus encyclopedia site [28]. To elucidate with an example, for the corruption type of virus, we looked at the signature of the last 300 discovered viruses [28] and noted common and rare events associated with them. Based on how commonly an event is associated with a virus, we classified that event as having a low, medium or high probability to be seen in case of a virus attack. Because of the inherent noise in this expert data, we classify $P(e_i|c_j)$ only into low, medium and high probability buckets which correspond to probabilities of 0.1, 0.5 and 0.9 respectively.

The events listed in the *Knowledge Base* and monitored by the *Event Analyzer* can be classified into *Configuration Changes*: addition, update (upgrade/downgrade firmware, driver or software level) or removal of hardware and software resources and changes in security access control. These events are checkpointed as it is common for data corruption problems to occur when one upgrades a software level, or when one introduces a new piece of software or hardware resource. *Background Checking Processes*: successful or unsuccessful completion of background checking processes like virus scan, hardware diagnostics, filesystem consistency like fsck or application provided consistency checkers. These checkpoints provide markers for consistency in specific filesystems, databases or volumes. *Application Specific Changes:*Applications can provide hints about abnormal behaviour that may indicate corruption and $SWEEPER$ allows one to monitor such events. *Hardware Failures:* checksum/CRC type errors, self diagnostic checks like SMART, warnings generated by SMART etc. *Performance Threshold Exceeding:* High port actitvity, high CPU utilization etc. Performance Threshold Exceeding events like high port utilization or high CPU utilization is usually a symptom of either a virus attack, or an application that has gone astray. *Meta-data Update Changes:* Changes in system directory etc. Abnormal *Meta-data updates* indicate application misbehavior, which, in turn, can potentially lead to data overwrite or corruption problems.

4.3 Event Filtering and Checkpoint Record Creation

The SRM has client agents that subscribe to various types of events from hosts, switches, storage controllers, file systems and applications. These events are consolidated and presented as part of an event bus. $SWEEPER$ is only concerned about a subset of the events in the event bus and gets the list of relevant events from the *Knowledge Database* (Table 2). Once the rel-

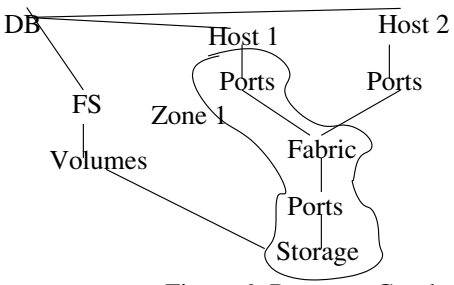


Figure 6: Resource Graph

evant events are filtered, the *Event Analyzer* generates a checkpoint record for the event along with its timestamp. Tight synchronization between the $SWEEPER$ event analyzer clock and the CDP system clock is not mandatory as the RPO granularity is no finer than 1 second. Hence, we perform hourly synchronization of the event analyzer clock with the CDP clock to ensure that the timestamps in the checkpoint records are reasonably accurate.

4.4 Checkpoint Record Scope Determination

The checkpoint record scope is useful in quickly filtering irrelevant checkpoint records, and thus, converge on the relevant CDP records. After the initial event filtering based on the information in the knowledgebase the checkpoint record generator examines the event type, and determines what data (files, DB tables or volumes) can be potentially affected by the event. We can only determine the scope for file/DB meta-data changes or configuration change related events. For other types of events the notion of scope is irrelevant. The value of scope is determined by traversing a resource graph. The resource graph information is stored in the systems resource manager configuration database. Fig. 6 shows a portion of the resource graph that is stored in the database. The nodes in the graph correspond to hardware and software resources, and the edges correspond to physical/logical connectivity or containment relationships. The basic structure of the resource graph is the SNIA SMI-S model. However, we have made extensions to this model to facilitate the modeling of application and database relationships. Fig. 6 illustrates how we traverse the resource graph when a configuration changing event occurs. If the user has added a new host and put its ports in Zone 1, then we determine all the storage ports (and the corresponding storage controllers) that are in zone 1. We then determine the storage volumes that are in those storage controllers and store the ids of the storage volumes in the scope field of the zoning event. During recovery, once the user has either manually or via an automated tool identified a corrupt file/table/volume, we search the checkpoint records that list the file/table/volume in its scope.

4.5 Checkpoint Record Probability Determination

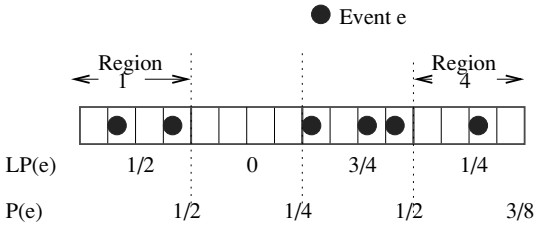


Figure 7: Estimating P(e) with window size (W) of 4 using Exponential-weighted Averaging

The key feature of the *SWEEPER* architecture is associating correlation probabilities with events to help any search strategy in speeding up the recovery flow. For every event e_i and corruption c_j, the correlation probability $P(c_j|e_i)$ denotes the probability that the corruption c_j happened in a given time interval t given that e_i has happened at t. The correlation probability is estimated using the Bayesian.

$$P(c_j|e_i) = (P(e_i|c_j).P(c_j))/P(e_i) \quad (6)$$

In order to compute the correlation probability, one needs to estimate $P(c_j)$, $P(e_i)$ and $P(e_i|c_j)$. $P(e_i)$ is estimated by looking at the event stream for the event e_i and using an exponential-weighted averaging to compute the average frequency of the event e_i. To elaborate further, the time line is divided into windows of size W each (Fig. 7), and for any window w_k, the number of occurrences n_i^k of each event e_i is noted. The local probability of event e_i in the window w_k (denoted by $LP(e_i^k)$) is calculated as n_i^k/W. In order to take into account the historical frequency of the event e_i and have a more stable estimate, the probability of an event e_i in the time window r_{k+1} ($k \geq 0$) is damped using the exponential decay function (Eq. 7). For the first window, the probability is same as the local probability.

$$P(e_i^{k+1}) = 1/2(P(e_i^k) + LP(e_i^{k+1})) \quad (7)$$

The $P(e_i|c_j)$ estimates are obtained from the *Knowledge Database*. The final parameter in Eqn. 6 is $P(c_j)$. However, note that whenever checkpoints are being examined to figure out the source of a corruption c_j, all the checkpoints would have the same common term $P(c_j)$. Hence, $P(c_j|e_i)$ is computed by ignoring the common term $P(c_j)$ for all the N events, and then normalizing the correlation probabilities so that $\sum_{i=1}^{N} P(c_j|e_i) = 1$. The correlation probabilities thus computed are stored in the checkpoint records for use in the recovery flow.

5 Evaluation

We conducted a large number of experiments to analyze the performance of our search algorithms and study the salient features of our checkpoint-based *SWEEPER* architecture. We now report some of the key findings of our study.

5.1 Experimental Setup

Our experimental setup is based on the implementation described in Sec. 4 and consists of the architectural components in Fig 2. Since real data corruption problems are relatively infrequent events, we simulate a *Fault Injector* component in the interest of time. The *Fault Injector* takes as input a probabilistic model of faults and its possible signatures and generates one non-transient fault along with the signature. Since our $SWEEPER$ implementation is not integrated with any CDP system, we have also simulated a *CDP System Modeler and Problem Determination Scanner*. We have assumed that the *Problem Determination Scanner* can accurately identify if a copy of data is corrupt or not. The *CDP System Modeler* models the underlying storage and CDP system and provides the cost and time estimates for various storage activities like the time of applying a CDP log, making a PIT copy available for use or the time to test a snapshot for corruption. Finally, we use an *Event Generator* that mimics system activity. It takes as input a set of pre-specified events and their distribution and generates events that are monitored by the SRM and fed to the $SWEEPER$ *Event Analyzer* via the SRM *Event Bus*.

The key contribution of the checkpoint-based architecture is to correlate checkpoint records with corruption failures using the correlation probabilities $p_{i,j}$. Hence, we test our search algorithms for various distributions of $p_{i,j}$, which are listed below. We use synthetic correlation probability distributions because of the lack of authoritative traces of system and application events that would be applicable on a wide variety of systems. We have carefully inspected the nature of event distributions from many sources and use the following distributions as representative distributions of event-corruption probability.

- Uniform Distribution: This captures the setting where correlation information between checkpoints and corruption is not known and all system events are considered to be equally indicator of corruption.
- Zipf Distribution: The zipf distribution is commonly found in many real-life settings and capture the adage that the probability distribution is skewed towards a handful of events. For our experimental setting, this captures the scenario where only a few events are the likely causes of most of the failures.
- 2-level Uniform Distribution: A 2-level (or generally speaking a k-level) uniform distribution has 2 (or k) types of event-types where all the events belonging to any given type have the same probability of having caused the corruption. However, certain event-types are more likely to have caused the error than other event-types and this is captured by having more than 1 level of probabilities.

One may note that the uniform and zipf distributions capture the two extremes in terms of skewness, that the correlation distribution $p_{i,j}$ may exhibit in practice. Hence, a study with these two extreme distributions not only capture many real settings, but also indicate the performance of the algorithms with other distributions as well.

Our first set of experiments studied the scalability and effectiveness of the *Checkpoint Generation Flow*. In the second set of experiments, we evaluate the various search strategies in the *Recovery flow.* We conducted experiments for scalability (increase in number of checkpoint records N_c) and their ability to deal with recovery time constraint (D_{rec}). We also study the usefulness of a 2-tier checkpoint record structre and the robustness of the $SWEEPER$ framework with false negatives (probability that the error is not captured in the event stream) and noisy data (error in correlation probability estimation). Since the *CDP system* was simulated, we had to manually fix the various parameters of the *CDP system* to realistic values. We kept the time taken to check the data corresponding to any given timestamp (C_t) as 10000 seconds, the time taken to get a PIT copy online (C_p) as 10 seconds, and the time taken to create the snapshot using the CDP logs ($C_l(T_i \% T_p)$) as 100 seconds.

5.2 Experimental Results

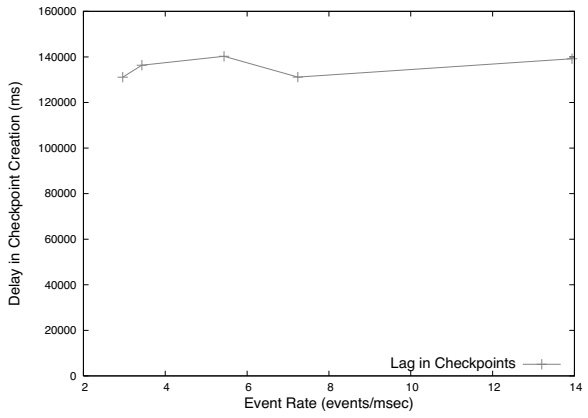


Figure 8: Lag in Checkpoint Records with Increasing Event Rate

We first investigated the scalability of our *Checkpoint Record Generation Flow* implementation to keep pace

with events as the SAN size grows. Hence, the *Event Generator* increases the number of resources managed by the Storage Resource Manager and generates more events, that are fed to the *Event Analyzer*. We observed that our *Event Analyzer* is able to efficiently deal with increased number of events (Fig. 8) and the lag in checkpoint record is almost independent of the event rate. We also observe that the checkpoint records lag by only 2mins and hence only the last 2 minutes of events may be unavailable for recovery flow, which is insignificant compared to the typical CDP windows of weeks or months that the recovery flow has to look into. The efficiency of the checkpoint flow is because (a) the computations in *Event Analyzer* (e.g., exponential-decay averaging) are fairly light-weight and (b) depend only on finite-sized window (Sec. 4.5), thus scaling well with number of events.

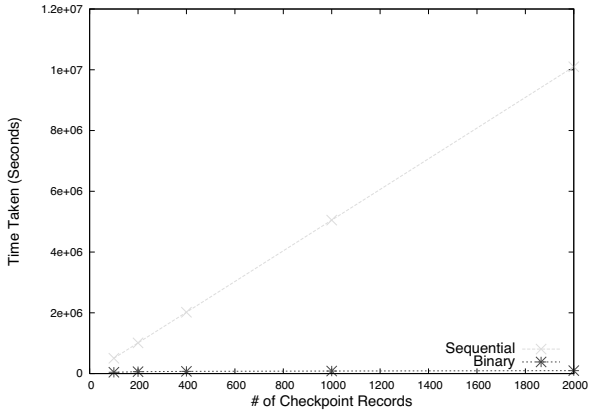


Figure 9: Recovery Time for Sequential and Non-sequential strategies under Uniform probability checkpoints

We next focus on the *Recovery Flow* and investigate the impact of using a non-sequential strategy as opposed to sequential checking. Fig 9 compares the time taken to find the most recent uncorrupted version of data by the sequential and the binary search strategies, for a uniform probability distribution. Since the probability of all checkpoints are equal, *Informed* as well as *Balanced* strategy have similar performance to *Binary Search*. For the sake of visual clarity, we only plot the performance of *Binary Search* algorithm. It is clear that even for small values of N, sequential algorithm fares poorly because of the $N/\log N$ running time ratio, and underlines the need for non-sequential algorithms to speedup recovery. For the remainder of our experiments, we only focus on non-sequential strategies and study their performance.

5.2.1 Performance under different distributions

We next studied the relative performance and scalability of the proposed non-sequential strategies for various correlation probability distributions. Fig 10(a) and Fig 10(b) studies the performance of the three non-sequential strategies with increase in the number of checkpoint records under Zipf and 2-level uniform probability distribution for checkpoints. We observe that the *Balanced search strategy* always outperforms the *Binary* search strategy. This validates our intuition that since *Balanced* strategy partitions the search space by balancing the likelihood of corruption in the partitions rather than the number of checkpoint records it converges much faster than binary. The gap in performance is more for the Zipf distribution than 2-level Uniform distribution, as the more skewed Zipf distribution increases the likelihood of partitions with equal number of checkpoints to have very different accumulated correlation probabilities. The *Informed* search strategy performs well under Zipf distribution as it has to examine very few checkpoint records, before it identifies the recovery point. For small N, *Informed* even outperforms the *Balanced* strategy, which takes $O(logN)$ time, while *Informed* runs in small number of constant steps, with very high proba-

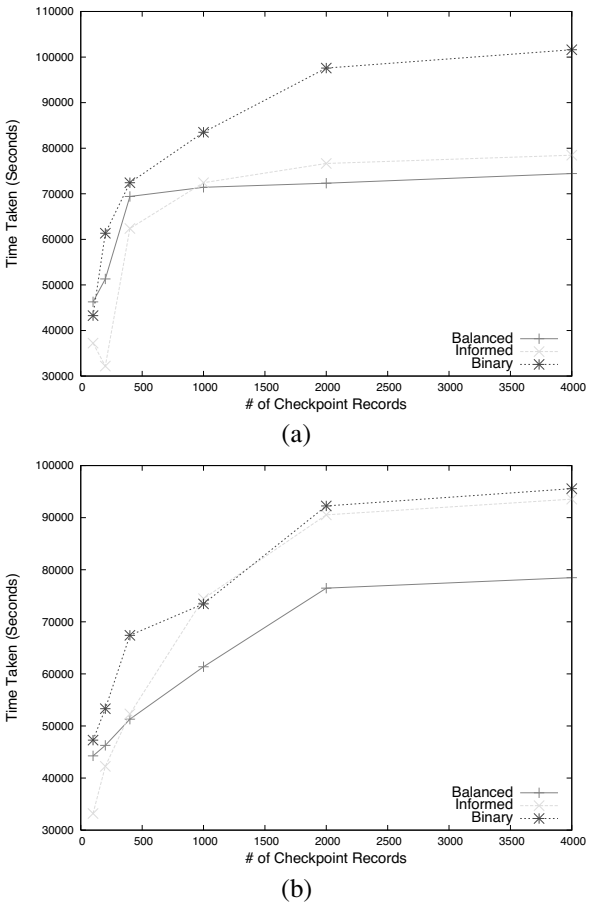
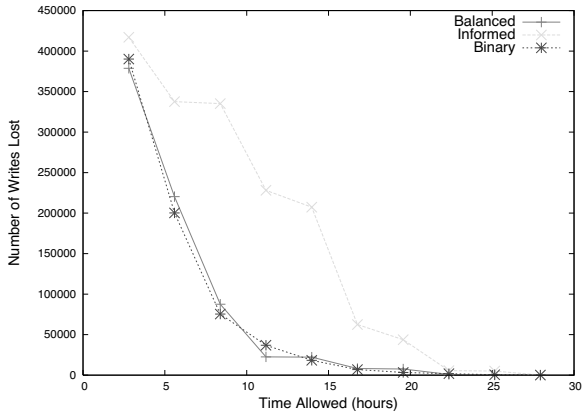


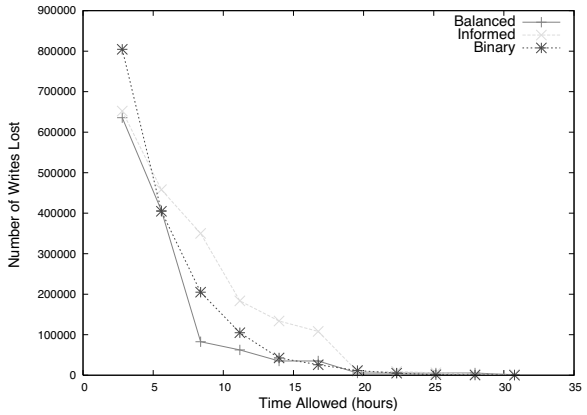
Figure 10: Recovery Time for Non-sequential strategies for (a) zipf distributed checkpoints and (b) 2-level uniform probability checkpoints

bility. Thus, if the operator has high confidence in the events associated with different types of corruption, *Informed* may be the strategy of choice. One may observe for the 2-level uniform correlation probability case that, as the number of checkpoints increase, the performance of *Informed* degrades to that of *Binary* search. This is because the individual probability of each checkpoint record (even the checkpoints associated with the higher of the 2 levels) falls linearly with the number of points and hence, convergence in constant steps is no longer possible and *Informed* search converges in $\log N$ time, as predicted by Theorem 1. These experiments bring out the fact that the greedy *Informed* strategy is not good for large deployments or when the the number of backup images are large.

5.2.2 Data Currency and Execution Time Tradeoff



(a)



(b)

Figure 11: Data Currency for Non-sequential strategies with Recovery Time Constraint under (a) 2-level uniform distribution and (b) Zipf Distribution

We next modify the objective of the search algorithms. Instead of finding the most recent clean datapoint, the recovery algorithms now have a constraint on the recovery time and need to output a datapoint, at the end of the time window. Fig 11(a) and Fig 11(b) examine the tradeoff between the recovery execution time and the data currency at the recovery point for 2-level uniform and Zipf distributions respectively. Data currency is measured in terms of lost write updates between the most recent uncorrupted copy and the copy returned by the algorithms.

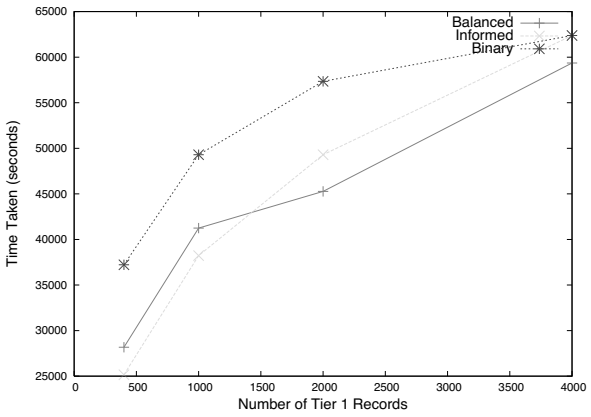


Figure 12: Recovery Time for Non-sequential strategies with 2-tier architecture

The largest difference in performance under the two distribution is for the *Informed* strategy. It performs well under Zipf, since it starts its search by focusing on the few high probability checkpoints to quickly prune the search space. Under 2-level uniform distribution, it performs poorly as compared to the other strategies overall but more so when recovery time is less. This is because it evaluates the uniform probability events in a random order, which on an average leads to more unbalanced partitions, as compared to the other two strategies. Intuitively, both the *Binary* and *Balanced* strategies aim to reduce the unexplored space in each iteration. Hence, they minimize the distance of the error snapshot from the set of snapshots checked by them. On the other hand, *Informed* does not care about leaving a large space unexplored by it, and hence before it finds the actual error times, its best estimate of error time may be way off the actual error time. A similar observation can be made if the algorithms aim to achieve a certain (non-zero) data-currency in the minimum time possible. By reversing the axis of Fig. 11, one can observe that both *Binary* and *Balanced* strategies achieve significant reduction in data-currency fairly quickly, even though *Informed* catches up with them in the end. Hence, when the recovery time window is small, the use of *Informed* strategy is not advisable.

5.2.3 Checkpoint Selection using 2-tiers

We next investigate the impact of using a 2-tiered checkpoint record structure on the performance of the algo-

rithms. In a 2-tiered record structure, the algorithms execute on only a subset of checkpoint records consisting of high probability checkpoint records. The idea is that the recovery point is identified approximately by running the algorithms on the smaller set of records and then locate the exact recovery point using the checkpoints in the neighborhood. For the plot in Fig 12, checkpoints are assigned probabilities according to 2-level uniform distribution with 5% of checkpoints having 90% cumulative probability. Further, only 10% of total checkpoints are promoted to the high probability tier, and hence the skew in the high-tier checkpoints is much lower than a single tier checkpoint record structure. We observe in Fig. 12 that, as compared to a single tier checkpoint records (Fig 10(b)), the performance gap between binary and balanced reduces significantly. This is because the binary strategy reaps the benefit of operating only on the high probability checkpoint subset, making it closer in spirit to the balanced strategy. Thus, a 2-tiered checkpoint architecture, makes the probability oblivious *Binary Search* algorithm also probability-aware, by forcing it to operate only on checkpoints that have a high correlation probability with the corruption.

5.2.4 Robustness of the Algorithms with incomplete information

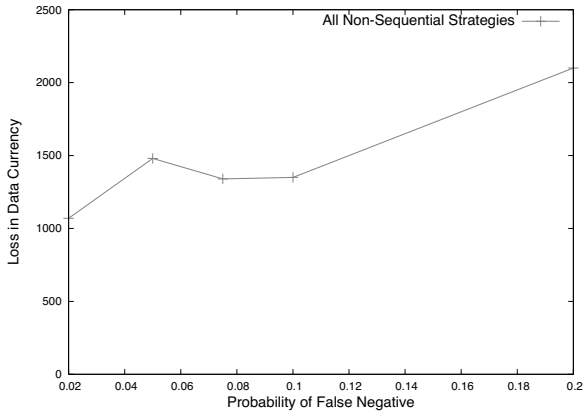


Figure 13: Data Currency Loss for Non-sequential strategies with Probability of False Negatives

We next investigate the robustness of our proposed algorithms to deal with silent errors; i.e. an error that does not generate any events. We model silent errors using false negatives (probability that the error is not captured in the checkpoint records). Fig. 13 studies the loss in data currency with increase in false negatives. For this experiment, the average number of CDP logs between any two events was kept at 2000, and we find that the non-sequential strategies are able to keep the data currency loss below or near this number even for a false negative of 20%. Our results show the correlation probability-aware algorithms like *Balanced* and *Informed* are no worse than correlation proability-unaware algorithms like *Sequential* and *Binary*. Hence, even though these strategies factor the correlation probability while searching, they do not face significant performance penalty, when the error event is not captured in the checkpoints.

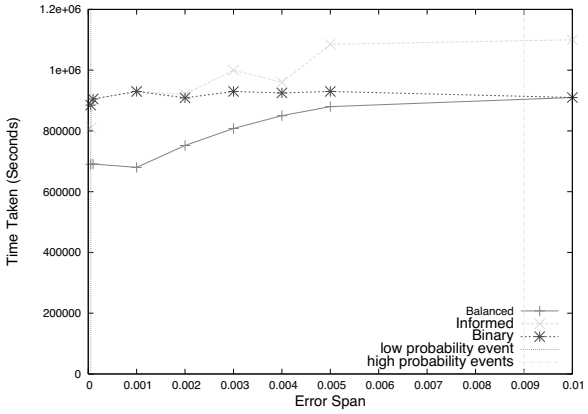


Figure 14: Recovery Time with Increasing Error for Non-sequential strategies

In practice, the expert-given values for $P(e_j|c_i)$ as well as the computed $P(e_j)$ have estimation errors and the algorithms should be robust enough to deal with noise in correlation probability estimates. Fig. 14 shows the recovery time taken by the various algorithms for the 2-level probability distribution, as the expert data and event stream becomes noisy. The noise is generated by adding a zero mean uniform distribution to the correlation probabilities, where the range of the noise is varied from 0 to the probability of the highest probability event. Note that the two vertical lines indicate the probability of the two types (levels) of events in the 2-level distribution and as the noise (error) approaches the right line, the standard deviation of the noise becomes greater than the mean of the original signal (or correlation probability). In such a situation, the correlation probabilities lose their significance as the complete data can be thought of as noise. The key observation in this study is the sensitivity of *Informed strategy* to the accuracy of correlation probabilities and the robustness of *Balanced Strategy* to noise. We observed that *Balanced Strategy* showed a graceful degradation with increase in error, degenerating to *Binary Strategy* even when the correlation probability had only noise, whereas *Informed Strategy* showed a steep increase in recovery time. This is not surprising, given that *Informed Strategy* only considers the individual correlation probability and suffers with increased estimation error. On the other hand, *Balanced Strategy* takes into account cumulative probabilities, which are not effected as much by the zero mean noise until noise dominates the original signal. Even in the case where error dominates

the original probabilities, *Balanced* performs as well as the *Binary* strategy underlining its usefulness as an effective, versatile and robust strategy.

6 Discussion and Related Work

We present in this paper a scalable architecture and efficient algorithms that help administrators deal with data corruption, by quickly rolling back to a an earlier clean version of data. The related work in this area can be broadly classified into techniques for (a) *Data Resiliency and Recovery*, (b) *Event Monitoring and Logging*, (c) *Indexing:* Correlating events with corruption and using the correlation values as index and (d) *Searching* the event logs for quick identification of the failure point.

Continuous Data Protection (CDP) solutions deal with data corruption by allowing an administrator to roll back at a granularity that is much finer than what was possible with traditional continuous copy or backup solutions. CDP solutions have been proposed at file level [26] and at block level in the network layer [16, 21, 30, 15]. Versioning file systems [25, 20] that preserve earlier versions of files also provide the CDP functionality. CDP logs allow users to revert back to earlier data versions but leaves the onus of determining a recovery point on the administrator. A brute-force approach examining all CDP logs could lead to unacceptably high recovery time. To alleviate this, some products such as [16, 21, 30] incorporate *Event Monitoring and Logging* with the basic *Data Resiliency* mechanisms and allow applications to record specific checkpoint records in the CDP log, which then serve as landmarks in the log stream to narrow down the recovery point search. However, these solutions present no *Indexing and Searching* mechanism and the administrator has to devise a search strategy between the checkpoints, where all checkpoints are as equally likely to be associated with the failure. Our work builds on existing solutions by (i) using system events along with application events to generate checkpoints, (b) attaching correlation probabilities with the checkpoints, and (c) providing CDP log processing algorithms that use these probabilities intelligently to automatically identify a good recovery point quickly.

The use of *Searching* and Mining techniques on an *Event Log* has been very popular in the area of problem [9] detection and determination in large scale systems. Numerous problem analysis tools [29], [32], [13] have been proposed that aid in the process of automating *Searching* the logs for problem analysis. A major issue in application of these techniques in large systems is the complexity of the event collection and subsequent analysis. Xu et al. [31] propose a flexible and modular architecture that enables addition of new analysis engines with relative ease. Kiciman et al. [12] use anomalies in component interactions in an Internet service environment for problem detection. Chen et al. [4] use a decision tree approach for failure diagnosis in eBay production environment. File system problem determination tools have been proposed [32] [13] that monitor system calls, file system operations and process operations to dynamically create resource graphs. Once the system administrator detects that there is a problem, these tools help to quickly identify the scope of the problem with respect to the affected files and processes. Similarly, Chronus [29] allows users to provide customized software probes that help in identifying faulty system states by executing the probe on past system states that have been persisted on disk. They select past system states (virtual machine snapshots for a single machine) using binary search. Hence, Chronus addresses two of the problems, namely *Event Monitoring* and *Searching* that $SWEEPER$ handles. Even though it solves a completely different problem from $SWEEPER$, Chronus is most similar to $SWEEPER$ in spirit. However, Chronus does not distinguish between different event checkpoints, whereas we index the checkpoints based on correlation probabilities and design a search strategy that uses this information for fast convergence. Further, we provide the user the flexibility to tradeoff on the data currentness/recovery time trade-off by appropriately setting the RTO and RPO values. Finally, the focus of our paper is on data corruption on disk in a distributed environment whereas Chronus deals with system configuration problems for a single machine.

The novelty of $SWEEPER$ lies in integrating *Event monitoring*, *Checkpoint Indexing*, and new search techniques that are able to make use of the index (correlation) information. A possible weakness of $SWEEPER$ lies in its inherent design that is based on checkpoint events: $SWEEPER$ depends on events to provide hints for corruption and silent errors or noise in the event-corruption correlation may degrade $SWEEPER$'s performance. However, the proposed search algorithms do a balancing act between searching events with high correlation probabilities and pruning the search space in logarithmic time. Our study suggests the use of *Balanced Search* as the most robust strategy for efficient *Recovery Point Identification*. The *Balanced Search* strategy finds a good recovery time for silent errors by degenerating to *Binary Search*. The only scenario where *Balanced Search* is (marginally) outperformed is in the case of *probability skew*: a few checkpoints capture most of the correlation probability and *Informed Search* is the best performer. Our study makes a strong case of using search algorithms that use the correlation between system events and corruption to quickly recover from data corruption failures.

7 Conclusion

In this paper we presented an architecture and algorithms to quickly identify clean data in CDP record stream. The basic idea of our system is to monitor system events and generate checkpoint records that provide hints about potential data corruption. Upon discovering data corruption, system administrators can pass RTO and RPO requirements as input to our system, and it returns the most relevant checkpoint records. These checkpoint records point to locations in the CDP record stream that potentially will provide clean data. We use expert knowledge, resource dependency analysis, and event co-relation analysis to generate the checkpoint records. Upon the discovery of data corruption, system administrators can use $SWEEPER$ to quickly identify relevant CDP records. We present different CDP record traversal algorithms to help traverse the CDP record stream to identify recovery points. Our studies suggest the use of *Balanced Search* strategy as the most robust strategy for efficient *Recovery Point Identification*. However, in an environment where checkpoints with high correlation probabilities are very few, the *Informed Search* strategy seems to be a good choice. Hence, the study emphasizes the need for either the log processing algorithms or the checkpoint architecture to be aware of correlation probabilities of various events. Furthermore, our study conclusively establishes the need for non-sequential search mechanisms to quickly identify good recovery points in a CDP environment as opposed to a linear sequential scanning of checkpoints.

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Notes

[1] Work done while at IBM India Research.